CITIES
Centre for IT Intelligent Energy Systems

What can we learn from meter data?

Kamstrup-AVA-DTU Meeting
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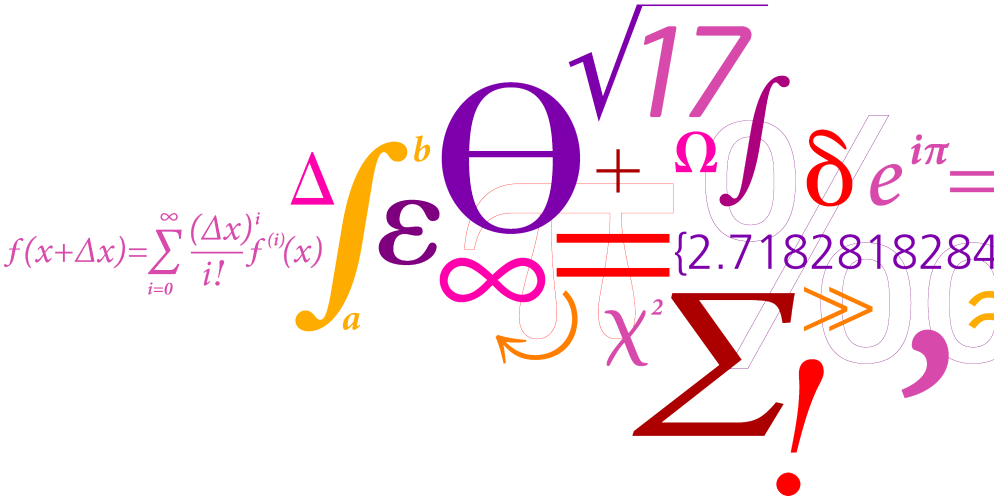


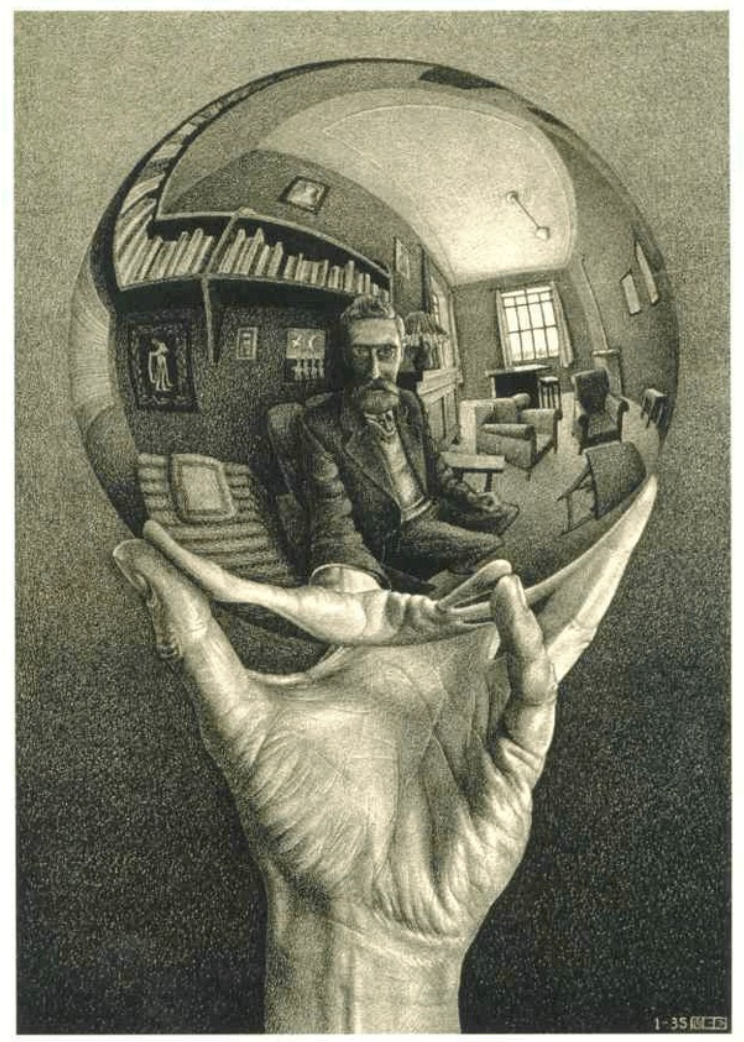
DTU Compute
Department of Applied Mathematics and Computer Science

Contents

- Non-parametric, conditional-parametric and semi-parametric models, ..
- RC-network, Lumped, ARMAX and grey-box models, ..
- Markov chain models, Generalized linear models, ..

Examples only!

Part 1
Non-parametric methods



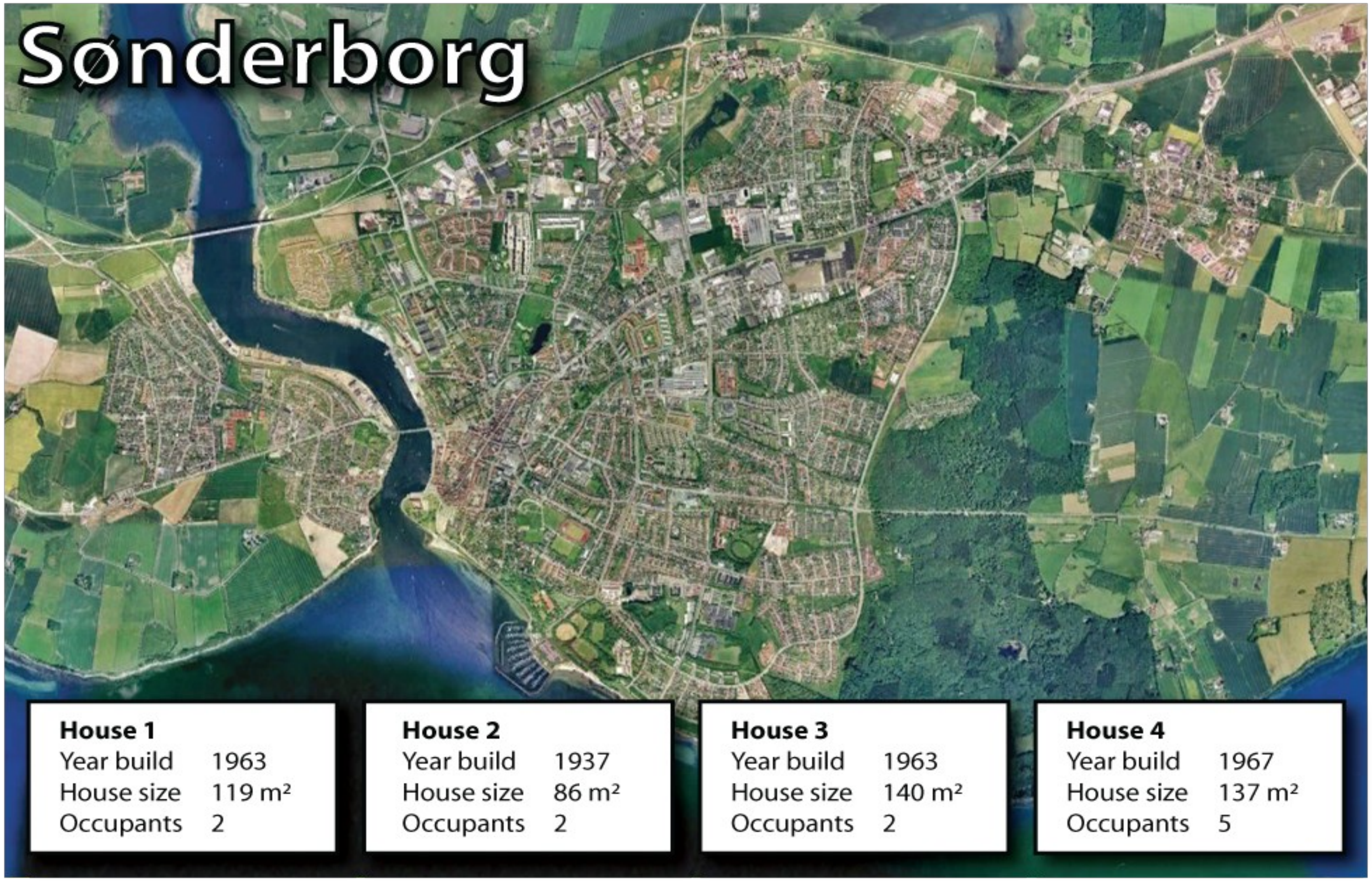
Typically only data from smart meter (and a nearby existing MET station)

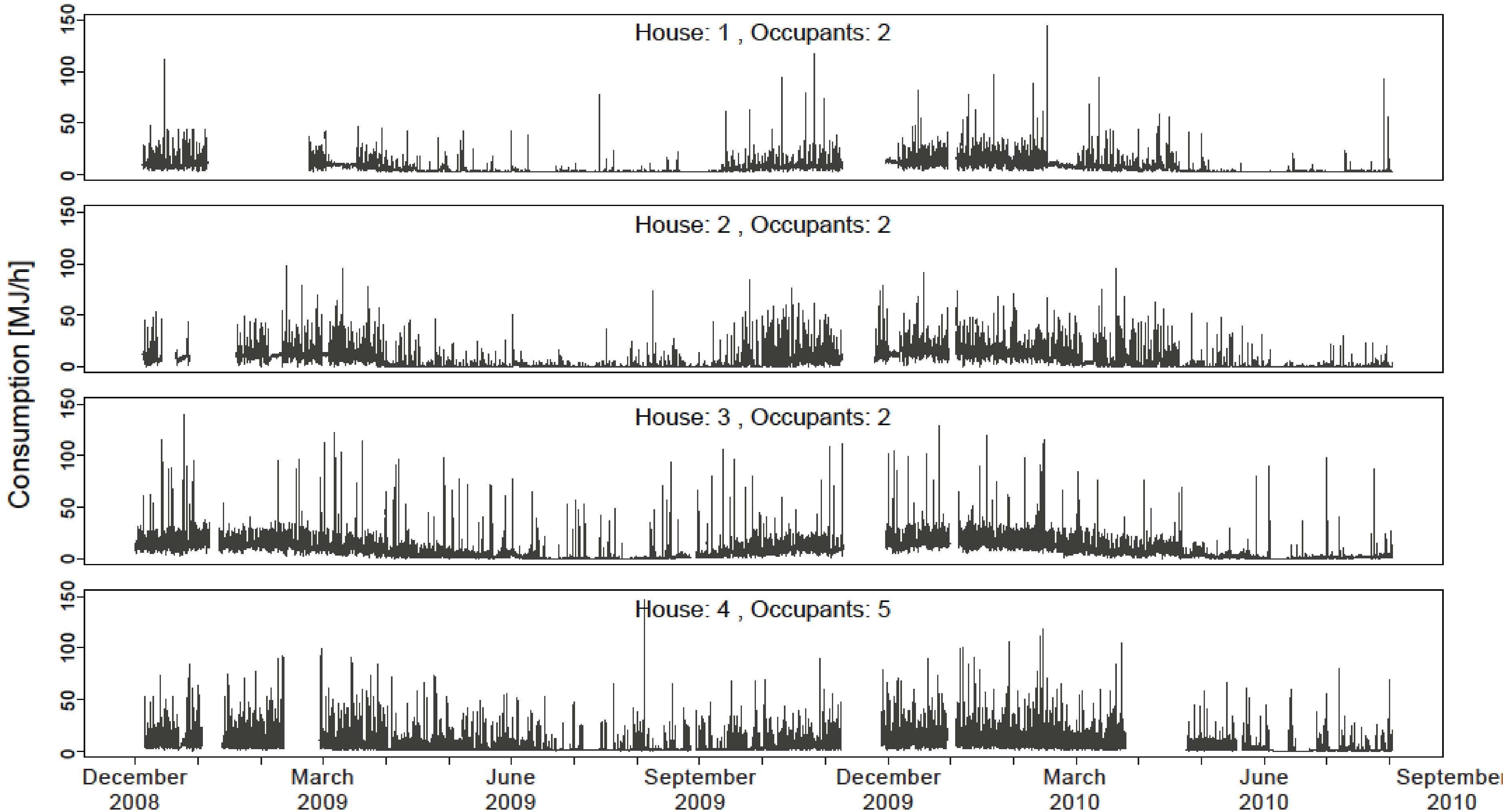
Case Study No. 1

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

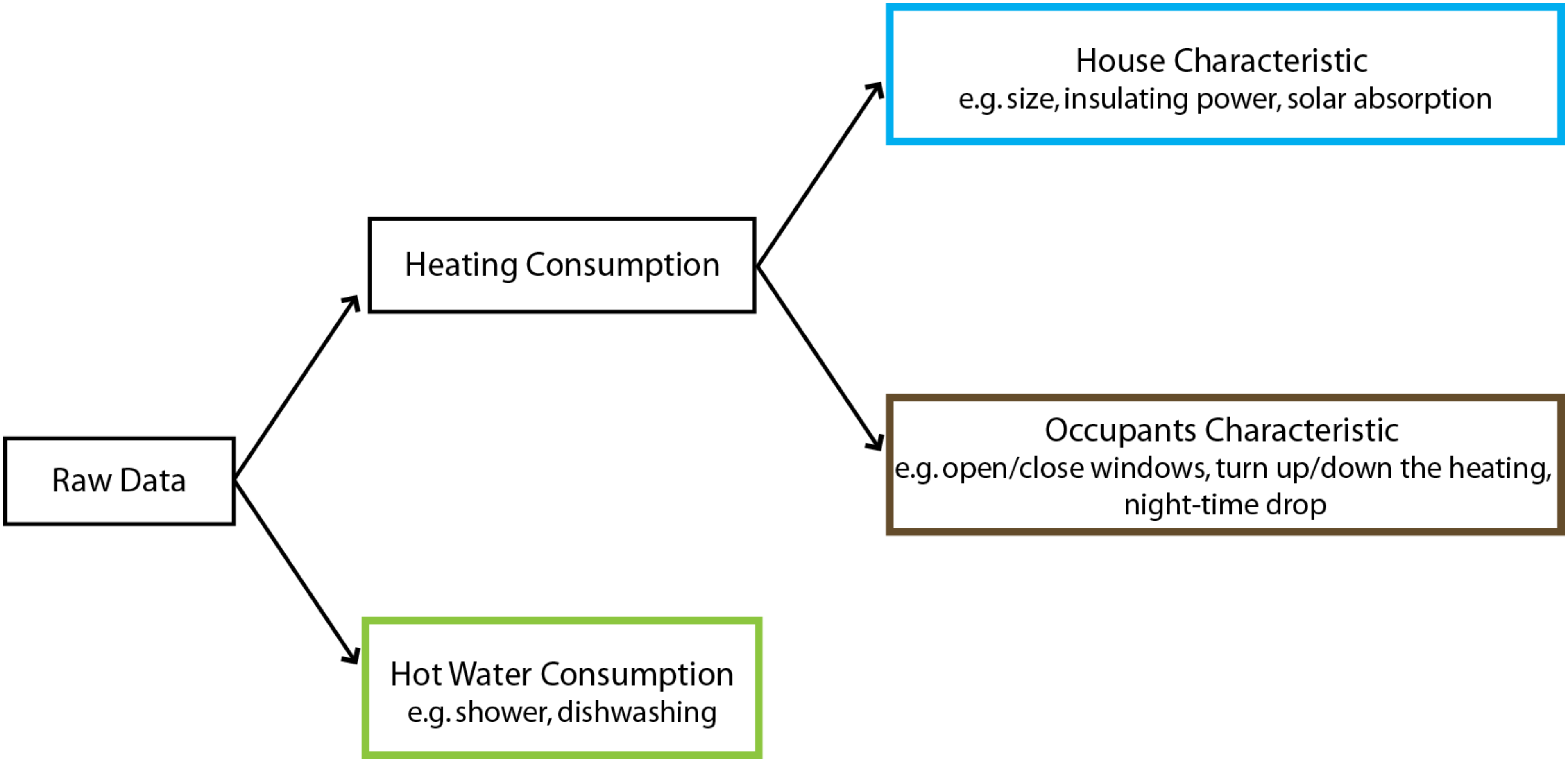
Data

- 10 min averages from a number of houses

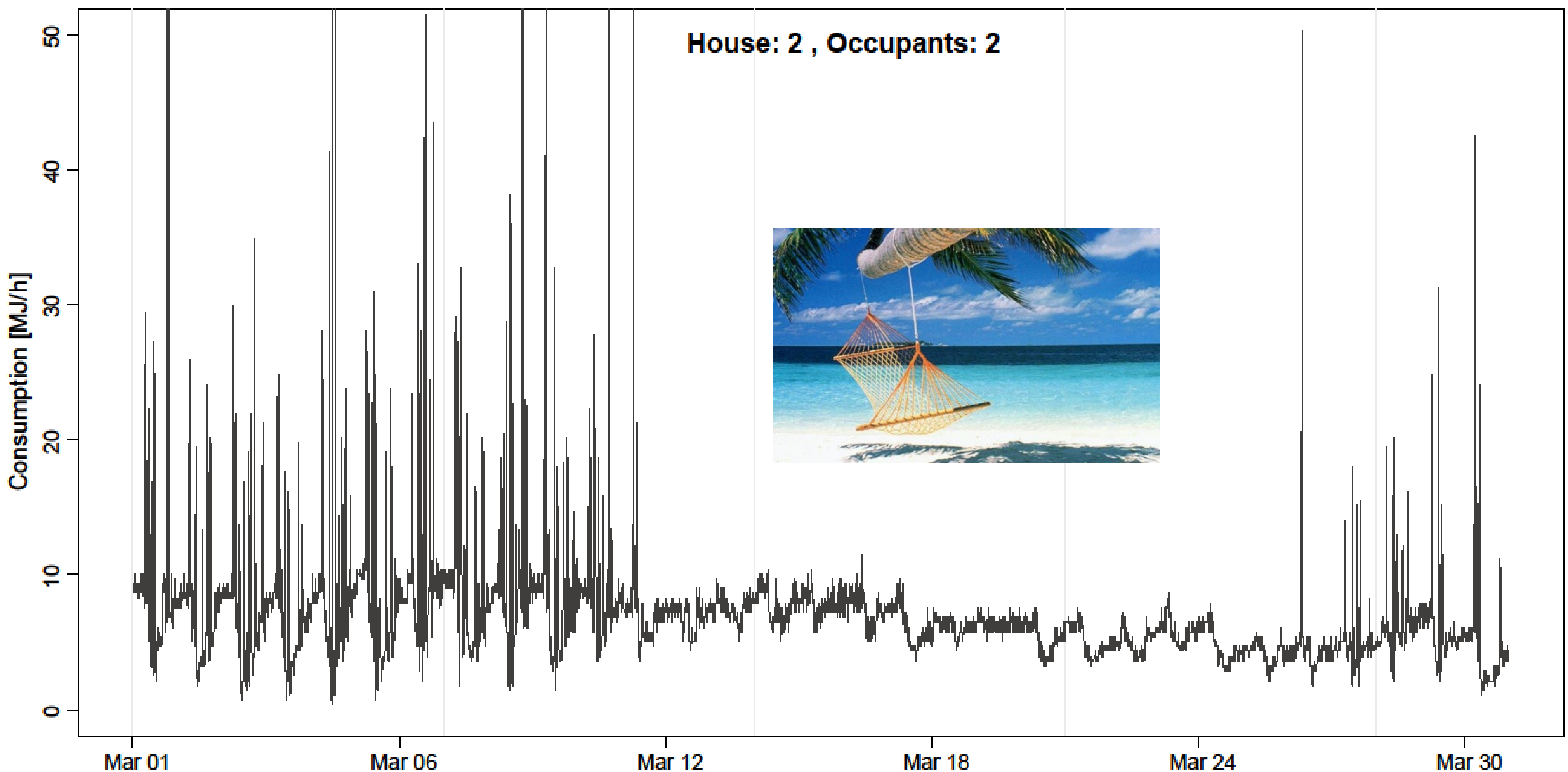



House: 1 , Occupants: 2
House: 2 , Occupants: 2
House: 3 , Occupants: 2
House: 4 , Occupants: 5
Consumption [MJ/h]
0
50
100
150
December 2008
March 2009
June 2009
September 2009
December 2009
March 2010
June 2010
September 2010

Splitting of total meter readings



Holiday period



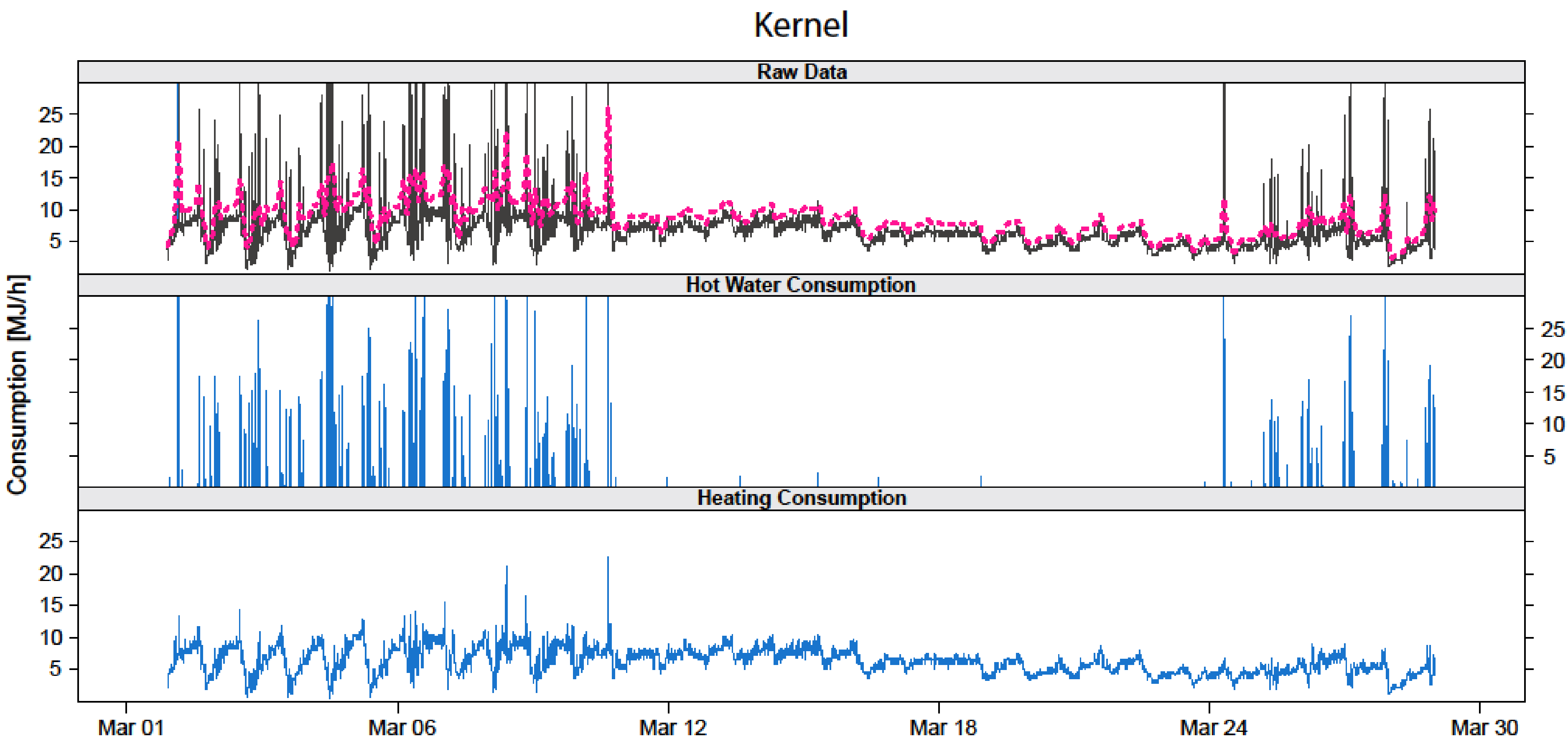
Non-parametric regression

$$\hat{g}(x) = \frac{\sum_{s=1}^{N} Y_s k\{\frac{x-X_s}{h}\}}{\sum_{s=1}^{N} k\{\frac{x-X_s}{h}\}}$$

$$k(u) = \frac{1}{2\pi} \exp\{-\frac{u^2}{2}\}$$

Weighted average

Every spike above $1.25 \cdot \hat{g}(x)$ Is regarded as hot water use.



Kernel
Raw Data
Hot Water Consumption
Heating Consumption
Consumption [MJ/h]
25
20
15
10
5
Mar 01
Mar 06
Mar 12
Mar 18
Mar 24
Mar 30

Robust Polynomial Kernel

To improve the kernel method

Rewrite the kernel smoother to a Least Square Problem

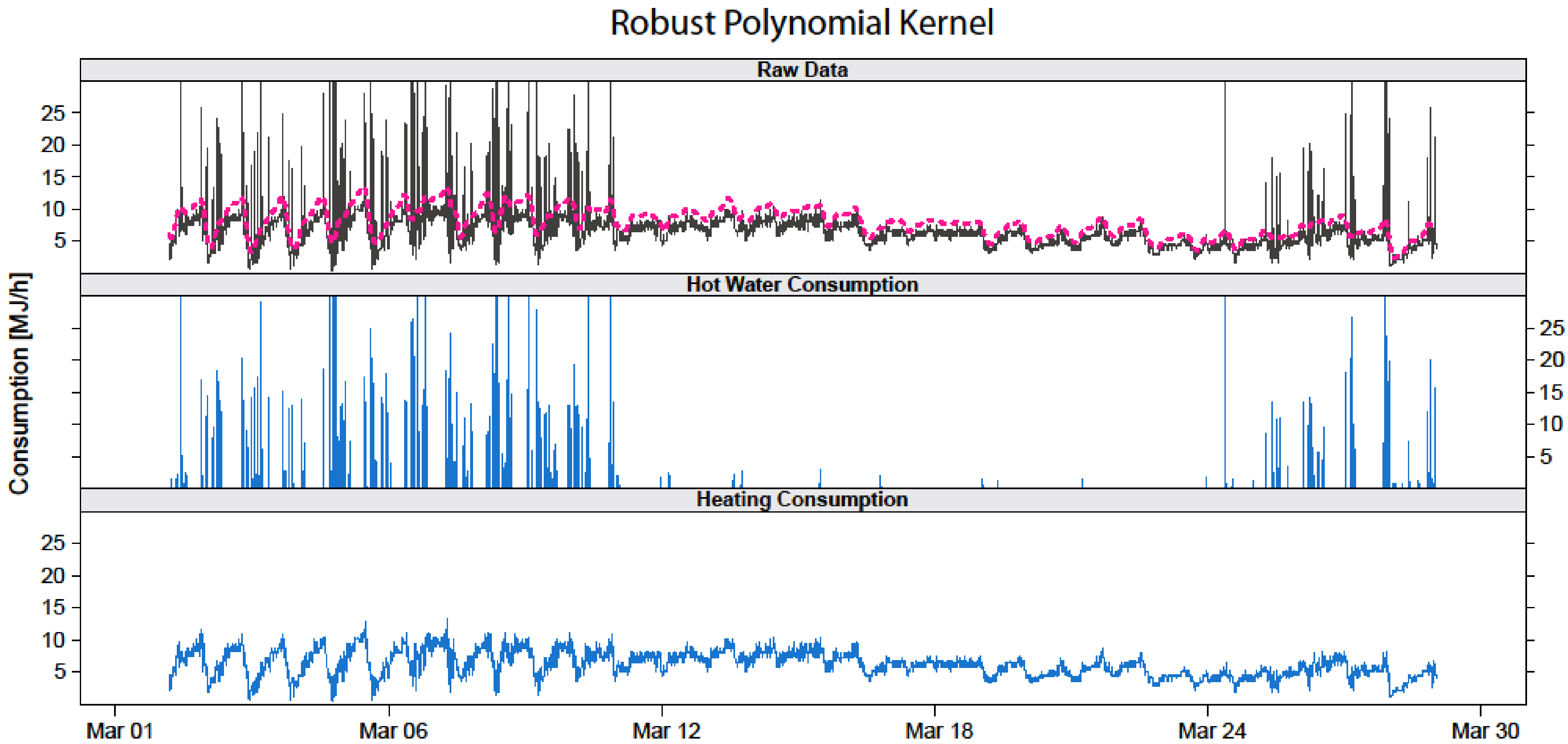
$$\arg\min_{\theta} \frac{1}{N}\sum_{s=1}^{N} w_s(x)\,(Y_s-\theta)^2 \qquad w_s(x) = \frac{k\{x-X_s\}}{\frac{1}{N}\sum_{s=1}^{N} k\{x-X_s\}}$$

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

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

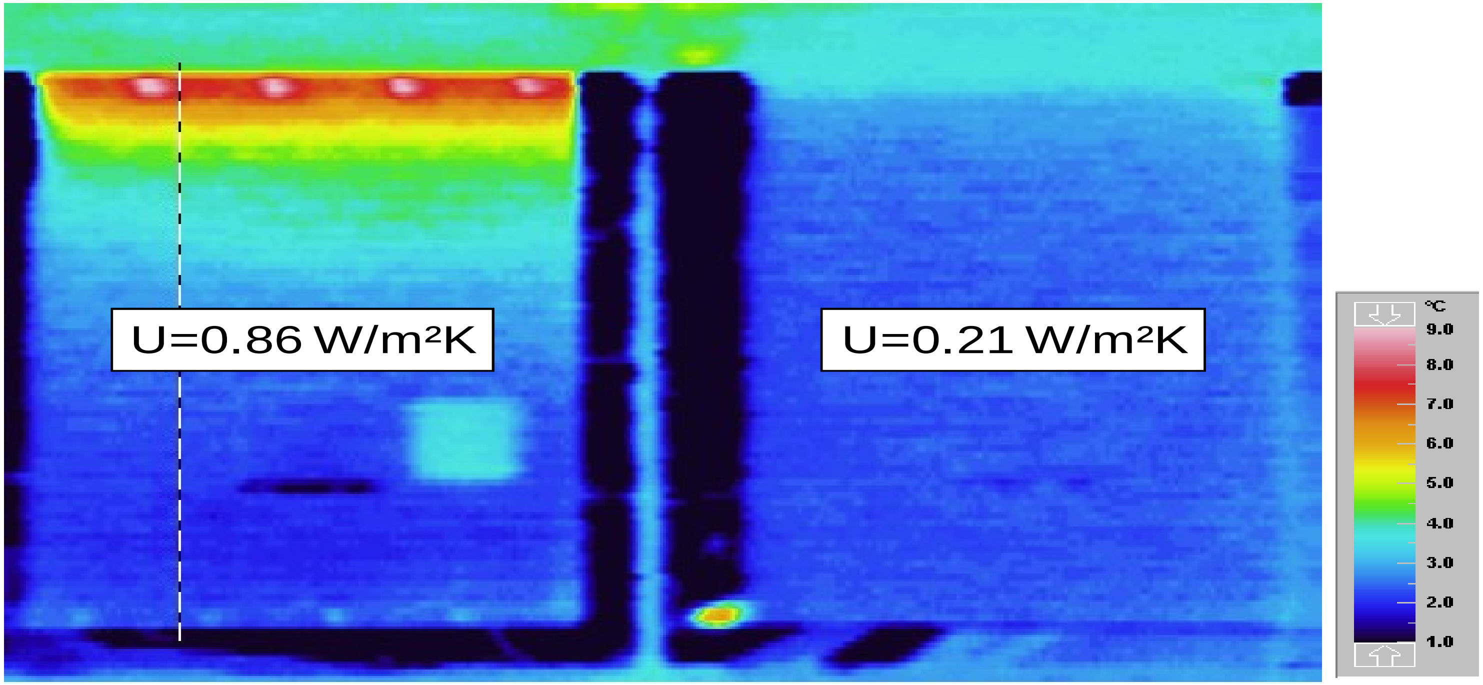


Robust Polynomial Kernel
Raw Data
Hot Water Consumption
Heating Consumption
Consumption [MJ/h]
25
20
15
10
5
Mar 01
Mar 06
Mar 12
Mar 18
Mar 24
Mar 30

Case Study No. 2

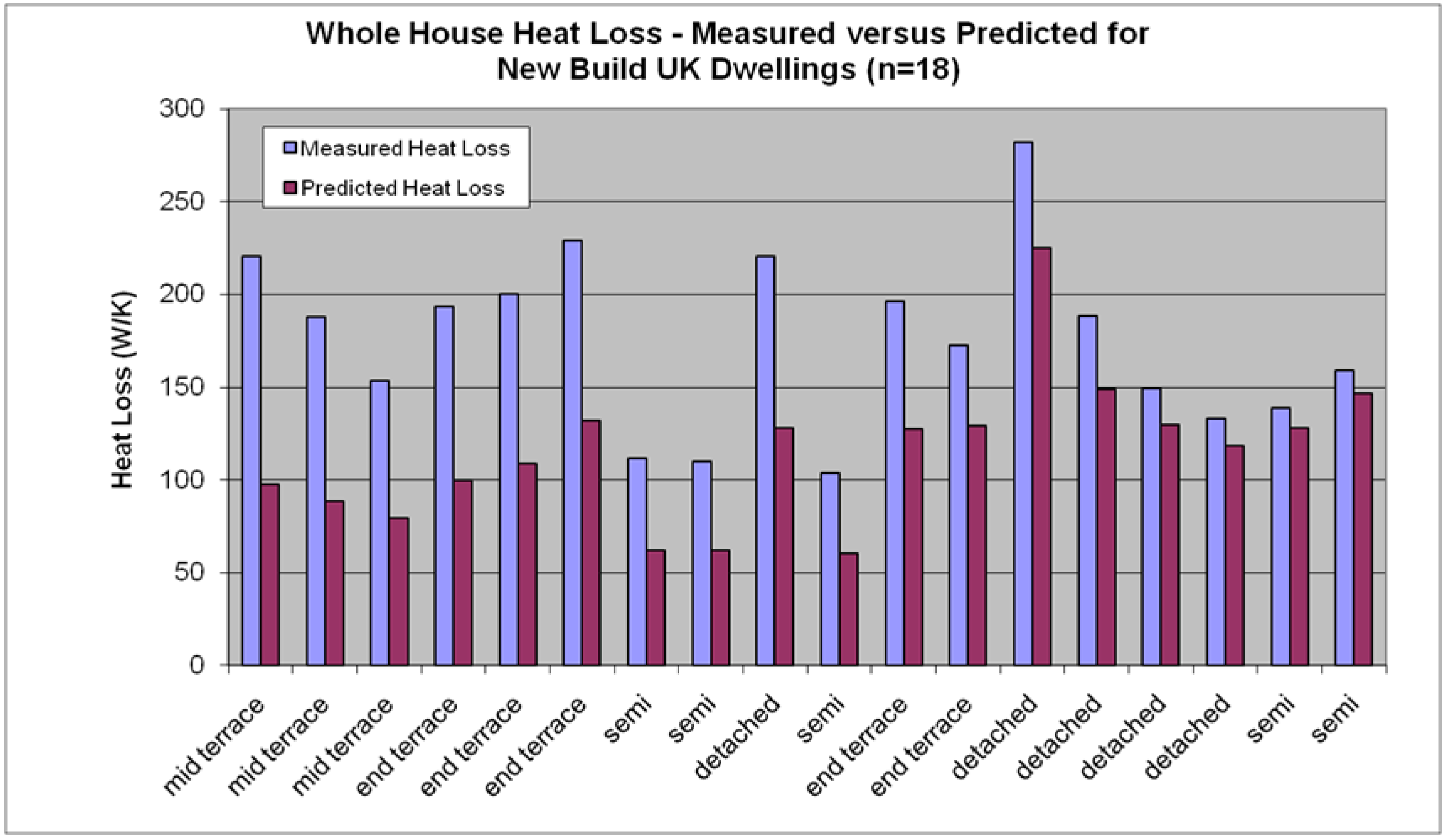
Ident. of Thermal Performance using Smart Meter Data

Example



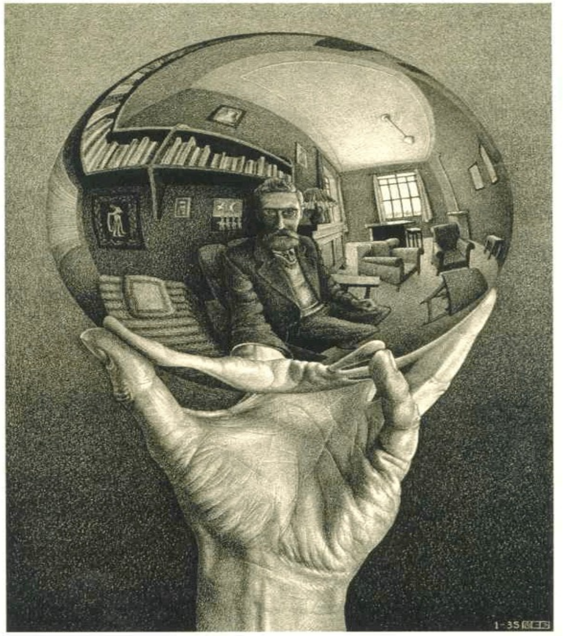
Consequence of good or bad workmanship (theoretical value is U=0.16W/m2K)

Examples (2)



Measured versus predicted energy consumption for different dwellings

Characterization using HMM and Smart Meter Data



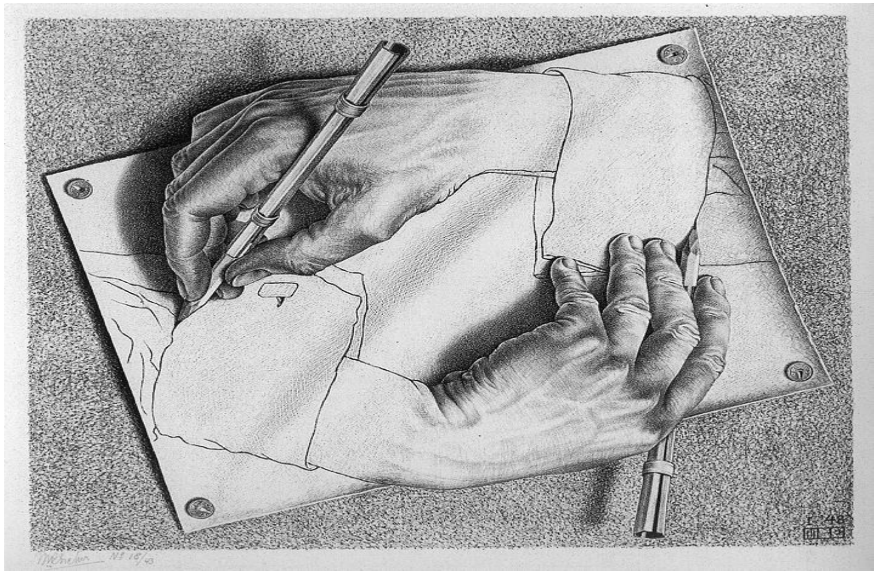
- Energy labelling
- Estimation of UA and gA values
- Estimation of energy signature
- Estimation of dynamic characteristics
- Estimation of time constants

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

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.

Perspectives for using data from Smart Meter

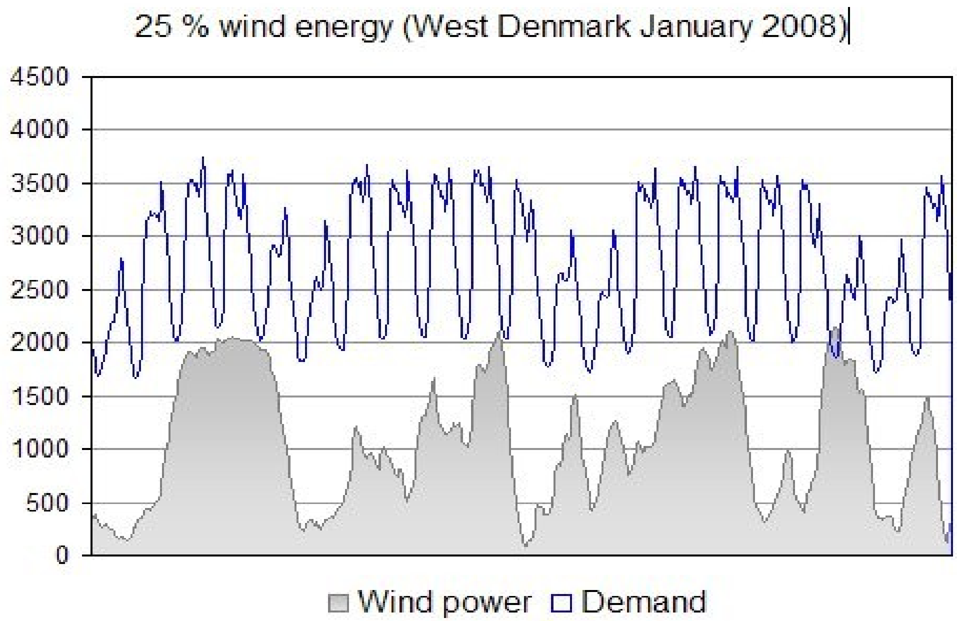
- Reliable Energy Signature.
- Energy Labelling
- Time Constants (eg for night set-back)
- Proposals for Energy Savings:
  - Replace the windows?
  - Put more insulation on the roof?
  - Is the house too untight?
  - ......
- Optimized Control
- Integration of Solar and Wind Power using DSM

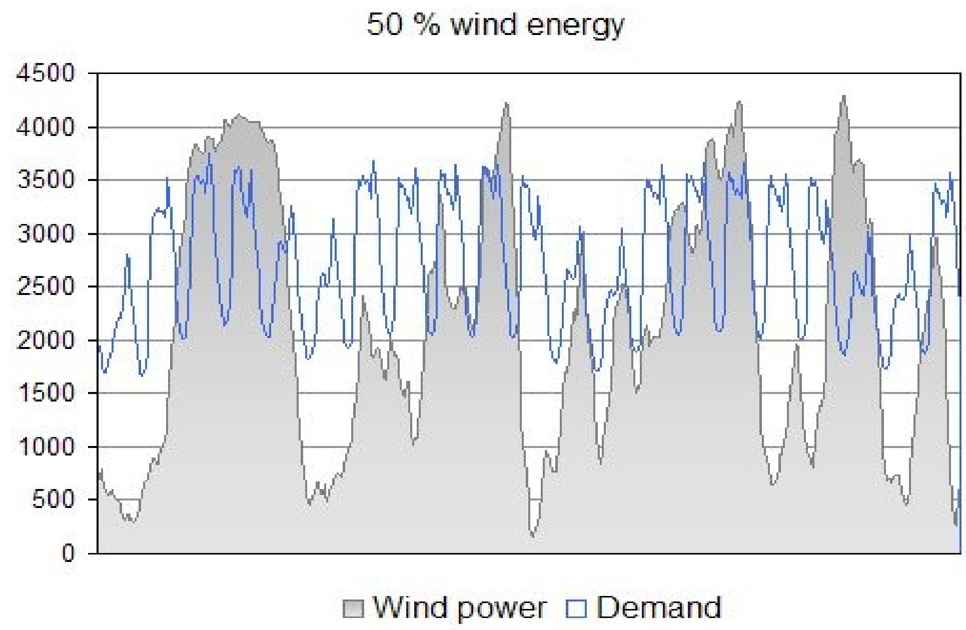
Case Study No. 3

Control of Power Consumption (DSM)

The Danish Wind Power Case

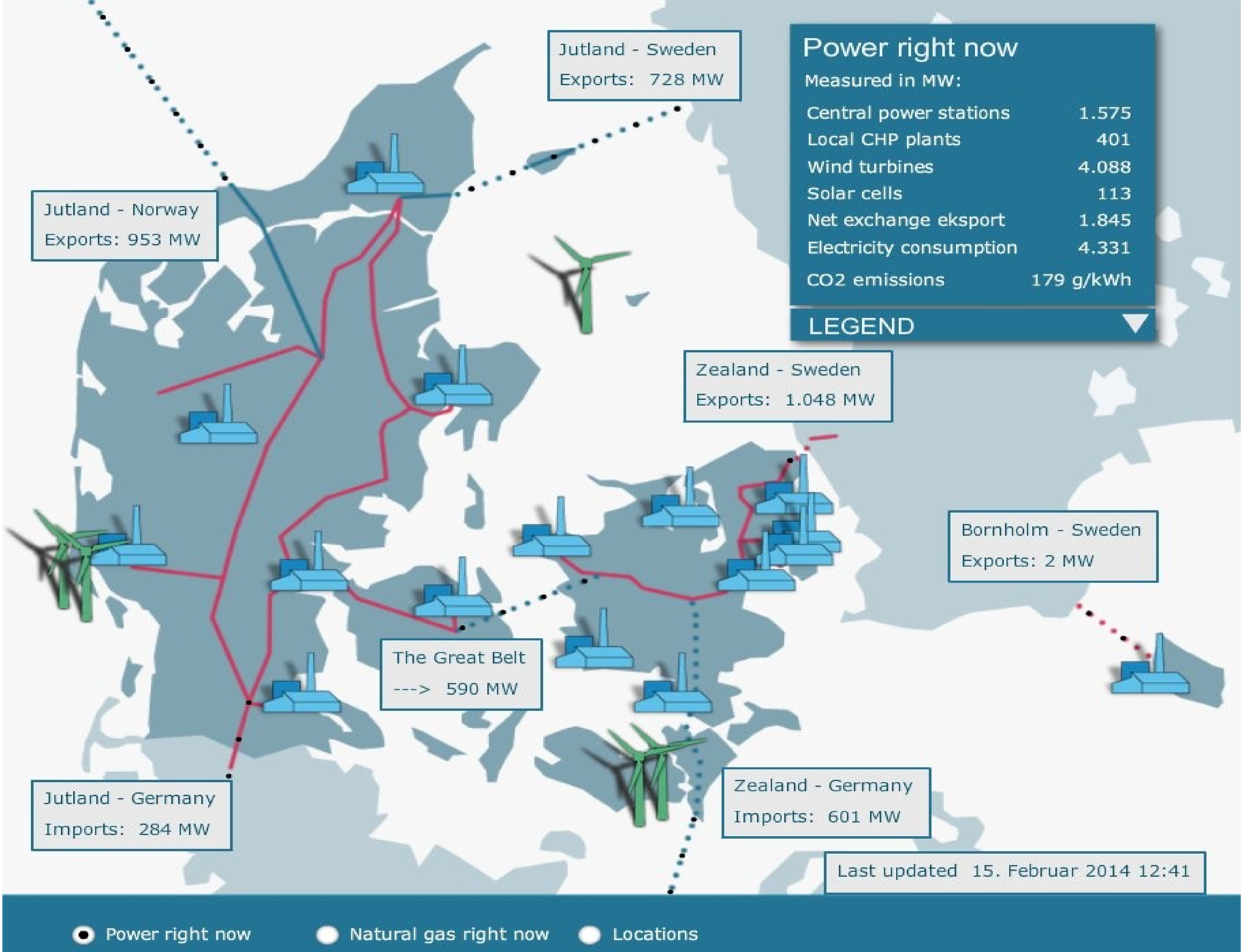
.... balancing of the power system





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

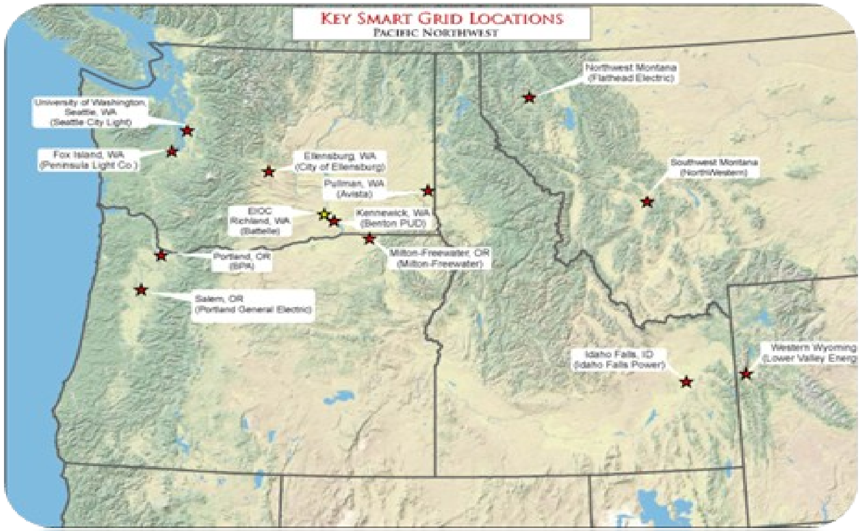
In December 2013 and January 2014 more than 55 pct of electricity load was covered by wind power. And for several days the wind power production was more than 120 pct of the power load


Jutland - Sweden
Exports: 728 MW
Power right now
Measured in MW:
Central power stations 1.575
Local CHP plants 401
Wind turbines 4.088
Solar cells 113
Net exchange eksport 1.845
Electricity consumption 4.331
CO2 emissions 179 g/kWh
LEGEND
Jutland - Norway
Exports: 953 MW
Zealand - Sweden
Exports: 1.048 MW
Bornholm - Sweden
Exports: 2 MW
The Great Belt
---> 590 MW
Jutland - Germany
Imports: 284 MW
Zealand - Germany
Imports: 601 MW
Last updated 15. Februar 2014 12:41
Power right now
Natural gas right now
Locations

Data from BPA

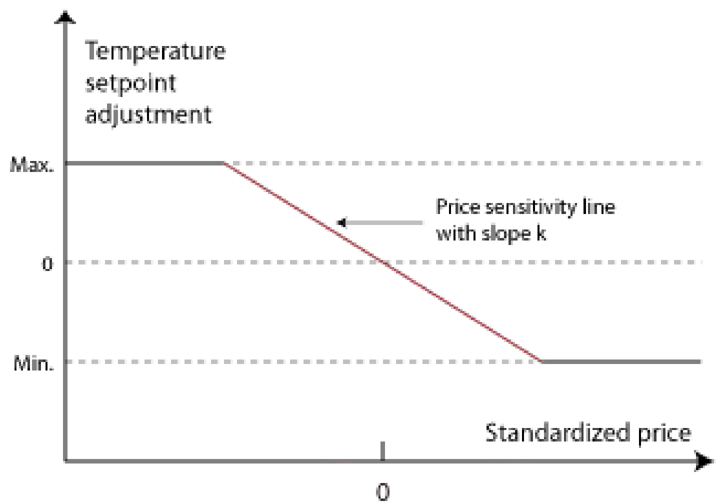
Olympic Pensinsula project

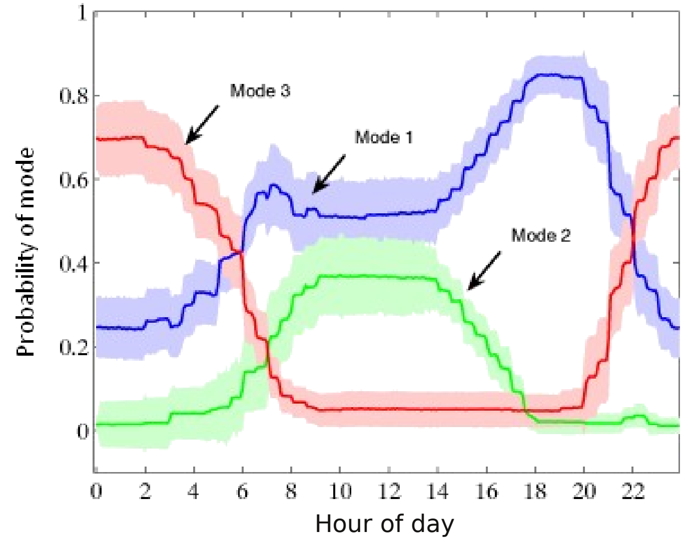
- 27 houses during one year
- Flexible appliances: HVAC,
  cloth dryers and water boilers
- 5-min prices, 15-min consumption
- Objective: limit max consumption

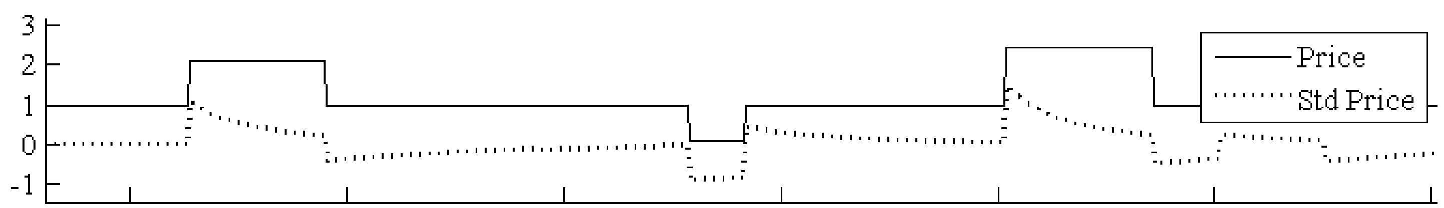


Price responsivity

Flexibility is activated by adjusting the temperature reference (setpoint)

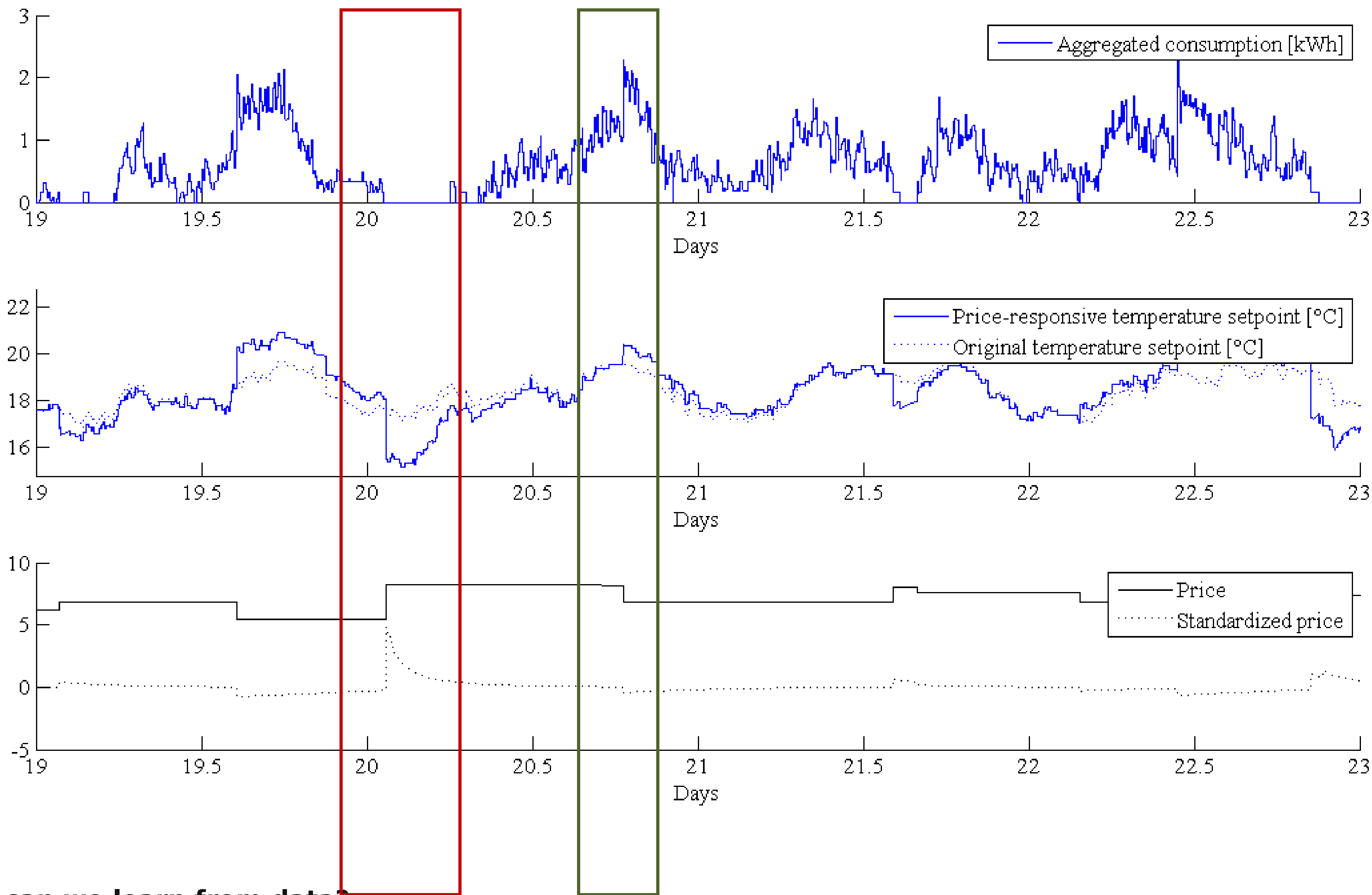






- **Standardized price** is the % of change from a price reference, computed as a mean of past prices with exponentially decaying weights.
- **Occupancy mode** contains a price sensitivity with its related comfort boundaries. 3 different modes of the household are identified (work, home, night).

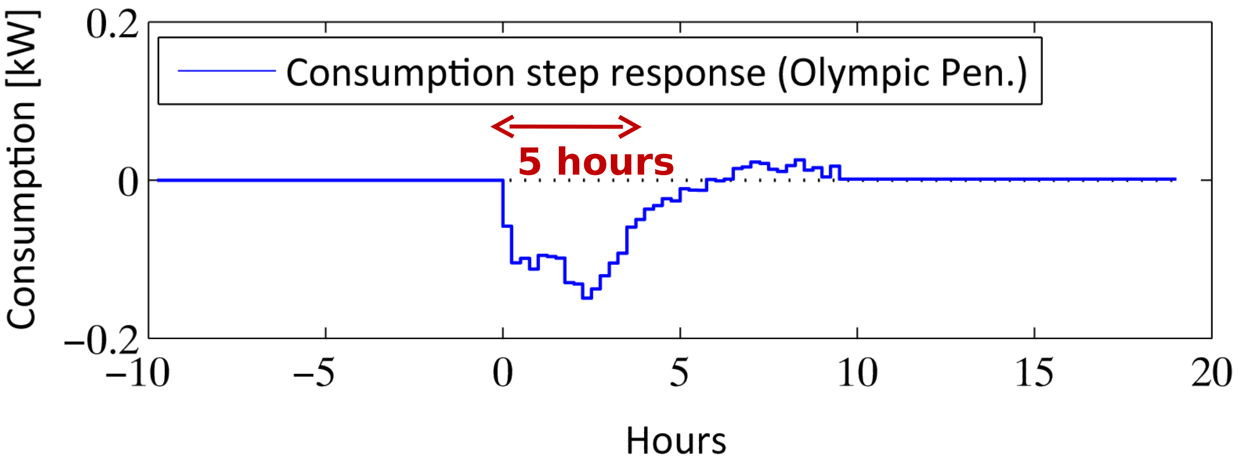
Aggregation (over 20 houses)



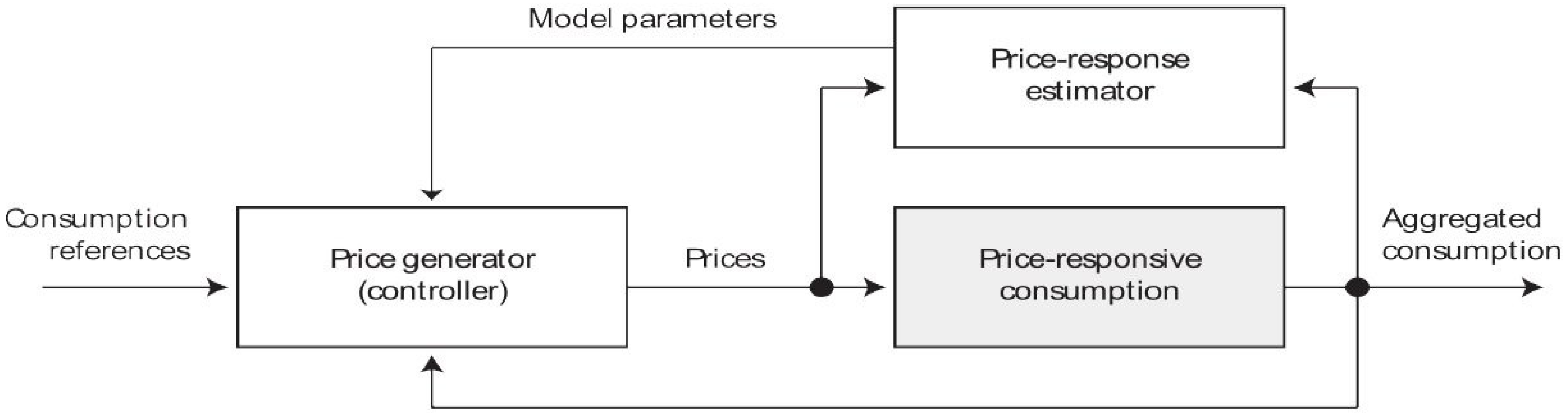
Non-parametric Response on Price Step Change

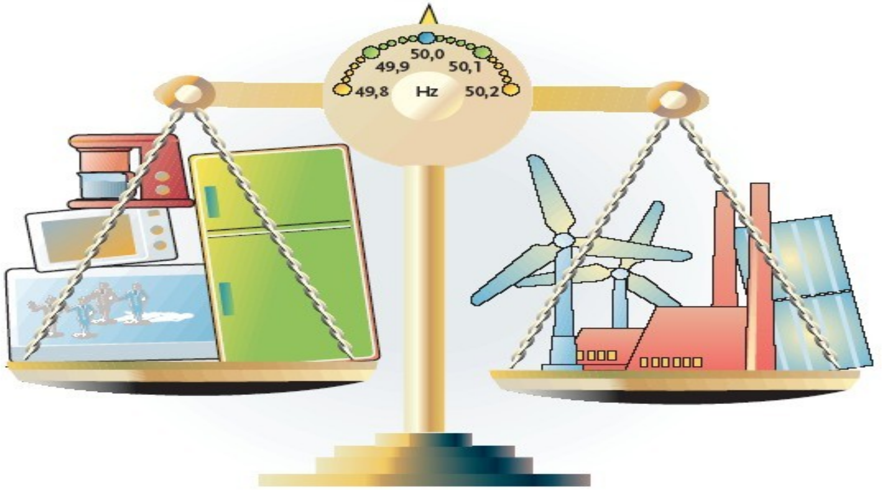
Model inputs: price, minute of day, outside temperature/dewpoint, sun irrandiance

Olympic Peninsula



Control of Energy Consumption

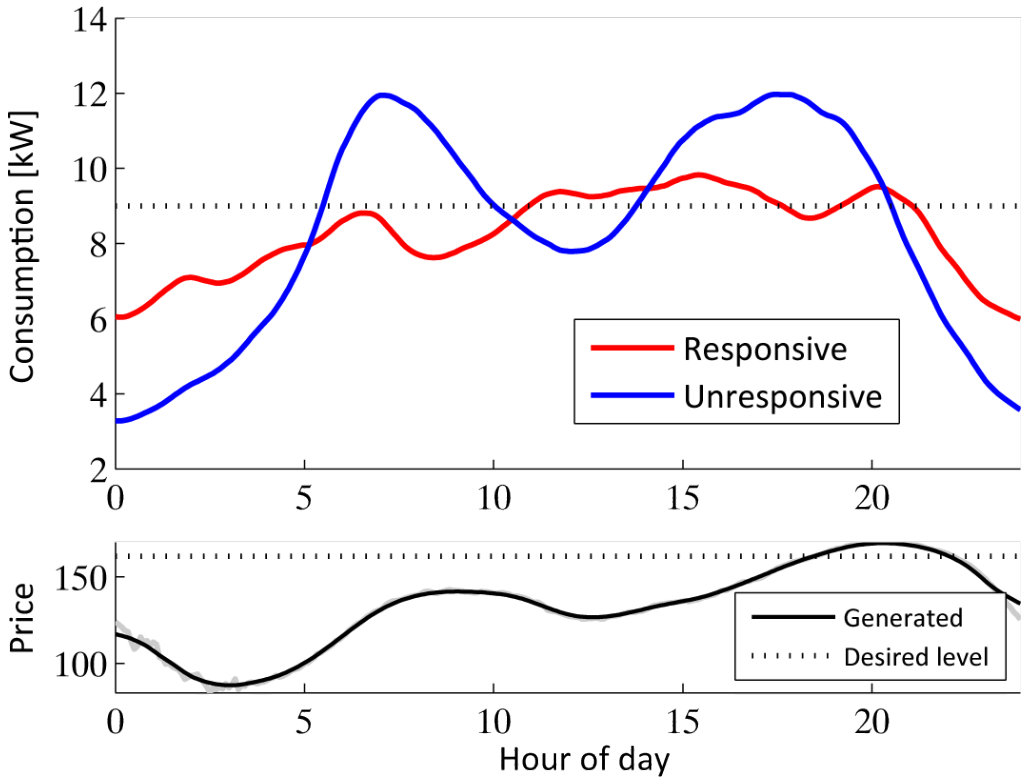




Control performance

With a price penality avoiding its divergence

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



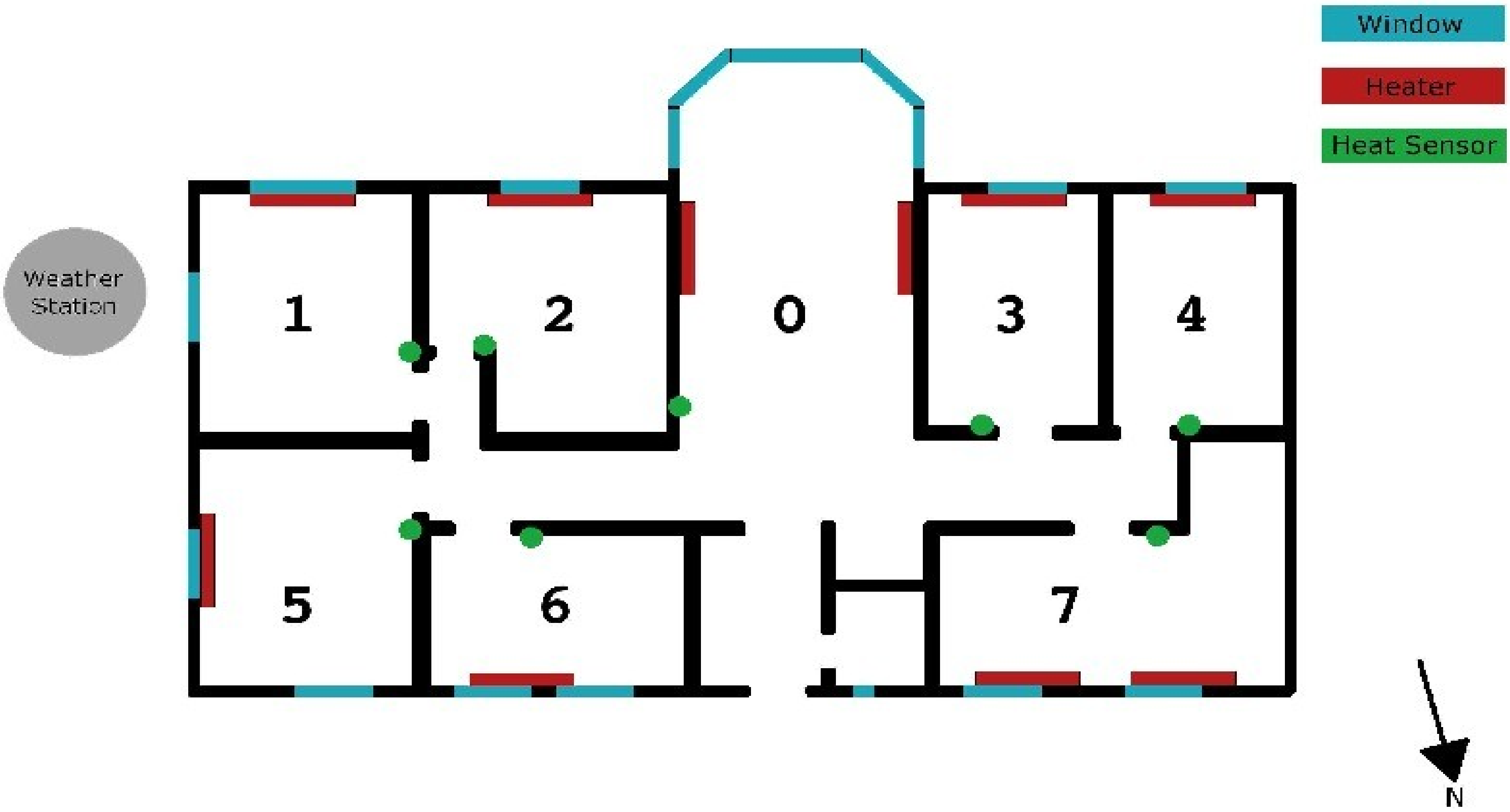
Part 2
Parametric Models

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

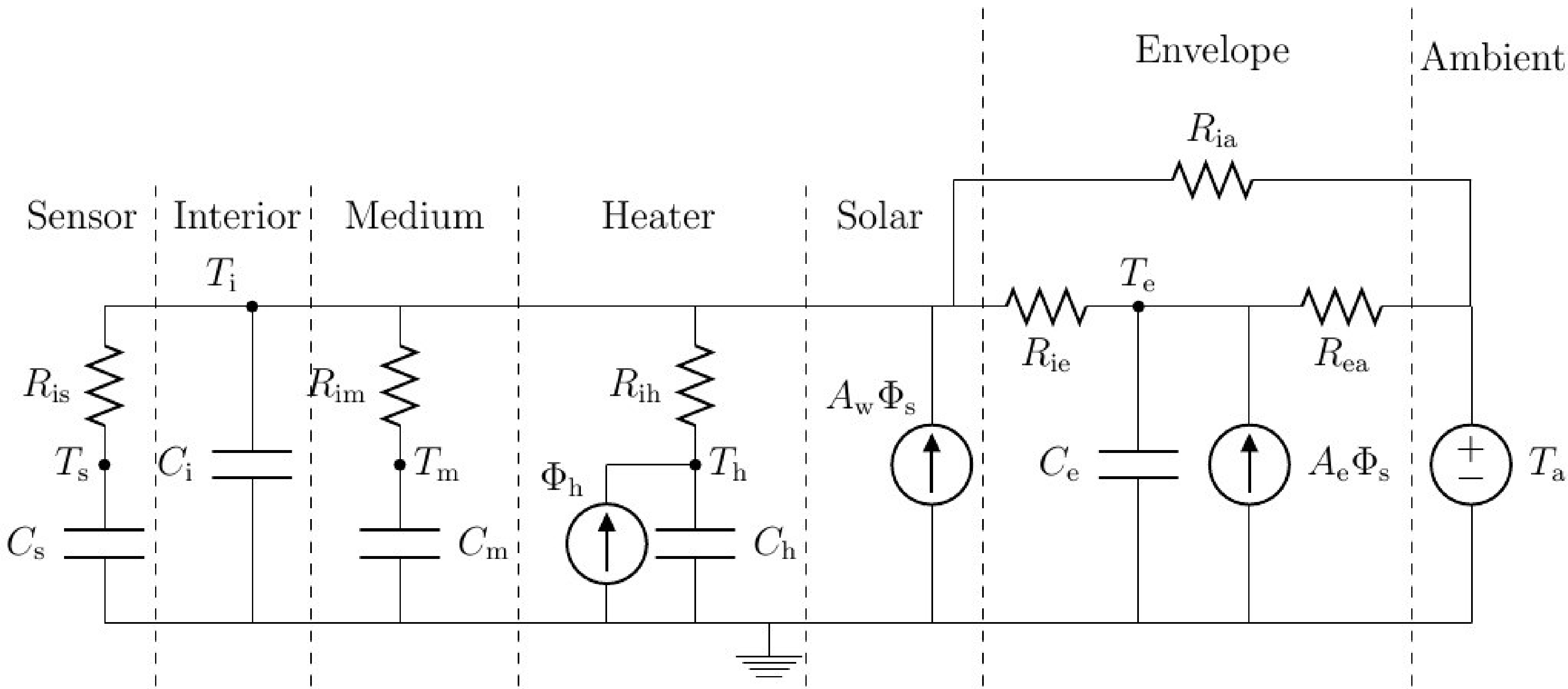
Case study

Model for the thermal characteristics of a small office building

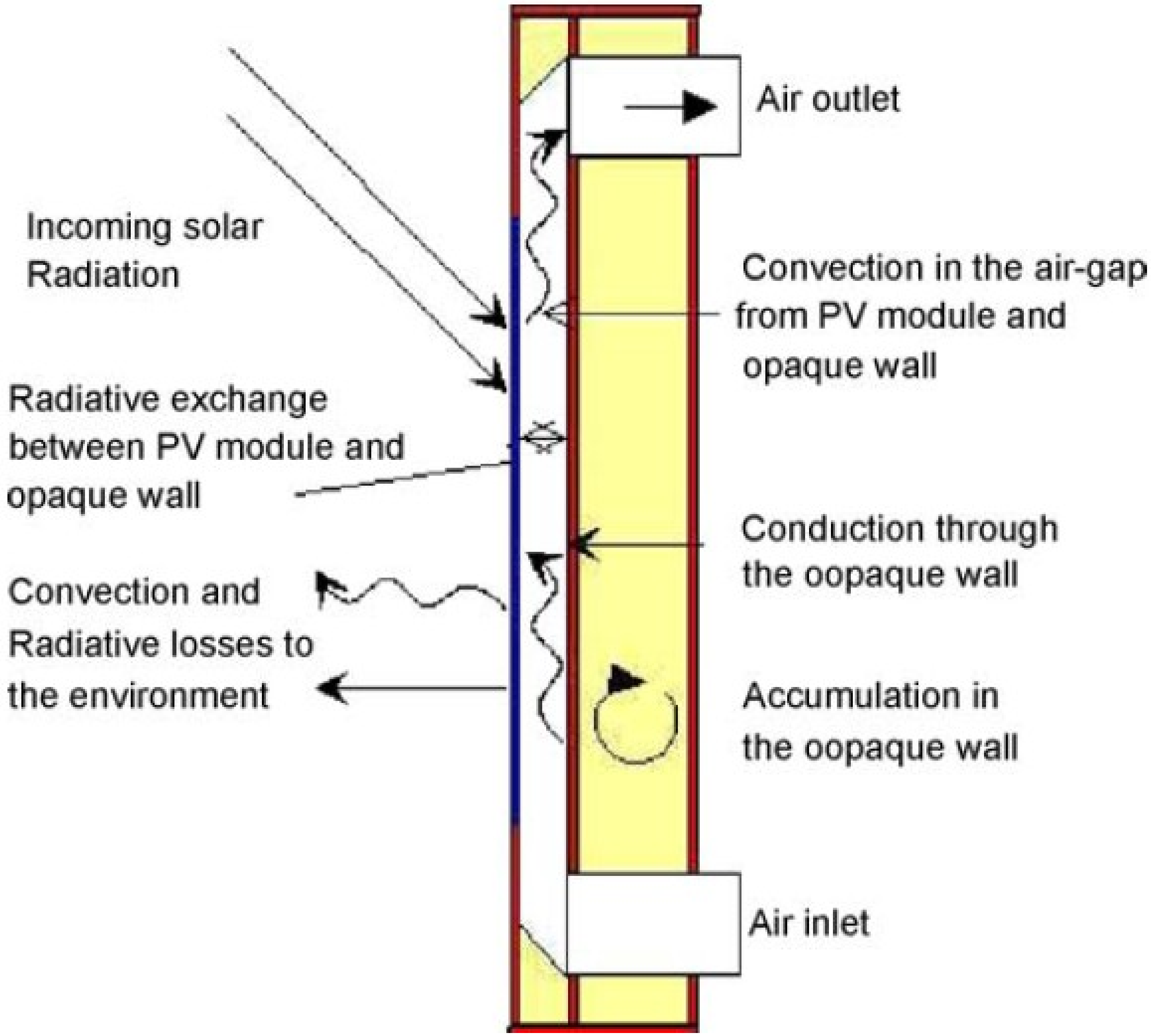
Flexhouse at SYSLAB (DTU Risø)



Model found using Grey-box modelling (using CTSM-R and a RC-model)
Here we estimate the physical parameters



Modelling the thermal dynamics of a building integrated and ventilated PV module

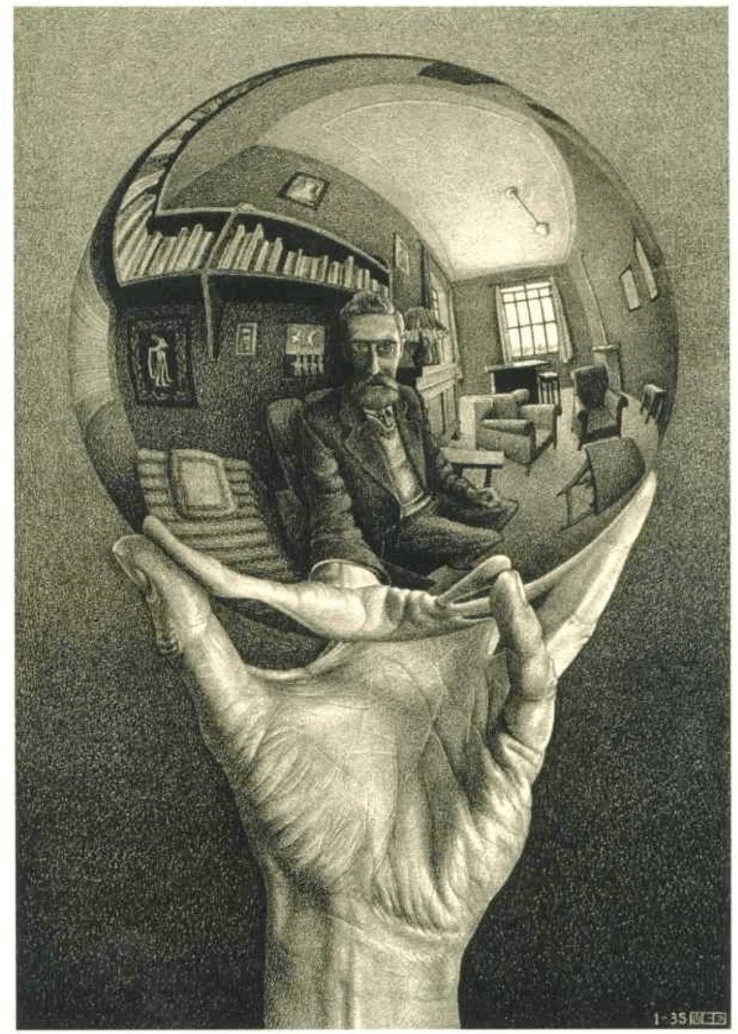


Several non-linear and time-varying phenomena.

Consequently linear RC-network models are not appropriate.

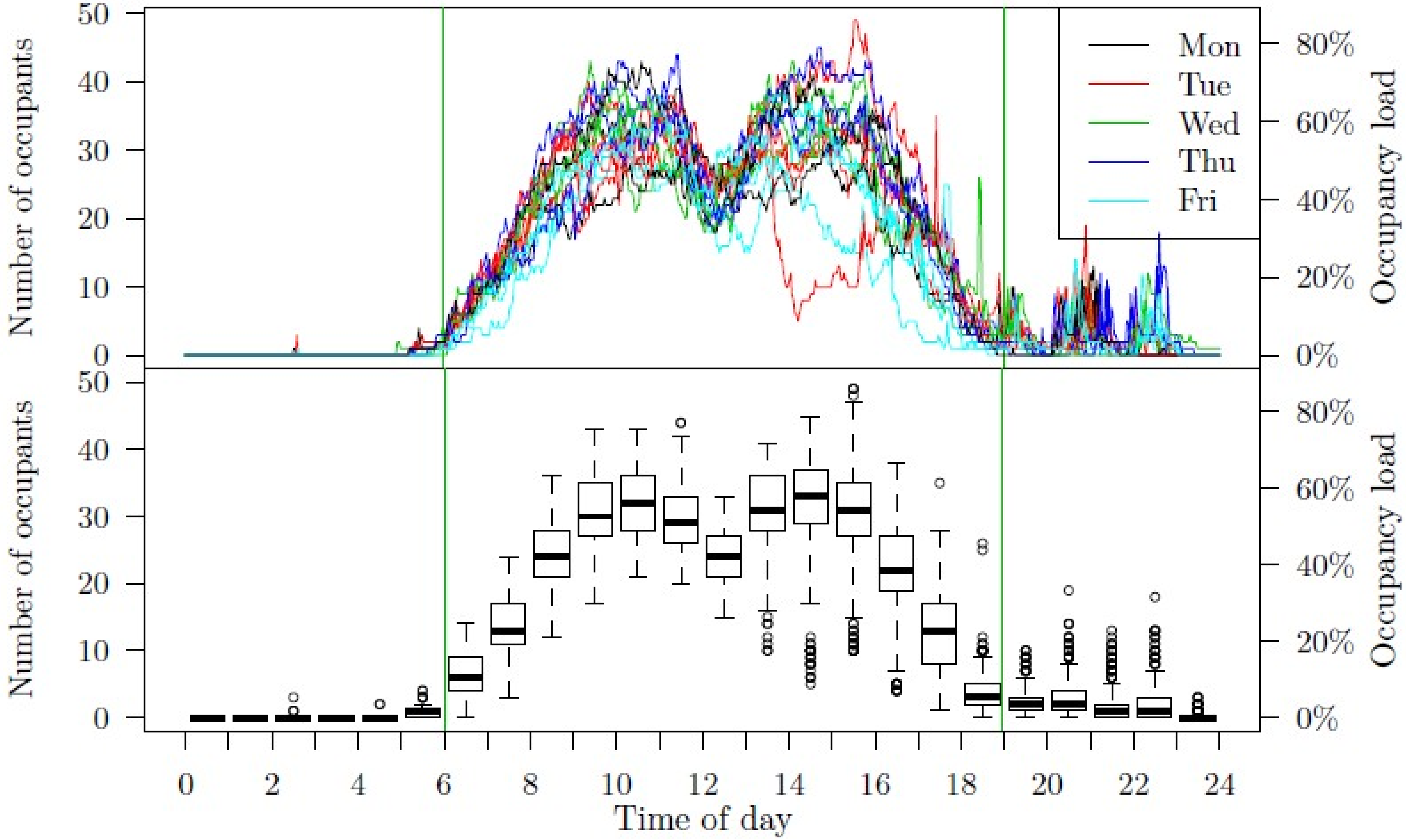
A grey-box approach using CTSM-R is described in Friling et.al. (2009)

Part 3
Non-gaussian models (Annex 66)



- Occupancy modelling is a necessary step towards reliable simulation of energy consumption in buildings

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

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

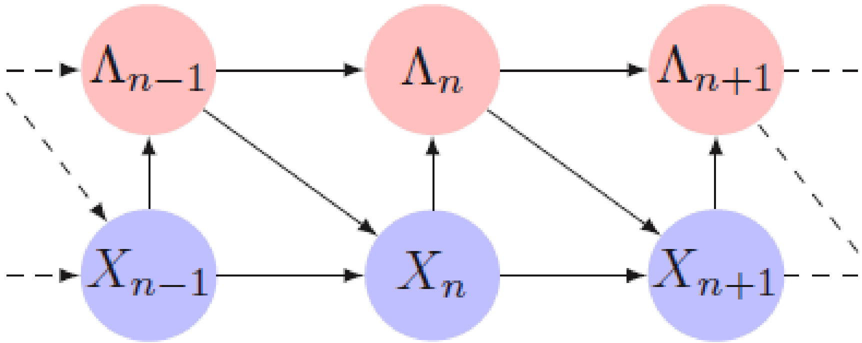
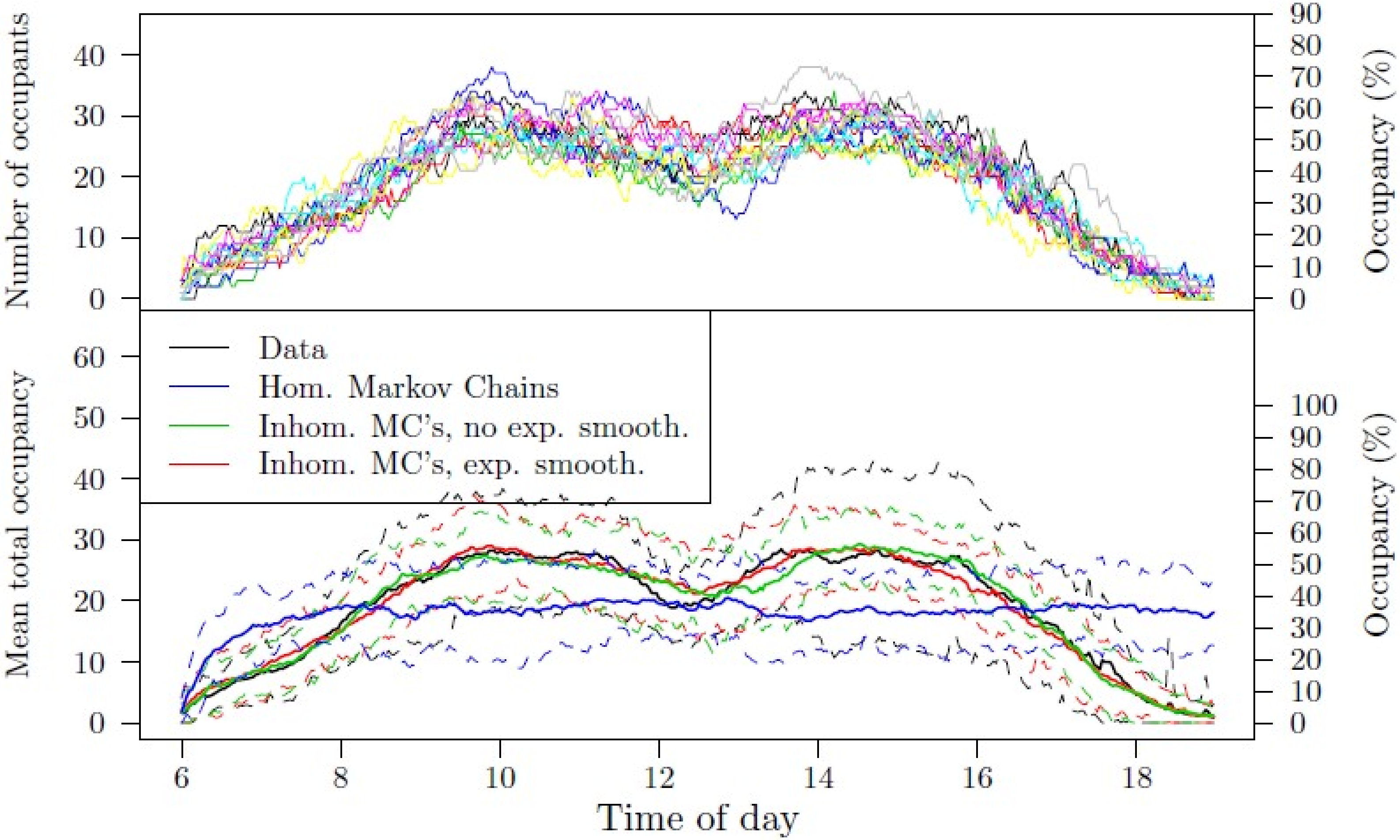


Fig. 3. A Markov chain with exponential smoothing as covariate in the transition probabilities.

Model simulations



Remarks and Summary

Other examples ... but not shown here:

- Shading (.. also dirty windows)
- Time-varying phenomena (.. eg. moisture in materials)
- Behavioural actions (opening of doors, windows, etc.)
- Appliance modelling
- Interactions with HVAC systems
- ....

... in general data and statistical methods (including tests) can be used to describe or model a number phenomena that cannot be described neither deterministically nor from first principles.

For more information ...

- See for instance

  www.henrikmadsen.org

  www.smart-cities-centre.org

- ...or contact

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- Acknowledgement CITIES (DSF 1305-00027B)