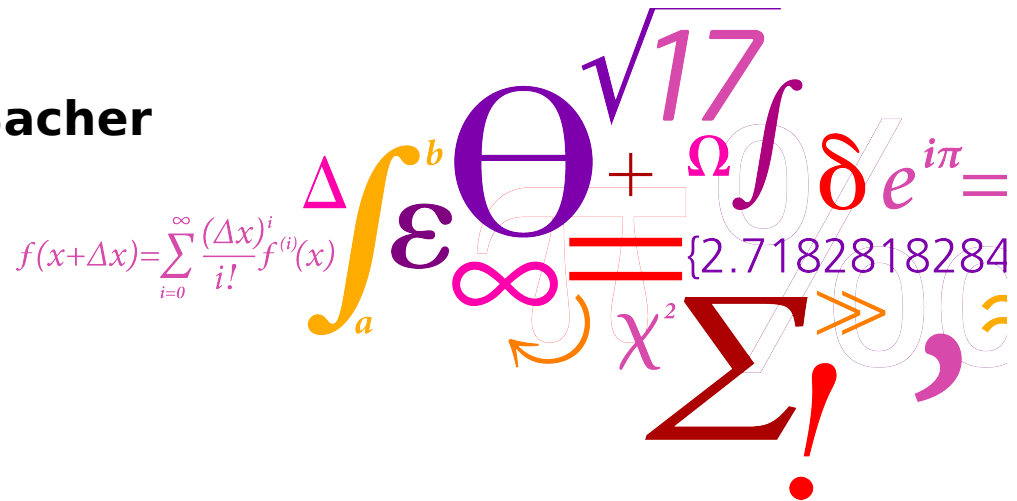


Some perspectives for the use of smart meter data

**Workshop in Preparation of New IEA EBC Annex,
Brussels, April 2016**

Henrik Madsen and Peder Bacher
www.henrikmadsen.org


$$f(x+\Delta x) = \sum_{i=0}^{\infty} \frac{(\Delta x)^i}{i!} f^{(i)}(x)$$

Contents

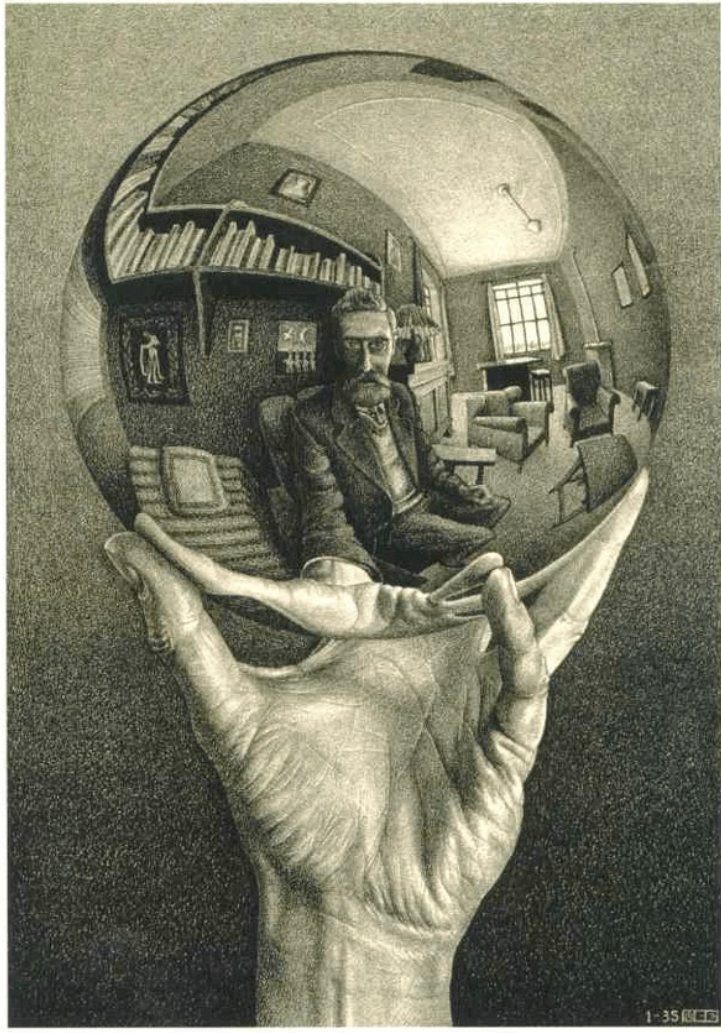


- Thermal characteristics of the building (**The fabric**)
- **Energy system** characterization (incl. demand-response)
- **Occupancy behavior.** Characterization using meter data

Examples only!

Part 1

Thermal Characteristics of the Building



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

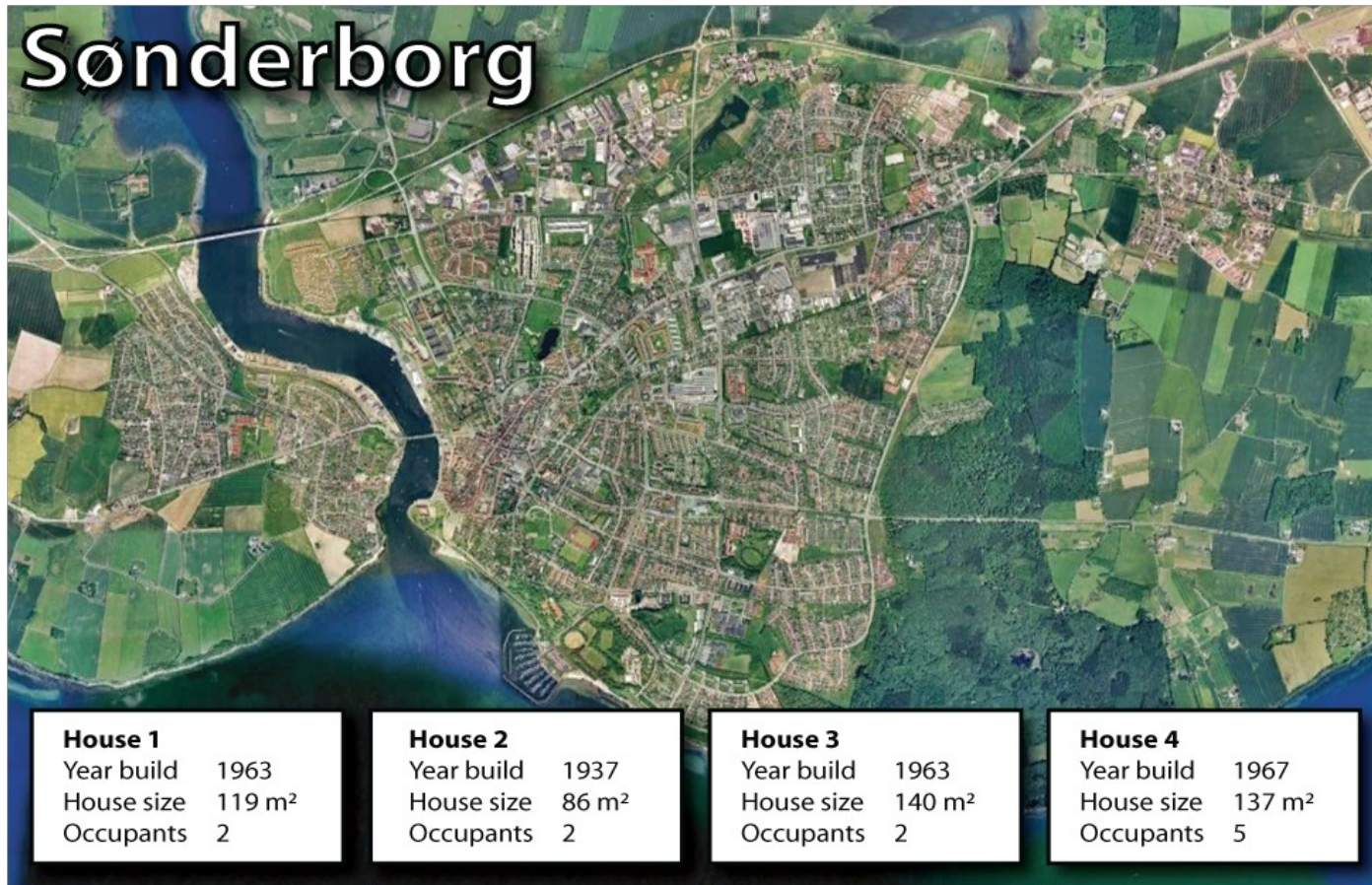
Case Study No. 1

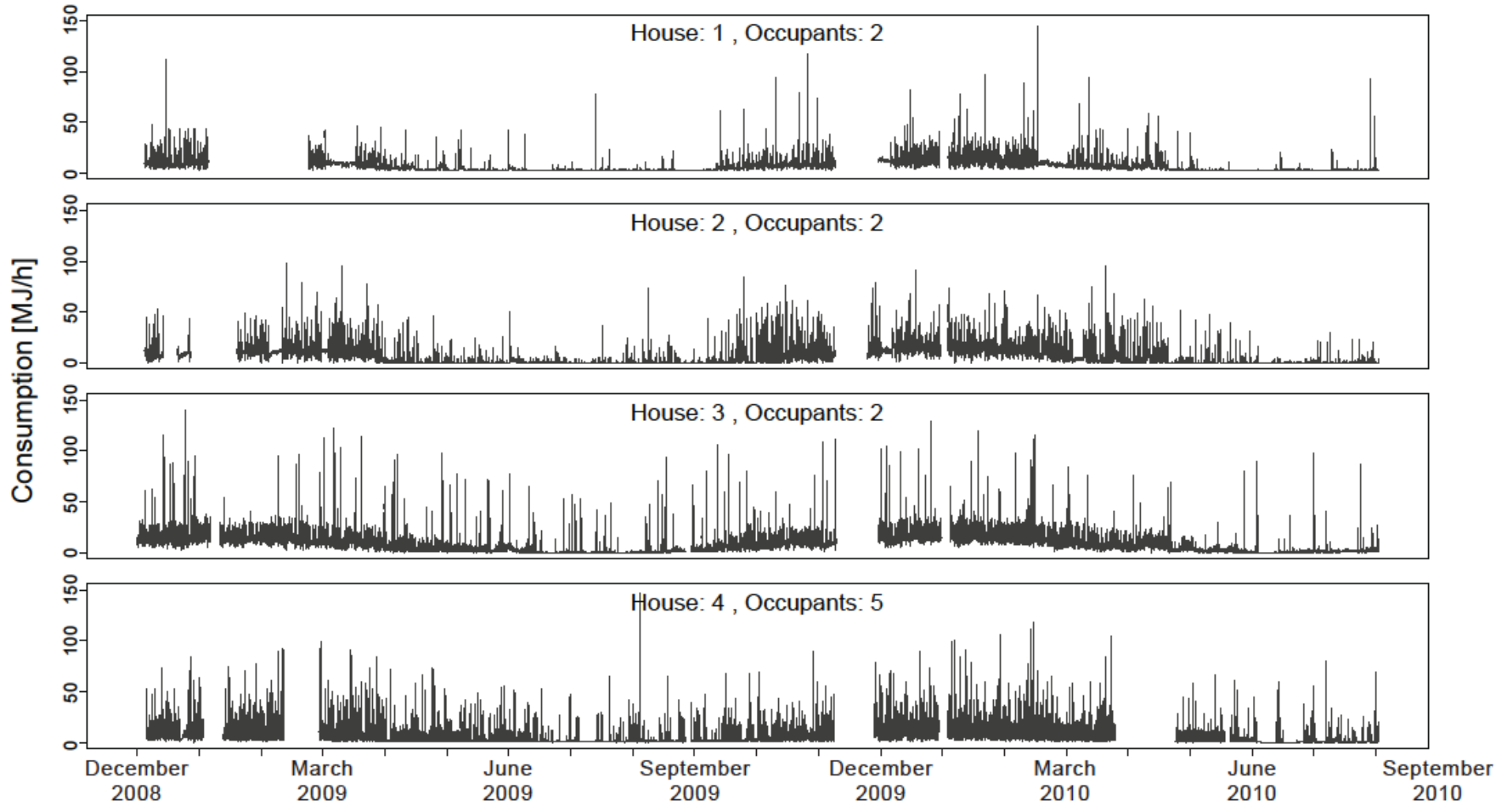
Split of total readings into space heating and domestic hot water using data from smart meters



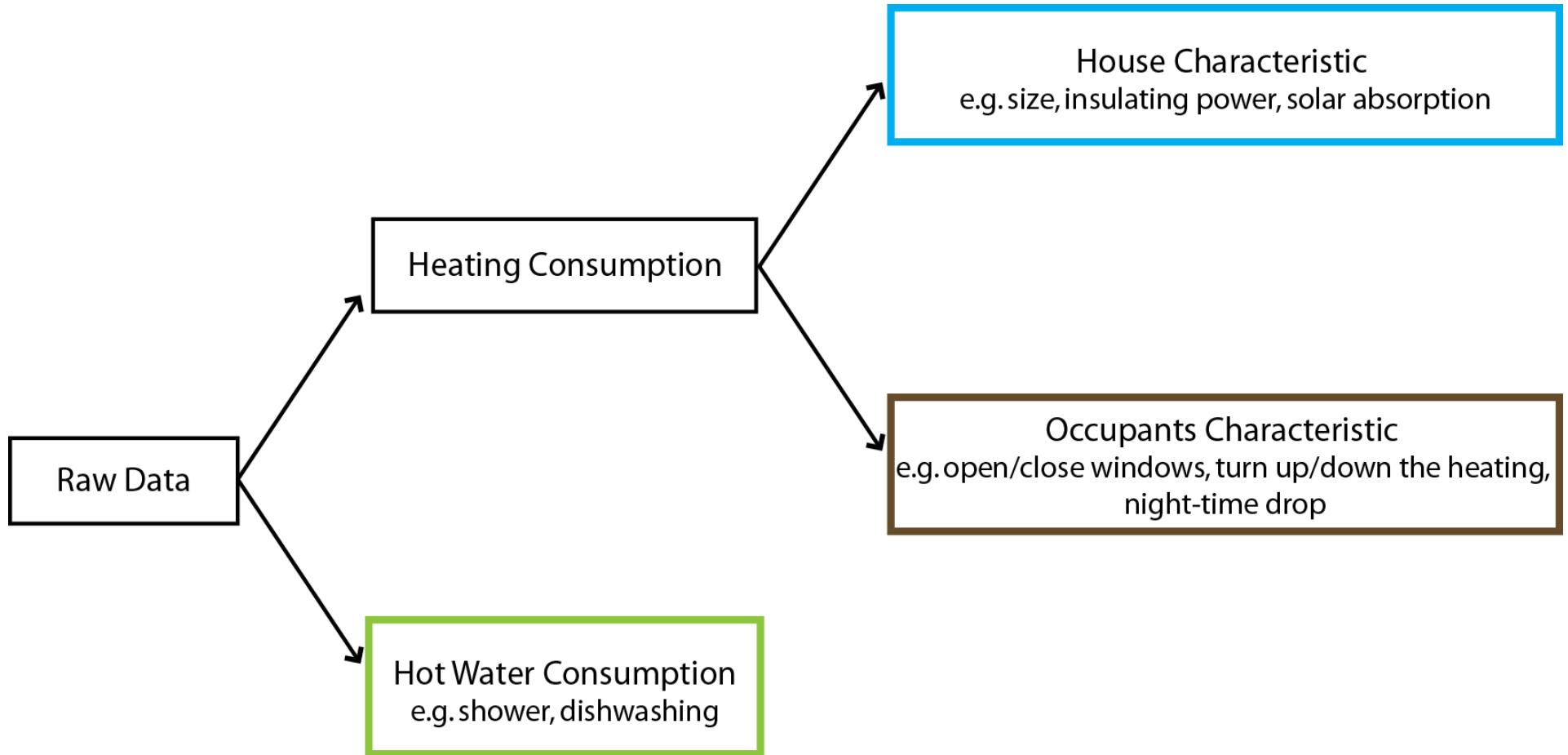
Data

- 10 min averages from a number of houses

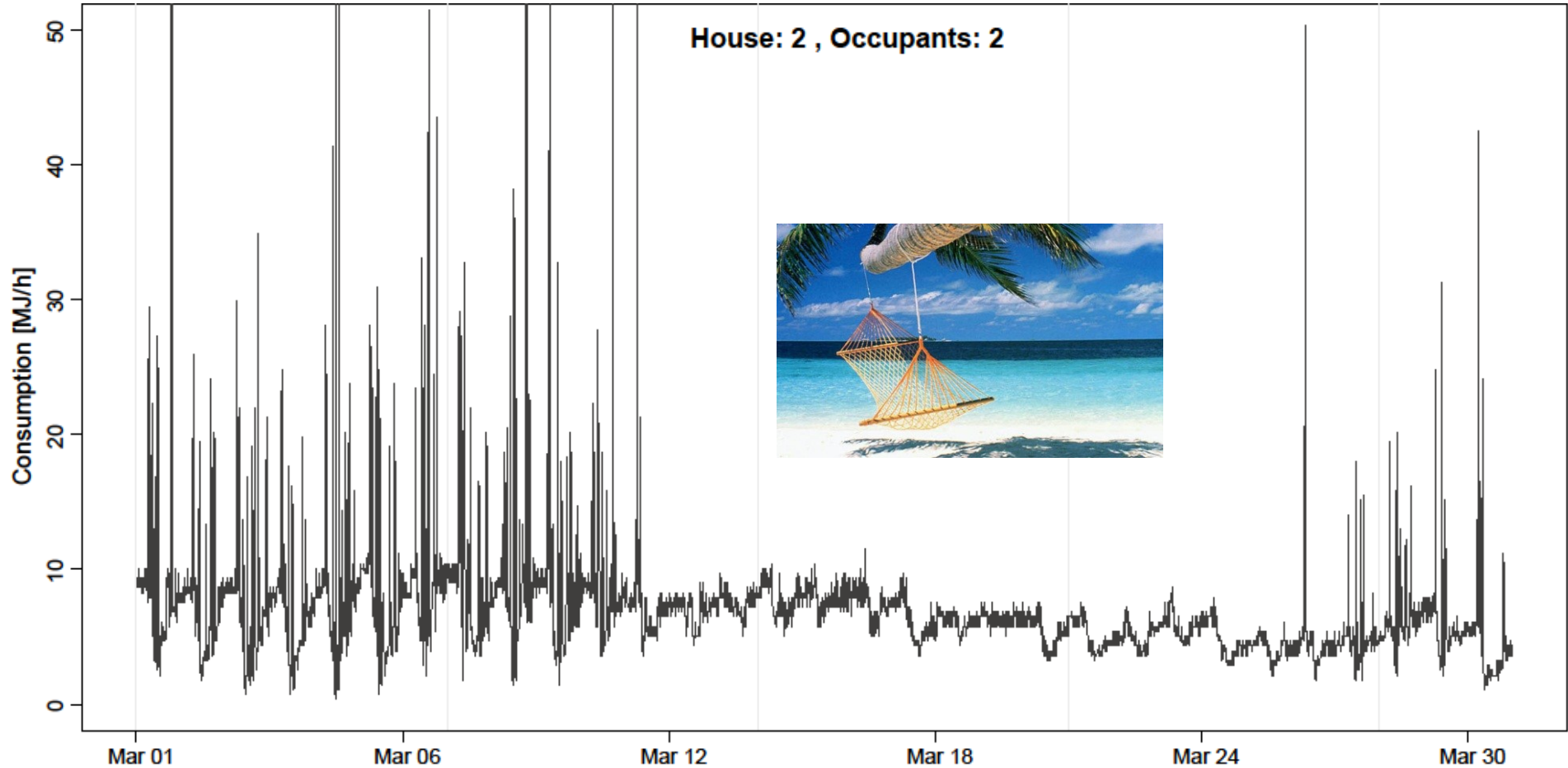




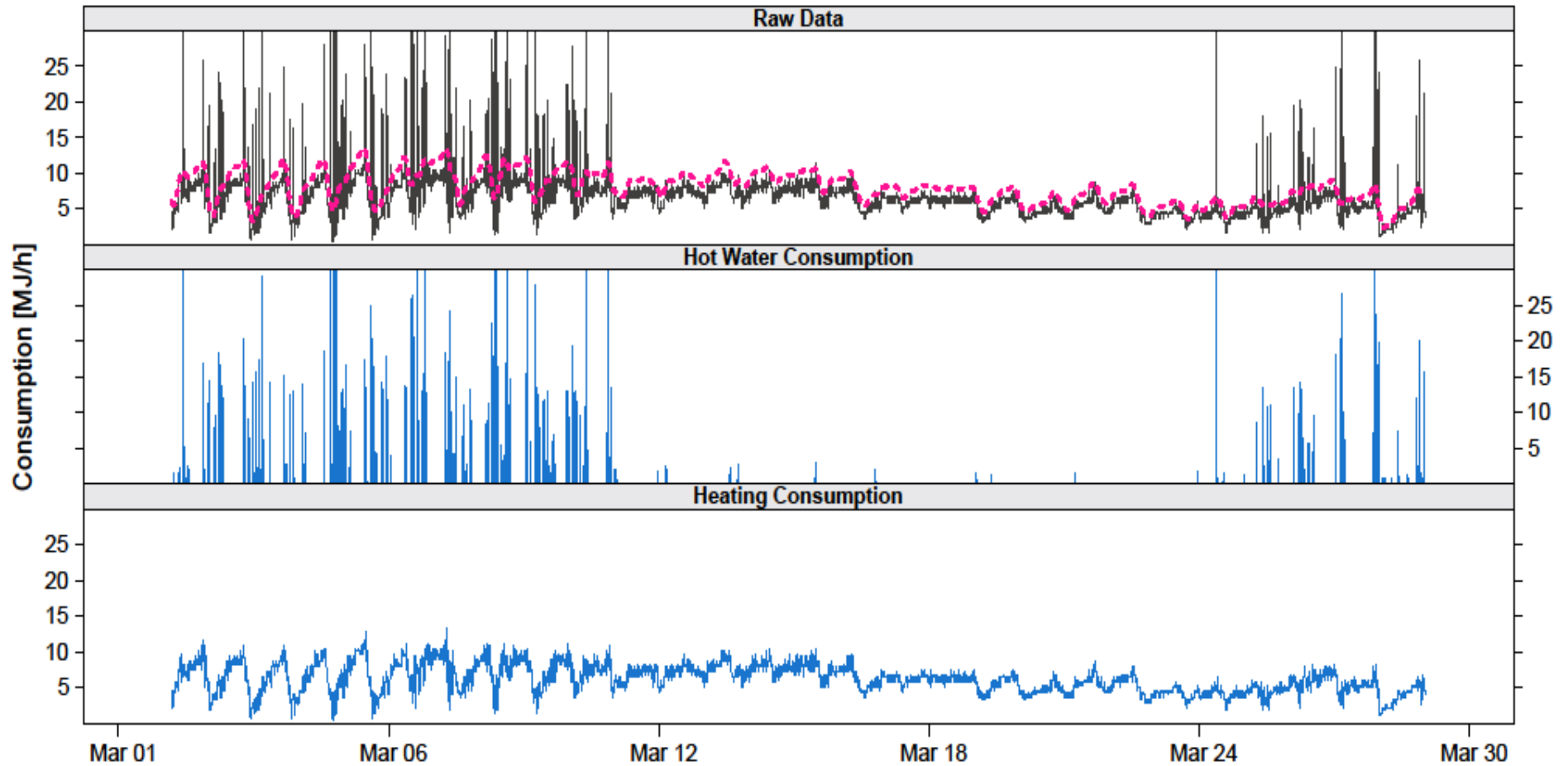
Splitting of total meter readings



Holiday period



Robust Polynomial Kernel

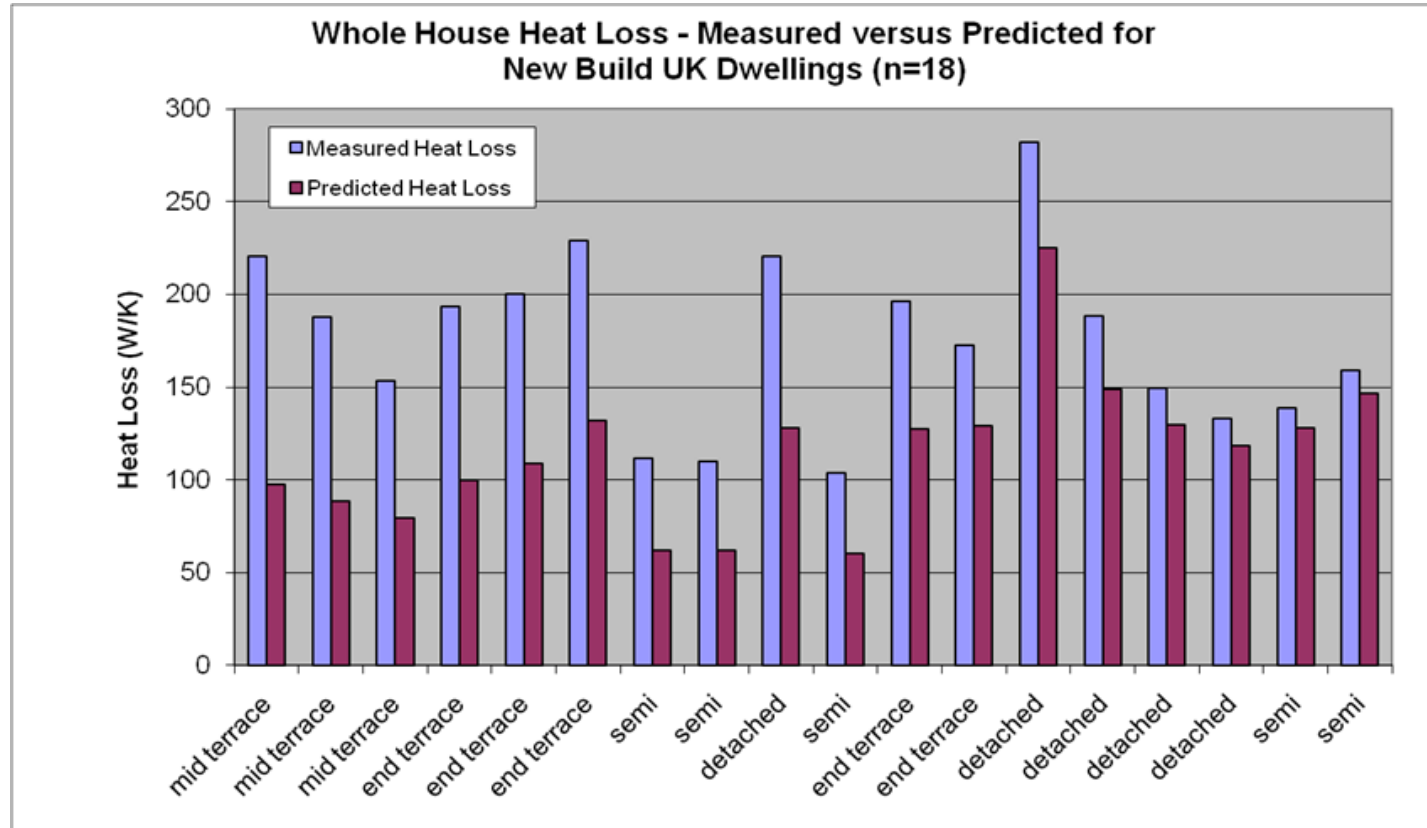


Case Study No. 2

Ident. of Thermal Performance using Smart Meter Data



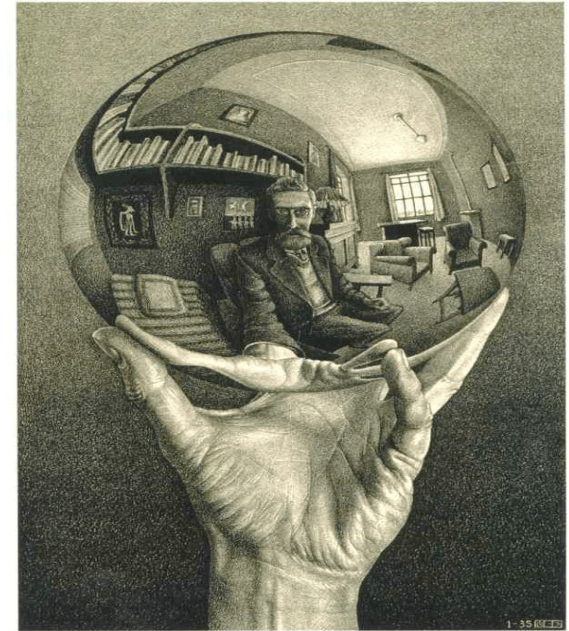
Examples



Measured versus predicted energy consumption for different dwellings

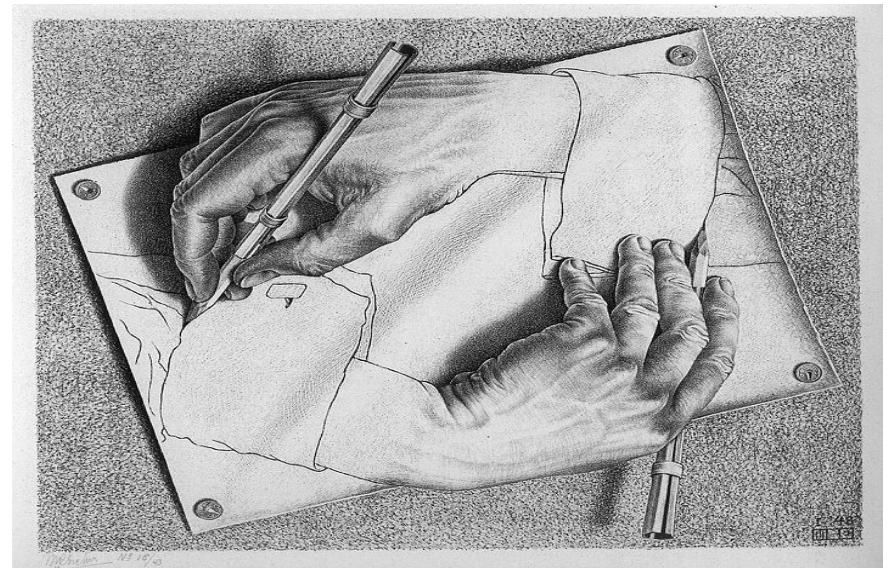
Characterizations using Smart Meter Data

- 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:

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

- The estimated UA-value is

$$\hat{UA}(t) = \hat{c}_0(t) + \hat{c}_1(t) \quad (2)$$

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

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
.

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 DR



Part 2

System – Incl. Demand Response



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

Case Study No. 3

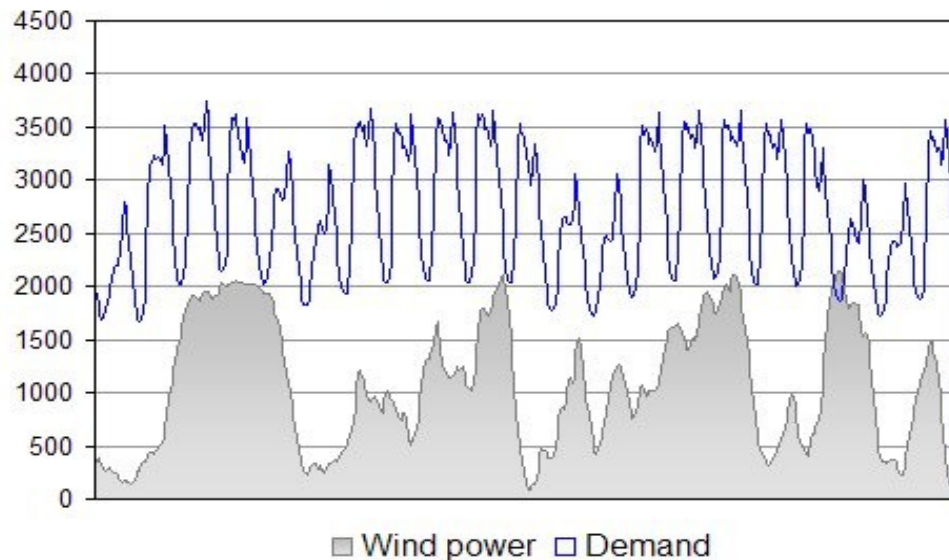
Control of Power Consumption



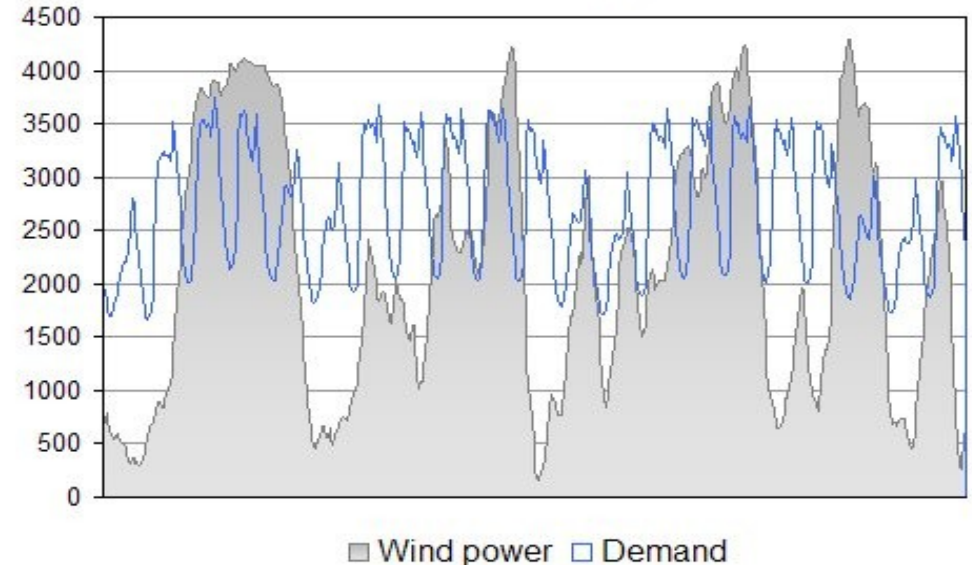
The Danish Wind Power Case

.... balancing of the power system

25 % wind energy (West Denmark January 2008)



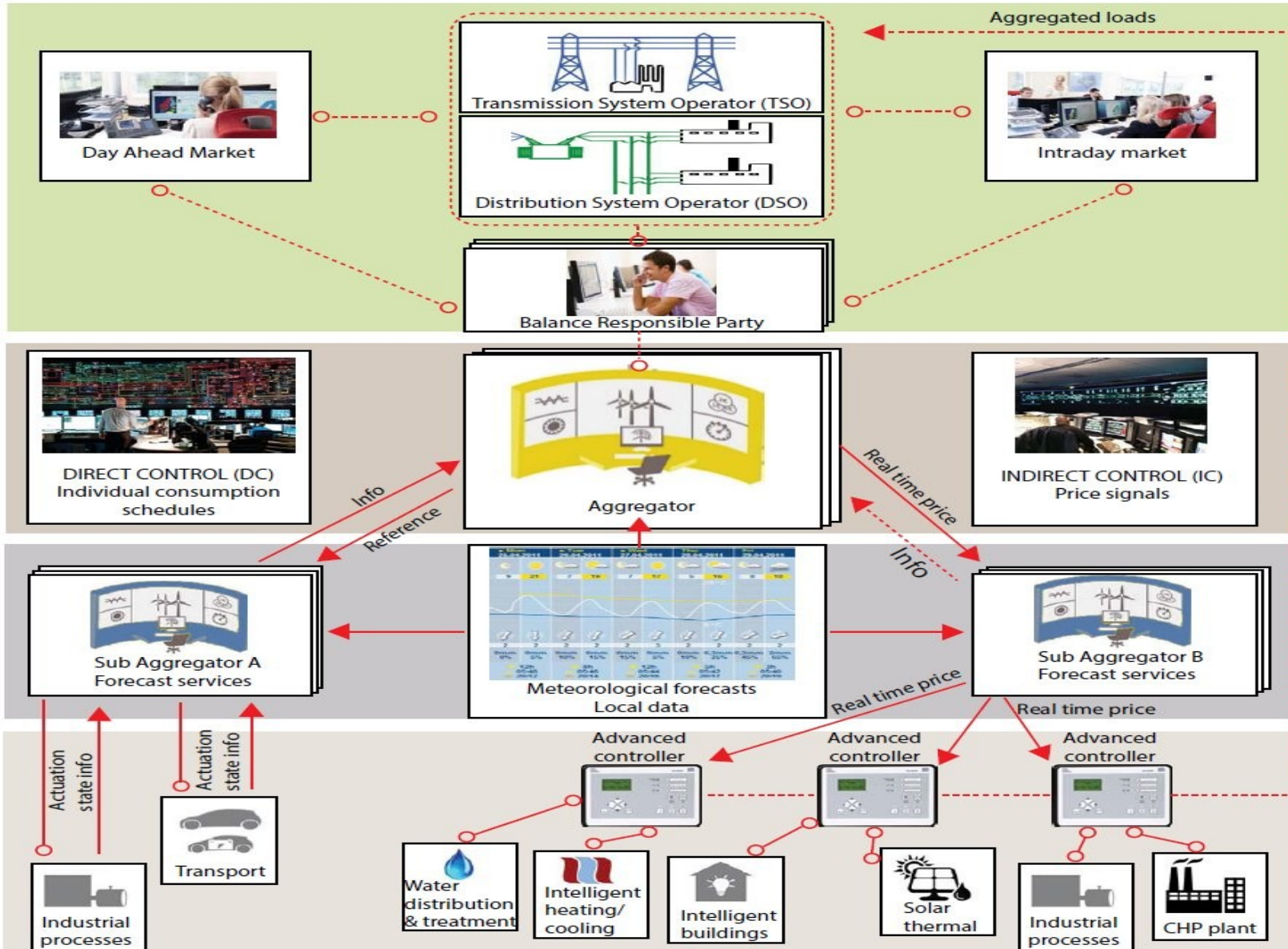
50 % wind energy



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

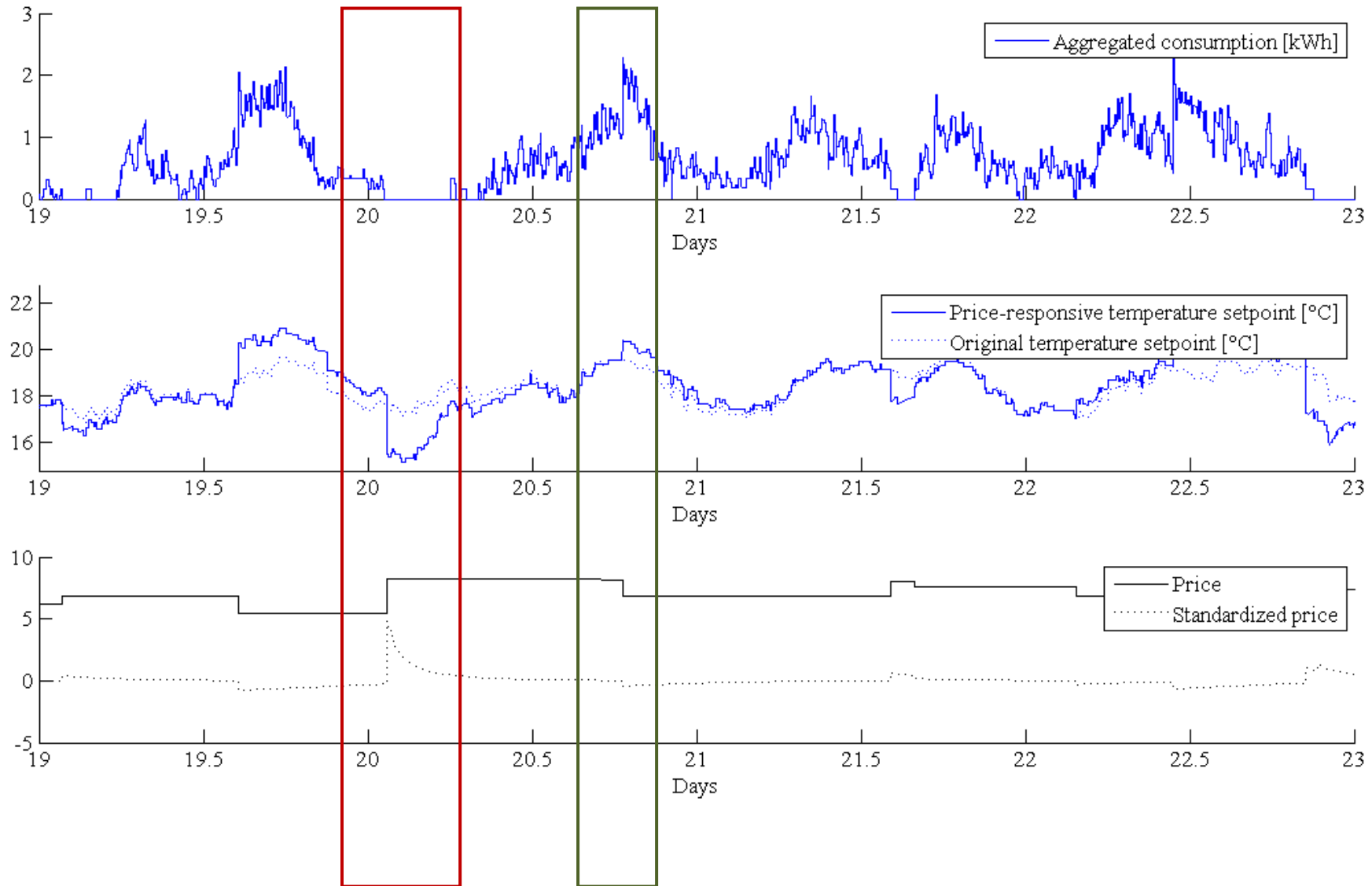
In 2015 more than 42 pct of electricity load was covered by wind power. And for several days the wind power production was more than 120 pct of the power load

Smart-Energy OS



Some perspectives in the used of smart meter data
 New Annex Meeting, Brussels, April 2016

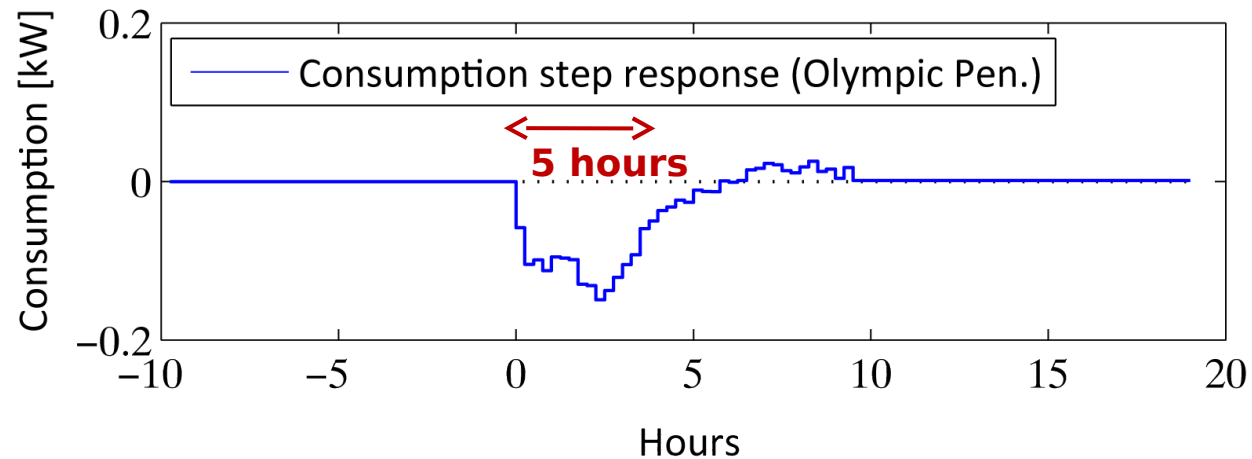
Aggregation (over 20 houses)



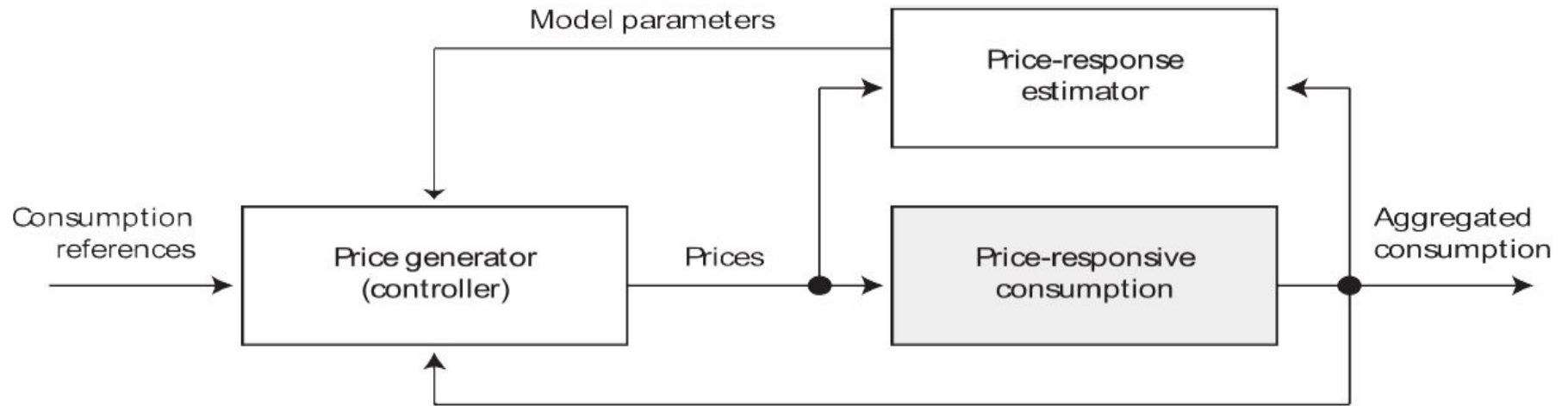
Non-parametric Response on Price Step Change

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

Olympic Peninsula



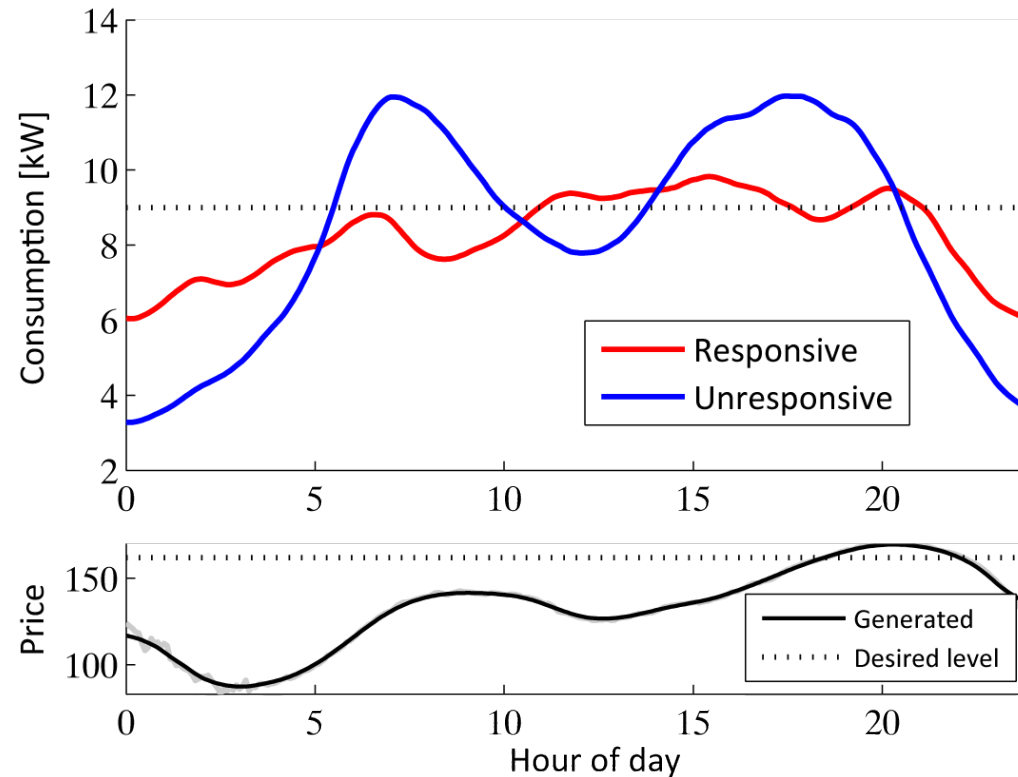
Control of Energy Consumption



Control performance

With a price penalty avoiding its divergence

- Considerable reduction in max consumption
- Mean daily consumption shift



Part 3

Occupancy behavior



- Occupancy modelling is a necessary step towards a full characterization of the energy consumption in buildings

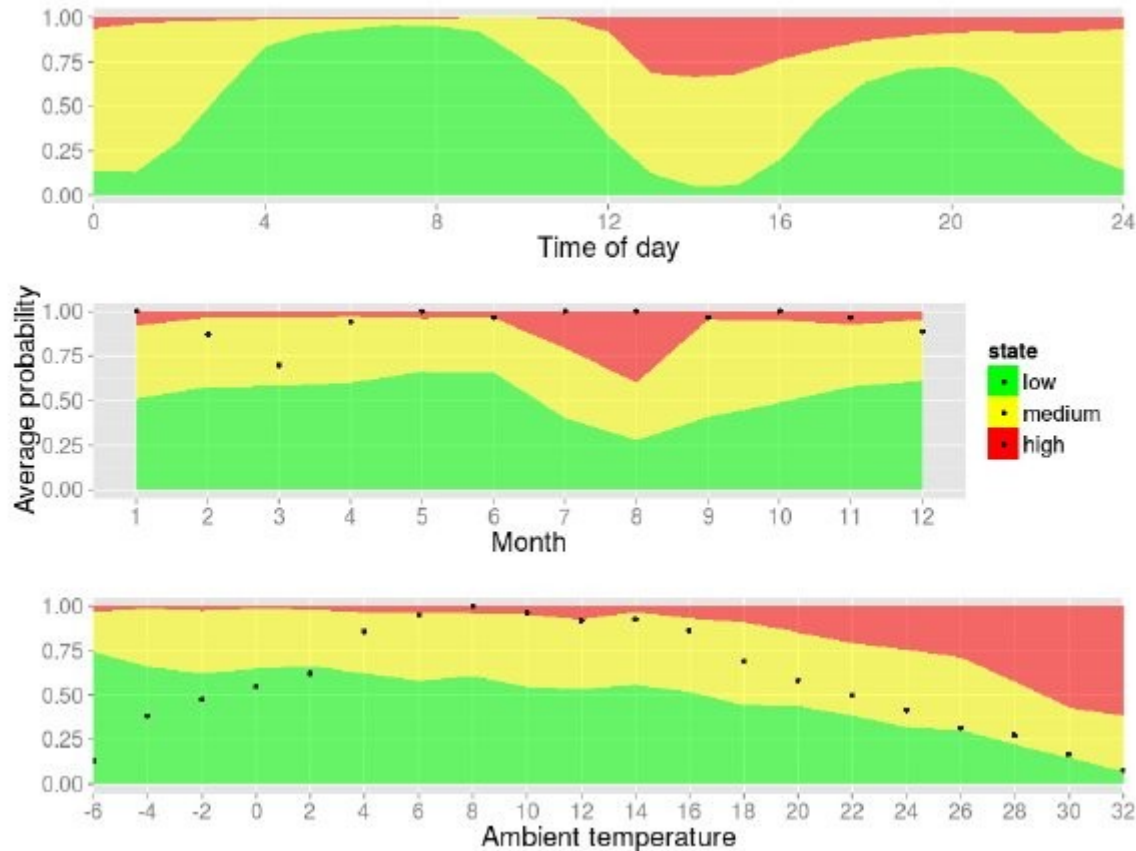


Metering and weather data from and nearby an apartment building in Catalonia, with 44 apartments. Also an occupant survey was available. Hourly observations from July 2012 to December 2013 consists of:

Variable	description
x_e	Electricity consumption in kWh
x_{sh}	Space heating in kWh
x_{hw}	Hot water consumption in kWh
x_w	Water consumption in liters
T_a	Ambient temperature in $^{\circ}C$
G	Solar radiation in W/m^2
W_s	Average wind speed in m/s
W_d	Average wind direction in $^{\circ}$
P	Precipitation in mm



Hidden Markov Chain Models



- ① Absent or asleep (green)
- ② Home, medium consumption (yellow)
- ③ Home, high consumption (red)

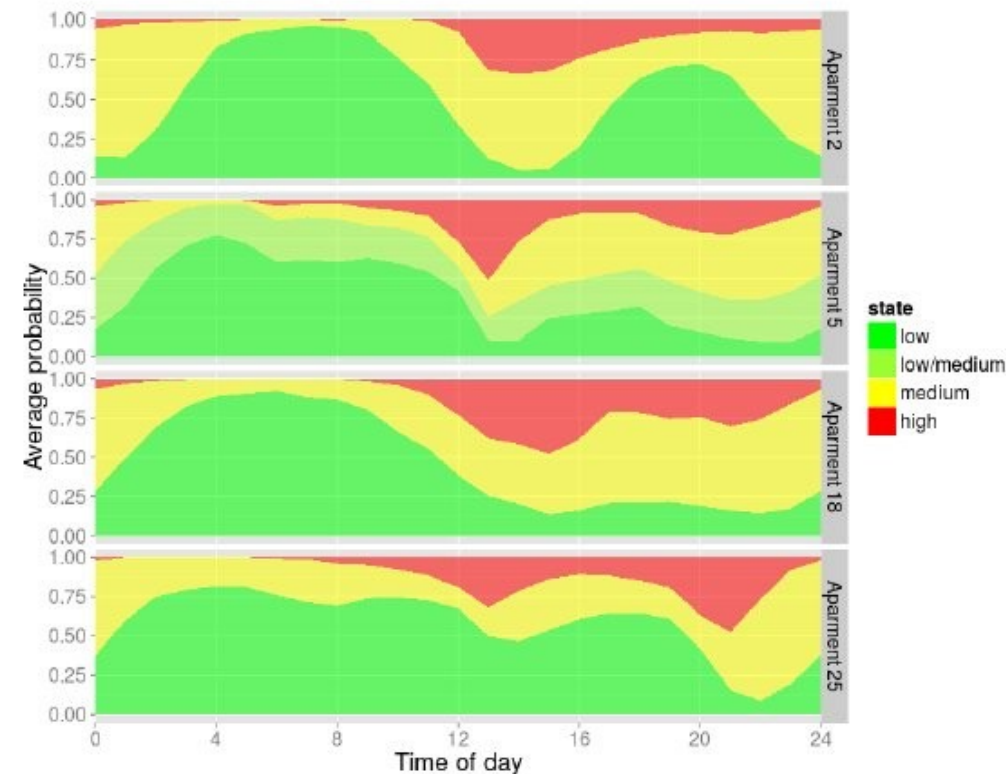
Consumption Characteristics

Four different profiles are observed and classified as:

- Afternoon/evening absence
- Equal probability for being home or absent.
- Mostly at home
- Mostly absent

Comparing different patterns with occupant survey, indication of common factors were observed.

- no. residents
- Income (work, pension or subsidies)



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

- Henrik Madsen

- hmad@dtu.dk

- Peder Bacher

- pbac@dtu.dk

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