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Price-based Control of Buildings; Examples from CITIES

iEnergy/DEHA Meeting, Risø November 2015

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Contents

- Use of data from smart meters
- Models for the termal dynamics of buildings
- Price-based control

Examples from CITIES

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Part 1
Simple non-parametric methods

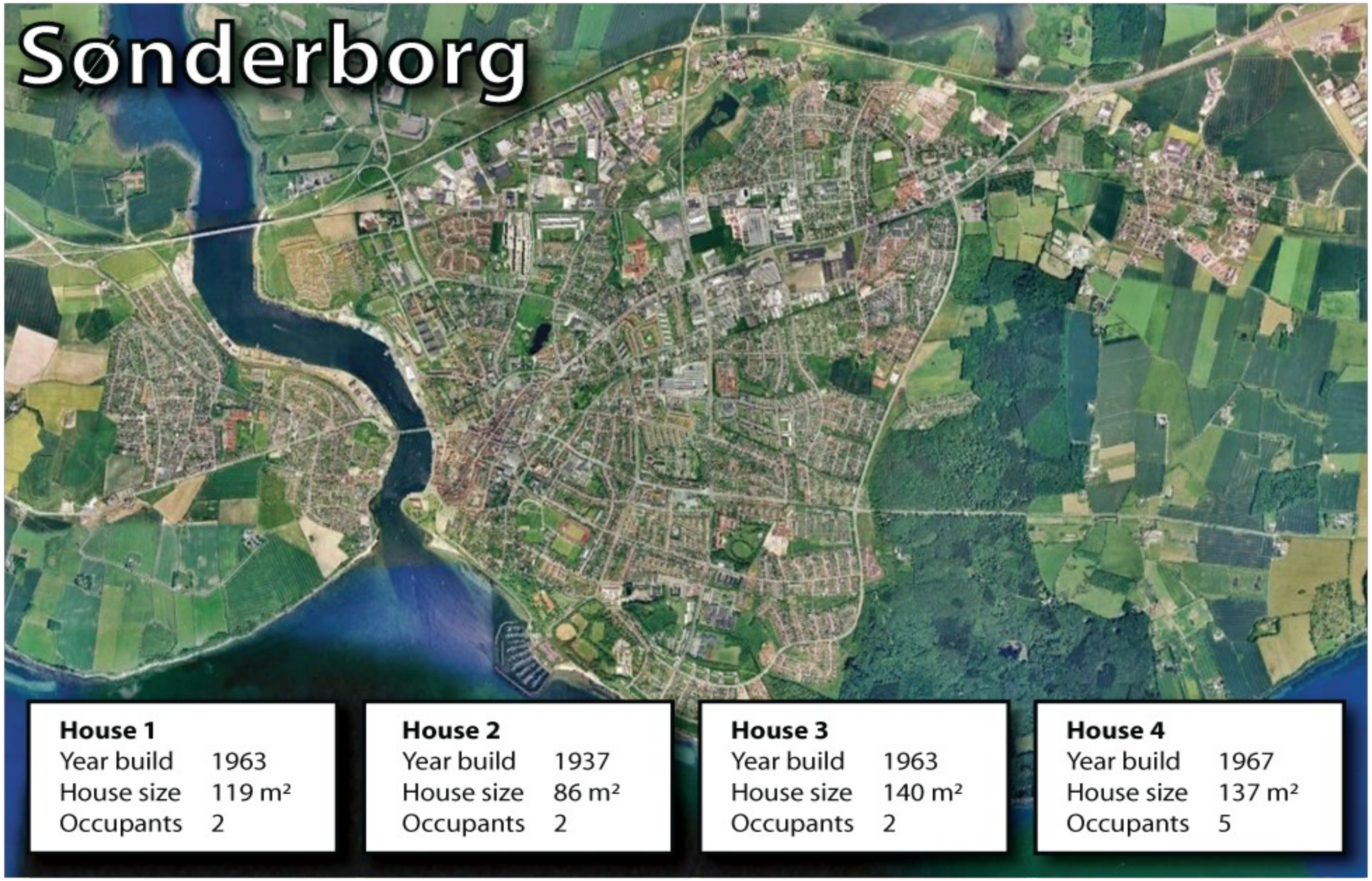
Typically only data from smart meter (and a nearby existing MET station)

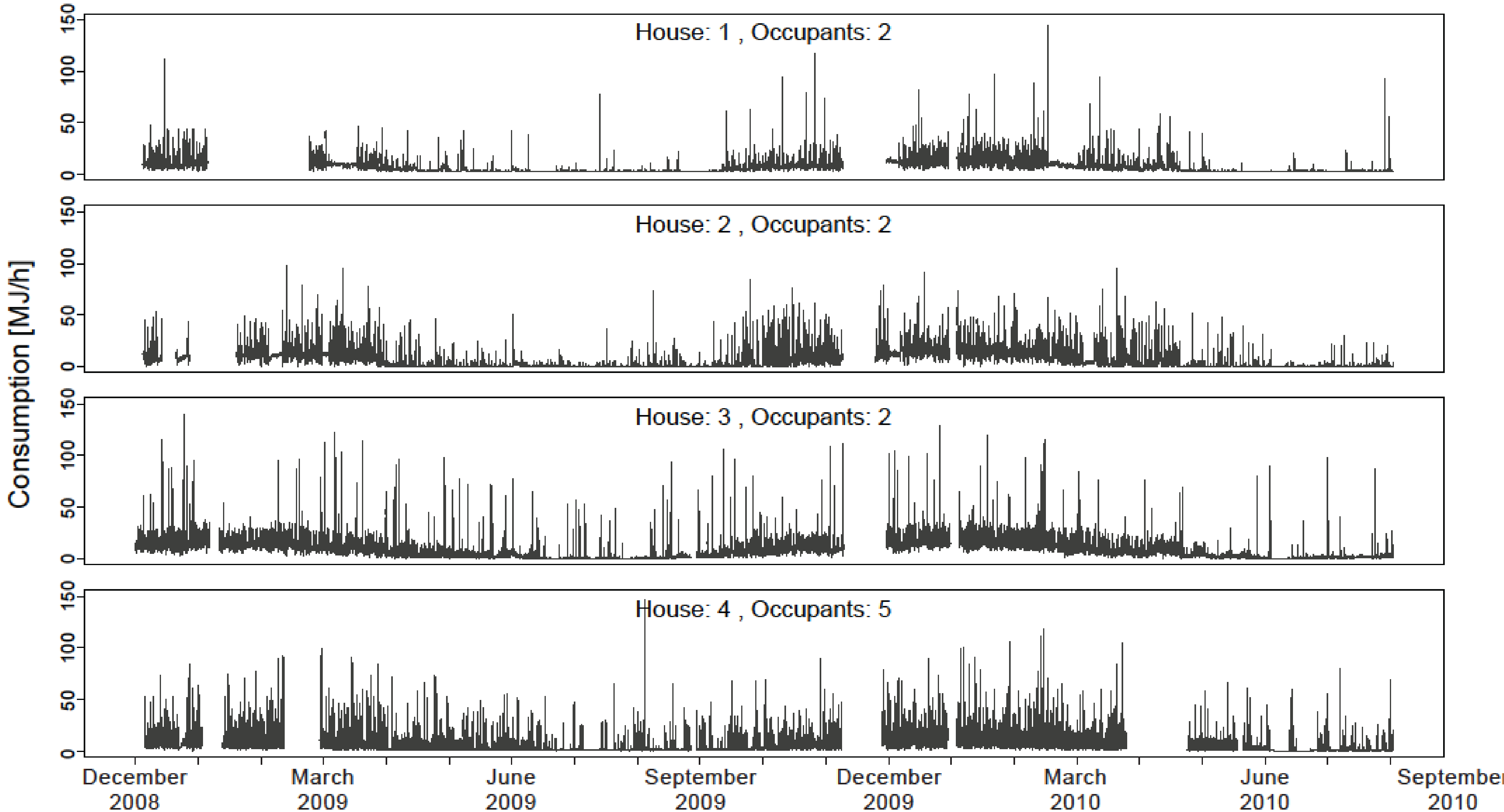
Case Study No. 1

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

Data

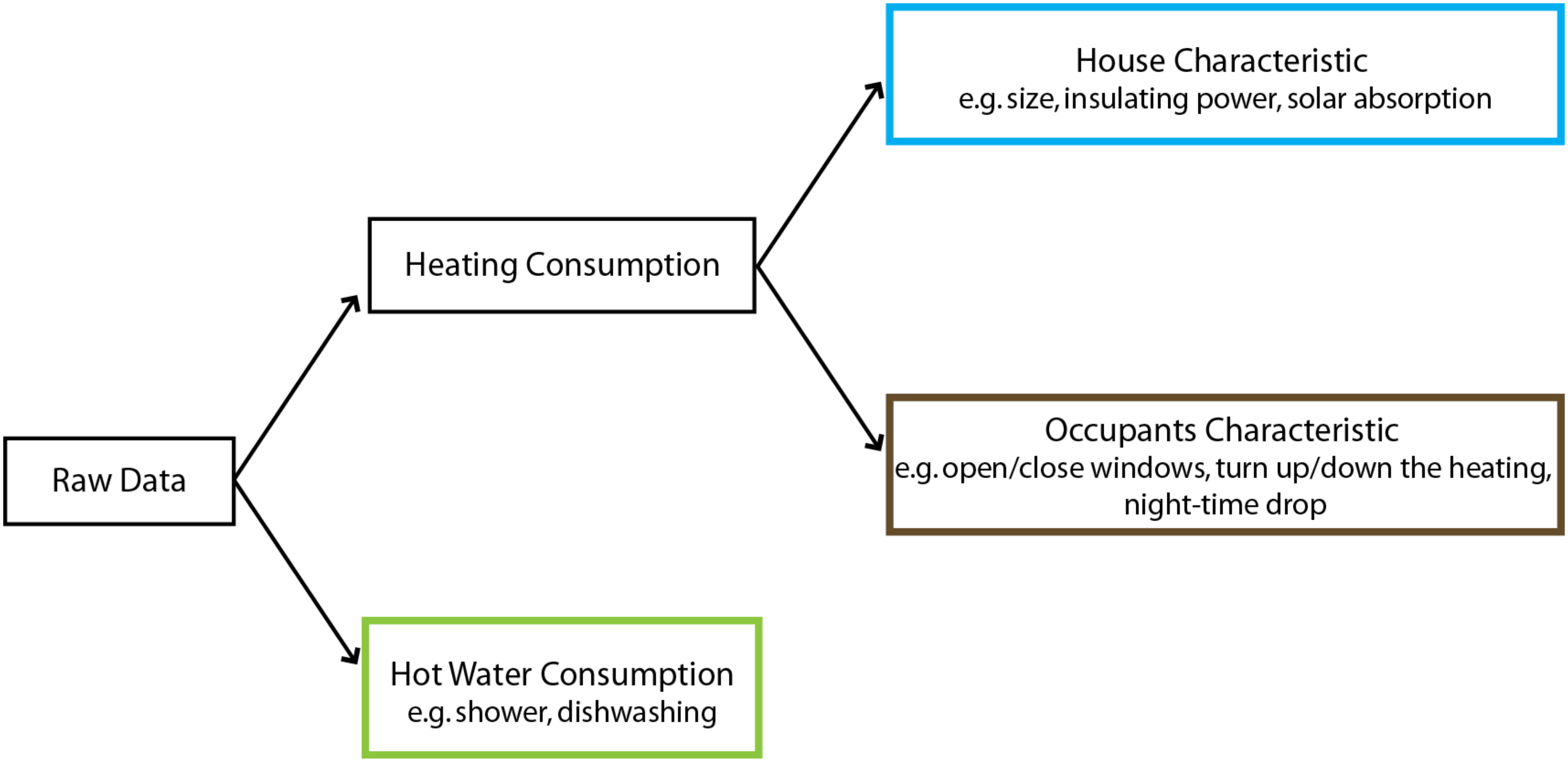
- 10 min averages from a number of houses



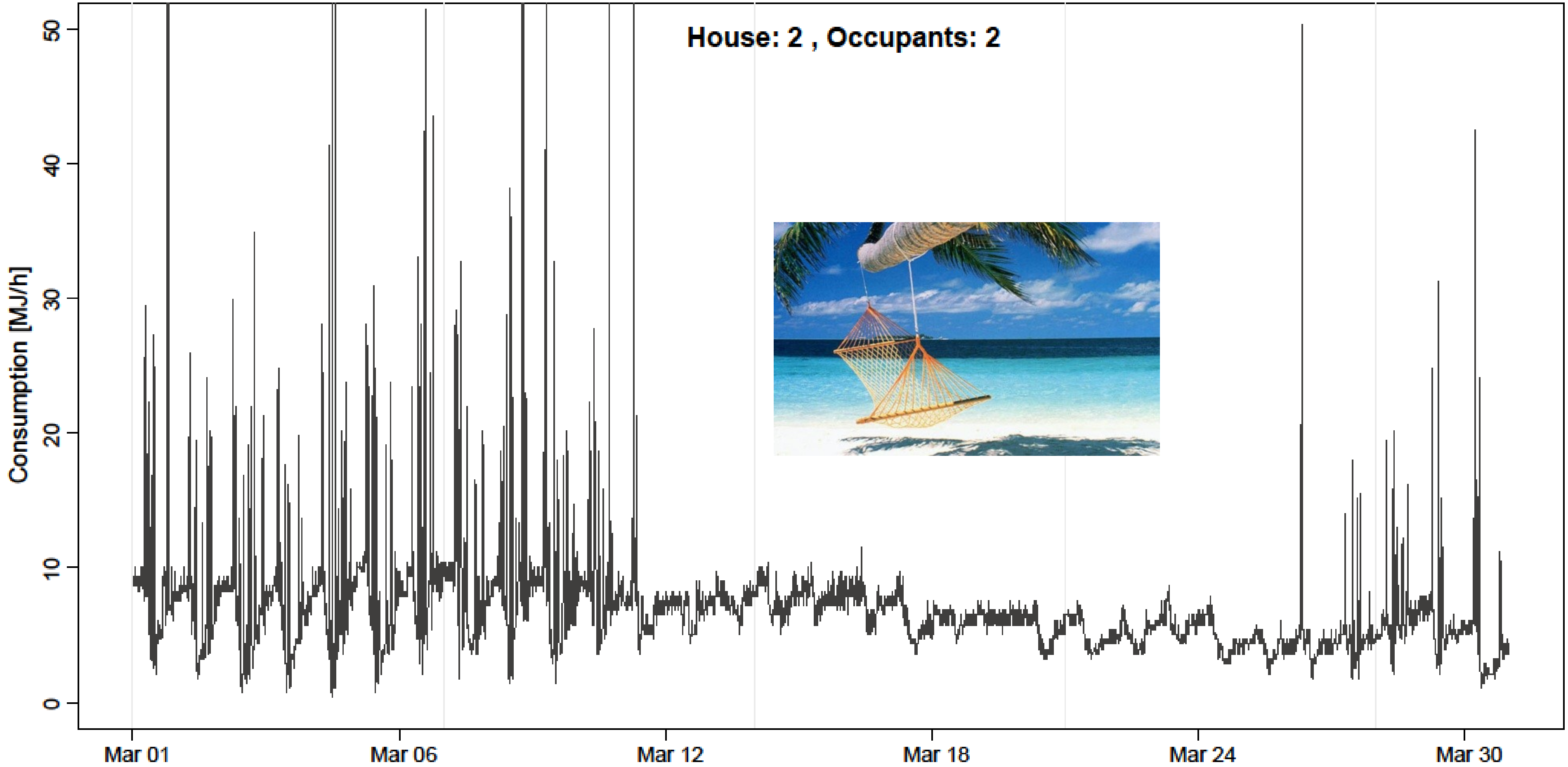


House: 1 , Occupants: 2
House: 2 , Occupants: 2
House: 3 , Occupants: 2
House: 4 , Occupants: 5
Consumption [MJ/h]
0
50
100
150
December 2008
March 2009
June 2009
September 2009
December 2009
March 2010
June 2010
September 2010

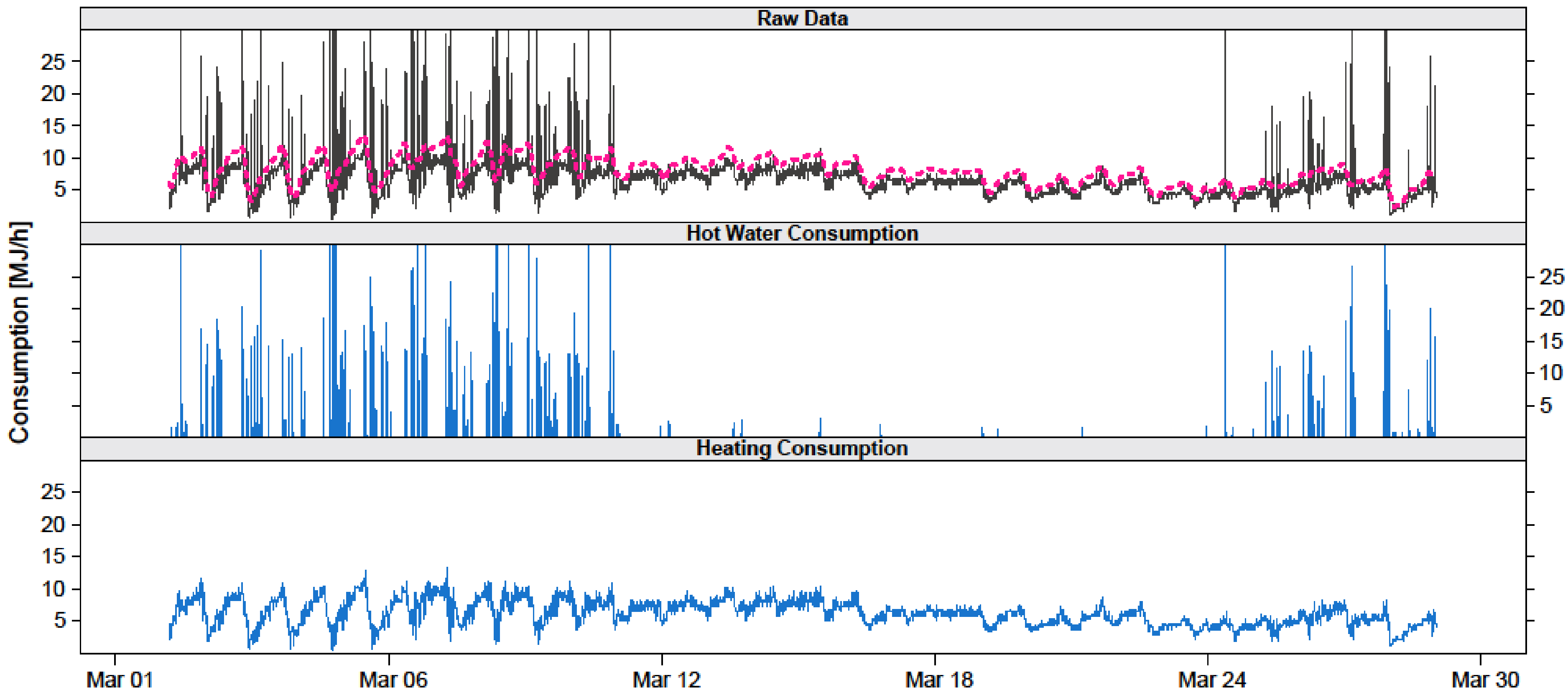
Splitting of total meter readings



Holiday period



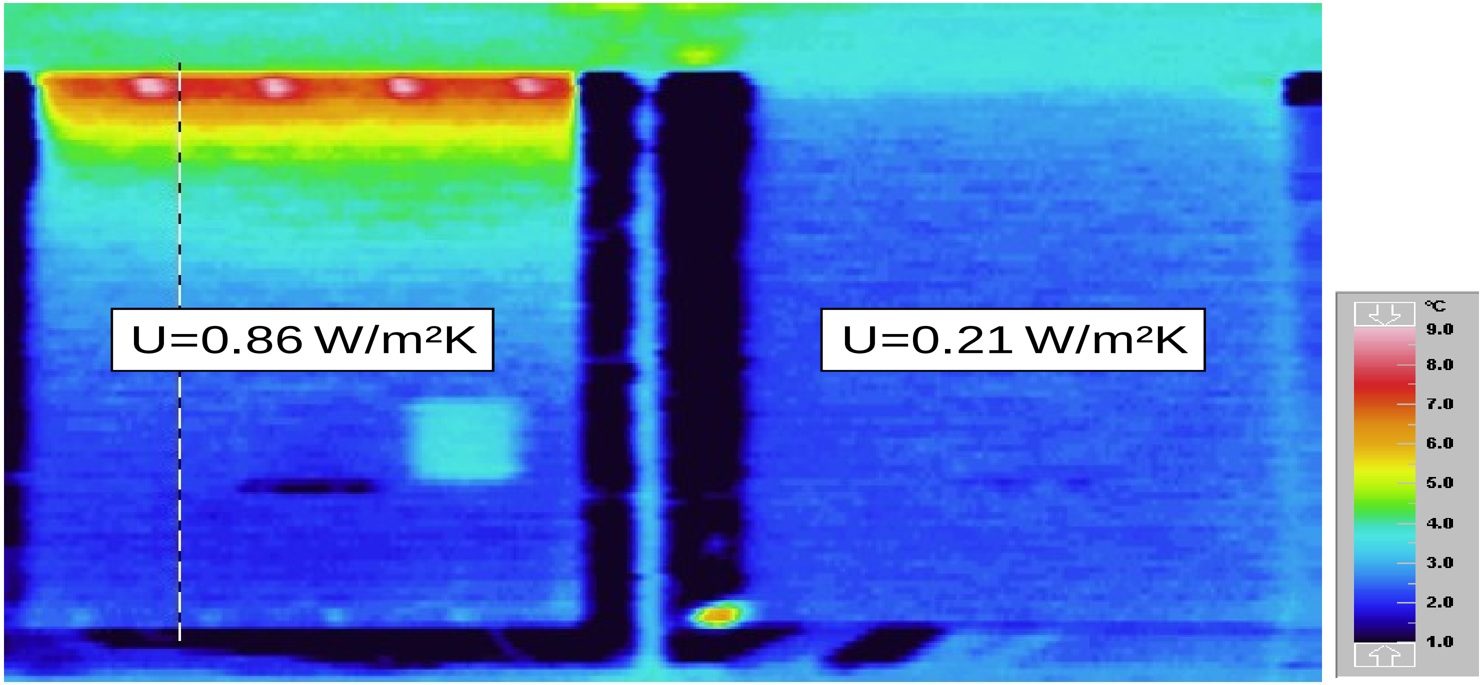
Robust Polynomial Kernel



Case Study No. 2

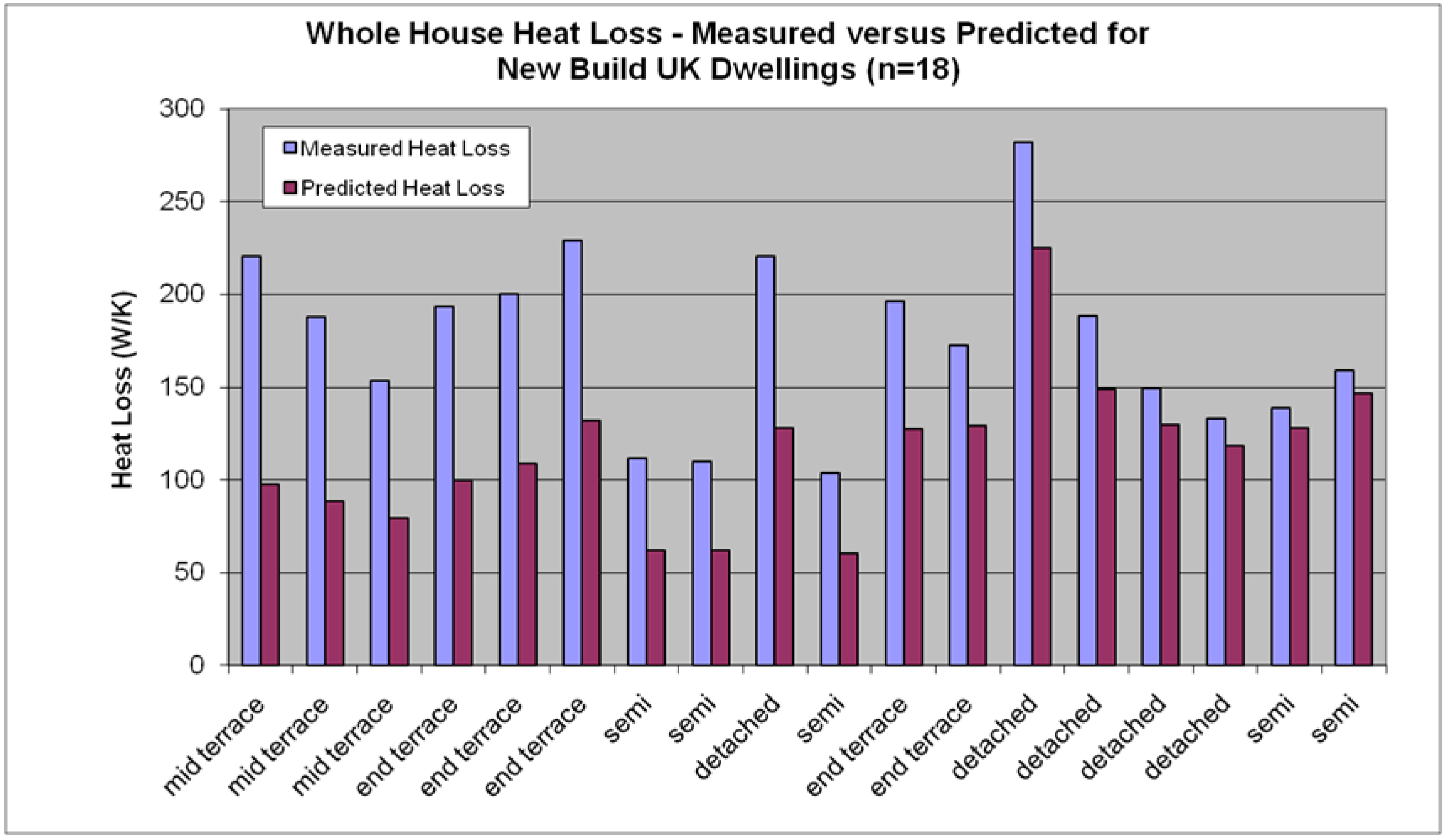
Modelling of Thermal Performance using Smart Meter Data

Example



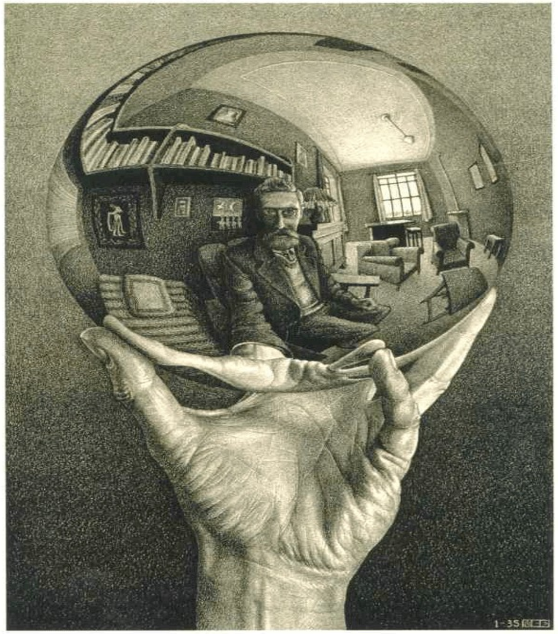
Consequence of good or bad workmanship (theoretical value is U=0.16W/m2K)

Examples (2)



Measured versus predicted energy consumption for different dwellings

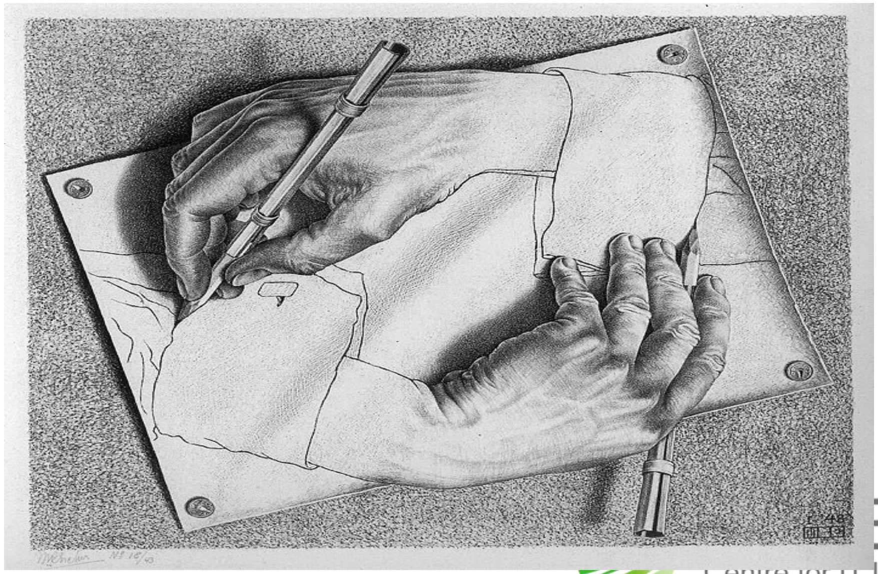
Characterization Smart Meter Data



- 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.



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
.	.	.	.	.	.	.	.	.

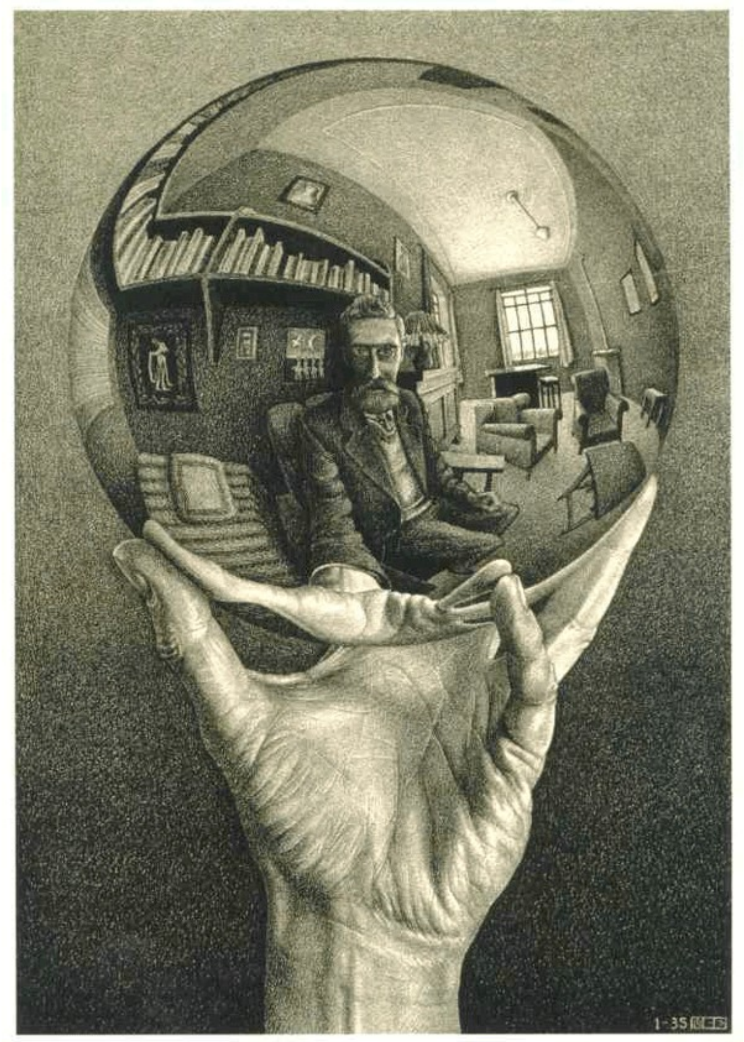
Perspectives for using data from Smart Meter

- 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 DSM

Case study No. 3

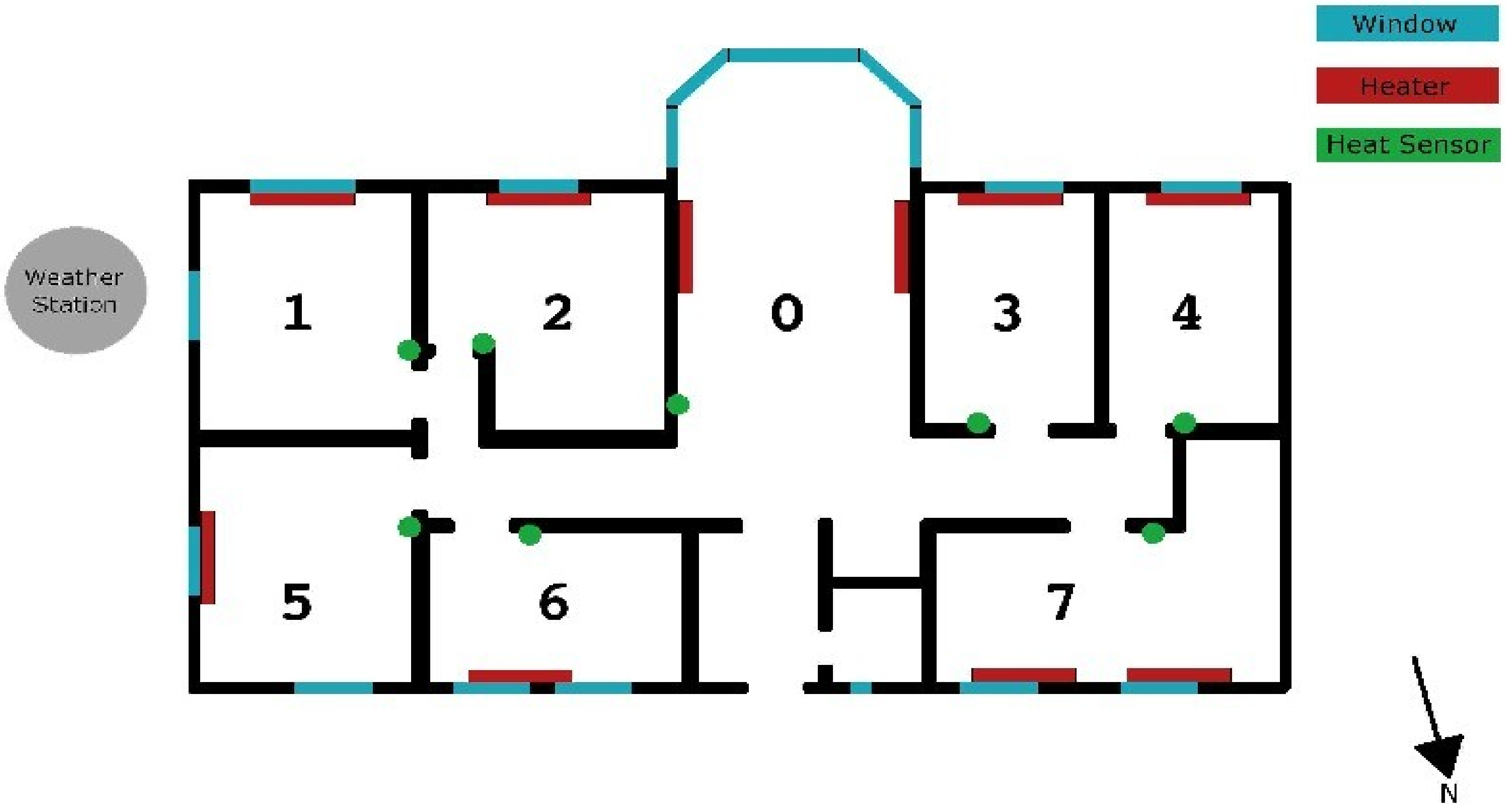
Modelling the thermal characteristics of a small office building

Part 2
Parametric Models

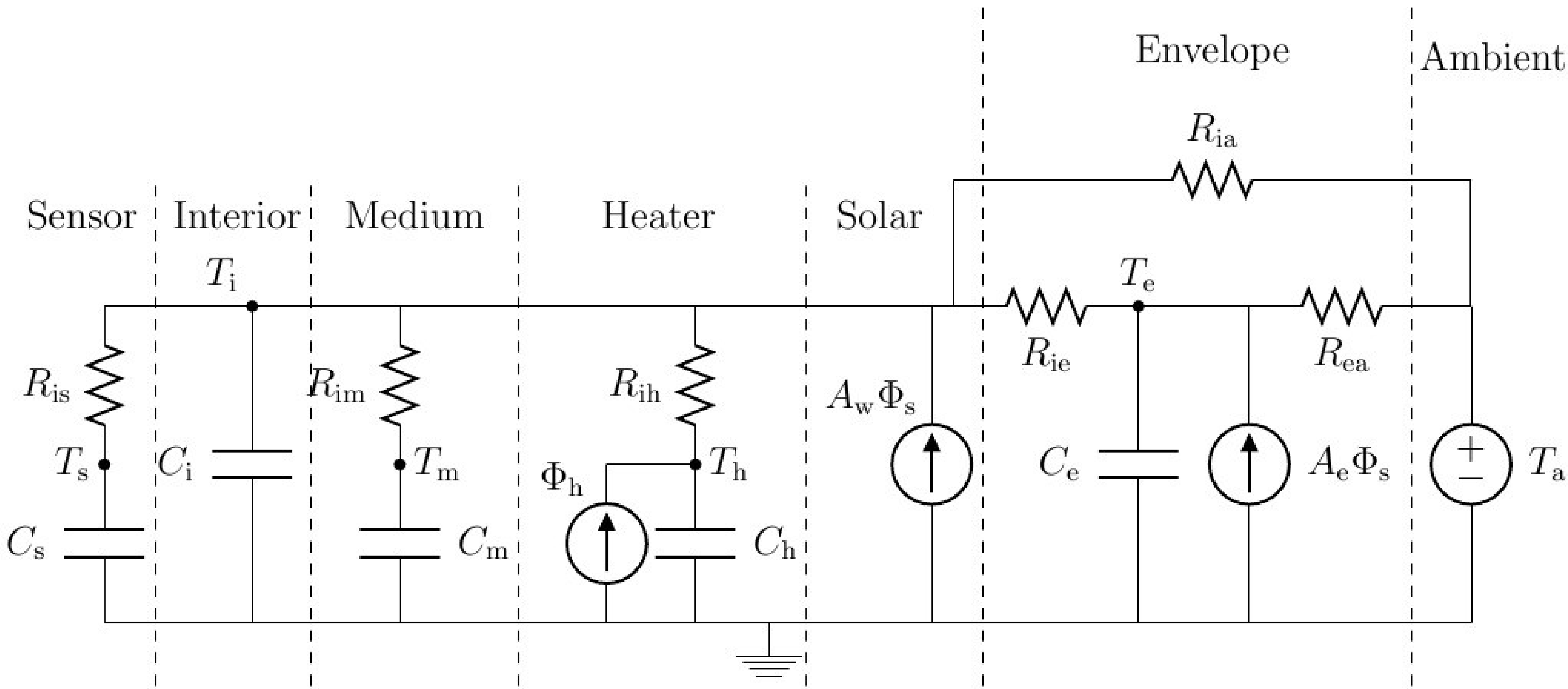


- A model for the thermal characteristics of a small office building

Flexhouse at SYSLAB (DTU Risø)

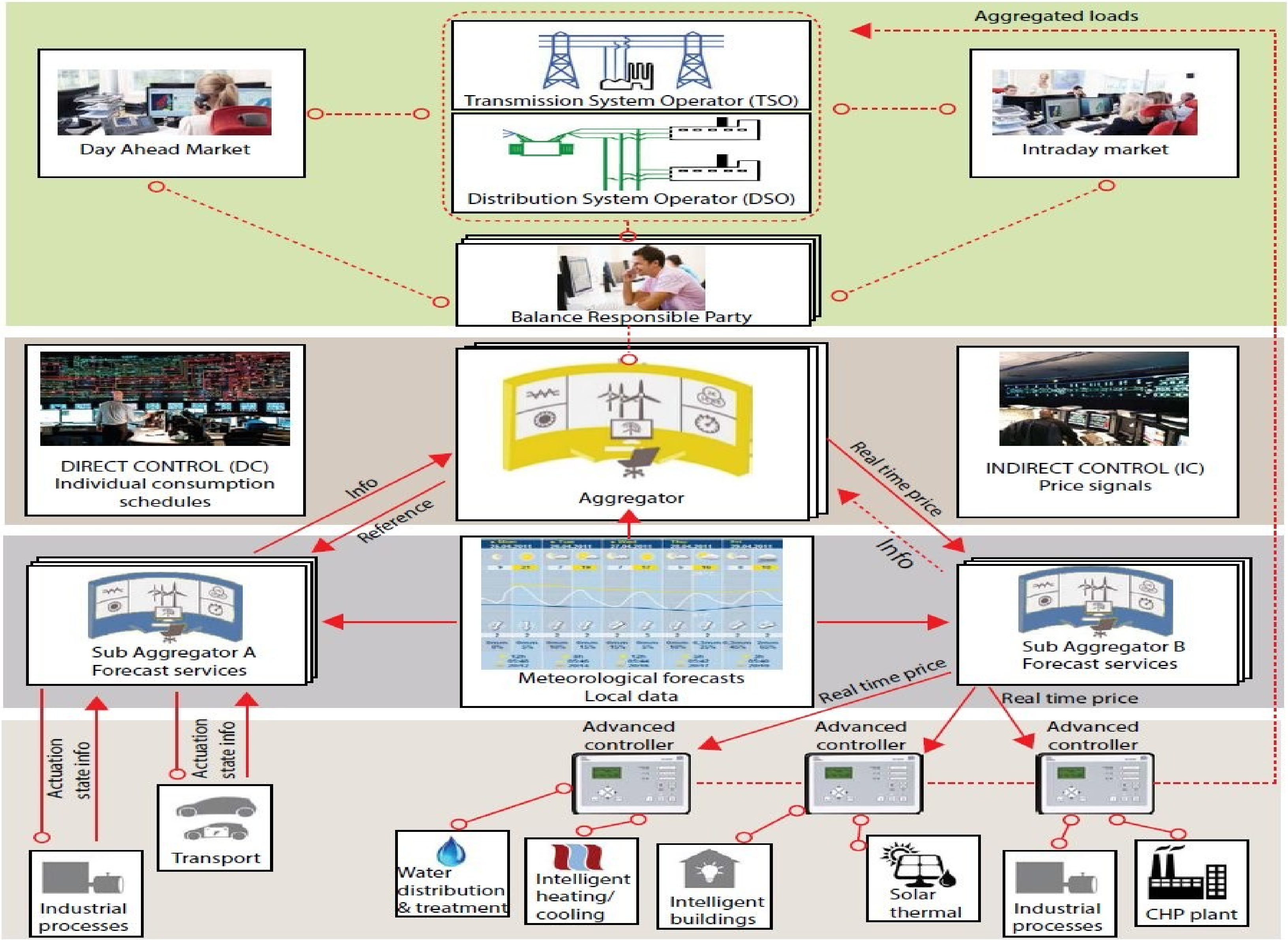


Model found using Grey-box modelling (..... using CTSM-R – http://smart-cities-centre.org/software-solutions/)



Control of Power Consumption

Control and Optimization



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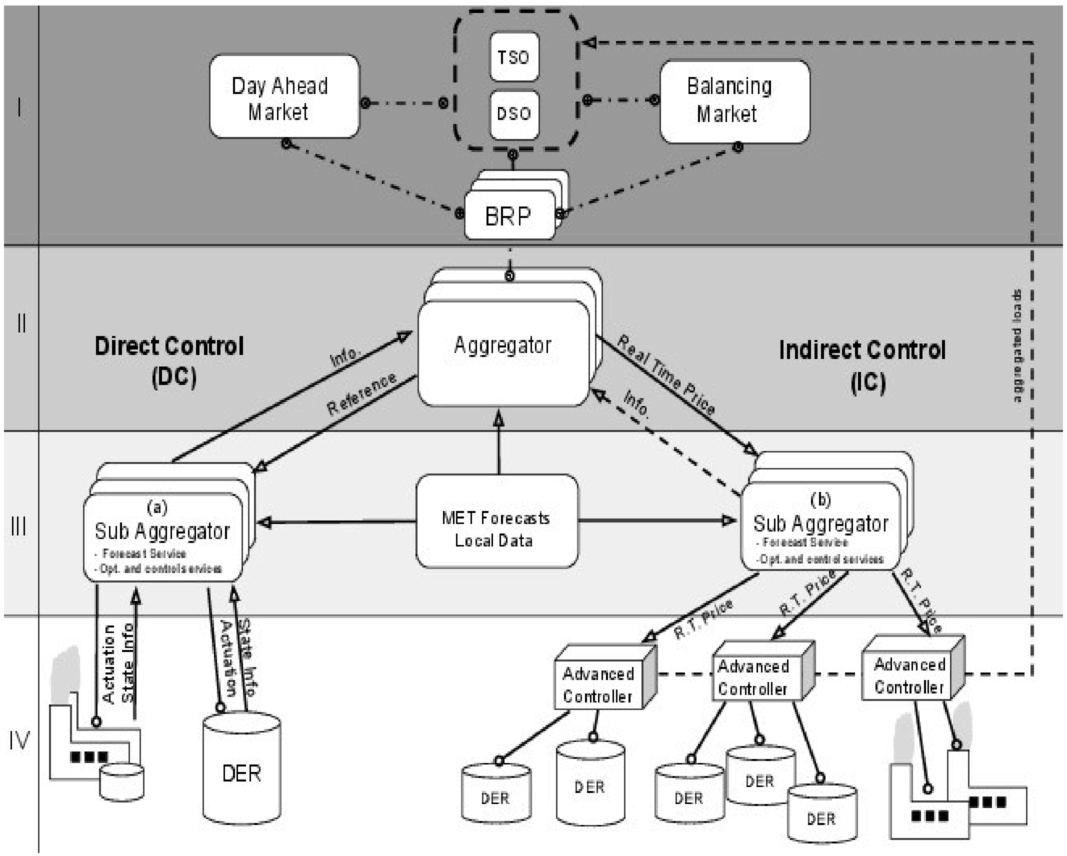
Control and Optimization



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

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

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.

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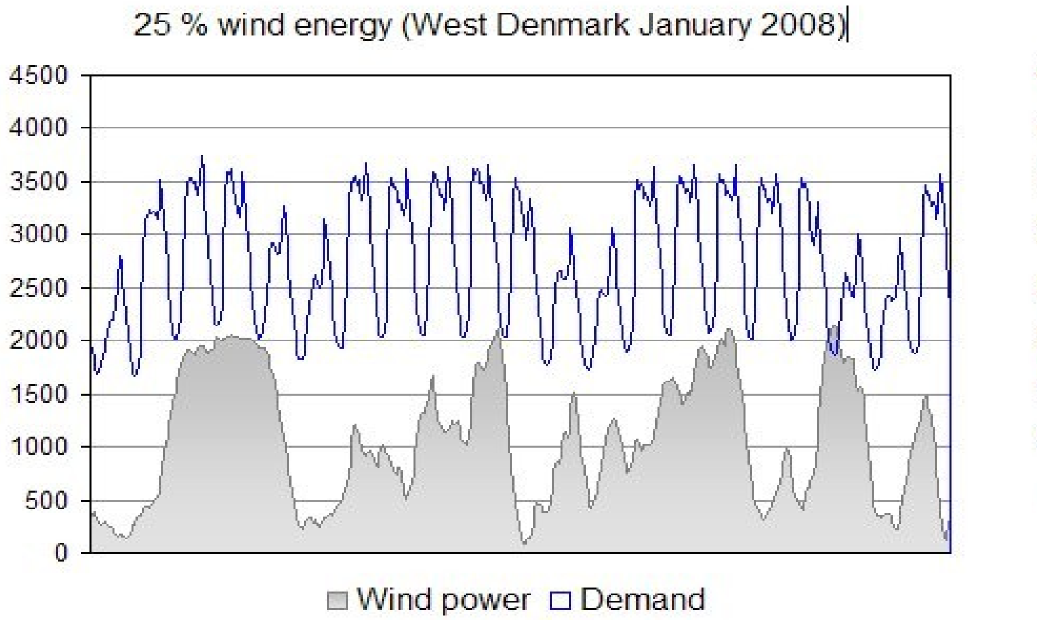
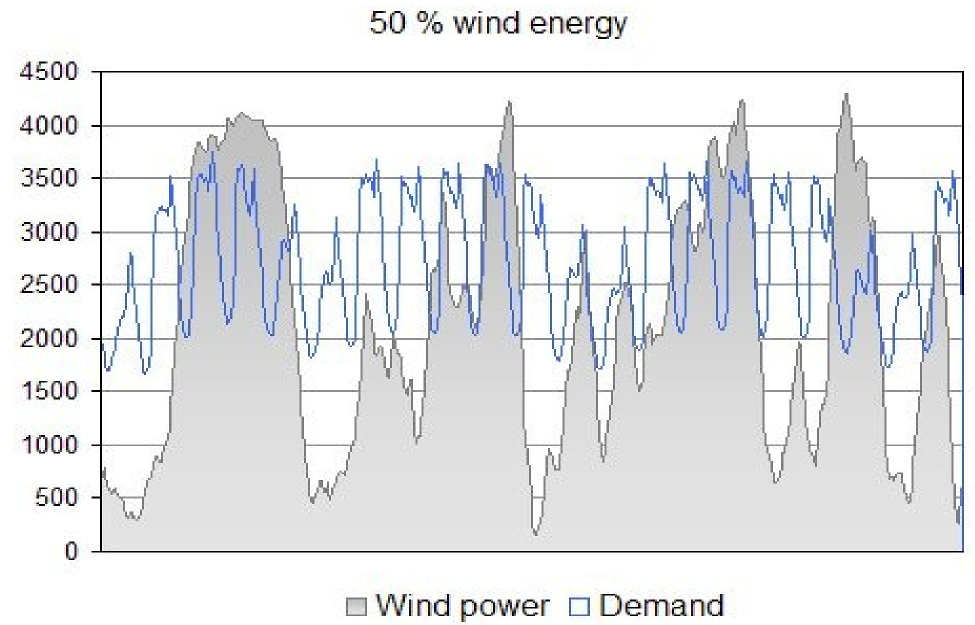
The Danish Wind Power Case

.... balancing of the power system





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

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

In 2014 more than 40 pct of electricity load was covered by wind power.

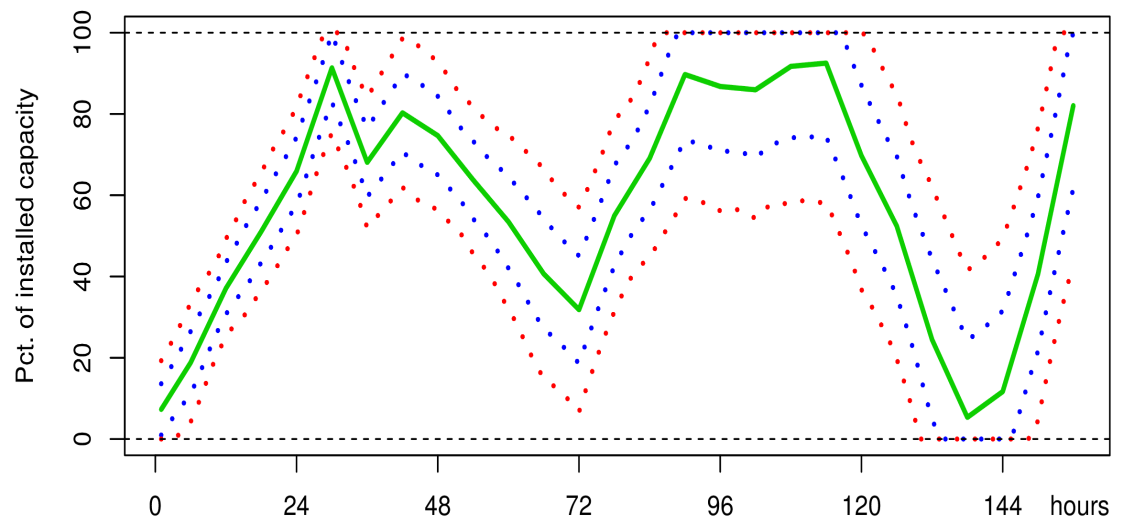
For several days in 2014 the wind power production was more than 120 pct of the power load.

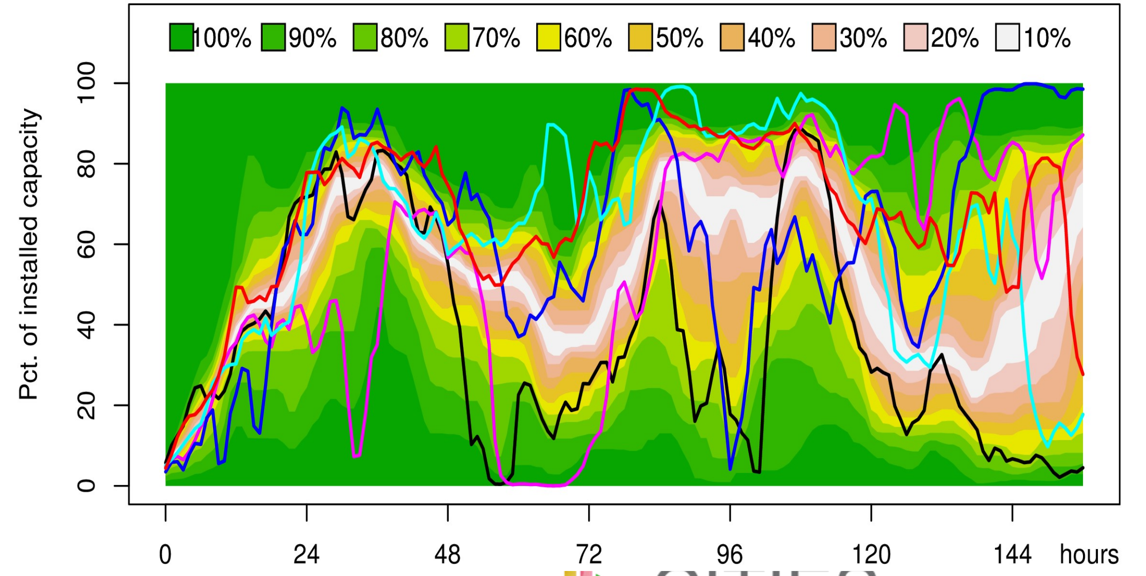
July 10th, 2015 more than 140 pct of the power load was covered by wind power

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)**





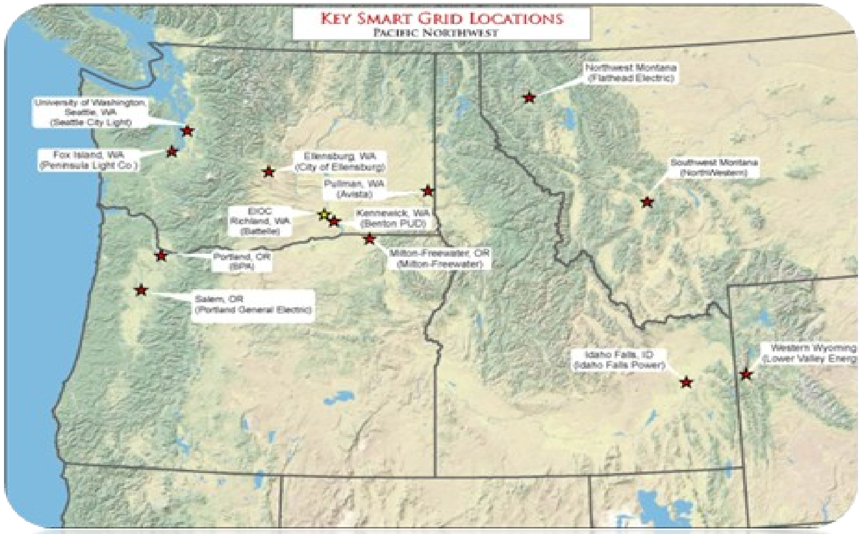
Case study No. 4

Price-based Control of Power Consumption

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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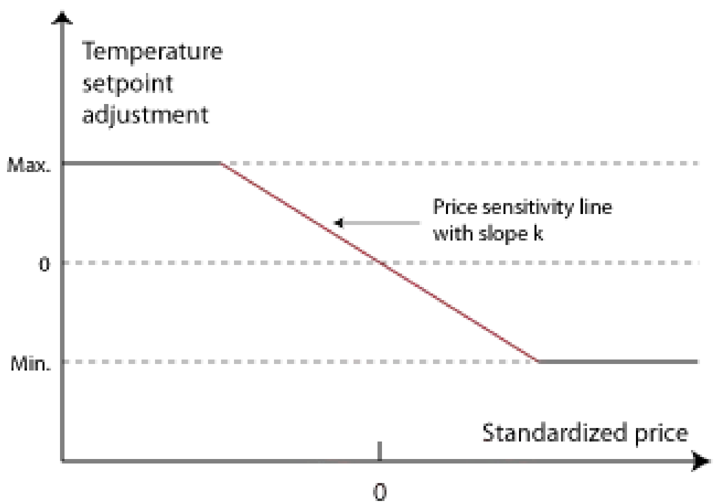
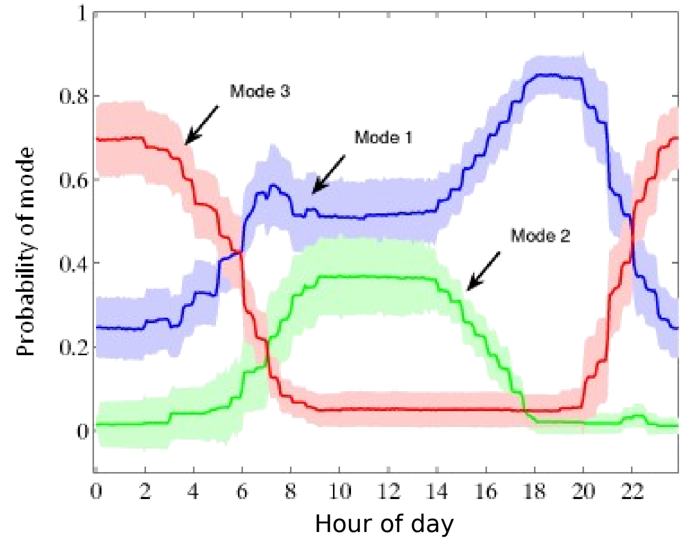
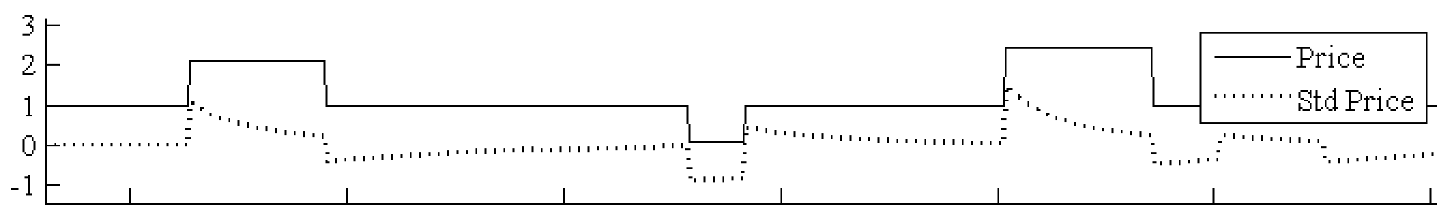
Price responsivity

Flexibility is activated by adjusting the temperature reference (setpoint)

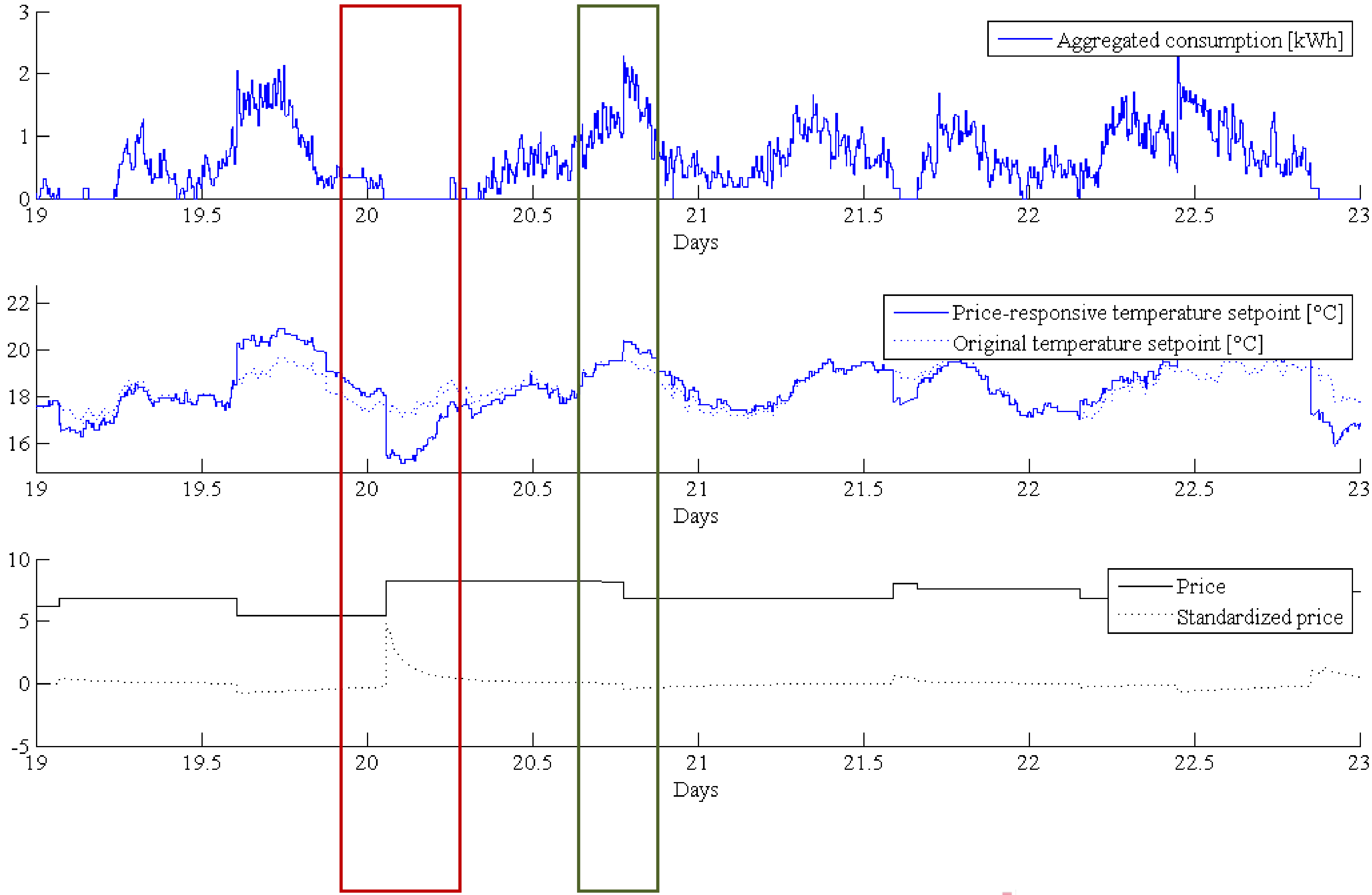






- **Standardized price** is the % of change from a price reference, computed as a mean of past prices with exponentially decaying weights.
- **Occupancy mode** contains a price sensitivity with its related comfort boundaries. 3 different modes of the household are identified (work, home, night).

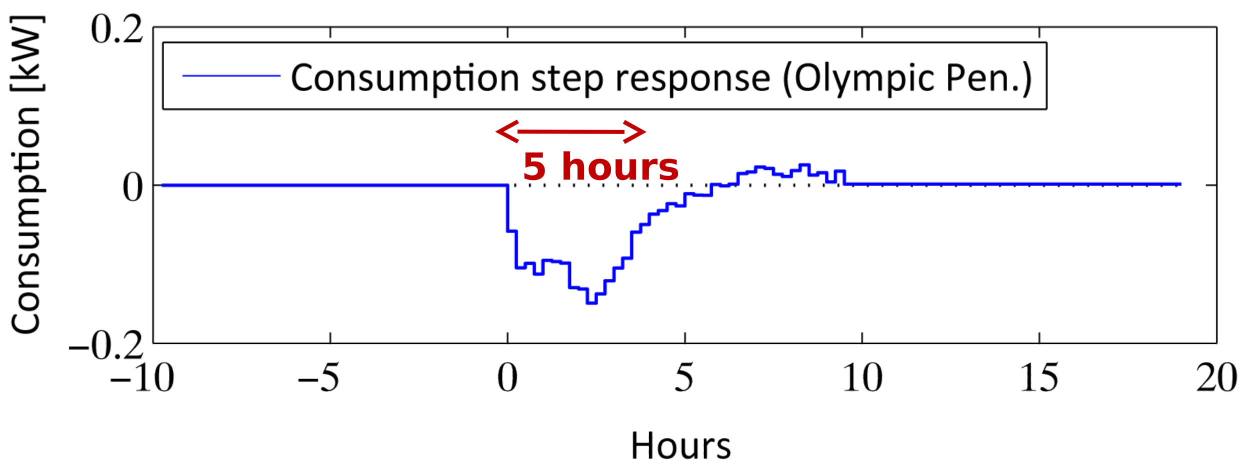
Aggregation (over 20 houses)



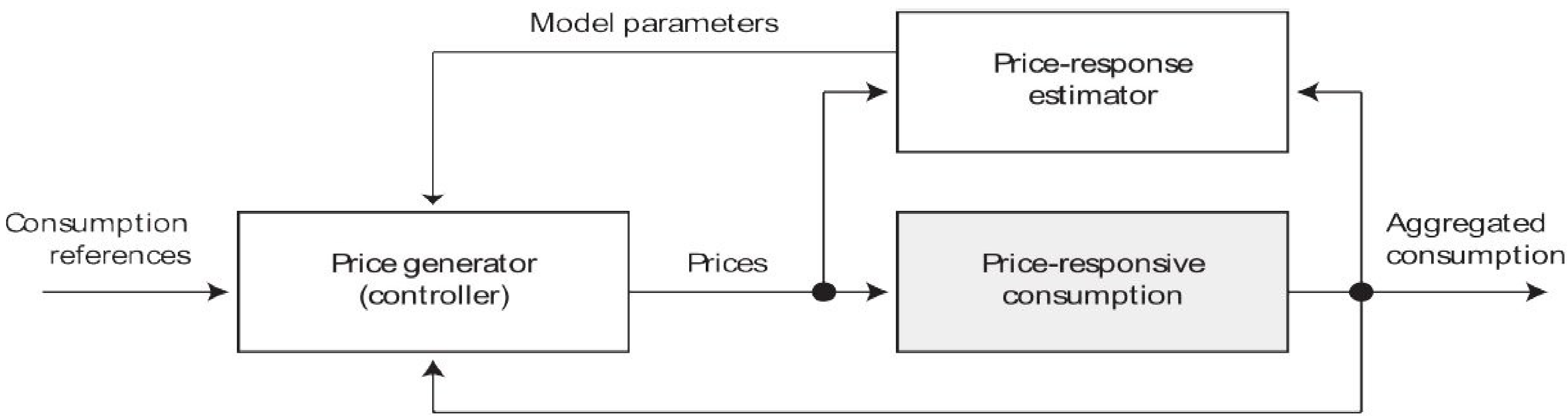
Non-parametric Response on Price Step Change

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

Olympic Peninsula



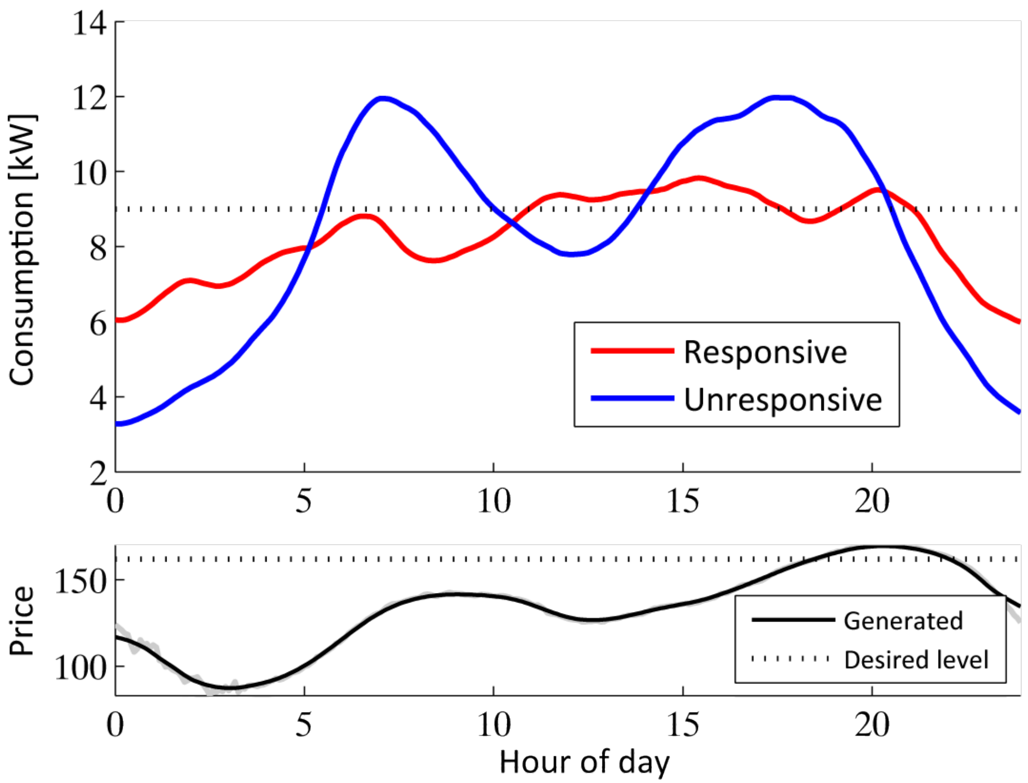
Control of Energy Consumption



Control performance

With a price penality avoiding its divergence

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

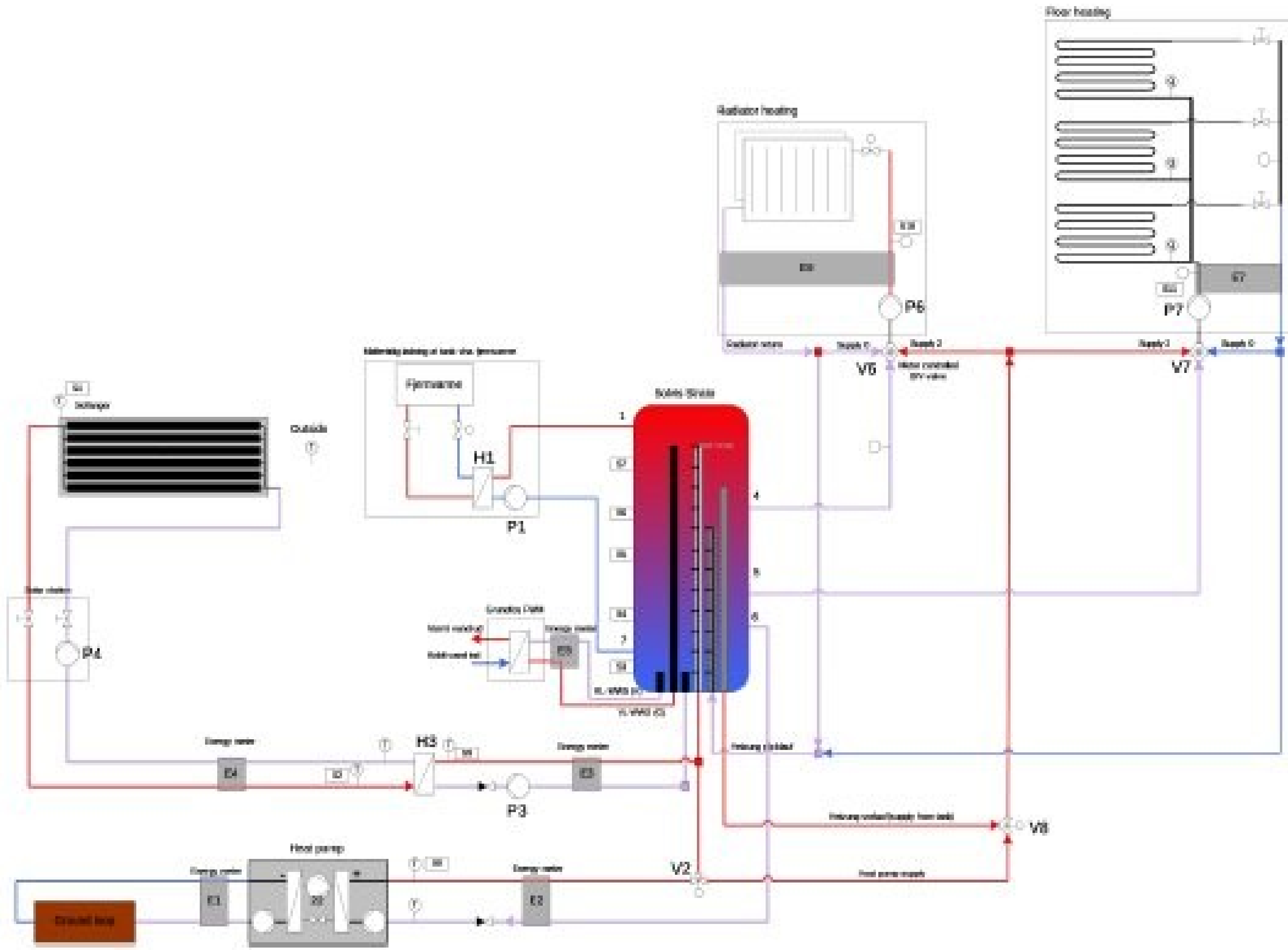


Case study No. 5

Control of Heat Pumps (based on varying prices)

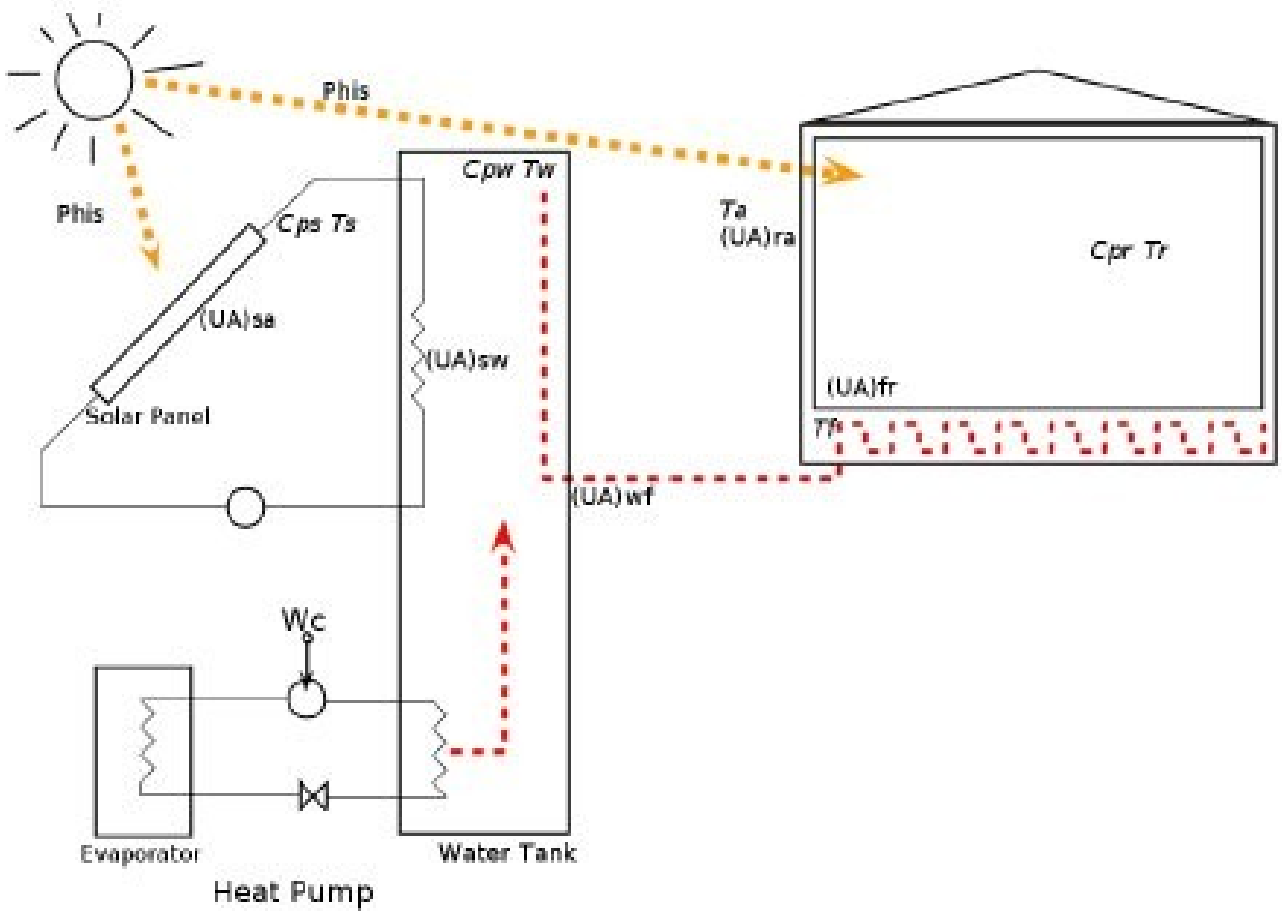
Grundfos Case Study

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

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

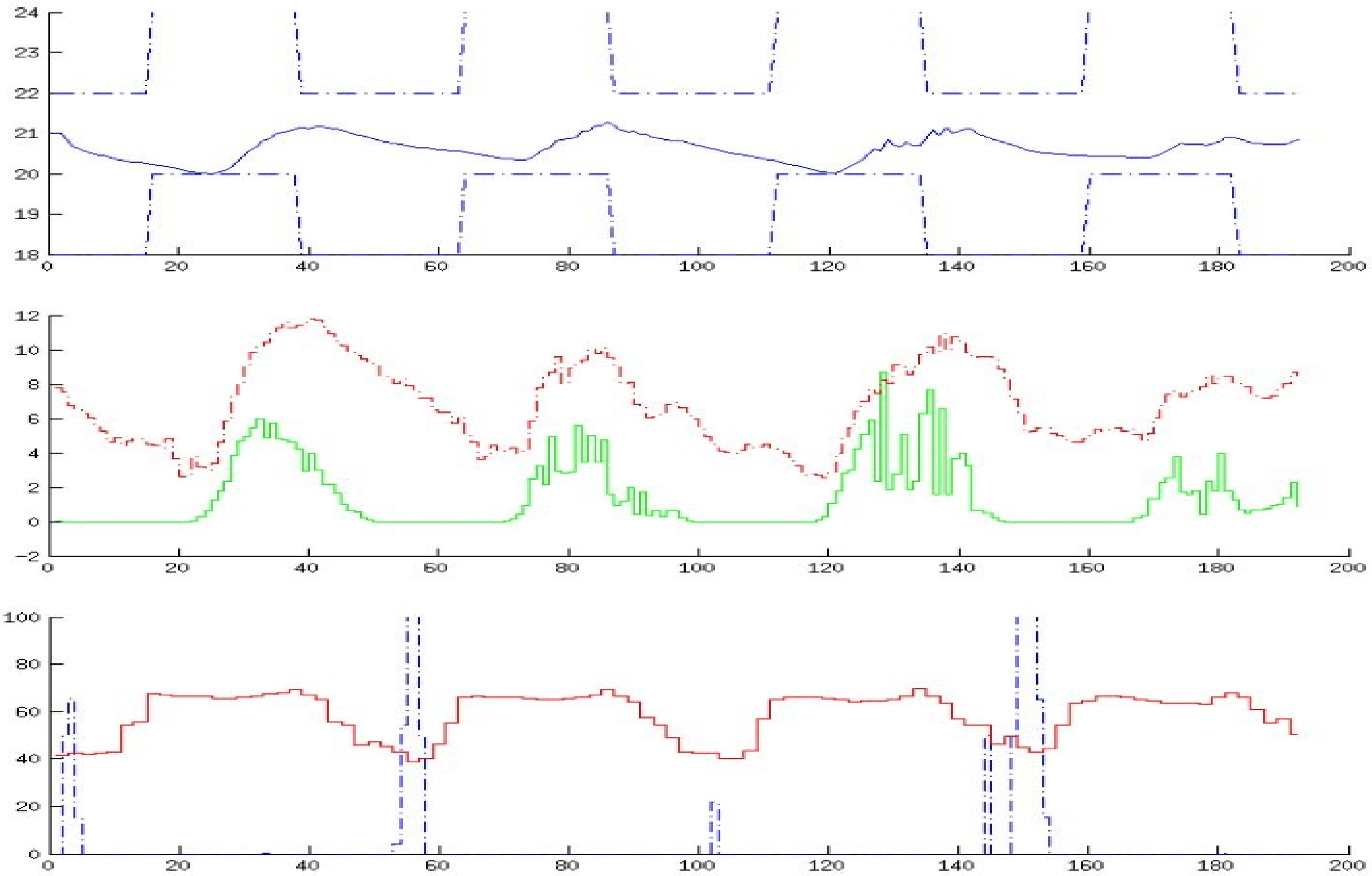
$$y_k = Cx_k \quad k = 1, 2, \ldots, N \tag{4c}$$

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

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

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

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

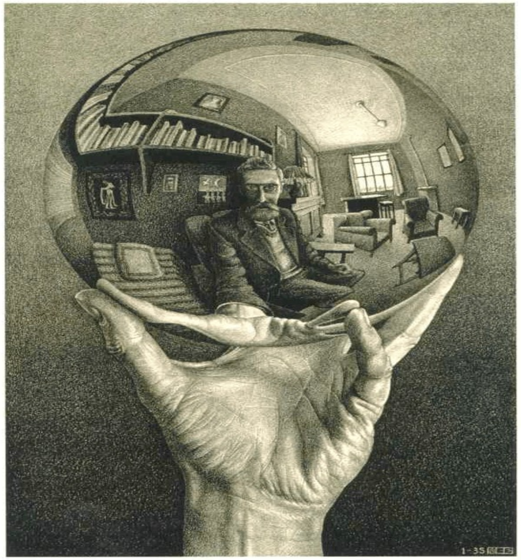
Ambassador Louise Bang Jespersen visited CITIES, October 29th 2015

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

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

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
- VE (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)

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- Acknowledgement CITIES (DSF 1305-00027B)