Data-Intelligent Energy Performance and Flexibility of Buildings

Henrik Madsen

DTU Compute (Applied Math and Computer Science)

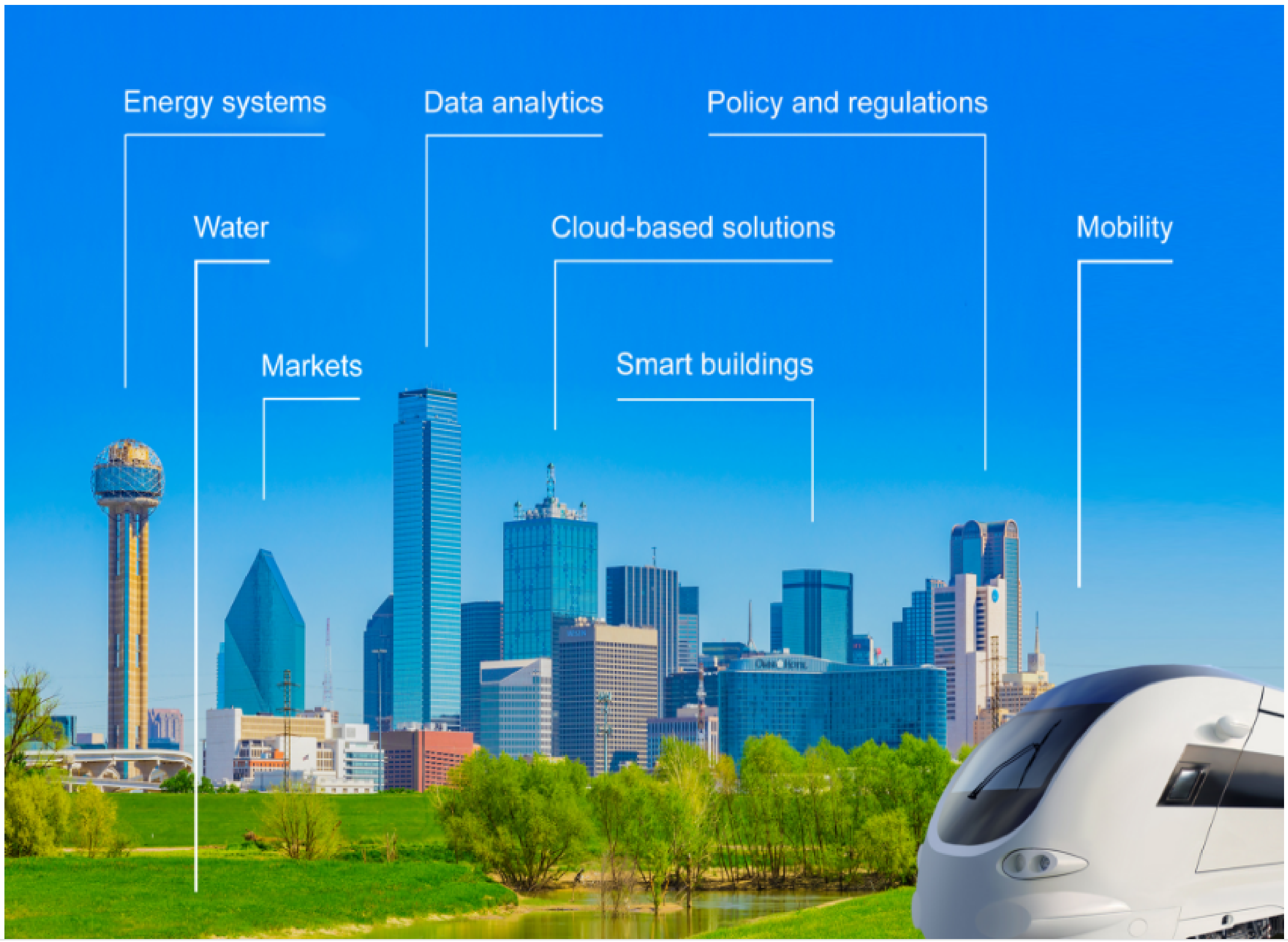
https://smartcitiesaccelerator.eu/

http://www.smart-cities-centre.org

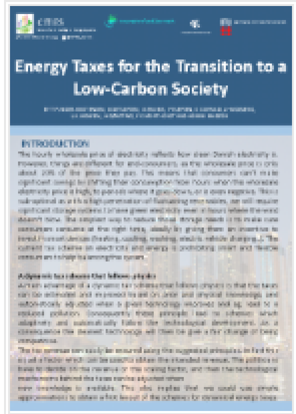
http://www.henrikmadsen.org

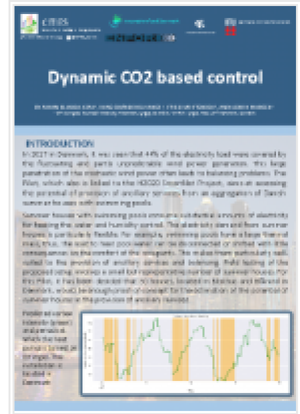
CITIES Centre for IT Intelligent Energy Systems

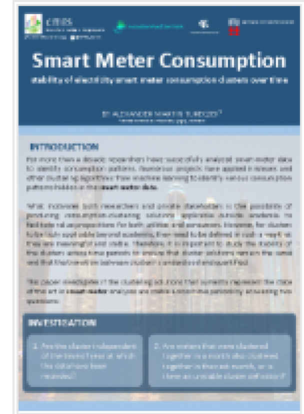
Topics


Energy systems
Data analytics
Policy and regulations
Water
Cloud-based solutions
Mobility
Markets
Smart buildings

CITIES Solutions Brochures



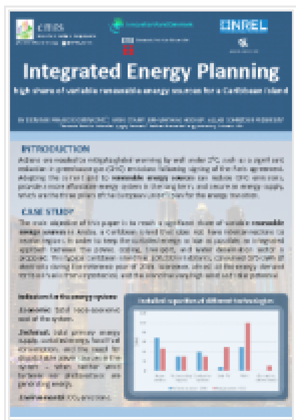


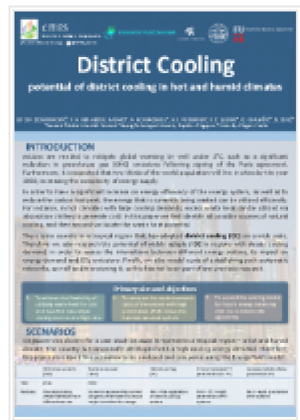


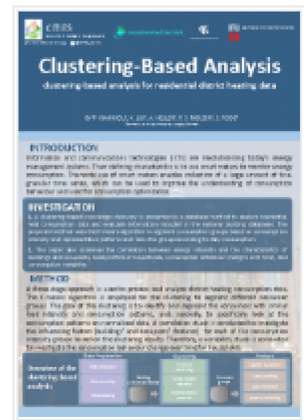
Energy taxes for the transition to a low-carbon society

Dynamic CO2 based control

Stability of electricity smart meter clusters







Integrated energy planning for a carribean island

Potential of district cooling

Clustering based analysis of residential district heating data

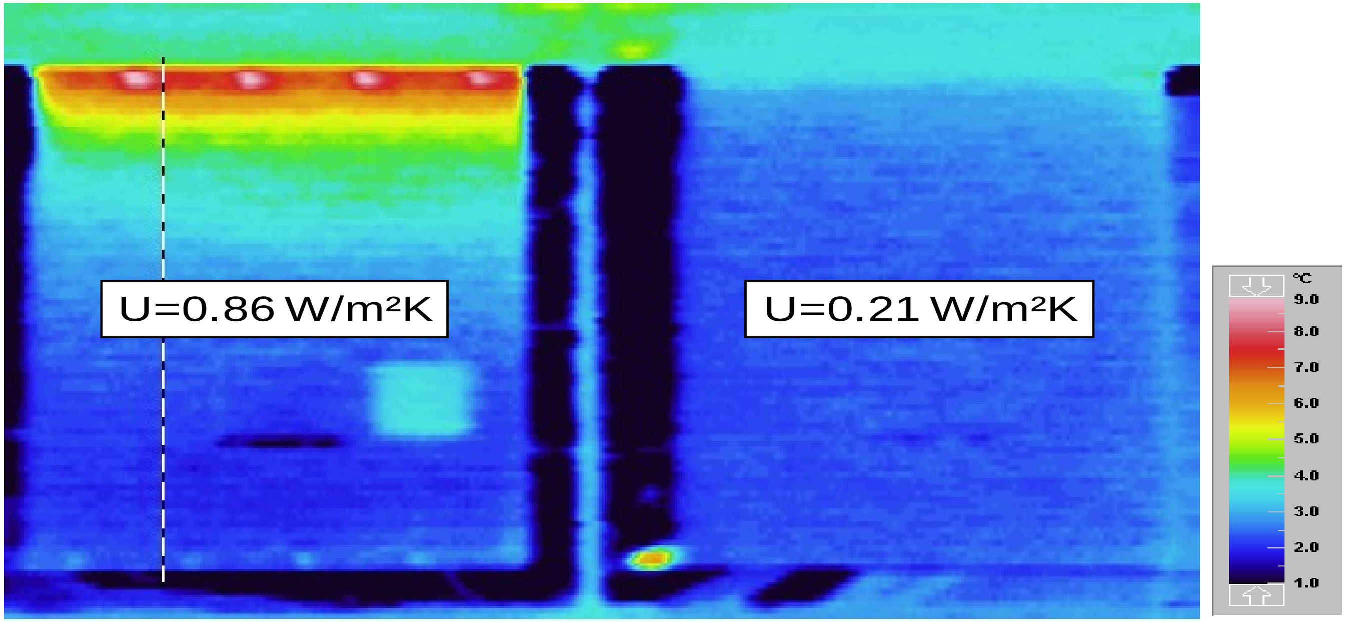
DTU

Case Study No. 1

Thermal Performance Characterization of Buildings using (Smart) Meter Data

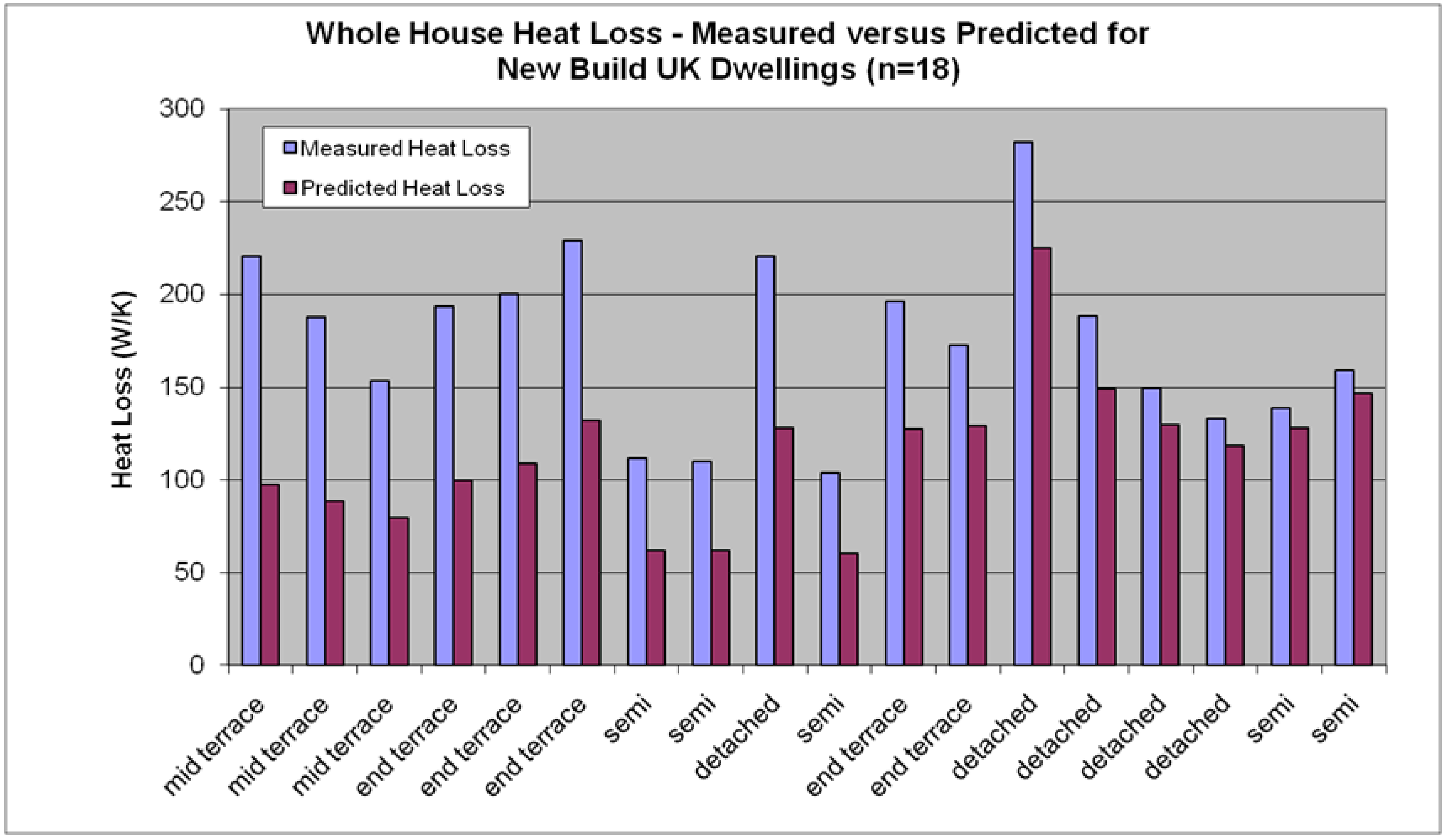
CITIES
Centre for IT Intelligent Energy Systems

Example



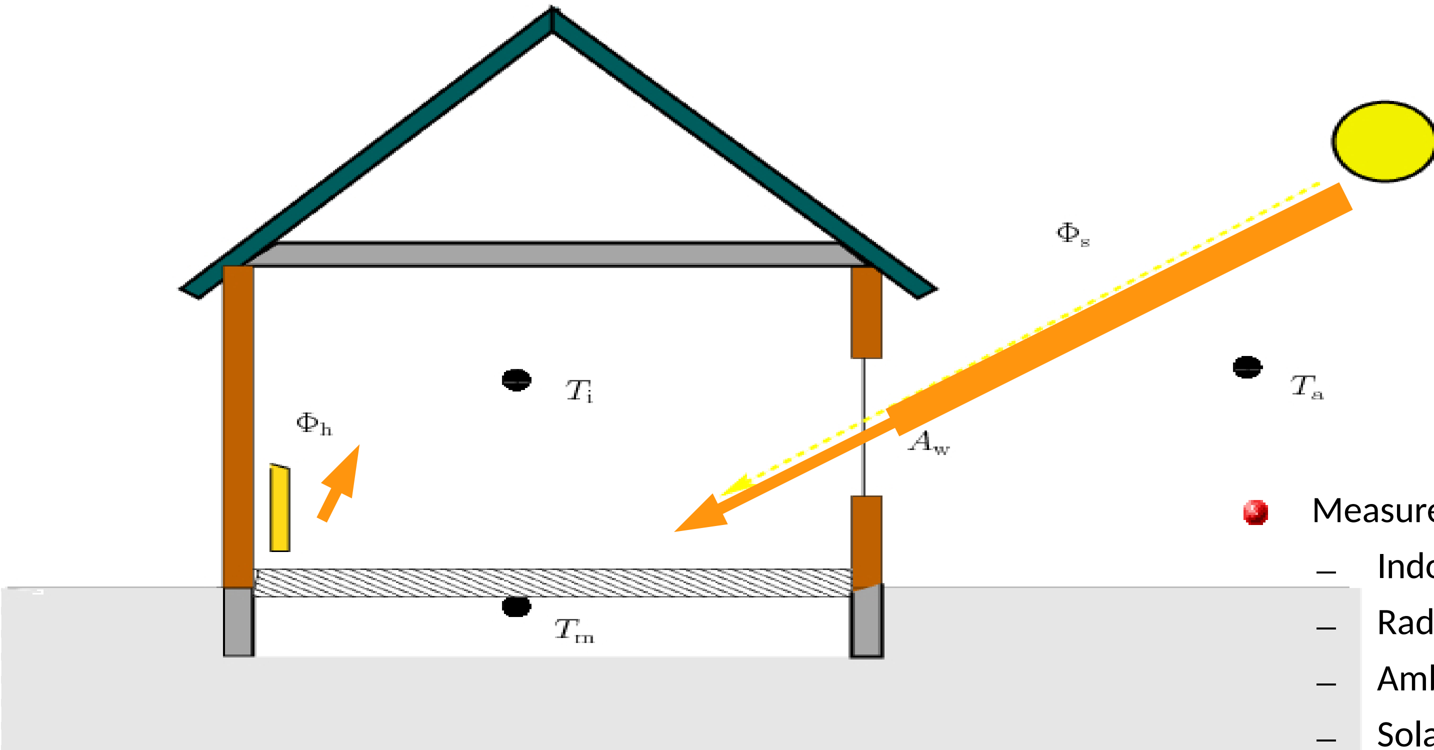
Consequence of good or bad workmanship (theoretical value is U=0.16W/m2K)

Examples (2)

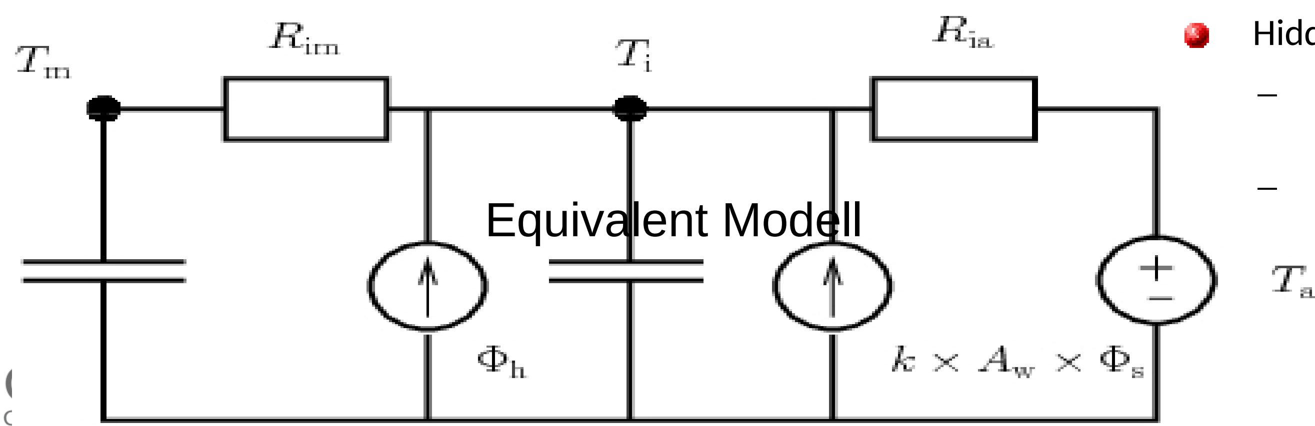


Measured versus predicted energy consumption for different dwellings

Model for the heat dynamics



- Measurements:
  - Indoor air temp
  - Radiator heat sup.
  - Ambient air temp
  - Solar radiations
- Hidden states are:
  - Heat accumulated in the building
  - *k*: Fraction of solar radiation entering the interior



DTU

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

- Identification of most problematic buildings
- Automatic energy labelling
- Recommendations:
    - Should they replace the windows?
    - Or put more insulation on the roof?
    - Or tigthen the building?
    - Should the wall against north be further insulated?
    - ……
- Better control of the heat supply (.. see later on ..)

Perspectives (2)

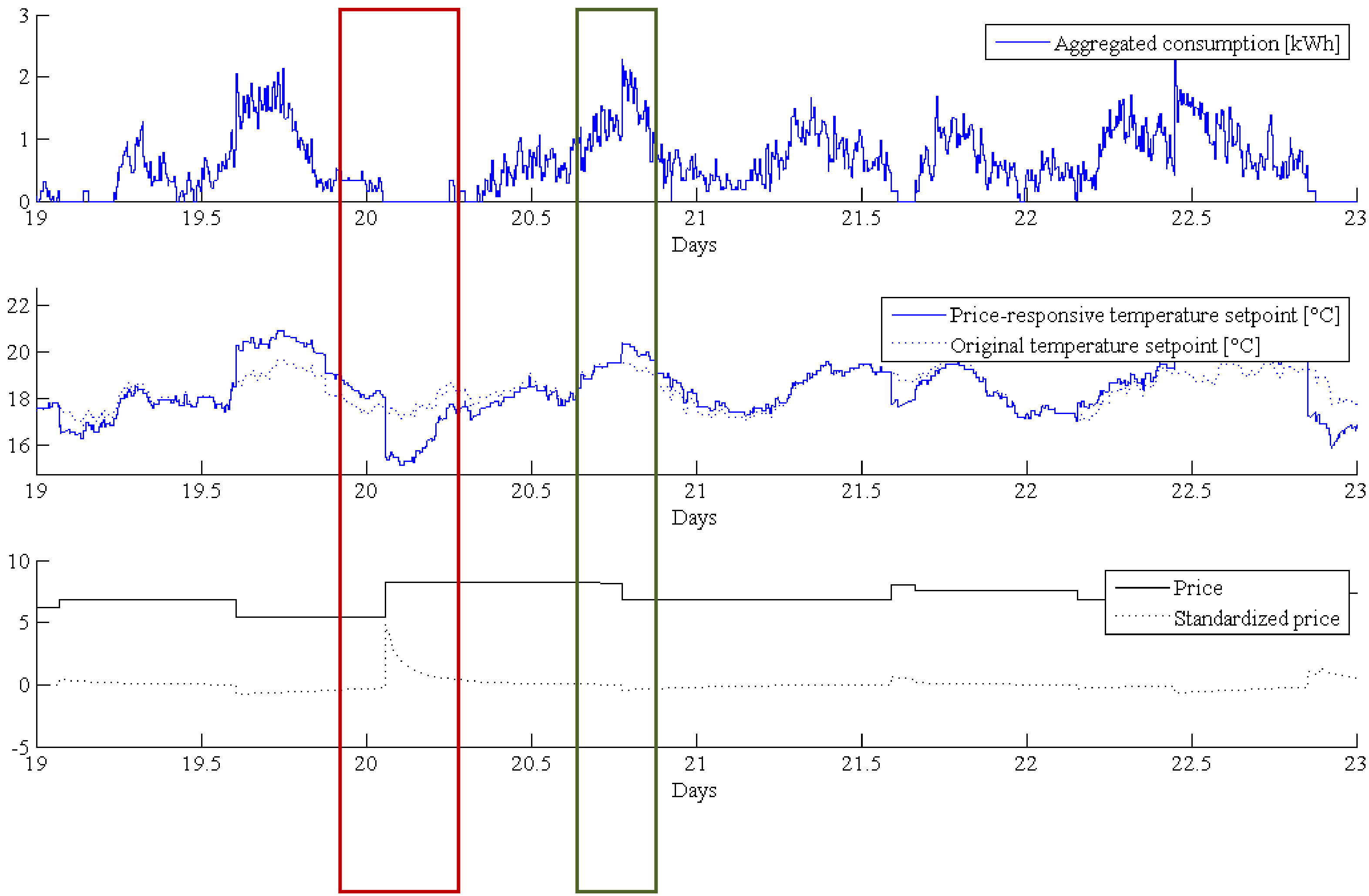
"Skat, jeg kan se på k-værdierne, at vinduerne skal pudses"

Case study No. 2

Control of Power Consumption using the Thermal Mass of Buildings (Peak shaving)

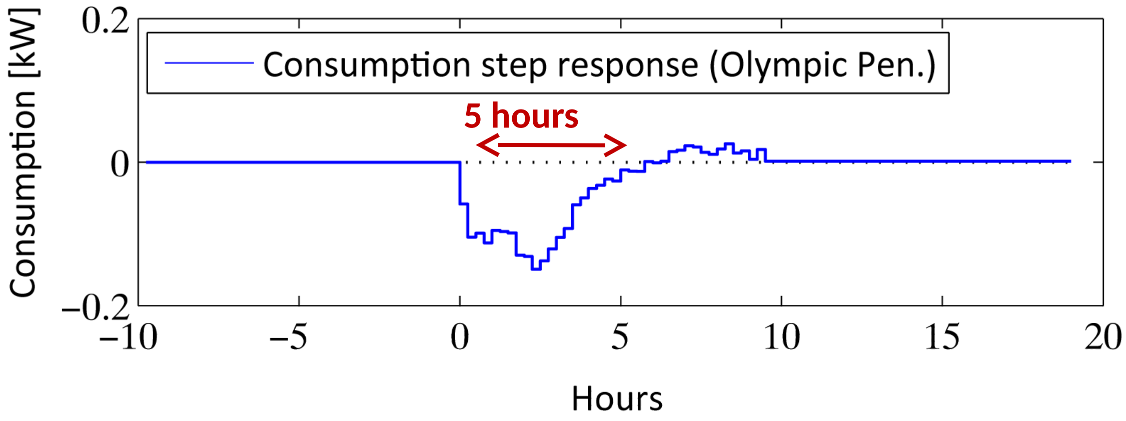
CITIES
Centre for IT Intelligent Energy Systems

Aggregation (over 20 houses)

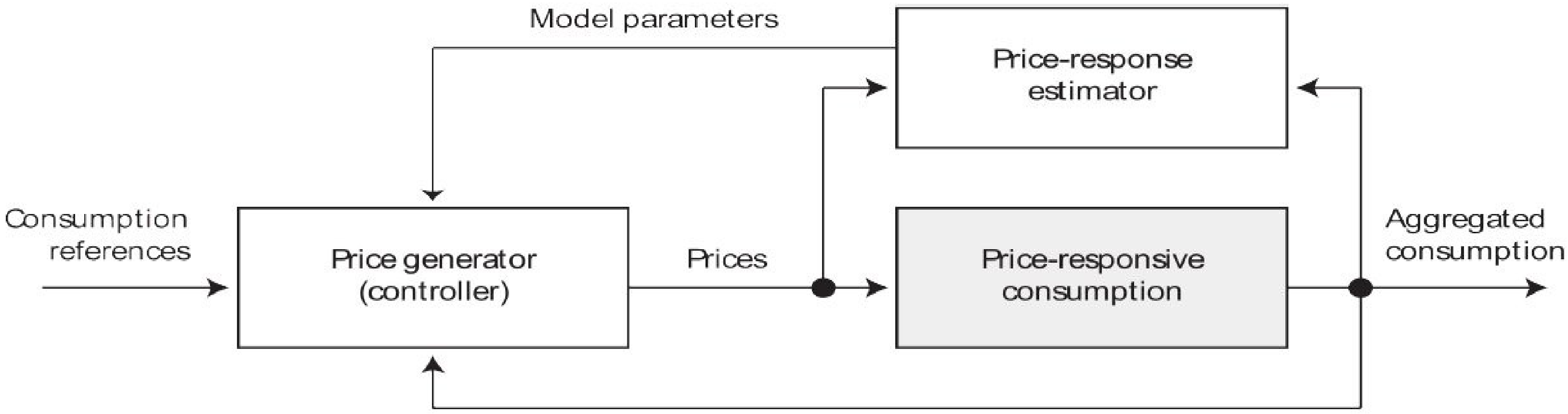


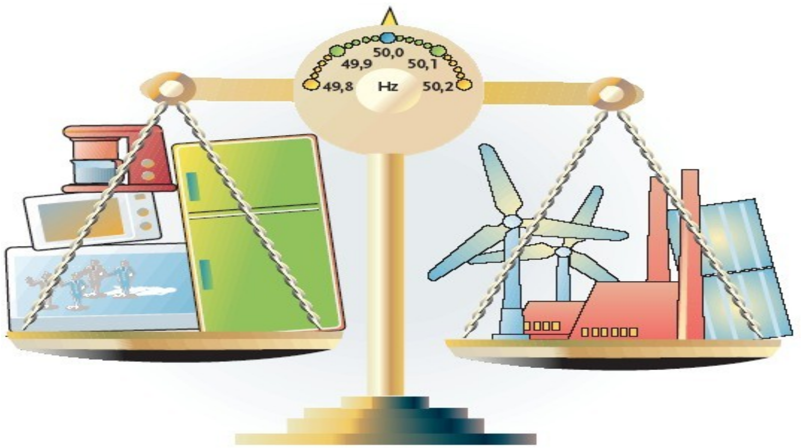
Response on Price Step Change

Olympic Peninsula



Control of Energy Consumption

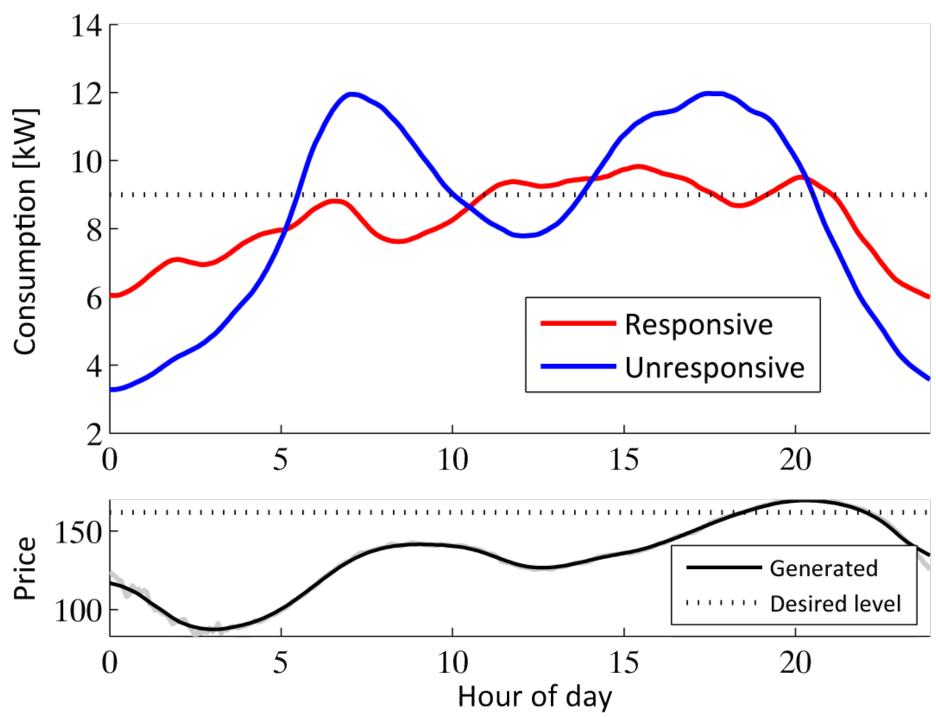




Control performance

Considerable **reduction in peak consumption**

Mean daily consumption shift



Flexibility Setup and Control

CITIES
Centre for IT Intelligent Energy Systems

Characteristics

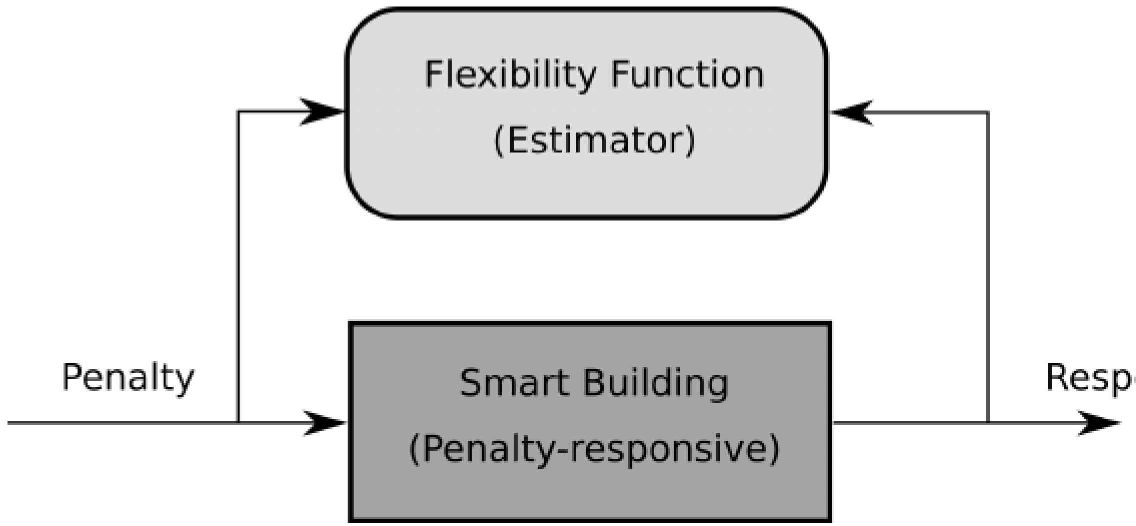


Figure 1: A smart building is able to respond to a penalty or external control signal.

Flexibility Function

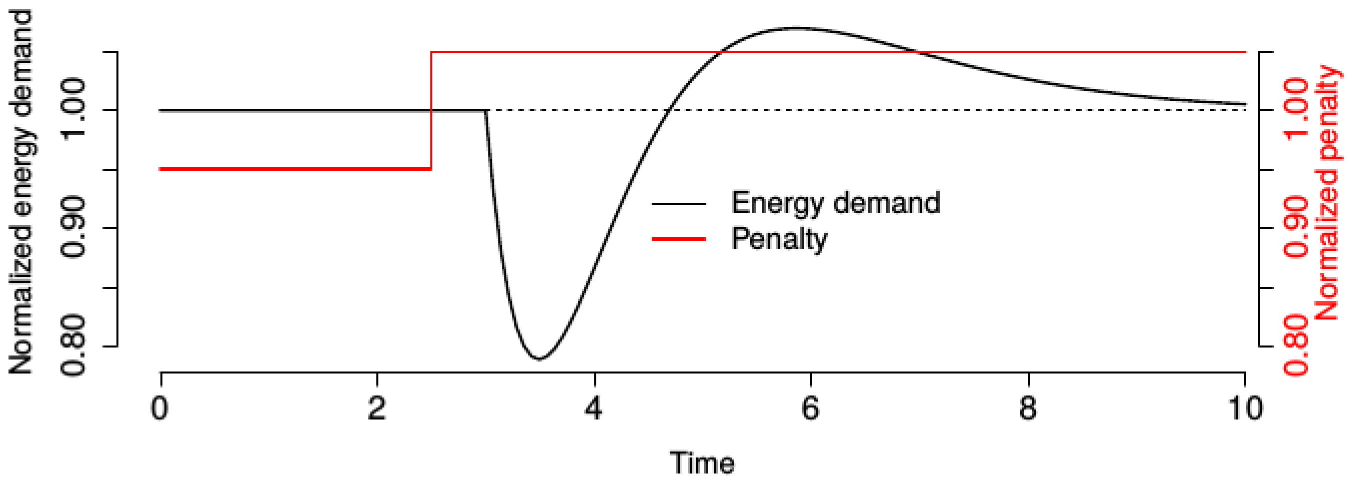


Figure 2: The energy consumption before and after an increase in penalty. The red line shows the normalized penalty while the black line shows the normalized energy consumption. The time scale could be very short with the units being seconds or longer with units of hours. At time 2.5 the penalty is increased,

Penalty Function (examples)

- **Real time CO_2.** If the real time (marginal) CO_2 emission related to the actual electricity production is used as penalty, then, a smart building will minimize the total carbon emission related to the power consumption. Hence, the building will be *emission efficient*.
- **Real time price**. If a real time price is used as penalty, the objective is obviously to minimize the total cost. Hence, the building is *cost efficient*.
- **Constant**. If a constant penalty is used, then, the controllers would simply minimize the total energy consumption. The smart building is, then, *energy efficient*.

Smart Grid Application

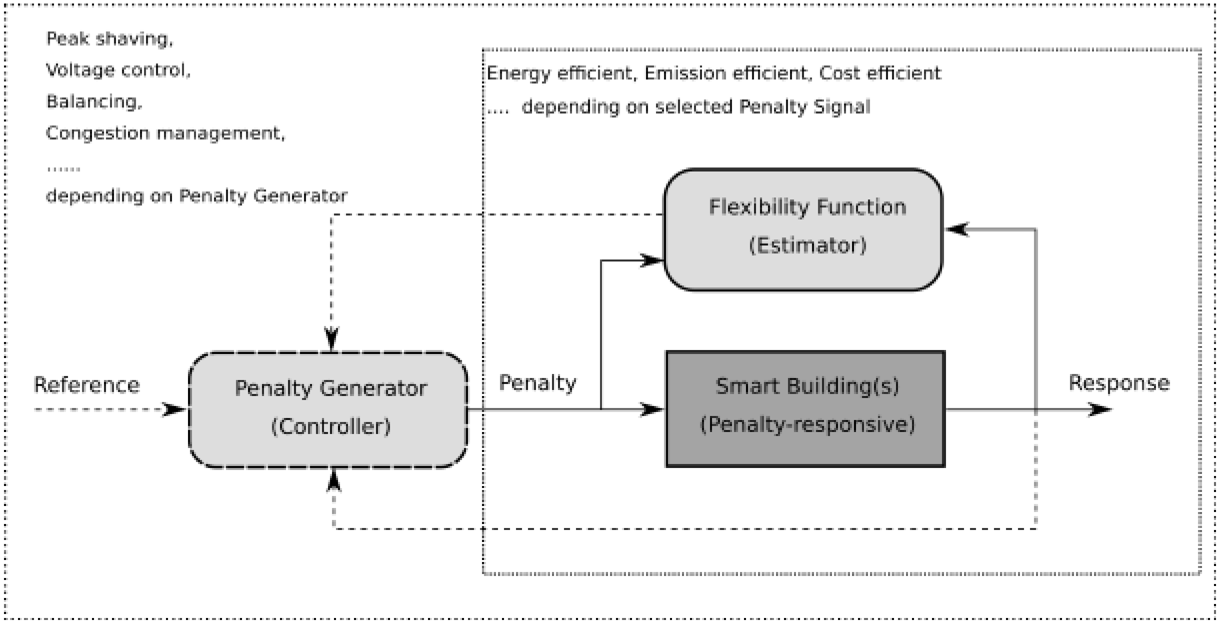
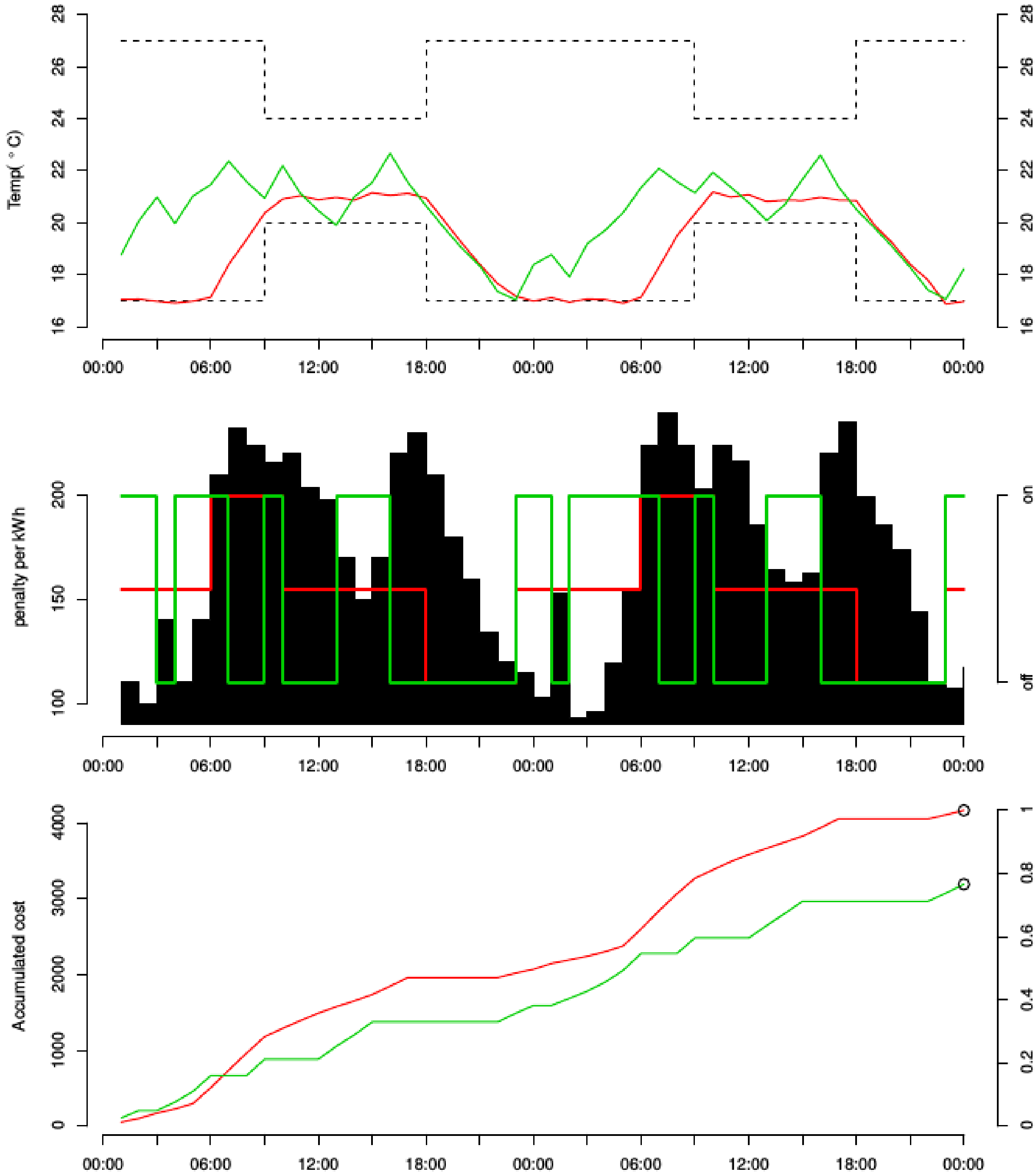


Figure 8: Smart buildings and penalty signals.



CITIES
Centre for IT Inte

FF for three buildings

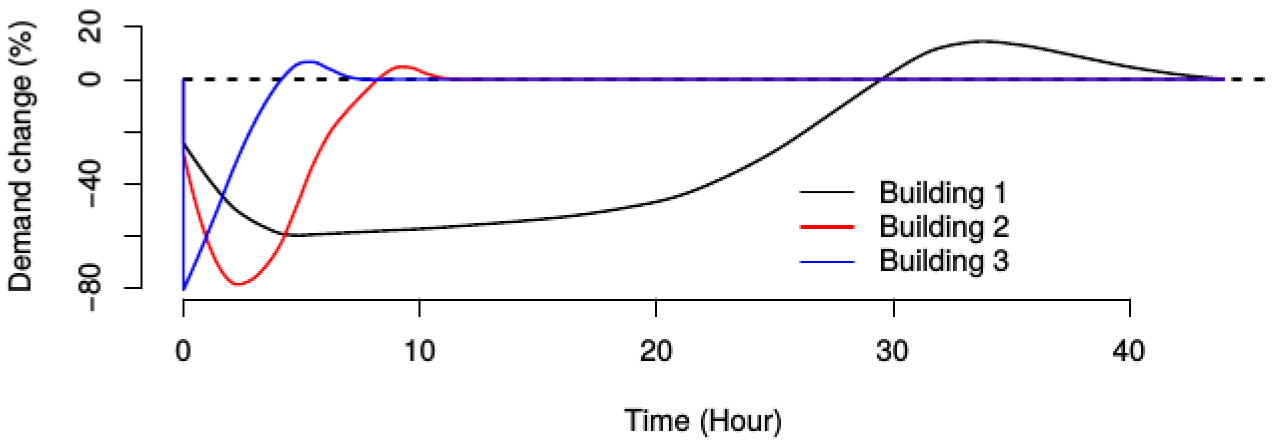


Figure 5: The Flexibility Function for three different buildings.

Realistic Penalties for DK

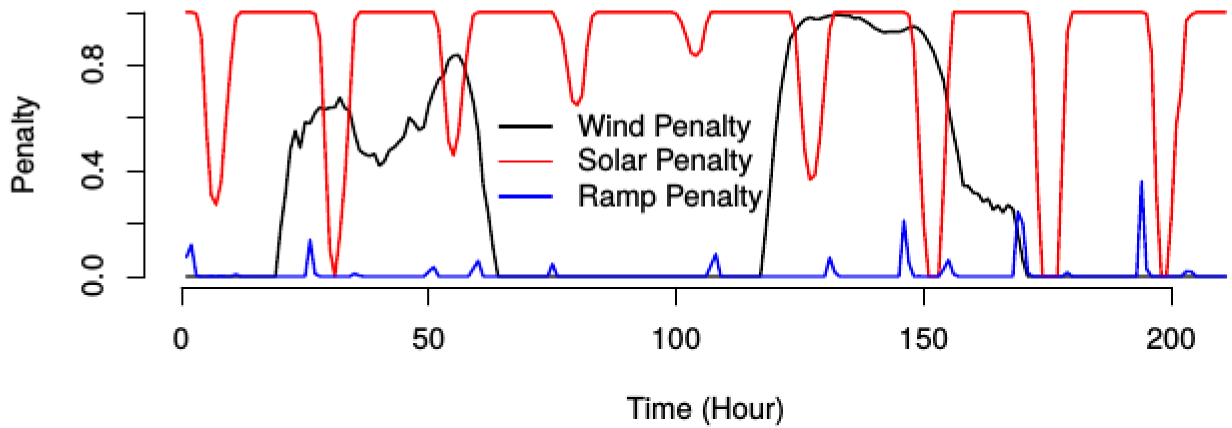


Figure 6: Penalty signals based on wind and solar power production in Denmark during some days in 2017.

Expected Flexibility Savings Index for Denmark

Table 1: Expected Flexibility Savings Index (EFSI) for each of the buildings based on wind, solar and ramp penalty signals.

	Wind (%)	Solar (%)	Ramp (%)
Building 1	11.8	3.6	1.0
Building 2	4.4	14.5	5.0
Building 3	6.0	10.0	18.4

Reference Penalties

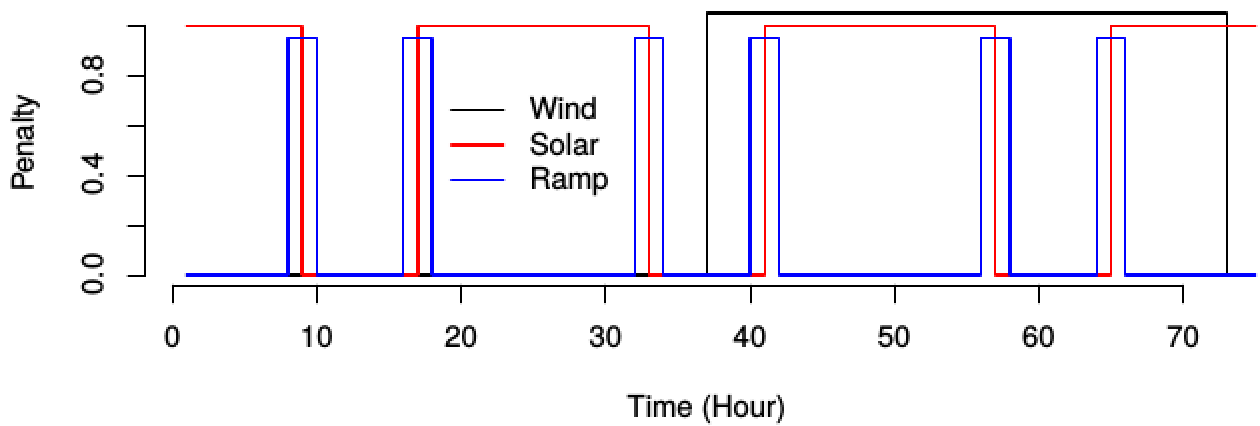


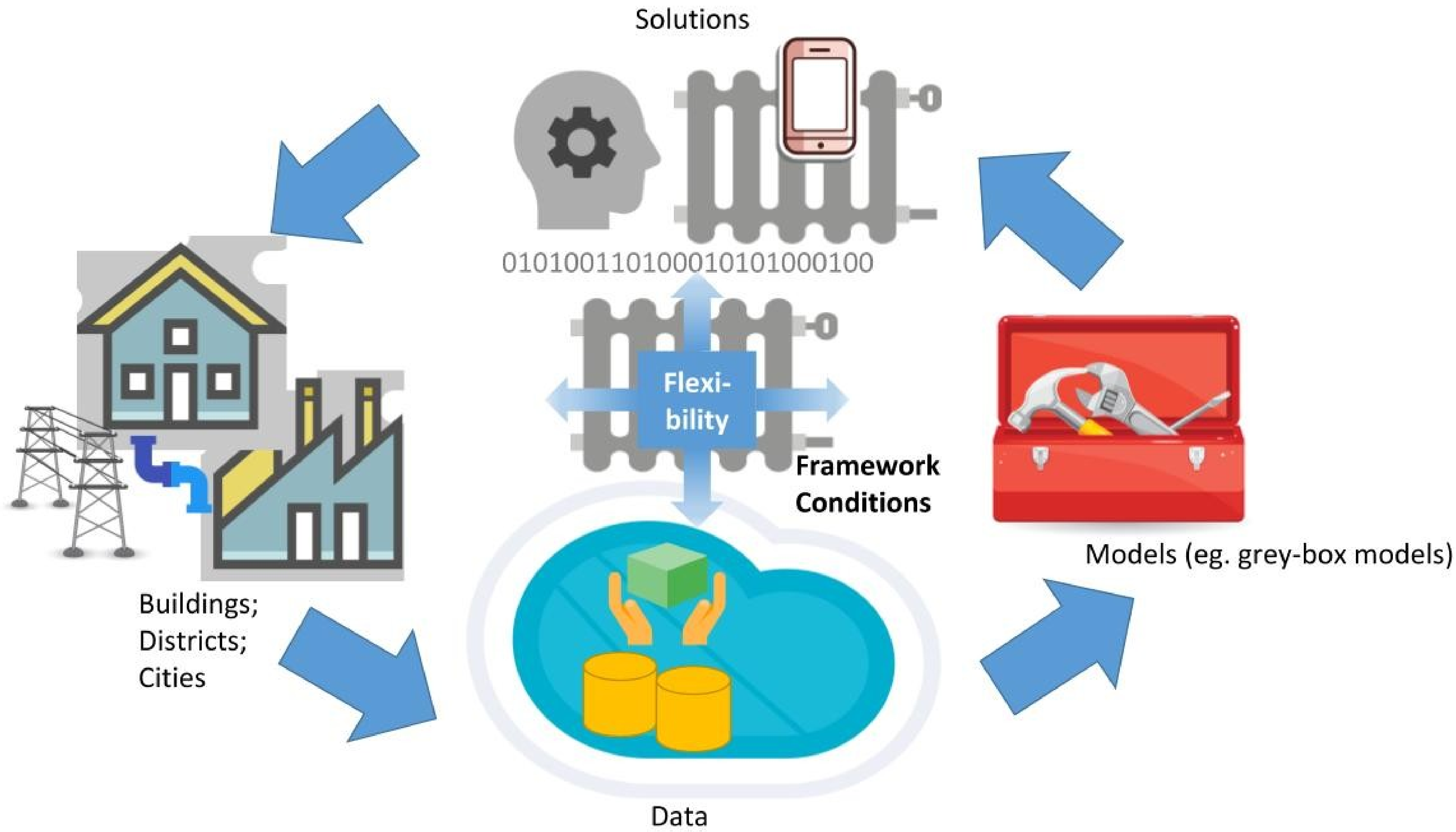
Figure 7: Reference scenarios of penalty signals related to ramping or peak issues as well as the integration of wind and solar power.

Flexibility Index

Table 2: Flexibility Index for each of the buildings based reference penalty signals representing wind, solar and ramp problems.

	Wind (%)	Solar (%)	Ramp (%)
Building 1	36.9	10.9	5.2
Building 2	7.2	24.0	11.1
Building 3	17.9	35.6	67.5

Flexibility enabled using grey-box modelling



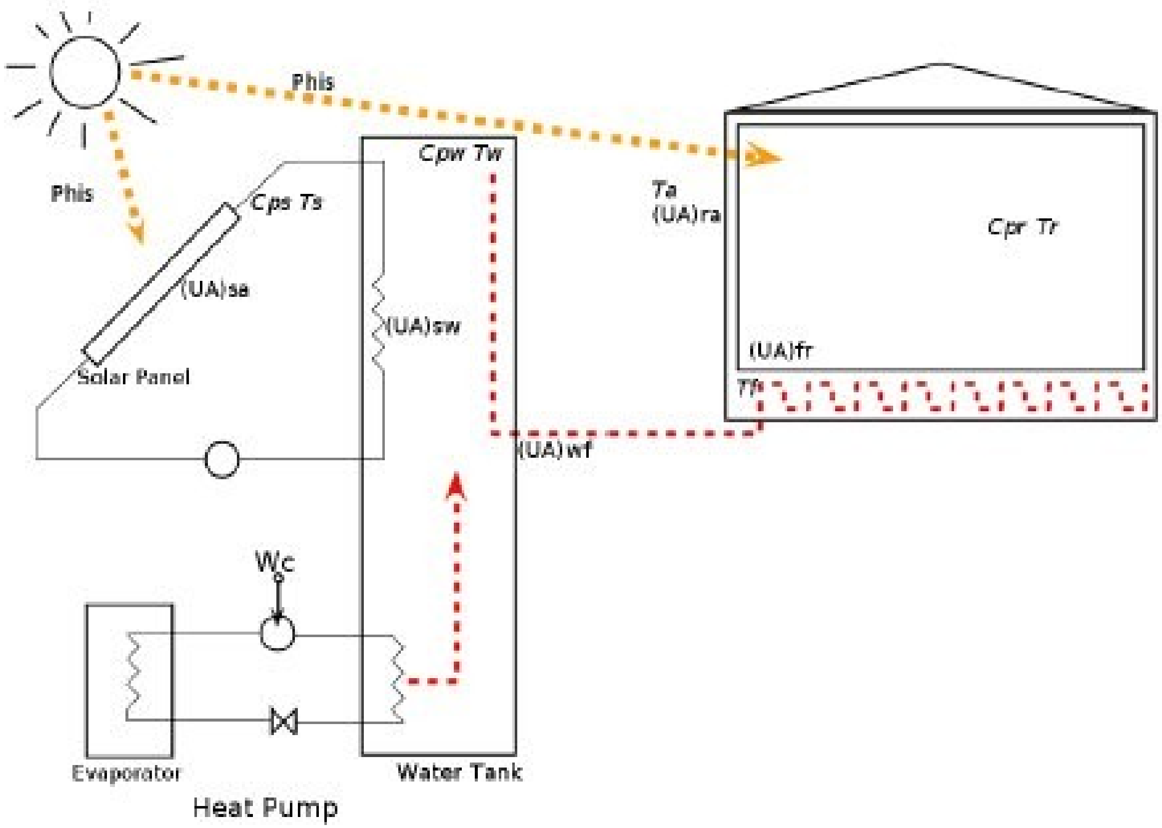
Case study No. 3

Control of Heat Pumps for buildings with a thermal solar collector (minimizing cost)

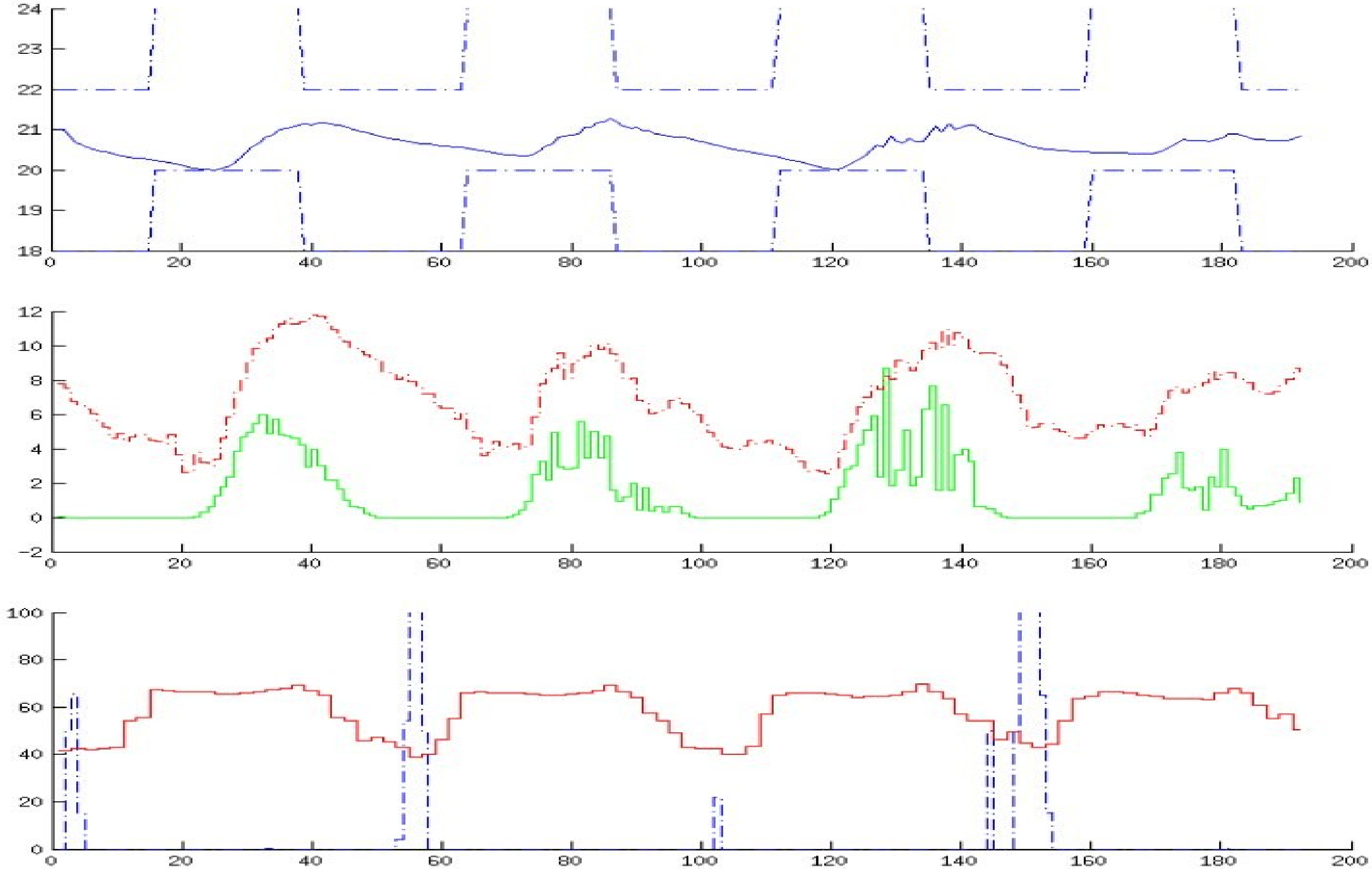
CITIES
Centre for IT Intelligent Energy Systems

Modeling Heat Pump and Solar Collector

Simplified System



EMPC for heat pump with solar collector (savings 25 pct; + 8 pct)



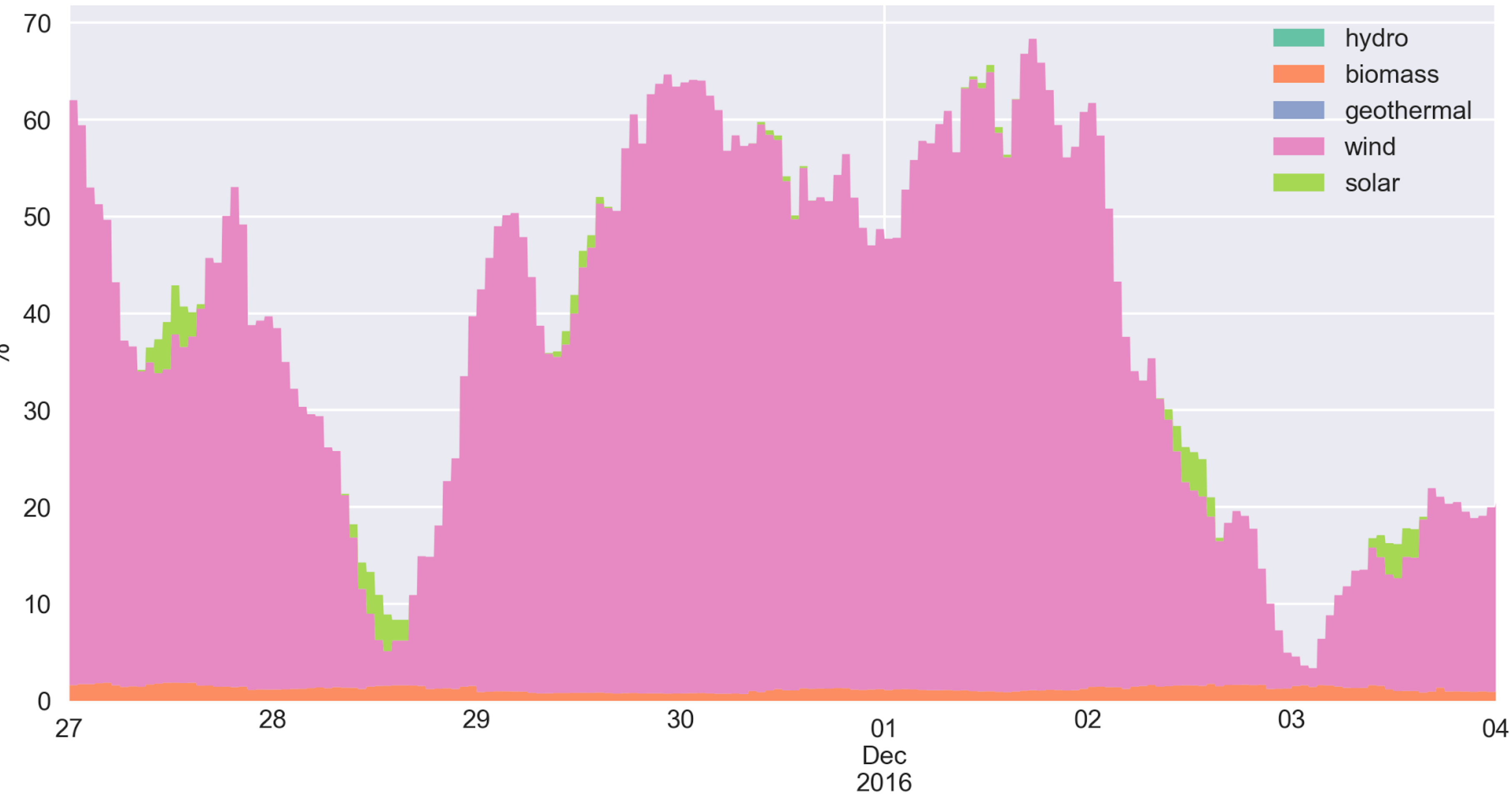
CITIES
Centre for IT Intelligent Energy Systems

Case study No. 4

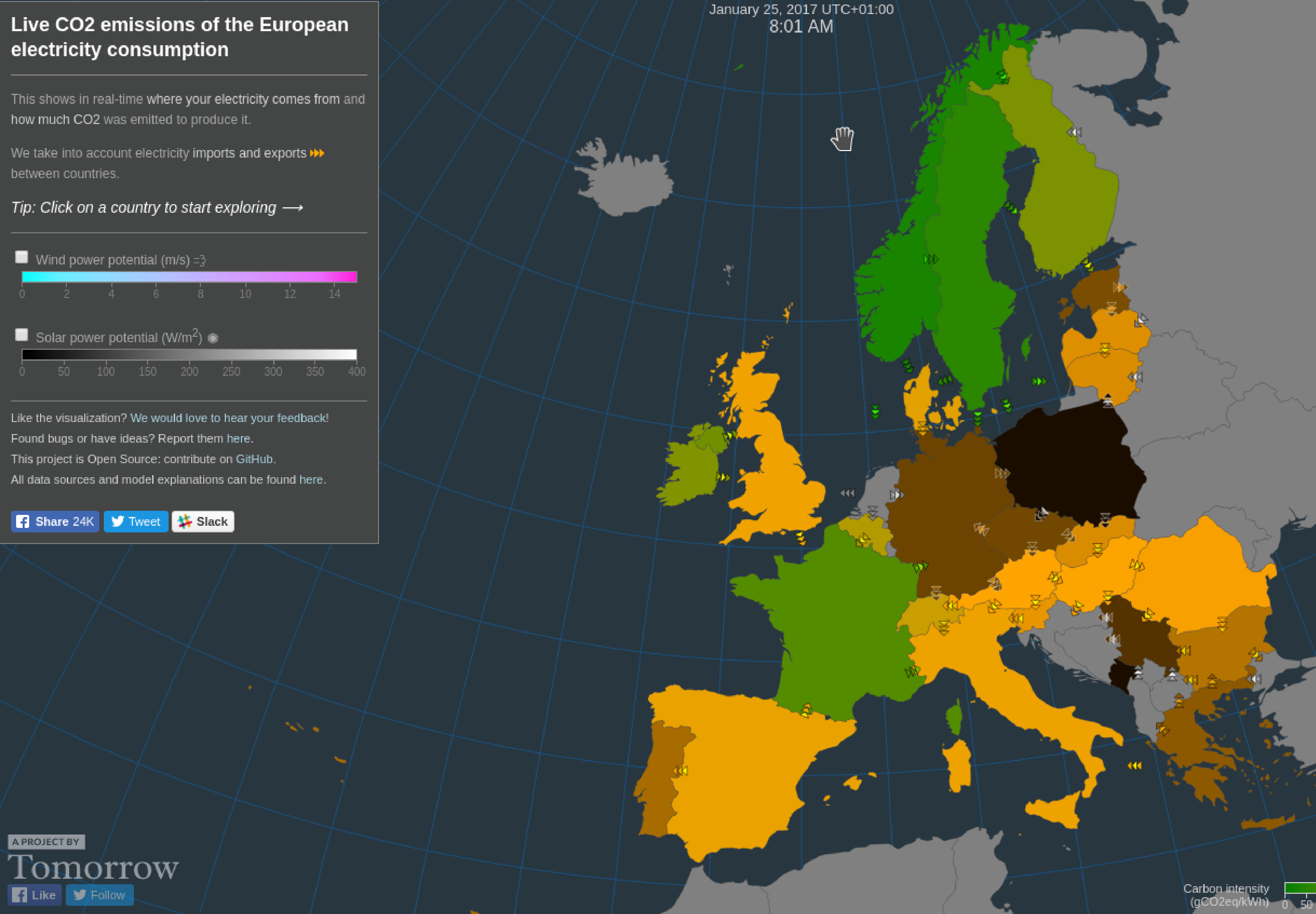
Control of heat pumps for summer houses with a swimming pools (CO_2 minimization)

DTU

Share of electricity originating from renewables in Denmark Late Nov 2016 - Start Dec 2016

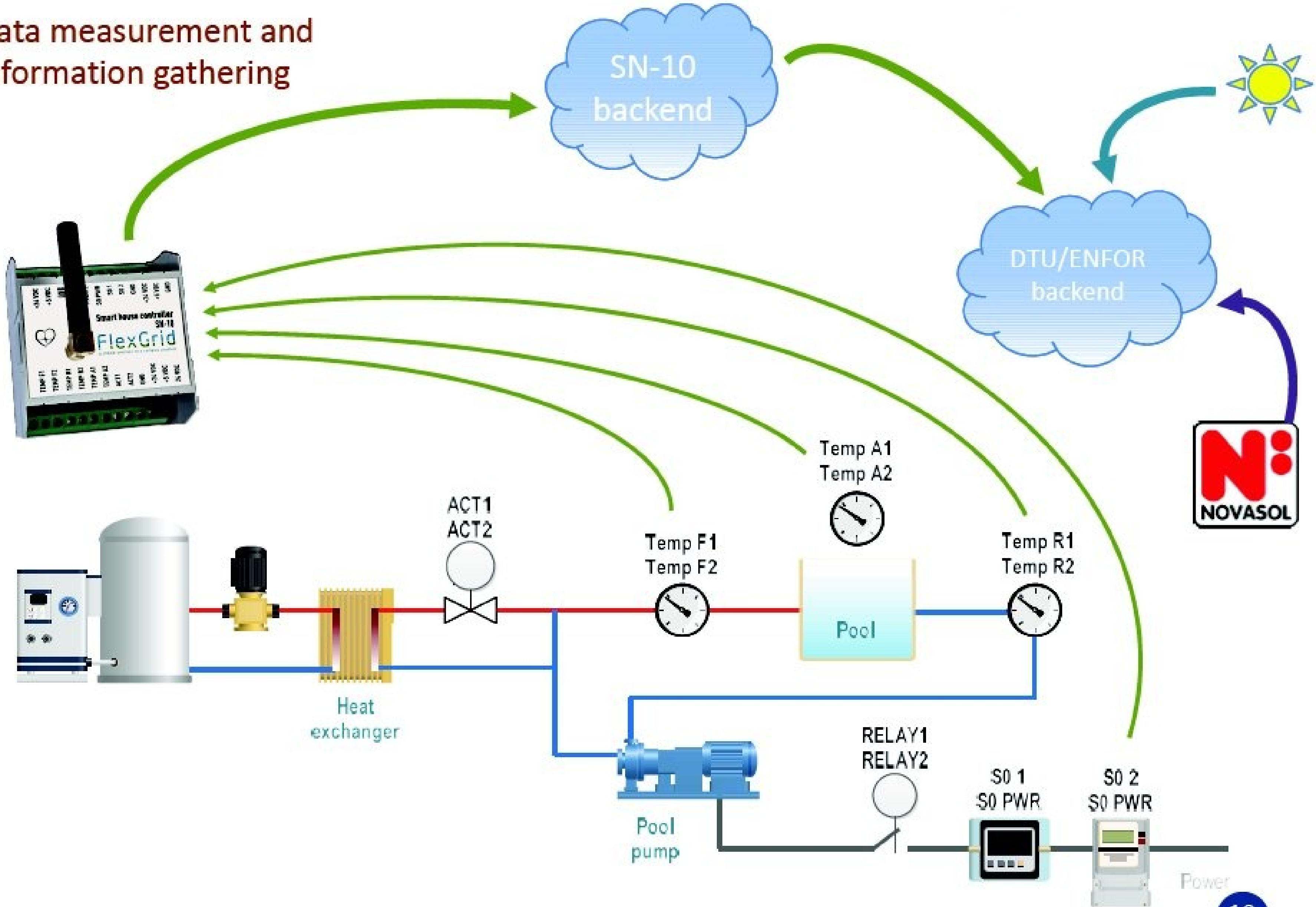


Source: pro.electicitymap.


Live CO2 emissions of the European electricity consumption
This shows in real-time where your electricity comes from and how much CO2 was emitted to produce it.
We take into account electricity imports and exports between countries.
Tip: Click on a country to start exploring ⟶
Wind power potential (m/s)
0 2 4 6 8 10 12 14
Solar power potential (W/m2)
0 50 100 150 200 250 300 350 400
Like the visualization? We would love to hear your feedback!
Found bugs or have ideas? Report them here.
This project is Open Source: contribute on GitHub.
All data sources and model explanations can be found here.
Share 24K
Tweet
Slack
A PROJECT BY
Tomorrow
Like
Follow
January 25, 2017 UTC+01:00
8:01 AM
Carbon intensity
(gCO2eq/kWh)
0 50

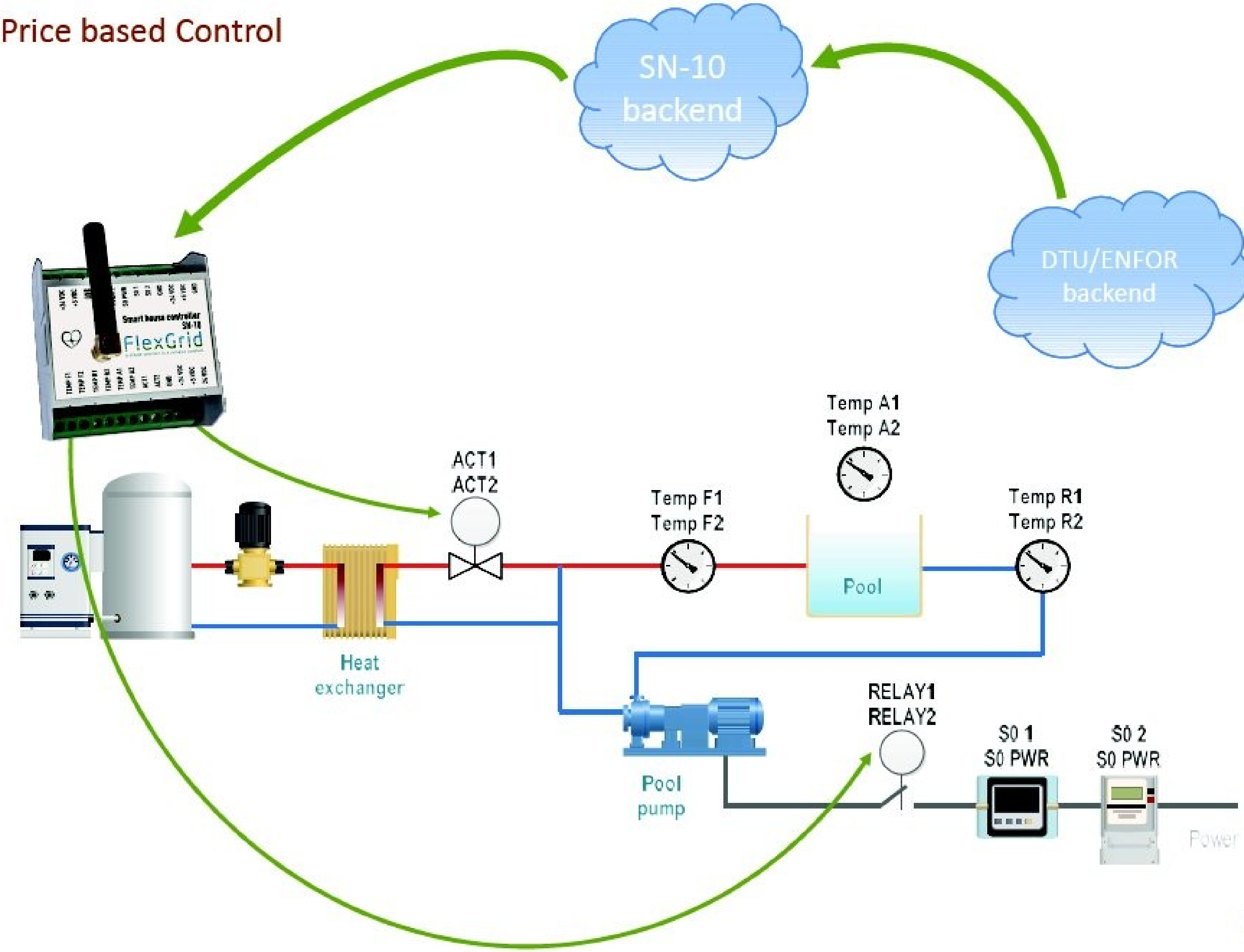
How does it work?

Data measurement and information gathering



How does it work?

Price based Control

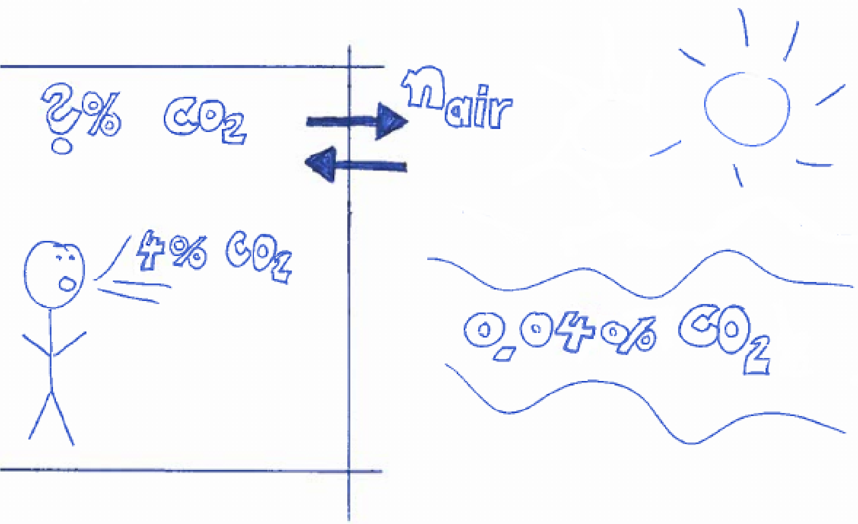


Example: CO2-based control (savings 15 pct)

Case study No. 5

Indoor Climate;
Grey-box Model for Occupancy Estimation

Occupancey estimation using CO2 measurements



- Reducing HVAC to required extent offers energy-saving potential
- Hence, occupancy estimates important for model-based control
- Occupancy estimation model based on CO_2 mass balance
- Presented model was tested in three scenarios (Copenhagen, Trondheim, Aachen)

CO2 mass balance equation

$$\frac{dX_t}{dt} = -\left(n_{\text{nat}} + n_{\text{mec}} + n_{\text{inf}}\right)\left(X_t - c_e\right) + \dot{c}_{occ} \cdot n_{occ}$$

States		
X_t	room CO_2 concentration	$[ppm]$
n_{occ}	number of occupants in the room	$[-]$
Known parameters		
V_r	room volume	$[m^3]$
Parameters estimated		
c_e	outdoor CO_2 concentration	$[ppm]$
$\dot{c}_{occ}$	CO_2 increment per occupant	$[ppm/h]$
n_{nat}	air exchange rate (nat. vent)	$[1/h]$
n_{mec}	air exchange rate (mech. vent.)	$[1/h]$
n_{inf}	air exchange rate (infiltration)	$[1/h]$

Grey-box Model
- and the states

System equation

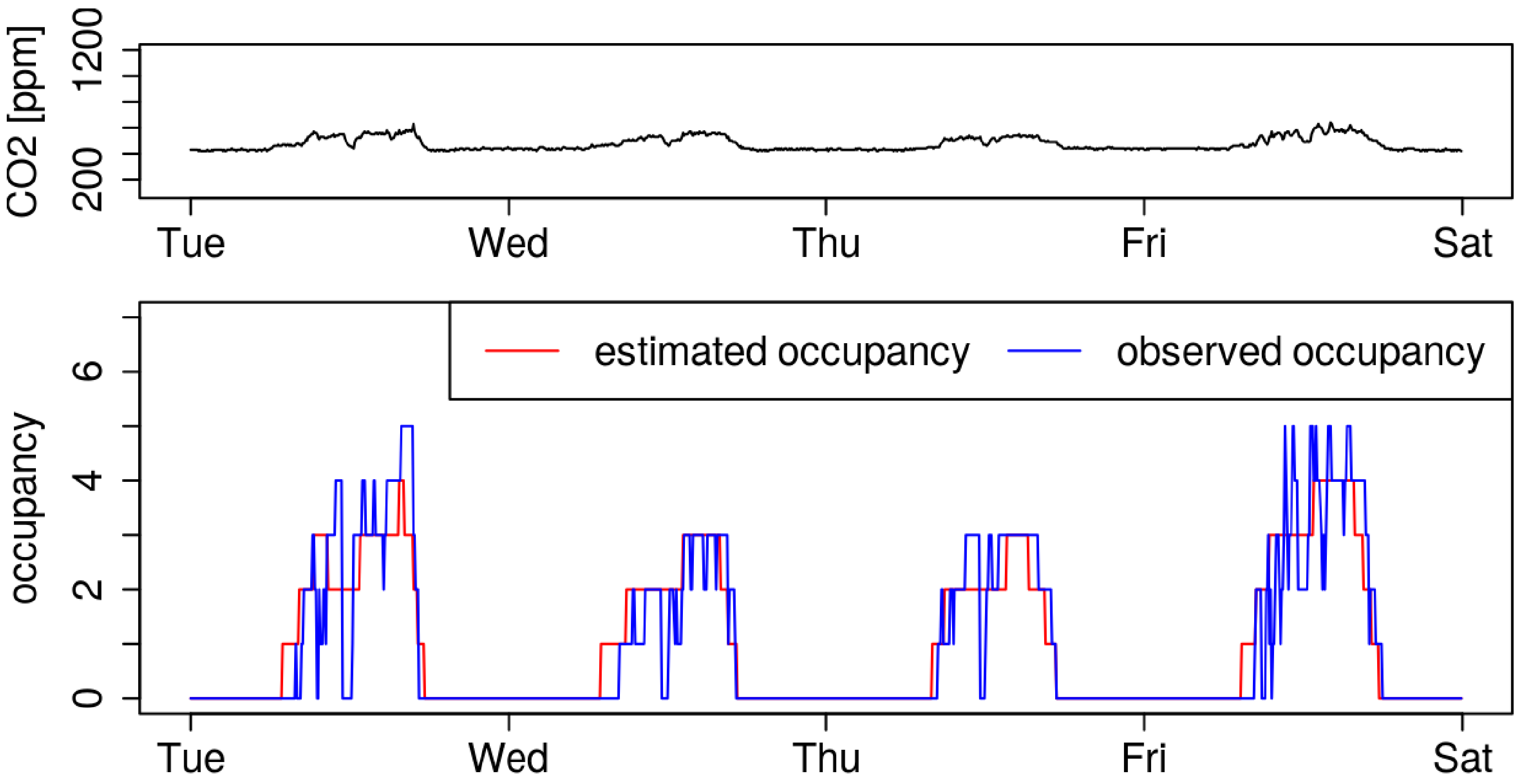
$$dX_t = -\left[n_{\text{inf}} \cdot (\boldsymbol{X_t} - c_e) + \dot{c}_{occ} \cdot \boldsymbol{n_{occ}}\right] dt + \sigma \cdot d\omega$$

$$n_{\text{air}} = n_{\text{nat}} + n_{\text{mec}} + n_{\text{inf}}$$

Observation equation

$$Y_k = \boldsymbol{X_{t_k}} + \varepsilon_k, \qquad \varepsilon_k \sim N(0, \sigma_\varepsilon)$$

Estimated and Observed Occupancy



CITIES
Centre for IT Intelligent Energy Systems

Summary

- Methods for evidence-based energy performance characterization is outlined for buildings
- Automated methods for evidence-based energy labelling
- Automated methods for evidence-based flexibility labelling
- Flexibility Index for buildings (peak, solar, wind, ...)
- Flexibility Functions and Index can be used for everything (eg. also wastewater treatment plants)
- Automated methods for providing hints on how to improve the energy performance of buildings
- Provides hints on how to design a building such that it is optimized for the given climate zone

Summary (2)

DTU

- We need to put more focus on energy efficiency – but using meter data (which is now possible)
- Procedures for data intelligent control of power load using FF are also suggested
- The controllers can provide
  - Energy Efficiency
  - Cost Minimization
  - Emission Efficiency
  - Peak Shaving
  - Smart Grid demand (like ancillary services needs, ...)
- We have demonstrated a large potential in Demand Response. Automatic solutions, and end-user focus are important
- We see large problems with the tax and tariff structures in many countries (eg. Denmark; we are working on a new design of taxes and tariffs.

For more information ...

See for instance

www.smart-cities-centre.org

...or contact

– Henrik Madsen (DTU Compute)

hmad@dtu.dk

Acknowledgement - DSF 1305-00027B

Some references

Grey-box models for buildings:

Madsen, H., & Holst, J. (1995). Estimation of Continuous-Time Models for the Heat Dynamics of a Building. Energy and Buildings, 22(1), 67–79.

Andersen, K. K., Madsen, H., & Hansen, L. H. (2000). Modelling the heat dynamics of a building using stochastic differential equations. Energy and Buildings, 31(1), 13–24.

Nielsen, H. A., & Madsen, H. (2006). Modelling the Heat Consumption in District Heating Systems using a Grey-box approach. Energy and Buildings, 38(1), 63–71.

Jiménez, M. J., Madsen, H., Bloem, J. J., & Dammann, B. (2008). Estimation of non-linear continuous time models for the heat exchange dynamics of building integrated photovoltaic modules. Energy and Buildings, 40(2), 157–167

Friling, N., Jimenez, M. J., Bloem, H., & Madsen, H. (2009). Modelling the heat dynamics of building integrated and ventilated photovoltaic modules. Energy and Buildings, 41(10), 1051–1057

Bacher, P., & Madsen, H. (2011). Identifying suitable models for the heat dynamics of buildings. Energy and Buildings, 43(7), 1511–1522

Lodi, C., Bacher, P., Cipriano, J., & Madsen, H. (2012). Modelling the heat dynamics of a monitored Test Reference Environment for Building Integrated Photovoltaic systems using stochastic differential equations. Energy and Buildings, 50, 273–281.

Naveros, I., Bacher, P., Ruiz, D. P., Jiménez, M. J., & Madsen, H. (2014). Setting up and validating a complex model for a simple homogeneous wall. Energy and Buildings, 70, 303–317.

Andersen, Philip Hvidthøft Delff ; Jiménez, María José ; Madsen, Henrik ; Rode, Carsten. Characterization of heat dynamics of an arctic low-energy house with floor heating. In: Building Simulation, Vol. 7, No. 6, 2014, p. 595-614.

Madsen, H., Bacher, P., Bauwens, G., Deconinck, A.-H., Reynders, G., Roels, S., … Lethé, G. (2015). Thermal Performance Characterization using Time Series Data - IEA EBC Annex 58 Guidelines.

Rasmussen, C., Frölke, L., Bacher, P., Madsen, H., & Rode, C. (2020). Semi-parametric modelling of sun position dependent solar gain using Bsplines in grey-box models. Solar Energy, 195, 249–258.

Some references

Grey-box modelling techniques:

Holst, J., Lindström, E., Madsen, H., & Aalborg Nielsen, H. (2003). Model Validation in Non-Linear Continuous-Discrete Grey-Box Models. Ifac Proceedings Volumes (Ifac-Papersonline), 36(16), 1495–1500.

Sadegh, P., Melgaard, H., Madsen, H., & Holst, J. (1994). Optimal experiment design for identification of grey-box models. Proceedings of the American Control Conference, 1, 132–137.

Kristensen, N. R., Madsen, H., & Jørgensen, S. B. (2004). Parameter Estimation in Stochastic Grey-Box Models. Automatica, 40(2), 225–237.

Kristensen, N. R., Madsen, H., & Jørgensen, S. B. (2003). A unified framefowk for systematic model improvement. Process Systems Engineering, 15, 1292–1297.

Kristensen, N. R., Madsen, H., & Jørgensen, S. B. (2002). Using continuous time stochastic modelling and nonparametric statistics to improve the quality of first principles models. Computer Aided Chemical Engineering, 10(C), 901–906

Jorgensen, J. B., Thomsen, P. G., Madsen, H., & Kristensen, M. R. (2007). A computationally efficient and robust implementation of the continuous-discrete extended Kalman filter. 2007 American Control Conference, Vols 1-13, 2468

Boiroux, D., Juhl, R., Madsen, H., & Jørgensen, J. B. (2016). An Efficient UD-Based Algorithm for the Computation of Maximum Likelihood Sensitivity of Continuous-Discrete Systems. Lecture Notes in Computer Science, 3048–3053.

Juhl, R., Møller, J. K., & Madsen, H. (2016). CTSM-R - Continuous Time Stochastic Modeling in R, 11p https://arxiv.org/pdf/1606.00242.pdf.

Some references (cont.)

Forecasting, Flexibility and Control:

Halvgaard, Rasmus; Bacher, Peder; Perers, Bengt; Andersen, Elsa; Furbo, Simon; Jørgensen, John Bagterp; Poulsen, Niels Kjølstad; Madsen, Henrik. Model predictive control for a smart solar tank based on weather and consumption forecasts. In: Energy Procedia, Vol. 30, 2012, p. 270-278.

Bacher, Peder; Madsen, Henrik; Nielsen, Henrik Aalborg; Perers, Bengt. Short-term heat load forecasting for single family houses. In: Energy and Buildings, Vol. 65, 2013, p. 101-112.

Corradi, Olivier; Ochsenfeld, Henning Peter; Madsen, Henrik; Pinson, Pierre. Controlling Electricity Consumption by Forecasting its Response to Varying Prices. In: IEEE Transactions on Power Systems, Vol. 28, No. 1, 2013, p. 421-430.

Madsen, H, Parvizi, J, Halvgaard, RF, Sokoler, LE, Jørgensen, JB, Hansen, LH & Hilger, KB 2015, 'Control of Electricity Loads in Future Electric Energy Systems'. in AJ Conejo, E Dahlquist & J Yan (eds), Handbook of Clean Energy Systems: Intelligent Energy Systems. vol. 4, Wiley.

Halvgaard, RF, Vandenberghe, L, Poulsen, NK, Madsen, H & Jørgensen, JB 2016, Distributed Model Predictive Control for Smart Energy Systems IEEE Transactions on Smart Grid, vol 7, no. 3, pp. 1675-1682.

Bacher, P, de Saint-Aubain, PA, Christiansen, LE & Madsen, H 2016, Non-parametric method for separating domestic hot water heating spikes and space heating Energy and Buildings, vol 130, pp. 107-112.

Junker, R. G., Azar, A. G., Lopes, R. A., Lindberg, K. B., Reynders, G., Relan, R., & Madsen, H. (2018). Characterizing the energy flexibility of buildings and districts. Applied Energy, 225, 175–182.

Junker, R. G., Relan, R., & Madsen, H. (2019). Designing Individual Penalty Signals for Improved Energy Flexibility Utilisation. Ifac-Papersonline, 52(4), 123–128.

De Zotti, G., Pourmousavi, S. A., Madsen, H., & Poulsen, N. K. (2018). Ancillary Services 4.0: A Top-To-Bottom Control-Based Approach for Solving Ancillary Services Problems in Smart Grids. Ieee Access, 6, 11694–11706.

De Zotti, G., Pourmousavi Kani, S. A., Morales, J. M., Madsen, H., & Poulsen, N. K. (2019). A Control-based Method to Meet TSO and DSO Ancillary Services Needs by Flexible End-Users. IEEE Transactions on Power Systems

Some references (cont.)

Indoor climate and occupancy:

Andersen, Philip Hvidthøft Delff; Iversen, Anne; Madsen, Henrik; Rode, Carsten. Dynamic modeling of presence of occupants using inhomogeneous Markov chains. In: Energy and Buildings, Vol. 69, 2014, p. 213-223.

Wolf, S., Calì Davide, Krogstie, J., & Madsen, H. (2019). Carbon dioxide-based occupancy estimation using stochastic differential equations. Applied Energy, 236, 32–41.

Wolf, S., Alonso, M. J., Cali, D., Krogstie, J., Mathisen, H. M., & Madsen, H. (2019). CO2-based grey-box model to estimate airflow rate and room occupancy. E3s Web of Conferences, 111,

Nienaber, F., Wolf, S., Wesseling, M., Calì, D., Müller, D., & Madsen, H. (2019). Validation, optimisation and comparison of carbon dioxide-based occupancy estimation algorithms. Indoor and Built Environment,

Wolf, S., Møller, J. K., Bitsch, M. A., Krogstie, J., & Madsen, H. (2019). A Markov-Switching model for building occupant activity estimation. Energy and Buildings, 183, 672–683

Wolf, S., Calì, D., Alonso, M. J., Li, R., Andersen, R. K., Krogstie, J., & Madsen, H. (2019). Room-level occupancy simulation model for private households. Journal of Physics.

Some 'randomly picked' books on modeling ....