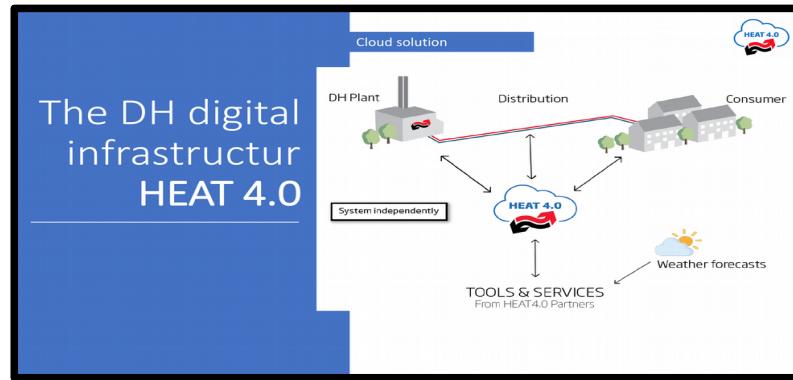


# New Opportunities and Smart Energy Systems Integration



## Digital Operation of DH Systems - HEAT4.0 - Lessons Learned

Henrik Madsen, Hjorleifur Bergsteinsson, Daniela Guericke,  
Amos Schledorn, Christian A. Thilker, Phillip B. Vetter, Jan K. Møller

Technical University of Denmark

<http://www.henrikmadsen.org>



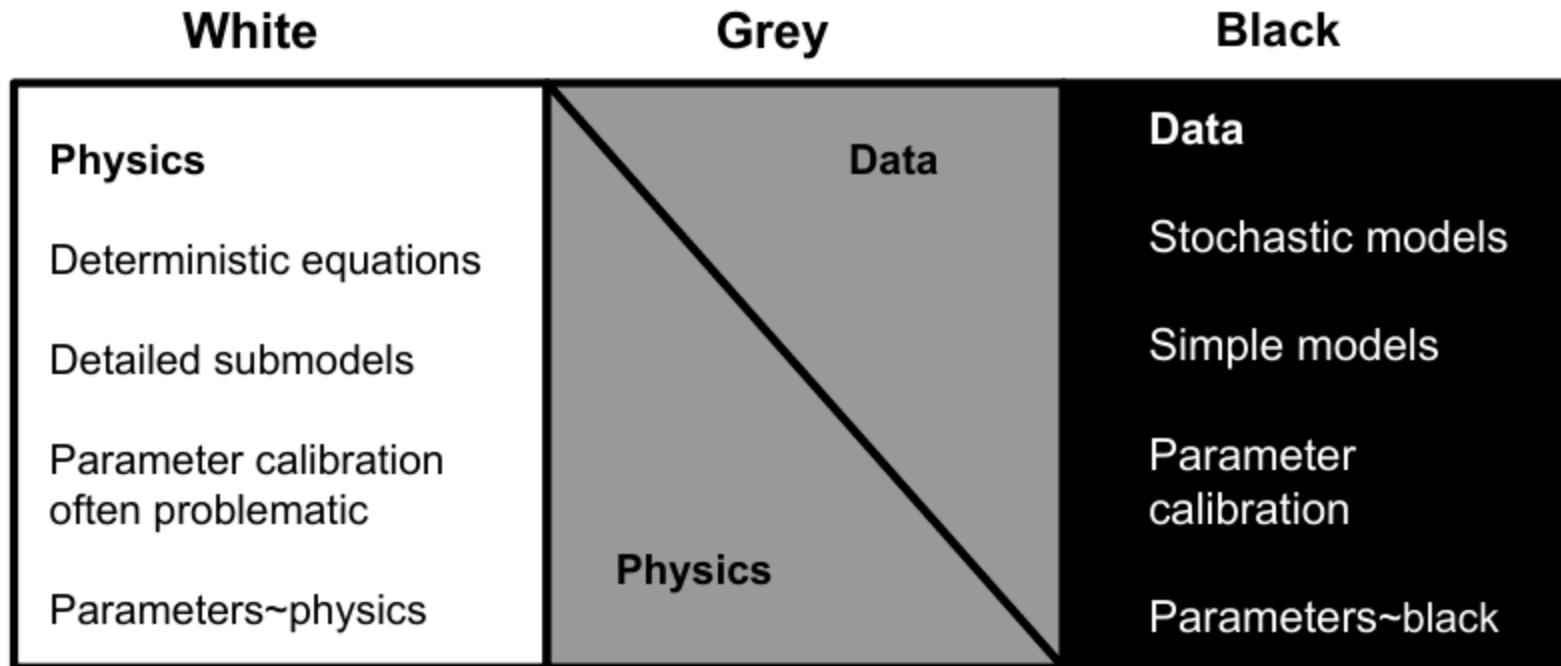
# Outline

- Bridging the gap between physical and statistical modelling (grey-box modelling)
- Combined and hierarchical forecasting
- Simulation versus data-driven/prediction-based methods
- Weather forecasting in cities
- Load forecasting
- Temperature Optimization
- Use of meter data
- Flexible load in buildings and DH systems
- Cloud Hub at Center Denmark (HEAT4.0 cloud)
- Optimal Bidding for District Heating Providers

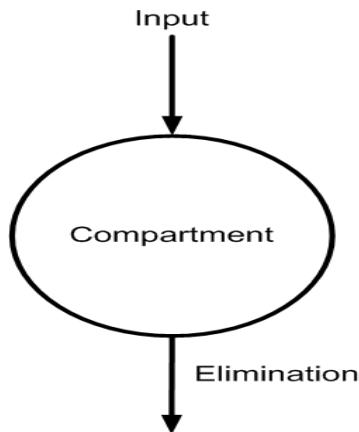
# Grey-box Modelling



# Grey-box Modelling



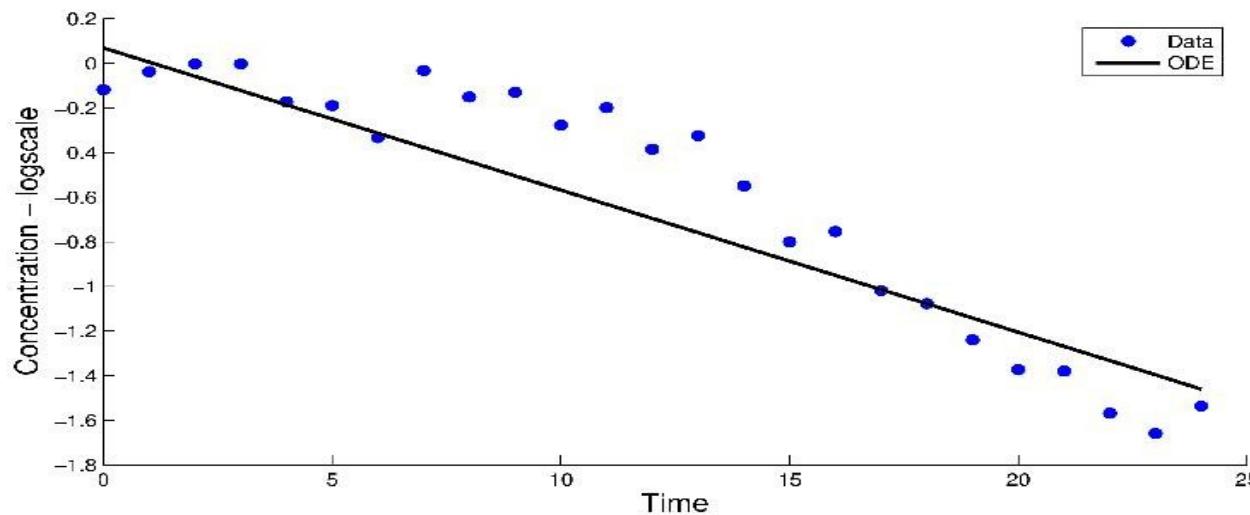
# Traditional Dynamic Model



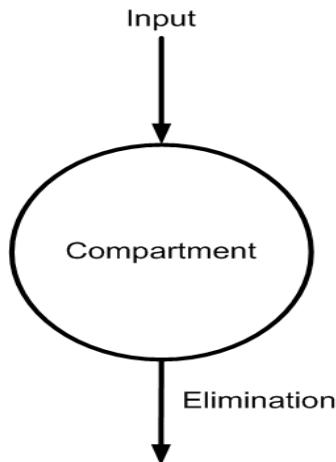
- Ordinary Differential Equation:

$$dA = -K A dt$$

$$Y = A + \epsilon$$



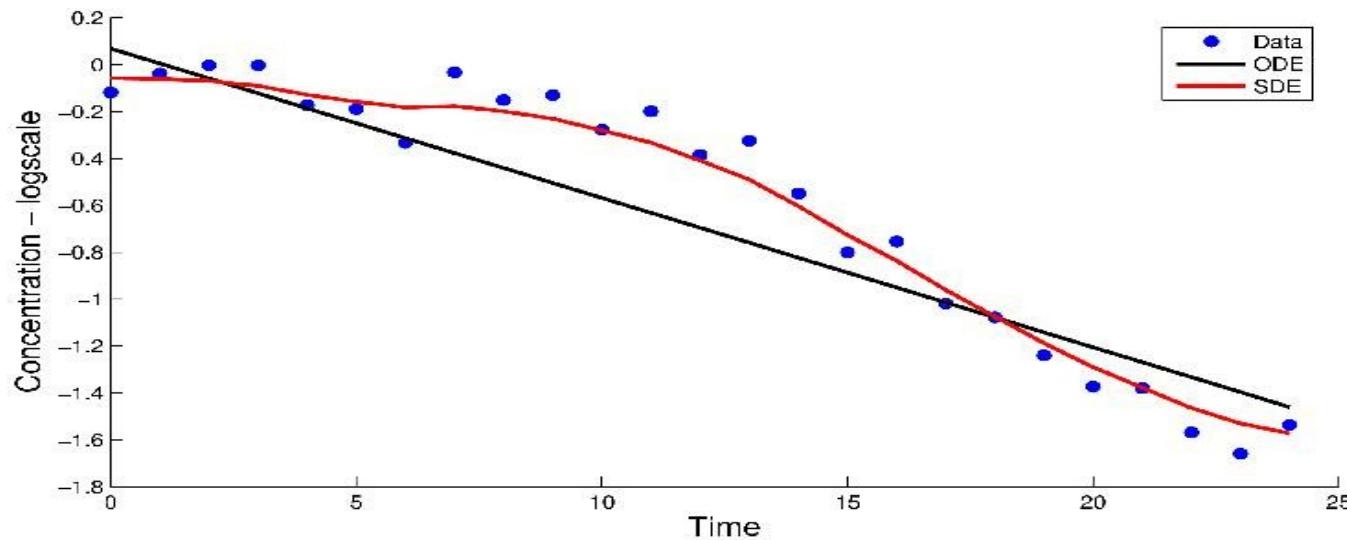
# Stochastic Dynamic Model



- Stochastic Differential Equation:

$$dA = -K A dt + \sigma dw$$

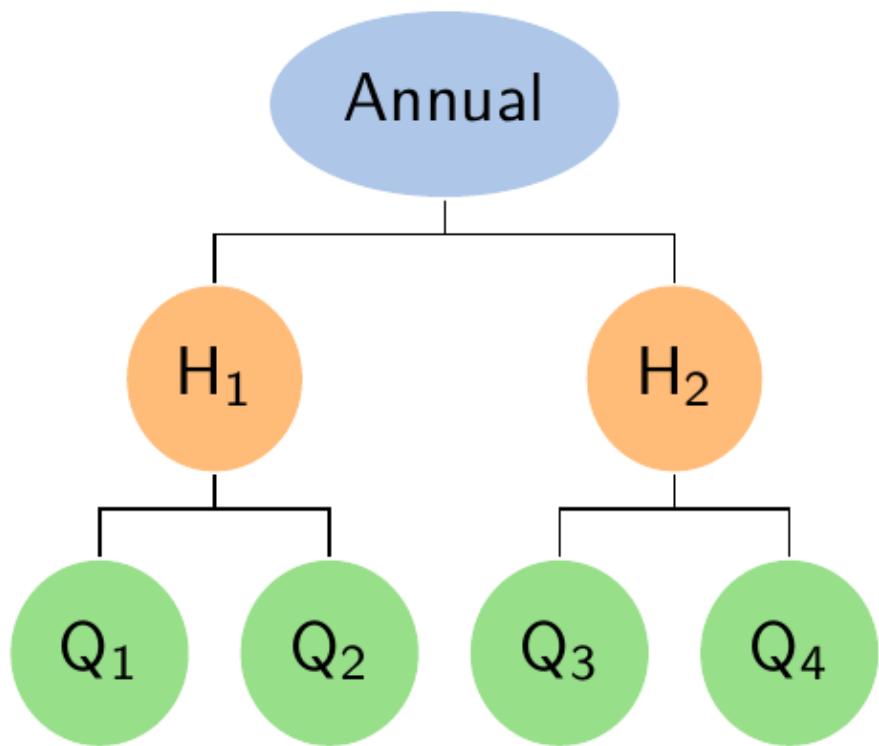
$$Y = A + e$$



# Forecasting using Temporal Hierarchies



# Temporal hierarchy for quarterly series (Consistent forecasting across scales)



$$S = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

# Weather Forecasting



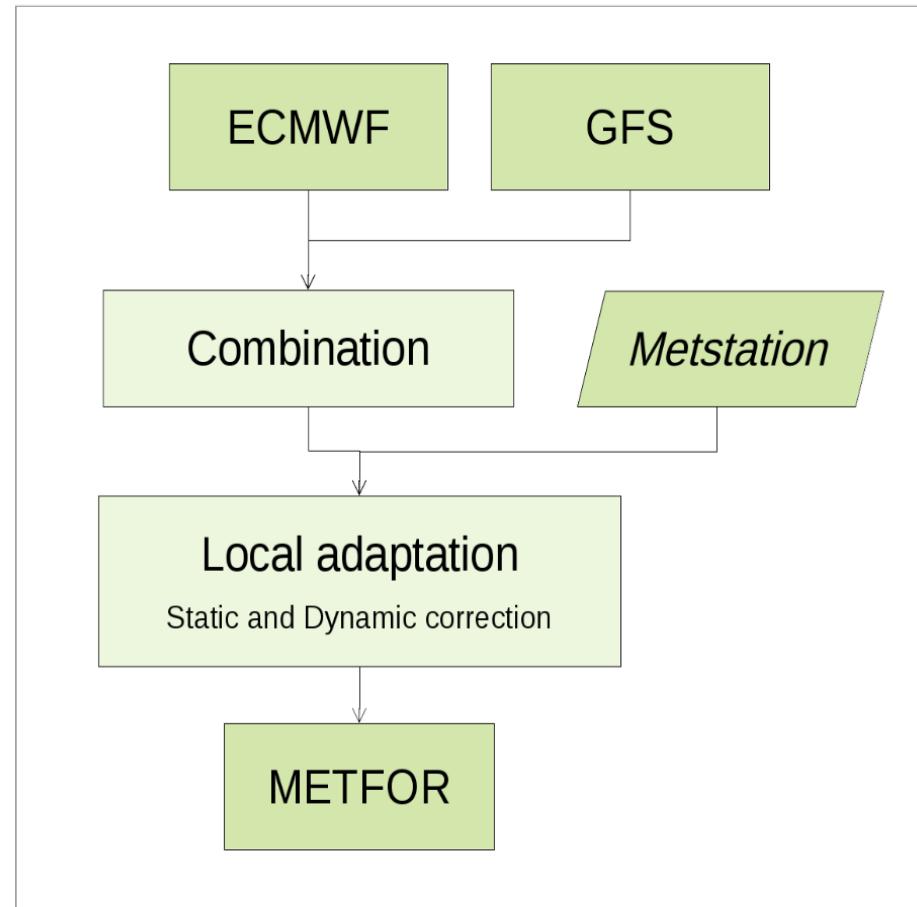
# Weather data and forecasts

## Combined forecasting

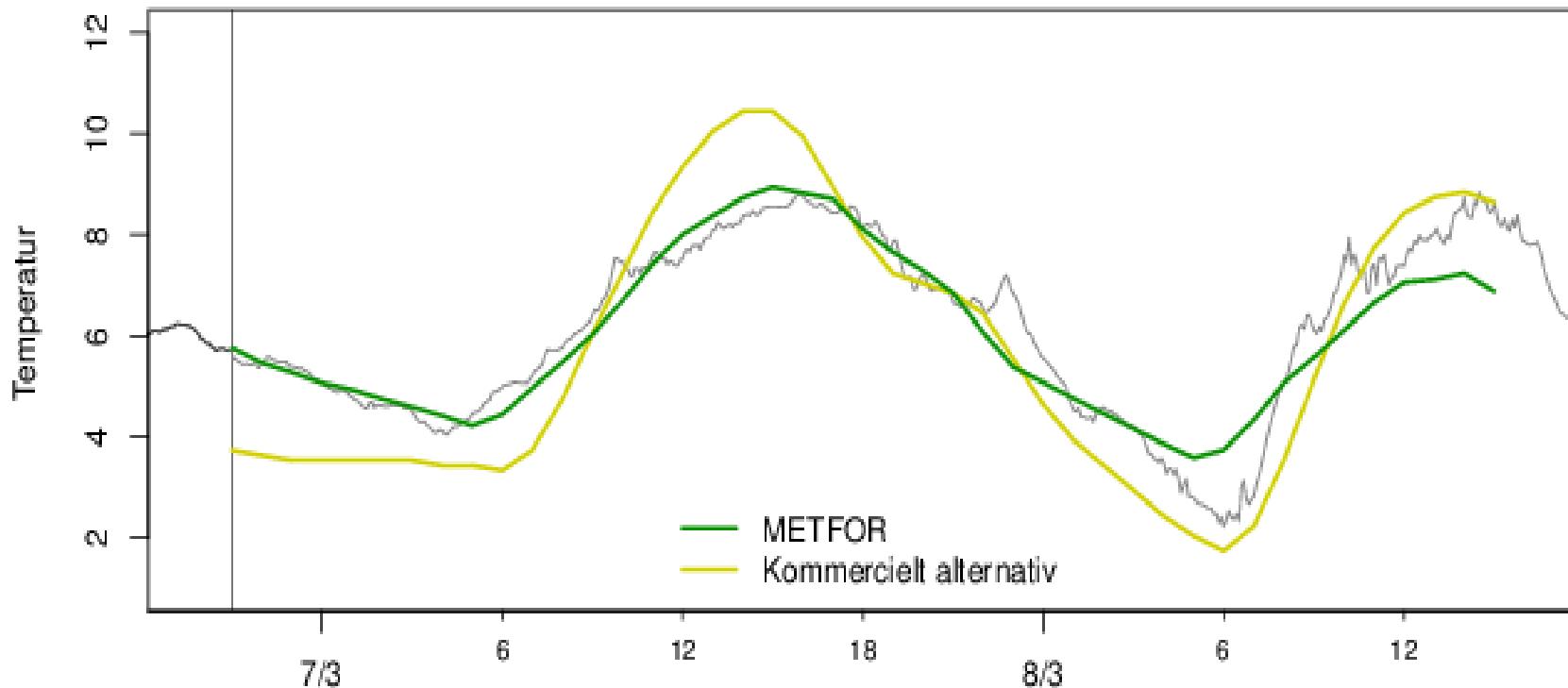


Optimize local weather forecast base on:

- Local climate data
- Several MET forecasts
- **Improvements in accuracy: 20 – 98 pct**



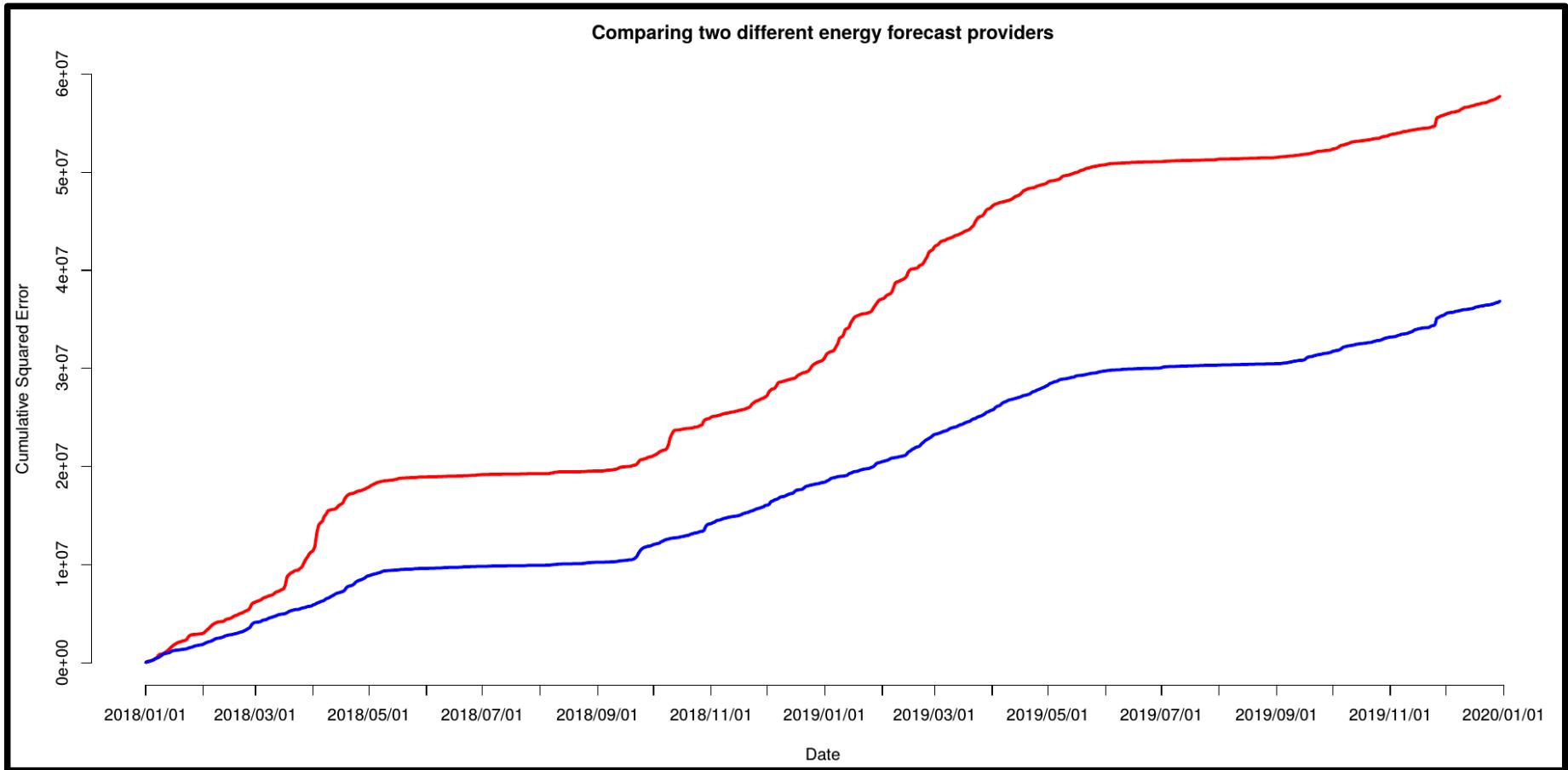
# METFOR forecast example



# Heat Load Forecasting



# Heat Load Forecasts at Varmelast



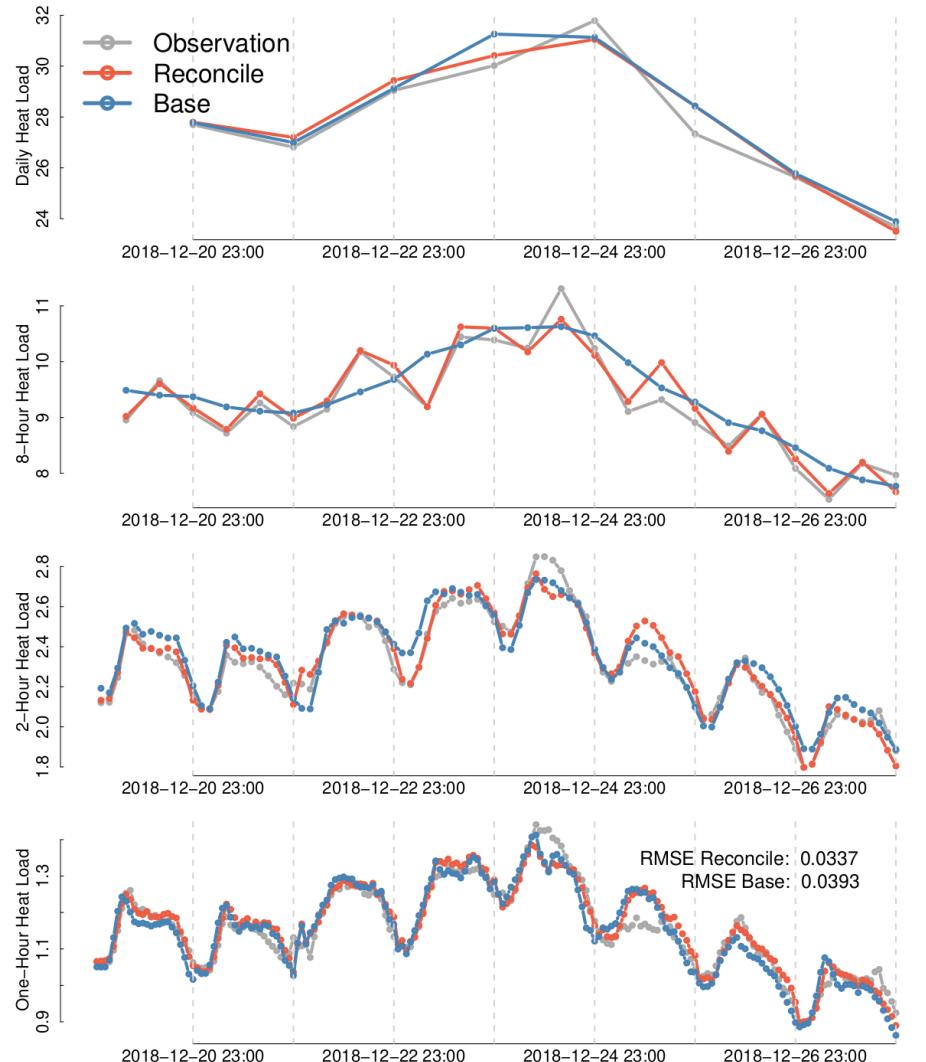
36 pct improvements with forecasting tool from HEAT4.0



# Improvements with Temporal Hierarchies



- Forecast for different aggregation levels
- Share information between levels
- Reconciled forecast is the process of optimally combining hierarchical forecast to yield coherent forecast
- The result are guaranteed to be at least as good as the base forecast



# Heat Load Forecasting

## Improvements Using

### Temporal Hierarchies in HEAT4.0



	2017				2018			
	Base RMSE	Expanding Window	Rolling Window	Exp. Smoothing	Base RMSE	Expanding Window	Rolling Window	Exp. Smoothing
Daily	0.5585	-17.88	-17.7	<b>-18.1</b>	0.6218	<b>-23.02</b>	-19.56	-22.94
Twelve-hourly	0.3151	-17	-16.72	<b>-17.19</b>	0.3766	-25	-22.25	<b>-25.01</b>
Eight-hourly	0.3333	-39.78	-39.61	<b>-39.9</b>	0.3508	-40.24	-38.56	<b>-40.48</b>
Six-Hourly	0.2628	-41.07	-40.77	<b>-41.17</b>	0.2876	-42.16	-40.21	<b>-42.23</b>
Four-hourly	0.1715	-35.24	-34.86	<b>-35.34</b>	0.1725	-31.81	-30.16	<b>-32.32</b>
Three-hourly	0.1273	-31.98	-31.62	<b>-32.09</b>	0.1315	-30.34	-28.62	<b>-30.75</b>
Two-hourly	0.0846	-29.07	-28.64	<b>-29.16</b>	0.088	-27.99	-26.33	<b>-28.51</b>
Hour	0.0372	-14.83	-14.26	<b>-14.92</b>	0.0389	-14.77	-12.91	<b>-15.44</b>
	2019				2017:2019			
	Base RMSE	Expanding Window	Rolling Window	Exp. Smoothing	Base RMSE	Expanding Window	Rolling Window	Exp. Smoothing
Daily	0.6022	-30.4	<b>-31.03</b>	-30.94	0.5947	-23.86	-22.7	<b>-24.07</b>
Twelve-hourly	0.3579	-29.22	-29.07	<b>-29.46</b>	0.3508	-24.16	-22.97	<b>-24.29</b>
Eight-hourly	0.3735	-49.89	-49.58	<b>-50.13</b>	0.3529	-43.5	-42.75	<b>-43.7</b>
Six-Hourly	0.3095	-49.84	-49.63	<b>-50.06</b>	0.2872	-44.68	-43.83	<b>-44.81</b>
Four-hourly	0.1839	-40.73	-40.3	<b>-41.06</b>	0.1761	-36.03	-35.19	<b>-36.34</b>
Three-hourly	0.1401	-36.35	<b>-35.62</b>	-36.55	0.1331	-33.01	-32.05	<b>-33.25</b>
Two-hourly	0.092	-33.06	-32.21	<b>-33.27</b>	0.0883	-30.12	-29.12	<b>-30.4</b>
Hour	0.0387	-14.52	-13.22	<b>-14.7</b>	0.0383	-14.71	-13.44	<b>-15.02</b>

**Table 2**

Out-of-sample RMSE for the base forecasts and RRMSE for the reconciled forecasts for daily heat load consumption in the Greater Copenhagen area. It shows the results for three different years and the whole period from 2017 to 2019.

- Further improvements: 15+ pct

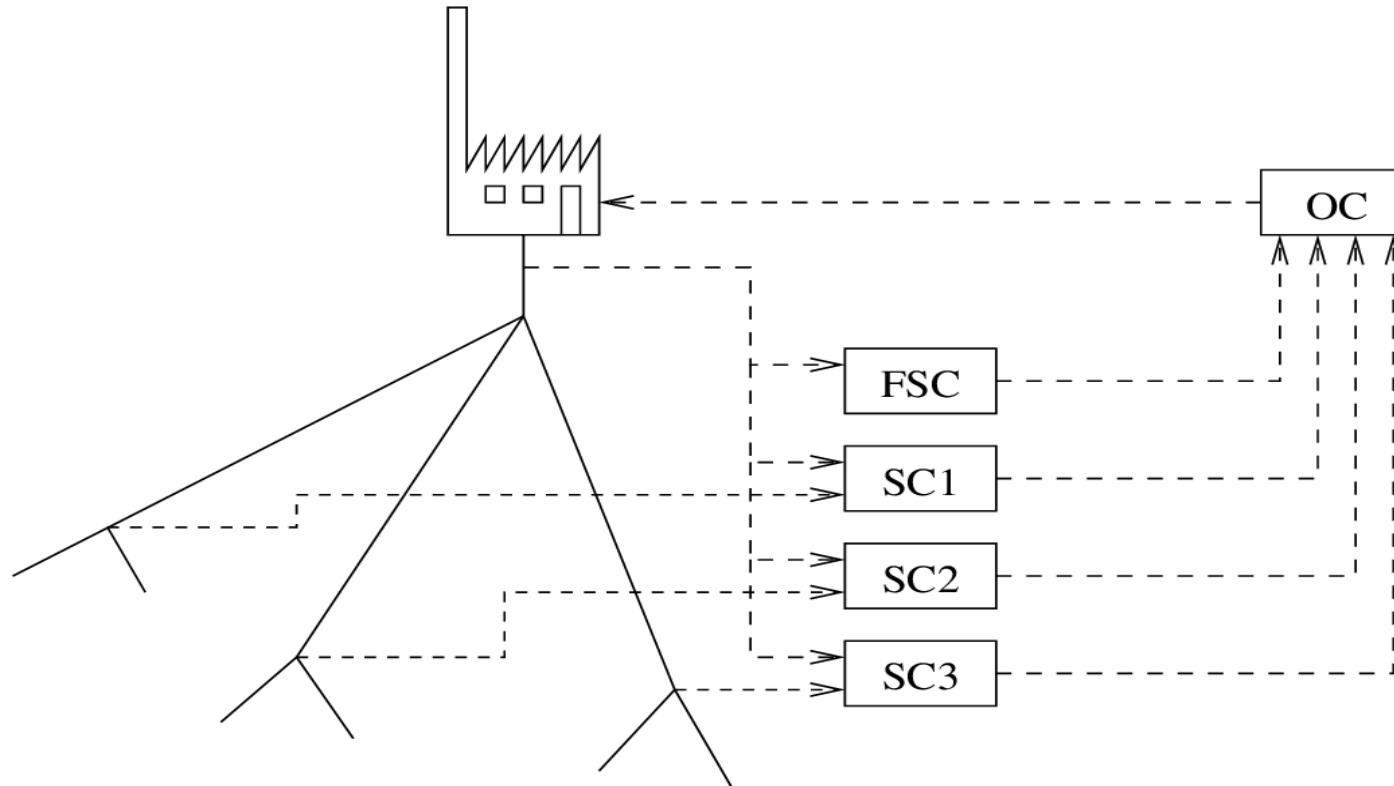


# Data-driven Temperature Optimization

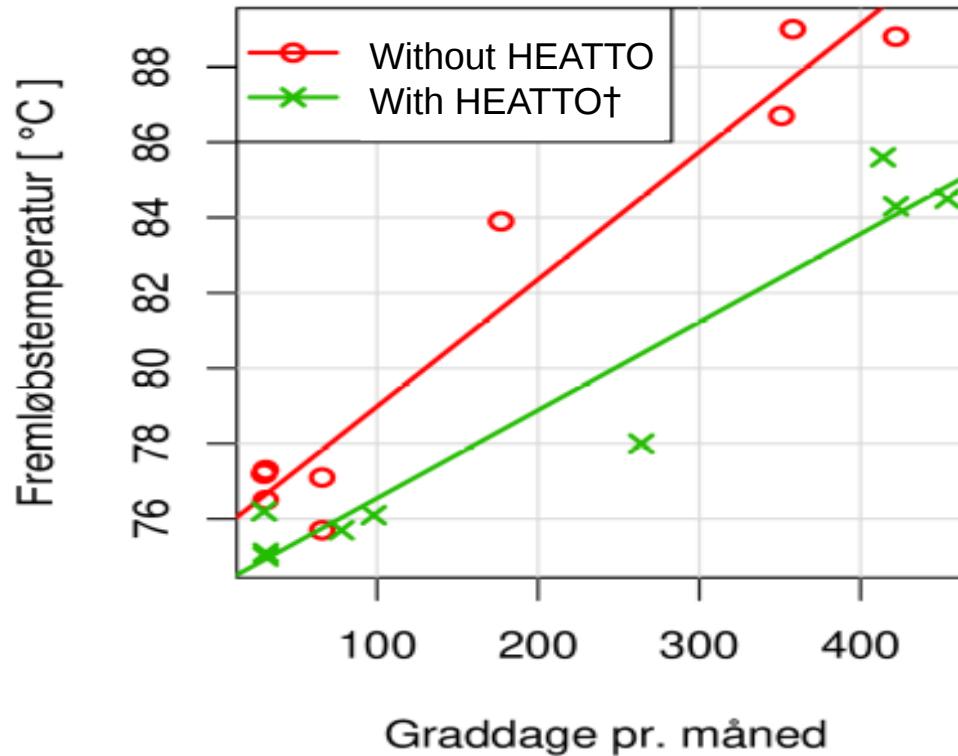


# Models and Controllers

(Highly simplified!)



# Supply temperature with/without data-driven temperature opt.



**Savings:**  
Reduction in heat loss  
18.4 pct  
Annual cost saving  
2.4 mill dkr

# DIGITALISER I FJERNVARMEN BIDRAGER TIL 2030-MÅL

Det sparer penge og CO<sub>2</sub>, når fjernvarmesektoren styrer temperaturen med data og lokale vejrudsiger i stedet for tegninger af ledningsnettet og mavefornemmelsen.

Hanne Kokkegård  
Sven Müller, DTU, Dansk Fjernvarme/Nils Rosenvold

1,7 mio. husstande i Danmark (ca. 64 pct.) bliver opvarmet med fjernvarme, der løber gennem 60.000 kilometer fjernvarmenet. Rejsen fra fjernvarmeværket til radiatorerne tager typisk flere timer, og derfor skal varmebehovet kunne forudsiges.

Man skal ikke skruer mere op for varmeproduktionen end nødvendigt, for det koster penge og er energispild, ligesom temperaturlabet i rørene er større ved højere temperaturer. Samtidig skal vandet være tilstrækkelig varmt på de såkaldt kritiske punkter i udkanten af ledningsnettet. Så det er en videnskab at styre fjernvarmeproduktion optimalt.

På DTU Compute arbejder professor Henrik Madsen og hans kolleger med datadrevet energi- og temperaturoptimering. Flere forskningsprojekter viser, at digitalisering forbedrer prognosene for varmebehovet og tilmed letter vejen til Danmarks 2030-klimamål.

En undersøgelse, som Damvad Analytics har lavet sammen med Danmarks største smart-city-projekt, CITIES, ledet af netop Henrik Madsen, samt tænkankonen Gron Energi under Dansk Fjernvarme, viser, at fjernvarmesektoren kan spare mellem 240 og 790

mio. kr. ved at indføre datadrevet temperaturregulering af fremlobstemperturen. Fordi temperaturen kan sænkes tre til grader. Lavere temperatur sparer også CO<sub>2</sub>, ligesom varmetabet i nettet mindskes.

"Der er store potentialet ved at gå fra erfaring og simulationsbaseret styring ud fra tegninger af ledningsnettet til datadynamisk optimering af fjernvarmen. Vores projekter viser, at når fremlobstemperturen er baseret på flere her og nu-datakilder, herunder vejdata fra lokale målestansjoner, optimerer vi produktionen og accelererer den gronne omstilling," siger Henrik Madsen.

## Lavere varmepriser

Svebølle Viskinge Fjernvarmeselskab med 535 husstande er et af de forsningsselskaber, der har øget digitaliseringen. Siden oktober 2019 har fjernvarmeselskabet i Nordvestsjælland benyttet bearbejdede data fra DTU-spitout-firmaet ENFOR til optimal styring af fremlobstemperturen.

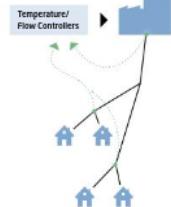
På få måneder har man kunnet sænke fremlobstemperturen med over 20 grader. Hvor temperaturen før lå på 80,9 grader, blev den først sænket til 68,1 grader, hvorefter den kunne sænkes yderligere til 60 grader.



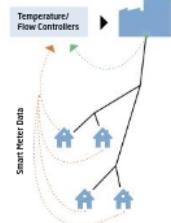
## Transformationen

Figuren skitserer, hvordan den digitale transformation i fjernvarmen kommer til at foregå med data fra fjernafståede målere (smartmeters).

KELDE: INTEGRERING AF LAUTERMÆRS-PROJEKTPARTNER TIL EKSTISTEREDE BRONDBÅDER, JUNI 2020, DTU/MFL.



## DIGITAL TRANSFORMATION + MACHINE LEARNING



Det giver en anslægt besparelse på mindst 550 MWh og en reduktion på 110.000 kr. i årlige produktionsomkostninger. Man regner med på sigt at senke varmetilstanden i nettet til under 30 pct., og at varmepriserne falder med 47 pct. i perioden 2015-2025.

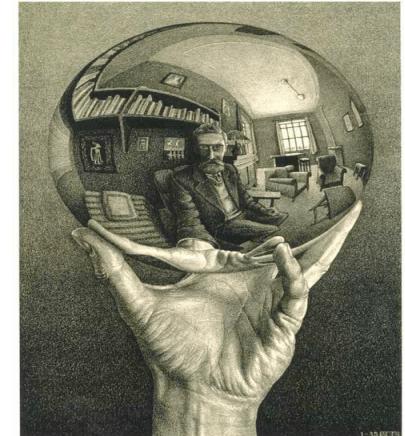
Inden Svebølle Viskinge Fjernvarmeselskab gik over til datadrevet drift, benyttede man såkaldt simulationsbaseret drift baseret på viden om fjernvarmenettet, erfaring og kun lidt forecast.

## Svebølle-Viskinge DH: Lowered the temperature with 15 – 20 degrees Brønderslev DH: Approx. 3 degrees

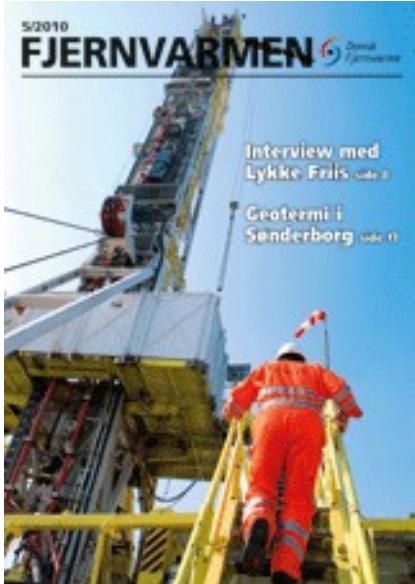


# Data-driven Temperature Optimization

- Able to take advantage of **information in data**
- **Self-calibrating** models for the DH network
- Easy to maintain
- Shows where to **upgrade** the DH network
- **Fast** (real time) calculations
- Use DH net for **peak shaving** and **storage**
- Able to use **online MET forecasts** etc.
- **Savings up to 800 mill DKK annually** by using data-driving temperature opt. (Damvad report 2019)



# Control of Supply Temperatures



FJERNVARMEN | 5 2010

Styring af temperatur rummer  
kæmpe sparepotentiale

## Lessons learned:

- Control using **simulation** of temperature gives **up to 10 pct reduction** of heat loss.
- Control using **predictions** gives **up to 20 pct. reduction** of heat loss.



## Which approach to use?

- Use **simulation based control** if:
  - No access to data from the DH network
  - Want an evaluation of new operational scenarios
- Use **prediction based control** if:
  - Access to network data online
  - Want to used meteorological forecasts online
  - Want to combine MET forecasts with local climate data
  - Want automated update of models

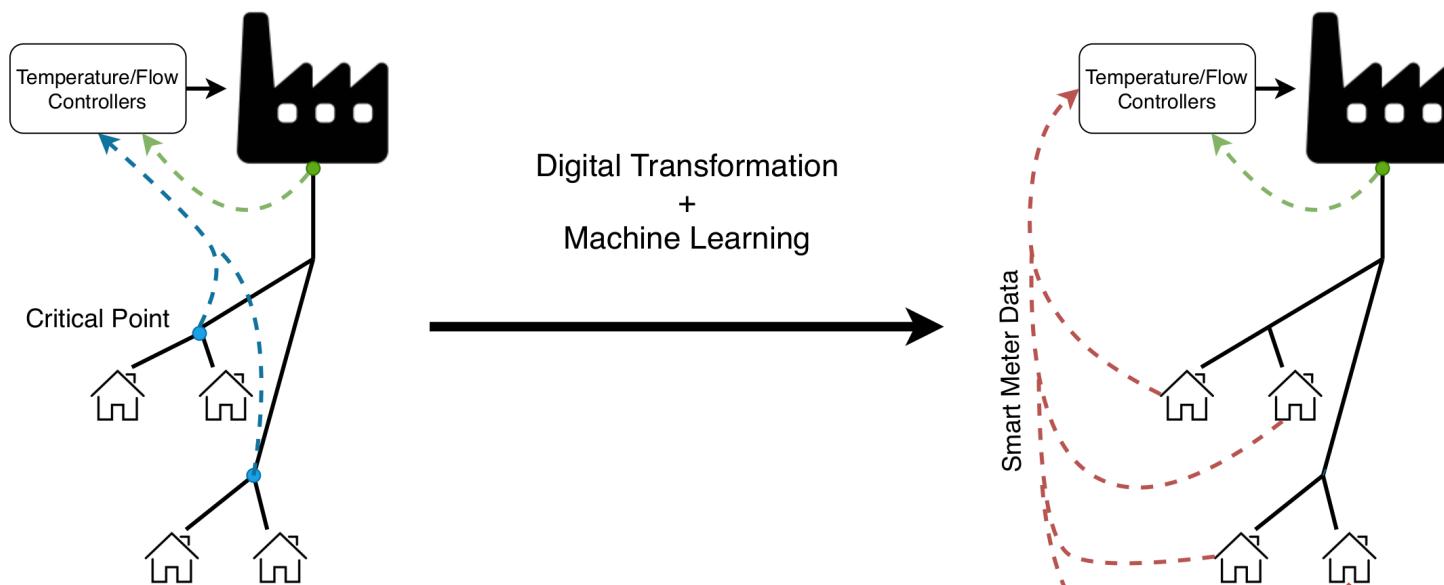


# Data-driven Temperature Optimization v.4.0 (Incl. use of meter data)

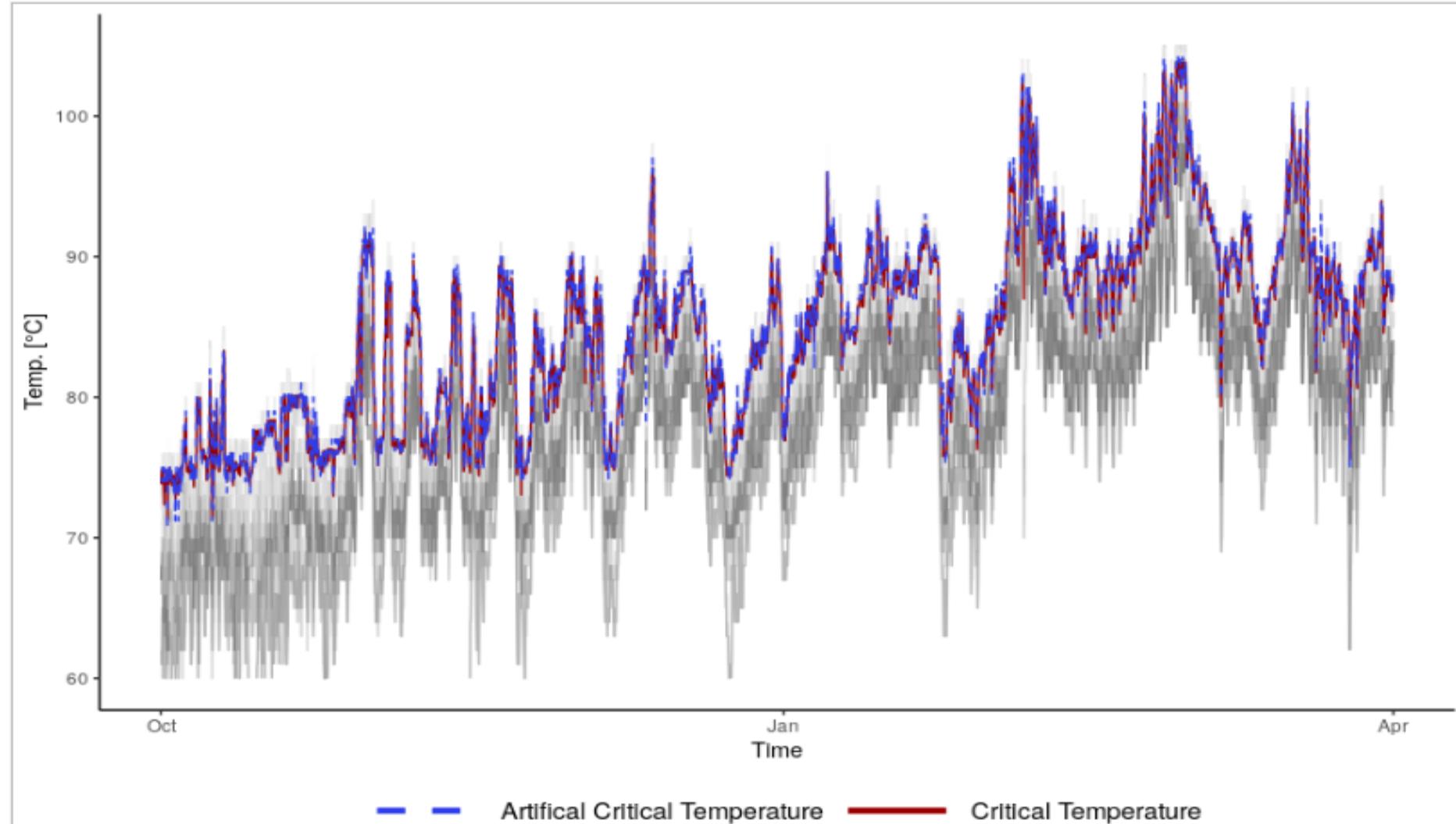


# Replacing the netpoint sensors at the critical point using meter data

- Use readings from end-user to create a **artificial critical temperature** for a distribution of houses in the network
- **Replacement** of critical netpoint sensors
- **Dynamic location** of netpoints



# Critical Temperature estimated from Smart-Meter Data (Brønderslev DH)

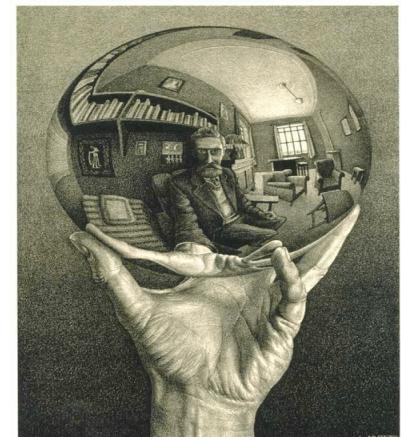


— Artifical Critical Temperature   — Critical Temperature



# Data Intelligent Temperature Optimization Using Smart Meter Data

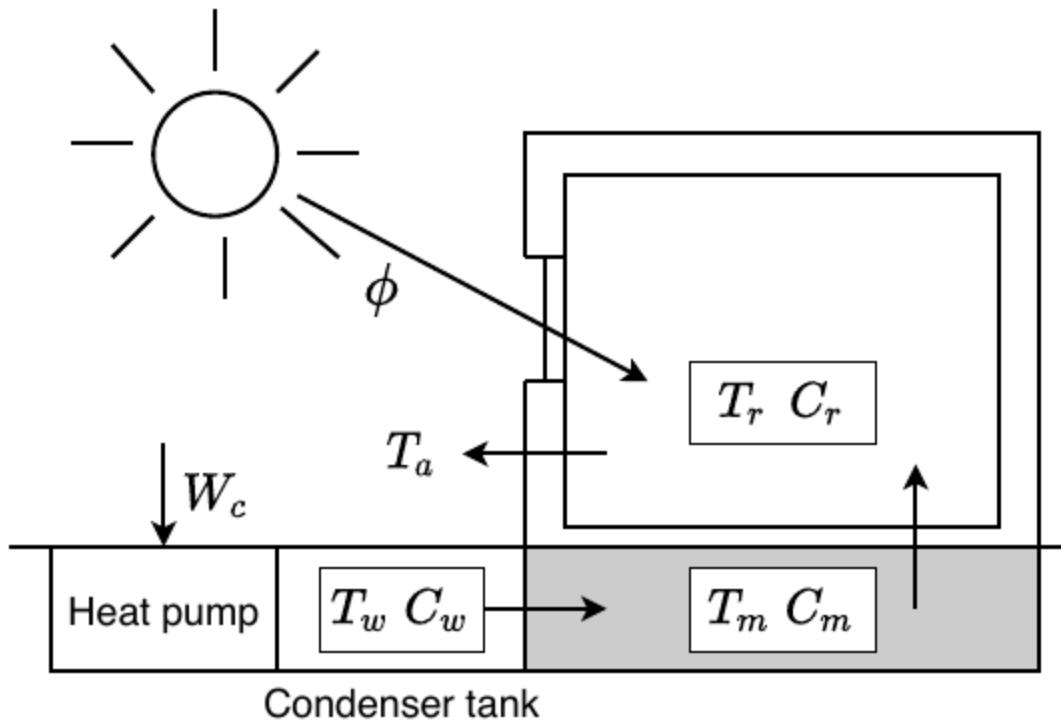
- Eliminates or reduces the need for critical points in the DH net
- Identify needs for upgrade of the local net
- Find users with a high flow and other issues
- Next generation of temperature zones
- Use user installations to store energy locally
- Time-varying prices – active use of end-users
- Establish a possibility for effect limitations  
(should be reflected in the contract)



# Integrated Forecasting and Control for Buildings

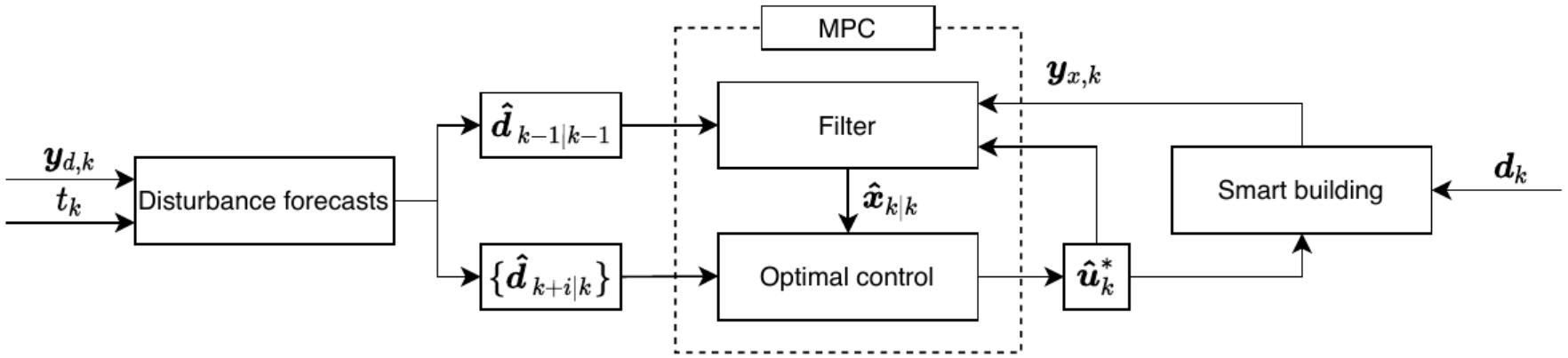


# Grey-box Model for a Smart Building



# Integrated Forecasting and Control

The MPC framework for smart house control and how disturbance forecasts are incorporated



$$\begin{aligned} d\mathbf{x}(t) &= f_s(\mathbf{x}(t), \mathbf{u}(t), \mathbf{d}(t))dt \\ &\quad + g_s(\mathbf{x}(t), \mathbf{u}(t), \mathbf{d}(t))d\omega_s(t), \end{aligned} \quad (1a)$$

$$d\mathbf{d}(t) = f_d(\mathbf{d}(t))dt + g_d(\mathbf{d}(t))d\omega_d(t), \quad (1b)$$

$$\mathbf{y}_s(t_k) = h_s(\mathbf{x}(t_k)) + \mathbf{v}_{s,k}, \quad (1c)$$

$$\mathbf{y}_d(t_k) = h_d(\mathbf{d}(t_k)) + \mathbf{v}_{d,k}, \quad (1d)$$

# The school used for smart district heating control

- Borgerskolen in Høje Taastrup

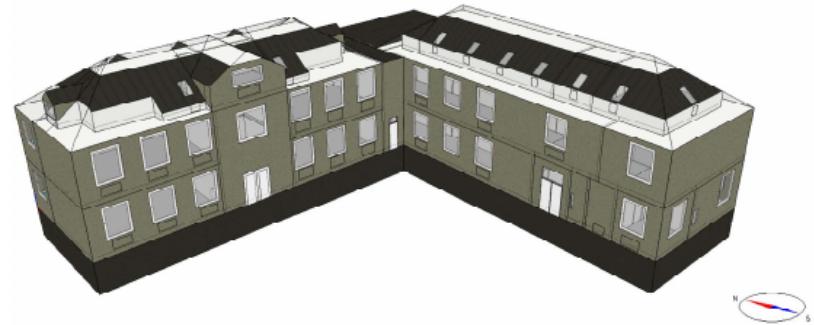


Figure 1: The building in question

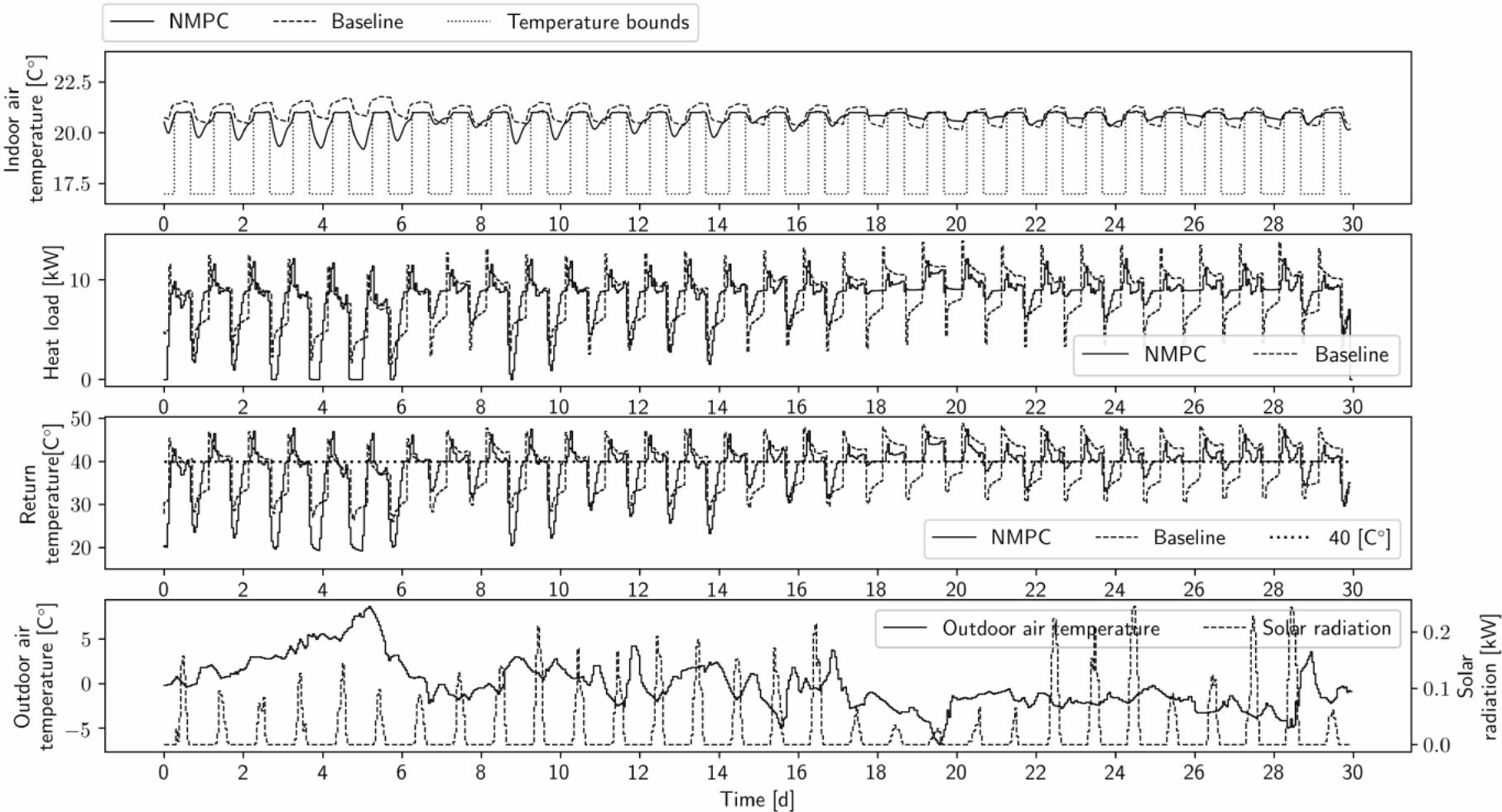


Figure 4: A simulation study that compares a current standard set-point control in today's buildings (Baseline) and the NMPC presented in this paper. The heat costs are constant at 0.1 EUR/kWh plus a penalty of 2% for each  $\text{C}^\circ$  the return temperature is above 40  $\text{C}^\circ$ . Results suggest an economic reduction by around 10%.

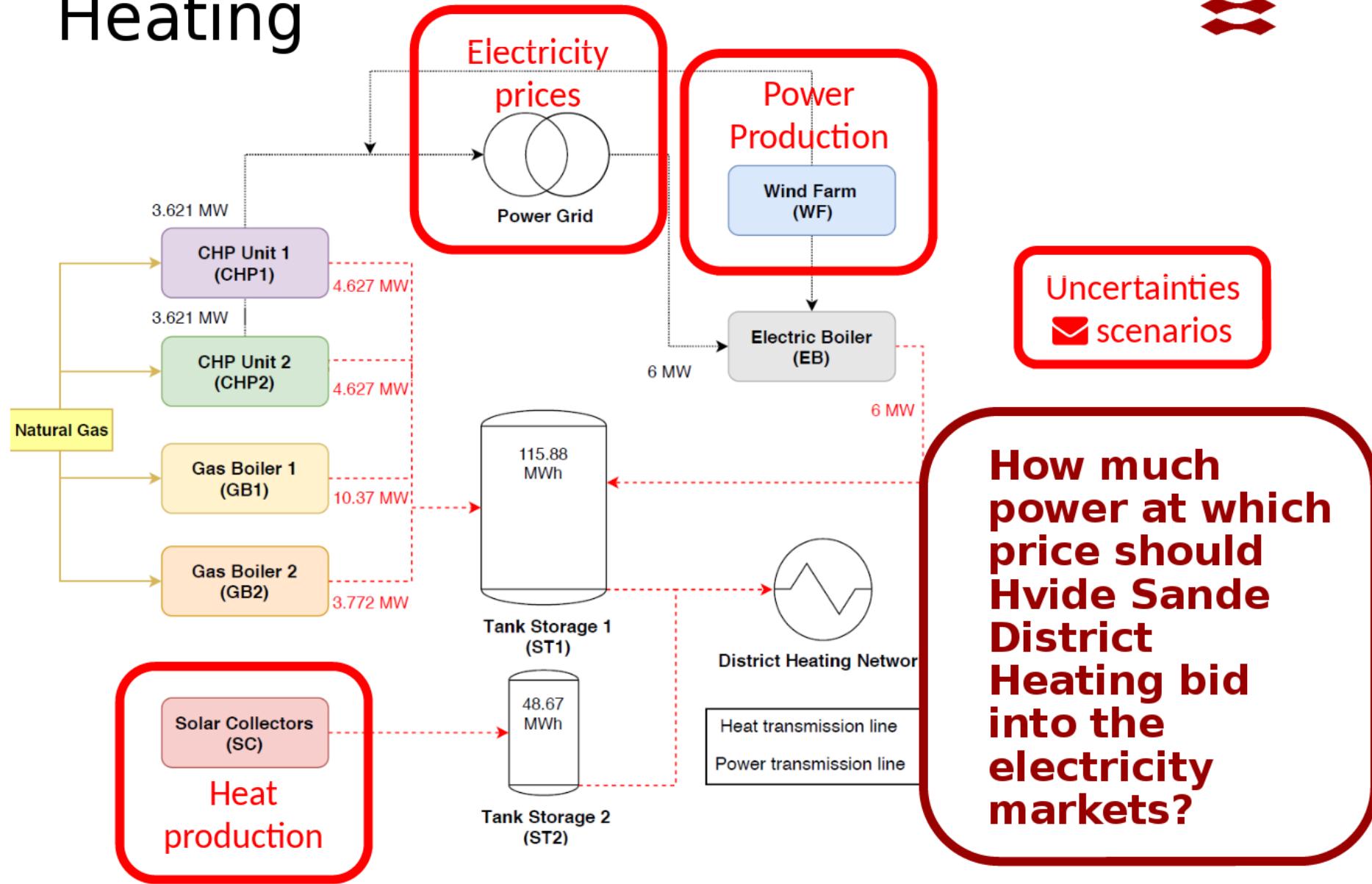
**Savings documented in HEAT 4.0: 8 – 10 pct**



# Optimal Operation and Bidding



# Test case - Hvide Sande District Heating



# Results - Bids

Percentage of hours with bids and won bids in one month averaged over several samples

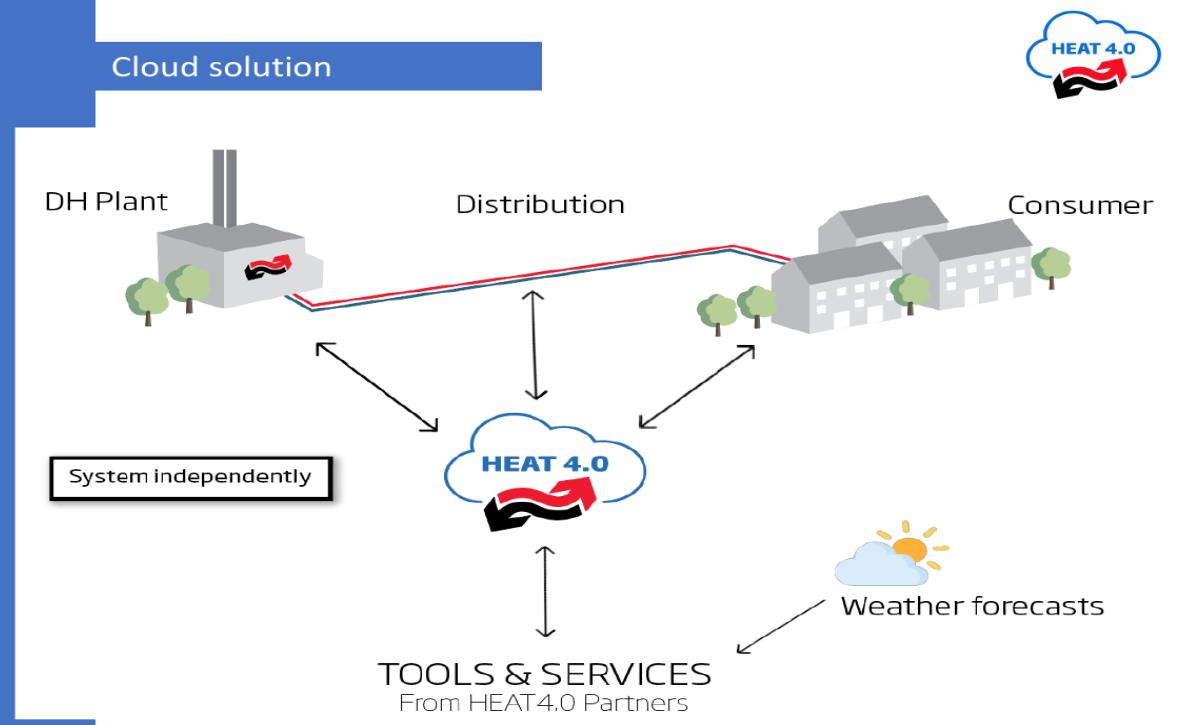
Method	Receding Horizon	CHP 1		CHP 2	
		Bids	Won	Bids	Won
HURB Worst	1	<b>98.91</b>	<b>41.95</b>	98.70	41.91
HURB Avg.	-	<b>99.79</b>	<b>42.19</b>	99.75	42.15
HURB Best	10	<b>99.89</b>	<b>42.28</b>	99.87	42.26
Conejo et al.	10	44.92	39.34	44.92	39.31
Rodriguez & Anders	5	82.52	35.85	82.40	35.82
Schulz et al.	12	45.02	18.54	45.01	18.53
Dimoulkas & Amelin	12	75.55	26.56	75.55	26.55
Ravn et al.	5	44.84	32.58	44.83	32.57

We can take advantage of the portfolio of heat production units and base the bidding amounts and prices on the heat production.

**HEAT4.0 savings approx. 5 pct**

# Summary – HEAT 4.0 savings

The DH digital  
infrastructure  
**HEAT 4.0**



# Savings by digital operation of DH Systems (CO2 + Costs)

- Many digital solutions for DH systems have already been established in HEAT4.0 (... and more will come)
- 10 – 40 pct improvements of heat load forecasts
- 800 mill dkr annually in Denmark by data-driven temperature optimization = (tons of CO2 savings)
- (TO v. 4.0 – use of meter data): Maybe 200 mill dkr extra (we don't know yet)
- 10 – 30 pct savings by predictive control of heat pumps
- 5 – 20 pct savings by integrating forecasts in smart house controllers
- Up to 10 pct savings by optimal operations of CHP and DH plants

# Thanks for your attention ...



# Center Denmark



Connect networks and data  
for a green world

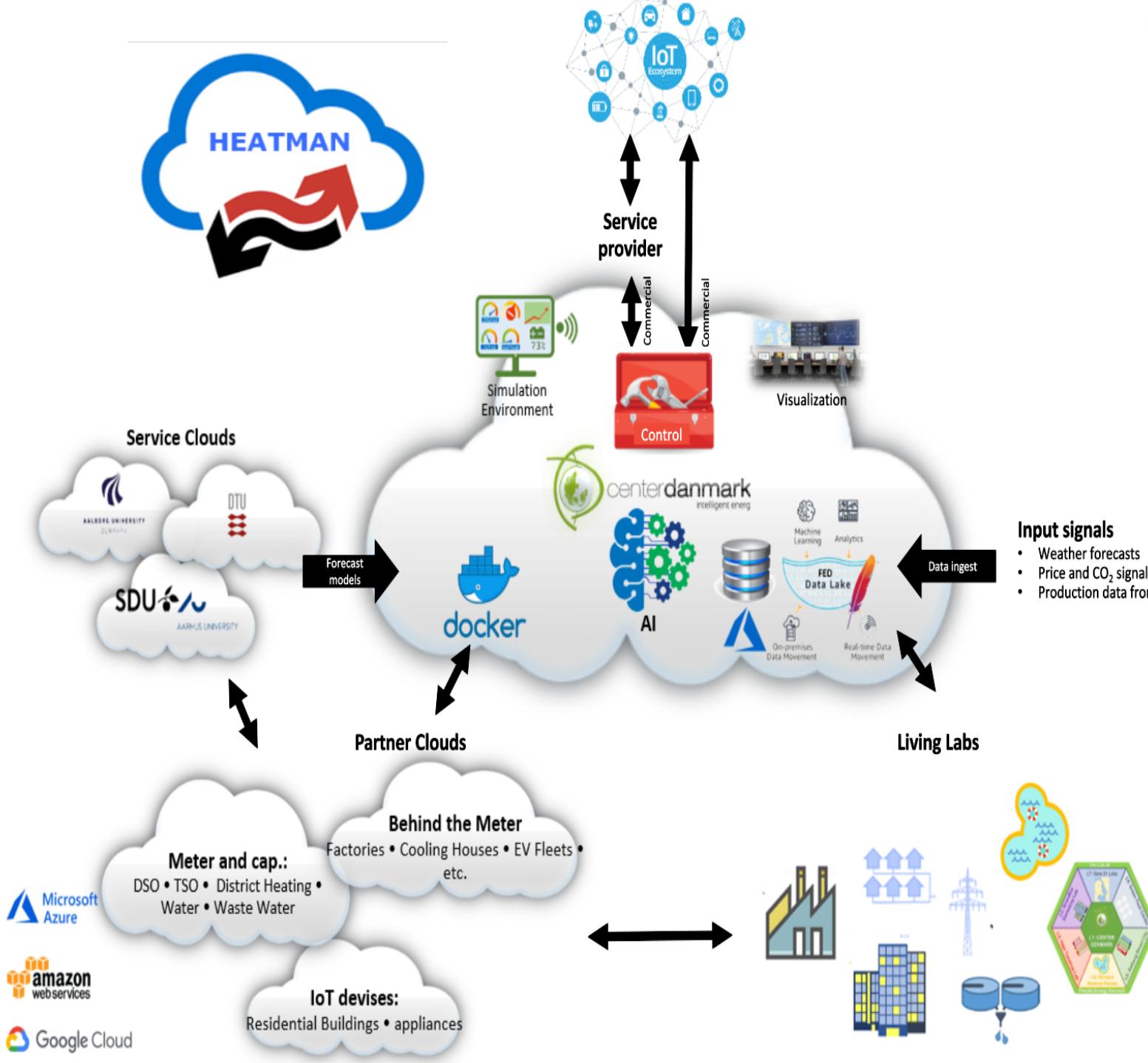


Danmarks  
nationale Center

Fremme den grønne omstilling.  
Samle og bygge bro, mellem  
forskning, teknologi, natur og formidling,  
på tværs af interesseorganisationer,  
virksomheder, skoler og  
universiteter.

# Center Denmark - Control Room





# Partnership

Sign-up here:

<https://www.centerdenmark.com/en/join-us/partnership/>

- Join a strong network for digital energy and sector coupling
- Access to a nationwide data platform with energy data
- Simulation environment for framework conditions and business models
- Focused research and demonstration program
- Access Incubator environment for business development and laboratories
- Access promotion show room



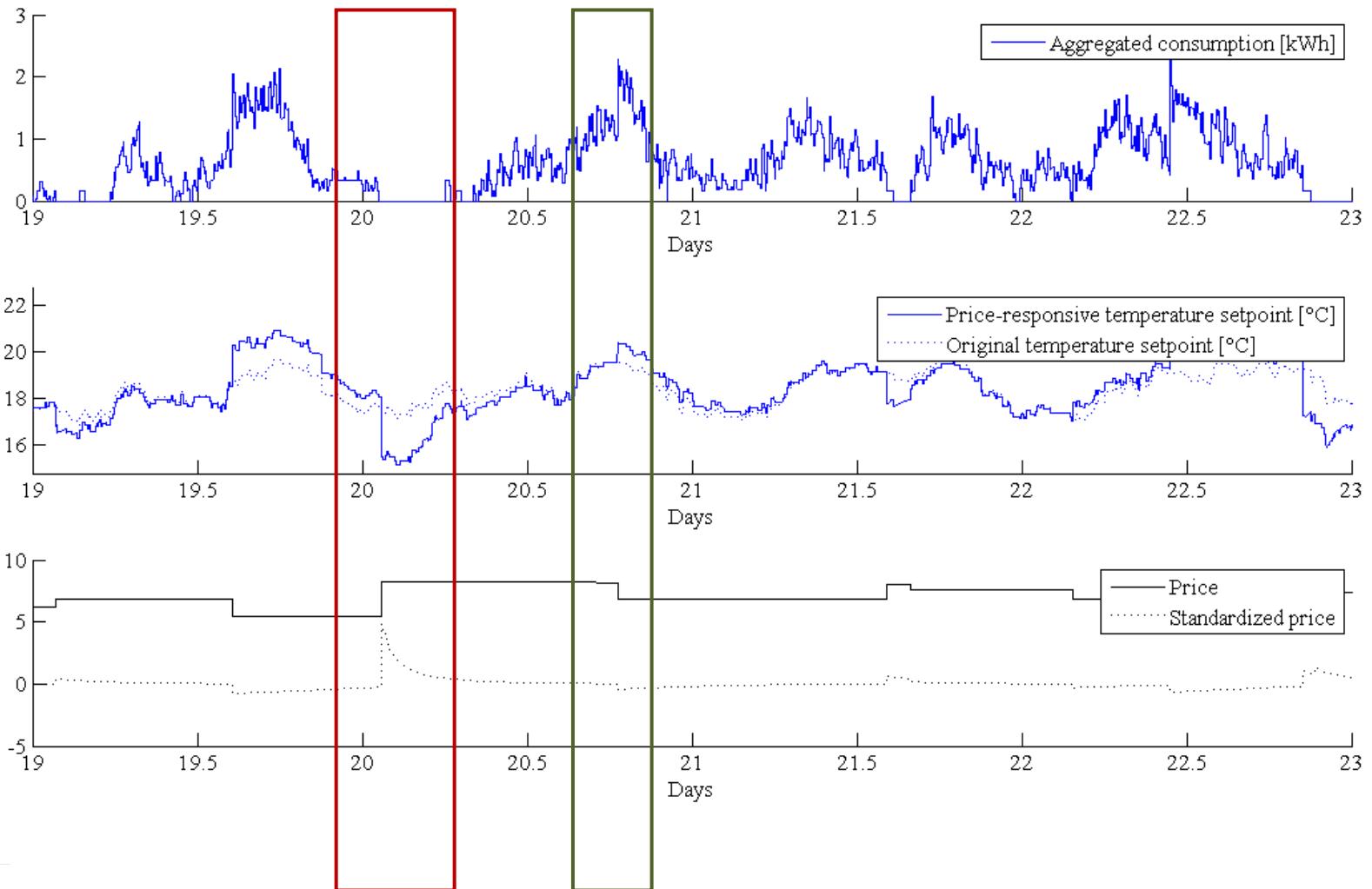
# Purpose based controllers for DH systems

- Peak shaving (morning peaks can be expensive)
- Capacity constraints
- Optimal control of temperature versus flow
- CO2 optimal control of heat pumps in DH systems
- Flow controllers – also for individual customers
- Minimize return temperature
- Use DH system for heat storage
- Use of excess heat from industry, supermarkets, etc
- Heat pumps (eg. dual HP with local seasonal storage)
- Optimal operation of Power2X facilities

# Price-based Control of Heat Consumption (Peak Shaving)



# Aggregation (over 20 houses)



# Flexibility Function

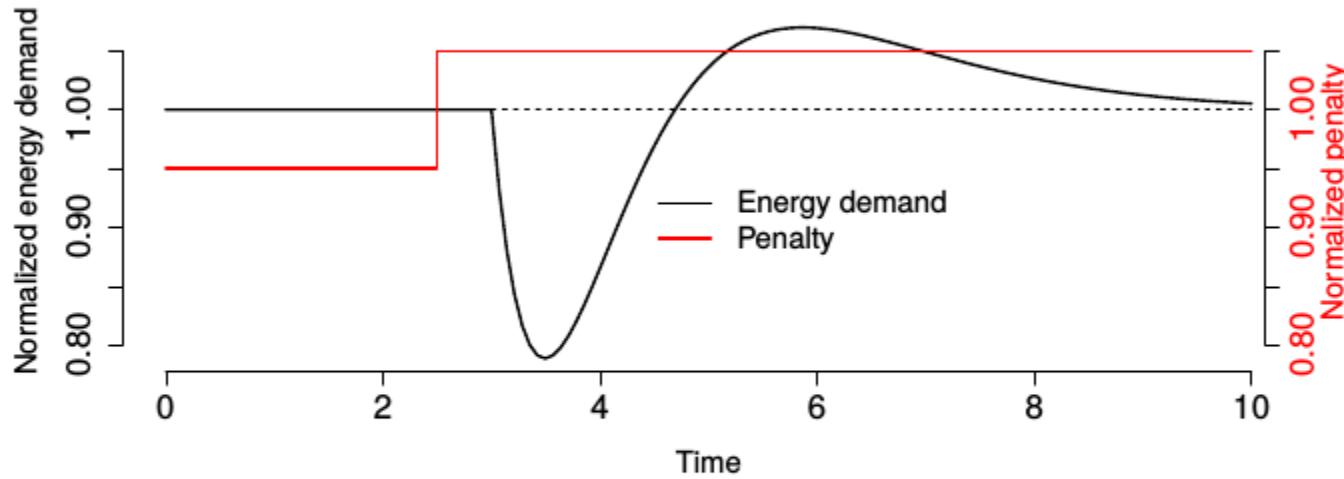
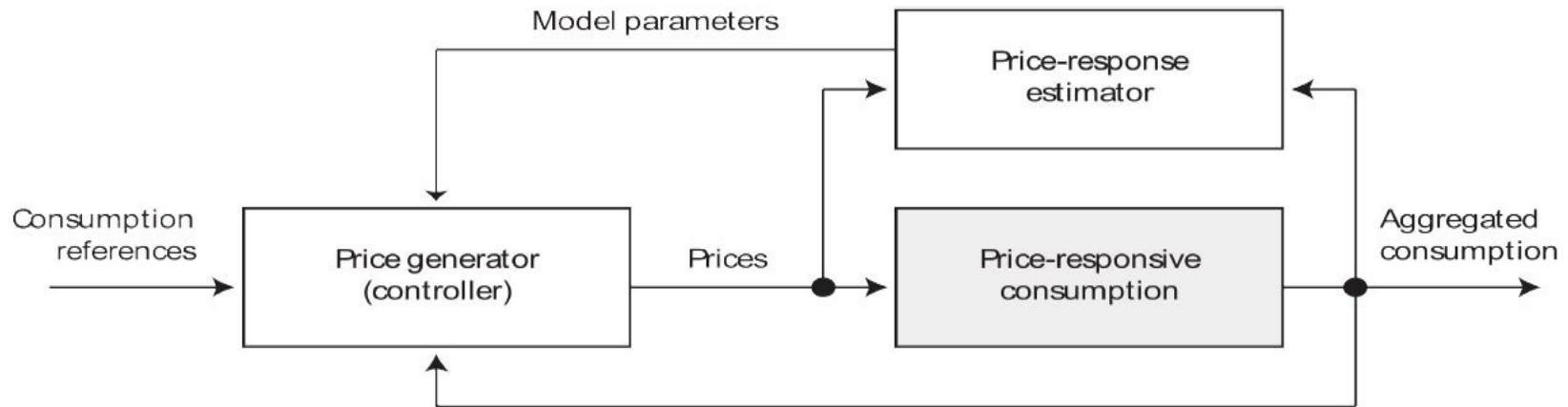


Figure 2: The energy consumption before and after an increase in penalty. The red line shows the normalized penalty while the black line shows the normalized energy consumption. The time scale could be very short with the units being seconds or longer with units of hours. At time 2.5 the penalty is increased,

# Control of Heat Consumption



# Control performance

Considerable **reduction in peak consumption**

