

Research results for Data-Intelligent Operation of District Heating Systems



Digitalisering af fjernvarmen – viden fra CITIES-projektet og konkret anvendelse

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Outline of the presentation

- **Load forecasting** – incl. Combined forecasts
- **Temperature Optimatizon v.2.0** (Current)
- **Temperature Optimatizon v.4.0** (Future – IDASC, CITIES, HEAT4.0)
- Usage cases of **smart-meter data**
- **Flexible load** in buildings (Preliminary results – SCA project)
- **Optimal Bidding** for District Heating Providers

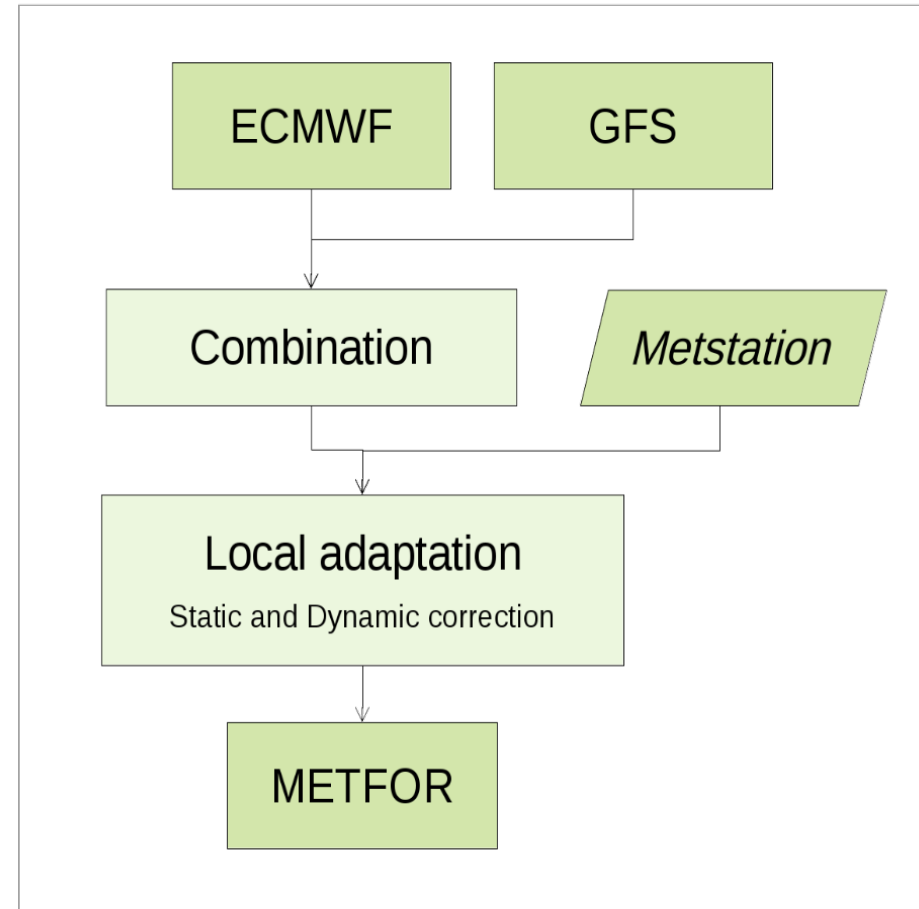
Data Intelligent Load Forecasting for DH Systems



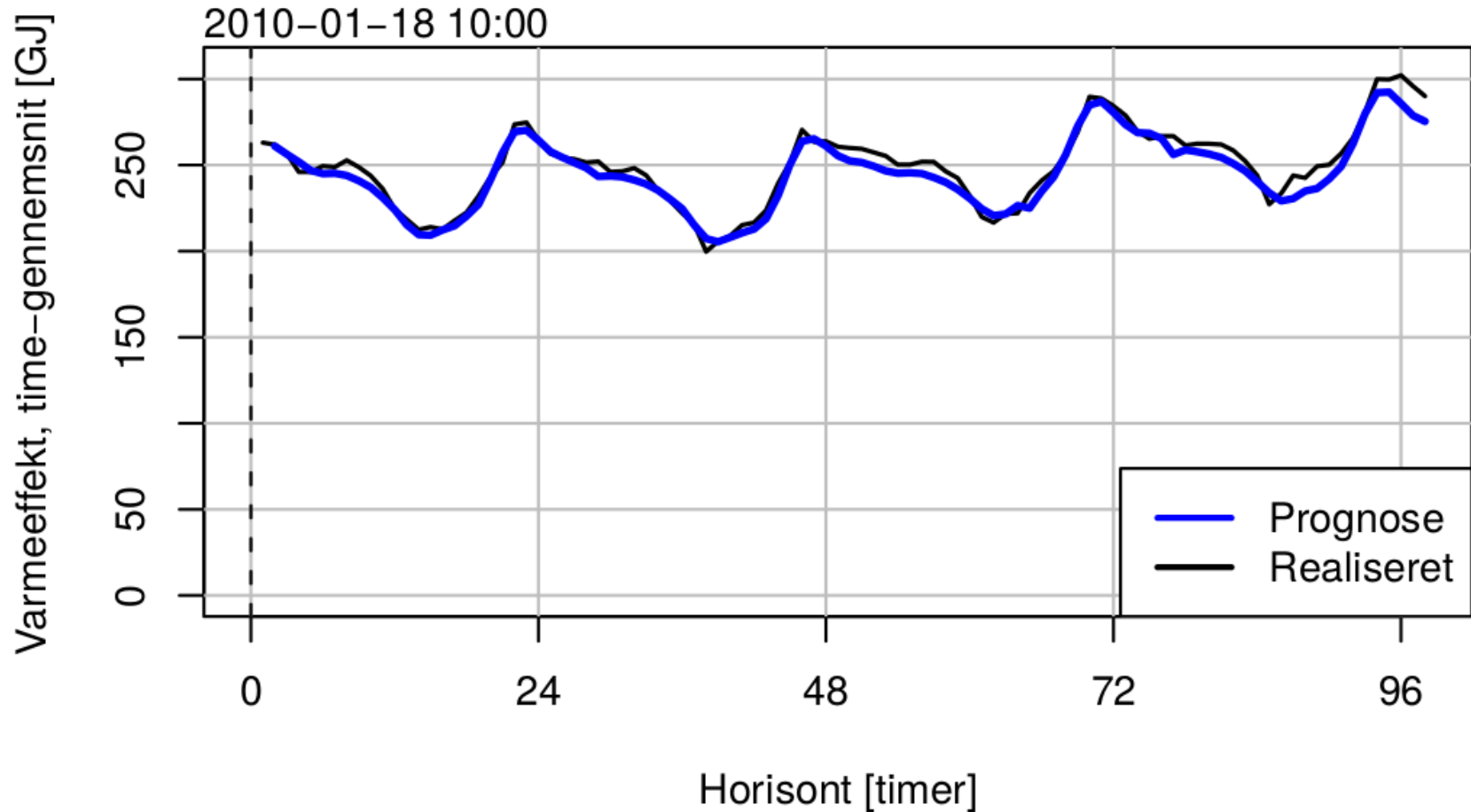
Weather data and forecasts

Optimize local weather forecast base on:

- Local climate data
- Several MET forecasts



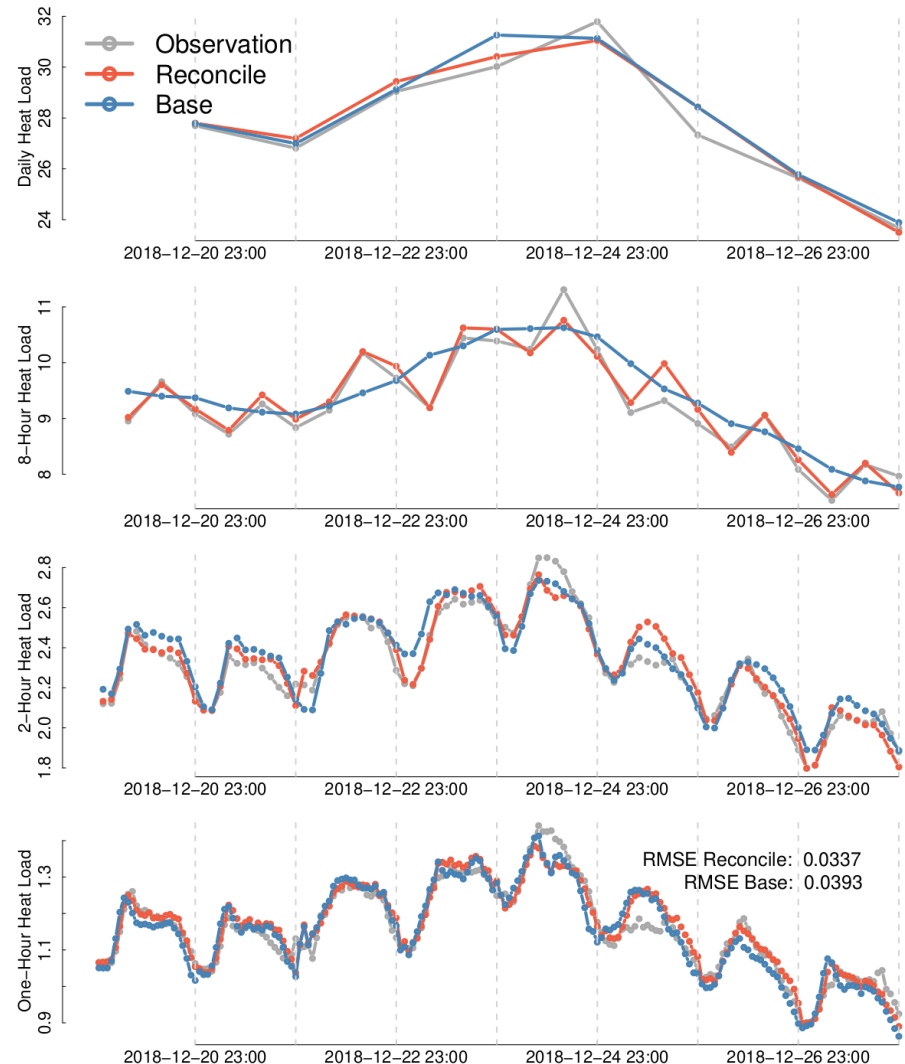
HEATFOR[†] Load Forecast (Example)



[†]ENFOR ~ <https://enfor.dk/>

Improve 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



Improved with temporal hierarchies

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

Table 2

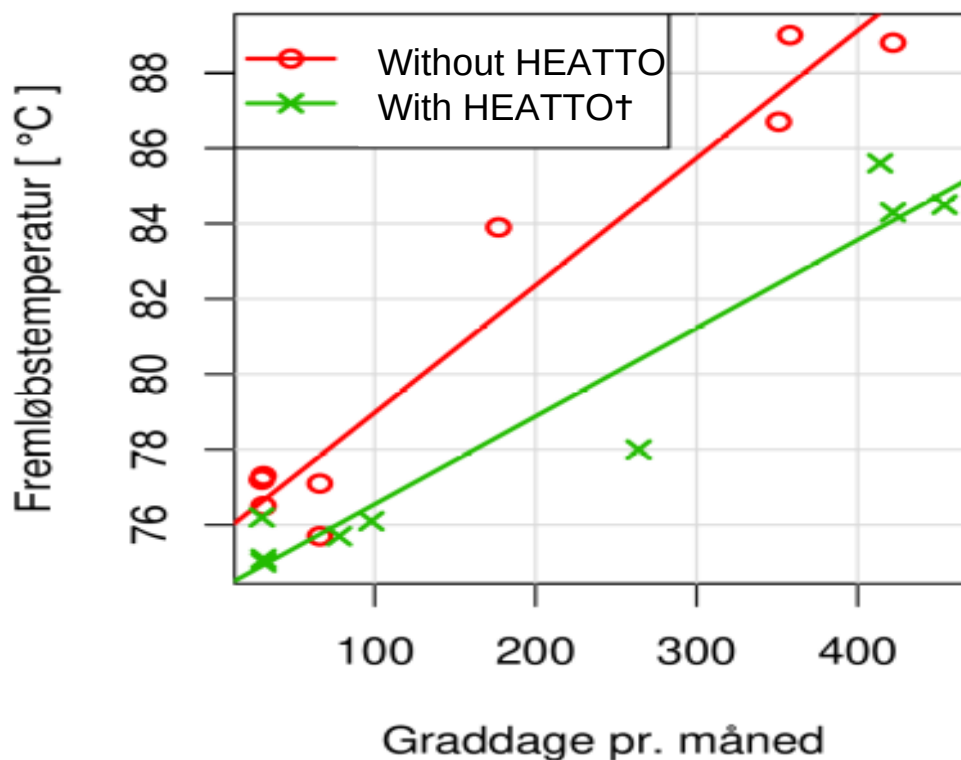
Out-of-sample RMSE for the base forecasts and RRMSE for the reconciled forecasts for daily heat load consumption in the Greater Copenhagen area. It shows the results for three different years and the whole period from 2017 to 2019.

- Negative value describe a percentage improvement of the reconciled forecast from the base forecast

Data Intelligent Temperature Optimization (current version 2.0)



Supply temperature with/without data intelligent control



†ENFOR ~ <https://enfor.dk/>

Savings

(Reduction of heat loss = 18.3 pct)

	Heat Supply		Electricity	
	GJ	1000 DKK	kWh	1000 DKK
Without HEATTO	653,000	30,750	499,000	648
With HEATTO [†]	615,000	28,990	648,000	842
Difference	37,400	1,760	-149,000	-194

Total savings (The 9 first months of normal year): 1,566,000kr

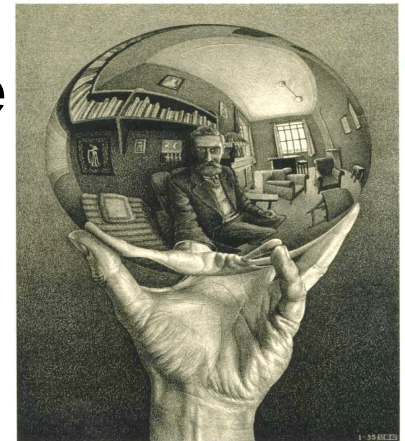
Savings for one normal year:

- 12/9 x 1,566,000kr = **2.1 millions**
- However, the period from Jan to Sept (75% of the year) is only ca. 65% degree days of the normal year
- $1.566.000/0.65 = \mathbf{2.4\ millions}$

[†]ENFOR ~ <https://enfor.dk/>

Data Intelligent Temperature Optimization for DH Systems

- Able to take advantage of **information in data**
- **Self-calibrating** models for the DH network
- **Temperature zones** are easy to establish
- 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.



Data Intelligent Operation of DH Systems (future, incl. Temp. Opt. v.4.0)



Meter Data in Data Intelligent Temperature Optimization (v.4.0)



- **Measurement feedback from end-users:**
 - Supply Temperature, Return Temperature and Flow measurements on e.g. 1 hour interval
 - Data for information, monitoring and control purposes
- End-users can be **more aware of their consumption** and can control it based on their needs (time-varying prices)
- Gives the opportunity take the advantage of meter reading using **big data analytics tools**: fault detection, etc.
- Having different **temperature zones** inside the network with additional pressure pumps and heat pumps
- **Enable for flexible load** in buildings

Multiple Temperature Zones inside a city



- **Combining temperatur optimization and smart-meter data** to control several different temperature zones inside a city
- **Controlling areas with new sustainable buildings with lower supply temperature** and large old unefficient buildings with higher temperature
- **Replacing pre-selected critical points** from the network using the meter data

Savings

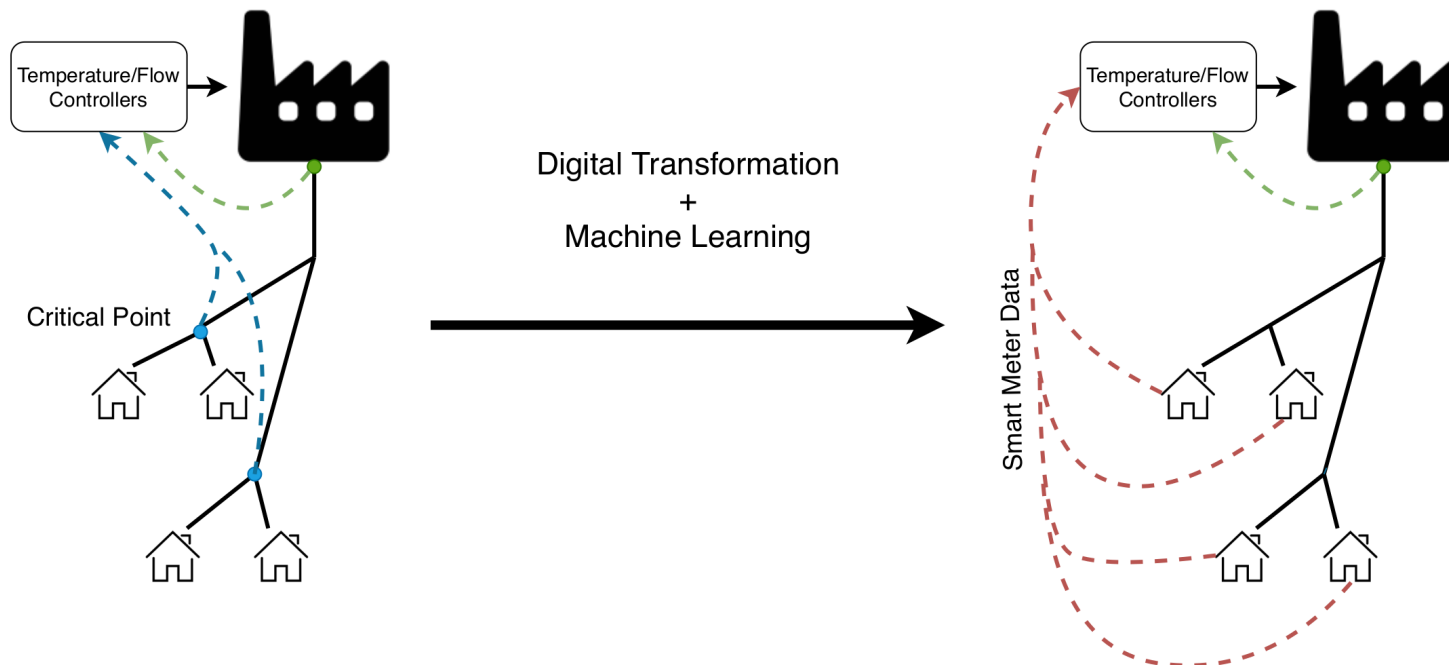
- A new report shows there is a **potential of saving about 240-790 Million DKK** by reducing the temperature of about 3-10 degrees using data-driven temperature optimization*.
- Addition savings when implementing tools using the meter data. **Only time will tell how much the additional savings** based on the meter data
- Also, **no need for critical points** – Savings on maintenance.

* Potentialet ved dynamisk datadrevet temperaturregulering i fjernvarmesektoren, DANVAD Analytics & Dansk Fjernvarme, 2019-02

Usecases of Smart Meters

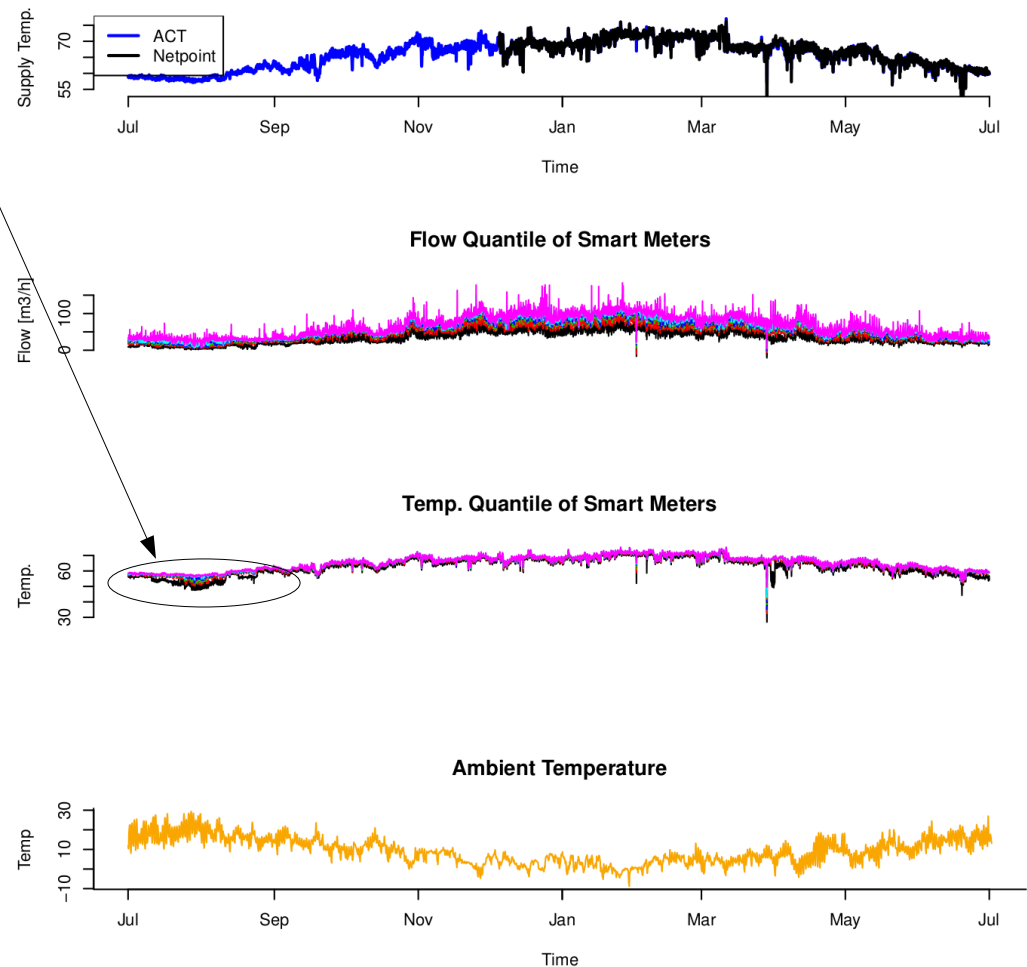
Replacing the netpoint sensors at the critical point using meter data

- 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



Replacing the temperature at the critical point using meter data

- Need models to filter out when there is a low flow (e.g. system is shut down)
- Data from 15 houses in Brønderslev
- 15 min. values
- Fine with one day latency of measurements
- Currently running in Tingbjerg demo for 15 apartment buildings, 2 buildings are used as reference



Estimate the thermal properties of the building from data

- Smart meter readings (**daily values only of heat**) and climate from Sønderborg
- Estimate the thermal performance** of individual building:
 - Heat loss coefficient (W/C per m2)
 - Uncertainty of HLC (sigma_UA)
 - Building absorbance of solar on very sunny day gA_{max} (W)
 - Change in HLC depending on Wind speed and direction
 - Estimate of "Indoor temperature" level

	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

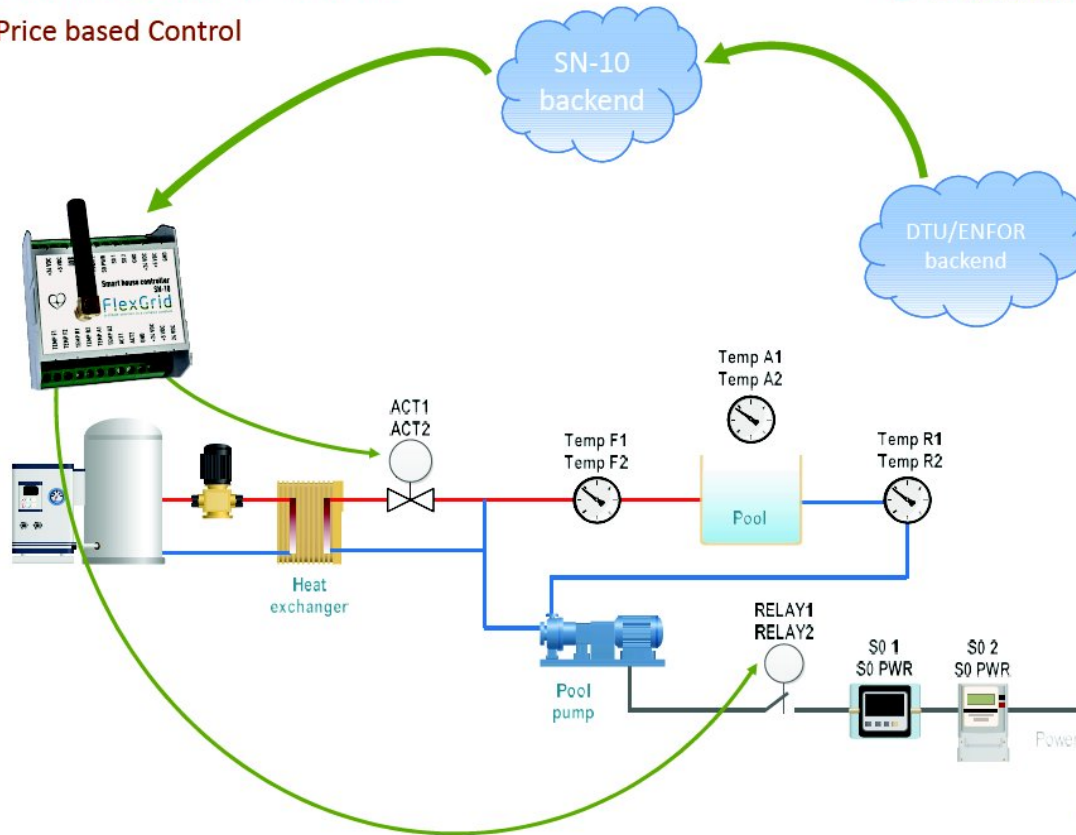
Flexible load in buildings

Flexible heating of swimmingpools DTU

How does it work?

Price based Control

SmartNet

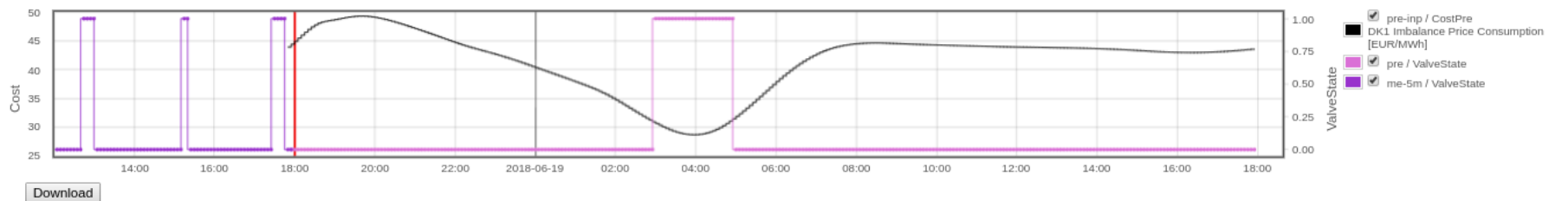
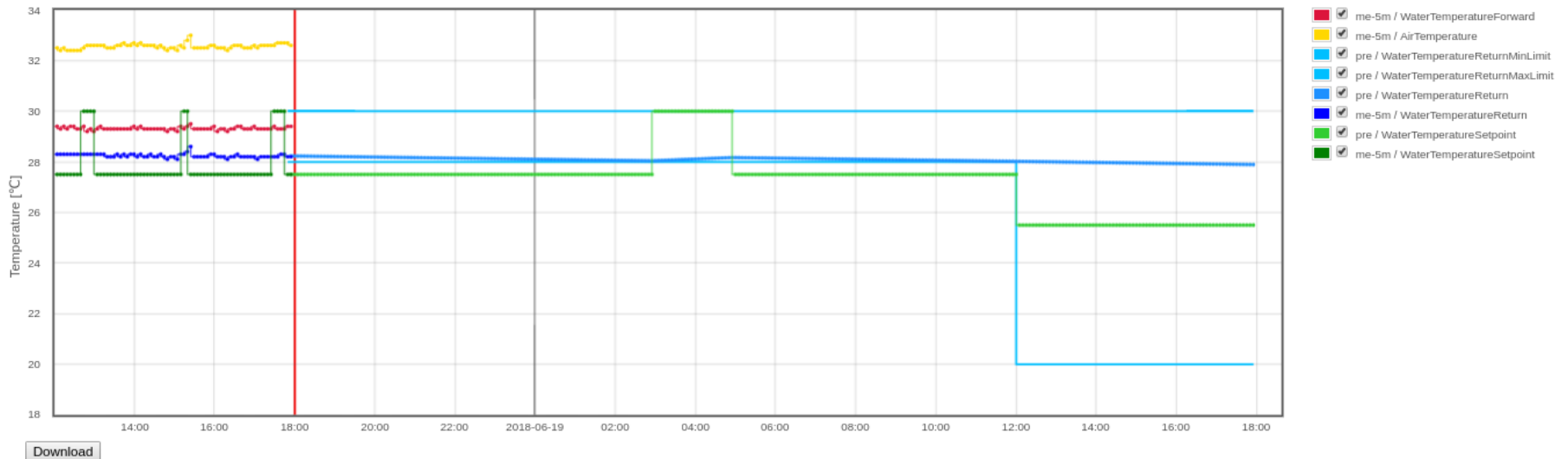


11

Example: Price-based control

A3074 Controller

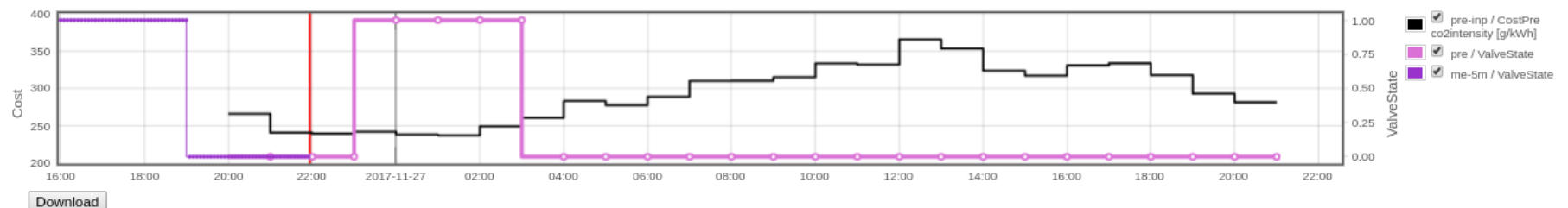
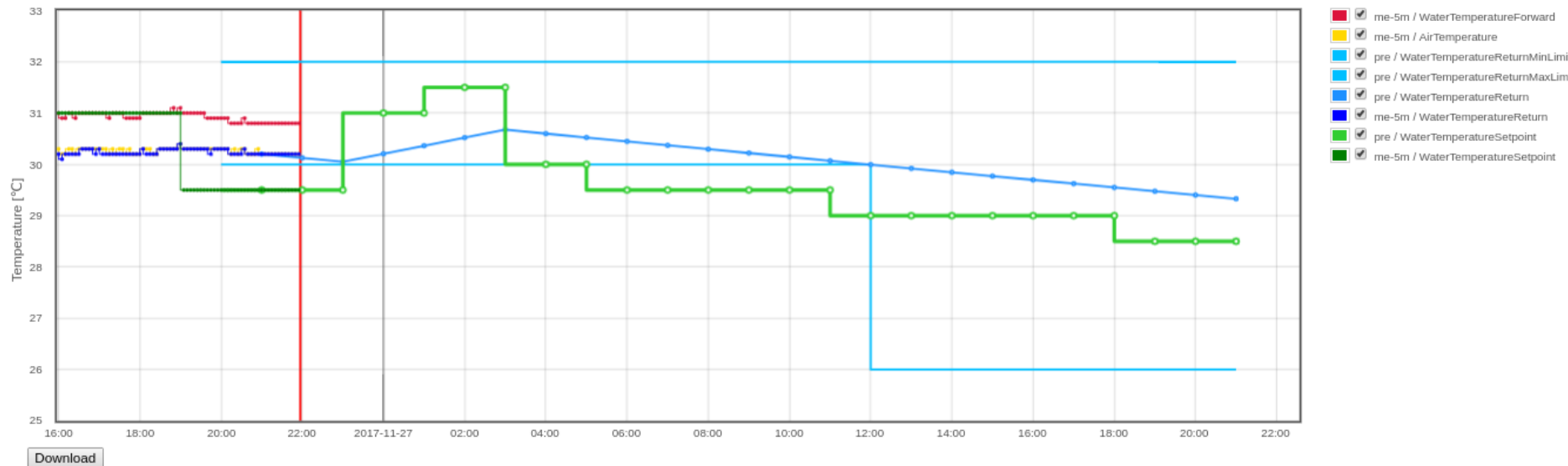
Cost: DK1 Imbalance Price Consumption [EUR/MWh], Adaptive Estimation



Example: CO2-based control

D7811 Controller

Cost: co2intensity [g/kWh]



Example: Flexible load in school building



- Part of Borgerskolen in Høje Taastrup
- DH heat exchanger and radiators
- Sensors in each room
- Thermostat setpoints control
- Forward temperature setpoint control

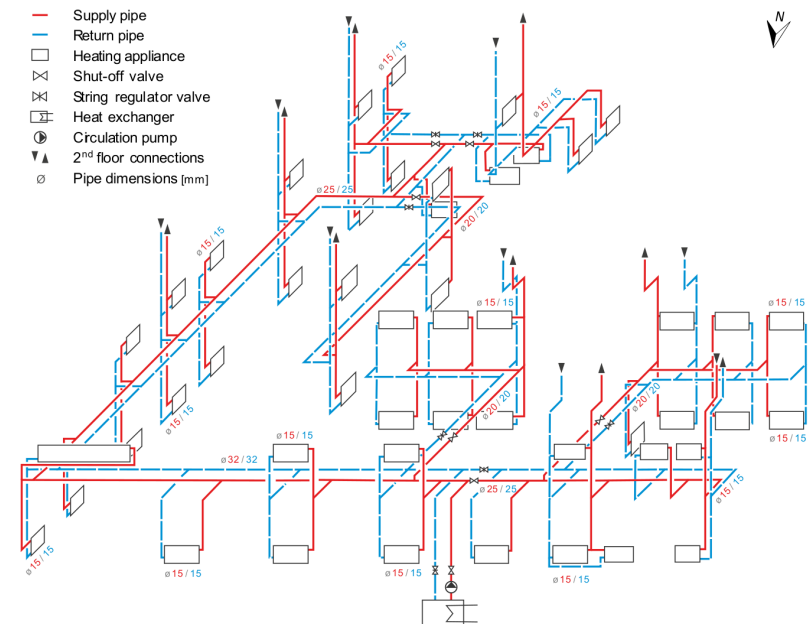
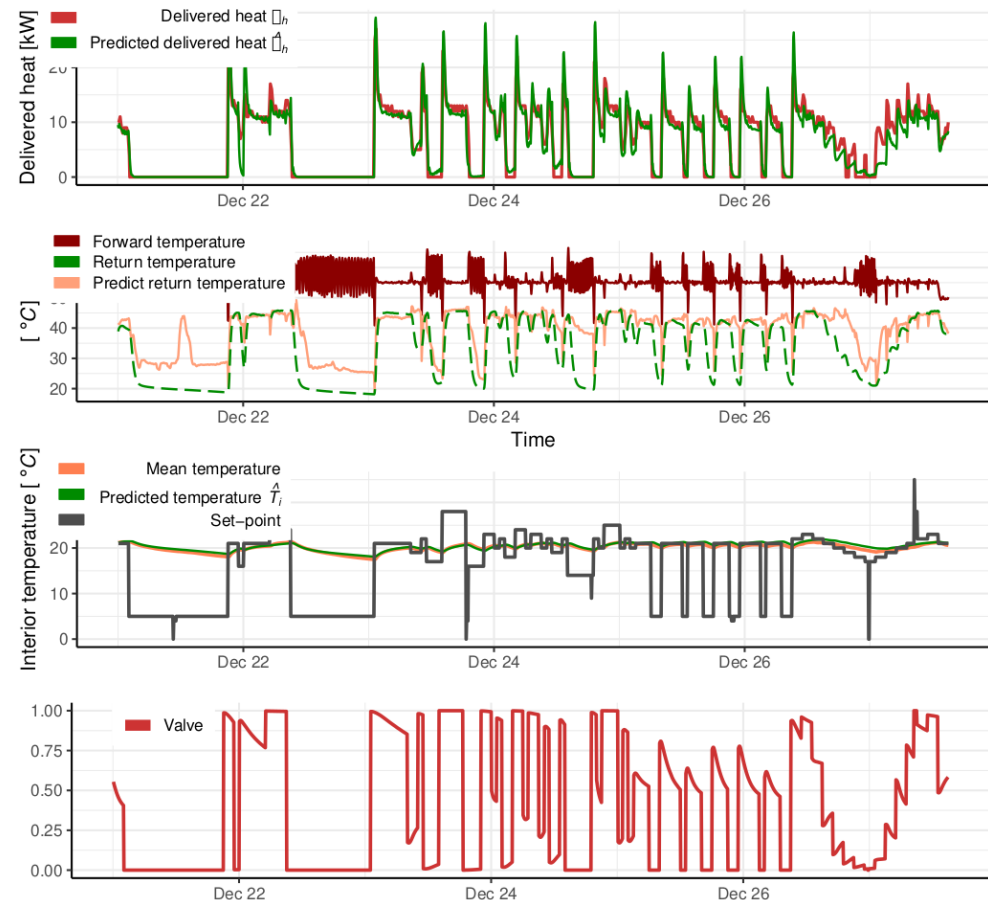


Figure 14. Diagram of the space heating distribution system (see also: Appendix I).

Model predictions

- Grey-box model fitted to data from experiment
- Forecast:
 - Load
 - Indoor temperature
 - Return temperature
- 5 min data from 7 days in Christmas vacation
- Thermostat setpoint control



MPC control for controlling load

- Optimization runs recursive (e.g. every 15 min.):
 - Find the optimal heating sequence considering prediction of weather var., temperature bounds, etc.
 - Implement the optimized heating first step
- Make load react to a “penalty signal”, e.g. price which is calculated centrally (actually not very complicated, need to model the summed response from many buildings)
- Control the load to optimize operation in DH grid:
 - Shaving the morning peak
 - Optimize towards surplus of energy, e.g. from solar

Optimal Bidding for District Heating Providers

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Bidding for district heating providers

Collaboration in CITIES between DTU Compute and EMD International

Setting:

- District heating provider with a portfolio of production units including combined heat and power (CHP) plants

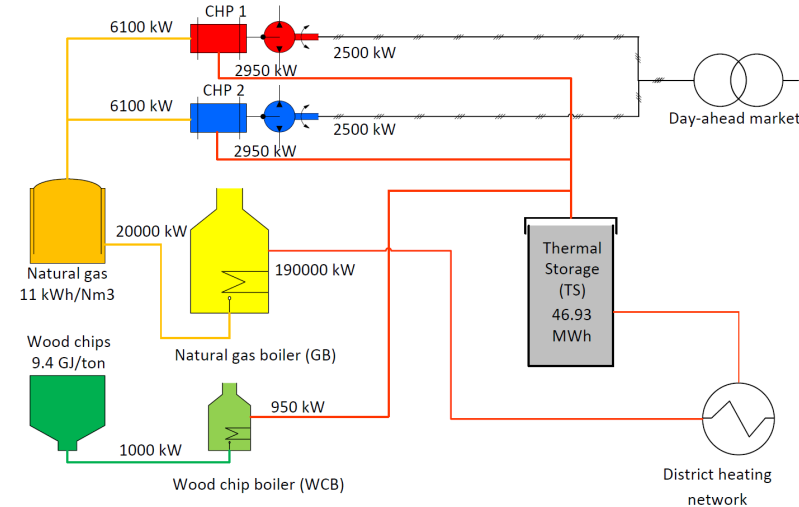
Goal:

- Optimize the daily production of the heat units to cover the heat demand at minimal cost

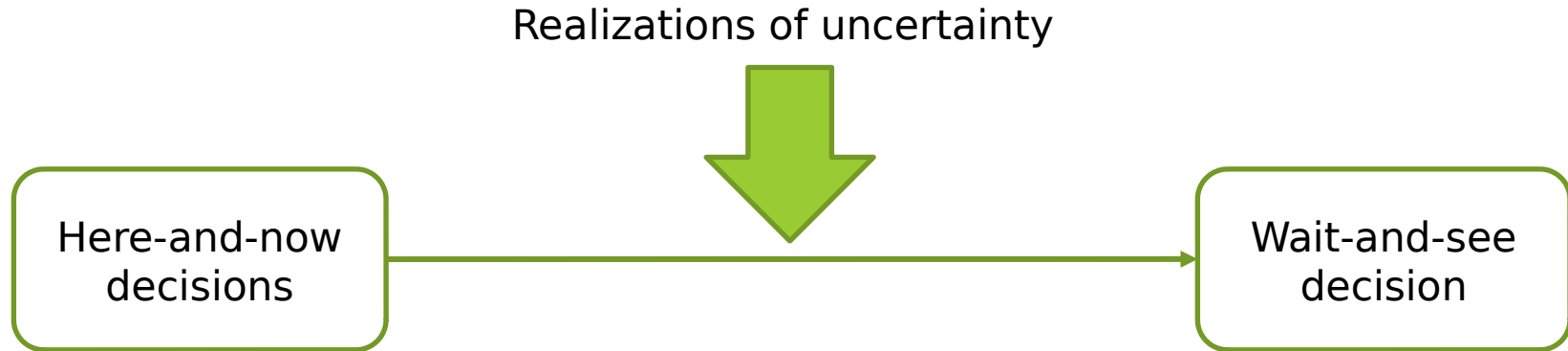
Opportunity:

- The expensive CHP plant produces electricity when producing heat
- Trade this electricity on the day-ahead market, if the income from the market lowers the overall cost

But the electricity price is uncertain



Decision-making under uncertainty



Here-and-now decisions:

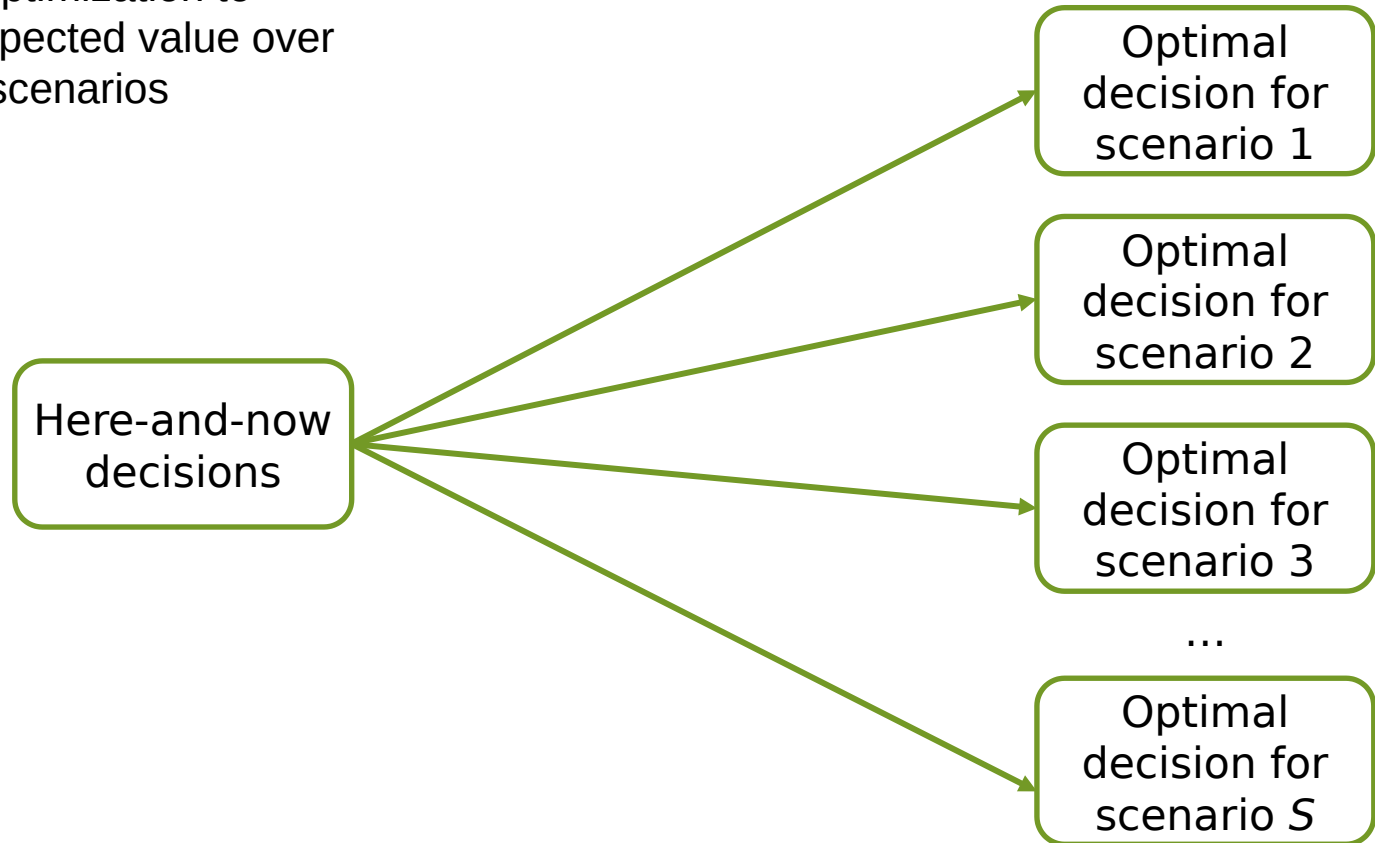
- have to be optimal for all considered future realization of uncertainties

Wait-and-see decisions:

- depend on the here-and-now decisions
- can be taken after realization of uncertainty (react to the uncertainty)

Decision-making under uncertainty

Stochastic programming uses mathematical optimization to optimize the expected value over all considered scenarios

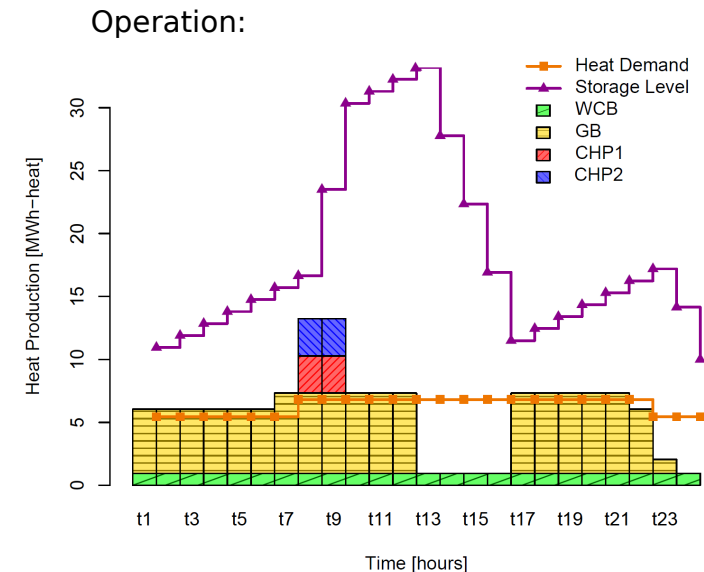


Our solution approach

Heat Unit Replacement Bidding (HURB) method

Iteratively replaces heat production of other units by CHP production to determine the price and amount

Cost minimal production based on a mixed-integer program



Improves the results over other state-of-the-art methods

Biomass supply planning for large-scale CHP plants

Daniela Guericke (dngk@dtu.dk)

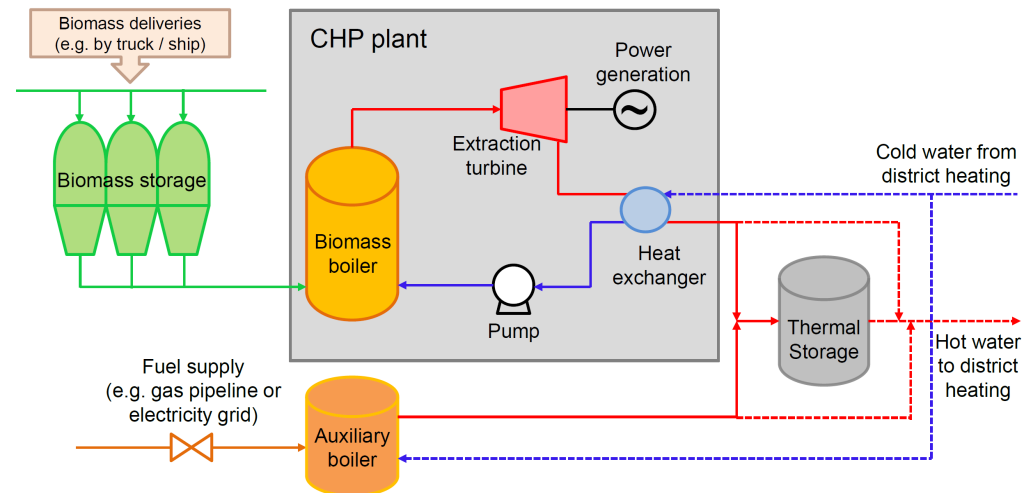
Henrik Madsen (hmad@dtu.dk)

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Biomass supply planning for large-scale CHP plants

Combined heat and power (CHP) plants

- produce electricity and heat at the same time
- are connected to the electricity grid and the district heating network
- in our case fueled by biomass



For a large scale producer the biomass is delivered based on **supply contracts**, which often have a runtime of one year.

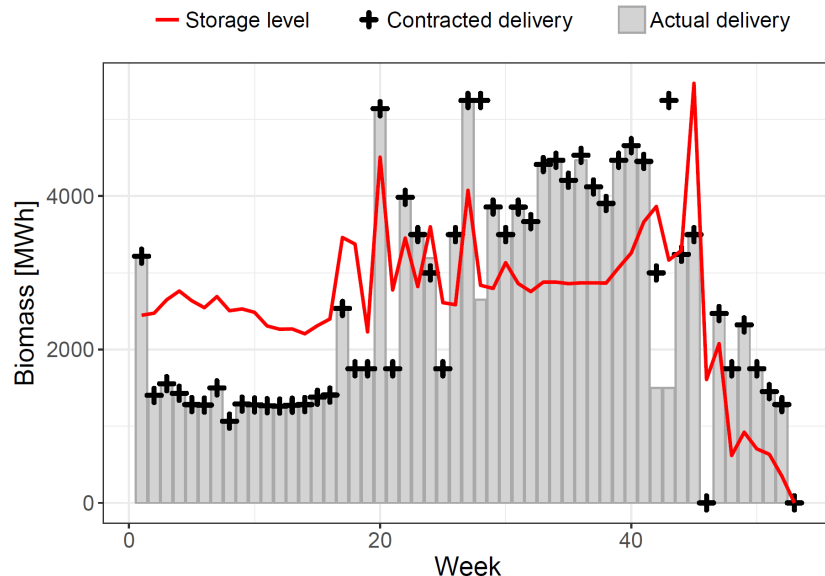
Our goal is to determine the **optimal portfolio of biomass contracts** minimizing the **costs** and taking **uncertainty** into account.

Our solution approach

A two-phase solution approach based on stochastic programming

- **Phase 1:** Biomass contract selection for one year based on a weekly time scale and heat demand uncertainty
- **Phase 2:** Weekly operation on an hourly basis modelling more technical characteristics of the systems as well as demand and price uncertainty

Biomass deliveries:



Operation:

