Flexible and Predictive Heat-Pumps:

When Digital Twins meet Model Predictive Control

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Joint work with

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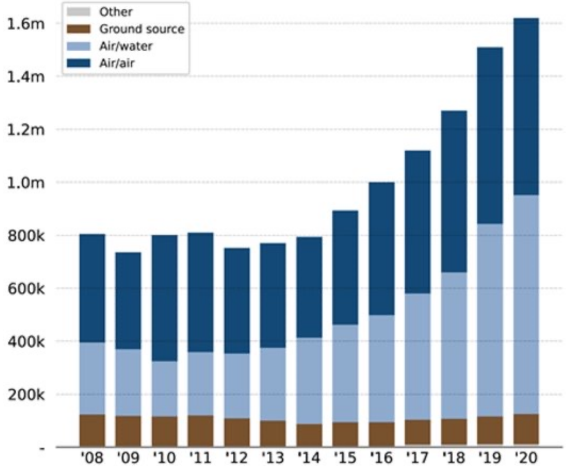
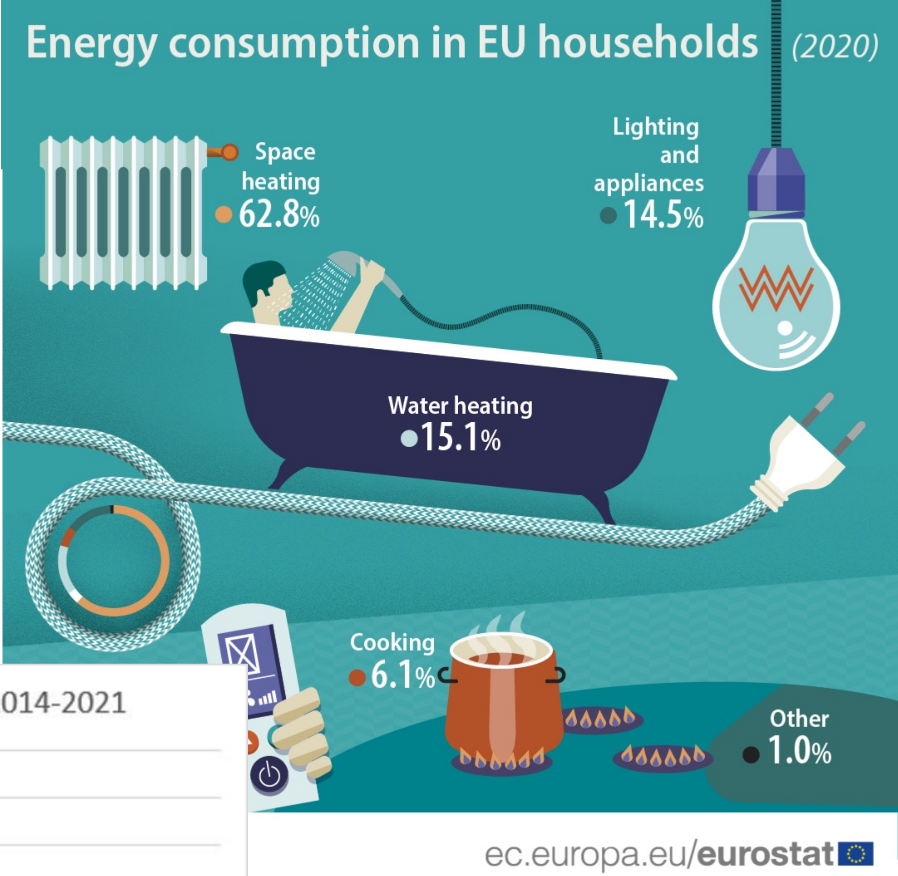
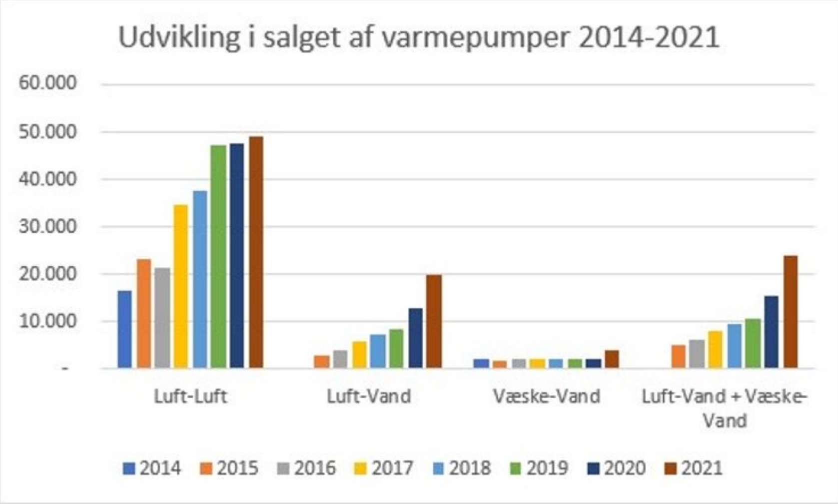
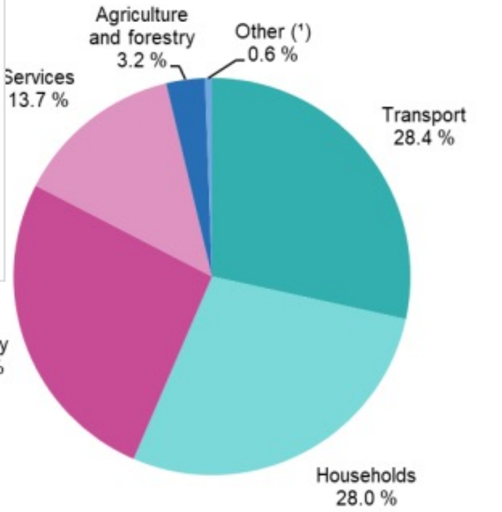
Heating is essential

- 78% of residential energy use is for heating
  - Hot water (15.1%)
  - Space heating (62.8%)
  - Amounts to 21% of total energy consumption (in EU)
- Solutions?
  - Renovation
    - Slow & expensive
  - District heating
    - Not always feasible
  - Electrification (Heat-pumps)
    - High efficiency
    - Potential to react on spot-pricing (cheap and gr
    - Can participate in flexibility market









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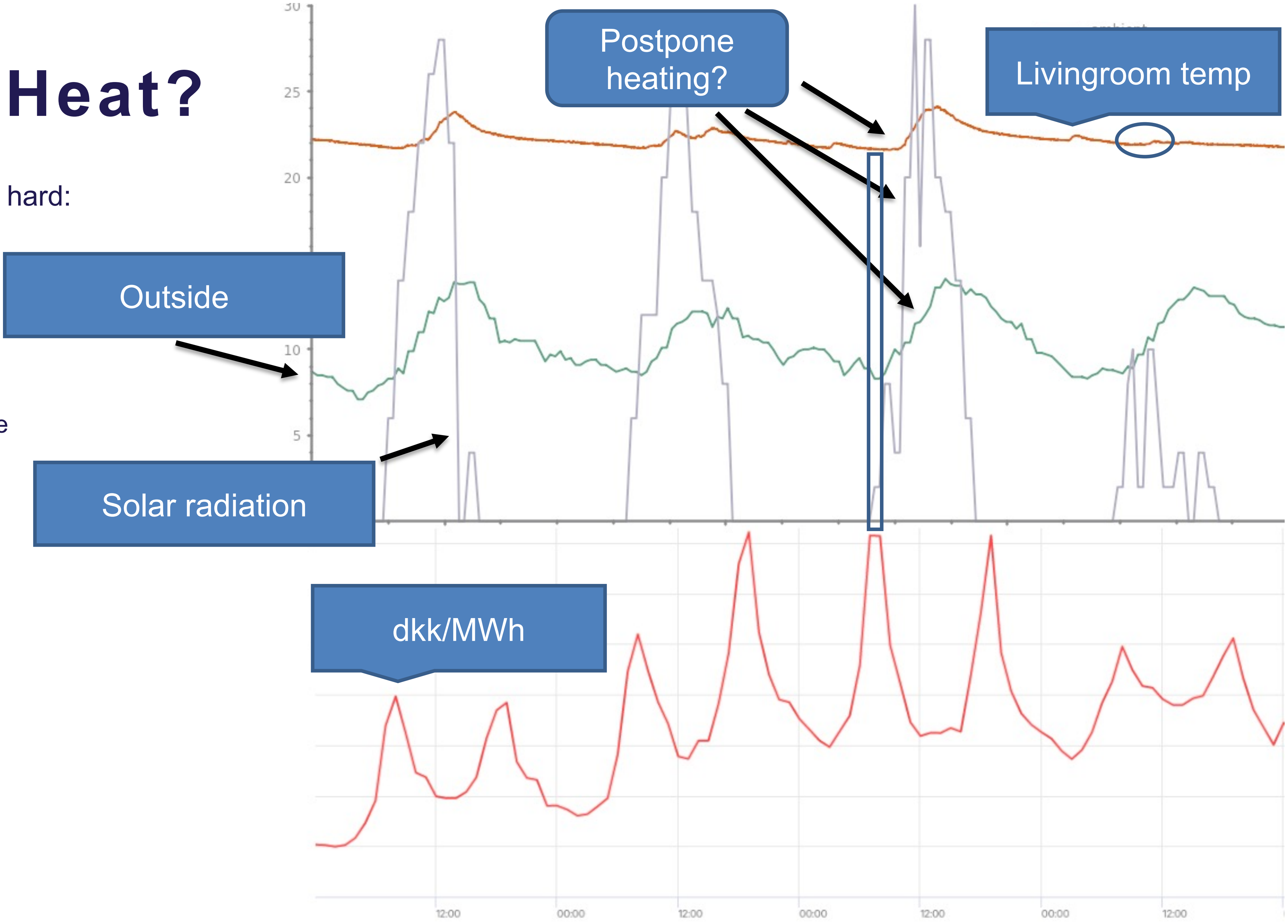
https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_statistics_-_an_overview#Final_energy_consumption

When to Heat?

Optimal heating control is hard:

- Slow response
- Predictable influence
  - Solar radiation
  - Outside temperature
  - ….
- Unpredictive influence
  - Inhabitant behavior
  - Hot water usage
- Price of electricity
- "Easy" in retrospect



Postpone heating?

Livingroom temp

Outside

Solar radiation

dkk/MWh

https://www.nordpoolgroup.com/

This Talk

- Heating is "easy" in retrospect
- We cannot know the future
    - But we can predict it well

1. Construct a predictive twin from data

   Stochastic model-estimation via CTSM-R

2. Derive a control strategy wrt. predicted future

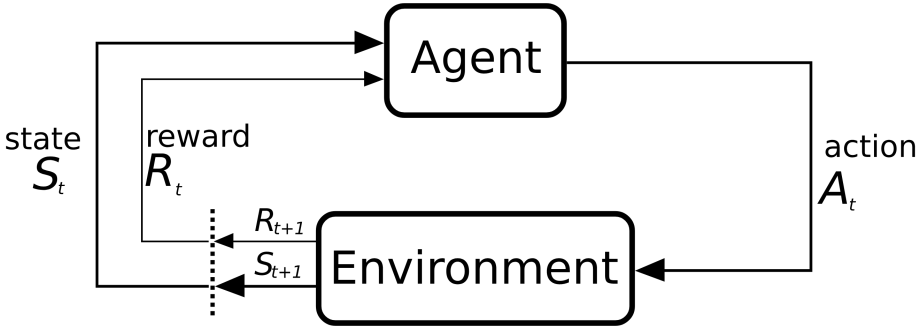
   Reinforcement learning engine of UPPAAL Stratego

   Optimize towards combined cost & comfort measure

3. Repeat from 1 in appropriate time-steps

Predictive Digital Twin

+



Constructing a Twin!

Goal:
Find α's and β's s.t.
Predicted room temperature matches historical.

Thermodynamic equations of building

Room temperature:

$$\frac{d\tilde{T}_r^i}{dt} = \alpha_h^i(\tilde{T}_h^i - \tilde{T}_r^i) + \alpha_e^i(\tilde{T}_e^i - \tilde{T}_r^i) + \alpha_s^i \cdot \dot{S}^i$$

Floor temperature:

$$\frac{d\tilde{T}_h^i}{dt} = \frac{\alpha_h^i}{\beta_h^i}(\tilde{T}_r^i - \tilde{T}_h^i) + \alpha_w^i \cdot \overline{M^i}(\overline{T}_{forward} - \tilde{T}_h^i)$$

Wall temperature:

$$\frac{d\tilde{T}_e^i}{dt} = \frac{\alpha_e^i}{\beta_e^i}(\tilde{T}_r^i - \tilde{T}_e^i) + \alpha_a^i(\dot{T}_{outdoor} - \tilde{T}_e^i) + \sum_{\substack{n=1 \\ n \neq i}}^{k} \alpha_n^i(\hat{T_r^n} - \tilde{T}_e^i)$$

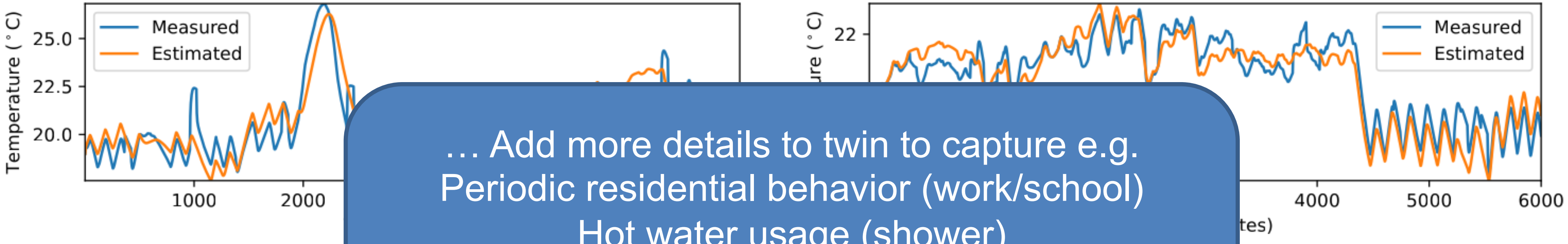
Historical data
- Weather
- Room temperatures
- Hot water use
- Energy input
  - I.e. kWh added by heating system

CTSM-R

Predictive Digital Twin

(equations + values for α and β)

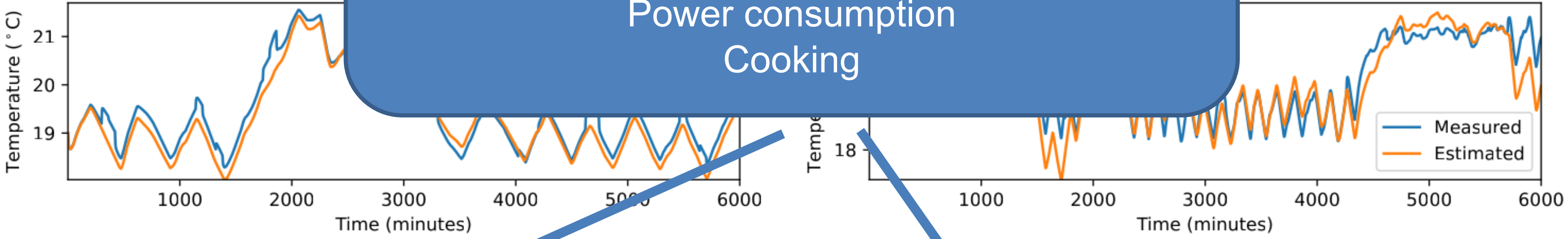
Quality of Twin



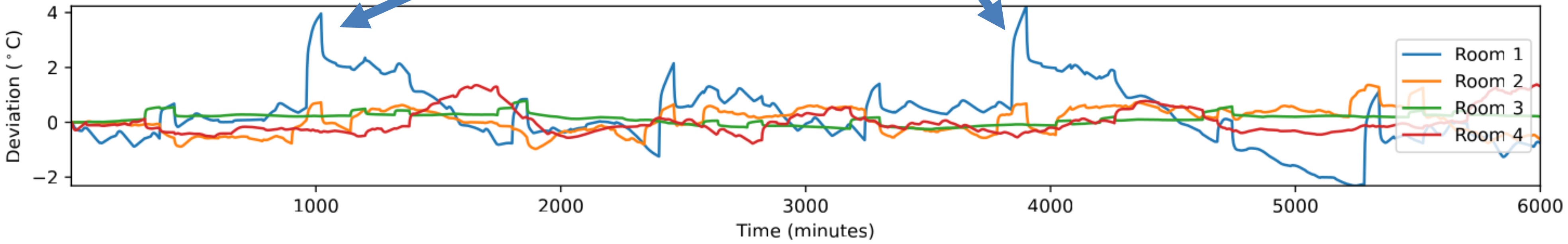
(a) Measured and estim

emperature for room 2

… Add more details to twin to capture e.g.
Periodic residential behavior (work/school)
Hot water usage (shower)
Specifics of heat-pump
Power consumption
Cooking



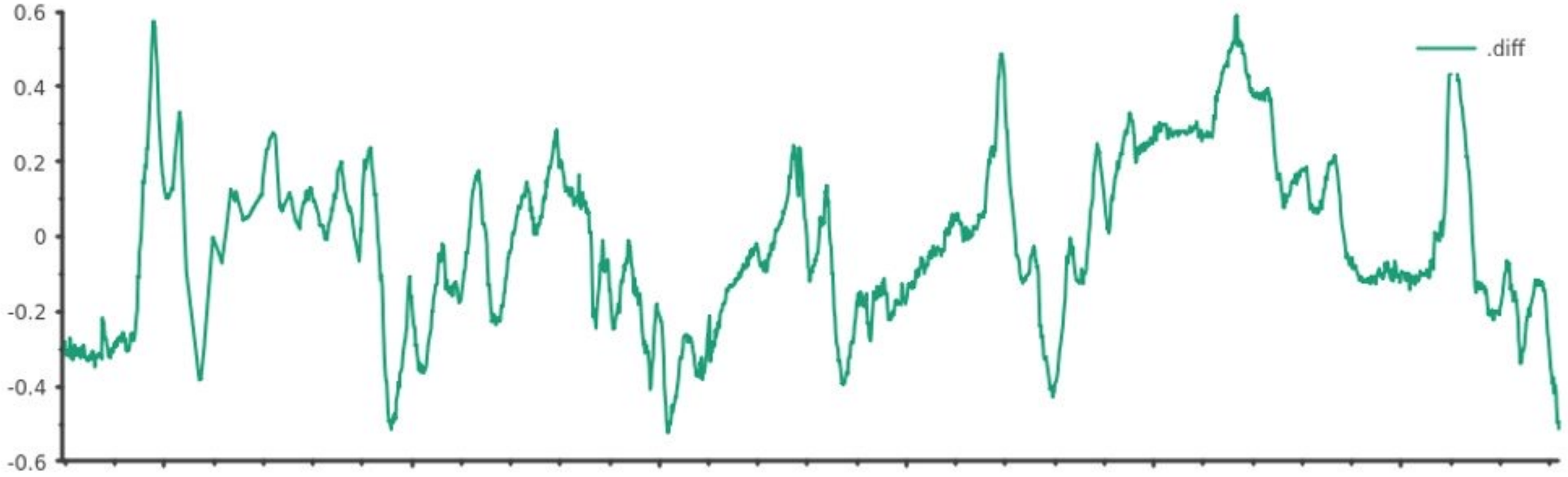
(c) Measured and estimated temperature for room 3 (d) Measured and estimated temperature for room 4



(e) Deviation of estimated temperature from measured temperature for each room

Quality of Twin FED Data

- Replayed using same
    - Heat input
    - Ambient temperature
    - Solar input
    - 15 day horizon
- Result
    - Deviation in [-0.4°, 0.6°]
    - Small and periodic influence unaccounted for



Degree difference between digital twin simulation and historical data on a 15-day window.

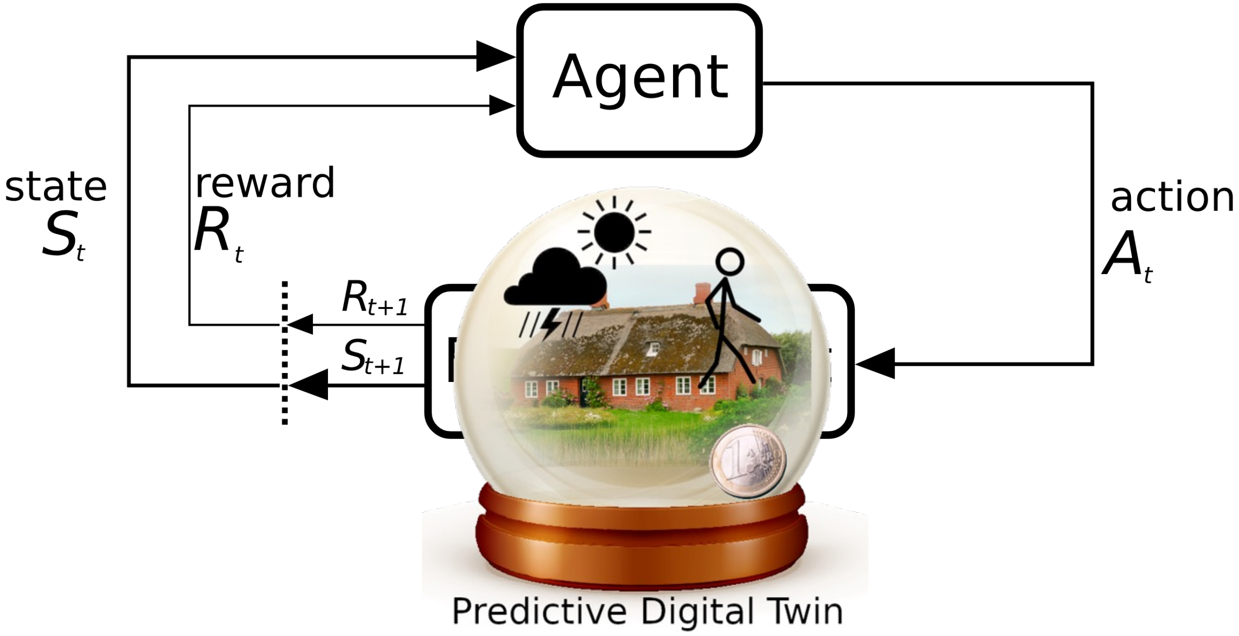
Twin + RL = Model Predictive Control

- Reinforcement learning
  - (Near-)optimal control in uncertain environments
    - Optimize both cost and comfort
  - Classically used in live environment
    - … we cannot experiment with live installation!
- Digital twin
  - Reasonable substitute for real world
  - Can be decorated with forecasts
    - Weather
    - Inhabitant behavior

      … cooking patterns

      … hot water usage patterns
    - Electricity price

Can and will try radical control strategies!
E.g. run the heat-pump at full power always.



Optimization Function

Balance between cost and comfort

$$\int_{\tau_0}^{\tau_n} \left(((1 - W_{comf}) \cdot \underbrace{cost(x))}_{\text{Cost of running heat-pump}} + W_{comf} \cdot \overbrace{\sqrt{\sum_{i}^{k} (T_g - \tilde{T}_r^i(x))^2}}^{\text{Discomfort: Root-Squared distance to target temperature}} \right) dx$$

Computed over near future (12 hours)

Why Digital Twins & Reinforcement Learning?

- Rapid response to changes
    - Weather changes a lot within a week
    - Inhabitant behavior changes over the year
    - Buildings change over time (they tend to break)
    - Efficient even with small historical dataset
- Reinforcement learning on complex models
    - Handle complexity of physical systems
    - Model stochastics of real world
        - Uncertainty of weather
        - Unpredictability of inhabitants

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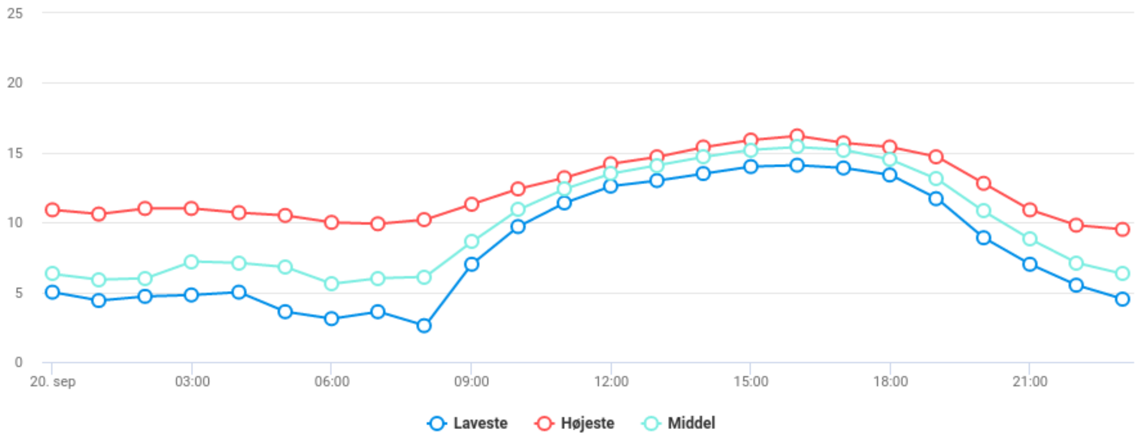

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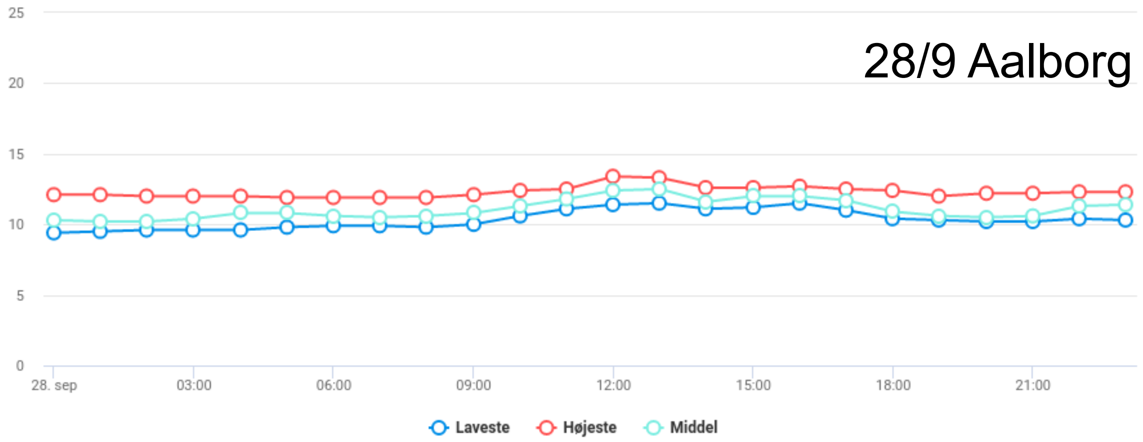


Digital Twin meets Reinforcement Learning

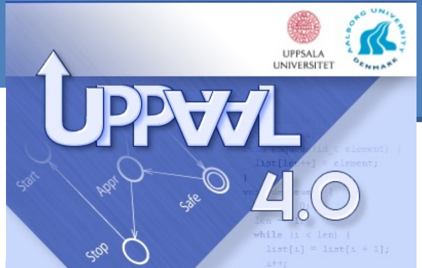
CTSM-R from DTU

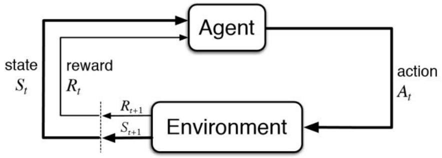
Repeat every 15 minutes
(6 hours for twin estimation)

behavior model

NORD POOL

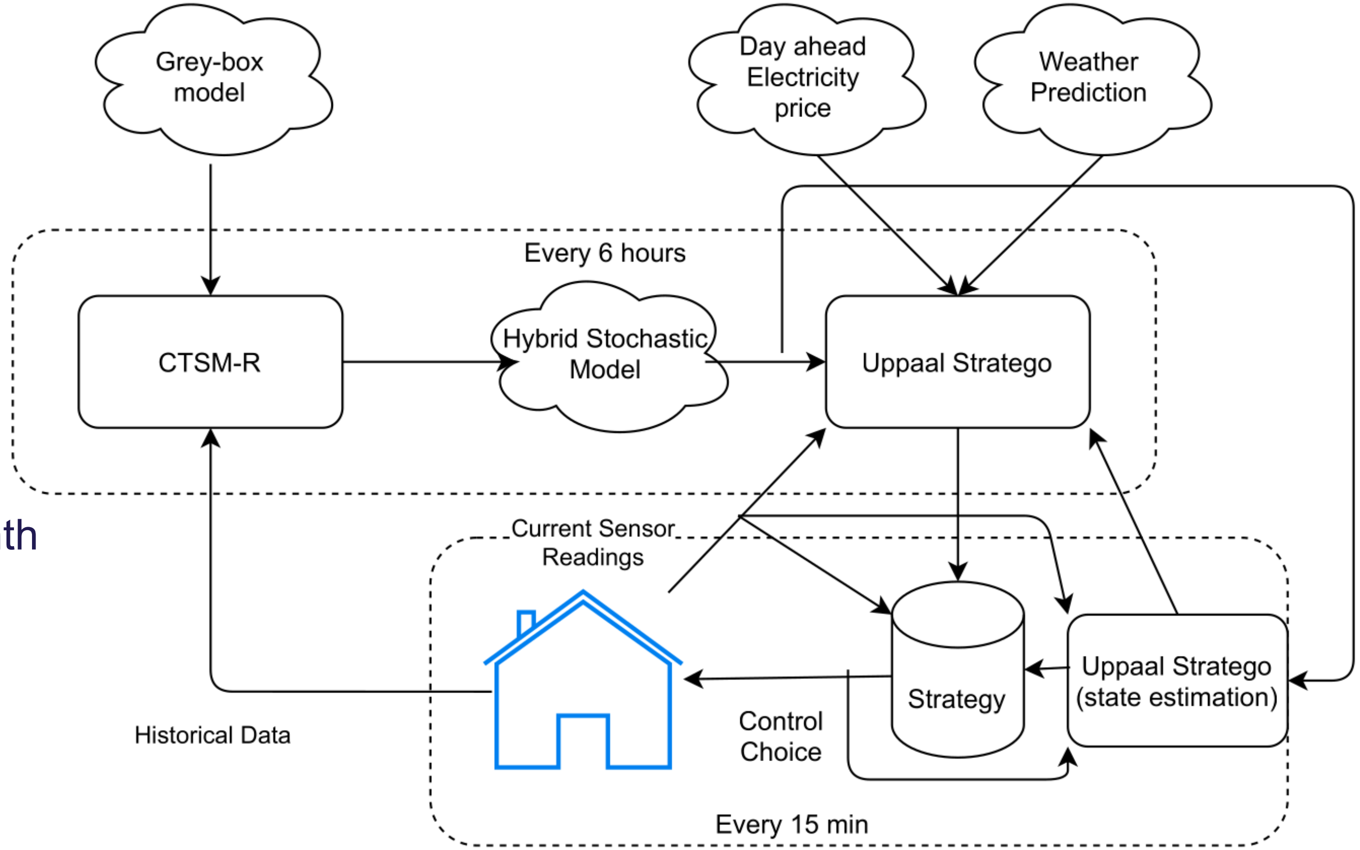
Optimization software





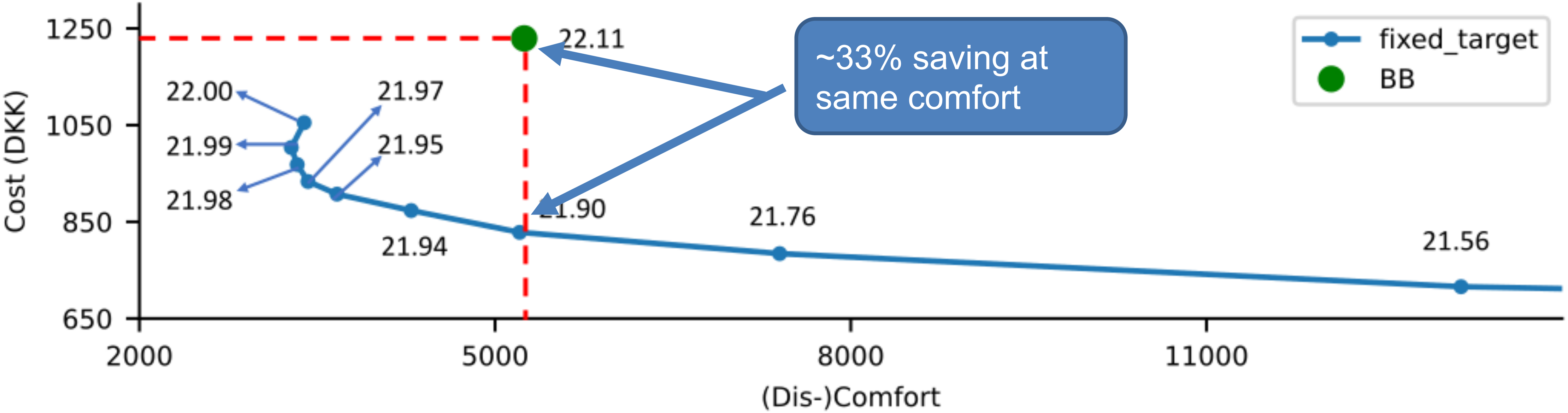
Disclaimer on Results

- Evaluation in real environment is under way
- Results that are presented are evaluated using virtual building models
- We use a Bang-Bang controller of heat-pump for reference
    - Comparison w. weather compensation controller
    - Highly dependent on "good curve"
        - "Good curve" appear specific to a given month



Performance

$$\int_{\tau_0}^{\tau_n} \left(((1 - W_{comf}) \cdot cost(x)) + W_{comf} \cdot \sqrt{\sum_{i}^{k} (T_g - \tilde{T}_r^i(x))^2} \right) dx$$



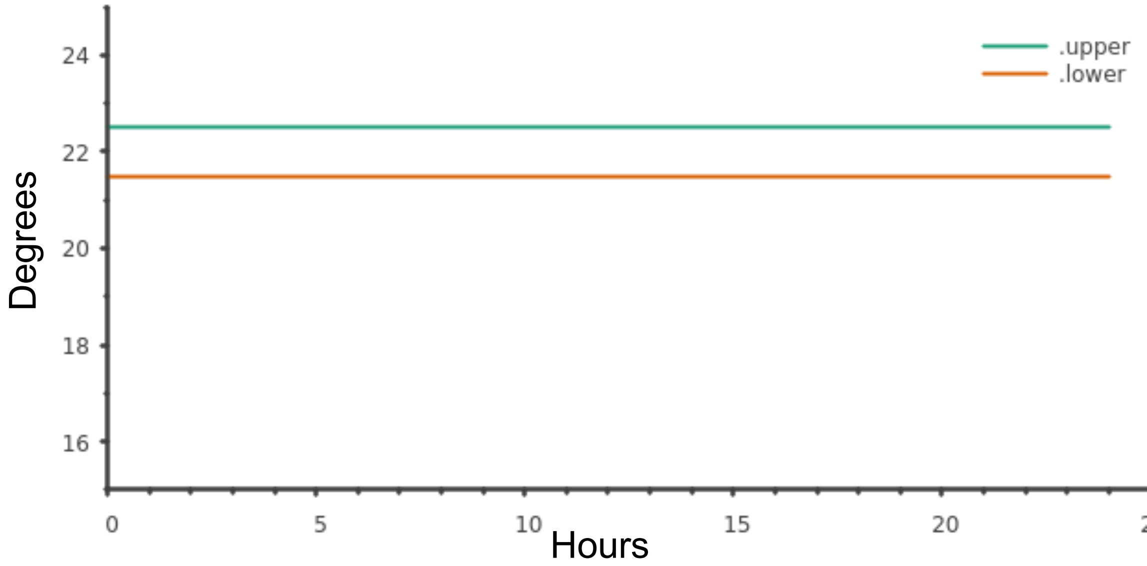
~33% saving at same comfort

Cost and (Dis-)comfort for a cold February week.
W_{comf} ranging from 1.0 to 0.1 in steps of 0.1.

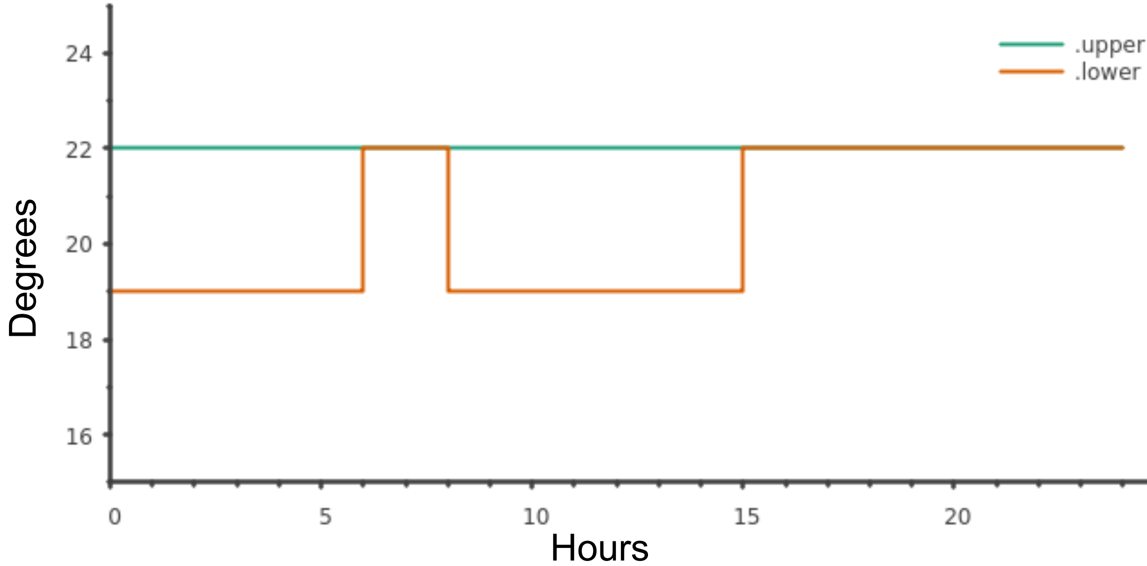
Adding Flexibility

- Target-Band
    - Target-temperature is a range
        - [21.5°, 22.5°]
    - Allows for more flexible control

- Setbacks
    - Allow for reduced temperature [19.0°, 22.0°]
        - During nighttime (24:00-06:00)
        - During working hours (08:00-15:00)
    - Target-temperature is otherwise [22.0°, 22.0°]
    - Large flexibility windows
    - Must meet target at time; i.e. start heating predictively



Target-Band target range



Setback target range

Cost at Equivalent Comfort

2009 Weather	Bang-Bang	Fixed-Target	% of BB	Target-Band	% of BB	Setbacks	% of BB
January (week 2)	967	584	60.4%	524	54.2%	487	50.4%
February (week 6)	1229	828	67.4%	748	60.9%	699	56.9%
March (week 10)	1126	704	62.5%	606	53.8%	591	52.5%
April (week 14)	653	308	47.2%	251	39.4%	221	33.8%
TOTAL	**3975**	**2424**	**61.0%**	**2129**	**53.6%**	**1998**	**50.3%**

DKK for one week of operation

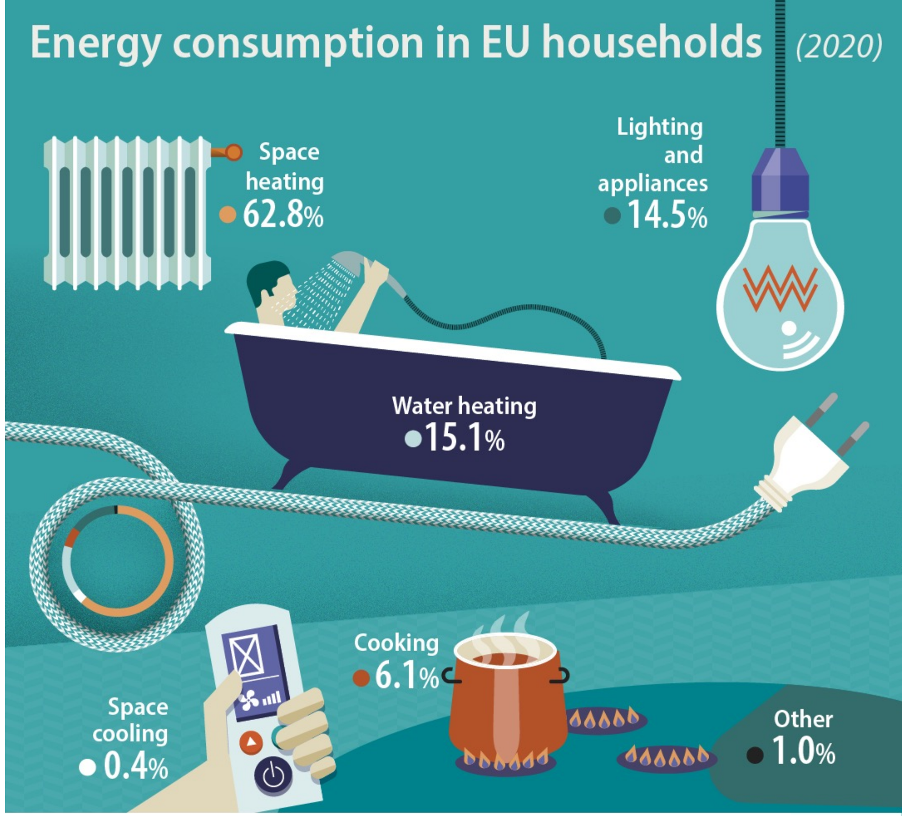
Analysis of Results

- Savings while keeping comfort
    - Pump efficiency increased
        - Operation at higher COP/ higher ambient temperature
        - Reduced cost pr kWh
    - Better utilization of solar radiation

- Actual performance dependent on many factors
    - Level of insulation
    - Construction materials
    - Inhabitant behavior
    - Exposed control of heat-pump

Conclusion

- Cost reduction > 40%
    - Focus on cost for customer incentive
- Reduced cost pr produced kWh
    - Exploiting spot-price
    - Running heat-pump more efficiently
        - More efficient at higher ambient temperature
- Potential for more
    - Better prediction of inhabitant behavior
        - Hot water consumption
    - Accumulation tanks (heat buffers)
    - Local utilization of solar power
    - Flexibility-cost signals from DSO/TSO



Final energy consumption by sector, EU, 2020
(% of total, based on terajoules)