

# Data-driven Methods for the Future Weather-driven Smart Energy Systems



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## SEM4Cities

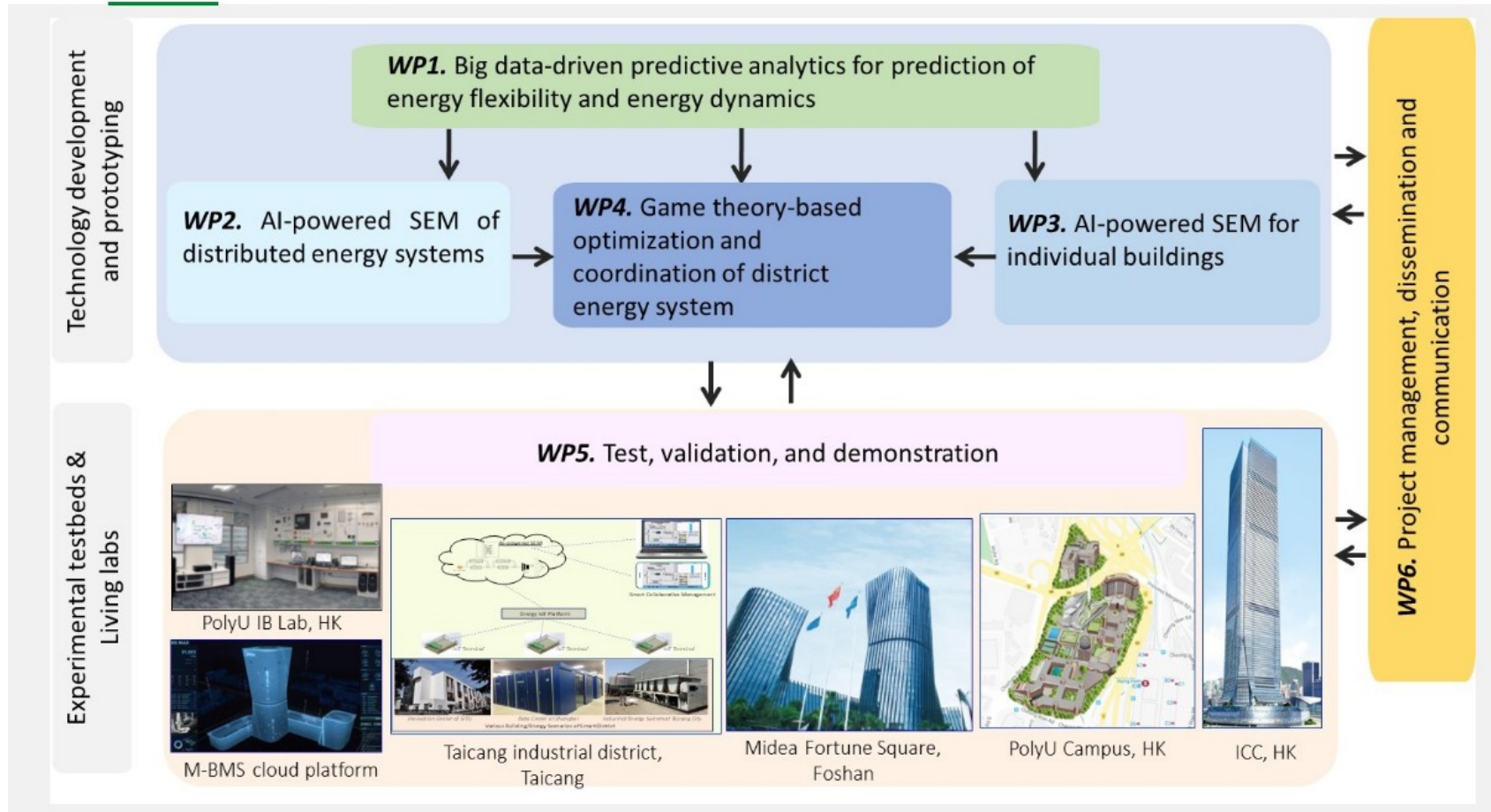
Development of Smart Energy Management Technologies for Buildings and Districts in High-Density Cities

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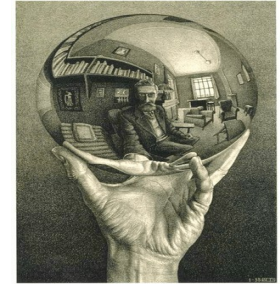
# SEM4CITIES

The SEM4Cities project aims to develop innovative smart energy management technologies and solutions for buildings and districts in smart and sustainable high-density cities by effectively leveraging advanced big data and AI technologies.



# Content

- Challenges
- Digitalized energy systems
- Smart-Energy Operating-System (SE-OS)
- Flexibility – and smart grids
- Peak shaving
- Energy or Emission efficiency?
- Integrated Forecasting and Control of Buildings
- Forecasting using spatial hierarchies



# Challenges

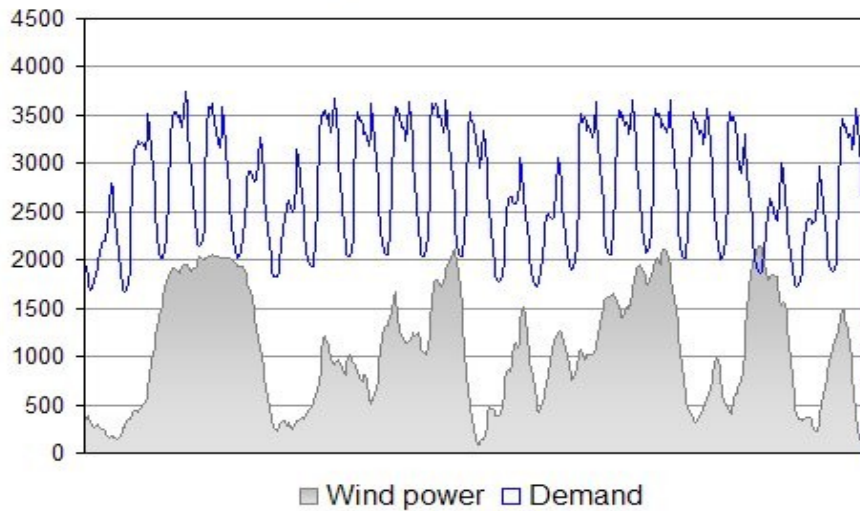




# The Danish Wind Power Case

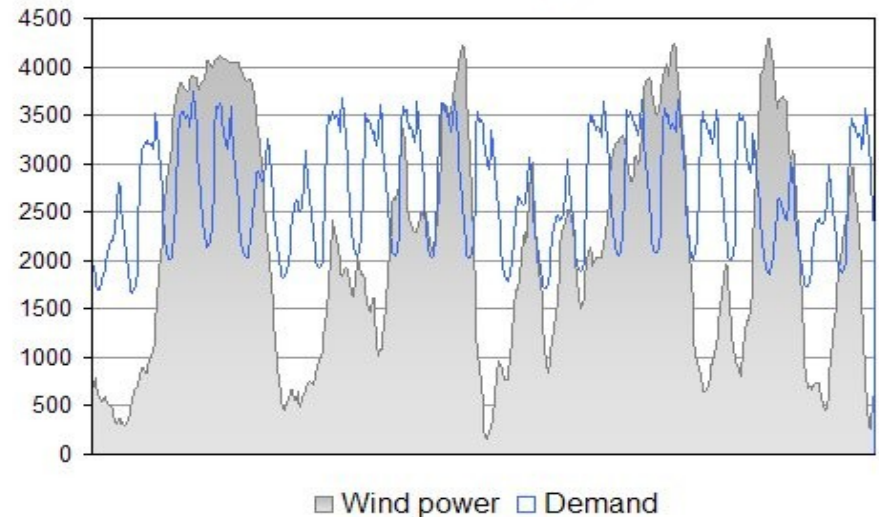
.... balancing of the power system

25 % wind energy (West Denmark January 2008)



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

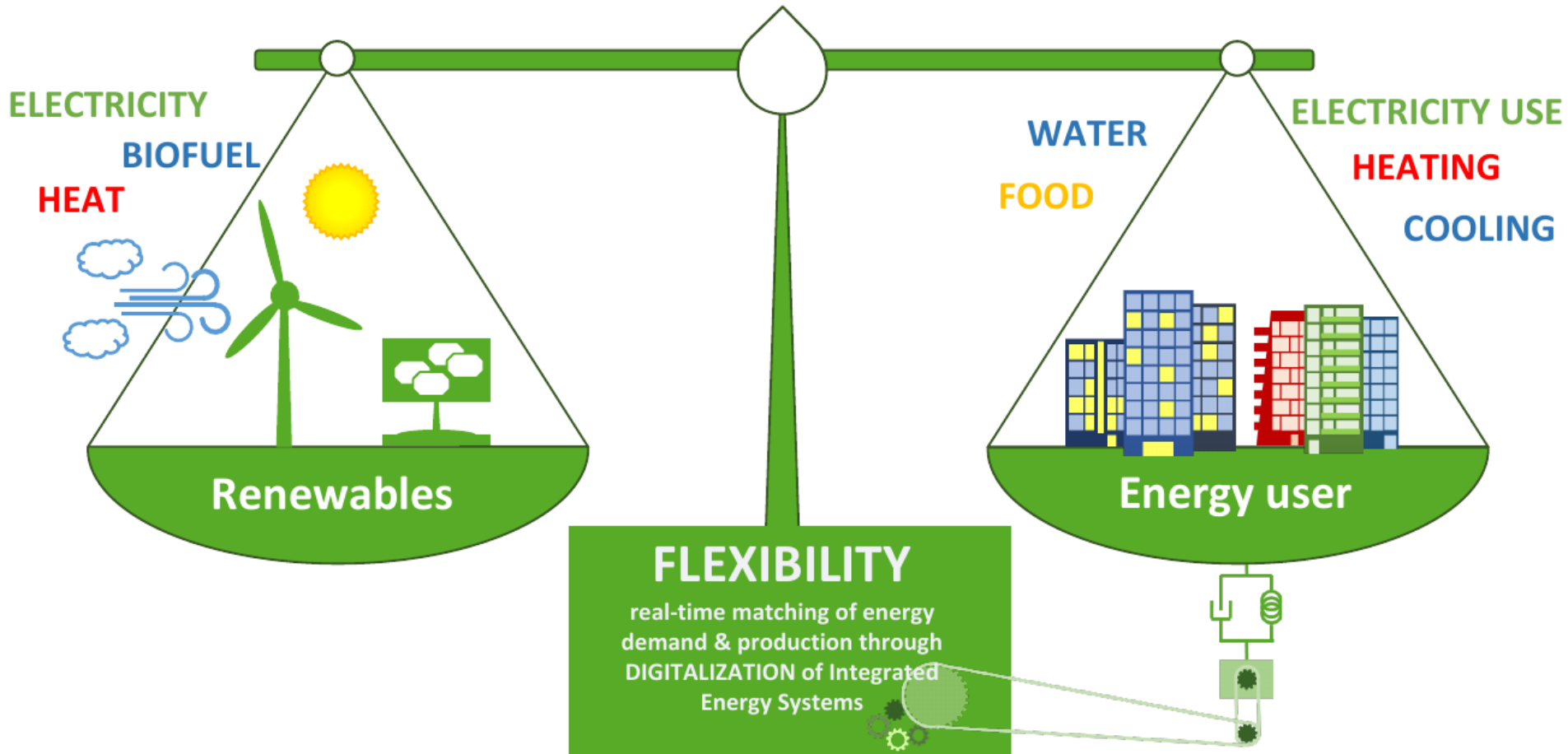
50 % wind energy



**Now flexibility of the load is essential**  
**That's the topic of 'Flexible Energy Denmark'**  
 (For several days the wind power production is more than 100 pct of the power load)

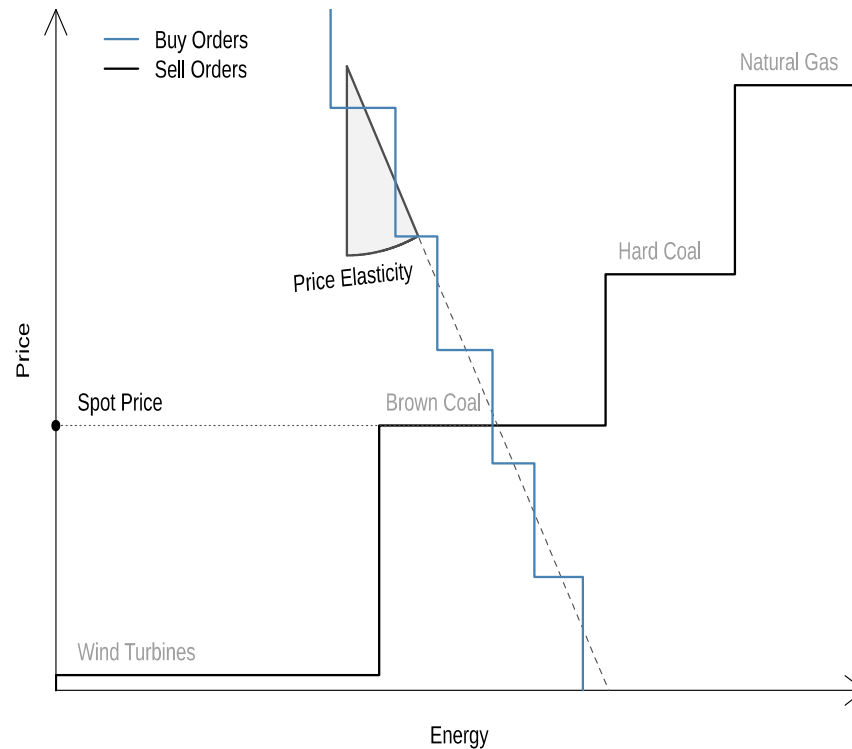
# Weather-driven Energy System

The Challenge: Denmark Fossil Free 2050



# Characterisation of Energy Flexibility

Today: Static Measures - Price elasticity





# Needed Modifications of Energy Markets

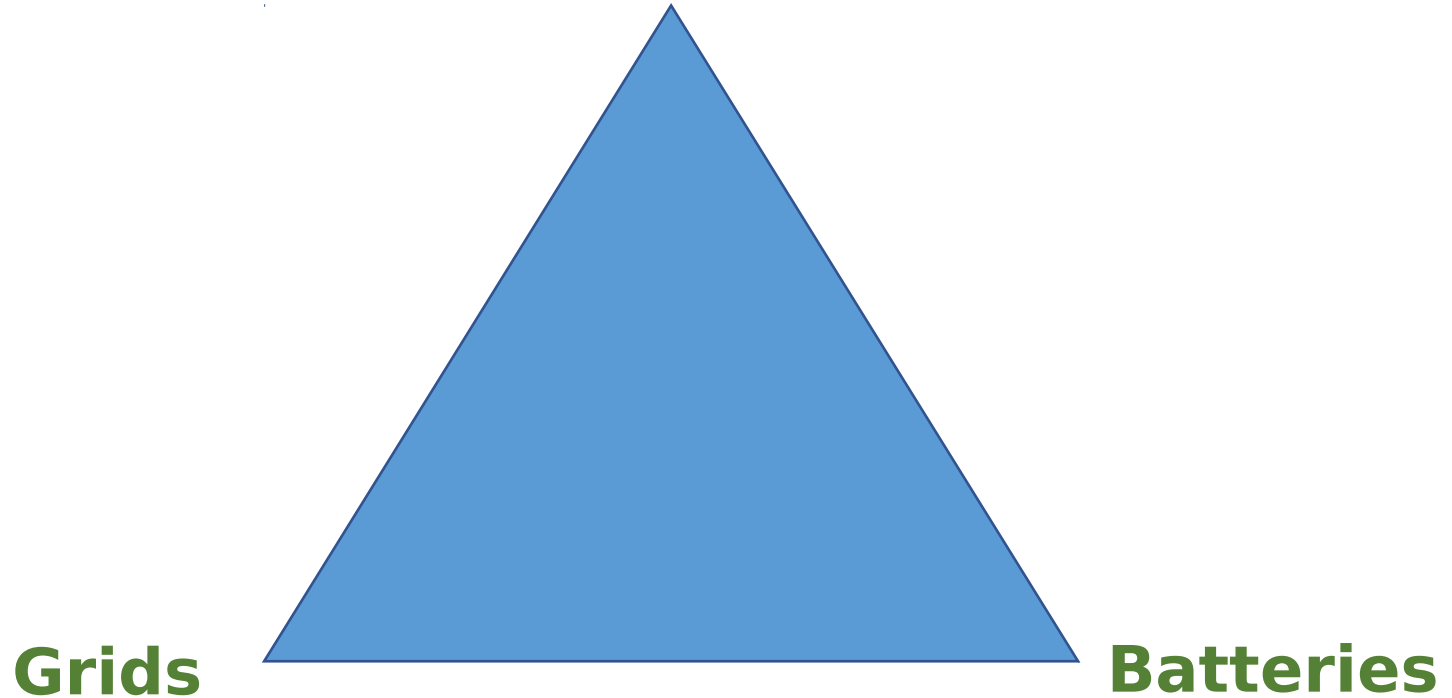
- Static -> **Dynamic**
- Deterministic -> **Stochastic**
- Linear -> **Nonlinear**
- Many power related services (voltage, frequency, balancing, spinning reserve, congestion, ...) -> **Coordination + Hierarchy**
- Speed / problem size -> **Decomposition + Control Based Solutions**
- Characterization of flexibility (bids) -> **Flexibility Functions**
- Requirements on user installations -> **One-way communication**

# Data-Intelligent and Flexible Energy Systems



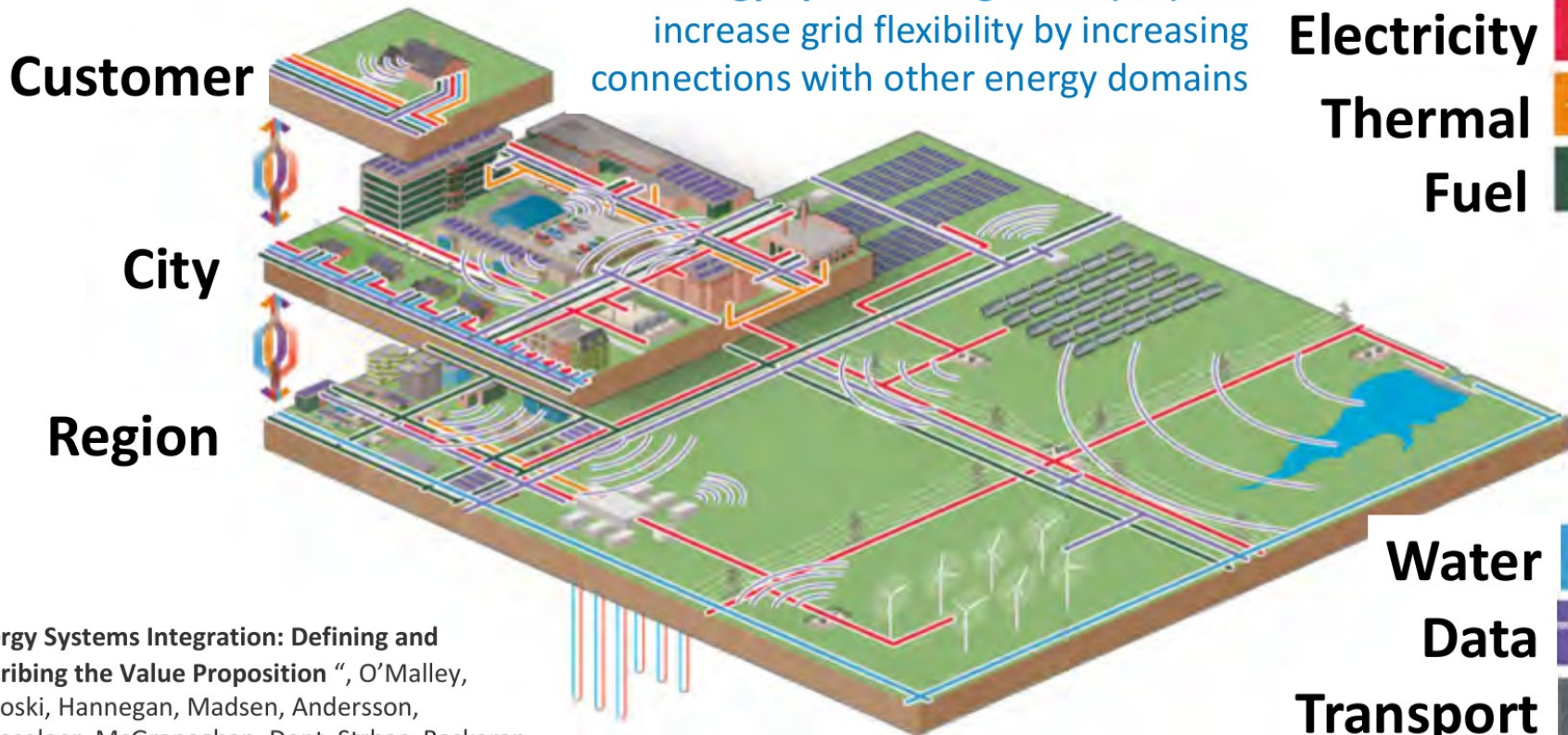
# Space of Solutions

**Flexibility** (enabled by energy Systems Integration, data-driven DT, and IoT)



# Energy Systems Integration

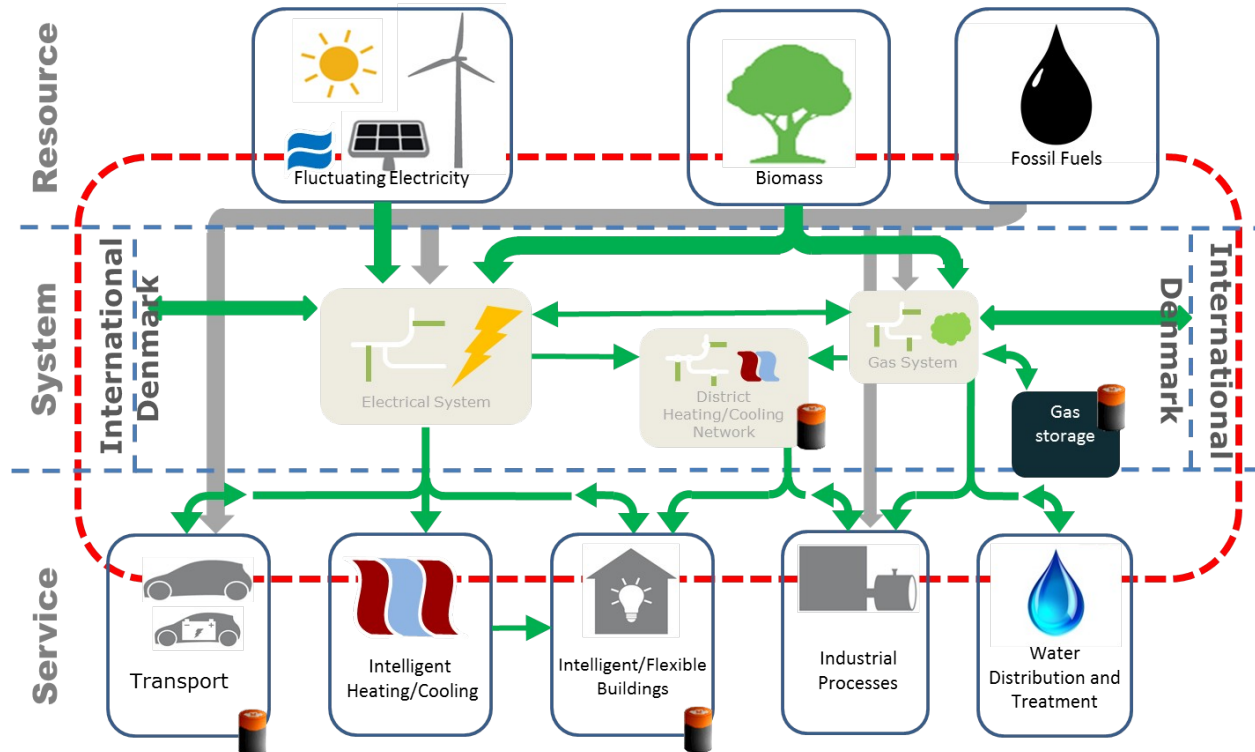
Energy System Integration (ESI) can increase grid flexibility by increasing connections with other energy domains



“Energy Systems Integration: Defining and Describing the Value Proposition”, O’Malley, Kroposki, Hannegan, Madsen, Andersson, D’haeseleer, McGranaghan, Dent, Strbac, Baskaran, Rinker., NREL/TP-5D00-66616. June 2016

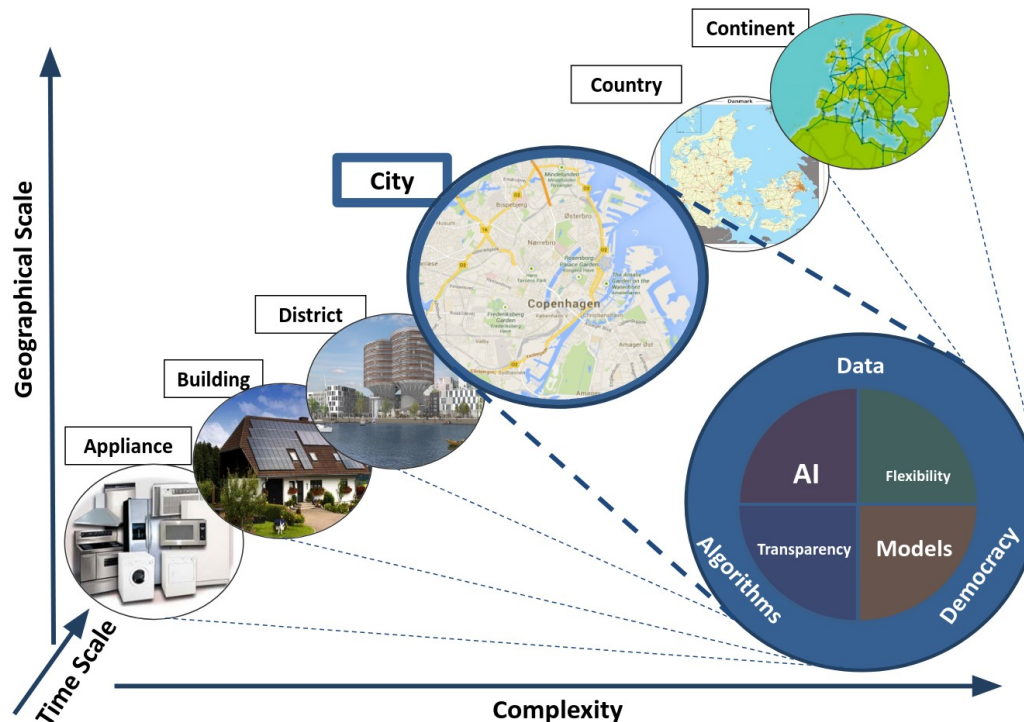
# Energy System Digital Twins for Real Time Applications and Data Assimilation

**Grey-box models** are simplified Data-driven Digital Twin models facilitating system integration and use of sensor data in real-time



# Temporal and Spatial Scales

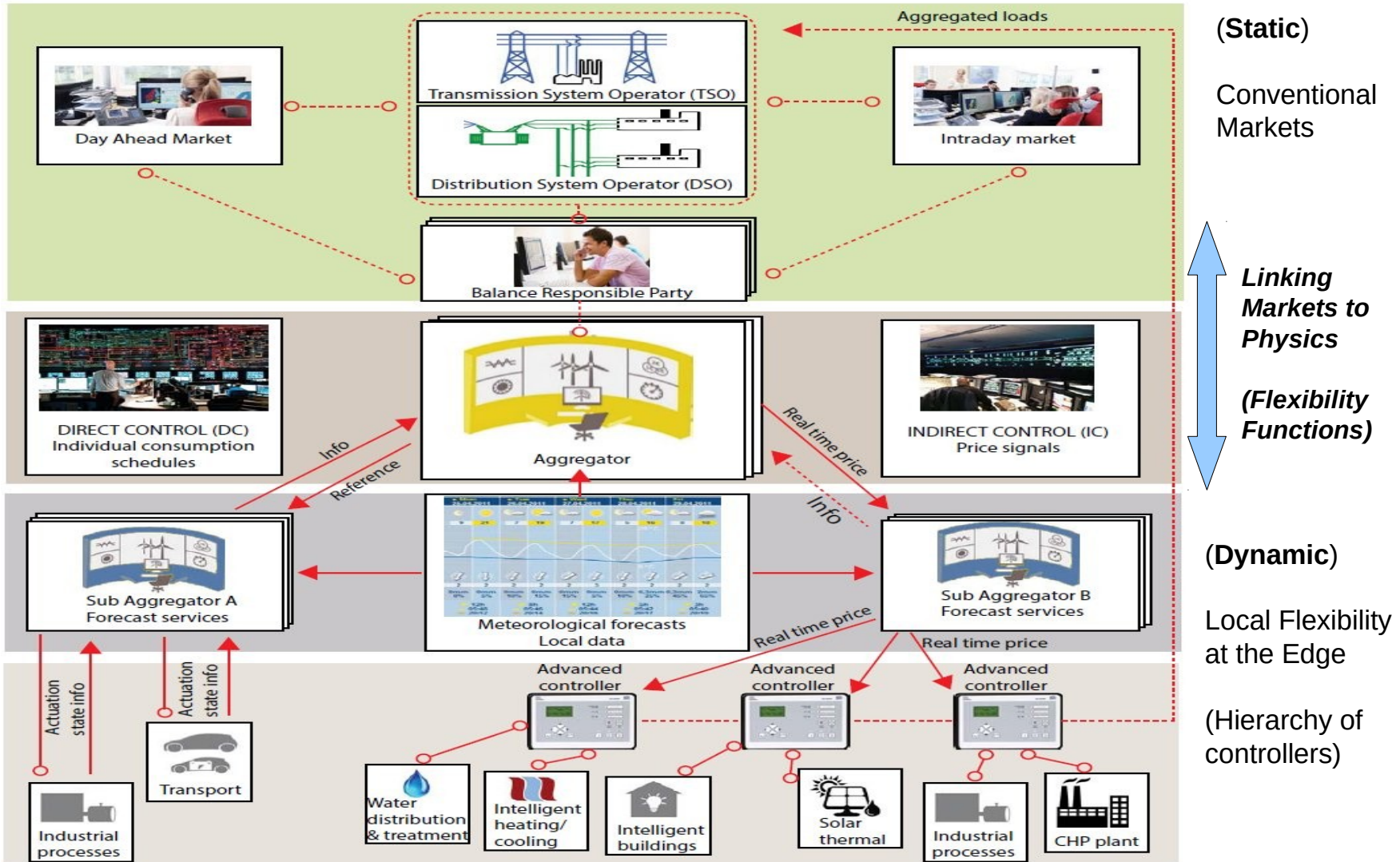
A so-called **Smart-Energy Operating-System (SE-OS)** is developed in order to develop, implement and test solutions (layers: data, models, optimization, control, communication) for **operating flexible electrical energy systems at all scales**.





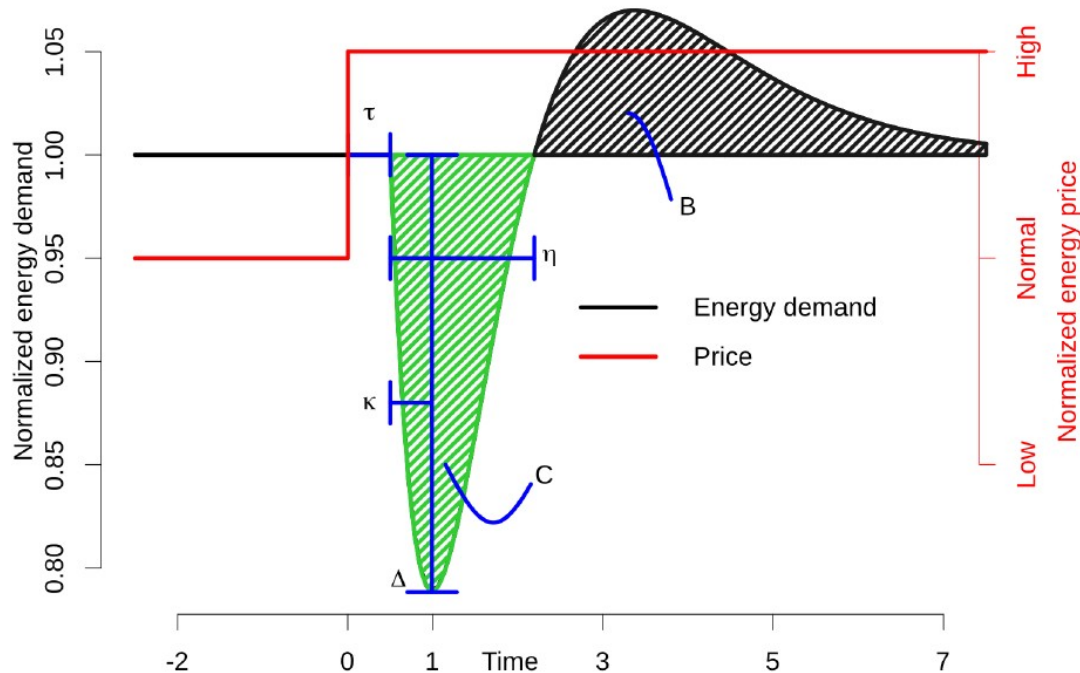
# Smart-Energy OS

## The Transformative Power of Digitalization



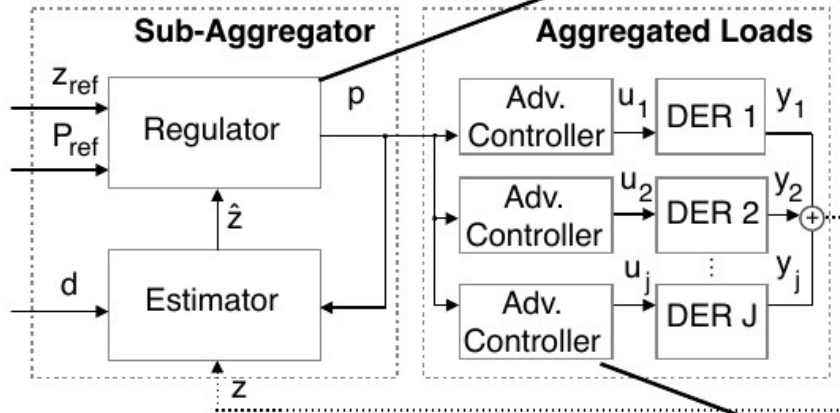
# Flexibility Function

The **Flexibility Function (FF)** is one of the **MIMs (Minimum Interoperability Mechanisms)** for energy systems used to characterizing flexibility and providing interface between local flexibility and high-level markets



# Proposed methodology

## Control-based methodology



$$\min_p \quad \mathbb{E} \left[ \sum_{k=0}^N w_{j,k} \|\hat{z}_k - z_{ref,k}\| + \mu \|p_k - p_{ref,k}\| \right]$$

$$\text{s.t.} \quad \hat{z}_{k+1} = f(p_k)$$

We adopt a control-based approach where the **price** becomes the driver to **manipulate** the behaviour of a certain pool flexible prosumers.

$$\min_u \quad \mathbb{E} \left[ \sum_{k=0}^N \sum_{j=1}^J \phi_j(x_{j,k}, u_{j,k}, p_k) \right]$$

$$\text{s.t.} \quad x_{k+1} = Ax_k + Bu_k + Ed_k,$$

$$y_k = Cx_k,$$

$$y_k^{\min} \leq y_k \leq y_k^{\max},$$

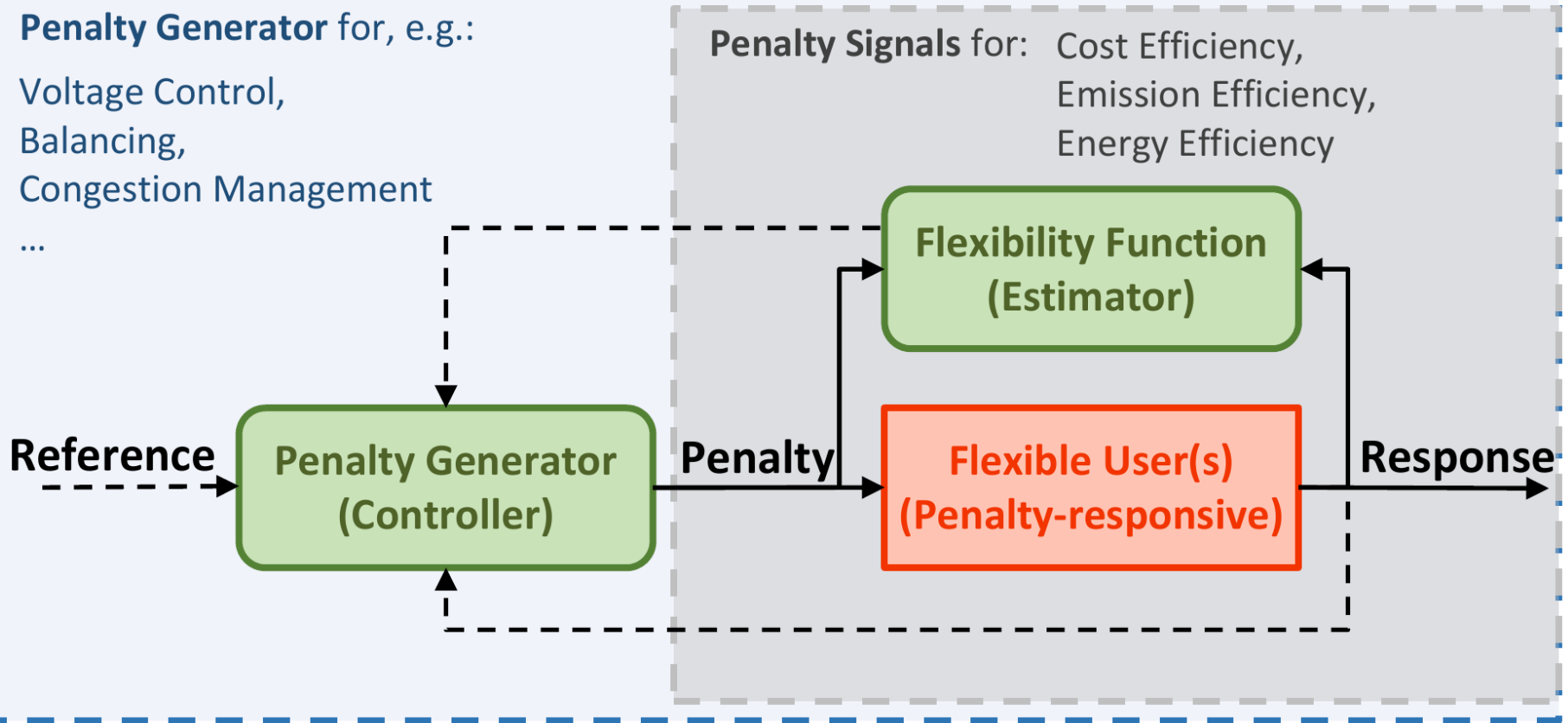
$$u_k^{\min} \leq u_k \leq u_k^{\max}$$



# A FED example: Flexible Users and Penalty Signals

**Penalty Generator** for, e.g.:

Voltage Control,  
Balancing,  
Congestion Management  
...



# Penalty (examples)

- **Real time CO<sub>2</sub>.** If the real time (marginal) CO<sub>2</sub> 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*.

# Flexibility Function Model

**Flexibility Function Model** describes the energy demand of a price-responsive systems as function of price and state of charge.

$$dX_t = \frac{1}{C}(D_t - B_t)dt + X_t(1 - X_t)\sigma_X dW_t$$

$$\delta_t = f(X_t; \alpha) + g(\lambda_{t-\tau}; \beta)$$

$$D_t = B_t + \delta_t \Delta (\mathbb{1}(\delta_t > 0)(1 - B_t) + \mathbb{1}(\delta_t < 0)B_t)$$

$$Y_t = D_t + \sigma_Y \epsilon_t$$

X = state of charge

B = demand (at constant price) / baseline

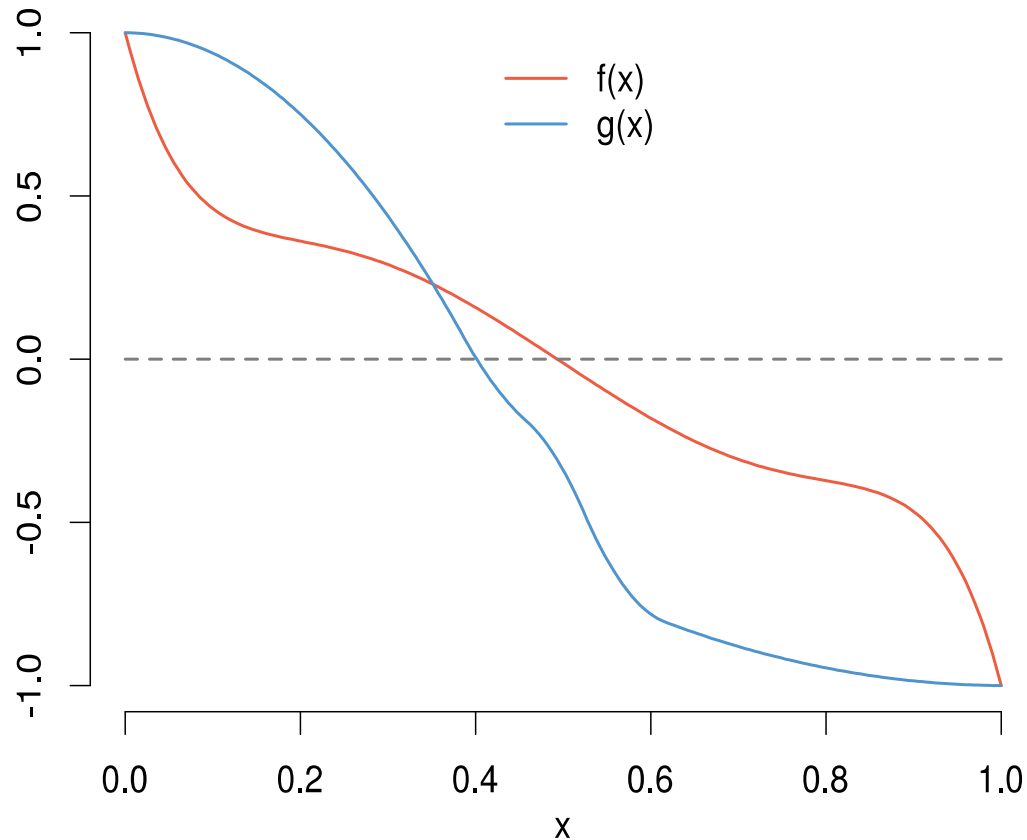
f(\*) = Demand-SoC relationship

g(\*) = Demand-Price relationship

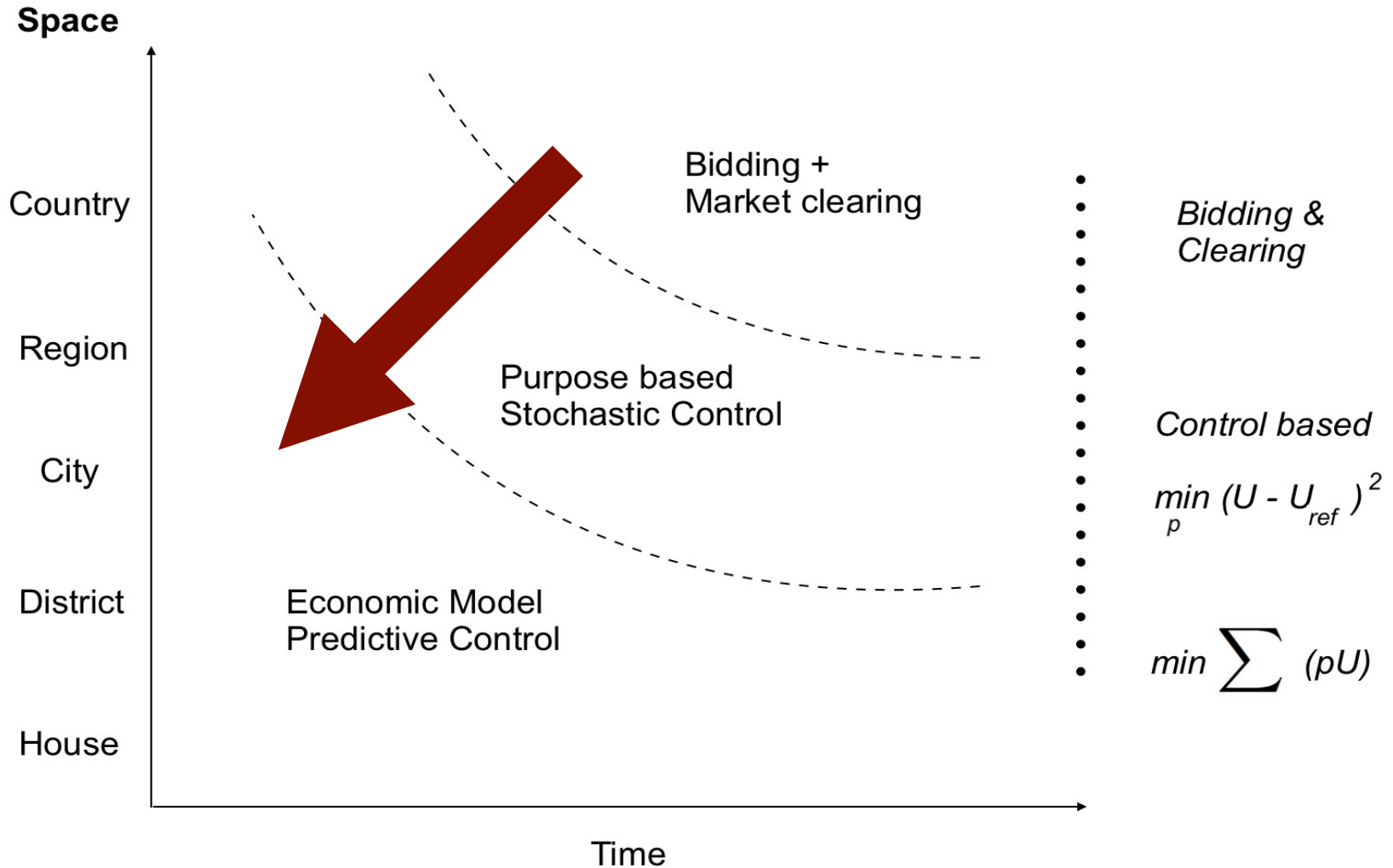


# Characterisation of Energy Flexibility

## Non-linear Flexibility Function using SDE's

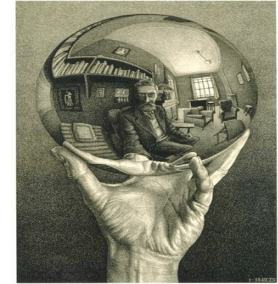


# The 'market' of tomorrow



# SE-OS Characteristics

- Security and Privacy by design
- Democracy and Transparency prioritized
- Able to unlock flexibility at end-users
- Embedded TSO-DSO coordination
- AI and Grey-Box models for data-intelligence
- Hierarchy of optimization (or control) problems
- Creates a link between markets and the physics
- Cloud, Fog, Edge based (IoT, IoS) solutions – eg. for forecasting and control
- Simple setup for the communication and contracts
- Allow for special (technical) aggregators
- Facilitates energy systems integration (power, gas, thermal, ...)

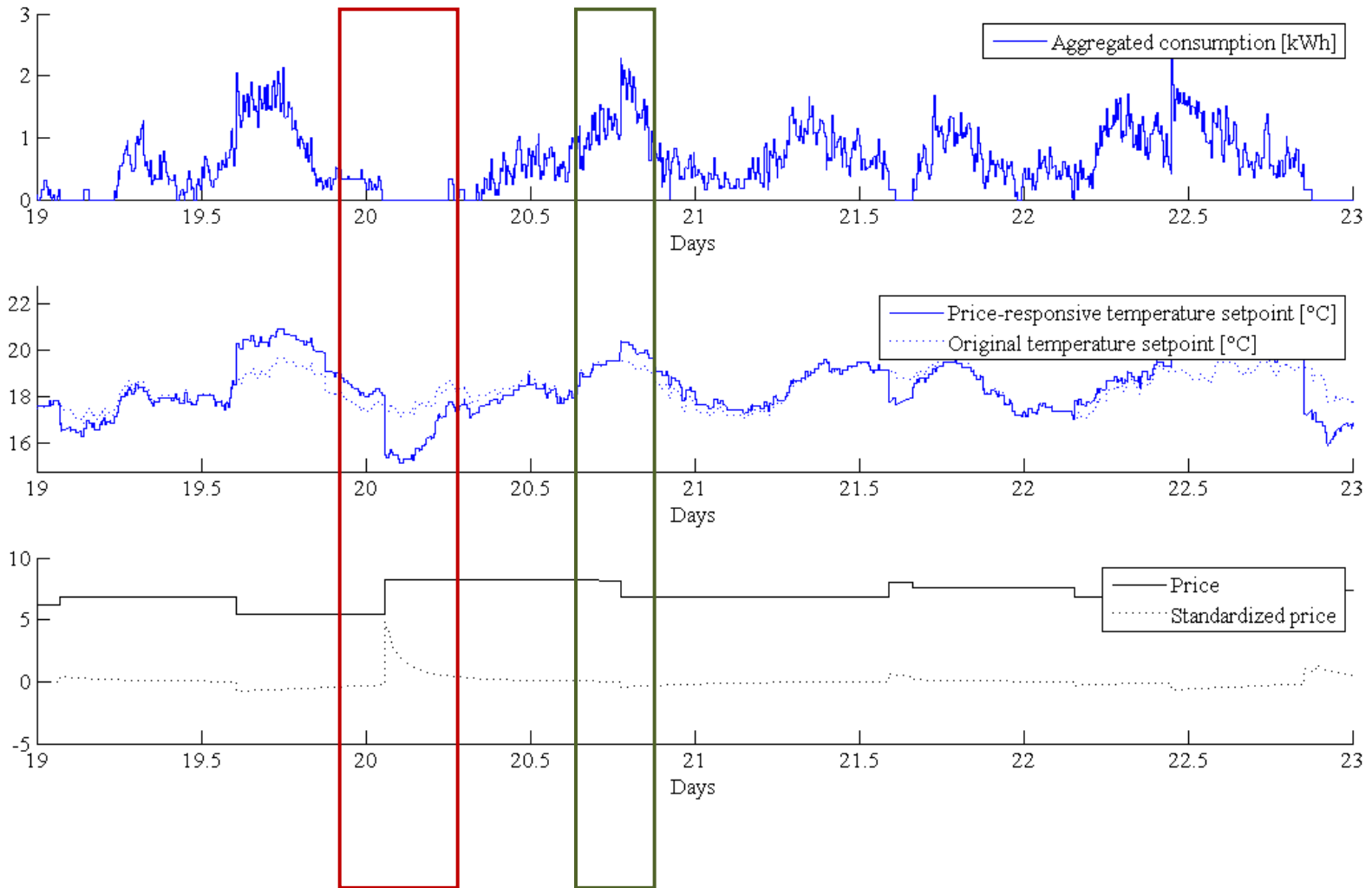


## Case study

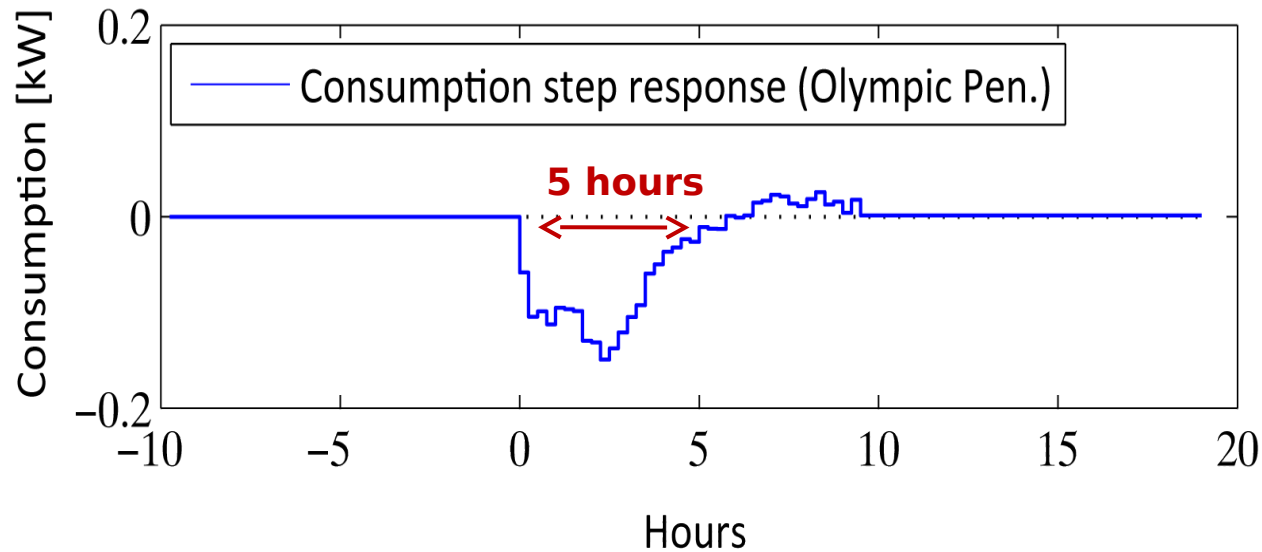
# Price-based Control of Power Consumption (Peak Shaving)



# Aggregation (over 20 houses)



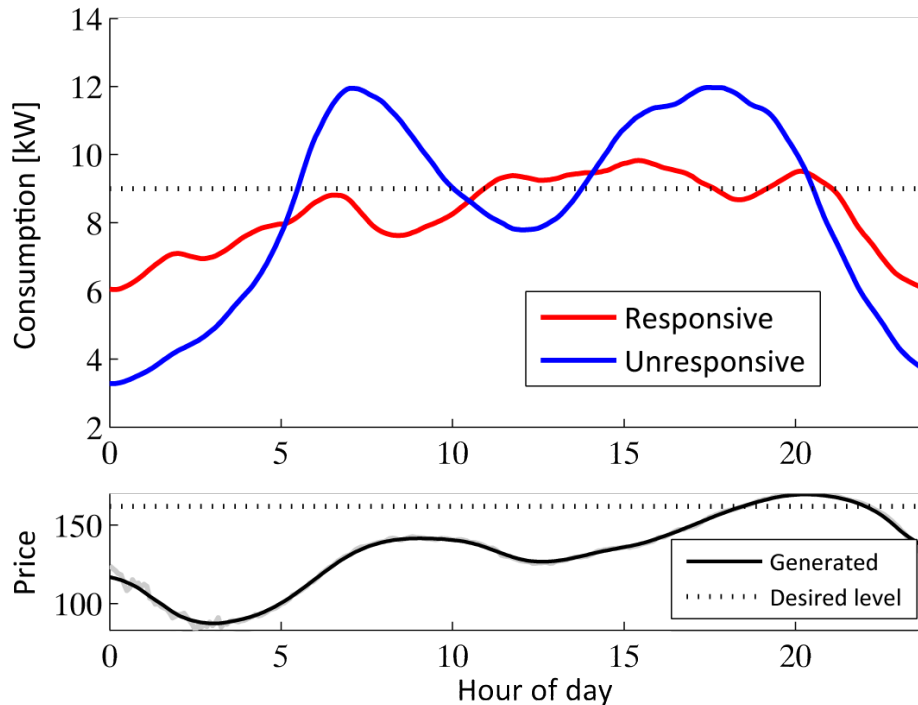
# Response on Price Step Change



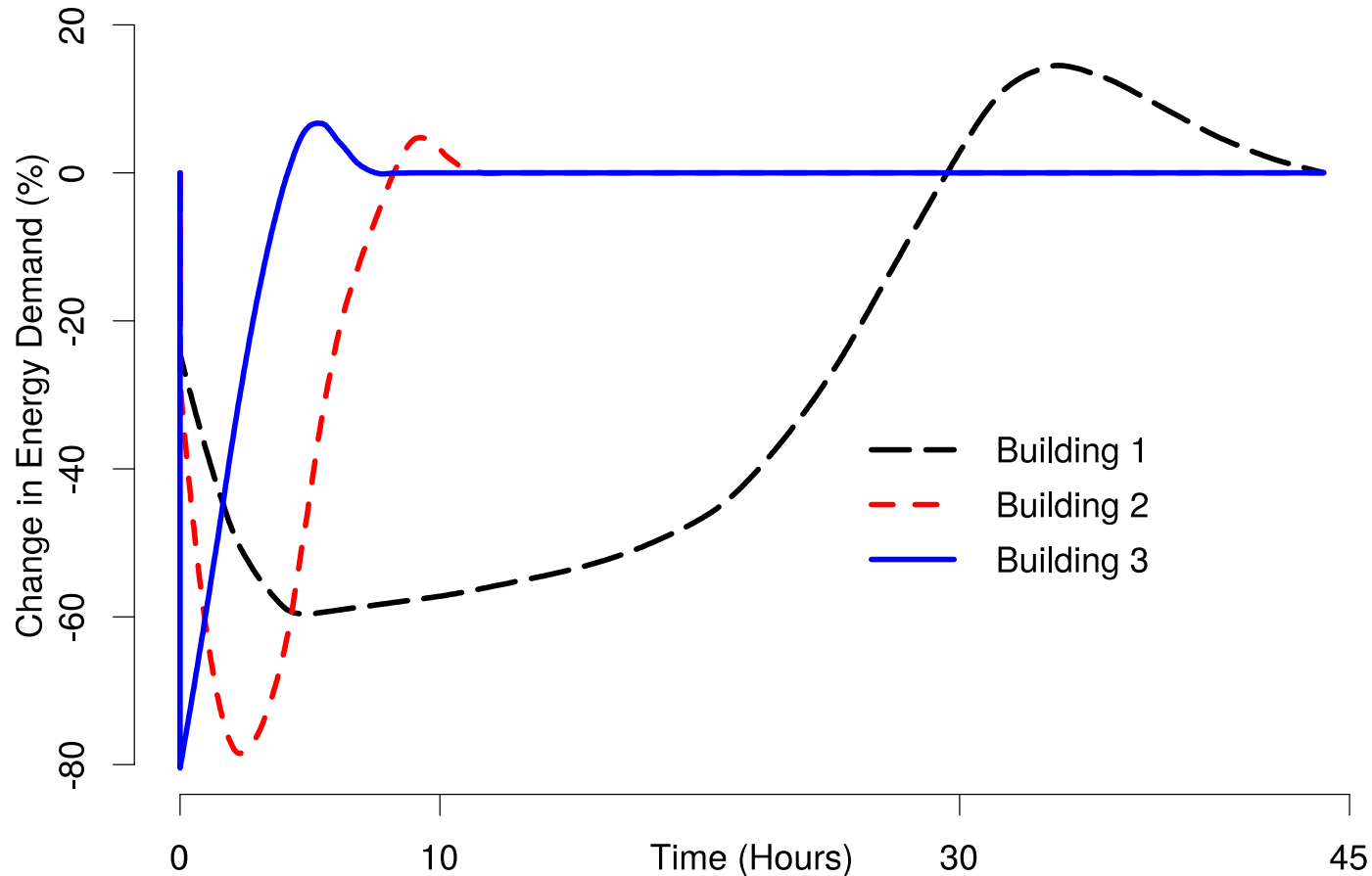


# Control performance

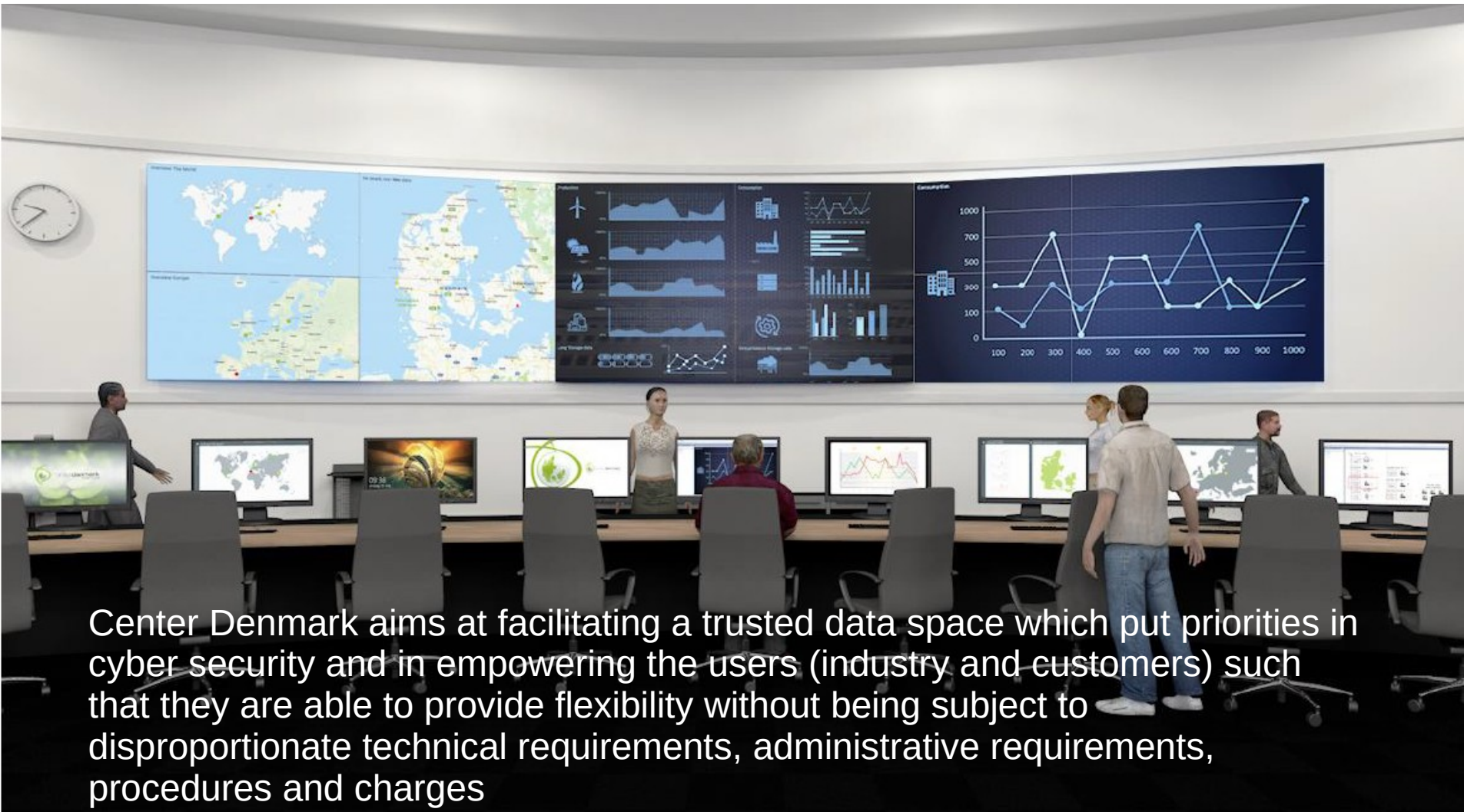
Considerable **reduction in peak consumption**



# Flexibility Function Examples



# Center Denmark Control Room and Data Space Spatial-Temporal thinking

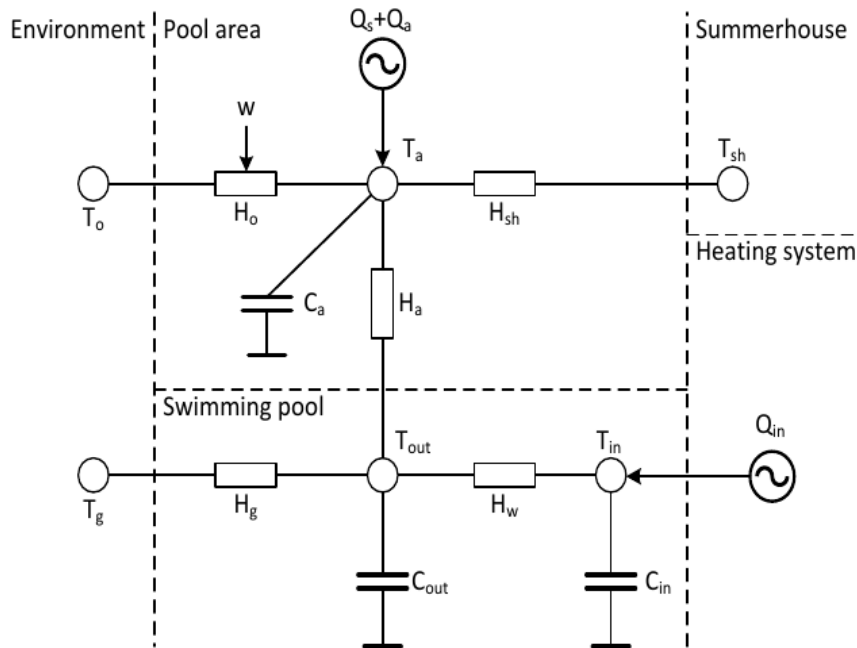


# Case study

## Summerhouses with a pool



# Data-driven models for the buildings (Using lumped parameter models)



- Based on equivalent thermal parameters model

- Dynamics:

$$\frac{dT_{in}}{dt} = \frac{1}{C_{in}} [H_w(T_{out} - T_{in}) + Q_{in}]$$

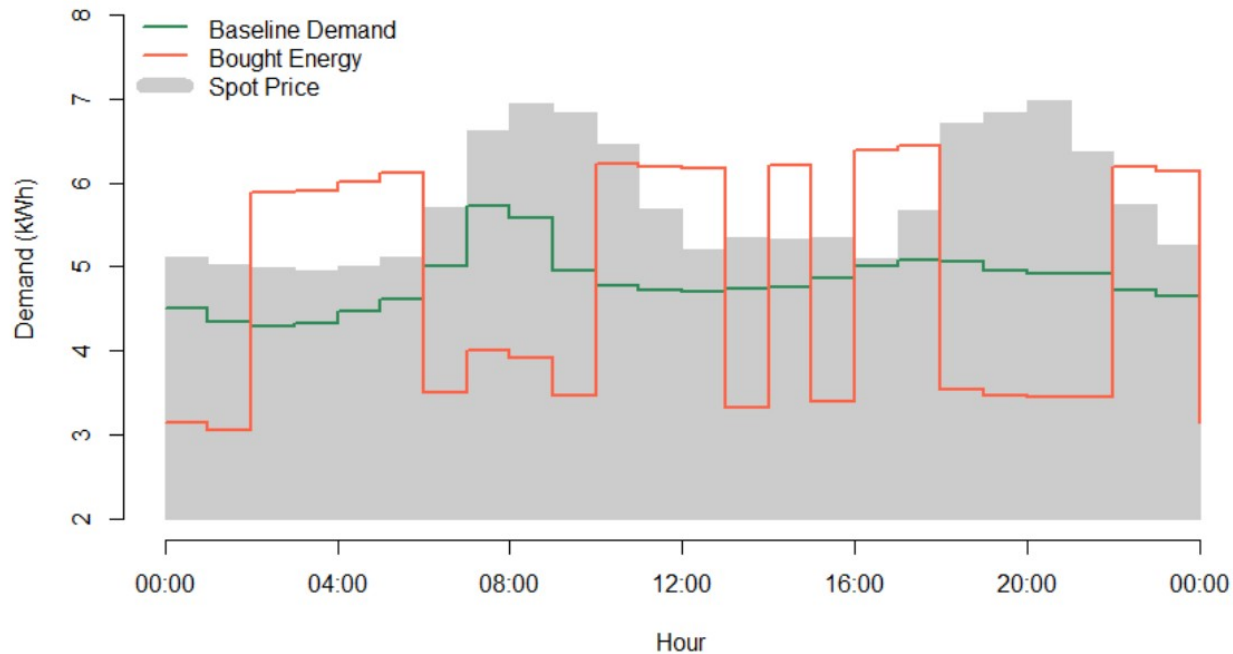
$$\frac{dT_{out}}{dt} = \frac{1}{C_{out}} [H_w(T_{in} - T_{out}) + H_g(T_g - T_{out}) + H_a(T_a - T_{out})]$$

$$\frac{dT_a}{dt} = \frac{1}{C_a} [H_o(w)(T_o - T_a) + H_a(T_{out} - T_a) + H_{sh}(T_{sh} - T_a) + Q_s + Q_a]$$



# Bidding Flexibility into Markets

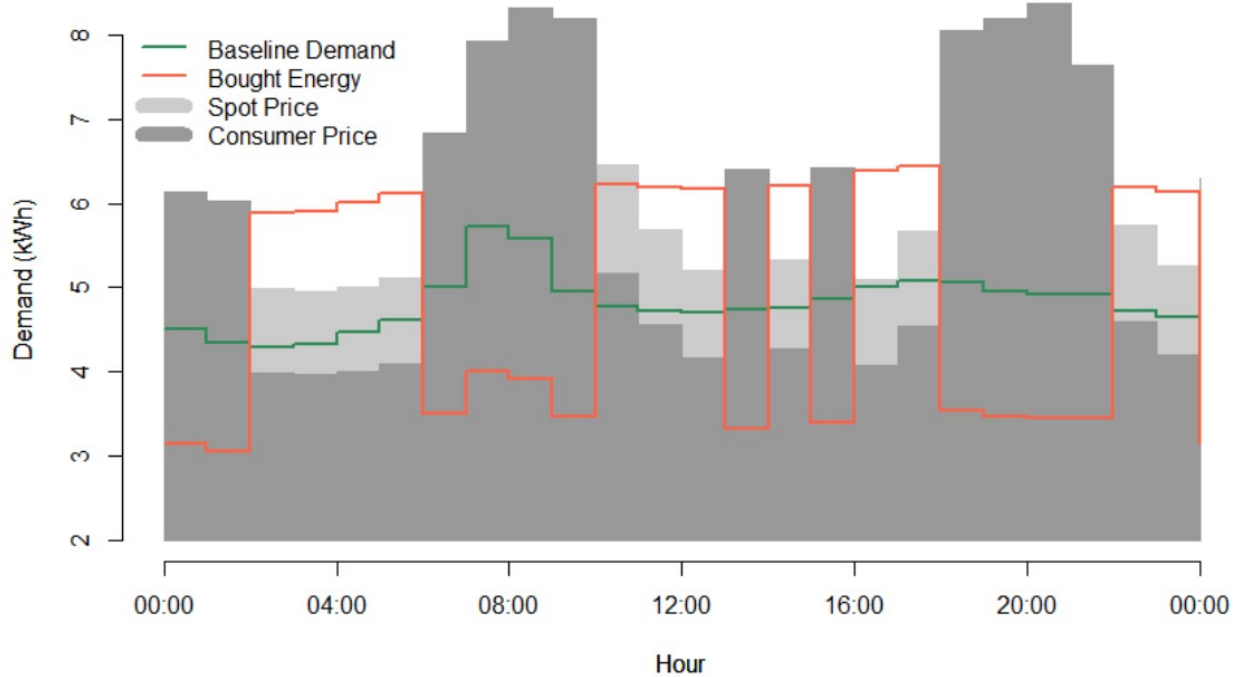
- 4 hours intervals consisting of 30% of consumption with durations of 2 hours:





# Bidding Flexibility into Markets

Solve  $FF(\text{Price}) = \text{Bought Energy}$ :

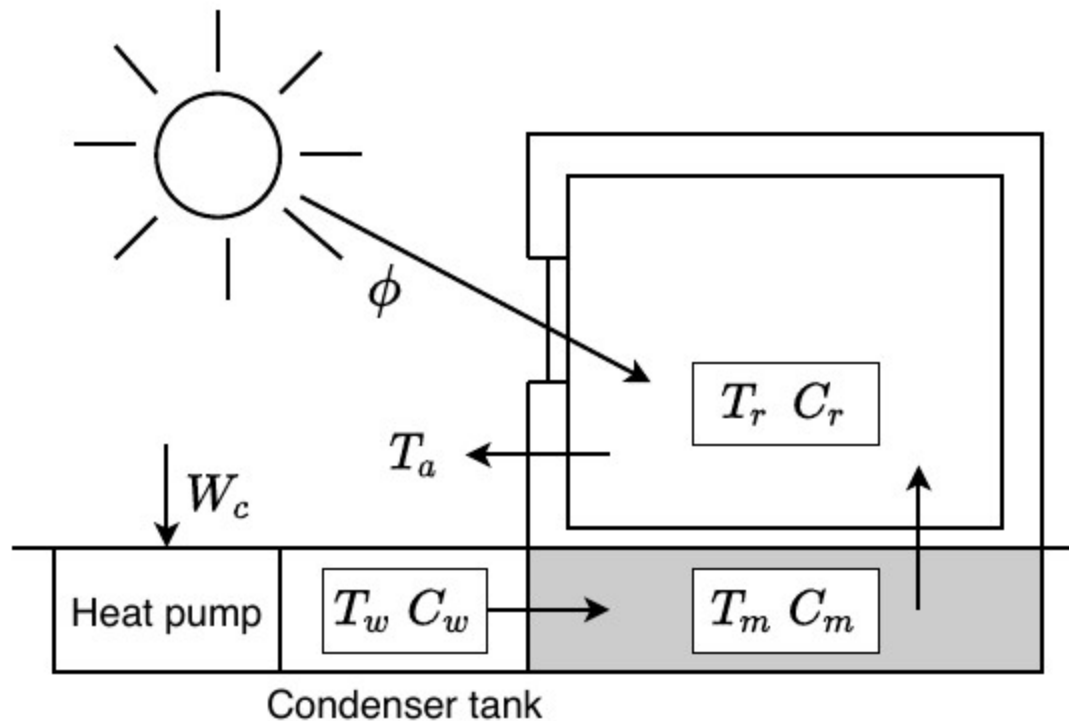




# Integrated Forecasting and Control for Smart Buildings



# Grey-box Model for a Smart Building



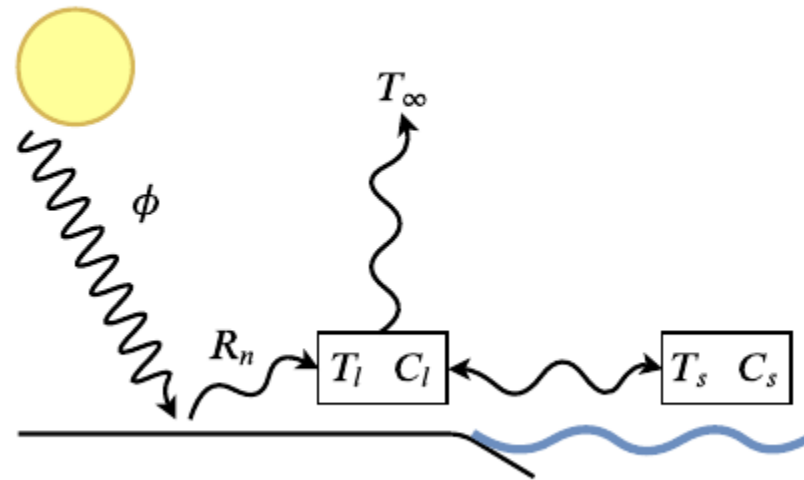
# Grey-box Model for Forecasting

(Cloud cover, solar radiation, ambient air temperature)

$$\begin{array}{l} \text{Disturbance} \\ \text{model} \end{array} \left\{ \begin{array}{l} dZ_{\kappa} = f_{\psi}(Z_{\kappa})dt + \sigma_{\psi}d\omega_{\kappa} \\ \kappa = \psi^{-1}(Z_{\kappa}) \\ \phi = I_N(\kappa, t) + I_D(\kappa, t) \\ R_n = R_n(\kappa, \phi, t) \\ dT_s = f_{T_s}(T_l, T_s)dt + \sigma_s d\omega_s \\ dT_l = f_{T_l}(T_l, T_s, R_n)dt + \sigma_l d\omega_a \\ \mathbf{d} = [T_a, \phi]^T \end{array} \right.$$
  
$$\begin{array}{l} \text{Observation} \\ \text{equation} \end{array} \left\{ \begin{array}{l} d_{\phi} = \phi + v_{\phi}, \quad v_{\phi} \sim N_{iid}(0, R_{\phi}) \\ d_{T_a} = T_l + v_{T_a}, \quad v_{T_a} \sim N_{iid}(0, R_{T_a}) \\ \mathbf{y}_d = [d_{T_a}, d_{\phi}]^T, \end{array} \right.$$

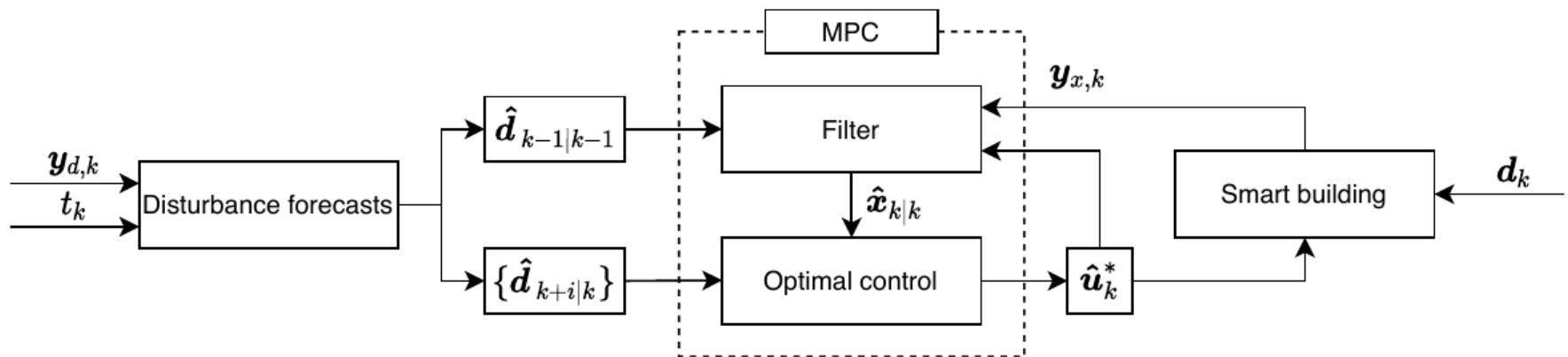
(13)

# Grey-box model for Ambient Air Temperature



# Integrated Forecasting and Control

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



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

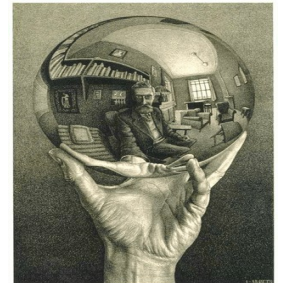
$$d\mathbf{d}(t) = f_d(\mathbf{d}(t))dt + g_d(\mathbf{d}(t))d\omega_d(t), \quad (1b)$$

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

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

# Heating strategies

- Strategy No. 1: Electrical heaters
- Strategy No. 2: Heat pump
- Strategy No. 3: Heat pump and electrical heaters
- Strategy No. 4: Heat pump plus electrical heaters and cooling

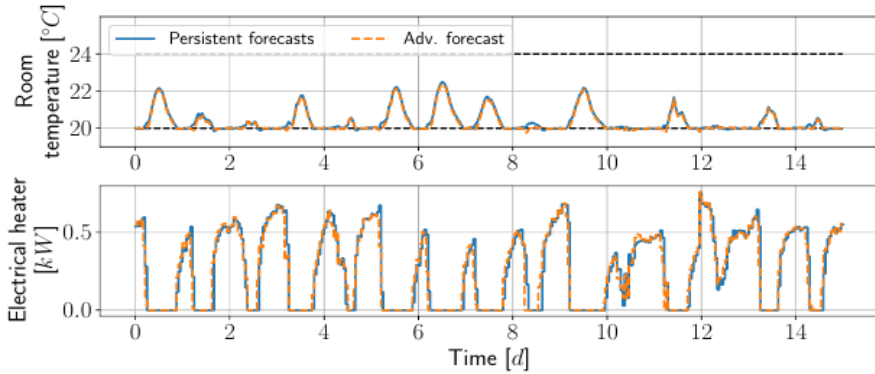




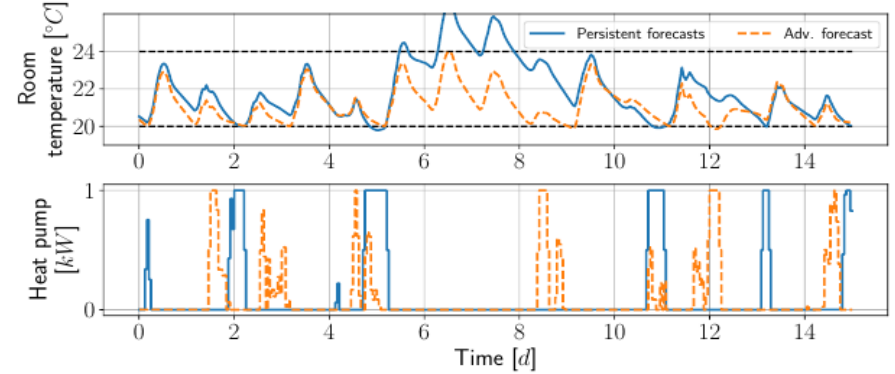
# 15 days out of 7 months simulation



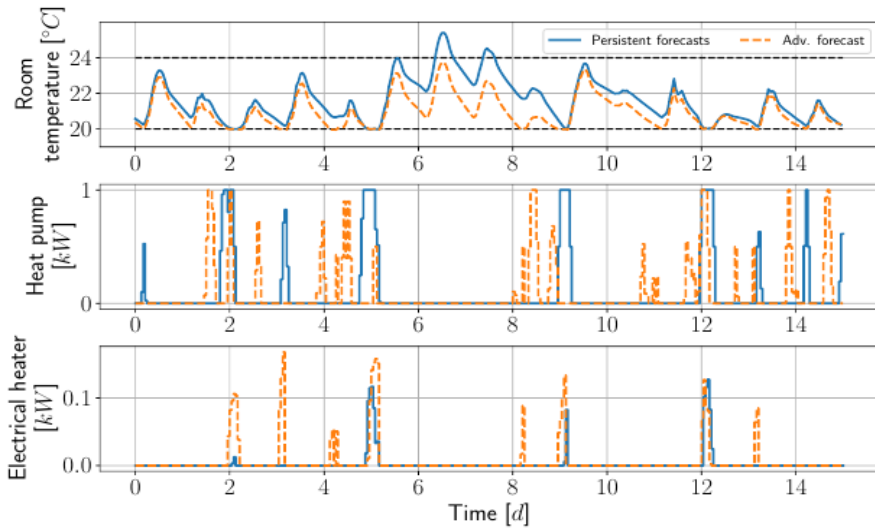
### Strategy 1: Electrical Heaters



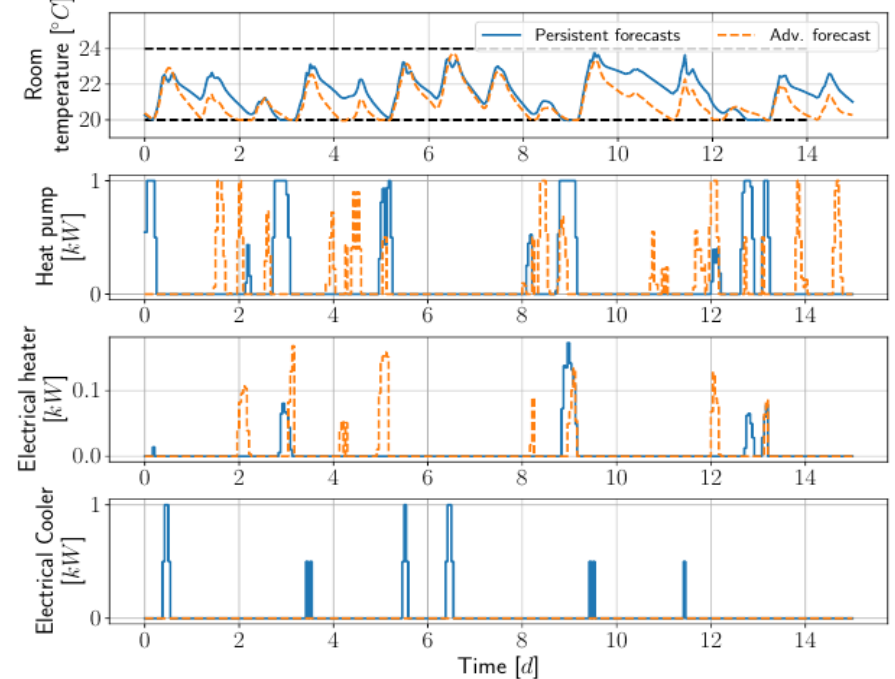
### Strategy 2: Heat Pump



### Strategy 3: Heat Pump & Electrical Heaters



### Strategy 4: Heat Pump & Electrical Heaters & Coolers



# Electricity cost in EUR

## Electricity cost of the simulations

Heating strategy	Persistent	Advanced forecasts	Perfect
Electrical heaters, $u_1$	303.2	302.2	302.0
Heat pump, $u_2$	117.3	110.4	107.7
Heat pump plus electrical heaters, $u_3$	113.0	108.2	107.5
Heat pump plus electrical heaters and coolers, $u_4$	117.9	108.3	107.5

# Constraint violations

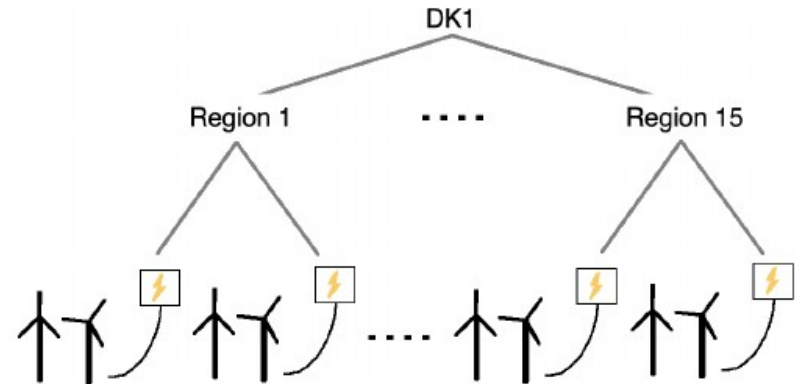
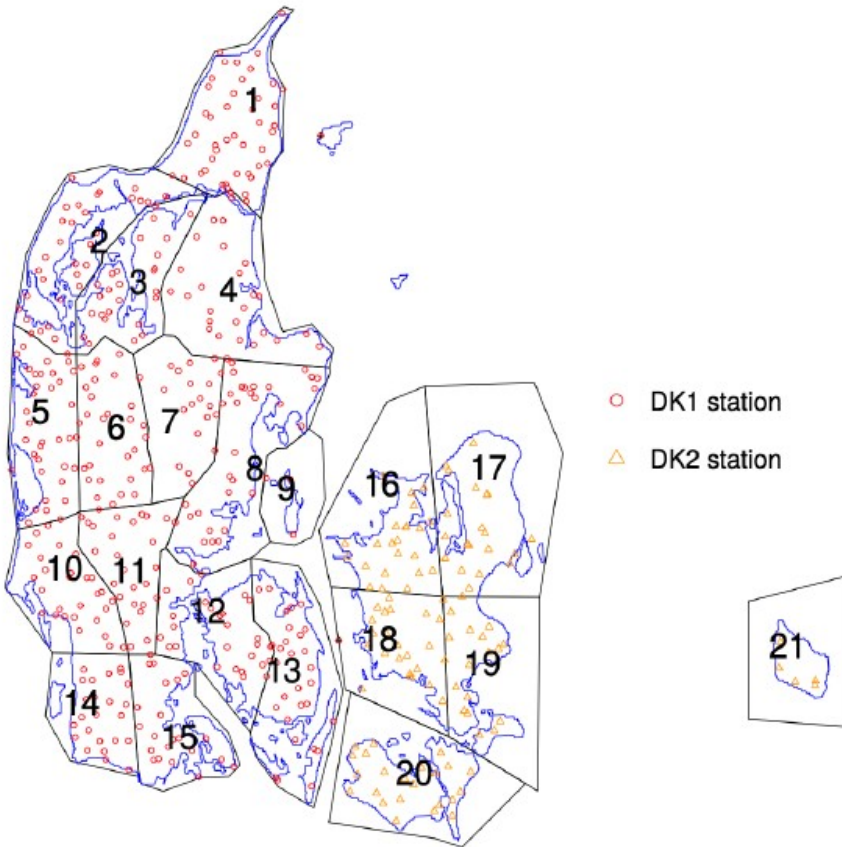
## Constraint violation of the control simulations

Heating strategy	Persistent	Advanced forecasts	Perfect
Electrical heaters, $u_1$	48.5	39.6	25.1
Heat pump, $u_2$	157.9	12.3	1.7
Heat pump plus electrical heaters, $u_3$	48.0	6.7	1.2
Heat pump plus electrical heaters and coolers, $u_4$	4.4	2.4	0

# Multivariate Forecasting using Spatial Hierarchies

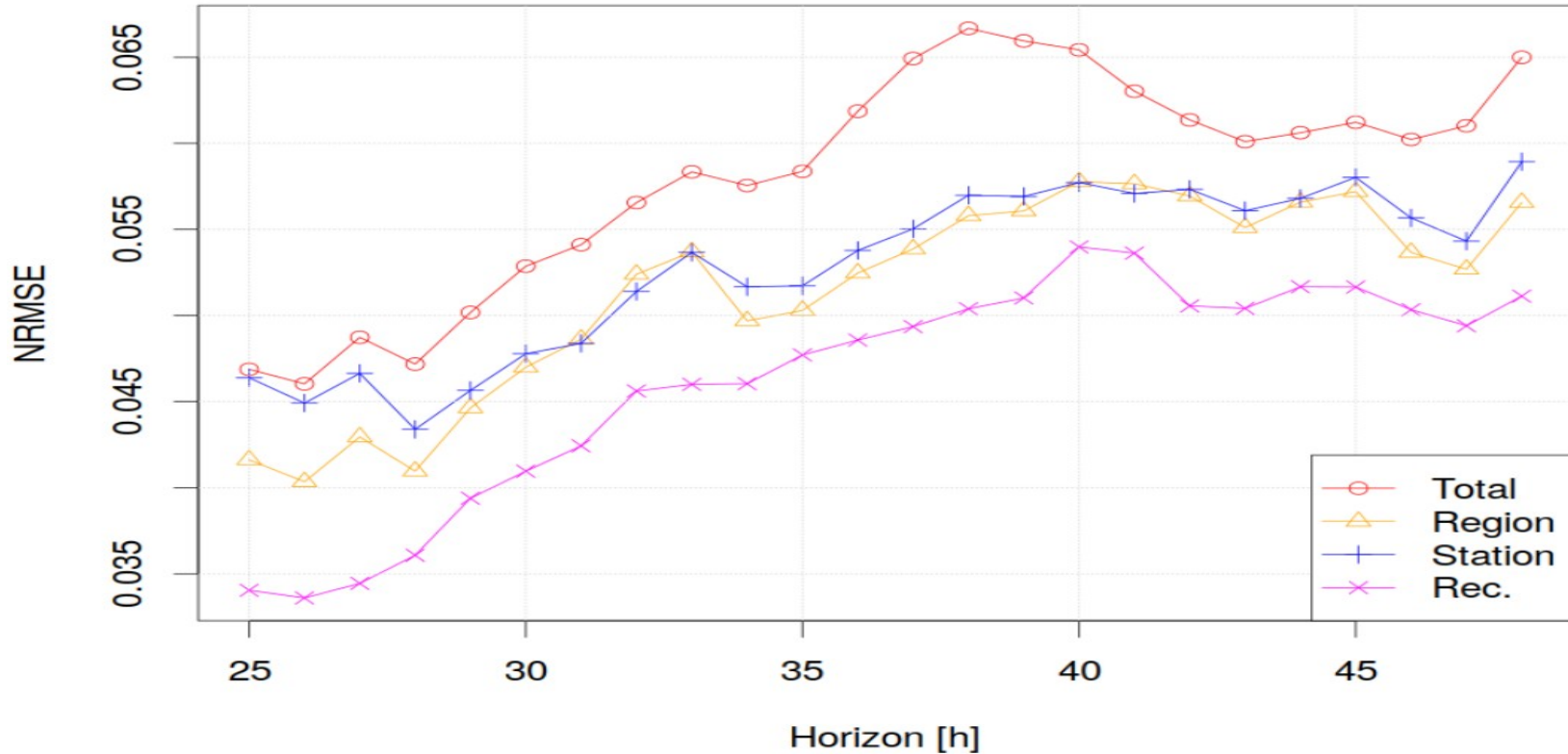


# Wind Power Forecasting



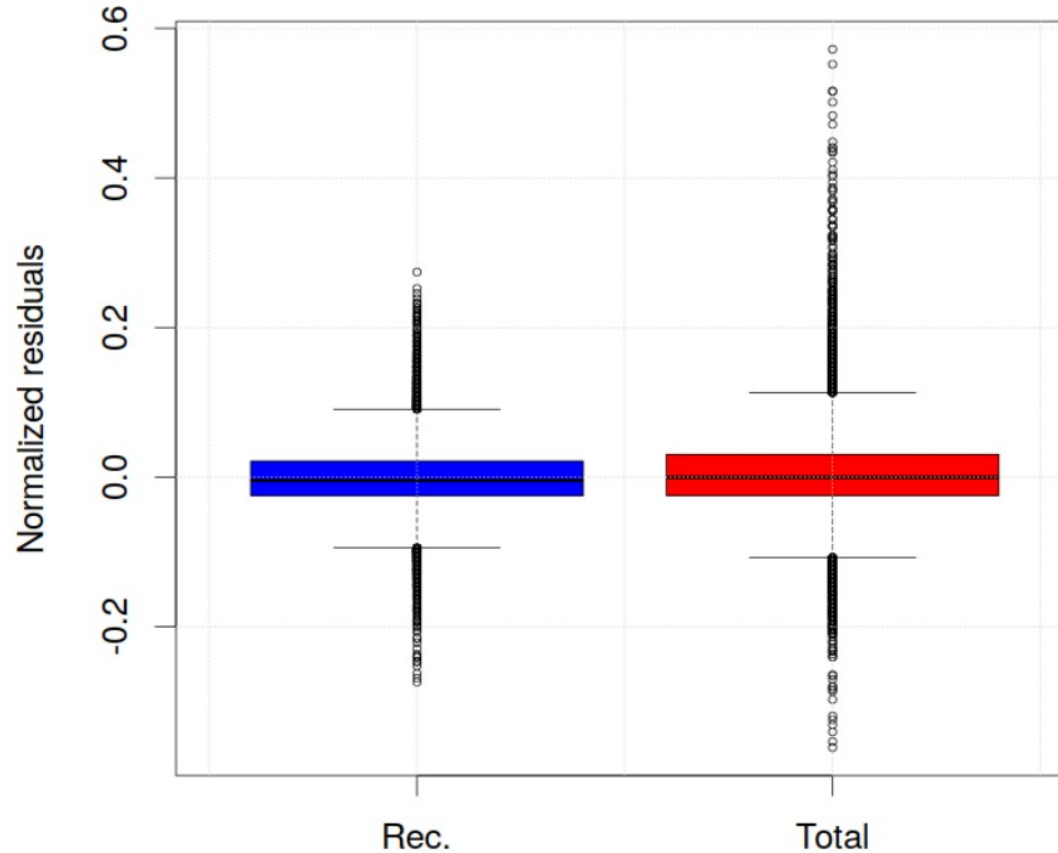
(b) Illustration of the spatial hierarchy for DK1 with 407 individual conversion stations at the bottom level, 15 regions at the middle level, and the total of Western Denmark at the top.

# Total Forecasts (DK1) Forecasting (improvements 20 pct)





# Box Plot of Forecast Errors



(b) Box plot of the residuals of the reconciled total forecast and the residuals of the base total forecast.

# Summary

- **Data-driven Methods are important for unlocking the needed flexibility for an efficient large scale integration of wind and solar energy**
- **We have demonstrated how to use Grey-box Modelling for as data-driven digital twins for integrated forecasting and control**
- **We have suggested the use of Flexibility Functions**
- **We have adopted a Spatio-Temporal thinking**
- **We have described the Smart-Energy OS, which is hierarchy of tools for aggregation, modelling, forecasting, optimization, and control**
- **The Smart-Energy OS can focus on**
  - ★ Peak Shaving
  - ★ Smart Grid demand (like ancillary services needs, ...)
  - ★ Energy Efficiency
  - ★ Cost Minimization
  - ★ Emission Efficiency

Thanks for your attention!

Some 'randomly picked' books on modeling, finance, markets and renewable integration ....

