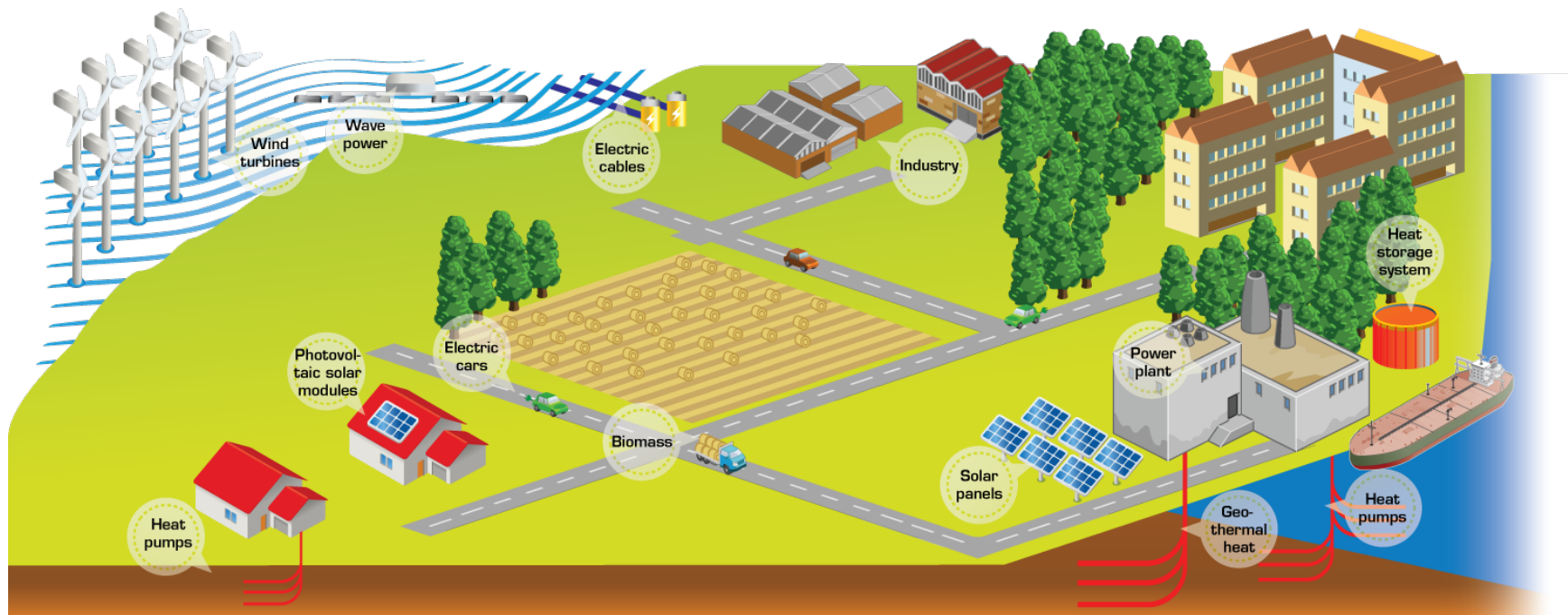


Model Predictive Control for Smart Energy Systems

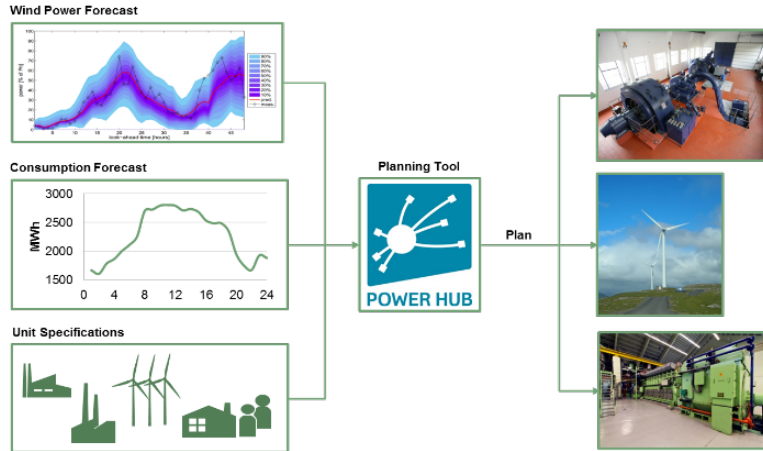
John Bagterp Jørgensen
Technical University of Denmark

CITIES Final Conference
November 9, 2020
ZOOM-DTU, Denmark

The Vision of Energy-Smart Cities / Municipalities



Optimization based control = Model Predictive Control (MPC)



$$\begin{aligned}\frac{\partial C_i}{\partial \alpha} &= -v_i \frac{\partial C_i}{\partial \alpha} + D \frac{\partial^2 C_i}{\partial \alpha^2} + \frac{k}{\varepsilon_i} \left(\frac{C_i}{\varepsilon_i} - C_i \right) \\ \frac{\partial C_i}{\partial \alpha} &= -v_i \frac{\partial C_i}{\partial \alpha} + D \frac{\partial^2 C_i}{\partial \alpha^2} + \frac{k}{\varepsilon_i} \left(C_i - \frac{C_i}{\varepsilon_i} \right) + \gamma_r \\ \frac{\partial w_{reg}}{\partial \alpha} &= -v_i \frac{\partial w_{reg}}{\partial \alpha} + D \frac{\partial^2 w_{reg}}{\partial \alpha^2} + r_r \\ \frac{\partial T_i}{\partial \alpha} &= -v_i \frac{\partial T_i}{\partial \alpha} + D \frac{\partial^2 T_i}{\partial \alpha^2} + \frac{h}{\varepsilon_i} (T_i - T_i) \\ \frac{\partial T_i}{\partial \alpha} &= -v_{ij} \frac{\partial T_i}{\partial \alpha} + D \frac{\partial^2 T_i}{\partial \alpha^2} + \frac{h}{\varepsilon_i} (T_i - T_i) - \Delta H_i r_r\end{aligned}$$

Mathematical / Statistical
Modelling

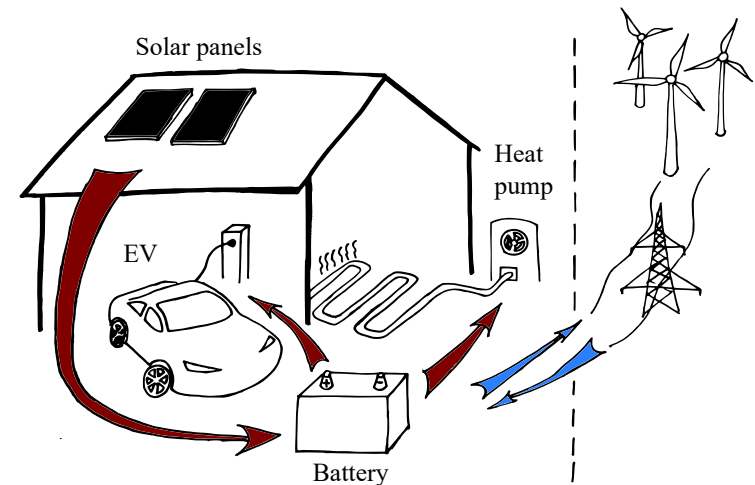
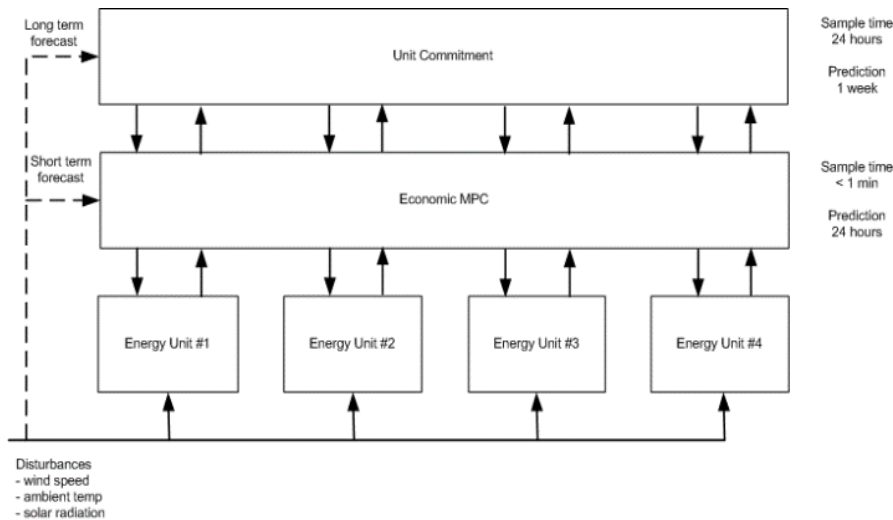


Powerful
Computers

$$\begin{aligned}\min_x \quad & x^T Q x + c^T x \\ \text{s.t.} \quad & A_{ieq} x \leq b_{ieq} \\ & A_{eq} x = b_{eq} \\ & l \leq x \leq u \\ & x_i x_j = 0 \quad \forall (i, j) \in \Phi\end{aligned}$$

Optimization
Algorithms

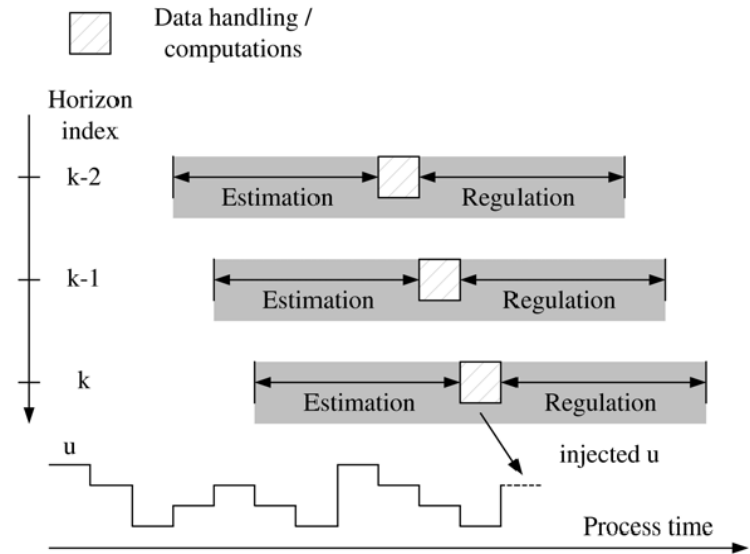
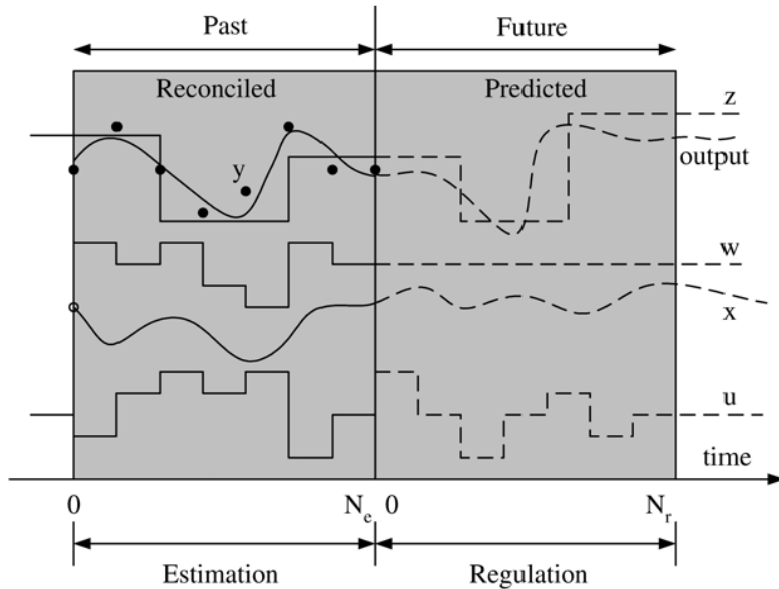
Hierarchical Control Structure



Digitalization, Control and Optimization of Smart Coordinated Energy Systems

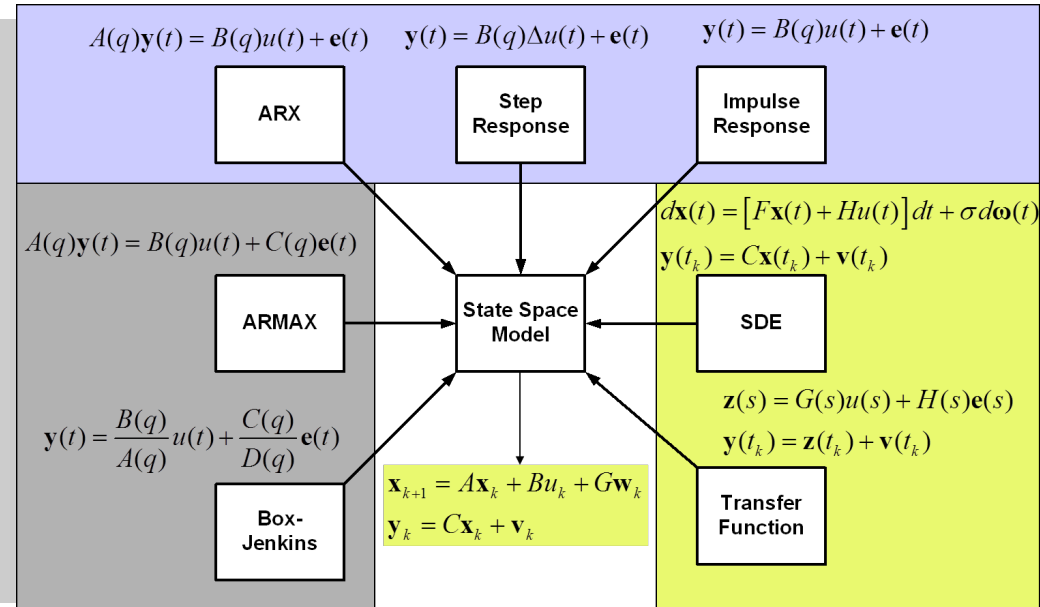
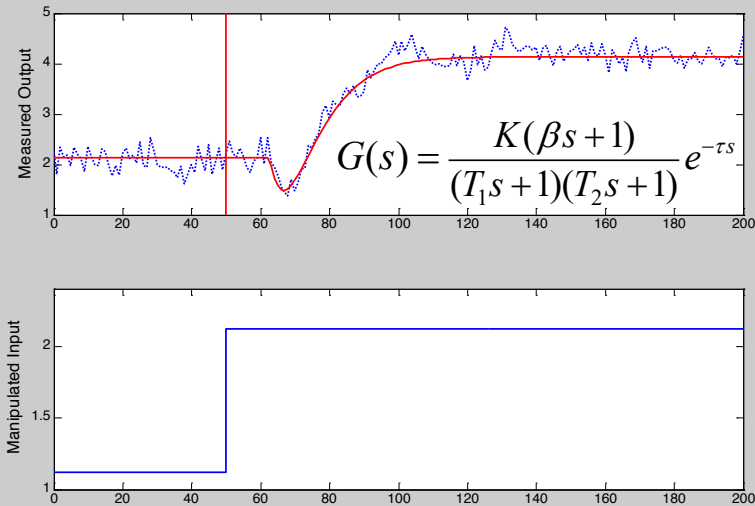


Model Predictive Control



$$\begin{aligned} \min_{\{u_k, x_{k+1}\}_{k=0}^{N-1}} \quad & \phi = \phi(\{u_k, x_{k+1}\}_{k=0}^{N-1}; x_0, \theta) \\ \text{s.t.} \quad & x_{k+1} = F_k(x_k, u_k, \theta) \quad k = 0, 1, \dots, N-1 \\ & u_k \in \mathcal{U} \end{aligned}$$

Data based prediction models

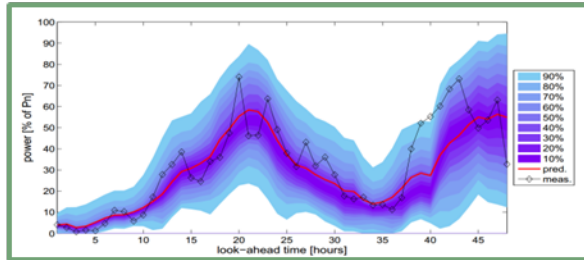


The models for filtering and prediction are

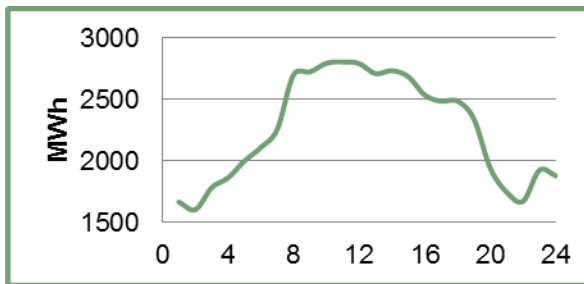
- Adaptive
- Data-based
- Combines a-priori (model) and a-posteriori (data) information
- Able to predict the mean values and the uncertainties

Control of Energy-Smart Systems = Economic Model Predictive Control

Wind Power Forecast



Consumption Forecast



Unit Specifications



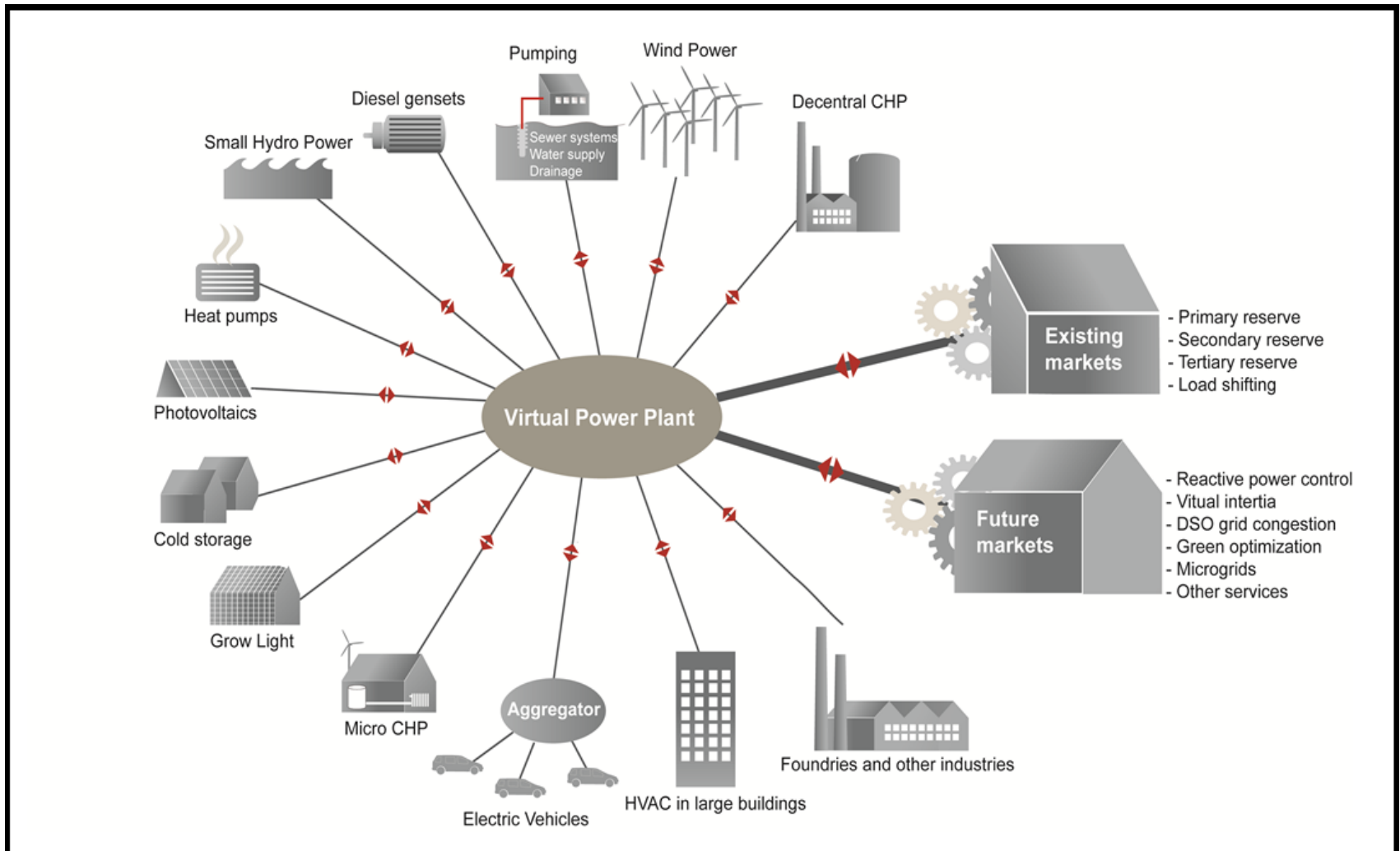
Planning Tool



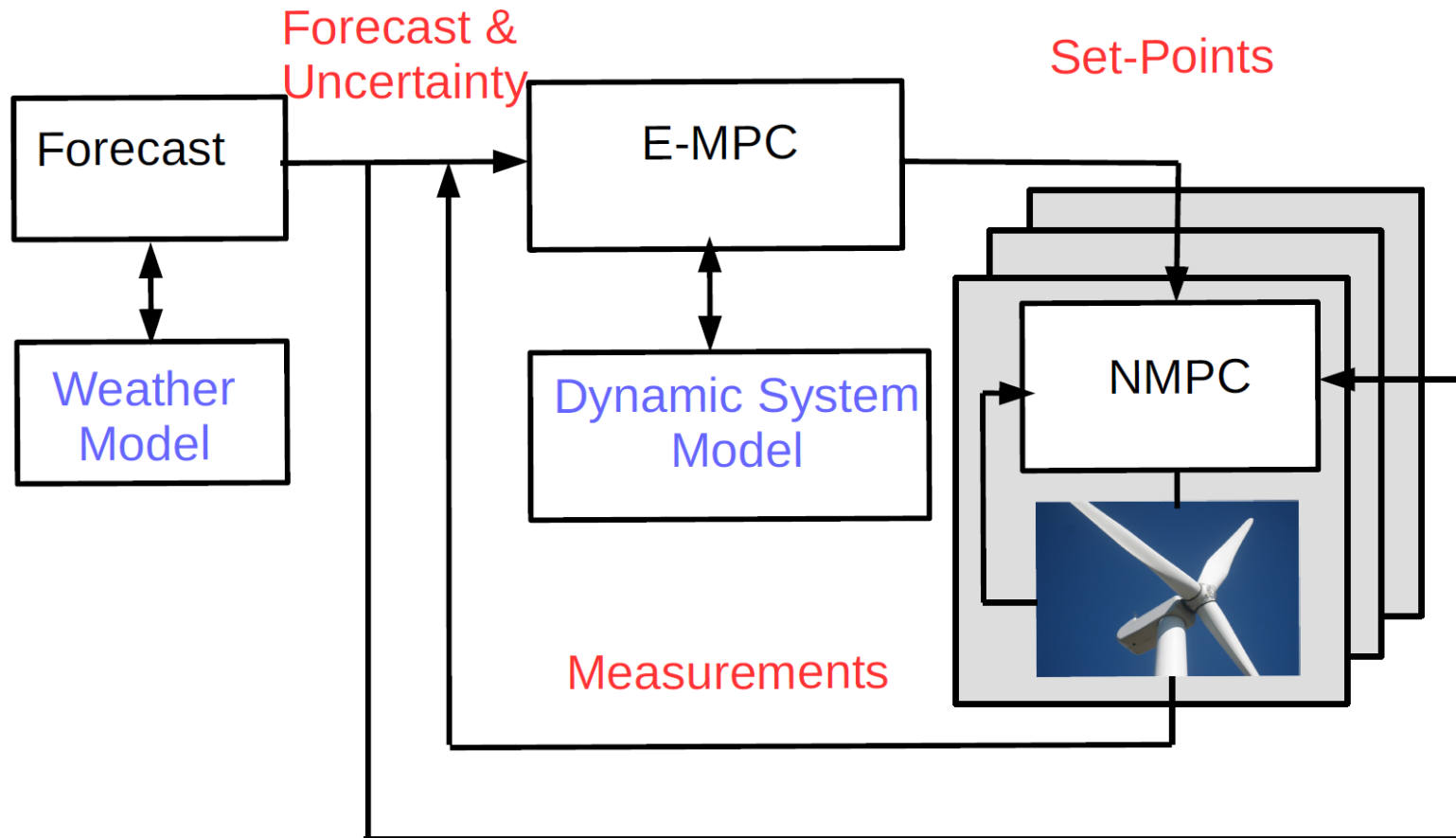
Plan



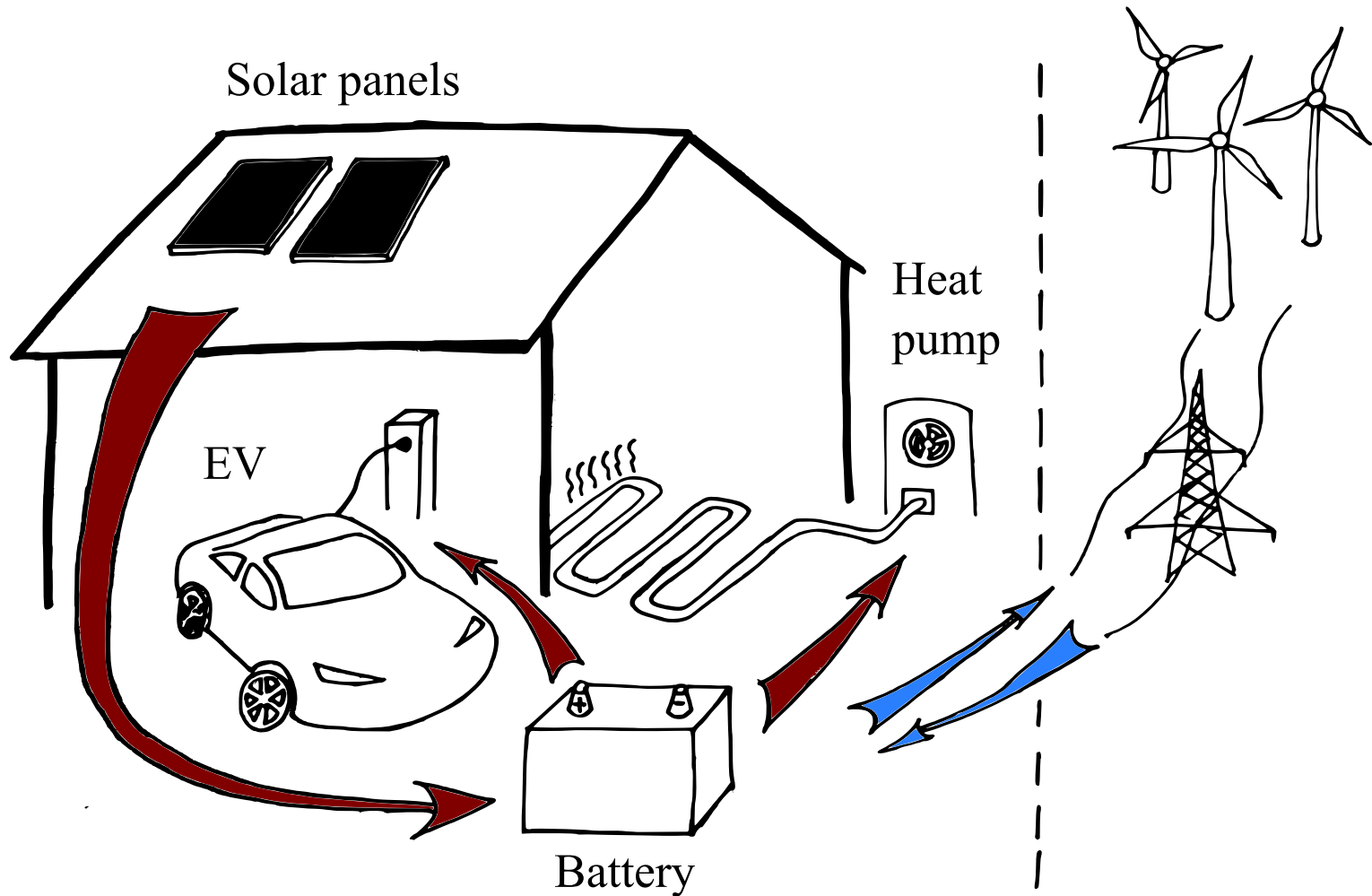
Virtual Power Plant



Forecast Based Hierarchical MPC



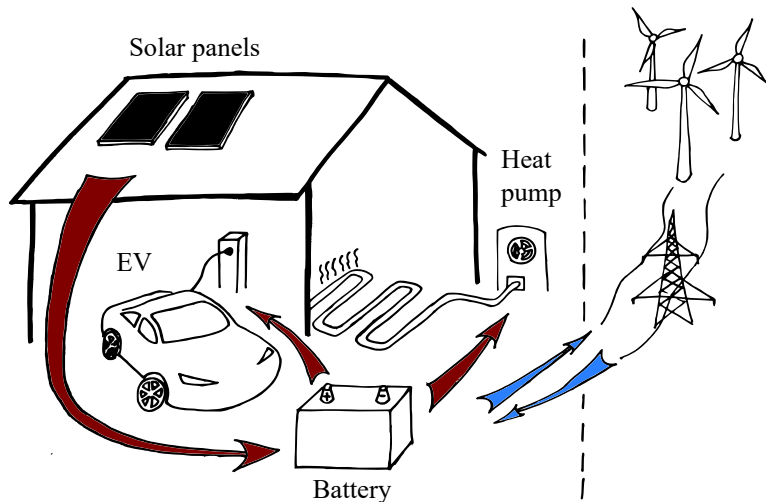
The Vision of Energy-Smart Homes



Elon Musk's vision of an energy-smart home



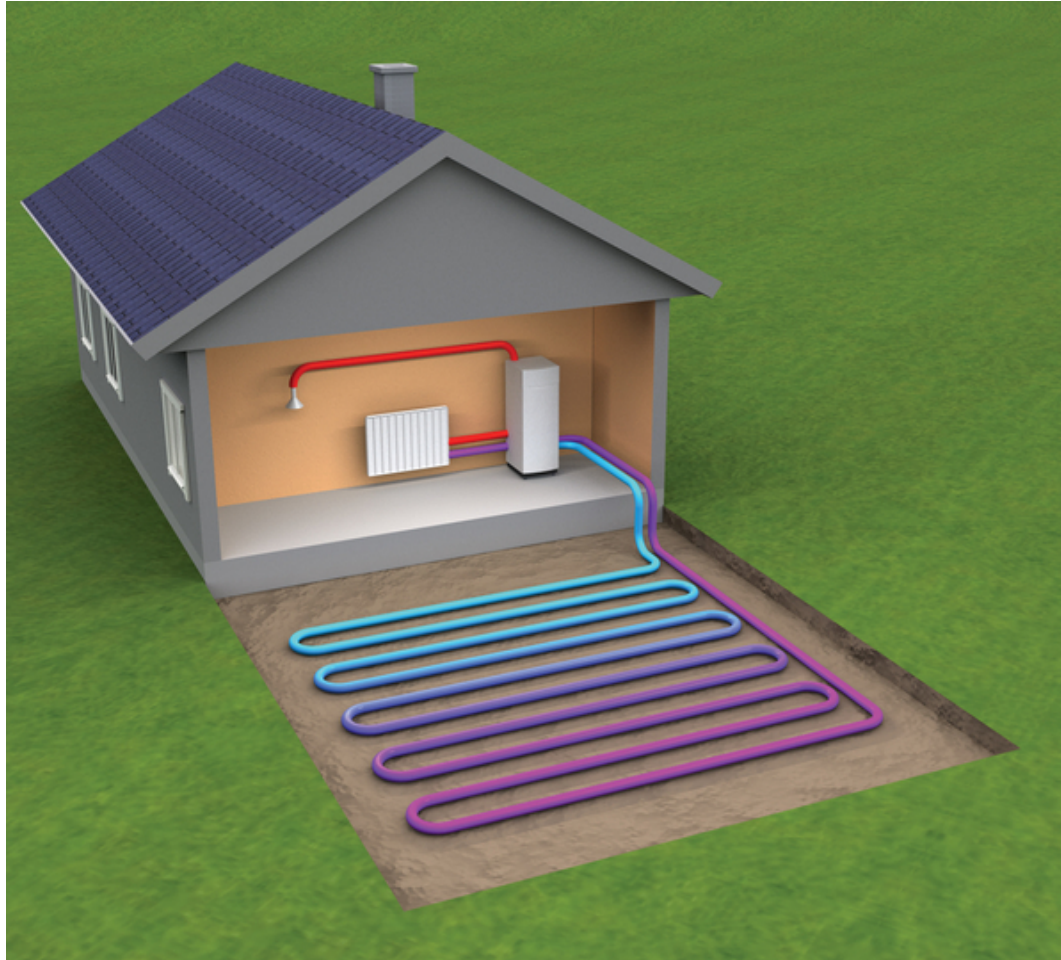
Scientific advances in Economic MPC to enable smart energy homes



Economic MPC for Smart Energy Homes – a number of scientific advances

- Multi-level soft constraints
- Cost-to-go function – value of energy stored at the end of the prediction horizon
- A simple model for simulation, control and optimization of such systems
- Efficient algorithms and computational technologies

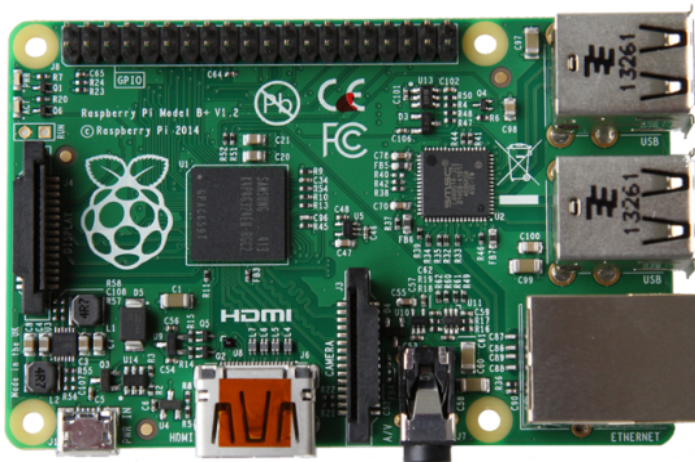
Heat Pumps



Smart Energy Consumption in a Residential Home

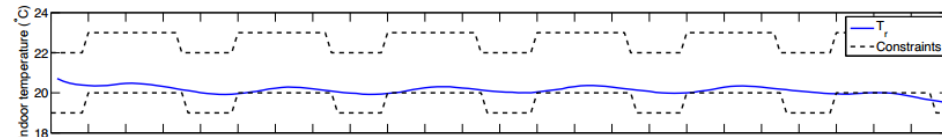
Raspberry Pi Embedded Control

Embedded MPC Algorithms for control of individual energy units



Control from the cloud

The control and forecasting systems are in the cloud.



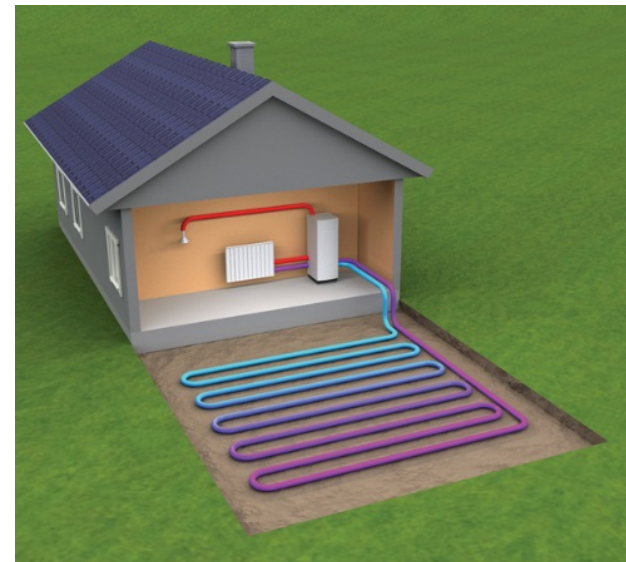
$$\min_{\{u_k, x_{k+1}\}_{k=0}^{N-1}} \phi = \sum_{k=0}^{N-1} l_k(x_k, u_k) + l_N(x_N) \quad (1a)$$

$$s.t. \quad x_{k+1} = A_k x_k + B_k u_k + b_k \quad k \in \mathcal{N} \quad (1b)$$

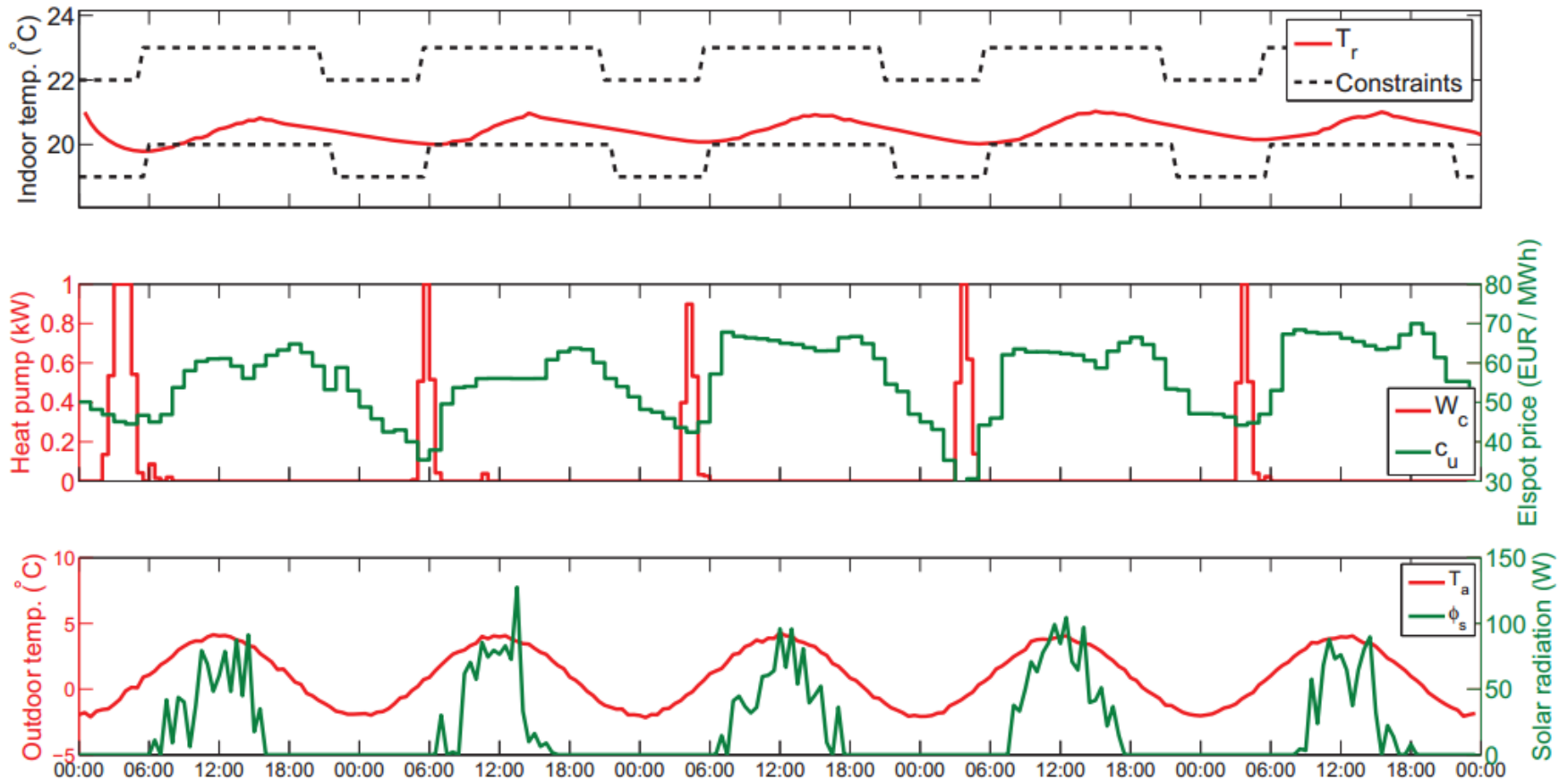
with $\mathcal{N} = \{0, 1, \dots, N-1\}$ and stage costs defined by

$$l_k(x_k, u_k) = \frac{1}{2} \begin{bmatrix} x_k \\ u_k \end{bmatrix}' \begin{bmatrix} Q_k & M_k' \\ M_k & R_k \end{bmatrix} \begin{bmatrix} x_k \\ u_k \end{bmatrix} + \begin{bmatrix} q_k \\ s_k \end{bmatrix}' \begin{bmatrix} x_k \\ u_k \end{bmatrix} + \rho_k \quad (2a)$$

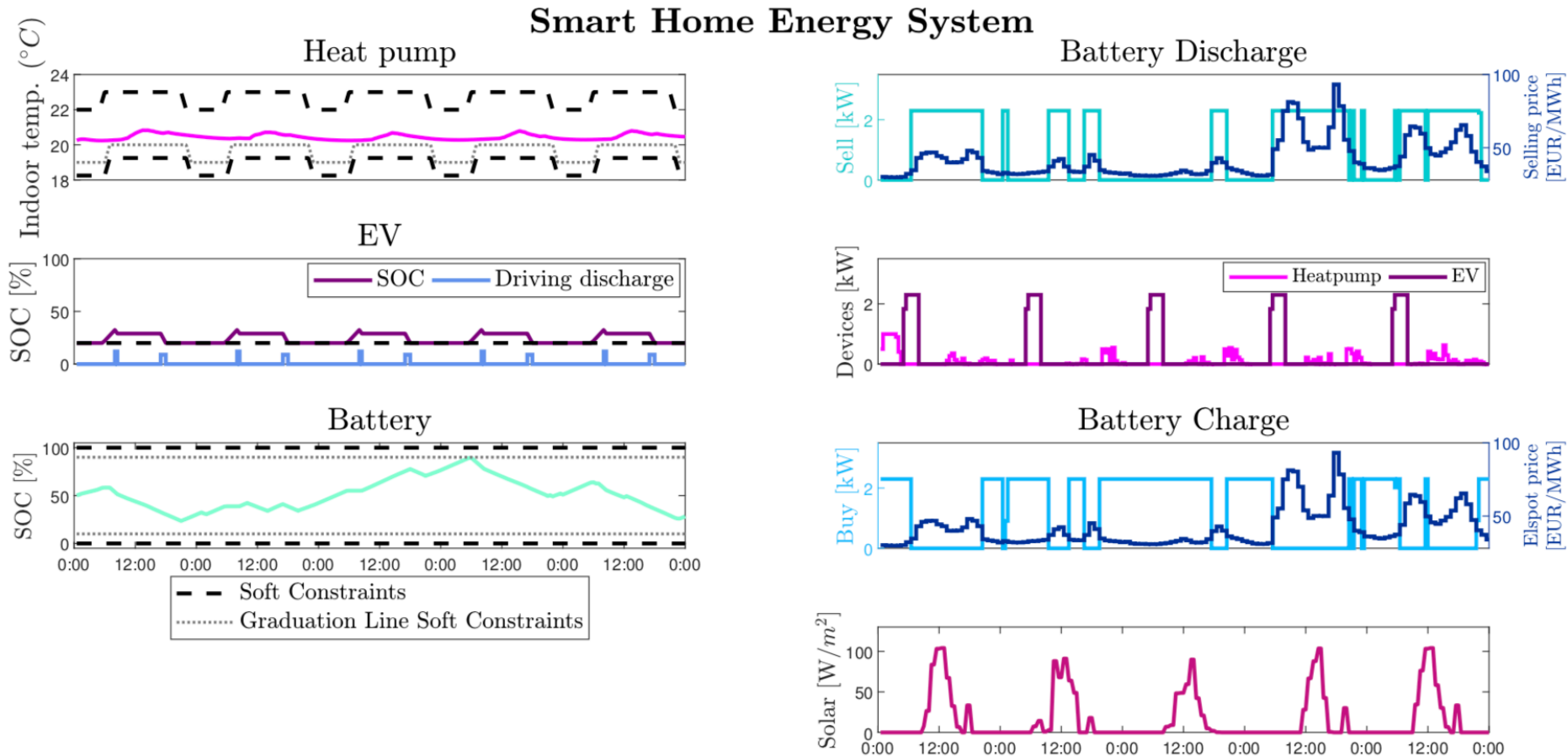
$$l_N(x_N) = \frac{1}{2} x_N' P_N x_N + p_N' x_N + \gamma_N \quad (2b)$$



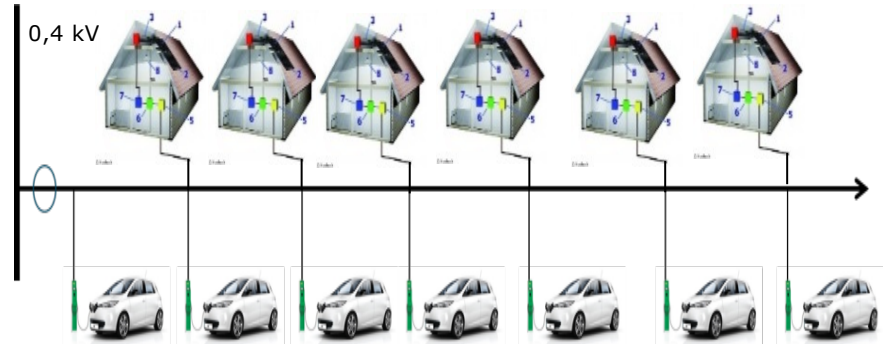
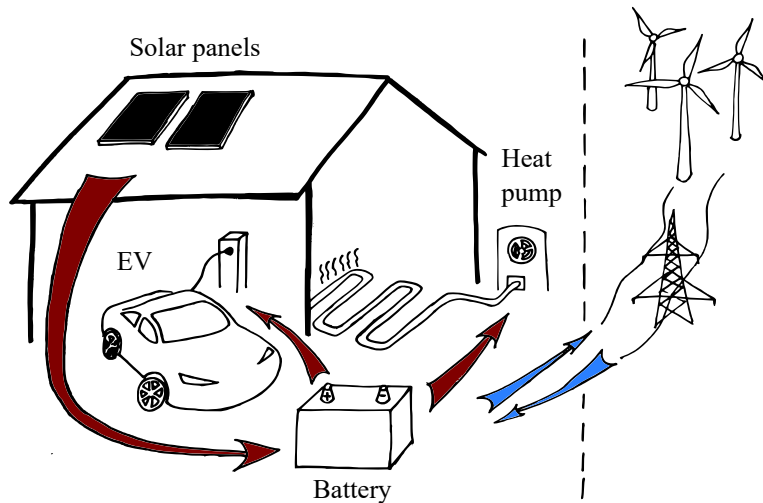
Economic MPC for Building Climate Control



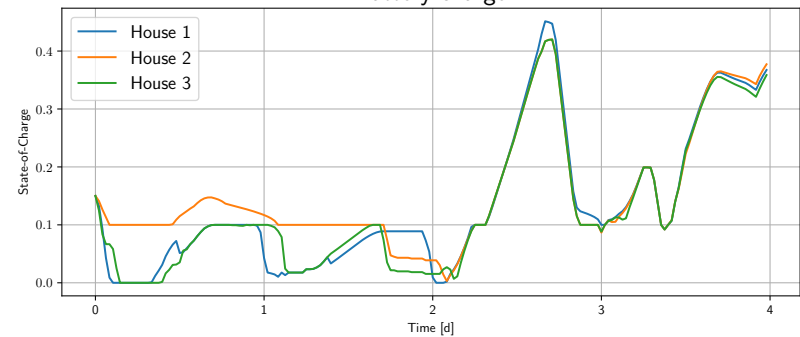
Model Predictive Control for a Smart Energy Home – Simulation Results



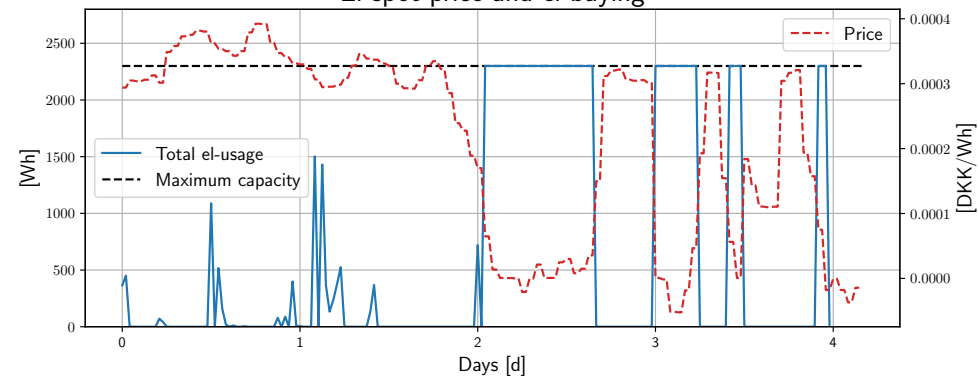
A neighborhood of smart energy homes - Lærkevej



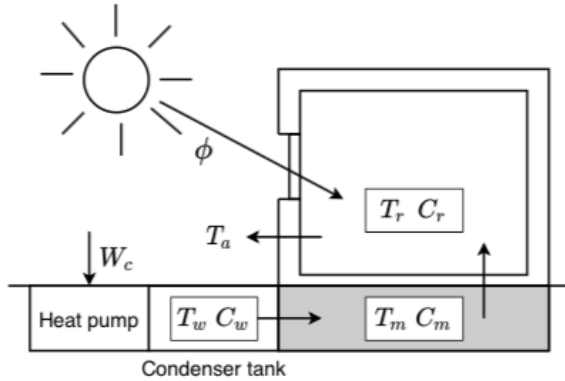
Battery charge



El-spot price and el-buying

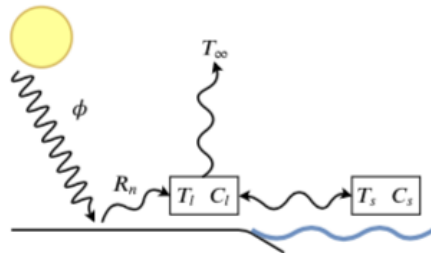
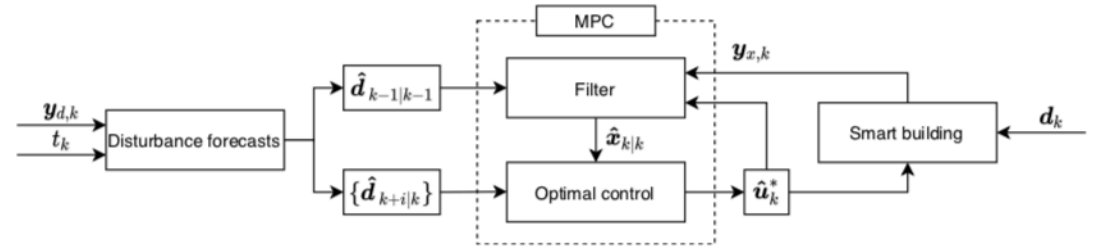


Advanced forecasting and predictive control



$$dx(t) = \underbrace{f(x(t), u(t), d(t), t)dt}_{\text{Drift}} + \underbrace{g(x(t), u(t), d(t), t)d\omega(t)}_{\text{Diffusion}},$$

$$y_k = h(x(t_k)) + v_k, \quad v_k \sim N(0, R_v),$$

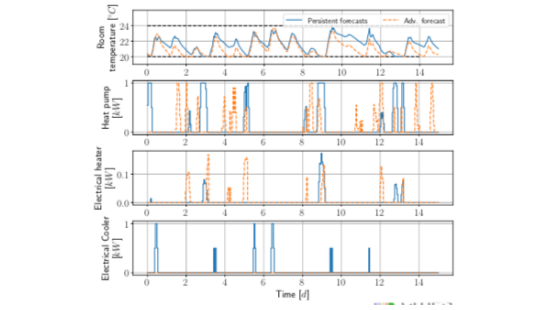
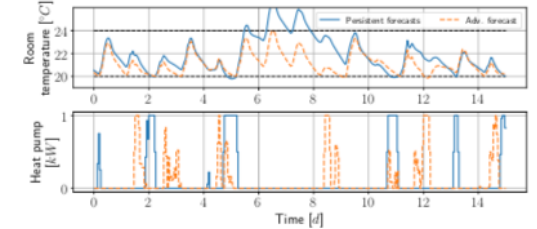
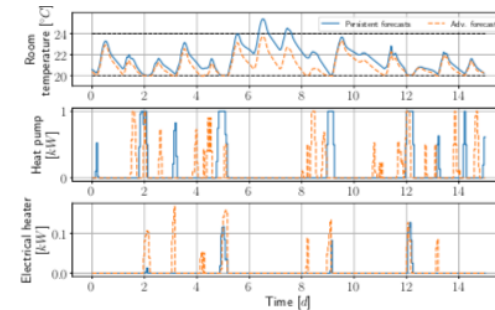
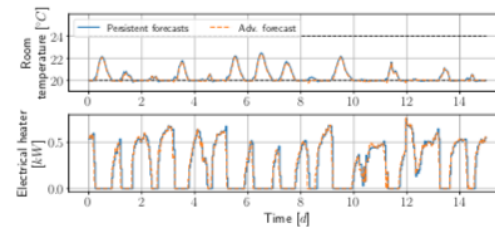


$$C_s dT_s(t) = \left(\frac{1}{R_{sl}} (T_l(t) - T_s(t)) \right) dt + \sigma_s d\omega_s(t),$$

$$C_l dT_l(t) = \left(\frac{1}{R_{sl}} (T_s(t) - T_l(t)) \right)$$

$$+ \frac{1}{R_{l\infty}} (T_\infty - T_l(t)) + R_n(t) \Big) dt + \sigma_l d\omega_l(t),$$

$$dT_a(t_k) = T_l(t_k) + v_{T_a}(t_k),$$



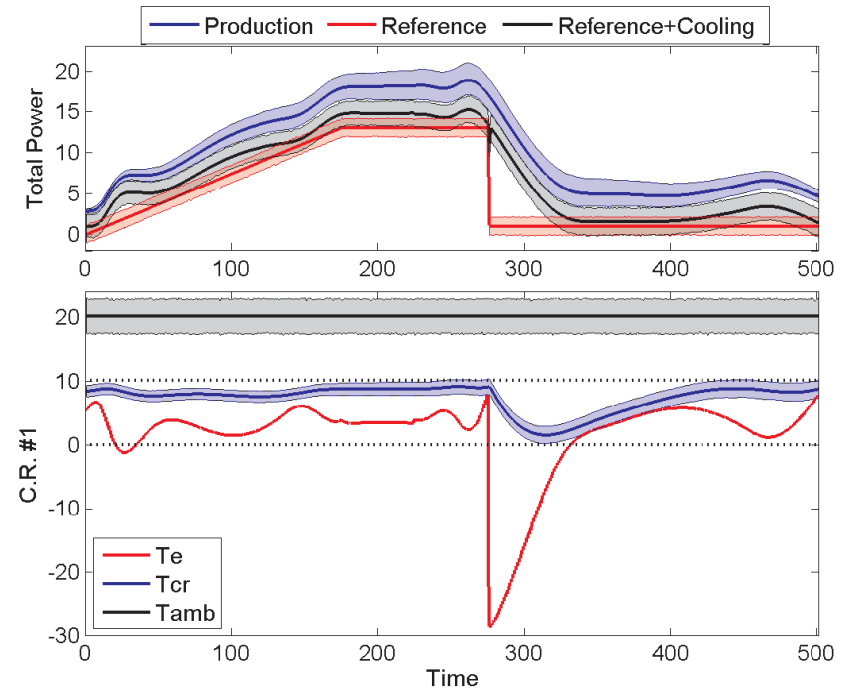
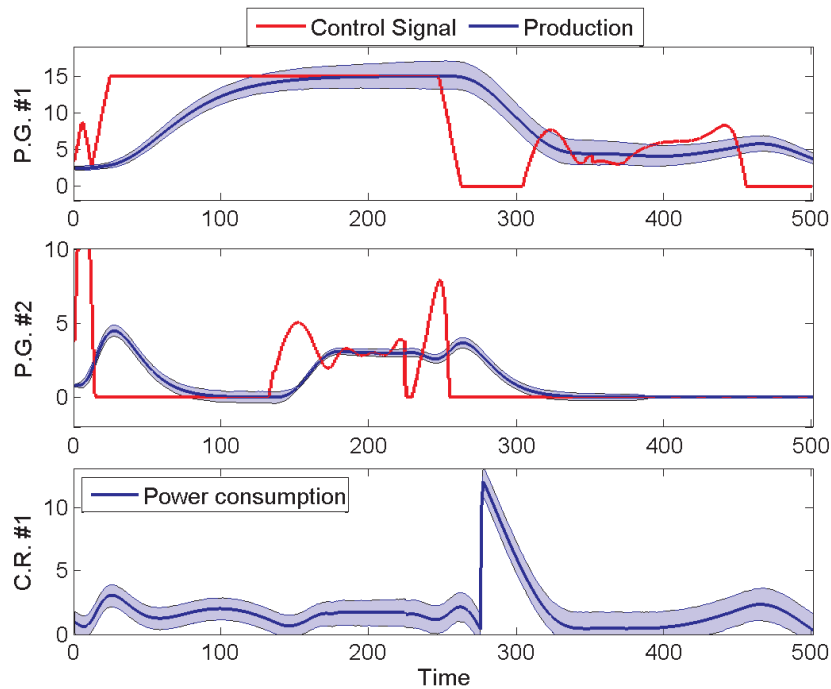
Electricity cost of the simulations

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 violation of the control simulations

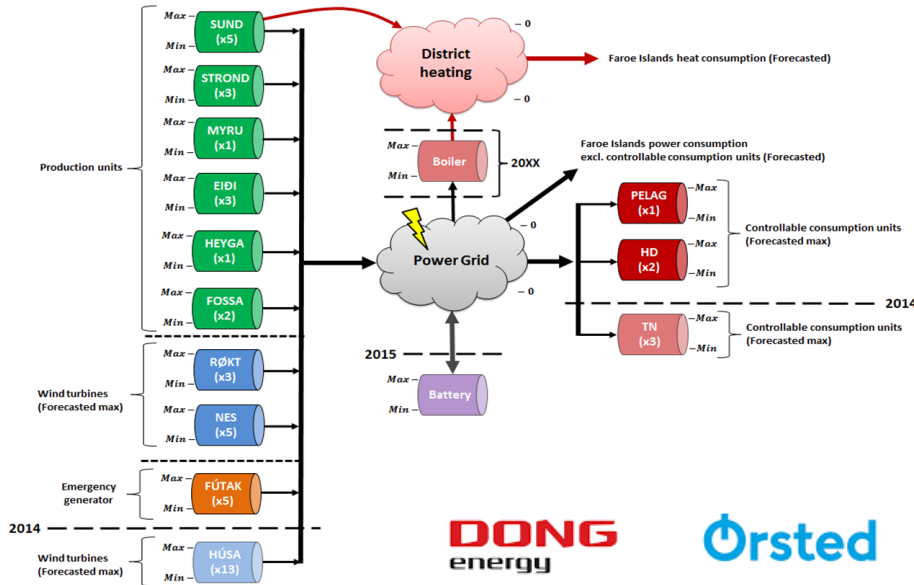
Heating strategy	Persistent	Advanced forecasts	Perfect
Electrical heaters, u_1	48.5	39.6	25.1
Heat pump, u_2	157.9	12.3	1.7
Heat pump plus electrical heaters, u_3	48.0	6.7	1.2
Heat pump plus electrical heaters and coolers, u_4	4.4	2.4	0

Supermarket Refrigeration – Demand Response

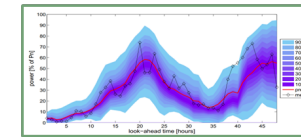




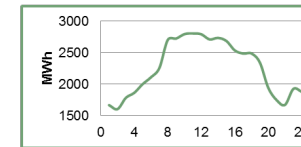
The Faroe Island Power System



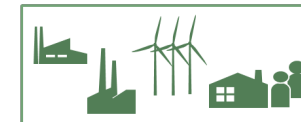
Wind Power Forecast



Consumption Forecast



Unit Specifications



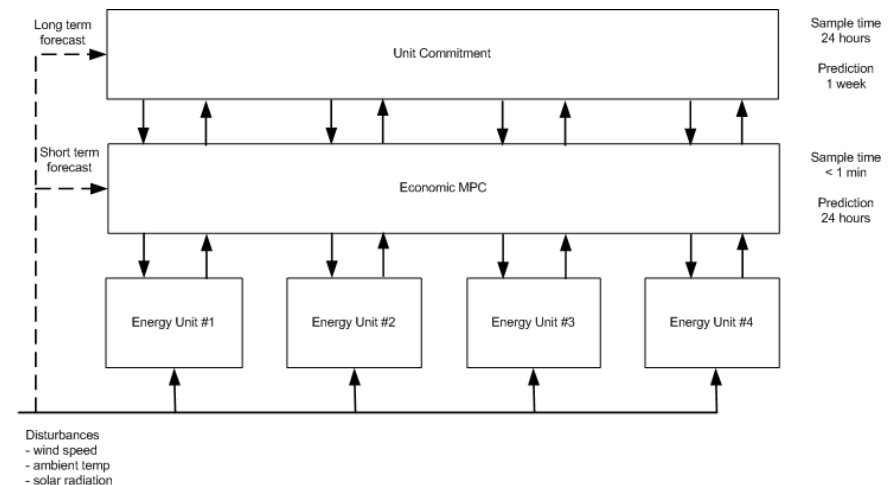
Planning Tool



Plan



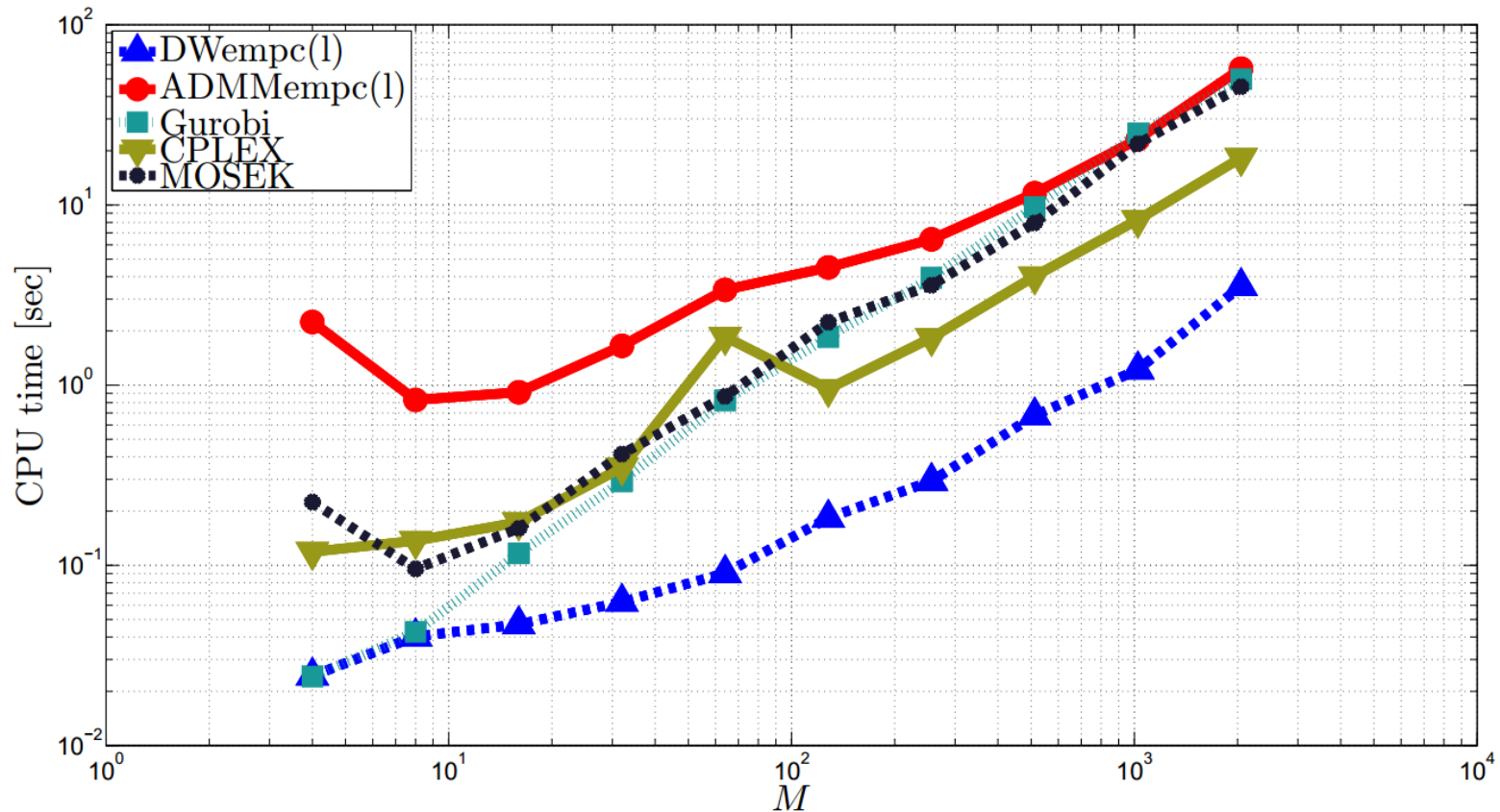
- Controlled the entire Faroe power system for 3 months
- Economic MPC system developed by Orsted (Dong Energy) and DTU Compute as part of an industrial PhD project



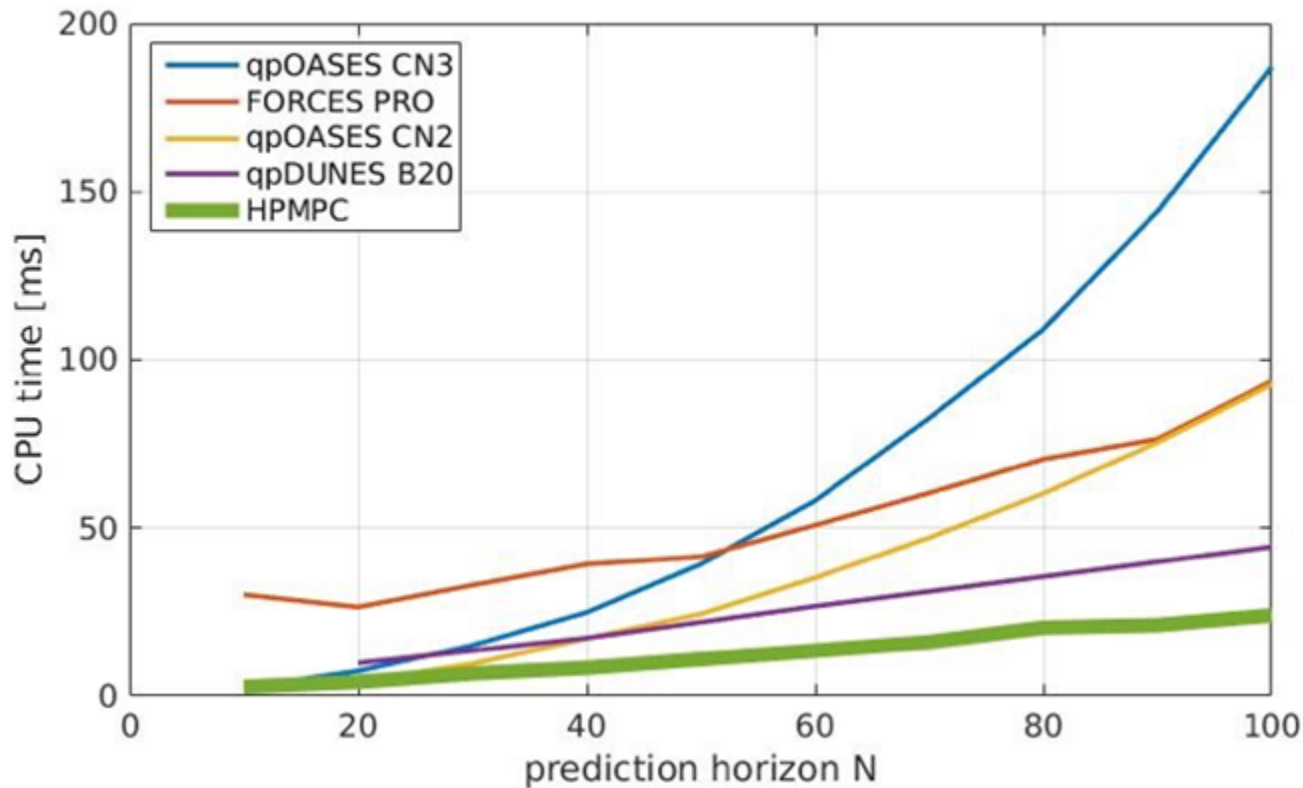
Fast Solver for Direct Control of an Entire City

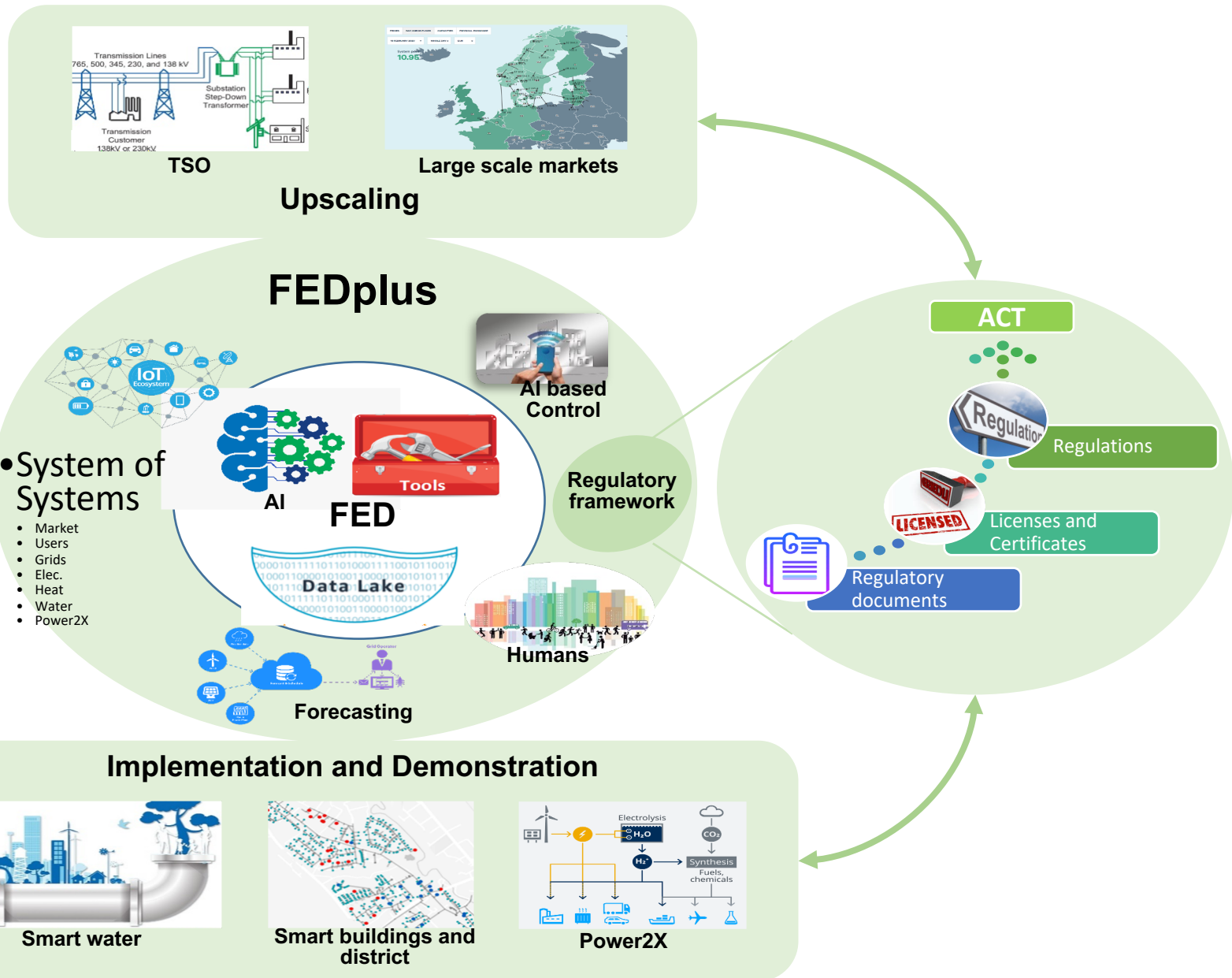
A Dantzig-Wolfe Decomposition Algorithm for
Linear Economic Model Predictive Control of Dynamically Decoupled Subsystems

L.E. Sokoler^{a,b}, L. Standardi^a, K. Edlund^b, N.K. Poulsen^a, H. Madsen^a, J.B. Jørgensen^{a,a}

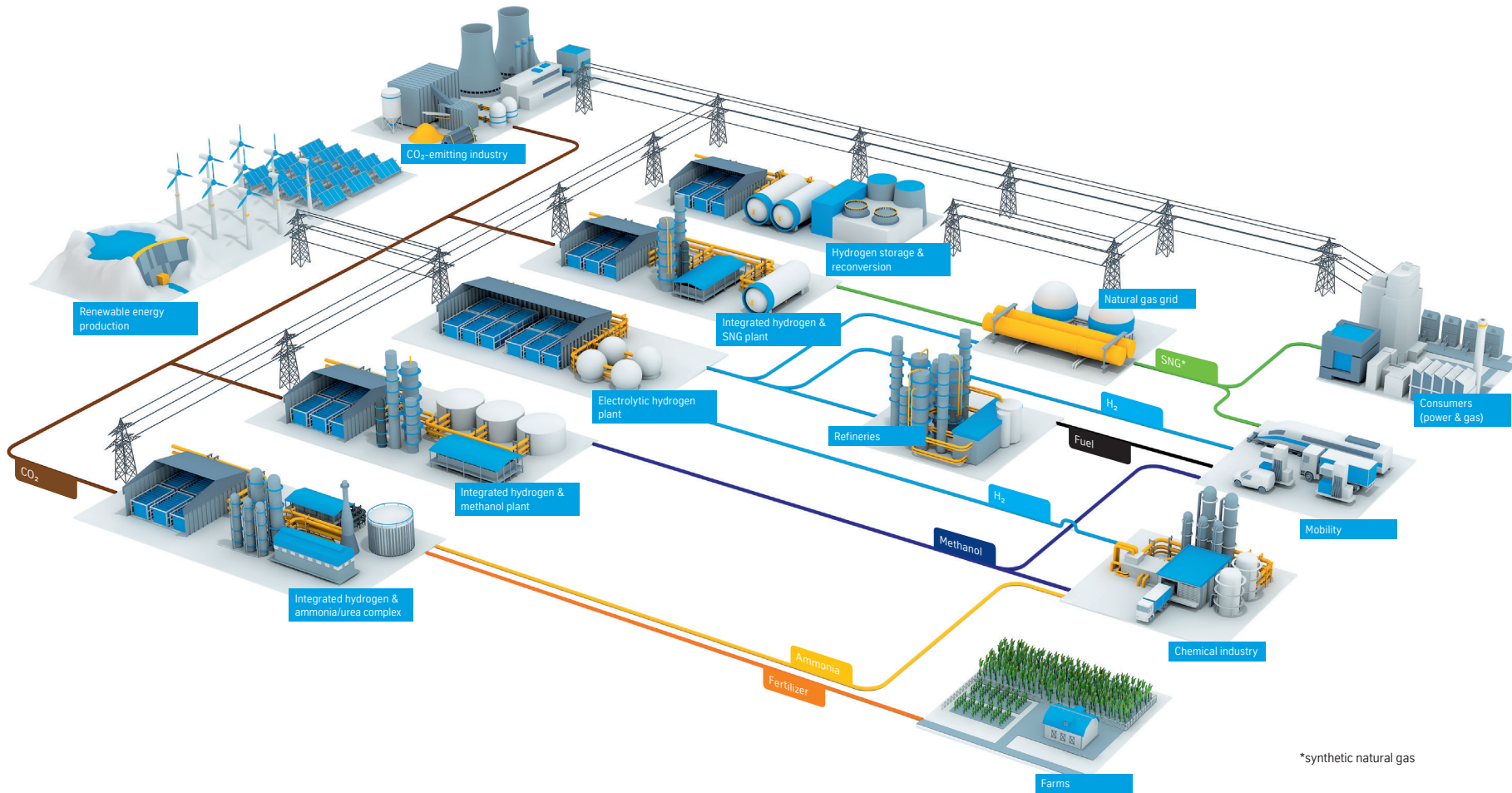


Fast Algorithms for Model Predictive Control - enable new applications

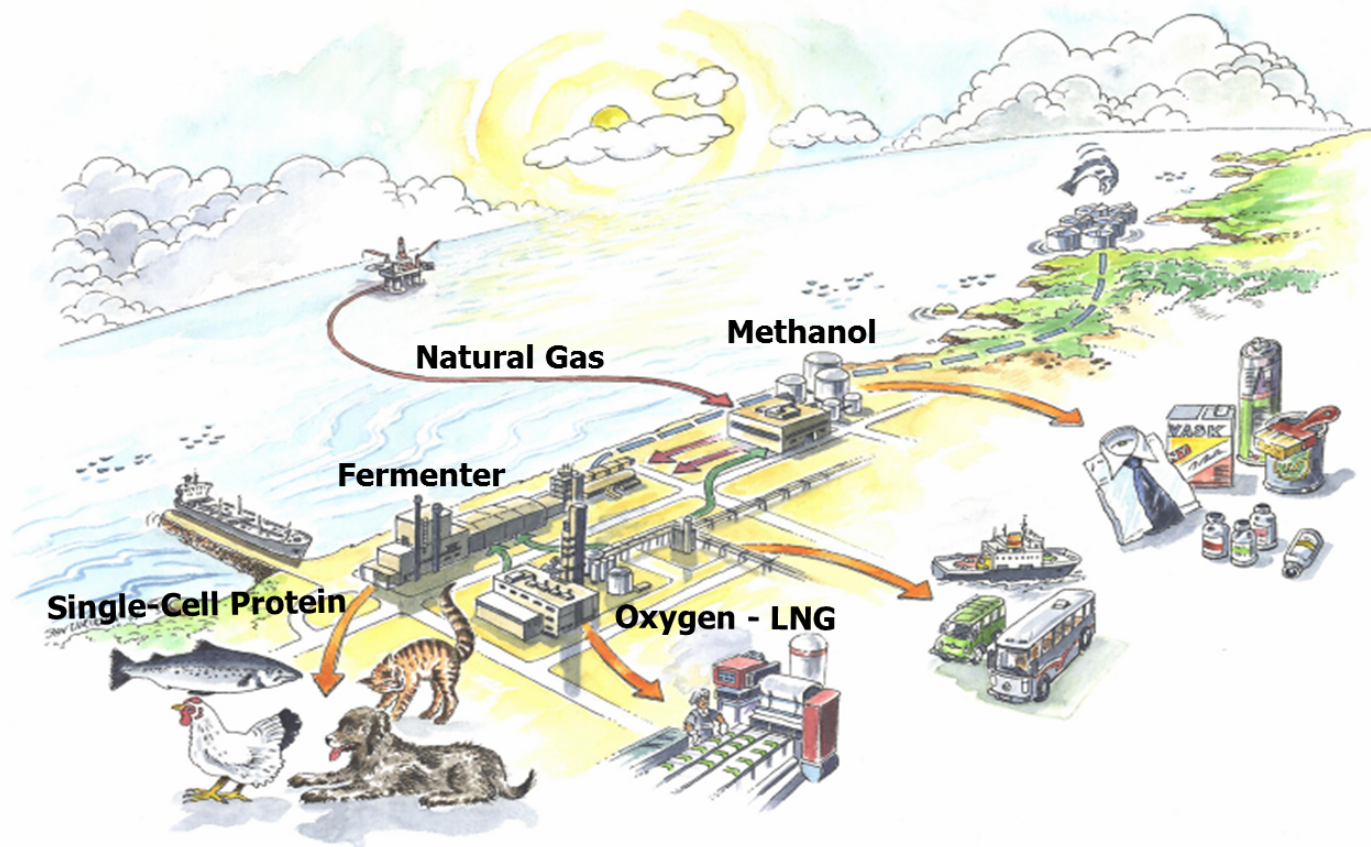




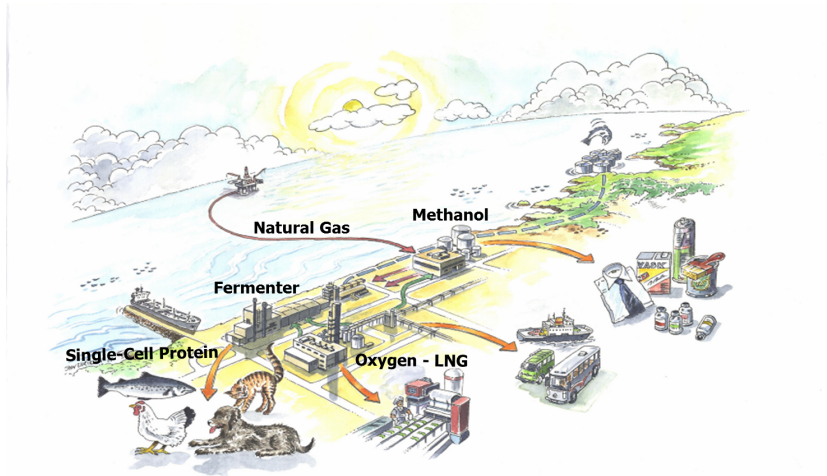
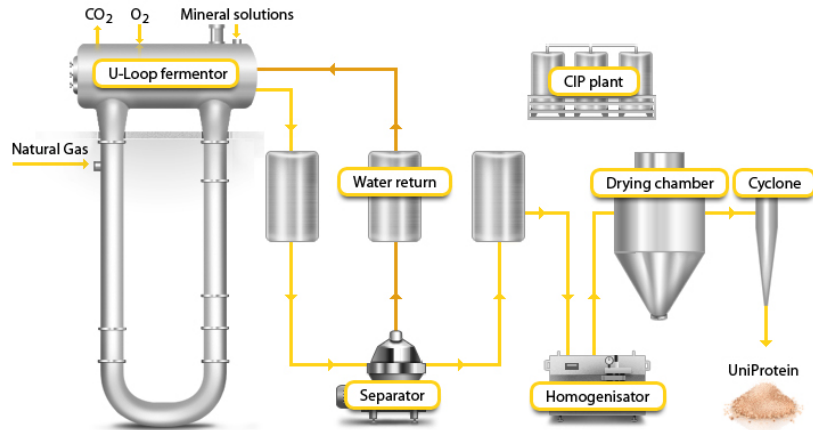
Power-2-X



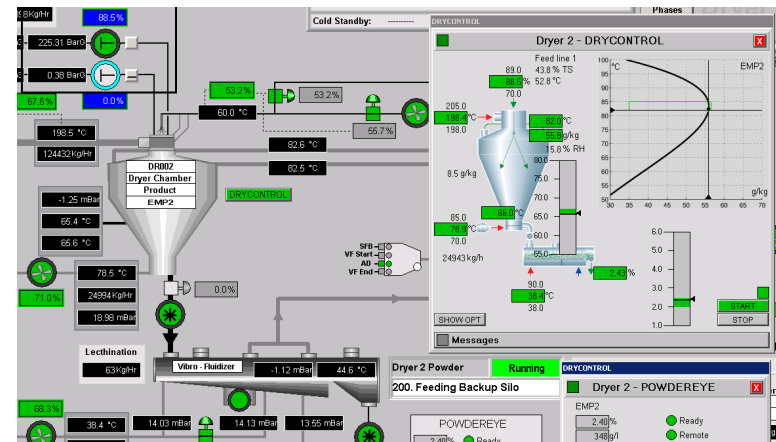
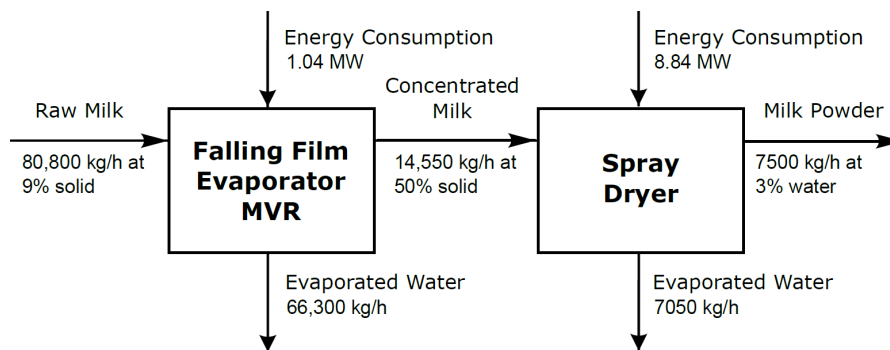
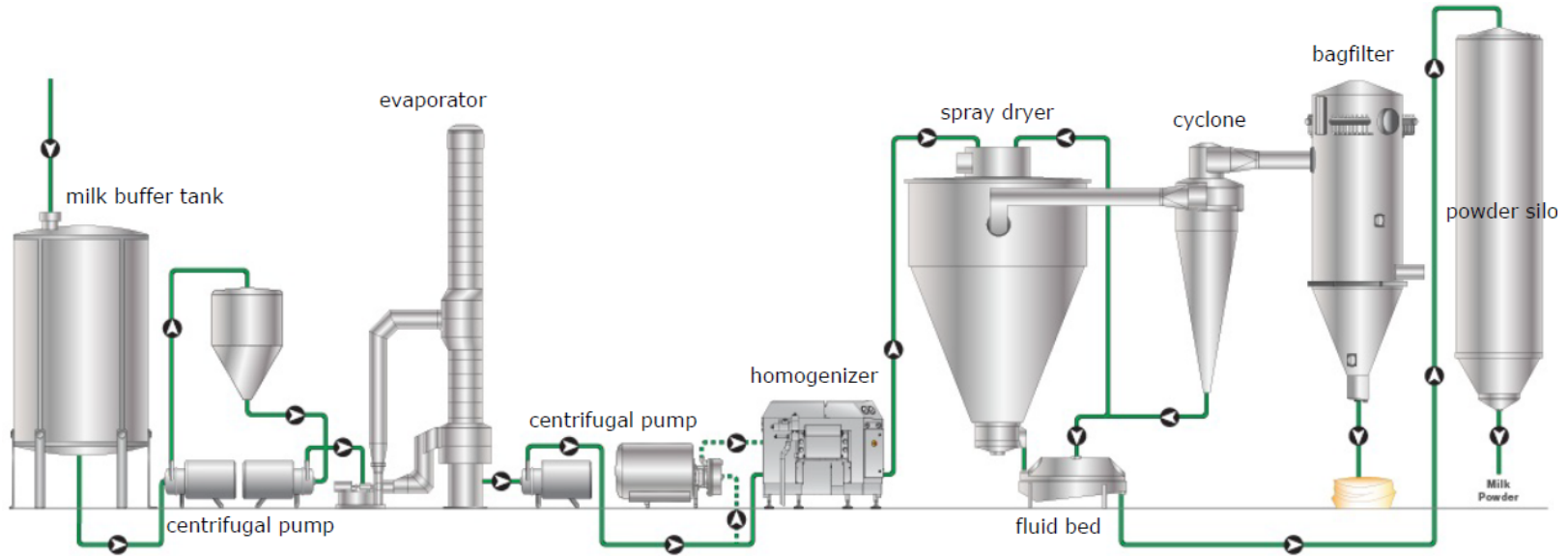
Proteins from methane - natural gas, biogas, SNG



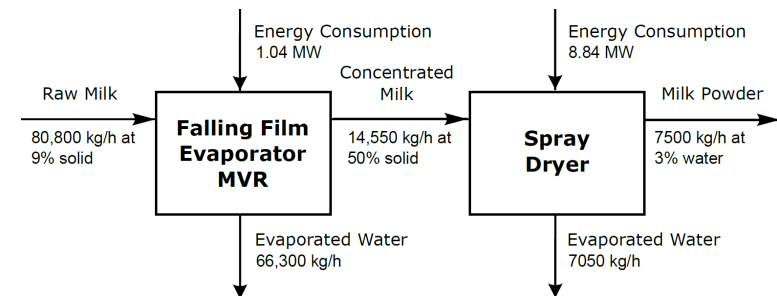
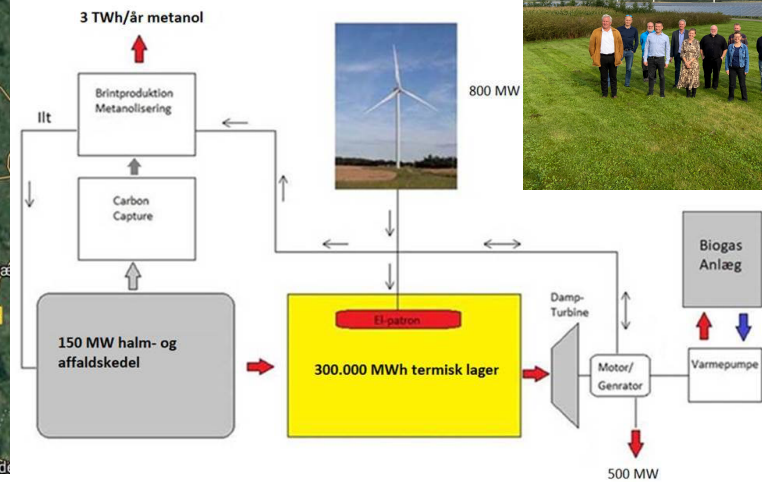
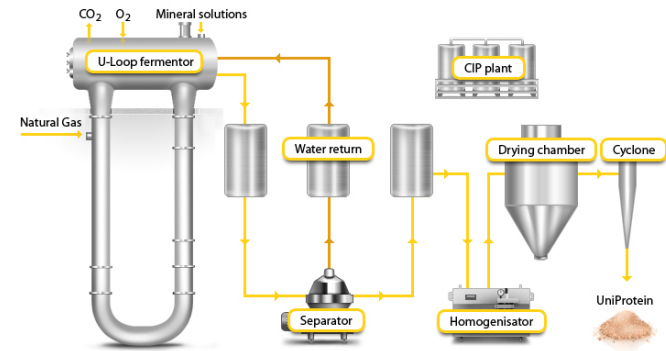
Single-Cell Protein – Unibio A/S



Milk Powder Plant – GEA Process Engineering A/S

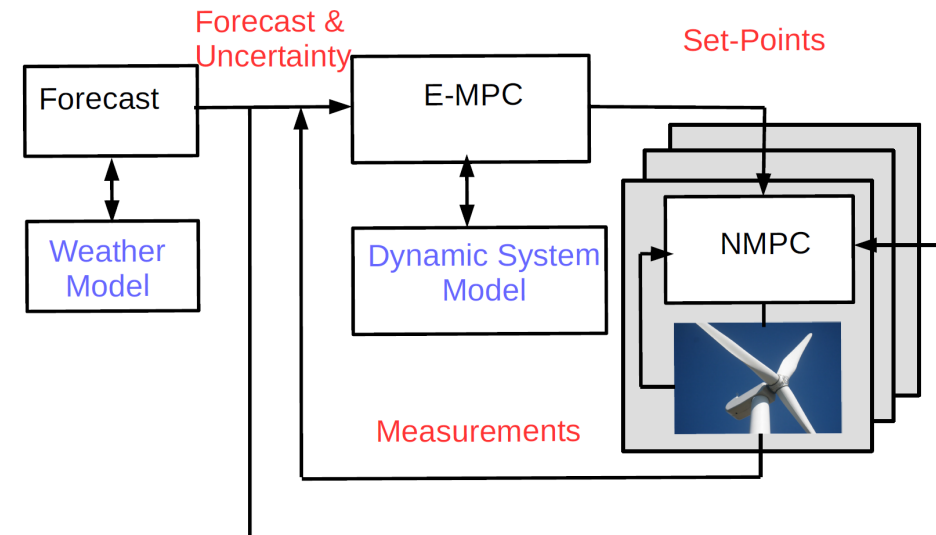
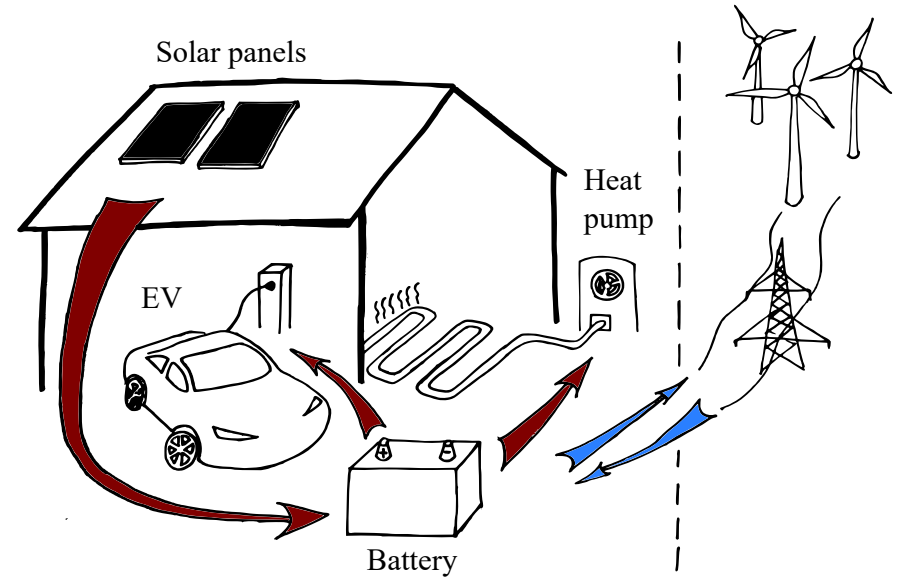


DTU Power-2-X – Local vision Ringkøbing-Skjern



Summary

- **Key MPC technology developments**
 - MPC based on stochastic differential equations (SDEs)
 - Algorithmic – speed, robustness, embedded, cloud
 - Integrated Forecasting and Control
 - Integrated system identification
- **Industrial energy related processes**
 - Cement processes (FLS)
 - Food processes (GEA)
 - Single-cell protein production (Unibio)
 - Carbon capture (DTU Chem. Eng)
- **Energy Processes**
 - Energy system control (Orsted)
 - Wind turbine control (Vestas)
 - Refrigeration and heating systems (Danfoss)
- **MPC technology is mature and ready** to be implemented on large scale for buildings to enable smart cities and smart energy homes.
- **MPC technology is the key enabler** for integrated and coordinated systems.
Implemented in many systems already to enable coordinated and efficient operation





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DTU Compute

Department of Applied Mathematics and Computer Science

