Model Predictive Control in connection with district heating networks

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Outline

Introduction

Who am I (mostly working with) I

... I am

- A PhD student at the Technical University of Denmark

... mostly working with

- Distributed Energy Resources (*DERs*) in Microgrid operation

Why Model Predictive Control (*MPC*) for District Heating Systems? I

Deferral of investments in additional infrastructure

Use installed system in a more efficient way

Sector coupling

Exploit additional degrees of freedom

→ In which situations can we benefit from using MPC approaches most?

Interleaved systems: Degrees of freedom in the control decisions

DER's in District Heating Systems: Solar Heating Injection station example I

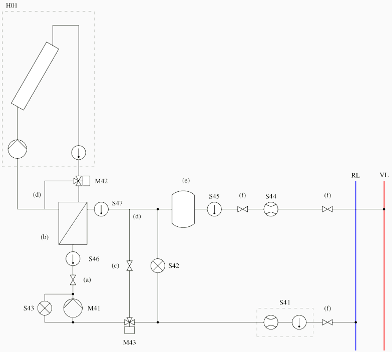
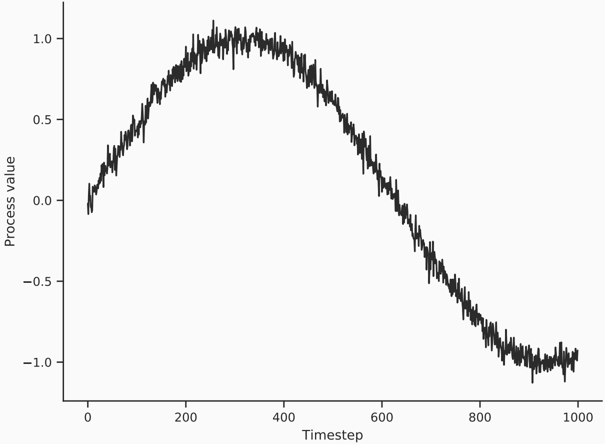


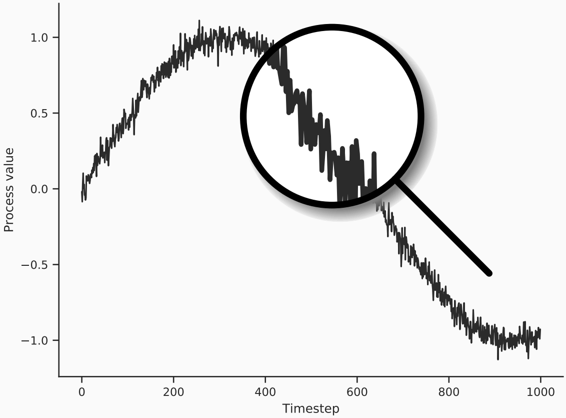
Figure 1: Solar heat injection station example.

Control hierarchy aspects with MPC

A random process.. I



A random process.. II



A random process.. III

A quote:

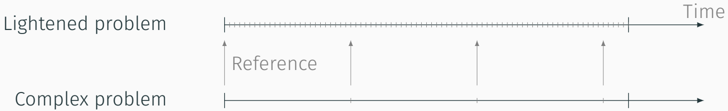
> *Sometimes, the best (control) decision is to do nothing*

(Source: Unknown Professor)

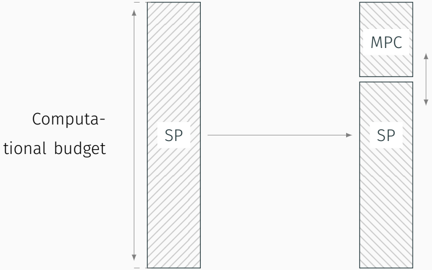
$\rightarrow$ *Sometimes the best control decision is to do it differently*

Why not split the control problem? An improvement... I

Real–time problem splitting: Optimized real–time controls



Dynamic resource allocation given system condition I

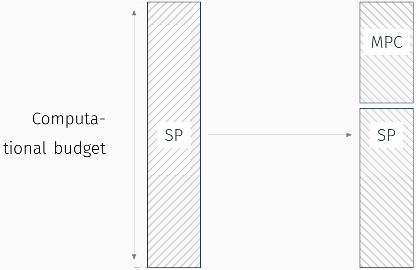


Disturbance compensation at real–time:

- Physical system
- sub–optimal controls

- Physical system
- optimal controls
- sub–optimal controls

Dynamic resource allocation given system condition I



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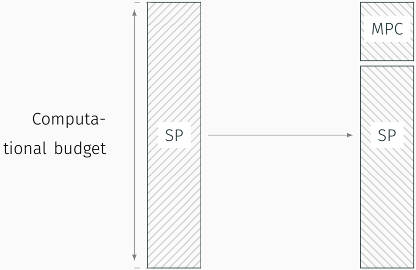
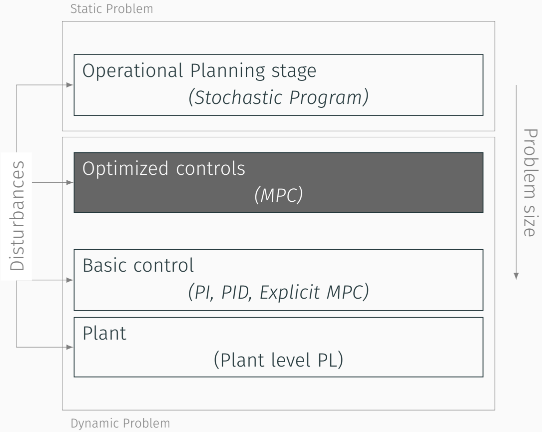


Disturbance compensation at real–time:

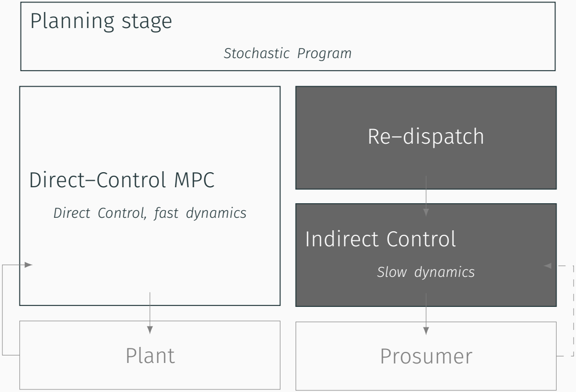
- Physical system
- sub–optimal controls

- Physical system
- optimal controls
- sub–optimal controls

Control hierarchy example: Lumped controls I



Control hierarchy example: Separated treatment of Indirect Controls I



Model Predictive Control in heating systems

Master–Slave controls I

The master problem

$$\dot{Q}^\star = c_p \dot{m}^\star \Delta\vartheta^\star \tag{1}$$

$\rightarrow$ can be determined by the planning stage

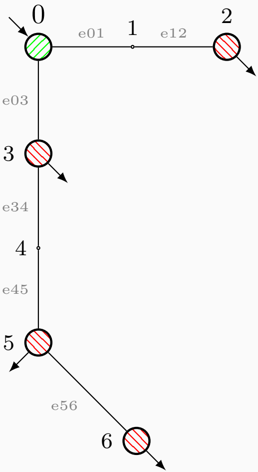
The slave problem

Determine $\vartheta^\star$ at controlled sub–stations:

- Directly controlled units
- Indirectly controlled units

$\rightarrow$ real–time collaborative MPC system support

A regulation example (Single actor) I



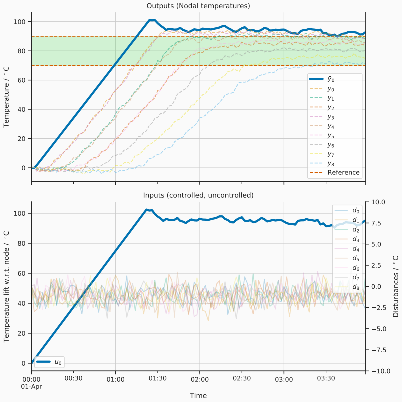


Figure 2: Single actor example.

A regulation example (Single actor) III

Bottlenecks: Sufficient influx temperature levels

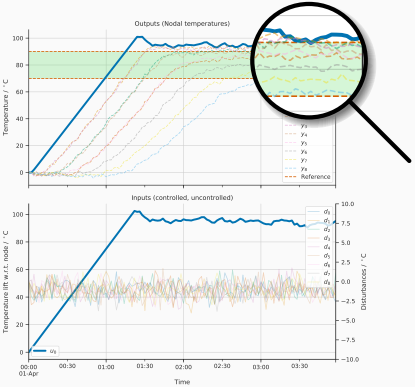
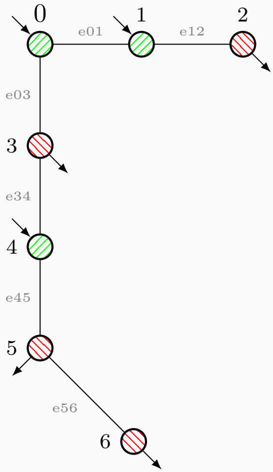


Figure 3: Bottleneck with respect to magnitude (line losses).

Collaborative MPC particularities I



Collaborative MPC particularities II

- System dynamics magnitudes highly matter for the controller performance
  - A homogeneous system is easier to control using MPC
- System gains should be normalized

Collaborative MPC particularities I

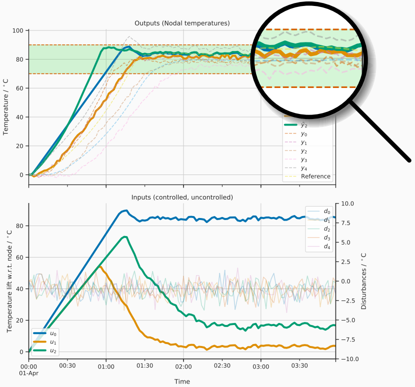


Figure 4: Improvement in the goal temperatures.

Example without predictions I

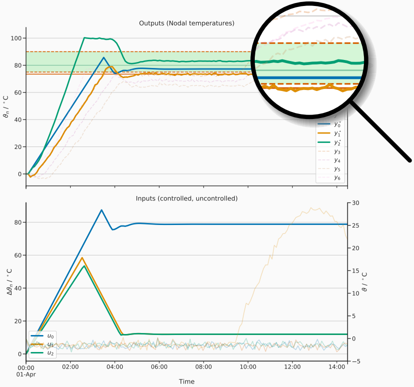


Figure 5: Improvement in the goal temperatures.

Example with predictions I

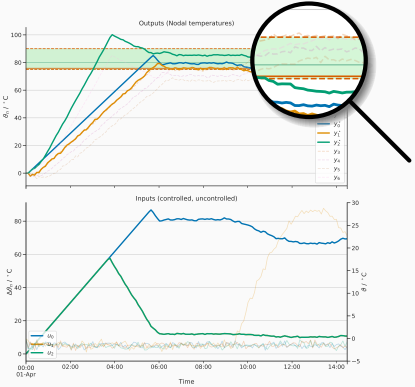


Figure 6: Improvement in the goal temperatures.

MPC formulations I

Classical regularized MPC

$$
\begin{aligned}
\min_{u} \quad & J = ||Y - R||_Q^2 + ||u||_R^2 & \text{(2a)} \\
\text{s.t.} \quad & x_{t+1} = Ax_t + Bu_t + Gd_t + w_t & \text{(2b)} \\
& y_t = Cx_t & \text{(2c)} \\
& G_t u_t \leq h_t & \text{(2d)}
\end{aligned}
$$

Tracking variation

$$\min_{u} \quad J = ||Y - R||_Q^2 + ||u - \bar{u}||_R^2 \tag{3a}$$

$$\text{s.t.} \quad x_{t+1} = Ax_t + Bu_t + Gd_t + w_t \tag{3b}$$

$$y_t = Cx_t \tag{3c}$$

$$G_t u_t \leq h_t \tag{3d}$$

Temporal clustering and online system identification I

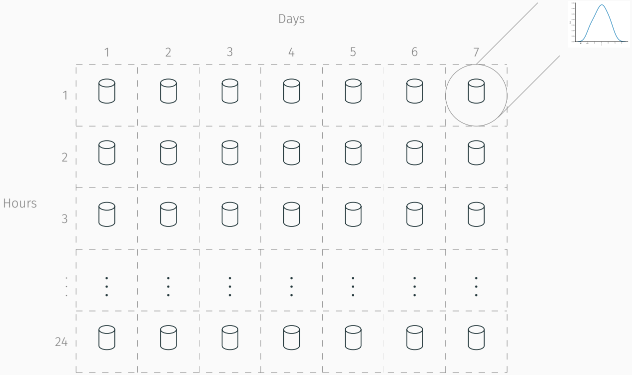


Figure 7: Topological toy model.

Summary I

- Co–optimizing ’certain’ and uncertain units as a collaborative MPC
- Tracking of trajectories determined by either planning or re–dispatch stage
    - Economically optimal
    - Risk optimal (Robust)
    - Trade-off trajectories

Thank you for your attention I

Thank you

Appendix

References

Gabriele Pannocchia and James B. Rawlings. "Disturbance Models for Offset-Free Model-Predictive Control". In: *AIChE journal* 49.2 (2003), pp. 426–437.

Gabriele Pannocchia and James B. Rawlings. "Robustness of MPC and Disturbance Models for Multivariable Ill-Conditioned Processes". In: *TWMCC, Texas-Wisconsin Modeling and Control Consortium* (2001).

Objective function I

Stabilization problem **T1**

$$J_{\infty,k} = ||\Phi_x(\hat{x}_k - x_{\infty,k}) + \Gamma_u(u_k - u_{\infty,k})||^2 \tag{4}$$

Dynamic Programming problem **T2**

$$J_{\text{DO},k} = ||u_k - u^{\star}_{k-1} + \gamma W_{\Delta u} \Delta u_k||^2 \tag{5}$$

Portfolio constitution **T3**

$$J_{\text{C},k} = (1 - \gamma)\Pi_k \tag{6}$$

Objective function: Overview I

$$\min_{u,k} \quad J_{\infty,k} + J_{\mathrm{DO},k} + J_{\mathrm{C},k} \tag{7}$$

$$\text{s.t.} \quad G_k u_k \leq h_k \tag{8}$$

(T1) Residual estimation I

Inferring input disturbance[1]

$$\begin{bmatrix} \hat{x}_{k+1|k} \\ \hat{d}_{k+1|k} \end{bmatrix} = \begin{bmatrix} A & B_d \\ 0 & I \end{bmatrix} \begin{bmatrix} \hat{x}_{k|k-1} \\ \hat{d}_{k|k-1} \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u_k + \begin{bmatrix} L_1 \\ L_2 \end{bmatrix} \left(y_{m,k} - C\hat{x}_{k|k-1} - C_d \hat{d}_{k|k-1} \right) \quad (9)$$

[1] We optimize over deviations encompassing the positive and negative domain → Only first optimal input required satisfactory, imposing these constraints for the whole sequence $u_{k+N-1|k}$ results in numerical issues.

(T1) Stabilizing gain I

Solving for g_∞[2] using least-squares approximation:

$$\underbrace{\begin{bmatrix} A - I & B \\ C & 0 \end{bmatrix}}^{M} \underbrace{\begin{bmatrix} g_{x,\infty} \\ g_{u,\infty} \end{bmatrix}}^{g_\infty} = \begin{bmatrix} B_d \\ 0 \end{bmatrix} \tag{10}$$

$$g_\infty \approx \begin{bmatrix} B_d \\ 0 \end{bmatrix} M^{-1} \tag{11}$$

[2]See Pannocchia and Rawlings 2003; Pannocchia and Rawlings 2001

(T1) Equilibrium point I

$$\begin{bmatrix} x_\infty \\ u_\infty \end{bmatrix} = g_\infty \hat{d} \tag{12}$$

(T2) Dynamic programming terms I

Ensure offset-free control
$\rightarrow$ Even when constraints are active on parts of the portfolio

(T3) Portfolio constitution I

$$
\begin{aligned}
\Pi_k = \alpha ||u_k - u_{\text{EMS},k}||^2_{W_{\Delta u}} + \\
\beta(\ ||\tilde{c}_k u_k||^2 + ||\tilde{c}_{\Delta,k}(u_k - u_{\text{EMS},k})||^2_{W_{\Delta u}}\ ) \\
\text{where:} \quad \alpha + \beta = 1
\end{aligned} \tag{13}
$$

Constraints I

General

Dynamic reformulation via supervisory system: considering additional system knowledge

$$G_k u_k \leq h_k \tag{14}$$

Particularity: Ramp rate

Only the first optimal input in the sequence required binding[1]

$$\Delta u_{\min} \leq u^{\star}_{k+1|k} - u^{\star}_{k|k} \leq \Delta u_{\max} \tag{15}$$