An introduction to Model Predictive Control (MPC) for energy systems operation

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Overview

- **Model Predictive Control**
  - General concept, advantages, and challenges
  - Advantages for energy system operation
- **Problem formulations and classes**
  - Formulation and solution of optimal control problems
  - Modeling and complexity
- **Software and methods**
  - Software frameworks and numerical solvers
- **Illustrative example of MPC performance**
  - One-year simulation study for a building energy system

- **General concept of Model Predictive Control (MPC)**
  - MPC describes a set of control methods that make explicit use of models for control of a system
  - MPC computes a sequence of control signals that are optimal for control of a system for a defined objective and time horizon
  - MPC is able to consider system dynamics, possible constraints for states and controls, and the current state of the system

  - Various fields of applications, from mechanical system to process control, and (of course) for energy system operation

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- **Advantages of MPC**
  - Suitable for systems with multiple inputs and outputs
  - Intrinsic compensation of dead times
  - Explicit consideration of constraints of states and controls
  - Can consider future system behavior, as well as current and future references and disturbances in current control decisions
- **Challenges of MPC**
  - Application of MPC requires prior formulation of an Optimal Control Problem (OCP) that describes system dynamics, relevant constraints and bounds sufficiently
  - MPC (typically) requires solution of this OCP within real-time suitable time scales for the considered system

Model predictive control III

- **Advantages of MPC for energy system operation**
  - Forecasts for availability and demand of thermal and electrical energy can be directly included in predictive control decisions
  - Thermal and electric storages can be used systematically for bridging times of low energy availability and load shifting
  - Situational and individual control decisions for utilization of components and machinery can be made

  - Availability of computation time for energy systems (at least for thermal systems) is rather high

- **Formulation of Optimal Control Problems (OCPs)**

$$\underset{x(\cdot),u(\cdot)}{\text{minimize}} \quad \int_{t_0}^{t_f} L\big(x(t), u(t)\big)\, \mathrm{d}t + M\big(x(t_f)\big) \tag{1a}$$

$$\text{subject to} \quad \text{for } t \in [t_0, t_f]:$$

$$\dot{x}(t) = f\big(x(t), u(t), c(t)\big) \tag{1b}$$

$$0 \leq h\big(x(t), u(t), c(t)\big) \tag{1c}$$

$$0 \leq r\big(x(t_f)\big) \tag{1d}$$

$$\vec{x}(t_0) = \vec{x}_0, \tag{1e}$$

$$\vec{x}(t) \in \mathcal{X}, \quad \vec{u}(t) \in \mathcal{U}. \tag{1f}$$

$\rightarrow$ OCP needs to be solved within real-time suitable time scales

- **Solution of optimal control problems**
  - For numerical solution, OCP needs to be discretized, for which different families of methods exist:
    - Hamilton-Jacobi-Bellmann equations
    - indirect methods (first optimize, then discretize)
    - direct methods (first discretize, then optimize)
  - For larger system of practical relevance, direct methods, especially *direct multiple shooting* and *direct collocation*, are favorable
  - Depending on the characteristics of the OCP, this yields optimization problems of different complexity

- **Linear vs. nonlinear problem formulations**
  - Linear modeling as in, e. g.,

$$\dot{x}(t) = Ax(t) + Bu(t) \tag{2}$$

    allows for linear optimization problems, which yields the possibility for global optimal and typically faster solutions of the problem

  - Nonlinear modeling as in, e. g.,

$$\dot{x}(t) = f\left(x(t), u(t)\right) \tag{3}$$

    can yield improved system descriptions, however, possibly at the cost of global optimality and increased solution times of nonlinear optimization problems

Problem formulation and classes IV

- **Continuous vs. discrete states and controls**
  - OCPs containing purely continuous states and controls as in, e. g.,

    $$x(t) \in \mathbb{R}^{n_x}, \; u(t) \in \mathbb{R}^{n_u}, \tag{4}$$

    results in continuous optimization problems that can be solved rather efficiently

  - OCPs where some or all states and controls only take discrete values as in, e. g.,

    $$u(t) = \begin{pmatrix} u_{\mathrm{c}}(t) \\ u_{\mathrm{d}}(t) \end{pmatrix}, \; u(t) \in \mathbb{R}^{n_{u_{\mathrm{c}}}}, u(t) \in \mathbb{Z}^{n_{u_{\mathrm{d}}}} \tag{5}$$

    result in mixed-integer optimization problems that are typically harder to solve

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- **Software frameworks and numerical solvers**
  - A wide variety of software frameworks and numerical solvers exist, whose suitability and applicability depends various factors, such as:
    - problem class (linear, nonlinear, mixed-integer, ...)
    - structure of the optimization problem (dense, sparse, ...)
    - available computation time (microseconds, seconds, minutes, ...)
    - computation platform (PLC, microcrontroller, PC, ...)
  - One framework we often use: **CasADi**
    - Open-source dynamic optimization framework for discretization of OCPs and implementation of the resulting optimization problems
    - Interfaces to several simulation and optimization routines
    - Automatic generation of derivatives using Algorithmic Differentiation (AD)
    - Many useful features, such as C-Code generation and automatic setup of Spline interpolations

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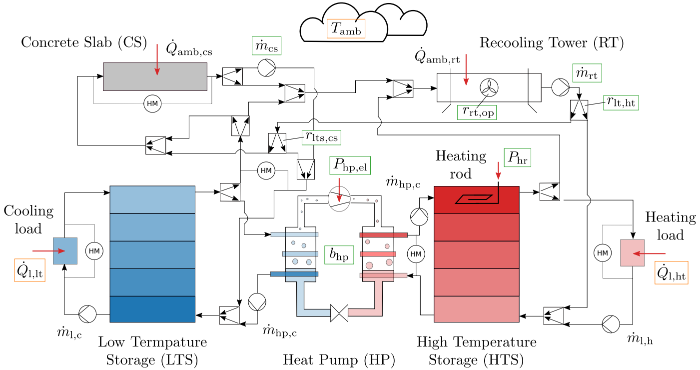
- One-year-simulation of a building energy system[1]



[1] Bürger A, Bohlayer M, Hoffmann S, Altmann-Dieses A, Braun M, Diehl M: A whole-year simulation study on nonlinear mixed-integer model predictive control for a thermal energy supply system with multi-use components. Applied Energy 258 (2020), 114064.

MPC performance example II

- **Setup and results of the study**[2]
  - Economic mixed-integer nonlinear MPC with 24 h prediction horizon using direct collocation in CasADi, IPOPT, and pycombina
  - Performance comparison to an elaborate conventional controller

  - MPC operation reduced yearly energy consumption of heat pump and heating rods by more than 18 %
  - Counter-intuitive control decisions identified new use cases for system components

  → MPC well suited for control of the system

  → Simulation study allowed to identify previously unknown, beneficial operation modes of the system

[2] Bürger A, Bohlayer M, Hoffmann S, Altmann-Dieses A, Braun M, Diehl M: A whole-year simulation study on nonlinear mixed-integer model predictive control for a thermal energy supply system with multi-use components. Applied Energy 258 (2020), 114064.

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Thank you for your attention!

I'm looking forward to your questions

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