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Self-adjusting model predictive control for modular subsystems in HVAC systems

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Abstract. In order to reduce the energy consumption and CO₂ emissions in the building sector, an efficient control strategy, such as model predictive control (MPC) is required. However, MPC is rarely applied in buildings since the implementation and modeling is complex, time consuming and costly. To bring MPC into practice, controllers and models are needed, that automatically adapt their behavior to the controlled system. In this work, such a self-adjusting MPC applicable to heating, ventilation and air-conditioning (HVAC) systems is developed. The MPC is based on a simple grey-box model that is able to cover the general dynamics of the considered subsystem. The controller adapts the model parameters online according to the past measurements of the controlled system using a moving horizon estimation. The developed self-adjusting MPC is applied to three heating coils in a simulation. Compared with a PID controller, the self-adjusting MPC is able to increase the control quality up to 10%, while no manual tuning is needed. Additionally, the model predictive approach is able to reduce the power consumption of the pump by 80%.

1. Introduction
To reduce the energy consumption and CO₂ emissions in the building sector, an efficient operation of the building energy system is required [1]. Advanced control strategies, such as model predictive control (MPC), have been developed in recent years leading to large energy saving potential compared to conventional controllers [2, 3]. Additionally, MPC can lead to an improved control quality and indoor comfort [4]. However, MPC is rarely applied in buildings since the implementation and modeling is complex, time consuming and costly [5, 6]. To bring MPC into practice, learning and self-adjusting controllers are needed, that automatically adapt their behavior to the controlled system. For this purpose, gray-box models combined with parameter estimation for continuous calibration are promising [7]. Compared to pure data driven approaches, such as ANN, gray-box models require less training data and can be more efficient in the optimization algorithm [8]. Additionally, gray-box models can provide a similar accuracy as black-box models for short prediction horizons as they occur in MPC approaches [9]. Gray-box models have been developed for HVAC systems [10] and building physics [11]. However, the performance of the MPC highly depends on the quality of gray-box model and has to be developed for each system.

The aim of this work is to develop and demonstrate a self-adjusting MPC applicable to heating, ventilation and air-conditioning (HVAC) systems. In order to reduce the system complexity and to exploit general system knowledge, the self-adjusting MPC is developed for...
frequently used subsystems in HVAC systems. The model parameters are determined by a moving horizon estimation continuously during operation. Thus, it is possible to apply the MPC to different subsystems of the same type. In the scope of this work, heating and cooling coil subsystems of air-handling units are investigated.

2. Methodology
The aim of this work is to provide a self-adjusting MPC approach for HVAC systems. The basic idea of the controller is illustrated in Figure 1. In each iteration, the model predictive controller solves an optimization problem in order to find the optimal inputs \( u \). In this work, we use gray-box models, whose behavior depends on a limited amount of parameters. Based on the past inputs and system outputs \( y \), these parameters are adjusted in a calibration process. Thus, the model is continuously adapted to the system behavior. However, a gray-box model requires basic equations describing the system dynamics. Nevertheless, a gray-box model can be applied to systems with the same structure. Thus, the MPC can be designed according to the requirements of a specific subsystem and, in contrast to pure data driven approaches, knowledge of the system can be considered for the controller. The focus in this work is on heating and cooling coil subsystems, which are frequently used in air-handling units and HVAC systems for heating and cooling an air volume flow. The investigated subsystem is illustrated in Figure 2 and consists of an air-water heat exchanger, a pump and a valve to control the water volume flow and temperature. The controlled variable is the supply temperature \( \vartheta_{\text{supply}} \) and the control variables are the valve opening \( H_{\text{set}} \) and the pump speed \( n_p \). The optimization problem can be written as equation 1 denoting \( u = [H_{\text{set}}, n_p] \) as inputs and the states as \( x = [\vartheta_{\text{supply}}] \).

\[
\begin{align*}
\min_{u} J(u, x) \\
\text{s.t. } \dot{x} & = f(u, x) \\
0 & \leq g(u, x)
\end{align*}
\]  

(1)

The objective function \( J \) to be minimized includes the squared deviation of the supply temperature from the set point \( \vartheta_{\text{set}} \), the control activity of the valve and the pump (deviation from the last value \( H_0 \) and \( n_{p,0} \)) as well as the pump speed in order to reduce the electricity consumption of the pump. Equation 2 represents the objective for discretized steps \( i \) and a prediction horizon \( N \). We choose the weight parameters depending on the gain \( K \) as \( q_1 = 1, q_2 = 1 \cdot K, q_3 = 0.5 \cdot K \) and \( q_4 = 0.1 \).

\[
J = q_1 \cdot \sum_{i=0}^{N} (\vartheta_{\text{supply},i} - \vartheta_{\text{set},i})^2 + q_2 \cdot \sum_{i=0}^{N} (H_i - H_0)^2 \\
+ q_3 \cdot \sum_{i=0}^{N} (n_{p,i} - n_{p,0})^2 + q_4 \cdot \sum_{i=0}^{N} n_{p,i}
\]  

(2)

In the following, the functions for the system model \( f \) and \( g \) for the coil subsystem are presented. The basis for the model is a PT\(_2\) element as shown in equation 3. Here, the variable \( u \) denotes the system input, the variable \( y \) the output, the parameters \( T_1 \) and \( T_2 \) the systems time constants and \( K \) the gain.

\[
T_1 T_2 \dot{y} + (T_1 + T_2) y + y = K u
\]  

(3)

In order to model the coil subsystem, the PT\(_2\) element is extended by an offset, which corresponds to the inflow air temperature \( \vartheta_{\text{in}} \). To consider the valve opening \( H \) and the pump
speed \( n_p \), we assume a proportional correlation between \( H \) and \( n_p \) leading to a multiplication on the right side of equation 4a. The pump speed is normalized by the maximal pump speed \( n_{\text{max}} \). Further, the non-linear opening characteristics of valves is considered by a sigmoid function \( f_v \), which depends on the parameters \( a \) and \( b \) (equation 4b). The constraints 4c - 4e limit the control and keeps the supply temperature in a physical range.

\[
T_1 T_2 \dot{\vartheta}_{\text{supply}} + (T_1 + T_2) \vartheta_{\text{supply}} + (\vartheta_{\text{supply}} - \vartheta_{\text{in}}) = K f_v(H) \frac{n_p}{n_{\text{max}}}
\]

\[
f_v(H) = \frac{\tanh(a) + \tanh(b \cdot H - a)}{\tanh(a) + \tanh(b - a)}
\]

\[0^\circ C \leq \vartheta_{\text{supply}} \leq 60^\circ C\]  
\[0 \leq H \leq 1\]  
\[n_{\text{min}} \leq n_p \leq n_{\text{max}}\]

The system behavior depends on the time constants \( T_1 \) and \( T_2 \), the gain \( K \) and the parameters of the sigmoid-function \( a \) and \( b \). The five parameters have to be determined for each specific heating or cooling coil. For this purpose, we apply a moving horizon estimation to the MPC, which calibrates the model parameters periodically [12]. The moving horizon estimation minimizes the error squared of the past measurement of the supply temperature \( \vartheta_{\text{supply,mea}} \) and the calculated temperature \( \vartheta_{\text{supply}} \) by optimizing the parameters to be estimated. Further, we include the squared error of the newly estimated parameters and the previous estimate (pre). The objective function for the past time step \( j \) and the estimation horizon \( M \) is formulated as follows:

\[
J = c_1 \cdot \sum_{j=0}^{M} (\vartheta_{\text{supply},j} - \vartheta_{\text{supply,mea},j})^2 + c_2 \cdot (T_1 - T_{1,\text{pre}})^2 + c_3 \cdot (T_2 - T_{2,\text{pre}})^2 + c_4 \cdot (K - K_{\text{pre}})^2 + c_5 \cdot (a - a_{\text{pre}})^2 + c_6 \cdot (b - b_{\text{pre}})^2
\]

The weights \( c_1 - c_6 \) are determined according to the typical range of the estimated parameters and the desired changing rate. We choose \( c_1 = 1 \), \( c_2 = 1 \), \( c_3 = 1 \), \( c_4 = 1 \), \( c_5 = 1000 \), \( c_6 = 10000 \). The parameters \( c_5 \) and \( c_6 \) are large values because the system behavior reacts quite sensitive to changes in the sigmoid function and therefore the parameters \( a \) and \( b \) may change only slowly.

3. Results

We apply the self-adjusting MPC to three different heating coils subsystems in a simulation. The heating coils subsystems distinguish in the nominal power (57 000 W, 57 000 W, 22 300 W) and the hydronic configuration (mixing circuit, throttling circuit, mixing circuit), which have different pipe diameters and length, pumps and valve characteristics. The simulation models are developed in the modeling language Modelica [13] and cover detailed system dynamics and non-linear behavior. The models are exported as functional mock-up units (FMU) and simulated in Python with the package FMPy [14]. The MPC is implemented in Python using the package Casadi and the solver IPOPT [15].
The simulation time is five hours, while the set point temperature is changed every 30 minutes. Additionally, the volume flow rate of the supply air is changed from 1500 m$^3$/h to 3000 m$^3$/h after 3 h in order to test the controllers reaction to changing boundary conditions. The step size of the simulation and the MPC is 10 s. The prediction horizon of the MPC is $N = 10$ and the estimation horizon $M = 60$ leading to a prediction of 300 s and an estimation for the past 600 s. As a reference control, we use a PID controller that varies the valve opening, while the pump speed is constant at maximal speed, since this control strategy is standard in practical applications. The PID is tuned for each heating coil using simulation-based optimization according to the method proposed in [16]. The objective function is the ISE and the optimization approach a genetic algorithm.

The results of the self-adjusting MPC and the PID controller are illustrated exemplary for the first heating coil in Figure 3. The upper plot show the supply air temperature for both approaches, the plot in the middle the valve opening and the plot at the bottom the pump speed. The integrated squared error and the consumed electricity of the pump are listed in table 1. During the first 30 minutes, the MPC oscillates around the set point temperature, since the initial parameters of the grey-box model do not match the controlled system. However, the parameters are adjusted in the periodic calibration process until the set point temperature is reached. Further, the MPC leads to slight temperature overshoots after each step of the temperature set point. Here, the valve opening as well as the pump speed is increased until the new temperature set point is reached. Afterwards, the pump speed is decreased to its minimum in order to reduce the power consumption. The PID oscillates during the first hours, but reaches the set point faster after 3 h. In comparison with the PID controller, the MPC has a lower ISE, which is due to the oscillations of the PID at the beginning and after the temperature drop at 2.5 h. Additionally, the MPC consumes only 9.99 Wh electricity, while the PID reference control consumes 58.58 Wh. Figures 4 and 5 summarize the relative improvement in the control quality and electricity consumption for all three heating coil models. The reduction of the ISE ranges from 0.2% to 10%, while the consumed electricity is reduced around 80% for all three cases. The results show that there is a high energy saving potential for the standard control with constant pump speed. Further studies should investigate a comparison with a PID controller that also manipulates the pump speed as presented in [17]. Nevertheless, the main advantage of the self-adjusting MPC is that no additional tuning is required. Thus, the implementation effort can be highly reduced by using this plug’n play approach.
Figure 3. Comparison of the self-adjusting MPC and the PID control for heating coil 1.

Table 1. Control quality and electrical power consumption for heating coil 1

| Controller | ISE \([K^2 \text{s}]\) | Power consumption \([\text{Wh}]\) |
|------------|-----------------|-----------------|
| MPC        | 47388.9         | 9.99            |
| PID        | 47516.6         | 58.58           |

Figure 4. Relative improvement of the integrated squared error (ISE) of the MPC compared to the PID.

Figure 5. Relative improvement of the electricity consumption of the MPC compared to the PID.

4. Conclusion
In this paper, we presented a self-adaptive MPC approach for heating and cooling coil subsystems, which are frequently used in HVAC systems. The MPC is based on a simple gray-box model that is able to cover the general dynamics of the coil subsystem. Further,
non-linear behavior of valve characteristics is modeled using a sigmoid-function. However, the specific behavior of the system depends on five parameters that have to be determined. The self-adjusting MPC adapts the five model parameters online according to the past measurements of the controlled system using a moving horizon estimation. In order to avoid huge changes in the model parameters in each iteration, we consider the deviation from the measurement as well as the deviation from the last determined parameter values in the objective of the moving horizon estimation. The objective function of the MPC considers the deviation of the supply air temperature from a given set point and the electrical power of the pump in order to reduce the energy consumption. In order to test and rate the self-adjusting MPC, we apply it to three different heating coils in a simulation. As comparison, we use a conventional control strategy that is based on a proportional-integral (PID) controller that is well tuned in an optimization process. Unlike for the conventional control method, the self-adjusting model predictive controller do not require any pre-use tuning. The control performance of the MPC increases during operation, since the model parameters are adapted according to the past behavior. Compared with the PI controller, the self-adjusting MPC is able to increase the control quality up to 10%. Additionally, the model predictive approach is able to reduce the power consumption of the pump by 80%. In summary, the proposed control algorithm leads to an efficient control while no manual calibration or tuning is needed. Thus, the effort for practical implementation can be significantly reduced.

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