

Economic multiple model predictive control for HVAC systems - A case study for a food manufacturer in Germany

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ABSTRACT

The following paper describes an economical, multiple model predictive control (EMMPC) for an air conditioning system of a confectionery manufacturer in Germany. The application consists of a packaging hall for chocolate bars, in which a new local conveyor belt air conditioning system is used and thus the temperature and humidity limits in the hall can be significantly extended. The EMMPC calculates the optimum energy or cost humidity and temperature set points in the hall. For this purpose, time-discrete state space models and an economic objective function with which it is possible to react to flexible electricity prices in a cost-optimised manner are created. A possible future electricity price model for Germany with a flexible EEG levy was used as a flexible electricity price. The flexibility potential is determined by variable temperature and humidity limits in the hall, which are oriented towards the comfort field for easily working persons, and the building mass. The building mass of the created room model is used as a thermal energy store. Considering electricity price and weather forecasts as well as internal, production plan-dependent load forecasts, the model predictive controller directly controls the heating and cooling register and the humidifier of the air conditioning system.

1. Introduction and problem description

A constantly increasing scarcity of resources, increasing emissions and the global warming proven in many scientific studies require differentiated and comprehensive solutions [1] [2] [3]. In addition to a more efficient use of resources, the conversion of the energy supply system to an increased use of renewable energies is also decisive for achieving these goals, which in turn leads to an increase in balancing fluctuating residual loads in the electricity grid. With regard to the global energy demand it can be seen that about one third is caused in the building sector [4], of which about half of the energy demand is accounted for by building heating, ventilation and air conditioning (HVAC) [5] [6]. In view of these circumstances, energy efficiency measures and the use of more flexible energy supply technologies in the building sector and in the field of building air conditioning are substantial solutions to the challenges described.

In the field of building HVAC, high energy saving potentials can be exploited in many ways. Scientific research focuses on different air routing concepts, the further development of the various components of an air conditioning system and, above all, the improvement of control technology [7] [8] [9]. Due to the volatile nature of wind and solar energy demand has to be made more flexible. Hence, energy demand can be adopted to energy supply and therefor stabilise the energy system through demand response on the one hand and increase the utilisation rate of renewable energy systems on the other hand [10] [11].

By developing and implementing an economical, multiple, model predictive control (EMMPC), this flexibility potential can be realised in an energy- or cost-optimised manner. Demand response can be fulfilled by integrating future, flexible electricity price models based on electricity supply and demand. For the flexible operation of the air conditioning the air mass of any hall is used as thermal energy storage. Hence, allowing a range of temperature and humidity specifications is key requirement [12] [13] [14]. Especially in industries, these ranges are often not given due to fixed settings and strict specifications of the product. Flexible and efficient control of full air conditioning systems requires the solution of complex tasks. Time-varying internal and external disturbances affect the controlled system, many processes involve time delays, the system goes through many operating conditions, and the required energy can also have variable price structures. An efficient control approach should therefore be able to take into account time-dependent disturbances, map a wide range of operating conditions and process variable price structures.

With regard to the current state of research, this paper applies an advanced EMMPC approach for the flexible operation of air conditioning systems in industrial productions. Hereby, the EMMPC approach combines both, the approach of multiple and economic MPC to control and optimise non-linear systems under several constraints. The realisation of the flexible air conditioning is shown for a real case of a packaging hall for chocolate bars. The product has strict temperature and humidity specifications. Therefore, the implementation of a new, local conveyor belt air conditioning system is indispensable to soften up these specifications for the hall [12] [15][14].

2. State of research

Due to the manifold tasks that an air conditioning system has to fulfil, the system control is highly complex. Depending on the design and application, the air temperature, humidity, air volume flow and air mixtures (fresh air/exhaust air ratio) must be adjusted and controlled. Since these variables influence each other, the degree of complexity increases significantly. For these reasons, a combination of different control approaches and sequence circuits, which control the respective sub-components and bring them into a meaningful connection, is often necessary to ensure efficient plant operation. In the field of efficient and flexible building air conditioning, a large number of scientific studies can be considered.

The publication of Afram and Janabi-Sharifi (2014) [16] gives a good overview of control approaches used or under development for air conditioning systems. A distinction is made between "classic control", "hard control", "soft control", and "hybrid control" for air conditioning systems as well as further approaches that cannot be assigned to these categories. The classic control corresponds to the state of the art and are widely and practically applied. The classic control methods for HVAC systems include two-point controllers (on/off), proportional (P), proportional integral (PI), and proportional integral differential (PID) controllers. The so-called "hard control" for air conditioning systems include gain scheduling, optimum control, robust control, model predictive control (MPC) and nonlinear and adaptive control. MPC, as described in this publication, use previously created models of the system to be controlled to predict and optimise future system behaviour under changing boundary conditions. Such controllers can be used both as a replacement for classic controllers and can also perform higher-level control tasks.

So-called fuzzy controllers or the use of artificial neural networks are summarised under the term "soft" or "soft control". These comparatively new methods for controlling HVAC systems can replace both higher-level and local controllers and perform a wide range of tasks. Fuzzy controllers are based on if-then-else instructions and require a sufficiently deep understanding of the system to be controlled.

Artificial neural networks, on the other hand, are trained with data, the understanding of the system is irrelevant [17]. Ruano et al. (2016), for example, investigated a predictive control in which a neural network predicts building and system behaviour and is optimised by including weather forecasts [18]. "Hybrid control techniques" deal with a combination of soft and hard control approaches [17].

Furthermore, the hierarchical arrangement of different controllers is also subject of some research. For example, MPC controllers can be used as so-called "super visory control", which in turn transmit higher-level setpoints to underlying control structures - this can also be another MPC controller [19] [20].

Publications dealing exclusively with the comparison of control methods for air conditioning systems and providing a comprehensive overview of the state of research favour the use of MPC to solve the challenges of flexible operation mentioned above [16] [21]. In both studies, the authors summarise that classical regulatory approaches are primarily suitable for less complex regulatory tasks. Outside the previously defined operating point, classic controllers often work too slowly or react too aggressively, for example. The soft methods require either a very extensive understanding of the system to be controlled or comprehensive measured value analyses. In addition, the acceptance of so-called "black-box" approaches, such as the soft approaches, is not widespread in industry; an introduction is usually very lengthy and impractical due to too little data. In opposite to that, hard methods like MPC require a complex and rigorous mathematical investigation of the system. The identification of linear subareas in the system behaviour, which is necessary for control using hard control techniques over non-linear operating ranges, often proves to be difficult and very complex. Nevertheless, the authors emphasize that the model predictive approach as a hard control technology is particularly well suited for complex control tasks in the field of air conditioning due to its capabilities and can fulfil the aforementioned tasks.

The many advantages are offset above all by the high and complex programming effort. A sufficiently precise understanding of the system is just as necessary as correspondingly modern hardware and software. The use of MPC controllers is primarily based on linear process models [16] while its definition is very challenging and not standardised. Especially for multi-variable systems with many non-linearities in system behaviour, as they often occur in building air conditioning and increase significantly due to the increasing complexity of an air conditioning system. However, the integration of so-called multiple MPC controllers or adaptive MPC control structures offers great prospects of success in controlling non-linear controlled systems in an optimised manner [22] [23]. This is where the publication comes in and is intended to contribute to the implementation and realisation of an EMMPC for HVAC systems.

3. Methodology and fundamentals of the used model predictive control

The developed, model-predictive control uses a linear, time-invariant (LTI) and time-discrete prediction model of the system to be controlled (time-discrete state space models of an air conditioning system with a connected building) to calculate future state and output changes over a finite prediction horizon. The aim is to minimise the set point deviation (fixed controlled variable, energy or costs) over the prediction horizon.

In order to determine the best possible control variable sequence for minimising the target function within a prediction horizon, an optimisation problem is solved. The prediction horizon describes the entire period under which the optimisation takes place. Up to a pre-determinable time step, optimised control signals of the MPC controller and adapted predicted boundary conditions are considered. The number of time steps over which predicted, optimised control signals are calculated is defined by

defining the control horizon. The control horizon is at most as long as the prediction horizon, which usually corresponds to half of the prediction horizon based on the calculation duration. At the end of the control horizon, the last control signal is kept constant until the end of the prediction horizon. [22] [23]

Individually defined limitations of output and control variables are included in the optimisation problem via slack variables. The first optimum control variable value is used for controlling the system. The measured actual values as well as current control and disturbance variables are used for the subsequent time step for the new calculation of the optimum control variable sequence.

The system to be controlled consists of physical models of a building and a HVAC system, which are described in more detail in section 4. From these physical models linear, time-discrete state space models are derived, which function as prediction models as part of the MPC as shown in figure 1. Using the optimisation algorithm, optimised control signals adapted to the boundary conditions are transmitted to the system to be controlled. The MPC directly controls the heating and cooling coil as well as the humidifier with control signals (manipulated variables). The control signals are limited between 0 and 1. The fans are not controlled via MPC and are operated with a constant volumetric flow of 2000 m³/h. The condition of the supply air is composed of fresh air conditions and the respective conditioning of the climate functions controlled via the control variables. The temperature and humidity of the indoor air is calculated from the proportion of indoor air, supply air and outdoor temperature.

A schematic overview of the structure and functionality of the MPC is given in the following figure (fig. 1).

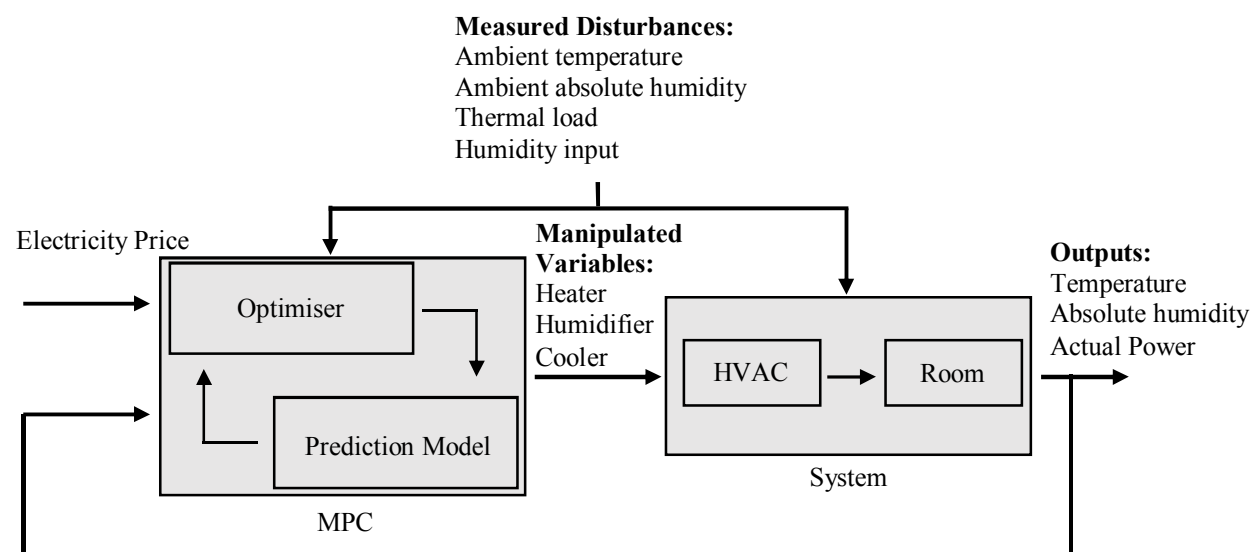


Figure 1: Schematic structure of the model predictive control system

Air cooling in the model can be realised with two processes: either a dehumidification process (condensate formation) or dry cooling (without condensate formation) is applied. This behaviour cannot be represented in one linear system, since a latent phase transition occurs after reaching the saturation temperature. Consequently, for both cases a multiple model predictive controller with two different prediction models is used in the following. If condensate formation occurs, the prediction model A is switched over to the prediction model B. The two prediction models are based on a multiple model predictive controller. The two prediction models are generated around different operating points (with and without condensation) by linearizing the whole model. Due to the thermal inertia of the system, a time step of 900 s is applied.

3.1 Time Discrete State Space Model

The developed MPC uses, as described before, time-discrete LTI systems instead of time-continuous systems. Hence, the equation of state does not describe the derivative $\dot{x}(t)$ of the states, but the states of discrete, future sampling times $x(k+1)$. The matrices A_D (state matrix) and B_D (input matrix) of the time-discrete state space representation result from the general solution of the temporal course of the state variable x from time t_0 .

Accordingly, the matrices A_D and B_D are formed at the sampling times T . The sampling time is the duration of a time step in the discrete system. The matrices C (output matrix) and D (feedthrough matrix) remain unchanged in comparison to the time continuous system [24] [25]:

The time-discrete representation used is as follows:

$$\begin{aligned} \text{input equation: } x(k+1) &= A_D x(k) + B_D u(k) \\ \text{output equation: } y(k) &= Cx(k) + Du(k) \end{aligned} \quad (1)$$

3.2 Optimisation problem and solution methods

The core of the developed MPC is an optimisation algorithm for calculating the optimal control variable sequence z_k :

$$z_k^T = [u(k|k)^T \quad u(k+1|k)^T \quad \dots \quad u(k+p-1|k)^T \quad \epsilon_k] \quad (2)$$

The deviations of the actual values from the target values of the controlled system are minimised over the prediction horizon, taking restrictions into account. The objective function $J(z_k)$ consists of four parts:

$$J(z_k) = J_y(z_k) + J_U(z_k) + J_{\Delta U}(z_k) + J_\epsilon(z_k) \quad (3)$$

Output Reference Tracking:

$$J_y(z_k) = \sum_{j=1}^{n_y} \sum_{i=1}^p \left\{ \frac{w_{ij}^y}{s_j^y} [r_j(k+i|k) - y_j(k+i|k)] \right\}^2 \quad (4)$$

Manipulated Variable Tracking:

$$J_U(z_k) = \sum_{j=1}^{n_u} \sum_{i=0}^{p-1} \left\{ \frac{w_{ij}^u}{s_j^u} [u_j(k+i|k) - u_{j,\text{target}}(k+i|k)] \right\}^2 \quad (5)$$

Manipulated Variable Move Suppression:

$$J_{\Delta u}(z_k) = \sum_{j=1}^{n_u} \sum_{i=0}^{p-1} \left\{ \frac{w_{i,j}^{\Delta u}}{s_j^u} [u_j(k+i|k) - u_j(k+i-1|k)] \right\}^2 \quad (6)$$

184 Constraint Violation:

$$J_{\epsilon}(z_k) = \rho_{\epsilon} \epsilon_k^2 \quad (7)$$

185 The output variables $y(k)$ can be described with the internal prediction model, the current states $x(k)$
 186 and inputs $u(k)$. From this it follows that the objective function $J(z_k)$ depends only on the decision
 187 variable z_k^T . [23]

188 In each step of a sequence $\{x_k\}$, an approximate quadratic subproblem is formed from the first and
 189 second derivatives of the objective function at point x_k .

190 By defining weights and scales, the aggressiveness of the control signals can be adjusted by defining
 191 the suppression of changes.

192 The described objective function is minimised by the method of sequential quadratic programming
 193 (SQP) which is an extension of quadratic programming (QP) and one of the most effective methods for
 194 solving nonlinear, nonlinear-restricted optimisation problems [26].

195

196 3.3 Multiple Model Predictive Control

197 In order to keep the deviations between a linear model for control and the real system small over a larger
 198 working range, there is the possibility of multiple model predictive control (MMPC). With the MMPC,
 199 several controllers with different internal models and parameters are combined in a block and selected
 200 via an additional input ("switch"). Depending on the environmental and operating conditions, the most
 201 suitable time-discrete state space model can be selected to calculate the optimum control variable
 202 sequence for the system.

203

204 3.4 Economic Model Predictive Control

205 The aim of the economic, model-predictive regulation is to minimise monetary costs. The objective
 206 function is formulated in such a way that the current and predicted electricity price multiplied by the
 207 current and predicted output over the prediction horizon p is minimised. The suppression of changes in
 208 the control variables $\sum_p \sum_{n_{mv}} (du \cdot W_{du})^2$ and the minimisation of restriction violations $W_{ecr} \cdot \epsilon^2$
 209 remain the same in comparison to set point compliance or energy optimisation.

$$J_{eco}(z_k) = \sum_{k=1}^p (P_{tot} \cdot k_{el}) + \sum_{k=1}^p \sum_{j=1}^{n_{mv}} (\Delta u \cdot W_{\Delta u})^2 + W_{ecr} \cdot \epsilon_k^2 \quad (8)$$

210 The room temperature and absolute humidity of the room air are kept above restrictions in the comfort
 211 field.

212

213 4. Model description

In this section, the analysed system based on a real confectionery manufacturer and the models used to calculate flexibility and savings potentials are described. The system consists of a packaging hall for chocolate bars, which are cooled by a novel, local air-conditioning system introduced by Heidrich et al. [12] and a connected air-conditioning system for providing conditioned air to the rest of the hall within the limits of the comfort field for workers.

Without local air-conditioning of the chocolate bars, the entire hall would have to be air-conditioned to 18°C and 50 % relative humidity in order to avoid deformation of the chocolate, which begins to melt at 18°C, condensation effects on the chocolate bar, which is cooled from the aisle to the conveyor belt at around 14-15°C, and problems with electrostatic charging of the packaging cardboard [14] [27] [28].

In the hall, there are also packaging machines and medium-heavy working staff emitting heat and water. The number of staff depends on the shift (production in operation, no production, cleaning shift).

In order to be able to model the hall, extensive measurements were carried out and physical models of the hall and the technical building equipment were created in MATLAB/SIMULINK. The most important parameters for modelling the system can be found in the table below.

Table 1: Important key parameters of the modelled packaging hall

Parameter packaging hall	Value	Unit
Room volume	800	m ³
Supply air volume flow	2000	$\frac{\text{m}^3}{\text{h}}$
Heat transfer coefficient walls/ceiling	0.28	$\frac{\text{W}}{\text{m}^2\text{K}}$
Heat transfer coefficient floor	1.00	$\frac{\text{W}}{\text{m}^2\text{K}}$
Ground temperature	15	°C
Storage capacity, medium according to DIN V 18599-2 [29]	90	$\frac{\text{Wh}}{\text{m}^2\text{K}}$
Inner thermal load (during production)	1292	W
Humidity entry max. (during production)	48	$\frac{\text{g}}{\text{h}}$

The models used for the room, the air conditioning system and the boundary parameters (internal loads, electricity prices, weather) are described below.

4.1 Physical building model

The physical room model used is based on a building model from the CARNOT toolbox (Conventional And Renewable eNergy systems Optimisation Toolbox) [30], which is freely available for MATLAB/SIMULINK.

The thermal heat-up and cooling behaviour is calculated by integrating the heat flow balance $\sum \dot{Q}$ divided by the thermal storage capacity of the building mass $m \cdot c_p$ over time.

$$\vartheta(t) = \int \frac{\sum \dot{Q}}{m \cdot c_p} dt \tag{9}$$

The change of the absolute air humidity is calculated analogously to the thermal behaviour.

4.2 Physical air conditioning system model

The HVAC system consists of an electric pre- and post-heater, a cooling register, which is supplied with cold by a compression chiller, an electrically operated steam humidifier, a supply and exhaust fan and is operated with 100% fresh air.

The HVAC simulation model is based on the physical laws of the Mollier diagram [31]. Furthermore, characteristic curves of the manufacturer are used for modelling the cooling supply (compression chiller with flow temperature of $-1\text{ }^{\circ}\text{C}$) and steam humidification (3 bar of saturated steam).

4.3 Boundary parameters - internal load

The internal thermal and water loads necessary for an optimised, model-predictive control of an air conditioning system are determined by real active power measurements of the machines in the hall, calculations for the heat of illumination according to VDI 2078 [31], humidity and heat emission of the persons in the hall according to VDI 2078 and the influence of the local air conditioning by transfer of laboratory results.

The following figure shows the temporal course of the determined, smoothed, internal loads as a function of time depending on the production plan. The maximum is reached during running production (three days per week). When production is switched off there is only a low thermal load due to the standby operation of the switch cabinets and machines. During the cleaning shift after every production shift the room lighting is switched on and a few hard-working employees are in the hall.

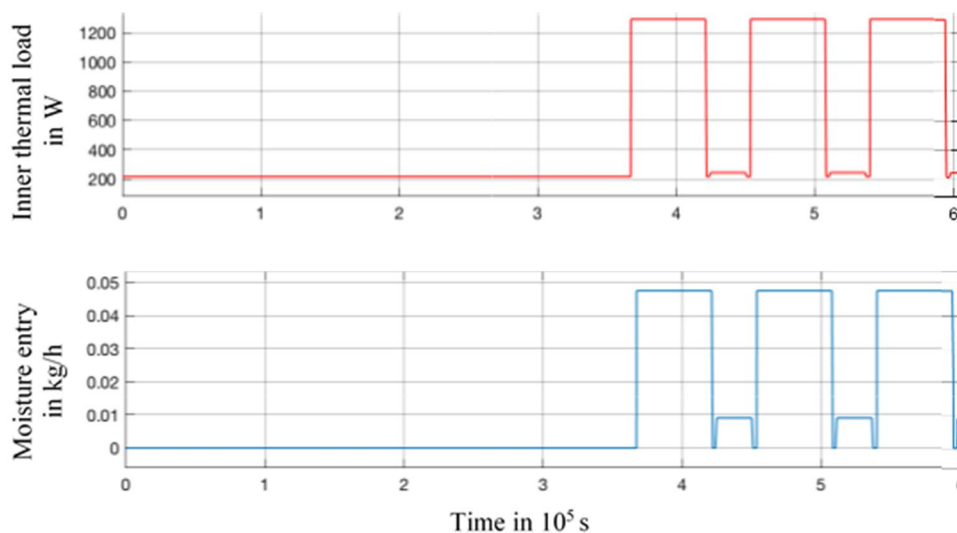


Figure 2: Scaled internal loads of the production hall over seven days

4.4 Boundary parameters - weather data

The weather data used for simulation and prediction consist of historical hourly values for air temperature and absolute humidity of the surroundings. These are test reference year data of a central German city (i.e. Kassel) in the observation period 1988-2007. Averaged weather data sets are understood as test reference years, which represent a typical weather course of one year. Real forecast values are indispensable for a later, real application operation and can be considered by the developed

control. However, historical weather data sets is used to determine savings and flexibility potentials, as these can cover a long period of time and reflect the expected value without annual deviations.

4.5 Boundary parameters - electricity price data

Two electricity price scenarios are defined for the analysis of an economic, model predictive control, a constant and a flexible model:

1. In the status quo scenario a standard, constant total electricity price (13.18 ct/kWh) for industrial customers in Germany is chosen.
2. In opposite to that, the second scenario reflects a possible future electricity price model of a dynamized renewable energy levy (EEG levy) and electricity procurement via the day-ahead exchange market in Germany. The current static EEG levy due in Germany, which is levied to promote renewable energies in Germany, is replaced by a dynamic EEG levy, which is calculated via the day-ahead exchange electricity price using a certain factor.

$$\text{Flexible EEG levy} = \text{Day-ahead electricity price} \cdot \text{multiplier}$$

This multiplier must be successively recalculated and determined for the differential cost compensation for Germany. For the following simulations, a factor of 1.9 has been defined. Furthermore, limits of the flexible EEG allocation upwards and downwards are foreseen. The upper limit of the dynamic EEG levy consists of twice the German, static EEG levy, the lower limit is 0, negative electricity prices are no longer possible according to this model. [32] [33]

In addition to the electricity price incidental electricity costs are considered in all analysed scenarios corresponding to the average costs of 4.28 ct/kWh for German industrial customers with an annual consumption of 160 to 20,000 MWh [34].

The exchange electricity price generally has two maximums and two minimums per day. Since the loads are to be shifted from a high tariff to a tariff as low as possible, a prediction of at least 12 hours is necessary. Regarding a time step of 900 s and a prediction horizon of 12 hours, this results in 48 prediction steps. To reduce calculation efforts the control horizon is set to 20 steps, i.e. 5 hours.

Comparable to the weather forecast, real electricity price forecast is also indispensable for real operation. The electricity price forecast is included in the developed MPC approach by downloading real electricity prices from EEX for the next day (day-ahead electricity prices) and script-based further processing. However, as already described in the section on weather forecasting, historical electricity price time series over longer periods are better suited for calculating flexibility and savings calculations.

4.6 MPC constraints

The constraints used to create the MPC do not vary in all considered scenarios. The constraints include the permissible temperature and humidity limits in the room as well as the control variable limitation. Both, the temperature as well as the air humidity depend on the limits of an average comfort field. The control variable limitation resulting from the air conditioning system control are as follows:

$$16^{\circ}\text{C} \leq \text{Room temperature} \leq 24^{\circ}\text{C}$$

$$0,005 \text{ kg/kg} \leq \text{Absolute humidity Room} \leq 0,009 \text{ kg/kg}$$

$$0 \leq \text{Control variable heating/moisture/cooling} \leq 1$$

4.7 MPC weights

The different weights of the sub-target functions that are required to create the MPC are described below. In all scenarios, the control variables should not adhere to a value and therefore have a weight of 0. The weight of the change suppression of the control variables is set to 0.1. This reduces the upswing and downswing of the control values that is too fast.

The weightings of the control variables vary depending on the scenario, which are described in section 5. A distinction is made between two cases:

1. The energy-optimal control keeps the indoor temperature and humidity above limits in the comfort field. The weights of the first two model outputs (indoor temperature and absolute humidity) are 0. The third output (i.e. power) is to be minimised hence it receives a weight of 1.
2. The regulation with economic objective function receives quasi the current electricity price as weight for the achievement. This is multiplied by 10, since this setting thus has a similar weight as with the energy-optimal regulation and better results are obtained. The temperature and humidity of the room are no longer included in the target function.

5. Scenario description and results

In order to evaluate the flexibility and savings potentials, the previously described control variants of the MPC at different seasons are analysed.

First, three days in January are graphically examined in order to illustrate a possible load shift (scenario I-III). Subsequently, electricity consumption and costs incurred by the three different operating variants are compared over 20 days in January. Since the weather influences change strongly in the summer, the load management potential is finally illustrated by a flexible electricity price and EMPC for 10 days in July.

The energy-optimal scenario I serves as a comparison for the scenarios in which load management is carried out. Scenarios II and III use the economic objective function in which the current AHU system output multiplied by the current electricity price over the prediction horizon is minimized. In the second scenario a constant electricity price is assumed, in the third scenario a flexible electricity price as described above is used. Table 1 shows an overview of the simulated scenarios.

Table 2: Overview of the simulated scenarios

Scenario	Objective function	Weights [temp. humidity power/costs]
I. Energy-optimised MPC	energy-optimised	[0 0 1]
II. EMPC with constant electricity price	economic-optimised	[0 0 $p \cdot k_{el}$]
III. EMPC with flexible electricity price	economic-optimised	[0 0 $p \cdot k_{el}$]

5.1 Comparison scenario I: Energy-optimised MPC - 3 days in January

In this scenario, the energy consumption of the air conditioning system is minimized. The weights for temperature and absolute humidity are 0. The comfort field is maintained by the restrictions. The weight for the performance of the system components is 1. The weight for the output of the system components

is 1. The target value for the output is 0. Thus, the summed quadratic deviation of the power from 0 over the prediction horizon is minimized.

As shown in figure 4, the room temperature is kept at the lowest limit of 16°C, as this is the least amount of energy required for supply air conditioning. The absolute humidity of the outside air is not raised by the humidifier if it is above the lower limit of 5 g/kg. Since the HVAC system is operated with 100 % fresh air from the outside, the absolute humidity of the room, provided that it remains within the specified limits, depends on the conditions of the fresh air, as can be seen in area 1 of figure 4.

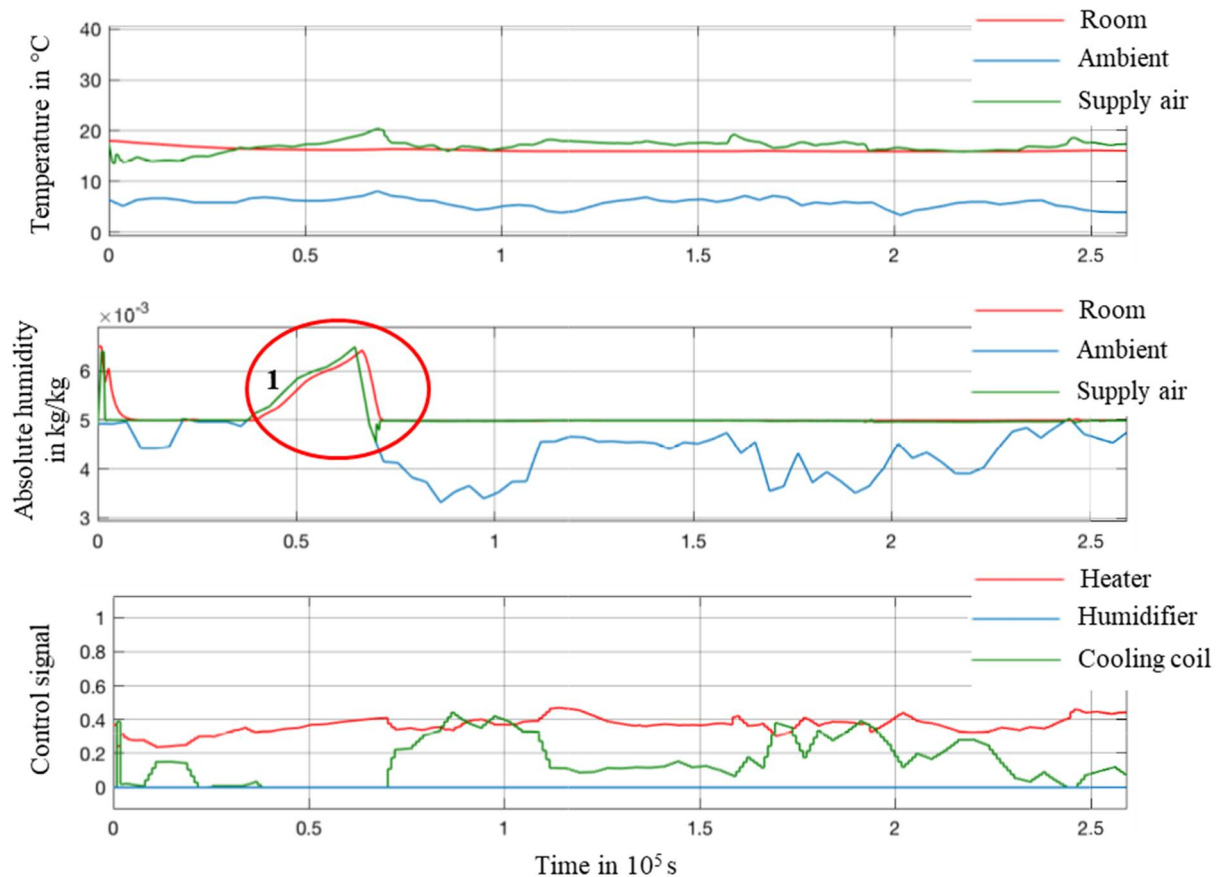


Figure 3: Energy-optimised MPC over three days in January

5.2 Scenario II: Cost-optimised MPC (EMPC) with constant electricity price - 3 days in January

In this scenario, the economic objective function is used to minimize costs. The output is multiplied by the current costs in each time step and minimized by adding up the prediction horizon. The electricity price in this scenario is constant at 13.18 ct/kWh. Therefore, this is a simultaneous energetic and economic optimisation. The difference between this regulation and the regulation in scenario I is that the current power consumption of the air conditioning system is no longer included in the target function as a square but linear value. As a result, energy cost peaks are no longer minimized, as they no longer flow disproportionately into the target function.

The behaviour is very similar to the previous scenario I. However, in contrast to scenario I, the heating coil remains switched off during the first hours (area 1, figure 5), so that the room temperature drops more quickly (area 2, figure 5). The room air restrictions

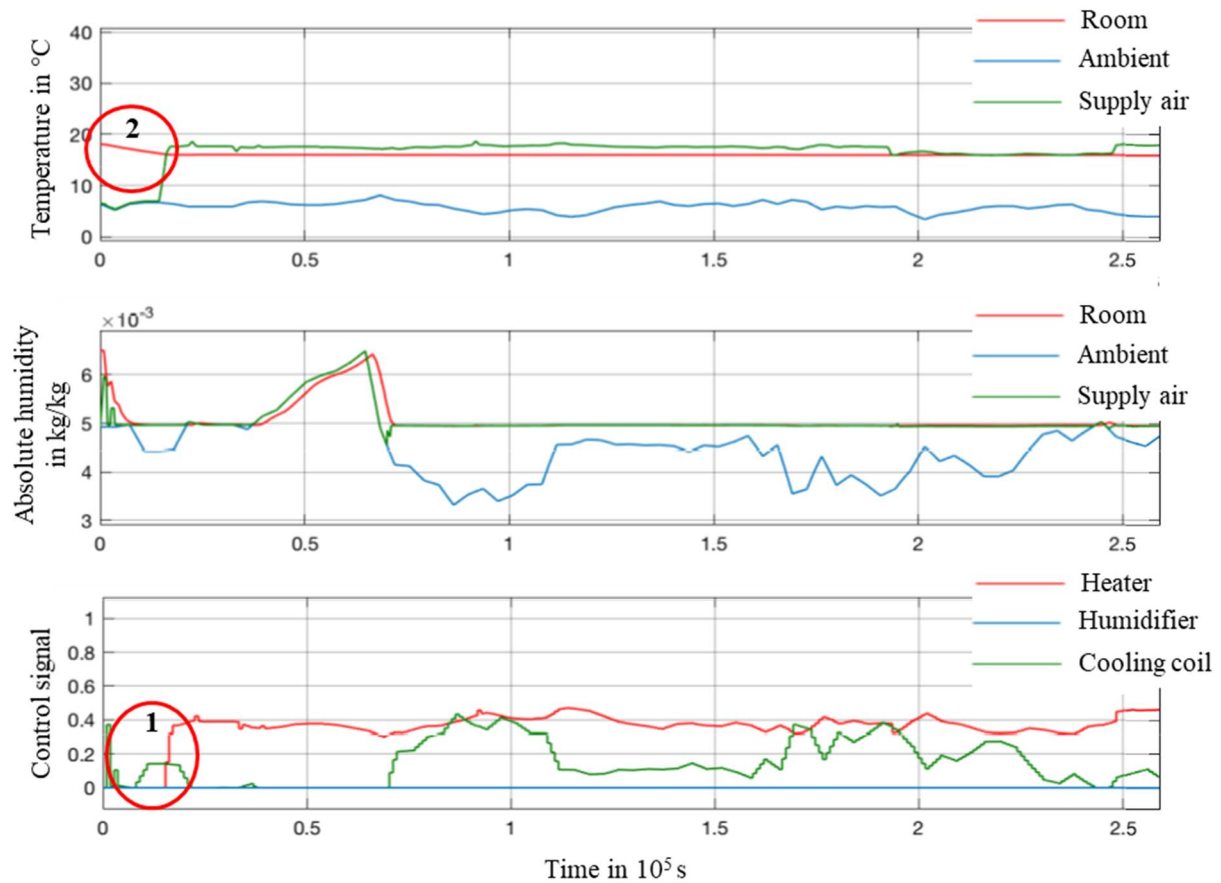


Figure 4: Energy-optimised and cost-optimised EMPC with constant electricity price over three days in January

5.3 Scenario III: Cost-optimised MPC with flexible electricity price - 3 days in January

In this scenario, a flexible electricity price is used as described in Section 4.6. This results in electricity price changes of up to 10 cents (figure 6). The indoor temperature varies between 16 and 21°C . The control variables of the heating coil vary between 0 and 1. Especially in low-price phases (area 1, figure 6) and before a sudden price increase, the heating register (area 2, figure 6) prematurely heats up the room (area 3, figure 6). The humidifier is only activated when the absolute humidity falls below 5g/kg . Load shifts are possible as shown in figure 6.

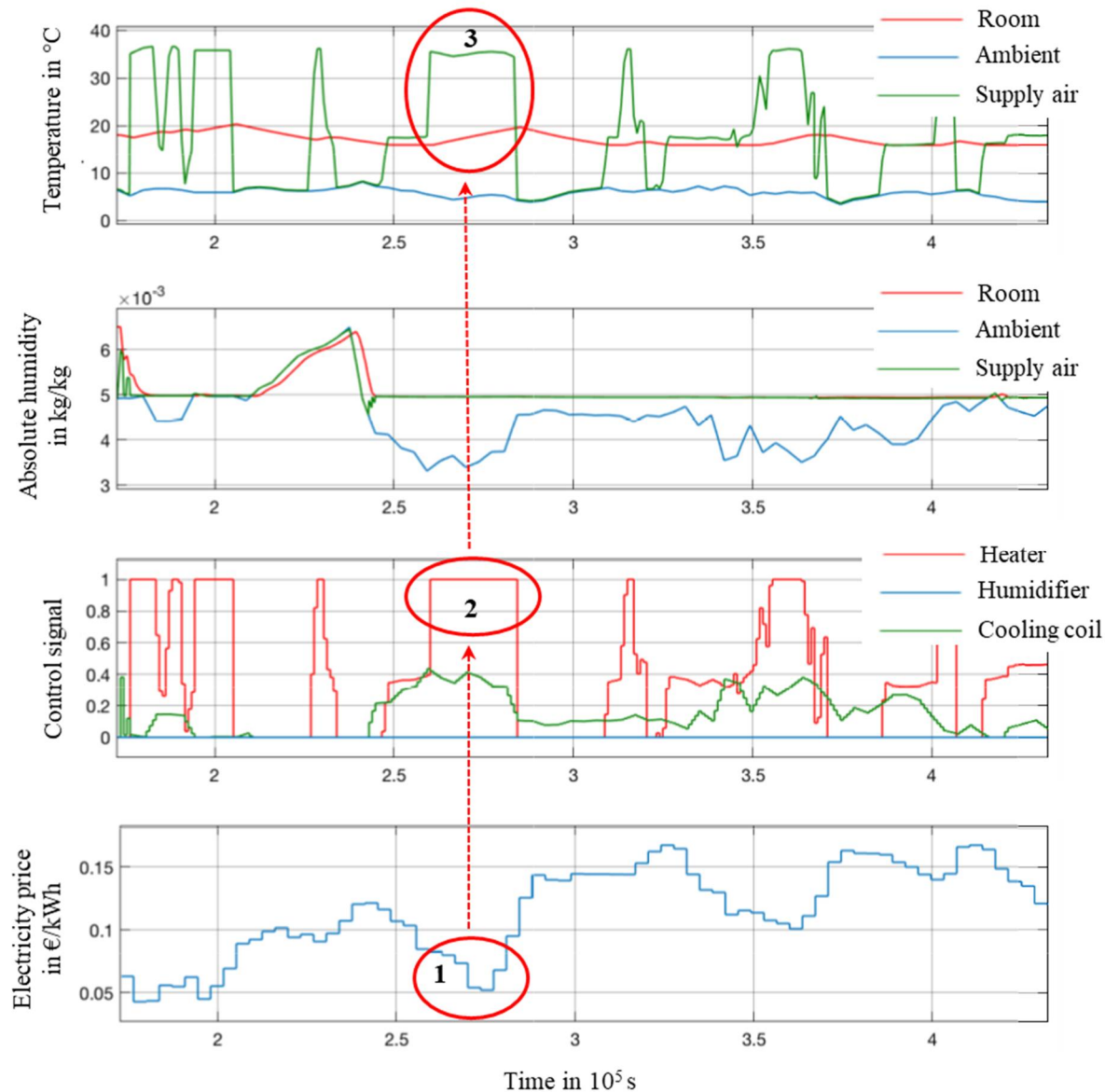


Figure 5: Cost-optimised EMPC with flexible electricity price over three days in January

5.4 Winter case - comparison of control variants over 20 days in January

Three scenarios were simulated over the first 20 days in January of the reference year. The energy consumption and the energy costs incurred by the air conditioning system are shown in Table 2. The relevant changes are also shown.

The comparison between energy-optimised control and EMPC already shows a reduction in energy consumption and a resulting cost reduction of 2.14%. Scenario III, with lower energy consumption, will henceforth be used as a comparison scenario.

The results of the simulation with dynamic EEG allocation show a reduction in costs of 2.10% compared to the energy-optimal scenario with changed target function and constant electricity price. However, energy consumption increases by 7.44%. This higher energy consumption is due to the fact that the room temperature for storing the shifted energy is raised, resulting in higher heat losses.

390 Table 3: Energy consumption and costs over 20 days in January under different scenarios

Scenario		20 days	
		Consumption in kWh	Costs in €
I	Energy-optimised MPC	3926	517.3
II	EMPC with constant electricity price	3842	506.4
	Change: I → II	-2.14%	-2.14%
III	Flexible EEG-Levy	4128	498.9
	Change: II → III	+7.44%	-2.10%

391

392 **5.5 Summer case - EMPC with flexible electricity price over 10 days in July**

393 In addition to the winter case, 10 days in summer (days 191-200) are simulated with an electricity price
394 including dynamic EEG allocation (see scenario III). It is investigated, to which extent the cooling
395 register can contribute to load management. The results are shown in figure 7.

396 In summer most of the energy is needed to dehumidify the supply air (area 1, figure 7). Since the room
397 air is exchanged relatively fast it is not possible to store energy by shifting the dehumidification output.
398 There is no correlation between the electricity price and the control signal of the cooling register. The
399 outside air is cooled by dehumidification. Therefore, despite high outside temperatures, low inside
400 temperatures must be noted (area 2, figure 7). A shift before cooling loads is therefore also not possible
401 and load management cannot be carried out under such weather conditions.

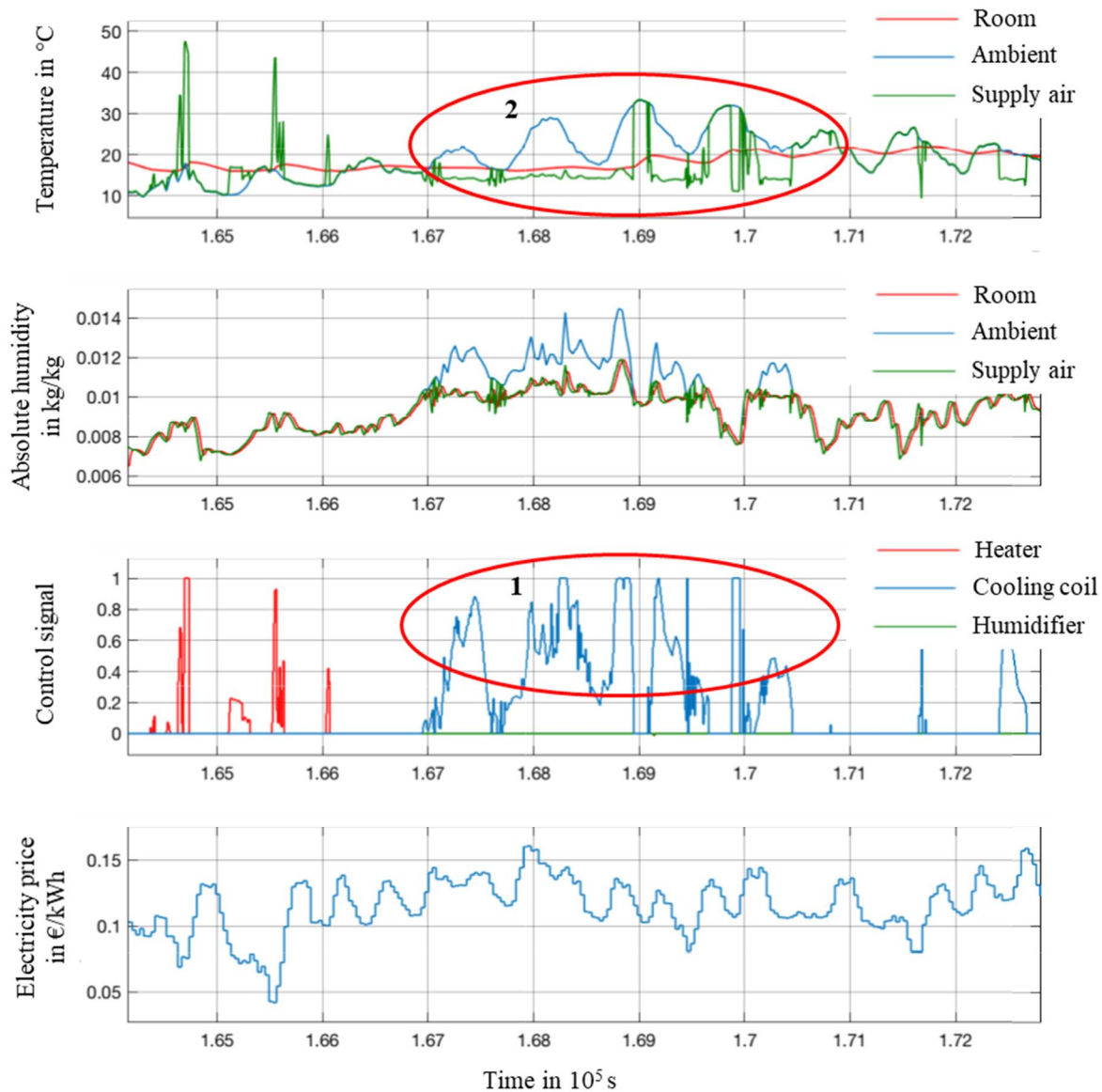


Figure 6: Cost-optimised EMPC with an electricity price with dynamic EEG allocation over ten days in summer

However, if one additionally varies the building weight, cost savings of 2.1% ($90 \frac{\text{Wh}}{\text{m}^2\text{K}}$ thermal storage capacity according to DIN V 18599-2 [29]) and 3.0% ($120 \frac{\text{Wh}}{\text{m}^2\text{K}}$ thermal storage capacity [29]) can be achieved for the heating case compared to the energy-optimised control.

Halvgaard, Poulsen, Madsen and Jørgensen [35] calculated cost savings of 25-35% through an economic model predictive control of concrete core activation. These significantly higher savings are due to the slower type of building air conditioning. The energy can be better stored in the heavy concrete ceilings before the rooms are slowly air-conditioned. Building component activation or storage in e.g. water reservoirs are other approaches to thermal energy storage in buildings which can be used for load management.

6. Conclusion and outlook

The paper illustrates an economic multiple model predictive control of a HVAC that can either meet room temperature and humidity targets, minimise energy consumption or alternatively minimise economic costs through a flexible electricity pricing model.

As a case study, a production hall for the packaging of chocolate bars is used, which are locally air-conditioned by a cross-flowing displacement ventilation for conveyor belts, so that the room air condition can be kept within a comfort zone with the help of restrictions and does not have to depend on the product requirements of the chocolate (18°C, 50% relative humidity) [12]. The internal loads of the production hall as well as weather data influence the system as disturbance variables and are taken into account by the MPC controller. To evaluate the EMMPC controller, various scenarios are evaluated taking seasonal weather influences into account.

Electricity costs in winter can thus be reduced by 2.1% compared to energy-optimised control. However, energy consumption increases by 7.44% due to higher heat losses when the room temperature is temporarily raised. It could also be shown that a larger thermal storage capacity of the building can increase the potential for load shifting.

For example, in order to be able to include a mixed air chamber, which causes even stronger non-linearities in the system behaviour, in a MPC control system, the extension of the MMPC by further MPC controllers is currently being worked on. In addition, the coupling to a production plan-dependent activation time optimisation adapted to the hall and outdoor air conditions, which determines an optimal start time for the air-conditioning of the hall, is in progress. In this way, energy consumption can be further reduced [13].

In order to demonstrate the functionality also in real operation, the coupling with full HVAC system with connected climate chamber, in which also internal loads can be simulated, is under construction. A further starting point is the creation of adaptive, self-learning state space models, which are generated on the basis of real measurement data in order to further improve the prognostic capability and thus the accuracy of the optimal control variables.

The publication shows that the use of an economic model predictive control is suitable for the efficient and economic prognostic guided control of HVAC plants, which could actively participate in load management. It is also shown that the approach of a multiple model predictive control can particularly control non-linear behaviour of typical HVAC processes like dry and wet cooling. Thus, EMMPC can be seen as a promising approach to optimise the flexible operation of complex HVAC systems. However, even more in-depth development work is required to map even more complex systems on the one hand and to be able to control real systems in real time on the other.

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Nomenclature

$x(t)$:	State vector
$u(t)$:	System input vector
$y(t)$:	System output vector
A :	State matrix
B :	Input matrix
C :	Output matrix
D :	Feedthrough matrix
y :	Plant output
u :	Manipulated variable
z_k :	Optimal control variable sequence
$J(z_k)$:	Objective function
n :	Number of plant output variables or manipulated variables
p :	Prediction horizon (number of intervals)
w :	Tuning weight
s :	Scale factor
r :	Reference
k :	Current control interval
ρ_ϵ :	Constraint violation penalty weight
ϵ_k :	Slack variable at control interval k
$\sum \dot{Q}$:	Heat flow balance in W
m :	Building mass in kg
c_p :	Specific heat capacity at constant pressure J/kg · K
$\vartheta(t)$:	Temperature at time t
t :	Time in s
P_{tot} :	Total power consumption of the HVAC system (without fan power consumption) in kW
k_{el} :	Electricity price in (€/kWh) / s

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