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titled:	*Cloud-based controller architecture for the testing of conventional and model predictive room heating controllers in a real-world environment*
by the authors:	Philipp Althaus and Sascha Johnen and André Xhonneux and Dirk Müller.

The work is accepted and was presented at CoDIT 2024.

Conference:	10th International Conference on Control, Decision and Information Technologies
Date:	01/July/2024 - 04/July/2024
Place:	Valletta, Malta

The original version is available at IEEE *Xplore*® under DOI: 10.1109/CoDIT62066.2024.10708077

Accepted paper, presented at CoDIT 2024.
Original version see: 10.1109/CoDIT62066.2024.10708077

Cloud-based controller architecture for the testing of conventional and model predictive room heating controllers in a real-world environment

Philipp Althaus[1] and Sascha Johnen[2] and André Xhonneux[3] and Dirk Müller[4]

***Abstract*— The prevailing problem of climate change urges the shift to climate-neutral energy supply and efficient energy use in all areas of society and industry. The share of energy usage for room heating is relatively high and therefore an important field to improve the efficiency as well as CO_2-footprint of the energy supply. Currently, there is still a gap between scientific knowledge about possible energy savings by the application of dedicated control strategies and a wide application in society. Within this work, we contribute to close this gap by showing the design of a cloud-based, configurable room heating control algorithm and investigate the effects on energy demand and occupant comfort in a living-lab field test. Results indicate that the use of forecasted schedules in combination with control algorithms to exploit them can significantly change the thermal demand while maintaining thermal comfort and is well applicable.**

I. INTRODUCTION

Coping with the challenge of climate change requires the urgent need to decrease greenhouse gas emissions quickly in a significant amount [1]. The building sector contributes a share of 36 % regarding the worldwide final energy consumption and 37 % of greenhouse gas emmissions [2]. Thus, it is a promising field to increase efficiency and introduce energy sources with low carbon footprint to effectively reduce the emissions in total. In Germany, for example 70 % of the energy consumption in the building sector is accounted by room heating [3].

Several works have shown that the choice of control algorithms for temperature control in buildings can significantly influence the thermal comfort as well as the energy consumption. Exemplary, the relative energy savings were found to range up to 30 % when applying model predictive control (MPC) to room heating [4], [5], [6]. Besides studies examining different controller behaviours in simulation studies under controlled conditions as e.g. [7], [8], [9], [10], [11], some studies like [12], [13], [14] also applied and evaluated control algorithms in real buildings.

Still, the application to several buildings with different usage type and year of construction and the inclusion of real users and their time-varying demand (respectively temperature setpoints) have been rarely studied yet (c.f. [6]). Thus, we contribute to close this gap, by first designing a cloud controller which a) can easily incorporate setpoint wishes by different sources, b) provides reliable fallback solutions, c) can apply different controllers for comparison and secondly applying it to several office buildings in regular use.

*The authors gratefully acknowledge the financial support by BMWK (German Federal Ministry for Economic Affairs and Climate Action), grant number 03ET1551A.

[1]Philipp Althaus is with IEK-10, Forschungszentrum Jülich GmbH, Jülich, Germany p.althaus@fz-juelich.de
[2]Sascha Johnen is with IEK-10, Forschungszentrum Jülich GmbH, Jülich, Germany sa.johnen@fz-juelich.de
[3]André Xhonneux is with IEK-10, Forschungszentrum Jülich GmbH, Jülich, Germany a.xhonneux@fz-juelich.de
[4]Dirk Müller is with IEK-10, Forschungszentrum Jülich GmbH, Jülich, Germany and E.ON EBC, RWTH Aachen, Aachen, Germany

II. METHODOLOGY

This work focusses on the architecture at the level of the cloud controller. Aspects of further elements in the full automation setup (e.g. the specific implementation of programmable logic controller (PLC) programs used, communication, bus protocols at field level and actuator devices) are as well important, but not described in detail here.

The controller architecture needs to deal with four major tasks, which the modules given in figure 1 relate to:

- First, all relevant data forming the input for the following algorithm steps needs to be collected. This task is highly dependent on the infrastructure used and is therefore not explained in detail here.
- Second, the setpoint which shall be considered for control at which time needs to be determined.
- Third, the control output needs to be calculated for each actuator considered.
- Fourth, such control output needs to be packaged and sent in a form which is compatible with the respective recipients. As this step also depends heavily on the infrastructure, it is not described in detail.

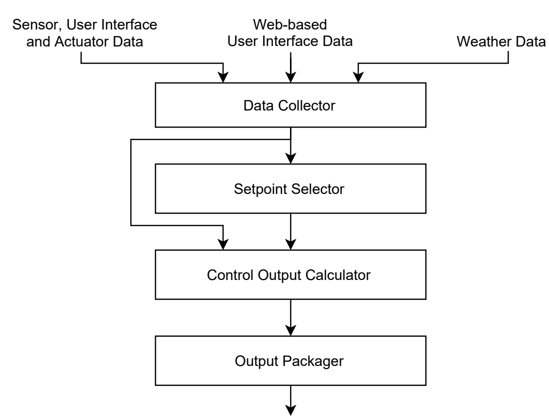

Fig. 1. Schematic on the different modules and the flow of information.

The modular structure of the architecture allows relatively easy adaptation to other infrastructures and the implementation of different control algorithms with significantly fewer effort.

A. Evaluation of active Setpoint Source and Setpoint Value over Time

To allow a flexible use and the exploitation of system knowledge, it is necessary to provide not only the current temperature setpoint, but also allow the extraction of the currently expected future temperature setpoint trajectory over time. Sophisticated control algorithms can utilise the additional information contained; MPC based algorithms conceptually do so and also dedicated rule-based algorithms can be designed to do. In case that the setpoint shall be adjustable via different interfaces, moreover all of such setpoint sources need to be considered. To enable the provision of such complete (future) trajectory information, a structure of several source evaluators and one builder for a combined schedule is set up. A schematic is shown in figure 2. Each source evaluator is responsible to detect user interactions of the respective source of interaction and to determine the wished setpoint (trajectory) as well as the timespan Δt_{valid} when such setpoints shall be valid. The builder for an integral, combined schedule uses the information on validity over time and desired setpoints over time for all source evaluators. The source to become active (as well as the related setpoint) is evaluated dependent on the setpoint validity, the priority and the activation time of each source. The timestamps which are included into the combined schedule are configurable.

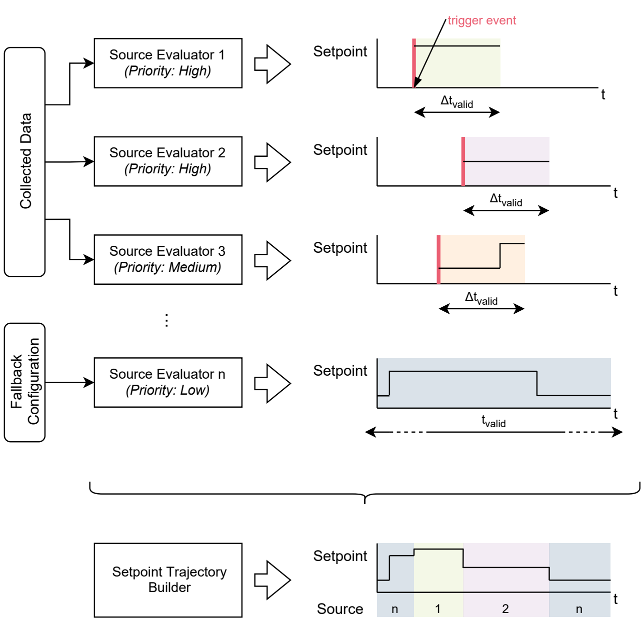

Fig. 2. Schematic of several source evaluators and the trajectory builder. All source evaluators are run in parallel and compute a setpoint trajectory and when the respective setpoint is valid (right side). The setpoint trajectory builder combines such information by the source evaluators to a single, valid trajectory.

In the specific current setup, users can interact with the room heating system in the following ways: First of all, temperature setpoints can be provideded at the electronic thermostat. Dependent on the infrastructure setup in the offices, an interaction via a KNX room control panel is also possible. Moreover, a web-application developed in-house and called JuControl provides two additional ways to influence the room temperature: Users can define a schedule when they plan to be at the office and set a range of minimum and maximum temperature during that time. Furthermore, they can also enter a temperature setpoint at any time [15].

The priorities of sources are set in such a way that a manual definition of a setpoint temperature has the highest priority; the JuControl schedule has an intermediate priority; and a fallback schedule the lowest priority. In case a user interaction occurred to provide a temperature setpoint, the resulting setpoint thus overrides the setpoints by the schedule for a certain timespan Δt_{valid}, currently set to 8 h. As soon as another setpoint is given, such interaction overwrites the previous one. When no such direct setpoint interaction occurred in the given timespan, the setpoint is chosen according to the schedule provided. For cases, where room users do not actively use the web-application JuControl, e.g. because not all users have signed the declaration of consent, a fallback-schedule is put in place. By this, reasonable setpoints are provided also when no active user wish was given within the last Δt_{valid}. Using a schedule instead of a single, fix fallback temperature allows significantly more flexibility and the possibility to combine aspects of energy savings and comfort much better.

B. Calculation of the Control Output

For the calculation of the control output, several different algorithms are set up and evaluated. A first, general distinction is the kind of command which is generated: In the given setup, there are the options to give a) a temperature setpoint only b) a temperature setpoint and a temperature measurement c) a valve position setpoint. Based on these possibilities to interact with the electronic thermostat, we developed different rule-based controllers and a model predictive controller:

1) Direct setpoint extraction: In such configuration, the setpoint is looked up from the resulting setpoint trajectory schedule at the time of controller calculation. In this case, the actuator (electronic thermostat) uses its own internal temperature measurement to evaluate an appropriate valve position. Based on the physical proximity to the hot radiator and previous evaluations (see also [16]), a control mismatch is to be expected. Nevertheless, this configuration allows the general setting of setpoints by different sources and represents a good fallback mode in case no further information is available for the room status (e.g. separate temperature measurement for the room air).

2) Temperature setpoint with pre-heating and measurement: To further increase control quality and comfort for users, this control approach introduces two additional aspects at the same time: As a first element, a rule-based pre-heating phase is introduced. To do so, the temperature schedule is shifted about the configured pre-heating time Δt_{ph}. For all experiments shown in this paper, Δt_{ph} had been set to 1 h. As a second element, the temperature measurement of a indoor air quality sensor is used in case it is classified as valid. In this case, the electronic valve uses this external measurement, which is typically more accurate and representative for the temperature perceived by the room occupants, for internal control instead of its own measurement.

3) P-Control based on pre-heating setpoint and measurement: Extending the previous case (using preheating and the external temperature measurement), a linear controller output is calculated, resulting in directly defining the desired valve position out of the cloud application. By default, the controller is configured with a proportional gain of K_p of $\frac{100\%}{1.25K}$ in our setup. The controller output is limited between 0 % and 100 % valve opening.

4) Model predictive control: To further exploit system knowledge in a model-based manner, a MPC is set up. The optimization problem (OP) solved is given in equation (1). Aiming for an identifiable model and fast optimization capabilities, the structure of the underlying dynamic model is kept small and in Hammerstein form. The linear part of the Hammerstein model is implemented as a single-node RC model, where the state x represents the room temperature. The transformed input ν_u contains the supplied heatflux $\dot{Q}_{sup}$ and the transformed disturbance inputs ν_z are considered as the ambient air temperature T_{aa} (cf equations (2),(4)). The transformation function f_u is chosen as piecewise linear formulation. Even though such formulation would still allow a direct mixed integer linear program (MILP) or mixed integer quadratic program (MIQP) formulation of the complete OP, the hammerstein form is kept to enable the simple exchange of the nonlineariety. Exemplary, an alternative formulation as sigmoid function as shown in equation (3) can be selected.[1]

The cost function aims to minimize the consumed energy while keeping the room temperature between a lower and upper limit for the set of all considered timesteps $\mathcal{K}$.[2] The first part of the cost function holds linear and quadratic terms of the supplied heatflux. The quadratic terms also allow to distribute the heatflux more evenly if several radiators with different maximum heatflux are present. The two further parts introduce mixed integer linear cost terms in big-M formulation for the temperature range violation. The comfort temperature limits (x_{upper}, x_{lower}) are determined based on the given combined temperature schedule over time. To avoid the violation of the lower limit forced by the avoidance of violating the upper limit in time spans of changing temperature boundaries, the maximum of the upper limit from the schedule ($x_{upper,sch}$) is calculated for a two-sided time-window as described in equation (5). The formulation as soft constraints avoids infeasabilities even when a measured temperature would exceed such bounds. Further constraints deal with the starting value of the state vector, the incorporation of the linear dynamics and bound the input heatflux. To apply the output of the optimization, the input u is computed by the inverse of f_u. For the parts of the piecewise linear formulation, where the original function is constant and thus not invertible, constant values of 0 % respectively 100 % are taken for the inverse.

$$
\begin{aligned}
\nu_u^* = &\min_{\nu_u, x} \left(f_c \left(x, \nu_u, x_{lower}, x_{upper}, \nu_z, x_0 \right) \right) \\
s.t.: & \\
& f_c = f_{c,u} + f_{c,x,cont} + f_{c,x,disc} \\
& f_{c,u} = \sum_{t_k \in \mathcal{K}} \left(W_{u,l} \cdot \nu_u(t_k) + W_{u,q} \cdot \nu_u^2(t_k) \right) \\
& f_{c,x,cont} = \sum_{t_k \in \mathcal{K}} \big(W_{x,cont,l} \cdot x_{diff,l}(t_k) \\
& \qquad\qquad + W_{x,cont,u} \cdot x_{diff,u}(t_k) \big) \\
& f_{c,x,disc} = \sum_{t_k \in \mathcal{K}} \big(W_{x,disc,l} \cdot y_{x,l}(t_k) \\
& \qquad\qquad + W_{x,disc,u} \cdot y_{x,u}(t_k) \big) \\
& \mathcal{K} = \{ t_{start}, ..., t_{end} \} \\
& x(t_{start}) = x_0 \\
& \dot{\vec{x}} = A \cdot \vec{x} + B_1 \cdot \vec{\nu_u} + B_2 \cdot \vec{\nu_z} \\
& \vec{\nu}_{u,lower} \leq \vec{\nu}_u \leq \vec{\nu}_{u,upper} \\
& x_{diff,l} \geq (x_{lower} - x) \\
& x_{diff,l} \geq 0 \\
& x_{diff,u} \geq (x - x_{upper}) \\
& x_{diff,u} \geq 0 \\
& M_{x,l} \cdot y_{x,l} \geq (x_{lower} - x), y_{x,l} \in \{0;1\} \\
& M_{x,u} \cdot y_{x,u} \geq (x - x_{upper}), y_{x,u} \in \{0;1\}
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
& \vec{\nu}_u = \left[\dot{Q}_{sup} \right] = \left[f_u(u) \right] \\
& f_u = \begin{cases} 0 & , u < k_l \\ \nu_{u,upper} \cdot \frac{u - k_l}{k_r - k_l} & , k_l \leq u \leq k_r \\ \nu_{u,upper} & , u > k_r \end{cases}
\end{aligned}
\tag{2}
$$

$$
\vec{\nu}_{u,sig} = \left[\frac{1}{1 + e^{-4 \cdot \frac{u - \frac{k_l - k_r}{2}}{k_r - k_l}}} \cdot \dot{Q}_{sup,max} \right] \tag{3}
$$

$$
\vec{\nu}_z = \left[T_{aa} \right] \tag{4}
$$

$$
\begin{aligned}
x_{upper}(\tau) = &\max \left(x_{upper,sch}(t) \right) \\
& , \tau - \Delta t_l \leq t \leq \tau + \Delta t_r
\end{aligned}
\tag{5}
$$

The prediction horizon $t_{mpc,h}$ considered is set to 12 h. The matrices A, B_1, B_2 as well as the parameters k_l and k_r have been identified by solving an OP to fit data of seven days. For the specific cost function, the weights are set as follows: $W_{u,l} = 0.01 \ \frac{1}{kWs}$, $W_{u,q} = 0.0001 \ \frac{1}{kWs}^2$, $W_{x,cont,l} = 10 \ \frac{1}{Ks}$, $W_{x,cont,u} = 10 \ \frac{1}{Ks}$, $W_{x,disc,l} = 0$, $W_{x,disc,u} = 0$. Additional parameters have been set like: $\nu_{u,lower} = 0 \ kW$, $\nu_{u,upper} = 2.5 \ kW$, $M_{x,u} = 50 \ K$, $M_{x,l} = 50 \ K$, $\Delta t_l = 4 \ h$, $\Delta t_r = 4 \ h$. The OP is formulated under use of Pyomo [17], [18] and solved with Gurobi [19].

[1] As such function is continuous, it allows the formulation of a continuous identification problem (not detailed here).

[2] Time-dependencies in constraints are omitted for reasons of readability.

Accepted paper, presented at CoDIT 2024.
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C. Use Case and Test-Bed Setup

The real-live tests are executed within a test-bed set up within the Living Lab Energy Campus project (LLEC) at the Forschungszentrum Jülich. The selection of buildings and equipment is described in detail in [16].[3] The cloud-based control application in this work relies on the following main components to close the control-loop:

- Field devices (sensors and actuators) communicating via the field bus protocols[4] [operational technology layer];
- a programmable logic controller (PLC) to run the low-level automation [edge layer];
- communication services between applications and edge layer as well as a database to store all operation data [data distribution layer];
- further applications to manage devices, metadata and user inputs [application layer].

An overview to the architecture of the infrastructure and communication technology (ICT) setup as well as the necessary software services and data models to reach operation by means of Internet of Things (IoT) is provided in [20]. As described before, users can interact with the system via appliances in rooms and via the web-application JuControl. Details regarding such application are presented in [15].

To allow a robust operation, several fallback-actions are put in place: In case of failure at the cloud controller level or the connecting services between cloud controller and PLC, the PLC program provides fallback possibilities, so the users can still set temperature set points at the appliances in their rooms. In case the PLC fails, the installed actuators switch to a stand-alone operation mode.

III. RESULTS

The data on which the results are based have been recorded in different configurations of operation. Appliances at room level have been installed since 2020. Building-wide energy consumption data is available also for previous years. Experiments have been conducted under real-world conditions and normal use of the equipped offices. The control algorithms under test are varied, but always have to consider providing an appropriate level of comfort and energy demand. From the various controller configurations being tested and experiments carried out several comparisons can be drawn, some of which are described in the following.

First of all, a comparison can be made between the heating demand before (with conventional thermostats) and after the installation of the electronic thermostats with the corresponding (ICT) infrastructure. Figure 3 shows exemplary time spans before and after the installation of electric thermostats. The operation shown in subplot b) resulted from the application of the control algorithm described in the section *"Temperature setpoint with pre-heating and measurement"*. The demand data is taken in one-minute interval and filtered with a moving average of ten minutes

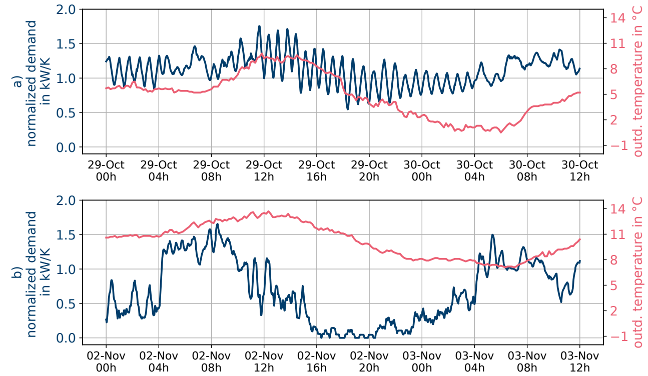

Fig. 3. Comparison of outdoor (outd.) temperature and normalized demand of a building in two phases: Subplot a) refers to operation with conventional thermostats (time range in 2019). Subplot b) corresponds to operation with electronic thermostats and the cloud controller (time range in 2023).

to each side. The outdoor temperature data is collected from the German Weather Service (DWD) with a time resolution of ten minutes from the nearest weather station in Aachen-Orsbach [21]. The normalization of the heating demand is taken against the temperature difference between 21 °C and the outdoor temperature.[5] It becomes well visible, that the new controller enables a significant reduction in demand at night. This effect can be explained by the setpoint reduction during night which is consistently applied for all thermostats in the new configuration while likely not all users have reduced the setpoints in the configuration with conventional thermostats. A steep increase in the morning to pre-heat the offices is visible on both days. In the afternoon, the demand is slightly lowered due to higher outside temperatures and solar radiation. The oscillation visible in the consumption data for the time span in 2019 but not in 2023 can be explained by a replacement of equipment for the building-wide supply station which effected the control quality of the supply temperature but not the general supply demand.

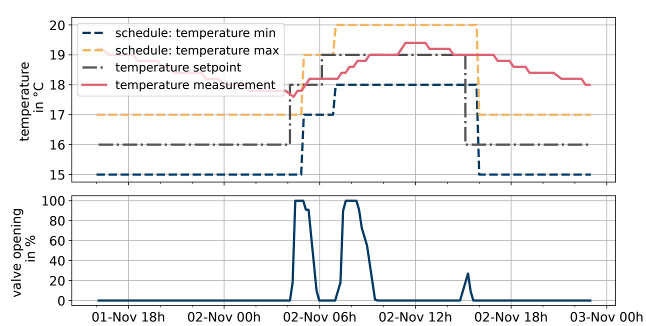

Fig. 4. Exemplary trajectories of given temperature schedules, sent temperature setpoint, measured room air temperature and valve opening.

The reduced demand during night hours can also be found in good correspondence to data at room level: Figure 4 shows data for an exemplary room which was operated in

[3] After finalization of the retrofit with sensors and actuators, about 700 rooms in 15 different buildings will be included in total.

[4] Specifically, EnOcean and KNX are used.

[5] As indoor temperature measurments or temperature setpoints are not available for both time spans, the same value is assumed in both cases.

the control configuration described in the section *"Temperature setpoint with pre-heating and measurement"*. The first subplot shows the schedule trajectory for a minimum and maximum desired temperature in the respective room. The control algorithm uses the mean of minimum and maximum values and shifts it forward one hour. At five a clock in the morning, the (shifted) temperature setpoint exceeds the measured temperature and the electronic thermostat opens the valve. The same behaviour is seen when the setpoint is further lifted to 19 °C. After that, the valve can be kept closed most of the time. In the evening, the scheduled temperature wishes are lower again due to non-occupancy and thereby support the aim of reducing energy demand. The measured temperature remains above the resulting setpoint until midnight and the valve remains closed.

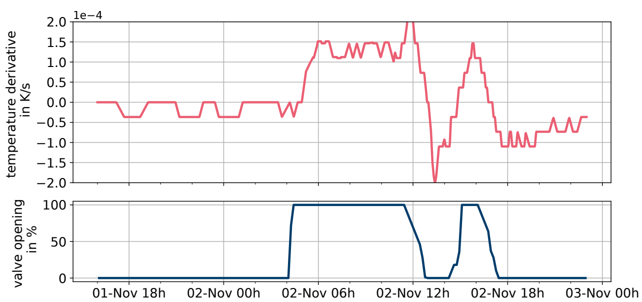

Fig. 5. Temperature derivative and valve opening, example 1.

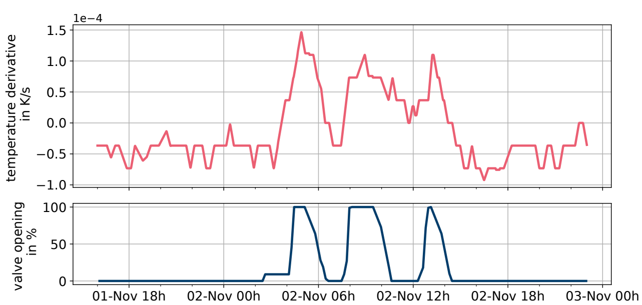

Fig. 6. Temperature derivative and valve opening, example 2.

Besides the fact that the thermal behaviour of rooms is typically slow and the heating system is typically low-actuated (cf. e.g. the rise time in figure 4), various rooms also differ in their thermal behaviour. This becomes well visible when looking to necessary pre-heating times respectively the time derivative of the room air temperature $\frac{\partial T_{air}}{\partial t}$: For some rooms the initially selected pre-heating time of 1 h seems to be well suited. Other rooms do need longer for heat-up and therefore do not reach their setpoint at the originally desired time. Figures 5 and 6 show the time derivatives of the room air temperature in two different rooms. The time series were recorded in 2023. The derivative is calculated numerically from the recorded sensor data as follows: All data points recorded are used, the time series is resampled to an interval time of one minute with linear interpolation for missing values. The central difference quotient is used to calculate the derivative. As the sensor data resolution of 0.2 K is quite large and the raw derivative is noisy as a result, additionally a moving average operation with 45 minutes to each side is performed.

The derivative in example 1 reaches a value of approximately 0.54 $\frac{K}{h}$ while example 2 only shows these values as an absolute maximum and the mean value at times of fully opened valves are near or lower to 0.36 $\frac{K}{h}$. This aspect demonstrates the typical advantages and disadvantages of rule-based control: While in most rooms a comfortable temperature can be restored in time after lowering the room temperature during absence to save energy with the parameterization used in the controller, the selected parameterization is not suitable for some rooms. Moreover, the tuning needs to balance the counteracting aspects of comfort and energy demand. Keeping the same parameterization for all rooms, enlarging the pre-heating time could decrease the number of rooms not reaching the desired temperature setpoint in time, while wasting energy in other rooms heated too early.

To further improve comfort and decrease energy demand, model-based control approaches like MPC can exploit system knowledge explicitly. Fitting the model inside the MPC based on recorded data upfront the application of the controller results in an overall closed-loop behaviour which typically anticipates the system behaviour and the expected upcoming temperature wishes well. Figure 7 shows exemplary data for another room within March 2024. The

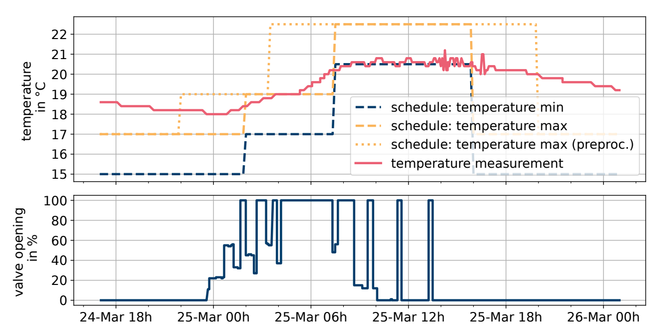

Fig. 7. Temperatures and valve opening during MPC operation.

upper subplot shows the scheduled temperature limits, the preprocessed upper limit (cf. equation (5)) and the measured temperature. The lower subplot gives the trajectory of the valve opening as reported by one of the two actuators available in the room of this experiment. The second actuator has been operated in the same manner. Due to the fact that the actuators are connected via EnOcean and communicate at discrete times only, a slight delay of at maximum five minutes between the valve opening as commanded by the cloud controller and the individual valve positions can occur in the used setup.

Several aspects appear from the specific example: In general, the dynamics of the thermal behaviour is captured and the temperature is successfully kept inside the given boundaries during working time. The operation close to the

Accepted paper, presented at CoDIT 2024.
Original version see: 10.1109/CoDIT62066.2024.10708077

lower bound of 20.5 °C correlates well with the cost function containing a term of the applied heatflux. A slight model mismatch is visible at the first time this boundary value is set. The controller reacts to this by fully opening the valve as expected. In times of upper bound values of 17 °C, these are exceeded as the room did not cool down as much. Compared to the previously presented control approach, the valve position is operated significantly more at intermediate values, indicating the adapted heatflux output. The controller also opens the valve fully when full heating power is required including short times, when a sensor measurement below the lower limit is reported. Moreover, considering the actually measured state (temperature) gives the opportunity to keep the temperature at a lower level for a longer time before a positive step in the lower temperature limit compared to e.g. the presented rule-based control with pre-heating, when the temperature did not fall to the lower limit during unoccupied times. In the result, more energy savings can be gained. Such behaviour especially comes into account, when the room temperature does not fall to the lower limit during unoccupied (night) times, e.g. during spring or autumn and in well insulated buildings. Most importantly, the trajectory planning decision and the control action decision are covered by the OP solved. Thus, the trajectory planning does no longer need to rely on dedicated rules according to which a trajectory is calculated seperately, but the structure and an interpretable weighting of elements of the cost function implicitly influence the trajectory of operation. Still, also such more abstract decisions need to be taken with care. In our use case, for example the time-window for lifting the upper limit might be extended even further.

IV. CONCLUSIONS

Overall, the presented modular structure proved to be beneficial for the development and evaluation of control algorithms in living labs of larger scale. The controller architecture enabling several ways for user interaction has shown to successfully combine long-term ahead assumptions (schedules) and short-term user wishes, either via interaction with appliances or the web-application JuControl.

The experiments with different controllers in our setup have shown, that the use of schedules providing the (future) temperature setpoint wishes of users can significantly save energy and improve the comfort in the same time. As expected by control theory, the use of an external temperature sensor improved control quality. This also applies to the selected wireless sensors, which provide temperature values relatively seldom. The rule-based controllers were capable to exploit implicit knowledge of the system behaviour (e.g. required time to heat up a room) in combination with the provided temperature setpoint schedules. Still, full potential to exploit system knowledge and setpoint schedules to satisfy comfort and energy aspects best is seen using MPC.

Future work is going to extend the experiment analysis comparing variations in additional aspects and multiple aspects at once. Moreover, the MPC algorithm is going to be improved based on the analysis results.

ACKNOWLEDGMENT

The collaboration with the respective colleagues at Forschungszentrum Jülich - especially the project partners, the colleagues from infrastructure departments and the building occupants - is greatly appreciated.

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