A Predictive Comfort- and Energy-aware MPC-driven Approach based on a Dynamic PMV Subjectification towards Personalization in an Indoor Climate Control Scenario

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Abstract: There exist two ways of improving the climate conditions within a building; upgrading the building insulation and applying modern heating technology, whereby the combination of both would obviously yield the best result. Recent heating technologies lay high emphasis on forward-looking behavior in order to be capable of providing both more comfort and a higher energy efficiency. Some rely on outdoor and indoor temperature predictive models. Other utilize occupancy prediction. The majority and in particular the ones based on the Predicted Mean Vote (PMV), employ a PMV-driven fixed single temperature point, range (e.g. 22-24C) or curve as reference. In this paper, we introduce a hybrid, personalized heating control approach. It combines a probabilistic occupancy prediction model together with an energy- and subjectified comfort-aware model-based predictive controller (MPC), which can be tailored dynamically to the users' preference of comfort. Starting with a default PMV and a corresponding first temperature set point, our system learns from the users' interaction with the system's comfort-driven UI and adapts online the MPC's target comfort and thereby the MPC's optimization function respectively. We conducted a user study in a real office environment and show that our dynamic customizable approach outperforms significantly the non-dynamic one in respect of both comfort and energy.

1 INTRODUCTION

According to a study funded by the U.S. Environmental Protection Agency (EPA), people spend almost 90% of their time indoors (Klepeis et al., 2001). It is evident that indoor climate conditions are of great importance, whether at home, at work or in other places. The term *Indoor Environmental Quality (IEQ)* is used to describe how far certain factors, such as air quality, visual comfort (lighting conditions), acoustic comfort (ambient noise) and thermal comfort, among others, affect occupants and especially their physical and mental health (Taylor, 2010). People are healthier, more focussed and more productive in buildings with a high IEQ. Modern, intelligent Heating, Ventilation and Air Conditioning (HVAC) solutions play a central role in promoting and maintaining the IEQ and are therefore a necessity today. This becomes more apparent if we take the rising temperatures on the one hand and the decreasing air quality in urban centers on the other hand additionally into account.

Among all IEQ factors, thermal comfort represents one of the more influential and thus important ones. This justifies the high interest and the growing research and development efforts in this field. In order to achieve high comfort values, while keeping a low energy profile, the vast majority of the approaches work towards a model predictive control methodology. Some others incorporate occupancy prediction models. However, most of them adopt a fixed temperature set point or range strategy aiming at satisfying the needs of the average occupant. This leads to impersonal solutions, which lie below the optimum.

In this work, we present a hybrid heating control system based on a dynamically adjustable model predictive controlling (MPC) unit. The users are able to tailor our controller to their needs in real time by giving feedback on their thermal discomfort. Moreover, our respective User Interface features a degree of fuz-

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ziness, that makes the adjustment more natural. In addition, an occupancy predictive component extends the MPC unit in order to endow our system with an additional proactive behavior and further enhance the overall outcome.

The remainder of this paper is organized as follows. Section 2 provides an overview of the related work in this area. Section 3 gives insight into the theory behind our framework, followed by section 4, which outlines in detail our control approach. In section 5, we describe first the user study we carried out in order to evaluate our approach, and the corresponding experimental setup. Then we present and discuss the evaluation's outcomes. Finally, section 6 summarizes our work and provides our final conclusions.

2 RELATED WORK

Comfort, as an experience, represents a subjective sensation of individual people (Nikolopoulou and Steemers, 2003). Not everyone shares the same view about whether a certain experience is comfortable or not. Furthermore, comfort is highly relative and depends strongly on the current situation. In (Ahmadpour, 2017) for instance, Ahmadpour confirms a high correlation between humans' concerns, like control, privacy, accessibility, style, etc., the situation in which they find themselves, and their general comfort experience. Lan et al. focus in (Lan et al., 2012) solely on thermal comfort and investigate how high or low temperatures affect human performance in an office environment. They came to the conclusion that deviations from the thermal comfort optimum produce a clear negativ impact on the overall performance. Furthermore, they establish a relation between energy saving system designs and a reduced performance of office workers. Analyzing the behavior of people in different thermal environments confirms that determining and setting the optimal thermal comfort is essential. Amasuomo et al. in (Amasuomo and Amasuomo, 2016) tested the stress behavior of students in lecture rooms. Their results indicate that discomfort leads to less concentration, more tiredness and irritation. A similar project was conducted by Steinmetz et al. (Steinmetz and Posten, 2017), where he showed that the response behavior differs in cold and warm environments.

In order to determine and describe the thermal comfort, Fanger defined in the 1970s' the Predicted Mean Vote (PMV) (Fanger, 1970). The PMV is a model, which considers indoor temperature, humidity and clothing level among others to calculate a thermal comfort index. Section 3.1 gives a brief insight into the theory behind the PMV model. However, Mors et al. proved in practice that the PMV is not perfect. Particularly, he showed that the PMV was not accurate enough to set the optimal comfort for primary school children (Mors et al., 2011). Yao et al. (Yao et al., 2009) created the adaptive PMV (aPMV) that uses additional seasonal differences to overcome the PMV's inaccuracies. The aPMV defines among others a much lower optimal indoor temperature in cold seasons than in hot ones. There are different studies regarding thermal comfort. Tham et al. (Tham and Willem, 2010) set up three test rooms, each with a different room temperature ($20°C$, $23°C$, and $26°C$). The study participants stayed in each room for 4 hours. Sensors on the forehead, lower arm, back, hand and foot measured the skin temperature. The research showed that for most people, $23°C$ reflects the optimal comfort. Barrios et al. (Barrios and Kleiminger, 2017) developed a framework called Comfstat to predict the users' comfort in an unsupervised way. They used body sensors to measure the heart rate of each person and showed inter alia that it is important to train the system on each user individually to get more accurate comfort settings. Beside that, a heating control system based on Comfstat would rely for the most part on the heart rate sensing technology that has to be as accurate as possible. Modern smartwatches and other wearables do provide the feature of heart rate measurement, but only very few of them, if any, would be good enough to set a HVAC system accurately enough.

There exists a great variety of indoor climate control approaches. Karatzoglou et al. presented in (Karatzoglou et al., 2017) a climate control approach based on both a Support Vector Regression (SVR)-driven occupancy prediction model, as well as a respective rule base, on top of a PID controller. Their approach was able to enhance the thermal comfort, while keeping the energy consumption low at the same time. Shi et al. in (Shi et al., 2017) use an occupancy prediction model as well to improve their MPC controller achieving a similar high comfort and energy efficiency. Vesely et al. (Veselỳ and Zeiler, 2014) propose an extension of HVAC systems in order to be able to control microclimates and promote that way both personalized air conditioning and energy performance.

Many researchers apply Model Predictive Control (MPC) in their work with promising results. The work of Martincevic et al. support this decision (Martinčević et al., 2016). They compared a conventional temperature controller to a MPC-based one. Their investigation showed that even the simplest variant of

MPC performs better than the conventional controller. Still, the MPC controller and the respective optimization problem have to be set carefully in order to get optimal values for comfort and energy efficiency.

Castilla et al. present in (Castilla et al., 2011) a hierarchical predictive strategy based on a high level nonlinear MPC with an optimization function aiming at improving both comfort and energy efficiency. A PID is additionally used as low level fan coil controller. Some years later, in (Castilla et al., 2014), Castilla et al. present the Practical Nonlinear MPC (PNMPC), using PID again as a low level controller. What is special about Castilla et al.s's work, is that their cost function is applied directly on the actual PMV value and not on the inferred temperature. Garnier et al. (Garnier et al., 2014) use an MPC controller to determine among others the optimal time to turn on and off the system to save energy. An Artificial Neural Network (ANN) model predicts the optimal PMV Value to increase the thermal comfort. Zong et al. (Zong et al., 2017) introduce the Economic MPC (EMPC). Instead of having hard constraints at each prediction step, Zong et al. use soft constraints. They tested their system in a 3-floor apartment in Denmark. The study showed that the EMPC controller is effective for buildings with large thermal storage capacity. Energy efficiency is closely linked to comfort. Occupants do not only want to feel comfortable, but they are also interested in reducing their energy costs. Deng et al. (Deng et al., 2016) investigates an approach, in which the current electricity price is taken additionally into account.

Chen et al. came to an interesting conclusion. In their work (Chen et al., 2015), they compared two different MPC systems. One was using the calculated PMV as thermal comfort feedback, while the other one was using a direct user feedback. The system with the user feedback achieved better results regarding thermal comfort and energy efficiency. Thus, the ability for the occupants to interact with the system in real-time is essential and has to be considered for future intelligent designs. Luo et al. confirm these findings. Their work (Luo et al., 2014) points out that occupants with control over the system are more satisfied regarding their thermal sensation in comparison to others with no control. Kim et al. (Kim et al., 2016) used questionnaires on smart phones to get the feedback of their study participants. Karatzoglou et al. followed a similar way by giving the users the opportunity to give their feedback via a web application (Karatzoglou et al., 2017).

3 THEORY

In this section, we give insight into the three most essential topics related to our paper, *thermal comfort*, *Model Predictive Control (MPC)*, and *Markov models*.

3.1 Thermal Comfort

In general, *comfort* describes a satisfying and enjoyable human experience. *Thermal Comfort* is more specific and according to the ANSI/ASHRAE Standard 55-2010 it is defined as follows (Ashrae, 2010):

> *A condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation.*

In addition, ASHRAE defines a 7-value comfort index scale displayed in table 1. Reaching and keeping

Table 1: ASHRAE Comfort Index.

cold	cool	slightly cool	neutral	slightly warm	warm	hot
-3	-2	-1	0	1	2	3

the optimal thermal comfort reflects the major objective of HVAC[1] systems. There are many factors that have an effect on thermal comfort, like air temperature, clothe insulation etc. Accordingly, there exists a variety of models that capture these factors and try to describe thermal comfort based upon them. Fanger introduced in the 1970's one of the most recognized models up to now, the *Predicted Mean Vote (PMV)* (Fanger, 1970). The PMV model relies on experimental studies on approx. 1300 subjects and takes 6 parameters explicitly into account, namely air temperature, mean radiant temperature, relative humidity, air speed, metabolic rate, and clothing insulation. It is described by the following equation:

$$PMV = (0,303e^{-0,036M} + 0,028) \cdot [(M-W) - H - E_c - C_{res} - E_{res}] \tag{1}$$

M - the metabolic rate, in $[W/m^2]$
W - effective mechanical power, in $[W/m^2]$
H - sensitive heat losses
E_c - heat exchange by evaporation on the skin
C_{res} - heat exchange by convention in breathing
E_{res} - evaporative heat exchange in breathing

with:

$$H = 3,96 \cdot 10^{-8} f_{cl} \cdot [(t_{cl}+273)^4 - (t_r+273)^4] - f_{cl} \cdot h_c \cdot (t_{cl} - t_a) \tag{2}$$

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$$E_c = 3,05 \cdot 10^{-3} \cdot [5733 - 6,99 \cdot (M-W) - p_a] \\ -0,42 \cdot [(M-W) - 58,15] \quad (3)$$

$$C_{res} = 0,0014 \cdot M \cdot (34 - t_a) \quad (4)$$

$$E_{res} = 1,7 \cdot 10^{-5} \cdot M \cdot (5867 - p_a) \quad (5)$$

I_{cl} - the clothing insulation in $[m^2 \cdot K/W]$,
$f_{cl} = 1.05 + 0.1 I_{cl}$ - the clothing surface area factor, with $I_{cl} > 0.5$ (due to winter conditions)
t_a - the air temperature, in $[°C]$,
t_r - the mean radiant temperature, in $[°C]$,
v_{ar} - the relative air velocity, in $[m/s]$,
$p_a = Humidity \cdot 6.1094 \cdot e^{(17.625 \cdot T_room)/(T_room+243.04)}$ - the water vapor partial pressure, in $[Pa]$
t_{cl} - the clothing surface temperature, in $[°C]$

As can be seen in the above equations, the PMV model tries to provide an average estimation about the thermal comfort in a certain room by using values that can be easily measured. This easiness of use reflects its greatest advantage. However, it is not capable of capturing the personal comfort vote of each occupant, since comfort is subjective as was mentioned before. The system presented in this work is premised on the PMV model and in particular on its *subjectification*, that is its personalized adaptation, as we will see later on.

3.2 Model Predictive Control (MPC)

Model Predictive Control (MPC) refers to a class of control algorithms that leverage a model of the (dynamic) process both in the offline (design), as well as in the online (operation) phase. The process model itself can be linear or nonlinear and is usually a result of system identification. MPC systems use this model in combination with the sequences of past input (or 'control') $[u_{k-1}, u_{k-2}, ...]$, output $[y_{k-1}, u_{k-2}, ...]$ and noise $[z_{k-1}, uk-2, ...]$ signal values, as well as a given future reference set point sequence $[r_{k+1}, r_{k+2}, ...]$ to predict the future open-loop system's output within a finite prediction horizon n_p. A finite sequence of future input (control) values $[u_{k+1}, u_{k+2}, ..., u_{k+n_c}]$ is then estimated by solving an optimization problem described through a cost function, which takes both the future system's output-set point deviation $\vec{r} - \vec{y}$, and the input variable's rate of change into consideration. Modern MPC solutions work on the basis of the so called *Receding Horizon*, where only the first element of the calculated input sequence is used by the system. The rest is being discarded. This optimization process is repeated at every time step during the operation phase resulting to the system's gliding horizon behavior. Equation (6) describes a typical linear, discrete and time-invariant state space process model.

$$x_{k+1} = Ax_k + Bu_k \\ y_k = Cx_k + Du_k \quad (6)$$

where $x \in \mathbb{R}^n$ is the *state vector*, $A \in \mathbb{R}^{n \times n}$ the *system matrix*, $u \in \mathbb{R}^p$ and $B \in \mathbb{R}^{n \times p}$ the *input vector* and *matrix* respectively, $y \in \mathbb{R}^q$ and $C \in \mathbb{R}^{q \times n}$ the *output vector* and *matrix* analogously, and finally $D \in \mathbb{R}^{q \times p}$ represents the *feedforward matrix*.

The MPC cost function, that is the optimization problem, can be formulated as in equation (7).

$$J = \sum_{k=1}^{n_p} w_{y_k} (y_k - r)^2 + w_{u_k} (\Delta u_k)^2 \quad (7)$$

where w_{y_k} and w_{u_k} represent *weighting coefficients* that help adapting the outcome to our needs. Finally, a set of boundary conditions is usually defined to complement the optimization function. It is expressed through a set of inequations shown in equation (8).

$$u_{min} \leq u_k \leq u_{max}, \quad k \in 1, ..., n_c \\ y_{min} \leq y_k \leq y_{max}, \quad k \in 1, ..., n_p \\ x_{min} \leq x_k \leq x_{max}, \quad k \in 1, ..., n_p \quad (8)$$

In section 4 we will proceed with the adaptation of MPC to our use case, the heating control.

3.3 Markov Model (MM)

A *Markov model (MM)* or *Markov Chain* represents a certain type of a stochastic process. The term *stochastic process* refers to an ordered collection of one or more random variables and is used usually to describe dynamic processes that change over time at random. Markov Chains define memoryless stochastic processes that satisfy additionally the Markov property, according to which, predictions for the future based on a short history yields similar results to those based on the whole history. Markov Chains are categorized by their *order* depending on how far back history is taken into account. A 1st-order Markov Chain is defined by the following conditional (Markov) property (Bishop, 2006):

$$p(z^{(m+1)} | z^{(1)}, z^{(2)}, ..., z^{(m)}) = p(z^{(m+1)} | z^{(m)}) \quad (9)$$

whereby $z^{(1)}$, $z^{(2)}$, ... is a series of random variables. Thus, the prediction relies in this case solely on the current state and is independent from the former ones. A 2nd-order Markov Chain would analogously consider both the current, as well as the previous state, etc. Higher order Markov Chains tend therefore to cluster the considered previous states together. In this paper, we use Markov Chains to model and predict the occupants' room attendance, as we will see in more detail in the following section.

4 OUR APPROACH

Our framework presented in this paper is characterized by a hybrid 3-model architecture. It combines a machine learning (ML) based room occupancy predictive model together with a dynamic PMV-driven Model Predictive Control (MPC) and a PI controller as a low-level actuator. Fig. 1 shows the corresponding layer diagram. Our goal is to achieve an individual optimal thermal comfort while keeping a low energy profile at the same time.

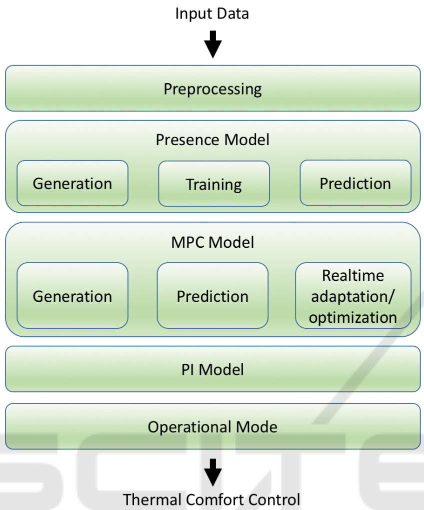

Figure 1: Layer Diagram of our framework.

In comparison to other systems that build upon a fixed temperature set point or zone, our approach relies on a variable PMV comfort index. It provides the capability of real-time individualization of the target PMV index through interaction with the user. In other words, the user can at every time tailor his own personal optimal PMV index according to his preferences and wishes. The system leverages this information and updates, that is it shifts the MPC's target PMV curve accordingly. At the very beginning, our systems starts with a default mapping between the optimal PMV = 0 and the corresponding optimal room temperature according to Fanger's field study results. We selected the default optimal temperature set point $T_{room_{opt,def}}$ to be 23.5°C due to the fact that our study took place in the late winter where the outdoor temperatures were not that extreme. Fanger's field study results indicate a temperature around 25°C for the cooling and 22°C for the heating season to be optimal. So, a value in-between represents a reasonable choice for our case. In the operating phase, the user can express his discomfort via an interface, which is described in detail in section 5.2. Every user interaction is utilized by our approach for *subjectifying*, that is customizing the PMV curve for that particular user. This is done, in which it shifts the curve according to the user's (dis)comfort feedback and the corresponding current room temperature. So, for instance if the default optimal temperature of 23.5°C is too warm for a certain user, his feedback would respectively be let us say $cVote = +1$ of the ASHRAE scale. The system corresponds to this deviation formulated in equation (10):

$$\Delta_{PMV} = PMV_{room_{opt,def}} - cVote = 0 - (+1) = -1 \tag{10}$$

by updating the optimal temperature and consequently the $PMV - Temperature$ mapping for that particular user. The updating step size varies depending on the comfort feedback of the user as shown in table 2. For instance a thermal comfort vote of -1.5 elicits an optimal temperature rise of $+0.6°C$. We selected an exponential course for the updating

Table 2: Comfort vote driven temperature updating steps $uStep$ (in ASHRAE and °C).

cVote	$[-3,-2)$	$[-2,-1)$	$[-1,0)$	0	$(0,1]$	$(1,2]$	$(2,3]$
uStep	$+1.2$	$+0.6$	$+0.2$	0	-0.2	-0.6	-1.2

steps (*uSteps*) in order for our system to feature both rapid response, as well as smoothness and stability. Our Graphical User Interface (GUI) maps the discomfort of the user to a continuous range between -3 and $+3$. Partitioning this value range in chunks as seen in the table 2 instead of using discrete values, awards our system with a certain degree of *fuzziness*, which in turns leads to a better user experience. We tested all in all two different types of partitioning. The one illustrated in the above table and the following: $[-3.0,-2.5],(-2.5,-1.5],\ldots,[2.5,3.0]$ which yielded slightly poorer results. Equation (11) describes the updating process.

$$T_{room_{opt,subj}}(t+1) = T_{room_{opt,subj}}(t) + uStep \tag{11}$$

with

$$T_{room_{opt,subj}}(0) = T_{room_{opt,def}} \tag{12}$$

In equation (13) we can see our MPC component optimization function.

$$J = J_{Comfort} + J_{Energy} = w_C(PMV - PMV_{Target})^2 + w_E(T_{heat} - T_{room})^2 \tag{13}$$

with $T_{heat} \leq 65°C$ the temperature on the radiator and $T_{room} \geq 18°C$ the room temperature. w_C and w_E are the weighting factors for comfort and energy respectively.

Due to the nonlinear nature of PMV (see formula (1)), we reduced the problem down to having the room temperature $T_{room_{opt,subj}}$ as a reference value in our cost function as shown in equation (14). In tangible terms, we converted the MPC's nonlinear PMV target sequence into a linear temperature target sequence.The particular approximation can be justified partly by the fact that indoor temperature represents the most significant factor in the PMV equation, and partly by the fact that most of the rest of the parameters, such as clothing level and air speed can in our case considered to be constant (see section 5.1). The dynamically, by the user updated $T_{room_{opt,subj}}$, is determined by the Δ_{PMV}, as mentioned above, and adapts the future set point trajectory in real-time. Moreover, the updating rate is implicitly taken into consideration by the MPC.

$$J = J_{Comfort} + J_{Energy} = w_C(T_{room} - T_{room_{opt,subj}})^2 + w_E(T_{heat} - T_{room})^2 \quad (14)$$

In this work, we decided to lend more weight to the comfort and we defined therefore a comfort-related weighting coefficient of $w_C = 100$ and the one for the energy to be $w_E = 1$. Our $100/1$ ratio choice is based on the one hand, on our previous work (Karatzoglou et al., 2017), and on the other hand, on some first observations during a short preliminary user study carried out shortly before the major study. Generally, indoor spaces exhibit inert temperature profiles and lack the necessity of fast actions. Therefore, we set our MPC component to perform a prediction every 20min with a prediction horizon of 10h. However, the MPC component is active only when the room is currently occupied or estimated to be occupied soon. In Fig. 2 we can see a detailed flow diagram of our approach. The prediction component is based on a Markov model, like the one described in section 3.3. Our Markov model is of 1st order and uses both *day of week* and *time of day* in the form of 24 one-hour slots as additional training features. It predicts the presence or absence of a room every 5 minutes. In order to derive presence or absence from the raw motion detector data, we used a 5 and 15 minutes long detection window respectively. The respective lengths help in filtering out short presence or absence situations, such as short toilet visits.

Finally, a PI controller with $k_p = 0.25$ and $k_i = 0.125$ following the MPC controller was used for the actual temperature setting.

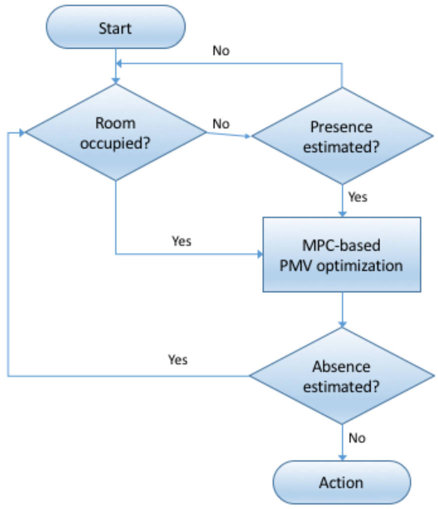

Figure 2: Flow Diagram of our framework.

5 EVALUATION

In order to evaluate our system in practice, we designed and carried out a 12 weeks long field experiment in an office building scenario. In particular, scope of our study was to test our heating control concept and compare it with a MPC control that uses a conventional, fixed PMV-based temperature set point for all occupants and lacks an occupancy prediction component. The reference MPC system was configured with the same parameters (length of prediction horizon, cost function weights, etc.) as our own MPC approach described in section 4. First, we collected 6 weeks of room occupancy data to train our Markov Model based attendance predictor. The user study itself took place afterwards and lasted 6 weeks, whereby we used the first two weeks for testing our infrastructure, while collecting sensor data at the same time. We used the remaining 4 weeks to test the performance of our approach in comparison to a reference systems: 2 weeks for each. We tested both controllers in 6 different rooms of an office environment. Each office room used in our experiment contained one to three people. All in all, we had 11 persons participating our study.

During the study, the participants were asked on a regular basis (hourly) to fill out a short survey via a smartphone application. The questions asked in the surveys aimed mainly at getting feedback from the users about their thermal sense of well being. These were used to derive the corresponding thermal comfort index (see section 3.1). An extra group of questions focusing on gaining a comprehensive view of the state of the user, such as her current activity and level

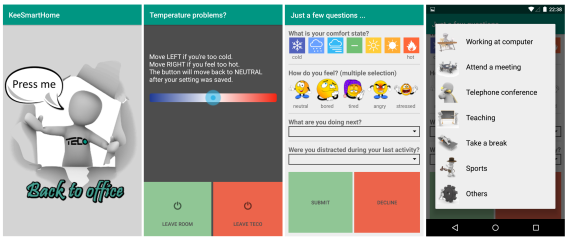

Figure 3: Login screen, UI screen (virtual thermostat), survey screen, and activity survey screen (from the left to the right).

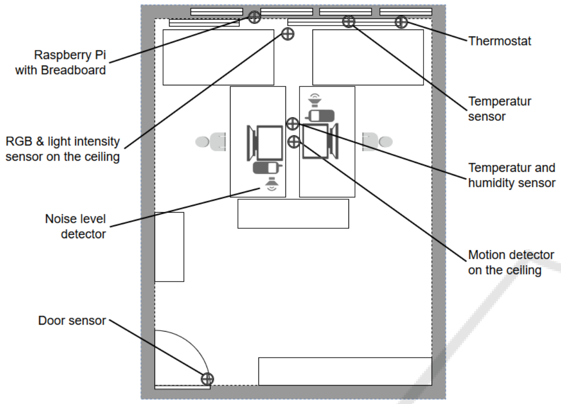

Figure 4: Sensor and HW deployment.

of workload experienced at that time, complemented the questionnaires. This can be shown in Fig. 3. In section 5.3.3 we discuss briefly some correlation outcomes between the users' activity and their thermal comfort.

The windows were kept closed and the window blinds at a constant level in order to maintain the same conditions during our experiment. Besides, the participants were asked not to change their daily clothing level (e.g. taking off their jacket, ...) in order to prevent related false study results. The radiators in the office environment used for our study are connected with exposed (outside the walls) heating pipes to each other. So, when a person turns on one of the radiators, the heating pipe in all previous rooms are getting hot too, which in turn has an effect on their temperature. To avoid such uncontrolled influences of following radiators we used an 22mm polyethylene pipe insulation with a thickness of 9mm to cover all exposed pipes within the test rooms. After that, heating tests showed no demonstrable influence of the water flow initiated by other radiators in the heating system.

5.1 Experimental Setup - Deployment

In this section, we discuss the deployed hardware infrastructure of our experiment. Fig. 4 gives an overview of a typical sensor and HW installation in one of the office rooms. The rest of the rooms are of similar size and architecture.

Each room was equipped with sensors to measure the prevailing environmental conditions. An HDC1080 temperature and humidity sensor was mounted indoors in every room, near to the participants and close to their working desk. We installed the same sensor outside the building on the same floor in an appropriate weather resistant shell to get the outdoor temperature and humidity values. Apart from that, we used it also in the corridor to infer eventual temperature gaps between the offices and the corridor. On the other hand, a DS1820 temperature sensor was fixed with insulation tape in the middle of the radiator front to measure directly its temperature. In order to control the hot water flow in each of the rooms, we mounted a wireless FHT8V valve operating mechanism on the radiators. The door state was monitored by a magnet switch and one to two motion detectors, depending on the size of the room, were mounted on the ceiling above the users. In addition, we used RGB-sensors to keep watch over the light conditions.

A User Interface (UI) is needed in our approach for customizing the MPC's comfort-related set point in real-time, as described in section 4, as well as to survey the users' feedback about their thermal comfort. For this purpose, we deployed a smartphone with an app running on it, designed by us (see section 5.2), at every workspace serving as a user interface. At the same time, we used the smartphones' sensors to measure the brightness and the ambient sound level near the user. We used clams to fix permanently the smartphones at the monitors in sight of the users as shown on the right of Fig. 5, so that they could send their comfort feedback in the most comfortable way. Moreover, with the smartphone at sight we were able to remind our participants to fill-out the survey by blinking smoothly the screen instead of annoying them with ringtones or other alerting functions. Fig. 5 shows a sample of pictures of the deployed sensors and the UI.

All sensor data were collected locally by a Raspberry Pi[2] board that served as a measurement server and forwarded the data to the central server for further processing. For this purpose, each sensor had to be connected through an appropriately designed prior circuit to the boards.

A Raspberry Pi equipped with a 868MHz dongle was setup outside the test rooms and functioned as a central valve control server controlling the mounted valve operating mechanisms mentioned above. The respective data transmission was realized with the

[2]https://www.raspberrypi.org/

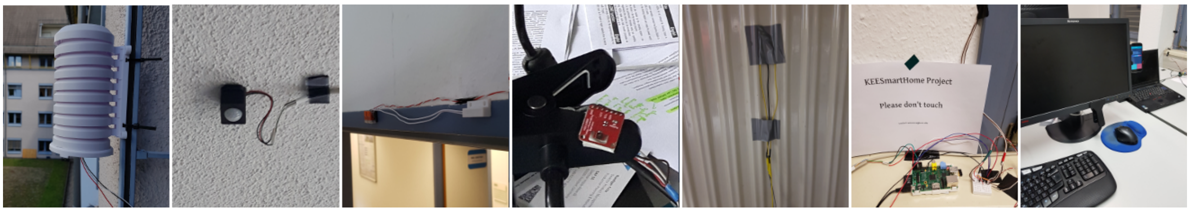

Figure 5: Sensors and UI. Outdoor temperature, motion detection, door, RGB, radiator temperature sensor, Raspberry Pi, and UI (from the left to the right).

help of the FHEM[3] framework and protocol which allows to register and control the FHT8Vs.

5.2 SW Infrastructure and User Interface

Our system uses a server based architecture and consists of three major components: a valve control server, a central data server and a sensor layout deployed in every room. In this section, we explain in detail our SW architecture. Fig. 6 gives an overview of the deployment and illustrates the participating components and their connections.

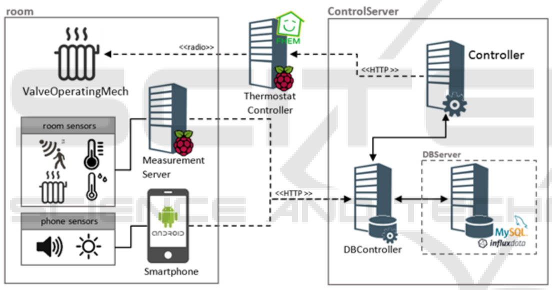

Figure 6: Deployment diagram of our framework.

We encapsulated the valve setting functionality by a HTTP valve control server with an appropriately defined interface to allow the server to control the valves of every test room over the local network. The interface was written in Python and we used the Tornado Web Server[4] for providing the HTTP commands to set and get the valve state.

The central server system processes can be divided into three categories: data storage, system monitoring and controlling. Each service on the server communicates over the local network via the HTTP-protocol. The data storage component consists of two databases. On the one hand, a special time series database (TSDB) is used to store the sensor values and the controller loggings. We have chosen the open solution *influxdata*[5] for this purpose. All comfort feedbacks made by the users during the study are also logged in the time series database. On the other hand, a *MySQL*[6] Database was used to store the complete surveys of the users. Like in the valve control server, all database transactions were handled by a HTTP server to encapsulate the database access. The same interface can be used to link other database systems as well. To identify sensor and HW malfunctions and check if everything works fine, the system was continuously monitored with the help of *Kapacitor*, a component of influxdata. Kapacitor allows sending automatic messages if predefined conditions do not match for a specific period. Additionally, we used influxdata's visualization tool *Chronograph* to check the measured data.

An Android application was written to allow users to inform the central control server about their current comfort state and interact with our controller (*virtual thermostat*). The android application has two different default views: the survey and the thermostat view. The survey view shows a set of questions and is used to perform the interviewing of the users. It is called regularly every hour. The thermostat view enables the users to give feedback about their current thermal comfort on a scale from very hot over neutral to very cold visualized as a gradient line from red to blue. The swipe button's position is mapped to a corresponding ASHRAE comfort index value and is in turn sent to the central server. Our controller utilizes this information to update and readjust the MPC's comfort set point sequence and thus influence the current room temperature on a personal basis. So, our approach learns about the optimal thermal comfort of each user in an interactive manner and uses this knowledge to provide a more personalized solution. After sending the comfort feedback, the swipe button switches back to neutral and is ready for the next feedback. In conflicting cases, where participants in the same room, within a short period of time (20 minutes), don't share the same opinion, our system calculates a weighted average to determine the optimal target temperature, whereby the last interaction is given more weight (60%-40% ratio). But if the second

[3] https://fhem.de/
[4] http://www.tornadoweb.org/
[5] https://www.influxdata.com/
[6] https://www.mysql.com/

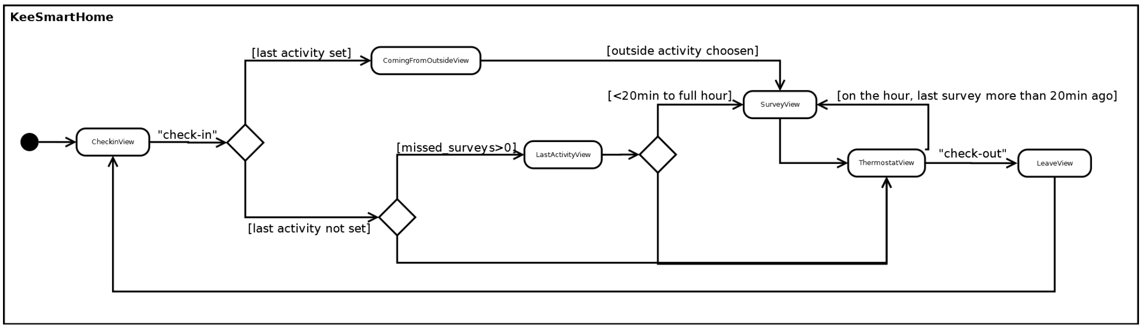

Figure 7: Detailed overview of the Flow diagram of our UI.

(conflicting) interaction occurs more than 20 minutes after the first one, then the last one ist the only one to be considered in our system. The application's workflow is described in Fig. 7, where both the Virtual Thermostat, as well as the Survey functionality can be seen. It should be noted here that the users were able to operate the virtual thermostat during the whole experiment. However, in the case of the reference controller of our evaluation, it has no effect due to being a standard fixed set point MPC controller.

Beyond that, we use additionally the users' interaction with the app to document the users' presence and activity ground truth. For this purpose, the participants were told to check themselves in and out when they arrived and left their workspace respectively. On the right of Fig. 3, we can see the set of activities, that users could choose of.

5.3 Results

We evaluated our dynamic approach in comparison to a standard invariable PMV-based MPC system 4 weeks long (2 weeks each) against two criteria: comfort and energy. The outcomes of our evaluation are presented in this section.

5.3.1 Comfort

Fig. 8 contains the daily average thermal comfort feedback over all users during our field study. Period 1 and 2 (P1 and P2) represent both a 2-weeks long period and reflect the behavior of the reference system and our own approach respectively. On the top of the figure lies the corresponding outdoor temperature curve. We can see that the temperature remained in average over both periods almost constant with the sole exception of the last two days. But all in all there are no great divergences to see between the outdoor temperatures in P1 and P2. With that fact in mind, we can now go on with our evaluation.

What stands out in the figure is that the the comfort vote of the users in period P1 is clearly above

Table 3: Thermal comfort average (*Avg*), variance (*Var*), and standard deviation (*Std*) over two periods (P1: reference system and P2: our system).

Period/Comfort [ASHRAE]	*Avg*	*Var*	*Std*
P1	0.329	0.392	0.621
P2	0.113	0.352	0.588

0, and thus above the optimum ($PMV = 0$). In contrast, the average of the users felt more comfortable in period P2, despite the last two warm days. In addition, the reference controller in period P1 shows both a greater scattering of comfort values, as well as the highest average discomfort vote of $+1$. Both differences are also highlighted in table 3. Apparently, most of our study participants felt in general slightly discomfort with the default target temperature of $23,5°C$ based on Fanger's PMV (see section 4. Even in the extreme situation of the last two extraordinary warm days during P2, our approach yields a stabilizing effect on the users' sense of well being and could again level off near the optimum.

Furthermore, we measured the number of interactions between the users and our virtual thermostat. In period P1, the study participants used the UI 148 times in total (apart from the times they were doing the survey), compared to only 88 times in P2. This fact illustrates once more the advantages of a dynamic and learnable comfort-driven MPC approach. Beyond that, we should not forget the predictive component and their role in achieving good results by proacting instead of just reacting on the users' comfort vote.

5.3.2 Energy

In order to evaluate both systems regarding their energy efficient, we applied the following formula (15):

$$\dot{Q}_{Op} = \dot{Q}_{Norm} \cdot \left[\frac{\frac{t_{V,Op} - t_{R,Op}}{\ln(\frac{t_{V,Op} - t_{L,Op}}{t_{R,Op} - t_{L,Op}})}}{\frac{75°C - 65°C}{\ln(\frac{75°C - 20°C}{65°C - 20°C})}} \right]^n \cdot B \cdot V \tag{15}$$

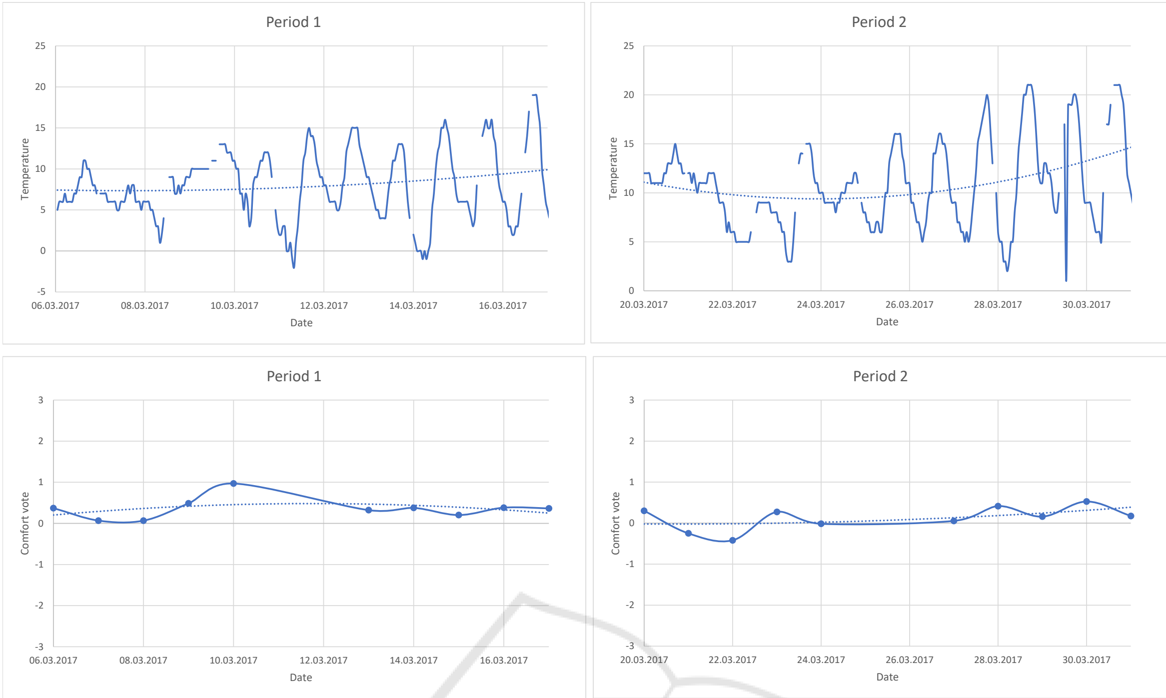

Figure 8: Daily average comfort feedback over all users within period P1 (reference controller) and P2 (our controller). On the top lies the corresponding outdoor temperature.

$\dot{Q}_{Norm}$ - the standard heat output (DIN EN 12831),
$t_{V,op}$ - the operational flow temperature,
$t_{R,Op}$ - the operational return flow temperature,
$t_{L,Op}$ - the roomtemperature,
n - the radiator coefficient (in our case for Typ 10),
B - the radiator's width in [m], and finally
V - the valve setting (0-100%).

Fig. 9 shows the hourly averaged energy consumption value course over all users within a period of 2 weeks for each of the controllers (P1 and P2 accordingly). It is apparent, that in addition to an overall raise of the users' thermal comfort, our system outperforms the conventional reference system in the matter of energy efficiency as well. The overall energy consumption of both systems can be found in table 4. In average, our approach reduced the energy consumption by a total of 51.59% contributing significantly towards a sustainable future. At the same time, our system produces far less energy peak values in contrast to the reference system. A fact that leads additionally to substantial lower energy supply costs. The low energy profile of our approach can be attributed on the one hand to the room occupancy predictive component. On the other hand, one can easily determine that in general customizing the target thermal comfort (PMV) to the users' desires and preferences facilitates further the energy efficiency. In particular, it can be assumed that most

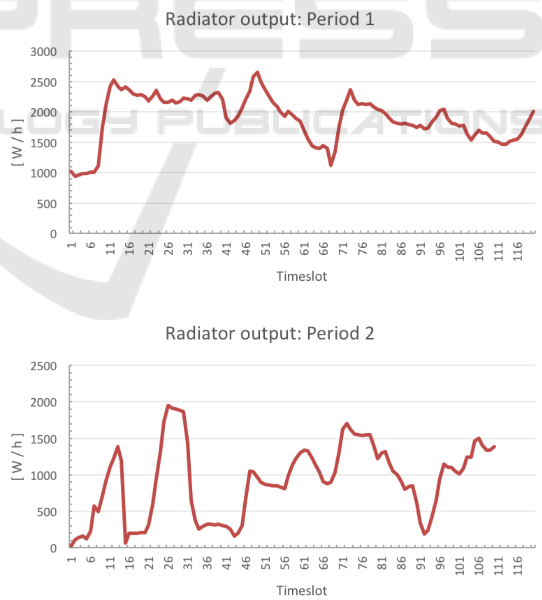

Figure 9: Energy consumption curves over a 4-week period in total (P1: reference MPC controller, P2: our approach).

of our user study participants feel slightly discomfort with the default target temperature of $23,5°C$ based on Fanger's PMV (see section 4. This induced a downward PMV shifting effect and as a result, a minimization of the overall energy demand.

Table 4: Average energy consumption(*Avg*), variation (*Var*), and standard deviation (*Std*) of our system (P2) compared to a reference system (P1).

Period/[W]	*Avg*	*Var*	*Std*
P1	1901.024	151833.2178	388.095
P2	913.158	260852.631	508.411

5.3.3 Activity

As already mentioned previously, during our experiment, we gathered additional context data from the users, like their current activity. A preliminary analysis we conducted gave some first insights into the interrelation between activity and thermal comfort. We could observe a slight correlation between users coming back from a break and a comfort vote over the optimal value 0 reflecting the fact that they felt warmer than usual. Beyond that, the data revealed a tenuous connection between early morning hours at the beginning of the day and optimal comfort. This could be attributed to the simple fact that the users are coming from a cold environment to a warmer and a more pleasant one. Such kind of information could be used to further optimize heat control systems. However, these results are solely indicative and further analysis is necessary in order to gain a deeper understanding of how activity and thermal comfort correlate with each other.

6 CONCLUSION

In this work, we propose a personalized heating control method on the basis of a dynamically customizable PMV-driven MPC core. Our systems responds to the occupants' feedback on their discomfort by adjusting the MPC's future sequence of (thermal) comfort target values. Moreover, we extended the MPC core by a probabilistic Markov-based occupancy predictor in order to further promote both the thermal comfort level, as well as the energy efficiency of our approach. We evaluated and compared our system to a reference MPC controller with a fixed comfort set point. We could show that our method outperforms the reference controller in both comfort and energy, providing a solid foundation for further investigation.

However, there is still room for improvement. In the future we plan to improve the autonomy of our system. That is, we intend to investigate and integrate various methods of inferring the users' sense of well-being without having to ask them permanently for their feedback. For this purpose, we plan to lay our focus on discomfort recognition algorithms based on the one hand on context information, such as the current activity of the occupants and on the other hand on semantical information, like their calendar entries and their schedule, among others.

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