Comfort-efficiency-equilibrium
A Proactive, at Room Level Individualized Climate Control System for Smart Buildings

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Abstract: Energy efficiency and thermal comfort depict two key topics in indoor climate controlling domain. HVAC systems are one of the biggest energy consumers in nowadays' households and yet they have difficulties in reaching the users' optimal comfort. We are presenting SVReCLCE, a proactive two-fold climate controlling approach that takes explicitly both energy consumption, as well as comfort in consideration. A user study in an office environment shows that our solution can in practice achieve up to 49% energy savings by keeping the personal comfort level high at the same time. Therefore, SVReCLCE sets a solid basis for future work in the field of climate control for low-energy buildings.

1 INTRODUCTION

Heating, ventilation and air conditioning systems (HVAC) represent the largest energy consumers in buildings. In expectation of hotter summers in the future, the energy requirement in the climate sector is expected to increase. Hence, optimizing HVAC systems is an important step towards decreasing our ecological footprint. Ideally, an optimal HVAC system would be fully aware both of environmental and contextual conditions as well as of individual characteristics of the occupants and their behavior. Recent products like Hive[1] and Nest[2] signalize the start of tangible intelligent climate control in buildings with focus on energy saving and a better human-machine-interaction. Still, there is room for improvement.

In this work, we introduce a proactive controlling concept capable of adapting and reacting on both the users' direct feedback of sense of comfort as well as the actuators energy consumption. In addition, a machine learning based model is built, trained and used for modeling and predicting the residents' attendance. Finally, a rule base considering common sense users' behavior is created to support additionally our system. We tested and evaluated our approach by comparing it with two other systems serving as a reference on a building cooling scenario. For this purpose we designed and conducted a 4-week experiment in an office environment. The details of our work are presented as follows. Our SVR enhanced controller is introduced in section 3. Section 4 describes our experimental setup. The results of our experiment are presented in section 5. The last section concludes the work.

[1]https://www.hivehome.com/
[2]https://nest.com/thermostat/meet-nest-thermostat/

2 RELATED WORK

Collecting a variety of sensor data and utilizing them for accurate temperature control plays a core role in many current researches. The art in which intelligent controllers handle these data varies widely. (Edwards et al., 2012) explore seven different machine learning techniques for predicting the next hour residential energy consumption, such as Feed Forward Neuronal Network (FFNN) and Support Vector Regression (SVR) a.o. Depending on the data set some techniques perform better than others. Overall, SVR represents one of the best methods applied across all the data sets. (Megri and El Naqa, 2016) use SVM to predict thermal comfort indices. For this purpose, the SVM was trained with a group of different factor

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data sets influencing the thermal comfort, such as air temperature, relative humidity, clothing value etc. An interesting SVM based approach close to our own but applied in a complete different domain is the one proposed by (Deng et al., 2014), which is used to improve the position precision of a servo system. They model and predict the position error with SVM and then feed it back to the system, thereby improving the precision. They show that combining SVM with a PID controller can raise significantly the prediction accuracy. Occupancy prediction is one way of reducing energy consumption by switching down the heating or cooling, if no one is in the room like in (Koehler et al., 2013) and (Scott et al., 2011). However, prediction is not restricted in occupancy when it comes to energy efficiency and user comfort. (Ellis et al., 2013) use temperature sensors, gas meter sensors, outdoor temperature sensors and boiler or furnace time in order to predict the indoor temperature. By predicting the temperature they are able to control the boiler or furnace more accurately. (Oldewurtel et al., 2012) use the weather forecast to control the temperature more efficiently. Feldmaier et al. swear by a great number of fixed and portable sensors in (Feldmeier and Paradiso, 2010). Beyond that they also collect the user's feedback about their thermal comfort by letting them push one of three buttons (hot, cold and neutral). A control module collects all information and decides whether to open or close the window or change the temperature. Thermal comfort describes the feeling that people have about the ambient temperature. There are different components that influence thermal comfort like air temperature, air velocity, air humidity, radiation, clothes, activity, outdoor temperature and other (Dentel and Dietrich, 2013). Fanger created an index to represent the comfort level - the Predicted Mean Value (PMV) (Fanger, 1970). It considers energy exchange, clothing, air temperature, humidity, velocity and radiation temperature. The Predicted Percentage of Dissatisfied (PPD), also developed by Fanger, describes the satisfaction of a group of people. PMV and PPD are widely used indices as in (Kalz et al., 2013) and (Yun and Won, 2012).

3 SVR ENHANCED CLOSED LOOP COMFORT-ENERGY CONTROLLER (SVRECLCE)

Our proposed closed loop comfort-energy controller consists of three core components: A PID based component, a SVR based prediction component and a rule based component that pieces i.a. the previous two together. The system takes both the comfort feedback of the users, as well as the energy consumption into account to control the temperature. Moreover, it is capable of adapting to occupancy patterns describing how, when and how long people do occupy their office or living space. The individual components and their part in the overall system will be discussed in the next paragraphs. An illustration of SVReCLCE is shown in figure 1.

3.1 PID-based Component

This section presents in detail the core of our comfort-energy controller. It is designed to control the room temperature, depending on both the user comfort and the energy consumption. To achieve this we built a twofold comfort-energy controller consisting of two independent PID controllers (PID_E and PID_C) respectively. One for each control variable. While the first aims at reducing the energy consumption, lies the scope of the second in optimizing the users' comfort.

$$PID_E(t)=K_{p,E}*e_{C,E}(t)+K_{i,E}*\int_0^t e_{C,E}(t)\partial t+K_{d,E}\frac{\partial e_{C,E}(t)}{\partial t} \qquad (1)$$

$$PID_C(t)=K_{p,C}*e_{C,E}(t)+K_{i,C}*\int_0^t e_{C,E}(t)\partial t+K_{d,C}\frac{\partial e_{C,E}(t)}{\partial t} \qquad (2)$$

$$PID_{Fused}(t)=w_E*PID_E+w_C*PID_C \qquad (3)$$

$$w_E=1-w_C \qquad (4)$$

In 1 and 2 we can see the output function of the two PID controllers. They describe the cumulative way, in which the value of the manipulated variable of the energy and the comfort PID controller respectively is being determined. Each function consists of three K_x-weighted terms: a proportional, an integral and a derivative term. The overall behavior of the controller is defined by the summation of the terms and consequently by the combination of the aforementioned coefficients. So, the steadiness of the system can be adjusted by tuning the integral term. Modifying the derivative term fine tunes the speed of the controller. PID_{Fused} represents the overall output of the comfort-energy core component, which is in our case the room temperature. This value stems from the weighted fusion of the two single PID controllers PID_E and PID_C. Configurating the weights w_C and w_E allows a twofold adjustment of the controller's behavior based on both comfort and energy efficiency accordingly. This enables us to shift from a comfort based system towards a more energy efficiency aiming one and vice versa.

The comfort of the user is represented by a comfort index described in chapter4. It is mapped to a numerical scale and is subsequently passed on the

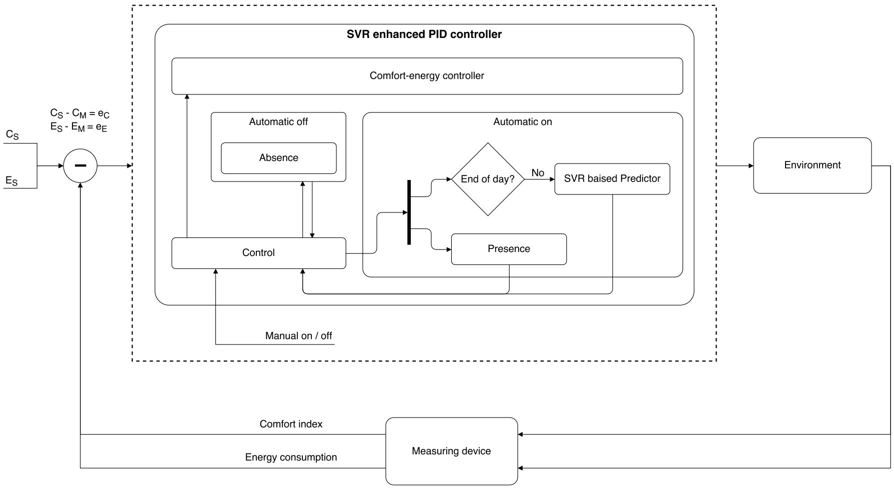

Figure 1: SVReCLCE control loop and its elements.

$PID_{comfort}$ controller, or more precisely, it is the system deviation from the user comfort set point $e_C(t)$, which is routed back to the input of the PID controller.

$$e_C(t) = C_{set}(t) - C_{meas}(t) \tag{5}$$

Analogous to PID_C the energy focused controller PID_E takes the system deviation from the energy set point $e_E(t)$ as input.

3.2 SVR-based Prediction Component

The twofold PID-based core component is extended by a prediction component. The predictor capacitates the overall controller to behave proactively according to the expected attendance of the user and thus enables the system to create a comfortable environment before the users arrives the temperature controlled area. The underlying presence model is built on the basis of a support vector machine/regression (SVM) (Abe, 2005) with a radial basis function (RBF) kernel described in 10. The goal in SV-based regression is to find a function $f(x)$, which shows a maximal deviation ε from the obtained objects y_i for all the given training data (x_i, y_i). The quality of the estimation of SVR is measured by the loss function shown in formula 6. The actual estimation is given in 9. $G(x_n, x)$ represents the kernel function of the SVM. ε defines the space in which no penalty is added in the loss function. The penalty error is defined by the parameter C. Finally N is the number of the support vectors and b gives the bias. The notation used in 6 to 9 corresponds to the dual formulation of SVR. Our presence model is built upon two features. The time of day and an indicator that distinguishes between workdays and non workdays. This basic day differentiating indicator yields a better true positive prediction rate despite the small amount of the training data. The prediction component adapts to the current situation by providing both a short- and a long-term prediction. For this purpose it considers two separate prediction horizons of different size. While a short horizon is sufficient during a normally busy workday in an office, longer inactivities, e.g. before the begin of the workday and in holidays, are handled and compensated by a larger horizon. The selection of the horizons type is determined by a set of rules comprised in a rule base.

$$\begin{aligned} L(\alpha) = \tfrac{1}{2} \textstyle\sum_{i=1}^{N} \sum_{j=1}^{N} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) G(x_i, x_j) \\ + \varepsilon \textstyle\sum_{i=1}^{N} (\alpha_i + \alpha_i^*) - \sum_{i=1}^{N} y_i (\alpha_i - \alpha_i^*) \end{aligned} \tag{6}$$

$$\textstyle\sum_{n=1}^{N} (\alpha_n - \alpha_n^*) = 0 \tag{7}$$

$$\forall n : 0 \leq \alpha_n \leq C ; \forall n : 0 \leq \alpha_n^* \leq C \tag{8}$$

$$f(x) = \textstyle\sum_{n=1}^{N} (\alpha_n - \alpha_n^*) G(x_n, x) + b \tag{9}$$

$$G(x_1, x_2) = \exp - \frac{\|x_1 - x_2\|^2}{2\sigma^2}) \tag{10}$$

3.3 Rule-based Component

The role of the rule based component lies in extending the residential behavior model built by SVR and therefore supporting the prediction and optimizing the overall control behavior. The rules cover situations like long absence, short lunch breaks, and even shorter absences like quick toilet stops during the day and help to revise inaccurate predictions by defining two core behavior modes concerning the automatic start and stop of the system respectively: *automatic on* and *automatic off*. The controller alternates between these two states during the day.

The *automatic on* mode relates to the wakening procedure of the system. During this mode the system monitors simultaneously both the current output of the present detection mechanism, as well as the outcome of the prediction component and reacts accordingly. If at least one of them triggers an event, the system is turned on and its mode is being set to automatic off, waiting for the right conditions to turn itself off again. The presence detection mechanism applies a detection time window to prevent the system from reacting too sensitive to the output of the motion detection sensor. An event in an area is only triggered if the duration of the motion in the particular area exceeds the detection window length. Some factors need to be taken into consideration when determining the length of the detection window. For example too short visits in the corresponding area should not start the system. A long enough observation window can filter this kind of short actions out. On the other hand if the window is too long, it can lead to discomfort of the user, due to a slower response time of the system. In addition to presence detection, a SVR based prediction model is used to estimate the day and time of the next appearance of a user. Such predictions supply the system with an extra series of triggering events enabling it to react in a forward-looking manner.

In the *automatic off* mode the system monitors continuously the presence of the users. After a certain period of time of motionlessness the system is turned automatically off and the automatic on mode is set. The length of the positive detected absence observation window plays again a significant role. On the one hand, short absence of the user should not be considered for sending a triggering event. On the other hand choosing a very long interval would result to a late turning-off and would therefore affect the overall energy efficiency of the system. A correct balance among these two extremes should be sought.

The user has at any time the possibility to bypass the automatic process. Sending a manual start signal would result in starting the system and setting the automatic off mode. In the case of manually turning the system off, the system can only be restarted automatically after an additional positive absence detection that sets it first to the automatic on mode. This promotes further the behavior stability of the controller.

4 USER STUDY AND EXPERIMENTAL SETUP

We designed and conducted a 4-week user study in five different rooms of an office building in order to evaluate our system in practice. Each office contained one to three people. All in all we had nine participants for the study, whereby one of them was our control person, serving as a comparison. We used the

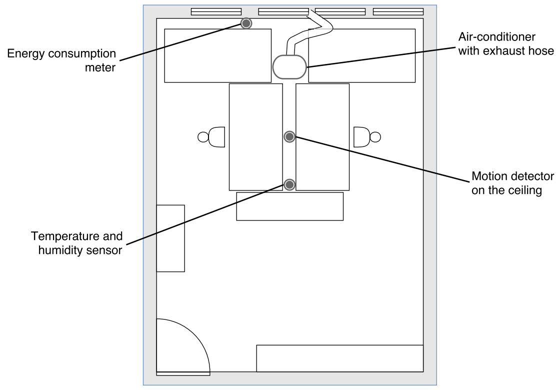

Figure 2: Sensor and actuator deployment.

first week for testing our infrastructure while collecting training data at the same time. The remaining 3 weeks were then used to test the performance of our approach among the one of two further reference systems: one week for each. Figure 3 gives an overview of our server-based experimental infrastructure.

A mobile air-conditioning device (AC) was installed in every room, except in the one of our test person. A Raspberry Pi served both as remote control unit for the ACs, as well as gateway for collecting and forwarding all sensor data to our server. In addition to the AC devices, each office was also equipped with a temperature and humidity sensor, one to two motion detectors, depending on the size of the room, and a smart meter for capturing the energy consumption of the ACs. A temperature and humidity sensor was also installed outside of the building in the same floor to gauge the outdoor temperature. Our server hosted two different databases. A time series database (TSDB) was used to store the sensor values. We have chosen an open solution called *influxdata*[3] for this purpose. At the same time, a MySQL Database was used to store the filled surveys of the users. To safeguard a flawless operation of our system, we monitored the data flow with *Kapacitor* and we used *Chronograph* (both from influxdata), a visualization tool, to conduct further periodical sample checks. In order to achieve room level controlling, a separate instance of the tested climate controller was initiated for each single room.

During the study, the participants were asked to fill out a set of ready-to-use e-surveys on an hourly basis via a web application. The users were given additionally the ability to set a temperature of their desire in their room at any time via the same web interface by adjusting a virtual thermostat. 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

[3]https://www.influxdata.com/

thermal comfort index, which in turn was fed back to our comfort-energy controller. Our comfort index is based on the 7-level ASHRAE scale[4], which describes 7 states from cold to hot surrounding a neutral (optimal) value which lies in the middle. Our comfort index leverages two different kinds of user feedback in parallel. Direct comfort is measured through the survey and the corresponding queries in which the user is asked to rank the current felt comfort. Indirect comfort is derived from her interaction with the virtual thermostat knob. The set value on the thermostat is mapped to the same 7-level scale of ASHRAE and is finally forwarded to the server after every user interaction. Some rooms in our testing environment occupy more than one users. In the case of receiving different comfort indices from multiple users, we obtain a mean value by averaging them in order to achieve the best possible comfort. The floor plan of one of the offices is shown in figure 2. The remaining offices show a similar topology.

5 EVALUATION AND DISCUSSION

In this section, we discuss the performance of our approach and report the final results of our experimental study. We implemented and tested three different climate controlling approaches during our study: a basic *open-loop (OL) controller*, the *closed-loop comfort-energy controller (CLCE)* and the *SVR enhanced closed loop comfort-energy controller (SVReCLCE)*. Each of them was field-tested for one week.

The *open-loop (OL) controller* allows the user to control directly the air conditioner in her room. Hence, the A/C unit reacts solely to input signals passed directly through the web thermostat. The basic principles of the *closed-loop comfort-energy (CLCE)* controller are described in section 3.1. It is a two-fold PID controller, which takes both comfort and energy consumption into account for regulating the temperature in a room. We choose a weight of $4/5$ in favor of the comfort. In contrast to the proactive *SVReCLCE*, starting and stopping of the system is performed here manually by the user. We modeled comfort and energy consumption separately with MATLAB Simulink [5] and chose a state space model with a state vector length of 3. The System Identification Toolbox was used to identify our models. The PID parameters were estimated by testing and leveraging the PID Tuner with the goal of obtaining rapid response and stability at the same time. The following parameters have been determined and subsequently applied on the PID comfort controller: $K_p = 2, K_i = 0.2, K_d = -0.2$. Analog, the parameters used by the PID energy controller are: $K_p = -0.02, K_i = -0.002, K_d = 0.0$. These values were utilized for the configuration of both the CLCE and the SVReCLCE controllers. Neutral comfort and 450W power have been chosen as reference values for the two controllers respectively. The energy consumed over a period of 60 minutes served as input for the energy controller.

After statistically analyzing the users' behavior we were able to define the appropriate moving time window lengths utilized by our prediction algorithm. So, we selected a 30 minutes time interval as prediction horizon to cover the night, before the workday begins, while the window during the day is set to 10 minutes due to the increasing change of attendance state in an office environment. The submission of the end of day online questionnaire served as an end-of-workday flag. A detection window of 5 minutes is used for the actual presence detection and a period of 15 motionless minutes is used to define absence in order to filter short breaks out.

5.1 Energy

Table 1 lists the average energy consumption values of each room, as well as of all rooms together during a period of one week respectively. The average of the energy consumption over one week and over both all rooms, as well as rooms B and C (in brackets) for each controller is displayed on the first row, while the remaining rows below contain the average one-week consumption in each room. Room D shows no energy consumption because no A/C unit was deployed there due to being our reference room, where our control person was. The control person serves as a reference for the study by providing information regarding her sense of comfort from an office without any climate control. This person is thus only able to fill out our e-questionnaires but he/she cannot control the temperature.

As can be seen from table 1, our proactive approach SVReCLCE yields the best overall results when it comes to energy efficiency among the rooms B and C. CLCE and OL take the second and third place respectively. Looking the total average, our SVReCLCE performs better than CLCE, but slightly worse than the OL approach. A closer look at the table, shows that room B clearly stands out in a positive manner. Our controller here helps saving the most energy. Nearly 14.37% could be saved by SVReCLCE

[4]American Society of Heating, Refrigerating and Air-Conditioning Engineers (https://www.ashrae.org/)

[5]https://de.mathworks.com/products/simulink.html

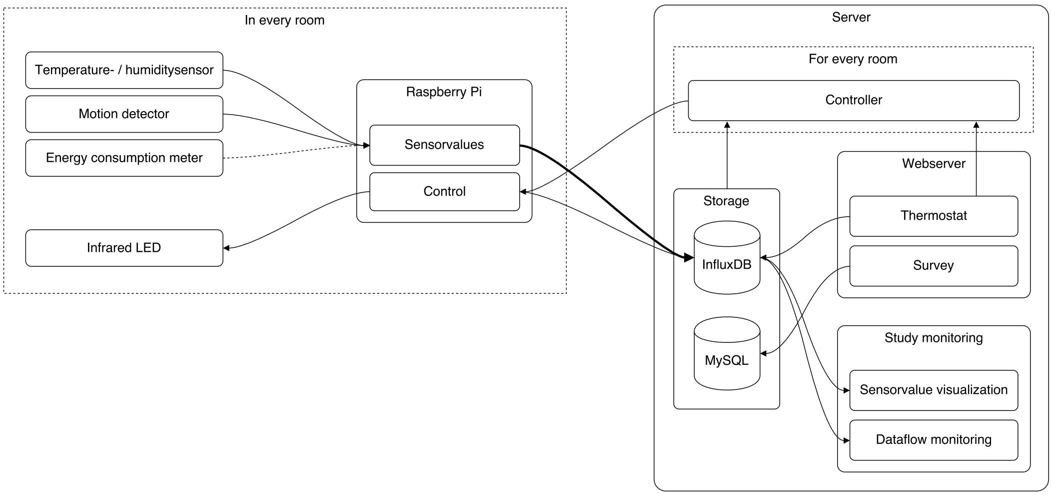

Figure 3: Overview of the HW and SW experimental infrastructure.

Table 1: Average power consumption over all rooms B and C only and over each room separately.

	OL	CLCE	SVReCLCE
average [W]	104.7426	109.6741	107.2958
(Avg of B and C only)	(113.9577)	(95.0499)	(90.6457)
room A [W]	86.3123	138.9226	140.5962
room B [W]	185.8407	110.4873	94.6095
room C [W]	42.0747	79.6124	86.6819
room D [W]	0	0	0

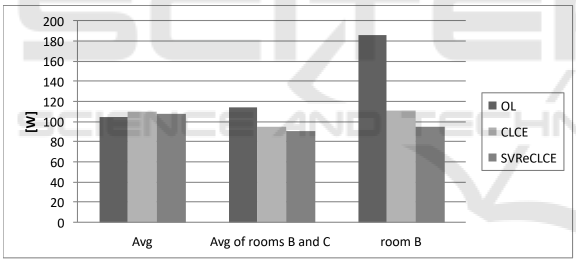

Figure 4: Average Power consumption [W] of our tested controllers among all three rooms (Avg), among rooms B and C and at room B.

compared to the CLCE and almost half the energy (49.09%) consumed by the open loop controller OL. Our controller does not provide us with similar good results at room A though. On the contrary, SVReCLCE led to a 62.89% increased energy consumption in comparison with the OL. This relies on the irregular absence of the associated study participant that used the particular room during the whole third week which our training data don't cover. In addition to the lack of an appropriate data set, two extra major influence factors have also to be noted here. Analysis of the questionnaires showed that the participant of the same room (A) felt disturbed by the operating noise of the A/C unit, resulting in extreme noise-sensitive behavior in which climate control was used only when absolutely necessary. This reflects, for the most part, the low power consumption during the first week, where the users are able to turn the system on and off manually themselves. A similar situation is found in room C, illustrated in 2, which was used explicitly to test the limits of all 3 controlling approaches. Both participants used the room on a quasi-irregular basis and did not occupy the room every day during the four weeks of our experiment. The time of day varied as well. Still, certain attendance days and corresponding times of day remained almost consistent during the study, building weak patterns. Our approach might consume higher amount of energy compared to OL, but is still more efficient than in room A due to recognizing and utilizing the aforementioned patterns. At the same time, our basic controller CLCE performs in case of room B better than OL, but worst compared to SVReCLCE. In rooms A and C though, it shows a slightly better behavior than SVReCLCE. This can be attributed to the same reasons as with OL mentioned above. It must be noted that in case of a direct controller like OL, the energy consumption depends highly on the users' behavior. The more energy-conscious a person handles, the higher the efficiency of OL would be. All in all, up to 49,09% energy could be saved with SVReCLCE. This is also visualized in figure 4. This extrapolates to almost 400kWh for a period of 6 months, say from April to September.

Table 2: Average comfort and standard deviation over all rooms, over rooms B and C only and over each room separately.

	OL		CLCE		SVReCLCE	
	∅	σ	∅	σ	∅	σ
average comfort	0.2877	1.0088	0.3657	1.3276	-	-
(Avg of B and C only)	(0.6087)	(0.9562)	(0.9057)	(1.1576)	(0.5837)	(0.8692)
comfort room A (1p)	-0.3542	0.8536	-0.7143	0.9124	-	-
comfort room B (2p)	0.4482	0.8544	0.8947	1.0205	0.8947	0.9676
comfort room C (2p)	0.7692	1.1200	0.9166	1.2555	0.2727	0.4453
comfort room D (1p)	1.4857	1.2732	0.0000	0.7071	2.7000	0.4582

5.2 Comfort

On the top of the table 2 we can see the average comfort and the corresponding standard deviation values over the respective 1-week period of use over both all rooms, as well as rooms B and C (in brackets) for each controller. The three rows below show the average comfort and standard deviation measured in office A, B and C respectively. At last, room D is the room of our control person. Minus comfort values [-3, 0) point out the fact that it is too cold for the user and positive ones (0, +3] state the opposite. The objective is to get a value close to zero (0). Table 2 indicates a similar overall performance distribution among the tested controllers, such the one seen in the energy related paragraph. Once again SVReCLCE provides the best results among rooms B and C with an average comfort value of 0.58. It is followed by OL and CLCE with a comfort value of 0.61 and 0.91 respectively. As mentioned before, room A was unoccupied during the third week and was therefore not considered in the averaging process. By looking closer at room B and C, one can see that our two test persons in room C found the temperature by SVReCLCE almost 3 (2.820) times more comfortable than by OL and 3.36 times than CLCE. And this, irrespective of SVReCLCE using an imperfect occupancy prediction model (see chapter 5.1). The particular outcome reflects in the end our weighting factors chosen for our 2-fold PID controller, namely 80% comfort and 20% energy efficiency. However in room B, the best comfort was achieved by the OL controller, where the users controlled manually the A/C devices themselves. SVReCLCE and CLCE take both the second place with exact the same value. Nevertheless, the difference between the corresponding comfort values is fairly small. Comfort value of one (+1) stands for ”slightly warm” on the ASHRAE scale. Hence SVReCLCE results in an environment that is even more comfortable than slightly warm, which in turn is a very good outcome for our controller. Looking in the table at room D we can see that our reference person felt significantly uncomfortable (in terms of thermal wellbeing) during week one and three. Furthermore, thermal comfort is a subjective feeling. Thus, table 2 expresses to a certain degree also the individual satisfaction of the participants of our study. Our test person in room A for instance felt the temperature in both first two weeks in average as slightly cold, despite the warm weather (especially in the first week) and the fact that he was able to turn off the A/C unit at any time during this time. The later raises also other issues. Namely, we must not forget that the table 2 gives only insight about the thermal and not general comfort. Users handling by themselves tend to be more easygoing with their own decisions and less critical about their own actions. On the other hand, they expect a perfect outcome from an ”intelligent” system like ours. This explains additionally the good thermal comfort values of OL, at the expense of the general comfort though. SVReCLCE works without the need of user interaction. This makes it overall more comfortable.

6 CONCLUSIONS AND FUTURE WORK

In this paper, we present SVReCLCE, a two-fold predictive cooling system that takes explicitly both thermal comfort and energy consumption into consideration in order to provide an optimal balanced outcome for the inhabitants. At the same time, adaptation and personalization stand in the foreground. SVReCLCE is able to shift its focus between energy and comfort at users' option. Thereby, our approach meets both needs of environmental awareness, as well as personal well being. We tested and evaluated our system in comparison to the non-predictive CLCE and OL, a simple open-loop controller used as baseline, in practice. We could show that SVReCLCE can significantly contribute to saving energy whilst keeping a high comfort level at the same time. We could also find a few weak spots in our approach though. Handling irregular attendance is a major issue. While SVReCLCE performs well by quasi-irregularity (see chapter 5.1 room C), this is not the case by total unexpected user behavior such as the visit of a 5-day conference. This is due to missing knowledge and inaccuracy of our occupancy model caused in turn by an incomplete training data set.

In our future work we plan to increase the quality of the prediction through a larger training data set. In addition, we plan to extend our approach and enrich it through semantic information comprising general, domain and user-specific knowledge such as the personal calendar of the inhabitants and their personal preferences. This would complement the missing information of our machine learner's model and help manage irregular behavior. Furthermore, a dynamic, situation-dependent balance between the two independent PID controllers could also improve our system both in terms of energy efficiency and user's' satisfaction. The needs and the requirements of the user vary over the day depending on the situation. Having an extra learning feature for keeping track of this information and feeding it back to the prediction model of our controller would improve further the final solution.

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