

Finding Good Trade-offs Between Energy Consumption and Occupant's Comfort in Smart Buildings

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Abstract. In buildings, classical heating controllers are based on user-preferred settings of the indoor temperature at particular times of day. The controllers alter the heating or cooling to achieve a desired temperature. Since comfort also relates to other factors, such as human activity rate and indoor air humidity, we developed a novel comfort regulator that computes the value of indoor set-point temperature to achieve the desired comfort dynamically. In this way, finding the best control strategies corresponds to identifying the most user-preferred balances between energy consumption and comfort experience. The second novelty is introduced through a new occupancy-prediction algorithm that improves the comfort experience when a home becomes occupied, and the expert rules that efficiently reduce unnecessary energy consumption during periods when the home is not occupied. Experimental results for a specific building are presented in a comfort/energy consumption space to demonstrate how the Pareto frontier is influenced by (i) different versions of control strategies and (ii) different comfort threshold values. The experiments show that the proposed control system achieved a better comfort experience with small increases in energy consumption compared to a reference approach – that is, a reactive control system that triggers based on occupancy events only.

Keywords: consumption; comfort; smart building; multi-agent architecture.

1. Introduction

Heating represents 70 percent of household energy consumption in European countries, and is the largest consumer of energy in residential spaces [1]. It is targeted in the directive accepted by the Euro-pean Parliament to promote the reduction of energy consumption and global gas emissions by 2020, by at least 20 percent below 1990 levels. In relation to this, installation of active control systems that aim to save energy is encouraged [2].

Regular domestic heating, ventilation and air conditioning (HVAC) systems perform temperature control, where schedules for heating operation are

normally given during installation and are very seldom refined. There are several reasons why occupants do not refine the settings in order to achieve more cost-effective operation of domestic HVAC systems [3, 4], including the following:

- Some people do not want to deal with the settings of the HVAC controllers, since they are afraid to cause malfunction, or because setting optimal schedules is too demanding for the average user due to a lack of knowledge and experience, or is too time-demanding for occupants.
- The indoor temperature that is denoted as comfortable is highly dependent on additional factors,

such as humidity, occupant's activity level, occupant's clothing insulation, etc., and the desired temperature may change frequently in order to achieve satisfactory comfort experience.

- The home occupancy schedule is rarely refined to reduce energy consumption, especially in un-predicted absent periods since users do not want to modify the present schedule too often.

As a consequence, there is a room for intelligent control.

The heating process is slow, dynamic and coupled with the environmental variables, such as out-door temperature and humidity. The time to heat a room to the desired temperature ranges from a few minutes to a number of hours. This highlights the importance of being able to create an occupancy schedule in advance. For example, if the occupancy schedule is known ahead of time, the desired room temperature can be prepared right before the person returns home.

The novelty of our approach relies on finding the best balances between energy consumption and comfort experience for domestic HVAC systems. The desired balance can be specified in advance, along with the choice of control strategy and the comfort threshold. The control strategy exploits a novel control system, which is composed of reactive, anticipative and rule-based components. The reactive component uses simple rule that triggers HVAC operation based on the current home occupancy state. The anticipative component improves the reactive strategy by means of the near-future occupancy prediction, and in case of correct prediction prepares the appropriate temperature within the home environment. The rule-based component uses a set of rules that define the dynamic time periods during which the home will not be occupied. This component is used to reduce energy consumption during such time periods, and also to reduce heating due to false occupancy predictions generated by the anticipative strategy. Furthermore, we implemented a novel comfort regulator that ensures the occupant's comfort, as directly specified as a comfort range by maintaining the indoor temperature through dynamic adaptation of the indoor temperature set-point value. As a consequence, the proposed system allows the occupant to:

- Control their comfort directly, and the temperature indirectly via this comfort, thereby making it user-centered.
- Choose a control algorithm whose operation results in the desired trade-off between energy consumption and comfort experience.
- Transmit the burden of dynamically setting the semi-optimal heating or cooling to the agent system performing the comfort balance on its own.

Section 2 presents the background and definition of comfort, and related work for unobtrusive occupant monitoring in a smart building, and for the

management of comfort and energy consumption. Section 3 presents our approach to comfort regulation.

Section 4 describes the control system architecture, which is composed of various types of agents and the implemented control strategies. Section 5 presents the experimental set-up, the simulation model, and datasets used to evaluate the proposed control system and control strategies. The results are discussed in Section 6, including a demonstration of how the trade-off between energy consumption and comfort experience in a conditioned environment depends on the selected control strategy and parameters. Finally, Section 7 concludes the paper.

2. Background and related work

Smart control of a conditioned environment should achieve robust and economical operation, where the occupant's comfort experience (the term "comfort experience" will be denoted as "comfort" in the rest of the paper) is not violated. The first challenge is how to define the set-point temperature at which the occupant feels comfortable, or how to express the comfort. The second challenge is how to monitor the occupant and environment, in order to obtain real values that express the comfort. The final challenge is how to maintain the comfort in order to achieve an appropriate balance between the energy consumption and comfort in residential buildings.

2.1. The notion of thermal comfort – predicted mean vote and predicted percentage dissatisfied indices

Thermal comfort denotes the thermal sensation of an occupant in a conditioned environment. The mathematical model for evaluating comfort – that is, the predicted mean vote (PMV) – was derived by Fanger et al. [5]. Thermal sensation is related to the thermal balance of the human body, which is influenced by physical activity and clothing, as well as by environmental parameters such as air temperature, mean radiant temperature, air velocity and air humidity. PMV can be calculated according to these factors, although comfort cannot be measured directly [6]. In related work on the control of comfort according to PMV, the computation of PMV is mostly conducted using assumptions of personal parameters, such as the occupant's metabolic rate and clothing rate, as fixed values or fixed ranges of values, such as in [7, 8, 9]. PMV expresses the thermal sensation on a seven-point scale ranging from 3 to +3, where negative values denote colder sensation and positive values denote warmer sensation. The value 0 denotes neutral sensation, which is the target value for indoor air conditioning (if the control objective is to achieve the best comfort). The greater the distance of PMV from 0, the colder (when negative) or hotter (when positive) the sensation.

The predicted percentage dissatisfied (PPD) index provides information on thermal comfort by predicting what percentage of people are likely to feel too warm or too cool in a given environment. The PPD is obtained from the PMV. Both indexes are specified and interpreted in international standard ISO 7730 [10], European standard CEN CR 1752, and other standards involved with ergonomics of the thermal environment [11]. A review paper on thermal comfort can be found in [12], where the model of heat exchange between the body and environment is described for different human activities, which are often simplified – such as sleeping or being awake – whereas the PMV model for sleeping environments was derived in [13]. The difference in comfort notation between genders was taken into account in [14], who stated that females are more critical of their thermal environments and that males use thermostats in households more often. The PPD index assumes that at least 5 percent of people in a group will never be satisfied with the thermal environment.

Figure 1 shows the relation between the PMV and PPD indices. We can observe that the PPD index rises slowly for PMV values until it is close to 0, has almost linear growth for PMV values between ± 1 and ± 2 , and stabilizes towards PPD value 100% at PMV close to ± 3 . The long-term evaluation of comfort according to the PPD is proposed in standard ISO 15251 [15]; this will be used in our long-term evaluation of comfort.

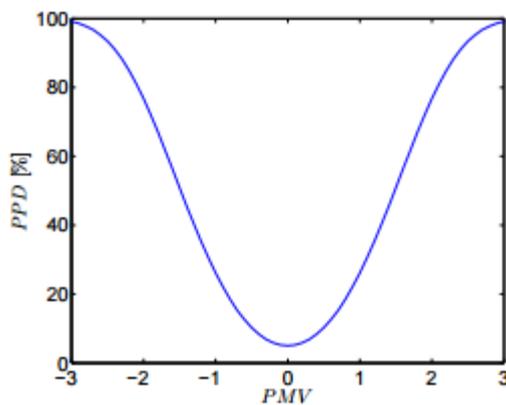


Figure 1. PPD as a function of PMV.

2.2. Monitoring of the occupant in a smart environment

In order to reduce energy consumption when the home is not occupied, and to prepare the appropriate indoor temperature right before occupancy begins, a robust and unobtrusive approach should be used for home occupancy detection. Nguyen et al. [16] conducted a survey of control systems for intelligent buildings and used sensor systems to detect occupant's behaviour. A review of a wide range of systems was conducted based on radio-frequency identification tags, motion sensors, passive infrared sensors, etc., which were implemented to detect room

or per-room occupancy, and to obtain feedback information from users. Several studies have exploited agent-based systems, in which agents are able to communicate in order to extract valuable information and thus achieve better results. Aswani et al. [17] used the, so called, “Berkeley Retrofitted and Inexpensive HVAC Testbed for Energy Efficiency” platform, which is able to monitor occupancy profiles and predict future occupancy based on historical data. Martani et al. [18] implemented a system that detects occupancy based on established wireless local area network connections. Our previous work exploited smartphone sensors to estimate the activity levels of an occupant; these were then used to estimate the clothing insulation, and finally for comfort evaluation (PMV and PPD) and control [19].

2.3. The balance between energy consumption and comfort

Traditionally, the set-point temperature is designated once every several weeks or months. It is included into the HVAC operation schedule. There are several approaches with respect to obtaining comfort by defining the fixed indoor temperature set-point value, or range of values, at which the person feels comfortable, such as those in [17] and [20]. Klein et al. [21] developed a distributed agent system that is able to identify an appropriate temperature setting with agent negotiations according to number of occupants, and coordinate the occupants' behaviour in a way that agents perform scheduling meetings and offices according to the number of occupants and the size of the offices. Vrecko et al. [22] and Yang et al. [23] developed an algorithm that calculates the optimal set-point temperature in buildings, where the time to start heating is computed based on a model predictive control (MPC), so that the correlation between the time-to-heat, the current indoor temperature and the desired indoor temperature is created and adapted automatically based on historical data, thereby expressing the thermal dynamics of a conditioned environment. Other research has focused on regulating comfort in terms of PMV, where the indoor temperature and/or humidity are typical variables that can be controlled in order to achieve the desired comfort, and reduce energy consumption where possible. Various HVAC control systems have been developed to regulate comfort; these include systems based on a fuzzy controller [7] or PID-fuzzy controller [8], which were compared with simple on-off controllers. Liang et al. designed an intelligent control system that is able to create home occupancy profiles based on historic data about occupancy using an artificial neural network, and uses this as an MPC to remove power demand [9]. Morosan et al. [20] developed a system that reduces energy consumption based on occupancy schedule, which is assumed to be known in advance. Examples of achieving the appropriate trade-off between the energy consumption and comfort in a thermal environment were shown in

[8, 9, 24], where comfort was denoted as a PMV index, and in [17, 25, 26], where other methods were used to evaluate comfort, such as static set-point value of indoor temperature and the summation of time periods that temperature was not achieved (often denoted as miss-time).

3. Comfort regulation

Comfort regulation maintains the indoor air temperature in such a way as to achieve the desired value of PMV, or a range of values. Other personal and environmental variables that influence the value of PMV (such as physical activity and clothing, mean radiant temperature, air velocity and air humidity) are assumed to be disturbances that must be compensated for with the change in indoor temperature.

A set-point delegation module (SDM) computes the value of T_s ; that is, the indoor temperature set-point to reach the comfort range, specified by PMV_{ref} . T_s is passed to a heat pump regulator, which regulates operation of the heat pump in order to equalise the T_{in} with T_s . The heat pump regulator is integrated within the simulation model, and is not part of our control architecture. Each control agent uses SDM to continuously compute the desired indoor temperature set-point variable T_s . As a consequence, the desired comfort of the occupant is achieved.

Each time the step k control agent obtains the value $PMV(k)$, which is computed according to the ISO-PMV model defined in Chapter 4 of the standard ISO 7730 [10]. The comfort range is defined as an interval $[-PMV_{ref}, +PMV_{ref}]$, where $PMV_{ref} \geq 0$ is the maximum permitted deviation of PMV from the ideal value of 0. In practical terms, when $PMV_{ref} \neq 0$, the controller will maintain the value of PMV at approximately $-PMV_{ref}$ when heating and approximately PMV_{ref} when cooling. PMV_{ref} enables manipulation of the trade-off between energy consumption and comfort, as will be demonstrated in the following sections.

When the control agent performs a control strategy that includes comfort regulation, each time step k occurs during operation, selected sensor agents provide state variables $s_i(k)$ to the control agents. These state variables are indoor temperature $T_{in}(k)$ and comfort $PMV(k)$. The indoor set-point temperature T_s for the next time-step $k+1$ is computed in order to achieve the comfort range, defined by PMV_{ref} according to Eq. (1): $T_s(k)$ is increased/decreased for the value $T_{inc}(k)$.

$$T_s(k+1) = T_s(k) - T_{inc}(k) \quad (1)$$

The value of $T_{inc}(k)$ corresponds to the following conditions: if $PMV(k)$ is close to the comfort range, the T_s should not change much. If $PMV(k)$ is distant from the comfort range, the T_s could change more. In order to prevent fluctuations of T_s , the following conditions must be met: If the difference between $T_{in}(k)$ and $T_s(k)$ is small, the T_s can change more; if the

difference between $T_{in}(k)$ and $T_s(k)$ is large, the T_s should not change greatly. In other words, the increment/decrement value $T_{inc}(k)$ is (i) proportional to the difference between the PMV(k) and comfort range, and (ii) inverse-proportional to the difference between $T_{in}(k)$ and $T_s(k)$. We want T_{in} to catch up with T_s , so that T_s does not significantly over- or undershoot the temperature at which the comfort range is achieved. Therefore, we derive the following equation:

$$T_{inc}(k) = A \cdot PMV_{diff}(k)^5 + B \cdot \frac{PMV_{diff}(k)}{C \cdot T_{diff}(k) + 1} + D \cdot PMV_{diff}(k) \quad (2)$$

where

$$PMV_{diff}(k) = \begin{cases} 0 & \text{if } PMV \in [-PMV_{ref}, PMV_{ref}] \\ PMV + PMV_{ref} & \text{if } PMV < -PMV_{ref} \\ PMV - PMV_{ref} & \text{if } PMV > PMV_{ref} \end{cases} \quad (3)$$

is the distance between the range of desired comfort values and the current value of comfort,

$$T_{diff}(k) = T_s(k) - T_{in}(k) \quad (4)$$

is the difference between the current set-point temperature and the current indoor temperature. The constant values $A=0.1$, $B=4$, $C=0.18$ and $D=1$ were obtained iteratively by means of several simulation runs in order to achieve a quick response and to prevent oscillations of indoor temperature.

We rewrite Eq. (2) as: $T_{inc}(k) = K_1 + K_2 \cdot K_3$, where $K_1 = A \cdot PMV_{diff}(k)^5 + D \cdot PMV_{diff}(k)$ represents the proportion of Eq. (2) to PMV_{diff} (represented in Figure 2 left), and $K_2 = \frac{1}{C \cdot T_{diff}(k) + 1}$ represents the inverse- proportion of

Eq. (2) to T_{diff} (represented in Figure 2 right). The multiplication of K_2 with $K_3 = B \cdot PMV_{diff}(k)$ and the sum of $K_1 + K_2 \cdot K_3$ gives the final shape of our comfort regulator function as presented in Figure 3. The comfort regulator function that computes the increment of indoor set-point temperature T_{inc} (z axis) is based on the difference PMV_{diff} between the desired comfort and current comfort.

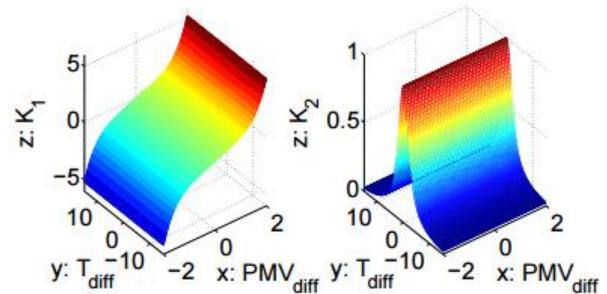


Figure 2. The constitutive parts of the comfort regulator function K_1 , left, and K_2 , right

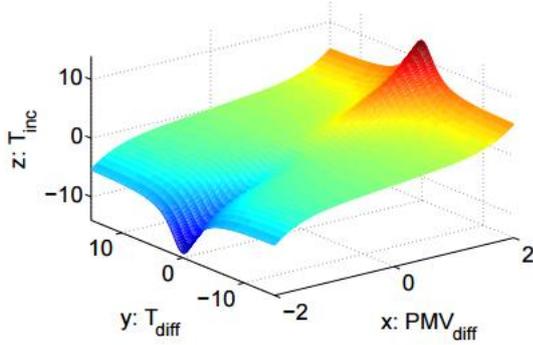


Figure 3. The comfort regulator function $T_{inc}(k) = K_1 + K_2 \cdot T_{diff} + K_3 \cdot PMV_{diff}$ that computes the increment of indoor set-point temperature T_{inc} (z axis)

The time series of the PMV_{ref} and the corresponding T_{in} is presented in Figure 4 for one day of simulation in winter on a test building.

In the middle of the day, when the temperature drops to 15°C, the building was not occupied. Figure 4 demonstrates the effect of comfort range: the higher the PMV_{ref} , the lower the comfort but also the less energy consumed for heating. The difference in PMV_{ref} for 0.2 results in a difference of indoor temperature of roughly 2°C.

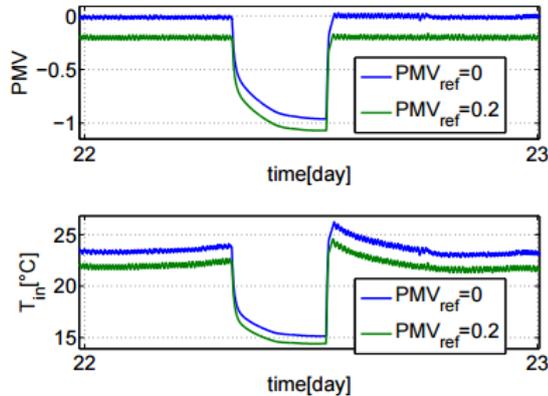


Figure 4. The comparison of PMV time series for different PMV_{ref} , and the corresponding T_{in} during one day of simulation

4. Control system

Our control system is realised as a multi-agent control system (MACS), because agents enable a dynamic and flexible performance that is suitable for our approach. Upgrades of our previous work [27] include advanced perception and regulation of comfort, and an added rule-based component. There are several types of agents. Sensor agents represent sensors in an environment; these obtain the environmental state composed of state variables such as air temperature, humidity, activity level, etc., and collect sensor readings from spatially distributed sensing devices, which also include the occupant’s smartphone to estimate their activity rate, as presented

in [19]. Control agents perform indoor temperature set-point delegation using a comfort regulator, where algorithms for defining indoor temperature set-point values are implemented as control strategies and include an occupancy prediction component that is used to predict near-future occupancy, a rule-based component to reduce false occupancy predictions, and a reactive component that triggers based on home-occupancy-state events. Machine learning (ML) agents perform historic data processing and generate machine learning models. The environment represents the controlled system, which takes set-point variable values as inputs and outputs the environment variable values. Routing agents are used to link the control system (sensor and control agents) with the environment.

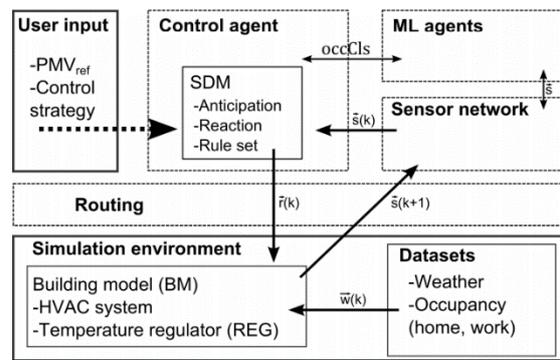


Figure 5. Comfort regulation schema

4.1. Control schema

Figure 5 presents the control schema for com-fort regulation in a building. It consists of our MACS and the simulator. The dashed rectangles encapsulate agents of the same type; the two-way arrows represents communication between agents, and the one-way solid arrows represent feedback control. The bottom part of the figure presents the simulation environment, including a model of a building with integrated HVAC system and temperature regulator (REG). The input to the simulation environment is a vector of set-point variables $\vec{r}(k)$ – that is, $T_s(k) \in \vec{r}(k)$ – obtained from control agents, and also the weather and occupancy dataset $\vec{w}(k)$ for each time step (k) during the simulation period. The output of the simulation environment is a vector that represents an environmental state, $\vec{s}(k + 1)$, at the next time step, ($k + 1$). Routing agents are used to link the simulation environment with the control system so as to map the environment variables to appropriate sensor states and to map set-point variables to appropriate inputs in a simulation environment. The sensor network includes sensor agents that are used to obtain and serve state variables and to generate training data for machine learning. ML agents generate machine learning models (*occCls*) by exploiting methods of artificial intelligence using the historic trends of environmental variables, which are

obtained on request from the control agent – when the control agent implements an anticipative mechanism. The control agent includes the SDM to compute the vector of set-point variables, $\vec{r}(k)$, using anticipative, rule-based and reactive components. User input represents the interface, which allows the occupant to set the comfort range specified by PMV_{ref} , and to choose the preferred control strategy implemented by the control agent. The following subsections describe the operation of each agent type.

4.1.1. Sensor network

The sensor network includes a set of sensor agents, where each sensor agent represents either a physical entity – that is, the sensor in an environment – or a virtual sensor entity. Sensor agents in a sensor network are used to perceive simple or complex sensor states, which represent the states of the i -th environment variable, denoted as s_i , where $s_i \in \vec{s}$ and \vec{s} represents a state vector of all environment variables. Virtual sensor agents estimate the complex sensor state (such as PMV) based on simple sensor states obtained from physical sensors (such as temperature or humidity). Examples of environment variables include indoor temperature, occupancy state and PMV. Sensor agents maintain the most recent value of the sensor state, and also retain a history log of sensor states and generate data for machine learning. Sensor agents are also able to receive and process messages from other agents in the control system. The content of the state vector changes over time, so that at time k it is defined as $\vec{s}(k) = [s_1(k), s_2(k), \dots, s_j(k)]$ if there are J environment variables.

4.1.2. Control agents

Control agents are used to compute set-point variable values. Set-point variables at time k are grouped into a vector of set-point variables $\vec{r}(k) = [r_1(k), r_2(k), \dots, r_K(k)]$ if there are K set-point variables. Control agents compute the set-point variable values in order to maintain the desired comfort, expressed with PMV (Section 3), according to their control strategies (Section 4.3).

4.1.3. Simulation environment

The simulation environment includes a model of a building with the temperature regulation module (REG in Figure 5). Inputs to the simulation environment are the vector of set-point values $\vec{r}(k)$ and the vector of weather and personal data $\vec{w}(k)$ at each time step k . Based on set-point values $\vec{r}(k)$, current states $\vec{s}(k)$, and weather and personal data $\vec{w}(k)$, the simulation environment computes the output vector $\vec{s}(k+1)$ according to the building model with the following equation:

$$\vec{s}(k+1) = BM(\vec{s}(k), \vec{r}(k), \vec{w}(k)). \quad (5)$$

The BM is a set of differential equations and represents the thermal dynamic model of a building with an integrated HVAC system.

4.2. Home occupancy prediction

Occupant behaviour modelling is performed using machine learning on real data about occupancy at work and at home over longer periods of time. Machine learning agents are used to generate machine learning models that are used by control agents in order to achieve better results regarding energy consumption and comfort in smart buildings. The machine learning procedure is used to create a behavior model of an occupant by which to predict occupancy in a building.

Home occupancy and work occupancy are denoted as state variables, $occ(k)$ and $occ_w(k)$, respectively. The occupancy is transformed into a time series with a frequency of one minute, where the occupancy state can leave one of two values: 0, signifying absence, or 1, signifying presence. Based on this data, and with a corresponding data-time value, the instance of machine learning, $occInst$, can be created using the following attributes: minute in a day, day in a week, week/weekend day, month in a year, occupancy at home exactly one week earlier, a daily sum of minutes that the person was at home, the elapsed time in minutes since the occupant left the work environment, occupancy at work exactly one week earlier, a daily sum of minutes the person was at work, occupancy at work, and occupancy at home. The last of these attributes represents the class value to be predicted. The true value of home occupancy is denoted as $occ(k)$, while the predicted value of occupancy is denoted as $occ^*(k)$, and assigned using Eq. (6).

$$occ^*(k) = cls(occInst(k), occCls) \quad (6)$$

where cls is a classification method that returns the predicted value – for instance, $occInst(k)$ – based on the machine learning model (classifier), $occCls$. In contrast to the state variable, $occ(k)$, for the current time, k , which can be obtained from the sensor network, we denote the future time for prediction as $k + k_{nf}$, and the instance to be classified, assumed at that time as $occInst(k + k_{nf})$, where k_{nf} represents the time, added to the current time at which the prediction is needed. In summary, $occ^*(k + k_{nf})$ represents the predicted value of the occupancy state variable in the near future; that is, at time $(k + k_{nf})$.

The machine learning procedure was implemented using Weka data-mining software [28]. A machine learning algorithm C4.5 decision tree was used for occupant behaviour modelling, since trees achieved the best results, as shown in our previous work [27].

4.3. Control strategies

We implemented several control strategies that were applied to delegate the indoor temperature setpoint value: *On*, *Off*, *Sense* and *Learning*. *On*

denotes always meeting the desired comfort, *Off* entails setting the HVAC control system to a default safety temperature, *Sense* indicates that on occupancy the comfort regulation is performed, and *Off* covers all other scenarios. The *Learning* strategy integrates a reactive component that is similar to the *Sense* strategy, rule sets and machine learning procedure to determine the set-point value.

In our experiments, the *Off* strategy maintains the temperature at 5°C (denoted as T_{sLo}) during the simulation in order to prevent the HVAC and other components of the building from freezing. The *On* strategy performs PMV regulation, regardless of whether the occupant is present. It is expected that the *On* strategy will consume the most energy. The *Sense* strategy performs PMV regulation, only during the time periods during which the occupant is present. If the apartment is not occupied, the T_{sLo} is maintained. Finally, the *Learning* strategy includes rules and classification methods to determine the future occupancy of a building. Based on a combination of rules and classification results, the SDM performs PMV regulation if the building is occupied, or if the building will be occupied in the near future. In other cases, the *Learning* strategy maintains the T_{sLo} temperature.

During the initialisation phase, each control agent first searches for the appropriate sensor agents that are needed to implement each strategy. Then subscribes for the states' values delivery to appropriate sensor agents, and finally starts the control operation, which is performed for each simulation time-step. In general, the control operation waits for state variables from all sensor agents the control agent is engaged with, computes the T_s , and passes the T_s to the regulator in the simulation environment.

4.4. Learning strategy

The *Learning* strategy performs PMV regulation when the building is occupied, or when occupancy in the near future is predicted. Near-future occupancy $occ(k + k_{nf})$ at time $k + k_{nf}$, where k_{nf} represents the addition of minutes to the current time k , is predicted using machine learning methods that exploit historical data to create a machine learning model for occupancy prediction, and expert knowledge defined by a combination of different rule sets.

We defined five rules, which can be used as a combination of rules by the *Learning* strategy. The first rule is simple and performs a similar operation to that of the *Sense* strategy, except that in the case of non-occupancy, the next rule is considered. If the building is occupied, the heating is on and the control agent performs PMV regulation:

Rule 1

If $occ(k) == 1$

then assign $T_s(k + 1)$ with Eq. (2)

Rules 2, 3 and 4 are used for lowering energy consumption. Rule 2 applies T_{sLo} if the occupant is absent for more than C_{tAbs} hours. This rule is used to apply T_{sLo} when the occupant is not at home for a longer time (where C_{tAbs} is 16 hours) due to vacation, business trips or any other similar circumstances:

Rule 2

if $(occ(k - n) == 0 \forall n; n \in [0, C_{tAbs}])$

then $T_s(k + 1) = T_{sLo}$

Rule 3 applies T_{sLo} if the person is absent between C_{t1} and C_{t2} , where C_{t1} and C_{t2} indicate the time period between, for example 01:00 and 07:00. In other words, if the person does not return home until C_{t2} . Note: if the rule is processed, occupancy equals 0.

Rule 3

if $(C_{t1} < k < C_{t2})$

then $T_s(k + 1) = T_{sLo}$

Rule 4 applies T_{sLo} if the C_{ND} -th departure happened, and if time from last departure k_{ND} is less than C_{ND} , and if the current day is a weekday ($WD = 1$). N_D represents the daily departure counter; that is, the counter of transitions from $occ(k) = 1$ to $occ(k + 1) = 0$. k_{ND} represents the expired time since the person left home – the time from last departure. The C_{ND} value is normally 1, which implies the following: if the first departure happened, the person probably went to work and will not return for at least C_{ND} hours.

Rule 4: if $((N_D == C_{ND}) \wedge (k_{ND} < C_{ND}) \wedge WD == 1)$

then $T_s(k + 1) = T_{sLo}$

Rule 5 is applied if none of the conditions in the previous rules have been met. If a person is not at home, the machine learning classification model returns the predicted occupancy for the near future $occ^*(k + k_{nf})$. If the occupancy is predicted, the PMV is controlled. Otherwise, T_{sLo} is applied.

Rule 5: if $occ^*(k + k_{nf})$

then assign $T_s(k + 1)$ with Eq. (2)

else $T_s = T_{sLo}$

It is possible to remove any of the rules from the set, or to add additional rules, but the order must be maintained in accordance with the order of rule numbers. Each combination of rules defines a different *Learning* strategy. If the condition of the first rule is not met, the next rule is checked, and so on. If a condition is met, then $T_s(k + 1)$ is assigned according to the appropriate rule statement. For example: the *Learning 7* strategy includes Rule 1, Rule 3 and Rule 6, as shown in Figure 6. Other learning strategies are specified in Table 1.

Table 1. Rule sets and rule constants for different *learning* strategies

Strategy	Rules	Rule constants $C_{ND} = 1, C_{ND} = 5$
<i>On</i>	/	/
<i>Sense</i>	1	/
<i>Learning1</i>	1,2,3,4,5	$C_{tAbs} = 24, C_{t1} = 1, C_{t2} = 7$
<i>Learning2</i>	1,2,3,4,5	$C_{tAbs} = 16, C_{t1} = 1, C_{t2} = 7$
<i>Learning3</i>	1,2,3,4,5	$C_{tAbs} = 16, C_{t1} = 0, C_{t2} = 8$
<i>Learning4</i>	1,5	$C_{tAbs} = 16, C_{t1} = 0, C_{t2} = 8$
<i>Learning5</i>	1,2,5	$C_{tAbs} = 16, C_{t1} = 0, C_{t2} = 8$
<i>Learning6</i>	1,2,3,5	$C_{tAbs} = 16, C_{t1} = 0, C_{t2} = 8$
<i>Learning7</i>	1,3,5	$C_{tAbs} = 16, C_{t1} = 0, C_{t2} = 8$

5. Experimental setup

The experimental set-up includes the simulation model of a single-floor L-shaped house with three

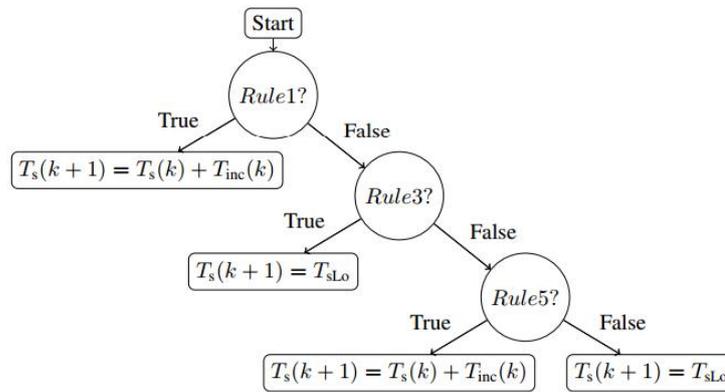


Figure 6. Example of *Learning7* strategy

However, the cooling (heating) coil operation is controlled using the total cooling (heating) capacity function of temperature and flow fraction, the energy input ratio of flow fraction curve and the part-load fraction correlation curve [30]. The location of the simulation is Rateče, Slovenia, so the weather file for that city for the simulation period is used for the experiment¹.

The building model is included in the simulation environment, as shown in Figure 5. The control system is implemented using Java Agent Development Environment (JADE) [31], where (i) a control agent is instantiated for temperature set-point delegation in the east zone; (ii) sensor agents are used for occupancy, indoor temperature and for other states that are needed to estimate the PMV and PPD; (iii) one machine learning agent is used to create the machine learning model for occupancy prediction; and (iv) a routing agent is used for data exchange between the simulation environment and the control system. The simulations were performed with the following assumptions: the Metabolic Equivalent of Task for the

heating zones. Each zone is conditioned using a packaged terminal heat pump, which consists of an outdoor air mixer, fan, cooling coil, heating coil and supplementary heater. Only the east zone, which represents a floor area of approximately 36 m², is considered for the experiment. The heating coil capacity is rated at 6700 W and COP 2.75. The cooling coil capacity is rated at 7200 W and COP 3.00. The supplementary heating coil is rated at 2000 W. The simulation model of the building is taken from example models that came with the installation of EnergyPlus simulation software [29]. The power rate of the heating coil is dynamic and depends on the dry bulb temperature, the wet bulb temperature and the air flow rate, while the regulator is already included in a simulation model.

occupant is assumed to have a constant value of 1.72 met² and clothing is assumed to have a constant value of 1 clo³. The mean radiant temperature is computed using a simulator on the assumption that the occupant is in the middle of the space. Air velocity is assumed as a constant value of 0.15 m/s. The data about home and work occupancy was collected by four volunteers, and transformed into a time series with one-minute intervals. Table 2 presents the properties of the occupancy datasets that were used for the experiment. The first row shows the number of days, and the second shows the proportion of home occupancy. The last row shows the number of arrivals for each person during the observation period. The data for person 1 was collected over a period of 85 days; the person has an approximately 48 % home occupancy rate, and around 1 arrival per day. The data for other people were collected over 30 and 41 days. Persons 2, 3 and 4 have approximately 0.9 arrivals per day, and home-occupancy rate ranges of between 35 % and 40 %.

¹ The data was obtained from the Slovenian environment agency (www.arso.gov.si) for the period between January and March 2014

² 1.72 met represents medium-light activity, such as domestic work [10]

³ 1 clo represents underwear, shirt, trousers, and sweater [10]

Table 2. Summary of occupancy datasets

Person	1	2	3	4
Number of days	85	30	41	30
Home occupancy[%]	47.7	34.8	38.3	38.7
Number of arrivals	88	26	35	26

6. Results and discussions

6.1. Comfort at the moment of arrival

Table 3 shows the average value of PPD at the moment of arrival for the *Sense*, *On*, and *Learning* strategies. As expected, the best results are obtained with the *On* strategy, and the worst with the *Sense* strategy. The difference varies by approximately 20 and 37 percentage points (pp). Among the learning strategies, *Learning4* and *Learning7* achieve the best improvements according to the results obtained from the dataset for each of the four people. *Learning4* and *Learning7* achieved between 4 pp (by person 1) and 9 pp (by persons 2 and 3) worse results than *On*, and around 15 pp (persons 1 and 3) and 29 pp (person 4) better results than *Sense*. Other strategies always achieved better results compared to *Sense*, and worse compared to *On*.

In order to demonstrate the difference in operation of the *Sense* and *Learning* strategies, we plotted the time series of their PPD curves (see Figure 7). On each figure, the x axis presents the date and the y axis presents the PPD value. Solid curves indicate the value of PPD for time periods in which the home is occupied. Dashed curves represent the time periods during which the home is not occupied. Figure 7(a) represents the time series of PPD where the *Sense*

strategy was applied, and Figure 7(b) represents the time series of the PPD index where the *Learning* strategy with Rules 1, 2, 3 and 5 (*Learning6*) was applied.

Due to the reactive nature of the *Sense* strategy, we achieved significant improvements in comfort upon the occupant returning home by using the *Learning* strategies. The spikes in PPD are larger under the *Sense* strategy, as indicated by the ellipses. This demonstrates that the comfort is often low during transitions of occupancy state from $occ(k) = 0$ to $occ(k+1) = 1$. The *Learning* strategy predicts occupancy early enough in many cases, so that the appropriate temperature, $T_s = T_{sHi}$, is ensured when the occupancy begins in order to provide satisfactory PMV. In contrast to the *Learning* strategy, the *Sense* strategy consumes almost no energy when the home is not occupied (it maintains the T_{sLo} temperature). Consequently, the dashed curve after transition

Table 3. Average PPD at the moment of arrival [%] for *Sense*, *On*, and *Learning* strategies

Person	1	2	3	4
<i>Learning1</i>	14.75	22.99	22.71	12.95
<i>Learning2</i>	14.78	23.31	22.85	15.00
<i>Learning3</i>	14.78	23.34	22.85	15.35
<i>Learning4</i>	9.37	13.90	14.15	10.87
<i>Learning5</i>	11.74	22.11	19.65	12.37
<i>Learning6</i>	11.78	22.25	19.65	12.96
<i>Learning7</i>	9.41	14.00	14.19	13.00
<i>Sense</i>	24.78	37.77	31.28	42.31
<i>On</i>	5.01	5.00	5.00	5.00

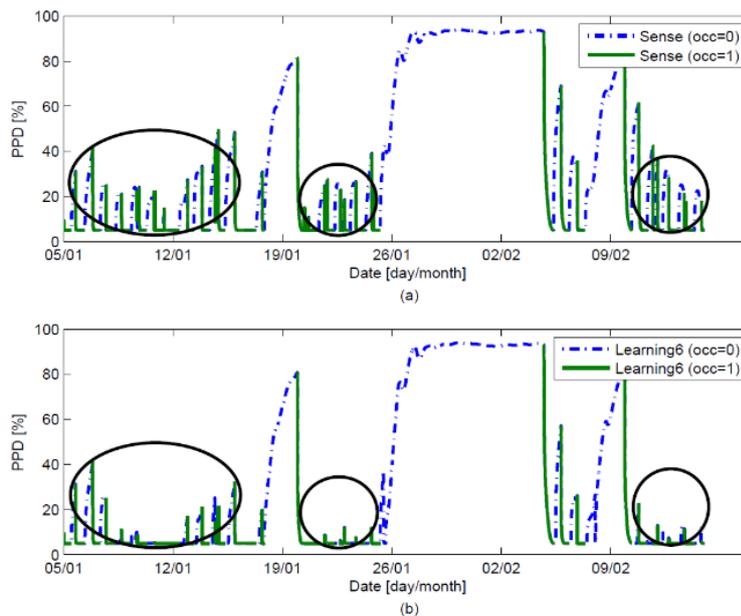


Figure 7. Comparison between PPD time series, produced by *Sense* strategy (a) and *Learning6* strategy (b); $PMV_{ref} = 0$. The solid curve represents the PPD during occupancy, while the dotted curve represents the PPD during non-occupancy. Ellipses indicate major differences between the PPD curves of the *Sense* and *Learning6* strategies

$occ(k) = 1$ to $occ(k + 1) = 0$ always starts to rise towards the value of 100 percent. The *Learning* strategy depends on the occupancy prediction algorithm, and sometimes also regulates PMV after the transition $occ(k) = 1$ to $occ(k + 1) = 0$ since occupancy in the near future was predicted. To conclude, the comfort achieved by the *Learning* strategy can only be as poor as that of the *Sense* strategy but never worse. On the other hand, the energy consumption obtained with the *Learning* strategy, can never be lower than the consumption obtained via the *Sense* strategy. Therefore, the *Sense* strategy achieves the lowest energy consumption when the PMV regulation is performed.

6.2. The objectives: energy consumption and comfort experience

In order to compare the performance of control strategies in terms of energy consumption and comfort, we performed simulations with different control strategies for the occupancy data of the four volunteers. Table 1 shows the control strategies included in the experiment. There are two basic strategies (*On*, *Sense*) for which no additional rules were included. Table 4 shows the simulation results in terms of energy consumption expressed in gigajoules (GJ), and average comfort expressed in percent (%) for those strategies that achieved the lowest and highest energy consumption and comfort during the simulation. The control strategies had a PMV_{ref} value of 0.

From the results in Table 4 we can observe the difference in energy consumption and average comfort of the *On* and *Sense* strategies. The *Sense* strategy consumes 36 % to 49 % less energy than the *On* strategy. On the other hand, the *Sense* strategy results in a worse comfort (average PPD is 14 % to 48 % greater).

Then there are seven versions of *Learning* strategies, where Rule 1 and Rule 5 are always

included. Different combinations of Rules 2, 3 and 4 and different constants - C_{tAbs} , C_{t1} and C_{t2} - enable the use of various *Learning* strategies.

The occupancy data for each of the four people were included in the experiment. Consequently, Figures 8, 9, 10 and 11 – were obtained for each person.

Table 4. Energy consumption and average PPD for *Sense* and *On* strategies

Person	1	2	3	4
Energy consumption [GJ]				
<i>Sense</i>	6.63	2.32	3.32	2.59
<i>On</i>	10.44	4.47	6.22	4.45
Average PPD [%]				
<i>Sense</i>	5.7	6.9	6.8	7.4
<i>On</i>	5.0	5.0	5.0	5.0

Each figure presents a comfort/energy-consumption space, where the x axis represents the consumed energy [GJ] in a conditioned room for the simulation period, and the y axis represents the average PPD value [%] for the simulation period, but only during occupancy. Each marker shape represents the results of a different control strategy, according to Table 1 for different PMV_{ref} . The lower marker of the same shape indicates the result for the depicted strategy with $PMV_{ref} = 0$ and each marker above represents that the PMV_{ref} increased to 0.05, so that each marker of the same shape belongs to the value PMV_{ref} 0.00, 0.05, 0.10, 0.15 and 0.20, from bottom to top, respectively. The solid line connects the nondominated values that form the Pareto frontier, representing the optimal solutions. This means that no better solutions were obtained for either the both comfort or energy-consumption aspects. It is worth noting that we did not include the results of the *Off* strategy because the *Off* strategy does not regulate PMV, and is therefore not relevant for comparison.

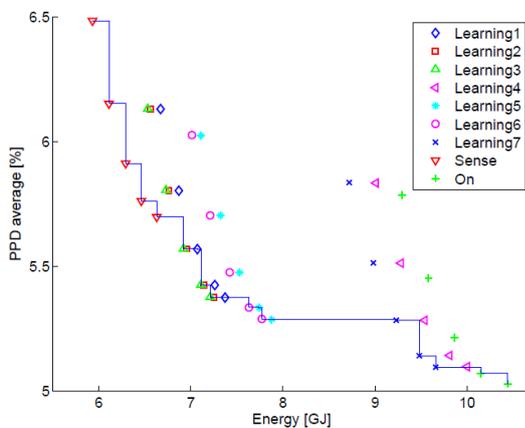


Figure 8. Simulation results for the person 1: PMV thresholds from 0-0.2 for strategies *On*, *Sense* and *Learning*

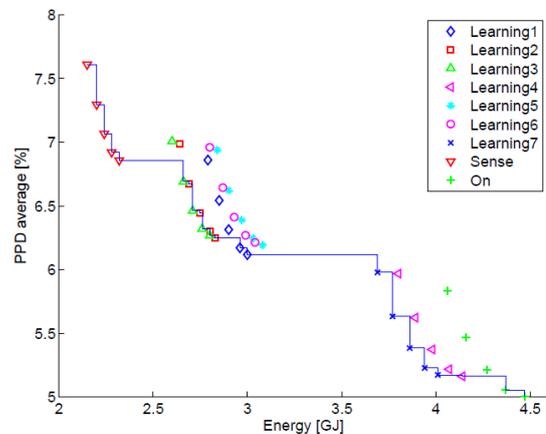


Figure 9. Simulation results for the person 2: PMV thresholds from 0-0.2 for strategies *On*, *Sense* and *Learning*

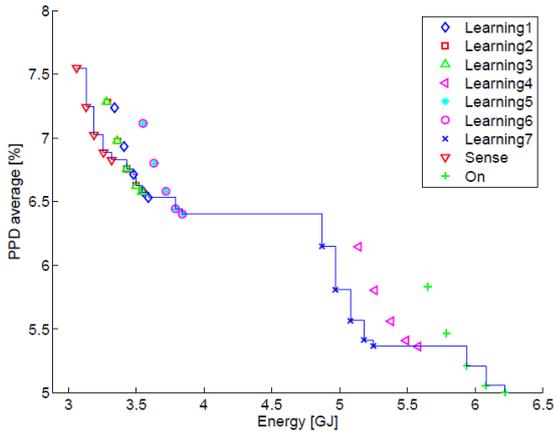


Figure 10. Simulation results for the person 3: PMV thresholds from 0-0.2 for strategies *On*, *Sense* and *Learning*

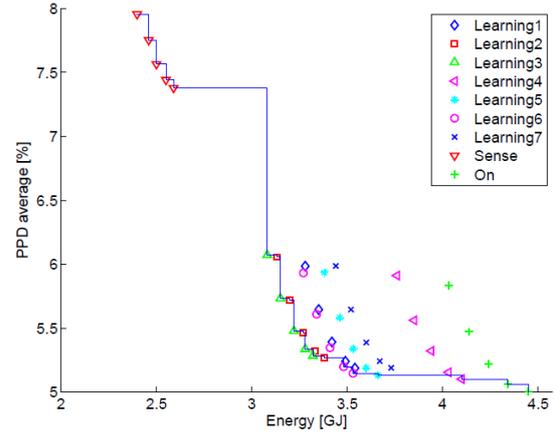


Figure 11. Simulation results for the person 4: PMV thresholds from 0-0.2 for strategies *On*, *Sense* and *Learning*

Figures 8-11 confirm the conclusions from Section 6.1. – that is, that the *Sense* strategy for each of the four people consumed the least energy for the fixed value of PMV_{ref} compared to *On* or any of the *Learning* strategies at the same value of PMV_{ref} .

Furthermore, the layout of the result markers for the comfort/energy-consumption space is relatively similar for all persons. If we fix the value PMV_{ref} , the strategies have the following order: the control strategy, at which the most energy is consumed, in *On*, then *Learning4*, *Learning7*, *Learning5*, *Learning6*, *Learning1*, *Learning2*, *Learning3* and *Sense*.

6.3. The comfort-consumption trade-off

Figure 12 shows the relations between PMV_{ref} and the control strategy for person 1 (as per Figure 8), where dotted lines connect the results of different strategies with the same PMV_{ref} , and solid lines connect the results of the same strategies with the different PMV_{ref} .

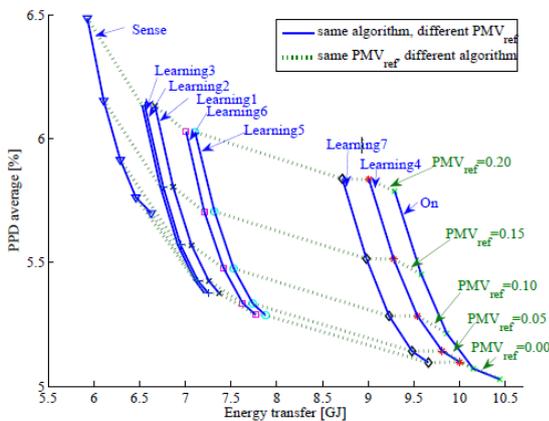


Figure 12. The influence of comfort threshold value (PMV_{ref}) control strategy on the shape and location of the Pareto frontier for person 1

Based on Table 1 and Figure 12, it can be inferred that rule constants affect energy consumption in a coherent way. *Learning1* and *Learning2* differ only for variant values of C_{tAbs} . If C_{tAbs} is lower, the energy consumption will also be lower. A similar effect can be obtained by changing the value of C_{t1} and C_{t2} . If the period expressed with $[C_{t1}, C_{t2}]$ is larger, the energy consumption will decrease. When fitting the parameter values, it is important not to destruct the effects of other rules. For example, if the value of C_{tAbs} were to be changed to a small value (such as 5), then Rule 5 would never be processed. In such a case, the strategy would become *Sense* strategy with higher energy consumption.

When comparing the results of the *Learning3* and *Learning7* strategies, it is clear that different combinations of rules affect both the energy consumption and the comfort. The *Learning4* strategy does not incorporate any rule to lower energy consumption. Therefore, the *Learning4* strategy depends only on the accuracy of the machine learning model for occupancy prediction. Indeed, *Learning4* always consumes more energy and results in better comfort than the *Sense* strategy, but is not significantly better than the *On* strategy in either aspect. The addition of Rules 2 and 3 significantly lowers the energy consumption, as shown in Figure 12 for *Learning5* and *Learning6* according to *Learning4*, but slightly decreases comfort which results in higher average PPD values.

7. Conclusion

This paper presents the implementation of a novel thermal comfort regulator for conditioned environments. The thermal comfort regulator is implemented as a control strategy within a control agent, which is part of a multi-agent system and performs indoor temperature set-point delegation in a usercentered way. The agent approach enables the design of flexible control strategies. A novel

occupancy prediction algorithm was implemented for predicting home occupancy in order to provide a comfortable environment when the occupant returns home. Multiple control strategies were tested in order to determine the relation between energy consumption and comfort. The trade-off between energy consumption and comfort is maintained by (i) changing the desired comfort threshold and (ii) changing the combination of rules and rule constants within an agent's control strategy.

The experiments show that the *Sense* strategy consumes 36 %, 48 %, 47 % and 42 % (for persons 1, 2, 3 and 4, respectively) less energy than *On* (both have $PMV_{ref} = 0$). On the other hand, the average discomfort (average PPD) of *Sense* (both have $PMV_{ref} = 0$) compared to *On* is increased by 13 %, 37 %, 37 % and 48 % (for persons 1, 2, 3 and 4 respectively).

The aim of comfort and energy management in smart buildings is to find a balance between the energy consumption limited by the *Sense* strategy and the comfort limited by *On*. In our experiments, the population of non-dominated results in the comfort/energy-consumption space was generated (the Pareto frontier). Since the location of results for various control strategies that define different comfort/energy-consumption trade-offs at fixed PMV_{ref} are very similar in comfort/energy-consumption spaces (see Section 6.2), one can conclude that the trade-off can be specified by the user with the choice of a control strategy, and also with the choice of PMV_{ref} .

To emphasize the influence of control strategy on comfort we analysed the PPD time series. The contribution of a machine learning approach for predicting near-future occupancy and rules for removing incorrect occupancy predictions significantly improved the comfort during periods in which the occupant enters the home. The PPD time series produced by the *Sense* strategy are prone to large deviations from the lowest PPD value (that is, 5 % when $PMV_{ref} = 0$) that should be maintained during occupancy. The *Learning* strategies reduced these deviations, since the prediction of occupancy makes it possible to prepare the indoor temperature before occupancy begins. Therefore, the average comfort at the moment of arrival increases with a reasonable increase of energy consumption.

In summary, this novel approach to combining a comfort regulator and different learning strategies enables users to select their preferred control strategy in the comfort/energy-consumption space. It is expected that future smart homes will apply the approach presented.

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