Smart-Home Energy Management in the Context of Occupants' Activity

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Energy consumption and occupants' comfort are key factors when evaluating smart-home environments. This paper focuses on occupants' comfort, which is affected by environmental factors (such as temperature, humidity, radiation of elements, and air movement), and occupant-related factors (such as occupants' level of activity, clothing insulation). To satisfy a thermal comfort objective, energy is needed for heating and cooling, which affects energy consumption. This paper presents a proof-of-concept analysis of smart-home control based on occupants' activity level in terms of human energy expenditure, and a trade-off analysis of the energy consumption versus thermal comfort when the activity level serves as an input into an intelligent home energy management system.

Povzetek: V članku je predstavljen inteligentni nadzor pametnega doma, ki temelji na kompromisu med porabo električne energije in udobjem uporabnika.

1 Introduction

Research has focused on regulation of the smart-home environment from various perspectives, including economic, ecological, and assistive. It is common to take into account the occupants' satisfaction and comfort, both depending on environment- and occupant-related factors. The regulation of occupants comfort is a complex and multivariate problem and, to simplify the problem, researchers have assigned static values to occupant-related factors [1, 2, 3].

The complexity of the problem can be expressed as follows. The occupants' comfort must be evaluated according to the knowledge about occupants' activity level and clothing rate and according to the environmental state, such as temperature and humidity. The heating process and its delay due to a room's thermal inertia must be taken into account. The problem is multivariate; the indoor temperature is affected by various heating bodies, such as heat produced by the occupant, the sun through the window, and mechanical heaters [4]. Occupant activity levels and clothing rates can also change much faster than the environmental state. Finally, the effect of the regulation affects comfort slowly and it takes time for an occupant to actually feel this change.

We implemented an agent-based control system that is able to process large data-sets from various external and data sources (weather station, environmental sensors and virtual sensors) and use the extracted knowledge for heating, ventilation and air-conditioning (HVAC) system control to provide occupants with a high level of comfort. We have also deployed a virtual sensing agent for monitoring the activity of occupants in order to provide additional information crucial for regulation of the occupants' thermal comfort. The activity of the occupant is estimated in terms of the human energy expenditure (EE), which is expressed in metabolic equivalent of task (MET), where 1 MET is the energy expended at rest.

The paper presents a multi-agent architecture with virtual sensing agents dedicated to monitoring the real-time state of the occupant (activity level, clothing rate, presence) and shows how the different personal lifestyles influence the HVAC energy consumption and comfort experience.

The rest of the paper is structured as follows. Section 2 presents the background on the topics of comfort experience, human energy expenditure and multi-agent control systems. The system architecture in terms of multi-agent system is presented in section 3. The experimental setup is described in section 4 and respective results are provided in section 5. Section 6 concludes the paper with conclusions and discussion.

2 Background

2.1 Thermal Comfort Experience

Thermal comfort experience is the notion of a person's thermal sensation in a conditioned environment. The predicted mean vote (PMV) index, derived by Fanger et al. [5], expresses the thermal sensation on a seven-point scale ranging from -3 to +3, where negative values denote cold sensation and positive values denote warm sensation. The value 0 denotes neutral sensation, which is the target value for indoor air conditioning. The more distant the PMV is from 0, the more cold (if negative) or hot (if positive) the sensation.

PMV is calculated with the following parameters: clothing insulation (clo_{rate} [clo]), human energy expenditure (EE_{rate} [MET]), air temperature (T_{in} [°C]), relative air velocity (v_{ar} [m/s]), relative humidity (RH [%]), and mean radiant temperature (T_{mr} [$^{\circ}C$]). The units that are important for this research are defined as follows: 1 clo=0.155 m^2K/W and 1 MET =58.2 W/m^2. In contrast to environmental factors, occupant-related factors are harder to perceive and include into a control system. In [6] we demonstrated the effect that indoor temperature on PMV and decided to regulate PMV maintaining the T_{in}.

The predicted percentage dissatisfied (PPD) measure is used for long term comfort evaluation. PPD predicts the percentage of people who are likely to be dissatisfied with the current thermal state of environment. It depends on PMV and transforms the value of comfort in the range of 5% - 100%. The lowest PPD value equals 5%, which is similar to when PMV equals 0 and is interpreted as follows: at least 5% of people are never satisfied with the thermal state of the environment. PPD and PMV indices formulation is internationally standardised in ISO 7730 [7].

PMV index regulation has been researched to some extent. Calvino et al. [1] developed fuzzy controller for PMV regulation. Ciglar et al. [2] and Liang et al. [3] used the model predictive controller for PMV regulation. Experiments were done in a simulated environment and they all assumed the clothing and activity of a person as a static, predefined value.

2.2 Estimation of Energy Expenditure

The cost of physical activity, namely energy expenditure, is usually expressed in metabolic equivalents of task (MET), where 1 MET is defined as the energy expended at rest. MET values range from 0.9 (sleeping) to over 20 in extreme exertion. Table 1 shows activity levels and their corresponding MET values.

There are a range of methods for reliably estimating energy expenditure (EE). EE can be directly measured using approaches such as direct or indirect calorimetry, or doubly labelled water [8]. These methods are expensive and cumbersome for free-living applications. Accessible commercial devices for estimating EE come in the form of one- [9] [10] or multi-sensor wrist-or armbands [11] that can be used in everyday life. They are based on the concept of high correlation between movement of inertial sensors and activity level, which are in some cases learned using machine-learning algorithms. Most of the methods based on machine learning techniques estimate energy expenditure using wearable sensors and seek linear or non-linear relations between the energy expenditure and the accelerometer outputs. The most basic methods use one accelerometer and one linear regression model. These approaches can be improved by utilising additional regression models. The method by Crouter et al. [12] uses data from one accelerometer attached to the hip to classify the type of activity (sitting, ambulatory activity or lifestyle activity). According to the recognised type of activity, an appropriate estimation regression model is used, except for sitting, for which a static value of 1 MET is assigned. The drawback of this method is that it can underestimate sedentary activities such as sitting, since such activities are usually accompanied by additional movements (such as office work). Previous research has accelerometers attached to the fixed position on the person's body to bypass the orientation problem of the accelerometer. Our research on estimating EE by using a smartphone in a person's pocket, regardless of orientation, has been shown to product results that are similar or even better [13] than the commercial device SenseWear [11], which is currently claimed to be the most accurate device for free-living situations [14].

Intesity	MET values
Low	EE < 3
Moderate	3 > EE < 6
Vigorous	EE > 6

Table 1: Corresponding MET values for different activity intensity levels.

2.3 Multi-agent control system

Modern buildings contain a range of systems, such as HVAC, domestic hot water system, lighting, safety, etc. Intelligent operation of such systems requires the collection and processing of large sets of heterogeneous data about sensor states, actuator actions, and occupant actions. Distributing tasks among devices, such as smartphones, can provide several types of benefits, such as distributed task solving as well as adding or removing systems and devices during system run-time. The multi-agent system (MAS) approach makes system decentralisation possible. The comparison between the traditional and agent approach was done by Wagner et al. [15], who argued that the agent approach results in a transparent software structure and dynamic and adaptive application software. Klein et al. [16] implemented MAS for coordination of occupant behaviour for building energy and comfort management. Dounis et al. [17] conducted a review on conventional and advanced control systems and implemented MAS for comfort and energy management in buildings, and stated that

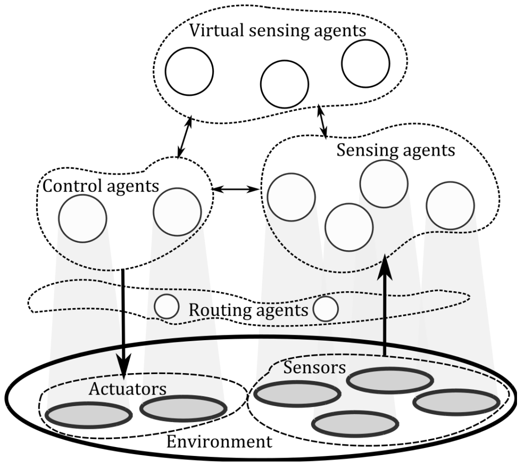

Figure 1: Architecture layers: The bottom layer is the environment with sensors and actuators. The middle layer are the routing agents. The top layer is the sensing, virtual sensing and control agents. The direction of communication is represented with arrows.

a controller has the characteristics of an intelligent agent. Moroşan et al. [18] compared the computational efficiency of centralised and distributed architectures and concluded that the distributed architecture is less computationally demanding than the centralizsed architecture, but achieves the same effect. Our previous research included the development of MAS control architecture, where the operation of each agent was formulated [19].

3 System Architecture

We implemented the smart-home control system as a multi-agent control system. Several agents are developed to operate in groups and each agent can communicate with any other agent. A simplified system architecture is presented in Figure 1. The bottom layer in Figure 1 is the environment including sensors and actuators. Routing agents are above the environment and are used for communication between physical elements of the environment and software agents. The top layer consists of the sensing agents, the control agents and the virtual sensing agents. A group of sensing agents are used to perceive simple environmental states, such as temperature, humidity, acceleration, etc., which can be measured directly, without complex pre-processing. A group of virtual sensing agents is used to perceive complex environmental states that utilise the data obtained from sensing agents or other virtual sensing agents. Control agents are used to affect the environment by changing control parameters and set-point values based on control algorithms, which are denoted as control behaviours. The roles of individual entity behaviour are described in the following subsections.

3.1 Environment

The environment in our research is implemented as a simulator of a building with integrated HVAC equipment. It collects weather data, contains an occupant and generates environmental states. These are represented as state variables and are perceived through sensors. Actions on the environment are performed through actuators. One-way arrows in Figure 1 represent the direction of precipitation and action.

For simulation purposes, we assume the time is represented as a discrete value k, $k \in [0, N-1]$, where N is the number of minutes in the simulation. In each simulation time-step, the environment accepts the vector of set-point values, represented as $\vec{r}(k) = [r_1(k), r_2(k), ...r_K(k)]$ and outputs the vector of state variable values, represented as $\vec{s}(k) = [s_1(k), s_2(k), ...s_J(k)]$ for J environment variables.

3.2 Sensing Agents

Sensor agents are software entities that are used to serve current and historic state variables, obtained through sensors. Sensing agents also include meta-data regarding the physical sensor they represent, such as location of sensor, sensor type, accuracy, drift, unit output, conversion factor, etc. Sensor agents return value of state variable $s(k)$, either on request or based on contract about periodical report between engaged agents using agent communication language (ACL) messaging. The process of contract assignment and cancellation is described in [19].

3.3 Virtual Sensing Agents

Virtual sensor agents are used to perceive and serve current and historic state variables, obtained through sensing agents and/or virtual sensing agents. These agents are used to estimate complex environmental states $cs(k)$ in time k, which cannot be obtained utilising only physical sensors. Examples of environmental states are PMV, PPD, and EE, where the additional processing has to be performed. The processing is based on models that define the relation between environmental states. Detailed functionalities of virtual sensing agents utilised for experiments are presented in the following subsections.

3.3.1 Occupancy Detection Agents

Occupancy detection agents detect the occupancy state of a building based on the data retrieved from sensing agents. For the purposes of this paper, the occupancy state was simulated-agent obtained data about occupancy from a predefined data-set. The approach described by Lu et al. [20] uses a combination of passive infrared motion (PIR) sensors installed in rooms and magnetic reed switches on doors to detect occupancy and sleeping. This approach is inexpensive, unobtrusive, simple to install, and can be used for occupancy detection to extract the occupancy state.

3.3.2 Activity-Monitoring Agents

The activity-monitoring agents communicate with sensing agents to determine current state of the occupant in terms of human energy expenditure (EE). Acceleration data received from sensing agents is collected into 10-second windows, each of which overlaps with the previous one by one half of its length. Each overlapping window is processed into a set of features forming a feature vector that is fed into the regression model to estimate the EE. To build an EE regression model, we have performed two subtasks: (i) machine-learning algorithm selection, and (ii) feature selection, to optimise the performance of the estimation and reduce computational load of the agent.

Selection of appropriate machine-learning regression algorithm was performed with 10-fold cross-validation on the data of 10 people, where one person represents a fold. Data for one person contains regular everyday activities such as rest, cleaning, cooking, and office work, and sporting activities such as walking, running, and stationary cycling. Reference EE expenditure was measured in a controlled environment using indirect calorimetry equipment Cosmed K4b2 [21]. The Table 2 presents the comparison results of regression machine-learning algorithms, Support Vector Regression (SVR), Linear Regression (LR), M5Rules, M5P and REPTree as implemented in Weka machine-learning suite [22]. The results are expressed in mean absolute error (MAE) calculated with Equation 1. We have chosen the SVR algorithm to be deployed in the activity-monitoring agent, since it performs with the lowest estimation error. The best-performing model was compared against the commercial device SenseWear, proving that the smartphone model is comparable to a dedicated device. Note that activity-monitoring agents can use any tri-axial inertial sensor for the EE estimation.

$$MAE = \frac{1}{n}\sum_{1}^{n} |MET_{true} - MET_{predicted}| . \quad (1)$$

Table 2: Results of regression machine-learning algorithms expressed in MAE and comparison against commercial system SenseWear.

Algorithm	MAE
SVR	0.83
LR	0.88
MLP	1.04
M5Rules	1.05
M5P	1.04
REPTree	1.01
SenseWear	0.86

The feature selection procedure was performed using the ranking algorithm RelifF, which ranks the features and assigns each a weight. We have selected only positively weighed features for the final feature set. We began with 67 features computed from acceleration signal and ended with 43 features. The remaining features are partially adopted from Tapia [23] (25 features) and partially developed by us (18 features). Adopted features are: mean of absolute signal value, cumulative sum over absolute signal value, quartiles, variance, inter quartile range, correlation and mean crossing rate. Features developed by us are: signal peak count, cumulative sum over peak absolute value, cumulative sum over signal absolute value, cumulative sum over signal absolute value after band-pass filtering, cumulative square sum over signal absolute value after band-pass filtering, cumulative sum of square components, square of cumulative sum of components after band-pass filtering, velocity, kinetic energy, vector length, integration of area under vector length curve. The highest-ranked features are quartiles (four features) and peak count (one feature).

3.3.3 Clothing Detection Agent

The clothing detection agent communicates with the activity-monitoring agent and sensing agents to predict the type of clothing a user is currently wearing. The output is expressed in unit clo, where one clo is the amount of insulation that allows a person at rest to maintain thermal equilibrium in an environment at 21°C.

The prediction is based on simple heuristics that utilise information about the current season, current weather, time of the day, and estimated EE in the indicated order. Examples of the rules can be observed in Rules 1 and 2.

Rule 1:
if $season$ is $winter$ and $weather$ is $sunny$
then if $time > 11\ PM$
then if $EE_{rate} > 2\ MET$
then $clo_{rate} = 1$
else $clo_{rate} = 2$

Rule 2:
if $season$ is $winter$ and $weather$ is $sunny$
then if $time > 7\ AM$ and $time < 11\ PM$
then if $EE_{rate} > 3\ MET$
then $clo_{rate} = 0.5$
else $clo_{rate} = 1$

Rule 1 predicts the clo_{rate} value according to the amount of activity in the evening, where a higher clo_{rate} value indicates higher thermal insulation due to clothes or blankets. Rule 2 predicts the clo_{rate} value according to the estimated EE during the day. If the occupant's EE_{rate} is higher than 3 MET, this indicates exercise.

3.3.4 Comfort Estimation Agent

A comfort estimation agent is used to perceive the state of comfort, expressed as PMV according to ISO 7730, Annex D [7]. For such purpose, it obtains values T_{in} and RH from sensing agents and clo_{rate} and EE_{rate} from the clothing detection agent and the activity monitoring agent, respectively, for the current time k. The T_{mr} is assumed equal T_{in} and v_{ar} is assumed fixed as 0.15 m/s.

3.4 Control agent

The control agent includes an algorithm for defining indoor temperature set-point values T_s in order to regulate PMV when the building is occupied. If the building is not occupied, the T_s is fixed at 5°C and 40°C for the heater and the chiller, respectively, in order to prevent freezing or overheating of HVAC components. There are two versions of control agents: the heater control agent and the chiller control agent. The desired range PMV_{range} includes acceptable PMV values and is specified with a value of PMV_{ref} so that $PMV_{range} \in [-PMV_{ref}, +PMV_{ref}]$. The control algorithm is designed in order to increment/decrement the set-point value of T_s in a way that brings the PMV value on the borders of PMV_{range}. The $-PMV_{ref}$ value is a target value for the PMV for the heater control agent and $+PMV_{ref}$ for the chiller control agent. The increment function for set-point temperature T_s for both versions is defined as:

$$T_s(k+1) = T_s(k) + T_{inc}(k), \tag{2}$$

where the set-point temperature in the next time step $T_s(k+1)$ is computed according to the previous set-point temperature $T_s(k+1)$, incremented by a value $T_{inc}(k)$. T_{inc} is computed according to the Equation 3. The PMV_{diff} definition is presented in Equation 4.

$$\begin{aligned} T_{inc}(k) = A \cdot PMV_{diff}(k)^3 + \\ + B \cdot \frac{PMV_{diff}(k)}{D \cdot T_{diff}(k)^2 + 1} + \\ + C \cdot PMV_{diff}(k) \end{aligned} \tag{3}$$

$$PMV_{diff} = \begin{cases} -PMV_{ref} - PMV, & \text{if heater} \\ +PMV_{ref} - PMV, & \text{if chiller} \end{cases} \tag{4}$$

The PMV_{diff} expresses the distance between the PMV and the value PMV_{ref} in case of chiller and the PMV_{diff} expresses the distance between the PMV and the value $-PMV_{ref}$ in the case of the heater, where the T_{diff} definition is presented in Equation 5.

$$T_{diff}(k) = T_s(k) - T_{in}(k) \tag{5}$$

Equation 3 represents the regulation algorithm, which is proportional to the difference between the current PMV and PMV_{ref} and tends to achieve the equality of mentioned values, which is the purpose of our algorithm. Furthermore, Equation 3 is inverse-proportional to the difference between the current T_{in} and current T_s with the purpose of reducing the fluctuation of the T_s value in order to reduce instability of regulation system. The constant values $A = 0.01$, $B = 3$, $C = 0.1$ and $D = 1$ were obtained iteratively with several simulation runs in order to achieve the desired control effect.

4 Experimental Setup

Experiment consists of two individual procedures: the EE model creation and evaluation in isolations already presented in Section 3.3.2, and evaluation of the model on two-day data of the occupants.

Data used in the first experiments was collected in a laboratory environment, where the persons performed predefined scenarios (rest, cooking, cleaning, walking, running, cycling). They carried a smartphone in their trouser pockets, from which we collected the raw acceleration data. For reference energy expenditure measurements, the Cosmed K4b2 indirect calorimeter was used. Both acceleration data and Cosmed data were synchronised to produce a training and testing data-set.

Since we could not collect the free-living reference data-set, due to the cumbersome nature of Cosmed, we have created synthetic two-day data with a one-minute sampling rate from the synchronised recordings (smartphone and Cosmed) for five people used in this experiment. This data-set was further enriched with weather data (including outdoor temperature, humidity, wind speed and solar radiation). The weather data was collected from the Slovenian Environment Agency (ARSO) portal [24] and represents two sunny days in February 2014, city Rateče.

The data represents one working day and one non-working day (e.g., a weekend) for each person. The characteristics of their lifestyles can be observed in Table 3. The goal was to produce data for people with different lifestyles. They are summarised as follows. Persons B, C and D have regular eight-hour jobs, where Person A works at night and Person E works from home. Person A does regular exercise such as walking and vigorous running on a treadmill. Person B does regular exercise on weekends. Person C is engaged in very intensive home chores over both days. Person D is an athlete and frequently exercises vigorously. Person E does not exercise and leaves home only for half an hour. Table 3 shows the percentage of time the occupant was at home, the absolute minutes of performed activities with low, moderate, and vigorous intensity. The new data-set were included into a simulation environment.

Experimental setup included the control system, developed using JADE [25]; the simulation model, developed using EnergyPlus software [26]; and the simulation environment, developed using BCVTB [27] software. Machine-learning models for energy expenditure were implemented using Weka [22].

We have instantiated sensor agents for acceleration, indoor temperature, mean radiant temperature, relative humidity and outdoor temperature. We then instantiated the activity-monitoring agent, comfort estimation agent, clothing detection agent, and occupancy detection agent. Fi-

		Intensity (hours)		
		Low	Moderate	Vigourous
Person	At home (%)	< 3	$3 \geq \leq 6$	> 6
A	54	20.8	2.1	2.8
B	71	32.2	1.2	0.7
C	56	22.9	4.1	0
D	67	27.7	2.9	1.9
E	99	45.5	1.9	0

Table 3: The characteristics of the occupants for the produced days. The percentage of time present at home and amount of activities in hours according to the intensity (MET).

nally, two instances of control agents - one heater and one chiller agent - were created.

A simulation model of a building containing one room was taken into account for the experiment; this model was obtained from the EnergyPlus software project examples and represents a thermal dynamic model of the room. The room has an integrated packaged terminal heat pump with chiller, heater and supplementary heater rated at 8500W, 8000 W and 3000 W respectively as a HVAC system, together with the temperature regulation module. The heating power produced by a person P_{pHeat} is computed according to Equation 6.

$$P_{pHeat} = EE_{rate} \cdot 58.2W/m^2 \cdot A_{body} \cdot phr \qquad (6)$$

A_{body} is the area of a human body, phr is the person heat rate. We took the $phr = 0.8$, which indicates that 80% of energy, consumed by a person is transformed to heat and $A_{body} = 1.8m^2$, as computed for an average person of weight 70 Kg and height 1.73 m [5] using the Dubios equation [28]. Table 4 presents some values of heating power, produced by a person at various EE_{rate}.

Table 4: Heating power produced by a human body at various EE_{rate} values

EE_{rate} [MET]	P_{pHeat} [W]
1	83.81
2	167.62
3	251.42
4	335.23
5	419.04
6	502.85
7	586.66
8	670.46

A simulation time-step was set to one minute. Each simulation time-step a simulation environment - BCVTB - (i) accepts temperature set-point variables from control agents, (ii) computes new environmental states based on EnergyPlus model and (iii) passes them to sensing agents. One routing agent was instantiated for variable mapping between the simulation environment - BCVTB and JADE agents.

5 Results

5.1 Energy Expenditure Estimation

The activity-monitoring agent processed the collected acceleration data for respective occupant returning the estimation of current energy expenditure. Results in terms of MAE for each occupant are presented in Figure 2. We can observe that the agent performs with low error in case of low- and moderate-intensity activities (rest, home chores, walking) and slightly underestimates more vigorous activities (cycling and running). This shortcoming can be solved by employing activity recognition as a part of activity-monitoring agents and utilising multiple regression models according to the specific activity.

5.2 Maintaining Comfort and Energy Consumption

We performed 41 simulations on the synthetic data-set explained in section 4. A simulation starts with $PMV_{ref} = 0.10$ and each further simulation has PMV_{ref} incremented for 0.01 until the value PMV_{ref}=0.40 (41^{st} simulation run). Note that 80% of energy consumed by a person was transformed to heat as defined in simulation model.

Simulation of part of a day (200 minutes) is presented on Figure 3. It shows the controller's performance when the intensity of the activity changes significantly. Between the 2200^{th} and 2220^{th} minutes, the occupants' intensity of activity decreases from 2.2 MET to 1.3 MET. PMV decreases immediately and the controller starts increasing the T_{in} as seen around the 2220^{th} minute. It increases the T_{in} until the PMV reaches value 0 in the 2230^{th} minute, where a small overshot can be seen (0.5°C difference between the values of T_{in} in 2230^{th} and 2250^{th}). Afterwards, the controller handles small changes of PMV due to small changes in the intensity of activity. Between the 2260^{th} and 2320^{th} minutes, the intensity of activity changes rapidly for approximately 1 MET. We can observe that the controller could not handle such changes on time, so in that period the PMV fluctuates between +1 and -1. In the next period (until the 2340^{th} minute), the controller increases the temperature and PMV is stabilised. Finally, in the period between the 2340^{th} and 2380^{th} minutes, we can observe more efficient handling of PMV since the PMV is not fluc-

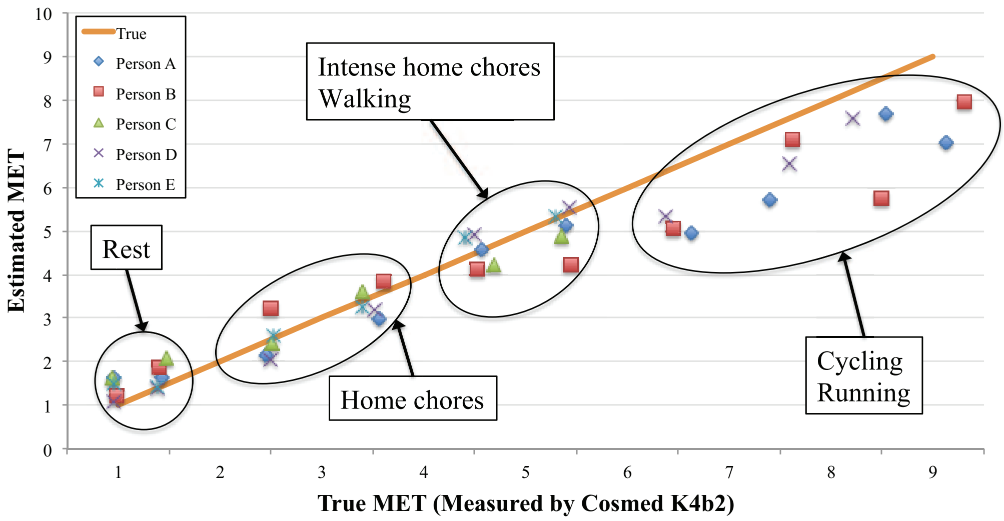

Figure 2: True MET vs. Estimated MET for each occupant. The utilised regression model performs with low MAE on low and moderate activities and slightly underestimates the vigorous activities.

tuating greatly. It changes between +0.2 and +0.7, which denotes a slightly warm sensation.

Each simulation run returns the energy consumed for HVAC and the average value of PPD during occupancy. The average value $\overline{PPD}$ is computed using Equation 7. The individual time-step is denoted with k, the number of time-steps with N, and $occ(k)$ represents the occupancy state (0 or 1) as returned by the occupancy detection agent.

$$\overline{PPD} = \sum_{k=1}^{N} PPD(k)\ \forall k,\ occ(k) = 1 \tag{7}$$

The obtained comfort/consumption plane is presented in Figure 4. Simulation results for one occupant are presented with the same marker. The right-most marker of each series is a simulation result when PMV_{ref} is 0.1. Higher values of PMV_{ref} shift result markers to the left, giving the left-most marker when PMV_{ref} is 0.4. Lower values of $\overline{PPD}$ and energy denotes better comfort experience and lower energy consumption. We can observe that Person C obtains the lowest values for both objectives, thus producing the best result. This is related to the person's low home presence rate (56%), as shown in Table 3. A low "At Home" rate implies lower energy consumption and 0 hours of vigorous actives implies that the control system did not need to handle severe PMV changes. The worst results are obtained for persons A and D, who have a lower "At Home" rate, but a higher EE_{rate}. A higher EE_{rate} results in higher $\overline{PPD}$, in this case above 20%, which indicates a low overall comfort rate. Persons B and E return average results. Their "At Home" rate is higher, which indicates high energy consumption for low PMV_{ref} values compared to other persons. High-intensity activities of Person B, compared to Person E, result in a worse overall comfort experience.

Figure 5 compares different parameter configuration for Person E, again simulated for 41 PMV_{ref} values. The estimated EE_rate and the clo_rate is a result of the estimated EE_{rate} and estimated clo_{rate}. The fixed EE_rate and the clo_rate denote 1.2 MET and 1 clo fixed during the entire simulation run, as seen in related work [2]. The fixed clo_rate is a result of the estimated EE_{rate} and the fixed clo_{rate}. The fixed EE_rate is a result of the fixed EE_{rate} and estimated clo_{rate}.

We can observe that using fixed values for EE_{rate} and clo_{rate} makes the regulation underestimate the $\overline{PPD}$ and consumes much more energy compared to the estimated values of EE_{rate} and clo_{rate}.

The fixed clo_{rate} implies higher energy consumption, but a similar range of $\overline{PPD}$. In such a case, the energy consumed for heating when the occupant is asleep is higher due to lower clothing insulation (1 clo) compared to the estimated value clo_{rate}, which is 2 clo when sleeping. A similar effect occurs when a person exercises. If the clo_{rate} is fixed, the energy consumed for cooling when the occupant exercises is higher due to higher clothing insulation (1 clo) compared to estimated value clo_{rate}, which is 0.5 clo when the occupant exercises.

The fixed EE_{rate} also makes the regulation underestimate the $\overline{PPD}$ and consume more energy than the estimated values of EE_{rate} and clo_{rate}. Energy consumption is lower than the fixed values of both EE_{rate} and clo_{rate}. In that case, clothing insulation reduces the energy consumption for heating (when occupant sleeps) and for cooling (when occupant exercises).

6 Conclusion and discussion

This paper presents the multi-agent system for HVAC, which regulates the occupant's comfort according to activity level, clothing rate, and occupant's presence. We argue that our dynamic treatment of occupants' comfort enables better comfort and lower energy consumption than activity-

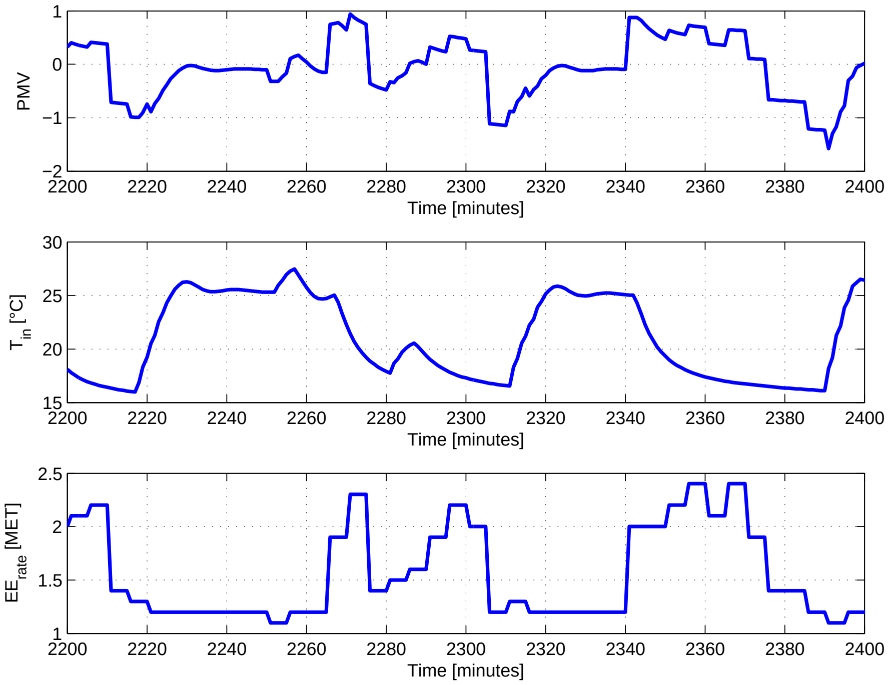

Figure 3: A section of a day, when a person performs low-intensity activities. Top figure: PMV value, Middle figure: indoor temperature, Bottom figure: EE_{rate}

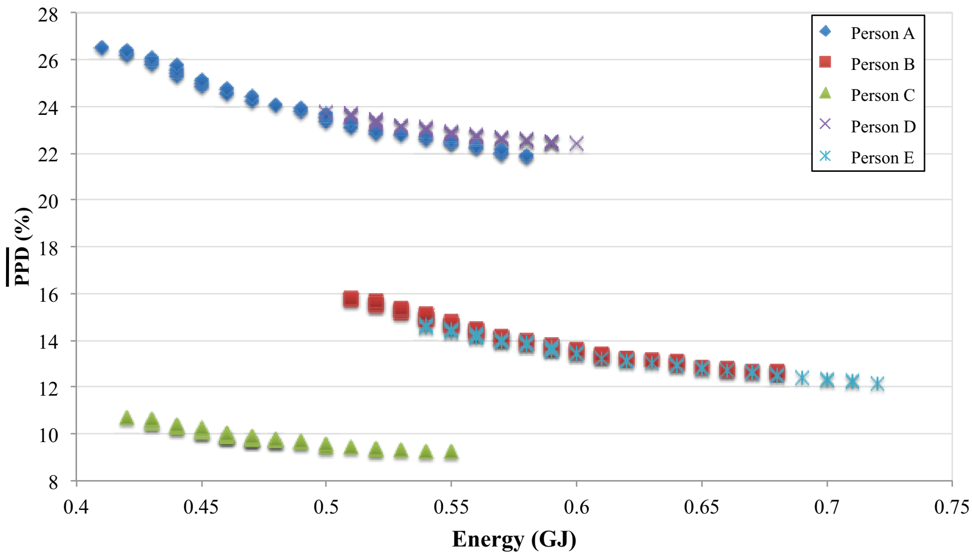

Figure 4: Comfort/consumption plane: the X axis represents the energy in GJ, consumed by HVAC; the Y axis represents the comfort experience - $\overline{PPD}$, expressed in %. Each marker presents a result of a simulation run for different PMV_{ref} and for different person

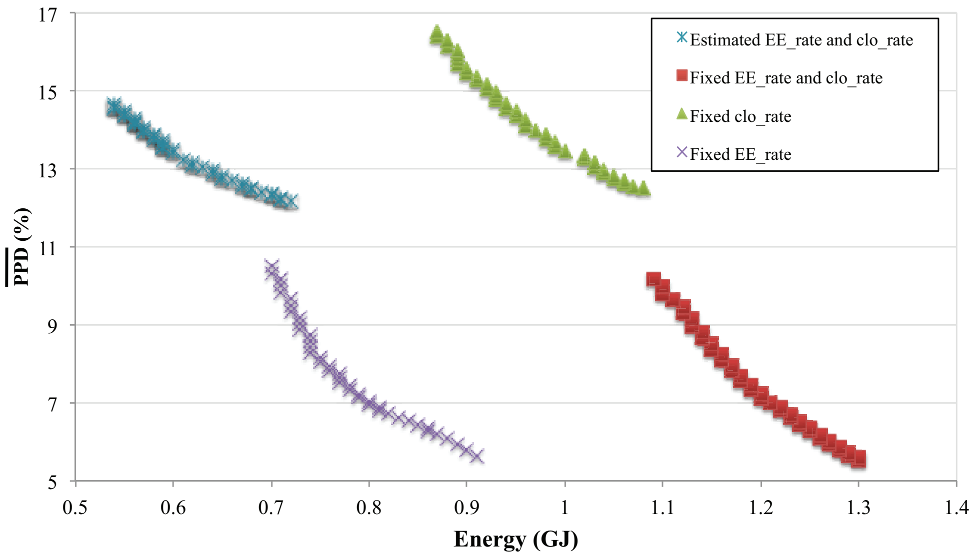

Figure 5: Comfort/consumption plane: The X axis represents the energy in GJ, consumed by HVAC; the Y axis represent the comfort experience - $\overline{PPD}$, expressed in %. Each marker presents a result of a simulation run for different PMV_{ref} and for a different assumption of the occupant's parameters configuration

and clothing-independent treatment of comfort presented in related work.

The multi-agent system consists of three virtual sensing agents. The first is the activity-monitoring agent, which, in contrast to other related research where activity level is assigned a static value, dynamically estimates the human energy expenditure of the occupant, utilising sensor agents such as smartphone accelerometer data. Second, the clothing detection agent utilises the environmental sensors (weather) and activity-motoring agent to predict the value of clothing isolation, which is adopted in related work as a static value. Third, the comfort estimation agent utilises data from the activity-monitoring agent, the environmental sensing agents (weather, indoor temperature, humidity), and clothing detection agent to estimate the occupant's comfort.

The control agent utilises the information from the sensing agents and virtual sensing agents to regulate comfort (to reach the comfort equilibrium) by maintaining the indoor temperature.

We have shown that our multi-agent system can efficiently regulate the comfort for people with certain lifestyles. We have analysed the trade-off between comfort and energy consumption, which is highly affected by heating objects or energy released by an occupant.

Future work will consist of adapting human energy expenditure estimation model to the specific person [29] and predicting the human energy expenditure, since the estimation contributes to delay in temperature regulation. We will implement the presence classification agent that will predict the occupant's time of arrival. Moreover, it is crucial to improve the control algorithm in order to achieve the quicker response needed to eliminate the delay in regulation.

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