COMFORT AND ENERGY MANAGEMENT IN SMART ENVIRONMENTS

Domen Zupančič

Doctoral Dissertation
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UPRAVLJANJE UDOBJA IN ENERGIJE V PAMETNIH OKOLJIH

Doktorska disertacija

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Abstract

The energy consumed for heating, ventilation and air-conditioning represents the largest share in household energy consumption. Therefore rational management leads to noticeable energy savings within households and lowers the depletion of limited energy sources. The key dilemma is how to save the most energy with minimum loss of comfort. An intuitive approach to find the appropriate trade-off is therefore in reducing the unnecessary energy consumption when comfort experience is not important, and providing a maximal comfort experience when needed. The best solutions are located in the space of two objectives: the comfort experience and the energy consumption.

In this dissertation two approaches were used to define the comfort experience during occupancy. The first approach assumes the measure of comfort as a static predefined value of indoor air temperature. The second approach assumes comfort as a dynamic value that depends on the indoor air temperature, humidity, velocity and radiant temperature, and occupant-related factors, such as occupant's activity intensity and clothing insulation. For the second approach we have introduced a comfort regulator that continuously adapts the set-point value of the indoor temperature in order to achieve the desired level of comfort.

Slow heating and cooling process dynamics prevent rapid changes of indoor temperature that are needed to achieve the comfort equilibrium in a short time span. To overcome these issues, we enriched the control system using the machine learning methods for a near-future home occupancy prediction that exploits the knowledge adopted during the on-line observation of an occupant. Furthermore we implemented the identification of the system dynamics to predict the time needed to change the indoor temperature according to a step response of a set-point value. Our control system is composed of an anticipative mechanism in order to prepare the indoor temperature which is needed to achieve the desired level of comfort. Since the occupant's behaviour is hardly predictable we implemented a reactive mechanism that mitigates the influences of mistakes made by the anticipative mechanism due to wrong absence predictions, and a rule-based mechanism that exploits expert rules and parameters to mitigate the influences due to wrong occupancy predictions.

The proposed management system was developed according to the multi-agent paradigm, where the software agents represent individual sensor, control, routing, management and learning software entities. Individual agents are able to interact and compose sensing, control and other organisations, however they are not limited to one central supervisory and control system. This implies a robust, modular, and flexible distributed system.

The experiments were performed with simulations using real weather data and data representing occupancy and the intensity of occupant's activity. Unlike the related work that typically assumes static and predefined values of occupant-related parameters we show that an unobtrusive and inexpensive approach to estimate those parameters enables better perception and regulation of comfort and results in better performance of control strategies. We have shown that various strategies could be used to achieve trade-offs in the comfort/energy consumption space where the occupant's comfort experience stays at a high level and the energy consumption is minimised.

Povzetek

Energija, ki se porablja za ogrevanje, prezračevanje in hlajenje, predstavlja večinski delež vse energije, ki se porablja v stanovanjskih objektih. Zato je s preudarnim upravljanjem mogoče doseči visoke prihranke pri stroških in zmanjšanje izčrpavanja omejenih virov energije. Pri tem je ključna dilema, kako privarčevati čim več energije ob čim manjšem vplivu na toplotno udobje uporabnika. Kompromis intuitivno najbolje določimo tako, da v trenutkih, ko je udobje potrebno, težimo k doseganju najvišje stopnje udobja, v nasprotnem primeru pa težimo k najnižji porabi energije. Najboljše rešitve predstavljajo približek Pareto fronte dveh kriterijev: udobja in porabe energije.

V disertaciji smo glede na sorodne raziskave uporabili dva pristopa za določanje toplotnega udobja ob prisotnosti stanovalca. Prvi pristop uporablja mero udobja kot statično in vnaprej določeno vrednost temperature zraka, medtem ko drugi pristop predvideva dinamično spremenljivko, odvisno od temperature zraka, vlažnosti, hitrosti zraka, temperature sevanja grelnega telesa in trenutnega stanje stanovalca, ki ga določa metabolizem in izolativnost njegovih oblačil. V ta namen smo razvili regulator, ki določa želene vrednosti temperature zraka tako, da stremi k zagotavljanu želene stopnje udobja.

Dinamika procesa ogrevanja in hlajenja onemogoča hitro spremembo temperature za zagotavljanje udobja v določenem trenutku. Za uspešno iskanje izboljšav smo uporabili metode strojnega učenja za napovedovanje prisotnosti v bližnji prihodnosti, ki na podlagi znanja, pridobljenega iz zgodovine opazovanj, predvidijo prisotnost stanovalca. Poleg tega smo izvedli tudi identifikacijo dinamike sistema, ki omogoča napovedovanje časa, potrebnega za spremembo temperature glede na stopničasto spremembo reference. Kontrolni sistem vsebuje mehanizem predvidevanja, ki uporablja ta znanja za predpripravo temperature in s tem zagotavlja udobje. Ker je narava posameznika težko predvidljiva, smo v kontrolni sistem vgradili reaktivni mehanizem, ki blaži posledice napak mehanizma predvidevanja zaradi napačno predvidenih odsotnosti, ter mehanizem, ki temelji na seznamu pravil in parametrov ter odpravlja napake zaradi napačno predvidenih prisotnosti.

Sistem upravljanja smo zasnovali po vzoru porazdeljene večagentne platforme, kjer posamezni programski agenti predstavljajo senzorske, kontrolne, usmerjevalne, upravljalne in učeče se programske enote. Ti agenti imajo možnost medsebojne interakcije in združevanja v senzorske, kontrolne in druge organizacje ter niso vezani na centralni sistem, zaradi česar je sistem porazdeljen, robusten, modularen in prilagodljiv.

Eksperimente smo izvajali s simulacijo, pri čemer smo kot vhodne podatke uporabili realne podatke o prisotnosti in aktivnosti človeka ter vremenske podatke. V sorodnem delu raziskovalci običajno privzamejo statične in vnaprej določene vrednosti parametrov človeka. Mi pa smo pokazali, da je mogoče uporabiti cenovno ugodno in uporabniku prijazno rešitev za oceno teh paramtrov in s tem doseči pravilnejše zaznavanje in regulacijo udobja. Posledično dosežemo večjo učinkovitost strategij upravljanja. Pokazali smo, da je mogoče z različnimi strategijami doseči različne kompromise v prostoru dveh kriterijev, udobja in porabe energije. Strategije so optimizirane glede na zahteve stanovalca tako, da se ohranja zahtevana stopnja udobja, obenem pa se občutno zmanjša poraba energije.

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Abbreviations

AAL	...	ambient assisted living
AID	...	agent identifier
ASHRAE	...	American Society for Heating, Refrigerating and Air-conditioning Engineers
BAS	...	building automation system
BCVTB	...	Building controls virtual test bed
C4.5	...	C4.5 algorithm
CEN	...	European Committee for Standardisation
COP	...	coefficient of performance
DF	...	directory facilitator
DHW	...	domestic hot water
EM	...	environment management
EMS	...	energy management system
FIPA	...	Foundation for Intelligent Physical Agents
GPS	...	global positioning system
GSM	...	global system for mobile communication
HEMS	...	home energy management system
HVAC	...	heating, ventilation and air-conditioning
IB	...	intelligent building
IP	...	internet protocol
ISO	...	International Organisation for Standardisation
JADE	...	Java agent development environment
kNN	...	k-nearest neighbours
MACS	...	multi-agent control system
MAPE	...	mean absolute percentage error
MAS	...	multi-agent system
MET	...	metabolic equivalent of task
MIMO	...	multiple-input multiple-output
ML	...	machine learning
MPC	...	model predictive control
PID	...	proportional-integrate-derivative (controller)
ISO-PMV	...	model that computes comfort experience – the predicted mean vote
PTHP	...	packaged terminal source heat pump
RBC	...	rule-based control
RFID	...	radio-frequency identification
SCADA	...	supervisory control and data acquisition
SE	...	smart environment
SISO	...	single-input single-output
SMPC	...	stochastic model predictive control
WLAN	...	wireless local area network

Symbols

Symbols related to the modelling and simulation of the environment:

Δt	...	simulation time-step
$\{\}_k$	...	variable or vector in time-step k
e	...	the difference between the set-point variable and the corresponding sensed or inferred value
$E_{Device,Behaviour}$	...	electric energy consumed by a device at control behaviour during the observation period
f_{act}	...	model of actuator dynamics that maps control signal u_{r} to action u
f_{reg}	...	regulation algorithm that maps error e to control signal u_{r}
k	...	discrete time variable
$\vec{o}$	...	inferred state vector
o_m	...	m-th inferred variable
P_{device}	...	electric power of a device such as heater, chiller, etc.
$\vec{r}$	...	vector of reference variables
r_l	...	l-th set-point (reference, desired) variable
$\vec{s}$	...	sensed state vector
s_j	...	j-th sensed variable
$\vec{s}_d$	...	measurement noise vector
k_{f}	...	simulation finish time
T_{out}	...	outdoor air temperature
T_{s}	...	set-point variable for indoor temperature
k_{s}	...	simulation start time
$\vec{u}$	...	input vector that contains actions
v	...	signal, produced by regulator
$\vec{w}$	...	vector of weather and occupant-related variables contribution to the dynamics of an environment
$\vec{x}$	...	environmental state vector
x_i	...	i-th environment variable

Symbols related to the thermal comfort of an occupant:

f_{cl}	...	clothing surface area factor
h_{c}	...	convective heat transfer coefficient
I_{cl}	...	clothing insulation of a person
$IC_{Behaviour}$	...	discomfort index computed for the observation period at control behaviour *Behaviour* according to a simple definition related to the predefined value of the indoor temperature
M	...	metabolic equivalent of task

occ	...	occupancy
p_{a}	...	water vapour pressure
PMV	...	predicted mean vote
PPD	...	predicted percentage dissatisfied
T_{cl}	...	clothing surface temperature
T_{in}	...	indoor air temperature
$\bar{T}_{\mathrm{r}}$	...	mean radiant temperature
T_{sHi}	...	predefined high set-point temperature
T_{sLo}	...	predefined low set-point (set-back) temperature
T_{sSl}	...	predefined set-point temperature for sleeping
v_{ar}	...	relative indoor air velocity
W	...	effective mechanical power of a person

Symbols related to the control strategies:

$\leftarrow$	...	variable assignment
abs^*_{JR}	...	binary variable that signifies the predicted job-related absence
abs^*_{LT}	...	binary variable that signifies the predicted long-term absence
abs^*_{N}	...	binary variable that signifies the predicted night absence
C_{LD}	...	parameter that signifies the number of minutes an occupant typically spend at work
C_{ND}	...	parameter that signifies the number of daily departures threshold for job-related absence detection
C_{t1}	...	parameter that signifies the start of a period for night absence detection
C_{t2}	...	parameter that signifies the finish of a period for night absence detection
C_{tAbs}	...	parameter that signifies the time threshold in minutes for long-term absence detection
cls	...	classification or regression method that return the classified value based on instance and classification model
k_{LD}	...	counter of minutes that have expired since the last departure
k_{nf}	...	addition of time-steps to current time representing near-future time-step $k + k_{\mathrm{nf}}$
K_{RFT}	...	rise/fall time coefficient
k_{RFT}	...	time that is needed to change the temperature
K^*_{RFT}	...	classified rise/fall time coefficient
N_{D}	...	daily departure counter
occ^*	...	classified occupancy variable
$occCls$	...	occupancy classification model, classifier
$occInst$	...	instance for occupancy prediction
$rtCls$	...	rise/fall time regression model or classification model
$rtInst$	...	instance for rise/fall time prediction
WD	...	binary variable signifying whether the current day represents weekend day

Symbols related to the multi-agent control system:

$\mathbb{A}$	...	a set of agents of any type

B	...	control behaviour
$\mathbb{C}$	...	a set of control agents
cfg_{beh}	...	behaviour configuration
cfg_{sock}	...	socket configuration and variable mapping
C_{ql}	...	l-th control agent in the environment q
EM_q	...	management agent of the environment q
ml	...	machine learning algorithm
ML_{qn}	...	n-th machine learning agent in the environment q
rm	...	meta-data of the controller
R_{qm}	...	m-th routing agent in the environment q
$\mathbb{RS}$	...	a set of resource agents
$\mathbb{S}$	...	a set of sensor agents
S_{qi}	...	i-th sensor agent in the environment q
tp	...	machine learning model template
xm	...	meta-data of a sensor

Chapter 1

Introduction

Smart environment (SE) represents a set of spaces within an intelligent building (IB), a part of an IB (e.g., a smart room), or can be, for example, composed of a smart home, a smart car, and a smart office. SE adapts to its occupant in order to make his life more comfortable (Cook & Das, 2004). Therefore SE during operation takes into account various objectives including occupant's comfort experience, resources availability, energy consumption, safety and security aspects, and others. The IB represents an automated building enriched with the "intelligent" software that is able to learn autonomously from observations, exploiting advanced machine learning (ML) methods to extract knowledge, and to adapt during the operation based on the extracted knowledge.

The intelligence in buildings appears in various forms: intelligent controllers that are able to adapt control parameters to achieve better effect of actuators; multi-sensor data fusion that is able to combine data from various sensors and extract knowledge about the state of an occupant and/or an environment; weather prediction system, environment or occupant behaviour prediction system that is used for autonomous strategic planning of IB operation and others. In addition to the automated building, the IB includes the ability to define the desired state of the environment autonomously based on observations, predictions, and constraints that are specified within a building management strategy. An automated building represents a system composed of hardware (sensors and actuators) and software entities connected over a communication network that constitute a building automation system (BAS). The BAS uses sensors to observe the state of the environment, actuators to affect the environment, and feedback control algorithms that transform the perceived state of the environment into actuator actions in order to achieve the desired state of the environment. The feedback control algorithms continuously compare the current state of the environment that is perceived through sensors and sensor systems with the predefined desired state of an environment, and delegate the control signals to actuators in order to minimise the difference (error) between the compared states.

In 2010 41 % of all energy produced in Europe was consumed by buildings (27 % for households and 14 % for the buildings of the tertiary sector). 65 % of this energy was used for space heating and represents almost 27 % of all energy, 12 % for domestic hot water (DHW), and 15 % for electric appliances (BPIE, 2011; IEA, 2010; The European Commission, 2010). The amount of energy spent to satisfy various objectives depends on the quality of a building construction and materials used, on the quality and efficiency of home appliances, and on the quality of control subsystems and management system components. Research shows that space heating is the largest consumer of energy in buildings. These major consumption sources are also targeted in the directive accepted by the European Parliament that promotes the reduction of the energy consumption and global gas emissions by at least 20 % below 1990 levels and encourages the installation

of active control systems that aim to save energy (Recast, EPBD, 2010). Based on these facts we infer that more efficient management of heating, ventilation and air-conditioning (HVAC) systems in buildings could maintain satisfactory occupant's comfort experience while lowering the energy consumption significantly.

Good comfort experience and low energy consumption are usually two contradictory objectives. Finding an appropriate trade-off is therefore essential for efficient management of the SE. In order to manage the occupant's comfort and the energy consumption, the SE has to (i) perceive the state of the environment and the state of an occupant, (ii) affect the environment using available control subsystems and the corresponding actuators in order to (iii) meet the objectives specified within the control strategy in a building management system.

There are two intuitive approaches to manage the trade-off between the comfort experience and energy consumption. The first one is striving to decrease the energy consumption while comfort is of no importance – that is when SE is not occupied. The second is maintaining sufficient comfort experience while SE is occupied. The problem arises when facing the fact that the HVAC process is slow and its delay due to a room's thermal inertia must be taken into account. The process is also multivariate; the indoor temperature is affected by various heating bodies, such as heat produced by the occupant, sunlight through windows, and mechanical heaters (Garcia, Prett, & Morari, 1989).

Assuming to know in advance when the building will be occupied (when the occupant's comfort will be evaluated) and what is an appropriate indoor temperature to satisfy the comfort objective, the problem can be reduced to "computing the time the HVAC process needs to achieve the desired indoor temperature". In this dissertation we denote this term as a "temperature rise/fall time" which is the time-to-heat/cool the environment from the current temperature to the desired temperature. To solve this problem the dynamics of the HVAC system should be modelled. With the model the control system is able to prepare comfortable environment right before it becomes occupied.

Another problem has to be solved, if it is not known in advance when the building will be occupied. It is the "occupancy prediction problem". To solve this problem the occupancy has to be modelled in order to use it for the occupancy prediction in the near-future. Exploiting the occupancy prediction model in combination with the rise/fall time prediction model could significantly reduce the energy consumption during the unoccupied periods due to prevention of the unnecessary HVAC operation.

The occupant's metabolic equivalent of task and clothing insulation can change significantly during the occupancy, since a person practices various activities at home. Occupant's needs change over time on a sub-hourly basis. Therefore the assumption of knowing the comfortable indoor temperature mentioned above is rough. Regular domestic HVAC systems perform temperature control, where schedules and parameters for HVAC operation are normally given during the installation process and are seldom refined. HVAC settings should be continuously adapted along with the occupant's needs in order to achieve an efficient operation.

There are several reasons why occupants nearly never refine the settings in order to achieve cost-effective operation of domestic HVAC systems (Karjalainen & Koistinen, 2007; Peffer, Pritoni, Meier, Aragon, & Perry, 2011), such as:

- Some people do not want to deal with the settings of the HVAC controllers, since they are afraid to cause malfunction – setting optimal schedules is too demanding for an average occupant because of the lack of knowledge and experience, or is too time-demanding for occupants.

- The indoor temperature that is denoted as comfortable is highly dependent on other

factors, such as humidity, occupant's metabolic equivalent of task, occupant's clothing insulation, etc., and the desired temperature should be changed frequently.

- The home occupancy schedule is rarely refined and ordinary people do not adapt HVAC operation schedule to reduce the energy consumption especially in periods, when they are not at home for a day or weekend.

The occupant's comfort experience is not affected by the surrounding air temperature alone. There are several other parameters that constitute the definition of thermal comfort, such as air humidity, air velocity, mean radiant temperature, occupant's metabolism and clothing (Fanger, 1970). In order to adapt the system operation along with the occupant's needs it is necessary to observe the occupant in order to evaluate and maintain the desired comfort experience. Therefore a platform that enables spatially distributed autonomous monitoring and data processing is needed. Extracting the knowledge about the occupant's current state and also the prediction of occupant's state in the future enables the autonomous operation of HVAC system and refutes the need for the occupant to refine and adapt the HVAC settings and schedules alone.

An agent-based management system presented in this dissertation enables the monitoring of an occupant in order to observe, evaluate and regulate the desired level of the occupant's comfort, and maintaining the trade-off in energy consumption. It is able to process large datasets from various external and local data sources (weather station, environmental sensors, smart-phone sensors, etc.) and use the extracted knowledge for HVAC system control. We analysed and evaluated the influence of reactive, anticipative, and rule-based mechanisms combined into various management strategies where each of the proposed strategy achieves a different trade-off between the comfort experience and energy consumption after a long-term period. To this end we exploited the home and work occupancy datasets, obtained from five volunteers through a one to three months period. In order to evaluate the comfort regulator and the influence of errors by monitoring and estimating the occupant's energy expenditure on final comfort experience and energy consumption we exploited the datasets that include the metabolic equivalent of task. That datasets were obtained from other five volunteers and include the actual and estimated values.

1.1 Hypotheses and Goals

This dissertation addresses the following hypotheses:

- Observing the occupant's behaviour enables determining the properties of an occupant's interaction with an environment that allows the control system to predict the occupant's future needs and thus significantly reduce the energy consumption without decreasing thermal comfort much or increase of thermal comfort without increasing energy consumption much.

- Observing the occupant's metabolic equivalent of task that is highly dynamic during occupant's various daily activities improves the direct regulation of occupant's comfort and enables finding the most preferred ratio between the occupant's comfort experience and energy consumption.

The goal of this dissertation is to develop a novel method for management and control of SE that exploits ML methods and MAS, and enables the search for an appropriate trade-off between the occupant's thermal comfort experience and energy consumption.

1.2 Scientific Contributions

The main scientific contributions of this dissertation are the following:

- The development of a multi-agent control system (MACS) which is presented in Section 4.3 that implements a reactive, an anticipative mechanism, and a novel rule-based mechanism which are presented in Section 4.1.1, Section 4.1.3, and Section 4.1.4 respectively. The anticipative mechanism uses home occupancy modelling to adjust HVAC activity based on near-future occupancy predictions. The rule-based mechanism incorporates domain knowledge to reduce wrong occupancy predictions made by the anticipative mechanism. The reactive mechanism ensures that HVAC operation is on in case of presence and off in case of absence, thus correcting errors in the reasoning of the anticipative and the rule-based mechanism.
- The analysis of the effect of occupancy prediction modelling on comfort experience and energy consumption which is presented in Section 6.3.1.
- The development of a novel comfort regulator, presented in Section 4.2, that enables specifying the desired comfort threshold in order to manage the comfort and energy consumption trade-off based on the occupant's preferences. The evaluation is presented in Section 6.3.2 and Section 6.3.4.
- The simulation and evaluation of HVAC control, where the dataset about the occupant's energy expenditure and clothing insulation is given as highly dynamic variables simulating real-life situation. Results are presented in Section 6.3.3.

The additional contributions of this dissertation include also: (i) the integration of an agent-based control system with the whole building simulation environment (Zupančič, Gams, & Luštrek, 2013) which is presented in Section 4.3.1 and the development of the simulation manager that was used for the experimental set-up and evaluation of results, related to this dissertation, and (ii) the analysis of the impact of the errors in occupant's energy-expenditure estimation using smart-phone on comfort computation, comfort regulation and HVAC energy consumption (Zupančič & Cvetković, 2014) presented in Section 6.3.3.

1.3 Dissertation Structure

Chapter 2 reviews the work related to the topics of occupant-aware comfort and energy management in SEs including the background of the thermal dynamics in building environment, taking into account the artificial intelligence, automation, and control aspects.

In Chapter 3 the uncontrolled and controlled model of an environment is briefly described. Uncontrolled model represents the building thermal dynamics that is affected by the heat produced within the human body (by an occupant) and by the heat that is accumulated in the outdoor air (weather-related heat gain). Uncontrolled model, which is extended version of controlled model, represents the environment that is affected by the control subsystems according to the control signals that are produced by the control subsystems. The relation of the occupant's interaction with an environment and the occupant's comfort experience are defined.

Chapter 4 firstly describes the development of set-point delegation strategies, where the reactive, anticipative, and rule-based strategies are integrated into a control algorithm. Next, the proposed comfort regulator is presented. Finally, the multi-agent architecture is presented with the definition of software agents and agent behaviours that were implemented and used throughout this dissertation.

Chapter 5 describes the experimental set-up and procedures for evaluating the occupancy prediction, indoor temperature rise/fall time prediction, and comfort and energy management strategies. Here the weather and occupant related datasets that were used for simulations are presented. The conceptually defined MAS that contain control, sensing, ML, and routing agents is also presented in this chapter.

Chapter 6 includes the results of evaluation procedures for the temperature rise/fall time prediction, the occupancy prediction, the comfort regulation and the long-term evaluation of control strategies.

Chapter 7 includes concluding remarks and briefly discusses the future work.

Chapter 2

Background and Related Work

Early definitions of an intelligent building (IB) focused on the technology aspect, where a building integrates various systems to effectively manage resources to maximise technical performance, investment and operating cost savings and flexibility. Later definitions emphasised the importance of the occupants and their well-being within an IB (Wong, Li, & Wang, 2005). An IB should be sustainable, healthy, technologically-aware, should meet the needs of one or more occupants and should be flexible and adaptable to deal with changes (Clements-Croome, 2013). It consists of various subsystems with corresponding sensors, controllers, regulators and actuators. Similarly to smart environments (SEs), IBs should adapt to an occupant in order to make his life more comfortable (Cook & Das, 2004).

In this chapter, first the background and related work on modelling and simulation of an environment dynamics are presented. Second, the occupant's perception of comfort in an environment is described including the review of related work that includes the management of the occupant's comfort. Third, the related work on home energy management systems (home EMS, HEMS), the automation and control aspects, and the concepts and strategies that aim to balance the comfort experience and energy consumption are reviewed including the occupant-aware energy management. And finally, the management architectures including communication aspects, agent, and multi-agent paradigm is described and proposed as a solution for complex system development, analysis and management.

2.1 The Thermal Dynamics and the Simulation of an Environment

The thermal dynamics describe the processes of heat flow within an environment. It is known from the theory of the dynamic systems control that the thermal dynamic processes are slow and time-variant, which means that the system response is not achievable at the moment immediately after actuation and the system behaviour varies according to the various initial states. Furthermore, these systems are also non-linear, which affects the control system with additional uncertainties, such as hysteresis or dead band (Garcia et al., 1989). The situation in an environment, taken into account for control and management purposes, can be described with an environmental state. During the lifetime of an environment (either simulated or real), the observation period describes the timespan in which the environment is managed – that is, observed and controlled according to some control strategy. Due to the above description of environment dynamics, we can summarise that the experimental evaluation of the heating process using real test-bed is time-consuming, expensive and most important regarding the development of control algorithms – in contrast to the simulated approach, experiments that are performed on the real test-bed can

not be repeated by the same conditions in order to compare various strategies and control algorithms.

In order to compare various control algorithms, numerous experiments by similar conditions have to be conducted. The home heating system heavily depends on weather conditions. Therefore, the experiments in real life can hardly be compared. For the study and analysis of system long-term behaviour, which requires from a couple of days to some months or even a year of runtime data, the real-time experiment with real occupants in the real environment is desirable.

For practical reasons, researchers in the fields of BAS and building EMS commonly use simulation techniques to evaluate the performance of control algorithms and management strategies using a thermal dynamic model of a building (Mozer, Vidmar, & Dodier, 1997; Adolph, Kopmann, Lupulescu, & Müller, 2014) and also for predicting the energy savings in order to facilitate the assessment whether the new management strategy is worth to introduce in an existing building. System simulation offers the following advantages in development compared to real tests: It is faster, it allows the comparison between several control algorithms with the same weather situation, and the price of an experiment is incomparably lower, which implies that failed experiments have less negative impact on research budgets. The simulated time-flow can either be quickened or slowed down. However, there are also disadvantages, since the simulated environment is just an approximation of a real dynamics in an environment. In order to evaluate the simulation results, knowledge about the process dynamics is crucial, even though the results can be wrongly interpreted and the reason for simulation malfunction is sometimes hard to identify (Zupančič, Karba, & Matko, 1995). We used the simulation approach in order to compare the performance of the proposed comfort and energy management strategies.

The modelling of an environment can be divided into the white box, black box and grey box approaches (Sohlberg, 2003). A white box model is created based on physical relations, so the detailed knowledge of the system operation is crucial. Such a model is known also as the first principle model. In contrast, a black box model is created based on an experimental observation of a process and does not reflect the physical structure of the system. The grey box modelling combines the first two approaches, where a priori knowledge of process is used to model known components and observations are used to model and estimate unknown parameters of the process. Bacher and Madsen (2011) described the procedure for identification of building's thermal dynamics.

2.2 Comfort Experience in a Conditioned Environment

An environment that is occupant-aware should be able to extract and perceive the knowledge about the occupant's mood, occupant's intensity of physical activity and preferences in order to bring the environment into a state denoted as thermal equilibrium. A lot of research activity was devoted to justify the perception of an occupant's comfort in an environment. It is worth to mention the conclusions by Chappells and Shove (2005), debating the future of comfort: *"comfort is a highly negotiable socio-cultural construct"*. The occupant's comfort experience in an environment is an expression of how the occupant feels in the environment. The full comfort experience is composed of several aspects: visual comfort, acoustic comfort, indoor air quality, and thermal comfort (Frontczak & Wargocki, 2011).

In this dissertation, the term *comfort* refers to the thermal comfort. Based on the related work on comfort management in conditioned environments we adopted two versions of comfort definition. They were taken into account by the evaluation of the proposed control architectures and algorithms for environment control related to the comfort experi-

ence further in this dissertation. The first, simple definition of comfort is evaluated strictly by means of indoor temperature, while the other takes into account various environmental and personal parameters that constitute the definition according to the international standards.

2.2.1 Simple Definition of Comfort

Heating control systems typically use a set of predefined set-point values for indoor temperature that are assumed as comfortable. Values are predefined for various situations, in control automation engineering known as scenes, regimes, modes. It is common to have one reference value for normal operation – normal control denoted as high set-point and one denoted as low set-point (also set-back) value that should be applied, when control is not needed. Other values could be further defined (sleeping, working, showering, party, etc.) for different activities and enforced into a control system, as traditionally through a set-point schedule.

Therefore the following cost functions are used to evaluate comfort or rather discomfort: (i) miss time that represents the total time the home is occupied and the indoor temperature is not within an interval of predefined values $+/-$ threshold (Lu et al., 2010; Pipattanasomporn, Kuzlu, & Rahman, 2012) or for example evaluation of comfort for the domestic hot water (DHW) system (Zupančič, Luštrek, & Gams, 2013) and (ii) the cumulative sum of time multiplied with the difference between the desired and actual temperature for each moment during the observation period (Moroşan, Bourdais, Dumur, & Buisson, 2010; Zupančič, Luštrek, & Gams, 2014a). The mentioned two cost functions assume the set-point temperature is the one that ensures comfort. Even though this particular definition is often used in scientific literature and real applications due to its simplicity the more accurate definition of comfort results in more reliable evaluation which is presented in Section 2.2.2.

2.2.2 Advanced Definition of Comfort

The thermal comfort experience is the notion of the thermal sensation of an occupant in a controlled environment. International definitions of thermal comfort are described in standards defined by the International Organisation for Standardisation (ISO), the European Committee for Standardisation (CEN), and the American Society of Heating, Refrigerating, and Air-conditioning Engineers (ASHRAE) – such as ISO EN 7730, CR 1752, or ASHRAE 55. The mathematical model for evaluating the comfort experience denoted as ISO predicted mean vote model (ISO-PMV) that assigns the index PMV was derived by Fanger (1970). It is roughly interpreted as follows: thermal sensation is related to the thermal balance of a human body which is influenced by the intensity of physical activity and clothing as well as by environmental parameters such as air temperature, mean radiant temperature, air velocity, and humidity. The PMV can be calculated according to the mentioned parameters although the comfort cannot be measured directly (Underwood, 2002). The environmental parameters that constitute the thermal comfort are temperature (indoor air, mean radiant), humidity, air velocity, and personal parameters (clothing insulation, metabolic equivalent of task) (Olesen, 2004).

The index PMV expresses the thermal sensation on a seven-point scale ranging from -3 to $+3$, where negative values denote a colder sensation and positive values denote a warmer sensation. The value 0 denotes a neutral sensation which is the target value for indoor air-conditioning, when the only control objective is to achieve the best comfort experience. The greater the distance between the value of PMV and 0, the more cold (when negative) or hot (when positive) the sensation. The discrete values are defined as

follows: Cold(−3), Cool(−2), Slightly cool(−1), Neutral(0), Slightly warm(1), Warm(2), Hot(3) where *PMV* is given in parenthesis. In related work on control of comfort according to ISO-PMV the computation of *PMV* is mostly performed with assumed fixed values of personal parameters (A. Dounis & Manolakis, 2001; Calvino, Gennusa, Morale, Rizzo, & Scaccianoce, 2010; Liang & Du, 2008). Freire, Oliveira, and Mendes (2008) used two predefined values of both metabolic equivalent of task and clothing insulation for sleeping and normal office work, those specified for predefined periods of a day when they evaluate the performance of a control system.

The predicted percentage dissatisfied index *PPD* 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* depends on *PMV* and both indices are specified and interpreted in international standard ISO 7730 (ISO, EN, 2005), European standard CEN CR 1752 and other standards involved with the ergonomics of the thermal environment (Olesen, 2004). The computation of *PPD* is made under the assumption that at least 5 % of people in a group is never satisfied with the thermal environment and according to ISO 7730, the index *PPD* should be used for long-term evaluation of comfort.

It is often assumed that environmental parameters are easier to obtain than parameters that express human activities and behaviours. The need for non-intrusive methods for measuring human energy expenditure was emphasised by Humphreys and Nicol (2002), who analysed the validity of the ISO-PMV model and recommended the guidelines for model improvement. Luštrek, Cvetković, and Kozina (2012) and Kozina, Gjoreski, Gams, and Luštrek (2013), presented a system that, based on the recognised activities of a person using a smart-phone, can estimate the energy expenditure expressed in MET (metabolic equivalent of task), where 1 MET is equal to energy expended at rest. A review on thermal comfort was conducted by Djongyang, Tchinda, and Njomo (2010) 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. Lin and Deng (2008) extended the ISO-PMV model for sleeping environments. The difference of comfort notation between genders was taken into account in (Karjalainen, 2007), which stated that females are more critical of their thermal environments and that males use thermostats in their households more often. To summarise, the notation and incorporation of comfort evaluation metric is crucial for an advanced EMS since the energy consumption in a domestic environment heavily depends on the comfort requirements of each individual or home-owner. Most energy is lost due to unnecessary control when the comfort experience is not important.

In this dissertation we show that the regulation of comfort with assumed fixed values of personal parameters results in reduced comfort experience and in higher energy consumption compared to estimated values of personal parameters. Therefore we improved our control system with a smart-phone-based application that is used to estimate personal parameters, such as the metabolic equivalent of task (Zupančič & Cvetković, 2014). We compared the performance of comfort regulator in terms of comfort experience and energy consumption where the dataset of true and estimated values of metabolic equivalent of task was used for comparison. We show that (i) the comfort experience is heavily underestimated when assuming the predefined and fixed values of personal parameters and (ii) the energy consumption is lower when using estimated values of metabolic equivalent of task for comfort regulation.

2.3 Energy Management in Smart Environments

Energy management plays an important role in controlling the energy consumption in buildings (Aman, Simmhan, & Prasanna, 2013). It manages the consumption of available

energy with respect to other objectives, such as the price, the availability of the energy resources, the comfort that could be visual, thermal, or acoustic, and/or others. If a building represents a smart (micro) grid that includes the energy production (such as photovoltaic plant) and energy storage capabilities, the energy management becomes even more important. Smart load balancing can significantly decrease the energy costs and exploit the available resources more effectively.

The scheduling in energy management represents a useful method that is often implemented to delegate set-point variable values. The set-point (reference) variable of a control system is a temporal variable of an environment that is passed to a regulator as a reference, to be compared with an actual state of an environment. A regulator perform feedback control so that it continuously compares set-point variable with the actual state in order to equalise that set-point value with the actual state of an environment, using the actuators. For example: if the indoor temperature represents the environment variable, then the desired indoor temperature represents the set-point value. In order to observe the occupant and the environment, to pre-process raw data, to extract knowledge and to use it for planning, scheduling and set-point delegation, a communication infrastructure is needed that allows interconnection and data transfer (information, knowledge, schedules, strategies and commands) between spatially distributed entities, the platform that is able to integrate all entities according to control strategies, and the availability to manipulate with all the resources.

2.3.1 Automation and Control

According to (Cook & Das, 2007) automation can be viewed as a cycle of perceiving the state of the environment, reasoning about the state together with task goals and outcomes of possible actions, and acting upon the environment to change the state of the environment. Perception of the environment is a bottom-up process, where sensors on the bottom layer monitor the environment using physical components and serve the measured values through a communication layer. The data obtained from sensors is processed in higher management layers according to knowledge models and transformation functions into a set of environment variables that constitute an environmental state. There is a wide variety of sensors and sensor systems used to perceive physical properties (pressure, temperature, humidity, flow sensors); motion properties (position, velocity, angular velocity, acceleration); contact properties (strain, force, torque, slip, vibration); presence (proximity, distance, motion); radio-frequency identification (RFID) and others. In contrast to sensing, actuation is the top-down approach. According to the decision that is made in the automation or management layer, the physical layer performs the action upon the environment using actuators or device controllers.

In order to manage a complex system and to achieve an efficient operation, the different approaches to control systems can be roughly classified into three categories (A. I. Dounis & Caraiscos, 2009): (i) conventional methods; (ii) computational intelligence; and (iii) agent-based intelligent control systems. Conventional methods include classical ON-OFF controllers with dead zone and Proportional–Integrate–Derivative (PID) controllers. Furthermore, optimal, predictive, and adaptive control can be classified into conventional control systems, where a model of an environment is necessary. Conventional methods do not use learning. Methods that contain computational intelligence include intelligent controllers that use a combination of fuzzy logic and ML methods for controller development, and evolutionary algorithms for the optimisation of controller parameters. Agent-based control systems include controllers that have the characteristics of intelligent agents. Various zones in buildings contain controllers that are considered as software agents. The overlapping between these categories is unavoidable.

Oldewurtel et al. (2012) classified controllers according to the methods used to model the operation of a controller – a mapping between the sensed states and controller actions. These are:

- A rule-based control (RBC) that is assumed as current control practice in home automation which determines all control inputs based on a series of rules in the form "if condition, then action". The conditions and actions are usually associated with numerical parameters (e.g., threshold values) that need to be chosen. A good performance of RBC critically depends on a good choice of rules and associated parameters.

- A deterministic model predictive control (DMPC, MPC) is determined as the standard model predictive control approach that is used in virtually all commercial MPC applications. It uses the imperfect/uncertain prediction and takes its control decision under the assumption that the predictions are correct.

- Stochastic MPC (SMPC) approach, where formulation accounts the uncertainty in prediction and allows to formulate the so-called chance-constraints. The last, stochastic approach was used to predict the weather impact on the thermal dynamics of the environment (Oldewurtel et al., 2012).

Control and regulation of individual subsystems, such as a single heating device, represent a matured research area with a wide range of scientific literature on control system design, and on several methods of implementing a particular controller that controls a specific individual subsystem, an example being the book by Strmčnik et al. (1998). The centralised approach is often proposed to control an individual subsystem. With the complexity of the control system, the complexity of the representation of such system grows as well. It results in complex and expensive computation methods for controller set-points delegation especially for multiple-input multiple-output systems. Algorithm implementation, complex behaviour model creation to be used by a control system, system organisation, user interfaces, multi-sensor data fusion, and other computationally expensive operations can be performed on spatially distributed computational entities. System decentralisation results in a faster and more fault-tolerant operation.

Due to complexity of the occupant-related management system that includes the regulation of comfort based on various data sources, we adopted the multi-agent control architecture. Multi-agent paradigm is summarised in Section 2.4.2; it enables spatial decentralisation of sensing, control, learning and other entities that are represented as intelligent agents.

2.3.2 Concepts and Strategies for Effective Management of HVAC Systems

There are two common strategies to reduce the energy consumption, that is required for heating and cooling. The first one includes the occupant so that the management system proposes methods, strategies or actions or also encourages the occupant to perform an action. In this approach the decision to follow the proposals and take actions or not is made by each individual on his own. In the second approach, the management system proposes and, in contrast to the first one, also implements the methods and perform the strategies or actions, while an occupant is still able to interrupt the depicted activity, change the strategy or refine the methods. The second strategy is strongly evolving also due to research work in the ambient assisted living (AAL) domain that examine the relation between humans and the environment exploiting pervasive methods of ambient intelligence to extract the

knowledge about personal state, personal needs and wishes. The final goal is to manage the home automation system with the strategy that is acceptable for the occupant in an environment with respect to comfort objectives, economic objectives, energetic objectives overlooking the pollution and carbon footprint, safety and security objectives.

In both new and existing buildings, methods for encouraging occupants to reduce the energy consumption used for heating and/or cooling already exist. More precisely, these methods encourage the occupants to decrease set-point temperatures for heating, or to increase set-point temperatures for cooling, using a visual representation of the energy consumed and self-reported data about occupant interactions with the environment (Kwak et al., 2012; Ouyang & Hokao, 2009; Holmes, 2007; Darby, 2006). Cho, Lai, Lai, and Huang (2013) proposed an appliance-aware activity recognition mechanism for home that notifies the occupant about an unused appliance or switches it off automatically. Yu, Fung, Haghighat, Yoshino, and Morofsky (2011) analysed the influence of the occupant's behaviour on building energy consumption and developed a technique for identifying energy-saving potential by changing occupant's behaviour to reduce the energy consumption. In common, such strategies influence an occupant who makes the final decision for each action, and the management system is used to provide information about the current state of the energy consumption, the appliances that could be turned off to save energy, and the proposals of how to behave in order to reduce energy consumption. In contrast, our approach does not assume the ability to change occupant's behaviour. It rather tends to observe an environment with an occupant in an unobtrusive manner, identify the environmental state, and maintain that state through actuators within the HVAC system in order to satisfy the requirements related to the occupant's comfort experience.

The second strategy assumes that the automation and management tasks are fully conducted by an intelligent system alone; however the occupant interaction with the system is still available. The occupant is able to make decisions and delegate tasks, but in such a case the occupant interaction could be denoted as an intervention – in this case the comfort loss. The IB control should tend to operate totally autonomously, where the system should take actions in order to make the occupant satisfied without his intervention. Therefore, reliable ubiquitous or pervasive computing, communication and actuation infrastructure is needed to acquire, process and effect the environment. We denote such a strategy as occupant-aware home energy management which is proposed in this dissertation.

2.3.3 Occupant-Aware Home Energy Management

"By incorporating new-type, higher-level variables that define comfort into the intelligent controllers (e.g., PMV that is assigned according to ISO-PMV model), it was possible to control comfort without going into the regulation of lower-level variables like temperature, humidity and air velocity. In such systems, users start to participate in the specification of the desired comfort." (A. I. Dounis & Caraiscos, 2009)

The occupant-aware home energy management observes an occupant and takes into account the occupant-related parameters by the management strategies in order to meet formulated objectives which are also related to the occupant. Related work includes several techniques to answer the questions regarding an occupant's relation with the environment. Several studies, including the one described in this dissertation, have included the data about one or more occupants in the control schema for the thermostat set-point delegation.

Gao and Whitehouse (2009) show that the value of set-back temperature significantly influences the energy consumption and therefore define the shallow and deep set-back values. Shallow set-back temperature should be used to reduce the risk of comfort loss in case the building becomes occupied at that time. Deep set-back should be used when it is obvious that control will not be needed for a longer period.

Mozer et al. (1997) implemented a neural network algorithm to predict occupancy and expressed the comfort as a misery unit in dollars. Scott et al. (2011) implemented an occupancy prediction algorithm in which the occupancy was predicted for a 15-minute interval. The improvement of the new algorithm was compared with the predefined schedule regarding the comfort experience and the energy consumption for individual rooms in an apartment. Lu et al. (2010) used occupancy sensors to obtain data regarding the behaviour patterns of the occupant and evaluated the comfort experience and the energy consumption where the comfort experience was evaluated as a miss time in minutes – that is, the summation of time when the indoor temperature did not reach the set-point temperature within the tolerance of 1°C. Bapat et al. (2011) used the data about home occupancy to optimise the schedule that delegates the operation of home appliances such as dishwashers and washing machines in order to minimise the energy costs. Krumm and Brush (2011) exploited the global positioning system (GPS) data to predict human occupancy, but did not evaluate the effect of the algorithm performance in terms of comfort experience or energy consumption. Bayir, Demirbas, and Cosar (2011) developed a web-based service that based on cell registration data and cell location changing patterns predicts the location of the cell phone owner. OBSERVE and Synergy systems were exploited by Erickson, Carreira-Perpiñán, and Cerpa (2011) and Agarwal et al. (2010) for sensing and processing the occupant related-data in order to predict occupancy for effective control of HVAC system. For this dissertation, the dataset for occupancy prediction modelling and energy simulations was obtained from volunteers. Similarly as by the related work we exploit an RFID system to register occupancy at work. To register occupancy at home we exploited a smart-phone application that enables manual logging.

Gao and Whitehouse (2009) optimised set-back temperatures based on home occupancy patterns. Vrečko, Vodopivec, and Strmčnik (2009) implemented the MPC, where the thermal dynamic model was implemented for predicting the temperature rise time needed by a HVAC system to heat the room, with the idea to make the HVAC operation schedule ideal in the sense of reducing the unnecessary control periods – that is, to control the zone only when the occupant's comfort is evaluated, which happens only in periods when the home is occupied. All these studies show that the energy consumption for HVAC systems, DHW systems and electric appliances can be significantly reduced if the knowledge about the occupant's interaction with the environment is taken into account within the algorithms of the control system, so that the inhabitant's comfort experience improves or stays at the same level.

Various computational methods to obtain and predict the state of an occupant in an environment were investigated in related studies. The perception of an occupant within an environment can be denoted as simple as presence or absence that could bring significant improvements regarding the comfort and energy consumption objectives, if the system is able to perceive such state accurately (Agarwal et al., 2010; Gao & Whitehouse, 2009). Furthermore, the ML algorithms were developed to create and adapt models of occupancy. Such models are able to predict the near-future occupancy for one person. Occupancy prediction models that are based on historic time series are implemented using evolving fuzzy predictor (Akhlaghinia, Lotfi, Langensiepen, & Sherkat, 2008), Hidden Markov Models (Erickson et al., 2011), Active LeZi prediction algorithm (Gopalratnam & Cook, 2007), and C4.5 classification algorithm (Zupančič, Luštrek, & Gams, 2014b). Scott et al. (2011) implemented an algorithm that, based on five most similar historical situations, predicts near-future occupancy probabilities using k-nearest neighbours (kNN) classification algorithm. Zupančič et al. (2014a) compared the performance of adaptive near-future occupancy prediction modelling and classification based on C4.5, random forest, and kNN algorithms. We have analysed the influence of occupancy prediction algorithms on the

performance of a HVAC system in terms of comfort experience and energy consumption. Results are presented in Chapter 6 of this dissertation.

Mamidi, Chang, and Maheswaran (2012) estimated the number of occupants in an office and also predicted the future occupancy using ML techniques and rule-based heuristics for a number of occupants. The per room occupancy prediction was taken into account by Roy, Das, and Basu (2007) in order to reduce the energy consumption for controlling the unoccupied rooms. They implemented estimation techniques and compared the performances of various machine learning algorithms, such as multilayer perceptron, Gaussian processes, linear regression and others upon various feature sets, including time, sound, carbon dioxide, temperature, humidity, motion and various derivations of mentioned features.

If the occupancy prediction methods are used for energy saving due to temporal predictions, the perception of the state of an occupant was further investigated to ensure comfort. Besides the state of an occupancy, it is also important for management of IB subsystems to take into account the information about the metabolic equivalent of task, clothing insulation and other information related to an occupant that helps to determine the thermal comfort or the deterioration in the occupant's health status, which is often related to AAL domain. When implementing a feedback control of comfort, various occupant-related factors, such as metabolic equivalent of task and clothing insulation, are always predefined as static values. In order to perceive such complex states, the data collection from various sensors types, the model creation including ML techniques, and the evaluation using unobtrusive methods and technologies is needed. In this dissertation we present an approach where metabolic equivalent of task is estimated using a smart-phone accelerometers and clothing insulation is estimated using rule-based heuristics. The estimations are used for the perception of comfort and for control (Zupančič & Cvetković, 2014; Zupančič, Cvetković, & Gams, 2014). We show that the comfort experience can be improved and the energy consumption reduced even though, the estimation of the metabolic equivalent of task of an occupant is performed with slight deviation.

2.4 Energy Management Architectures

Energy management architectures are either centralised, decentralised or distributed. Moroşan et al. (2010) compared the computational efficiency of these architectures with a conclusion that the distributed architectures are less computationally demanding than the centralised architecture while achieving the same effect. In a review of advanced methods for management of energy and comfort in the building environment, A. I. Dounis and Caraiscos (2009) stated that the future control systems for building management will be intelligent and have a human-centric approach. Advanced control systems are composed of (i) a low-level feedback control system of each building's zone; and (ii) a high-level supervision and planning system, where the set-point schedules are generated and passed to the low-level system.

2.4.1 About Communication Infrastructures

A large amount of research projects took into account the communication aspect of the EMS. The amount of sensing, control, actuation and other entities, such as graphical, voice or gesture user interfaces, data storage components and communication technologies, protocols and standards that constitute the EMS increase the complexity, the transparency and the fault tolerance of the system. The communication infrastructure should integrate the interoperability of those entities based on the communication and interaction protocols

and standards. These are often implemented by various vendors on their own and are more or less derivations of well-known intentional protocols. In order to integrate the appliances that are able to communicate in compliance with various protocols and standards, the ability of routing between various products within the management system is crucial. The middleware layer in home automation and management architecture is responsible for the integration of such technologies (Warriach, 2013).

Sauter (2010) did a review of field-level networks. Until 1980s automation hierarchy was composed of field area networks, local area networks and wide area networks. These layers were used to vertically integrate the devices with the so-called management layer that enables monitoring and strategic planing. Today an IP-based network connectivity is available for individual devices of the lowest layer of home automation (sensors and actuators). Therefore the building automation hierarchy today, according to (Sauter, 2010), is composed of field layer at the bottom, automation layer at the middle, and management layer at the top, where the IP-based network ranges through the whole hierarchy. The common wired and wireless technologies, such as X10, ZigBee and Bluetooth for establishing a network of control devices were critically revised in (Bordencea, Valean, Folea, & Dobircau, 2011). They develop devices with processing and storage capabilities based on the Paxos communication protocol for a reliable BAS.

A wireless network of sensors and actuators was also implemented for a system decentralisation of mobile control appliances (Xia, Tian, Li, & Sung, 2007). An agent platform for the personalised control of buildings and appliances was analysed for example by Qiao, Liu, and Guy (2006). They proposed a system architecture composed of an (i) application layer, (ii) communication layer and (iii) devices layer. Agents are deployed in an application layer. A communication layer contains control networks for feedback control, IP-based backbone network for internet-related services and applications, and middleware that is used to integrate disparate control and backbone networks. The devices layer includes physical sensors and actuators.

A typical communication aspect of a SE is shown in a general manner in Figure 2.1. The SEs should be closely integrated. Every physical component should have cyber capabilities including processing, storage and networking capabilities within a home area network using WLAN, Bluetooth, GSM or other wired and wireless technologies (Shi, Wan, Yan, & Suo, 2011). Furthermore SE, here represented as cyber-physical system, should allow (i) spatial and temporal distribution thus related to real time information exchange regardless of the distance between the information sources and sinks, (ii) dynamic reorganising/reconfiguring – that is, to allow adaptation, (iii) high degree of automation, where advanced feedback control approaches increase stability and the desired operation of control systems, and (iv) should be aware of safety and security in cyber and physical aspects. An example of a technological solution for totally integrated building automation was presented by Palčič (2008), which includes a portable controller as a central unit of a controlled subsystem that could be extended using various input/output modules, user interface and communication modules, and completely managed through the application layer in order to compose a management system.

Dynamic environments are complex and therefore the corresponding control systems are complex, composed of a large number of intersecting components. Jennings and Bussmann (2003) argue that the agent-based approach to analyse, design, and implement such complex software systems as a collection of interacting, autonomous, flexible components (i.e., as agents) offers several significant advantages over contemporary methods.

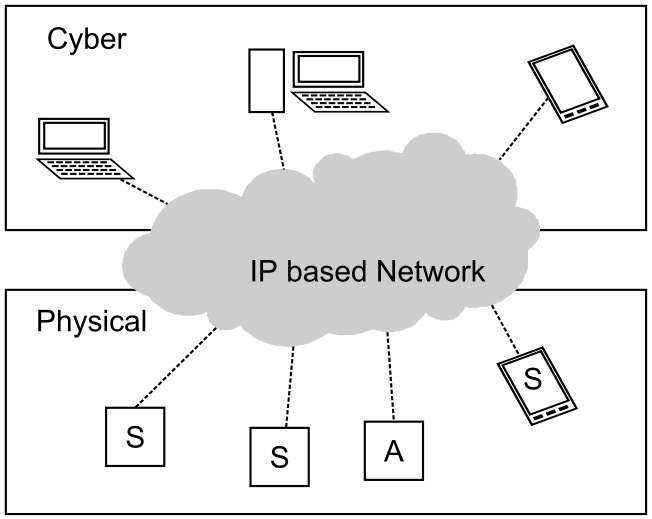


Figure 2.1: Communication aspect of home energy management architecture – smart environment or cyber physical system layout. S and A represent sensors and actuators in an observed and controlled environment. Adopted from Shi, Wan, Yan, and Suo (2011).

2.4.2 Agent Definition

A definition of an agent concept by Wooldridge (1997) was widely adopted: *"An agent is an encapsulated computer system that is situated in some environment and can act flexibly and autonomously in that environment to meet its design objectives"*. Macal and North (2006) extended a definition with the statement: *"An agent label is reserved for components that can in some sense learn from their environments and change their behaviour in response"*. In order to better understand the agent-based modelling, we list some important characteristics that an agent should have (Macal & North, 2006):

- *"An agent is identifiable, discrete individual where one can easily determine whether something represents a part of an agent"*.
- *"An agent is situated, living in an environment with which it interacts along with other agents. Agents have protocols to interact with other agents and the capability to respond to the environment"*.
- *"An agent may be goal-directed, having goals to achieve. This allows an agent to compare the outcome of its behaviour relative to its goals"*.
- *"An agent is autonomous and self-directed so it functions independently at least over a limited range of situations that are of interest"*.

As seen above, the agent concept is not strictly defined. Therefore agents can be classified according to the tasks they are used to perform, the environment they are located in, the communication language they use, the organisation in which they take part, etc. Franklin and Graesser (1997) classified autonomous agents on biological agents, robotic agents and computational agents. Computational agents were further divided into artificial life agents and software agents, the later including task-specific agents, entertainment agents and viruses. Each agent type could be classified further based on specific properties that agents of the same type have, such as same control structures, programming languages and applications.

The fundamental aspects, which distinguish a single-agent system from a MAS, are the following Vlassis (2007):

- Agent design: An agent can be created for one or various operating systems, or agents implementing same or different behaviours. Therefore an agent can be heterogeneous or homogeneous, so agents differ according to their incidence, according to the hardware or software an agent may involve;
- Environment: An environment could be static (time invariant) or dynamic (nonstationary);
- Perception: In MAS, a world state is partially observable to each agent, due to spatially distributed sensors, temporally variable data (varying time-steps) or semantically variable data that require different interpretations;
- Control: Control in MAS is typically distributed, where no central process exists to collect all the information from each agent and then decide what action each agent should take. Decisions are made by each individual agent resulting in asynchronous (faster) computation, however MAS requires a coordination mechanism to enable good joint decisions;
- Knowledge: In MAS, the level of knowledge of each agent can differ, but the crucial concept is that of common knowledge, demonstrated with a red traffic light convention that is supposed to be common knowledge to all other drivers;
- Communication: is often associated with same form as interaction. All agents are potentially senders and receivers. Communication can be used for coordination, negotiation and knowledge sharing among agents. It is important that agents use appropriate network protocols that allow safe and timely information exchange, and that they "understand each other" so that they speak the same language.

2.4.3 Multi-Agent Building Control and Management

There are many research projects where a MAS was applied to manage various complex systems; however, our focus was on the agent-based systems developed to control IBs or building subsystems. A comparison between the traditional and the agent approach for control and management systems in buildings was performed by Wagner (2003), who argues that the agent approach results in a transparent software structure and dynamic and adaptive application software.

Many works proposed and implemented sensor-actuator network based on agent architecture. Sharples, Callaghan, and Clarke (1999) used it for IB sensing and control, emphasizing the role of learning and contrast with existing non-agent-based solutions. They highlighted the role of learning ability and the importance of acquiring information from sensors rather than relying on preprogrammed models to determine occupant's needs. Furthermore, they introduced the device agent and types of control behaviours, such as simple, fixed, parallel, learned and others.

Agent's anticipative and reactive mechanism for IB management was demonstrated for comfort and energy management in IB (Abras, Pesty, Ploix, & Jacomino, 2008). We adopted this approach and extended with a rule-based mechanism. The anticipation is used for long-term goal-oriented behaviour to avoid emergency situations, while the reaction (reactive mechanism, emergency mechanism) is used to react if the emergency situation occurs. Rules are specified optionally by the user to reduce wrong anticipations. Sun, Yu, Kochurov, Hao, and Hu (2013) developed a belief-desire-intention model for agent

behaviour design and a policy-based method for multi-agent group behaviour design that enables a systematic generation of individual behaviour for different agents in home automation (representing smart sensors, actuators, decision making agents, database agents), development of a framework to control a group behaviour of multiple agents, and the development of a set of metrics to evaluate the performance of individual and group agents behaviours.

Various well known software solutions in the agent and multi-agent community were used for IB management and control. Many of them were implemented in Java agent development environment (JADE) (Bellifemine, Bergenti, Caire, & Poggi, 2005) strictly according to FIPA[1] specifications.

A MAS should be considered for applications that have the following characteristics (McArthur et al., 2007):

- There is a requirement for interaction between distinct conceptual entities, such as different control subsystems and plant items, e.g., controlling microgrid taking into account the thermal constraints, voltage control, renewable energy sources.
- A very large number of entities must interact, where it would be impossible to explicitly model overall system behaviour.
- There is enough data/information available locally to undertake an analysis/decision without the need for communication with central point.
- New functions need to be implemented within existing plant items and control systems, such as adding new data interpretation functions to extend monitoring and control systems.

The MAS approach is commonly used for monitoring and diagnostics, delivering information in the correct format, fault diagnostics, for distributed control that is replacing the centralised supervisory control and data acquisition (SCADA) systems, for modelling and simulation purposes for scenario analysis especially in energy marketplace domain, for protection systems, power management in micro-grids and smart cities, and other purposes.

By the modelling of a complex system the agent approach benefits in scalability, as demonstrated with MavHome architecture (Cook et al., 2003), where a building is represented as an agent that could be decomposed into lower-level agents responsible for subtasks within the home environment with the ability to dynamically reorganise the hierarchy to maximise the performance. The concept of a MavHome agent is composed of four layers: the decision layer, information layer, communication and physical layer. Each layer could be represented as a network of task-specific agents, such as robots, agents for occupant's interaction with a building, sensor agents, etc.

Finally, there are complete smart-home projects, starting with the Neural Network House in the 1990s that used neural networks for intelligent control (Mozer, 1998). IHome (Lesser et al., 1999) and MavHome (Cook et al., 2003) continued with an intelligent multi-agent approach, using several techniques for user-behaviour modelling and predicting their actions. The Gator Tech Smart House (Helal et al., 2005) is a project for researching pervasive computing methods in a smart building. When possible, research systems employ real data about the weather and occupant preferences for the management of simulated objects, an example being ThinkHome (Reinisch, Kofler, Iglesias, & Kastner, 2011).

[1] FIPA: The Foundation for Intelligent Physical Agents, with a mission statement: The promotion of technologies and interoperability specifications that facilitate the end-to-end interworking of intelligent agent systems in modern commercial and industrial settings. More info on FIPA web page at http://www.fipa.org

MACS architecture for intelligent control and management of domestic HVAC and other systems, such as lighting, safety, security, DHW systems is commonly used in related work. Due to its modular control architecture that enables autonomous operation and communication abilities of individual agents, more fault tolerance, spatial decentralisation and others, we adopted the MACS approach that was realised using well known JADE platform.

Chapter 3

Energy and Comfort Model of an Environment

An intelligent building (IB) represents a part of a smart environment (SE) to be controlled. An IB is affected by (i) the weather, (ii) one or more occupants, and (iii) physical actuators that are part of the building automation system (BAS). Note that the state of an IB affects occupants and actuators. The situation is illustrated in Figure 3.1.

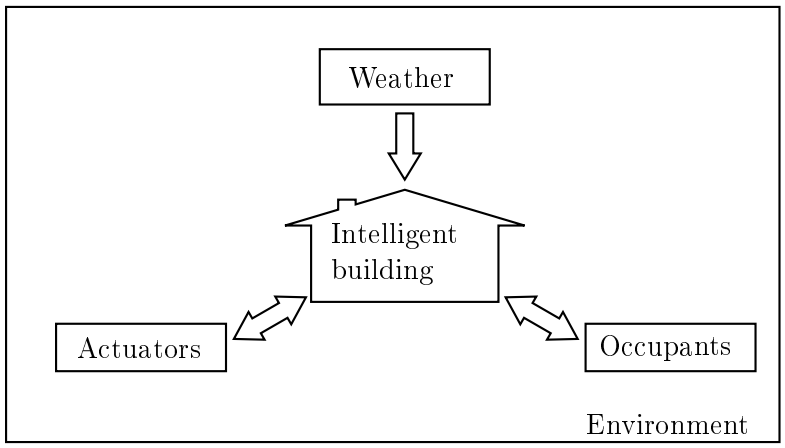


Figure 3.1: An IB affected by weather, occupants and actuators.

An environment variable is a theoretical value also known as the hidden variable. The value of an environment variable is not known accurately – it depends on the accuracy of the sensing equipment. A state of an environment at a certain time is composed of a set of environmental variables that could be folded into a vector of environmental variables. A sensed variable can be obtained through sensing, which results in an approximated value of the environment variable. A sensed state at a certain time is represented as a vector of sensed variables. An inferred variable represents an inferred value of an environment variable that is obtained based on sensed variables during the observation period that includes computation of observed variables according to an observation model.

In order to lay the foundations for environment perception we define the observation period with Definition 3.1. Environment variable and environmental state are defined with Definitions 3.2 and 3.3 respectively.

Definition 3.1 (Observation period and moment). Observation period is defined as a time period between start time k_s and final time k_f of observation, while the variable k

represents the discrete moment of observation, when the observation period is divided into n equidistant time periods Δt so that $k_\mathrm{s} = 1 \cdot \Delta t$ and $k_\mathrm{f} = n \cdot \Delta t$ where $k \in \{1, 2, \ldots, n\}$.

Definition 3.2 (Environmental variable). The value of i-th environmental variable at time-step k is denoted as $x_{i,k}$. The time k represents the moment within the observation period according to Definition 3.1. We assume I environmental variables and therefore $i \in \{1, 2, \ldots, I\}$.

Definition 3.3 (Environmental state). A set of I environment variables $x_{i,k}$ at time t forms an environmental state vector $\vec{x}_k$, where $x_{i,k} \in \vec{x}_k \; \forall \; i$; $i \in \{1, 2, \ldots, I\}$

The environmental state vector $\vec{x}_k$ includes the discrete dynamic environmental variables (for example: indoor temperature, humidity, iluminance, etc.), the weather variables (for example: outdoor temperature, air pressure, etc.), and the occupant-related variables (for example: accelerations that happen on the surface of a human body during movement) at time k. To sum up, with environment variables placed at certain time we denote the exact values that determine the actual state (the ground truth) of an environment.

In the following sections, first the conceptual model of an environment used for an experiment, is derived. Then the model of a HVAC control subsystem is presented. Finally, the formulation of the occupant's thermal comfort experience that is commonly used in related works as well as in this dissertation is derived.

3.1 The Model of the Uncontrolled Environment

For the modelling of such an environment we refer to Figure 3.1 and exclude the actuators from the model. Thus we get the model of an environment that is affected by the weather and occupants, represented in Figure 3.2.

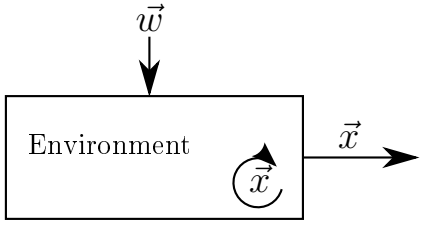


Figure 3.2: The model of the uncontrolled environment. The state of an environment (represented as $\vec{x}$) is affected by the weather and occupants (represented as $\vec{w}$).

The state in the next moment of observation depends on the current state, the weather, and the occupants. Therefore we can say, that the environment is affected by the weather and occupants. In order to briefly describe thermal dynamic model, we adopted the state space representation (Ceylan & Meyers, 1980; Seem, 1987). State space representation is widely used for representation and simulation of dynamic systems also by the simulation software EnergyPlus (Crawley et al., 2001) that was exploited for evaluation of energy management strategies in this dissertation.

The state of an environment $\vec{x}_k$ that is affected by the weather and occupants[1] $\vec{w}_k$ changes over time according to the model, described as:

$$\vec{x}_{k+1} = \mathbf{A}\vec{x}_k + \vec{w}_k \tag{3.1}$$

[1]Occupants and weather represent the heat gain that influences the building thermal dynamics.

where $\vec{x}_k$ is a column vector containing environment variables (i.e., indoor air temperature and humidity), $\mathbf{A}^{\mathrm{I}\times\mathrm{I}}$ is the system matrix and $\vec{w}_k$ represents the weather-, and occupant-related heat gains that are assumed as disturbances that affect the system. In order to derive the first principle model the information about the architectural parameters of an environment to be modelled, and the properties of construction and insulation materials, is needed. Such approach allows the formulation of the heat transfer by means of thermal capacitance and resistance of the indoor air and construction materials and such model is known also as the RC model. Since the purpose of this thesis is not in accurate modelling of real environment but rather evaluation of control and management strategies, we will adopt the model of an environment obtained from an example models that are included in the EnergyPlus (Crawley et al., 2001) software model examples.

3.2 Environmental Sensing

With environmental sensing using sensors and sensor systems it is possible to obtain approximated values of environmental variables, denoted as sensed variables and defined with Definition 3.4. A set of sensed variables form a sensed state, denoted as sensed state vector and defined with Definition 3.5. Since sensing is a discrete process, we define sensed variable and sensed state in a discrete time space.

Definition 3.4 (Sensed variable). Sensed variable $s_{j,k}$ represents a value that is obtained within a sensing process using sensor systems in a discrete time-step k. We assume J sensed variables and therefore $j \in \{1, 2, \ldots, J\}$.

Definition 3.5 (Sensed state). A set of J sensed variables $s_{j,k}$ in a certain discrete time-step k forms a sensed state vector $\vec{s}_k$ where $s_{j,k} \in \vec{s}_k \ \forall j; j \in \{1, 2, \ldots, J\}$.

The mapping between the environmental states and the sensed state vector is performed according to:

$$\vec{s}_k = \mathbf{C}\vec{x}_k + \vec{s}_{\mathrm{d},k} \tag{3.2}$$

where $\mathbf{C}^{\mathrm{J}\times\mathrm{I}}$ represents the output matrix containing the relations between environmental state $\vec{x}_k$ and sensed state $\vec{s}_k$ and $\vec{s}_{\mathrm{d},k}$ represents the unwanted contribution of the measurement noise.

3.3 Inferring Environmental State

In some cases various environmental variables either can not be measured directly or the sensing of such variable is an expensive or obtrusive process. This happens in the context of smart control of BASes when the environmental variable expresses a state of an occupant in a building, such as the metabolic equivalent of task, clothing insulation, comfort experience, etc. In such case an environmental state could be inferred either through a theoretical model and known states or through a model which is a result of an estimation process supported with machine learning (ML). The later method requires a sufficient amount of training data to create a model which can estimate the desired variable within the predictable error range. In general the inference process extracts the additional knowledge about the environment that could not be sensed directly using physical sensors alone.

In control theory, observability represents the property of a controlled system of how well the system states can be inferred by knowledge of its measured or sensed outputs. If the control system is observable, than its behaviour can be determined in finite time (Kalman, 1959). Inferred environmental variable and inferred environmental state are defined with Definitions 3.6 and 3.7 respectively.

Definition 3.6 (Inferred variable). Inferred variable $o_{m,k}$ represents a value that is obtained within an inference process using advanced ML or theoretical methods in a discrete time-step k. We assume M inferred variables and therefore $m \in \{1, 2, \ldots, M\}$.

Definition 3.7 (Inferred state). A set of M inferred variables $o_{m,k}$ in certain time-step k forms an inferred state vector $\vec{o}_k$ where $o_{m,k} \in \vec{o}_k \ \forall m; m \in \{1, 2, \ldots, M\}$.

To sum up, an inferred variable at a certain time is adapted based on sensed variable values (measurements) and/or other inferred variables according to the observation model processed within an inference process with an inference method. The inferred state is represented as a vector of inferred variables at a certain time of observation. Kalman filter (Kalman, 1959) is typically used to handle such tasks due to its status of an optimal estimator for linear systems (Faragher et al., 2012).

3.4 The Environment that is Affected by the Weather, Occupants, and Control Subsystems

Referring again to the schema in Figure 3.1, the actuators represent the influence which can be controlled in order to affect the environment in the context of an IB control. In such context the occupants' interactions with an environment to change the environmental state represent the comfort loss since the intelligent building should represent a self-controllable (intelligent) system in order to serve the occupant to achieve desired objectives, such as comfort, safety, security, low energy consumption, etc. In Section 3.1 we described the environment that is affected by the weather and occupants by means of heat gain generated by the outdoor air and occupant. In this section the model of the uncontrolled environment is extended with the control subsystems that constitute the feedback control loop.

A group of subsystems perform actions $\vec{u}$ to affect the environment in order to change the environmental state. Actions are performed according to control and regulation algorithms based on a set of reference variables $\vec{r}$ and a set of inferred states $\vec{o}$. Each action is performed in order to equalise the value of a certain environment variable x_i to the reference value r_l (desired value, set-point value) of that variable. The situation is presented in Figure 3.3.

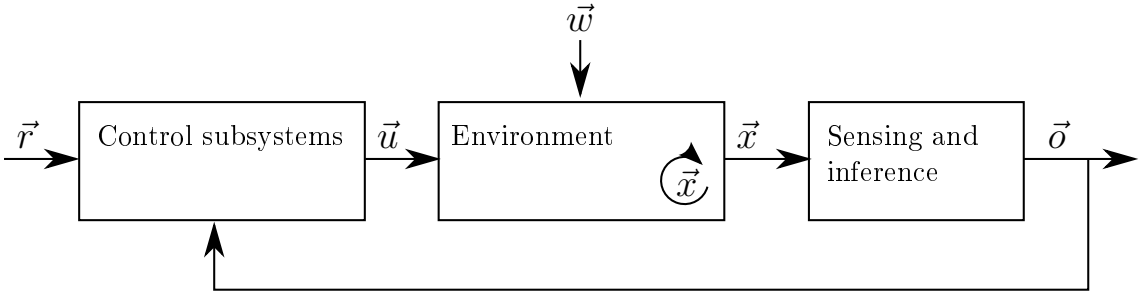


Figure 3.3: The model of an environment that is affected by the weather and occupant, and by the actuators of the control subsystems.

Definition 3.8 (Reference variable). The value of l-th reference variable at a discrete time k is denoted as $r_{l,k}$. The time k represents the moment when the reference variable value was imposed to the control subsystem within the observation period according to Definition 3.1. We assume L reference variables and therefore $l \in \{1, 2, \ldots, L\}$.

Definition 3.9 (Reference variable vector). A set of L reference variables $r_{l,k}$ at discrete time k forms a vector of reference variables $\vec{r}_k$, where $r_{l,k} \in \vec{r}_k \; \forall \, l; \, l \in \{1, 2, \ldots, L\}$.

A schematic representation of a single-input single-output control subsystem is presented in Figure 3.4. An error $e_{l,k}$ represents the difference between the desired value of an environment variable $r_{l,k}$ and the actual value of inferred variable $o_{l,k}$ according to Eq. (3.3).

$$e_{l,k} = r_{l,k} - o_{l,k} \tag{3.3}$$

A control value $v_{l,k}$ represents a magnitude of the control signal, produced by a regulator and is imposed to an actuator. $v_{l,k}$ is computed according to a regulation algorithm f_{reg}, based on $e_{l,k}$ with Eq. (3.4)

$$v_{l,k} = f_{\text{reg}}(e_{l,k}) \tag{3.4}$$

An action $u_{l,k}$ is produced by an actuator and represents an input to a system. A model of an actuator represents a relation that, based on the control signal $v_{l,k}$ produced by a regulator, performs an action $u_{l,k}$. Model of an actuator expresses the dynamics of an actuator that is represented with f_{act}. Action $u_{l,k}$ is generated using an actuator dynamics f_{act} based on control signal $v_{l,k}$ with Eq. (3.5).

$$u_{l,k} = f_{\text{act}}(v_{l,k}) \tag{3.5}$$

While inserting Eq. (3.3) in Eq. (3.4) and Eq. (3.4) in Eq. (3.5), a relation between the inferred environment variable value $o_{l,k}$, the desired environment variable value $r_{l,k}$ and the control action $u_{l,k}$ is obtained with Eq. (3.6).

$$u_{l,k} = f_{\text{act}}(f_{\text{reg}}(r_{l,k} - o_{l,k})) \tag{3.6}$$

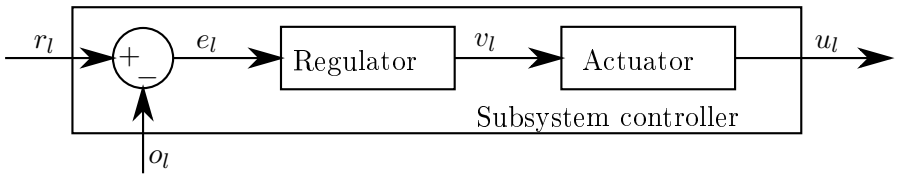


Figure 3.4: A model of the subsystem controller.

Actuators represent the core elements in a BAS since they are able to change the state of the environment. The range the acutators' are able to impact the environment is denoted as the sphere of influence. Furthermore, the ability to bring the current environmental states to the desired environmental states in an IB depends on the actuators only with an assumption, that the system is controllable which implies that the desired environmental states can be achieved within a limited time (Kalman, 1959). Since an IB is an autonomous system that observes an environment and affects environmental state in order to ensure the occupant's comfort, the activities performed by the occupant, such as modifying control and management system parameters, are denoted as a decrease of comfort. In an IB an occupant's intervention is not desired.

In order to include the actuators in the model of an environment, Eq. (3.1) is modified to Eq. (3.7) that differs for the input vector $\vec{u}_k$ which contains the magnitudes produced by actuators and input matrix $\mathbf{B}^{\text{I}\times\text{L}}$. Eq. (3.7) expresses an impact of the current environmental state, the actuators' reference value settings, the weather and the occupants on the next environmental state.

$$\vec{x}_{k+1} = \mathbf{A}\vec{x}_k + \mathbf{B}\vec{u}_k + \vec{w}_k \tag{3.7}$$

With Eq. (3.7) the thermal model of the environment, that includes occupants and weather heat gains, and control subsystems, is defined.

3.4.1 Heating, Cooling and Air-Conditioning

HVAC system represents an essential component of an IB to control the thermal comfort of an occupant. The necessity to include a variant of such a system depends on the climate conditions. In warm climate conditions is therefore the larger impact on cooling technologies, whereas in cold climate conditions the heating technologies are of greater importance. HVAC technology solutions available on the market are based on energy sources, such as electric energy, oil, coal, gas and wood. Since the HVAC and DHW systems represent the largest energy consumers, the choice of technology to use depends on the availability, the price, and the financial input for the installation of an individual HVAC system. For the experiments in this dissertation the model of an air-source heat pump with supplementary electric heating coil was applied, denoted as a packaged terminal source heat pump (PTHP).

The formulation of the energy consumption model of a PTHP is based on the schema presented in Figure 3.5. The model consists of an air mixer and several actuators: fan, cooling coil, heating coil and supplementary heating coil.

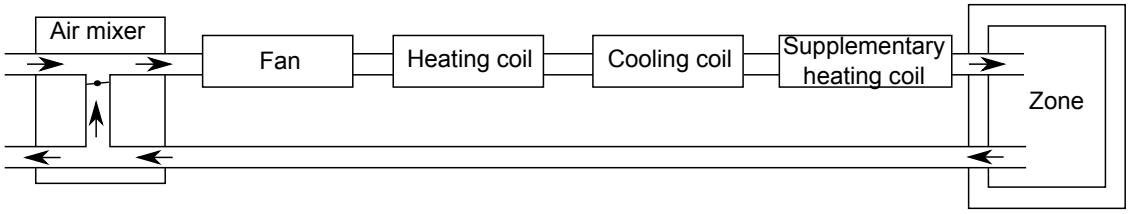


Figure 3.5: HVAC schema: packaged terminal source heat pump.

The electric power P_{PTHP} of a PTHP in a discrete time-step k is a sum of power, consumed by heater P_{H}, chiller P_{C}, supplementary heater P_{SH} and fan P_{F} as defined with Eq. (3.8).

$$P_{\mathrm{PTHP},k} = P_{\mathrm{H},k} + P_{\mathrm{C},k} + P_{\mathrm{SH},k} + P_{\mathrm{F},k} \tag{3.8}$$

The energy that is consumed by PTHP is the cumulative sum of power during the observation period. Since the observation period was already defined with Definition 3.1, the energy consumption of PTHP during the observation period is defined with Eq. (3.9) where Δt is a time-step.

$$E_{\mathrm{PTHP}} = \Delta t \sum_{k=1}^{n} P_{\mathrm{PTHP},k} \tag{3.9}$$

3.4.2 Occupancy

The observation of the occupant's behaviour in an intelligent environment represents an important task with the implementation of occupant-aware SEs. The most trivial state of a certain occupant-related to an IB can be simply represented as *present* or *absent*. Such interpretation of human behaviour can be simply implemented within the reactive control of building subsystems for lighting or security control. Systems with large inertia,

such as DHW or HVAC system show a highly increased performance in the context of the occupant's comfort and the energy consumption if the occupant's behaviour can be predicted for the near-future.

We denote the occupancy state at the certain moment in a smart building as occ_k, which can be either 0 or 1 representing unoccupied or occupied building respectively. An occupancy state can be denoted as a substate of the environmental state, defined with Definition 3.3. The variable occ_k, expressing that state is therefore denoted as an environmental variable.

The value *present* could be further divided into *sleeping*, *cooking*, *eating*, *showering*, *working*, *resting*, etc., and the value *absent* could be further divided into *vacation*, *on the way home*, *business trip*, etc. From the comfort management point of view, the management system should know what is the comfort state of a person in a certain environment in order to modify the thermal state of the environment to achieve the occupant's comfort equilibrium. According to the thermal comfort model (Fanger, 1970), one can say that an occupant feels *hot*, *warm*, *neutral*, *cool*, etc.

3.5 Thermal Comfort

To evaluate comfort performance of an IB, we applied two approaches, both used in related work – see Section 2.2. The first approach belongs to a simple definition of comfort and is defined as the predefined set-point temperature that should be achieved during occupancy. The second approach belongs to an advanced definition according to standardised evaluation of comfort.

By means of state space representation of the controlled system, where the system output represent the inferred state of environment, we can represent the relation in terms of Eq. (3.2) where $\mathbf{C}$ represents the mapping between the system state $\vec{x}_k$ and sensed state $\vec{s}_k$ or inferred system state $\vec{o}_k$ in which we are interested in this dissertation.

3.5.1 Comfort as a Predefined Temperature

To evaluate comfort performance, we defined a discomfort index IC_{Behaviur} that computes the comfort experience for the simulation run during home occupancy only where the label Behaviour represents control behaviour, such as Sense, On, Learning. We differentiate between two values when an occupant is present at home: $occ_{\text{h},k} = \{present.default, present.sleeping\}$. If an occupant is present and sleeping, the value $present.sleeping$ describes the state of occupancy. If an occupant is present and awake, than the value $present.default$ describes the state of occupancy as well. IC_{Behaviur} is computed with Eq. (3.10):

$$IC_{\text{Behaviur}} = \sum_{k=1}^{n} \begin{cases} |T_{\text{sHi}} - T_{\text{in},k}| & \forall k : occ_{\text{h},k} = present.default \\ |T_{\text{sSl}} - T_{\text{in},k}| & \forall k : occ_{\text{h},k} = present.sleeping \end{cases} \tag{3.10}$$

where n is the total number of time-steps in the simulation (number of minutes); T_{sHi} is high set-point temperature representing comfort temperature for presence; T_{sSl} is sleeping set-point temperature representing comfort temperature for sleeping; and $T_{\text{in},k}$ is the indoor temperature in a time-step k and represent the sensed variable of a sensed state $T_{\text{in},k} \in \vec{s}_k$ and $occ_{\text{h},k}$ represent an inferred variable of an inferred state $occ_{\text{h},k} \in \vec{o}_k$ since the occupancy can not be represented as a simple mapping, but has to be inferred taking into account various information sources such as RFID, motion sensors and others (see Section 2.2). The $IC_{\text{Behaviour}}$ index represents the sum of per-minute differences between the actual

temperature and the desired temperature for the depicted control behaviour Behaviour – meaning the smaller the index, the greater the comfort.

3.5.2 Thermal Comfort Model

To observe the occupant's thermal comfort experience, we adopted the Fanger's thermal comfort model (Fanger, 1970) that based on environmental and occupant variables infer the thermal comfort index predicted mean vote *PMV* that denotes occupant's thermal sensation and the index predicted percentage dissatisfied *PPD* that denotes the percentage of people that would likely not been satisfied.

Equations used to compute *PMV* and *PPD* were obtained from ISO 7730: 2006, Annex D (ISO, EN, 2005) that applies Eq. (3.11) to (3.22) including the iteration for clothing surface temperature T_{cl} and convective heat transfer coefficient h_{c}.

Equation (3.11) is used to compute the *PMV* index where *TSTC* is a thermal sensation transfer coefficient that was derived by Fanger (1970) based on experimental studies involving a large number of subjects, *IHP* is an internal heat production in the human body, *HLD* is heat loss difference through skin, *HLS* is heat loss by sweating, *LRHL* is latent respiration heat loss, *DRHL* is dry respiration heat loss, *HLR* is heat loss by radiation and *HLC* is heat loss by convection.

$$PMV = TSTC \cdot (IHP - HLD - HLS - LRHL - DRHL - HLR - HLC) \tag{3.11}$$

The coefficient, heat production and heat looses are computed according to Eq. (3.12) – Eq. (3.19)

$$TSTC = 0.303e^{-0.036 \cdot M} + 0.028 \tag{3.12}$$
$$IHP = (M - W) \tag{3.13}$$
$$HLD = 3.05 \cdot 10^{-3} \cdot [5733 - 6.99 \cdot (M - W) - p_{\mathrm{a}}] \tag{3.14}$$
$$HLS = 0.42\,[(M - W) - 58.15] \tag{3.15}$$
$$LRHL = 1.7 \cdot 10^{-5} \cdot M \cdot (5867 - p_{\mathrm{a}}) \tag{3.16}$$
$$DRHL = 0.0014 \cdot M \cdot (34 - T_{\mathrm{in}}) \tag{3.17}$$
$$HLR = 3.96 \cdot 10^{-8} \cdot f_{\mathrm{cl}} \cdot \left[(T_{\mathrm{cl}} + 273)^4 - \left(\bar{T}_{\mathrm{r}} + 273^4\right)\right] \tag{3.18}$$
$$HLC = f_{\mathrm{cl}} \cdot h_{\mathrm{c}} \cdot (T_{\mathrm{cl}} - T_{\mathrm{in}}) \tag{3.19}$$

where

$$\begin{aligned} T_{\mathrm{cl}} &= 35.7 - 0.028 \cdot (M - W) \\ &\quad - I_{\mathrm{cl}} \cdot \left\{3.96 \cdot 10^{-8} \cdot f_{\mathrm{cl}} \cdot \left[(T_{\mathrm{cl}} + 273)^4 - \left(\bar{T}_{\mathrm{r}} + 273\right)^4\right] + f_{\mathrm{cl}} \cdot h_{\mathrm{c}} \cdot (T_{\mathrm{cl}} - T_{\mathrm{in}})\right\} \end{aligned} \tag{3.20}$$

and

$$h_{\mathrm{c}} = \begin{cases} 2.38 \cdot |T_{\mathrm{cl}} - T_{\mathrm{in}}|^{0.25} & \text{for } 2.38 \cdot |T_{\mathrm{cl}} - T_{\mathrm{in}}|^{0.25} > 12.1 \cdot \sqrt{v_{\mathrm{ar}}} \\ 12.1 \cdot \sqrt{v_{\mathrm{ar}}} & \text{for } 2.38 \cdot |T_{\mathrm{cl}} - T_{\mathrm{in}}|^{0.25} < 12.1 \cdot \sqrt{v_{\mathrm{ar}}} \end{cases} \tag{3.21}$$

and

$$f_{\mathrm{cl}} = \begin{cases} 1.00 + 1.290 \cdot I_{\mathrm{cl}} & \text{for } I_{\mathrm{cl}} \leq 0.078 \text{ m}^2 \cdot \text{K/W} \\ 1.05 + 0.645 \cdot I_{\mathrm{cl}} & \text{for } I_{\mathrm{cl}} > 0.078 \text{ m}^2 \cdot \text{K/W} \end{cases} \tag{3.22}$$

The above equations for computation of PMV use the following states, that can be obtained by sensing and inference:

- M is metabolic equivalent of task $\left[\mathrm{W/m^2}\right]$;
- W is the effective mechanical power $\left[\mathrm{W/m^2}\right]$;
- I_{cl} is the clothing insulation $\left[\mathrm{m^2 \cdot K/W}\right]$;
- f_{cl} is the clothing surface area factor;
- T_{in} is the indoor air temperature [°C];
- $\bar{T_{\mathrm{r}}}$ is the mean radiant temperature [°C];
- v_{ar} is the relative air velocity [m/s];
- p_{a} is the water vapour partial pressure [Pa];
- h_{c} is the convective heat transfer coefficient $\left[\mathrm{W/\left(m^2 \cdot K\right)}\right]$;
- T_{cl} is the clothing surface temperature [°C].

The index should be used only for intervals of PMV between -2 and $+2$, and when the six main parameters are within the following intervals:

- $M \in [46, 232]\,\mathrm{W/m^2}$ or $M \in [0.8, 4]$ MET[2];
- $I_{\mathrm{cl}} \in [0, 0.310]\,\mathrm{m^2 \cdot K/W}$ or $I_{\mathrm{cl}} \in [0, 2]$ clo[3];
- $T_{\mathrm{in}} \in [10, 30]$ °C;
- $\bar{T_{\mathrm{r}}} \in [10, 40]$ °C;
- $v_{\mathrm{ar}} \in [0, 1]$ m/s;
- $p_{\mathrm{a}} \in [0, 2700]$ Pa.

Related work typically include predefined values of occupant-related states, such as M, I_{cl} since they are difficult to identify accurately. In Section 6.3.3 of this dissertation we analyse the effect of such variables on the performance of control strategy in terms of occupant's comfort and energy consumption and show that the usage of estimated values improves the perception and regulation of occupant's comfort and that the predefined values of M results in extensive energy consumption due to misleading perception of comfort during control.

The PPD index is computed with Eq. (3.23). Figure 3.6 shows the relation between the PMV and PPD indices. The PPD index rises slowly for PMV values close to 0, has almost linear growth for PMV values between 1 and 2 (and between -1 and -2) and stabilises towards the PPD value of 100 % at PMV close to 3 or -3. If PMV equals 0, then PPD equals 5 %. In other words: there is always 5 % of people who are never satisfied with conditions that describe neutral sensation. The long-term evaluation of comfort according to PPD is proposed in standard ISO 15251 (EN, CEN, 2007), which is used in our long-term comfort evaluation.

$$PPD = 100 - 95 \cdot e^{-0.033 \cdot PMV^4 - 0.2179 \cdot PMV^2} \tag{3.23}$$

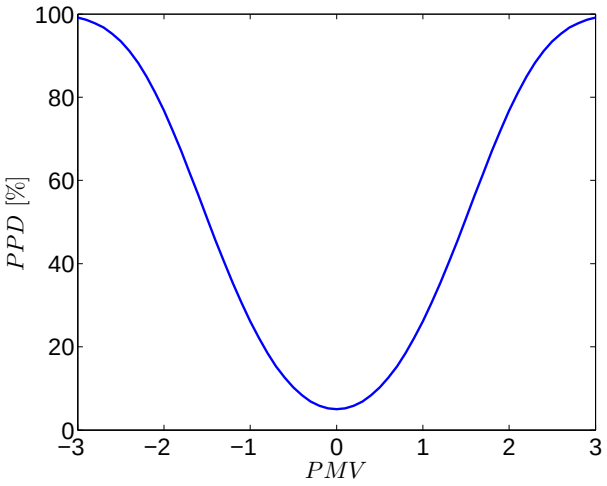


Figure 3.6: PPD as a function of PMV. There is 5 % of people who are dissatisfied with conditions that describe neutral sensation ($PMV = 0$). If PMV is close to 3 or -3, than PPD stabilises towards 100 %.

The average PPD, denoted as $\overline{PPD}$, is computed for occupied period according to Eq. (3.24) and gives an information about what percentage of people is predicted to be dissatisfied over that period.

$$\overline{PPD} = \sum_{k=1}^{n} PPD_k \; \forall k; occ_{\mathrm{h},k} = present \tag{3.24}$$

[2] 1 MET = 58.2 W/m^2, see (ISO, EN, 2005)
[3] 1 clo = 58.2 K $\cdot$ m^2/W, see (ISO, EN, 2005)

Chapter 4

Control System

The control system that controls an environment should be composed of a well designed combination of hardware and software that is able to perceive the environment, to process the perceived data and to affect the environment based on strategic objectives. Since the intelligent environment is composed of several subsystems, the control system also contains a number of control subsystems. In Figure 3.4 the model of one subsystem controller is presented and in Figure 3.3 the model of an environment is presented, in which, besides the heat gain due to the weather and occupants, a number of control subsystems affects the environment according to Eq. (3.7).

In order to equalise the sensed variable value s_j (Definition 3.4) or inferred variable value o_m (Definition 3.6) with the set-point variable value r_l (Definition 3.8), the regulators such as ON-OFF, PID, Fuzzy and others can be used. These regulators compute the appropriate control value v_l according to Eq. (3.4) based on the difference between the sensed value or inferred value of state variable. Besides the control and regulation algorithm, the magnitude of the action depends on the capability of the actuator and the system dynamics. However, the problem arises: When and what should be the value of the reference? The answer is not straight-forward, since the reference variable values are normally delegated according to various needs and objectives. In this dissertation the trade-off between the comfort experience and the energy consumption is emphasised and based on that trade-off the delegation of the set-point (reference) variable values as well.

4.1 Temperature Set-Point Delegation

The temperature set-point delegation is an important task that should be optimised in order to achieve an effective performance of the heating system. In practice, the heating controllers normally have the option to choose between two reference values that are known as high set-point and low set-point (also set-back) values. High set-point value is assumed as the indoor temperature at which the person feels comfortable. Typically heating, ventilation and air conditioning (HVAC) control systems allow to define additional set-point values, such as sleeping set-point value, party set-point value etc. These values are normally predefined in order to be included within control schedules. The occupants can also modify schedules and predefined set-point values during system operation. On the other hand, an intelligent scheduling for slow control systems, such as HVAC or domestic hot water (DHW) systems, is an interesting research area, where the set-point schedules are determined using advanced methods. Those methods include the observation of one or more occupants and the observation of building thermal dynamics. Based on such observations it is possible to predict the optimal schedule that will be used to control the environment in order to satisfy the occupant's comfort and to minimise the energy consumption. Control

schedule should be compliant with the occupant schedule in the occupant-aware control system.

In the following sections the set-point delegation strategies are described. Strategies are based on the (i) pure reactive control according to the home occupancy state detection, denoted as reactive or sense strategy, (ii) predefined scheduling strategy, (iii) anticipative strategy, where an occupancy prediction method is used for the near-future schedule generation and where the prediction of the time-to-heat/cool the room is implemented, and (iv) rule-based absence prediction strategy that includes additional rules in order to reduce the false occupancy predictions within the anticipative strategy. The predefined scheduling is well known in related work and commonly used in commercial systems. The anticipative and reactive mechanisms were firstly introduced by Abras et al. (2008). The integration of the rule-based mechanism with the reactive and anticipative mechanism represents a scientific contribution of this dissertation.

4.1.1 Reactive Mechanism

The reactive mechanism requires information when an occupant is at home and when sleeping. The reactive mechanism is due to its simplicity and robustness known also as an emergent mechanism. It is used to perform emergent actions in conditions, where advanced methods fail. The observation variable occ_{h} has three nominal values: *present.default*, *present. sleeping* and *absent* and for the reactive mechanism that is aware of home occupancy and sleeping the three corresponding set-point variables are defined: T_{sHi}, T_{sSl} and T_{sLo}. When occ_{h} changes its value, the control operation of that mechanism is straightforward and shown in Algorithm 4.1: When presence is detected, assign T_{sHi}, when presence and sleeping is detected, assign T_{sSl}, otherwise (when no presence is detected) assign T_{sLo}. If there are other mechanisms (such as predefined scheduling, anticipative or rule-based mechanism) available, than one of those can be applied; such approach is presented in the following sections.

Algorithm 4.1: Reactive mechanism: Set-point delegation strategy based on current occupancy state.

Data: k, $occ_{\mathrm{h},k}$, T_{sSl}, T_{sHi}, T_{sLo}
Result: $T_{\mathrm{s},k+1}$
if *(*$occ_{\mathrm{h},k}$ == *present.default)* **then**
  $T_{\mathrm{s},k+1} \leftarrow T_{\mathrm{sHi}}$;
else if *(*$occ_{\mathrm{h},k}$ == *present.sleeping)* **then**
  $T_{\mathrm{s},k+1} \leftarrow T_{\mathrm{sSl}}$;
else
  $T_{\mathrm{s},k+1} \leftarrow T_{\mathrm{sLo}}$; `// Or apply some other mechanism`
end

Since the heating process is slow, the reactive mechanism results in a poor comfort experience. By such control strategy the occupant will never be satisfied when he arrives home. The amount of time needed to heat/cool the room depends on the power of the HVAC system components, the volume of the controlled space and its thermal inertia, the insulation of the building, the current temperature and the weather conditions such as the outdoor temperature. Consequently the amount of time can vary from some minutes to some hours. Therefore the reactive mechanism should not be used as the main set-point delegation strategy but rather as an emergent mechanism in combination with some advanced control strategy.

4.1.2 Predefined Scheduling

The predefined scheduling is commonly used for home and office heating. The schedule of set-point values is composed of daily schedules that define the set-point values throughout the typical days, such as weekdays or weekends as well as some other special days such as the days during vacation, where the occupant is probably not at home for a longer period. The daily schedules are then merged into a weekly schedule. An illustrative example of a predefined weekly and daily schedule for heating is presented in Table 4.1 and in Table 4.2 based on the following predefined set-point values: T_{sHi}, T_{sLo} and T_{sSl}.

Table 4.1: An example of a weekly schedule, created by a volunteer.

Weekday	Daily schedule
Monday	Weekday
Tuesday	Weekday
Wednesday	Weekday
Thursday	Weekday
Friday	Weekday
Saturday	Weekend
Sunday	Weekend

Table 4.2: An example of daily schedules for a weekday and weekend created by a volunteer.

Weekday	Weekend
until 00:30: T_{sHi}	until 10:00: T_{sSl}
until 08:30: T_{sSl}	until 24:00: T_{sHi}
until 09:45: T_{sHi}	
until 18:30: T_{sLo}	
until 24:00: T_{sHi}	

On one hand, predefined scheduling has advantages, since it is relatively simple to understand. Furthermore, the occupant knows exactly what is the control strategy for each moment during the operation. In order to create a scheduling control, a couple of set-point values, such as T_{sHi}, T_{sLo} or T_{sSl}, have to be defined firstly. Than the daily schedules, that include the time moments at which the set-point variable changes, should be created. As defined in Weekday schedule in Table 4.2, the day begins with a high set-point temperature that lasts until 0:30 (the occupant goes to sleep at that time), then it continues with a sleeping set-point temperature until 8:30. Until 9:45 the occupant performs morning activities and thus the high set-point is assigned. From 9:45 to 18:30 the low set-point is assigned. Finally, the workday schedule concludes with a high set-point temperature being set until 24:00. On the other hand, a few drawbacks of predefined scheduling exist, such as:

- The occupant's home occupancy schedule should be compliant with the heating schedule, which is practically impossible due to the inability of predicting the home occupancy schedule neither for one week nor for one month or even one year in advance.

- Predefined scheduling does not allow adaptation, since it is "predefined" and therefore fixed unless the occupant manually adapts it.
- The temperature at which the occupant feels comfortable depends on various environment and occupant-related factors, mentioned in Section 3.5.2, which are used to infer the PMV index.

In order to mitigate the mentioned drawbacks, we propose the following solutions. First, the occupancy prediction method that predicts the home occupancy based on historical data and prepares the room temperature, denoted as comfortable; second, the prediction of the time-to-heat/cool the air temperature of the controlled zone; and finally, the comfort regulator delegating the set-point temperature in order to achieve the thermal comfort range defined as an interval of PMV values.

4.1.3 Anticipative Mechanism

The anticipative mechanism implements the machine learning (ML) algorithms to predict near-future occupancy at home. The reactive mechanism starts the heating/cooling process when the presence, absence or sleeping begins. The predefined scheduling uses the heating/cooling set-point schedules that are created in advance. In contrast to the reactive mechanism or predefined scheduling the anticipative mechanism uses historical observations of occupancy events to create an occupancy prediction model as explained in Section 4.1.3.1 and historical observations of heating/cooling dynamics to create the time-to-heat prediction model as explained in Section 4.1.3.2.

4.1.3.1 Occupancy Prediction

An occupancy prediction is performed using ML, which exploits the data about the occupancy at home and at work. The home and work occupancy are denoted as inferred variables $occ_{\mathrm{h},k}$ and $occ_{\mathrm{w},k}$ respectively. In order to create a training dataset for a ML model, the data about the occupancy must be transformed into the time series, where the occupancy state can have two values: 0, signifying absence, and 1, signifying presence. Based on that data, with the corresponding date-time value, the instances for ML *occInst* can be created using the following list of attributes, where each attribute is given either as (i) an unsigned integer value or (ii) a nominal value from the set of values, listed in curly braces:

- minute in a day (unsigned integer),
- day in a week $\{1, 2, ..., 7\}$,
- weekend $\{0, 1\}$: 1 for Saturday or Sunday, 0 otherwise,
- month in a year $\{1, 2, ..., 12\}$,
- a.m./p.m. $\{0, 1\}$: 1 represents time before midday, 0 represents time after midday,
- number of days before Saturday $\{0, 1, 2, 3, 4, 5\}$ signifying the number of days before weekend,
- the elapsed time in minutes since an occupant left home (unsigned integer),
- number of occurrences in a day when an occupant left home (unsigned integer),
- occupancy at home exactly one week earlier $\{0, 1\}$,

- a daily sum of minutes during which an occupant was at home (unsigned integer),
- the elapsed time in minutes since an occupant left the work environment (unsigned integer),
- occupancy at work exactly one week earlier $\{0, 1\}$,
- a daily sum of minutes during which the occupant was at work (unsigned integer),
- occupancy at work – occ_{w} $\{0, 1\}$: 1 represents presence and 0 represents absence at work,
- occupancy at home – occ_{h} $\{0, 1\}$: class value to be predicted, 1 represents presence and 0 represents absence at home.

After the training dataset is created, the ML algorithm such as C4.5, random forest, kNN, etc., can be used to create a ML model. We implemented C4.5, random forest and kNN algorithms for occupancy prediction, where C4.5 and kNN are implemented in two variants: (i) C4.5 and kNN representing the classification for a nominal class value as a result, which can be either 0 or 1; and (ii) the $\mathrm{C4.5_{dist}}$ and $\mathrm{kNN_{dist}}$ representing the distribution for class value 1 which is a continuous value between 0 and 1. Other parameters remain default as defined in the Weka ML software (Hall et al., 2009).

The predicted value of occupancy at home $occ^*_{\mathrm{h},k}$ is assigned according to Eq. (4.1) where *cls* is the classification method that returns the predicted value for instance $occInst_k$ based on the ML model (classifier) *occCls*.

$$occ^*_{\mathrm{h},k} = cls(occInst_k, occCls) \tag{4.1}$$

In contrast to the state variable $occ_{\mathrm{h},k}$ for the current time k, which can be obtained through sensing and inference, we denote the future time for prediction as $k + k_{\mathrm{nf}}$ and the instance that is assumed for the future time as $occInst_{k+k_{\mathrm{nf}}}$, where k_{nf} represents the number of time-steps, added to the current time at which the prediction is requested. To summarise, $occ^*_{\mathrm{h},k+k_{\mathrm{nf}}}$ represents the predicted value of the occupancy state variable for the near-future time $k + k_{\mathrm{nf}}$.

4.1.3.2 Temperature Rise/Fall Time Prediction

In order to predict the time that is needed to achieve some predefined indoor temperature with heating or cooling we implement the adaptive classifier that is generated based on the historical data trends during simulation runtime. Our approach implements the approximation of the temperature rise/fall time as a black box model (Juditsky et al., 1995), where the black box model is a regression model used to predict the indoor temperature rise/fall time according to the indoor temperature, the outdoor temperature and the difference between the set-point temperature and the indoor temperature. Each instance *rtInst* for ML is composed of the following numeric attributes, that are given as rational numbers:

- outdoor temperature (numeric) [°C],
- indoor temperature (numeric) [°C],
- set-point temperature (numeric) [°C],
- rise/fall time coefficient (numeric) [min/°C] that represents the class value.

The rise/fall time coefficient ($K_{\mathrm{RFT},k}$) is a linearised factor, since we assume that the indoor temperature rises/falls in a linear manner during heating/cooling. $K_{\mathrm{RFT},k}$ is computed according to:

$$K_{\mathrm{RFT},k} = \frac{T_{\mathrm{sHi}} - T_{\mathrm{in},k}}{k_{\mathrm{RFT},k}} \tag{4.2}$$

where T_{sHi} is the desired temperature, $T_{\mathrm{in},k}$ is the indoor temperature and $k_{\mathrm{RFT},k}$ is the number of time-steps needed to heat or cool the room from $T_{\mathrm{in},k}$ to $T_{\mathrm{in},k+k_{\mathrm{RFT},k}} = T_{\mathrm{sHi}}$. Figure 4.1 shows the process of attribute extraction to create an instance from historical data trends of sensor states and states of set-point values. Each instance *rtInst* is created using the attributes listed above where the outdoor (T_{out}) and indoor temperatures (T_{in}) can be measured through sensing. The set-point temperature (T_{sHi}) is predefined. The measurement of the rise/fall time of indoor temperature (k_{RFT}) starts when the T_{s} changes from T_{sLo} to T_{sHi} and $K_{\mathrm{RFT},k}$ is computed according to Eq. (4.2). The predicted rise/fall

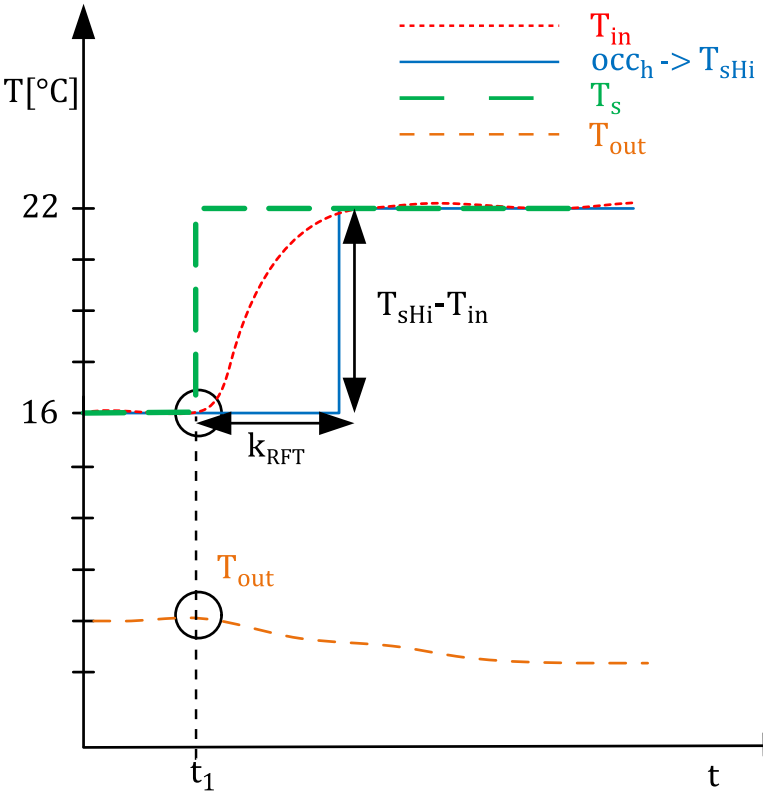


Figure 4.1: Attribute extraction to generate a temperature rise/fall time regression model.

time coefficient $K^*_{\mathrm{RFT},k}$ is assigned according to Eq. (4.3).

$$K^*_{\mathrm{RFT},k} = cls(rtInst_k, rtCls) \tag{4.3}$$

Eq. (4.3) represents the classification where the *cls* is the process of classifying the instance $rtInst_k$ using the classifier *rtCls*. Finally, the predicted rise/fall time $k^*_{\mathrm{RFT},k}$ is computed according to Eq. (4.4):

$$k^*_{\mathrm{RFT},k} = \frac{T_{\mathrm{sHi}} - T_{\mathrm{in},k}}{K^*_{\mathrm{RFT},k}} \tag{4.4}$$

The process of creating the regression model is similar to that in Section 4.1.3.1, except that the ML methods are used to create the regression models for the rise/fall time. The

fall time differs from the rise time only in detection of the negative change of the set-point temperature, instead of the positive change as depicted in Figure 4.1.

In order to include the prediction models, Algorithm 4.1 has to be modified. First we assume that the time-to-heat/cool the room takes no longer than the fixed period of time, and that during the operation the algorithm continuously checks whether the occupant is present after that period of time. The heating or cooling process then modifies T_{s} according to the result obtained with the occupancy prediction according to Eq. (4.1). Since the occupancy prediction model can make false predictions (i) the comfort loss can be expected if the model does not predict the occupancy which, however, would occur later and (ii) a substantial consumption can be expected if the model predicts the occupancy which would not occur later. The first event can be denoted as the false negative prediction and the second as the false positive prediction. In order to mitigate the influences of false predictions, the anticipative mechanism should be combined with the reactive mechanism.

In contrast to the operation of the reactive mechanism that waits for the event of changing the observation variable occ_{h}, by the anticipative mechanism, the time-to-heat k^*_{RFT} and occupancy occ^*_{h} are constantly classified throughout the control operation if the occupancy state is absent. Every time the observation value occ_{h} is checked and whether present.sleeping or present.default is detected the corresponding set-point values T_{sSl} or T_{sHi} are assigned to T_{s}. The function of the reactive mechanism is to correct the set-point whether the anticipative mechanism make false prediction. If occ_{h} returns absent, then the *rtInst* has to be created and classified according to *rtCls*. The result is then used as a near-future time at which the occupancy prediction is needed. In such as case the *occInst* has to be created first and classified according to *occCls* afterwards. The anticipative mechanism is shown in Algorithm 4.2.

Algorithm 4.2: Anticipative mechanism: Set-point delegation based on near-future occupancy state prediction.

Data: k, $occ_{\mathrm{h},k}$, $occ_{\mathrm{w},k}$, $T_{\mathrm{in},k}$, $T_{\mathrm{out},k}$, T_{sLo}, T_{sHi}
Result: $T_{\mathrm{s},k+1}$

Create $rtInst_k$; `// see Section 4.1.3.2`
$K^*_{\mathrm{RFT},k} \leftarrow cls(rtInst_k, rtCls)$; `// Eq. (4.3)`
$k^*_{\mathrm{RFT},k} \leftarrow \frac{T_{\mathrm{sHi}} - T_{\mathrm{in},k}}{K^*_{\mathrm{RFT},k}}$; `// Eq. (4.4)`
Create $occInst_{k+k^*_{\mathrm{RFT},k}}$; `// see Section 4.1.3.1`
$occ^*_{\mathrm{h},k+k^*_{\mathrm{RFT},k}} \leftarrow cls(occInst_{k+k^*_{\mathrm{RFT},k}}, occCls)$; `// Eq. (4.1)`
$T_{\mathrm{s},k+1} \leftarrow T_{\mathrm{sLo}} + occ^*_{\mathrm{h},k+k^*_{\mathrm{RFT},k}} \cdot (T_{\mathrm{sHi}} - T_{\mathrm{sLo}})$;

The classifiers *occCls* and *rtCls* are updated once a day. The *cls* method is able to return the exact values for predicted occupancy, such as 0 for absent and 1 for present, or the probability distribution that could be any value from the interval $[0, 1]$. Both variants can be used, since the last statement in Algorithm 4.2 remains unchanged. However, the last variant scales T_{s} according to the assigned probability and therefore results in a smoother set-point delegation since T_{s} could represent any value from the interval $[T_{\mathrm{sLo}}, T_{\mathrm{sHi}}]$.

Figure 4.2(a) shows an example in which T_{s} was scaled according to the probability of the near-future occupancy using the Isotonic Regression model to predict the rise/fall time and $\mathrm{kNN}_{\mathrm{dist}}$ classifier for occupancy prediction. It is clear that the occupancy was predicted approximately one hour before it really happened. In this case, the system consumes more energy than it would with the strategy of including the reactive mechanism only. On the other hand, the comfort experience is better, because the occupant enters the home with

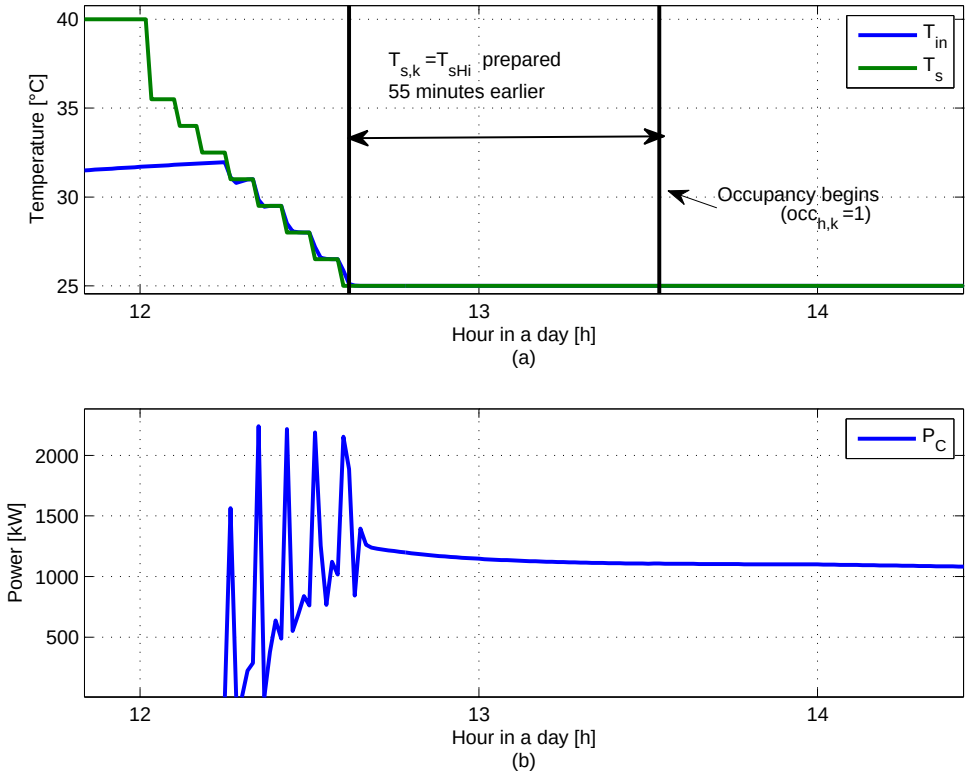


Figure 4.2: An example in which T_{s} was scaled according to the probability for occupancy at $k + k^*_{\mathrm{RFT},k}$. (a): T_{in} and T_{s}. The left vertical line highlights the moment at which the room temperature is prepared and the right indicate the moment at which IB becomes occupied. (b): the corresponding power rate P_{C} of the chiller.

an already comfortable temperature, which is not the case with the reactive mechanism. Figure 4.2(b) presents the power rate of the chiller P_{C}.

4.1.4 Rule-Based Absence Prediction

The anticipative mechanism was developed in order to predict the occupancy and the time the HVAC system needs to heat/cool the environment to some predefined temperature. The predictions are used to increase the comfort experience during the transition of the occupancy state, when it changes from absent to present. The anticipative mechanism tends to prepare the appropriate indoor temperature right before the occupancy state transition. Since it often happens that the occupancy is predicted but does not happen later (false prediction), a large amount of energy is lost due to unnecessary operation of the HVAC system. In order to reduce the negative influence of false predictions on energy consumption we introduced rules that can be used within a rule list in combination with the reactive and the anticipative mechanism.

Rules 1, 2 and 3 are used to identify the reason for absence. We have derived these rules based on experiences from typically real-life events. We differentiate between the three types of absence and define the corresponding variables: long-term absence $abs^*_{\mathrm{LT},k}$, night absence $abs^*_{\mathrm{N},k}$, and job-related absence $abs^*_{\mathrm{JR},k}$. An absence type is represented as a binary variable that can be assigned either true or false.

Rule 1 detects long-term absence and sets $abs^*_{\mathrm{LT},k}$ variable when an occupant is not at home for a longer period (i.e., C_{tAbs} is $16 \cdot 60$ minutes) due to vacation, business trip or any other similar circumstances.

Rule 1 (Long-term absence). Long-term absence in time-step k is detected if the person was absent for more than C_{tAbs} minutes:

if $(occ_{\mathrm{h},k-\mathrm{n}} == 0 \; \forall n; n \in \{0, 1, ..., C_{\mathrm{tAbs}}\})$ **then**
  $abs^*_{\mathrm{LT},k} \leftarrow$ true;
else
  $abs^*_{\mathrm{LT},k} \leftarrow$ false;
end if

Rule 2 detects night absence and sets $abs^*_{\mathrm{N},k}$ variable if the person is absent at the time period between, for example 01:00 and 07:00. In other words, if the person does not return home until 01:00, he will probably not return until 07:00:

Rule 2 (Night absence). Night absence in time-step k is identified if the person was absent in period between C_{t1} and C_{t2}:

if $((occ_{\mathrm{h},k} == 0) \; \forall k; k \in \{C_{\mathrm{t1}}, C_{\mathrm{t1}} + 1, ..., C_{\mathrm{t2}}\})$ **then**
  $abs^*_{\mathrm{N},k} \leftarrow$ true;
else
  $abs^*_{\mathrm{N},k} \leftarrow$ false;
end if

Rule 3 detects job-related absence and sets $abs^*_{\mathrm{JR},k}$ variable, if C_{ND}-th departure happened and if the time from last departure $k_{\mathrm{LD},k}$ is less than C_{LD} and if the current day represents a weekday (WD = true). $N_{\mathrm{D},k}$ represents the daily departure counter; that is, the counter of transitions from $occ_k = 1$ to $occ_{k+1} = 0$. C_{LD} represent the typical working-time in minutes (such as $8 \cdot 60$ minutes), $k_{\mathrm{LD},k}$ represents the number of time-steps during which the building was not occupied – 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_{LD} hours.

Rule 3 (Job-related absence). Job-related absence is identified if the C_{ND}-th departure happened in the same day and if the time from last departure $k_{\mathrm{LD},k}$ is less than C_{LD} and if the current day represents a weekday (WD_{k} = true):

if $((occ_{\mathrm{h},k} == 0) \wedge (N_{\mathrm{D},k} == C_{\mathrm{ND}}) \wedge (k_{\mathrm{LD},k} < C_{\mathrm{LD}}) \wedge (WD_{\mathrm{k}} == \text{true}))$ **then**
  $abs^*_{\mathrm{JR},k} \leftarrow$ true;
else
  $abs^*_{\mathrm{JR},k} \leftarrow$ false;
end if

Different combinations of rules and parameter values are possible for composing a list of rules and each combination of rules defines different control behaviour. If the condition of the first rule is not met, the next rule is checked, and so on. It is possible to remove any rule from the list of rules, but the order must be kept in accordance with the order of rule number – the long-term absence is always checked before the night absence and the night absence is always checked before the job-related absence. If a condition is met, then the $T_{\mathrm{s},k+1}$ is assigned according to the appropriate rule statement. If the absence can not be predicted within the rule list, then to $T_{\mathrm{s},k+1}$ the previous set-point $T_{\mathrm{s},k}$ is assigned or the anticipative mechanism continues the delegation of the set-point variable. Algorithm 4.3 represents the rule-based mechanism in which the set-point variable value is assigned according to the predicted absence types that are determined with the rules and parameters.

Algorithm 4.3: Rule-based mechanism: Set-point delegation based on a list of rules.

Data: k, T_{sLo}, $T_{\mathrm{s},k}$, $abs^{*}_{\mathrm{LT},k}$, $abs^{*}_{\mathrm{N},k}$, $abs^{*}_{\mathrm{JR},k}$
Result: $T_{\mathrm{s},k+1}$
if $abs^{*}_{\mathrm{LT},k}$ **then**
  $T_{\mathrm{s},k+1} \leftarrow T_{\mathrm{sLo}}$;
else if $abs^{*}_{\mathrm{N},k}$ **then**
  $T_{\mathrm{s},k+1} \leftarrow T_{\mathrm{sLo}}$;
else if $abs^{*}_{\mathrm{JR},k}$ **then**
  $T_{\mathrm{s},k+1} \leftarrow T_{\mathrm{sLo}}$;
else
  `// Additional conditions and rules can be placed here`
  $T_{\mathrm{s},k+1} \leftarrow T_{\mathrm{s},k}$ `// Or proceed to the anticipative mechanism`
end

4.1.5 The Proposed Set-point Delegation Strategy

In previous sections the operation of reactive, rule-based, and anticipative mechanisms is described. The proposed novel set-point delegation strategy is a combination of described mechanisms presented in Figure 4.3. We have defined several control behaviours that represent a combination of mechanisms. The control behaviour that includes the reactive mechanism alone is denoted as Sense behaviour. The behaviour that includes the anticipative mechanism is denoted as Learning behaviour. The behaviour Learning5 includes the reactive mechanism, the list of rules composed of Rule 1 and Rule 2, and the anticipative mechanism. Other Learning behaviours are specified in Table 4.3.

Table 4.3: Control behaviours composed of reactive, anticipative, and rule-based mechanisms. The names of control behaviours are listed in the first column. The second column includes information about the mechanisms the behaviour is composed of. R, RB and A denote the reactive, the rule-based, and the anticipative mechanism. If a behaviour includes a rule-based mechanism than the binary variables used are given in parentheses. The last column contains the rule constants. Note: each constant represent the number of hours and has to be multiplied with 60 minutes, except C_{ND} which is a counter.

Behaviour	Mechanisms (Type of absence)	Rule constants [· 60 min]
		$C_{\mathrm{ND}} = 1$,$C_{\mathrm{LD}} = 5$
On		
Sense	R	
Learning1	R, RB(abs^{*}_{LT},abs^{*}_{N},abs^{*}_{JR})	$C_{\mathrm{tAbs}} = 24$, $C_{\mathrm{t1}} = 1$, $C_{\mathrm{t2}} = 7$
Learning2	R, RB(abs^{*}_{LT},abs^{*}_{N},abs^{*}_{JR}), A	$C_{\mathrm{tAbs}} = 16$, $C_{\mathrm{t1}} = 1$, $C_{\mathrm{t2}} = 7$
Learning3	R, RB(abs^{*}_{LT},abs^{*}_{N},abs^{*}_{JR}), A	$C_{\mathrm{tAbs}} = 16$, $C_{\mathrm{t1}} = 0$, $C_{\mathrm{t2}} = 8$
Learning4	R, A	$C_{\mathrm{tAbs}} = 16$, $C_{\mathrm{t1}} = 0$, $C_{\mathrm{t2}} = 8$
Learning5	R, RB(abs^{*}_{LT}), A	$C_{\mathrm{tAbs}} = 16$, $C_{\mathrm{t1}} = 0$, $C_{\mathrm{t2}} = 8$
Learning6	R, RB(abs^{*}_{LT},abs^{*}_{N}), A	$C_{\mathrm{tAbs}} = 16$, $C_{\mathrm{t1}} = 0$, $C_{\mathrm{t2}} = 8$
Learning7	R, RB(abs^{*}_{N}), A	$C_{\mathrm{tAbs}} = 16$, $C_{\mathrm{t1}} = 0$, $C_{\mathrm{t2}} = 8$

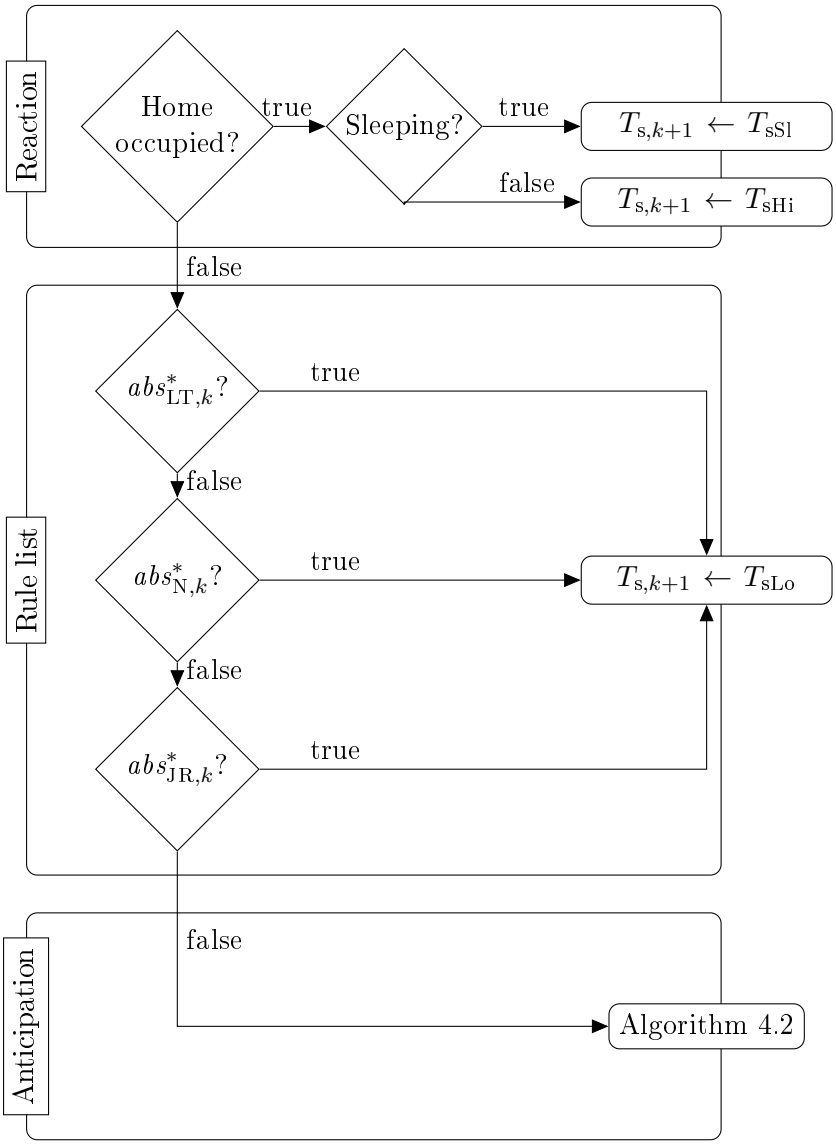


Figure 4.3: The proposed set-point delegation strategy composed of reactive, rule-based, and anticipative mechanism.

4.2 Comfort Regulator

In Section 4.1, the set-point delegation is carried out with the assumptions that the high set-point temperature $T_s = T_{sHi}$ should be set when an occupant is present and $T_s = T_{sLo}$ should be set when an occupant is present and sleeping. Since the comfort depends on the equilibrium among several state variables, such as humidity, indoor temperature, occupant's metabolic equivalent of task and clothing insulation, and others, the set-point T_s should be dynamically adapted when the other state variables are changing. Therefore we developed the novel comfort regulator that adapts the value of indoor set-point temperature in order to achieve the equilibrium determined with the desired value of PMV or with a range of PMV values.

The proposed comfort regulator includes two feedback control loops combined into a cascade control structure which is presented in Figure 4.4. The internal loop represents the

temperature regulator where the sensed variable is indoor temperature T_{in}, the reference variable is indoor set-point temperature T_{s}, and the output is the signal to actuator that performs an action u. The main loop (extrnal loop) represents the comfort regulator where the sensed and inferred variables are T_{in} and PMV respectively, reference variable is the comfort range PMV_{ref} and the output is T_{s} which is passed as a reference to the internal loop.

The index PMV depends heavily on the indoor temperature. The comfort regulator regulates the index PMV by maintaining the indoor temperature T_{in} through the indoor temperature set-point T_{s}. The input to the comfort regulator is the range of desired PMV values with which the occupant is satisfied. The desired values for the PMV (the comfort range) are included in the interval $[-PMV_{\text{ref}}, +PMV_{\text{ref}}]$, where $PMV_{\text{ref}} \geq 0$ is the maximum allowed deviation of PMV from the ideal value of 0, where 0 denotes the neutral sensation (ISO, EN, 2005). In practical terms, when the $PMV_{\text{ref}} \neq 0$, the controller maintains the value of PMV at $-PMV_{\text{ref}}$ when heating and at PMV_{ref} when cooling. The integration of the comfort regulator into the HVAC control subsystem is presented in Figure 4.4.

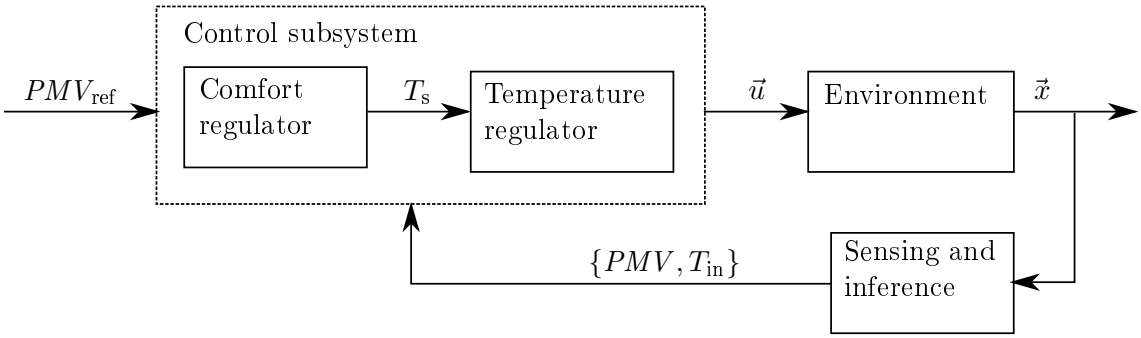


Figure 4.4: The comfort regulator integrated into the HVAC control subsystem.

The sensed variable T_{in} and the inferred variable PMV are used as a feedback for regulation. The indoor set-point temperature T_{s} for the next time-step $k+1$ is computed in order to achieve the comfort range, defined with PMV_{ref} according to Eq. (4.5): $T_{\text{s},k}$ is increased/decreased for the value $T_{\text{inc},k}$.

$$T_{\text{s},k+1} = T_{\text{s},k} - T_{\text{inc},k} \tag{4.5}$$

The value of $T_{\text{inc},k}$ must obey the following conditions: if PMV_k is close to the comfort range, T_{s} should not change much. If PMV_k is distant to the comfort range, T_{s} can change more. In order to prevent fluctuations of T_{s} the following conditions must be met: If the difference between $T_{\text{in},k}$ and $T_{\text{s},k}$ is small, then T_{s} can change more, and if the difference between $T_{\text{in},k}$ and $T_{\text{s},k}$ is large, then T_{s} should not change greatly. We want T_{in} to catch up with T_{s} so that T_{s} does not significantly over- or undershoots the temperature at which the comfort range is achieved. In other words, the increment/decrement value $T_{\text{inc},k}$ is (i) proportional to the difference between PMV_k and the comfort range, and (ii) inversely proportional to the difference between $T_{\text{in},k}$ and $T_{\text{s},k}$. Therefore, we derive the equation of the form:

$$\begin{aligned} T_{\text{inc},k} &= K_1 + K_2 \cdot K_3 \\ &= A \cdot PMV_{\text{diff},k}^3 + B \cdot \frac{PMV_{\text{diff},k}}{C \cdot T_{\text{diff},k}^2 + 1} + D \cdot PMV_{\text{diff},k} \end{aligned} \tag{4.6}$$

where

$$PMV_{\mathrm{diff},k} = \begin{cases} 0 & \text{if } PMV_{\mathrm{k}} \in [-PMV_{\mathrm{ref,k}}, PMV_{\mathrm{ref,k}}] \\ PMV_{\mathrm{k}} + PMV_{\mathrm{ref,k}} & \text{if } PMV_{\mathrm{k}} < -PMV_{\mathrm{ref,k}} \\ PMV_{\mathrm{k}} - PMV_{\mathrm{ref,k}} & \text{if } PMV_{\mathrm{k}} > PMV_{\mathrm{ref,k}} \end{cases} \tag{4.7}$$

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

$$T_{\mathrm{diff},k} = T_{\mathrm{s},k} - T_{\mathrm{in},k} \tag{4.8}$$

is the difference between the current set-point temperature and the current indoor temperature. $K_1 = A \cdot PMV^3_{\mathrm{diff},k} + D \cdot PMV_{\mathrm{diff},k}$ represents the proportion of Eq. (4.6) to $PMV_{\mathrm{diff},k}$ (represented also in Figure 4.5a). $K_2 = \frac{1}{C \cdot T^2_{\mathrm{diff},k}+1}$ represents the inverse proportion of Eq. (4.6) to $T_{\mathrm{diff},k}$ (represented also in Figure 4.5b).

The proposed regulator structure was determined intuitively. $PMV_{\mathrm{diff},k}$ is raised to an even power in order to distinguish between warmer and colder comfort experience so the regulator outputs negative or positive signal to the actuator that enables cooling or heating respectively. The reason to choose an even power of three in the first term of Eq. (4.6) relies in emphasizing the impact of larger values of $PMV_{\mathrm{diff},k}$; larger deviations between T_{in} and T_{s}. $T_{\mathrm{diff},k}$ is raised to an odd power in order to prevent rapid changes of T_{s}. The multiplication of K_2 with $K_3 = B \cdot PMV_{\mathrm{diff},k}$ and the summation of $K_1 + K_2 \cdot K_3$ gives the final shape, defined with Eq. (4.6) and presented in Figure 4.6. The constants $A = 0.1$, $B = 4$, $C = 0.18$ and $D = 1$ were obtained iteratively. For each iteration we perform a simulation run and observe the output variables T_{in} and PMV and modify constants A, B, C and D in order to achieve the desirable trade-off: to minimise the overshot and fluctuations, and to decrease the rise/fall time of output variables.

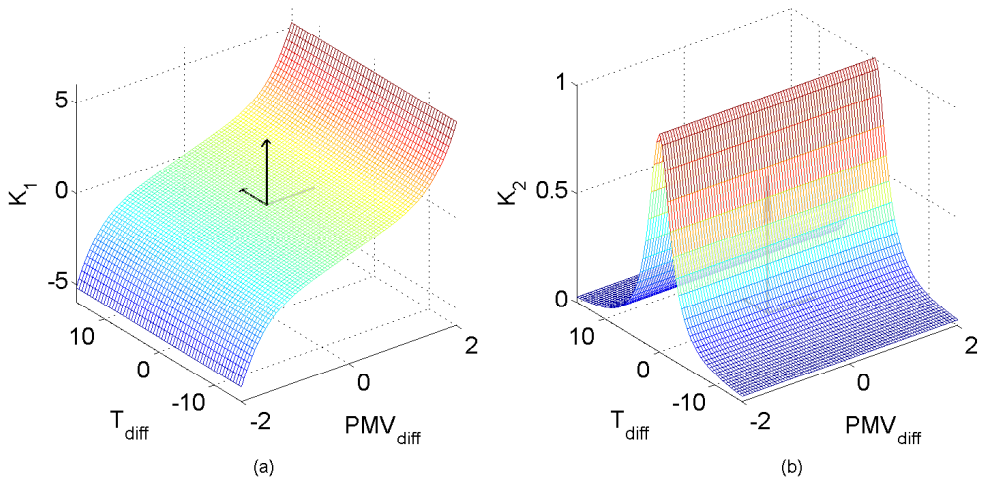


Figure 4.5: The constitutive parts of the temperature set-point increment defined with Eq. (4.6): (a) K_1, (b) K_2.

Figure 4.7 shows the time series of PMV for different thresholds, that are specified with PMV_{ref}, during a simulation of a winter day. It is clear that the higher the PMV_{ref} the lower the comfort experience. In such a case less energy is consumed for heating. T_{s} denotes the set-point value for temperature regulator that regulates the operation of the heat pump in order to minimise the difference between T_{in} and T_{s}. We can observe that the

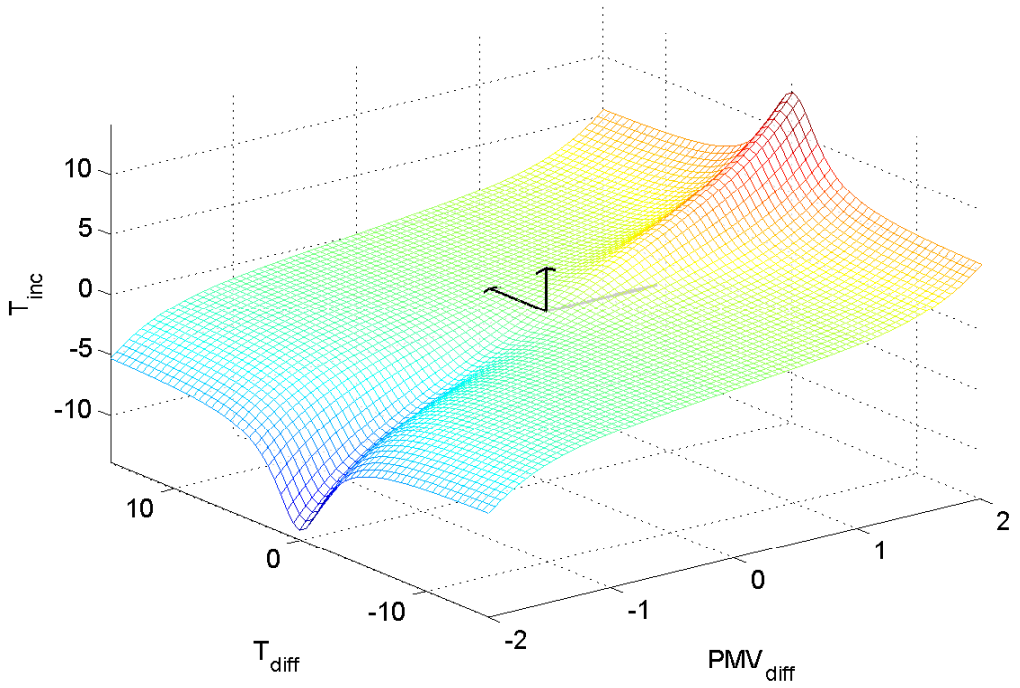


Figure 4.6: Increment function of two variables: X axis represents the PMV_{diff} according to Eq. (4.7), Y axis represents the T_{diff} according to Eq. (4.8) and Z axis represents T_{inc} according to Eq. (4.6).

comfort regulator performs room control so that it tends to achieve the comfort threshold which is specified with PMV_{ref}. When the PMV is positive, the regulator tends to equalise the PMV with PMV_{ref} and when the PMV is negative, the regulator tends to equalise the PMV with $-PMV_{\text{ref}}$.

4.3 Hierarchical Multi-Agent Architecture

The control architecture is implemented as a multi-agent control system (MACS) with several types of agents: sensor agents, control agents, routing agents, ML agents, and environment management (EM) agents. In this dissertation, the proposed architecture represents a scientific contribution. Layers in building automation and management are shown in Figure 4.8.

The environment layer is located at the bottom of the Figure 4.8. It is composed of the (i) building that represents the energy consumer; (ii) occupants that interact with the building; and (iii) weather that influences the thermal dynamics of the building. The physical layer is located above the environmental layer where physical entities, such as sensors and actuators, are located. The automation layer includes the physical controllers linking the physical layer and management layer. Controllers are used for feedback control according to the algorithms, which are created and adapted by the control agents in the management layer. When a simulation is used instead of real environment, the environmental, physical, and automation layers are integrated in the simulation environment. The management layer is the top layer and represents a multi-agent system (MAS). It is composed of several sublayers: routing, control and data fusion, ML and environment man-

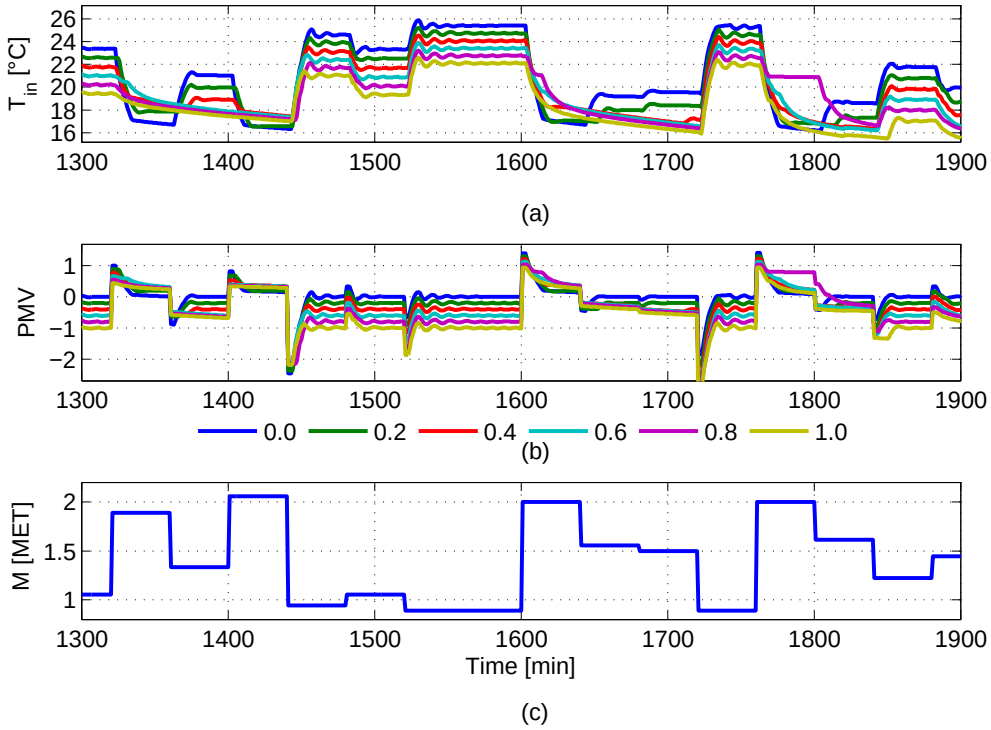


Figure 4.7: The comparison of T_{in} and PMV at $PMV_{\text{ref}} \in \{0.0, 0.2, .., 1.0\}$, I_{cl} is fixed at 1 clo: (a) T_{in}, (b) PMV, (c) M.

agement. Each agent type carries out specific tasks, which are specified within the agent behaviours. Each agent belongs to a specific sublayer of management layer according to the type of that agent.

During the runtime each agent waits for a message and responds to it, meaning that the agent operation is data-driven or event-driven. The routing agents are denoted as the interfaces between the simulation environment and the control system. The routing agents are used to transform sensed and inferred environment variables into states of sensor agents. In order to improve the lack of communication reliability between MACS and simulation environment that was firstly implemented without routing (Zupančič & Gams, 2012a, 2012b), we introduced the routing agent (Zupančič, Gams, & Luštrek, 2013). The sensor agents are used to obtain the sensed values from the physical sensors through the routing agents and to obtain inferred values as a result of the data fusion process (the inference process) performed among several sensor states according to an inference model. The control agents represent virtual control entities that schedule the operation of the actuators of the controlled subsystems, such as the room temperature control subsystem. The control output is the input to the feedback control loop and delegates the set-point values. The machine learning (ML) agents are used to create ML models when requested, using data prepared by the appropriate sensor agents. Control agents use the ML models for control operations. An environment management (EM) agent represents the top-level agent in a smart building that monitors and manages subordinate agents. The operation of each agent is explained in the following sections.

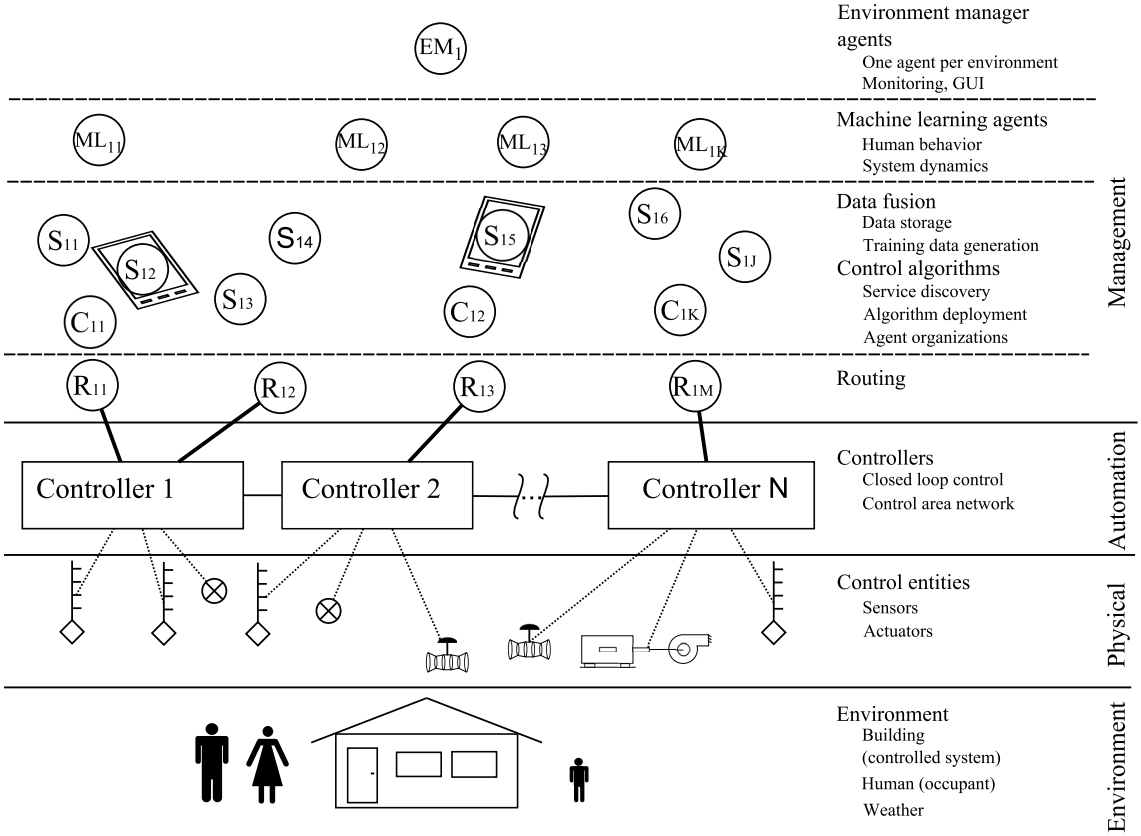


Figure 4.8: Layers in building automation and management.

4.3.1 Routing Agents

Routing agents represent an interface between the MACS architecture and simulation (or real) environment. Routing agents accept values that are obtained from a physical environment through the physical and automation layer and distribute these values to appropriate sensor agents. On the other side, routing agents pass the control parameters, variables, and schedules, that are computed by control agents, to the automation layer, where the new values are used as set-point values to perform feedback control in the automation layer.

Routing agents are used either for simulation or real operation purposes. By simulation, the routing agent creates and manages mapping from the simulation environment to the control system and vice versa. In real operation, the routing agent represents an interface between the controller and the control system.

Each routing agent in an environment q is denoted as R_{qm} where the first index q represents q-th environment and the index m represents the unique number of that agent in the depicted environment. Thus, an environment has a set of M routing agents $R_{qm} \in \{R_{q1}, R_{q2}, \ldots, R_{qM}\}$.

Definition 4.1 (Routing agents). Routing agent R_{qm} is a tuple $\langle \mathbb{C}, \mathbb{S}, cfg_{\text{sock}} \rangle$ where:

- $\mathbb{C}$ is a set of control agents that compute set-point values,
- $\mathbb{S}$ is a set of sensor agents that provide sensed or inferred state variable values,
- cfg_{sock} is a socket configuration and variable mapping of either the simulation environment or the controller in a physical environment.

4.3.2 Sensor Agents

Knowledge about the operation of sensors and sensor systems is crucial for the integration of sensing entities into the control system. Sensor agents represent the physical entity – that is, the sensor in an environment. The state of a sensor agent represents a sensed or an inferred variable (temperature, occupancy, power, comfort, etc.) that a sensor agent can perceive and serve. Sensed variables are those that can be obtained using standardised sensors and sensor systems with detailed information about sensing accuracy, drift, unit of sensed output, conversion factors, sampling frequency, and quantisation for the digitalisation process and other relevant information. Inferred variables are those which are computed from states of other sensor agents. These variables are inferred based on the expert knowledge about the sensing domain and/or according to the ML methods. To create ML models for estimation, additional processing and memory capabilities are required. The process at which information is extracted from several data sources is denoted as the data fusion or the multisensor data fusion (Khaleghi, Khamis, Karray, & Razavi, 2013).

We denote the inferred state as a sink of the fusion process within the sensor organisation that is created and managed by a sensor agent. Sensor agents that represent inferred states include the knowledge about inference process that could be represented as a mathematical model such as the model to compute the comfort index PMV, or the ML model, such as the one that is used to estimate the metabolic equivalent of task M. The later uses the data from smart-phone accelerometers as described in (Zupančič & Cvetković, 2014).

A sensor agent performs several tasks. First, it creates an organisation of sensors that are needed to infer its state. Therefore it subscribes to the appropriate sensor agents to provide their states. An example is a sensor agent that represents the state according to the ISO-PMV model with index PMV. Such sensor requires sensed values from an indoor temperature sensor, a metabolic equivalent of task sensor, a humidity sensor, etc. The organisation set-up by a sensor is schematically presented in Figure 4.9.

According to Figure 4.9, the sensor agent S_a searches for agents that are needed to infer its state according to the inference model. In order to find such agents, the sensor agent S_a exploits yellow pages service that is managed by a special agent, called directory facilitator (DF)(Bellifemine et al., 2005), which is one of the standard agents in JADE software. DF agent returns a list of agent IDs (AID list) of available agents that contain information about the requested state. S_a then sends request to each agent from the AID list and subscribes for the state variable delivery. Than S_a waits for these variables and continuously updates its state x_a according to the inform messages from agents S_b, S_c and S_d. Sensor agents always maintain the most recent value of the sensor state. If it contains an inferred state, then it continuously obtains information from other sensor agents that compose sensor organisation.

Sensor agent also registers its service at the DF agent. In Figure 4.9 that is represented with RegisterDF message that S_a agent sends to DF agent. That allows other agents, to find that service. Therefore sensor agents are also able to receive and process messages from other agents that wish to subscribe to or to unsubscribe from receiving the information about sensor states. Finally, sensor agents also keep the history log of sensor states and generate data for ML.

Each sensor in an environment q is represented as a S_{qi}, where the first index q represents q-th environment and the index i represents the unique number of the sensed or inferred variable of that environment. Thus, the environment q has a set of I sensor agents $S_{qi} \in \{S_{q1}, S_{q2}, \ldots, S_{qI}\}$.

Definition 4.2 (Sensor agent). Sensor agent S_{qi} is a tuple $\langle x, xm, \mathbb{A}, \mathbb{RS} \rangle$ where:

- x is a sensed or inferred variable object,

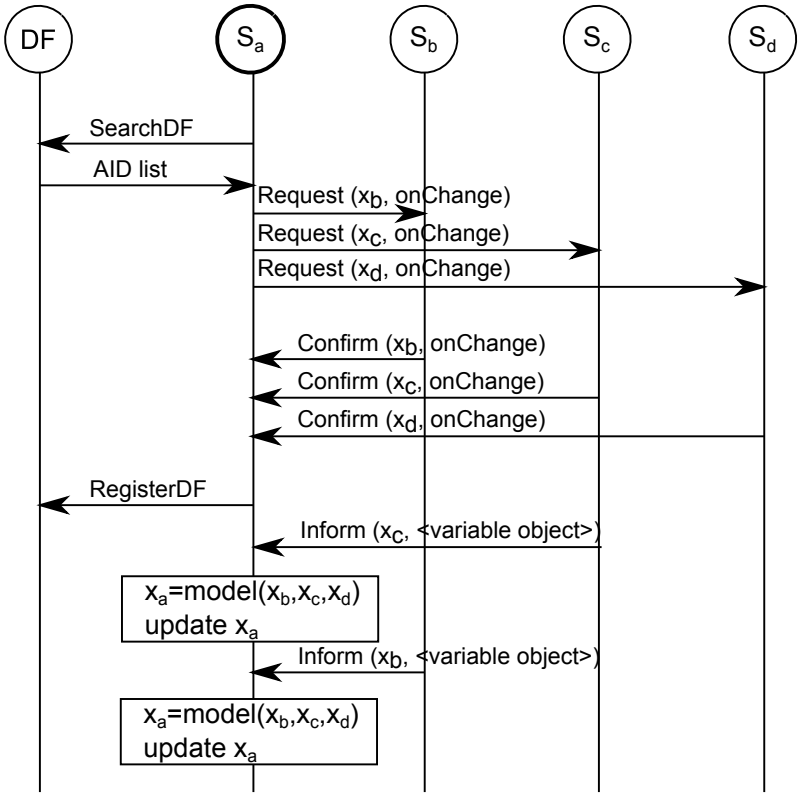


Figure 4.9: Sensor organisation set-up process diagram.

- xm is a meta-data of that sensor,
- $\mathbb{A}$ is a set of agents that receive variable object from S_{qi}, where $\mathbb{A}$ can include agents from any environment q.
- $\mathbb{RS}$ is a set of resource agents that are used to create sensor organisation. If x represents a sensed variable object, then $\mathbb{RS}$ includes an AID of an appropriate routing agent that delivers the sensed variable value from automation layer. If x represents an inferred variable object, than $\mathbb{RS}$ includes AIDs of sensor agents that provide variable objects used to infer state x.

4.3.3 Control Agents

Control agents represent software entities (threads), where the algorithms for defining set-point values are implemented as control behaviours. Control agents have a predefined set of control behaviours. There are (i) simple behaviours such as On and Off behaviours; (ii) Schedule behaviours; (iii) Sense behaviours; and (iv) Learning behaviours.

On and Off behaviours use predefined set-point temperatures (T_{sHi} and T_{sLo} respectively). Schedule behaviour acts according to schedule instructions, where the temporal occurrence of set-point values T_{sHi}, T_{sLo} and others, such as T_{sSl}, are predefined in advance. Sense behaviour acts according to an occupancy state, so that T_{sHi} is applied if the building is occupied, T_{sLo} is applied when the building is not occupied, and T_{sSl} is applied when the occupant is sleeping. Sense behaviour is denoted also as reactive control behaviour. Learning behaviour exploits ML models to assign the set-point values according to the model predictive control (MPC), such as control based on occupancy prediction in a

controlled environment and control based on identified behavioural patterns of heating dynamics of that environment. Learning behaviour is adaptive, since it continuously adapts its own knowledge model about the environment, used for MPC, during the observation of an environment.

Control behaviour can be a combination of the predefined set of behaviours, such as Sense behaviour in combination with Learning behaviour for predicting the time needed to heat a room. Control agents can also implement a comfort regulator, described in Section 4.2 within the control behaviour. When the comfort regulator is used, T_{sHi} is not a fixed set-point value, but adapted dynamically in order to satisfy a higher-level objective, defined with PMV_{ref}. In order to perform control within a depicted control behaviour, an agent has to acquire the current information about the environmental state and the patterns of environmental behaviour that could be obtained with long-term observation.

When a control agent implements control behaviour, it first searches for appropriate data sources – sensor agents through the yellow pages service using DF agent similar to sensor agents. Then it subscribes to the appropriate sensor agents for the delivery of information about the desired sensor states, using a request message as shown in the diagram in Figure 4.9, when S_a agent is replaced with a control agent – for example C_a. If a control behaviour needs data about the outdoor temperature, indoor temperature, and occupancy, it engages with the appropriate sensor agents for information delivery. In such a way, the control agent creates a control organisation that is composed of the control agent and the appropriate sensor agents.

If a control agent implements Learning behaviour, it periodically updates its knowledge about environment dynamics (the regression or classification models, the ML models) that is generated by a ML agent. ML agent creates a ML model based on the historic observations of an environment and actions performed in the environment. Until the ML agent returns a new ML model, the old ML model is used. The control agent implements Sense behaviour if there is no ML model available, which happens at the beginning of control operation (first days), when there is not enough knowledge about the environment acquired yet. The control agent passes a newly determined set-point value to the appropriate physical control entity in an automation layer through the routing agent and saves the set-point value in a control agent history file.

The notation of control agents is similar to the notation of sensor agents; each control agent in an environment q is denoted as C_{ql} from a set of L control agents $C_{ql} \in \{C_{q1}, C_{q2}, \ldots, C_{qL}\}$.

Definition 4.3 (Control agent). Control agent C_{ql} is a tuple $\langle r, rm, R, B\rangle$ where:

- r is a set-point variable object,
- rm is a meta-data of the controller,
- R is a routing agent and delivers the set-point variable values to the automation layer,
- B is a tuple that defines the control behaviour.

4.3.4 Control Behaviour

Control algorithms are implemented as control behaviours within a control agent. The control agent reads temperature set-point parameters from its configuration, determined with T_{sHi}, T_{sLo} and T_{sSl} and PMV_{ref}. T_{sHi} represents the desired indoor temperature at which the occupant feels comfortable at home. T_{sLo} represents the temperature that should be used when the occupant is not present at home. T_{sLo} is used to reduce the

energy consumption for heating or cooling. If the outdoor temperature is low and heating is necessary, then T_{sHi} is higher than T_{sLo}. If the outdoor temperature is high and cooling is necessary, then T_{sHi} is lower than T_{sLo}. T_{sSl} represents the temperature at which the occupant feels comfortable when sleeping. If the control agent performs regulation of comfort by means of PMV, then PMV_{ref} is applied in order to define a range of comfort values the agent should maintain in order to satisfy the objective regarding the occupant's comfort experience.

Definition 4.4 (Behaviour). Behaviour B is a tuple $\langle cfg_{\text{beh}}, \mathbb{S}, MLA \rangle$ where:

- cfg_{beh} is a behaviour configuration, where mechanisms and rules are specified for set-point delegation strategy (see Table 4.3),
- $\mathbb{S}$ is a set of sensor agents from any environment q, needed for state variable values delivery for control behaviour implementation,
- MLA is a ML agent used to generate ML models.

We defined five control behaviours for control agents: On, Off, Schedule, Sense and Learning behaviour (explained in Sections 4.3.4.1-4.3.4.4) and based on temperature set-point delegation strategies, defined in Section 4.1. During the initialisation phase of a control behaviour, the control agent searches for the appropriate sensor agents that are needed for the implementation of depicted behaviour, subscribed for a state variable delivery and after the contract with sensor agents is created, it starts with the control algorithm. During the execution of control behaviour, the control agent continuously exchanges information with sensor and ML agents. The following sections describe the operation of the proposed control behaviours.

4.3.4.1 On and Off Behaviour

On and Off behaviours are the most trivial control behaviours, since the set-point temperatures are both static. On behaviour is the most wasteful but the most comfortable. In contrast, Off behaviour is the most economical but does not provide comfort. The two behaviours are used to obtain extreme points regarding the trade-off between the comfort experience and the energy consumption. There is only one set-point value in each of the two behaviours: $T_{\text{s}} = T_{\text{sHi}}$ for On behaviour and $T_{\text{s}} = T_{\text{sLo}}$ for Off behaviour. When an agent regulates PMV, T_{sHi} varies according to Eq. (4.5).

4.3.4.2 Schedule Behaviour

Schedule behaviour currently represents the most widely used control approach for heating in BASes. Schedule behaviour acts according to a predefined schedule for each day in a week, where the predefined set-point value is applied for each minute in a day.

Schedule is defined as Sch_{ql}, and represents the schedule used by control agent C_{ql} for each minute in a week. The weekly schedule is composed of daily schedules, and each day in a week can have a unique schedule. An example of a schedule is described in Section 4.1.2. When an agent regulates PMV, T_{sHi} varies according to Eq. (4.5).

4.3.4.3 Sense Behaviour

Sense behaviour represents simple reactive behaviour. Sense behaviour uses simple rules that based on sensed states change the set-point values. One example of Sense behaviour by heating is a scenario where the heater ensures a high set-point temperature when the

home is occupied and the occupant is awake, a sleep set-point temperature when the home is occupied and the occupant is sleeping, and a low set-point temperature when the home is not occupied.

During the initialisation the Sense behaviour subscribe to sensor agents in order to provide sensor states during runtime and rules that define the impact of sensor states on the set-point value assignment. When an agent regulates PMV the T_{sHi} varies according to Eq. (4.5).

4.3.4.4 Learning Behaviour

Learning behaviour implements a control behaviour composed of anticipative, reactive, and rule-based mechanisms. During its runtime the anticipative mechanism adapts according to historical observations of an occupant within an environment. The anticipative mechanism is used to predict the occupant's behaviour and the dynamics of heating or cooling processes in a building. In order to include the anticipative mechanism, the control agent searches for an appropriate ML agent, using the yellow pages service. If an appropriate ML agent is found, the knowledge between these agents is shared on behalf of the control agent, otherwise a new ML agent is created for that purpose. The rule-based mechanism uses expert rules to reduce the false occupancy predictions. The reactive mechanism of a behaviour is similar to Sense behaviour. If the constraints regarding the occupant's comfort are violated the Sense behaviour is applied.

Algorithm 4.2 describes an implementation of the behaviour for room heating, that is based on the following environmental variables: outdoor temperature (T_{out}), indoor temperature (T_{in}), occupancy at home (occ_{h}), and/or occupancy at work (occ_{w}). Actual values are obtained during each simulation time-step from appropriate sensor agents. The control behaviour computes the room set-point temperature value T_{s} and passes to the controller in the automation level so to achieve the desired indoor temperature. When an agent regulates PMV the T_{sHi} varies according to Eq. (4.5).

4.3.5 Machine Learning Agents

The machine learning (ML) agents are created by the control agents. When a control agent performs a model-predictive control, it employs a ML agent to perform ML in order to generate classification or regression models. There are two types of learning in the proposed architecture: (i) the learning of human behaviour and (ii) the identification of system dynamics. The training data used for ML is generated by a ML agent in cooperation to sensor and control agents. The data that is used for human behaviour learning is obtained from sensor agents that contain information about occupancy at home and at work. The data that is used for the identification of system dynamics is obtained from a control agent (such as temperature set-point values) and appropriate sensor agents (indoor temperature, outdoor temperature) that participate in a control organisation presented in Section 4.3.3. A ML agent merges the instances into a training dataset. When an agent creates its first ML model, it registers the properties of that model at a yellow pages through a DF agent (similar as sensor and control agents) service in order to be used by other control agents. A ML model for occupancy prediction can be used by several control agents used for the control of HVAC or DHW system.

Each ML agent in environment q is denoted as MLA_{qn} from a set of N ML agents $MLA_{qn} \in \{MLA_{q1}, MLA_{q2}, \ldots, MLA_{qN}\}$.

Definition 4.5 (ML agent). ML agent MLA_{qn} is a tuple $\langle \mathbb{C}, \mathbb{S}, ml, tp \rangle$ where:

- $\mathbb{C}$ is a set of control agents that implement Learning behaviour and require the ML model generated by that ML,

- $\mathbb{S}$ is a set of sensor agents that store historic data of its states for the ML procedure,
- *ml* is a ML algorithm and algorithm configuration used to generate ML model,
- *tp* is a ML model template, that contains the list of attributes and the class value.

4.3.6 Environment Management Agent

The environment management (EM) agent represents the highest instance in the comfort and energy management system in buildings. It could also be denoted as a *housekeeper* agent and is used as an interface for the administration of the controlled system. It serves the information about the states of the environment and manages the operation of individual control systems in that environment. The EM agent also interacts with smart grid suppliers, such as a solar power plant, in order to provide data about current and future power demand.

We denote the q-th EM agent in environment q as EM_q from a set of Q environments $EM_q \in \{EM_1, EM_2, , EM_{\mathrm{Q}}\}$. For example, in the experimental set-up instantiation described in Chapter 5, EM_1 is the EM agent at home and EM_2 is EM agent at work.

Definition 4.6 (Environment management agent). Environment management agent EM_q is a tuple $\langle \mathbb{S}, \mathbb{C}, \mathbb{R} \rangle$ where:

- $\mathbb{S}$ is a set of sensor agents in environment q,
- $\mathbb{C}$ is a set of control agents in environment q,
- $\mathbb{R}$ is a set of routing agents in environment q (there is one routing agent only if an environment behaviour is simulated).

Chapter 5

Experimental Set-up and Evaluation Procedures

Experimental set-up was prepared in order to test the comfort regulator and the performance of algorithms for occupancy prediction and for predicting the time, that is needed to heat or cool the temperature in the controlled environment. Therefore, the simulation and control system was implemented, including the simulation environment with a dynamic model and a multi-agent control system (MACS), that was used to observe, control and manage the environment. Simulation environment is used to simulate a model of an intelligent environment as formulated in Chapter 3, including the weather and occupancy datasets. In order to test the occupant-aware comfort management, the dataset about occupant's metabolic equivalent of task was also included.

In this chapter firstly the simulation environment and the dynamic model of a building are presented. Then the weather, occupancy, metabolic equivalent of task, and clothing datasets used for evaluation are presented. Then the instance of the multi-agent control system including the control behaviours that were implemented for the experimental evaluation of the performance of the control system presented. Finally the methodologies that were used to evaluate the prediction models and the proposed control strategies are presented.

5.1 Simulation Environment

The simulation environment, which is illustrated in Figure 5.1, was used to integrate the software for simulation and control purposes. The free co-simulation software, entitled Building controls virtual test bed (BCVTB) was used to couple simulation and control modules (Wetter, 2011). The dynamic model was created using the EnergyPlus (Crawley et al., 2001) software (represented as E+ block). The weather data, occupant-related data, and set-point values are inputs to the EnergyPlus model. The output of the EnergyPlus model are the environmental states that are forwarded to MACS. MACS represents the control system, which was implemented with the Java agent development environment (JADE) (Bellifemine et al., 2005). The TCP/IP protocol stack realised the communication between the MACS and EnergyPlus model.

5.1.1 Dynamic Model of a Building

The experimental set-up included the selected model of packaged terminal heat pump (PTHP), which is included in the installation of the EnergyPlus software. The building is represented as a single-floor, L-shaped structure with the three heating zones. Only

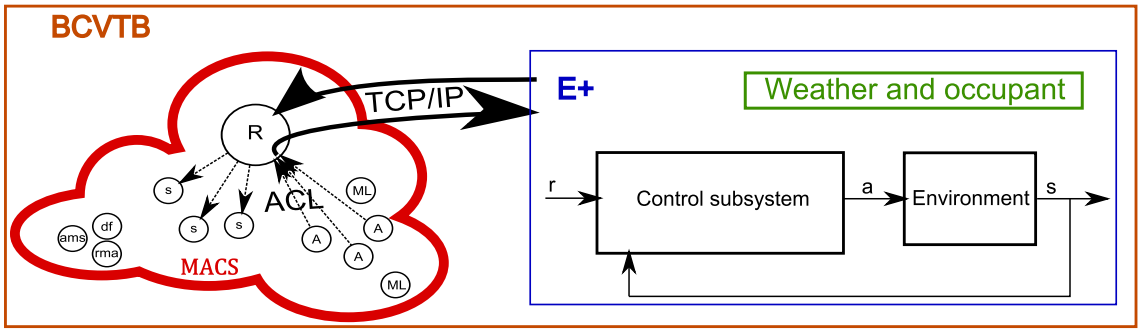


Figure 5.1: Coupling of MACS with the dynamic model.

the west zone, representing a floor area of approximately 36 m^2, was considered for the experiments. The cooling coil total cooling capacity was rated at 3700 W and the coefficient of performance (COP) at 3.00. The coefficient of performance is the factor that defines the quality (efficiency) of a heat pump. The thermal power that is produced by the heat pump is equal to the electric power consumed by a heat pump multiplied with the COP. The heating coil total heating capacity was rated at 3700 W and COP at 2.75. The coefficients for both heating and cooling functions remain default as defined in the obtained model. The power rate of each coil is dynamic and depends on the dry-bulb temperature, wet-bulb temperature and the air flow rate. The locations of the simulation were Ljubljana and Rateče, Slovenia. The corresponding weather files for those locations were used for the experiment.

5.2 Datasets

5.2.1 Home and Work Occupancy Dataset

To obtain the occupancy dataset, five volunteers have recorded the date-time stamps of the start and stop times of the certain activities – sleeping, home occupancy, and work occupancy – over a period of at least one month in late summer and autumn, 2013. The data about the occupancy at home was logged manually using a smart-phone logger, and the data about the occupancy at work was logged utilising the radio-frequency identification (RFID) system installed at our research institute. In Section 3.3 we consider the occupancy state to be an inferred state, because the result of the occupancy detection or activity recognition is not necessarily the result of a single sensor; rather, it requires additional processing of data obtained from various sources. The scope of our work did not include the occupancy detection, person identification, estimation of the number of occupants in a building, or activity recognition to recognise the sleeping activity. In the experiment we assumed that only one person uses the controlled environment. The data was transformed into the time series with one-minute time-steps. In Table 5.1 the details of the dataset for each person are given.

In Table 5.1 the first column represents a list of persons, labelled as Person 1 to Person 5. The second and third columns represent the period during which the data was collected and the number of days respectively. The last two columns represent the percentage of time the person was at home and at work. The percentage of sleep is given in parentheses and represents the percentage of time that was spent for sleeping during home occupancy. We can observe that the time spent at home ranges from roughly 48 % to roughly 67 %. The proportion of sleeping during home occupancy ranges from roughly 50 % to roughly

Table 5.1: Home and work occupancy datasets used for evaluation. The table presents the data collection period and the percentage of time a person was at home, at work, and sleeping. The percentage of time for sleeping is given in parentheses and represents the percentage of time that was spent for sleeping during home occupancy.

Person	Period	Number of days	% Home (% Sleep)	% Work
Person 1	22/07/2013 – 25/11/2013	126	66.5 (49.5)	16.2
Person 2	02/08/2013 – 20/11/2013	110	52.2 (58.6)	19.0
Person 3	21/07/2013 – 30/08/2013	40	54.4 (50.5)	16.1
Person 4	01/08/2013 – 19/10/2013	79	47.7 (53.6)	17.6
Person 5	01/09/2013 – 31/10/2013	60	66.8 (63.8)	23.8

64 %. The time spent at work ranges from roughly 16 % to roughly 24 %.

5.2.1.1 Metabolic Equivalent of Task and Clothing Dataset

The reference measurement of the metabolic equivalent of task is typically performed in the controlled environment using the dedicated equipment – the indirect calorimetry equipment, an example being Cosmed K4 b^2 ("Cosmed K4 b2," 2014). Cosmed K4 b^2 is an indirect calorimeter composed of a gas mask that measures pulmonary gas exchange, a battery worn on the users back or front which makes it cumbersome for everyday usage, and a control system that calculates the human energy expenditure from breath by breath analysis. Since we could not collect the free-living reference dataset due to the cumbersome nature of Cosmed K4 b^2, we created the synthetic two-day dataset with a one-minute sampling rate from the synchronised recordings (smart-phone and Cosmed K4 b^2) for five people participating in this experiment.

The data represents one workday and one weekend day for each person. The characteristics of their lifestyles can be observed in Table 5.2. The goal was to produce the dataset for people with different lifestyles. They are summarised as follows. All persons have regular eight-hour jobs in the office. 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 exercises on weekends. Person C is engaged in the highly 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 a half an hour. Table 5.2 shows the percentage of time the occupant was at home and the summation of time in hours during which the occupant performed activities with low, moderate, and vigorous intensity.

In addition we created synthetic dataset that represent clothing for the two-day period with one-minute sampling rate for each of five people. The three values of clothing insulation were predefined: 0.5 clo, 1 clo and 2 clo that represent clothing during vigorous activities (sports clothes), clothing for regular daily activities and clothing for sleeping respectively, based on European standard (ISO, EN, 2005). The clothing insulation 0.5 clo assumes that an occupant is wearing underwear, a shirt with short sleeves, light trousers, light socks and shoes during vigorous activities. 1 clo means an occupant is wearing underwear, a shirt, trousers, socks and shoes. 2 clo means an occupant is wearing underwear, a shirt, trousers, a jacket, a heavy quilted outer jacket and overalls, socks, shoes to simulate the bedding and nightwear for sleeping, however we did not use a special model for sleeping environments, as proposed by Lin and Deng (2008).

Values were assigned based on simple heuristics that utilise the information about the time of the day and the estimated metabolic equivalent of task of each person according

Table 5.2: The characteristics of the metabolic equivalent of task datasets for two days. The percentage of time the person was at home and the amount of activities in hours according to the intensity M.

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

to Rule 4 and Rule 5.

Rule 4 (Clothing at night). Clothing insulation during the night and sleeping:
if $((daytime > 23:00) \wedge (daytime < 7:00) \wedge (M > 2 \text{ MET})$ **then**
$I_{\text{cl}} \leftarrow 1$;
else
$I_{\text{cl}} \leftarrow 2$;
end if

Rule 5 (Daily clothing). Clothing insulation during the day and vigorous activities:
if $((daytime > 7:00) \wedge (daytime < 23:00)) \wedge (M > 3 \text{ MET}))$ **then**
$I_{\text{cl}} \leftarrow 0.5$;
else
$I_{\text{cl}} \leftarrow 1$;
end if

Rule 4 assigns 1 clo during the night (between 23:00 and 7:00), when occupant's metabolic equivalent of task is higher than 2 MET, otherwise it assigns 2 clo. Rule 5 assigns 0.5 clo during the day (between 7:00 and 23:00), when occupant's metabolic equivalent of task is higher than 3 MET and 1 clo otherwise.

5.2.2 Weather Datasets

This dataset was further enriched with the weather information (including outdoor temperature, humidity, wind velocity and solar radiation). The weather dataset was obtained from the Slovenian Environment Agency portal[1]. Figure 5.2 shows the outdoor temperature for Ljubljana, Slovenia, for the summer-autumn period between 22 July 2013 and 25 November 2013 (Figure 5.2(a)), and for Rateče, Slovenia for the winter-spring period between 6 January 2014 and 1 April 2014 (Figure 5.2(b)).

5.3 Multi-Agent Control System

The control system was instantiated according to the proposed multi-agent control architecture implemented in JADE (Bellifemine et al., 2005). JADE is a software framework

[1]Slovenian Environment Agency, Web page: http://www.arso.gov.si/en/, last accessed: 23 February 2013

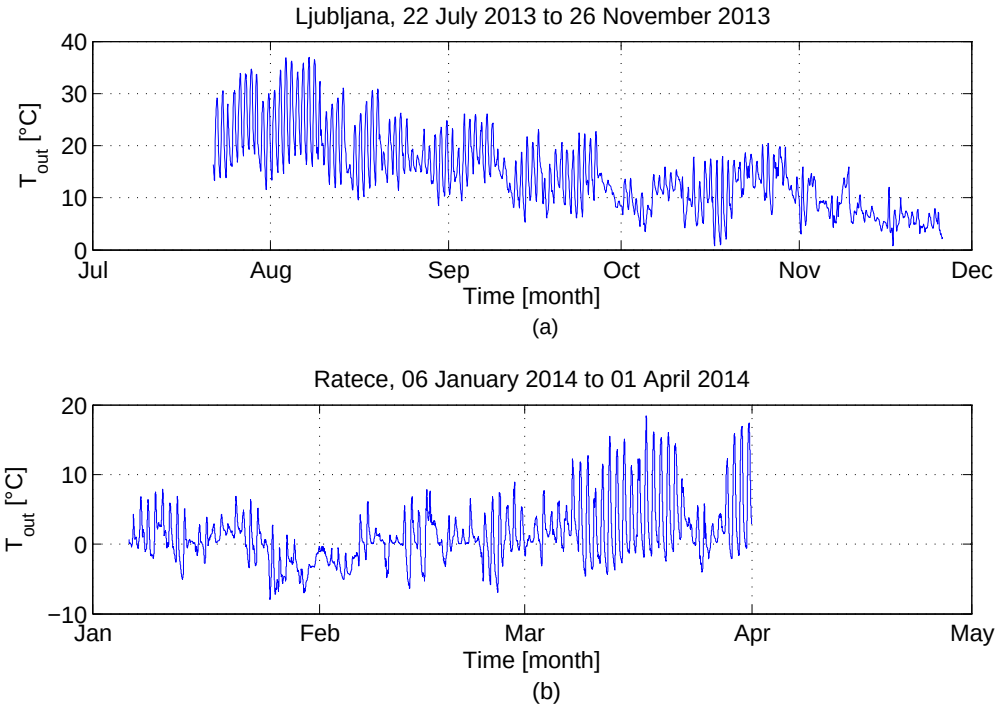


Figure 5.2: Outdoor temperature for weather stations: (a) Ljubljana, Slovenia, between 22 July 2013 and 25 September 2013, (b) Rateče, Slovenia, between 6 January 2014 and 1 April 2014.

for the development of agent applications for interoperable intelligent MASes. For experimental set-up the multi-agent control system (MACS) was deployed using the following sets of agents, where the sensed, inferred, and set-point variables are shown in parentheses and units in brackets:

- EM agents
  $EM_q \in \{EM_1, EM_2\}$
  1. Home environment
  2. Work environment
- Control agents
  $C_{1j} \in \{C_{11}, C_{12}\}$
  1. Heater (T_{sHeat} [°C])
  2. Chiller (T_{sChill} [°C])
- Sensor agents
  $S_{1j} \in \{S_{11}, S_{12}, S_{13}, S_{14}, S_{15}, S_{16}\}$
  1. Indoor temperature (T_{in} [°C])
  2. Outdoor temperature (T_{out} [°C])

3. Occupancy at home (occ_{h} [0 - absent, 1 - present, 2 - sleeping])
4. Relative humidity (RH [%])
5. Clothing insulation (I_{cl} [clo])
6. Metabolic equivalent of task (M [MET])

- Sensor agent
  $S_{2j} \in \{S_{21}\}$
  1. Occupancy at work (occ_{w} [0 - absent, 1 - present])

- ML agents
  $MLA_{1l} \in \{MLA_{11}, MLA_{12}, MLA_{13}\}$
  1. ML agent to generate temperature rise time regression model
  2. ML agent to generate temperature fall time regression model
  3. ML agent to generate home occupancy classifier

- Routing agent
  $R_{1m} \in \{R_{11}\}$
  1. Routing BCVTB-MACS

5.4 Prediction Models

5.4.1 Home Occupancy Prediction

We used the occupancy data described in Section 5.2.1 in order to evaluate the performance of the occupancy prediction models. At the end of each day during the simulation the training dataset and prediction model were created utilising the historical data that was accumulated during the previous days. After each day the new training instances were added to the instances from previous days. The structure of instances that were used for ML is described in Section 4.1.3.1. From the testing instances we removed the instances of the time-steps at which the person was home yet for more than one hour. Those instances were marked as non-interesting for testing. In practical terms, the test instances that would never happen in practice have been removed, since the occupancy had already happened and the reactive mechanism of the control agent would take over the HVAC control operation before such instance would have been classified.

The prediction model was evaluated on the next day using the Weka data mining software (Hall et al., 2009) so that each instance of the next day was classified utilising the prediction model and compared with the real class value. The results in terms of true present, false present, true absent and false absent were stored for the evaluation of prediction models. The occupancy prediction models were evaluated for algorithms C4.5, kNN, and random forest where the output of the prediction model is the predicted occupancy occ^{*}_{h} that has the nominal class value of either 0 or 1. Then we computed the number of transitions of occupancy state at home from $occ_{\mathrm{h}} = 0$ to $occ_{\mathrm{h}} = 1$ (the number of arrivals) for each occupancy dataset, the number of early predictions, and the temporal difference between the predicted and the true transition. The early prediction indicates that the transition was predicted to occur earlier than the real transition happened. The late prediction, in contrast, indicates that the transition was predicted to occur later than it really happened.

5.4.2 Indoor Temperature Rise/Fall Time Prediction

To evaluate the occupancy prediction models, the simulation is not needed, since the evaluation can be performed based on the occupancy dataset alone. In contrast, to evaluate the regression model for the prediction of the rise/fall time of indoor temperature, the simulation has to be performed in order to obtain the training instances. The structure of instances that were used for ML is described in Section 4.1.3.2 and the process of attribute extraction for an instance is shown in Figure 4.1. Regression models are built during the runtime after each change of the set-point T_{s}, when the new instance *rtInst* has been created. The instances for evaluation were obtained from the simulation results of Sense behaviour by occupancy dataset for Person 1.

From the simulation run we obtained O – true rise/fall time k_{RFTT} values, and the corresponding O – predicted rise/fall time k_{RFTP} values. The regression model for the temperature rise/fall time was evaluated incrementally in a similar way as the occupancy prediction model. The rise/fall time classifiers were built and evaluated using Multilayer Perceptron, Gaussian Processes, and Isotonic Regression algorithms. After the evaluation of the testing instances, the vectors $\vec{t}_{\mathrm{RFTT}}$ and $\vec{t}_{\mathrm{RFTP}}$ containing the true and predicted values respectively were created. The mean absolute percentage error (MAPE) was computed according to Eq. (5.1).

$$MAPE = \frac{100}{O} \sum_{i=1}^{O} \left| \frac{k_{\mathrm{RFTT}_i} - k_{\mathrm{RFTP}_i}}{k_{\mathrm{RFTT}_i}} \right| \tag{5.1}$$

5.5 Performance of Control Strategies

In order to interpret the results, taking into account the comfort and the energy consumption, we computed the energy consumed by the HVAC system during the simulation period – Eq. (3.9) and the comfort experience. The comfort experience was evaluated according to (i) the time the indoor temperature differs from a predefined temperature, denoted as comfort temperature, multiplied with the temperature difference – Eq. (3.10), and (ii) the thermal comfort model, where the index PPD was averaged for the occupied period – Eq. (3.24).

For each simulation the comfort experience and the consumed energy was represented as the point in the comfort/consumption space.

5.5.1 Exploiting the Adaptive Prediction Models

We evaluated the performance of control algorithms that include the adaptive occupancy classifiers and the rise/fall time regression models, where the thermal comfort is denoted with the predefined temperature. The term adaptive prediction models indicates that the machine learning is performed on a daily basis in order to improve the models with the fresh data and knowledge, obtained during the last day. The values of set-point parameters for control agents C_{11} and C_{12} are listed in Table 5.3. The home and work occupancy data for five people (see Table 5.1) including the corresponding weather dataset for Ljubljana (see Fig. 5.2) were used for simulation. The metabolic equivalent of task and clothing insulation were fixed at 1.3 MET and 1 clo respectively.

There are three set-point values: T_{sHi}, T_{sLo}, and T_{sSl}. T_{sHi} and T_{sSl} represent the predefined values for indoor temperature at which the occupant feels comfortable during presence and sleeping, respectively. Each control agent implemented either On, Off, Sense or Learning control behaviour. When a control agent implements Learning behaviour,

Table 5.3: Controller set-point parameters.

C	T_{sHi} [°C]	T_{sLo} [°C]	T_{sSl} [°C]
C_{11}	21.5	5.0	18.5
C_{12}	25.0	40.0	26.0

it firstly creates and launches the appropriate ML agent, which is used to generate classification or regression models, as described in Section 4.3.5. Classification models for occupancy prediction were generated utilising the $\text{C4.5}_{\text{dist}}$, C4.5, random forest, kNN, and kNN_{dist} (where $k = 5$) algorithms. Regression models for rise/fall time prediction of indoor temperature were generated utilising a multilayer perceptron, Gaussian processes, and isotonic regression. Results of the models are presented in Section 6.1. The performances of various control behaviours are presented in the comfort/consumption space, where the comfort experience is evaluated according to Eq. (3.10) and compared to reactive strategy, realised with the Sense behaviour.

5.5.2 Comfort Regulation at Dynamic Metabolism and Clothing

We performed simulations on the synthetic dataset described in Section 5.2.1.1. A simulation starts with $PMV_{\text{ref}} = 0.00$ and for each further simulation the PMV_{ref} is incremented for 0.01 until the value $PMV_{\text{ref}} = 0.50$ (51-st simulation run). Note that 80 % of the energy consumed by a person was transformed to heat as defined in dynamic model.

We inspect various results regarding the comfort experience and the energy consumption with simulations for five people on five different synthetic datasets. The true (reference) M was obtained using Cosmed K4 b^2 equipment and the estimated M was obtained using a smart-phone accelerometers with software developed by Cvetković, Kaluža, Milić, and Luštrek (2013) who proposed the estimation of human energy expenditure M using the smart-phone. In order to use smart-phone-based estimation of M to compute and regulate the occupant's comfort experience, we performed a number of experiments to analyse the influence of error in estimation of energy expenditure on computation and regulation of comfort. Furthermore, we analysed the influences on the evaluation of the occupant's thermal comfort, when the personal parameters such as M and I_{cl} are assumed as fixed as simplified in related work and compared to the evaluation where dynamic personal parameters are used. The later approach enables better simulation of the real living domain. The simulation results are presented in the comfort/consumption space and shown in Section 6.3.3.

5.5.3 Comfort Regulation with Occupancy Prediction and Rules

Finally, we performed a long-term evaluation of control system performance, where the occupant's metabolic equivalent of task and clothing insulation were fixed. The weather dataset for the winter-spring period in Rateče (see Fig. 5.2) was taken into account for simulation. The occupancy datasets were similar as given in Table 5.1, but shifted to the winter time in order to examine the heating performance of the HVAC system.

Section 5.5.1 describes the experimental set-up, where (i) the simple definition of comfort was used to evaluate the comfort experience and (ii) the reactive and anticipative mechanism of control strategy were implemented to delegate the indoor set-point temperature. In contrast, this section describes the experimental set-up, where the comfort experience was regulated by means of ISO-PMV model of comfort, the comfort experience

was evaluated by means of predicted percentage dissatisfied index *PPD* and the control strategy was enriched with the rule-based mechanism for absence prediction.

Subsection 6.2.2 presents the results that show the improvement of comfort experience due to occupancy prediction and expert rules in comparison to reactive strategy. The results in comfort/consumption space are presented in Section 6.3.2 where the comfort experience is evaluated with Eq. (3.24).

Chapter 6

Results

In this chapter the experimental results are presented. Firstly the accuracy of the incrementally generated regression models for the rise/fall time of the indoor temperature is presented. Than the accuracy of the incrementally generated prediction models for home occupancy is presented. The simulations were performed utilising the reactive and anticipative mechanisms of the control system in order to evaluate the performance of the control strategies over a longer period of time. For that purpose the dynamic model of a building and the data about the home and work occupancy were used in order to perform the occupancy prediction at home and also for the evaluation of the occupant's comfort experience. The best occupancy prediction models, that were obtained by the C4.5 decision tree, were further improved with expert rules. Then the short-term simulations were performed for the two days period in order to evaluate the performance of the comfort regulator. For that purpose the dynamic data about the metabolism and clothing of an occupant were included. Finally the comfort regulator operating at various control strategies was evaluated. The control strategies include the combinations of anticipative, reactive, and rule-based mechanisms. For that purpose the simulation of winter conditions was performed in order to study the relations between the energy consumption, the comfort experience, and the various control strategies. The relations could be presented as a grid that expresses the comfort/consumption trade-off.

6.1 Indoor Temperature Rise/Fall Time Prediction

In 126 days there were 64 instances for rise time and 166 instances for fall time. An example of attribute extraction to create an instance is shown in Figure 4.1. Table 6.1 shows the MAPE for each of the regression algorithms for rise time and fall time. According to the results we decided to choose the modelling approach utilising the Isotonic Regression for further simulations, because it achieves the lowest MAPE for both rise time and fall time prediction models – that is, 29.3 % and 19.7 %, respectively.

Table 6.1: MAPE for each of the regression algorithms for rise time and fall time. Bold values represent the best results.

Regression algorithm	Rise time	Fall time
Gaussian processes	36.0	24.7
Isotonic regression	**29.3**	**19.7**
Multilayer perceptron	37.0	24.5

The reason for low accuracy relies on a simplified structure of a regression model. The impact of wrong occupancy prediction on energy consumption is presented in the following sections is much higher in comparison to the impact of wrong rise/fall time prediction. Therefore we did not aim to improve the rise/fall time regression model at this stage. That could be improved with a better model structure, such as proposed by Vrečko et al. (2009). They incorporated a dead-band and a non-linear relation between the rise/fall time coefficient, indoor temperature and set-point temperature.

6.2 Home Occupancy Prediction

6.2.1 Home Occupancy Classification

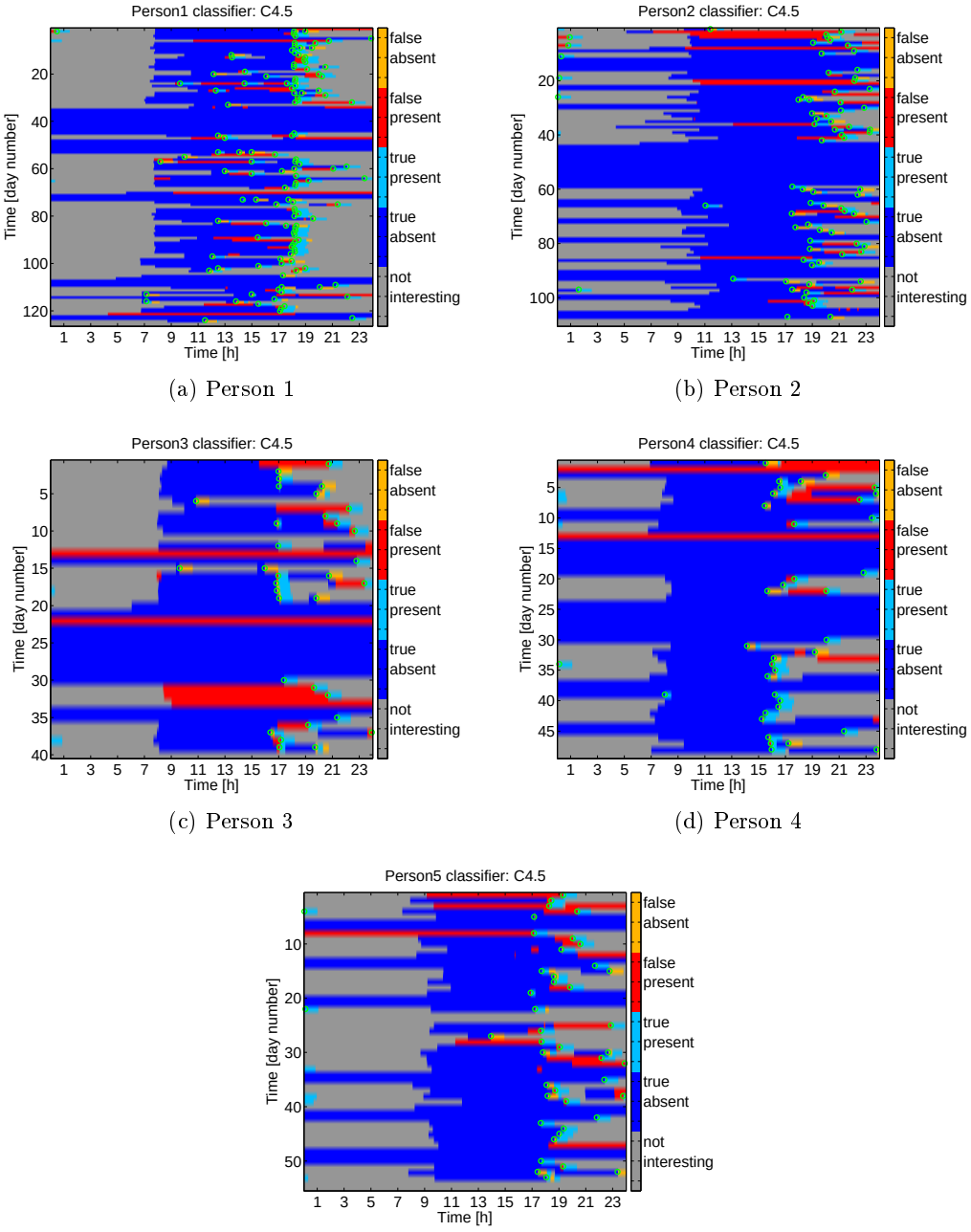
Occupancy prediction was evaluated before the simulation of the heating process. Results are shown in Figure 6.1. The interesting parts of each subfigure are indicated with the green points that represent the transition of the occupancy state from absent to present. The best transitions are blue → light-blue signifying that the classifier made an exact prediction so there were no misclassified instances. Interesting transitions are also blue → red → light-blue which signify that the occupancy was predicted too early. In such cases, Learning behaviour turns on heating or cooling before the occupant arrives, thereby improving the comfort experience but increasing the energy consumption. The orange areas signify that the occupancy was predicted too late. Such events are not desirable. The C4.5 algorithm did the most early predictions, as shown in Table 6.2. Random forest was slightly better on the dataset for person 2.

Table 6.2: The results of the occupancy predictions. Bold values indicate the best result by each person. Note: RF indicates the random forest algorithm.

Person	No. arrivals	Early predictions (%)		
		C4.5	RF	kNN
Person 1	126	**62 (49)**	59 (47)	59 (47)
Person 2	78	43 (55)	**44 (56)**	33 (42)
Person 3	33	**17 (52)**	15 (45)	14 (42)
Person 4	37	**15 (40)**	14 (38)	14 (38)
Person 5	45	**30 (67)**	26 (58)	24 (53)

In order to analyse the time gaps for occupancy predictions (early or late predictions), we computed the difference in minutes between the true arrivals and the predicted arrivals. For each of the three classifiers the time gaps for all people were combined and sorted from the earliest to the latest prediction of the arrival. The early predictions are represented as negative numbers and the late predictions are represented as positive numbers.

Figure 6.2 shows the results, where each of the three classifiers is represented with its corresponding curve. The horizontal axis indicates the number of instances. According to the Table 6.2 we compute that the sum of transitions for all people is 319. The vertical axis indicates the time gap in minutes. The amount of the early predictions and the corresponding time gaps is of greater importance in contrast to the late predictions. By early predictions, room conditioning is therefore less efficient because more energy is lost due to unnecessary operation of HVAC system. By late predictions the reactive mechanism of set-point delegation strategy overrides the anticipative mechanism. We can observe that the classifier that is generated using the algorithm C4.5 shows the best results. C4.5



(a) Person 1

(b) Person 2

(c) Person 3

(d) Person 4

(e) Person 5

Figure 6.1: Occupancy prediction results for five people. The horizontal axis indicates the time of a day with a minute granularity. The vertical axis indicates the sequential number of days from the start of simulation. The orange, red, light blue, dark blue, and grey colours represent the results of occupancy prediction in terms of the false absent, the false present, the true present, the true absent, and the periods that are not interesting, respectively. The green dots indicate the transition of occupancy state from the real absent to the real present.

produces the minimum gaps of early predictions.

In order to analyse the result of classification algorithms around smaller gaps more precisely, the vertical axis is magnified and the result is shown in Figure 6.3. We can observe that the C4.5 classification algorithm outperforms the other two. C4.5 algorithm predicts occupancy more than one hour prematurely 41 times, that is by roughly 13 % of all instances. More than one hour prematurely prediction is done by random forest 67 times (21 % of all instances) and by kNN 90 times (28 % of all instances). The effect of prematurely predicted occupancy results in extensive energy consumption. That will be demonstrated later in Section 6.3.1. In the following section we present the results, where the false occupancy predictions were reduced when a rule-based mechanism was included.

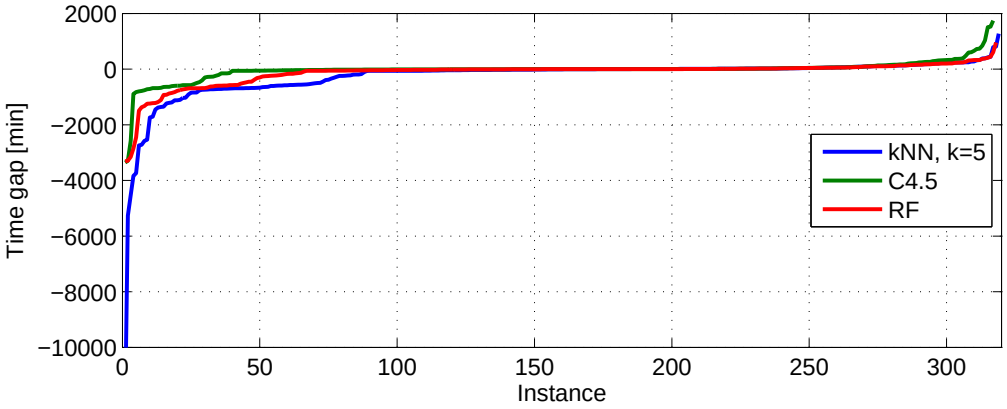


Figure 6.2: The time gaps between the true and the predicted occupancy obtained with the occupancy prediction algorithms kNN where $k = 5$, C4.5 and random forest (indicated as RF). The horizontal axis indicates the number of instances. The vertical axis indicates the time gap in minutes.

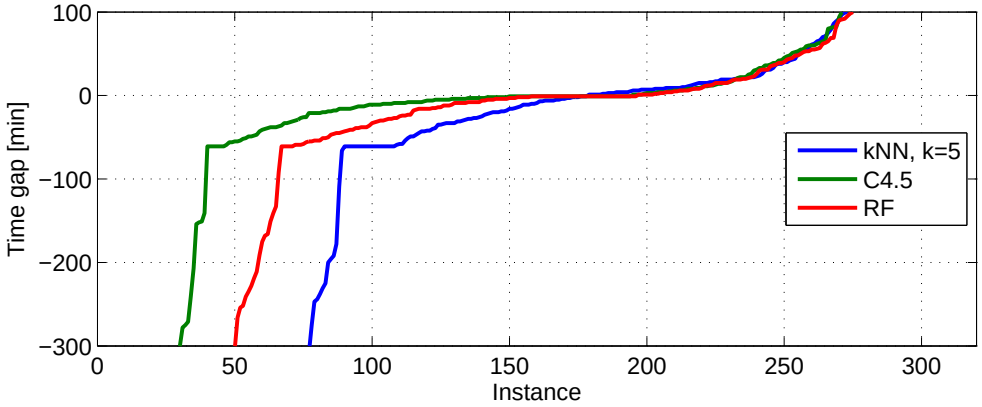


Figure 6.3: The magnified time gaps between the true and predicted occupancy as obtained with kNN where $k = 5$, C4.5 and random forest (indicated as RF) classifier. The horizontal axis indicates the number of instances. The vertical axis indicates the time gap in minutes.

6.2.2 Expert Rules to Reduce False Occupancy Predictions

In order to show the difference between the operation of reactive and anticipative control strategies, we plotted the time series of the corresponding *PPD* curves. The result is shown in Figure 6.4. In each subfigure, the horizontal axis indicates the date (the tick labels show the day/month) and the vertical axis indicates the value of *PPD*. Solid curves indicates the value of *PPD* for the time periods during which the home was occupied. Dashed curves indicates the time periods during which the home was not occupied. Figure 6.4(a) represents the time series of *PPD* where the Sense behaviour (specified in the Table 4.3) was applied and Figure 6.4(b) represents the time series of the *PPD* where a Learning behaviour (specifically the Learning6 according to the Table 4.3) was applied.

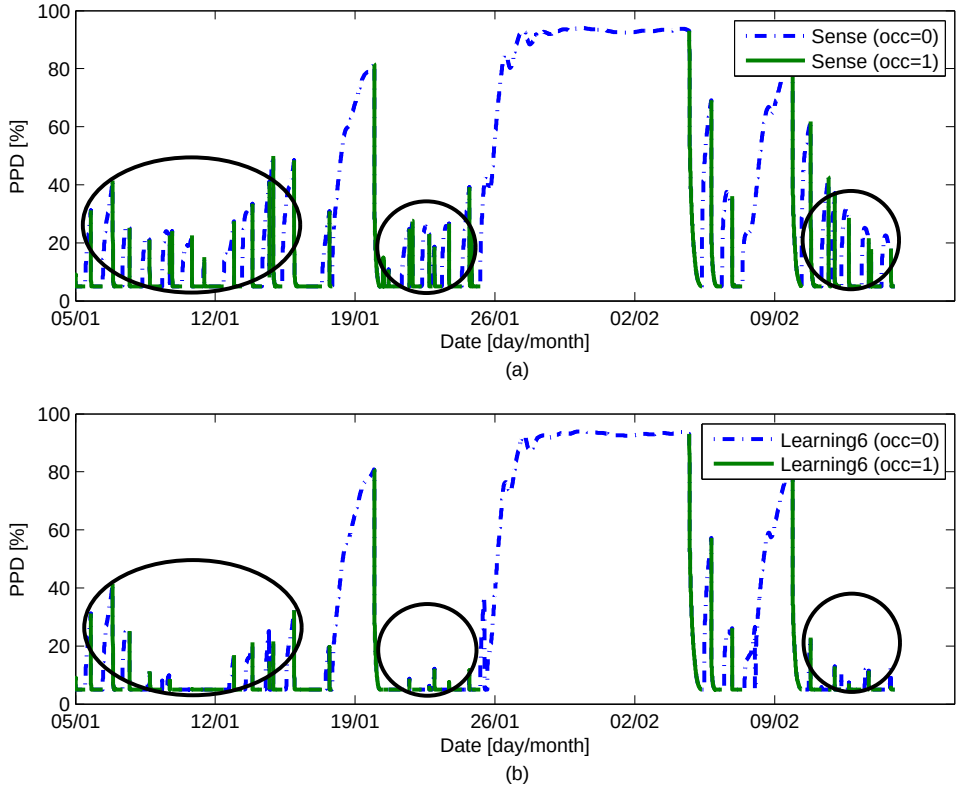


Figure 6.4: The comparison between the *PPD* time series, produced by: the (a) Sense behaviour, and (b) Learning behaviour. The solid curve indicates the *PPD* during the occupancy, while the dotted curve indicates the *PPD* during non-occupancy. Ellipses indicate the difference between the Sense and Learning behaviours.

Learning behaviour in comparison with Sense behaviour achieved a significant improvement in terms of comfort at time periods during which the occupant returns home. The extremely high values of *PPD* are much larger and more frequent by Sense behaviour, which is indicated with the ellipses and demonstrates an often low comfort experience during the transitions of occupancy state from $occ_k = 0$ to $occ_{k+1} = 1$. Learning behaviour predicts the occupancy transition early enough in many cases so the appropriate temperature $T_s = T_{sHi}$ is ensured when the occupancy begins in order to provide satisfactory range of *PMV* values. Sense behaviour in contrast to Learning consumes almost no energy when the home is not occupied (it maintains the T_{sLo} temperature). Consequently the dashed

curve after transitions $occ_k = 1$ to $occ_{k+1} = 0$ always rise towards the value of 100 %. Learning behaviour depends on the occupancy prediction algorithm and rules and often performs regulation of PMV also after the transition $occ_k = 1$ to $occ_{k+1} = 0$, since the occupancy in near-future was predicted.

To summarise, the comfort experience with Learning behaviour can only be as poor as by Sense behaviour, but never worse. On the other hand the results in terms of energy consumption obtained with Learning behaviour is never lower than the result obtained with Sense behaviour. Sense behaviour achieves the lowest possible energy consumption when the regulation of PMV is performed.

6.3 Simulation of Heating Ventilation and Air-Conditioning Control

In the following sections the results of the control strategies are presented. In Section 6.3.1 the simulation results where the temperature set-point delegation was supported with the rise/fall time modelling and with the occupancy prediction modelling are presented. Section 6.3.2 presents the results, where the rule-based absence prediction mechanism was included to reduce the overall energy consumption, the comfort regulator was used for comfort regulation with respect to the ISO-PMV model (regulation of PMV index), and the comfort experience was evaluated by means of PPD index. In Section 6.3.3 the simulation results where the comfort regulator was evaluated by dynamic M and I_{cl} are presented.

6.3.1 Control Strategy With Occupancy Prediction Algorithms

The dynamic model of a building was used to simulate the occupant's comfort experience and the energy consumption. The occupancy datasets for each person was used and the following control behaviours were used in order to control the heating and cooling processes (in that experiment the rule-based mechanism was not included):

- On,
- Off,
- Learning with C4.5, $\mathrm{C4.5_{dist}}$, random forest, kNN, and $\mathrm{kNN_{dist}}$ where $k = 5$ that represent the anticipative and the reactive mechanisms,
- Sense that includes reactive mechanism only.

We adopted the Sense behaviour as a baseline for evaluating the other control behaviours. To evaluate different behaviours we devise the index D_{Learning}:

$$D_{\mathrm{Learning}} = \frac{IC_{\mathrm{Sense}} - IC_{Behaviour}}{E_{\mathrm{PTHP},Behaviour} - E_{\mathrm{PTHP,Sense}}} \frac{E_{\mathrm{PTHP,Sense}}}{IC_{\mathrm{Sense}}} \tag{6.1}$$

where $IC_{Behaviour}$ and E_{PTHP} are computed according to Eq. (3.10) and Eq. (3.9), respectively. The index D_{Learning} represents the ratio between the normalised decrease in discomfort (which should be as large as possible) and the normalised increase in energy consumption (which should be as small as possible) with respect to comfort and energy consumption that is achieved with Sense behaviour. The greater the index D_{Learning}, the better the control behaviour.

Improvements of the agent's control behaviour with respect to Sense behaviour are shown in Table 6.3. If the value of D_{Learning} is higher than 1, then the relative decrease

of comfort by other behaviour compared to Sense behaviour is higher than the relative increase of energy consumption. If the value of D_{Learning} equals 1, the relative increase of energy consumption is the same as the relative decrease of comfort. If D_{Learning} is lower than 1, then much more energy is required for a relatively small improvement in terms of comfort. We intend to achieve as high D_{Learning} as possible. In our experiments the Learning behaviour that uses the occupancy classifier C4.5 always provided greater comfort at the expense of an increase in energy consumption.

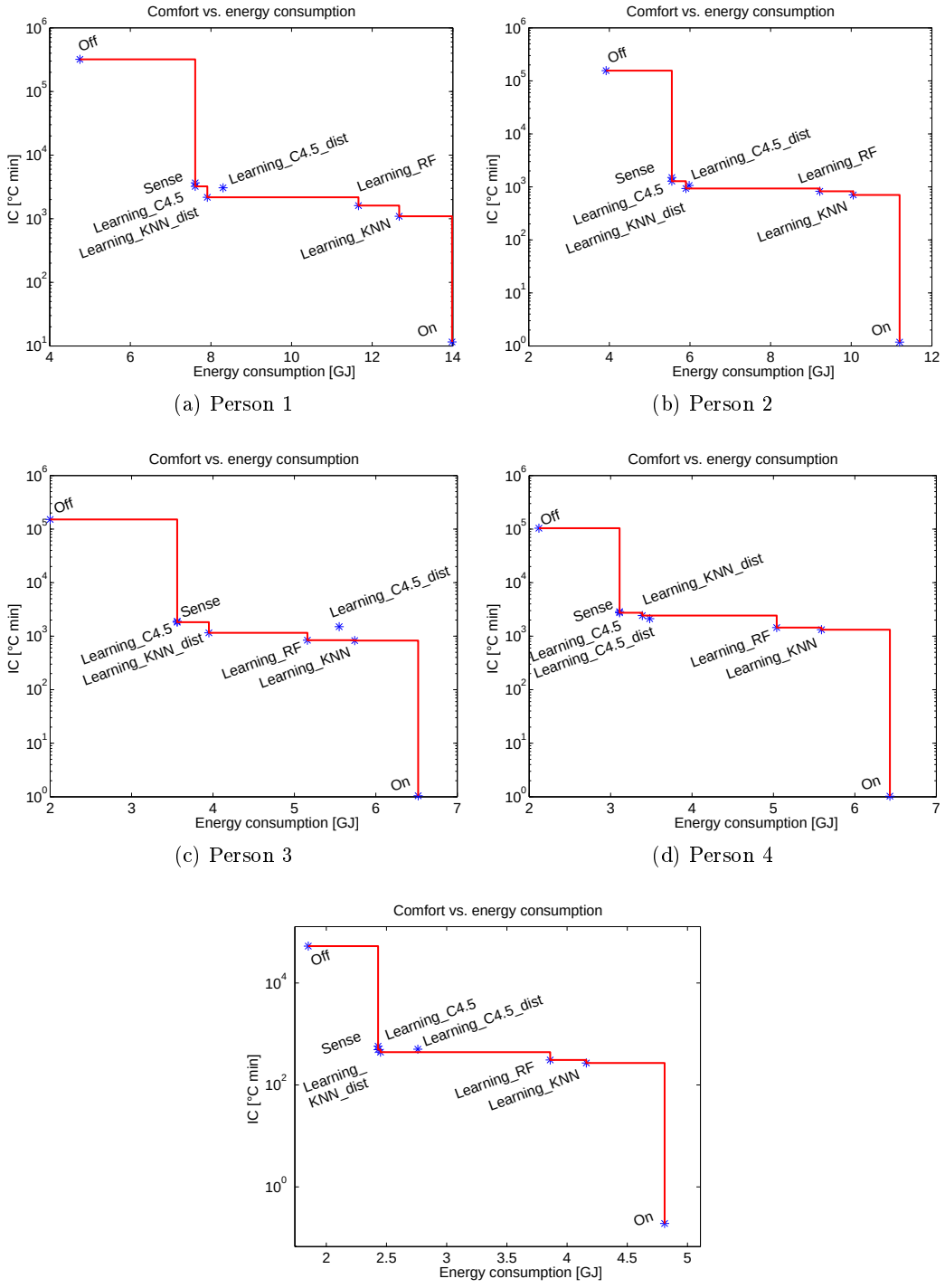
Table 6.3: Index D_{Learning} representing comfort vs. energy improvement of different versions of Learning behaviours with respect to Sense behaviour. Bold values indicate the best results for each person.

	Classification			Distribution	
D_{Learning}	C4.5	RF	kNN	$\text{C4.5}_{\text{dist}}$	kNN_{dist}
Person 1	**372.42**	0.99	9.15	1.93	9.15
Person 2	**818.67**	0.68	0.66	3.78	6.01
Person 3	**136.78**	1.24	0.92	0.37	3.58
Person 4	**151.44**	0.80	0.68	2.20	1.75
Person 5	**357.97**	0.79	0.75	0.95	28.85

Results are shown in Figure 6.5. Each subfigure shows the results for the simulated control behaviour where the data about the occupancy was obtained for one person. As expected, On behaviour results in the best comfort experience and the highest energy consumption, while Off behaviour results in the worst comfort experience and the lowest energy consumption. The red line connects the non-dominated results – solutions in the comfort/consumption space and represents an attainment surface which can be assumed as an approximation of the Pareto frontier. Non-dominated points are those that are not worse than any other point in terms of both the comfort experience and the energy consumption. By Learning behaviour the most promising results were obtained with the implementation that utilises the C4.5 classification algorithm for occupancy prediction if the occupant prefers to spend less energy, or an algorithm like the kNN (both variants) or the random forest if the occupant prefers a higher comfort experience. Note that the vertical axis, which indicates the value of the *IC* index, uses a logarithmic scale for better visualisation. In practical terms, Person 5 consumes 2.43 GJ of energy for heating and cooling and achieved an *IC* of 577 by the Sense behaviour. By the Learning behaviour which implements the kNN_{dist} algorithm, 2.45 GJ of energy (0.02 GJ more) is spent and the *IC* of 440 (133 less) is achieved. In other words, by Person 5 0.8 % more energy is spent and 23.7 % better comfort experience is achieved, which results in $D_{\text{kNN}_{\text{dist}}}$ of 28.85.

6.3.2 Control Strategy Enriched with Expert Rules and Comfort Regulator

To compare the comfort experience and the energy consumption for different implementations of control behaviours, we performed simulations with settings for different control behaviours for occupancy data of five volunteers. Table 4.3 shows the control behaviours included in the experiment. There are two basic behaviours (On, Sense) for which no additional rules were included. Then there are seven versions of Learning behaviours, where anticipative and reactive mechanism are always included. Different combinations of mechanisms and variables that signify the absence type with the corresponding constants C_{tAbs}, C_{t1} and C_{t2} make Learning behaviours different.



(a) Person 1

(b) Person 2

(c) Person 3

(d) Person 4

(e) Person 5

Figure 6.5: The results in terms of comfort and energy consumption for five people, where the horizontal axis indicates an electric energy consumption by a heat pump that is used for heating and cooling, for the whole simulation period in GJ. The vertical axis indicates the index *IC* for the whole simulation period. Each star in the figure indicates a result of a control behaviour. The red line connects the non-dominated solutions in the comfort/consumption space.

In Figure 6.6 the simulation results where the occupancy data of five persons was included for the experiment are presented in subfigures for each person. Each subfigure represents a comfort/consumption space. The horizontal axis indicates the consumed energy [GJ] in a controlled room for the simulation period and the vertical axis indicates the average value of *PPD* [%] for the simulation period, but only during the occupancy. Different marker shapes indicate the results of different control behaviours, according to Table 4.3 for different PMV_{ref}. The lower marker of the same shape indicates the result for the depicted algorithm with $PMV_{\text{ref}} = 0.00$ and each marker above represents the PMV_{ref} increased for 0.05 so that each marker of the same shape belongs to the value PMV_{ref} of 0.00, 0.05, 0.10, 0.15 and 0.20, from bottom to top, respectively. The solid line connects the non-dominated solutions in the comfort/consumption space and indicates an attainment surface which can be assumed as an approximation of the Pareto frontier. This indicates that there were no better solutions found in terms of both the comfort and the energy consumption aspects. We did not include the results of Off behaviour, because Off behaviour does not regulate comfort in terms of ISO-PMV index *PMV* and is therefore not relevant for the comparison.

Figure 6.6 confirms that by each of the five people Sense behaviour consumes the least energy for the fixed value of PMV_{ref} compared to On or any version of Learning behaviour at the same value of PMV_{ref} threshold. Furthermore it is clear that the layout of markers that indicate the results in the comfort/consumption space is equal for each person. If we fix the value of PMV_{ref}, the behaviours have the following order: control behaviour, at which the most energy is consumed is On, followed by Learning4, Learning7, Learning5, Learning6, Learning1, Learning2, Learning3 and Sense.

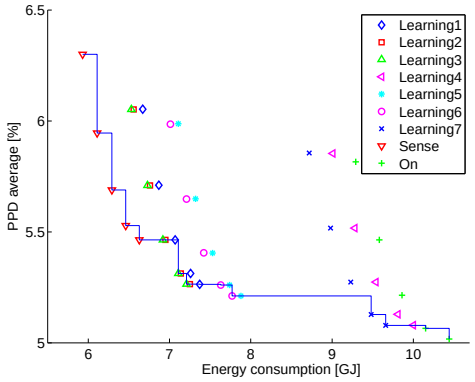
6.3.3 Comfort Regulation During Occupant's Various Daily Activities

We performed 51 simulations on the synthetic dataset explained in Section 5.2.1.1. A simulation starts with $PMV_{\text{ref}} = 0.00$, and each further simulation has PMV_{ref} incremented for 0.02 until the value $PMV_{\text{ref}} = 1.00$ (51-st simulation run). Note that 80 % of the energy consumed by a person was transformed to heat as defined in the dynamic model.

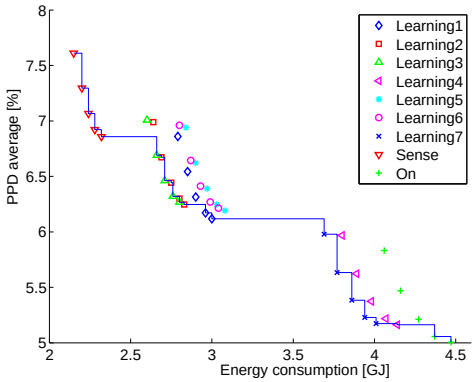
A simulation result of a section of a day (200 minutes) is shown in Figure 6.7 where the PMV_{ref} was set to 0.10. It shows the controller's performance when the metabolic equivalent of task M is highly dynamic. Between the 2200th and 2220th minute M decreases from 2.2 MET to 1.3 MET. As a consequence the *PMV* decreases immediately and the controller starts increasing the T_{in} which can be observed around the 2220th minute. It increases T_{in} until the *PMV* reaches the value of 0.10 in the 2230th minute, where a small overshot can be observed (0.5 °C difference between the values of T_{in} in the 2230th and 2250th minute). Afterwards, the controller handles small changes of *PMV* due to small changes of M. Between the 2260th and 2320th minute M changes rapidly for approximately 1 MET. We can observe that the controller could not handle large changes in a short timespan, so in that period the *PMV* fluctuates between $+1$ and -1. In the next period (until the 2340th minute), the controller increases the temperature and consequently stabilises the *PMV*. Finally, in the period between the 2340th and 2380th minute we can observe more efficient handling of *PMV* since the *PMV* is not fluctuating greatly. It changes between $+0.2$ and $+0.7$, which denotes a slightly warm sensation.

After each simulation run the energy that was consumed by HVAC was computed according to Eq. (3.9) and the average value of *PPD* during occupancy was computed according to Eq. (3.24). 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.

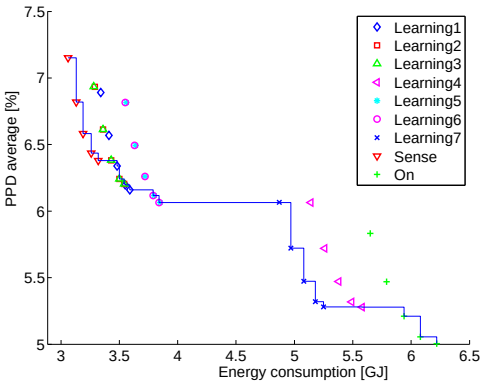
The results are shown in Figure 6.8 in the comfort/consumption space. Simulation



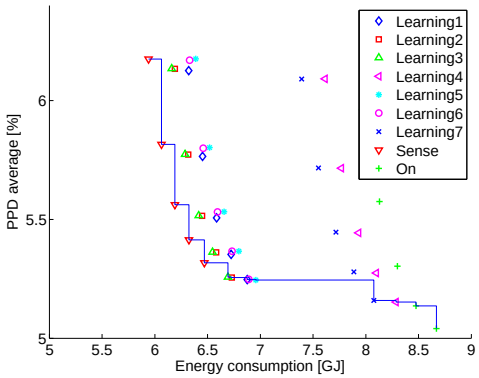
(a) Person 1



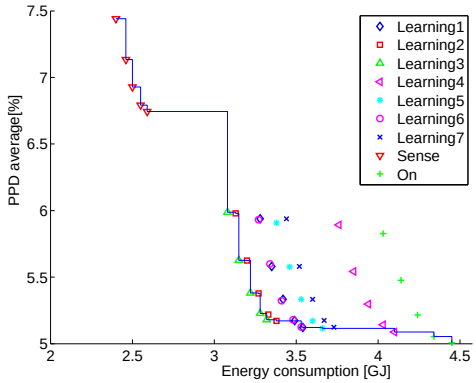
(b) Person 2



(c) Person 3



(d) Person 4



(e) Person 5

Figure 6.6: Simulation results for five people and for the values of PMV_{ref} fixed at $0.00, 0.05, 0.10, 0.15$ and 0.2. Control behaviours: On, Sense, and all versions of Learning behaviour.

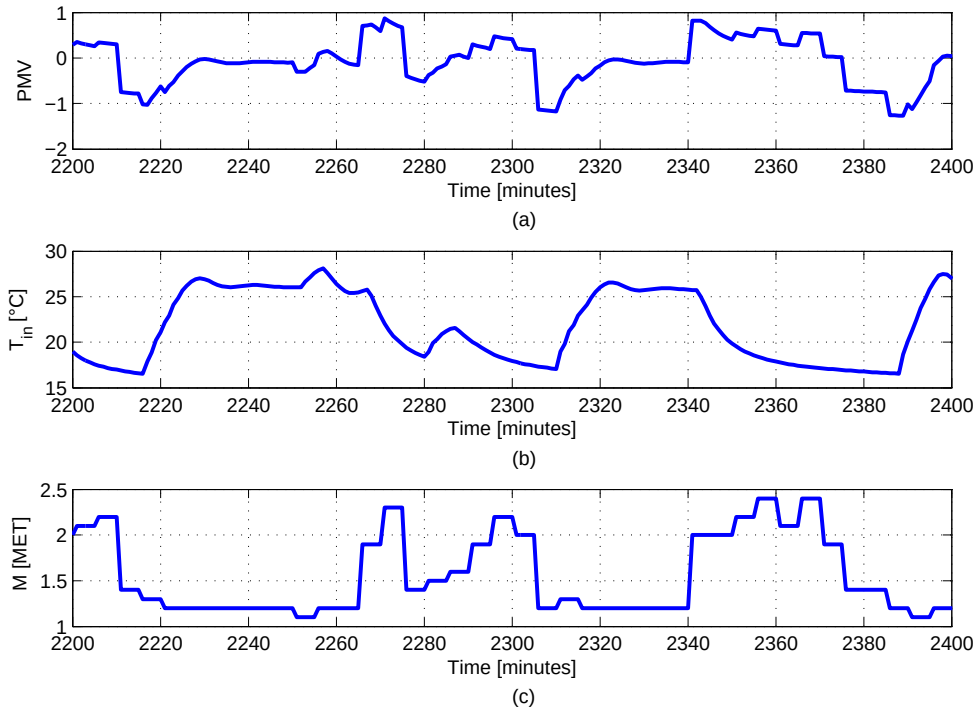


Figure 6.7: A section of a day, when a person performs low-intensity activities. PMV (a), T_{in} (b), M (c).

results for one occupant are represented with the same marker. The rightmost marker of each series is a simulation result when PMV_{ref} is 0.00. Higher values of PMV_{ref} shift the result markers to the left, giving the leftmost marker when PMV_{ref} is 1.00. Lower values of $\overline{PPD}$ and energy represent better comfort experience and lower energy consumption. Synthetic dataset, that was composed of heuristically assigned values for clothing insulation and of estimated values for occupant's metabolic equivalent of task, is presented in Section 5.2.1. It was used for experimental evaluation of comfort regulator at dynamic occupant related variables M and I_{cl}.

We can observe that by Person C the lowest values for both objectives were achieved, thus producing the best result. This is related to the person's low home presence rate (56 %), as shown in Table 5.2. A low "At Home" rate implies a lower energy consumption and 0 hours of vigorous activities implies that the control system did not need to handle severe changes of PMV. The worst results are obtained for persons A and D, who have lower "At Home" rate and higher M. A higher M results in higher $\overline{PPD}$, in this case above 20 %, which indicates a low overall comfort experience. Persons B and E obtain average results. Their "At Home" rate is higher, which results in higher energy consumption at low values of PMV_{ref} in comparison to the other persons. Because person B perform high-intensity activities in comparison to Person E, the worse overall comfort experience is achieved.

Figure 6.9 compares the different parameter configurations for Person E, again simulated for 51 different values of PMV_{ref}. The configuration parameters, listed in the legend, are the following:

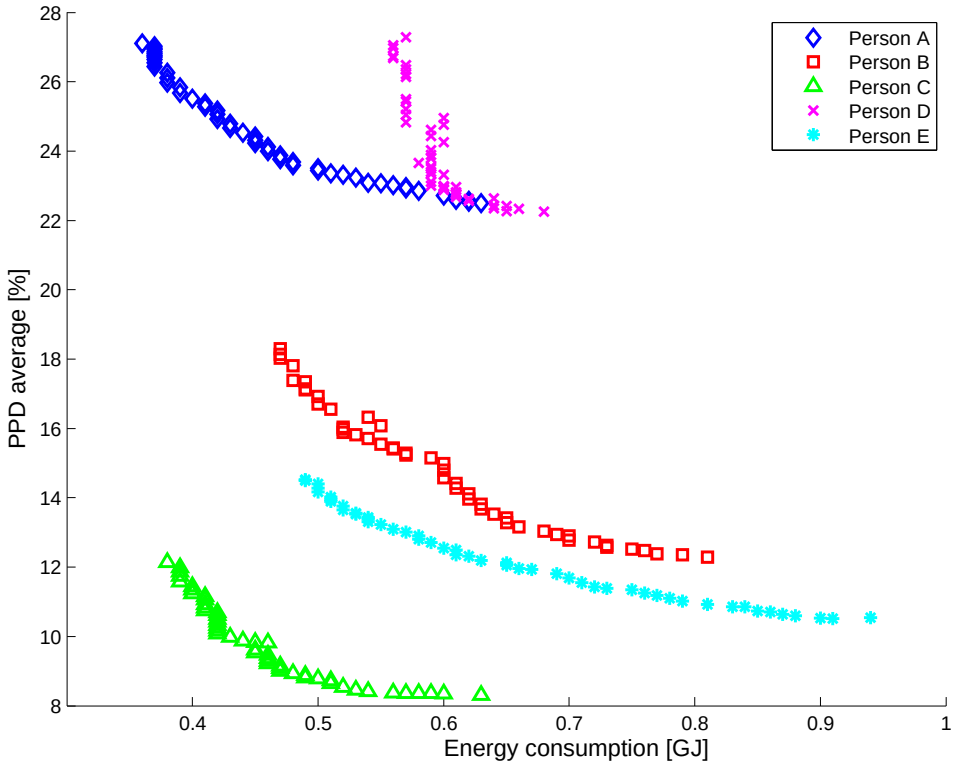


Figure 6.8: The comfort/consumption space: the horizontal axis indicates the energy consumed by HVAC in GJ and the vertical axis indicates the comfort experience – $\overline{PPD}$ expressed in percent (%). Each marker indicates a result of a simulation run for a different PMV_{ref} and different marker shape indicates different person. The relation between the marker style and a person is shown in the legend.

- the fixed M indicates a group of simulation results where the fixed M (1.2 MET) and the estimated I_{cl} were used for both regulation and evaluation,
- the fixed I_{cl} indicates a group of simulation results where the estimated M and the fixed I_{cl} (1 clo) were used for both regulation and evaluation,
- the fixed M and I_{cl} indicates a group of simulation results, where $M = 1.2$ MET and $I_{\text{cl}} = 1$ clo were fixed during the entire simulation run as seen in related work (Cigler, Prívara, Váňa, Žáčeková, & Ferkl, 2012),
- the measured M indicates a group of simulation results where the true M obtained with Cosmed K4 b^2 and estimated I_{cl} were used for both regulation and evaluation,
- the estimated M and I_{cl} indicates a group of simulation results, where the estimated M and estimated I_{cl} were used for both regulation and evaluation,
- the last marker in the legend indicates simulation results, obtained when the regulation of PMV was performed with an estimated M, but final evaluation of comfort – PPD was computed with the corresponding true M, obtained with Cosmed K4 b^2. Estimated value of I_{cl} were used for both regulation and evaluation.

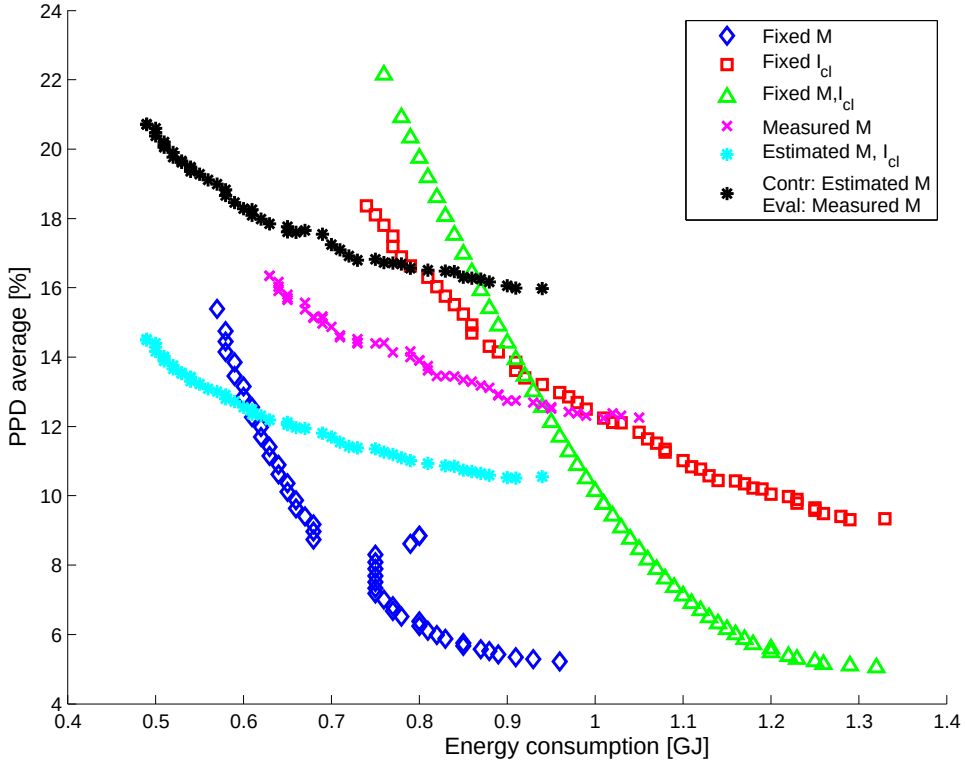


Figure 6.9: The comfort/consumption space: The horizontal axis represents the energy in GJ, consumed by HVAC and the vertical axis represent the comfort experience - $\overline{PPD}$, expressed in percent (%). Each marker represents a result of a simulation run for different PMV_{ref} and different assumption of the occupant's parameters configuration. Relation between the marker style and the parameter configuration is shown in the legend.

Measured M indicates the results that would be obtained by ideal conditions if M would be measured accurately and so the computation of PMV and PPD would also be accurate. The difference in locations of results, that were obtained with measured M and those obtained with estimated M and I_{cl}, occurs due to the error in estimation of M. The results obtained with estimated values slightly underestimate the $\overline{PPD}$ and the energy consumption. The perception of the occupant's comfort experience is wrong for approximately 2 % and the energy consumption is lower for 0.15 GJ in two days.

Therefore we performed simulations, where PMV was computed and regulated according to the estimated M and evaluated according to the measured M. Therefore the energy consumption is similar as by evaluation according to the estimated M. The difference between the $\overline{PPD}$ values is approximately 6 %. Those results show the evaluation using the true values of PMV and PPD (computed with true M), however for the regulation of PMV the estimated M was used.

We can observe that using fixed values of M and I_{cl} makes the regulation underestimate the $\overline{PPD}$ and consumes much more energy in comparison to the measured M at lower PMV_{ref} thresholds. At higher PMV_{ref} thresholds the $\overline{PPD}$ is overestimated and the energy consumption is higher.

The fixed I_{cl} implies higher energy consumption, but a similar range of $\overline{PPD}$. In such a case, the energy consumed for heating when the occupant sleeps is higher due to the

lower clothing insulation (1 clo) in comparison to the estimated I_{cl} value that was assumed as 2 clo for sleeping. A similar effect occurs when a person exercises. If the I_{cl} is fixed, the energy consumed for cooling when the occupant exercises is higher due to the higher clothing insulation (1 clo) in comparison to the estimated value of I_{cl} that is assumed as 0.5 clo when the occupant exercises.

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

6.3.4 The Grid Expressing the Comfort/Consumption Trade-off

Based on the results shown in Figure 6.6 we connected the points in the comfort/consumption space in a way to demonstrate the relationships between the energy – comfort and the PMV_{ref} – behaviour. In Figure 6.10 the results for Person 1 (as Figure 6.6(a)) are shown. The dotted lines connect the results of different behaviours with the same PMV_{ref} and the solid lines connect the results of the same behaviours with the different PMV_{ref}.

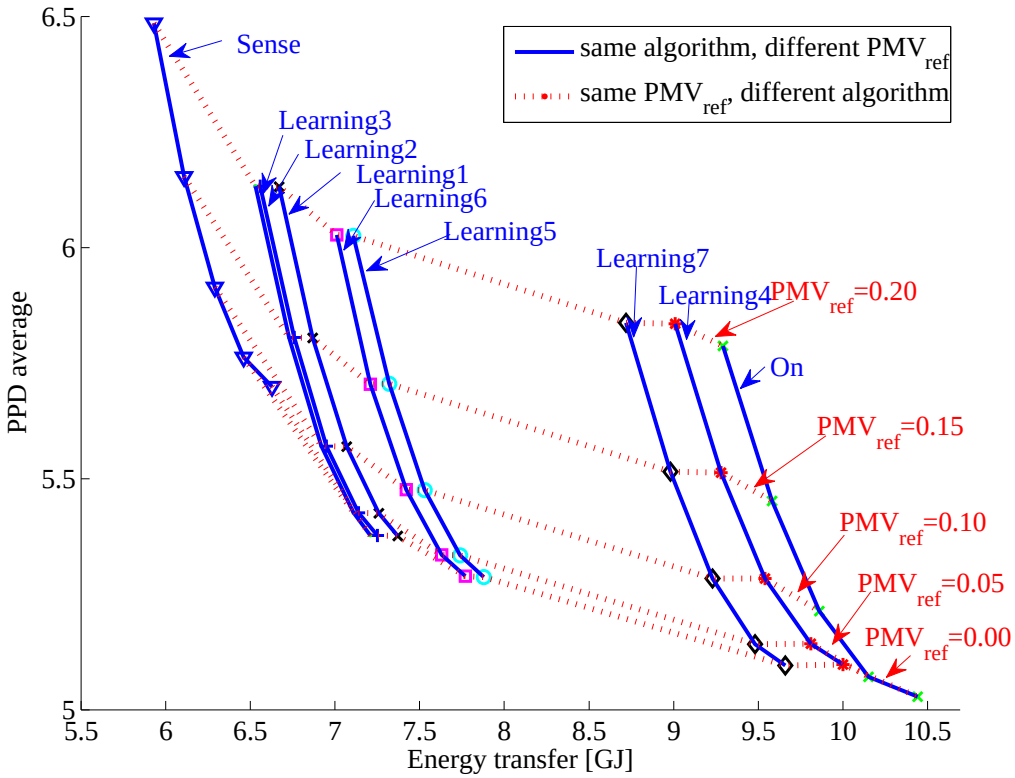


Figure 6.10: The grid on the comfort/consumption space, where red lines connect the results of different control behaviours with the same PMV_{ref} and blue lines connect the results of same control behaviours with the different PMV_{ref}.

Based on Table 4.3 and Figure 6.10 we can observe that rule constants affect the energy consumption. Learning1 and Learning2 differ only for a different value of C_{tAbs}. If C_{tAbs} is lower, the energy consumption will also be lower, as demonstrated with the

simulation results for Person 2 and 3 in Figures 6.6(b) and 6.6(d). Similar effect can be obtained when changing the values of C_{t1} and C_{t2}. If the period expressed with the interval $[C_{t1}, C_{t2}]$ is larger, then the energy consumption will decrease, which is obvious by Person 4 (Figure 6.6(d)). When fitting the parameter values, one have to be careful not to destruct the effect of other rules. For example, if the value of C_{tAbs} is changed to a small value (such as 5), then Rule 3 would never be processed. In such a case, the Learning behaviour becomes similar to the Sense behaviour but consumes more energy.

Comparing the results obtained by Learning3,4,5,6,7 behaviours, we can observe that the different combinations of rules (the different rule lists) slightly affect the comfort experience and significantly affect the energy consumption. Learning4 behaviour does not have any rule to lower the energy consumption. Therefore, the Learning4 behaviour depends only on the accuracy of the occupancy prediction algorithm. Indeed, Learning4 always consumes more energy and shows better comfort than the Sense behaviour, but is not significantly better than the On behaviour in both aspects. The addition of the Rule 2 and Rule 3 significantly lowers the energy consumption, which is shown in Figure 6.10 if we compare the Learning5 or Learning6 with the Learning4 behaviour, but slightly increases the discomfort.

Chapter 7

Conclusions and Future Work

7.1 Conclusions

This dissertation presents a novel strategy for the control and management of domestic heating, ventilation and air-conditioning (HVAC) system. The proposed strategy is occupant-aware and is composed of an anticipative, reactive, and rule-based mechanism. These mechanisms enables to increase the occupant's comfort and to decrease the energy consumption in comparison to conventional methods, that do not take into account the knowledge about the occupant. Such knowledge can be obtained through a non-intrusive observation of an occupant and an environment. The strategy includes the three approaches that are used for both ensuring the satisfactory level of comfort and lowering the energy consumption:

- The occupancy prediction algorithms predicts the occupancy in the near-future utilising the incrementally generated classification model that is used to delegate set-point values of the home heating control system. The process of model creation is based on machine learning (ML) methods that exploit historic observations of an occupant in relation to the domestic and work environment.
- The time-to-heat/cool prediction algorithm that predicts the time which is needed to heat/cool the room utilises the incrementally generated regression model which is used to delegate the set-point values of the home heating control system. The regression model of the system dynamics is based on ML methods that exploit the historic observations of the control system operation in relation to the conditioned environment.
- The comfort regulator is used to regulate the occupant's comfort in a way to alter the set-point of the indoor temperature. It exploits the ambient intelligence technologies to observe and estimate the complex states of an occupant, such as the metabolic equivalent of task which is typically assumed as a static and predefined value in related work, in order to perceive the occupant's comfort experience in a controlled environment.

In this dissertation we adopted the evaluation of comfort based on related work and standards which address the problem of comfort evaluation for controlled spaces in relation to the occupant. We also reviewed the methods and approaches that are used for control and management of comfort experience and energy consumption within the domestic and commercial environments. We observe that the occupant's comfort experience is often evaluated according to some predefined values of occupant-related parameters that are

typically assumed as static values. Therefore we proposed an unobtrusive and inexpensive method to estimate the occupant-related parameters such as the metabolic equivalent of task, and show that with such approach (i) the better perception and regulation of occupant's comfort can be achieved and (ii) the better performance of control strategies can be achieved. In order to evaluate the proposed control system and the corresponding algorithms, we used the dynamic model of an intelligent building (IB) with an air-source heat pump as a HVAC system and integrate it with our proposed management system composed of control, sensor, ML, routing and environment management (EM) agents.

In order to evaluate the prediction models we asked the volunteers to collect the data about occupancy and sleeping at home and occupancy at work for the period of one to three months. This data was used to create and evaluate the occupancy prediction models. The weather data was retrieved from the public source – the environmental weather agency and used for the simulation of IB thermal dynamics.

The simulation results are presented in a temporal space and in a comfort/consumption space. The temporal space representation shows a significant improvement regarding the comfort experience in transient conditions, where a person returns home and the anticipative mechanism of the management system prepares the indoor temperature enough in advance, and the performance of comfort regulator. On the other side, the comfort/consumption space representation was used to compare and study larger sets of simulation results that were obtained by various combinations of control strategies. The best solutions in the comfort/consumption space are connected in order to better visualise the attainment surface in objective space. These solutions can be assumed as an approximation of the Pareto frontier that enables finding the strategy that results in the preferred ratio between the comfort experience and the energy consumption related objectives.

The experiments have confirmed the hypotheses of this dissertation.

Observing the occupant's behaviour enables the management system to extract and aggregate the facts about the occupant's interaction with an environment. Occupant's interaction with an environment is demonstrated with the occupancy state and the ML methods are used to create the occupancy prediction models. Using the ML models allows the control system to predict when to reduce the HVAC operation and consequently lower the energy consumption.

Observing the occupant-related parameters enables the management system to achieve significant improvements regarding the occupant's thermal comfort experience. Taking into account the occupant-related parameters, such as metabolic equivalent of task and clothing insulation, significantly influences the perception and also the regulation of the occupant's thermal comfort experience. The performance of various activities during the occupancy at home results in the variable occupant-related parameters and therefore the perception of comfort experience differs also, when the environment-related parameters such as indoor temperature, relative humidity, air velocity, etc. are fixed. In order to compensate the effect of occupant-related parameters on thermal comfort, the environment-related parameters should be continuously adapted. We have developed the comfort regulator and demonstrated the effect of comfort regulation with an indoor-temperature set-point value that was continuously adapted during the control operation.

The evaluation has shown that the information that is obtained in a non-obtrusive manner allows the control system to significantly decrease the energy consumption for heating or cooling. Furthermore, the comfort regulator enables the dynamic modification of indoor temperature in order to achieve a predefined range of the occupant's comfort that varies due to many environment and occupant-related factors. A multi-agent system provides the information needed for the learning and estimation of the state of an environment, and allows the control operation from asynchronous and specially distributed sources

(such as smart information aggregation from home and work environment and knowledge generation – the prediction model).

In this dissertation four scientific contributions are presented. First, the development of a multi-agent control system that besides the well known anticipative and reactive mechanism includes a rule-based mechanism that incorporates the domain knowledge to reduce the wrong predictions which are made by anticipative mechanism and significantly reduces the unnecessary energy consumption which is made by the HVAC system. Second, the analysis of the effect of the occupancy prediction modelling on comfort experience and energy consumption that is presented in a comfort/consumption space. Third, the development of a novel comfort regulator in which the desired comfort threshold can be specified in order to manage the trade-off between the comfort experience and the energy consumption. And final, the simulation and evaluation of the HVAC control system, where the occupant's energy expenditure and the clothing insulation are given as highly dynamic variables. Wich such approach the real-life situation was more realistic. We performed the analysis of the errors' impact of the occupant's energy-expenditure estimation using the smart-phone on the computation of comfort, on the regulation of comfort and on the HVAC energy consumption.

7.2 Future Work

In the future work we plan to deploy an instance of a real building in a smart environment (SE) – a living lab in order to simplify the retrieval of the environmental and occupant-related parameters and to evaluate the identification of the building's thermal dynamics. Therefore the instrumentation of a living-lab with a sensor-actuator network is highly desirable. Furthermore, we claim that the development of per-room occupancy detection methods and per-room comfort and energy consumption management could additionally reduce the energy consumption because the occupancy of the rooms within the domestic building changes frequently and the occupant's comfort experience is therefore determined on a spatial basis. Then the multi-user problem should be analysed and solved in a way to allow the prediction of the occupancy states of many occupants and to determine the satisfactory comfort experience for all occupants.

Since there is a growing interest in energy management in large urban areas, such as in smart cities, we plan to integrate separate environments – buildings into smart districts or cities. The evaluation of comfort experience and the energy consumption at a domestic level should therefore be extended with the evaluation of the price for the consumed energy. A management system of a smart building should change the management strategy for the indoor set-point temperatures according to the dynamic energy price and according to the occupant's comfort experience. We believe that the comfort threshold could be set according to the energy supply and demand within the smart grid in order to achieve the equilibrium regarding the comfort and energy on a smart city level.

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Biography

Domen Zupančič received his Diploma in 2010 from the Faculty of Electrical Engineering, University of Ljubljana, Slovenia, by defending the thesis entitled *The implementation and the analysis of the web simulator for multi-variable systems.* During the undergraduate studies, he worked as a student developer of supervisory control systems with an emphasis on the heating, ventilation, and air-conditioning systems for the company Hidria d.o.o.

In 2010 he enrolled in the doctoral-degree study program at the Jožef Stefan International Postgraduate School. The formal cooperation with the company Robotina d.o.o. and the Jožef Stefan Institute, Department of Intelligent Systems, was established in 2011 after the Slovenian Technology Agency approved funding for a joint research project under a public call *Young researches from industry – Generation 2010.*

Domen continues as a research assistant at the company Robotina d.o.o. under the supervision of Prof. Dr. Matjaž Gams and Dr. Mitja Luštrek, and is currently pursuing a Ph.D in information and communication technologies. His research focuses on the control and management of the appliances within smart buildings from a comfort and energy aspects. During the study, he participated in several national and international projects where his multi-agent control system architecture for the management of smart buildings was also applied. His research achievements were published in scientific articles and conference papers.