Agent-based stochastic model of thermostat adjustments: A demand response application

Marika Vellei, Simon Martinez, Jérôme Le Dréau

Agent-based stochastic model of thermostat adjustments: a demand response application

Marika Vellei[1], Simon Martinez[1] and Jérôme Le Dréau[1]

[1] LaSIE (UMR CNRS 7356) - La Rochelle University, La Rochelle, France, and corresponding author: marika.vellei@univ-lr.fr

Abstract

Demand Response (DR)-activated smart thermostats can be used to exploit the flexibility of residential heating and/or cooling systems. However, the acceptance/rejection of DR events depends on how occupants interact with their thermostats during the activated setpoint modulations. This interaction is mainly driven by their thermal comfort needs. Thus, understanding and modelling occupants' comfort-driven interactions with thermostats is crucial for the design, assessment, and control of DR strategies. In this paper, we describe, calibrate, and show the in-use potentialities of a novel framework which is able to model occupants' interactions with thermostats in residential buildings in winter. The framework includes a stochastic agent-based model of thermostat adjustments, whose dynamic thermal discomfort predictions are based on a two-node thermo-physiological model coupled with a dynamic thermal perception model. This represents a novelty with respect to the most often used static PMV/PPD model. Furthermore, the agent-based model is built on an activity and presence model and, therefore, is able to account for the diversity of the activities carried out by the occupants. User interaction data from about 9,000 connected Canadian thermostats included in the Donate Your Data (DYD) dataset are used to calibrate and establish the empirical foundation of the thermostat interaction model. Finally, we simulate typical DR-activated setpoint modulations in two residential buildings characterized by different levels of insulation and we use the framework to predict occupants' override rates as a function of the indoor temperature and the time since the start of the DR event. The derived relationship can be directly used to inform the design and control of setpoint modulations in residential buildings.

Keywords: Occupant Activity, Thermostat Adjustment/Override, Dynamic Thermal Comfort (Gagge + Fiala), Demand Response, Heating Energy Use

1. Introduction

1.1. Context

Demand response (DR) can modify consumption patterns in response to signals and, therefore, play a key role in enhancing the resilience of the future electricity grid. As the future peak electricity loads will be mainly driven by thermal comfort needs, of which heating mostly occurring at times when solar power is no longer available, a widespread implementation of DR-activated smart thermostats could represent an inexpensive and efficient solution for shifting thermal loads towards off-peak hours. Developments in low-cost power electronics, information and communication technologies and technical infrastructures, e.g. smart meters, are favouring the uptake of DR across small commercial and residential groups [1]. Altogether, this makes the use of smart thermostats in residential buildings a favourite candidate to offer significant DR capacity worldwide [2].

However, fully automated DR programs based on smart thermostats having direct control over the users' setpoint temperatures are a challenge for the comfort of the occupants and for the acceptance of the implemented setpoint modulations. Recent pilot studies have evidenced that not providing occupants with override possibilities is likely to be the cause of rejection and failure [3,4]. Thus, understanding and modelling occupants' comfort-based interactions with smart thermostats is crucial for the design, assessment, and control of DR strategies. Given the highly dynamic thermal conditions induced during DR events, a detailed modelling of occupants' dynamic thermal perception is also required.

1.2. State-of-the-art

Dynamic thermal comfort

For evaluating the dynamic thermal environments induced by DR events, building modellers have so far mostly used Fanger's PMV/PPD method [5–12]. However, Fanger's model is derived from a steady-state heat balance equation and steady-state laboratory experiments [13] and is, therefore, only suited to predict thermal comfort under steady-state or slowly changing indoor conditions (temperature gradients less than 2 °C/h) [14]. Furthermore, the model is not able to predict thermal comfort under dynamic levels of activity.

The recently developed multi-segment and multi-node thermo-physiological models (e.g. Tanabe [15], Fiala [16,17], the Berkeley Comfort Model [18] and ThermoSEM [19]) allow to model the physical interaction between an occupant and a dynamic indoor environment. In particular, they are able to simulate body core and skin temperatures for different regions of the human body under asymmetric environmental conditions. However, this high level of precision (and the computational burden associated with their implementation) is of little utility in most building energy simulations, which only provide average environmental conditions for the simulated thermal zones. Thus, they have not been largely applied for the prediction of thermal sensation and thermal comfort in the built environment.

Thermostat adjustments

In the context of building performance simulation, regression-based models are most often used for modelling the stochastic interactions of occupants with windows, shadings, lightings and thermal systems [20]. A majority of the regression-based studies focuses on window-opening behaviours and mainly use data collected from office buildings [21–25], while only a few studies have modelled occupants' interaction with heating and/or cooling systems [21,26–32].

Regression-based models of occupants' interaction with thermal systems are presented and reviewed in Table 1. A majority of these studies uses logistic regression models. Despite being simple to communicate and implement, logistic regression models only partially incorporate the diversity of occupant behaviour since they are often derived from a limited set of empirical data coming from small samples [33]. Furthermore, they only incorporate indoor temperature and relative humidity as predictors of thermal comfort and, therefore, are not able to account for the complexity and diversity of the dynamic thermal perceptual processes triggering thermal decisions [34].

Table 1. Regression-based models of occupants' interaction with heating and/or cooling systems.

Reference	Model Type	Modelled Behaviours	Predictors										Used Data	
			Outdoor temperature (°C)	Indoor temperature (°C)	Outdoor relative humidity (%)	Indoor relative humidity (%)	Solar irradiance (W/m^2)	Wind speed (m/s)	Time of day	Occupancy	Type of activity	Occupants' characteristics	Monitored Building	Monitored Period
[21]	logistic regression	p of having the heating on	x										11 office buildings in Sweden, UK, France, Portugal and Greece	1 heating season
[26]	sigmoid function	p of adjusting the AC-unit (both on and off)	x	x									8 dwellings in Japan	1 cooling season
[27]	logistic regression	p of having the AC-unit on	x									x	39 rooms in a student dormitory in Tokyo, Japan	6 weeks (cooling season), 4 weeks (heating season)
[28]	three-parameter Weibull distribution	p of adjusting the AC-unit (both on and off)		x						x	x		3 dwellings in Beijing, Nanchang and Guangzhou, China	2 months (cooling season)
[29]	logistic regression	p of adjusting the thermostatic radiator valve (both increasing and decreasing)	x			X	x	x	x			x	13 dwellings in Copenhagen, Denmark	6 months (both heating and cooling seasons)
[30]	logistic regression	p of adjusting the thermostat (both increasing and decreasing)		x						x			1 office building in Ottawa, Canada	1 year (both heating and cooling seasons)
[31]	logistic regression	p of adjusting the thermostat	x	x		X	x		x				10 dwellings in Torquay, UK	1 heating season
[32]	logistic regression	p of adjusting the thermostat	x	x	x			x				x	11 dwellings in Cébazat, France	1 heating season

As an alternative to regression-based models and as a way to address the challenges outlined above, agent-based models (ABMs) are now emerging. ABMs offer a framework to model occupants as autonomous agents, which adapt their behaviour to be better suited to their environment. In the context of building performance simulation, ABMs have been developed for modelling various types of behaviours, including interactions with lighting and shading [35], while only few ABMs have attempted to model occupants' interactions with

heating and/or cooling systems. ABMs of occupants' interaction with thermal systems are presented and reviewed in Table 2.

Table 2. Agent-based models of occupants' interaction with heating and/or cooling systems.

Reference	Tools	Comfort Metric	Human Behavioural Framework	Modelled Behaviours								Used Data	
				Adjust thermostat/AC	Use local heater/fan	Adjust clothing	Contact manager	Open/close window	Adjust activity level	Open/close blind		Monitored Building	Monitored Period
[36]	Brahms environment + MATLAB/ Simulink + java interface	PMV-based	BDI architecture (rule-based)	X		x		x				-	-
[37]	EnergyPlus + MATLAB	PMV-based	cost function optimization		x	x		x	x	x		-	-
[33]	MATLAB	survey-based	PCT architecture (rule-based)	X	x			x				1 office building in Philadelphia, USA	1 year (both heating and cooling seasons)
[38]	EnergyPlus + NetLogo	survey-based	utility function minimization	X	x	x	x					2 office buildings in Philadelphia, USA	1 year (both heating and cooling seasons)
[39]	EnergyPlus + C++ + Functional Mockup Interface	PMV-based	Q-learning	X								-	-

Kashif et al. use the Brahms language for modelling the casual relationships between environmental factors and occupants' actions using the Belief-Desire-Intention (BDI) architecture [36]. Langevin et al. develop an ABM of fan, heater, and window use based on the theoretical framework of Perceptual Control Theory (PCT), by developing rules that always make occupants adopt the most immediate, unconstrained adaptive behaviour [33]. In Putra et al. occupant's adaptive actions are estimated using a utility function (comprising environmental impact, effort, cost, and thermal discomfort), that occupants seek to minimize [38]. In the work of Chapman an agent learns the best setpoint daily schedules by using a Q-learning algorithm, which allows to reduce heating demand and improve occupants' thermal comfort compared to deterministic schedules [39,40]. A limitation of these agent-based models, except of Kashif's and Langevin's approach which are rule-based, is that they assume a quasi-optimal heating behaviour, which is rarely true for real occupants, who have been shown to have imperfect grasps of how their thermostats and heating systems operate [41]. Furthermore, occupants' thermal discomfort is mostly evaluated using the static Fanger's PMV/PPD model [36,37,39]. However, the environmental

conditions experienced by the occupants in residential buildings are rarely steady-state due to, for example, the use of setback and/or unheated spaces. Moreover, the occupants themselves are a possible cause of transient conditions because of the time-varying metabolic rates associated with the different activities carried out during the day [14]. Another limitation of these models is that they are either not calibrated or are calibrated with a limited set of empirical data coming from samples with a very small demographic basis.

1.3. Research aims

This paper describes, calibrates, and shows the in-use potentialities of a novel framework which can be used to model occupants' interactions with thermostats in residential buildings in winter (Figure 1). The framework includes a stochastic agent-based model of thermostat adjustments, whose dynamic thermal discomfort predictions are based on a two-node thermo-physiological model coupled with a dynamic thermal perception model. This represents a novelty with respect to the most often used PMV/PPD model. However, the adopted solution is as simple to implement and run as Fanger's model, far from the computational complexity represented by multi-segment and multi-node thermo-physiological models. For the first time (in the context of thermostat adjustments modelling) we use a model which is able to dynamically simulate occupants' thermo-physiological responses, thus allowing to model the dynamic thermal perceptual processes triggering thermal actions. Furthermore, the agent-based model builds on an activity and presence model and, therefore, has the advantage of being able to account for the diversity of the activities carried out by the occupants, which leads to diverse setpoint schedules and metabolic rates.

The three main components of the framework (occupant activity and presence model, thermostat adjustment model and dynamic thermal comfort model) are described in Section 2. The three models are coupled with the Building Energy Simulation (BES) tool incorporated within the python-based simulation platform DIMOSIM (DIstrict MOdeller and SIMulator), which can be used to predict energy demand at district level [42]. Thus, all the models are developed in Python and are directly embedded within DIMOSIM.

For calibrating the thermostat adjustment model we use data from about 9,000 connected Canadian thermostats included in the Donate Your Data (DYD) dataset and presented in Sections 3.1 and 4.1. This calibration represents a further strength of the model since, for the majority of the thermostat models, calibrations are either not carried out or are performed over a limited set of empirical data. Finally, in Sections 3.2 and 4.2 we show an example of use of the framework: a simulation of occupants' thermostat interactions under different types of setpoint modulations typically used to decrease the winter heating peak load in France. Limitations and future possible developments of the framework are discussed in Section 5.

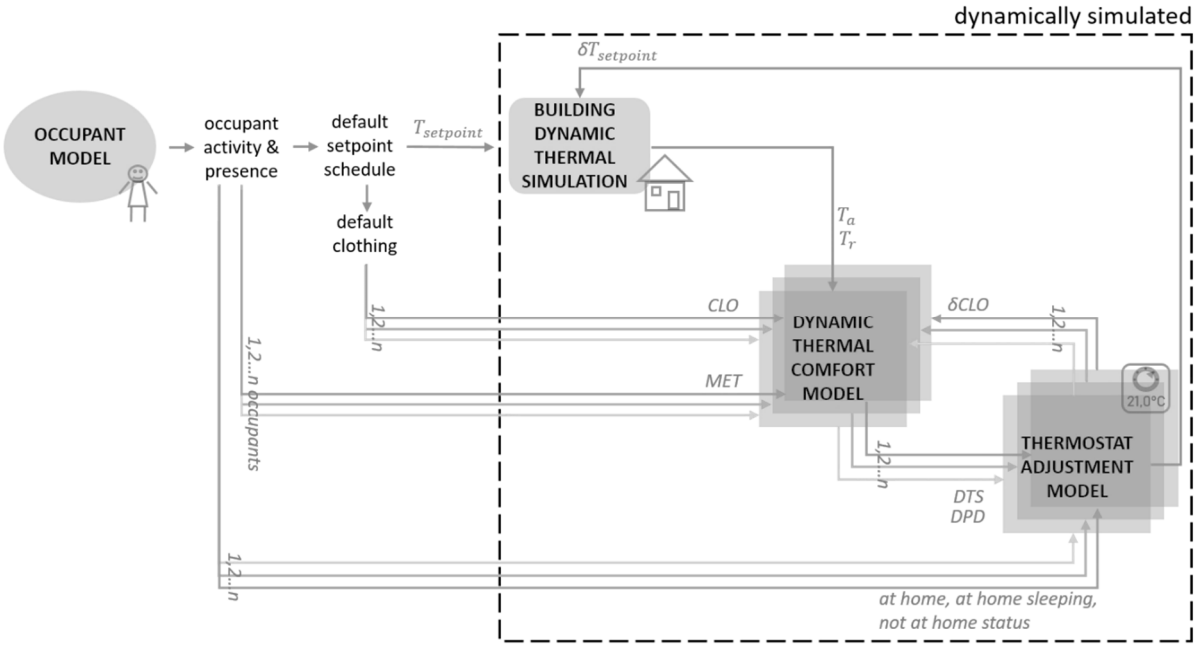


Figure 1. Schematic view of the novel modelling framework.

2. Models

In this Section we describe the different models used. The stochastic activity and presence model and the dynamic thermal comfort model have been introduced, validated, and used in our previous works [43,44]. Thus, they are described with fewer details than the thermostat adjustment model, which instead represents the specific focus of this paper.

2.1. Occupant model

To model occupants' activity and presence, we use a novel approach which directly employs the activity sequences or activity profiles (*i.e.* the daily times series of occupant activities) available from the French Time Use Survey (TUS) data (2009-2010 TUS campaign) [45]. About 27,900 daily logbooks are used to build the model. These 27,900 daily times series are first grouped according to the type of occupant (*employed*, *unemployed*, *retired*, *student*, *stay-at-home* and *other*) and the day of the week (*weekend* and *weekday*); this makes a total of 12 groups. Based on the assumption that most human behaviour is habitual and, therefore, characterized by daily routines which repeat themselves over the year, a hierarchical agglomerative clustering (HAC) is performed within each group to find clusters of similar daily profiles. The elbow method is used to find the appropriate number of clusters for each group, with each cluster containing between 80 and 500 logbooks. The following stochastic procedure is then applied to create different yearly synthetic activity patterns:

- Draw both a weekend and a weekday cluster in the list of clusters corresponding to the type of occupant being simulated.
- Draw the weeks of vacation according to the INSEE data [46].

For each day of the simulation:

- If it is a weekday, draw a daily schedule within the weekday cluster and apply it.
- If it is a weekend, draw a daily schedule within the weekend cluster and apply it.
- If it is a vacation day, set the activity to other outside.

Thus, in this modelling approach we do not use a few number of averaged probability distribution functions or transition probabilities as most current approaches do [47–53].

Instead, our method uses the actual TUS activity sequences and, therefore, allows to account for the diversity of the real population in terms of occupancy and activities carried out at home [43]. As an example we show in Figure 2 the probability of the start times of the 'doing laundry' activity (at a given hour of the day) from about 600 households. This diversity is a key aspect of occupant behaviour modelling as evidenced by recent works [54–56] and is especially important for peak demand studies.

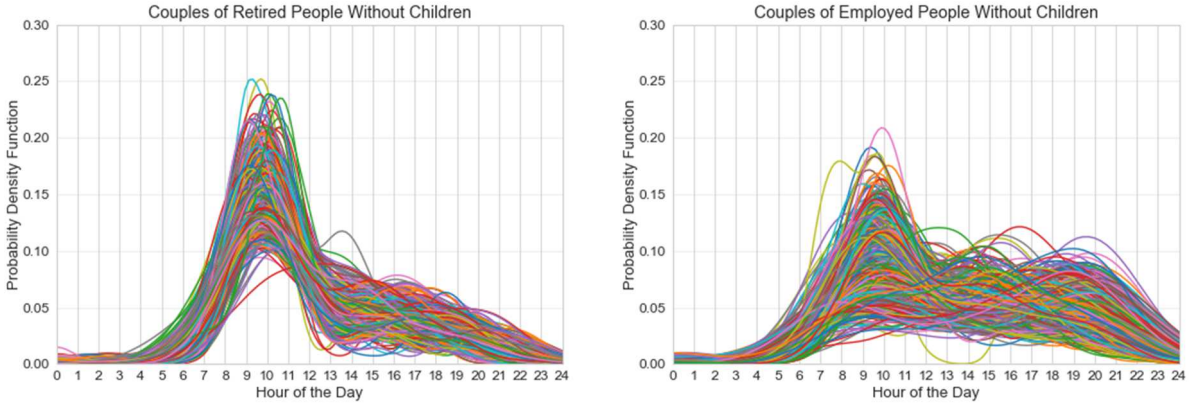


Figure 2. Probability of the start times of the 'doing laundry' activity at a given hour of the day for the simulated Couples of Retired People Without Children (left) and Couples of Employed People Without Children (right) from [43]. Each figure shows about 600 households.

The stochastic activity profiles are assumed to be independent of the environmental inputs and, therefore, are computed in a pre-process respect to the thermal simulation (see Figure 1). Since the synthetic activity patterns are drawn independently for each member of the household, a limitation of this approach is the possible incoherence between occupants of the same household. However, holiday periods are predicted at the level of the household and, therefore, are the same for all the occupants. Another limitation is the lack of seasonal patterns. For more details on the derivation and validation of the activity and presence model the reader is referred to our previous paper [43].

The output of the occupant model is made up of the time series of activity and presence (*i.e.* occupant at home and awake) derived for each occupant of the household. The activity time series are then converted into time series of metabolic heat rate by using distributions obtained from the ASHRAE reference tables of metabolic rates for common activities [57]. The estimated metabolic heat associated with the occupant's activity (*MET*) is, in turn, an input of the dynamic thermal comfort model. While the status of the occupant (*at home*, *at home sleeping*, *not at home status*), which is also deduced from the occupant activity time series, is an input of the thermostat adjustment model. See Figure 1 for an overview of the input and output variables of the different models.

2.2. Dynamic thermal comfort model

For the dynamic thermal comfort predictions, we use a novel model, which comprises two main elements:

- a simple two-node thermo-physiological model able to simulate the body core and mean skin temperatures under uniform conditions,
- a dynamic thermal perception model which uses the simulated body core and mean skin temperatures to predict both thermal sensation and thermal comfort.

The selected thermo-physiological model is an updated version of the classical Gagge's two-node model, also known as Pierce's two-node model [58]. For predicting the dynamic

thermal sensation, we opt for an updated version of Fiala's Dynamic Thermal Sensation (DTS) model [59]. Finally, for the prediction of thermal comfort, we derive a new model, which calculates the Dynamic Percentage of Dissatisfied (DPD) from the dynamic thermal sensation, thus mimicking the structure of the classical Fanger's PPD index. A schematic view of the dynamic thermal comfort model is given in Figure 3. The inputs of Gagge's two-node model are the six basic parameters: air temperature (T_a), mean radiant temperature (T_r), air velocity (V_a), relative humidity (RH), clothing insulation (CLO) and metabolic heat generated by human activity (MET). The inputs of the Dynamic Thermal Sensation (DTS) model are the mean skin and body core temperature (T_{core} and $T_{sk,mean}$) and the rate of change of the mean skin temperature ($\frac{\partial T_{sk,mean}}{\partial t}$). The inputs of the Dynamic Percentage of Dissatisfied (DPD) model are the DTS and the $\frac{\partial T_{sk,mean}}{\partial t}$.

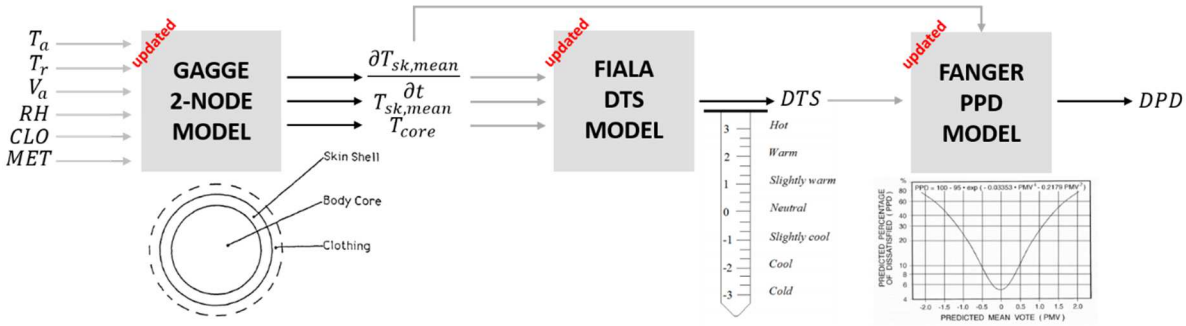


Figure 3. Schematic view of the novel dynamic thermal comfort model.

In Gagge's two-node model [58], the human body (*i.e.* the passive/controlled system of human thermoregulation) is simulated as two concentric thermal compartments: a core cylinder (representing muscle, subcutaneous tissue and bone) surrounded by a thin skin outer layer. The model simulates the heat transfers between the two compartments and between the outer layer and the environment. The temperature within each compartment is assumed to be uniform. The active/controlling system is based on a linear, temperature-based control theory of human thermoregulation and is made of empirical equations simulating the regulatory responses of shivering, vasoconstriction, vasodilatation, and sweating.

Despite its simple representation of the human body, Gagge's two-node model is accurate for practical applications in the built environment where environmental conditions are usually near the neutrality and activity levels are mostly lower than 3.5 met [60–62]. However, we have further extended the predictive capabilities of Gagge's two-node model by substituting its simple linear, temperature-based active system model with Fiala's non-linear, temperature-based active system model, whose empirical control equations for shivering, vasoconstriction, vasodilatation, and sweating have been derived from statistical analysis of a wide range of data coming from 27 climate chamber experiments covering air temperatures between 5°C and 50°C and exercise intensities between 0.8 met and 10 met [16]. For more details on the accuracy of the updated Gagge's two-node model the reader is referred to our previous work [44].

Fiala's DTS model [59] is able to predict the whole-body thermal sensation on the seven-point ASHRAE scale and is composed of three main parts:

- a first part - as a function of $T_{sk,mean}$ - to model the response of sedentary subjects under steady-state environmental conditions,
- a second part - as a function of T_{core} weighted by $T_{sk,mean}$ - accounting for effects associated with exercise and warm body core temperatures,
- a third part - as a function of both positive and negative $\frac{\partial T_{sk,mean}}{\partial t}$ - dealing with the dynamic components of thermal sensation observed in transient thermal conditions.

Fiala refers to the first and second parts as the *static* comfort model, while the third part represents the *dynamic* component of human thermal sensation. The model was developed from regression analysis of data coming from 220 climate chamber exposures to air temperatures between 13°C and 48°C and activity levels between 1 met and 10 met [59]. However, for the dynamic component, Fiala used a limited set of experimental data coming from only two exposures to sudden step-changes in air temperature: 28-18-28°C and 28-48-28°C [63]. Given this limitation, we have updated the dynamic part using additional experimental data coming from both cyclical [64] and step-change transient thermal conditions [65,66]. For more details on the accuracy of the updated Fiala DTS model the reader is referred to our previous work [44].

Finally, we have derived a new model, which is able to calculate the Dynamic Percentage of Dissatisfied (DPD) from the dynamic thermal sensation, thus mimicking the structure of the classical Fanger's PPD index. Fanger's well-known non-linear relationship between PMV and PPD is derived from steady-state laboratory experiments involving 1300 subjects and is given by:

$$\mathbf{PPD} = \mathbf{1} - \mathbf{0.95} \cdot \mathbf{e}^{(-\mathbf{0.03353 \cdot PMV^4} - \mathbf{0.2179 \cdot PMV^2})} \quad \textbf{(1)}$$

By using experimental data derived from dynamic experiments in climate chambers [64], we have derived a new dynamic version of Fanger's static PPD index, which is given by:

$$\mathbf{DPD} = \mathbf{1} - \mathbf{0.95} \cdot \mathbf{e}^{\left(-0.03353 \cdot \left(\mathbf{DTS} + \mathbf{a} \cdot \tanh\left[\frac{\partial \mathbf{T_{sk,mean}}}{\partial \mathbf{t}}\right]\right)^{4} - 0.2179 \cdot \left(\mathbf{DTS} + \mathbf{a} \cdot \tanh\left[\frac{\partial \mathbf{T_{sk,mean}}}{\partial \mathbf{t}}\right]\right)^{2}\right)} + \mathbf{b} \cdot \tanh\left[\frac{\partial \mathbf{T_{sk,mean}}}{\partial \mathbf{t}}\right] \quad \textbf{(2)}$$

where:

- The parameter a accounts for the fact that the dynamic thermal perception horizontally shifts subjects' neutral conditions (at which maximum comfort is felt) towards warm thermal sensations during warming transients and cold thermal sensations during cooling transients. This is due to the warming and cooling overshoots of thermal sensation occurring during warming and cooling transients, respectively. In warm and cold conditions, the coefficient a is equal to -0.2151 for cooling gradients $\frac{\partial T_{sk,mean}}{\partial t}^{(-)}$ and -0.5424 for warming gradients $\frac{\partial T_{sk,mean}}{\partial t}^{(+)}$.
- The parameter b accounts for the alliesthesial effect which causes a vertical thermal comfort shift: in warm conditions cooling transients elicit pleasure and, therefore, increased satisfaction, while warming transients elicit displeasure and, therefore, decreased satisfaction. The opposite is true in cold conditions. In warm conditions, the coefficient b is equal to -0.0251 for cooling gradients $\frac{\partial T_{sk,mean}}{\partial t}^{(-)}$ and -0.0679 for warming gradients $\frac{\partial T_{sk,mean}}{\partial t}^{(+)}$, while in cold conditions the opposite is true, *i.e.* the coefficient b is equal to $+0.0251$ for cooling gradients $\frac{\partial T_{sk,mean}}{\partial t}^{(-)}$ and $+0.0679$ for warming gradients $\frac{\partial T_{sk,mean}}{\partial t}^{(+)}$.

The parameters a and b of Equation (2) are obtained by minimizing the RMSE during both cooling and warming transients using the Nelder-Mead Algorithm. Accuracy of the novel DPD in terms of RMSE falls between 4 and 6%.

For the literature on the phenomenon of thermal alliesthesia the reader is referred to the works of Cabanac [67], Attia [68], Zhang [69–71], Parkinson [72] and Vellei & Le Dréau [73]. For more details on the derivation and validation of the dynamic thermal comfort model the reader is referred to our previous work [44]. The dynamic thermal comfort model coded in Python is available for download in the supplementary materials.

An example of the simulated DTS and DPD over the course of a day for both the case of a constant metabolic rate equal to 1.2 met and a time-varying metabolic rate is shown in Figure 4. We only calculate DTS and DPD for time-steps where the occupants are at home and awake. After periods of sleeping or periods when the occupant is not at home, we assume that the initial comfort conditions are equal to the final conditions of the previous - at home and awake - period. In Figure 4 we can observe that the met variations have a non-negligible effect on the comfort of the occupants. This is a confirmation of the importance of modelling the stochastic time-varying met levels which, as we will see in the Results, also influence the comfort-driven thermostat adjustments.

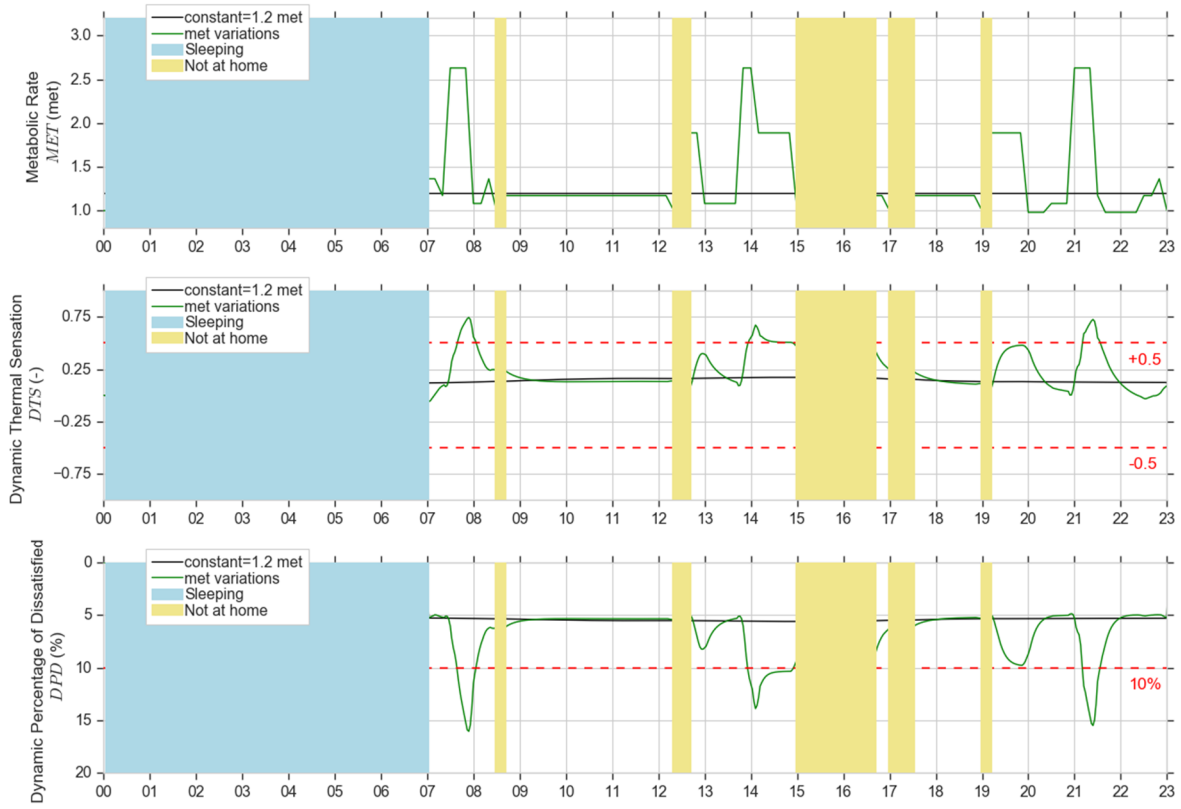


Figure 4. Example of dynamic thermal comfort predictions for an occupant of type unemployed during typical daily MET variations. All the other parameters are fixed ($T_a = T_r = 21°C$, $V_a = 0.1\ m/s$, $RH = 50\%$, $clo = 1.2$). Only time-steps where the occupant is at home and awake are shown.

2.3. Agent-based thermostat model

Modelling the interactions with thermal systems is even more challenging than window and lighting interactions since programmable thermostats give the opportunity to schedule in advance different temperatures at different times of the day. Thus, there are the multiple challenges of modelling:

- the default setpoint temperatures,
- the operation schedule,
- and the manual overriding behaviour.

In our agent-based thermostat model, we assume that each household is equipped with a programmable thermostat which can be used to set a schedule for:

- the day setpoint temperature ($T_{setpoint,day}$) for when somebody who is not sleeping is at home (*at home status*),
- the night setpoint temperature ($T_{setpoint,night}$) for when everybody who is at home is sleeping (*at home sleeping status*),
- the set-back temperature ($T_{setback}$) for when nobody is at home (*not at home status*).

The default setpoint temperatures ($T_{setpoint,day}$, $T_{setpoint,night}$, and $T_{setback}$) can be modelled as a function of a variety of different factors (the household's socio-economic characteristics and composition, the dwelling's features, the type of heating system, heating delivery system and user interface to control it, the outdoor weather, etc.). In this paper, we do not model the diversity of the default setpoint temperatures but we rather focus on modelling the operation schedule and the manual overriding behaviour. For the simulations of Sections 3.1 and 3.2, the default setpoint temperatures are set to some fixed values.

For each household, the operation schedule is estimated based on the occupants' activity and presence profile time series by calculating the hourly probability of having each household's status (*at home, at home sleeping, not at home)* over the simulated period. For each hour of the day, the status with the highest probability of occurring defines the corresponding hourly scheduled/default temperature ($T_{setpoint,day}$, $T_{setpoint,night}$, and $T_{setback}$) for the household. This hourly profile is then repeated for each day throughout the simulation period. Thus, the hourly setpoint schedule is defined for each household in a pre-process with respect to the dynamic thermal simulation (see Figure 1 for the overall modelling framework), while the manual overriding behaviour is dynamically simulated. Some examples of operation schedules are shown in Figure 5. Since having a programmable thermostat does not necessarily implies using programmable features [41], defining an operation schedule does not necessarily imply that each household is using a night setpoint temperature or a setback temperature. In the process of drawing the default setpoint temperatures, some households might have $T_{setpoint,night} = T_{setpoint,day}$ and/or $T_{setback} = T_{setpoint,day}$ and, therefore, not use any schedule. But, again, this depends on the model of the default setpoint temperatures, which is not covered in this paper.

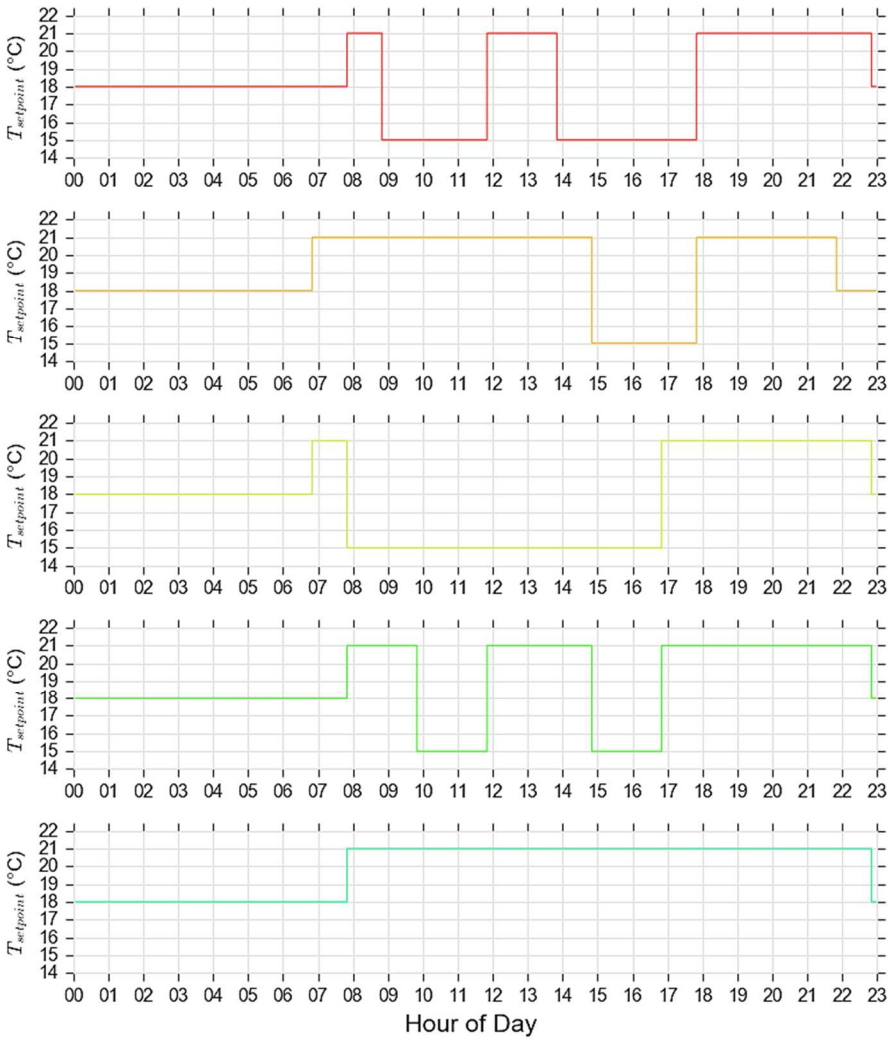


Figure 5. Example of operation schedule for different occupants of type unemployed. The default setpoint temperatures are set equal to: $T_{setpoint,day} = 21°C$, $T_{setpoint,night} = 18°C$, *and* $T_{setback} = 15°C$.

The manual overriding behaviour is modelled using an ABM approach: each member of the household is represented as an agent with a set of attributes (status, clothing, and metabolic rate) and a set of possible adaptive actions (setpoint and clothing adjustment).

Data-driven ABM model foundation

The empirical foundation of the ABM model is the DYD dataset which contains usage data from more than 100,000 ecobee connected thermostats mainly installed in North America and collected over multiple years [74–77]. The dataset is made of five-minute time series of indoor air temperature, relative humidity and passive infrared (PIR) motion, which are sensed at the thermostat and at any connected remote sensors whose placement depends on the user. The monitored indoor air temperature (T_a) is the temperature compared to the setpoint temperature and, therefore, used to control the thermal system. In the simplest configuration, T_a is given as a mean of the temperature sensed at the thermostat and at any connected remote sensors. However, depending on the choice of configuration made by the user, the sensed temperatures can be weighted by either the programmed thermostat schedule or the detected occupancy. The dataset also includes user-reported metadata of home and occupant characteristics. An overview of the dataset can be found in [74].

An Internet-connected thermostat, such as the ecobee thermostat, allows users to set a weekly operation schedule (*i.e.* to set different heating and cooling setpoint temperatures at different times of the day) and has manual control functionalities through web, mobile and voice platforms. For the derivation of the thermostat adjustment model we want to understand how occupants interact with their thermostats and, therefore, we focus on the analysis of the manual setpoint adjustments, which are deliberate user overrides of a scheduled/default setpoint temperature. For each manual setpoint adjustment, we compute the corresponding setpoint temperature change, which could be either an increase or decrease. A time-step is considered occupied if any motion is detected by any motion sensor (remote, or on the thermostat itself), *i.e.* if the occupants are at home and are not sleeping. The resulting occupancy time series are further processed to 'fill in' short unoccupied periods of 30 min where the occupants may have been temporarily hidden from the sensor, using a similar approach of [75] and [77]. The PIR sensors give many false negatives but have the advantage to have only few false positives [75]. We apply the following selection criteria to the DYD dataset:

- we only consider thermostats in Canadian homes,
- we only take data from winter months characterized by a mean monthly outdoor temperature lower than 15°C,
- we exclude thermostats containing less than 10 days of detected occupied time-steps.

Thus, our data comes from about 9,000 thermostats.

In Figure 6 we show aggregated mean data from the selected 9,000 thermostats. In Figure 6 (left) we can observe that, at equal indoor air temperature, the mean number of manual setpoint adjustments per hour of occupancy differs for the different default setpoint temperatures ($T_{setpoint,default}$). The default setpoint temperature is calculated for each thermostat as the mean heating setpoint temperature during occupied time-steps. In Figure 6 (right) we can further observe that when the occupants decide to change their heating setpoint they do so differently at different default setpoint temperatures. In particular, at $T_a = T_{setpoint,default}$ the mean setpoint change is approaching zero when the default setpoint temperature is higher than 20°C. This means that occupants adapt to their chosen prevailing setpoint temperature. In our ABM modelling approach we assume that this adaptation consists in selecting the occupants' default clothing level based on the $\mathrm{T_{setpoint,day}}$. Thus, for each occupant we calculate a default clothing level for comfort by using the PMV model and by setting $T_a = T_r = \mathrm{T_{setpoint,day}}$. As an example, for the simulations described in Sections 3.1 and 3.2 and run at $T_{setpoint,day} = 21°C$ the default clothing insulation is calculated to be equal to 1.2 clo, *i.e.* the value corresponding to a $PMV \approx 0$ at average values of the other comfort parameters ($RH = 50\%$, $V_a = 0.1 m/s$ and $MET = 1.2\ met$). The default clothing insulation and the default setpoint temperature are then modified by the occupants over the course of the dynamic simulation.

From the patterns of Figure 6 (left and right), we can further observe that the mean number of manual adjustments decreases at increasing indoor air temperatures, while we would expect the curve to be symmetrical around the setpoint. Also, the mean temperature change per manual adjustment saturates at a value approximately equal to -0.5°C. This could be due to the phenomenon of seasonal thermal alliesthesia according to which occupants tend to accept warmer thermal sensations in winter and colder ones in summer [78–80]. However, this could also be due to the fact that when the air temperature is higher than the setpoint, setting a very low heating setpoint would not imply to actively cool the

building given that the large majority of the heating systems in Canada are either forced-air furnaces or electric baseboard heaters (i.e. not reversible). In order to account for this asymmetrical adjustment behaviour, in our ABM model we separately model manual adjustments during warm and cold conditions. This is further explained in the next paragraph.

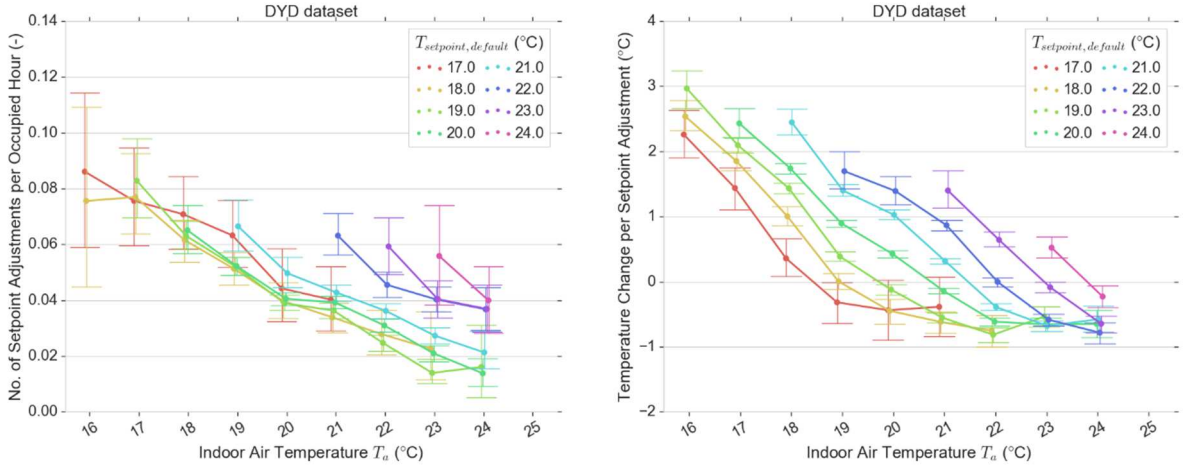


Figure 6. Mean number of manual heating setpoint adjustments per hour of occupancy (left) and mean heating setpoint changes per manual adjustment (right) for the DYD thermostats at different levels of the setpoint temperature. The data are from about 9,000 thermostats and are binned as function of the indoor air temperature. Error bars represent confidence intervals of the estimated mean for each bin.

Theory-driven model foundation

The *adaptive principle (*"if a change occurs such as to produce discomfort, people react in ways that tend to restore their comfort" [81]) is assumed to be at the base of the manual overriding behaviour. When the occupant agent is at home and is not sleeping, he reacts to environmental and personal changes according to this principle. For modelling the agent's adaptive behaviour, we use a particular type of agent: the Belief-Desire-Intention (BDI) agent, which is characterized by certain mental attitudes of belief, desire, and intention, representing its informational, motivational, and deliberative states respectively [82]. First, a BDI agent obtains a belief about the state of its current environment. In our case, environmental and personal conditions form the occupant's thermal dissatisfaction, which is represented by the Dynamic Thermal Sensation (DTS) and Dynamic Percentage of Dissatisfied (DPD). Then, the agent translates its thermal dissatisfaction into a desire about what to achieve, *i.e.* whether to change its current thermal state. This is predicted using a time-dependent Bernoulli process. A uniformly distributed random number n is drawn in [0,1[and compared to the DPD. If the DPD is more than the random number n, the desired outcome is to change its current state. Finally, the agent translates its desire into an intention to act (occupant's adaptive behaviour). The agent's intention is defined by the probabilities of reactively adjusting the clothing $p_{adj,clothing}$ (before) and the setpoint temperature $p_{adj,setpoint}$ (afterwards) using a time-dependent Bernoulli process. Thus, it is assumed that the adjustment of the clothing insulation is the preferred adaptation strategy. The probably of adjusting the setpoint during warm exposures $p_{adj,warm,setpoint}$ is different than during cold exposures $p_{adj,cold,setpoint}$ according to the alliesthesia-based asymmetry observed in Figure 6 of the previous paragraph. It is further assumed that when the agent decides to adjust its clothing, he does it modularly by either increasing or decreasing the clothing of $\delta CLO = 0.1\ clo$, where $0.1\ clo$ is, for example, the clothing insulation change

made when passing from a thin long-sleeved sweater to a thick long-sleeved sweater [57]. While, when the occupant decides to adjust the setpoint of $\delta T_{setpoint}$, he does it to restore thermal neutrality (*i.e.* towards a $PMV \approx 0$). The $T_{setpoint}$ has a lower limit equal to $T_{setpoint,day}$-1°C during warm exposures and an upper limit equal to $T_{setpoint,day}$+6°C during cold exposures, always based on what observed in Figure 6 of the previous paragraph.

Conflicts between members of the households also need to be taken into account because, at a given simulation time-step, an occupant might want to increase the setpoint temperature and another to decrease it. We solved these conflicts by ranking the members of the households by importance order (the ranking is random and it does not depend on the type of occupant). The decisions of the first-ranked occupant prevail over the others; the decisions of the second-ranked prevail over the others with the exception of the first-ranked and so on. Thus, if the first-ranked decides to change the setpoint temperature, the other members of the household are not able to override its decision. The model does not account for any learning of the agent over time. The agent-based modelling framework for the manual overriding behaviour is represented in Figure 7.

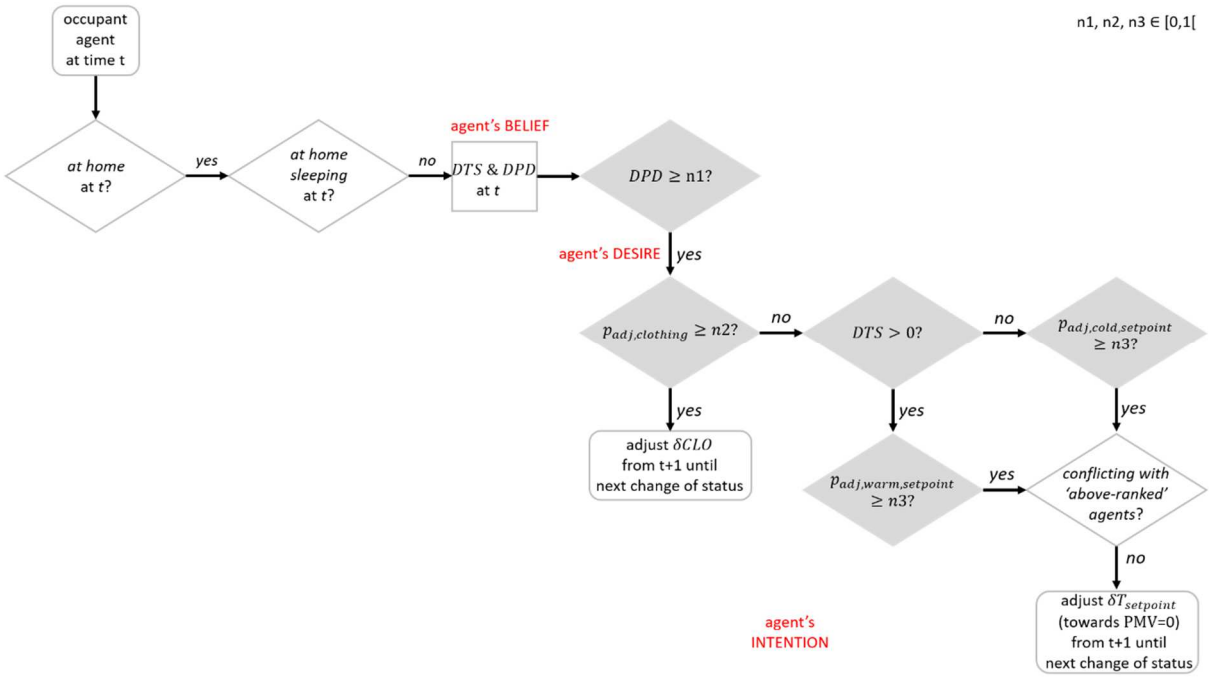


Figure 7. Simplified flowchart of the framework used to model agent's adaptive behaviour.

3. Methods

The methodology used for calibrating the thermostat adjustment model is described in Section 3.1, while in Section 3.2 we show an example of application of the model for the study of DR events. In both cases, dynamic thermal simulations are used to reproduce typical indoor environmental conditions encountered in residential households during the heating season. All the presented dynamic thermal simulations are carried out within DIMOSIM, which use a mono-zone building model [42]. The thermal model of each household is composed of more than 20 thermal capacities (discretisation of walls in 4 layers) and is solved using finite difference methods. For all the simulations, we select a time-step of 2 minutes in order to better capture perceptual and behavioural dynamic processes. We assume that each household is equipped with a programmable thermostat and is using a schedule for setting $T_{setpoint,day} = 21°C$, $T_{setpoint,night} = 18°C$ and $T_{setback} =$

15°C. Since the calibration is done with respect to the indoor temperature, we not need to simulate the actual $\mathrm{T}_{\mathrm{setpoint,night}}$ and $\mathrm{T}_{\mathrm{setback}}$ of the 9,000 Canadian buildings where the thermostats are located. However, $\mathrm{T}_{\mathrm{setpoint,day}}$ has to be set equal to 21°C since we are calibrating the model against ecobee households having a mean heating setpoint temperature during occupied time-steps equal to 21°C. The winter default clothing level of the occupants is set equal to 1.2 clo, as seen in Section 2.3. For the inputs of the DTS/DPD model, the air velocity (V_a) is set to be equal to 0.1 m/s and the relative humidity (RH) equal to 50%.

3.1. Calibration with connected thermostat data

The calibration of the thermostat adjustment model consists in estimating $p_{adj,clothing}$, $p_{adj,warm,setpoint}$ and $p_{adj,cold,setpoint}$ which are the key probabilities needed to map occupant thermal perception onto its adaptive behaviour. To do this, we first set $p_{adj,clothing} = n * p_{adj,cold,setpoint}$ and $p_{adj,warm,setpoint} = p_{adj,cold,setpoint}/m$. Then, we estimate n, m, and $p_{adj,cold,setpoint}$ by simulating a diverse set of households and buildings and using a simple iterative qualitative method in which we visually compare the simulated and empirical values of two different metrics: the number of manual setpoint adjustments per hour of occupancy and the setpoint change per manual adjustment, given as a function of the indoor temperature. Thus, the model is calibrated at an aggregated level and not at the level of the individual household. The empirical values are coming from the DYD dataset, which has been already introduced in Section 2.3 (see also Figure 6). The simulated data origins from a combination of the following selected cases:

- Two residential buildings characterized by different levels of insulation: a typical existing single-family house (SFH 1982) and a newly-built single-family house (SFH 2012). For more details of the case study buildings see Section 3.3. It is important to highlight that the calibration is done with respect to the indoor temperature and, therefore, we not need to simulate the actual 9,000 Canadian buildings where the thermostats are located. However, by simulating two very different buildings in terms of insulation (SFH 1982 and SFH 2012) we can at least ensure them having a wide range of temperature and dynamics. Furthermore, we equipped the buildings with convectors, which are mainly emitting heat by convection (80%) and, therefore, we can assume that the thermal dynamics are very similar to those associated with forced-air furnaces, which represents the large majority of the heating systems in the DYD dataset and, in general, in Canada.
- Four different types of households: family of 4 (2 *employed* +2 *students*), couple of retired (2 *retired*), couple of employed (2 *employed*) and single adult living alone unemployed (1 *unemployed*).

Given the stochastic nature of the occupant model each simulation is repeated 50 times.

3.2. DR application

As an example of application of the thermostat adjustment model, we show how the model can be used to predict occupants' override actions during DR events. In particular, we want to derive a relation that links override rates with both the indoor temperature and the time since the start of the DR event. We use here the term 'override' instead of 'adjustment' since this is the most often used term in the context of DR studies when referring to occupants' adjustments. We simulate different occupants (family of 4, couple of retired, couple of employed and single adult living alone unemployed) and buildings (SFH 1982 and SFH 2012) under three different scenarios:

- A scenario without any DR event indicated as "*w/o DR*".
- A scenario with DR event indicated as "*with DR*".
- A scenario with DR event but without the modelled manual adjustments. This case is indicated as "*with DR no Adj*".

The simulated DR events take the form of 2 and 4 hours continuous downward modulations (to a lower limit of 15°C) of the heating setpoint temperature. These modulations can be implemented in response to the typical two-rate Time Of Use (TOU) tariffs available nowadays in France and are useful to directly decrease the load during winter peak hours. The simulated DR events are activated daily during the coldest month of January and the starting time is set at 6:00 pm, which coincides with the daily peak of the electrical load in winter in France [83]. Table 3 shows an overview of all the simulated cases for each studied parameter (a total of 48 cases repeated each 50 times).

Finally, in order to derive the override rates as a function of the distance from the setpoint temperature and the time from the start of the DR event we re-simulate all the building and occupant types under the 4 hours setpoint modulation with the modelled manual adjustments ("*with DR*") but with the setpoint change per manual adjustment always equal to zero. In this way, for each interval of time from the start of the DR event and at equal minimum indoor temperature reached in this interval, we are able to derive the observed mean override rate. If the manual adjustment was not set equal to zero, we would not been able to estimate the minimum indoor temperature reached in each interval.

Table 3. Selected cases for each studied parameter.

Single Family House	1982	2012		
Occupant Type	Couple of Employed	Couple of Retired	Single Unemployed	Family of 4
DR	with 2h	with 4h	without	
Setpoint Manual Adjustments	with	without		

3.3. Case study buildings

Two typical single-family houses are chosen as case studies: SFH 1982 (old existing house) and SFH 2012 (newly-built house). The main thermal characteristics of the simulated buildings can be found in Table 4. They are insulated from the inside and are equipped with mechanical extraction, which is automatic for the old building (SFH 1982) and humidity-controlled for the new building (SFH 2012). Both single-family houses are two-storey buildings and have a floor area of 141 m². Regarding the type of emitter, convectors are selected. Since the type of controller influences the dynamics of the building and, thus, the dynamic thermal comfort prediction, a proportional-integral controller is implemented for each convector.

Table 4. Main thermal characteristics of the simulated buildings.

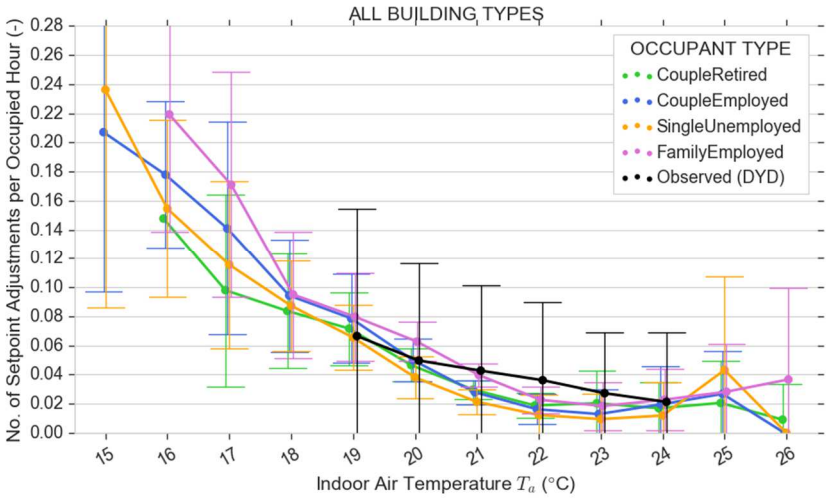
Thermal characteristic	***SFH 1982***	***SFH 2012***
Insulation Walls	*4 cm IWI (U=0.64 W/m²K)*	*18 cm IWI (U=0.18 W/m²K)*
Insulation Roof	*8 cm (U=0.58 W/m²K)*	*28 cm (U=0.13 W/m²K)*

Insulation Floor	*8 cm* *(U=0.45 W/m²K)*	*16 cm* *(U=0.23 W/m²K)*
Windows	*double glazing* *(U_w=3.1W/m²K,g=0.75)*	*double glazing* *(U_w=1.5W/m²K,g=0.63)*
Ventilation	*0.54 ACH*	*0.42 ACH (mean)*
Infiltration	*0.35 ACH*	*0.12 ACH*
HLC	*336 W/K*	*122 W/K*

4. Results

4.1. Calibration of the agent-based thermostat model

As a result of the calibration shown in Figure 8 and Figure 9, we have estimated $n = 3, m = 6$ and $p_{adj,cold,setpoint} = 0.025$ based on a time-step of 2 minutes. In Figure 8 (upper) we show the distribution (mean and standard deviation) of the number of manual heating setpoint adjustments per hour of occupancy and binned as a function of the indoor air temperature for both observed and simulated data. The observed data are from DYD connected thermostats having a default setpoint temperature of 21°C. From the observed DYD data at $\mathrm{T_a} = 21°\mathrm{C}$ we have a mean number of manual setpoint adjustments per hour of occupancy (*i.e.* occupants at home and not sleeping) equal to about 0.04. For a dwelling occupied for 6 hours per day, this corresponds to about 1 manual adjustment every four days. The mean number of manual setpoint adjustments per hour of occupancy can be also interpreted as the mean probability of having a manual adjustment during an occupied hour. In Figure 8 (lower) we show the distribution (mean and standard deviation) of the heating setpoint change per manual adjustment binned as a function of the indoor air temperature for both observed and simulated data. At $\mathrm{T_a} = 21°\mathrm{C}$ the observed mean heating setpoint change is nearly equal to zero. From Figure 8 (lower and upper) we can observe that there is a good agreement between observed and simulated data. In particular, the similarity of the curve slope demonstrates the validity of the structure of the model, which is comfort-based (i.e. based on DTS and DPD). The large observed variation within the different occupant types is due to the diversity of the 50 simulated households in terms of activity patterns.



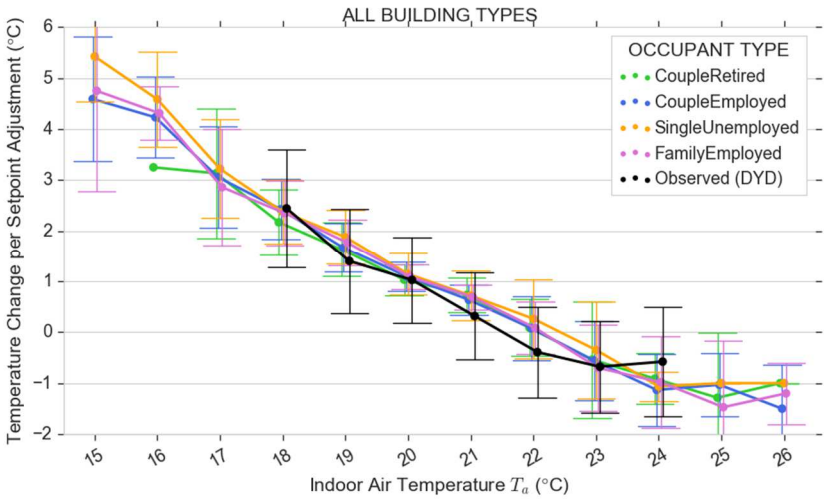
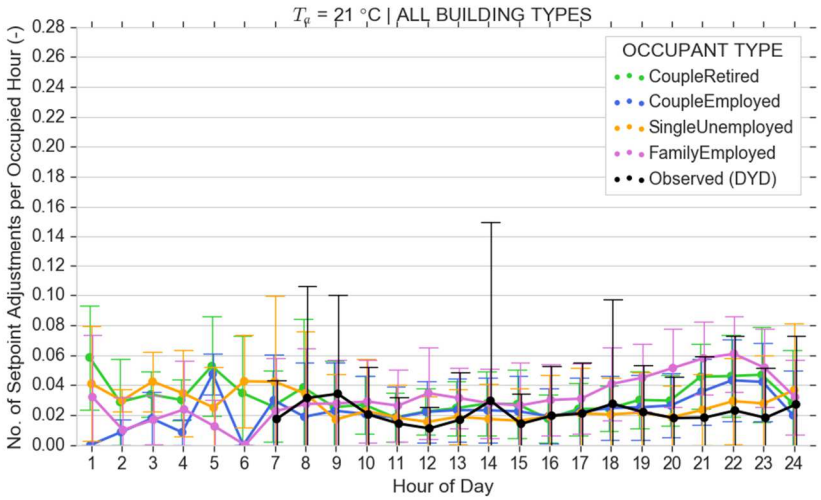


Figure 8. Mean number of manual heating setpoint adjustments per hour of occupancy (upper) and mean heating setpoint changes per manual adjustment (lower) for observed (DYD) in black and simulated in colours data. Data are binned as function of the hour of the day and are for the two types of buildings confounded. Error bars represent the standard deviation of the observations for each bin.

In Figure 9 we show the number of manual heating setpoint adjustments per hour of occupancy (upper) and the heating setpoint change per manual adjustment (lower) at $T_a = 21°C$ and binned as function of the hour of the day. From the patterns of Figure 9 (upper and lower), we can see that between 6:00 pm and 24:00 pm there is an increase in the simulated manual adjustments compared to the observed ones and also an increase in the setpoint change per manual adjustment. This is due to the lower metabolic rates observed during these hours of the day (see also Figure 10). The difference between simulated and observed data could be related to the fact that, when the metabolic rate is lower than 1 met, occupants are in a reclining position so they adjust the clothing more than under higher metabolic rates (by, for example, covering up with a blanket while watching TV). This behaviour is currently not accounted for in our model.



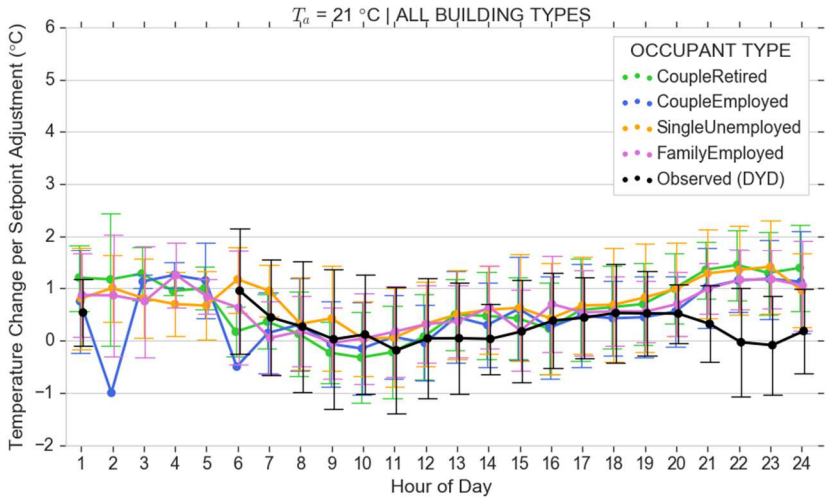


Figure 9. Mean number of manual heating setpoint adjustments per hour of occupancy (upper) and mean heating setpoint changes per manual adjustment (lower) for observed (DYD) in black and simulated in colours data at an indoor air temperature equal to 21°C. Data are binned as function of the hour of the day and are for the two types of buildings confounded. Error bars represent the standard deviation of the observations for each bin.

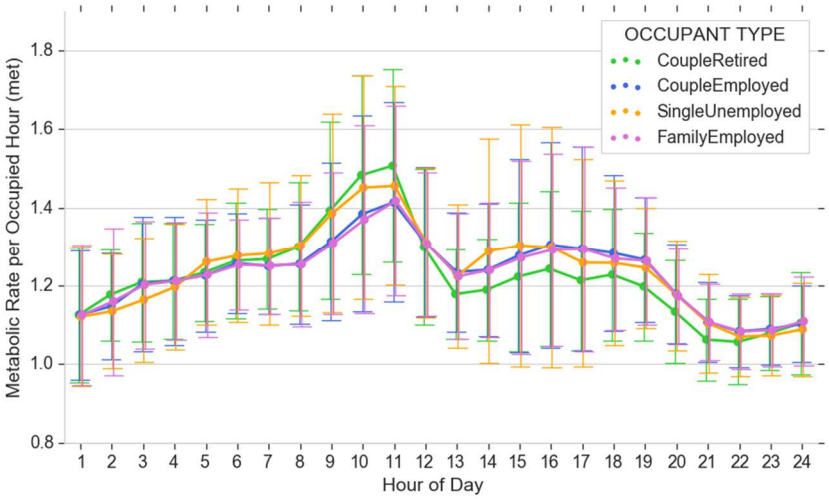


Figure 10. Mean metabolic rates binned as function of the hour of the day for the different types of simulated occupants. Error bars represent the standard deviation of the observations for each bin.

Finally, Figure 11 shows the mean clothing insulation values for the different types of occupants as a function of the indoor air temperature. This plot shows the results of the simulated occupants' clothing adaptive behaviour.

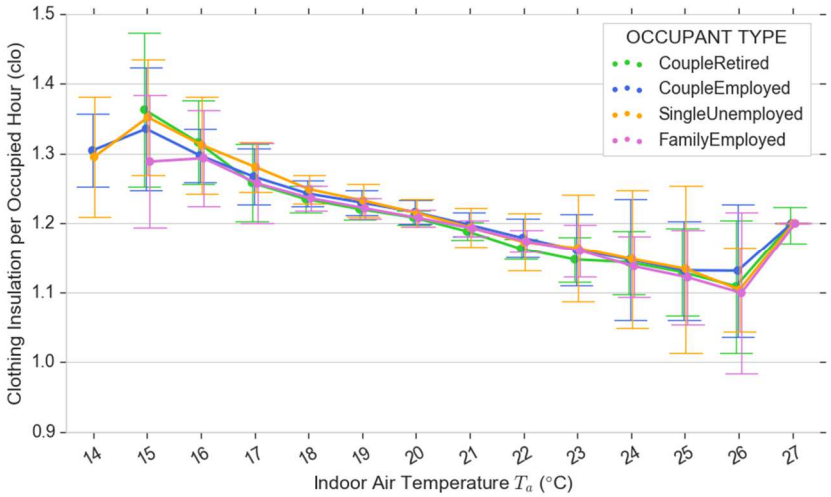
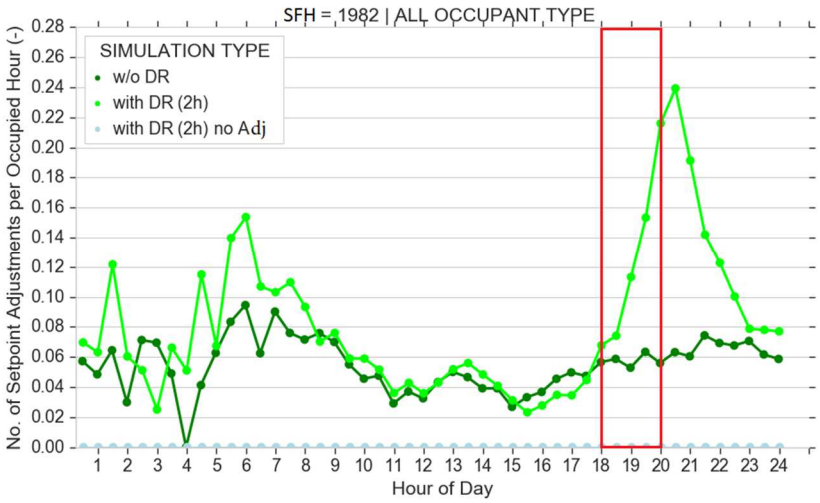


Figure 11. Mean clothing insulation values binned as function of the indoor air temperature for the different types of simulated occupants. Error bars represent the standard deviation of the observations for each bin.

4.2. DR application

In Figure 12 we show the number of manual heating setpoint adjustments per hour of occupancy binned as a function of the hour of the day for three different simulated scenarios (without DR event, with 2h DR event with Adjustments, with 2h DR event without Adjustments) in the old (upper) and new (lower) buildings. The scenario simulated without DR event corresponds to the lower number of adjustments; these adjustments are due to scheduled variations in the indoor temperature and to the time-varying metabolic rates, which cause an increase of the number of adjustments especially between 6:00 pm and 24:00 pm due to the lower metabolic rates observed during these hours of the day (see also Figure 10). In the case of the old building, the number of these adjustments is limited compared to the increase in number of adjustments caused by the 2-hours downward temperature modulation. While for the new building, the increase is of the same magnitude than the other adjustments. Thus, we can draw a first conclusion by saying that, in new buildings, 2 hours downward modulations cause an adjustment effort similar to that normally experienced by occupants during the day. While for the old buildings this effort is much bigger and, therefore, DR events have to be more carefully designed and controlled.



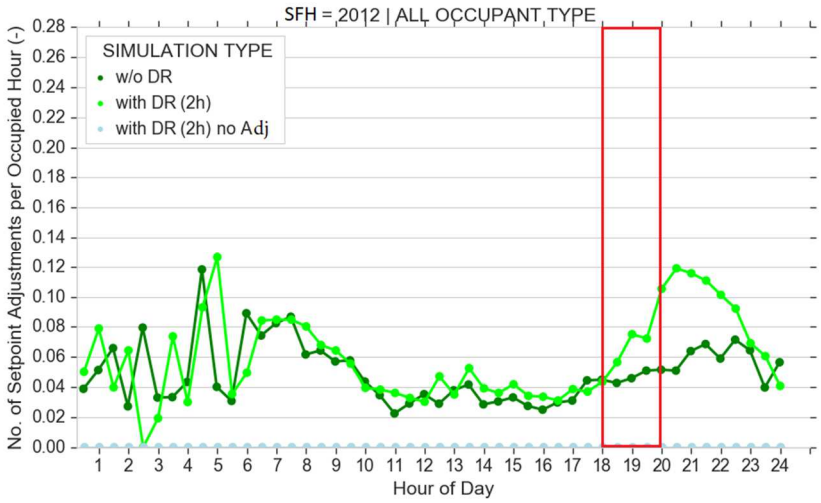
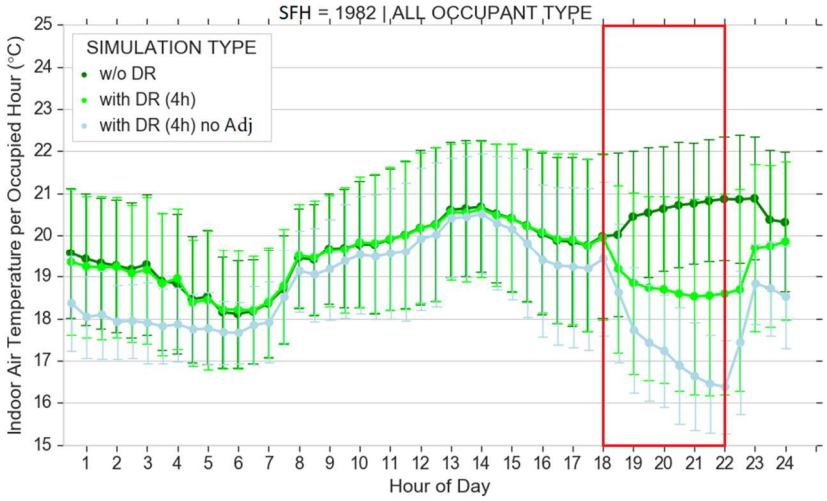


Figure 12. Mean number of manual heating setpoint adjustments per hour of occupancy for the old (upper) and the new (lower) building type for all the different types of occupants confounded. The 2-hour DR event is highlighted in red. Data are binned as function of the hour of the day.

In Figure 13 we show the indoor air temperature per hour of occupancy for three different simulated scenarios (without DR event, with 4h DR event with Adjustments, with 4h DR event without Adjustments) in the old (upper) and new (lower) building. In the scenario simulated with Adjustments, we can observe that the indoor temperature saturates to a minimum value equal to 18.5°C for the old building and 19°C for the new building.



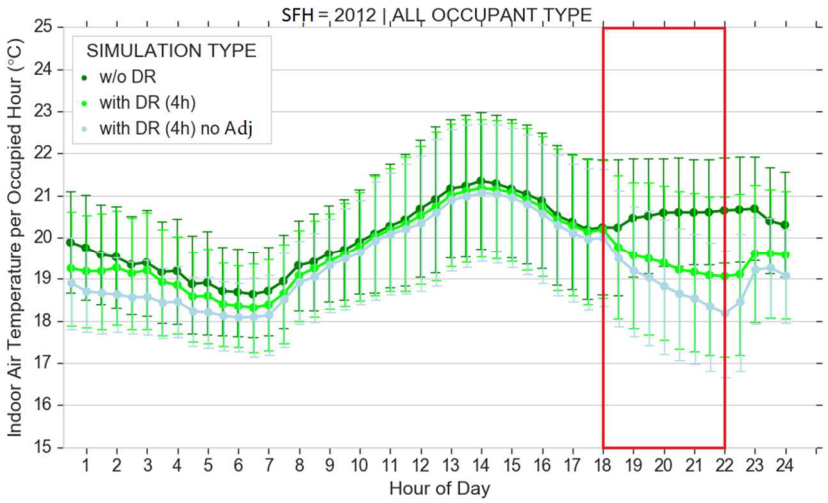


Figure 13. Indoor air temperature per hour of occupancy for three different simulated scenarios in the old (upper) and new (lower) building type and for all the different types of occupants confounded. The 4-hour DR event is highlighted in red. Data are binned as function of the hour of the day. Error bars represent one standard deviation of uncertainty for each bin.

Finally, in Figure 14 we derive the override rates as a function of the distance from the setpoint temperature and the time from the start of the DR event. This plot can be read in the following way: if at time $\delta Time$ from the start of the DR event we are at distance $\delta T_{setpoint}$ from the setpoint temperature, then the probability of adjusting the thermostat is given by the override rate OR. Similarly, in Figure 15 we show curves at equal Override Rate as a function of the distance from the setpoint temperature and the time from the start of the DR event. For example, in the case of having a $\mathrm{T_{setpoint,day}} = 21°\mathrm{C}$, a 20% rejection rate corresponds to going either as low as 16°C for 1 hour or as low as 19°C for 3 hours. Figure 14 and Figure 15 also tell us that for a setpoint modulation of 30 minutes the override rate is always lower or equal than 10% so this is the safer option for a DR utility company.

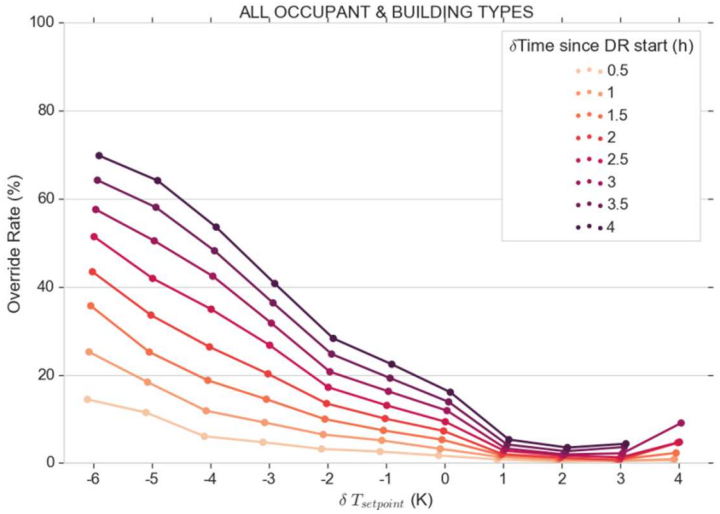


Figure 14. Override rate as a function of the distance from the setpoint temperature and the time from the start of the DR event.

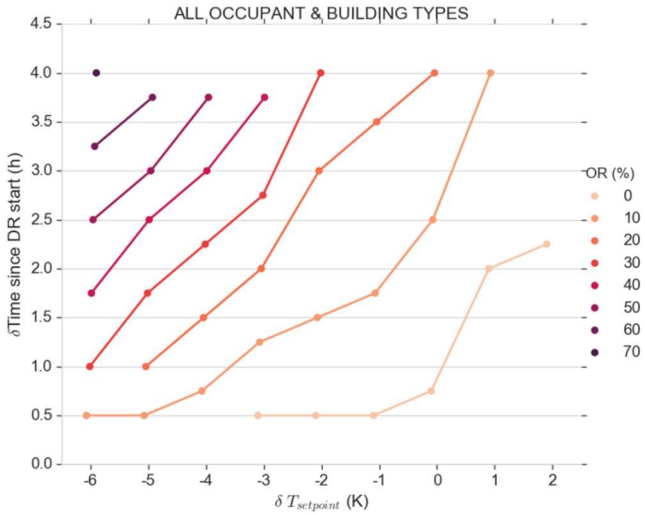


Figure 15. Curves at equal Override Rate (OR) as a function of the distance from the setpoint temperature and the time from the start of the DR event.

5. Limitations and future developments

Drivers of occupants' interactions with thermal systems and, in particular, with heating systems are related not only to the physiological conditions of the occupants, but also to their psychological situations, which in turns depend on several factors:

- the household's socio-economic characteristics and composition,
- the dwelling's size, type, energy-efficiency, and ownership,
- the type of heating system, heating delivery system and user interface to control it,
- the heating costs (e.g. heating bills already included in the rent or not, individual or collective heating systems).

The same factors also influence the chosen setpoint temperatures [29]. In this paper we do not model any influence of the above factors on the thermal adaptive behaviour of the occupants. However, the agent-based modelling framework can be extended to account for some of the above factors by adding new attributes to the agents. For example, by using the DYD dataset it would be possible to differently calibrate the probabilities $p_{adj,clothing}$, $p_{adj,warm,setpoint}$ and $p_{adj,cold,setpoint}$ depending on the composition of the household or the type of heating system. Also, these probabilities could be easily derived for the summer case and, therefore, the framework could be extended to model interactions with the air conditioning system.

Another limitation of this study is that the calibration is done with the DYD dataset which contains data from a population able to afford an ecobee thermostat and which can, thus, be supposed to belong to a high socio-economic class. This also defines the boundaries of applicability of this model.

Regarding the relationship that we derived between the override rates and the distance from the setpoint temperature and the time from the start of the DR event, this relationship is only comfort-based and does not account for any psychological factors (for example related to economic aspects, such as higher electricity prices during a DR event) that might affect the reactions of the occupants to the setpoint modulations. Furthermore, the DTS and DPD models have been derived using experimental data collected in climate chambers. Thus, they do not account for any form of occupants' adaptation. For example, it has been shown that people are much more tolerant than what PPD predicts at the extremes and less tolerant close to thermal neutrality [84].

A further limitation of our model is that it is based on a monozone building model, so assuming homogenous temperature of the household and a centralised controller. In case of a decentralised control system, the occupants' interactions with the heating system might be different and more heterogeneity in the indoor environment might occur.

6. Conclusions

In this paper, we describe and calibrate a novel agent-based stochastic model of occupants' interactions with thermostats in residential buildings in the heating season. The thermal discomfort predictions of the thermostat adjustment model are based on a two-node thermo-physiological model coupled with a dynamic thermal perception model. This represents a novelty with respect to the most often used static PMV-based discomfort predictions. Furthermore, the adjustment model is built on an activity and presence model and, therefore, is able to account for the diversity of the activities carried out by different types of occupants. The empirical foundation of the thermostat adjustments model is represented by user interaction data from about 9,000 connected Canadian thermostats included in the Donate Your Data (DYD) dataset, which are also used to calibrate the model. This represents a further strength of the model since, in most studies, calibration are either not carried out or are performed over a limited set of empirical data. Finally, we show how the framework can be used to predict the acceptance/rejection of DR events during downward setpoint modulations in two case study buildings. By using these simulations we are able to model occupants' override rates as a function of both the indoor air temperature and the time since the start of the DR event. The novel modelling framework is meant to be used for energy performance simulations at district level. Different types of applications could be conceivable. For example, the model could be used for developing and testing different DR signals (in terms of duration, time of the day, temperature drop) and strategies for energy aggregators. Another possible application could be the quantification of peak demand and the related uncertainty at different district scales. For now, the model is embedded within the simulation platform DIMOSIM but, being developed in python, it could re-adapted in the future within another simulation interface. When such modelling effort is not possible, it would be still possible to use our simplified time/temperature relationship for modelling overriding rates.

Acknowledgements

This research was funded by the French National Research Agency, project ANR CLEF (ANR-17-CE22-0005-01).

References

[1] J. Torriti, M.G. Hassan, M. Leach, Demand response experience in Europe: Policies, programmes and implementation, Energy. 35 (2010) 1575–1583. doi:10.1016/j.energy.2009.05.021.

[2] K. Vanthournout, H. Gerard, A. Virag, D. Ectors, S. Bogaert, S. Claessens, G. Mulder, S. De Breucker, D. Six, J. Viegand, M. Perret-gentil, Ecodesign Preparatory study on Smart Appliances (Lot 33) MEErP Tasks 1-6, (2017).

[3] M.H. Christensen, R. Li, P. Pinson, Demand side management of heat in smart homes: Living-lab experiments, Energy. 195 (2020) 116993. doi:10.1016/j.energy.2020.116993.

[4] T. Sweetnam, C. Spataru, M. Barrett, E. Carter, Domestic demand-side response on district heating networks, Build. Res. Inf. 47 (2019) 330–343.

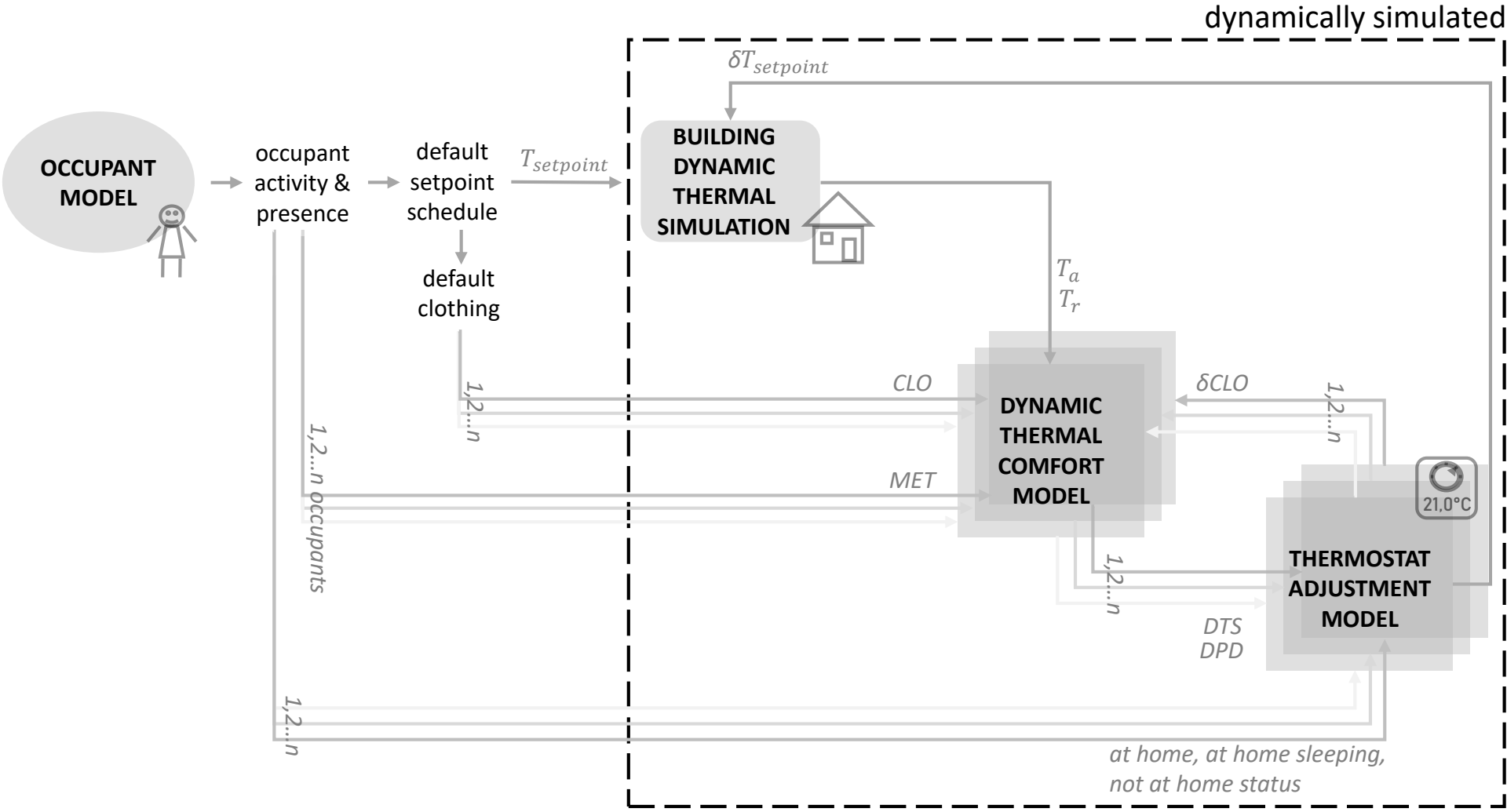
doi:10.1080/09613218.2018.1426314.
[5] D. Da Silva, Analyse de la flexibilité des usages électriques résidentiels : application aux usages thermiques, École Nationale Supérieure des Mines de Paris, 2011.
[6] M.-A. Leduc, A. Daoud, C. Le Bel, Developing winter residential demand response strategies for electric space heating, in: BS2011 12th Conf. Int. Build. Perform. Simul. Assoc., Sydney (AU), 2011.
[7] P. Morales-Valdés, A. Flores-Tlacuahuac, V.M. Zavala, Analyzing the effects of comfort relaxation on energy demand flexibility of buildings: A multiobjective optimization approach, Energy Build. 85 (2014) 416–426. doi:10.1016/j.enbuild.2014.09.040.
[8] J. Le Dréau, P. Heiselberg, Energy flexibility of residential buildings using short term heat storage in the thermal mass, Energy. 111 (2016) 991–1002. doi:10.1016/j.energy.2016.05.076.
[9] G. Masy, E. Georges, C. Verhelst, V. Lemort, P. André, Smart grid energy flexible buildings through the use of heat pumps and building thermal mass as energy storage in the Belgian context, Sci. Technol. Built Environ. 21 (2015) 800–811. doi:10.1080/23744731.2015.1035590.
[10] T.Q. Péan, J. Ortiz, J. Salom, Impact of Demand-Side Management on Thermal Comfort and Energy Costs in a Residential nZEB, Buildings. 7 (2017).
[11] T. Weiß, A.M. Fulterer, A. Knotzer, Energy flexibility of domestic thermal loads – a building typology approach of the residential building stock in Austria, Adv. Build. Energy Res. (2017) 1–16. doi:10.1080/17512549.2017.1420606.
[12] S. Agapoff, M. Jandon, T. Guiot, Impact of a tariff based heating load control on energy, comfort and environment : a parametric study in residential and office buildings, in: Int. SEEDS Conf. 2017 Sustain. Ecol. Eng. Des. Soc., Leeds (UK), 2017.
[13] P.O. Fanger, Thermal comfort: analysis and applications in environmental engineering, McGraw-Hill, 1972.
[14] B. Koelblen, A. Psikuta, A. Bogdan, S. Annaheim, R.M. Rossi, Thermal sensation models: Validation and sensitivity towards thermo-physiological parameters, Build. Environ. 130 (2018) 200–211. doi:10.1016/j.buildenv.2017.12.020.
[15] S. Tanabe, K. Kobayashi, J. Nakano, Y. Ozeki, M. Konishi, Evaluation of thermal comfort using combined multi-node thermoregulation (65MN) and radiation models and computational fluid dynamics (CFD), Energy Build. 34 (2002) 637–646. doi:10.1016/S0378-7788(02)00014-2.
[16] D. Fiala, K.J. Lomas, M. Stohrer, Computer prediction of human thermoregulatory and temperature responses to a wide range of environmental conditions, Int. J. Biometeorol. 45 (2001) 143–159. doi:10.1007/s004840100099.
[17] D. Fiala, G. Havenith, P. Bröde, B. Kampmann, G. Jendritzky, UTCI-Fiala multi-node model of human heat transfer and temperature regulation, Int. J. Biometeorol. 56 (2012) 429–441. doi:10.1007/s00484-011-0424-7.
[18] C. Huizenga, Z. Hui, E. Arens, A model of human physiology and comfort for assessing complex thermal environments, Build. Environ. 36 (2001) 691–699. doi:10.1016/S0360-1323(00)00061-5.
[19] B.R.M. Kingma, L. Schellen, A.J.H. Frijns, W.D. van Marken Lichtenbelt, Thermal sensation: a mathematical model based on neurophysiology, Indoor Air. 22 (2012) 253–262. doi:10.1111/j.1600-0668.2011.00758.x.
[20] D. Yan, W. O'Brien, T. Hong, X. Feng, H. Burak Gunay, F. Tahmasebi, A. Mahdavi, Occupant behavior modeling for building performance simulation: Current state and

future challenges, Energy Build. 107 (2015) 264–278. doi:10.1016/j.enbuild.2015.08.032.
[21] J.F. Nicol, Characterising occupant behavior in buildings: Towards a stochastic model of occupant use of windows, lights, blinds heaters and fans, Seventh Int. IBPSA Conf. (2001).
[22] H.B. Rijal, P. Tuohy, M.A. Humphreys, J.F. Nicol, A. Samuel, J. Clarke, Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings, Energy Build. (2007). doi:10.1016/j.enbuild.2007.02.003.
[23] G.Y. Yun, K. Steemers, Time-dependent occupant behaviour models of window control in summer, Build. Environ. (2008). doi:10.1016/j.buildenv.2007.08.001.
[24] F. Haldi, D. Robinson, On the behaviour and adaptation of office occupants, Build. Environ. 43 (2008) 2163–2177. doi:10.1016/j.buildenv.2008.01.003.
[25] F. Haldi, D. Robinson, Interactions with window openings by office occupants, Build. Environ. (2009). doi:10.1016/j.buildenv.2009.03.025.
[26] J. Tanimoto, A. Hagishima, State transition probability for the Markov Model dealing with on/off cooling schedule in dwellings, Energy Build. 37 (2005) 181–187. doi:10.1016/j.enbuild.2004.02.002.
[27] M. Schweiker, M. Shukuya, Comparison of theoretical and statistical models of air-conditioning-unit usage behaviour in a residential setting under Japanese climatic conditions, Build. Environ. (2009). doi:10.1016/j.buildenv.2009.03.004.
[28] X. Ren, D. Yan, C. Wang, Air-conditioning usage conditional probability model for residential buildings, Build. Environ. 81 (2014) 172–182. doi:10.1016/j.buildenv.2014.06.022.
[29] V. Fabi, R.V. Andersen, S.P. Corgnati, Influence of occupant's heating set-point preferences on indoor environmental quality and heating demand in residential buildings, in: HVAC R Res., 2013. doi:10.1080/10789669.2013.789372.
[30] H.B. Gunay, W. Shen, G. Newsham, A. Ashouri, Modelling and analysis of unsolicited temperature setpoint change requests in office buildings, Build. Environ. 133 (2018) 203–212. doi:10.1016/j.buildenv.2018.02.025.
[31] A. Bruce-Konuah, R. V. Jones, A. Fuertes, Physical environmental and contextual drivers of occupants' manual space heating override behaviour in UK residential buildings, Energy Build. 183 (2019) 129–138. doi:10.1016/j.enbuild.2018.10.043.
[32] W. Belazi, S.-E. Ouldboukhitine, A. Chateauneuf, A. Bouchair, Experimental and numerical study to evaluate the effect of thermostat settings on building energetic demands during the heating and transition seasons, Appl. Therm. Eng. 152 (2019) 35–51. doi:10.1016/j.applthermaleng.2019.02.020.
[33] J. Langevin, J. Wen, P.L. Gurian, Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors, Build. Environ. 88 (2015) 27–45. doi:10.1016/j.buildenv.2014.11.037.
[34] M. Kruusimagi, S. Sharples, D. Robinson, Living with an autonomous spatiotemporal home heating system: Exploration of the user experiences (UX) through a longitudinal technology intervention-based mixed-methods approach, Appl. Ergon. 65 (2017) 286–308. doi:10.1016/j.apergo.2017.06.017.
[35] C.J. Andrews, D. Yi, U. Krogmann, J.A. Senick, R.E. Wener, Designing buildings for real occupants: An agent-based approach, IEEE Trans. Syst. Man, Cybern. Part ASystems Humans. 41 (2011) 1077–1091. doi:10.1109/TSMCA.2011.2116116.
[36] A. Kashif, S. Ploix, J. Dugdale, X.H.B. Le, Simulating the dynamics of occupant

behaviour for power management in residential buildings, Energy Build. 56 (2013) 85–93. doi:10.1016/j.enbuild.2012.09.042.
[37] Y.S. Lee, A.M. Malkawi, Simulating multiple occupant behaviors in buildings: An agent-based modeling approach, Energy Build. 69 (2014) 407–416. doi:10.1016/j.enbuild.2013.11.020.
[38] H.C. Putra, C.J. Andrews, J.A. Senick, An agent-based model of building occupant behavior during load shedding, Build. Simul. 10 (2017) 845–859. doi:10.1007/s12273-017-0384-x.
[39] J. Chapman, P.-O. Siebers, D. Robinson, On the multi-agent stochastic simulation of occupants in buildings, J. Build. Perform. Simul. 11 (2018) 604–621. doi:10.1080/19401493.2017.1417483.
[40] J. Chapman, Multi-agent stochastic simulation of occupants in buildings, The University of Nottingham, 2017.
[41] M. Pritoni, A.K. Meier, C. Aragon, D. Perry, T. Peffer, Energy efficiency and the misuse of programmable thermostats: The effectiveness of crowdsourcing for understanding household behavior, Energy Res. Soc. Sci. 8 (2015) 190–197. doi:10.1016/j.erss.2015.06.002.
[42] P. Riederer, V. Partenay, N. Perez, C. Nocito, R. Trigance, T. Guiot, Development of a Simulation Platform for the Evaluation of District Energy System Performances, in: BS2015 14th Conf. Int. Build. Perform. Simul. Assoc., Hyderabad (IN), 2015.
[43] M. Vellei, J. Le Dréau, S.Y. Abdelouadoud, Predicting the demand flexibility of wet appliances at national level: The case of France, Energy Build. 214 (2020) 109900. doi:10.1016/j.enbuild.2020.109900.
[44] M. Vellei, J. Le Dréau, On the prediction of dynamic thermal comfort under uniform environments, in: 11th Wind. Conf. Resilient Comf. a Heat. World, Windsor (UK), 2020.
[45] INSEE, 2009-2010 Time Use Survey, (2010). https://www.insee.fr/en/metadonnees/source/operation/s1362/presentation.
[46] INSEE, Statistics on income and living conditions 2010, 2010. https://www.insee.fr/en/metadonnees/source/operation/s1074/presentation.
[47] C.F. Walker, J.L. Pokoski, Residential Load Shape Modelling Based on Customer Behavior, IEEE Trans. Power Appar. Syst. PAS-104 (1985) 1703–1711. doi:10.1109/TPAS.1985.319202.
[48] A. Capasso, W. Grattieri, R. Lamedica, A. Prudenzi, A bottom-up approach to residential load modeling, IEEE Trans. Power Syst. 9 (1994) 957–964. doi:10.1109/59.317650.
[49] I. Richardson, M. Thomson, D. Infield, C. Clifford, Domestic electricity use: A high-resolution energy demand model, Energy Build. 42 (2010) 1878–1887. doi:10.1016/j.enbuild.2010.05.023.
[50] J. V. Paatero, P.D. Lund, A model for generating household electricity load profiles, Int. J. Energy Res. 30 (2006) 273–290. doi:10.1002/er.1136.
[51] M.M. Armstrong, M.C. Swinton, H. Ribberink, I. Beausoleil-Morrison, J. Millette, Synthetically derived profiles for representing occupant-driven electric loads in Canadian housing, J. Build. Perform. Simul. 2 (2009) 15–30. doi:10.1080/19401490802706653.
[52] D. Fischer, A. Härtl, B. Wille-Haussmann, Model for electric load profiles with high time resolution for German households, Energy Build. 92 (2015) 170–179.

doi:10.1016/j.enbuild.2015.01.058.
[53] S. Yilmaz, S.K. Firth, D. Allinson, Occupant behaviour modelling in domestic buildings: the case of household electrical appliances, J. Build. Perform. Simul. 10 (2017) 582–600. doi:10.1080/19401493.2017.1287775.
[54] W. O'Brien, H.B. Gunay, F. Tahmasebi, A. Mahdavi, A preliminary study of representing the inter-occupant diversity in occupant modelling, J. Build. Perform. Simul. 10 (2017) 509–526. doi:10.1080/19401493.2016.1261943.
[55] F. Haldi, D. Calì, R.K. Andersen, M. Wesseling, D. Müller, Modelling diversity in building occupant behaviour: a novel statistical approach, J. Build. Perform. Simul. 10 (2017) 527–544. doi:10.1080/19401493.2016.1269245.
[56] F. Tahmasebi, A. Mahdavi, On the utility of occupants' behavioural diversity information for building performance simulation: An exploratory case study, Energy Build. 176 (2018) 380–389. doi:10.1016/j.enbuild.2018.07.042.
[57] ASHRAE, ANSI/ASHRAE Standard 55-2017 - Thermal Environmental Conditions for Human Occupancy, 2017.
[58] A.P. Gagge, J.A.J. Stolwijk, Y. Nishi, Effective temperature scale based on a simple model of human physiological regulatory response, ASHRAE Trans. 77 (1971) 247–263.
[59] D. Fiala, K.J. Lomas, M. Stohrer, First principles modeling of thermal sensation responses in steady-state and transient conditions, in: ASHRAE Trans., 2003: pp. 179–186. doi:10.1590/S1517-838220080002000021.
[60] R.A. Haslam, An evaluation of models of human response to hot and cold environments, Loughborough University, UK, 1989.
[61] C. Smith, A Transient, Three-Dimensional Model of the Human Thermal System, Kansas State University, USA, 1991.
[62] T. Doherty, E. Arens, Evaluation of the physiological bases of thermal comfort models, ASHRAE Trans. 94 (1988) 1371–1385.
[63] A.P. Gagge, J.A.J. Stolwijk, J.D. Hardy, Comfort and thermal sensations and associated physiological responses at various ambient temperatures, Environ. Res. 1 (1967) 1–20. doi:https://doi.org/10.1016/0013-9351(67)90002-3.
[64] F. Zhang, R. de Dear, C. Candido, Thermal comfort during temperature cycles induced by direct load control strategies of peak electricity demand management, Build. Environ. 103 (2016) 9–20. doi:10.1016/j.buildenv.2016.03.020.
[65] X. Du, B. Li, H. Liu, D. Yang, W. Yu, J. Liao, Z. Huang, K. Xia, The Response of Human Thermal Sensation and Its Prediction to Temperature Step-Change (Cool-Neutral-Cool), PLoS One. 9 (2014) e104320. doi:10.1371/journal.pone.0104320.
[66] H. Liu, J. Liao, D. Yang, X. Du, P. Hu, Y. Yang, B. Li, The response of human thermal perception and skin temperature to step-change transient thermal environments, Build. Environ. 73 (2013) 232–238. doi:10.1016/j.buildenv.2013.12.007.
[67] M. Cabanac, Sensory Pleasure, Q. Rev. Biol. 54 (1979) 1–29. doi:10.1086/410981.
[68] M. Attia, Thermal pleasantness and temperature regulation in man, Neurosci. Biobehav. Rev. 8 (1984) 335–342. doi:10.1016/0149-7634(84)90056-3.
[69] H. Zhang, E. Arens, C. Huizenga, T. Han, Thermal sensation and comfort models for non-uniform and transient environments, part III: Whole-body sensation and comfort, Build. Environ. 45 (2010) 399–410. doi:10.1016/j.buildenv.2009.06.020.
[70] H. Zhang, E. Arens, C. Huizenga, T. Han, Thermal sensation and comfort models for non-uniform and transient environments, part II: Local comfort of individual body

parts, Build. Environ. 45 (2010) 389–398. doi:10.1016/j.buildenv.2009.06.015.
[71] H. Zhang, E. Arens, C. Huizenga, T. Han, Thermal sensation and comfort models for non-uniform and transient environments: Part I: Local sensation of individual body parts, Build. Environ. 45 (2010) 380–388. doi:10.1016/j.buildenv.2009.06.018.
[72] T. Parkinson, R. De Dear, C. Candido, Thermal pleasure in built environments: Alliesthesia in different thermoregulatory zones, Build. Res. Inf. 44 (2016) 20–33. doi:10.1080/09613218.2015.1059653.
[73] M. Vellei, J. Le Dréau, A novel model for evaluating dynamic thermal comfort under demand response events, Build. Environ. 160 (2019) 106–215. doi:10.1016/j.buildenv.2019.106215.
[74] B. Huchuk, W. O'Brien, S. Sanner, A longitudinal study of thermostat behaviors based on climate, seasonal, and energy price considerations using connected thermostat data, Build. Environ. 139 (2018) 199–210. doi:10.1016/j.buildenv.2018.05.003.
[75] M. Kane, K. Sharmaa, Data-driven Identification of Occupant Thermostat-Behavior Dynamics, ArXiv. (2019).
[76] H. Stopps, M.F. Touchie, Managing thermal comfort in contemporary high-rise residential buildings: Using smart thermostats and surveys to identify energy efficiency and comfort opportunities, Build. Environ. 173 (2020) 106748. doi:10.1016/j.buildenv.2020.106748.
[77] B. Huchuk, S. Sanner, W. O'Brien, Comparison of machine learning models for occupancy prediction in residential buildings using connected thermostat data, Build. Environ. 160 (2019) 106177. doi:10.1016/j.buildenv.2019.106177.
[78] R. de Dear, G. Brager, D. Cooper, Developing an Adaptive Model of Thermal Comfort and Preference - Final Report on RP 884, Sydney, 1997.
[79] M. Schweiker, K. Schakib-Ekbatan, X. Fuchs, S. Becker, A seasonal approach to alliesthesia. Is there a conflict with thermal adaptation?, Energy Build. 212 (2020) 109745. doi:10.1016/j.enbuild.2019.109745.
[80] R.-L. Hwang, M.-J. Cheng, T.-P. Lin, M.-C. Ho, Thermal perceptions, general adaptation methods and occupant's idea about the trade-off between thermal comfort and energy saving in hot–humid regions, Build. Environ. 44 (2009) 1128–1134. doi:10.1016/j.buildenv.2008.08.001.
[81] M. Humphreys, F. Nicol, S. Roaf, Adaptive Thermal Comfort: Foundations and Analysis, Taylor & Francis Group, London, 2015.
[82] A.S. Rao, M.P. Georgeff, BDI Agents: From Theory to Practice, in: ICMAS95 1st Int. Conf. MULTI-AGENT Syst., San Francisco (USA), 1995. doi:10.1.1.37.7970.
[83] RTE, Réseaux électriques intelligents : valeur économique, environnementale et déploiement d'ensemble, 2017.
[84] T. Cheung, G. Brager, T. Parkinson, P. Li, S. Schiavon, Analysis of the accuracy on PMV – PPD model using the ASHRAE Global Thermal Comfort Database II, Build. Environ. (2019). doi:10.1016/j.buildenv.2019.01.055.


dynamically simulated
OCCUPANT MODEL
occupant activity & presence
default setpoint schedule
default clothing
$T_{setpoint}$
$\delta T_{setpoint}$
BUILDING DYNAMIC THERMAL SIMULATION
T_a
T_r
CLO
MET
1,2...n
1,2...n occupants
DYNAMIC THERMAL COMFORT MODEL
δCLO
1,2...n
21,0°C
THERMOSTAT ADJUSTMENT MODEL
1,2...n
DTS
DPD
1,2...n
at home, at home sleeping, not at home status