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1 Agent-based stochastic model of thermostat adjustments: a 2 demand response application

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8 9 **Abstract**

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

31
32 **Keywords:** Occupant Activity, Thermostat Adjustment/Override, Dynamic Thermal Comfort
33 (Gagge + Fiala), Demand Response, Heating Energy Use

34 **1. Introduction**

35 **1.1. Context**

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

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

9 **1.2. State-of-the-art**

10 Dynamic thermal comfort

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

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

26 Thermostat adjustments

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

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

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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 Cézabaz, France	1 heating season

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

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

3 *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								-	-

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

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

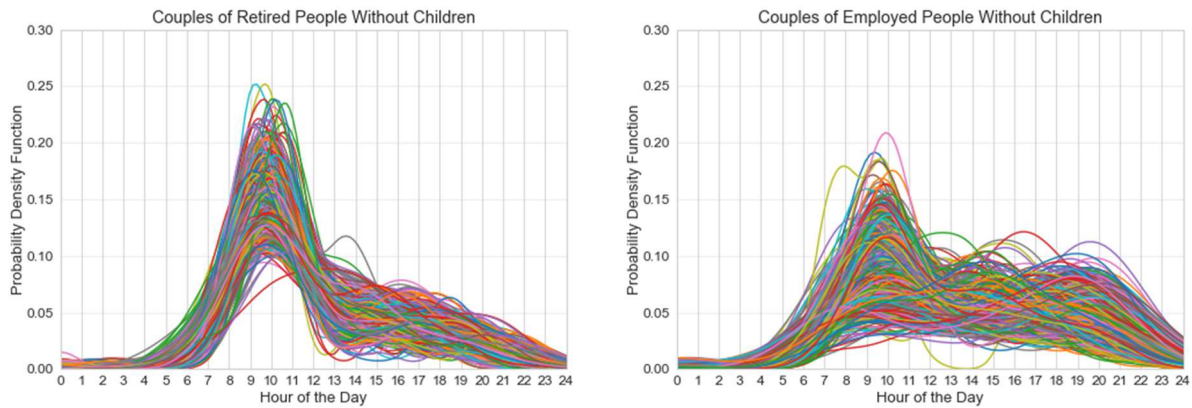
8 **1.3. Research aims**

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

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

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

1 Instead, our method uses the actual TUS activity sequences and, therefore, allows to
 2 account for the diversity of the real population in terms of occupancy and activities carried
 3 out at home [43]. As an example we show in Figure 2 the probability of the start times of
 4 the ‘doing laundry’ activity (at a given hour of the day) from about 600 households. This
 5 diversity is a key aspect of occupant behaviour modelling as evidenced by recent works [54–
 6 56] and is especially important for peak demand studies.



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

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

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

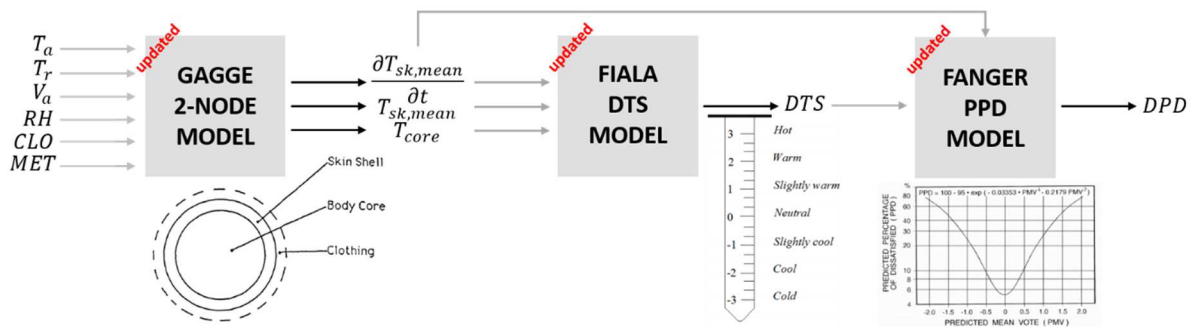
27 **2.2. Dynamic thermal comfort model**

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

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

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

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



12
 13

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

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

23 Despite its simple representation of the human body, Gagge’s two-node model is accurate
 24 for practical applications in the built environment where environmental conditions are
 25 usually near the neutrality and activity levels are mostly lower than 3.5 met [60–62].
 26 However, we have further extended the predictive capabilities of Gagge’s two-node model
 27 by substituting its simple linear, temperature-based active system model with Fiala’s non-
 28 linear, temperature-based active system model, whose empirical control equations for
 29 shivering, vasoconstriction, vasodilatation, and sweating have been derived from statistical
 30 analysis of a wide range of data coming from 27 climate chamber experiments covering air
 31 temperatures between 5°C and 50°C and exercise intensities between 0.8 met and 10 met
 32 [16]. For more details on the accuracy of the updated Gagge’s two-node model the reader is
 33 referred to our previous work [44].

34 Fiala’s *DTS* model [59] is able to predict the whole-body thermal sensation on the seven-
 35 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:

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

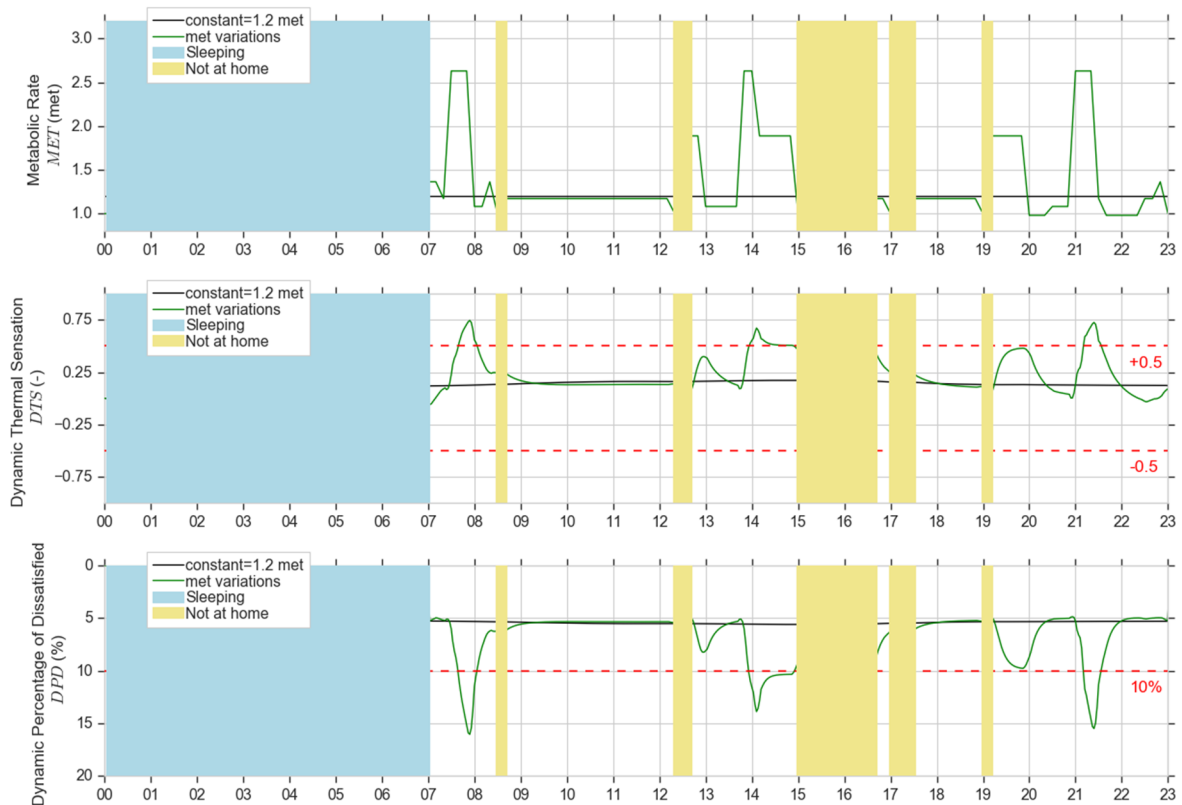
By using experimental data derived from dynamic experiments in climate chambers [64], we have derived a new dynamic version of Fanger's static PPD index, which is given by:

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

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 $\frac{\partial T_{sk,mean}}{\partial t}^{(+)}$.

1 The parameters a and b of Equation (2) are obtained by minimizing the RMSE during both
 2 cooling and warming transients using the Nelder-Mead Algorithm. Accuracy of the novel
 3 DPD in terms of RMSE falls between 4 and 6%.
 4 For the literature on the phenomenon of thermal alliesthesia the reader is referred to the
 5 works of Cabanac [67], Attia [68], Zhang [69–71], Parkinson [72] and Vellei & Le Dréau [73].
 6 For more details on the derivation and validation of the dynamic thermal comfort model the
 7 reader is referred to our previous work [44]. The dynamic thermal comfort model coded in
 8 Python is available for download in the supplementary materials.
 9 An example of the simulated DTS and DPD over the course of a day for both the case of a
 10 constant metabolic rate equal to 1.2 met and a time-varying metabolic rate is shown in
 11 Figure 4. We only calculate DTS and DPD for time-steps where the occupants are at home
 12 and awake. After periods of sleeping or periods when the occupant is not at home, we
 13 assume that the initial comfort conditions are equal to the final conditions of the previous -
 14 at home and awake - period. In Figure 4 we can observe that the met variations have a non-
 15 negligible effect on the comfort of the occupants. This is a confirmation of the importance
 16 of modelling the stochastic time-varying met levels which, as we will see in the Results, also
 17 influence the comfort-driven thermostat adjustments.



18
 19 *Figure 4. Example of dynamic thermal comfort predictions for an occupant of type unemployed during typical*
 20 *daily MET variations. All the other parameters are fixed ($T_a = T_r = 21^\circ\text{C}$, $V_a = 0.1 \text{ m/s}$, $RH = 50\%$, $clo =$*
 21 *1.2). Only time-steps where the occupant is at home and awake are shown.*

22 2.3. Agent-based thermostat model

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

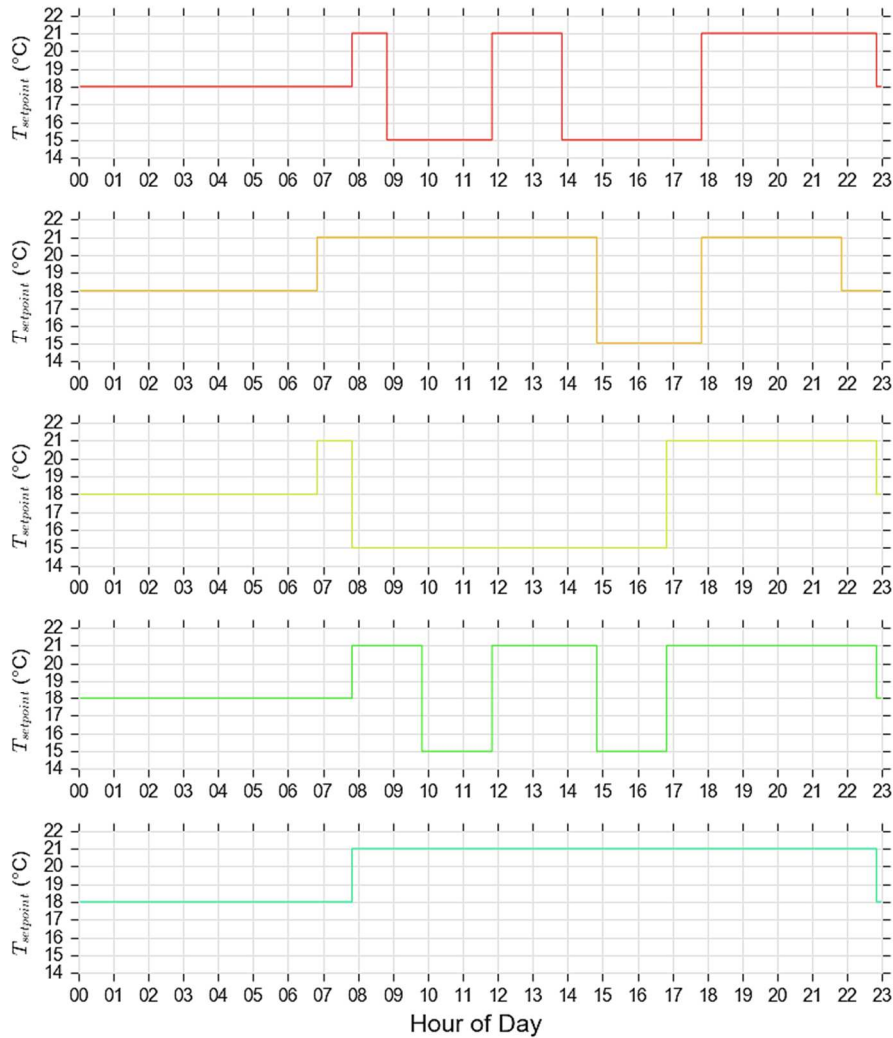
- 1 • the default setpoint temperatures,
- 2 • the operation schedule,
- 3 • and the manual overriding behaviour.

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

- 6 • the day setpoint temperature ($T_{\text{setpoint,day}}$) for when somebody who is not sleeping
7 is at home (*at home status*),
- 8 • the night setpoint temperature ($T_{\text{setpoint,night}}$) for when everybody who is at home is
9 sleeping (*at home sleeping status*),
- 10 • the set-back temperature (T_{setback}) for when nobody is at home (*not at home*
11 *status*).

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

19 For each household, the operation schedule is estimated based on the occupants' activity
20 and presence profile time series by calculating the hourly probability of having each
21 household's status (*at home*, *at home sleeping*, *not at home*) over the simulated period. For
22 each hour of the day, the status with the highest probability of occurring defines the
23 corresponding hourly scheduled/default temperature ($T_{\text{setpoint,day}}$, $T_{\text{setpoint,night}}$, and
24 T_{setback}) for the household. This hourly profile is then repeated for each day throughout the
25 simulation period. Thus, the hourly setpoint schedule is defined for each household in a pre-
26 process with respect to the dynamic thermal simulation (see Figure 1 for the overall
27 modelling framework), while the manual overriding behaviour is dynamically simulated.
28 Some examples of operation schedules are shown in Figure 5. Since having a programmable
29 thermostat does not necessarily implies using programmable features [41], defining an
30 operation schedule does not necessarily imply that each household is using a night setpoint
31 temperature or a setback temperature. In the process of drawing the default setpoint
32 temperatures, some households might have $T_{\text{setpoint,night}} = T_{\text{setpoint,day}}$ and/or $T_{\text{setback}} =$
33 $T_{\text{setpoint,day}}$ and, therefore, not use any schedule. But, again, this depends on the model of
34 the default setpoint temperatures, which is not covered in this paper.



1

2

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

3

4

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).

6

7 Data-driven ABM model foundation

8

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].

19

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

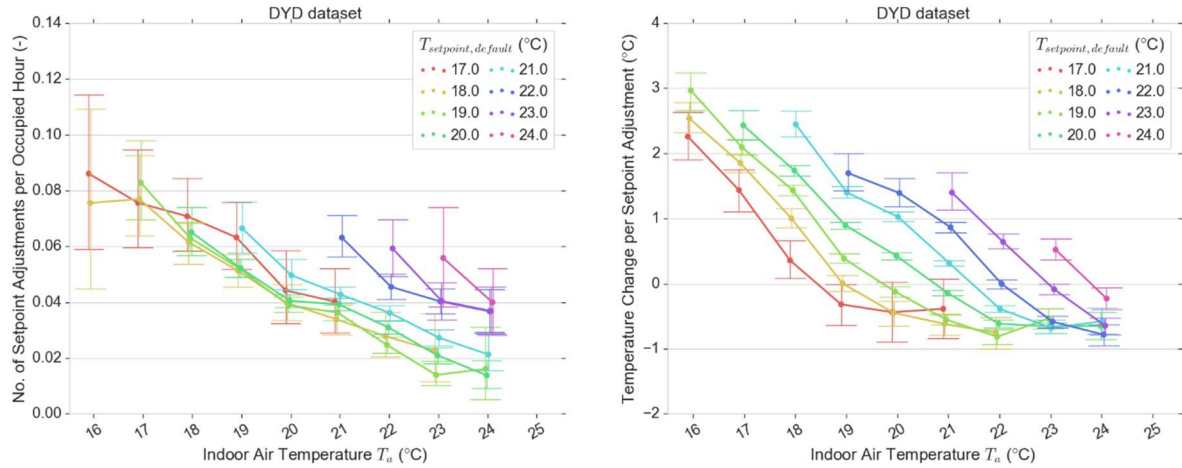
- 16 • we only consider thermostats in Canadian homes,
- 17 • we only take data from winter months characterized by a mean monthly outdoor
18 temperature lower than 15°C,
- 19 • we exclude thermostats containing less than 10 days of detected occupied time-
20 steps.

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

22 In Figure 6 we show aggregated mean data from the selected 9,000 thermostats. In Figure 6
23 (left) we can observe that, at equal indoor air temperature, the mean number of manual
24 setpoint adjustments per hour of occupancy differs for the different default setpoint
25 temperatures ($T_{setpoint,default}$). The default setpoint temperature is calculated for each
26 thermostat as the mean heating setpoint temperature during occupied time-steps. In Figure
27 6 (right) we can further observe that when the occupants decide to change their heating
28 setpoint they do so differently at different default setpoint temperatures. In particular, at
29 $T_a = T_{setpoint,default}$ the mean setpoint change is approaching zero when the default
30 setpoint temperature is higher than 20°C. This means that occupants adapt to their chosen
31 prevailing setpoint temperature. In our ABM modelling approach we assume that this
32 adaptation consists in selecting the occupants’ default clothing level based on the
33 $T_{setpoint,day}$. Thus, for each occupant we calculate a default clothing level for comfort by
34 using the PMV model and by setting $T_a = T_r = T_{setpoint,day}$. As an example, for the
35 simulations described in Sections 3.1 and 3.2 and run at $T_{setpoint,day} = 21^\circ\text{C}$ the default
36 clothing insulation is calculated to be equal to 1.2 clo, *i.e.* the value corresponding to a
37 $PMV \approx 0$ at average values of the other comfort parameters ($RH = 50\%$, $V_a = 0.1\text{m/s}$ and
38 $MET = 1.2\text{met}$). The default clothing insulation and the default setpoint temperature are
39 then modified by the occupants over the course of the dynamic simulation.

40 From the patterns of Figure 6 (left and right), we can further observe that the mean number
41 of manual adjustments decreases at increasing indoor air temperatures, while we would
42 expect the curve to be symmetrical around the setpoint. Also, the mean temperature
43 change per manual adjustment saturates at a value approximately equal to -0.5°C. This
44 could be due to the phenomenon of seasonal thermal alliesthesia according to which
45 occupants tend to accept warmer thermal sensations in winter and colder ones in summer
46 [78–80]. However, this could also be due to the fact that when the air temperature is higher
47 than the setpoint, setting a very low heating setpoint would not imply to actively cool the

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

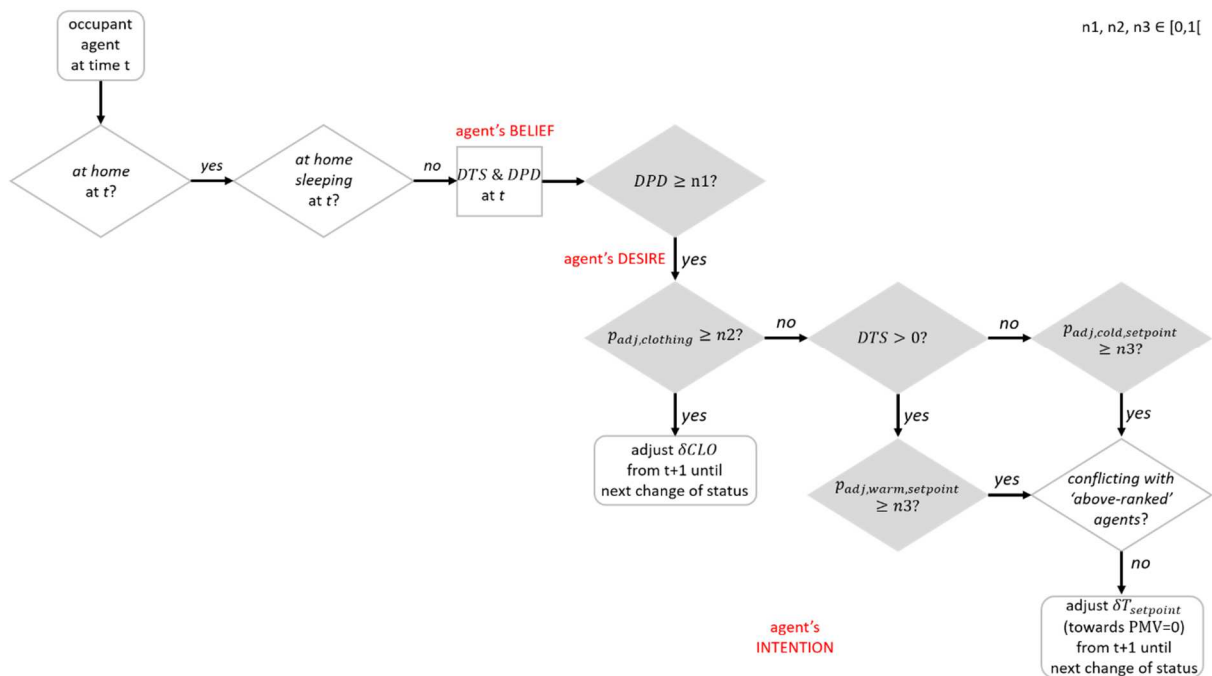


6 *Figure 6. Mean number of manual heating setpoint adjustments per hour of occupancy (left) and mean heating*
 7 *setpoint changes per manual adjustment (right) for the DYD thermostats at different levels of the setpoint*
 8 *temperature. The data are from about 9,000 thermostats and are binned as function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

10 Theory-driven model foundation

11 The *adaptive principle* (“if a change occurs such as to produce discomfort, people react in
 12 ways that tend to restore their comfort” [81]) is assumed to be at the base of the manual
 13 overriding behaviour. When the occupant agent is at home and is not sleeping, he reacts to
 14 environmental and personal changes according to this principle. For modelling the agent’s
 15 adaptive behaviour, we use a particular type of agent: the Belief-Desire-Intention (BDI)
 16 agent, which is characterized by certain mental attitudes of belief, desire, and intention,
 17 representing its informational, motivational, and deliberative states respectively [82]. First,
 18 a BDI agent obtains a belief about the state of its current environment. In our case,
 19 environmental and personal conditions form the occupant’s thermal dissatisfaction, which is
 20 represented by the Dynamic Thermal Sensation (*DTS*) and Dynamic Percentage of
 21 Dissatisfied (*DPD*). Then, the agent translates its thermal dissatisfaction into a desire about
 22 what to achieve, *i.e.* whether to change its current thermal state. This is predicted using a
 23 time-dependent Bernoulli process. A uniformly distributed random number n is drawn in
 24 $[0,1]$ and compared to the *DPD*. If the *DPD* is more than the random number n , the desired
 25 outcome is to change its current state. Finally, the agent translates its desire into an
 26 intention to act (occupant’s adaptive behaviour). The agent’s intention is defined by the
 27 probabilities of reactively adjusting the clothing $p_{adj, clothing}$ (before) and the setpoint
 28 temperature $p_{adj, setpoint}$ (afterwards) using a time-dependent Bernoulli process. Thus, it is
 29 assumed that the adjustment of the clothing insulation is the preferred adaptation strategy.
 30 The probably of adjusting the setpoint during warm exposures $p_{adj, warm, setpoint}$ is different
 31 than during cold exposures $p_{adj, cold, setpoint}$ according to the alliesthesia-based asymmetry
 32 observed in Figure 6 of the previous paragraph. It is further assumed that when the agent
 33 decides to adjust its clothing, he does it modularly by either increasing or decreasing the
 34 clothing of $\delta CLO = 0.1 clo$, where $0.1 clo$ is, for example, the clothing insulation change

1 made when passing from a thin long-sleeved sweater to a thick long-sleeved sweater [57].
 2 While, when the occupant decides to adjust the setpoint of $\delta T_{setpoint}$, he does it to restore
 3 thermal neutrality (*i.e.* towards a $PMV \approx 0$). The $T_{setpoint}$ has a lower limit equal to
 4 $T_{setpoint,day} - 1^\circ\text{C}$ during warm exposures and an upper limit equal to $T_{setpoint,day} + 6^\circ\text{C}$ during
 5 cold exposures, always based on what observed in Figure 6 of the previous paragraph.
 6 Conflicts between members of the households also need to be taken into account because,
 7 at a given simulation time-step, an occupant might want to increase the setpoint
 8 temperature and another to decrease it. We solved these conflicts by ranking the members
 9 of the households by importance order (the ranking is random and it does not depend on
 10 the type of occupant). The decisions of the first-ranked occupant prevail over the others;
 11 the decisions of the second-ranked prevail over the others with the exception of the first-
 12 ranked and so on. Thus, if the first-ranked decides to change the setpoint temperature, the
 13 other members of the household are not able to override its decision. The model does not
 14 account for any learning of the agent over time. The agent-based modelling framework for
 15 the manual overriding behaviour is represented in Figure 7.



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

18 3. Methods

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

1 15°C. Since the calibration is done with respect to the indoor temperature, we not need to
2 simulate the actual $T_{\text{setpoint,night}}$ and T_{setback} of the 9,000 Canadian buildings where the
3 thermostats are located. However, $T_{\text{setpoint,day}}$ has to be set equal to 21°C since we are
4 calibrating the model against ecobee households having a mean heating setpoint
5 temperature during occupied time-steps equal to 21°C. The winter default clothing level of
6 the occupants is set equal to 1.2 clo, as seen in Section 2.3. For the inputs of the *DTS/DPD*
7 model, the air velocity (V_a) is set to be equal to 0.1 m/s and the relative humidity (*RH*) equal
8 to 50%.

9 **3.1. Calibration with connected thermostat data**

10 The calibration of the thermostat adjustment model consists in estimating $p_{\text{adj, clothing}}$,
11 $p_{\text{adj, warm, setpoint}}$ and $p_{\text{adj, cold, setpoint}}$ which are the key probabilities needed to map
12 occupant thermal perception onto its adaptive behaviour. To do this, we first set
13 $p_{\text{adj, clothing}} = n * p_{\text{adj, cold, setpoint}}$ and $p_{\text{adj, warm, setpoint}} = p_{\text{adj, cold, setpoint}}/m$. Then, we
14 estimate n , m , and $p_{\text{adj, cold, setpoint}}$ by simulating a diverse set of households and buildings
15 and using a simple iterative qualitative method in which we visually compare the simulated
16 and empirical values of two different metrics: the number of manual setpoint adjustments
17 per hour of occupancy and the setpoint change per manual adjustment, given as a function
18 of the indoor temperature. Thus, the model is calibrated at an aggregated level and not at
19 the level of the individual household. The empirical values are coming from the DYD dataset,
20 which has been already introduced in Section 2.3 (see also Figure 6). The simulated data
21 origins from a combination of the following selected cases:

- 22 • Two residential buildings characterized by different levels of insulation: a typical
23 existing single-family house (SFH 1982) and a newly-built single-family house (SFH
24 2012). For more details of the case study buildings see Section 3.3. It is important to
25 highlight that the calibration is done with respect to the indoor temperature and,
26 therefore, we not need to simulate the actual 9,000 Canadian buildings where the
27 thermostats are located. However, by simulating two very different buildings in
28 terms of insulation (SFH 1982 and SFH 2012) we can at least ensure them having a
29 wide range of temperature and dynamics. Furthermore, we equipped the buildings
30 with convectors, which are mainly emitting heat by convection (80%) and, therefore,
31 we can assume that the thermal dynamics are very similar to those associated with
32 forced-air furnaces, which represents the large majority of the heating systems in
33 the DYD dataset and, in general, in Canada.
- 34 • Four different types of households: family of 4 (2 *employed* +2 *students*), couple of
35 retired (2 *retired*), couple of employed (2 *employed*) and single adult living alone
36 unemployed (1 *unemployed*).

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

38 **3.2. DR application**

39 As an example of application of the thermostat adjustment model, we show how the model
40 can be used to predict occupants' override actions during DR events. In particular, we want
41 to derive a relation that links override rates with both the indoor temperature and the time
42 since the start of the DR event. We use here the term 'override' instead of 'adjustment'
43 since this is the most often used term in the context of DR studies when referring to
44 occupants' adjustments. We simulate different occupants (family of 4, couple of retired,
45 couple of employed and single adult living alone unemployed) and buildings (SFH 1982 and
46 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.

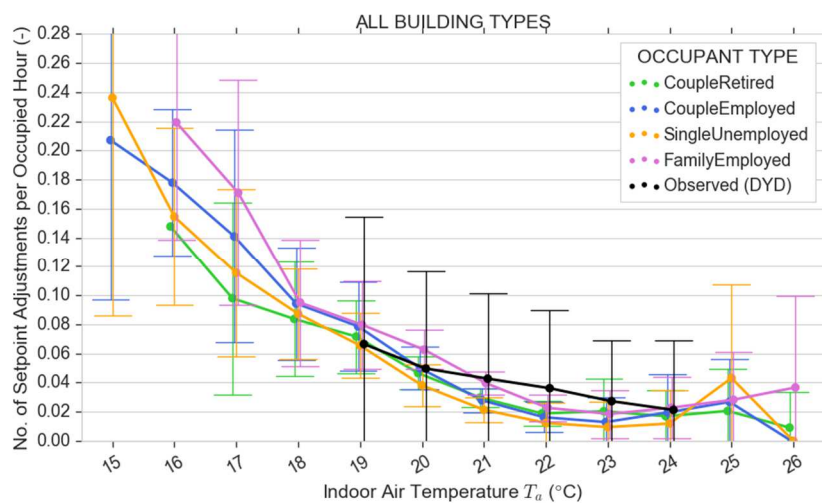
Thermal characteristic	SFH 1982	SFH 2012
Insulation Walls	4 cm IWI (U=0.64 W/m ² K)	18 cm IWI (U=0.18 W/m ² K)
Insulation Roof	8 cm (U=0.58 W/m ² K)	28 cm (U=0.13 W/m ² K)

Insulation Floor	8 cm ($U=0.45 \text{ W/m}^2\text{K}$)	16 cm ($U=0.23 \text{ W/m}^2\text{K}$)
Windows	double glazing ($U_w=3.1 \text{ W/m}^2\text{K}, g=0.75$)	double glazing ($U_w=1.5 \text{ W/m}^2\text{K}, g=0.63$)
Ventilation	0.54 ACH	0.42 ACH (mean)
Infiltration	0.35 ACH	0.12 ACH
HLC	336 W/K	122 W/K

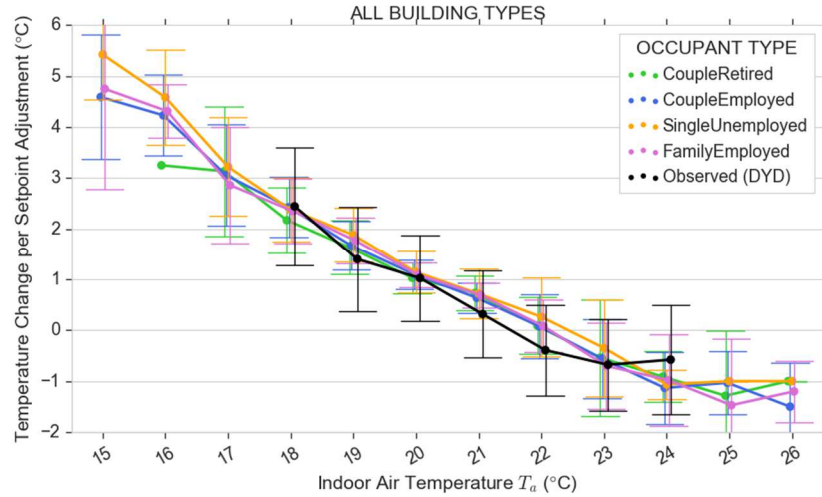
1 4. Results

2 4.1. Calibration of the agent-based thermostat model

3 As a result of the calibration shown in Figure 8 and Figure 9, we have estimated $n = 3, m =$
4 6 and $p_{adj,cold,setpoint} = 0.025$ based on a time-step of 2 minutes. In Figure 8 (upper) we
5 show the distribution (mean and standard deviation) of the number of manual heating
6 setpoint adjustments per hour of occupancy and binned as a function of the indoor air
7 temperature for both observed and simulated data. The observed data are from DYD
8 connected thermostats having a default setpoint temperature of 21°C . From the observed
9 DYD data at $T_a = 21^\circ\text{C}$ we have a mean number of manual setpoint adjustments per hour of
10 occupancy (*i.e.* occupants at home and not sleeping) equal to about 0.04. For a dwelling
11 occupied for 6 hours per day, this corresponds to about 1 manual adjustment every four
12 days. The mean number of manual setpoint adjustments per hour of occupancy can be also
13 interpreted as the mean probability of having a manual adjustment during an occupied
14 hour. In Figure 8 (lower) we show the distribution (mean and standard deviation) of the
15 heating setpoint change per manual adjustment binned as a function of the indoor air
16 temperature for both observed and simulated data. At $T_a = 21^\circ\text{C}$ the observed mean
17 heating setpoint change is nearly equal to zero. From Figure 8 (lower and upper) we can
18 observe that there is a good agreement between observed and simulated data. In particular,
19 the similarity of the curve slope demonstrates the validity of the structure of the model,
20 which is comfort-based (*i.e.* based on *DTS* and *DPD*). The large observed variation within
21 the different occupant types is due to the diversity of the 50 simulated households in terms
22 of activity patterns.



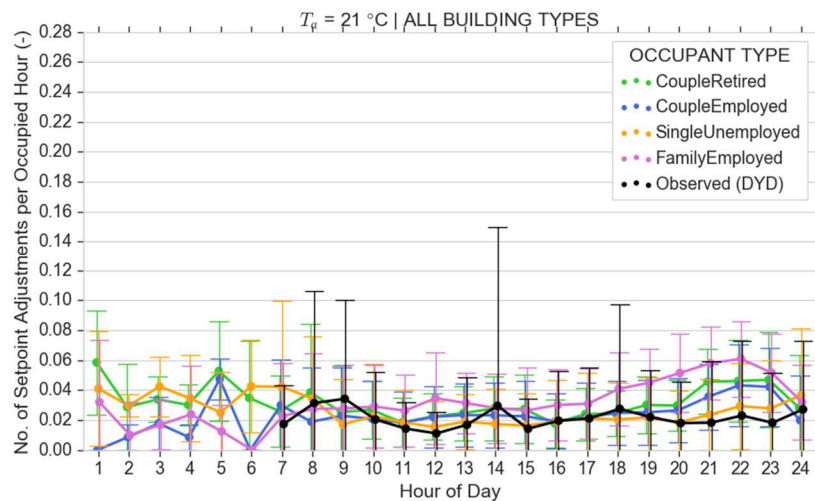
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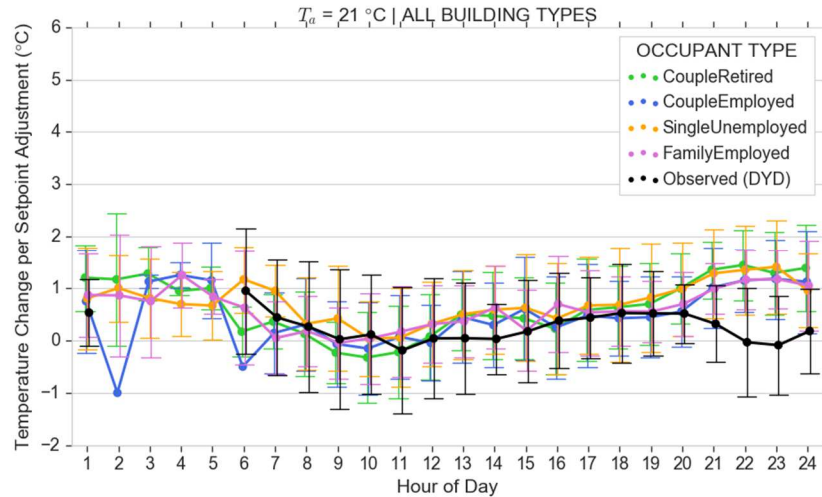
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Figure 8. Mean number of manual heating setpoint adjustments per hour of occupancy (upper) and mean heating setpoint changes per manual adjustment (lower) for observed (D.Y.D.) in black and simulated in colours data. Data are binned as function of 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.

6 In Figure 9 we show the number of manual heating setpoint adjustments per hour of
 7 occupancy (upper) and the heating setpoint change per manual adjustment (lower) at $T_a =$
 8 21°C and binned as function of the hour of the day. From the patterns of Figure 9 (upper
 9 and lower), we can see that between 6:00 pm and 24:00 pm there is an increase in the
 10 simulated manual adjustments compared to the observed ones and also an increase in the
 11 setpoint change per manual adjustment. This is due to the lower metabolic rates observed
 12 during these hours of the day (see also Figure 10). The difference between simulated and
 13 observed data could be related to the fact that, when the metabolic rate is lower than 1
 14 met, occupants are in a reclining position so they adjust the clothing more than under
 15 higher metabolic rates (by, for example, covering up with a blanket while watching TV). This
 16 behaviour is currently not accounted for in our model.

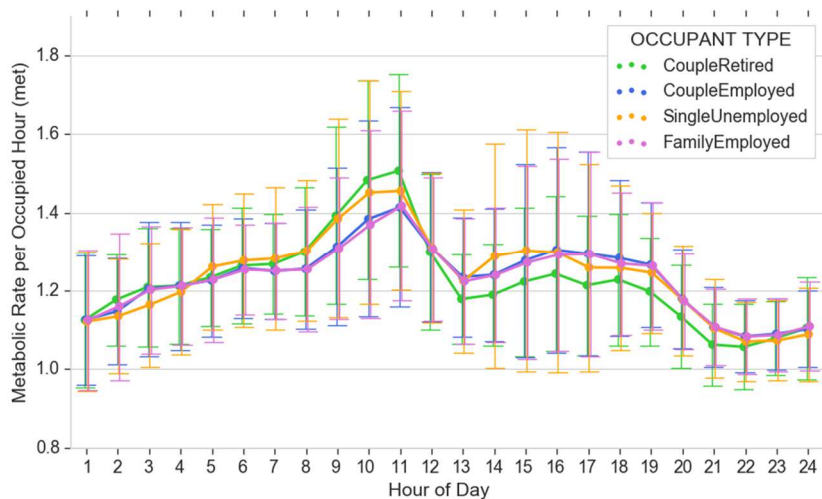


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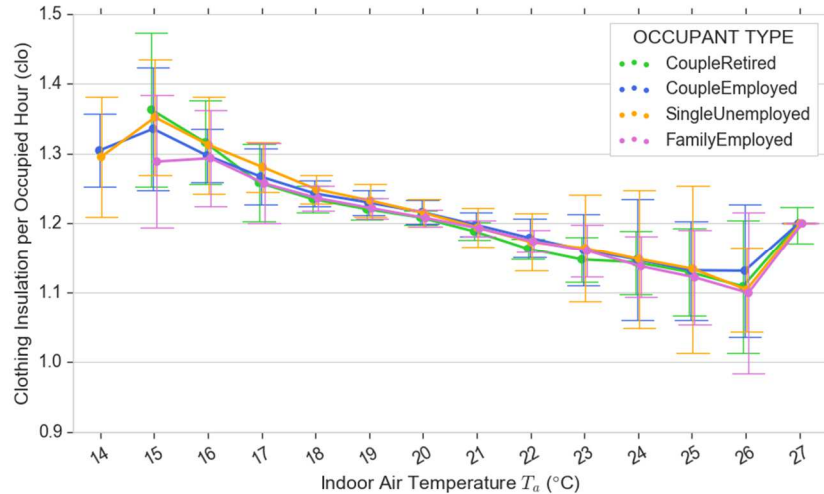
Figure 9. Mean number of manual heating setpoint adjustments per hour of occupancy (upper) and mean heating setpoint changes per manual adjustment (lower) for observed (DyD) in black and simulated in colours data at an indoor air temperature equal to 21°C. Data are binned as function of the hour of the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



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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.

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

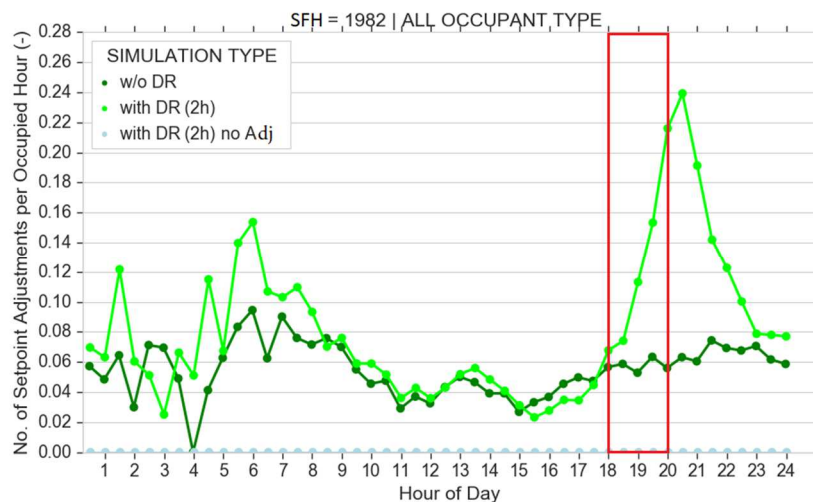


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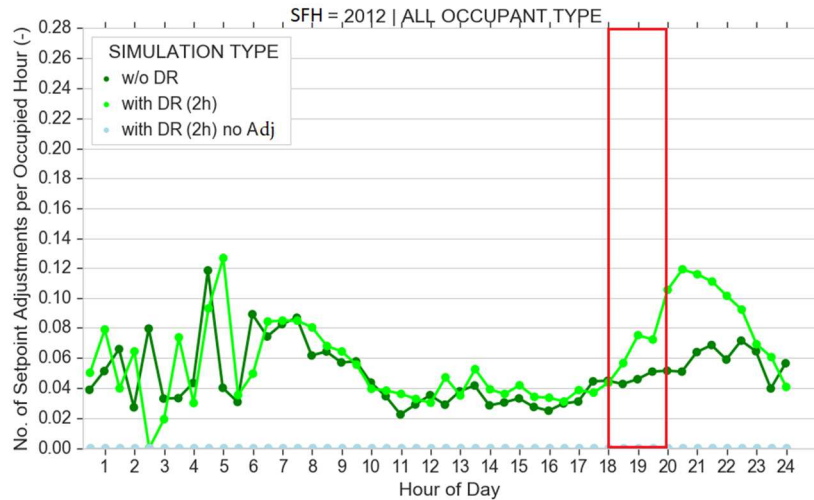
2 *Figure 11. Mean clothing insulation values binned as function of the indoor air temperature for the different*
 3 *types of simulated occupants. Error bars represent the standard deviation of the observations for each bin.*

4 **4.2. DR application**

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



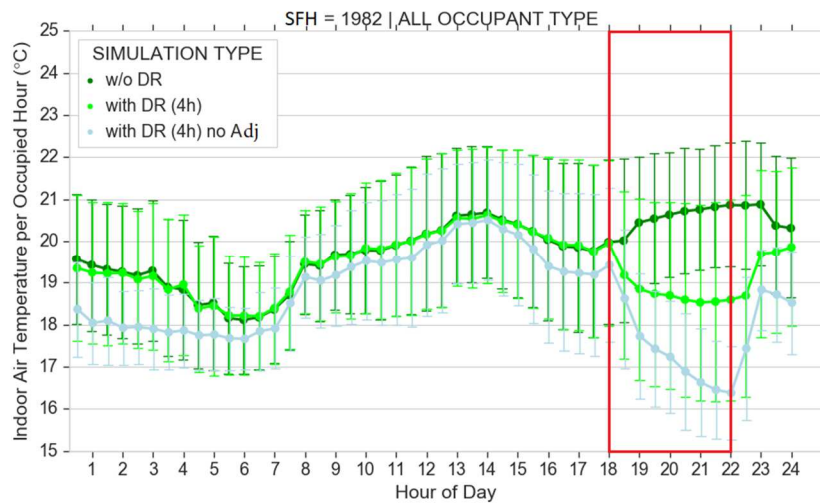
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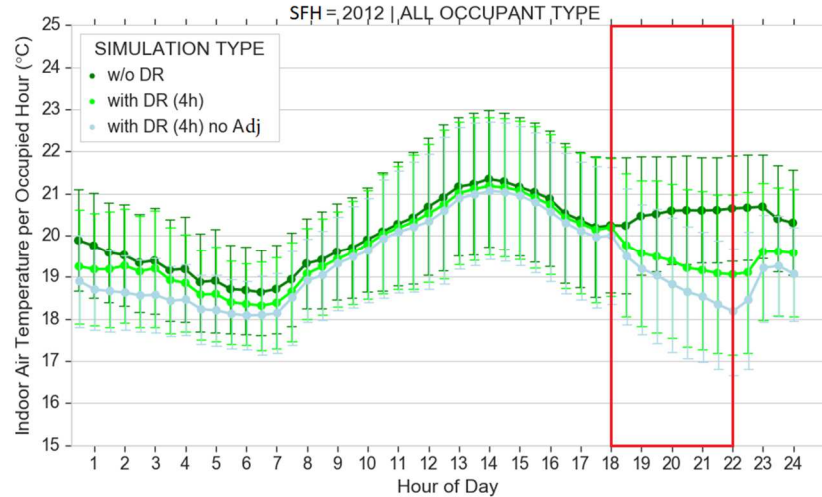
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2 *Figure 12. Mean number of manual heating setpoint adjustments per hour of occupancy for the old (upper) and*
 3 *the new (lower) building type for all the different types of occupants confounded. The 2-hour DR event is*
 4 *highlighted in red. Data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

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



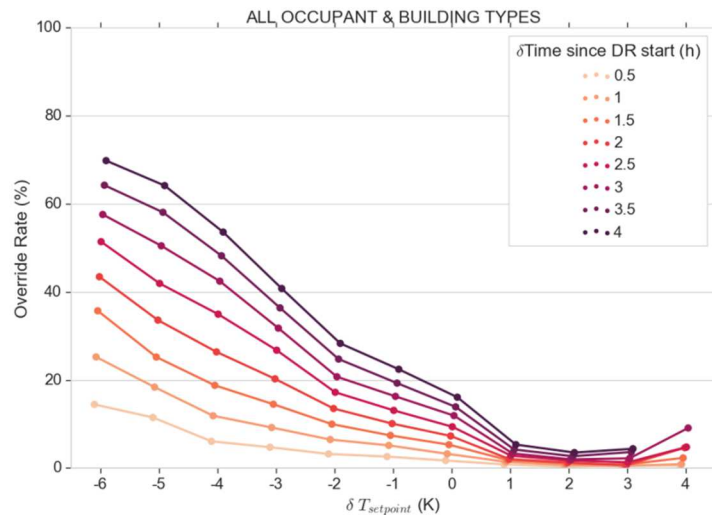
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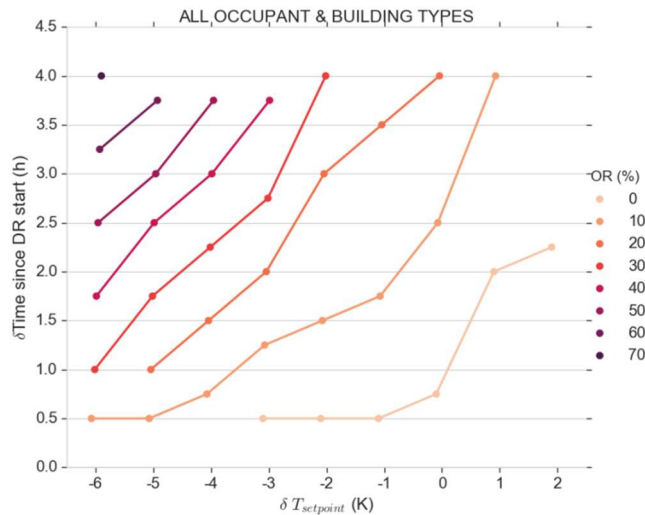
Figure 13. Indoor air temperature per hour of occupancy for three different simulated scenarios in the old (upper) and new (lower) building type and for all the different types of occupants confounded. The 4-hour DR event is highlighted in red. Data are binned as function of the hour of the day. Error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

6 Finally, in Figure 14 we derive the override rates as a function of the distance from the
7 setpoint temperature and the time from the start of the DR event. This plot can be read in
8 the following way: if at time $\delta T_{setpoint}$ from the start of the DR event we are at distance
9 $\delta T_{setpoint}$ from the setpoint temperature, then the probability of adjusting the thermostat
10 is given by the override rate OR . Similarly, in Figure 15 we show curves at equal Override
11 Rate as a function of the distance from the setpoint temperature and the time from the
12 start of the DR event. For example, in the case of having a $T_{setpoint,day} = 21^{\circ}\text{C}$, a 20%
13 rejection rate corresponds to going either as low as 16°C for 1 hour or as low as 19°C for 3
14 hours. Figure 14 and Figure 15 also tell us that for a setpoint modulation of 30 minutes the
15 override rate is always lower or equal than 10% so this is the safer option for a DR utility
16 company.



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



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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.

4 5. Limitations and future developments

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

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

13 The same factors also influence the chosen setpoint temperatures [29]. In this paper we do
14 not model any influence of the above factors on the thermal adaptive behaviour of the
15 occupants. However, the agent-based modelling framework can be extended to account for
16 some of the above factors by adding new attributes to the agents. For example, by using the
17 DYD dataset it would be possible to differently calibrate the probabilities $p_{adj, clothing}$,
18 $p_{adj, warm, setpoint}$ and $p_{adj, cold, setpoint}$ depending on the composition of the household or
19 the type of heating system. Also, these probabilities could be easily derived for the summer
20 case and, therefore, the framework could be extended to model interactions with the air
21 conditioning system.

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

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

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

5 **6. Conclusions**

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

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