Modeling Human-in-the-Loop Behavior and Interactions with HVAC Systems

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Abstract—**Building occupants, building physics, HVAC systems, and controls make up a complex dynamical system with continuous and discrete states and interactions, i.e., a hybrid system. Traditionally, occupant physics and behavior are abstracted from the building engineering through static design requirements and simple setpoints. At most, the interaction between the systems is captured by changing setpoints based on occupancy. This abstraction neglects the autonomy of users to change setpoints and create over-rides that often forfeit the savings that the control system aimed to achieve. As users increasingly interact with home energy IoT devices, this shared autonomy will grow in significance. This research proposes a framework that may serve as a model-based estimator for building controls that realize energy savings without invasive and ineffective behavioral interventions. The human-in-the-loop (HITL) framework consists of three components to model a single-zone single-occupant system: zone thermodynamics, a physiological comfort model, and a behavior model based on Social Cognitive Theory (SCT). Simulations of the HITL control system demonstrate the importance of capturing the hybrid dynamics from discrete actions (e.g., changes to the thermostat) and transients associated with physiological comfort and decision-making.**

I. Introduction

The economic, environmental, and social impacts of HVAC systems have driven a demand for increased efficiency and effectiveness. The energy consumed by HVAC systems comprise 14% of all energy consumed in the US annually [1], [2], and more comfortable work environments can increase productivity by eight percentile points [3]. The physical characteristics of a building may explain 42% of a building's efficiency, while human behavior explains at least 4.2% [4]. Another study shows that the same house can experience a 300% difference in energy use depending on user behavior [5]. As such, the design of new HVAC control algorithms should focus not only on optimizing the hardware system, but also on the linked dynamics between the hardware and users. Future microgrids and zero-energy homes will further require closer, more dynamic interaction between building energy use, user behavior, and controls.

Studies of the impact of occupants on building energy use generally fall within three categories: detecting occupants, occupant thermal comfort, and behavioral interventions.

Detecting occupants' presence, and optionally detecting the number of occupants, enables automatic changes to more efficient albeit uncomfortable setpoints while zones are unoccupied, and reductions in energy-intensive fresh air intake based on the dynamic demand (i.e., "demand controlled ventilation") as opposed to static ventilation requirements set by code. Various theoretical, simulated, and empirical studies of occupancy driven controls have demonstrated 10–75% reduction in HVAC energy consumption [6]–[11]. However, current, real-world occupancy-driven controls struggle to achieve these savings either due to poor detection performance, high costs, or untrustworthiness [12].

Occupant thermal comfort has long been a design criteria for building engineers, and is well established in the ASHRAE standards [13]. However, these standards are intended only for the design specifications, and do not inform real-time behavior-customized controls. The science and deployment of real-time, human-in-the-loop (HITL) controls for HVAC systems are still in their infancy [14], [15]. The science of HITL HVAC systems lacks models of decision-making that are strongly based on theories of psychology, instead the science relies on phenomenological mathematics frameworks, such as if-then decision trees or Markov decision processes.

Behavioral interventions by utility companies and employers target habits, appliance purchases, and real-time decisions. Studies and commercial products have explored using social and mobile games [16]; peer-performance information in billing [17]; and strategies using education, advice, self-monitoring, goals, comparisons, engagement, communications, control, and rewards [18]. Goal setting and feedback interventions were investigated by McCalley [19] who concluded that there's a need to develop new theoretical HITL frameworks founded in human psychology. Additionally, Hong et al. recognized the inherent feedback around detecting, understanding, and improving the impact of occupant behavior; however, their studies iterate over product lifecycles, not in real-time [20]. Models of decision-making in energy use have been broadly developed [21] with foundations in conventional and behavioral economics, technology adoption theory and attitude-based decision-making, social and environmental psychology, and sociology. However, these models have not been converted into dynamic numerical tools that can be integrated into control systems.

Human behavior and system performance are closely linked in many fields besides building energy. In robotic systems, automation outperforms human trajectory planning for systems with many degrees of freedom; however, humans are better suited to identify targets and obstacles. Analytical models of such shared autonomy were developed by Vinod et al., adapting the ACT-R model of memory retrieval/forming, decisions, and delay. A Markovian process was fit to the ACT-R framework with continuous inputs and discrete output choices that act on a continuous plant [22]. Their analysis of the HITL system can determine the reachable sets for robotic swarms. Similar challenges are faced in the field of behavioral

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health, where mobile devices present interventions for behaviors that negatively affect health, e.g., smoking, poor diet, lack of physical activity, and unsafe sex. This field is building new computational models to support such behavioral interventions [23]. Of particular interest is a new model founded on the decades-old Social Cognitive Theory (SCT), which dynamically describes interactions between behavior, personal states, and the environment [24]. The psychology theory has been adapted into a control theoretic model using a flow and reservoir analogy to create a linear dynamical system with constraints [24]. With an accurate behavior model in hand, optimal behavioral interventions can be developed [25].

The proposed framework will apply the SCT dynamical model to single-zone single-occupant energy use decisions, capturing how the HVAC system affects user temperature, and how the user affects the system primarily through changes in the thermostat. The purpose of this work is to develop an integrated model founded in psychology, physiology, and building physics for more accurately estimating the largely unknown or "noisy" process between the dynamics of users' thermal comfort desires and the control objective, e.g., the thermostat setpoint. Ultimately, such a model-based estimator may be incorporated into a control system to improve the impact of occupant behavior.

This paper is organized as follows. Section II presents context and models of the three primary components considered: the building physics model, the physiological comfort model, and the SCT behavior model. Section III integrates these subsystems into the proposed framework for modeling human-in-the-loop behavior of HVAC systems and presents preliminary insight into the closed-loop behavior based on the model properties. Section IV presents simulations to investigate the response of the proposed model for varying weather conditions, personal traits, and activities. Section V concludes with a summary of the framework's characteristics and proposes improvements and applications.

II. CONSTITUENT SYSTEM MODELS

Three processes significantly govern the response dynamics in the proposed framework: a building physics model controlling the room temperature according to a setpoint, a thermal comfort model of the physiological thermal processes in the user's body yielding a core body temperature that determines thermal comfort driven by the room temperature, and a behavior model that drives the user to intermittently change the thermostat setpoint to enforce thermal comfort. For simplicity of proposing this novel framework, the following assumptions are made.

- A1) Room temperature is the only building physics variable that drives physiological thermal comfort.
- A2) Only the heater setpoint is controlled. There is no air conditioning.
- A3) Heat produced by the user is negligible.
- A4) The user can either be in the room of interest, or in another environment outside the system's control, whether outside or in another unlinked zone.

Relaxing these assumptions should be a straightforward matter of replacing the process models used herein with models that capture the ignored dynamics.

A. Building physics model

The building physics model determines room temperature T_r as a function of the outside temperature T_o and the thermostat setpoint $T_{r_{ref}}$. A single zone is considered with a standard simple thermostatic heating system identical to the "Model a Dynamic System" example provided with Simulink [26]. The energy balance model shown in Eq. (1) describes the rate change of the room temperature T_r times the room heat capacity $m_{r_{air}} c_{p_{air}}$, equal to the difference of heat gain $\dot{Q}_{gain}$ and the heat loss $\dot{Q}_{loss}$

$$\dot{T}_r(t)\left(m_{r_{air}} c_{p_{air}}\right) = \dot{Q}_{gain}(t) - \dot{Q}_{loss}(t) \tag{1}$$

Heat is lost through the walls (with total thermal resistance R_w) to the outside with temperature T_o as shown in Eq. (2).

$$\dot{Q}_{loss}(t) = \left(T_r(t) - T_o(t)\right)\left(\frac{1}{R_w}\right) \tag{2}$$

When the heater turns on ($q_h = 1$), a mass flow of $\dot{m}_{h_{air}}$ of hot air (with temperature T_h) is injected into the room.

$$\dot{Q}_{gain}(t) = \left(T_h(t) - T_r(t)\right)\dot{m}_{h_{air}} c_{p_{air}} q_h(t) \tag{3}$$

The heater is controlled according to a thermostat with setpoint $T_{r_{ref}}$ and deadband $\pm T_{r_{db}}$.

$$q_h(t) = \begin{cases} 1, & (q_h(t) = 0), \left(T_r(t) \le T_{r_{ref}}(t) - T_{r_{db}}\right) \\ 0, & (q_h(t) = 1), \left(T_r(t) \ge T_{r_{ref}}(t) + T_{r_{db}}\right) \end{cases} \tag{4}$$

The specific properties of the model under consideration in this paper are presented in Table I.

B. Physiological thermal comfort model

Thermal (dis-)comfort is a subjective value determined by an individual's environment, expectations, and actions. This subjective phenomenon is generally modeled in one of two ways: the heat balance model and the thermal adaptation model. The **heat balance model** maps the room physics (e.g., temperature, humidity, radiation, air velocity) to a physiologic model of the human body and accessories (e.g., core temperature, perspiration, clothing), the parameters of which determine levels of discomfort. All practical implementations of this model consider the heat balances only in steady-state. This framework forms the foundation of ASHRAE Standard 55 [13]. The **thermal adaptation** model was developed to incorporate the effect of user expectations and actions, which are lacking in the heat balance model. Interacting with the physiological response, these adaptations (of expectations and actions) fall into three groups: behavioral adjustments, physiological comfort, psychological comfort [27]. Little research has been published on transient thermal adaptation models, aside from work that fit simple exponential decay models to changes in clothing due to outside temperature dynamics [27]. The issue of behaviors that affect the building systems (e.g., changing the setpoint and opening windows) has also received little attention, despite calls to do so by leading researchers [28], [29].

A minimal heat balance model is used here to map room temperature dynamics to a measure of discomfort. A more complex heat balance model or thermal adaptation model could suffice, yet this model yields a simple linear system that will aid in understanding the closed-loop response for these initial investigations. This physiologic model, (5)–(7), generally follows the energy balance model in [30, p. 9.2–10], neglecting skin heat capacity, work, respiratory and evaporative losses, and radiation heat transfer.

$$M_b(t) = C(t) + S_{cr}(t) \tag{5}$$

Where

M_b = rate of metabolic heat production, $\frac{W}{m^2}$

C = convective heat loss from skin, $\frac{W}{m^2}$

S_{cr} = rate of heat storage in core compartment, $\frac{W}{m^2}$

$$C(t) = \left(\frac{1}{0.155 I_{cl}(t)}\right)\left(T_b(t) - T_r(t)\right) \tag{6}$$

Where

T_b = body (core) temperature, °C

I_{cl} = clothing ensemble insulation, clo

$$S_{cr}(t) = \left(\frac{m_b c_{p_b}}{A_b}\right)\dot{T}_b(t) \tag{7}$$

Where

m_b = body mass, kg

c_{p_b} = specific heat capacity of body, $\frac{J}{kg\,°C}$

A_b = DeBois surface area of body $= (0.202\, m_b^{0.425} h_b^{0.725}),\, m^2$

h_b = height of body, m

The effort (e.g., sweating, shivers) that the body must undergo to maintain normothermia (e.g., $T_{b_{ref}} = 98.6°F$) is generally considered to be proportional to thermal comfort factors [31]. As such, a measure of thermal discomfort can be defined as $k_{comf} T_{b_e}$, where k_{comf} is a constant scaling factor and $T_{b_e} = \left|T_b - T_{b_{ref}}\right|$. The integration of this proposed model with the following SCT behavior model could lead to a unification of the heat balance and thermal adaptation frameworks by linking the adaptation decision process with the physiological heat dynamics.

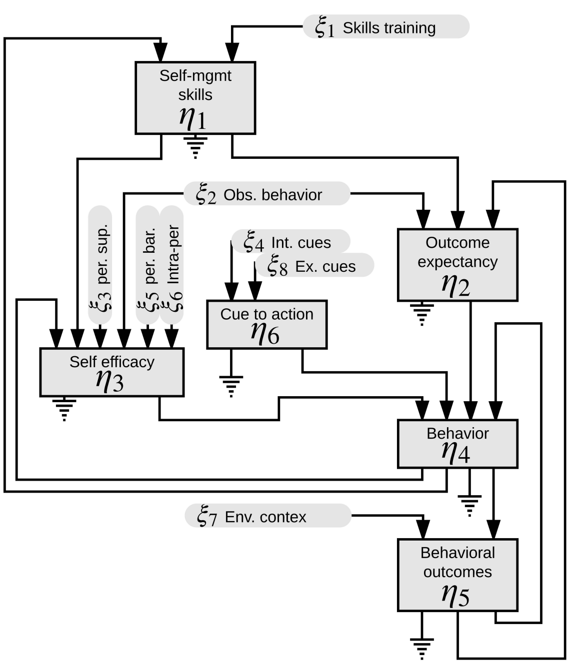

Fig. 1 Block diagram of SCT behavior model, with eight inputs and six first-order integrator states that are constrained from $[0 - 100]$.

C. SCT behavior model

A user's desire to act (e.g., change the thermostat setpoint) is a complex function of their current and past discomfort, as well as other internal and external dynamics. This paper employs a dynamical systems model of Social Cognitive Theory (SCT), as proposed in [24], to model these dynamics and effects. This rectangularly constrained linear time-invariant system contains six states $\eta_{1\ldots6}$, eight inputs $\xi_{1\ldots8}$, and one output. The six states are

- *self-management skills* (η_1),
- *outcome expectancy* (η_2),
- *self-efficacy* (η_3),
- *behavior* (η_4),
- *behavioral outcomes* (η_5), and
- *cue to action* (η_6).

These states are analogous to fluid levels in tanks representing amount of the given theoretical construct at any given time. The dynamics of each state η_i is governed by a differential equation, (8), and constrained to the set $[0 - 100]$.

$$\tau_i\, \dot{\eta}_i(t) = \sum_{j=1}^{6} \beta_{i,j}\, \eta_j(t) + \sum_{k=1}^{8} \gamma_{i,k}\, \xi_k(t) \tag{8}$$

Each state has a time constant τ_i, a state transition gain $\beta_{i,j}$ with each state η_j that flows into η_i in Fig. 1, and a gain $\gamma_{i,k}$ for each input ξ_k. Conservation of mass in the fluid analogy mandates that the state transition gains must satisfy (9).

$$\begin{array}{ccc} \beta_{2,1} + \beta_{3,1} \le 1 & \beta_{4,2} \le 1 & \beta_{4,3} \le 1 \\ \beta_{5,4} + \beta_{3,4} + \beta_{1,4} \le 1 & \beta_{2,5} + \beta_{4,5} \le 1 & \beta_{4,6} \le 1 \end{array} \tag{9}$$

Eight exogenous inputs drive the state responses along with feedback between the states. The eight inputs are

- *skills training* (ξ_1),
- *observed behavior* (ξ_2),
- *perceived social support* (ξ_3),
- *internal cues* (ξ_4),
- *perceived barriers* (ξ_5),
- *intrapersonal states* (ξ_6),
- *environmental context* (ξ_7), and
- *external cues* (ξ_8).

The primary inputs of interest in this study are the internal cues (ξ_4), which are defined as the level of discomfort. A flow of internal cues (ξ_4) increases the level of cue to action (η_6), which flows into and increases the behavior (η_4).

$$\xi_4 = k_{comf}\left|T_b - T_{b_{ref}}\right| \tag{10}$$

However, other inputs may still affect the user's thermostat behavior. For example, an increased desire to save energy could act as a perceived barrier (ξ_5), decreasing the amount of self-efficacy (η_3) that leads to increases in behavior (η_4).

The single output is a discrete instantaneous action, e.g., a change to a thermostat, that occurs when the behavior state fills half way, $\eta_4 = 50$. When the action occurs, the level of η_4 is reset to zero and must fill again to trigger another action. The change ($\Delta T_{r_{ref}}$) to the thermostat setpoint ($T_{r_{ref}}$) is proportional (with gain k_{dT}) to the amount of discomfort (ξ_8) with an appropriate sign to increase comfort. The thermostat has limits (e.g., 10°C – 35°C) both for practical considerations, and to prevent wind-up in cases of high discomfort and high k_{dT}, reducing overshoot and oscillations.

III. Integrated Human-in-the-Loop Model

The proposed integration of the building physics, comfort, and behavior models is schematically shown in Fig. 2, forming a feedback control system. The output of the physiological thermal comfort model in the upper right drives the internal cue input to the behavior model below. When the SCT model behavior output $\eta_4 = 50$ and the user is inside, a trigger occurs that resets the SCT behavior state and drives the changes in the thermostat setpoint in the bottom left. This setpoint steers the building physics model dynamics in the upper left, resulting in the room temperature that drives the comfort model when the user is inside. Otherwise, the user's comfort is determined by the outside temperature. Each of the subsystems are linear hybrid dynamical systems, as are some of the interconnections. Thus, the entire closed-loop system can be modeled as a linear hybrid dynamical system [32], lending a large set of tools for analysis and control. This hybrid system has 8 states with continuous flow ($T_r, T_b, \eta_1 \dots \eta_6$); 8 discrete modes representing the saturation of $\eta_1 \dots \eta_6$ and $T_{r_{ref}}$, and the relay switching the heater on/off; and 10 jump sets, 8 for each of the 8 modes, the reset condition for η_4, and each discrete change applied to the thermostat $\Delta T_{r_{ref}}$.

A Simulink model was developed to understand and test this novel hybrid-systems framework. All the code to reproduce these results is available [33], under the GPLv3 license. The **building physics model** parameters used for the simulations are shown in Table I and represent a simple 1-zone house. These are the default parameters used in the model from MathWorks [26]. The **physiological thermal comfort model** parameters are shown in Table II and represent a "seated, quiet" person wearing "Trousers and a short-sleeved shirt" [30, p. 9.2–10]. The person's activity and clothing will be changed in the simulations below to investigate their dynamic effects on behavior. The **SCT behavior model** parameters are shown in Table III. These parameters are modifications of the model parameters in [24], where the timescale was changed from days to hours. Certain parameters were tuned to result in a "typical behavioral response," defined as changes to the thermostat setpoint every ~30 minutes and reach a steady-state thermostat setpoint within ~16 hours when the outside temperature is $10°C$ and the room is initially at $T_{r_{ref_0}} = 16°C$.

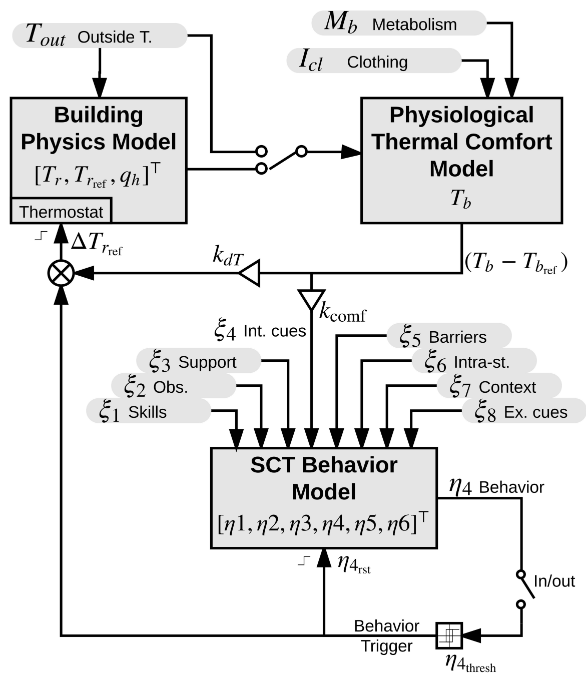

Fig. 2 Block diagram of integrated human-in-the-loop model of heating system

A. Tuning the SCT behavior model

First, the thermal discomfort to internal cue gain was set to $k_{\text{comf}} = 50$ such that a significant discomfort of $T_{b_e} \cong 2°C$ results in $\xi_4 \cong 100$, the upper limit of the inputs seen in [24]. The system time-constants were then reduced by a factor of 0.1 such that significant discomfort ($\eta_6 = 100$) is felt within 1 minute (from $\eta_6 = 0$), assuming $\xi_4 = 100$ and all other η_6 inputs are zero. Similarly, set $\beta_{46} = 0.55$ to generate an action ($\eta_4 = 50$) after 30 minutes of discomfort (i.e., $\eta_6 = 100$). A settling time of 16 hours in the integrated closed loop simulation was then fixed by setting $k_{dT} = 1$. An important point of future work is to update these parameters based on data collected from actual thermostat usage.

B. Proposed data-driven SCT model tuning

The aforementioned "typical behavioral response" is admittedly arbitrary and used in leu of experimentally-validated models solely for introducing the proposed framework. In practice, an experimental program should be developed that excites the inputs to the SCT model, lending the parameters to be observable. Such a procedure is proposed for model estimation of an SCT model for behavioral health applications in [34]. Messages from a mobile app were used to excite the inputs, and the model was fit using ARX model estimation

TABLE I
BUILDING PROPERTIES

$m_{r_{air}} = 1470\ (kg)\ (\sim 1{,}200\ m^3)$	$c_{p_{air}} = 1005.4\ \left(\frac{J}{kg\ K}\right)$
$R_w = 4.329 \cdot 10^{-7}\ \left(\frac{hr\ K}{J}\right)$	$T_h = 50\ (°C)$
$\dot{m}_{h_{air}} = 3600\ \left(\frac{kg}{hr}\right)$	$T_{r_{db}} = 1\ (°C)$

TABLE II
PHYSIOLOGICAL PROPERTIES

$m_b = 100\ (kg)$	$c_{p_b} = 4{,}180\ \left(\frac{J}{kg\ K}\right)$
$h_b = 2\ (m)$	$M_b = 60\ \left(\frac{W}{m^2}\right)^{*\dagger}$
$I_{cl} = 0.57\ (clo)^{*\ddagger}$	$T_{b_{ref}} = 37\ (°C)$

*The parameters of this model are then converted from units of (1/s) to (1/hr) to be consistent in Simulink with the building physics model and SCT behavior model.
† Seated, quiet [30]
‡Trousers and a short-sleeved shirt [30]

TABLE III
SCT BEHAVIOR MODEL PROPERTIES

$\tau_1 = \tau_2 = \tau_3 = \frac{1}{2}\tau_4 = \tau_5 = \frac{1}{3}\tau_6 = 0.1$			$k_{\text{comf}} = 50$	$k_{dT} = 1$
$\beta_{2,1} = 0.3$	$\beta_{3,1} = 0.5$	$\beta_{4,2} = 0.3$	$\beta_{4,3} = 0.8$	$\beta_{1,4} = 0.23$
$\beta_{3,4} = 0.2$	$\beta_{5,4} = 0.3$	$\beta_{2,5} = 0.3$	$\beta_{4,5} = 0.0$	$\beta_{4,6} = 0.55$
$\gamma_{1,1} = 0.8$	$\gamma_{2,2} = 0.75$	$\gamma_{3,2} = 1.6$	$\gamma_{3,3} = 0.75$	$\gamma_{6,4} = 20$
$\gamma_{3,5} = -1$	$\gamma_{3,6} = 1$	$\gamma_{5,7} = 2$	$\gamma_{6,8} = 5$	$\xi_1 = 3$
$\xi_2 = 5$	$\xi_3 = 5$	$\xi_5 = 3$	$\xi_6 = \xi_7 = \xi_8 = 0$	

*Unless otherwise specificed in the simulations below methods. Where persistently exciting inputs are not possible, model reduction techniques could be used to prevent over fitting.

IV. Simulation Results

Simulations were conducted to investigate the behavior of the closed-loop system under conditions that would not be captured if a non-dynamic model of behavior and/or comfort was used. The three test cases all start with a person outside, then walking into a cold room.

In the **first case**, a user, wearing "*Trousers, long-sleeved shirt, plus a suit jacket*" ($I_{cl} = 0.96$ clo), reaches a comfortable equilibrium T_b while walking at a modest pace ($M_b = 150\,\frac{W}{m^2}$) outside where the temperature is $T_{out} = 7°C$. After 1 hour, the user enters the building, where the setpoint was set to an energy saving $T_{r_{ref}}(0) = 16°C$, changes into "*Trousers and a short-sleeved shirt*" ($I_{cl} = 0.57$ clo), and sits quietly ($M_b = 60\,\frac{W}{m^2}$). The **second case** is identical to the first case except it occurs on a warmer day ($T_{out} = 14°C$). The **third case** is also identical to the first except this user is more energy conscious, therefore, experiences a higher personal cost when increasing the setpoint (input 5, *perceived barriers*, $\xi_5 = 40$ rather than 3, as in the other cases).

The closed-loop responses of the building physics, physiological thermal comfort, and behavior models were simulated over a 120-hour horizon, where the initial conditions of the states were set as the steady-state response with the initial inputs held constant. **Case 1** first reaches comfort (i.e., $T_b = T_{b_{ref}}$) after 9.5 hours partially due to the extreme discomfort from being in the cold (see Fig. 3, ξ_4 in the first axis). After overshoot and oscillations, it reaches a steady-state value of $T_{r_{ref}}(\infty) = 31.5°C$. Such a setpoint would be abnormally high; however, it represents a situation of a man sitting completely still in a t-shift. Within the first four hours, the user changes the thermostat 3 times (see Fig. 3, T_b, black line, and $T_{b_{ref}}$, red dotted line), saturating $T_{r_{ref}}$ until corrected. **Case 2** first reaches comfort after 5.4 hours, $T_{r_{ref}}(\infty)$ =31.6°C, and switches 8 times within the first four hours. Comfort was achieved earlier, not only because the room was easier to heat due to the higher outside temperature, but also because the user was already comfortable before entering the building, thus reducing the overshoot and preventing saturation of $T_{r_{ref}}$. **Case 3** indicates that the dynamics of behavior (η_4) are principally governed by the flow from cue to action (η_6). This is reinforced by the negligible effect reducing self-efficacy (η_3, by way of increased perceived barriers, ξ_5) has on $T_{r_{ref}}(\infty)$. In fact, due to the hybrid nature of the system, the steady-state response of $T_{r_{ref}}$ does not strictly depend on the behavior of the SCT behavior model as long as the *dwell time* (i.e., the time between switches [35]) is finite. An infinite dwell time may result if $\beta_{46} < 0.5$, i.e., the steady-state flow from η_6 prevents η_4 from ever reaching 50 and triggering a change to $T_{r_{ref}}$. A continuous domain approximation of the closed-loop system would not capture this behavior. Additionally, a continuous domain system would not capture the connected behavior between the heater switching on/off and the thermostat setpoint changing. This is especially notable since the two switching processes operate on similar time-scales, and thus could not be time-scale separated in a continuous approximation.

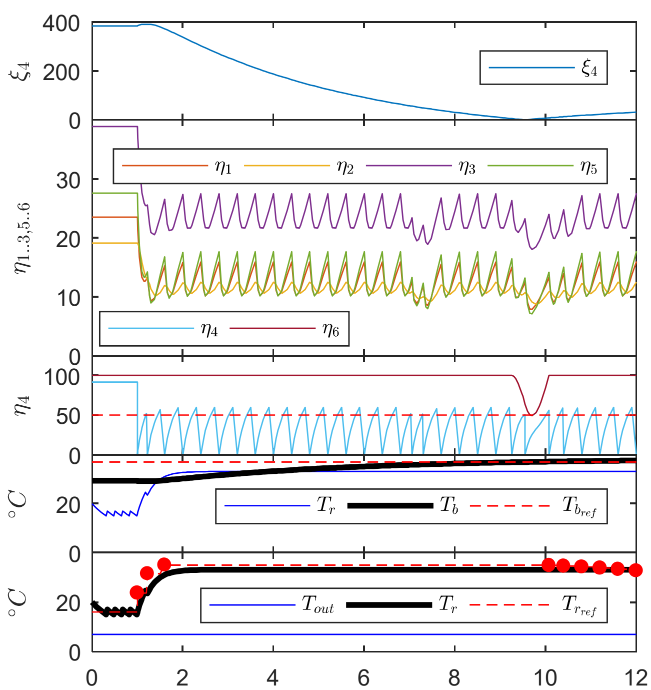

Fig. 3 Response of the HITL model simulation for Case 1 showing discomfort input (i.e., internal cues ξ_4) to the SCT behavior model in the first axis; the six states being skills η_1, expectancy η_2, efficacy η_3, behavior η_4, outcomes η_5, and cue to action η_6 in axes 2-3; the physiological comofrt model temperature responses in axis 4; and the building physics temperature responses in axis 5.

V. Conclusion and Future Work

In this work, a novel framework was proposed to capture the hybrid dynamical behavior of human-in-the-loop control of building heating systems. The closed-loop system integrates subsystem models of building physics, comfort physiology, and a model of behavior based on social cognitive theory. Simulations were conducted to investigate the unique and valuable properties of the proposed framework. From these simulations, the discrete changes to the thermostat was modeled, as well as the impact due to changes in behavior, weather, and activities. Ultimately, the steady-state response varied little; however short-term behavior could vary significantly while waiting for jumps in the hybrid-dynamics.

The ultimate goal of this framework is to develop online estimators of behavior that could enable improved closed-loop control response, without costly and difficult changes to behavior. Before this can be realized, the models must be validated and fitted to real data, e.g., from sources such as Ecobee, Pecan Street, and/or ASHRAE RP-844 database. However, additional experimental subject testing will likely be required to provide measured persistently-exciting inputs. This model doesn't capture that people are generally good at detecting when they're going to be cold before their core temperature drops. This and other shortcomings could be mitigated with more accurate and rigorous physiological thermal comfort models, such as the multi-modal models by Zhang et al. that capture transient and nonuniform environments [36]–[38]. The recent growth and acuity of hybrid-systems theory may also prove valuable to this new application, providing opportunities to prove observability of the behavior and analyze the closed-loop stability.

A HITL control system which uses this proposed framework could effectively share decision-making autonomy between users and a building energy management system, leaving the users to focus on thermal comfort and other quality-of-service constraints, and the automatic controls to balance the complex dynamics between the HVAC system, onsite energy storage and renewable generation, and other energy demands, such as onsite charging of electric vehicles.

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