Home Energy Management with Clothing Integrated Thermal Comfort and EV SOC Concern

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***Abstract*—This paper proposes a home energy management system (HEMS) while considering the residential occupant's clothing integrated thermal comfort and electrical vehicles (EV) state-of-charge (SOC) concern. An adaptive dynamic programming (ADP) based HEMS model is proposed to optimally determine the setpoints of heating, ventilation, air conditioning (HVAC), the donning/doffing decisions for the clothing conditions and charging/discharging of EV while taking into account the uncertainties in outside temperature and EV arrival SOC. We use model predictive control (MPC) to simulate a multi-day energy management of a residential house equipped with the proposed HEMS. The proposed HEMS is compared with a baseline case without the HEMS. The simulation results show that a 47.5% of energy cost saving can be achieved by the proposed HEMS while maintaining satisfactory occupant thermal comfort and negligible EV SOC concerns.**

I. Introduction

In the US, around 100 million single-family homes consume 36% of the total electricity and cause the peak system load, especially on hot summer days [1]. The Home Energy Management System (HEMS) is one of the most promising tools to conserve electricity cost while in the presence of the internet of things (IoT), smart appliances, smart meters, wireless sensors, and energy storage. Various studies show that it is imperative to include the occupant's thermal comfort in the HEMS [2]–[4]. However, existing studies merely consider thermal comfort through the predicted mean vote (PMV) and neglect other behaviors of the residential occupants. For example, the occupant's clothing actions can significantly affect occupant thermal comfort by changing the occupant's body thermal insulation directly. Most recently, Liu *et al.* [5] proposed a novel HEMS that yields the best occupant's clothing decisions, i.e., donning and doffing, in tandem with optimal heating, ventilation, and air conditioning (HVAC) thermostat schedules. Their simulation results show a significant electricity cost savings can be accomplished, particularly on hot summer days.

Meanwhile, the transportation industry, including both commercial and residential sectors, is experiencing one of the greatest technology transitions towards electrical vehicles (EVs) [6]. By 2030, EV sales are estimated to be more than 10% of the US new-vehicle market share in a medium growth scenario [7]. EVs, as the home energy storage, will play an important role in shaping future electricity demand and providing vehicle-to-home (V2H) services. As EVs may become the major (only) transportation for a household and even for a sustained community, the expected EV state of charge (SOC) would be another serious concern for residential occupants [8]–[10]. In [8], the authors incorporated dynamic driver's behaviors into the EV charging model and proposed a stochastic game approach to address the renewable energy uncertainty. Reference [9] introduces a time anxiety concept to address the uncertain events in the charging duration and a game theory-based approach to solve the optimal EV charging problem. Yan *et al.* [10] proposed a new index to measure driving anxiety that to characterize the driver's discomfort on the driving range and uncertain events which are changed by the driving experience quantitatively. However, little work has been done thus far to study the complex interactions between EV and HVAC while taking into account the occupant's clothing behaviors and EV-related concerns.

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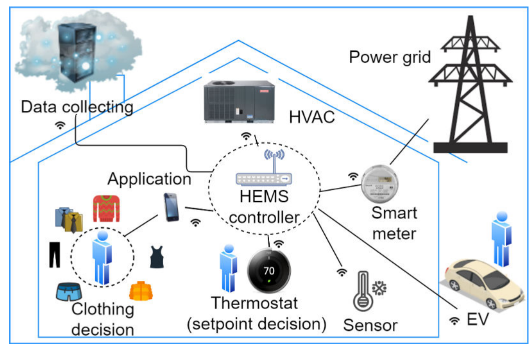

Fig. 1: Illustration of proposed HEMS concept.

This paper tries to fill this gap by investigating the optimal coordination of HVAC and EV while considering the residential occupant's clothing behaviors, EV SOC concerns, and PMV-based thermal comforts. By extending our prior work [11], a stochastic adaptive dynamic programming (ADP) model is developed to optimally determine the setpoints of HVAC, occupant's clothing decisions, and the EV's charge/discharge schedule with uncertain outside temperature and EV's arrival SOC. Nonconvex models of thermal discomfort, EV SOC concerns, and clothing behaviors are embedded in the ADP-HEMS model.

II. Problem Formulation

A. ADP-HEMS Formulation

The scheme of the proposed HEMS, shown in Fig. 1, is a typical optimization problem modeled as a Markov Decision

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Process (MDP) to minimize the occupant's utility function while considering various constrains. In this paper, we focus on three types of controllable variables, i.e., $i = \{\mathrm{H}, \mathrm{C}, \mathrm{E}\}$. We use the indoor temperature s_t^H, the level of clothing insulation s_t^C, and the SOC of EV s_t^E to represent the variable state at time t. The associated actions for those variables are HVAC input power a_t^H, clothing decision a_t^C, i.e., donning and doffing, and EV charging/discharging power a_t^E. We use positive a_t^E values to denote charging actions and negative values for discharging actions. In addition, uncertainty is taken into account such as the outside temperature is $\tilde{u}_t^{\mathrm{OUT}}$, and the EV arrival SOC $\tilde{u}_t^{\mathrm{SOC}}$. Arithmetically, we use set tuple $\{s_t, a_t, \tilde{u}_t\}$ to simply depict state, action, and uncertainty of proposed HEMS:

$$\{s_t, a_t, \tilde{u}_t\} = \{(s_t^{\mathrm{H}}, s_t^{\mathrm{C}}, s_t^{\mathrm{E}}), (a_t^{\mathrm{H}}, a_t^{\mathrm{C}}, a_t^{\mathrm{E}}), (\tilde{u}_t^{\mathrm{OUT}}, \tilde{u}_t^{\mathrm{SOC}})\}$$

The primary function of HEMS is to find the optimal actions a_t^* for minimizing the expected weighted sum of the objective function O_t over the entire look-ahead horizon:

$$a_t^* = \arg\min_{a_t} \ \mathbb{E}\{\sum_{t=1}^{T} O_t(s_t, a_t, \tilde{u}_t)\} \tag{1}$$

where O_t is a function of state s_t, action a_t and uncertainty $\tilde{u}_t$, which is defined as follows:

$$O_t(s_t, a_t, \tilde{u}_t) = \tau_t^{\mathcal{D}} \cdot \mathcal{D}_t\left(s_t, a_t, \tilde{u}_t\right) + \tau_t^{\mathcal{C}} \cdot \mathcal{C}_t\left(s_t, a_t, \tilde{u}_t\right) \tag{2}$$

where the objective function is composed of two components: 1) a discomfort function $\mathcal{D}_t$ and 2) an energy cost function $\mathcal{C}_t$. In (2), parameters $\tau_t^{\mathcal{D}}$ and $\tau_t^{\mathcal{C}}$ are respectively weighted coefficients associated with the discomfort and the energy cost. The occupant discomfort function $\mathcal{D}_t$ is defined as:

$$\begin{aligned}\mathcal{D}_t\left(s_t, a_t, \tilde{u}_t\right) =& \beta^{PMV} \cdot |PMV(s_t)| + \beta^{SOC} \cdot EV_t^{concern} \\ &+ \beta^{C} \cdot Clo_t^{penalty} + \beta^{Bat} \cdot Bat_t^{penalty}\end{aligned} \tag{3}$$

where PMV_t, $EV_t^{concern}$, $Clo_t^{penalty}$, $Bat_t^{penalty}$ are the occupant's thermal comfort, EV SOC concern, penalties on frequent clothing adjustments, and penalties on frequent switches between charge and discharge, respectively; parameters β^{PMV}, β^{SOC}, β^{C}, and β^{Bat} are the corresponding coefficients. Additionally, $|PMV(s_t)|$ is expressed in an absolute value format since the most comfortable thermal state for the occupant is when PMV = 0. The energy cost function $\mathcal{C}_t$ is defined as: $\mathcal{C}_t\left(s_t, a_t, \tilde{u}_t\right) = \mathrm{c}_t \, \mathrm{p}_t^{\mathrm{G}} \, \Delta t$, where parameters $\mathrm{p}_t^{\mathrm{G}}$ is the power exchange in kW between the grid and the house, c_t is the electricity price in \$/kW paid by the occupant, and Δt in hr is the time interval resolution. Note that a positive $\mathrm{p}_t^{\mathrm{G}}$ denotes the action to purchase power from the utility and a negative $\mathrm{p}_t^{\mathrm{G}}$ for selling power back to the utility (using ToU as selling price). The power balance equation for the residential home is expressed as: $\mathrm{p}_t^{\mathrm{G}} = a_t^{\mathrm{H}} + a_t^{\mathrm{E}}, \forall t$.

B. Occupant's Comfort Model

1) Thermal Comfort: Here, we adopt a simplified PMV model from [12]:

$$\begin{aligned}\mathrm{PMV}(s_t) =& \mathrm{a}(s_t^C) \cdot s_t^{\mathrm{H}} + b(s_t^C) \cdot \mathrm{Pa}(s_t^{\mathrm{H}}, rh_t) - c(s_t^C), \\ & t_w < t < t_s\end{aligned} \tag{4}$$

where $\mathrm{a}(s_t^C)$, $b(s_t^C)$ and $c(s_t^C)$ are associated coefficients, which are relevant to the clothing insulation of the occupant and can be obtained under different clothing insulation levels [12]; rh_t is the relative humidity; t_w and t_s are the occupant's times of waking up and going to bed, respectively. In general, the PMV is only considered when the occupant is active at home, excluding the sleeping time. We use the desired sleeping temperature instead of the PMV model to validate the performance of the HEMS during the occupant's sleeping time. As seen, this model is only dependent on the indoor air temperature and water vapor pressure $\mathrm{Pa}(s_t^{\mathrm{H}}, rh_t)$ in kPa. The water vapor pressure function is defined:

$$\begin{aligned}&\mathrm{Pa}(s_t^{\mathrm{H}}, rh_t) = \\ &rh_t \cdot 0.61121 \cdot e^{(18.678 - s_t^{\mathrm{H}}/234.5) \cdot (s_t^{\mathrm{H}}/(257.14 + s_t^{\mathrm{H}})}\end{aligned} \tag{5}$$

2) Clothing Behavior Model: The thermal insulation offered by the occupant's clothing state is called clothing insulation, which is quantified by the unit of clo. One unit of clo equates to 0.155 K×m^2/W, indicating the amount of clothing needed by a sedentary person to maintain thermal comfort in an environment with 21 °C of air temperature, 50% of relative humidity, and 0.1 m/s of airspeed [13]. We defined the clothing insulation as three ranges i.e., Clo 1, Clo 2 and Clo 3, which are from 0.25 to 0.50, 0.51 to 1.00, and 1.01 to 1.65, respectively. More details can be obtained from previous work [5].

$$s_t^C = s_{t-1}^C + a_t^C, \forall t > 1 \tag{6}$$

$$\underline{\mathrm{s}}_t^C \leq s_t^C \leq \overline{\mathrm{s}}_t^C, \forall t \tag{7}$$

$$\underline{a}_t^C \leq a_t^C \leq \overline{a}_t^C, \forall t \tag{8}$$

$$Clo_t^{penalty} = |a_t^C \cdot a_{t-1}^C|, \forall t > 1 \tag{9}$$

Here, we incorporate the occupant clothing states and actions in the proposed HEMS model. The clothing state transition of the occupant is expressed in (6). The upper and lower bounds on the clothing state and actions are modeled in (7) and (8). a penalty on clothing changing behavior in consecutive time periods as modeled in (9). It is worth mentioning that the proposed HEMS model optimally determines the recommended clothing adjustment, if any, to the occupant through a smartphone application or a speaker in a smart home hub (e.g., Amazon Echo). The occupant decides whether to follow the clothing adjustment recommendation or simply ignore it. Then, the feedback will be sent to the HEMS controller (see Fig. 1), in which the occupant's clothing state is updated. The above setting is widely available in today's smart home environment [1].

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3) EV Model with the Occupant's SOC Concern: Due to the inaccurate estimation of the EVs driving range, unforeseeable traffic conditions, and potential earlier-than-expected departure time, an EV driver is typically fearful of completely depleting the EV battery before reaching the destination. Here, we define a term, namely the SOC concern, to represent the occupant's concern caused by all these factors. The SOC concern can be viewed as a reflection of the occupant's behavior proneness for charging the EV when it is parked at home. Therefore, a mathematical model is formulated here to describe the occupant's EV SOC concern as follows:

$$EV_t^{concern} = \max\left(SOC_t^e - s_t^E, 0\right), t_a \leq t \leq t_d \tag{10}$$

The SOC_t^e is the occupant's expected SOC during the charging as follows:

$$SOC_t^e = \frac{k_1\left(e^{-k_2(t-t_a)/(t_d-t_a)} - 1\right)}{e^{-k_2} - 1}, t_a \leq t \leq t_d \tag{11}$$

where t_a and t_d are the EV arriving time and departing time, respectively; k_1 and k_2 are the shape parameters which can be established based on insights of the occupant's driving behavior, the occupant's sensitivity to electricity price and the tolerance to the SOC concern [10].

$$s_t^{\mathrm{E}} = (1-\lambda^{\mathrm{E}})s_{t-1}^{\mathrm{E}} + \frac{\eta^{\mathrm{E}} a_t^{\mathrm{E}}}{C^{\mathrm{E}}}, \quad t_a + 1 \leq t \leq t_d \tag{12}$$

$$\underline{\mathrm{s}}_t^{\mathrm{E}} \leq s_t^{\mathrm{E}} \leq \overline{\mathrm{s}}_t^{\mathrm{E}}, \forall t \tag{13}$$

$$\underline{a}_t^{\mathrm{E}} \leq a_t^{\mathrm{E}} \leq \overline{a}_t^{\mathrm{E}}, \forall t \tag{14}$$

$$Bat_t^{penalty} = \max\left(-(a_{t-1}^E \cdot a_t^E), 0\right) \tag{15}$$

Constraint (12) shows the state transition of an EV when it is parked at home. λ^{E} in (12) captures its SOC loss caused by self-discharging when transitioning from one state to the next [14]; η^{E} represents the EV charge/discharge efficiency, which may differ between charge and discharge actions made by the HEMS. Constraints (13) and (14) indicate that the EV state and action (i.e., charging and discharging) must lie within its recommended SOC and power limits. Equation (15) defines a penalty to prevent frequently switching between charging and discharging of the EV battery since the frequent switches would reduce the lifetime of the EV battery [15]. Note that the EV model with the occupant's EV SOC concern in (10)-(15) are non-linear and non-convex, which is naturally suited for the MDP-based solution rather than using linearization techniques.

C. HVAC Model

A first-order thermodynamic model is used to describe the evolution of the room temperature as a function of the previous state, the power consumed by the HVAC as well as the outdoor temperature. Since the 1R1C model is a first-order linear model and its coefficients can be accurately estimated based on historical data, it is widely used in the HVAC optimization, scheduling, and energy management [1], [3], [5], [11], [16], [17]. The thermal dynamic equation and other HVAC constraints are listed as follows:

$$s_t^{\mathrm{H}} = \gamma^{RM} s_{t-1}^{\mathrm{H}} - \gamma_c^{\mathrm{H}} a_t^{\mathrm{H}} + \gamma^{\mathrm{OUT}} \tilde{u}_t^{\mathrm{OUT}}, \forall t \tag{16}$$

$$\underline{\mathrm{s}}_t^{\mathrm{H}} \leq s_t^{\mathrm{H}} \leq \overline{\mathrm{s}}_t^{\mathrm{H}}, \forall t \tag{17}$$

$$\underline{a}_t^{\mathrm{H}} \leq a_t^{\mathrm{H}} \leq \overline{a}_t{}^{H}, \forall t \tag{18}$$

Equation (16) shows the state transition of the room temperature for a prescribed mode, i.e., cooling. Note that in this HEMS model, the HVAC efficiency is embedded in the HVAC related coefficients γ_c^{H} and γ_h^{H}. These coefficients, together with other thermal coefficients, i.e., γ^{RM} and γ^{OUT}, can be obtained by using a polynomial fitting based on historical data. Also, the control action, a_t^H, is computed in units of thermal energy added or removed. This control can be straightforwardly adapted to corresponding thermostat settings. Equations (17)–(18) indicate that the states and actions have to lie within the specified bounds set either by the occupants. The ADP is approached by an effective combination of Sobol sampling backward induction and a K–D tree nearest neighbor techniques for the value function approximation to improve computational performance. The detailed solution procedure of the ADP can be found in our prior work [5], [11].

III. Numerical Results

We simulate the proposed ADP-HEMS within a MPC framework in Matlab. The proposed HEMS formulation is coded on the Dynamic Programming for Adaptive Modeling and Optimization toolkit developed by National Renewable Energy Laboratory [18]. The proof-of-the-concept evaluation is based on the proposed formulation. This paper focuses on proposing a novel HEMS mathematical formulation and thereby building a novel simulator that considers all the newly introduced factors (i.e., clothing behaviors + EV SOC concerns) is out of the scope of this paper. The HVAC parameters in Equation (16) were obtained from data of a residential house located in Hillsboro, Oregon [16], [17], and the EV parameters can be found in [19], [20]. The operational temperature range of an HVAC is from 18°C to 30°C, and the EV SOC range is 20% to 100%.

TABLE I: The clothing condition and EV event

Time range	**Clothing conditions**	$\hat{s}^i$
[10 pm, 6 am]	Sleeping with Clo 1	$22°C$
Time range	**EV behavior**	$\tilde{u}^{SOC}$
[8 am, 6 pm]	Not at home both Days 1 & 3	30%
[7 pm, 9 pm]	Not at home Day 2	10%

We consider a 54-hour simulation for a single family consisting of a young couple, one works from home and the other drives to work. We create a scenario for the occupant's driving and sleeping schedules as shown in Table I for the co-simulation. In Table I, the EV is not at home between 8 am to 6 pm with an estimated 30% SOC consumption for the first day, and not at home from 7 pm to 9 pm with an estimated

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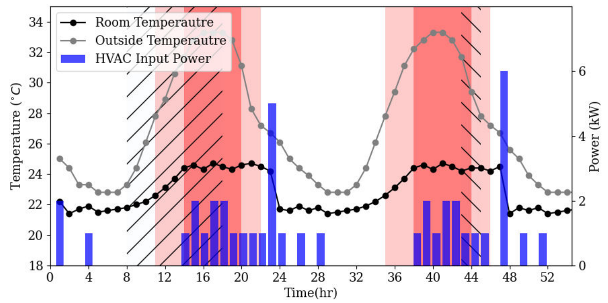

Fig. 2: Baseline HVAC simulation.

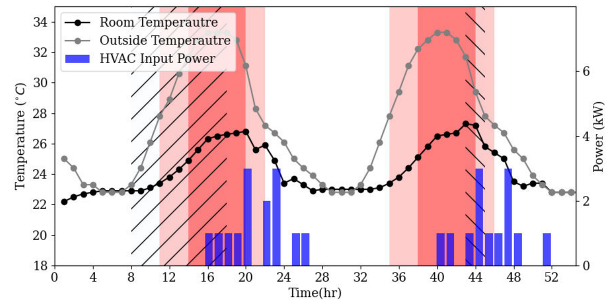

Fig. 4: HVAC simulation results for the proposed HEMS.

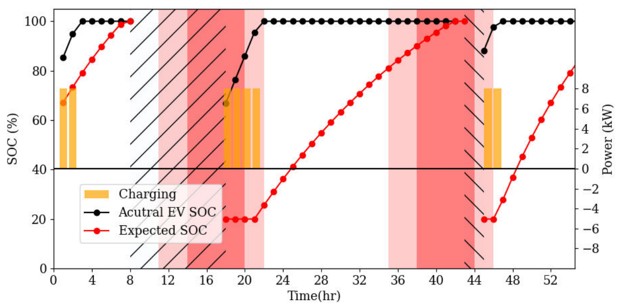

Fig. 3: Baseline EV simulation.

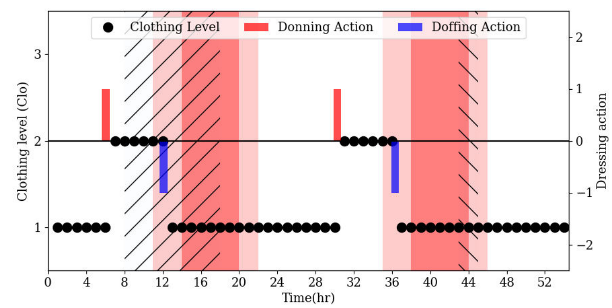

Fig. 5: Clothing simulation results for the proposed HEMS.

9.7% SOC consumption for the second day. We use Pacific Gas & Electric (PG&E) ToU electricity rate, i.e., EToU-E6, which a base prices \$0.244/kWh, shoulder prices \$0.32/kWh, and peak prices \$0.436/kWh, respectively.

A. Baseline Simulation

A baseline case is proposed that includes 1) using a fixed setpoint for a thermostat during both sleeping time and active time and 2) charging the EV instantly upon arrival home with no discharging. Therefore, the baseline case is designed to represent typical decisions a household makes with an EV and no optimization. Fig. 2 shows the simulation results for the HVAC in the baseline. The white, light red and dark red areas show base, shoulder, and peak prices, respectively, and two slashed areas represent the occupant's EV driving schedules when the EV is not at home. As shown in Fig. 2, the main goal of the baseline is to maintain the room temperature around the desired value, i.e., 22 $^\circ C$ during sleeping time, 24$^\circ C$ otherwise. The HVAC acts similarly on both Days 1 and 2.

Fig. 3 displays the baseline EV simulation results. As seen, on both days, the EV is charged at the maximum charging power as soon as it reaches home. The resulting charging schedule brings up the EV SOC as soon as possible, representing the quickest way to relieve the EV SOC concern. However, the schedule overlaps with the peak and shoulder price in some hours.

B. Proposed HEMS Simulation

In this case, the proposed HEMS is simulated within the same MPC framework as in the baseline. Fig. 4 and 5 show the simulation results for the HVAC and the occupant's clothing actions by the proposed HEMS, respectively. It is seen in Fig. 4 that between midnight to 4 pm on Day 1, the HVAC is idle. At 6 am on Day 1, a donning action is recommended by the proposed HEMS immediately after the occupant wakes up. As the outside temperature increases, the room temperature climbs up to 24 $^\circ C$. Then, the proposed HEMS recommends a doffing action instead of turning on HVAC to save energy costs. The HVAC remains idle until 4 pm, and subsequently, several cooling actions happen from 4 pm to 7 pm when the temperature is slowly climbing to 26.7 $^\circ C$. These cooling actions are small due to the peak price for balancing energy cost saving and thermal comfort. Immediately following those small cooling actions, one 3 kW HVAC input power at 8 pm takes place at the shoulder price (i.e., delayed cooling when the price decreases) to ensure the room temperature can be cooled to the desired temperature for sleeping. On Day 2, the proposed HEMS suggests a donning action at 6 am, which is similar to that on Day 1. As the temperature increases to 24 $^\circ C$ at noon on Day 2, a doffing action is proposed by the HEMS. The remaining cooling actions scheduled are similar to those on Day 1.

Fig. 6 shows the EV simulation results by the proposed HEMS. In Fig. 6, the EV is discharged in the first two hours on Day 1 when the actual SOC is greater than the expected SOC for making a profit. Notice that according to Equation (10), the EV SOC concern exists only at times when the expected SOC is greater than the actual SOC. The expected SOC increases when the EV approaches the departure time, i.e., 8 am on Day 1; thereby, a series of charging actions are presented to charge the EV SOC to 98.5% at departure to minimize the SOC concern. After the driving event on Day 1, the EV returns home with around 62% SOC. Then, a few discharging actions

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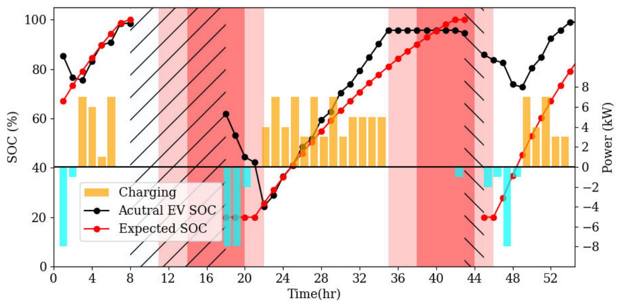

Fig. 6: EV simulation results with the proposed HEMS

TABLE II: Comparative results

	Baseline	**Proposed HEMS**
Avg. PMV	- 0.06	[0.2,0.3]
Avg. EV Concern	0%	[0.4%,1.2%]
Tot. Energy Cost	$25.9	[$10.9, $13.6]

are implemented when the EV is parked at home at peak hours to sell the electricity, thus earning a profit. A clustering of charging actions is scheduled during the night between Day 1 and Day 2 once the peak price and shoulder price are passing to minimize the SOC concern. Two discharging actions are proposed at 6 pm (peak price), 9 pm (shoulder price) on Day 2, and from 10 pm to 1 am on Day 3 to make a profit.

Table II compares the average PMV, average EV SOC concern and total energy cost over the scheduling horizon between the baseline and the proposed HEMS. In Table II, the Sobol sampling is applied to sample state, action and uncertainty space [11] for 10 times, and therefore a range is given for the proposed HEMS. As seen, the proposed HEMS shows a higher average PMV and average EV SOC concern. However, the maximum average EV SOC concern of 1.2% and the maximum average PMV of 0.3 are still quite small, both of which are within acceptable and comfortable ranges, indicating the occupant is still quite thermally comfortable and has little EV SOC concern. The most prominent difference lies in total energy costs. As seen, the proposed HEMS reduces the energy cost from $25.9 in the baseline to the maximum total energy cost of $13.6 in the proposed simulation, which is a 47.5% increase in the electricity cost saving.

IV. Conclusion

This paper proposes a stochastic HEMS model that accounts for the occupants' thermal comfort, clothing behaviors and EV's SOC concerns. This model optimally determines the setpoints of HVAC, occupant's clothing decisions and the EV's charge/discharge schedule. Comparative simulations between the proposed HEMS and a baseline case are conducted and the simulation results demonstrate that the electricity cost can be dramatically saved by using the V2H services while a high level of the occupant's comfort and expectations are still retained. In addition, the occupant's clothing behaviors can provide the HEMS with an additional dimension of decisions, which, in turn, enhances the flexibility of the HVAC and leads to better utilization of the house thermal storage. The proposed HEMS model is built for a residential home with one occupant and one EV. However, this model can be straightforwardly extended to include multiple occupants and EVs for more building types. This will be investigated in the future work We will also develop a novel and complex simulator that combines some existing tools (e.g., EnergyPlus+GridLAB-D) for more accurate evaluation of this formulation.

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