Journal of Building Engineering 40 (2021) 102708

Contents lists available at ScienceDirect

Journal of Building Engineering

journal homepage: www.elsevier.com/locate/jobe

Hourly occupant clothing decisions in residential HVAC energy management

Xuebo Liu [a,*], Yingying Wu [b], Haifeng Zhang [c], Hongyu Wu [a]

[a] Mike Wiegers Department of Electrical and Computer Engineering, Kansas State University, Manhattan, KS, 66506, USA
[b] Department of Interior Design and Fashion Studies, Kansas State University, Manhattan, KS, 66506, USA
[c] School of Mechanical and Automotive Engineering, Shanghai University of Engineering Science, Shanghai, 201620, China

ARTICLE INFO

Keywords:
Home energy management
Occupant's clothing condition
Approximate dynamic programming
Model predictive control
Heating
Ventilation and air conditioning

ABSTRACT

The state-of-the-art energy management for the heating, ventilation and air conditioning (HVAC) system uses a static clothing model that calculates the occupant's clothing insulation as a fixed value based on outdoor air temperature measured at a particular time of the day. However, the static clothing model can hardly capture the occupant's intra-day clothing behaviors, leading to inaccurate thermal comfort assessment and unrealistic HVAC energy management. This paper proposes a novel HVAC energy management scheme to optimally schedule the thermostat setpoints of HVAC and to provide recommendations on occupants' optimal hourly clothing decisions through a predicted mean vote model, while considering uncertainties in the outside temperature. The proposed HVAC energy management scheme is solved by applying an approximate dynamic programming approach. Further, a model predictive control framework with a long short-term memory based forecaster is developed for more realistic simulations. We study the HVAC schedules in a residential home with summer and winter time of use electricity tariffs for both male and female occupants. Compared with non-optimized cases, proof-of-concept simulation results demonstrate that the proposed scheme can achieve a 53.8% and a 29.8% cost saving in a summer-male scenario and a winter-female scenario, respectively.

1. Introduction

Approximately 100 million single-family homes in the United States account for 36% of the electricity load, and often they determine the peak system load, especially on hot summer days when the use of residential air-conditioning (AC) is high [1]. Increased consumer adoption of home automation products such as smart thermostats for heating, ventilation and air conditioning (HVAC) is a prominent trend in residential buildings.

In addition to energy cost savings, occupant's thermal comfort is one of the most significant factors considered in the thermostat control of the HVAC. One popular index of the thermal comfort is the Predicted Mean Vote (PMV) model and Predicted Percentage of Dissatisfied (PPD), which was proposed by P.O. Fanger and his colleagues in Kansas State University and Technical University of Denmark in the 1970s [2]. In additional, PMV-PPD is included in ISO 7730 [3] in 2005 and the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) standard 55 [4] in 2004. Buratti et al. [5] developed a linear regression approach to the PMV with a wider range of clothing thermal insulation in moderate environments based on measured air temperature and relative humidity. Jia et al. applied an event-based optimization control via Markov Decision Process (MDP) with PMV while considering the effect of multi-rooms [6]. Luo et al. proposed a metaheuristic algorithm based energy management system (EMS) to optimally schedule energy resources (including residential PV) while using adaptive PMV to account for the occupant's thermal comfort [7]. Clothing condition has a drastic impact on the human body thermal insulation, which in turn influences occupants' thermal comfort significantly. Therefore, the occupant's clothing condition is taken as a given parameter in building energy modeling and simulations. For example, since clothing has a drastic impact on the human body thermal insulation, it still remains unclear as to how human clothing decisions, i.e., donning and doffing, can influence optimal schedules of HVAC thermostats in terms of the occupant's electricity costs and thermal comfort.

The current state of the art in building energy modeling and simulations (e.g., EnergyPlus [8]) is that the thermal comfort condition is calculated based on a dynamic clothing model. In this model, the clothing insulation is calculated as a function of outdoor air temperature measured at 6 o'clock and this clothing insulation value remains

* Corresponding author.
E-mail address: xuebo@ksu.edu (X. Liu).

https://doi.org/10.1016/j.jobe.2021.102708
Received 2 February 2021; Received in revised form 18 April 2021; Accepted 7 May 2021
Available online 13 May 2021
2352-7102/

Nomenclature

HVAC	Heating, ventilation and air conditioning
EMS	Energy management system
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
MDP	Markov decision process
EV	Electrical vehicle
WFH	Work from home
WH	Water heater
ADP	Approximate dynamic programming
ToU	Time-of-use
MPC	Model predictive control
LSTM	Long short-term memory
ASHRAE	The American Society of Heating, Refrigerating and Air-Conditioning Engineers
KDNN	K-D tree nearest neighbor
SSBI	Sobol sampling backward induction
RNN	Recurrent neural network
MAPE	Mean absolute percentage error
COP	Coefficient of performance

Parameters and variables

t	Time interval
i	HVAC or clothing index, $i \in \{H, C\}$
Δt	Resolution of time interval
T	Total number of time intervals
T_{kd}	K-D tree
s_t^i	At time t, pre-decision state of i (°C)
$\dot{s}_t$	At time t, post-decision state (°C)
$s_t^{'}$	At time t, sampled state (°C)
$\mathbf{S}$	State space
x_t^i	At time t, decision of i
$\mathbf{X}$	Decision space
$\widetilde{u}_t$	At time t, uncertain outside temperature (°C)
$\widetilde{\mathbf{U}}$	Uncertainty space
rh_t	Relative humidity at time t (%)
$\alpha_t^{\mathcal{D}}$	At time t, discomfort weight
$\alpha_t^{\mathcal{C}}$	At time t, cost weight
β_t	Discomfort penalty at time t
c_t	Electricity price at time t ($/kWh)
γ^{OUT}	Thermal coefficient of outside temperature
γ^{RM}	Thermal coefficient of room temperature
γ_c^H	Cooling coefficient of HVAC
γ_h^H	Heating coefficient of HVAC
$\underline{s}_t^i$	Lower bound of state i at time t
$\overline{s}_t^i$	Upper bound of state i at time t
$\underline{x}_t^i$	Lower bound of decision i at time t
$\overline{x}_t^i$	Upper bound of decision i at time t
$\mathcal{D}$	Function of discomfort
$\mathcal{C}$	Function of electricity cost
$\mathcal{F}_s$	Sobol sampling function
$(\cdot)'$	Superscript representing sampled

unchanged during the entire day. While there is no standardized guideline on how to set clothing insulation schedules, the dynamic clothing model leads to HVAC systems that are incorrectly operated and to the inaccurate assessment of occupant comfort conditions. In reality, residential occupants can frequently adjust their clothing, depending on the thermal conditions around them, on an hourly or sub-hourly basis, as opposed to a constant clothing value in an entire day. Such adjustments can improve home demand flexibility and thus enable a higher energy cost saving. The frequent clothing adjustment is even more plausible under the COVID-19 outbreak, whereby many businesses worldwide shift from traditional office-based work operations to work from home (WFH) arrangements. Therefore, the hourly or sub-hourly clothing adjustment should be fully captured and optimized in the residential home energy management to model HVAC systems realistically. There has been no work to date that addresses this issue. In addition, it is challenging to incorporate occupant's clothing adjustments in the HVAC energy management due to the complex nonlinear relationship between the clothing conditions and the occupant's thermal comfort.

Various home energy management models and solution algorithms have been proposed. Among them, approximate dynamic programming (ADP) represents a promising class of algorithms for decision-making under uncertainty [9,10]. Past research efforts have used ADP for grid-battery management [11–16], real-time microgrid operations [17], and air conditioner to minimize electricity consumption while considering the occupant thermal comfort [18–20]. Nevertheless, to the best of our knowledge, there has been no work to date that uses the ADP to address the HVAC energy management issue while considering occupant's hourly clothing decisions.

This paper bridge this gap by proposing an HVAC energy management scheme that aims to minimize the electricity cost and the occupant's thermal discomfort while taking into account the occupant's optimal clothing decisions. Under the time-of-use (ToU) electricity tariff, the proposed scheme optimally determines the thermostat setpoints of HVAC and simultaneously provides the best recommendations on the occupant's clothing conditions, while accounting for uncertainties in outside temperature. The proposed HVAC energy management scheme is solved by using an ADP-based algorithm. Further, a model predictive control (MPC) framework with a Long Short-Term Memory (LSTM)-based forecasting technique is developed to simulate the complex decision making considering the electricity prices, HVAC schedules, and occupants' thermal comfort and clothing conditions. We systematically study the optimal HVAC schedules and hourly clothing decisions for both male and female occupants in the summer and winter seasons. Comparative results with and without considering the hourly clothing decisions are also revealed. The main contributions of this work are three-fold:

1) This paper proposes a novel HVAC energy management scheme that is the first of its kind to explicitly consider the occupant's hourly dynamic clothing conditions as an additional dimension of decisions for minimizing the electricity cost and the occupant thermal discomfort under uncertainty.
2) An ADP-based algorithm is applied to include the occupant's clothing states and actions. An MPC framework with the ADP algorithm as an optimization engine and an LSTM as an embedded outdoor temperature forecaster is proposed to simulate HVAC energy management. This framework simulates the HVAC operation under uncertainty in a more realistic environment.
3) Proof-of-concept simulation results show that, if the occupant follows the optimal clothing decisions produced, 53.8% and 29.8% of daily electricity cost savings can be achieved respectively for a summer-male scenario and a winter-female scenario, only with negligibly compromised thermal comfort. Table 1 compares related work in this area to the contributions of this paper in terms of proposed approaches, energy management system, occupant comfort, clothing factor and study scope.

Table 1
Comparison of related works in the literature.

References	Approaches	EMS	Comfort	Clothing	Study scope
[5]	linear regression		✓	Fixed values	HVAC
[6]	complexity-based approach	✓	✓	Fixed values	HVAC
[7]	MPC	✓	✓		PV, HVAC, battery
[11]	temporal difference ADP	✓	✓		PV, battery
[12]	distributed iterative ADP	✓			battery
[13–15]	action-dependent heuristic DP	✓			PV, battery
[16]	iterative ADP	✓			battery
[17]	spatiotemporal ADP	✓			microgrid
[18,19]	ADP	✓	✓		thermal storage
[20]	ADP-based MPC	✓	✓		HVAC, WH, EV
This work	ADP-based MPC with LSTM	✓	✓	Hourly decis.	HVAC

2. Problem formulation

2.1. ADP-based optimization problem

The HVAC energy management problem is a discrete-time MDP, which contains an objective function, a group of state transition functions and physical constraints. We provide a detailed formulation in this section. The physical setting of the HVAC energy management scheme including the component connection, data and control flows within a residential home is illustrated in Fig. 1. Here, the ADP-based HVAC controller is a central device that connects the sensors, meters and an HVAC thermostat. All the data from the sensors and smart meters will be sent to the cloud data center for data collection. A weather forecaster will deliver the predicted weather data back to the ADP-based controller. Then, the controller determines optimal schedules for the setpoints of the HVAC thermostat and sends the optimally 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 ADP-based controller, in which the occupant's clothing state is updated. The above setting is available in today's smart home environment [21], in which various measurements (e.g., indoor and outdoor temperatures, relative humidity, and electricity prices) can be collected frequently to facilitate real-time control.

The aim of ADP is to minimize the weighted sum of the occupant's electricity consumption and thermal discomfort. This model contains discrete states, discrete actions, and stochastic factors. At each time interval t, a state consists of the room temperature s_t^{H} and the occupant clothing state s_t^{C}. A decision contains HVAC power x_t^{H} and occupant's clothing adjustment x_t^{C}, i.e., doffing or donning. The stochastic variables $\tilde{u}_t$ are the outside temperature. Additionally, the HVAC is in state s_t^{H} when a decision x_t^{H} is determined at the beginning of each time interval. Then, the decision is implemented instantly and affects the rest of the time intervals. After the decision is applied, the outdoor temperature as the uncertainty variable is realized and affects the rest of the time intervals.

The state-decision set tuple $\{s_t, x_t\} = \{(s_t^{\mathrm{H}}, s_t^{\mathrm{C}}), (x_t^{\mathrm{H}}, x_t^{\mathrm{C}})\}$ contains HVAC- and clothing-related state and decisions for all time periods. The objective function is to minimize the expectation value of the reward:

$$minE\left\{\sum_{t=1}^{T} R_t(s_t, x_t, \tilde{u}_t)\right\} \tag{1}$$

$$R_t(s_t, x_t, \tilde{u}_t) = \alpha_t^{\mathcal{D}} \cdot \mathcal{D}_t(s_t) + \alpha_t^{\mathcal{C}} \cdot \mathcal{C}_t(s_t, x_t) \tag{2}$$

Equation (2) shows that the reward R_t consists of thermal discomfort $\mathcal{D}_t$ and the electricity cost $\mathcal{C}_t$ of the occupant. Additional, $\alpha_t^{\mathcal{D}}$ and $\alpha_t^{\mathcal{C}}$ are respectively weight discomfort coefficient and cost coefficient. These value can be calculated based on the occupant's preferences [20]. The occupant's discomfort $\mathcal{D}_t$ consists of PMV at time t is defined as follows:

$$\mathcal{D}_t(s_t) = \beta_t \cdot \mathrm{PMV}(s_t) \tag{3}$$

In equation (3), the occupant's thermal discomfort HVAC is modeled as an absolute value of the PMV times a coefficient β. The PMV equation for the thermal comfort model is expressed as follows:

$$\mathrm{PMV}(s_t) = a(s_t^{C}) \cdot s_t^{\mathrm{H}} + b(s_t^{C}) \cdot \mathrm{P}(s_t^{\mathrm{H}}, rh_t) - c(s_t^{C}) \tag{4}$$

$$\mathrm{P}(s_t^{\mathrm{H}}, rh_t) = rh_t \cdot 0.61121 exp\left(\left(18.678 - s_t^{\mathrm{H}} / 234.5\right) \cdot \left(s_t^{\mathrm{H}} / (257.14 + s_t^{\mathrm{H}})\right)\right) \tag{5}$$

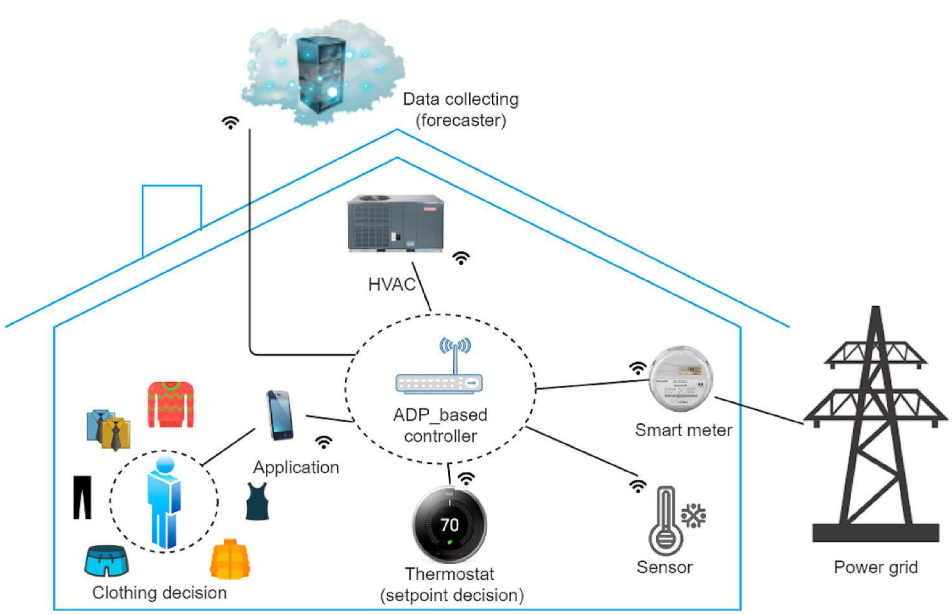

Fig. 1. The schematic diagram of proposed energy management.

where $P(s_t^H, rh_t)$ is the water vapor pressure in ambient air (kPa) and rh_t is the relative indoor humidity. In order to study the occupant's dynamic clothing behaviors, we adopt a simplified PMV model from Ref. [5]. This model is dependent only from air temperature and relative humidity because these two parameters are widely available due to their easy measurement in residential buildings. The boundary conditions (e.g., metabolic rate, air velocity) and the parameters $a(s_t^C)$, $b(s_t^C)$ and $c(s_t^C)$ in the PMV model can be found in Ref. [5]. The contribution of electricity cost $\mathcal{C}_t$ is defined:

$$\mathcal{C}_t\left(s_t^H, x_t^H\right) = c_t\, x_t^H\, \Delta t \tag{6}$$

where c_t is the electricity price. In this paper, we adopt a ToU tariff such that the electricity prices are available beforehand. The cost function in (6) is calculated as the total electricity cost of HVAC in the scheduling horizon. The physical constraints of the HVAC are listed as follows:

The constraints of the energy management scheme are associated with the physical operational limits of the HVAC. We adopt a first-order, 1R1C (i.e., 1 resistor-1 capacitor) thermodynamic model that is widely used in the literature [1,22–24]. The equivalent capacitor C represents the thermal mass of the building and the equivalent resistor R represents the resistance to heat transfer. The differential equation of 1R1C model is transferred in the Laplace domain and derived to get a set of linear Equation (7). The resultant linear equations consider the room temperature as a function of the room temperature at the previous time period, HVAC power consumption, and the outside temperature. The HVAC constraints are shown below:

$$s_t^H = S^M\left(s_{t-1}^H, x_t^H, \widetilde{u}_t\right) = \begin{cases} \gamma^{RM} s_{t-1}^H - \gamma_c^H x_t^H + \gamma^{OUT}\widetilde{u}_t, \forall t, \text{cooling} \\ \gamma^{RM} s_{t-1}^H + \gamma_h^H x_t^H + \gamma^{OUT}\widetilde{u}_t, \forall t, \text{heating} \end{cases} \tag{7}$$

$$\underline{s}_t^H \le s_t^H \le \overline{s}_t^H, \forall t \tag{8}$$

$$\underline{x}_t^H \le x_t^H \le \overline{x}_t^H, \forall t \tag{9}$$

In (7), thermal coefficients are computed according to either the values of equivalent resistor and capacitor or a regression analysis [1, 23]. Equation (8) suggests that the states should be within the lower and upper bounds prescribed by the occupants. Equation (9) indicates that the decisions should be limited by the physical cooling or heating capability of the HVAC. In Table 3, parameters of the HVAC first-order model and details of the clothing conditions are clearly displayed.

Table 3
HVAC parameters and clothing conditions.

State Range			State Revolution	
[18 30]			0.1	
Cooling case parameters				
γ^{RM}	γ^{OUT}	γ_c	COP	$\overline{x}$(kW)
0.94	0.06	0.116	4.75	4
Heating case parameters				
γ^{RM}	γ^{OUT}	γ_h	COP	$\overline{x}$(kW)
0.95	0.05	0.15	2.95	8
Time range	Occupant's clothing conditions			
[10pm, 6am]	Clo 1			
[6am, 10pm]	optimal hourly decision			

2.2. Occupant's clothing conditions

Clothing insulation, measured in the unit of clo, is the thermal insulation provided by clothing as well as any layer of trapped air between skin and clothing. One unit of clo equates to 0.155 $K \cdot m^2/W$, which means the amount of clothing needed by a sedentary person to maintain thermal comfort in an environment with 21 °C air temperature, 50% relative humidity (RH), and 0.1 m/s airspeeds. The ASHRAE Standard 55 [4] and ASHRAE Handbook [25] contains a list of clo values for selected garment types and formulas for estimating the insulation provided by a total clothing ensemble.

On the other hand, a simplified method of estimating clothing insulation is to multiply the weight of a clothing ensemble in lbs by 0.15. However, this method assumes there is no wind penetration in the nearby environment or body movements pumping air around. In general, the higher a clo value, the more insulating value is provided by a total clothing ensemble. Schiavon and Lee [26] found that the median clothing insulation is 0.59 clo in summer and 0.69 clo in winter. Clothing adjustment behaviours, i.e. adding or reducing layers of clothing, have a direct impact on the occupants' thermal comfort, thus the optimum operative temperature changes with clo values. The effect of changing clothing insulation on the optimum operative temperature is approximately 6 °C per clo for a sedentary man whose metabolic rate is approximately 1.2 met and this effect is greater with the higher metabolic rate [4].

Table 2 shows the estimated clo values of some typical business casual clothing ensembles. All the estimated clo values are from Ref. [27]. The range of clo values are traditionally divided into three groups [5], which are Clo 1: 0.25–0.5, Clo 2: 0.51–1.00, and Clo 3:1.01–1.65. Studying dressing behaviors is complicated particularly with the WFH arrangement during the COVID-19 pandemic. Some people value comfort, therefore prefer to dress down when they are working at home while some others believe dressing in a routine manner, such as wearing business casual outfits while working from home, can help them maintain a sense of control, degree of normality, and productivity. Even though business casual ensembles are used to demonstrate the relationship between clo values and the occupant's donning and doffing

Table 2
Clo values of typical business casual clothing ensembles.

Range (clo)	Male Ensembles	Female Ensembles
Clo 1: 0.25–0.50	Estimated clo = 0.42 Outfit: A short-sleeve shirt (0.19), a pair of thin straight trousers (0.15). Underwear: a man's brief (0.04). Footwear: A pair of stockings (0.02), shoes (0.02).	Estimated clo = 0.41 Outfit: A short-sleeve dress shirt (0.19), a thin skirt (0.14) Underwear: a bra (0.01) and a panty (0.03). Footwear: A pair of stockings (0.02), shoes (0.02).
Clo 2: 0.51–1.00	Estimated clo = 0.82 Outfit: A long-sleeve shirt (0.25), a thin long sleeve sweater (0.25), a pair of thick straight trousers (0.24). Underwear: a man's brief (0.04). Footwear: A pair of stockings (0.02), shoes (0.02).	Estimated clo = 0.81 Outfit: A long-sleeve shirt (0.25), a thin long sleeve sweater (0.25), a thick skirt (0.23) Underwear: a bra (0.01) and a panty (0.03). Footwear: A pair of stockings (0.02), and a pair of shoes (0.02).
Clo 3: 1.01–1.65	Estimated clo = 1.23 Outfit: A long-sleeve shirt (0.25), a thick single-breasted suit jacket (0.42), a pair of thick straight trousers (0.24). Underwear: a man's brief (0.04), a pair of long underwear bottoms (0.15). Footwear: A pair of calf-length socks (0.03), a pair of boots (0.10).	Estimated clo = 1.11 Outfit: A long-sleeve shirt (0.25), a thick single-breasted suit jacket (0.42), a pair of thick straight trousers (0.24). Underwear: a bra (0.01), a panty (0.03). Footwear: A pair of knee socks (thick) (0.06), and a pair of boots (0.10).

behaviors at a residential home in this paper, this relationship exists in other types of ensembles as well.

According to Table 2, if a male is dressing in Clo 2 but feeling cold, he can exchange his thin sweater for a thick suit, swap the stockings for a pair of calf-length socks, trade his shoes for boots, and even add a pair of long underwear bottoms. Differently, if he is feeling hot when he is dressing in Clo 2, he can take off his thin sweater, exchange the long-sleeve shirt for a short-sleeve shirt, and swap the thick trousers for a pair of thin trousers. On the other hand, if a female is dressing in Clo 2 and feeling cold, she can exchange her thin sweater for a thick suit, swap her stockings for a pair of thick knee socks, and trade her shoes for boots. She may also place a blanket on her laps to warm-up her body (clo value varies based on the thickness and materials of the blanket, so its clo value is not included in Table 2. If she is feeling hot when she dresses in Clo 2, she can take off her thin sweater, exchange the long-sleeve shirt for a short-sleeve one, and swap the thick skirt for a thin skirt.

Based on the above analysis, we for the first time incorporates the occupant clothing conditions in the proposed model. Similar to the HVAC, the state transition of clothing conditions is expressed as follows:

$$s_t^C = s_{t-1}^C + x_t^C \tag{10}$$

$$\underline{s}_t^C \le s_t^C \le \overline{s}_t^C, \forall t \tag{11}$$

$$\underline{x}_t^C \le x_t^C \le \overline{x}_t^C, \forall t \tag{12}$$

3. ADP algorithm and MPC framework

In this section, we first describe the ADP algorithm, including state transition, the K-D tree Nearest Neighbor (KDNN), and the Sobol Sampling Backward Induction (SSBI). Then, we introduce the MPC framework that incorporates the ADP algorithm and an LSTM forecaster.

3.1. State transition and ADP

In our ADP algorithm, the value function $V(s_t)$, the expected value of the state s_t while applying all feasible decisions x_t and uncertainty $\widetilde{u}_t$ at time t:

$$V(s_t) = \sum_{s_{t+1}} P(s_{t+1}|x_t, s_t, \widetilde{u}_t)[R(s_t, x_t, \widetilde{u}_t) + V(s_{t+1})] \tag{13}$$

where $P(s_{t+1}|x_t, s_t, \widetilde{u}_t)$ is the probability of s_{t+1} given x_t, s_t and $\widetilde{u}_t$. An optimal action x_t^* is attained by $V_t^*(s_t)$ along with qualifying the Bellman optimality condition in (14)

$$V_t^*(s_t) = \min_{x_t}[R_t(s_t, x_t, \widetilde{u}_t) + E(V_{t+1}(s_{t+1})|s_t)] \tag{14}$$

Fig. 2 shows a diagram of state transition when $T = 3$, in which a red-highlighted path represents the optimal decision sequence. At the terminal state ($t = T$), $V_t(s_t)$ is calculated according to discomfort value for all possible s_T in the state space **S** as defined in equation (8). Next, for all previous states ($t = 1$ and $t = 2$), we apply a backward induction to identify the optimal value $V_t^*(s_t)$ and the best decision x_t^*. While traversing backward in the state transition diagram, x_t^* and $V_t^*(s_t)$ at each time index t are collected. At the initial time period ($t = 1$), $V_1^*(s_1)$ corresponding to x_1^* is obtained.

The well-known "curse of dimensionality" [9] dictates that an extremely long or even infeasible run time may occur due to a vast amount of state, decision and uncertainty spaces. Here, we use KDNN and SSBI to address this challenge [20]. SSBI is similar to the classic backward induction, but it contains a supplementary Sobol sampling

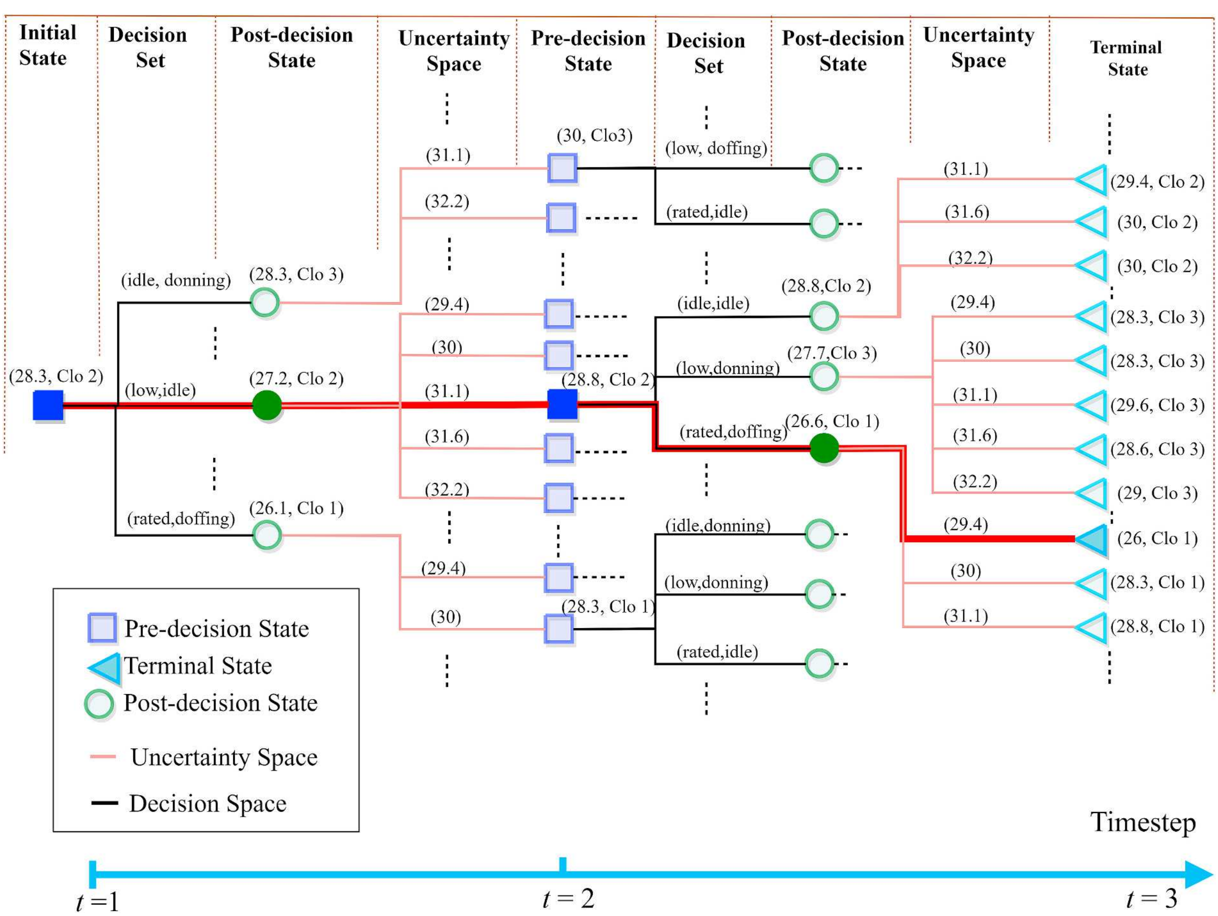

Fig. 2. Illustration of a state transition diagram considering occupant's clothing states and actions in winter (when $T = 3$).

function $\mathcal{F}_s$, which compacts the workload efficiently since only necessary state, action and uncertainty sets are considered. KDNN is one important approach of value function approximation. In order to achieve a fast computation, KDNN traverses the nearest point of $s_t^{'}$, and looks for an approximation value of $V(s_t^{'})$ instead of calculating from equation (13). The combination of KDNN and SSBI has shown promising performances in finding the optimal decision x_1^*. The ADP algorithm used in this paper minimizes the electricity cost and the occupant's thermal discomfort while taking into account the occupant's clothing decisions. The algorithm is modified based on Algorithm 3 in Ref. [20], but the main difference between them is the introduction of clothing factor into the state and decision spaces. More details about the algorithm can be found in Ref. [20].

3.2. ADP-based MPC framework with LSTM

The methodology of the ADP-based MPC framework is illustrated in Fig. 3, which is developed to test the effectiveness of the proposed HVAC energy management scheme in a more practical simulation that represents the state of the art in smart home applications. The MPC framework minimizes objective function (1) subject to the constraints (2)–(12) through a look-ahead horizon from the present time to the future ($t = T$). As shown in Fig. 3, the MPC framework collects three classes as inputs: 1) ADP-based MPC configurations including parameters pertaining to HVAC and ToU prices; 2) occupant's preferences including the weight of both discomfort and cost, desired sleeping temperature, PMV and clothing conditions; and 3) an outside temperature forecast, which is updated over time. After the ADP is solved, the decisions made for the present time interval are adapted to the real-time operation simulation module. Then, the thermostat setpoint and occupant's clothing adjustment are simulated with given optimal decisions. Initial states of the HVAC, the occupant's clothing, the PMV value and the electricity cost, all for the next window, are returned. The above steps repeat in the next window to form a receding horizon control. The ADP-based MPC sums up the simulated thermal discomfort and electricity costs over the whole horizon and determines an overall objective value.

The proposed HVAC energy management model can either receive weather forecasts of hourly outside temperature from the internet, or use the embedded LSTM forecaster to predict the outside temperature. Here, we unitize an LSTM technique to predict the hourly outside temperature based on the historical data by leveraging our previous work [28]. The LSTM is one type of recurrent neural networks (RNNs) and is capable of learning order dependence in sequence prediction problems such as speech recognition and context recognition [29,30]. The superiority of the LSTM is that it solves the long-range dependence more accurately than the conventional RNN [31]. According to the testing results, the mean absolute percentage error (MAPE) of the outside temperature forecast is about 0.02 and 0.38 for summer and winter, respectively, signifying an accurate forecast well suited in the proposed MPC framework.

4. Simulation results

The ADP-based energy management model is implemented in MATLAB via DYNAMO toolbox [32]. The HVAC parameters and occupant's clothing conditions are shown in Table 3. The HVAC parameters in Equation (7) are obtained using a linear regression method on a historical dataset of a residential home in Hillsboro, Oregon [22,23] with both a cooling case and a heating case.

We use the ToU electricity tariff, i.e., Pacific Gas & Electric EToU-E6 as the summer rate, and the Southern California EDISON TOU-D-5-8PM as the winter rate. For the summer, this tariff contains three price levels: Base, Peak A, and Peak B prices, i.e., \$0.244/kWh, \$0.32/kWh, and \$0.436/kWh, represented by white, light grey and dark grey in Fig. 4 (a), respectively. Peak A takes place in Hours 11–13, 20, and 21, and Peak B occurs during Hours 14–19. Base prices are utilized in the rest of the hours. Similarly, for the winter, as shown in Fig. 4 (b), Base, Peak A, and Peak B are \$0.24/kWh, \$0.28/kWh, and \$0.42/kWh, respectively.

In order to demonstrate the benefit of using the proposed HVAC energy management scheme, simulation results in both summer and winter under a traditional fixed setpoint thermostat (i.e., without the proposed energy management scheme) are shown in Fig. 5. We assume a medium clothing state (i.e.$s_t^C = 2$) with the desired temperature the occupant sets is 22.8 °C in winter for female and 20 °C in summer for the

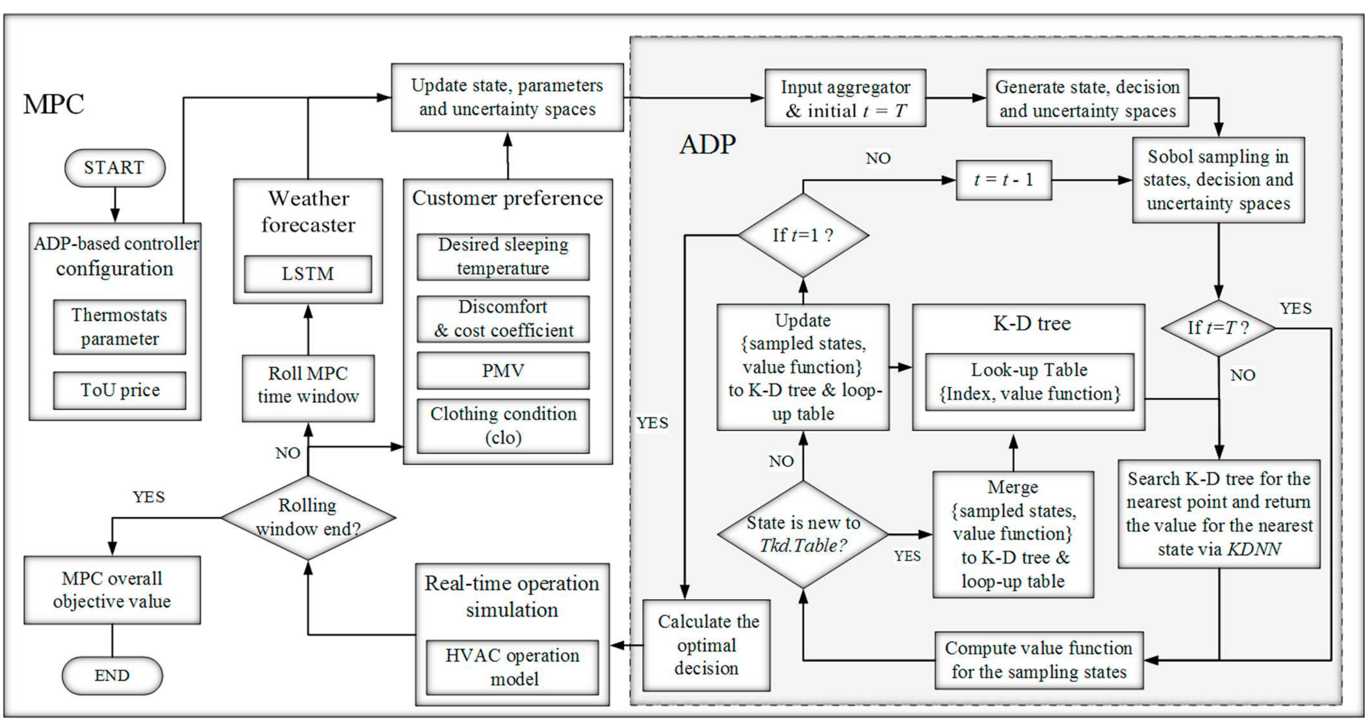

Fig. 3. Flowchart of the ADP based MPC framework.

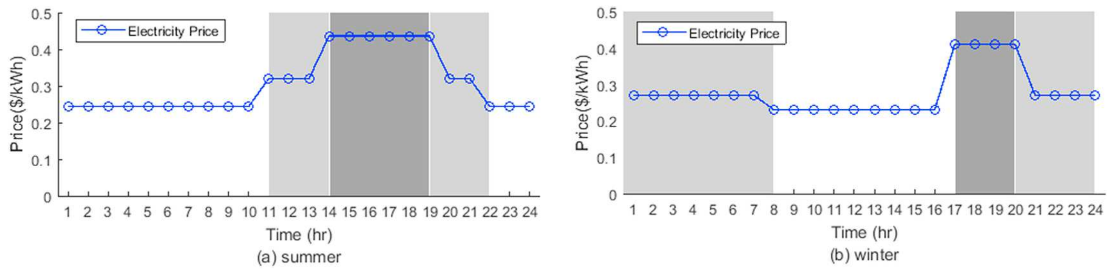

Fig. 4. The time-of-use electricity tariff.

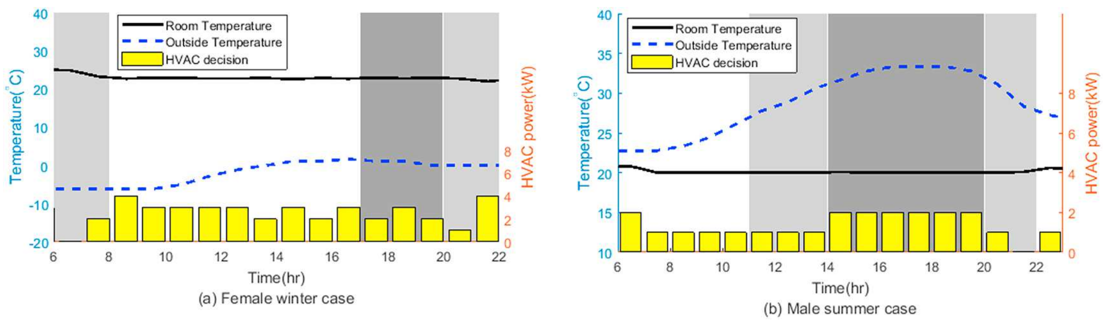

Fig. 5. Simulation results of a female winter case and a male summer case, both without the proposed HVAC energy management scheme.

male. This is because 22.8 °C is the most comfortable (PMV = 0) temperature for the female when the cloth state s_t^C is set to Clo 2, while that is 20 °C for male. Without loss of generality, we simulate the winter case for a female occupant and the summer case for a male occupant. In the winter, i.e., a heating case, the outside temperature is 22.4 °C lower than the room temperature at the initial time, i.e., 6:00. For the summer, i.e., a cooling case, the outside temperature is around 2.2 °C higher than the room temperature at 6:00 and becomes 11.1 °C higher at 18:00. In Fig. 5, we only show the simulation results from 6:00 to 22:00 because the other hours are considered as the occupant's sleeping time, when the fixed setpoint of the thermostat is respectively set to 25 °C and 22 °C in winter and summer as a comfortable temperature for female and male occupants [33]. It is seen the traditional fixed-setpoint thermostat keeps the room temperature around the desired temperature regardless of the electricity price and energy cost, implying the cost-saving potential for the energy management scheme.

With the proposed scheme, Fig. 6 shows the MPC simulation results for a female occupant. Specifically, Fig. 6 (a) shows the indoor temperature, outside temperature and the HVAC power, while Fig. 6 (b) shows the clothing state and dressing decisions. To facilitate our comparison and focus exclusively on the hours with clothing behavior, we adopt the same fixed setpoint control during the sleeping time as in the non-optimized case. At 6:00, the user's cloth state is Clo 1 and the indoor temperature is 25 °C. From 6:00 to 12:00 (noon), there is no HVAC heating but the donning decisions are made at both 6:00 and 8:00 to eventually get a clothing state Clo 3 at 10:00. This result shows that the occupant's clothing behavior plays an additional role in maintaining a satisfactory thermal comfort even with an extremely low outdoor temperature.

Meanwhile, the indoor temperature decreases due to the dropping outside temperature until it reaches the lowest temperature during the day. The outside temperature is rolling down to the minimum while the clothing state is reaching the maximum, without any HVAC heating to save the cost. Then, the HVAC energy management scheme makes a maximum heating decision at 12:00 since it is in an off-peak period, which in turn drives the indoor temperature to rise. The turning point of the indoor temperature occurs at 12:00 while the occupant makes a doffing decision to change its cloth state from Clo 3 to Clo 2. With an

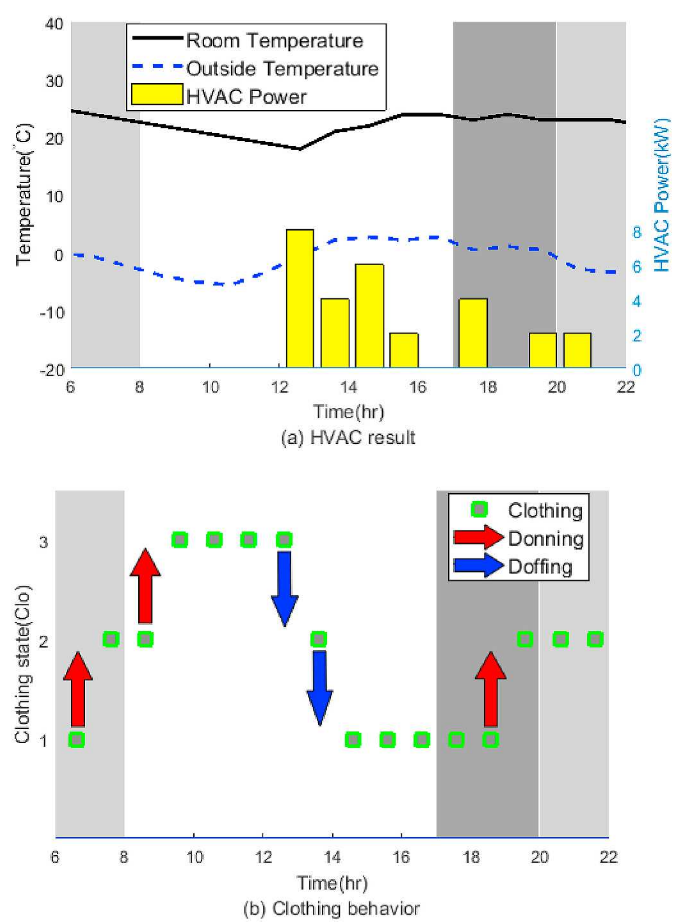

Fig. 6. Simulation results of a winter day for female with ADP.

increasing outside temperature, the energy management scheme makes several heating decisions from 13:00–15:00. As a result, the indoor temperature increase and the clothing state also decreases from Clo 3 to Clo 1. The above results in Fig. 6 suggest that in concert with the well-known pre-heating effect of the scheme, the ability to make optimal clothing decisions can provide an additional mechanism to better consider the occupant's thermal comfort while more effectively utilizing the thermal storage in the residential building.

At 16:00, both the outside temperature and indoor temperature come to the peak temperature of the daytime. At 17:00, in order to get a comparatively high indoor temperature (around 23.9 °C), the HVAC heats up the room and the female occupant stays with the minimum clothing state. Then, the occupant doffs at 18:00 when the indoor temperature decreases slightly. The HVAC slightly heats up the room at 19:00 and 20:00 to make the indoor temperature ends at the sleeping temperature we set at 22:00. It is worth mentioning the optimal clothing state follows the relationships between the PMV values and indoor temperatures for all three clothing states are referred from Ref. [5].

For a summer day, the simulation result of the HVAC energy management scheme for a male occupant is demonstrated in Fig. 7. At 6:00, the occupant's clothing state is Clo 1 and the indoor temperature is 20.6 °C. The occupant dons (e.g., adding a pair of long underwear bottoms) and his clothing state increases from Clo 1 to Clo 2 at 6:00. There is no HVAC power during 6:00–12:00 when the outside temperature is rising. At 12:00, the HVAC energy management scheme decides to slightly pre-cool the house. With the increasing outside temperature to the maximum at 92 °F, the scheme cools the house at 15:00, 17:00, and 18:00 to maintain the maximum of indoor temperature around 23.3 °C. Accordingly, the dressing decision made is doffing from Clo 2 to Clo 1 at 14:00 (i.e., the beginning of Peak B), and keep the minimum clothing state unchanged from 14:00 to 20:00 when both the peak electricity price and outside temperature are on the peak. To save the electricity cost, the proposed scheme postpones a cooling decision at its rated power (i.e., 4 kW) until 21:00 right after Peak B, to drastically brings down the room temperature. Meanwhile, The clothing state increases from Clo 1 to Clo 2 while the indoor temperature is drastically drooped to around 21.1 °C. The simulation result in Fig. 7 shows again that the ability to make optimal clothing decisions enhances the occupant's thermal sensation and provides an extra means to balance the occupant's thermal comfort and electricity cost.

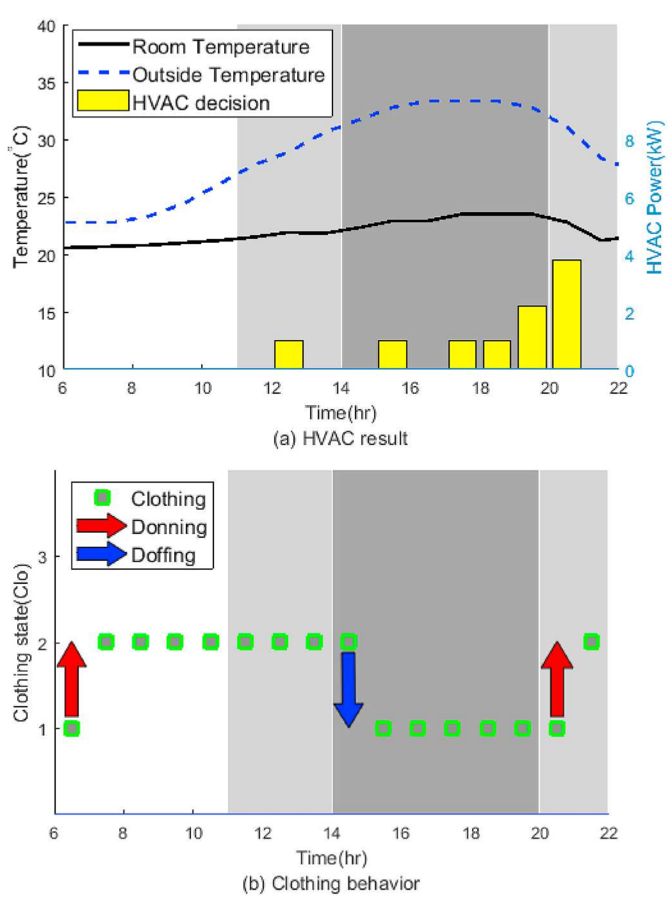

Fig. 7. Simulation results of a summer day for male with ADP.

In order to unequivocally show the benefit of the proposed scheme considering optimal clothing decisions, we perform a comparative study between the non-optimized and the optimized scenarios by the HVAC energy management. The comparative simulation results are listed in Table 4, in which two aforementioned scenarios, i.e., the summer case for a male occupant and the winter case for a female case, are compared. To facilitate the comparison, from 6:00 to 22:00, the initial and end temperatures of the non-optimal case are identical to those of the optimized case. However, the differences between the non-optimized and optimized cases are that the most comfortable temperatures under the dynamic clothing model (i.e., Clo = 2 on this day) are taken as manual temperature setpoints in the non-optimized case, while the temperature setpoints in the optimized case are optimally determined by the proposed scheme. For example, in the summer-male scenario, the non-optimized thermostat setpoints are set to a most comfortable temperature, which is 19.8 °C for Clo 2. For the winter-female scenario, they are set to 22.8 °C for Clo 2.

As seen in Table 4, the optimized electricity cost of the summer-male scenario is 3.8 US dollars and the average PMV from 6:00 a.m. to 10:00 p.m. is −0.1, whereas that of the winter-female scenario is 7.88 US dollars and the average PMV is −0.06. In either scenario, the optimized electricity cost by the HVAC energy management scheme is much superior to the non-optimized cost when the dynamic clothing model [8] is used. Recall that this dynamic model calculates the clothing insulation as a function of outdoor air temperature measured at 6 o'clock of the scheduling day and this clothing insulation value remains unchanged during the entire day. Therefore, this model cannot capture the intricacy of occupant clothing adjustment on an hourly basis. Through optimally determining the hourly clothing conditions, the proposed HVAC energy management scheme achieves a cost saving of 53.8% in the summer-male scenario, while a cost saving of 29.8% in the winter-female scenario. This much higher cost saving percentage in the summer-male scenario can be explained by comparing the average PMV values in Table 4. It is seen the average PMV value in the optimized summer-male scenario has a larger deviation from zero than that in the winter-female scenario, indicating a larger compromise in his thermal comfort. However, since the average PMV values are still close to zero, the occupant can hardly feel obvious thermal discomfort. The comparative results in Table 4 demonstrate that the proposed energy management scheme can significantly save the occupant's electricity cost with a negligibly compromised comfort.

5. Conclusions

In this paper, we propose a novel HVAC energy management scheme that is the first of its kind to take into account the occupant's hourly dynamic clothing behaviors to minimize the electricity cost and the occupant's thermal discomfort. We adopt a PMV model that accounts for

Table 4
A daily comparison between non-optimized and optimized cases.

Case	Item	Non-optimized	Optimized
Summer	Cost ($/day)	8.22	3.80
Male	Avg-PMV	−0.02	−0.10
Winter	Cost ($/day)	11.23	7.88
Female	Avg-PMV	0.06	−0.06

the indoor temperature, humidity, occupant gender, and a wide range of clothing thermal insulation. Then, the proposed scheme is embedded in an ADP-based MPC framework that includes the occupant's clothing states and actions. Under a ToU tariff, the ADP optimally determines the setpoint of the HVAC thermostat and provides recommendations on occupant's optimal clothing decisions based on typical business casual clothing ensembles for both genders, while considering outside temperature uncertainties. Such clothing recommendations can be sent to the occupant through a smartphone application or a speaker in a smart home hub. We systematically compare HVAC schedules with and without the optimal clothing decisions for both summer-male and winter-female scenarios. The proof-of-concept simulation results demonstrate the validity of the proposed HVAC energy management scheme and the effectiveness of the proposed ADP approach.

The benefits of considering the occupant's optimal hourly clothing decisions as opposed to a constant clothing condition in an entire day are shown in this paper. In particular, simulation results show that, if the occupant follows the optimal clothing decisions produced, a 53.8% and a 29.8% of daily electricity cost savings can be achieved respectively for a summer-male scenario and a winter-female scenario, only with negligibly compromise in the occupant's thermal comfort. Our simulation results also illuminate that the proposed HVAC energy management scheme has great capabilities of utilizing the building thermal storage in terms of pre-cooling, pre-heating, and delayed-cooling, etc. In future work, we will conduct real-world implementation and verification of the proposed HVAC energy management scheme. Furthermore, we will focus on enhancing the proposed energy management scheme using deep machine learning techniques for a variety of applications in next-generation residential and commercial buildings.

Credit Author Statement

Xuebo Liu: Conceptualization, Methodology, Software, Validation, Visualization, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. Yingying Wu: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision. Haifeng Zhang: Methodology, Writing – review & editing. Hongyu Wu: Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work is supported in part by Kansas State University new faculty startup fund and in part by the U.S. National Science Foundation under Grant No. 1856084.

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