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Real-time building heat gains prediction and HVAC setpoint optimization: an integrated framework

Zu Wang [1*], John Kaiser Calautit [2], Shuangyu Wei [2], Paige Wenbin Tien [2], Liang Xia [1]

[1] Research Centre for Fluids and Thermal Engineering, University of Nottingham, Ningbo China, 315100, China.

[2] Department of Architecture and Built Environment, University of Nottingham, Nottingham NG7 2RD, United Kingdom.

ABSTRACT

This paper proposes an integrated framework to achieve a simultaneous real-time reduction of occupants' thermal dissatisfaction and room HVAC energy consumption. The framework can optimize the HVAC setpoint temperature according to the internal heat gains predicted by a vision-based approach. When there are no occupants found by cameras, this framework will just turn off HVAC systems to reduce energy consumption. When occupants are present, the framework will determine an optimal setpoint temperature to balance occupants' thermal satisfaction and room HVAC energy consumption. During the simulated four days in the winter in a temperature climate, the utilization of this framework can lead to a reduction of heating energy by up to 36.8% and occupants' thermal dissatisfaction by up to 5.26%. During another simulated four days in the summer, the cooling energy savings would range from 3.5% to 33.9%, whilst occupants' thermal dissatisfaction could be decreased by 0.17-2.89%.

Keywords: Artificial intelligence, HVAC setpoint adjustment, building internal gains prediction, building energy reduction, occupants' comfort satisfaction.

NONMENCLATURE

Abbreviations	
HVAC	Heating, ventilation and air conditioning system
SNN	Shallow neural network
PPD	Predicted percentage dissatisfied

1. INTRODUCTION

1.1 Background

Nowadays, it is widely accepted that buildings can account for over 30% of energy use and greenhouse gas emission [1]. In particular, it is realized that heating, ventilation and air-conditioning (HVAC) systems are the main contributors to the high energy consumption of buildings. HVAC systems are responsible for providing occupants with a thermally satisfying environment. Therefore, simultaneously increasing the energy efficiency of HVAC systems without compromising occupants' thermal satisfaction has become an essential research topic.

A large number of studies showed the benefits of optimizing the setpoint temperature of HVAC systems. In HVAC systems [2-4], the setpoint temperature is one of the key factors influencing occupant's thermal satisfaction but also energy consumption of the systems. In general, the optimal setpoint temperature is derived by balancing the trade-off relationship between the energy consumption of HVAC systems and occupants' thermal satisfaction.

1.2 Research gap

Based on a literature review of the previous studies [3-5], there are two realized problems. Firstly, the previous studies assumed that the internal heat gains in buildings were constant or even zero [5]. Because of inevitable and stochastic occupants' behaviors, internal heat gains in real life is more complicated. Although this assumption can simplify the complexity of the optimization problem, it is also very likely that this assumption would influence the optimal setpoint temperature derived. Secondly, the previous studies were dependent on building energy simulation tools, making the real-time setpoint optimization much harder.

Currently, the two problems realized can be overcome by adopting prevailing artificial intelligence techniques. Our previous work showed the possibility of identifying real-time building internal heat gains by implementing vision-based cameras [6-7]. In this paper, heavy building energy simulation tools were replaced by shallow neural networks (SNNs) when optimal setpoint temperature was derived. Because SNNs require low computation cost and responses fast, they can be efficiently connected to vision-based cameras. This connection enables a good utilization of real-time internal heat gains and real-time HVAC setpoint optimization.

1.3 A combined framework

This paper develops an integrated framework comprising of six modules: images capture, real-time internal gains generation, room energy estimation, occupants' thermal satisfaction estimation, HVAC setpoint optimizer and setpoint controller. The details of the framework are described in subsection 2.5.

2. METHODOLOGY

In subsection 2.1, images capture and real-time internal gains generation are introduced. Subsection 2.2 shows the building energy simulation tool as a data-provider. Subsection 2.3 demonstrates the development of predictive energy and comfort models. Section 2.4 describes HVAC setpoint optimizer. Section 2.5 shows the proposed integrated framework.

2.1 Images capture and internal gains identification

In our previous works [6-7], vision-based cameras were used to identify the indoor activity of occupants and equipment. The cameras were deployed in a seminar room in the sustainable research building in Nottingham, UK, from Jan 8th – 11th. The cameras generated a real-time internal gains profile based on the captured images, as shown in Fig 1.

2.2 Building energy simulation tool and setup

In this paper, a building energy simulation tool called integrated environmental solution virtual environment (IES VE) was used to model the energy and comfort performance of the room where cameras were deployed. The obtained simulation data would be used to develop predictive energy and comfort models. 70 simulation scenarios were created to investigate the relationship between HVAC setpoint temperature, HVAC energy and occupants' thermal dissatisfaction. They are shown in Table 1.

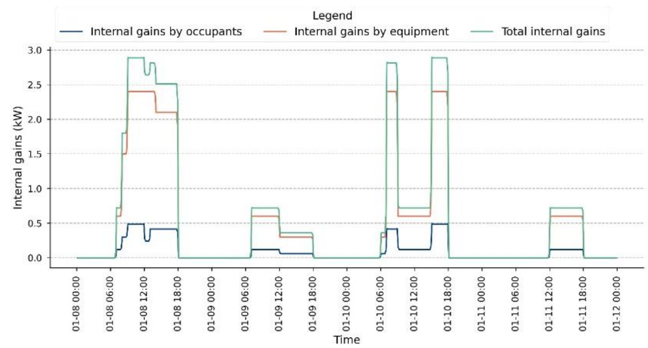

Fig 1 The generated internal gains profile

Table 1 The created *70* simulation scenarios for acquiring data

Scenario	Description	Purpose
1-25	5 heating setpoints × 5 internal gains profile	Develop predictive heating and cooling energy models
26-50	5 cooling setpoints × 5 internal gains profile	
51-55	5 heating setpoints × The generated internal gains profile	Verify the developed predictive heating and cooling energy models
56-60	5 cooling setpoints × The generated internal gains profile	
61-65	5 heating setpoints (clo=1)	Develop winter and summer comfort model
66-70	5 cooling setpoints (clo=0.5)	

2.3. Energy and comfort modelling by SNNs

In this paper, four predictive models were developed based on shallow neural networks (SNNs). They were winter heating energy model, summer cooling energy model, winter comfort model and summer comfort model, respectively. They were developed by using MATLAB neural fitting tool GUI. Particularly, there were

8 inputs to predictive heating and cooling modes: outdoor air temperature, wind speed, direct radiation, diffuse radiation, internal gains, HVAC setpoint, annual time step and daily time step. Based on the trial-and-error method, adding annual and daily time steps could significantly improve the fitting performance of SNNs. The inputs to the predictive comfort models were HVAC setpoint and the relative air humidity. To keep the models lightweight without compromising their effectiveness, there were only 10 hidden units in 1 hidden layer.

2.4. Setpoint optimizer and optimization rules

The role of setpoint optimizer is to determine the optimal setpoint temperature according to a internal heat gains identified by vision-based cameras. Simply, there are two optimization rules. When occupants are absent, internal heat gains from occupants shall be zero and there is no need of heating or cooling. Therefore, the optimal setpoint temperature under this situation would be -60℃ in winter and 100℃ in summer.

When occupants are present and identified by the cameras, heating or cooling shall be provided. Under this situation, optimal setpoint temperature is determined by referring to a performance indicator, called distance D, presented in equation (1)-(3). Based on the predictive energy models developed, HVAC energy consumption can be written as a function of HVAC setpoint temperature, shown in equation (1). Similarly, occupants' thermal dissatisfaction, i.e. PPD, can also be represented as a function of HVAC setpoint temperature, shown in equation (2). Depending on equation (1)-(2), equation (3) shows a performance indicator D used to quantify the goodness of a setpoint temperature. In this paper, it is assumed that a setpoint temperature with a

$$Energy_t = f(setpoint_t) \qquad \text{Equation (1)}$$
$$PPD_t = f(setpoint_t) \qquad \text{Equation (2)}$$
$$D_t = \sqrt{(Energy_t)^2 + (PPD_t)^2} \qquad \text{Equation (3)}$$

lower D has better performance than the one with a larger D. When looking for the optimal setpoint temperature, a number of different setpoints in the acceptable ranges were generated, and the setpoint with the lowest D was chosen as the optimal setpoint temperature.

To show the superiority of applying optimal setpoint temperature, 22 cases were set up, as shown in Fig 2. In the case, 1-5, Fixed heating setpoint profile with different setpoint temperatures was used. In case 6-10, a flexible heating setpoint profile was used. In this profile, the setpoint temperature would be -60℃ if cameras identified no occupants. In case 11, the optimal heating setpoint profile was adopted. Similarly, an optimal cooling setpoint temperature profile was used in case 22.

2.5. An integrated framework

Fig 3 shows the integrated framework.

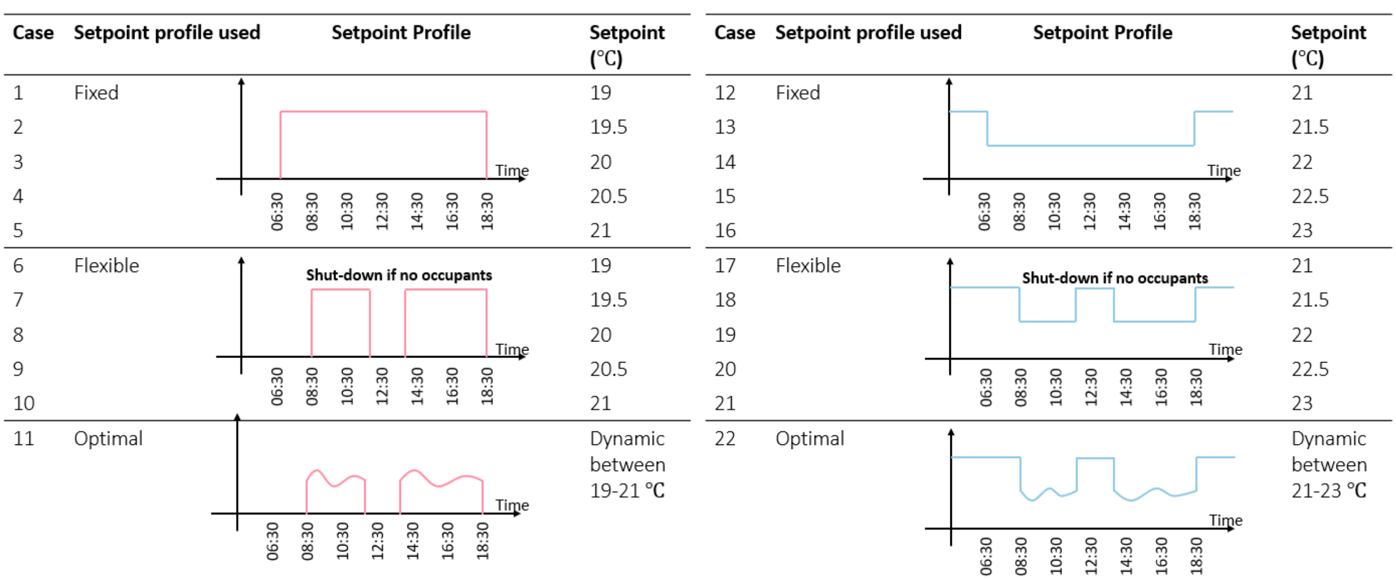

Fig 2 The explanation of created cases to show the superiority of optimal setpoint temperature profile

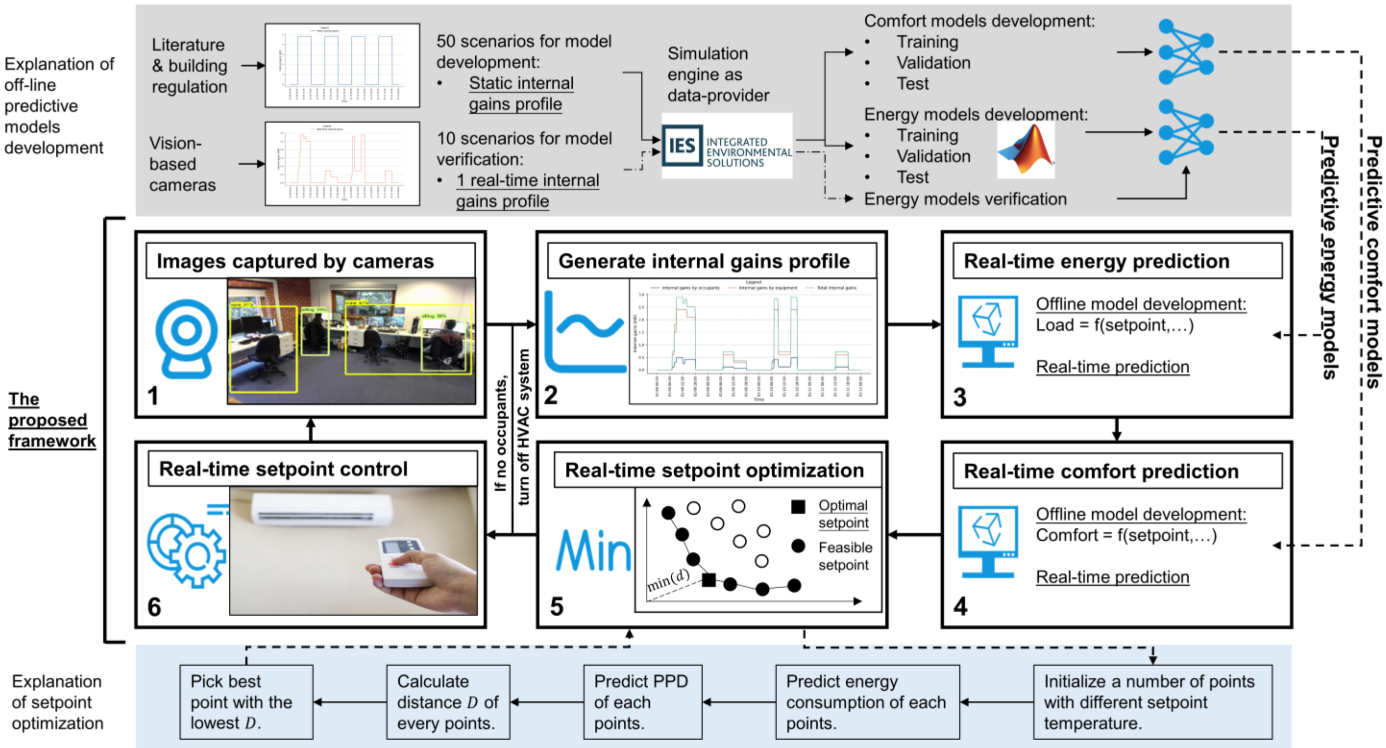

Fig 3 The integrated framework: real-time internal gains identification and HVAC setpoint optimization

3. *RESULTS AND DISCUSSION*

3.1 Predictive energy and comfort models developed

The fitting performance (R^2) of the four developed predictive models are all larger than 0.95 on training, validation and test datasets.

In the scenario 1-50, fixed internal gains profile was used. In order to ensure that the developed predictive energy models were able to learn the relationship between internal gains and HVAC energy consumption, the models were verified. In the scenario 51-60, the generated internal gains profile was used. Figure 4 compares the simulated and predicted energy consumption under the scenario 51 and 56. As can be seen, the simulated and predicted energy curves shared a very similar profile. The verification results are shown in Table 2. Because the R^2 in scenarios 51-60 were higher than 0.85, it was believed that the developed models were effective in predicting energy consumption based on real-time internal gains.

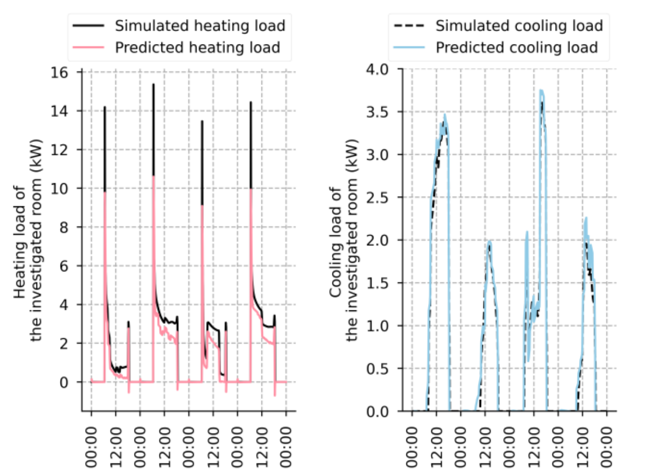

Fig 4 Comparison of energy between simulations and predictive energy models (Left) heating load in scenario 51, setpoint 19°C. (Right) cooling load in scenario 56, setpoint 21°C.

Table *2* The verification of the developed predictive energy models using the generated internal gains profile

Scenario	51	52	53	54	55	56	57	58	59	60
Setpoint (°C)	19	19.5	20	20.5	21	21	21.5	22	22.5	23
R^2	0.886	0.889	0.89	0.853	0.890	0.972	0.971	0.969	0.968	0.960

3.2 *Optimal setpoint profile* and *benefits*

The optimal setpoint profile is shown in Fig 5.

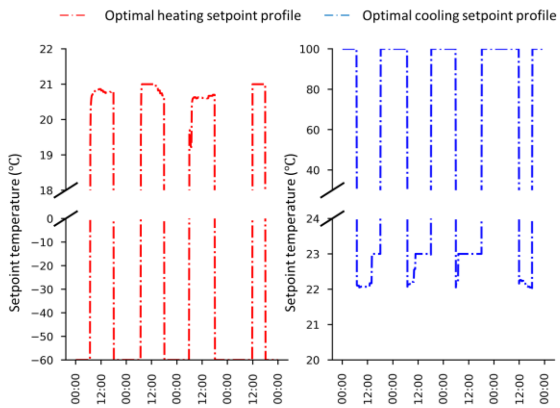

Fig 5 Optimal setpoint temperature profile (left) Heating (right) Cooling

The benefits of adopting the optimal heating setpoint profile are demonstrated in Figure 6. Based on a visual inspection of cases 1-5, it is noticed that as heating setpoint temperature increased, the total heating energy increased, but the averaged PPD decreased. This suggests that a high heating setpoint temperature was good to reduce the occupants' thermal dissatisfaction. As for cases 6-10, the utilization of the flexible setpoint profile led to noticeable energy savings while the PPDs were hardly influenced. In case 11, where the optimal setpoint profile was used, the total heating energy was 608.8 kW, higher than the case 6-9 but lower than case 10. This was the cost of increasing occupants' thermal satisfaction. Among all cases, case 11 has the lowest PPD value, 4.31%. Compared to cases 1-5, using the optimal heating setpoint profile provided savings of heating energy between 3.8-36.8%, whilst PPD was improved by 5.26-0.01%.

The benefits of adopting an optimal cooling setpoint profile are shown in Figure 7. It is noticed that generally, a higher cooling setpoint temperature led to a lower cooling energy consumption. In addition, the utilization of flexible cooling setpoint profile in case 17-21 can slightly minimize cooling energy consumption. Compared with case 12-16, case 22 achieved both the lowest PPD and cooling energy. As a result of using optimal cooling setpoint profile, savings of cooling energy were between 3.5-33.9 and occupants' thermal dissatisfaction can be declined by between 0.17-2.89%.

3.3 Assumptions and limitations

Some assumptions and limitations of the prospoed framework are discussed in this section. Assumptions regarding to geometry, thermal parameters and ventilation strategy of the room investigated were made in order to simplify the complexity of room models.

In addition, it is suggested further improving or upgrading the framework with following considerations. (1) all the predictive energy and comfort models in the framework were simulation-based and data-driven. On

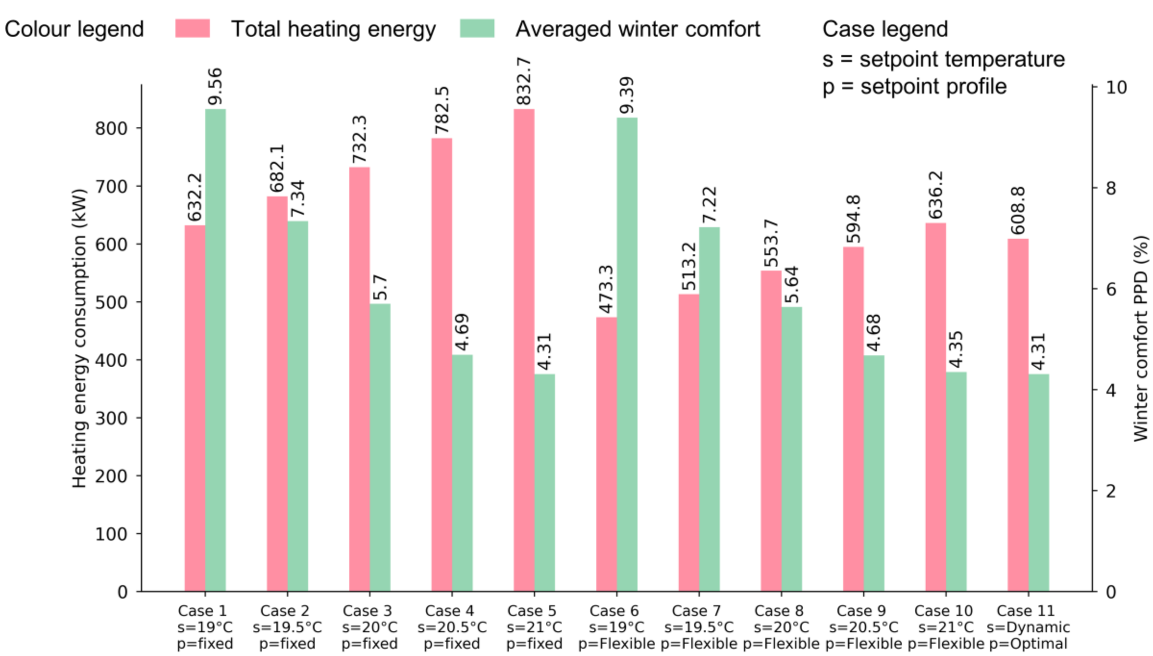

Fig 6 The comparison of heating energy and comfort performance between case 1-11

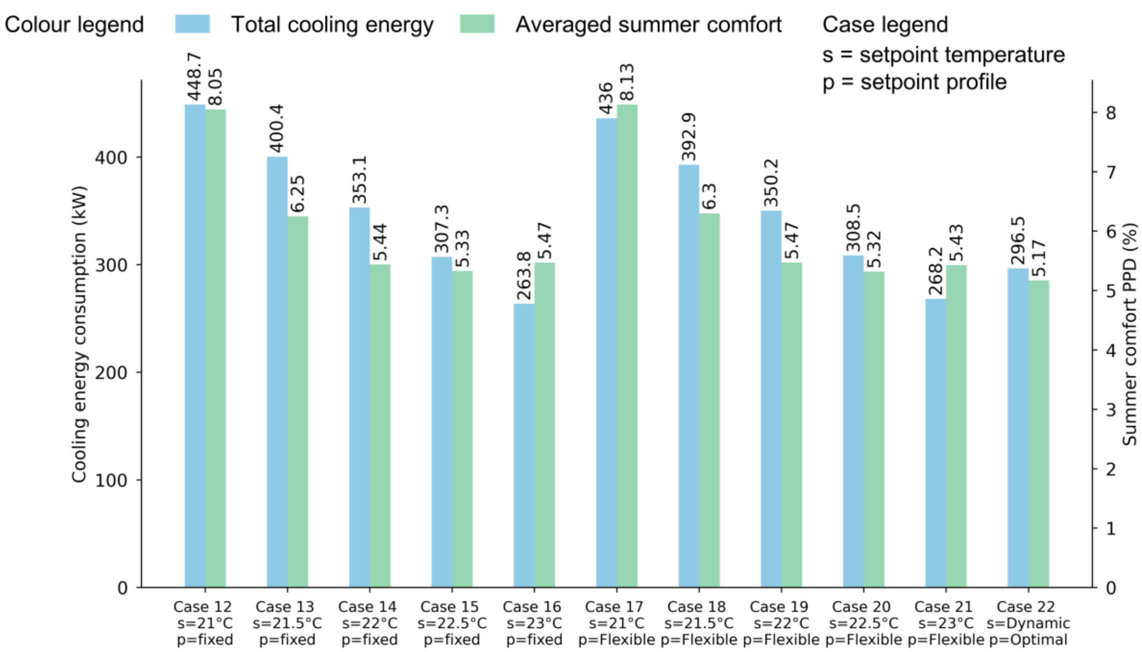

Fig 7 The comparison of cooling energy and comfort performance between case 12-21

the one hand, the simulation results require further verification in the future. On the other hand, the predictive comfort models need more investigation to increase their reliability. In this paper, the averaged PPD appear to be less than 5% in some cases. It must be noticed that the theoretical minimum of PPD is 5%. Therefore, the estimated improvement of PPD in this paper can be slightly overestimated. (2) efforts should also be made to conducting a longer real-time identification of internal gains profile. (3) The proposed framework should also be tested on different types of rooms, buildings and climate.

4. *CONCLUSIONS AN FUTURE WORKS*

This paper proposes an integrated framework to effectively reduce occupants' thermal dissatisfaction and room HVAC energy consumption. The framework can change the HVAC setpoint temperature according to the internal gains obtained by vision-based cameras. It was estimated that during the monitored four days in January, the proposed framework was able to potentially offer savings of heating energy between 3.8-36.8% and a reduction of occupants' thermal dissatisfaction by between 5.26-0.01%. For another four days monitored in August, the savings of cooling energy would be between 3.5-33.9% and occupants' thermal dissatisfaction could drop by 0.17-2.89%. Future work should focus on experimentally verifying the predictive energy models and putting the framework into practice.

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