Energy co-simulation of the hybrid cooling control with synthetic thermal preference distributions

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ABSTRACT

Thermal comfort and energy efficiency are always the two most significant objectives in HVAC operations. However, for conventional HVAC systems, the pursuit of high energy efficiency may be at the expense of satisfactory thermal comfort. Therefore, even if centralized HVAC systems nowadays have higher energy efficiency than before in office buildings, most of them cannot adapt the dynamic occupant behaviors or individual thermal comfort. In order to realize high energy efficiency while still maintain satisfactory thermal environment for occupants indoors, the integrated hybrid HVAC system has been developed for years such as task-ambient conditioning system. Moreover, the occupant-based HVAC control system such as human-in-the-loop has also been investigated so that the system can be adaptive based on occupant behaviors. However, most of research related to personalized air-conditioning system only focuses on field-study with limited scale (i.e. only one office room), this paper has proposed a co-simulation model in energyplus to simulate the hybrid cooling system with synthetic thermal comfort distributions based on global comfort database I&II. An optimization framework on cooling set-point is proposed with the objective of energy performance and the constraints of thermal comfort distribution developed by unsupervised Gaussian mixture model (GMM) clustering and kernel density estimation (KDE). The co-simulation results have illustrated that with the proposed optimization algorithm and the hybrid cooling system, HVAC demand power has decreased 5.3% on average with at least 90% of occupants feeling satisfied.

Author Keywords

Thermal comfort; Energy co-simulation; Synthetic distribution; Hybrid cooling.

ACM Classification Keywords

I.6.1 SIMULATION AND MODELING (e.g. Model Development).

1 INTRODUCTION

Thermal comfort and energy efficiency are always the two most significant objectives in heating, ventilation and air-conditioning (HVAC) operations. However, for conventional HVAC systems, the pursuit of high energy efficiency may be at the expense of satisfactory thermal comfort. Therefore, even if centralized HVAC systems nowadays have higher energy efficiency than before in office buildings, most of them cannot adapt the dynamic occupant behaviors or individual thermal comfort. In order to realize high energy efficiency while still maintaining satisfactory thermal environment for occupants indoors, the hybrid air-conditioning system has been developed for years such as task-ambient conditioning system. Moreover, the occupant-based HVAC control system such as human-in-the-loop has also been investigated so that the system can adapt the system based on occupants' feedback actively or passively. The following sections will introduce recent developments of adaptive thermal comfort and the occupant-based control.

1.1 Adaptive thermal comfort

Since innovations in HVAC are inspired with the targets to improve energy efficiency and improve thermal comfort for individuals, it is of great importance to have comprehensive understandings in these targets.

As defined by ANSI/ASHRAE 55 and ISO7730 [1], thermal comfort is a condition of mind which expresses satisfaction with thermal environment and is assessed by subjective evaluation. For the past 40 years, many researchers have been investigating the principle indicators of thermal comfort. The Danish scientist Fanger believed that thermal comfort was same as neutral state in terms of thermal sensation based on experimental studies. He also derived a well-known equation called predicted mean vote (PMV). Moreover, for indoor environment, since heat exchange and evaporation loss are owing to the difference between thermal environment conditions and human body conditions, for PMV equation, the following six measurable variables are accepted to be the indicators of thermal comfort, which are indoor air temperature, indoor relative humidity, indoor air velocity, mean radiant temperature, clothing insulation and metabolic rate [2].

However, since in regular office buildings, thermal environments are different from such well-controlled experimental test-bed, many researchers are turning to adaptive thermal comfort model instead of static thermal

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comfort model such as PMV for years. For instance, one of the milestone projects of adaptive thermal comfort is ASHRAE RP-884 (comfort database I) [3] which collected a total of 22000 sets of data from the real office environments across the world. This project has been widely used to develop various adaptive thermal comfort models, which have been integrated into personalized HVAC controls. With RP884 dataset, Seungjae et al. [4] has proposed a method for learning personalized thermal preference profiles by formulating a combined classification and inference problem with 5-cluster model. However, instead of predicting 7-point thermal sensation described in ASHRAE 55, the paper predicts thermal preferences with 3 classes, namely “want cooler”, “want warmer” and “no change” by Bayesian approach. Rather than classification of thermal sensation, it predicts the probability of a test occupant falling into each of the classes by clustering all occupants with Gaussian mixture model (GMM). Moreover, Frederik et al. [5] has also proposed a personalized thermal comfort model using Bayesian network to predict thermal sensation indoors in a specific area such as San Francisco with ASHRAE RP-884 dataset. Moreover, a newly released dataset called ASHRAE global thermal comfort database II (Comfort database II) intends to support diverse inquiries about adaptive thermal comfort in field settings [6].

In all, factors to adaptive thermal comfort in indoor environment can be categorized into environment-related factors and occupant-related factors, as shown in the following tables.

Variable	Unit
Indoor air temperature	℃
Indoor relative humidity	%
Indoor air velocity	m/s
Mean radiant temperature	℃

Table 1. Environment-related factors to thermal comfort

Variable	Unit
Metabolic rate	met
Clothing insulation	clo

Table 2. Occupant-related factors to thermal comfort

1.2 Occupant-based HVAC control

In order to reduce energy consumption of the existing HVAC systems and improve occupant comfort, occupant-responsive HVAC controls have been being investigated for years. One of the key to designing occupant-responsive HVAC system is to understand the occupant behaviors.

Besides meeting thermal comfort requirements mentioned above, occupant-responsive HVAC system also plays a role in determining the energy consumption of the entire building. For most of the commercial buildings, particularly office buildings and schools, the heating and cooling loads are largely dependent on the occupanct behavioral patterns like occupant presence and activities. However, the conventional HVAC systems have been operated without the ability to adjust supply air rate accordingly. Therefore, much of the energy use for HVAC is wasted, particularly when the conditioned spaces being unoccupied or the operation being under the maximum levels. On the contrary, since occupant-responsive HVAC system can be responsive to the dynamic occupancy profile, it has a large potential to reduce energy consumption.

Occupant behaviors have two distinctive effects on building performances, which are passive and active effects [9]. Passive effects are derived from dynamic occupancy schedules like the presence of the occupants during a day or occupancy behaviors like using the microwave in the lunchtime or doing computer-based work. Active effects are derived from individual preferences of the indoor environment such as personal thermal comfort or occupancy behaviors like turning on/off lights or opening/closing windows based on their own preferences. In other words, to understand passive effects of human on the building systems, it requires objective occupancy information like occupancy schedules or location of occupants. However, to understand active effects of human on the building system, it requires subjective occupancy feedback describing individual preferences such as thermal comfort, visual comfort. Both passive and active effects could play important roles in operations of building systems and building diagnostics.

With the comprehensive understanding of effects of occupant behaviors on building performances, it is of great importance to incorporate occupant pattern recognition system with HVAC controls to improve occupant comfort and increase energy savings. Besides, among different occupant-based HVAC systems, the personalized task-ambient conditioning system is not only able to provide occupants with individual control to adapt individual thermal comfort preferences but also ensure that the centralized HVAC system is operated with high energy-efficiency.

The personal comfort system (PCS) from Centre for Built Environment (CBE), UC Berkeley is an innovation to develop a low-energy personalized systems as micro-zones and integrate them into centralized HVAC operations as a macro-zone in open plan office environments [10]. The project has invented the personalized heating and cooling chairs with wireless internet connectivity and tested the performances in different real office environments in California. PCS adjusts the local thermal environment based on occupants’ inputs regarding heating/cooling set-points of the chair. Meanwhile, the whole framework gets further optimized with communication between chairs and the centralized HVAC system by controlling the set-points of the centralized system based on feedbacks of all micro-zones. In the case study, the test energy performances were optimized with the mode of widening HVAC temperature setpoint dead band in conjunction with proposed chairs. In addition, Zhang et al. [11] has developed a task-ambient system heating only the feet and hands, and cooling only the hands and face, to provide comfort in a wide range of ambient environment. The simulated annual heating and cooling energy savings with such task-ambient system is as much as 40%. Last but not least, Lu et al. also [12] has conducted a field study to evaluate the energy and thermal comfort performances of a hybrid cooling system consisting of personalized cooling fans and split air-conditioning system in Shanghai.

Based on the literature review, much more attention has been paid to occupant-based HVAC control, especially task-ambient conditioning system than before. Moreover, compared to static thermal comfort, the adaptive thermal comfort has become more popular, particularly developing thermal comfort model with advanced machine learning algorithms. However, few studies have applied adaptive thermal comfort models trained with machine learning algorithms into the whole-building energy simulation for evaluating the hybrid cooling system such as task-ambient conditioning system. Therefore, this paper aims to evaluate the energy and thermal comfort performances of a task-ambient cooling system where each task system consists of a personal fan and ambient system is a typical VAV system with energy co-simulations. Moreover, this paper has also proposed to use comfort database I&II to create synthetic thermal preference distributions so as to design an optimization control framework for the task-ambient conditioning system.

2 METHODOLOGY

2.1 Development of thermal preference distribution

Even if individuals have different thermal preferences under the same thermal environment in air-conditioned open-plan offices, most of the thermal preference distributions can be approximated as Gaussian distributions where the majority are satisfied while only a few of occupants vote for either being uncomfortably warmer or uncomfortably cooler. Therefore, in order to simulate different thermal preferences in a shared space, Figure 1 shows the diagram of developing the synthetic thermal preference distributions with the comfort database I&II. As shown in the figure, the pipeline is comprised of clustering of the thermal environments, thermal preference distribution synthesis and sampling as well as calculation of the number of occupants under each thermal preference given the total number of occupants.

The subset of the comfort database I&II was used where a total of 2354 instances were collected. In the subset, data were collected either from hybrid cooling system consisting of ceiling fans and the centralized cooling or from the conventional centralized cooling system. Among the subset, 815 instances were collected with the task-ambient cooling system while 1539 instances were collected with the conventional centralized cooling system.

Since the indoor environments are expected to vary a bit in the database, the unsupervised clustering is implemented so as to cluster the similar thermal environments into a single cluster and see the histogram of thermal preference in each cluster. Instead of using K-means, similar thermal environment conditions. Since the setpoint is optimized with the thermal environment in core zone where discomfort due to non-uniform radiation can be ignored, only air velocity, air temperature and relative humidity were used to represent thermal environment conditions. Then, similar thermal environment conditions were clustered with Gaussian mixture model (GMM) where the number of clusters were selected based on BIC score. After clustering, the histogram of thermal preference under each cluster was developed so that in the energy model, the number of occupants for each thermal preference can be sampled from the synthetic thermal preference distribution with kernel density estimation (KDE) under the given cluster. Moreover, since Energyplus cannot simulate the thermal environment changes after fans were operated, the subset without fan operations and the subset with fan operations were clustered, respectively.

2.2 Thermal preference synthesis algorithm

As mentioned before, the synthetic thermal preference distributions were approximated with Gaussian distribution. Therefore, kernel density estimation (KDE) was implemented based on the dataset. Kernel *K(x; h)* is a function controlled by the bandwidth parameter h, which can

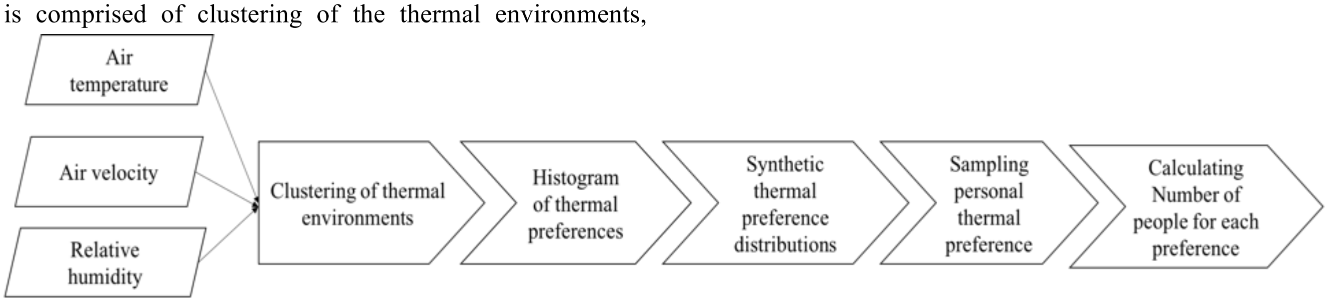

Figure 1 The diagram of developing the synthetic thermal preference distributions

be seen as smoothing parameter controlling the tradeoff between bias and variance in the result. Given the kernel form, the density estimate at a point y within a group of points x_i; $i=1..N$ is given by:

$$\rho_K(y) = \sum_{i=1}^{N} K(\frac{y-x_i}{h}) \quad \text{Eq. 1}$$

where h is bandwidth and the bandwidth is tuned with 5-fold cross-validation from 5 candidate values between 0.1 and 1.

2.3 Co-simulation with the proposed framework

The energy simulation was implemented with the co-simulation between energyplus and python. The one-story small office building was simulated in Shanghai from July 1st to August 31st. The total ground floor area is 512 m^2 and 5 thermal zones are built. Moreover, the cooling is supplied with packaged DX cooling coil and the heating is supplied with gas heating coil. The 3D rendering and floor plan are shown in Figure 2 and Figure 3. The co-simulation framework was developed in [13].

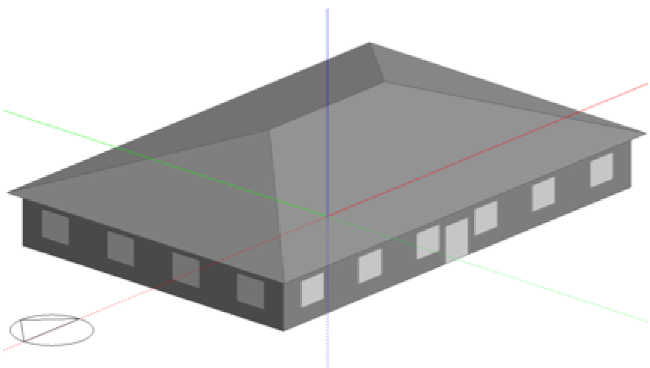

Figure 2 3D rendering of the reference building

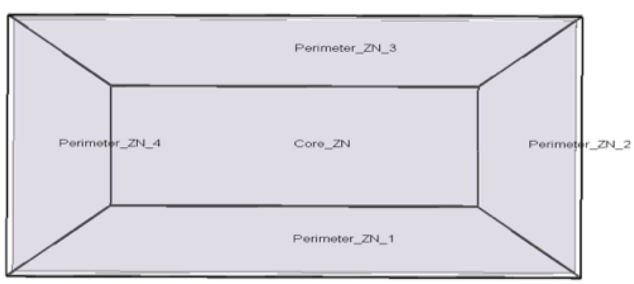

Figure 3 Thermal zones of the building

The baseline and optimized simulation were both conducted with dual setpoint schedule. The baseline cooling setpoint schedule is the default schedule where the cooling setpoint is predetermined and fixed to be 22℃ (Figure 4) and the heating setpoint is constant to be 21 ℃. Even if the heating set-point schedule is the same as baseline, the cooling setpoint schedule is based on the proposed optimization framework in the optimized simulation. Meanwhile, the setpoint schedules are the same for all zones so as to ensure the system responses the dynamic setpoint changes in time in both simulations. Moreover, it is assumed all perimeter zones are unoccupied and Figure 5 shows the occupancy schedules of core zone used in both simulations.

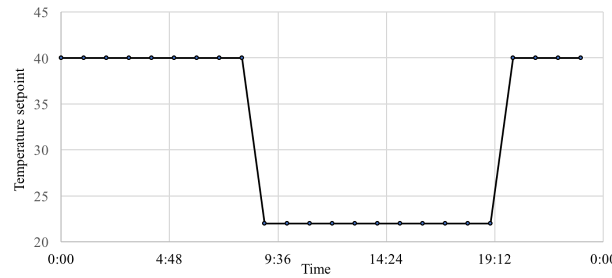

Figure 4 The fixed temperature set-point schedule in baseline

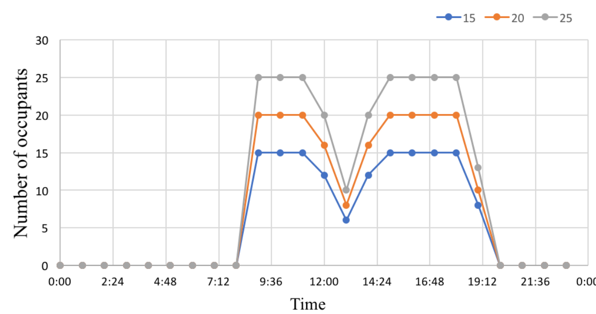

Figure 5 The occupancy schedule in both simulations

Besides baseline setpoint schedule, Figure 6 shows the flow diagram of the proposed optimization framework. As shown in the diagram, two histogram models were implemented to simulate the conditions when the personalized fan is operated or not, respectively. Moreover, the initial cooling set-point is 24℃ and the setpoint is increased by 1℃ or no change when the space is occupied at each time step. However, it is assumed that the reason for turning on fans is only because of feeling warm. Meanwhile, it is also assumed that all the fans will be turned off when determining a new set-point.

The control law of the proposed optimization framework is shown below:

Objective function:

min. Sensible cooling loads Eq.2

subjective to:

% of occupants feeling warm < δ Eq.3

20 ℃< cooling set-point t < 30 ℃ Eq.4

where δ is threshold tuned with simulation episodes

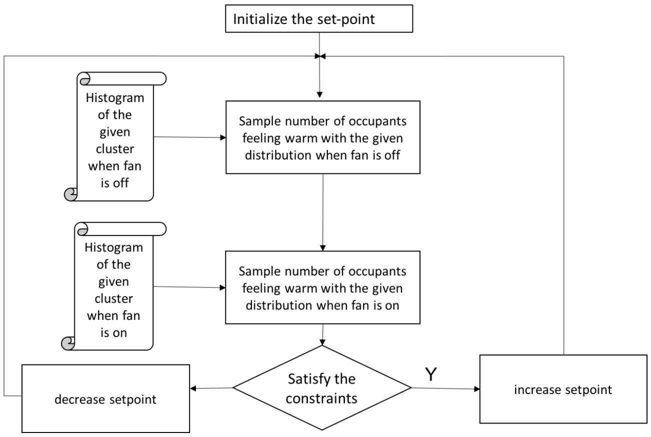

Figure 6 Flow diagram of the proposed optimization framework

As shown in the control law, the cooling set-point is controlled every 30 minutes. In addition, since the objective function of sensible cooling loads is monotonously decreasing when cooling set-point is increasing, it will reach the optimal state under the constraints after several time steps in the end. Meanwhile, if the number of occupants feeling warm exceeds the threshold or the setpoint exceeds the boundary, the updating will decrease 1℃ for this time step. The threshold can be tuned with benchmark of multiple simulation episodes.

3 RESULT ANALYSIS

3.1 Synthetic thermal preference distributions

As a result, with comfort database I&II, 7 clusters were selected for the subset without fans and 6 clusters were selected for the subset with fans on according to the lowest BIC scores. Table 3 shows the mean of each cluster and the correspondent best bandwidth for KDE without fans. In addition, Figure 7 shows the histogram of thermal preference distribution within each cluster for the subset without fans, respectively. As shown in the table, except cluster 1, different clusters have similar indoor air temperature and indoor air velocity. Since no fans were deployed for the system, the air velocity is smaller than 0.2 m/s. However, relative humidity varies a lot among different clusters. This may result from lack of humidity control in common office buildings. In addition, except cluster 1, thermal preference histograms have shown that the majority vote is "no change" in different clusters. Moreover, compared to thermal preference vote of "want cooler", all clusters but cluster 1 have more votes for "want warmer". This may be because of low air temperature. Therefore, there is a potential to increase cooling set-point to save energy while maintaining occupant thermal comfort.

Velocity [m/s]	Temperature [℃]	Relative Humidity [%]	Optimal bandwidth
0.56	25.78	58.65	1
0.11	23.76	63.34	0.18
0.16	23.96	56.12	0.56
0.12	22.59	67.19	0.56
0.13	23.7	38.1	1
0.12	23.91	58.6	0.18
0.12	23.13	48.85	0.18

Table 3 The centroid of each cluster and the correspondent optimal bandwidth with fan off

Similarly, Table 4 shows the means of the clusters and Figure 8 shows the histograms of the thermal preference distribution within each cluster for the subset with fans on, respectively. As shown in the table, the mean air velocity of each cluster is higher than those in most of clusters without fans, which is because of the operation of fans. Meanwhile, the table has illustrated the average value of the mean air temperature in each cluster with fans on is larger than that without fans. In addition, the figure has illustrated that the majority votes within each cluster is "no change", which means such task-ambient cooling system has potential to increase air temperature to save energy while still maintaining high thermal comfort level.

Velocity [m/s]	Temperature [℃]	Relative Humidity [%]	Optimal bandwidth
0.31	25.98	66.24	0.56
0.34	26.72	58	0.32
0.47	25.85	63.09	0.32
0.28	24.83	75.68	0.32
0.17	23.5	44.54	0.56
0.19	25.36	63.27	0.32

Table 4 The centroid of each cluster and the correspondent optimal bandwidth with fan on

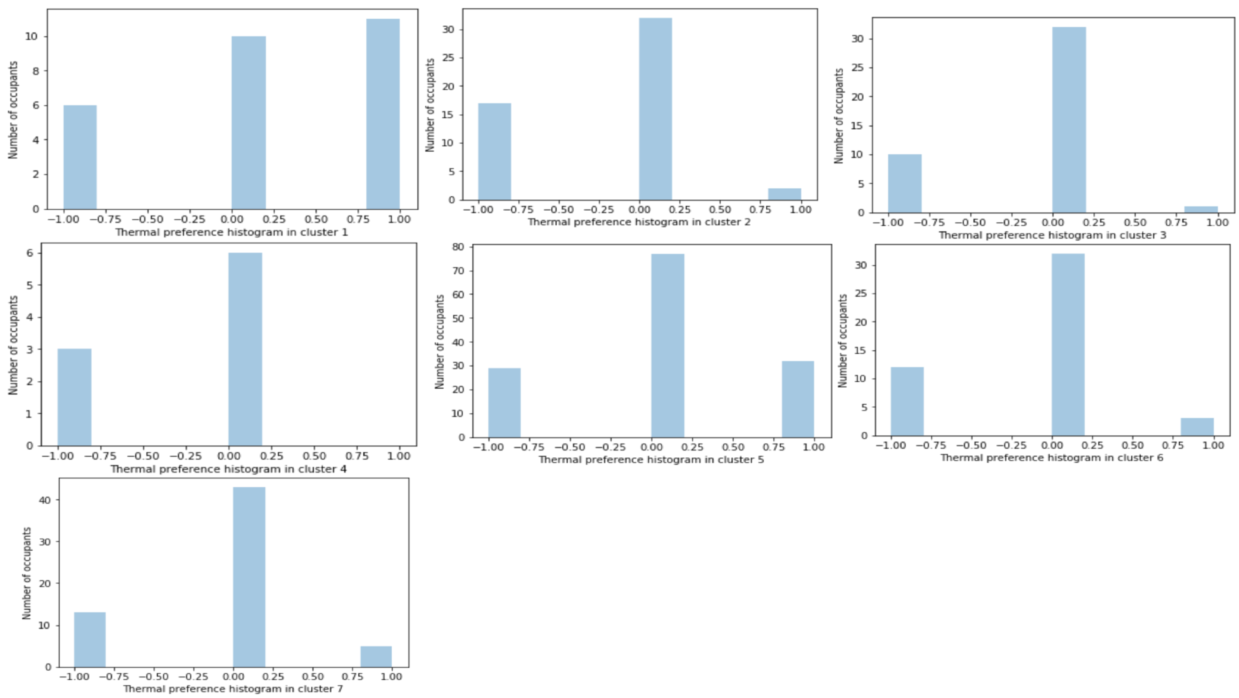

Figure 7 The histogram of thermal preference distribution with fan off

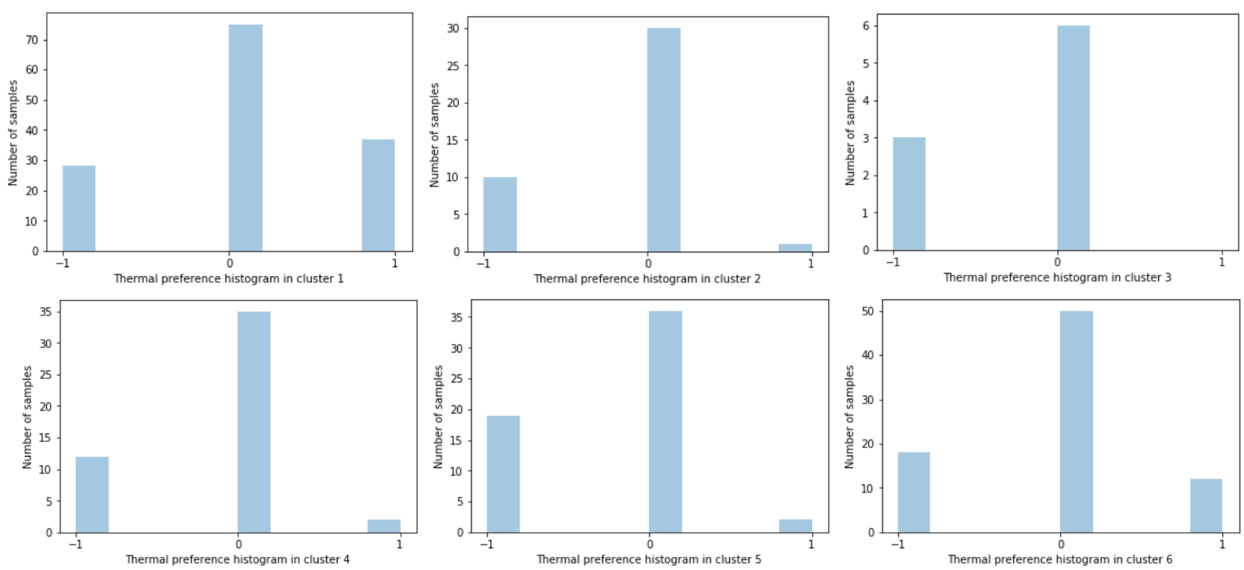

Figure 8 The histogram of thermal preference distribution with fan on

3.2 Energy benchmark of the proposed framework

In terms of energy benchmark between baseline control and the proposed control framework, HVAC electric demand power was used to evaluate the energy performances. Meanwhile, the percentage of occupants feeling warm is controlled within 10%. As a result, Figure 9 shows the comparisons of HVAC electric demand power between baseline and the proposed optimized models with different occupancy schedules. As shown in the figure, the proposed framework has achieved 5%, 5.3% and 5.6% demand power reduction compared to baseline models with 90% of occupants are comfortable when the number of occupants are 15, 20 and 25, respectively. Therefore, it is meaningful to develop the task-ambient conditioning system which not only creates comfortable local environment but also improves the overall energy performance.

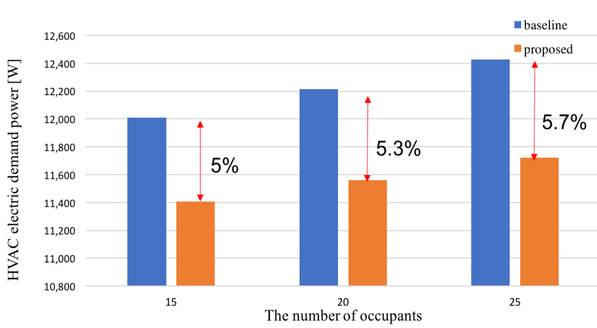

Figure 9 HVAC electric demand power between baseline and the proposed optimized simulations

4 DISCUSSIONS

The simulation study has evaluated the energy performances of the task-ambient cooling system consisting of personalized fans and the centralized cooling system. In order to simulate individuals, have different thermal preferences in a shared office space, the synthetic thermal preference distributions have been developed so as to generate "virtual" occupants with various thermal preferences in the same thermal environments. The results have validated that the proposed optimization framework could achieve 5.3% of HVAC electric demand power savings on average without the compromise of occupant thermal comfort. However, there are still limitations in the energy models. Firstly, due to lack of data, instead of common task conditioning systems such as personalized fans, this energy simulation has applied comfort database where the hybrid cooling system is comprised of ceiling fans and the ambient conditioning system. As a result, the thermal preference distributions based on comfort database may be different from actual task-ambient conditioning systems. In addition, the objective function in the control law can be improved to not only take sensible cooling loads but also take latent cooling loads into consideration.

5 CONCLUSION

This study has proposed an optimization framework to maximize the energy efficiency and thermal comfort with a task-ambient conditioning system by updating the cooling setpoint. In order to evaluate energy performances with the proposed optimization framework, a co-simulation of a typical office building was conducted with Energyplus. Moreover, in order to simulate the fact that different people have different thermal preferences in Energyplus, synthetic thermal preference distributions were generated with kernel density estimation in each cluster based on GMM clustering of the thermal environment given in the comfort database. The results have shown that with the proposed framework, the proposed framework has achieved 5%, 5.3% and 5.6% demand power reduction compared to baseline models with 90% of occupants are comfortable when the number of occupants are 15, 20 and 25, respectively. In future, more work could be done to optimize the energy performances in the simulation by updating other parameters such as relative humidity.

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REFERENCES

1. Standard, A. S. H. R. A. E. (2010). Standard 55-2010: "Thermal Environmental Conditions for Human Occupancy"; ASHRAE. Atlanta USA.
2. Fanger, P. O. (1970). Thermal comfort. Analysis and applications in environmental engineering. Thermal comfort. Analysis and applications in environmental engineering.
3. De Dear, R. J., Brager, G. S., Reardon, J., & Nicol, F. (1998). Developing an adaptive model of thermal comfort and preference/discussion. ASHRAE transactions, 104, 145.
4. Seungjae Lee, Ilias Bilionis, Panagiota Karava, and Athanasios Tzempelikos. A Bayesian approach for probabilistic classification and inference of occupant thermal preferences in office buildings. Building and Environment, 118:323–343, 2017.
5. Frederik Auffenberg, Sebastian Stein, and Alex Rogers. A Personalised Thermal Comfort Model using Bayesian Network. Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence, (Ijcai):2547–2553.
6. Licina, V.F. et al. (2018), Development of the ASHRAE global thermal comfort database II. Building and Environment, 142, 502-512.
7. Choi, J.H. CoBi: bio-sensing building mechanical system controls for sustainably enhancing individual thermal comfort. 2010.
8. Ghahramani, A., Castro, G., Karvigh, S. A., & Becerik-Gerber, B. (2018). Towards unsupervised learning of thermal comfort using infrared thermography. Applied Energy, 211, 41-49.
9. Park, J. (2015). Are humans good sensors? Using Occupants as sensors for indoor environmental quality assessment and for developing thresholds that matter.
10. Andersen, Michael P., et al. "Well-connected microzones for increased building efficiency and occupant comfort." Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments. ACM.
11. Zhang, H. et al. "Comfort, perceived air quality, and work performance in a low-power task–ambient conditioning system." Building and Environment 45.1 (2010): 29-39.
12. Lu, S., Hameen, E.C., Zou, Y. (2019) An interactive building control for the integrative HVAC system featuring personalized cooling in office buildings. ASHRAE Annual Conference, Kansas City, USA.

13. Zhang, Z., Chong, A., Pan, Y., Zhang, C., Lu, S., & Lam, K. P. (2018). A deep reinforcement learning approach to using whole building energy model for hvac optimal control. In *2018 Building Performance Analysis Conference and SimBuild*.