Occupant-oriented mixed-mode EnergyPlus predictive control simulation

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Abstract

Model predictive control (MPC) has been studied in the building science realm for about three decades. However, the following two aspects of the building control have not been studied thoroughly in MPC research. One is the impact of the mixed-mode cooling system on the active heating ventilation and air conditioning (HVAC) energy consumption, and the other is the differences of individual thermal comfort preference and its impact on energy. This paper proposes an occupant-oriented mixed-mode EnergyPlus predictive control system to optimize HVAC energy consumption while meeting the individual thermal comfort preference. A web-based dashboard is implemented in the test-bed building for three months to collect individual thermal comfort preference data. The data analysis results suggest that occupants have various tolerances and preferences about thermal comfort. The simulation results show that, during one week of a typical swing season, the mixed-mode system further reduces the active HVAC energy consumption, and the diversified occupant thermal comfort preference has significant impact on HVAC energy consumption.

Keywords

Individual thermal comfort; mixed-mode; model predictive control; EnergyPlus; energy optimization; Matlab/Simulink

1. Introduction

Building energy efficiency has been improved greatly for the past decades, thanks to the adoptions of new technologies and more stringent building codes and standards. These energy efficiency measures mostly happen during the design, construction and retrofit phases, which are critical yet very short periods of the entire building life cycle. More light should be shed on building controls during the operation stage, which has much longer time spent and stronger impact on energy. On one hand, without proper control and management, a building that is designed with advanced energy-efficient technology may still consume tons of energy. On the other hand, from the facility managers' standpoint, to ensure occupant comfort (without complaints) is often the prioritized responsibility. A building control system is the means to deliver this commitment. Therefore, for both energy efficiency and occupant comfort purposes, building control is the key for the daily building operation in commercial buildings.

To achieve the goal of reducing energy and improve occupant comfort in commercial buildings, model predictive control (MPC) has been investigated for the past three decades. Generally, MPC algorithms allow current control inputs to be optimized in real-time control operations with certain constraints while anticipating future events using mathematical models. Heating, ventilation, and air conditioning (HVAC) systems can usually take advantage of this algorithm to optimize its energy consumption with the constraints of occupant thermal comfort among others. Numerous studies have established simulation and experimental results to demonstrate MPC's effectiveness in reducing energy and ensuring thermal comfort, such as [1-10].

Most of MPC studies focus on active HVAC systems, such as variable air volume (VAV) and radiant heating systems. Mixed-mode passive/active HVAC systems that incorporate window opening strategies may have a greater energy saving potential during cooling and swing seasons in some climates. A few researchers have applied MPC algorithms to mixed-mode HVAC systems. May-Ostendorp et al. developed an MPC control system that can optimize window opening schedules for a mixed-mode HVAC system to reduce energy consumption [11]. On the basis of this offline optimization framework, Corbin et al. developed a real-time optimization framework for the MPC system by linking EnergyPlus, Matlab and a building automation system (BAS). The test cases reported that the MPC system resulted in “54% energy savings with often improved occupant comfort” [12].

Although most of MPC studies on HVAC systems have addressed thermal comfort, air temperature is often used as the only indicator or constraint. Air temperature is indeed a very influential factor, but is not the only factor that could influence human thermal comfort. Predicted mean vote (PMV) which can be calculated by six major human thermal comfort influencers – air temperature, relative humidity, mean radiant temperature, air speed, metabolic rate, and clothing insulation factors, may better represent occupant thermal comfort as suggested in the following studies [5, 13-15].

One difference between using PMV and using air temperature as the thermal comfort indicator is that PMV is able to take into consideration of individual thermal preferences. Several studies have indicated that occupants do not have uniformed thermal sensation in the same thermally controlled space [16, 17]. In order to meet the thermal comfort requirements of different occupants, several studies have developed individual thermal

comfort voting systems to feedback the subjective thermal preference information into HVAC control systems [14, 15, 17, 18]. For example, Choi (2010) developed a wearable control system that can collect thermal measurement data from individual bio-sensors to automatically adjust HVAC system setpoints [19]. The experiment and simulation results of these previous studies show that providing occupants with individual thermal controls not only can improve occupant satisfaction [15, 19] and comfort [14, 17-19], but also impact the HVAC energy consumption [14, 15, 17-19].

This study develops four control schemes using a test-bed office building to optimize its energy performance while maintaining the occupant thermal comfort. In the “Methodology” section, a systematic method of creating four control models is presented. First, a baseline rule-based control model is created to demonstrate a co-simulation platform and establish a baseline energy and thermal comfort performance. Second, an EnergyPlus predictive control (E^+PC) system is developed to reduce the active HVAC energy consumption while maintaining the average occupant thermal comfort. Then, on the basis of E^+PC , a mixed-mode EnergyPlus predictive control (ME^+PC) is modeled to further reduce the test-bed building’s energy consumption by incorporating passive cooling strategies in the active MPC system. At last, in order to meet individual thermal comfort requirements, a subjective feedback data collection dashboard is designed and experimented in the test-bed building for three month. Based on the data analysis results, an occupant-oriented mixed-mode EnergyPlus predictive control (OME^+PC) model is developed and simulated. In the “Results and discussions” section, the simulation results as well as the data analysis results of the occupant subjective thermal comfort experiment are presented and discussed. The conclusions are made at the end of this study.

2. Methodology

2.1. Case study overview

A 2-story, 2,262m² office building (Phipps Center for Sustainable Landscapes (CSL) located in the suburban area of Pittsburgh, Pennsylvania, USA) is chosen as a test-bed building to conduct the simulation and experiment.

A baseline control system is developed to establish a co-simulation framework using Matlab/Simulink and EnergyPlus. The baseline energy and thermal comfort performance using rule-based algorithm is simulated as a benchmark for the MPC algorithms. On the basis of this baseline model, an EnergyPlus Predictive Control (E⁺PC) model is developed. The objective of E⁺PC is to maintain the same PMV comfort criteria as the baseline control but to minimize the active HVAC power consumption by optimizing the air handling unit (AHU) supply air temperature. Detailed development and implementation schemes of the baseline and E⁺PC have been captured in a previous study at [20].

2.2. Mixed-mode EnergyPlus Predictive Control (ME⁺PC)

On the basis of E⁺PC, a mixed-mode EnergyPlus Predictive Control (ME⁺PC) model is developed. The objective of ME⁺PC is to incorporate the passive cooling strategy into E⁺PC, so that the control system can handle both active HVAC system and passive motorized window opening system to further reduce the HVAC energy consumption with the constraint of occupant thermal comfort. The motorized window opening control logic is shown in Figure 1. The logic is selected based on the actual BAS settings at the test-

bed building and adjusted for the module of “AvailabilityManager:HybridVentilation” in EnergyPlus, see details at [21].

Figure 1 Window opening control logic.

2.3. Occupant subjective feedback experiment

E⁺PC and ME⁺PC are designed to be automated systems that can optimize energy consumptions of HVAC systems based on averaged occupant thermal comfort criteria (average PMV value). Clearly, occupant individual thermal comfort preference is not considered in these systems. It is worthwhile to investigating the actual thermal comfort

preference from individual occupants, and then to design a control system to meet the needs of the preference. Here, a web-based data collection system is developed for the occupants in the test-bed building, as shown in Figure 2. A web-based dashboard is designed to collect occupants' individual thermal comfort level with the question of "How are you feeling (thermally)?" and clothing insulation factor with the question of "What are you wearing?" The thermal comfort band ranges from -2 to 2 based on the PMV definition. The clothing insulation band ranges from 0.4 to 1.9, representing from "shorts & T-shirts" to "jacket and overcoat". The occupants are required to provide the two pieces of information concurrently when they are not feeling thermally comfortable. All the data are stored in a web-based MySQL [22] database with timestamps.

Figure 2 Web-based occupant subjective feedback data collection system.

2.4. Occupant-oriented ME⁺PC (OME⁺PC)

The design of OME⁺PC aims to take in the real-time individual occupant subjective feedback information from the web-based databases and customize each zone setpoint based on this feedback information.

Figure 3 shows the implementation schema of OME⁺PC. There are four layers in this scheme. In the “Data input layer”, weather, occupancy, lighting, and equipment information is contained in independent text files (CSV, Comma Separated Values). It is essential and beneficial to override the EnergyPlus internal weather and schedule data by using the “Data input layer” and “Receding horizon” module in the “Control layer”. More detailed information is available from [20]. In the “Data input layer”, a web-based MySQL database, which stores the real-time occupant subjective feedback data, is connected to the “Control layer”.

Two Python [23] scripts are written to query the latest thermal comfort and clothing insulation feedback data from the web-based MySQL database, respectively. The Python scripts compare the date and time of the two pieces of feedback information to ensure they are collected at the same time (within the same hour). If the occupant does not provide both data points at the same time, the Python script assumes the missing data as default value (PMV=0 and clo=1). A Matlab script is written to execute the Python scripts in the Matlab/Simulink environment.

The “Multi-zone temperature setpoints rule-based control” module takes in the occupant subjective feedback information and computes the adjusted PMV setpoints for the zones that are occupied by voters.

Figure 3 OME⁺PC implementation scheme.

The “Data exchange layer” is used for data communication and time synchronization functions, technical details can be found in [24]. In the “Simulation layer”, the direct inputs of the EnergyPlus model are “AHU supply air temperature setpoint”, “Weather and schedules information”, and “Multi-zone temperature setpoint”. The window opening logic, as shown in Figure 1, is implemented in the EnergyPlus model in this layer. The outputs are “HVAC power demand”, “Multi-zone air temperature, relative humidity, and radiant temperature”, and “Real simulation time”, which is used for time synchronization between Matlab/Simulink and EnergyPlus.

3. Results and discussions

3.1. Simulation results of ME⁺PC

E⁺PC and ME⁺PC are simulated for one typical design week in the swing season (October 1st – October 7th) using 2013 annual meteorological year (AMY) weather information in Pittsburgh, Pennsylvania, USA [25]. The same initial warm-up condition is set to be October 1st for both E⁺PC and ME⁺PC.

Figure 4 shows the supply air temperature, outdoor air temperature, and supply air mass flow rate of E⁺PC and ME⁺PC. The outdoor air temperature fluctuates from 10°C up to 28°C during the seven simulation days, which represents a typical swing season temperature range in Pittsburgh, PA. E⁺PC uses full air conditioning maintains the supply air temperature between 15°C and 18°C and mass flow rate fairly constant (less than 2 kg/s) for both occupied and unoccupied periods, thanks to the optimization. During unoccupied night time, ME⁺PC's passive mode is active and the AHU supply air flow rate is zero. During occupied daytime, ME⁺PC has slightly lower or similar supply air temperature and higher flow rate for most times with spikes when outdoor temperature rises above 25 °C (e.g., on the afternoon of 10/02 and the morning of 10/06). The results suggest that ME⁺PC can reduce fan power and cooling power consumptions greatly by taking advantage of night time passive cooling, but it may create spikes at times when the outdoor conditions are close to the upper setpoint boundary (25°C). In future work, window opening logic setpoints could be optimized to identify the optimal balance point between the night time cooling and daytime AHU operation.

Figure 4 Outdoor temperature and control variables of E⁺PC and ME⁺PC in the swing season.

In order to distinguish whether the energy savings are from the passive strategy or from the optimization algorithm, the HVAC power demand are compared among the four control models: active mode baseline control, mixed-mode baseline control, E⁺PC and ME⁺PC, as shown in Figure 5. The setting of the active mode baseline control uses typical rule-based control algorithm with the same model inputs as E⁺PC. The mixed-mode baseline control is created based on the active mode baseline control and uses the same window opening logic as ME⁺PC.

The first observation is that the mixed-mode baseline control and ME⁺PC can reduce energy significantly during most of the unoccupied night time, due to the shutdown of AHU while opening windows. Another important observation is that ME⁺PC has more power spikes during daytime, compared to E⁺PC, especially when transiting from the passive mode to the active mode. The reason could be that the E⁺PC's optimization algorithm shifts the energy consumptions earlier in the morning and maintains the zone air temperature at a lower level, so that during the warmer daytime, AHU does not need to consume high power to deliver super cooled air at a high air flow rate. However, ME⁺PC cannot do this because the passive strategy often takes over the control during unoccupied night time hours as long as the criteria are met.

Figure 5 One week plot of the power consumptions of the active mode baseline, mixed-mode baseline, E⁺PC, and ME⁺PC in the swing season.

Figure 6 shows the total HVAC energy consumption of the active mode baseline control, mixed-mode baseline control, E⁺PC, and ME⁺PC during the simulation period. There are four pairs of comparisons in this figure.

Comparison A shows that merely using the passive window opening strategy on a baseline rule-based control system without any predictive control algorithm results in a 33.84% energy saving during the simulation period. Comparison B suggests that only optimizing the active HVAC control system can save 61.20% energy during the simulation period. Comparison C shows that compared to the rule-based mixed-mode control system, ME⁺PC can save 44.03% energy during the simulation period, thanks to the predictive control algorithm. Comparison D indicates a 4.56% energy savings between ME⁺PC and E⁺PC, which suggests that passive strategy can be used along with the predictive control algorithm to further reduce the energy consumption. In summary, the four comparisons suggest that both passive window opening strategy and the model-

based predictive control algorithm are very effective to reduce the active HVAC energy consumption. However, improvements could be made to further investigate and optimize the passive control strategies in order to make the mixed-mode predictive control works better when the MPC algorithm has been used in the controls.

Figure 6 One week total HVAC energy consumption of the active mode baseline, mixed-mode baseline, E⁺PC, and ME⁺PC in the swing season.

Figure 7 shows the average zone PMV comparison between E⁺PC and ME⁺PC. In general, E⁺PC has better capability to maintain the PMV value under 0.5 during the occupied hours. E⁺PC keeps a lower PMV value during unoccupied night hours to “prepare” for the daytime temperature rise. In contrast, ME⁺PC has a few minor violations during warmer hours during the daytime. The comfort criterion is loosen during weekends for October 6th and 7th.

Figure 7 Thermal comfort performance of E⁺PC and ME⁺PC in the swing season.

3.2. Occupant subjective feedback data analysis

In order to find useful patterns of occupant thermal comfort preference, the subjective thermal comfort votes from the web-based database and the objective thermal environment measurement data from the test-bed building BAS system are mapped based on spatial and temporal information [21]. A total of 15 volunteers have participated and provided their subjective feedback on thermal comfort and clothing insulation information from October to December 2013. Among the 15 volunteers, only three occupants (20%) have more than 30 effective voted instances on both thermal comfort and clothing insulation concurrently. Eight (53%) occupants have less than 30 effective voted instances and four occupants (27%) have no effective voted instance over the experiment period. From the statistics point of view, three datasets with more than 30 effective voted instances are mapped with the measured air temperature in their corresponding thermal zones.

Figure 8 - Figure 9 illustrate Subject A's marginal plots of air temperature and clothing insulation (y-axis) versus the thermal comfort vote (x-axis), respectively. The histograms (N = 60) of the variables are shown on the top and right sides of the plot areas. In general, Subject A feels cold for the majority of votes regardless of actual air temperature (20 - 25°C) measurements. One noticeable pattern is that all the “very cold” votes are the times when the air temperature drops below 21°C. Figure 9 shows that most of the “feeling cold” votes are correlated with clothing insulation factor above 1.5, which suggests that although Subject A has adapted his/her clothes based on the thermal comfort feeling, he/she was still feeling cold during the study period.

Figure 8 Marginal plot of air temperature vs. comfort vote of Subject A.

Figure 9 Marginal plot of clothing insulation vs. comfort vote of Subject A.

Figure 10 - Figure 11 show Subject B's marginal plots of air temperature and clothing insulation (y-axis) versus the comfort vote (x-axis), respectively. The histograms (N = 36) of the variables are shown on the top and right sides of the plot areas. In general, Subject B feels cold for the majority of votes regardless of actual air temperature (20 - 25°C) measurements. Figure 11 shows that almost all the "feeling cold" votes (except for one vote) are correlated with clothing insulation factor around 0.5, which suggests that Subject B has relatively thin clothes in the office compared to the typical business dress. Arguably, Subject B could have improved his/her thermal comfort level easily by adding a jacket or another layer of clothes. This result is very different from the data of Subject A, who has already had thick clothes but still feels cold.

Figure 10 Marginal plot of air temperature vs. comfort vote of Subject B.

Figure 11 Marginal plot of clothing insulation vs. comfort vote of Subject B.

Figure 12 - Figure 13 show Subject C's marginal plots of air temperature and clothing insulation (y-axis) versus the comfort vote (x-axis), respectively. The histograms (N = 41) of the variables are shown on the top and right sides of the plot areas. In general, Subject C feels warm, especially when the air temperature is above 22°C. Figure 13 shows the clothing insulation factor is mostly below 1.0, which suggests that Subject C has relatively thin clothes in the office compared to typical business dress, but the subject still feels warm in general. This is clearly different from the other two subjects' profiles.

Figure 12 Marginal plot of air temperature vs. comfort vote of Subject C.

Figure 13 Marginal plot of clothing insulation vs. comfort vote of Subject C.

3.3. Simulation results of OME⁺PC

OME⁺PC is simulated using the same weather, occupancy, equipment, and lighting schedule inputs as the ones used in ME⁺PC. The only different input between OME⁺PC and ME⁺PC is the occupant thermal comfort preference range. As shown in Table 1, ME⁺PC uses the default value (PMV = 0) for all the occupants in the six open office zones, while in OME⁺PC, three different occupant preferences learned from the occupant

subjective feedback study are simulated in the three open office zones, respectively. The default value is implemented in the other three zones.

Table 1. Thermal comfort and clothing insulation preferences in OME⁺PC.

	Thermal comfort preference range in occupied hours (PMV)	Clothing insulation preference (Clo)
Default value	(-0.5, 0.5)	1.00
Occupant A	(0.19, 1.19)	1.25
Occupant B	(-0.14, 0.86)	0.57
Occupant C	(-0.78, 0.22)	0.74

Figure 14 shows the simulation results of the PMV values of different zones in OME⁺PC. It is clear that the default PMV performance obeys the original (-0.5, 0.5) range in occupied hours, but the three adjusted thermal zone PMV values are shifted either up or down to meet the individual comfort preference. Therefore, this result demonstrates that OME⁺PC is capable of providing individualized thermal environment based on occupants' comfort preferences.

Figure 14 Thermal comfort performance of different zones in OME⁺PC in the swing season.

In order to further investigate the energy implications of allowing occupants to choose their own thermal comfort preferences, the OME⁺PC's AHU supply air temperature, flow rate, and power consumption data are compared with ME⁺PC's. As shown in Figure 15, OME⁺PC has generally higher supply air temperature and lower mass flow rate during occupied daytime for cooling. In addition, OME⁺PC has fewer occupied cooling hours during the first four weekdays. In accordance with the performance of control variables, the power consumption of OME⁺PC is lower than ME⁺PC, as illustrated in Figure 16. During the one week simulation period in the swing season, OME⁺PC has a 37.37% energy reduction compared to ME⁺PC.

Figure 15 Outdoor temperature and control variables of ME⁺PC and OME⁺PC in the swing season.

Figure 16 One week plot of the power consumptions of ME⁺PC and OME⁺PC in the swing season.

However, the energy reduction is mainly caused by the “warmer” thermal preference of Subject A and B in the cooling dominated period, so the setpoints of zone temperatures are higher than the default value. The occupant preference can vary significantly based on season, location, physical and psychological changes. For instance, even with the same group of occupants given the same setting of OME⁺PC, the energy consumption could be increased during heating seasons, since the occupants demand warmer environment than the default mode. Therefore, the conclusion of OME⁺PC simulation study is that introducing the individual occupant thermal comfort preference in the control system may have significant energy impact while providing customized thermal environment to individuals. More in-depth investigation could be conducted in future.

3.4. Discussions

Three limitations need to be discussed in this study. First, one week of simulation has been conducted for different control models in various weather conditions. The baseline and E⁺PC are simulated in both heating and cooling seasons. The E⁺PC, ME⁺PC, and

OME⁺PC are simulated in swing seasons. For generating one hourly of actual control output, the control optimization algorithm needs about five minutes of simulation time in the Matlab/Simulink and EnergyPlus co-simulation platform. Therefore, one week of actual control simulation takes about 14 hours to finish. Although the computation time can be improved, in reality, when the control step is adjusted hourly, five minutes of optimization is still acceptable. However, more long-term investigations are needed to discover the annual impact of the different control schemes on energy and occupant comfort.

The second limitation is that a rule-based passive cooling control algorithm is implemented together with the MPC control algorithm for the active HVAC system. The control system worked well in terms of saving energy and maintaining occupant thermal comfort in general, but there are times when thermal comfort is compromised and there are other times when the active system has to push its operation to extremes in order to meet the setpoint. In future, researchers could first focus on improving the passive cooling control algorithm with physical experiments and/or simulations to identify a proper algorithm for a specific building in a specific location. Then based on the optimized passive algorithm, further improvement of the mixed-mode control algorithm could be made.

Furthermore, the sample size and the climate conditions of the occupant subjective thermal comfort feedback study could be enlarged and diversified. This study has already found very interesting patterns, despite the small sample size (15 people) and the relative short duration (three months). One could imagine that if future studies could incorporate more individuals under different seasons and locations that could also represent culturally

behavioral differences, the findings would be very valuable for understanding occupant thermal comfort and behavior, and for developing more appropriate occupant-oriented control systems.

4. Conclusions

This paper describes the development procedures and simulation results of an occupant-oriented mixed-mode EnergyPlus predictive control (OME⁺PC) system. Three interim control models are created to compare different energy saving and thermal comfort improving strategies, which are the baseline rule-based control (Baseline), EnergyPlus predictive control for the active HVAC system (E⁺PC), and mixed-mode EnergyPlus predictive control (ME⁺PC). Figure 17 shows the development processes, methods, and outcomes of the four control schemes.

The first set of outcomes is that a co-simulation platform is created for EnergyPlus and Matlab/Simulink via MLE+. The co-simulation platform is tested numerous times during the development process and it can be systematically updated with minimum effort. The second set of outcomes is that during the simulation periods (heating, cooling, and swing seasons), E⁺PC, ME⁺PC, and OME⁺PC can reduce HVAC energy consumptions and maintain occupant thermal comfort with the model-based predictive control algorithm. The third set of outcomes is that using the mixed-mode active/passive control algorithm, more energy savings can be achieved and the occupant thermal comfort can be maintained. Last but not least, the final outcome of implementing the real-time thermal comfort feedback system, OME⁺PC can provide individualized thermal environment for occupants and has considerable impact on the HVAC energy consumption. These conclusions are drawn based on several one-week simulation results in the study in

typical heating, cooling and swing seasons, thus the results cannot be applied to annual-based simulation studies at this point. Future studies could run annual simulation studies and investigate the annual energy and comfort impact of the control schemes.

Figure 17 Different control schemes, as well as their methods and outcomes.

In the data analysis study of the occupant subjective thermal feedback, a total of 11 out of 15 volunteers express their opinions on their thermal comforts when they do not feel thermally comfortable, which indicates thermal comfort is something important for the test group to consider at workplaces. However, people have very different sensitivities and tolerances to thermal comfort. Three subjects voted over 30 times during the three months experiment periods, but most people voted less than 30 times. In addition, among

the three subjects, the data shows very different comfort preferences and clothing choices. However, the thermal comfort preference and clothing choice of each individual are mostly consistent for the majority of time during the entire experiment period. Therefore, it is necessary to develop a control system that can accommodate individual occupant thermal comfort preference, and based on the individual preference, the control system could make consistent adjustment to meet individual needs.

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