Multi-system Model Predictive Control for Multi-Zone Building Automation and Control

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ABSTRACT

In this paper, a multi-zone Model Predictive Control (MPC) system with coordination between multiple systems including Air Conditioning and Mechanical Ventilation (ACMV), lighting, and shading has been presented. MPC system includes data-driven models for forward prediction of thermal conditions, illumination, and artificial lighting power for each test spaces. The thermal prediction model was trained with historical data from humidity, indoor air and globe temperature sensors, and disturbances including weather parameters and occupancy. The disturbance data were from machine-learning-based weather forecasting and a real-time occupancy detection system. Illumination and artificial lighting power prediction models were trained with historical data of lighting power meters, blind positions, and indoor illumination levels collected via sensors. Nonlinear autoregressive exogenous model with external inputs (NARX) neural network was employed to develop these data-driven models. With these data-driven models, MPC system simultaneously optimizes multiple targets including energy consumption, thermal and visual comfort by solving nonlinear optimization problems. In the case of thermal comfort, the predicted mean vote (PMV) was optimized to seek a default reference PMV setpoint of 0 representing thermal neutrality while constrained to within -0.5 to 0.5. Similarly for optimum visual comfort, daylight glare probability (DGP) should be within 0.35 and the work-plane illuminance was constrained to 500-3000 lux. An algorithm to take in occupant feedback as an additional consideration was also incorporated into the MPC system. As per occupant feedback, their preferences can bias the reference PMV set point. MPC system was implemented in a multi-use test space located in Singapore with area of approximately 850 m^2. The test space was partitioned into 6 learning zones, 2 office spaces, and 3 open spaces. ACMV system serving the test space consisted of 2 Primary Air-Handling Units (PAHUs) and 16 Fan Coil Units (FCUs). Chilled water is supplied to cooling coils of these units from central chiller plant of the building. Conditioned air is distributed to test space through motorized diffusers. Lighting and shading system consisted of LED lighting fixtures with dimmable control and motorized roller blinds respectively. Control performance of MPC system was compared against the test building's original thermostat-based (reactive) control. MPC system (without occupant feedback) achieved over 33% energy savings with higher thermal and visual comfort. When occupant feedback was considered, it was found that the occupants preferred a thermal environment cooler than thermal neutrality (i.e., negative PMV) for certain periods of the day (e.g., when the occupants have just arrived at the space in the morning or after lunch). This led to higher energy consumption compared to MPC without occupant feedback. Overall, MPC with occupant feedback still achieved over 23.5% of energy savings when compared to that of original reactive control system. Despite advantageous control performance, MPC system requires additional sensors for occupancy comfort evaluations, leading to high implementation cost. Much effort is also needed to construct accurate building models,

which further adds hurdles for MPC adaptation. In future deployments of MPC, these shortcomings can be mitigated by building comfort models only based on existing sensors in the building.

1. INTRODUCTION

In Singapore, owing to its hot and humid climate throughout the year, a commercial building has more than 60% of its electrical energy consumption expended on its air conditioning, mechanical and ventilation (ACMV) system (Building Construction Authority (BCA), 2018). On Mar 31, 2020, Singapore submitted its Long-Term Low Emissions Development Strategy (LEDS) to the United Nations Framework Convention on Climate Change, to halve its emissions from its peak to 33MTCO2e and to achieve net zero emissions by 2050 (Singapore Green Building Council, 2020). Currently, BCA (2021) has reported that high-performance buildings in Singapore are able to achieve more than 65% improvement in energy efficiency over their 2005 levels. BCA further aims to raise energy efficiency to 80% by 2030 through its Green Building Innovation Cluster programme.

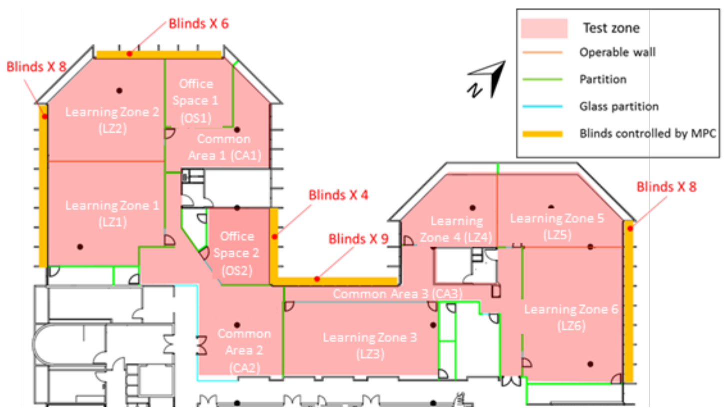
Generally, green building technologies such as efficient ACMV systems, automated dimmable lighting systems and dynamic shading systems have been employed to raise building efficiency. However, each of these systems have been deployed using segregated control approach, and therefore lack coordination between multiple systems operating in the building. This limits the dynamic operation of building systems from achieving higher overall efficiency and often results in lower occupant comfortability. Furthermore, the current practice of building automation and control system is ‘reactive’ as it generates control signals based on deviations of past measured information from a control set point. Consequently, due to the thermal capacity of the building and the non-linear operation of its ACMV system, reactive control systems are not able to achieve optimal operation in terms of efficiency and comfort.

As reported by Das (2024), the studies on solutions to determine optimum ACMV operation in recent decades can broadly be divided in terms of model architecture into: 1) Model Predictive Control (MPC) and 2) Reinforced Learning (RL). Over the years, Yang et al. (2018 and 2021) have demonstrated various techniques to simplify the building models by employing linear building models. A data-driven building automation and control using MPC as the constrained control technique have shown considerable promise to achieve optimum thermal comfort and high building energy efficiency. For example, Široký et al. (2011) reported 15-30% energy savings in a university building using MPC integrated with weather forecasting capabilities. Ma et al. (2012) reported a 19% efficiency improvement by implementing a hierarchical MPC system for a chiller plant. In an experimental study, compared to heuristic control methods, Pang et al. (2018) demonstrated reduction in the chilled water consumption by 42% in a radiant slab system. MPC systems have two main obstacles: they require accurate model to predict the system state evolution, and high computation cost to perform optimization across multiple zones and multiple systems. Yang et al. (2021) employed two-level distributed computation scheme using MPC to develop a scalable control method to optimize thermal comfort and internal air quality (IAQ) across multiple zones. Specifically, the first level computes optimum zonal mass flow rates to provide optimum thermal comfort and the second level further regulates the computed zonal mass flow rates and the ventilation rate to achieve desired IAQ in multizone. Similarly, Yang et al. (2023) employed MPC in which the optimization is triggered by an event-based triggering mechanism leading to reduced computational load by up to 12-22% while achieving energy savings of over 9%.

As demonstrated by Yang et al. (2021), one of the key advantages of MPC over reactive control system is its ability to control and coordinate multiple building systems. In this paper, an occupant-centric multi-zone MPC for coordinated control of multiple building systems including ACMV, lighting and shading for optimum occupant comfort and energy optimization has been presented. The key novelties of this MPC system are stated as follows: 1) multi-objective MPC for coordinated control of ACMV, lighting and shading system for multiples zones in the building; 2) predictive disturbance inputs for MPC including weather forecasting and real-time occupancy detection system; 3) real-time occupant feedback system to bias MPC for higher subjective occupant comfortability. The MPC system was deployed in a multi-use test space of 850 m^2. For the performance comparison, the energy consumption, thermal and visual comfort following the coordinated control by the MPC system were compared with the conventional reactive control using (proportional-integral-derivative) PID system.

2. Testbed setup

For the test-bedding, a commercial building located in Jurong East of Singapore was selected. The building is served by 2 York chillers, each with the capacity of 438 RT. The ACMV system in the building is scheduled to operate from 7AM to 7PM during the weekdays. The experiments were conducted in an 850 m^2 multi-use test space which was partitioned into 11 zones including Office Spaces (OS) 1-2, Learning zones (LZ) 1-6, and some Common Areas (CA) 1-3, as shown in Figure 1. MPC has been implemented to coordinate and control different building systems as provided in Figure 1. There is an operable partitioning wall between LZ1 and LZ2, and LZ1, LZ 2 and LZ3. This partitioning wall can be operated such that the two zones in LZ1 and LZ2 (or up to three zones in LZ4, LZ5 and LZ6) can be merged into one zone. The open/closed state of these walls are determined using proximity sensors which has an output of '1' if the walls are closed (and hence we have 2 separate rooms in case of LZ1 and LZ2) or an output of '0' if the walls are open (that is the rooms are merged to form one big room).



Space	System	Locations
Learning Zones (LZ)	ACMV, Lighting and shading	LZ1-6
Office Space (OS)		OS1-2
Common Areas (CA)		CA1-3

Figure 1: Layout of spaces in the test zone

2.1 ACMV system

The schematic for the ACMV system installed in the test space is shown in Figure 2. The ACMV system serving the test space consisted of Primary Air-handling Units (PAU) for fresh air supply and Fan Coil Units (FCUs) for cooling and dehumidification. The cooling coils in PAU and FCUs are supplied with chilled water from the central chiller plant (not shown in Figure 2) of the building. Since MPC only controls the airside of the ACMV system in the test space, which is a small portion of the building, the net effect of MPC on chiller plant functioning is not considered in this study. The PAU is integrated with an on/off damper, a cooling coil, and a supply fan. PAU is operated under constant conditions, that is, its off-coil temperature was set at 24°C, and its supply airflow was set constant at 2.2 m^3/s. Thus, the PAU takes in fresh air from outside, cools and dehumidifies at 24°C and supplies cooled fresh air to each of the test zones. On the other hand, multiple FCUs are installed at each zone. Each FCU is equipped with a cooling coil and a supply fan. The FCU draws in the mixed air of fresh air supplied by PAU and the return air from the zones, cools and dehumidifies the mixed air and then supplies it back to the test zones via motorized diffusers. Each FCU is set at constant supply fan speed while MPC is allowed to regulate the chilled water flow in its cooling coil via a motorized water valve. The cooling energy consumed in each FCU is measured using BTU (British thermal unit) meters. When the test space is controlled by the existing BMS of the test building, (namely "default mode" or "baseline BMS mode" in this study), the BMS regulates the motorized water valve is controlled via PID controller using a temperature setpoint of 22°C in the thermostat measuring the air temperature at the outlet of the diffuser.

Each zone consisted of a set of sensors including globe and ambient temperature, and humidity sensor for the measurement of thermal comfort inside the zone. The ambient air velocity inside the room, metabolic rate and clothing factor for each occupant were assumed constant at 0.1 m/s, 1.2 met and 0.5 clo per occupant respectively for the evaluation of predicted mean vote (PMV). In the PAU and FCUs at both the supply and return side, duct air temperature, humidity, and flow sensors were installed for the precise measurement of the cooling capacity of supply air for each zone. Additionally, duct CO2 sensors were also installed at both the supply and return sides of FCUs. Using the duct CO_2 and flow sensors at FCU and PAU and the indoor CO2 sensor at each zone, the occupancies of each zone were determined.

A weather station including outdoor temperature, humidity and solar radiation sensors was installed on the rooftop of the building. All the readings from the indoor, ACMV and outdoor sensors were first stored in the database at the frequency of every 1 minute and then fed to MPC system for its optimization and control.

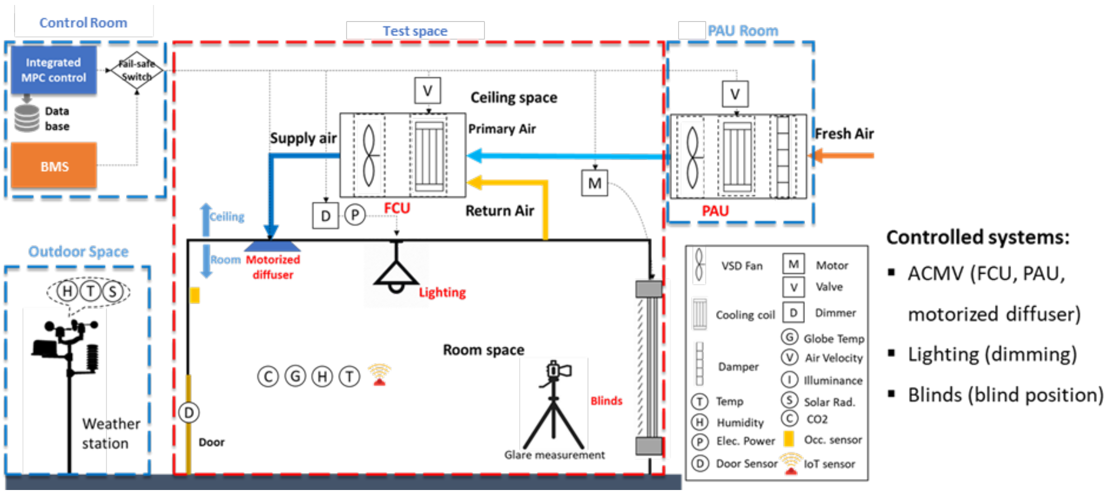


Figure 2: Sensors, actuators and other hardware installed in test space for MPC.

2.2 Lighting and shading system

The lighting system in the learning zones consisted of LED lighting fixtures integrated with dimmable control as shown in Figure 3(a). Other areas in the test space were equipped with T5 fluorescent lighting with on/off switches. Based on the amount of daylighting in each of the zones, the lighting system in the test space has been divided into 37 lighting sub-zones for optimal visual comfort throughout the zones. Each 37 sub-zones also included an illuminance sensor to monitor the illuminance inside the zone. The lighting power was also measured using power meter installed at each zone level.

As can be seen in Figure 3(a), the shading system consisted of 11 groups of motorized roller blinds. Depending on the daylighting conditions, the blinds can roll up to open or roll down to close and they can be set at 0%, 20%, 40%, 60%, 80% or 100% closed.

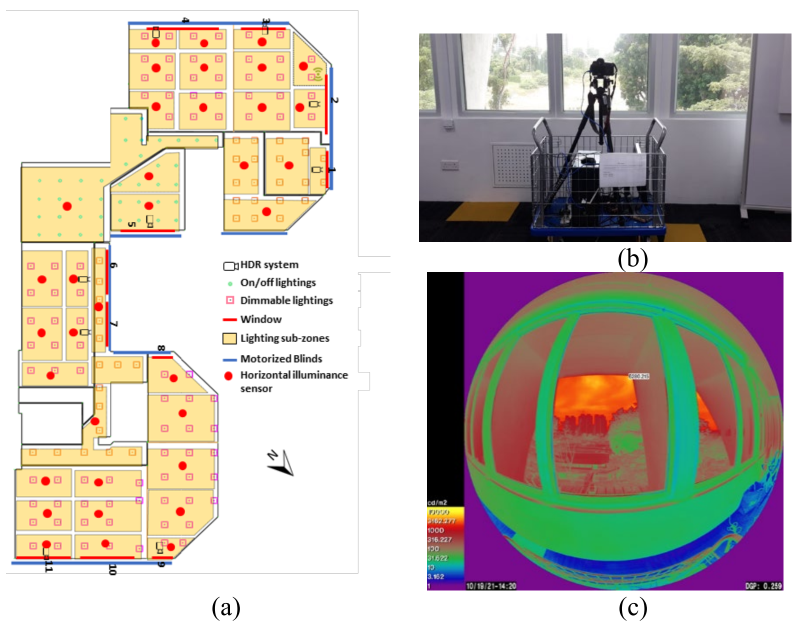


Figure 3: (a) Lighting and shading system in the test space. (b) HDR camera for measurement of DGP. (c) DGP measured using HDR camera

In each of the test zones, a high dynamic range (HDR) imaging system using Cannon 5D Mark IV camera was used to measure lux and daylight glare probability (DGP). As shown in figure 3(b), the HDR camera was mounted on a tripod at 1.2m height facing the window façade.

2.3 MPC system

The proposed MPC system for coordinated control of ACMV, lighting, and shading systems is shown in Figure 4. The MPC system controls the FCUs/PAU chilled water valves in coordination with the lighting power level and motorized blinds position in the lighting and shading system.

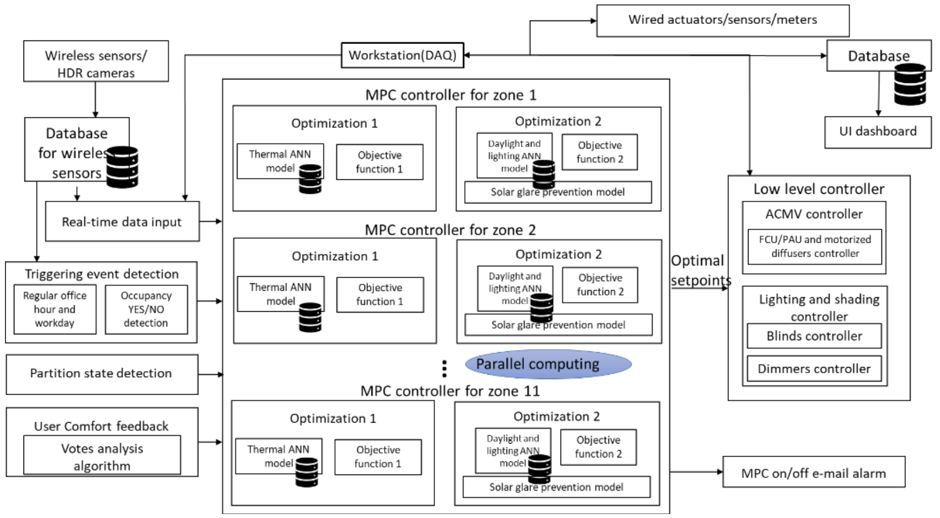


Figure 4: MPC system architecture

2.3.1 MPC controller for ACMV: The MPC system for ACMV control for each zone consists of an MPC controller and a low-level controller using PID as illustrated in Figure 4. The MPC controller includes a machine learning (ML) based predictive model and an optimization solver. The input variables for the MPC controller include measured disturbances such as outdoor conditions and indoor heat loads, state variables such as PMV, and feedback from measured manipulated variable (cooling power supplied by the FCU cooling coil). The ML model for the prediction of indoor PMV is built using a nonlinear autoregressive exogenous model with external inputs (NARX) feedback neural network. NARX is a recurrent neural network commonly used for time-series modeling. For the MPC controller, cooling power supplied by the FCU cooling coil, as the manipulated variable, is the control signal to be optimized and the current cooling power is measured as feedback from the BTU meter installed in each FCU in the zone. The number of occupants, representing the internal heat load, in a zone is feedback from the occupancy detection system (briefly described in section 2.4). Outdoor temperature and solar radiation are measured from the weather station on the rooftop of the test building. Solar heat gain from the windows, Q_{win}, is derived as a function of solar radiation as shown in Equation 1. In Equation 1, the solar heat gain constitutes heat gain from the window shaded by blinds and the unshaded region of the window, where, *SR* is the ratio of area shaded by the blinds to the total area of the window, A_{win} is the total window area, E_{inc} is the incident solar radiation, *SHGC* is the solar heat gain coefficient and *IAC* is the indoor attenuation coefficient from blinds which are made of light translucent fabric. *SHGC* and *IAC* are assumed constant with values 0.287 and 0.75 respectively. The feedback from room air temperature, humidity and globe temperature are used to determine PMV (as defined in American Society of Heating, Refrigerating and Air-conditioning Engineers, ASHRAE 55).

$$Q_{win} = \underbrace{SR * A_{win} * E_{inc} * SHGC * IAC}_{region\ shaded\ by\ blinds} + \underbrace{(1 - SR) * A_{win} * E_{inc} * SHGC}_{unshaded\ region} \tag{1}$$

The objective of MPC for ACMV is two-folds: firstly, to minimize the cooling power (Q_{cool}) consumed by ACMV system, and secondly, to minimize the thermal discomfort which is the offset between indoor PMV and the thermal neutrality (that is, PMV = 0). The objective function for ACMV can be written as shown in equation (2).

$$J = Minimize(\sum_{k=0}^{N} \frac{W_{cool} * Q_{cool,\,t+k|t}}{COP} + \sum_{k=0}^{N} W_{PMV} * (PMV_{t+k|t} - PMV_{ref})^2 + \sum_{k=0}^{N} W_{\epsilon}(\epsilon_{t+k|t})^2) \tag{2}$$

subjected to inequality constraints are as per equations 3 and 4.

$$Q_{cool,lb} \leq Q_{cool} \leq Q_{cool,ub} \tag{3}$$

$$-0.5 - \epsilon \leq PMV \leq 0.5 + \epsilon \tag{4}$$

where, Q, W, N and ϵ refer to cooling power, weight, number of control intervals in one prediction horizon, and slack variable respectively. Subscripts *cool*, *t*, *k*, *ref*, *lb* and *ub* refer to cooling, current time, index of time step, reference PMV or setpoint PMV (that is PMV = 0), lower and upper bound respectively. The slack variable ϵ is used for constraint relaxation. Similarly, *COP* is the coefficient of performance of the cooling system which is assumed constant at 3.7 as per the specification of the ACMV system. The three terms on the right-hand side of equation (2) represent the cost in terms of cooling energy consumption, thermal discomfort, and the constraint violation respectively.

2.3.2 MPC controller for lighting and shading: For the indoor visual comfort prediction, two sub-models are developed, the artificial lighting sub-model for the prediction of horizontal illuminance at the work plane due to the artificial light using the lighting power of the current sub-zone and its adjacent sub-zones, and the daylight penetration sub-model for the prediction of DGP using vertical illuminance near the window due to daylight. The upper allowable limit for glare discomfort is 0.35 in DGP (Wienold and Christoffersen, 2006). As per Lindelöf and Morel (2008) and as per the standards for lighting in workplaces (2013), the acceptable lower and upper limits for horizontal illumination at the work plane are 500 and 3000 lux, respectively. Regression analysis was used to build the artificial daylighting sub-model.

In case of the daylight penetration sub-model, the vertical position of the blinds is the manipulated variable as it controls the amount of daylight into the room. The incident illuminance on the windows measured using illuminance sensor installed outside the windows, global horizontal irradiance and diffuse horizontal irradiance measured using weather station are the measured disturbance to this sub-model. Again, NARX was used to build the ML model for daylight penetration. The true value of vertical illuminance near the window was obtained from the HDR system.

In the MPC controller for the lighting and shading, as shown in equation (5), the objective is again two-folds, firstly, to minimize the heat gain from the windows by searching for the optimum blinds position, secondly, to optimize the lighting power such that visual comfort constraints shown in equation (6) and (7) are always satisfied.

$$J = Minimize(\sum_{k=0}^{N} \frac{Q_{win,\,t+k|t}}{COP} + \sum_{k=0}^{N} \frac{P_{light,\,t+k|t}}{COP} + \sum_{k=0}^{N} P_{light,\,t+k|t} \tag{5}$$

$$DGP \le 0.35 \tag{6}$$

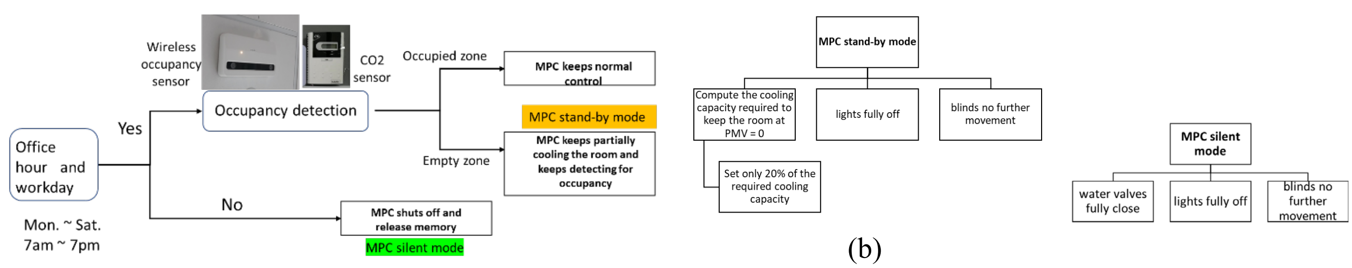
$$500\ lux \le I_{wp} \le 3000\ lux \tag{7}$$

Additionally, the lighting power level and the blind position should be within the constraints as specified in equation (8) and (9).

$$0\% \le P_{light} \le 100\% \tag{8}$$

$$0 \le SR \le 1 \tag{9}$$

where, *COP*, *Q*, *P*, *I* and *SR* refer to Coefficient of Performance of the cooling system (COP = 3.7), heat flowrate (through window), electric power, illuminance and shaded ratio. Subscripts win, i, *k*, *light* and *wp* refer to windows, current time, time step index, lighting system, and work plane. Similarly, the three term in equation (5) refer to: heat gain through the windows, heat gain through the lighting system and the power consumed by the lighting system.



(a) (b) (c)

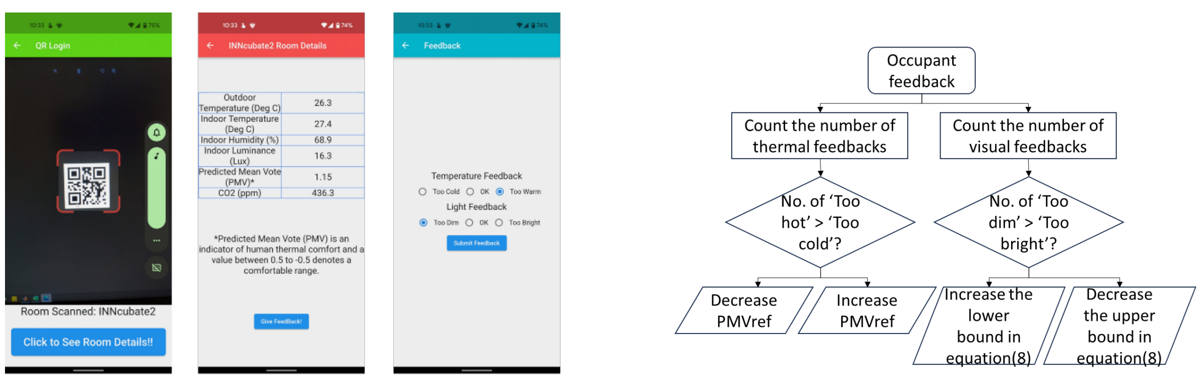
Figure 5: (a) Occupancy based triggering system for MPC (b) Stand-by mode for MPC during working days but when test zones are empty (c) Silent mode for MPC during non-working days

2.4 Occupancy detection system

Figure 5(a-c) shows the overall concept of occupancy-based trigger system developed for MPC. During the working days, that is 7AM to 7 PM on Monday to Saturday, MPC stays active and keeps reading the zones for occupancy using wireless occupancy sensor and CO2 sensor. MPC performs optimization and predictive control based on its indoor and outdoor conditions. However, in case the room is unoccupied, MPC for that zone changes to stand-by mode, in which, in case of ACMV system, the cooling power setpoint for that zone is set at 20% of the required setpoint for that zone. In case of lighting and shading, all lights in the zone are switched off and the blind operations are also suspended. In case of non-working days, MPC switches off all FCU water valves and lightings in the test space and suspends all blinds operation.

2.5 Occupant feedback system

A web-based occupant feedback system, which can bias the thermal and visual comfort as per the requirement of the occupants, has been developed and integrated with MPC. Each room has been provided with its unique quick response (QR) code. The occupant can scan the QR code, obtain the thermal and visual condition of the room, and provide feedback in the app as shown in figure 6(a). To bias the thermal comfort of the room, occupants can provide the feedback as 'Too cold' or 'OK' or 'Too hot'. Similarly, occupants feedback as 'Too Dim' or 'OK' or 'Too bright' to bias the visual comfort as required. The feedback system in MPC records the current time, room name from where the occupant is providing the feedback, and the occupant feedback. MPC adopts the voting system and in case of thermal comfort biasing, the MPC counts the number of feedbacks from every last 18 mins, whereas, in case of visual comfort biasing, the feedbacks are counted from every last 12 mins. For example, as seen from the flowchart for occupant feedback system in Figure 6(b), in case of at least 20% of the room population have voted for last 18 mins, and, the number of 'Too hot' feedback is higher than the number of 'Too cold', MPC will decrease the reference PMV (PMV_{ref} in equation 2) by -0.2 as long as it does not reduce the hard constraint of PMV_{ref} below -0.5. This way, by reducing the PMV_{ref} below its default condition of PMV = 0, this allows the MPC to search for cooling capacity which results in PMV of the room to be lower than 0, thereby further cooling the room. Similar control logic was also applied to bias visual comfort as per the occupant requirement. However, in case of visual comfort as can been seen in figure 6(b), if the feedback from voting is that the room is 'Too bright', the MPC will lower the upper constraint for lighting and shading power level in equation (8) to 60% while keeping lower constraint same, such that it allows MPC to search for optimum lighting power within power level of 40% to 60% only and thereby resulting in the room to be dimmer as required by the occupants.



(a) (b)

Figure 6: (a) Demonstration of mobile app pages for Occupant feedback (b) Occupant feedback system for ACMV, lighting and shading

3. RESULTS AND DISCUSSION

In this section, the performance of MPC without occupant feedback and MPC with occupant feedback has been compared with baseline BMS mode of operation. During the testing, it was noted that, the test space had intermittent occupancy as the tenants pre-selected dates for operation. It was also found that, during the days of its operation, only administrative office and learning zones selected for operation during that day was fully occupied. LZ1 (see Figure 1) was found to have been used most frequently by the users. Hence, for the performance testing, up to 5 days of data from LZ1 has been used here for the analysis. The test periods were selected such that they had median outdoor temperature between 30-32°C and their sky clearness index (SKI) between 0.2 and 0.65. The key parameters examined are the variations of PMV, indoor temperature and the cooling power delivered to different zones in the test space.

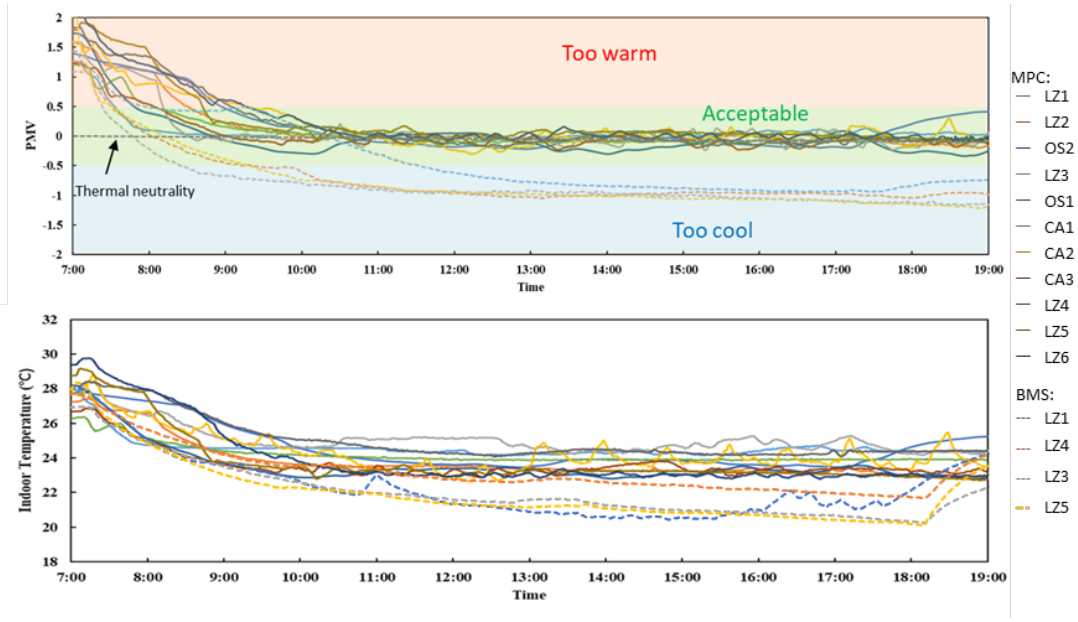


Figure 7: PMV and indoor temperature variations in the 11 zones of the test space on a typical day from 7 am to 7 pm

Figure 7 illustrates the variation of PMV and indoor temperature of all the 11 zones in the test space for a typical day. As can be seen from the figure, the ACMV system operates from 7 am to 7 pm. While the baseline BMS aggressively cools the rooms, due to its temperature setpoint, it keeps cooling until the room temperature meets the setpoint temperature. Meanwhile, MPC, triggered by occupancy after 8.30AM, starts aggressively cooling until the PMV of the room approaches 0 (thermal neutrality). Once, the PMV of the room reaches 0, MPC adjusts the cooling power of the room such the PMV stays around the thermal neutrality.

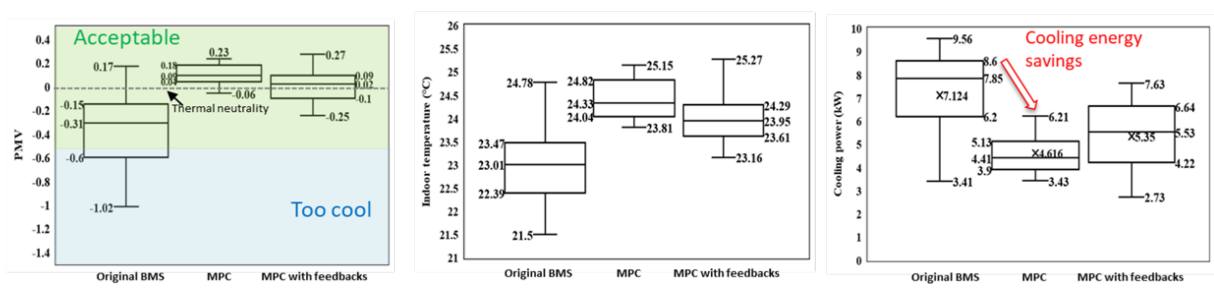


Figure 8: Distribution of PMV, temperature and cooling power for BMS, MPC systems without occupant feedback and with feedback for LZ1

Figure 8 summarizes the distribution of PMV, indoor temperature and the cooling power of ACMV system in LZ1 during the occupancy period from 9.30AM to 6PM for the same typical day as in Figure 7. In case of baseline BMS, the PMV often exceeds the comfortable threshold to "too cool" region. The overcooling by BMS and the comparative saving in cooling energy can also be inferred from Figure 8(c). This overcooling from BMS is mainly because, BMS lacks predictive response to varying outdoor and indoor heat loads and as a result it needs to operate at constant setpoint temperature to meet the cooling demands of the test space. Comparatively, MPC can predict the indoor thermal condition based on the outdoor and indoor heat load, and hence can vary the cooling power as required to meet the thermal neutrality (PMV = 0) in the zones.

Figure 9 illustrates the variation of lighting power and the horizontal illuminance measured for LZ1 on a typical day. As it can be seen from the figure, MPC adjusts the lighting power such that it can keep the work-plane illuminance of the room within comfortable region between 500 – 3000 lux. However, for baseline BMS system, due to the constant setpoint of lighting power level at 100%, the illuminance level exceeds the maximum threshold of 3000 lux during the brighter part of the day.

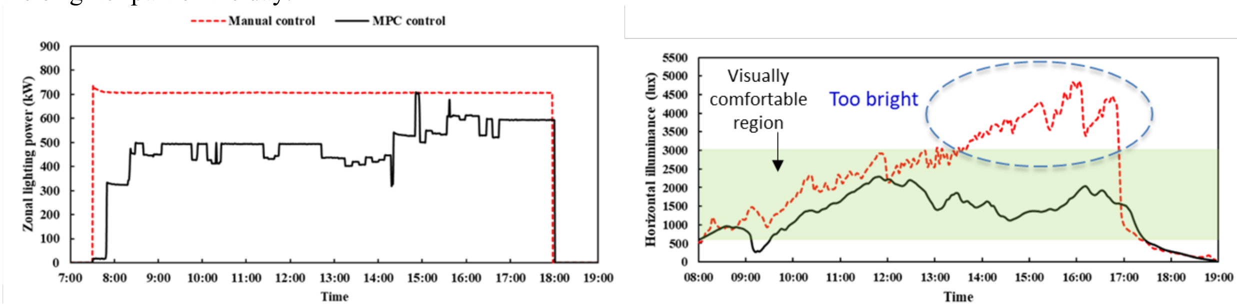


Figure 9: Variation of lighting power and horizontal illuminance for BMS and MPC system in LZ1 on a typical day from 7 am to 7 pm

The total energy consumed by each zone for the same typical day as in Figure 7 was analyzed by including BTU meter reading for chilled water consumption, fan energy consumption in PAU and FCUs, and the lighting power consumption. For this analysis, by assuming similar occupancy throughout the test space, the total energy consumed was measured for LZ1 and then projected for the whole test space. The energy consumed by baseline BMS and MPC system with maximum uncertainty of approximately 5% are shown in Figure 10. The MPC without occupant feedback saves approximately 35% and 20% cooling energy in ACMV and lighting respectively. Compared to while using baseline BMS, Approximately, 33% of the energy was saved while using MPC without occupant feedback. Similarly, MPC with occupant feedback system saved approximately 25% and 12% in ACMV and lighting system compared to the baseline BMS. Through the study, we found that occupants desired cooler conditions in the rooms, especially during the morning and after the lunch time when they have returned from hot and humid outdoor of Singapore. Their feedback during those time were to have PMV lower than 0, consequently, the total energy saving reduced to 23.5% compared to 33% of the same from MPC without occupancy feedback.

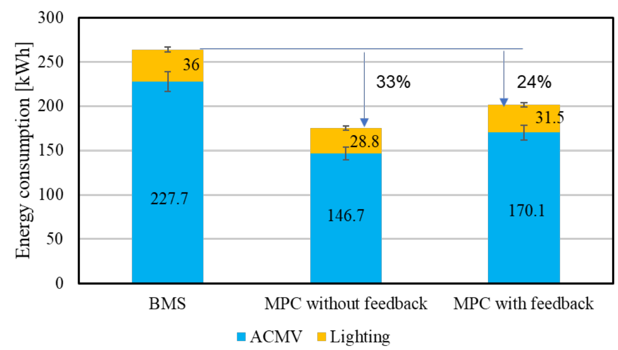


Figure 10: Comparison of energy consumption for BMS, MPC systems without feedback and with feedback

4. CONCLUSIONS

In this paper, an enhanced model predictive control system for coordinated control of multi-zone building automation and control system including ACMV, lighting and shading has been proposed and developed. The MPC system employs NARX to build the ML model to capture the thermal and visual dynamics of the building to predict indoor thermal and visual comfort level. Then, using the ML models-based optimization, MPC determines the optimum cooling power and lighting power as a setpoint to the actuators. The coordinated control of ACMV, lighting and shading system in the building has allowed for higher energy efficiency and improved occupant comfort for the building.

The proposed MPC system was implemented at a test space in Singapore and its performance was compared to the baseline BMS in the building. The MPC system also included occupant feedback system which can bias the comfort level and hence, for example in case of MPC, it allows MPC to overcool or undercool as required by the occupant. Therefore, the performance testing was studied for two types of MPC system: MPC without occupant feedback and MPC with feedback. It was found that MPC systems can achieve 33% and 23.5% energy efficiency respectively for MPC without feedback and with feedback compared to the same for baseline BMS. While analyzing for LZ1 which is the most frequently occupied zone in the test space, MPC was also able to maintain the indoor thermal comfort within comfortable range of -0.5≤PMV≤0.5 for 91.3% of operating time from 7.00AM to 7.00PM. In comparison, BMS was able to maintain the indoor thermal comfort within comfortable range for only about 35% of time.

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