SIMULATION OF ANTICIPATORY CONTROL STRATEGIES IN BUILDINGS WITH MIXED-MODE COOLING

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ABSTRACT

The paper aims to demonstrate the potential performance bounds of model predictive control strategies (MPC) for buildings with mixed-mode cooling, exposed thermal mass and high solar gains. A transient multi-zone energy prediction model with a coupled thermal and airflow network has been developed in MATLAB and it is used within an offline MPC framework with GenOpt as an optimizer. Simulation results show that mixed-mode cooling strategies (window opening and fan assist schedule) decided by the MPC optimizer can significantly reduce the cooling requirement compared to baseline night set back and simple heuristic control with the operative temperature maintained within acceptable limits for occupant thermal comfort. Results also show that additional energy savings can be achieved with shading control coordinated with anticipatory control strategies for mixed-mode cooling.

INTRODUCTION

Mixed-mode cooling refers to a hybrid approach for space conditioning, employing a combination of natural ventilation, where the flow is driven by wind or thermal buoyancy forces sometimes assisted by a fan, and mechanical systems, along with smart switching between systems to minimize building energy use and maintain occupant thermal comfort (Brager et al., 2007). Existing control strategies for mixed-mode buildings are heuristic and may lead to increased operating costs or occupant discomfort since they are not optimized for the local climate and particular building features such as thermal mass, façade orientation, building construction, etc. These problems can be avoided by employing model predictive control (MPC) strategies (Spindler and Norford, 2009b; Coffey, 2011; May-Ostendorp et al., 2011). Based on weather forecasts and cooling load anticipation, the MPC optimizer seeks optimal control sequences to balance operating costs and occupant comfort in future time frame.

Spindler and Norford (2009b) applied a real-time or “online” predictive strategy for a multi-zone mixed-mode building to find the optimal ventilation mode, based on an energy prediction model that was trained from extensive measurement data. May-Ostendorp (2011) developed an “offline” MPC framework for a mixed-mode building (not optimized for natural ventilation use) through combining an optimization toolbox in MATLAB with EnergyPlus to generate optimal window opening schedules. The generated optimal results were further used to create a generalized linear model to extract near-optimal heuristics.

The present study, extends previous work by examining mixed-mode strategies such as window opening and fan assist in a multi-zone high performance building with exposed thermal mass, an atrium and coordinated shading control. It also establishes a detailed (physical) prediction model integrating thermal and airflow simulation that will be used for parameter identification in simplified models that can facilitate MPC implementation in real buildings.

MODEL DEVELOPMENT AND METHODOLOGY

This study was inspired by the work done in Karava et al. (2012). The study conducted extensive measurements in an institutional building (located in Montreal, Canada) with motorized façade openings integrated with an atrium for hybrid ventilation. The mixed-mode cooling strategy used in the building allowed natural ventilation when the outdoor air temperature was between 15 °C and 25 °C and the relative humidity less than 70%. The building has high levels of thermal mass in the form of exposed concrete floor slabs at the corridors which are located adjacent to the inlet grilles on the southeast and northwest ends and extended all the way to the atrium. The study demonstrated significant potential for cooling load reduction and suggested that a predictive control strategy would be necessary for maximizing the benefits of natural ventilation without comprising thermal comfort.

Thermal model

For simplicity, the present study focuses on a generic section of the mixed-mode building described above with an atrium connected to six corridors as shown in Figure 1. The total floor area of the atrium is 108 m^2 with a height of 11.6 m and the curtain wall façade faces southwest. Each corridor has one exterior façade where the inlet grilles are installed. The corridors have dimensions of 30 m × 1.8 m × 3 m and act as long air “duct” for delivery of outside air into the atrium zone.

Thermal dynamics of the interior building zones are predicted by applying the heat balance method which explicitly models the heat transfer rate to the interior and exterior surfaces and to the zone air. The thermal

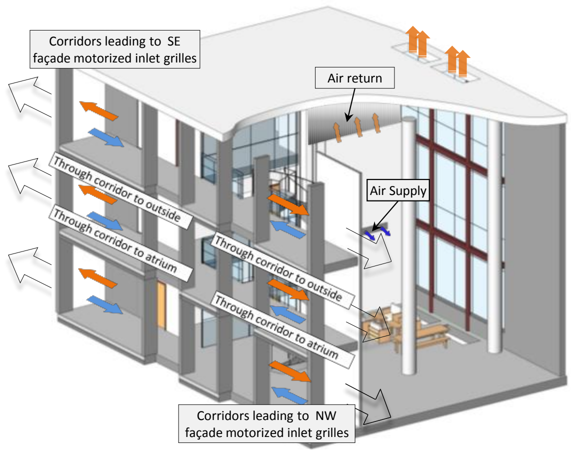

Figure 1: Mixed-mode cooling concept

network for the atrium and the corridor zone are shown in Figure 2. The radiation heat transfers between internal surfaces are not shown in respect of simplicity but were included in the simulations. Due to the corridor's large dimension (30 m long) a significant temperature difference is anticipated in the slab surface, thus, the surfaces are divided into 4 sections but are connected with the same corridor air node. The thermal model for the corridor zones has been verified using data from an experimental study (Karava et al., 2012; Hu and Karava, 2012). The atrium is modeled with three zones to account for the temperature stratification (Karava et al., 2012). Therefore, the thermal model includes three atrium zones plus six corridor zones (three in southeast and northwest orientation).

Airflow model

A multi-zone airflow network model (Figure 3) has been developed in MATLAB using the Newton-Raphson method to solve the non-linear airflow problem by iteration of solutions of linear equations. The airflow through each opening is given by

$$F_{j,i} = C_d A \left(\frac{2\Delta P_{j,i}}{\rho}\right)^n \tag{1}$$

where, C_d is the discharge coefficient, set to be 0.65 as the study assumed that the openings were "large", A is the effective opening area, ρ is the air density that depends on the flow direction, $\Delta P_{j,i}$ is the pressure difference between zones:

$$\Delta P_{j,i} = P_j - P_i + P_S + P_W \tag{2}$$

where, P_j and P_i are total pressure in zone j and i, P_S is the pressure difference due to the stack effect and P_W is the wind-effect pressure.

The "Multiple Opening Model" (Stuart et al., 1997) was used to model the air exchange between zones connected with large openings. The model divides the large opening ($W \times H$) into multiple thin strip openings ($W \times \Delta h$) so that the flow rate through each strip could be calculated separately (Figure 3).

An assisting exhaust fan is located on the roof of the atrium that operates in case of insufficient natural ventilation. The airflow network model was compared with CONTAM and the predicted differences of both flow rates and pressure drops were less than 5%.

For building with mixed-mode cooling, natural ventilation is an essential feature where airflow is

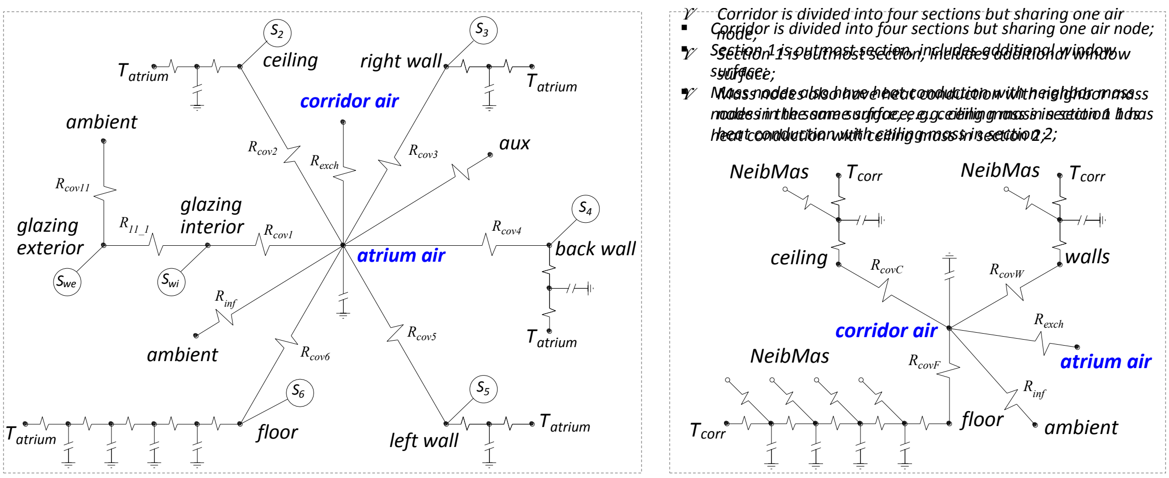

Figure 2: Thermal network for the atrium (left) and the corridor zone (right)

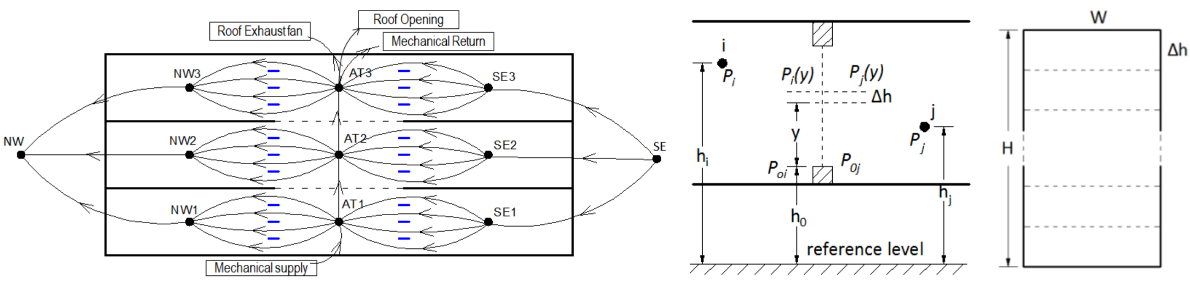

Figure 3: Schematic of the airflow network (left) and Multiple Opening Model (right)

mainly driven by wind and buoyancy forces, i.e. involving strong coupling between heat and air flow. In the present study, the "onion" coupling method (Hensen, 1999) in which thermal and flow simulation iterate on each time step was implemented.

MPC FRAMEWORK

With regards to the use of MPC for building energy management, the sequence for building climate control (e.g. air temperature set-point, natural ventilation) is formulated at a given point in time for a future planning horizon, based on the prediction of upcoming weather conditions. The "offline" deterministic MPC framework for buildings with mixed-mode cooling that was implemented in the present study is illustrated in Figure 4. This method is based on the assumption that future predictions are exact (Oldewurtel et al., 2012).

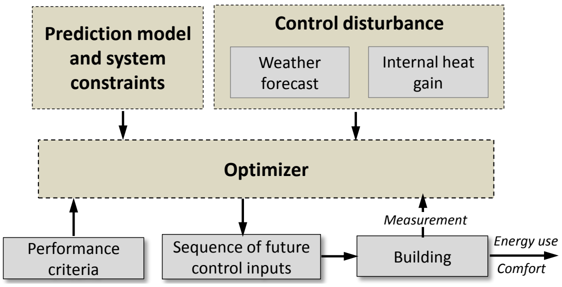

Figure 4: Framework of model predictive control for mixed-mode cooling

Cost function and constraints

The goal of MPC for mixed-mode buildings is to optimize the switching between natural and mechanical cooling. In the present study, the decision space is the operating schedule of the motorized openings and the objective is to minimize energy use with comfort constraints. The problem can be mathematically formulated as:

Minimize: $J(\overrightarrow{IO_t}) = E$ (3)

Subject to: $\overrightarrow{IO_t} = \{0, 1\}$;

W_{speed}<7.5 m/s; $T_{dew} \leq 13.5$ °C;

$T_{ope} \in$ [23 °C, 27.6 °C] during occupancy hours;

$T_{setpoint} \in$ [21 °C, 24 °C] during occupancy hours;

where, E is the energy cost (mechanical cooling and mechanical fan) determined through energy simulation, $\overrightarrow{IO_t}$ is the vector of binary (open/close) decisions for the motorized openings.

Optimal decisions are also constrained by a maximum wind speed W_{speed} (i.e. 7.5 m/s) (Aggerholm, 2002). In order to avoid excessive moisture accumulation into the building, the outside dew point temperature T_{dew} is limited to 13.5 °C – the same value applied in air economizer for high-limit shutoff control (ASHRAE, 2010). During occupied hours (8:00 am – 6:00 pm), the set point temperature $T_{setpoint}$ is allowed to fluctuate between 21 °C to 24 °C (ASHRAE, 2010). A typical nighttime setback control strategy is applied with a set point temperature range from 13 °C to 30 °C. The operative temperature T_{ope} during the occupied period is maintained between 23 °C and 27.6 °C, (corresponding to 80% occupant satisfaction, ASHRAE, 2010). The operative temperature constraint is not applied when the building is not occupied.

Optimization environment

The nature of the optimization problem does not allow the use of traditional gradient or pattern search techniques to find minima as the decision space contains discontinuities, i.e. the open/close (1 or 0) position of the motorized openings. Thus, the meta-heuristic search technique particle swarm optimization (PSO) is used to search the decision space for optimal solutions (Kennedy et al., 2001). PSO has already been embedded in GenOpt (Wetter, 2011) – an optimization module for the minimization of a cost function that is evaluated by an external simulation program. Figure 5 shows the optimization environment and the general solution approach. In one generation, potential operation schedules ("seed") of envelope openings are generated by the PSO algorithm and the schedules are evaluated in MATLAB where the building energy prediction model is used to evaluate the cost function. Results are read back into GenOpt and the PSO algorithm decides how to proceed to the next generation of potential schedules. The iteration continues until the desired criteria are reached. However, PSO requires careful adjusting of parameters such as neighborhood topology, decision space discretization, and seeding to achieve converged results. The approach suggested by Kennedy and Eberhart (2001) was applied for the settings. Based on the analysis performed, the von Neumann neighborhood topology method and a population size of 30 with 1000 generations worked well for the optimization problem in this study.

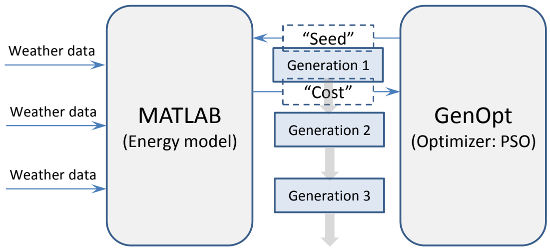

Figure 5: Optimization environment

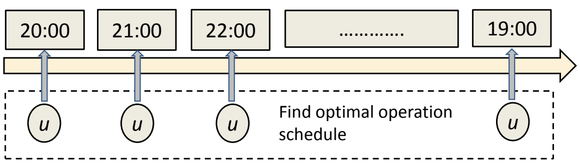

Figure 6: Optimization horizon

For the cases under consideration, one optimal control sequence which is the hourly operation schedule of the motorized openings is formulated over a 24-h planning horizon beginning from 20:00 at night to 19:00 in following day (Figure 6). The thermal history of the building is preserved by running the simulations for a historical horizon.

Based on initial analysis, a period of seven days was found to be sufficient for capturing the thermal memory of the building.

SIMULATION RESULTS

Simulations were performed using Montreal TMY3 data for six consecutive days (Figure 7) during summer to demonstrate the potential performance bounds of MPC strategies through its comparison with (a) baseline simulations (mechanical cooling with night set back); (b) standard heuristic rules used in current practice ($T_{amb} \in [15℃, 25℃]$, $T_{dew} \leq 13.5$ ℃, $W_{speed} < 7.5$ m/s). The main assumptions are outlined below:

- Mean velocity and turbulence intensity were not used in the thermal comfort evaluation;
- Local controllers were ideal such that all feedback controllers follow set-points exactly;
- Internal heat gains (occupancy, lighting) were not considered;
- An idealized mechanical cooling system with a COP value of 3.5 was modeled.

The analysis presented in this paper is limited to southwest orientation (atrium zone) due to the higher risk of overcooling during morning hours. Results for the operation schedule are presented in Table 1 with the daily energy consumption and mean operative temperature deviation from the desired shown in Figure 8. The mean operative temperature deviation is obtained by

$$\overline{\Delta T}_{ope} = \frac{\sum_{occupied}(\Delta T^{i}_{ope} \cdot \Delta\tau^{i})}{\sum_{occupied}(\Delta\tau^{i})} \quad (4)$$

where ΔT_{ope} is the operative temperature deviation, at each time step, $\Delta\tau$.

Generally, compared with the baseline case, the mixed-mode cooling strategy effectively reduces building cooling energy by 83% for the heuristic case and 75% for the MPC case (Figure 8). However, the heuristic strategy can lead to mean operative temperature deviation up to 0.7 °C, which may decrease the comfort acceptability from 80% to 60% (Olesen, 2006). This problem was avoided by the MPC optimizer with fewer cooling hours at night or early morning (Day 1, 4, and 5). In summary, Figure 8 shows that better thermal comfort is achieved with the MPC optimizer though there were possibilities of less cooling load reduction (i.e. Day 1 and 5).

Furthermore, the trade-off between thermal comfort and cooling energy reduction resulted in natural ventilation during hours with lower temperatures with the MPC optimizer, which were excluded by the heuristic strategy, but with less total opening hours (Day 5).

Impact of shading control

Besides local weather conditions, high performance features such as shading control, thermal mass, and exhaust fan assist affects the optimal control sequence for buildings with mixed-mode cooling. Simulations were performed with shading devices (roller shades with total transmittance of 6.4% and total absorptance of 47.1%) and the following heuristic control rule: the façade would be fully shaded when the transmitted solar irradiance is higher than 400 W/m^2, otherwise, the façade would not be shaded. Table 2 lists the operation schedule for the cases with and without shading while Fig. 9 shows results for the daily cooling energy consumption and mean operative temperature deviation.

Different schedules are observed during days with high solar heat gain. The MPC optimizer did not allow warm air drawn into the building by natural ventilation (15:00 ~ 17:00 for Day 1, 14:00 ~ 16:00 for Day 5) to avoid increase of the operative temperature beyond the upper bound.

With shading control, there is more direct cooling during the day, significantly reducing the cooling requirement, and less natural ventilation hours at night which further eliminates the need for overcooling in the morning. Furthermore, decrease of solar heat gains with shading control leads to less heat storage in building mass and shorter free cooling time is needed in the following night (i.e. Day 5 and Day 6).

Impact of thermal mass

Model predictive control strategies typically show good performance for dynamic systems whose response time is large. This section looks into the impact of thermal mass on optimal decisions by having different floor capacitance: 38 Wh/°C·m^2 and 64 Wh/°C·m^2, representing a light and heavy floor respectively. Results indicate significant differences in the night ventilation schedules obtained with the predictive strategy compared to those based on

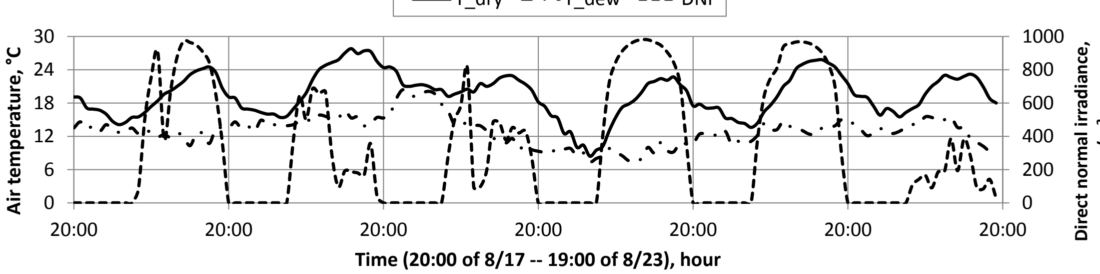

Figure 7: Weather conditions used for the simulation study

Table 1: Operation schedule using heuristic and MPC strategies (hours during which windows are open are illustrated by cells with dark background)

	Time	20:00	21:00	22:00	23:00	24:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00
Day 1 (8/18)	Heuristic																								
	MPC																								
Day 2 (8/19)	Heuristic																								
	MPC																								
Day 3 (8/20)	Heuristic																								
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Day 4 (8/21)	Heuristic																								
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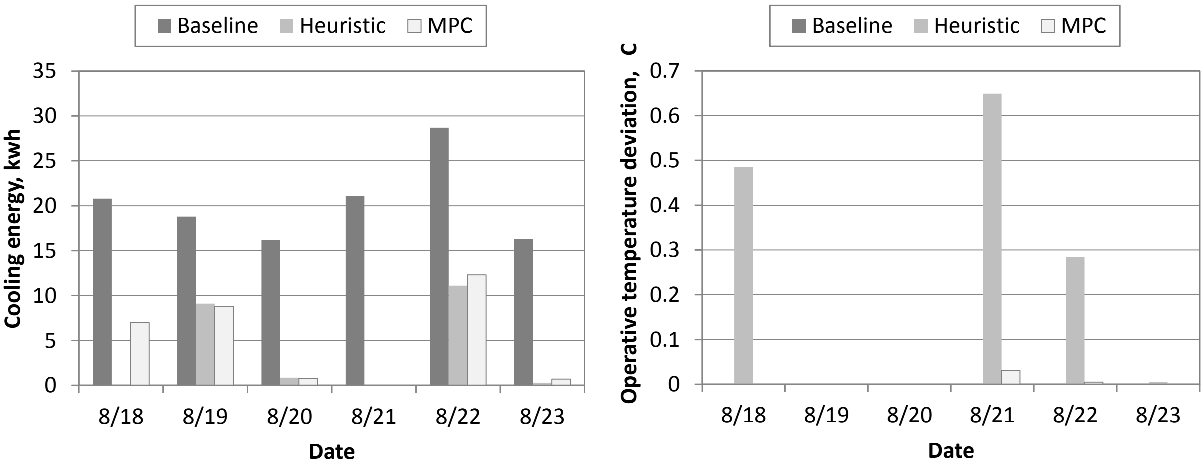

Figure 8: Cooling energy consumption (left) and mean operative temperature deviation (right)

Table 2: Operation schedule using heuristic and MPC strategies with shading control (hours during which windows are open are illustrated by cells with dark background).

	Time	20:00	21:00	22:00	23:00	24:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00
Day 1 (8/18)	Heuristic																								
	MPC (No)																								
	MPC (Yes)																								
Day 2 (8/19)	Heuristic																								
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	MPC (Yes)																								
Day 3 (8/20)	Heuristic																								
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Day 4 (8/21)	Heuristic																								
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	MPC (Yes)																								
Day 5 (8/22)	Heuristic																								
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Day 6 (8/23)	Heuristic																								
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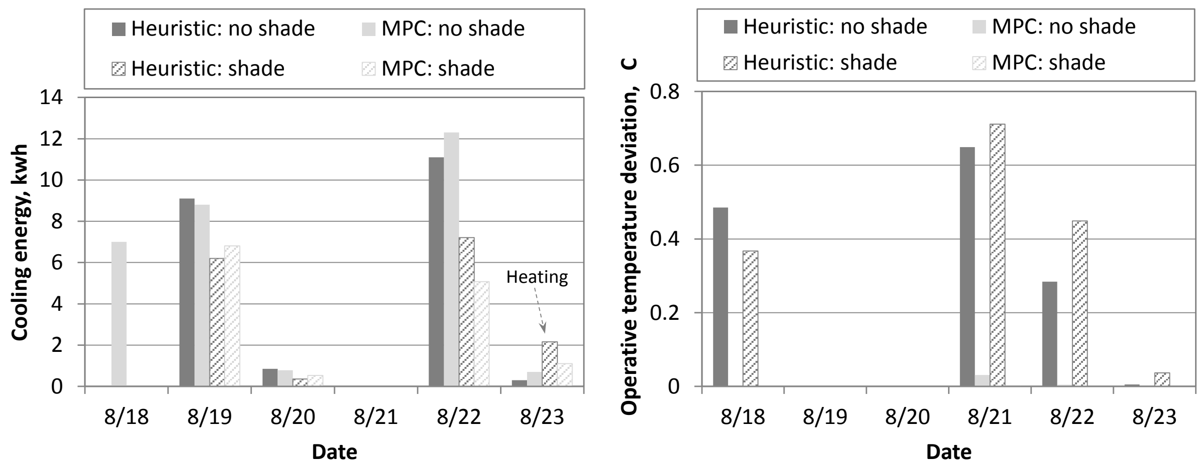

Figure 9: Simulation results for the impact of shading control: cooling energy consumption (left) and mean operative temperature deviation (right)

heuristics. With heavier mass, the MPC optimizer scheduled either longer night cooling hours or cooling during hours with low outdoor air temperatures as heavier thermal mass stores more heat. Although there is no significant difference in the overall energy consumption (Figure 11), the predictive control strategy results in 5% peak load reduction in Day 1 and 5 for the case with higher thermal mass (Figure 12).

Impact of exhaust fan

This section investigates the influence of exhaust fan on optimal control strategies for mixed-mode cooling. In this case, the MPC optimizer seeks the operation schedule for motorized openings and the flow rate for the exhaust fan. The cost function also includes the exhaust fan energy consumption:

$$\text{Minimize: } J(\overrightarrow{IO}_t) = E + E_{fan} \qquad (4)$$

The operation of the exhaust fan was restricted to unoccupied hours when the motorized openings were open. The comparison between cases with and without the exhaust fan is restricted to unoccupied hours (planning horizon: 20:00 – 07:00). Table 3 lists the optimal decisions for the two cases and shows that less cooling hours are required with the exhaust fan. Results for the flow rate and pressure drop through the openings show that the exhaust fan strengthens the airflow into building (Figure 13).

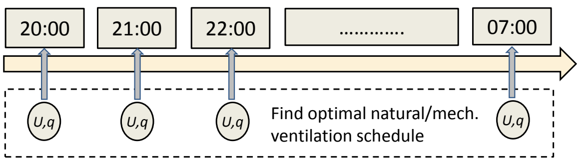

Figure 10: Optimization horizon for the case with exhaust fan assist

CONCLUSIONS

The paper presents an MPC framework and demonstrates optimal control sequences for mixed-mode cooling (window opening, fan assist, and night cooling) coordinated with the operation of shading devices for the control of solar gains, in a multi-zone building optimally designed for natural ventilation, with high levels of exposed thermal mass and a highly glazed atrium façade that assists buoyancy-driven flows. A simulation study of the building operation over a period of six consecutive summer days was conducted using Montreal TMW3 data and the following conclusions can be drawn:

1. For the simulation period considered in the present study, mixed-mode cooling strategies effectively reduced building energy consumption by 83% when decisions were made based on heuristics and 75% for anticipatory control. However, the heuristic strategy can lead to a mean operative temperature deviation up to 0.7 °C, which may decrease the comfort acceptability from 80% to 60%. On the other hand, the predictive control strategy maintained the operative temperature in desired range.
2. The coordinated use of predictive control for mixed-mode cooling and shading devices in building zones with high solar gains significantly affects the natural ventilation schedules and results in higher energy savings.
3. For the weather conditions considered in this study, the predictive control strategy results in 5% peak load reduction for the case with higher thermal mass.

The optimal control sequences presented in this paper although limited to a short period of time demonstrate intelligent mode switchings with superior overall performance that are significantly different than those based on heuristics and could not have been developed without the use of an optimization algorithm and a careful tuned building model that captures the relevant thermal and airflow dynamics (convective heat transport from massive floor slabs, air exchange between zones, natural ventilation flow rates) in multi-zone buildings with mixed-mode cooling. Although this approach is computationally expensive, it allows simulation of

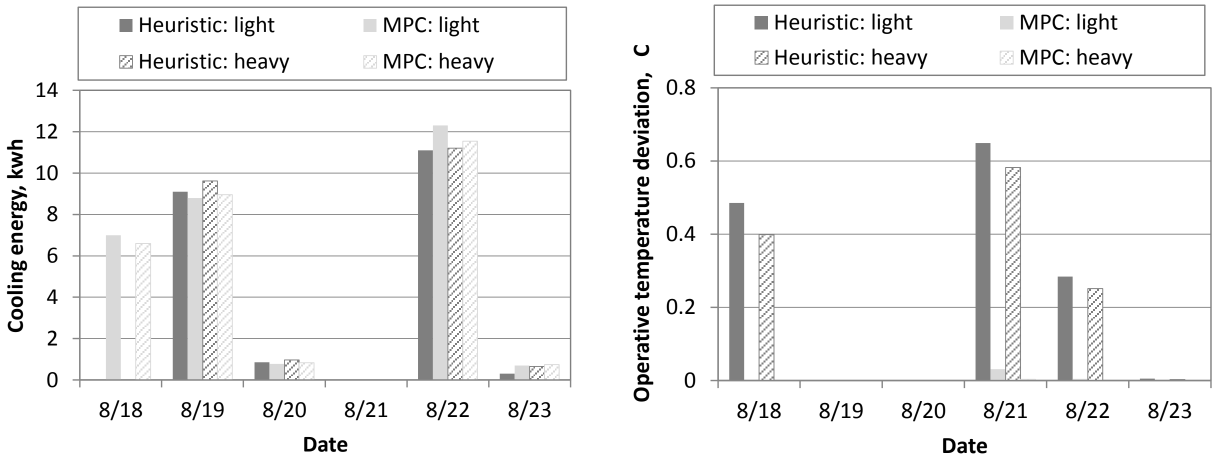

Figure 11: Simulation results for the impact of thermal mass: cooling energy consumption (left) and mean operative temperature deviation (right)

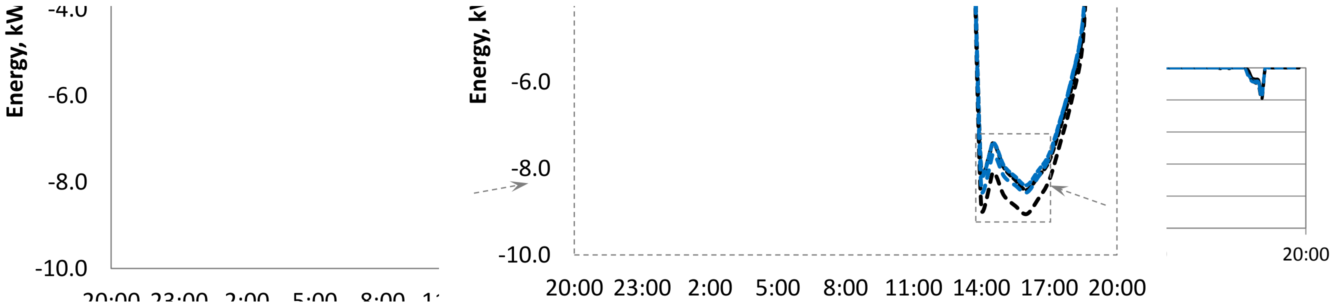

Figure 12: Cooling load profile for different thermal mass

Table 3: Motorized openings and exhaust fan operation schedule based on the MPC optimizer

Time		20:00	21:00	22:00	23:00	24:00	1:00	2:00	3:00	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00
Day 5 (8/22)	M. (NoF)																								
	M. (Fan)		(0)				(0.5)	(0.5)			(0)														

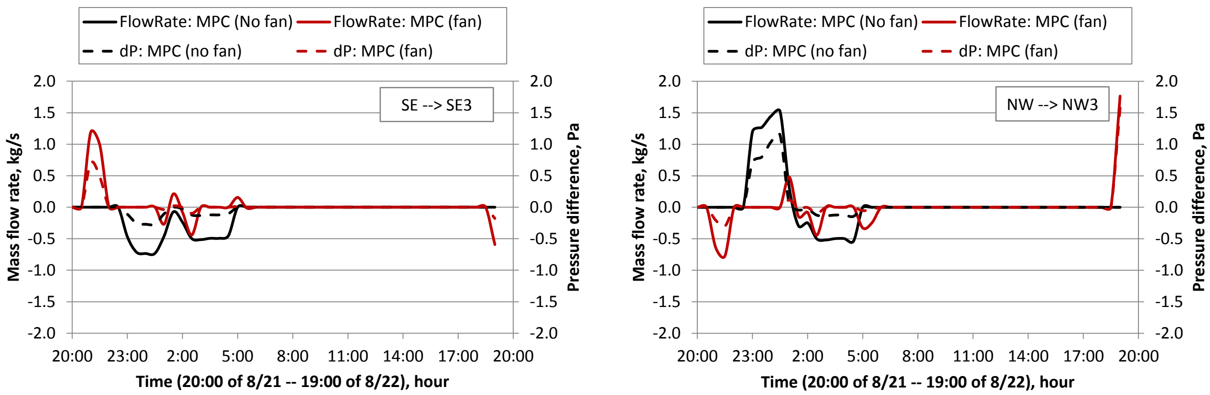

Figure 13: Mass flow rate and pressure difference across top level openings (SE and NW orientation: with and without exhaust fan)

optimal control sequences in consideration of both energy optimization and comfort maintenance and provides insight into the relevance of different design and control parameters. Current research efforts are focused on the development of simplified models in compact and flexible form (such as those based on state-space representation) which are necessary for real-time application of anticipatory control strategies in buildings. These models can be easily extended to incorporate uncertainty due to weather forecast and facilitate the development of robust control strategies. However, these simplifications would not be possible without the detailed model and the MPC framework developed in the present study, as model complexity is not known *a priori*.

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