Centralized Management of HVAC Energy in Large Multi-AHU Zones

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ABSTRACT

HVAC control strategies that exploit temporal variations in zone occupancy have been well studied. However, at a given time, occupancy can also vary spatially within a single large zone with no internal wall partitions, that is served by multiple AHUs. We complement prior work by studying how spatial variations in a large zone can be leveraged to save energy and improve occupant comfort. Specifically, we propose a novel strategy for centralized reactive control of all the AHUs serving a large zone, MAZIC (Multi-AHU Zone Intelligent Control). To decide control outputs, we use a thermal model to capture the mixing of heat loads across different regions of the large zone served by different AHUs. We study MAZIC's performance in terms of energy consumption and comfort using real-world occupancy data. When the spatial skew in occupancy is high, MAZIC reduces energy consumption by 11% over individual PID controllers running at each AHU, while maintaining similar comfort levels. Sensing temperature and occupancy at finer spatial resolution helps both MAZIC and PID controllers to save more energy when the occupancy is skewed. Finer spatial sensing does not add much value when the occupancy is not so skewed. We also find that augmenting MAZIC with a MPC (Model Predictive Control) approach yields insignificant improvement ($< 3\%$) during normal occupancy. With ON-OFF occupancy patterns, MPC improves energy savings by up to $\sim 6\%$ over reactive MAZIC.

Keywords

Energy, HVAC, optimization, occupancy sensing, control

Categories and Subject Descriptors

G.1.6 [**Optimization**]: Constrained optimization; J.2 [**Physical Sciences and Engineering**]: Engineering

1. INTRODUCTION

The raison d'être of HVAC systems is to ensure building occupant comfort. Understanding when and where people are present inside a building can help to better control the HVAC systems. Occupancy based control strategies are useful when there is skewness in occupancy, so that the instances of lean occupancy can be exploited. Researchers have proposed reactive and predictive control strategies that exploit temporal variations in occupancy to reduce HVAC energy consumption with little or no negative impact on occupant comfort. Our work stems from the observation that apart from time, occupancy can be skewed across space – i.e., different areas within a zone can have different occupancy levels at the same time. This skewness can become more pronounced in large zones. Such large zones can be typically found in commercial and office buildings with open floor workspaces, airports, cinemas, and concert halls. These large zones will be served by several air handling units (AHUs), or in some configurations, by variable air volume terminal units (VAVs).

Definition: We refer to a large zone served by multiple AHU's as a Multi-AHU Super-zone (MAS). Within a MAS, we refer to the primary regions of influence of individual AHUs as *zones*. A key feature of a MAS is that zones served by individual AHUs within the MAS are *not* separated by any physical walls or partitions.

Problem: In a MAS, significant spatial variations in occupancy can occur across the constituent zones, especially during off-design operating conditions such as weekend shifts in offices. This can allow us to condition zones with varying occupancy densities differently. Specifically, occupied zones can be maintained at a desired set-point temperature, while vacant zones can drift to a setback temperature. Such a skewed set-point strategy could potentially conserve energy without compromising on occupant comfort. To the best of our knowledge, this potential to save energy in MAS configurations by exploiting the spatial skew in occupancy has not been investigated previously.

Challenges: Exploiting spatial heterogeneity in a MAS is nontrivial for the following reasons. In a MAS, the air mass and heat across different zones mix due to lack of partitions between them. Therefore, the conditioned temperature within a zone not only depends on the air flow setting of that zone's AHU but also on the settings of the AHUs serving the neighboring zones. In other words, AHUs of different zones remain thermally coupled and are not independent. Consequently, *the individual AHUs, if controlled independently in isolation as done by conventional PID controllers, may not give the best performance*. Further, the mixing of air mass and heat across different zones limits the ability to maintain desired temperature skewness in the super-zone. Therefore the extent to which the zone temperatures can drift during lean occupancy (and hence the energy savings achievable) is also limited.

Given these observations, the following questions arise:

- Can we control the AHUs serving a MAS in a centralized manner, taking into account the influence of mixing of air-mass and heat across the various zones?

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- Can such a strategy better exploit the spatial skew in occupancy to save energy and/or improve comfort when compared to conventional individual PID controllers?
- How will different occupancy patterns and the associated sensing infrastructure (i.e., sensing at different spatial resolution) affect the centralized controller's performance?
- Can model-based population predictive control (MPC) improve the HVAC performance in the case of MASes or is a reactive control sufficient?

We address the above questions in our work. To the best of our knowledge, this is one of the first few works to study the control of AHUs in a MAS configuration. Our specific *contributions* are:

- We develop a thermal model to capture the influence of mixing of heat and air-mass between the various zones in a MAS. We solve this model using a fixed point iteration technique to obtain the temperatures and humidities at various zones for given boundary conditions.
- Based on this thermal model, we develop a centralized reactive control strategy MAZIC (Multi-AHU Zone Intelligent Control) for setting the flow rates of the AHUs serving the MAS. Our strategy minimizes the HVAC energy consumption subject to the constraints given on occupant comfort.
- We collect occupancy traces and HVAC system configuration from large multi-AHU zones in a real-world office building. We study the performance of MAZIC on this real-world data through co-simulations involving MLE+ [10] and EnergyPlus. We also study the effect of sensing occupancy and temperature at different spatial resolutions on the resulting energy savings/comfort improvement.
- We evaluate the performance of MAZIC with and without MPC strategy for these real-world occupancy traces.

Our findings from these studies are as follows:

- When the spatial skew in occupancy is high, MAZIC reduces energy consumption by 11% when compared with conventional PID controllers while maintaining similar comfort levels **confirming that centralized coordination of multiple AHUs in a MAS helps over individual control.** When the spatial skew is not high, the performance of the two controllers are comparable as there is not enough opportunity to maintain a temperature skew.
- Sensing temperature and occupancy at finer spatial resolution helps MAZIC and PID controllers to save more energy when the occupancy is skewed. Finer spatial sensing does not add much value when the occupancy is not so skewed.
- MAZIC's performance is robust to reasonable inaccuracies in estimating the values of thermal model parameters.
- For the real world occupancy patterns observed in our office facilities, we find that **the difference in energy savings between MAZIC with and without MPC is not high ($<$ 3% even with perfect occupancy prediction)**. However, we find that with ON-OFF occupancy patterns that occur in MASes in other facility types such as cinemas and concert halls, the difference increases up to $\sim 6\%$.

The rest of the paper is organized as follows. We present our reactive control strategy for MASes in Section 2. Section 3 presents the thermal model for a MAS which is used by our controller. Section 4 discusses the experimental set-up and the occupancy traces collected. Section 5 evaluates the performance of the proposed control strategy under MAS configurations found in our facilities using the collected traces. Section 6 presents a survey of related work. Section 7 concludes the paper.

Symbol	Meaning	Units
t	Time instant	s
Δt	Time step at which the HVAC system is controlled.	s
N	Number of zones	Count
E_H	HVAC energy over $[t, t+\Delta t]$	kWh
M_i	Supply mass flow rate of AHU i	kg/s
$\mathbf{M}$	Vector of mass flow rates across all AHUs	kg/s
Π_i	Population in region i	Count
$\mathbf{\Pi}$	Vector of population across all regions	Count
T_i	Temperature of region i	$^{\circ}$C
$\mathbf{T}$	Temperature vector across all regions	$^{\circ}$C
W_i	Humidity ratio of region i	$kg_{\text{water}}/kg_{\text{air}}$
$\mathbf{W}$	Humidity ratio vector across all regions	$kg_{\text{water}}/kg_{\text{air}}$
$\mathbf{RH}$	Relative humidity vector across all regions; can be obtained from $\mathbf{W}$ and $\mathbf{T}$.	$\%$

Table 1: Notation used in the control problem formulation

2. HVAC CONTROL IN *MAS*

A MAS is served by several AHUs. A MAS is logically partitioned into zones. A zone is defined as the area that comes under the influence of one AHU. Each zone, in turn, is further logically partitioned into cells or sub-zones. A cell is region of space such that temperature and humidity ratio remain uniform within it. Figure 1 shows a partitioning of a MAS into zones and cells.

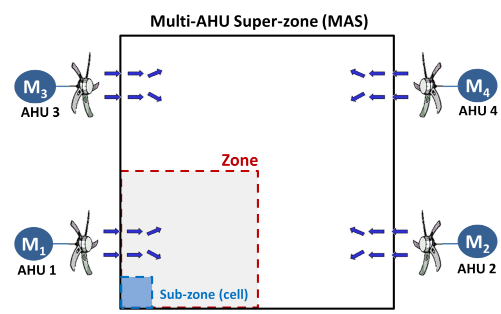


Figure 1: Schematic representation of a MAS. The controlled parameters are the AHU flowrates: M1, M2, M3, and M4, in both the conventional and proposed control methods. There are no physical partitions inside the super-zone. All figures are best seen in color.

Conventional control: In a MAS configuration with conventional individual PID controls, each AHU senses the temperature of its zone (T_i) through the returning air, and adjusts its flow rate to maintain a set-point for its zone within a given dead-band. Since air mixes across the zones, an AHU's flow influences the temperature and humidity in neighboring zones as well. While the PID controller can indirectly sense this mixing and adjust the AHU flow rates accordingly, it need not be energy optimal for the same comfort level. This is because, the set of control actions each AHU can take in isolation is a subset of any joint action across all AHUs. Therefore, we expect potential energy saving opportunities when the AHUs are jointly or centrally controlled in comparison to individual PID control. With this insight, we propose a new control strategy MAZIC (Multi-AHU Zone Intelligent Control) that operates the ensemble of AHU's in a centralized way.

2.1 MAZIC

Notation used is summarized in Table 1. In our coordinated control, the control decision taken at time t identifies the mass flow rates for all AHUs, $\mathbf{M}(t)$, to be maintained over $[t, t+\Delta t]$ to achieve comfort at $t+\Delta t$ while minimizing HVAC energy over $[t, t+\Delta t]$. Therefore, given the operating conditions at t, the controller should search through the space of all possible flow rate vectors $\mathbf{M}$ and identify an optimal $\mathbf{M}_{opt}(t)$ that can meet the comfort and minimize energy.

For a given flow rate $\mathbf{M}$, the power consumed by the HVAC system can be obtained from the power models of the AHU fans and chiller as a continuous function $E_H(\mathbf{M})$. This continuous function can be minimized using standard techniques provided the search-space is constrained to those regions where comfort is met. Because the comfort is a function of zone temperatures $\mathbf{T}(t+\Delta t)$ and humidity ratio $\mathbf{W}(t+\Delta t)$, we need to solve for $\mathbf{T}$ and $\mathbf{W}$ as a function of any candidate $\mathbf{M}(t)$ that the optimizer considers. The thermal model that we develop in Section 3 does this.

The goal of the control strategy then is to minimize the (objective function) total HVAC energy $\min E_H(\mathbf{M})$ over $[t, t+\Delta t]$ subject to the constraint that comfort provided is acceptable. The optimization problem is formally specified below.

2.2 Optimization problem

Mathematically, the optimization problem solved by MAZIC in each time step can be expressed as follows:

$$\min_{\mathbf{M}} \qquad E_H(\mathbf{M}) = \mathcal{F}_{ahu}(\mathbf{M}) + \mathcal{G}_{chiller}(\mathbf{M}) \tag{1}$$

$$\text{subject to} \begin{cases} \mathcal{T}_{Low} & \leq \frac{\mathbf{\Pi}.\mathbf{T}}{\sum_i \Pi_i} \leq \mathcal{T}_{High}, \text{if } \sum_i \Pi_i \neq 0, \\ \widehat{\mathcal{T}}_{Low} & \leq \frac{\sum_i T_i}{N} \leq \widehat{\mathcal{T}}_{High}, \text{otherwise} \end{cases} \tag{2}$$

$$\begin{cases} \mathcal{H}_{Low} & \leq \frac{\mathbf{\Pi}.\mathbf{RH}}{\sum_i \Pi_i} \leq \mathcal{H}_{High}, \text{if } \sum_i \Pi_i \neq 0, \\ \widehat{\mathcal{H}}_{Low} & \leq \frac{\sum_i RH_i}{N} \leq \widehat{\mathcal{H}}_{High}, \text{otherwise} \end{cases} \tag{3}$$

$$\forall i, \qquad M_{min} \leq M_i \leq M_{max} \tag{4}$$

where N is the number of regions in the MAS and $\mathcal{T}, \widehat{\mathcal{T}}, \mathcal{H}$ and $\widehat{\mathcal{H}}$ are tunable parameters for the controller.

Objective function: MAZIC minimizes HVAC energy – the sum of AHU energy consumption and the energy usage of chiller/boiler units which depends on the coolth/heat drawn by the AHU coils. The energy consumed by the AHUs is a non-linear function of several parameters such as fan speeds, efficiency and the pressure difference across the fan blades, to name a few. Assuming that the AHUs are operating without any fault, given the fan speed, the value of other parameters can be derived from the manufacturer specifications. Similarly, under the assumption that the cooling coils in the AHU are operating normally, the energy consumed by the chiller can be expressed as another non-linear function of the mass flow rate across the coils [25]. Therefore, the energy consumption of both AHUs and the chiller are represented as non-linear functions of the mass flow rates in Equation 1. Before we explain the constraints, we formally define the notion of comfort.

Definition of comfort: Occupant comfort is typically characterized by Fanger's PMV (Predictive Mean Vote), as a function of temperature, humidity, velocity of air, etc. [20]. Of these parameters, we focus on zone temperature and humidity that are easily measurable. Specifically, we define an occupant to be comfortable if the temperature in their zone is within $24-26^{\circ}C$ and humidity is within $30-60\%$. We note that in reality, within these ranges of temperature and humidity, PPD (Predicted Percentage Dissatisfied) is expected to be $\leq 10\%$ as per ASHRAE Standard $55-2010$ when averaged across all people in that zone.

Constraints: Equations 2 and 3 specify that the people-weighted averages of temperature and humidity should be within given limits. Note that the comfort constraints are specified on the global people weighted temperature and humidity across the MAS rather than an individual zone. Having independent comfort constraints for each individual zone would deprive the controller of the global view needed to trade comfort in under occupied zones for energy.

The global people-weighted temperature and humidity constraints are more relaxed than enforcing the temperature and humidity constraints for comfort locally in each occupied zone. For this reason, it is possible that the optimizer provides solutions that do not provide comfort in sufficiently occupied zones. Parameters $\mathcal{T}_{Low}$, $\mathcal{H}_{Low}$, $\mathcal{T}_{High}$, and $\mathcal{H}_{High}$ help us tune the controller's bias to save energy by compromising comfort in occupied zones. When an occupancy pattern with high spatial skew (less spatial skew) is expected then the controller's bias can be made high (low) by setting the temperature range to be wide (narrow). Parameters $\widehat{\mathcal{T}}_{Low}$, $\widehat{\mathcal{H}}_{Low}$, $\widehat{\mathcal{T}}_{High}$, and $\widehat{\mathcal{H}}_{High}$ allow us to fix the set-back limits for the regions where there is no occupancy in the MAS.

A minimum amount of fresh-air must be circulated as per ASHRAE Standard $62.1-2013$ [3] to maintain air quality. The maximum amount of supply air from an AHU is also bounded. This is specified in Equation 4.

Solution: We solve this optimization problem using sequential quadratic programming (SQP) technique. The MAS state is gathered every Δt minutes and the optimization problem is solved by the controller. Based on the solution, the flow rates of the AHUs are set. We note that the resolution of the occupancy and temperature sensors could be several levels – sub-zone, zone, or the entire MAS. Accordingly, the value of the comfort vector will change thereby affecting the state space of the solution. This in turn, could affect the quality of the solution found. We study this in Section 5.

3. THERMAL MODEL FOR *MAS*

Recall that a MAS is virtually partitioned into several zones, which are in turn partitioned into sub-zones or cells. The state of a MAS is defined as the collection of temperature and humidity values across all the cells. For a given setting of AHUs fan flow rates serving the MAS, a thermal model can estimate the MAS state after factoring in the mixing of air mass across zones. Such a model can be used by a centralized controller to decide the coordinated fan settings for the AHUs while maintaining comfort.

3.1 State model

Model for temperature: As shown in Figure 1, a cell i can be bounded by surfaces (walls) and/or other cells. Cell i's temperature, T_i, is the result of several heat gains (or losses): (i) internal heat gained due to lighting, equipment, and people present within cell i; (ii) heat convected from adjoining walls and windows; (iii) heat gained from neighboring cells due to mixing of air mass; and (iv) coolness supplied by AHUs serving the cell. Accordingly, with reference to the notations in Table 2, T_i can be expressed as:

$$\begin{aligned} C_i \frac{dT_i}{dt} = Q_{i,int} &+ \sum_{w \in \mathcal{W}_i} h_w A_w (\tau_w - T_i) \\ &+ \sum_{j \in \mathcal{N}_i} \dot{m}_{i,j} C_{P_i} (T_j - T_i) \\ &+ \dot{m}_{i,sup} C_{P_i} (T_{i,sup} - T_i) \end{aligned} \tag{5}$$

Symbol	Meaning	Units
C_i	Heat capacitance of air mass in cell i.	$J/°$C
C_{P_i}	Specific heat capacity of air in cell i	$J/kg/°$C
ρ_i	Density of air in cell i	kg/m^3
V_i	Volume of cell i	m^3
$\mathcal{N}_i$	Set of cells that adjoin cell i	Count
$\mathcal{W}_i$	Set of walls that adjoin cell i	Count
h_w	Convective heat transfer coefficient of wall w	$W/m^2/°$C
τ_w	Surface Temperature of wall w	°C
A_w	Area of wall w	m^2
$Q_{i,int}$	Internal heat load of cell i	W
$\dot{m}_{i,j}$	Mass flow rate of air from cell j that mixes with cell i.	kg/s
$T_{i,sup}$	Temperature of the air mass supplied by AHU to cell i	°C
$\dot{m}_{i,sup}$	Flow rate of the air mass supplied by AHU to cell i	kg/s
$\dot{m}_{i,mstr}$	Rate of moisture addition to cell i	kg/s
$W_{i,sup}$	Supply air humidity ratio of AHU to cell i	kg_{water}/kg_{air}

Table 2: Notation used for thermal model

We can discretize equation 5 using first-order **backward** Euler method. After some algebra, we get the following equation to determine T_i:

$$T_i^{t+\Delta t} = \frac{\alpha_T + \beta_T \cdot \dot{m}_{i,sup}}{\gamma_T + \zeta_T \cdot \dot{m}_{i,sup}} \text{ where} \tag{6}$$

$$\alpha_T = \left(\sum_{w\in\mathcal{W}_i} h_w A_w \tau_w\right)^{t+\Delta t} + \left(\sum_{j\in\mathcal{N}_i} \dot{m}_{i,j} C_{P_i} T_j\right)^{t+\Delta t} + Q_{i,int}^{t+\Delta t} + \left(\frac{C_i}{\Delta t} T_i\right)^t$$

$$\beta_T = \left(C_{P_i} T_{i,sup}\right)^{t+\Delta t}$$

$$\gamma_T = \sum_{w\in\mathcal{W}_i} A_w h_w{}^{t+\Delta t} + \left(\sum_{j\in\mathcal{N}_i} C_{P_i} \dot{m}_{i,j}\right)^{t+\Delta t} + \left(\frac{C_i}{\Delta t}\right)^t$$

$$\zeta_T = C_{P_i}{}^{t+\Delta t}$$

Model for humidity. Cell i's air humidity ratio, W_i can be written from first principles as:

$$C_i \frac{dW_i}{dt} = C_{P_i} \cdot \left(\dot{m}_{i,mstr} + \sum_{j\in\mathcal{N}_i} \dot{m}_{i,j}(W_j - W_i)\right) + C_{P_i} \dot{m}_{i,sup}(W_{i,sup} - W_i) \tag{7}$$

As with the temperature, equation 7 can be discretized using first-order **backward** Euler method and after some manipulations, the cell humidities at $t + \Delta t$ can be expressed as

$$W_i^{t+\Delta t} = \frac{\alpha_W + \beta_W \cdot \dot{m}_{i,sup}}{\gamma_W + \zeta_W \cdot \dot{m}_{i,sup}}, \text{ where} \tag{8}$$

$$\alpha_W = \dot{m}_{i,mstr}^{t+\Delta t} + \left(\sum_{j\in\mathcal{N}_i} \dot{m}_{i,j} W_j\right)^{t+\Delta t} + V_i \left(\frac{\rho_i W_i}{\Delta t}\right)^t,$$

$$\beta_W = W_{i,sup}^{t+\Delta t},$$

$$\gamma_W = \left(\sum_{j\in\mathcal{N}_i} \dot{m}_{i,j}\right)^{t+\Delta t} + V_i \left(\frac{\rho_i}{\Delta t}\right)^t, \quad \zeta_W = 1.$$

3.2 Solving for the state

Note that Equations 6 and 8 are implicit in terms of the state variables T_i and W_i at time $t+\Delta t$. Because air mass and heat flow across the sub-zone boundaries, these equations also involve the state variables $T_j^{t+\Delta t}$ and $W_j^{t+\Delta t}$ of other cells, $j \neq i$. We have a set of such equations – two for the state of each cell. This set can be solved simultaneously using a fixed-point iteration technique to arrive at the state of all the cells at $(t + \Delta t)$.

However, to solve these equations, several inputs (listed in Tables 1 and 2) are required. Some of these such as T_i^t, W_i^t, $\dot{m}_{i,sup}$, $T_{i,sup}$, and $W_{i,sup}$ can be measured through commonly available temperature, humidity and flow rate sensors. The surface area of the walls and surfaces, A_w, can be obtained from plan drawings or actual measurements. The internal heat load, $Q_{i,int}$, can be estimated using the connected electrical loads and people count. Parameters such as $C_{P\,i}$ and C_i can be estimated using standard psychrometric functions [26]. The inter-zone mixing flow rates, $\dot{m}_{i,j}$'s, can be arrived at using standard density based estimations [21]. Since our work focuses on MASes in office buildings, moisture addition $\dot{m}_{i,str}$ is mainly due to people which can be estimated using a model [16].

The major challenge comes in obtaining the surface temperature τ_w of walls. This can be measured by deploying sensors such as infra-red temperature recorders. Since such sensors may not be readily available in most facilities, we have developed an alternative empirical model that estimates τ_w as a function of the easily measurable ambient and zone temperatures. We do not discuss this model for the sake of brevity. From τ_w and T_i, the surface convective heat transfer coefficient h_w can be estimated [16]. To summarize, the inputs required for solving for the MAS state with our thermal model can be obtained using a combination of sensory measurements, psychrometric properties, and empirical models.

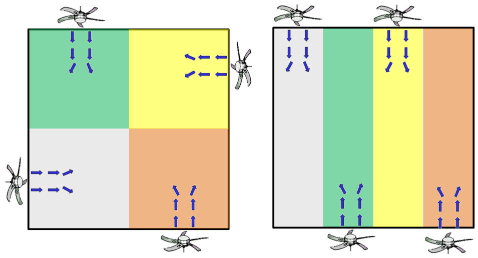
4. SETUP FOR PERFORMANCE STUDY

We now evaluate the performance of the controller and the associated MAS thermal model. Ideally, MAZIC's performance should be studied in a real-world MAS for adjusting the MAS state as per the occupancy information. The AHU control systems in our facilities take temperature values as reference set-points; based on this set point and the actual zone temperature, their PID controllers throttle the flow rates. Setting the flow rates directly while bypassing the PID control was not immediately possible with our facility's existing hardware. Due to this limitation, we study MAZIC's performance through energy and comfort simulations in EnergyPlus [16] using calibrated models of MAS zones found in our office buildings along with corresponding occupancy traces. In real-world settings, MAZIC can be implemented using programmable logic controllers by appropriately wiring the feedback sensors and AHU's VFDs. We evaluate MAZIC for space cooling though it is equally applicable for space heating as well.

4.1 MAS Configuration

Two different MAS configurations are present in our office facilities: (1) Cross-flow configuration; and (2) Parallel-flow configuration. These are shown in Figure 2. The region of influence of each AHU in these configurations is indicated as a shaded area. A zone in a cross-flow configuration shares its boundaries with several neighboring zones; therefore the extent of thermal coupling among the zones is higher in cross-flow configuration than that in parallel-flow configuration.

We study a MAS located in a multi-storey office facility in a city with a tropical hot and humid climate in southern India. This building has seven floors, and each floor has two wings. Each wing



(a) Cross-flow (b) Parallel-flow

Figure 2: Two MAS configurations found in our offices.

in a floor is a *cross-flow* MAS served by four AHUs. We simulate the performance of MAZIC in one such MAS.

The studied MAS has an area of $20,000$ ft^2. It is rectangular in shape with an aspect ratio of 2.0. Each of the four AHU's has a capacity of 20 TR, capable of delivering a flow rate of 11000 cfm. The AHU system is sized for an occupancy of 200 people (100 ft^2 per person). The office hours are 09:00 to 18:00 on Monday through Saturday. The region of influence of each AHU is obtained from the actual air-flow ducting in the floor and the location of the supply diffusers from each AHU. The duct layout was symmetric and hence, the regions of influence for all AHUs are uniform. Based on the temperature profile sampled within various zones, we logically divide each AHU zone into four equal sub-zones.

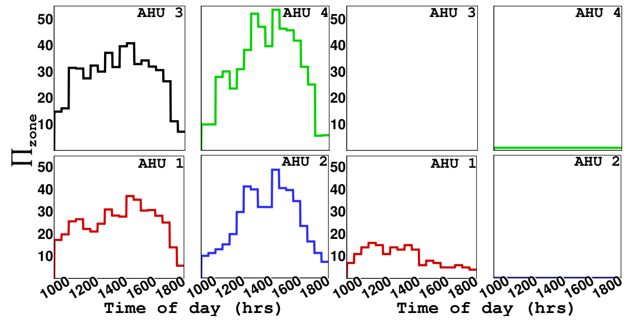
4.2 Calibrating MAS model in EnergyPlus

To study the performance of MAZIC using simulations, the EnergyPlus simulation model of the real-world MAS should be well calibrated. A proper model calibration of the MAS in EnergyPlus requires that for each value of AHU fan flow vector $\mathbf{M}$, the simulation should produce conditions equivalent to the real-world MAS in terms of (1) AHU energy consumption; and (2) Zone temperature vector ($\mathbf{T}$) and zone humidity vector ($\mathbf{W}$). Calibration involves modeling the building shell, heat loads, and the HVAC systems.

While obtaining data related to the building shell and heat load was relatively easier, we found that modeling with respect to the HVAC energy consumption was not straight forward. The reason is as follows. The MAS under study is served by a common chiller facility that is shared by several buildings. Therefore, obtaining floor-specific chiller consumption was not possible. Therefore a chiller of suitable equivalent size is modeled in the simulations. Specifically, we choose a chiller of suitable tonnage that is capable of maintaining the temperature of the air mass supplied by the AHUs at 13^oC (as is the case in the real-world facility under study). For the AHU fans, we have used the actual AHU fan power curves from manufacturer specifications in our simulation model. Finally, to calibrate the zone temperatures, we have used temperature readings at regular grid points (underneath selected flow vents) in the office obtained using an infrared gun thermometer. The simulation model's internal heat gain parameters were tuned till the sub-zone temperatures computed by the model match with the corresponding actual readings within a maximum error of $\pm 0.6^oC$.

4.3 Occupancy traces

In our office set-up, each cubicle has one desktop. We collected floor occupancy data through a desktop application that was installed in each desktop. The application detects the presence of an employee through monitoring the desktop activity at periodic intervals of 30 minutes. We collected this data for 2 months with 50 (working) weekdays, 8 weekends and 3 holidays. We clustered these occupancy traces and obtained a set of eight different design days –four each for weekdays and weekends. We performed sanity checks to ensure that the sum of sub-zone level occupancies obtained from the desktop applications matches with the aggregate swipe card information of the facility. In the interest of space and clarity, we show the occupancy pattern (at zone level) that occurs more often in Figure 3. We note the following from the pattern:



(a) Weekday (b) Weekend

Figure 3: Design-day zone level occupancy in the MAS

- The MAS has been designed for an occupancy of 200. However, the actual peak head-count we observed is about 180.
- On weekdays, there is little spatial skew in terms of the occupancy.
- The occupancy is sparse during weekends. Specifically, only one project group comes to work on most weekends. The other zones are almost unoccupied. This skew creates an opportunity that can possibly be exploited by MAZIC to save energy without compromising the comfort.

5. EVALUATION

Experiment design space: Recall that the key questions that motivated this work are: (1) in a MAS, can centralized AHU control (based on inter-zone air mixing model) exploit spatial skew in occupancy better than individual AHU control (based on PID) to save energy and/or improve comfort? (2) how will different occupancy patterns and the associated sensing infrastructure affect the controller's performance? and (3) is a reactive controller sufficient or can a model-based population predictive control (MPC) improve the performance of a centralized controller in the case of MASes?

While each question addresses an orthogonal facet of the problem, the design space of our experiments needs to handle them all at a time and identify general observations that answer these questions. To this end, we consider an elaborative set of experimental scenarios summarized in Table 3. Each scenario is characterized by the following attributes: (i) control strategy used along with the prediction horizon used by the controller (reactive or predictive). (ii) the spatial resolution at which occupancy and temperature information is sensed; and (iii) the comfort constraints used.

For ease of understanding, the signal that is fed back to the controller is also listed. We implement MPC as a receding horizon control starting from the current system state. Since temperature sensing at resolutions finer than occupancy (and vice-versa) does not add any value in estimating the people weighted temperature, both temperature and occupancy are sensed at the same resolution (as used in Equation 2). Henceforth, the term "sensing" refers to both temperature and occupancy sensing.

The baseline strategy considered is a PID controller that uses MAS design occupancy value for each AHU individually. All the scenarios conform to the ASHRAE standard 62.1-2013 for ventilation [3] that requires fresh air in proportion to the occupancy. The baseline scenario uses the design occupancy for outside air ventilation irrespective of the actual occupancy count.

We evaluate these strategies for the 8 design-days that we obtained from the office floor. For sake of brevity, we present results on the commonly occurring pattern – one each for weekday and weekend. The gain constants for the PID controllers for all the AHUs were tuned as per the standard Ziegler-Nichols technique [4]. We have set the control window $\Delta t = 15$ minutes.

Metrics: We compare the strategies using two metrics: (1) HVAC energy consumption and (2) the resultant comfort metric as perceived by MAS occupants. The averaged comfort metric is computed in a two-step way as follows: (i) First, in each time step, in each zone, we evaluate the temperature and humidity to see if that zone is comfortable or not. We then calculate the percentage of the aggregate occupancy in that time step which falls under the zones classified as comfortable. This is the comfort metric for one time step. (ii) Next, across all time steps over a 24 period which has some occupancy, we find the (24-hr) averaged value of the comfort metric (computed in step 1) calculated in a single time step. We use this population averaged, time averaged comfort metric. Occupant comfort is acceptable if this metric is at least 90%.

	Strategy name	Control	Sensing resolution	Comfort constraints (setpoint, setback)	Controller Feedback signal
Individual	PID-BL	PID	Design value	$(25, 25) \pm 1^oC$	Avg. zone temperature
Individual	PID-AG	PID	Aggregate MAS	$(25, 28) \pm 1^oC$	Avg. zone temperature
Individual	PID-SZ	PID	Sub-zone level	$(25, 28) \pm 1^oC$	Ppl wt zone temperature
Centralized	MAZIC-AG	Reactive MAZIC	Aggregate MAS level	As per Eqns. 2 & 3	Avg. MAS **T & W**
Centralized	MAZIC-SZ	Reactive MAZIC	Sub-zone level	As per Eqns. 2 & 3	Ppl wt MAS **T & W**
Centralized	MAZIC-MPC	MPC + MAZIC	Sub-zone level (Oracle)	As per Eqns. 2 & 3	Ppl wt MAS **T & W**

Table 3: Strategies compared and associated parameters.

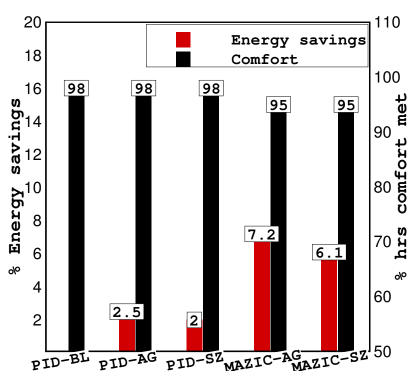


Figure 4: Controller performance during weekday occupancy.

5.1 Centralized vs Individual AHU control

We first focus on the performance of the reactive control strategies. The performance of the various reactive strategies under the cross-flow AHU configuration is summarized in Figure 4 for the weekdays and in Figure 5a for the weekends respectively. For weekdays, where the expected spatial skew in occupancy is less, we set $\mathcal{T}_{Low} = 24^oC$ and $\mathcal{T}_{High} = 25^oC$. For weekends, where the expected spatial skew in occupancy is more, we set $\mathcal{T}_{Low} = 24^oC$ and $\mathcal{T}_{High} = 26^oC$. For both the occupancy patterns, we set $\mathcal{H}_{Low} = 30\%$ and $\mathcal{H}_{High} = 60\%$. The set-back limits for temperature and relative humidity are $\widehat{\mathcal{T}}_{Low} = 27^oC$, $\widehat{\mathcal{T}}_{High} = 29^oC$, $\widehat{\mathcal{H}}_{Low} = 20\%$, and $\widehat{\mathcal{H}}_{High} = 70\%$. The parameters for the individual PID control are specified in Table 3. The performance is quantified in terms of the energy savings obtained over the baseline scenario and comfort achieved. We will refer to and elaborate on the data-points in Figures 4 and 5a in the following discussions.

We find that MAZIC gives higher energy savings than the baseline for both weekday and weekend occupancy patterns, while maintaining acceptable comfort levels. We get savings of $\sim 6\%$ and $\sim 25\%$ for the weekday and weekend occupancy patterns respectively. This is because there is some room to optimize the baseline – this scenario uses design occupancy of 200 irrespective of the actual occupancy and is bound to consume more energy due to fixed amount of outside air intake. Further, we find that individual PID control is unable to cut down on this baseline inefficiency even when fed with sensory information at finer resolutions (through people weighted temperature feedback). When we compare MAZIC with equivalent PID cases, we observe that MAZIC gives additional energy savings in the range of 4% to 11%, all with respect to the baseline shown in Figure 5a.

To understand how MAZIC achieves these savings, we refer to Figures 5b and 5c. These figures show the variation in AHU fan speeds and instantaneous occupant comfort for various control strategies for weekend occupancy. Essentially, MAZIC throttles the AHU fan speeds to a finer degree and does this more frequently than distributed PID control. Consequently, it is able to maintain a higher temperature gradient when the occupancy is sparse and achieve reasonable energy savings. On the other hand, due to the presence of dead-band – which is $\pm 1^o$C around the set-point of 25^oC, PID does not vary the AHU fan speed often and maintains a slightly lower zone temperature. Reducing the tolerance of the dead-band may not always improve the PID controller's energy consumption since it also decreases the extent to which zone temperature can be allowed to overshoot the set-point.

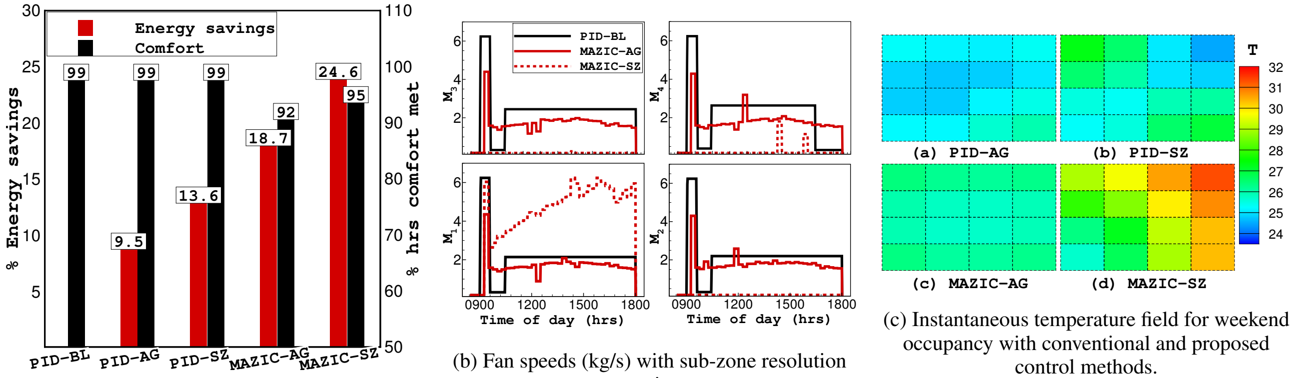
In sum, centralized control of AHUs improves on the energy consumption of individual AHU control while maintaining acceptable comfort.

5.2 Effect of occupancy and sensing

The performance of a controller depends on the occupancy patterns (extent of spatial skewness) and the sensing infrastructure (sensing resolution). We now study the impact of both in this section. Figure 5a shows the performance of various reactive control strategies on weekend occupancy pattern. Comparing this with the weekday performance in Figure 4, we observe the following:

- Under the weekday pattern – when the spatial skew in occupancy is not much, the performance of both PID and MAZIC does not change much with the spatial resolution of sensing. In other words, deploying a denser sensing infrastructure does not improve the performance of both the controllers. This is because, when the spatial sensing resolution is low, both the controllers assume that the occupancy and temperature feedback they receive from the sensors is uniformly spread across all the sub-zones and carry out their control actions. Since this assumption is reasonable for weekday pattern (when the spatial skew in occupancy is less), finer sensing does not bring in additional information that will help refine the actions of the controllers.

- On the other hand, we find that a denser sensing infrastructure helps both the controllers when the occupancy is skewed as in the weekend pattern. This is because, finer sensing allows the controllers to identify that some zones are unoccupied which enables them to refine their control actions. Con-



(a) Energy & Comfort

(b) Fan speeds (kg/s) with sub-zone resolution sensing

(c) Instantaneous temperature field for weekend occupancy with conventional and proposed control methods.

Figure 5: Performance of centralized and individual AHU control strategies on cross-flow MAS configuration for weekend occupancy.

sequently, energy savings increase for both PID controller and MAZIC without affecting the comfort. Also, MAZIC-SZ considerably outperforms PID-SZ in the weekend pattern (11%) than in the weekday pattern (4%) in terms of energy consumption. This shows that MAZIC utilizes the additional information more effectively than PID controllers.

In sum, we note that when the spatial skew in occupancy is low, a dense sensing infrastructure is not needed. When the spatial skew in occupancy is high, a dense sensing infrastructure will result in higher energy savings without compromising the comfort levels. We note that the quantum of energy savings also depends on the configuration of the MAS, i.e., cross-flow vs. parallel-flow. In the interests of space, we do not discuss the parallel-flow configuration.

5.3 MAZIC's sensitivity to thermal model

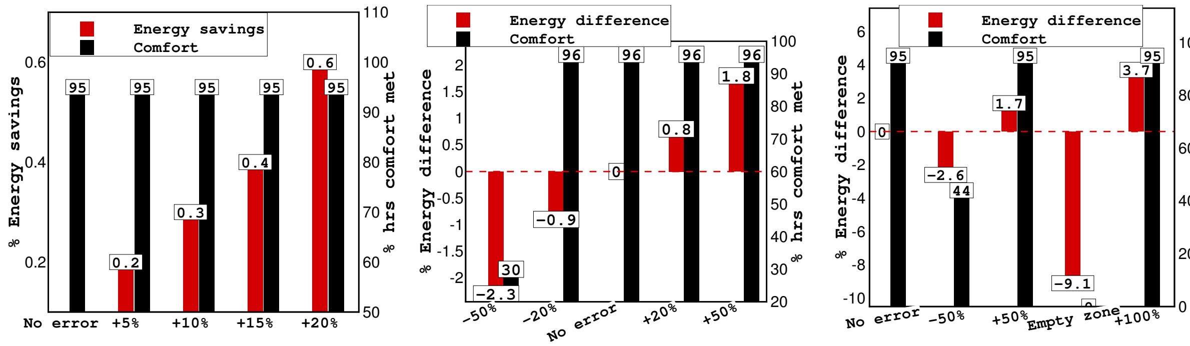
The performance of MAZIC also depends on the zone thermal model (discussed in Section 3) that models inter-zone air mixing. Any deviations in the values of the model parameters from reality could undermine MAZIC's control actions. In this section, we discuss the sensitivity of MAZIC to errors in the model parameters that are not readily measurable using sensors but have to be estimated from pyschrometric functions or standard models. The rationale is that pyschrometric functions and standard models are approximations at best and may not exactly correspond to the conditions existing at a real-world MAS. For brevity, we present results on MAZIC's sensitivity to errors in the internal heat load Q_{int}, air capacitance C_i, inter-zone air mass mixing rates $\dot{m}_{i,j}$s, and estimated wall temperatures τ_w. In many facilities, temperature is often the controlled parameter and taken as the primary indicator of thermal comfort. Therefore, we conduct the sensitivity analysis with respect to temperature alone in this work. We note that one source of error in the moisture balance equation can be from the estimation of moisture generation in the room, apart from the inter-zone mixing which we discuss as a part of the temperature model. The other variables such as the supply air and zone air humidity ratios can be obtained by delopying sensors at appropriate locations. As discussed in Section 3.2, occupants are the primary source of moisture generation in office spaces. For simplicty, we have used the occupant moisture model of [15, 16]; a sensitivity analysis for moisture generation will be required for facilities where a tighter bound on humidity levels for comfort are needed.

Internal heat load: Q_{int} captures the heat emanated from lighting, computing and people in the zone. While we have assumed rated values for these respective loads, the actual loads typically are lesser than the rated values. We introduce errors (for overestimation) in the range 0% to 20% for Q_{int} in the zone thermal model and study its effect in Figure 6a. Overestimating Q_{int} even by 20% has negligible effect on the comfort/energy; there is a maximum energy difference of only 0.6% and no change in comfort. This is because Q_{int} is a small fraction of the overall heat load.

Inter-zone mixing rates: The effect of error in estimating the inter-zone air mass mixing rates, $\dot{m}_{ij}$, is shown in Figure 6b. Typically, $\dot{m}_{ij}$s are arrived at using standard density based estimations. As can be seen, under-estimating the amount of inter-zone air mass mixing – exemplified by high negative errors, severely impacts the occupant comfort. On the other hand, over-estimation of $\dot{m}_{ij}$s increases the energy consumption only slightly ($< 2\%$) and does not affect the comfort. Therefore, we err on the side of caution by over-estimating $\dot{m}_{ij}$s.

Zone capacitance: Capacitance C_i of a zone varies with the contents. A zone with more furniture will have a higher capacitance than a zone with less furniture. The capacitance of a zone can be estimated in practice by carefully measuring the heat loads, HVAC refrigeration supplied, and the temperature evolution over time. Nevertheless, estimation errors may still creep in. Estimation error in zone thermal capacitance is taken to be in the range -100% to +100% of the estimated value and MAZIC's performance for these errors is studied. Figure 6c shows that under-predicting C_i by 50% can have an adverse effect with the comfort being met for only 44% of the time. An 100% error in under-predicting C_i, results in the comfort not being met for the entire occupied period. On the other hand, over-estimating C_i consumes slightly higher energy ($\sim$ 4% for 100% over-estimation) with no negative effect on comfort. Given this, as with $\dot{m}_{ij}$s, we over-estimate C_i.

Surface temperature: MAZIC's performance is also affected by errors in estimation of the surface temperature, τ_w. It may not be practical to deploy sensors for various surfaces such as the roof, floor, walls and windows in a MAS to measure τ_w accurately. Therefore we developed a linear model for τ_w in terms of the ambient temperature T_{amb} and indoor zone temperature T_i. Such a model for a given MAS surface can be developed by conducting experiments on a wall sample with the same material properties in a small test bed for varying T_{amb} and T_i. In our study, we consider the calibrated EnergyPlus model of the MAS to be the ground truth and compare our linear model for τ_w against this. The effect of radiation via windows is implicitly accounted in the surface temperature model from EnergyPlus. We find that our model has an accuracy of $\pm 0.2^o$C. At times, we find that due to this error, a lower convective heat load is presented to MAZIC than the actual affecting the occupant comfort. This can be corrected by biasing the optimizer's constraint limits $\mathcal{T}_{Low}$ and $\mathcal{T}_{high}$.



(a) Error in Q_{int}.

(b) Error in inter-zone mixing

(c) Error in zone capacitance

Figure 6: MAZIC's sensitivity to errors in thermal model parameters.

Occupancy sensing: The accuarcy of occupancy information will also affect the performance of MAZIC. In our studies, we found that a 20% error in occupancy sensing resulted in a maximum deviation of 0.5% in energy savings and 4% in comfort around their respective mean values. Due to lack of space, we do not present these results. We have assumed perfect occupancy information and impicitily accounted for radiation effects via the surface temperature model. However, in reality these have stochastic disturbances and approaches such as [33] are required to handle such effects; we defer this to future work.

5.4 Predictive vs Reactive control

So far, we discussed a reactive MAZIC controller for MAS – i.e., the controller senses the MAS occupancy at time t and for this occupancy, finds out the optimal HVAC settings for the interval $[t, t + \Delta t]$ using the thermal model. This process repeats every $\Delta t = 15$ min. If one were to develop a model for occupancy evolution in a MAS, then this can be used in conjunction with the thermal model to design a model based predictive control (MPC) strategy for MAS. Since the MPC controller has knowledge into the future, it may perform better than a reactive strategy.

Under the assumption that there is an Oracle that gives accurate information about future occupancy in all sub-zones, we study the performance of a MPC strategy in a MAS. Note that this performance of MPC will act as the upper bound since practical realizations of occupancy prediction will have a non-zero error. We study the performance of MPC under four different prediction horizons of 15 minutes, 30 minutes, 1 hour and 2 hours with control action taking place every 15 minutes. Figure 7a shows the relative performance of MPC MAZIC with respect to the reactive MAZIC for the weekday occupancy pattern. We find that while the comfort improves marginally ($\sim 5\%$), there is no significant further energy saving ($< 3\%$) due to MPC when applied to MAZIC. The comfort improves because at the time of facility start-up, a predictive strategy helps to quickly push the people weighted temperature within acceptable limits when compared to the reactive control. Given that: (i) the reactive strategy's comfort is acceptable ($\sim 95\%$), and (ii) MPC needs a good model for occupancy which demands additional efforts, we see that there is little incentive to adopt a MPC strategy for weekday operations. A similar performance, albeit weaker, is observed in the case of weekend occupancy too. This observation is in line with the conclusions of [22] for a single zone.

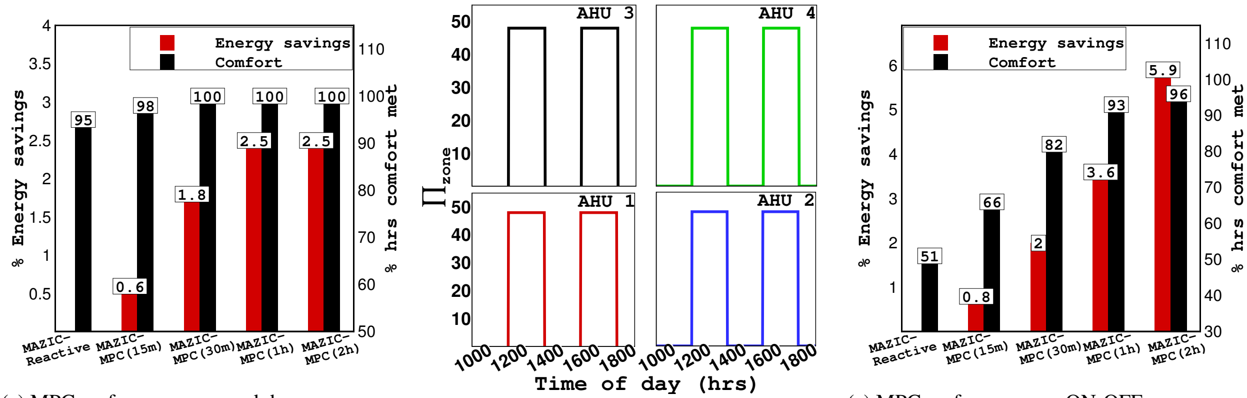
Multi-AHU super-zone configuration can exist in facility types other than offices such as cinemas and concert halls. In these facilities, the occupancy pattern is pre-determined (through ticket sales) and has ON-OFF patterns corresponding to the show times as shown in Figure 7b. The performance of MPC strategy in a MAS with such ON-OFF occupancy patterns is shown in Figure 7c. We see that reactive control is unable to maintain desired occupant comfort. An MPC strategy not only improves the comfort (by 45%), but also saves moderate amount of energy (6%) with respect to the reactive controller. Clearly, an MPC strategy is helpful in such scenarios. This observation too, is similar to the one reported in [8] for conference rooms.

5.5 Costs & benefits of MAZIC

The dollar costs involved in MAZIC are primarily towards installing additional sensors for detecting occupancy and temperature at finer spatial levels. As discussed under Section 4.3, occupancy at finer levels can be sensed in an office setting with almost no additional dollar costs. A more dedicated sensing infrastructure such as PIR could cost $\sim$ \$40 per node (sensor plus assembly) plus a maintenance cost of \$10 per year [18]. In MASes such as concert halls or cinemas, again, one may able to get the occupancy at no additional cost through ticket sales (where tickets are mapped to specific numbered seats). In other cases, finer occupancy sensing can be obtained by placing low cost micro-switches that cost < \$10 to individual seats [27]. Room temperature sensors can be developed at low cost ($\sim$ \$15 per unit) using arduino boards and LM35 sensors. We believe that the control algorithm itself could be implemented in hardware (such as PLCs) that may already exist in present AHU controls. Given this, for our case study MAS, the additional cost would be that of temperature sensors. As we had divided the MAS into 16 sub-zones, we would need a total of 16 temperature sensors – i.e., 12 more than existing setup, resulting in a dollar cost of $\sim$ \$200. This \$200 investment will save roughly 15% energy (or 62 kWh) with respect to existing control (PID with aggregate occupancy information) over one weekend day. Assuming a life time of 3 years for the sensors and an energy cost of \$0.1 per kWh, the dollar costs of energy saved by MAZIC would roughly be \$1900. If a deployment uses a sophisticated network of PIR sensors for occupancy detection, the total sensory cost (temperature and occupancy) would be about $\sim$ \$850.

6. RELATED WORK

Sensing people & comfort: The ability to detect people's presence and estimate their count through PIR sensors, cameras, CO_2 sensors, and the like have been demonstrated by researchers [9, 30, 32, 36]. Indirect sensing such as using WiFi logs, desktop activity, and DHCP server logs have also been studied to estimate occupancy count [13]. Some works have modeled occupancy patterns through rigorous data collection and computing techniques [34].



(a) MPC performance on weekday occupancy.

(b) Example ON-OFF occupancy pattern.

(c) MPC performance on ON-OFF occupancy.

Figure 7: MPC does not improve upon a reactive strategy in the test occupancy pattern, but is helpful for ON-OFF occupancy patterns.

Generally, temperature sensors from zones are used to get the feedback signal for the HVAC system. Approaches to obtain feedback directly from the occupants using smart phone applications have also been investigated [5, 23, 28].

Occupancy based HVAC control: Based on the estimated occupancy and the perceived comfort, different reactive and proactive strategies to control HVAC assets have been proposed. Typical control strategies include adjusting the outside air intake and varying the zone set-point temperatures as per the estimated occupancy and the comfort preferences of the occupants in both commercial and residential buildings [1, 2, 6, 9, 17–19]. In a field study [11], even simple binary sensing (presence/absence) of occupancy was shown to yield significant saving ($\sim 35\%$) in small office configurations, primarily through reduction of air flow during unoccupied periods.

Model Predictive Control (MPC) in HVAC systems: Model based predictive control strategies have been shown to save HVAC energy [18, 31, 35, 38]. Stochastic MPC strategies have been proposed [31, 35] which dynamically use statistics of weather conditions and building loads to minimize the expected energy cost and satisfy the indoor temperature and air quality levels. The benefits of MPC have been shown through a real-world implementation [35], in which the stochastic MPC has outperformed a conventional PI controller in terms of both energy use and the thermal comfort range. Ref [29] reports an MPC, coupled with a simple thermal resistance capacitance (RC) network to model building's thermal dynamics. A detailed discussion on implementing suitable MPC in real buildings considering several aspects that could influence the control is made in [14].

Coordinated control in HVAC systems: Core HVAC components such as chillers will have operational sweet-spots. The operating point might deviate from the optimality due to part-loading and conflicting sweet-spots among the various system components. Systems in which multiple chillers share a common load, integrated control approaches have been reported, by optimizing the (part) loading and the operational settings [7, 12, 24]. However, similar strategy on air-side, like ours, is not widely studied. In [37], a large office zone is divided into inner (core) and outer (perimeter) regions separated by physical partitions. Outer regions are exposed to the ambient, while the internal equipment are the heat sources in the core region. The two (inner/outer) regions are mapped to two separate AHUs, and with AHU coordination, energy savings are demonstrated. In this approach, however, the AHUs are only duct-linked, and do not serve a common zone with inter-zone mixing.

To summarize, the focus of the prior art, especially those on HVAC control, has been on controlling an individual AHU that serves one zone or multiple zones. We complement the existing literature by focusing on controlling multiple AHUs that serve a large zone simultaneously, which has not been explored earlier. We note that the savings obtained in our study is with respect to the baseline is 25% (Figure 5a). Related work on single individual zones have reported energy savings up to $\sim 35\%$ using occupancy information. The extent of savings in MASes is slightly less due to limitations on maintaining the desired setback temperature in unoccupied spaces (due to flow mixing from neigbhoring occupied zones that are conditioned by different controllers).

7. CONCLUSIONS

We studied how spatial variations in zone occupancy can be leveraged to save energy and improve occupant comfort in large zones with multiple AHUs. We modeled the influence of mixing of heat loads across different regions served by different AHUs and proposed a reactive coordinated control strategy, MAZIC, for the AHUs that uses this model. We then studied the performance of MAZIC using real-world occupancy patterns. When the spatial skew in occupancy is high, MAZIC reduced energy consumption by 11% when compared with conventional PID controllers while maintaining similar comfort levels. When the spatial skew is not high, the performance of the two controllers are comparable. We found that fine resolution sensing of temperature and occupancy does not bring in additional value to both MAZIC and conventional PID controllers when the spatial skew in occupancy is low. We observed that MAZIC's performance was robust to realistic inaccuracies in estimating the values of the thermal model parameters. For the real world occupancy patterns observed in our office facilities, we found that the difference between reactive MAZIC and a MPC MAZIC is not high ($< 3\%$ for energy). However, with ON-OFF occupancy patterns occur in MASes in other facility types such as cinemas and concert halls, the savings improve to 6%. We are currently working towards implementing MAZIC in an appropriate hardware and integrating it with the AHUs in a test MAS in our facility.

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