

Adaptive and Distributed Operation of HVAC Systems: Energy and Comfort Implications of Active Diffusers as New Adaptation Capacities

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Abstract

Human-aware HAVC operations have been shown to be effective in improving energy efficiency, which is constrained by the HVAC system configuration and operational logic. These constraints can result in a lack of operational flexibility, which in turn reduces the adaptation capacity for energy efficiency. Therefore, in this study, we investigated the energy efficiency implications of novel adaptive capacities for HVAC including the use of proposed active diffusers, which add to the dynamics of the HAVC systems by adjusting the behavior of diffusers using two modalities of (1) binary actuation of air flow (turning flow on and off), and (2) adjusting the flow direction to target individual needs in an environment. Computational fluid dynamics was used to model and predict the behavior of a “real-world” thermal zone to evaluate five scenarios of adaptive operations using distributed feedback from the environment, as well as active diffusers. Three scenarios used binary actuation at the thermal zone (collection of rooms) level, and two examined the adaptive operations at diffusers level. Moreover, we examined the integration of distributed feedback at occupant locations into the control loop using averaged temperatures (in the first three scenarios) and individual feedback (in scenarios with diffuser level actuation). The coupling of distributed feedback and independent directional flow at diffuser level considerably improved the thermal comfort requirements while reducing energy demands by ~25% – reflecting a considerable impact on improved energy efficiency. These findings demonstrate the potentials that artificial intelligence frameworks could bring about by enabling autonomous adaptive operations.

Keywords: Adaptive operations; HVAC systems; Load Flexibility; Energy Efficiency; Smart Buildings; Adaptive Diffuser; Robotic Diffuser

1. Introduction

In the United States, Heating, Ventilation and Air Conditioning (HVAC) systems account for 40% of the total energy consumption and ~75% of electricity consumption in buildings [1, 2]. Therefore, research efforts have sought to enhance their efficiency by introducing novel control techniques. Among the recent efforts are the human-centered operations [3], in which building systems account for human dynamics such as personalized thermal comfort [4-8] and occupancy patterns [9-12]. These methodologies promote context-aware adaptive control strategies, in which HVAC systems operate according to the contextual needs. Examples include smart operation of HVAC systems in a thermal zone – a group of sub-spaces that are served by an air supply unit such as a variable air volume (VAV) box – according to the occupancy and number of occupants or actual thermal comfort preferences of its occupants [6].

Human-centered control strategies have been shown to improve efficiency in energy management [3, 6] of building systems in both simulation and field studies. However, these efforts have focused on adaptive capabilities of building systems from operational settings’ standpoint and within the constraints of the existing componential design of HVAC systems. In other words, studies have focused on enhancing the detection and prediction of contextual thermal preferences and occupancy with limited research on the impact of air temperature distribution, distributed measurements, and integration of adaptive air distribution on the operational flexibility of building systems. Control at the thermal zone (which is the smallest unit of operation) is at the mercy of system boundary conditions including the building characteristics and air

distributing components such as diffusers, as well as the spatiotemporal granularity of feedback from the environment. Accordingly, in this study, we have investigated the impact of creating new adaptive capacities including distributed feedback from the environment, coupled with adaptive air distribution (air supply) in thermal zones. Traditional air distribution in HVAC systems relies on air outlets (diffusers) that direct the air in preset directions (most commonly diffusing the conditioned air in all directions) to all the sub-spaces of a thermal zone to ensure that the entire space will be uniformly conditioned.

In the absence of information about occupants in an environment, the concept of uniform air diffusion is the most reliable solution to ensure that the space is properly conditioned for all potential scenarios. This strategy commonly results in conservative operation, which brings about higher energy consumption. The context-aware operations have been motivated by such limitations. Although the Internet of Things (IoT) technologies have led to a better understanding of the dynamics in an environment with demonstrated energy efficiency benefits, there are obstacles that limit the potential of energy conservation efforts in IoT-enabled buildings. The lack of information about the temperature distribution in control loops, limitations from uniform air diffusion (regardless of occupants' dynamics), and rigidity of HVAC actuation are among these obstacles. Therefore, we are investigating the potentials of adaptive thermal conditioning strategies that could be coupled with IoT-based techniques to achieve improved efficiency of HVAC operations in terms of energy use and thermal satisfaction. To this end, we are investigating the potentials of active air supply at diffuser level that is defined as the capability of adjusting the *direction of the air flow* to the location of need (the spatial vicinity of occupants' location) and binary operation (on/off setting) of individual diffusers, as well as distributed measurement of ambient conditions as feedback to the control loop.

Although in case of active directional flow, uniform air distribution may not happen, we still call this new concept active "diffusion". To evaluate the feasibility and energy efficiency implications of creating new adaptive capacities, we sought to answer the following questions: (1) what is the impact of direct feedback at the location of occupants on improving the performance of a given HVAC system; and (2) how does the active diffusion concept affect energy efficiency of HVAC operations and the thermal comfort of individual occupants in a thermal zone and its subspaces. In doing so, we adopted computational fluid dynamics (CFD) for simulating the HVAC operation in (i) conventional operational mode, (ii) operation with distributed feedback, and (iii) active diffusion. In the context of this study, CFD provides a flexible tool for our investigation considering its high fidelity in simulating the air flow and temperature distribution in an environment by accounting for flow direction, velocity and turbulence. To this end, we have investigated the questions through a case study simulation of a real-world thermal zone.

The rest of this paper is structured as follows. Section 2 provides a background for research on human-centered (human-in-the-loop) operation of thermal conditioning in buildings and point of departure in this study. Section 3 describes the potential design alternatives, the CFD simulation methodology, and elaborations on simulated operational scenarios. The results of simulation and answers to the questions are presented in Section 4. We present discussions on the implications of the proposed concept in Section 6 and conclude in Section 7 including the future of the research efforts.

2. Context-Aware and Adaptive HVAC Operations

As noted, human-in-the-loop HVAC operation has been the subject of several research efforts in the past few years [3], given the enhancements in the mobile sensing and communication technologies. An overview of these studies shows that the efforts could be divided into two main categories of occupancy-driven (e.g., [13-15]) and (thermal) comfort-driven (e.g., [16, 17]) research efforts. In the former category, studies focus on characterizing the occupancy of spaces for thermal conditioning. Among different efforts, the detection of occupancy state (occupied vs. unoccupied) (e.g., [18-20]) and the number of occupants in a thermal zone (occupancy counting) (e.g., [21, 22]) have received more attention. Control of HVAC systems according to

the occupancy state of thermal zones is implemented as reciprocation between setpoint and setback temperatures. In other words, when the space is inferred to be unoccupied, the temperature setpoint is configured to the setback that is closer to outside temperature to reduce energy consumption. In a class of techniques, this process is carried out through reaction to occupancy information (e.g., [23-25]). To address the potential discomfort from reactive techniques, due to either HVAC system reaction time, or the false positives in occupancy detection, occupancy prediction methods have been proposed. Using probabilistic techniques, the state of occupancy in an environment is predicted for proactive operations (e.g., [26-28]). Similarly, in case of occupancy counting, the estimate of the number of occupants is used to adjust the ventilation load and save energy in the building using either reactive or proactive control techniques (e.g., [29-31]).

The control signal, in HVAC systems, is communicated at the thermal-zone level through a thermostat, which measures the temperature in the space at an arbitrary point and compares it against the temperature [32]. Once the temperature at the thermostat location is sufficiently different from the setpoint, the conditioned air supply is actuated. In this control paradigm, comfort-driven research efforts have come to play in improving the setpoints configuration. In the standard approach, the setpoints are configured according to generic models of thermal comfort that has been designed for collective occupants' satisfaction according to different environmental and human-related variables. The most commonly used model is the predicted mean-vote (PMV) and predicted percentage of dissatisfied (PPD), i.e., PMV-PPD model [33, 34]. These models are used to design the HVAC system characteristics. During the operation, facility managers (following generic standard recommendations) or occupants adjust the setpoint on the thermostat. Therefore, the setpoint could be unrepresentative of real-world preferences of occupants and could result in inefficient operations of HVAC systems [35, 36]. Accordingly, research efforts have sought to enable human-centered comfort quantification, which focuses on context-aware inference of comfort by relying on feedback from actual occupants of the buildings. In doing so, different methods could be divided into two groups of utilizing user feedback systems through mobile devices (leveraging a voting mechanism) [4, 6, 8, 37-41] and physiological sensing [42-54] for reflecting thermoregulation processes. The outcome of these methods is the creation of personal comfort models [5, 55] that could be used to optimize the temperature setpoints in real-time operations. In multi-occupancy scenarios, the optimization pertains to the use of operational strategies to maximize collective comfort based on individual preferences [56-58]. Thus, occupants will experience a level of discomfort unless their preferences are similar, and the building system could keep a balance in indoor thermal condition distribution and experience.

In both modalities of human-centered operations, the efficiency is at the mercy of building systems' flexibility. The limitations of control feedback from an arbitrary point in thermal zones (i.e., thermostats) and the rigidity of air supply systems in an environment will drive the experience of the users and limit the potentials for efficiency. For example, in state-of-the-art human-centered control, as long as one sub-space is inferred to be occupied, the entire thermal zone is conditioned resulting in considerable inefficiency in energy consumption. On the other hand, if all subspaces are occupied, the thermal condition in rooms are affected by the balance in the HVAC system that in turn is affected by temperature measurement location, the distribution of the diffusers, and the physical characteristics of buildings. The lack of flexibility in building systems could hinder the realization of energy efficiency potentials even in the case of using context-aware operations. Therefore, our study contributes by (1) investigating the impact of different control configurations for HVAC systems in an example thermal zone (reflecting a real-world imbalanced system), as well as (2) proposing and evaluating a new control paradigm at the diffuser level to increase the flexibility of the control processes. To this end, there are limited research and development efforts that account for higher fidelity of information and control flexibility. In a category of studies, using computational simulations, research efforts have evaluated the impact of control based on occupant position, specifically in the open office spaces [59, 60]. In these efforts, the air supply was suggested to be controlled according to varied occupant positions by different variable air volume (VAV) boxes. In recent years, moving towards increasing flexibility of central air conditioning systems in residential buildings, smart vent

systems (e.g., Keen smart vents [61]) were developed for control of individual diffusers in a binary mode by using room level portable thermostat points (smart vents, coupled with ecobee portable sensing nodes [62]). These technologies have been designed to enable sub-zoning through plug-and-play smart vent replacement in residential buildings. Nonetheless, the energy efficiency impact of such strategies, as well as user-centered feedback, has not been systematically studied.

3. Adaptive Operation Assessment Methodology

3.1. Control Strategy

The premise of this study centers on evaluating adaptive control frameworks in indoor environments, and thus, the methodology is based on simulated scenarios of operations in a surrogate model of a thermal zone and the associated energy efficiency implications. We have proposed a new paradigm of control strategy for added adaptation capacity through the concept of active diffusers – i.e., robotic diffusers with non-intrusive sensing for locating occupants (e.g., by using infrared thermal array sensors [12]) and additional degrees of freedom for adaptive air flow adjustments (both throughput and direction of air flow) to target the location of need (occupants' surrounding). The concept of active diffusers draws on the notion of personal air conditioning that has received attention in research and through initiatives such as ARPA-E's DELTA Program [63], which seeks to achieve energy efficiency by using Localized Thermal Management Systems (LTMSs). The LTMS concept has been defined as modifying the physical space around the human body rather than the entire building to service energy. Figure 1 illustrates the concept of using active diffusers and distributed feedback in the vicinity of the users.

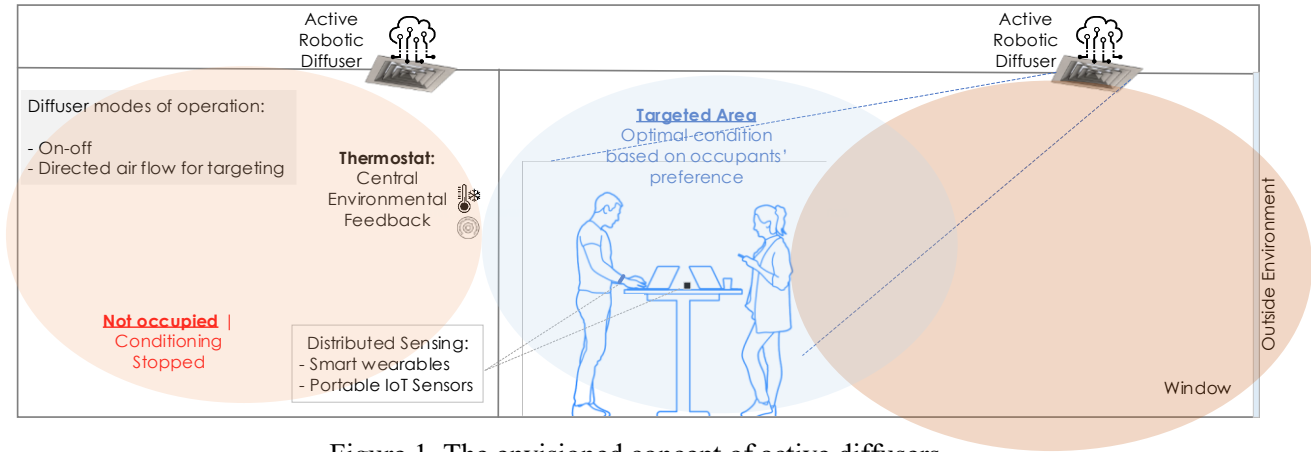


Figure 1. The envisioned concept of active diffusers

The adaptation, in this study, has been represented from different perspectives: (1) distributed feedback from individual user locations (measuring comfort-proxy in the vicinity of occupants), (2) binary control (shutting a diffuser on-off) of diffusers in sub-spaces, and (3) binary and directional control at the location of diffusers. These strategies could be realized given the prevalence of IoT-enabled technologies. For example, distributed measurement of temperature could be achieved through portable sensing technologies that are paired with mobile devices such as smartphones [64] or IoT-specialized portable temperature sensing systems (e.g., [65]), as shown in Figure 1. These measurements could be also communicated to smart thermostats (e.g., ecobee) in the new paradigm of smart building systems. Alternatively, sensors that enable the inference of thermal comfort, such as wearables that measure skin temperature, could be used. Other technologies, such as adaptive sub-zoning by using smart vents with on/off control (e.g., Keen smart vents) in residential buildings, are also receiving attention in recent years [61]. Accordingly, the control strategies, in this study, will be affected by two main parameters of sensor location and the adaptation capability of diffusers. The scenarios that we have explored were compared against the legacy control strategy as the baseline:

- **Scenario 1** (Baseline) – Binary control at the air supply unit (i.e., VAV box) by feedback from a central thermostat. This control strategy switches the air supply to the entire thermal zone on and off depending on the temperature measurement at the thermostat location. Air is distributed uniformly from the diffusers.
- **Scenario 2** – Binary control at the air supply unit (i.e., VAV box) by feedback from a thermostat that is connected to distributed sensors. The air supply to the entire thermal zone is switched on and off depending on the averaged distributed temperature measurements at the occupants' locations. This strategy reflects the notion of control based on personal thermal comfort preferences [6]. Averaging temperature will reduce the bias of only accounting for the temperature variation at the location of the central thermostat. Air is distributed uniformly from the diffusers.
- **Scenario 3** – Scenario 2, augmented with directional control of the supplied air at the diffusers. Similarly, the feedback from the distributed sensors (average temperature) near the occupants is used to control the operation of the VAV box. This scenario investigates energy efficiency impact of directional flow for user-centered conditioning [63] and distributed feedback.
- **Scenario 4** – Binary control at individual diffuser level by independent feedback from distributed sensors at occupants' locations. Air is distributed uniformly from the diffusers, but the air to individual diffusers could be shut off once the condition in one sub-space reaches the satisfactory condition.
- **Scenario 5** – Binary and directional control of the air supply at individual diffuser levels by independent feedback from distributed sensors at occupants' locations. This is the most flexible actuation approach that enables the HVAC system to target the location of demand.

Given that the dynamics of air and the associated temperature distribution is critical in evaluating these scenarios, we have used CFD to simulate and predict the air dynamics with high-fidelity calculations as a case study. The simulations were based on a real thermal zone with an imbalanced behavior – i.e., the temperature distributions in sub-spaces of the zone could be different with discomfort for occupants in sub-spaces. Figure 2 shows the layout and characteristics of this thermal zone, which includes three rooms, served by a VAV box, two of which have windows facing south to the outside environment. Each room has a diffuser and an exhaust and can be isolated from the other rooms by doors. The fixed thermostat is in Room A (near the door adjacent to Room C), as shown in Figure 2. Scenarios 3-5 simulate the actuation at the diffusers. In a real-world implementation of such a system, the control loop would also include actuation and flow adjustment at the VAV box. We assumed a constant flow rate through each diffuser with constant temperature for different durations according to the demand. Therefore, the complete control loop for the VAV box behavior is not included in the scope. All three rooms are considered occupied although Rooms B and C are accessed through Room A. Figure 3(a)-(b) show the schematics of the air distribution method used for uniform and directional air distributions, respectively. The diffuser behavior was modeled in CFD simulations through boundary conditions and user-defined functions.

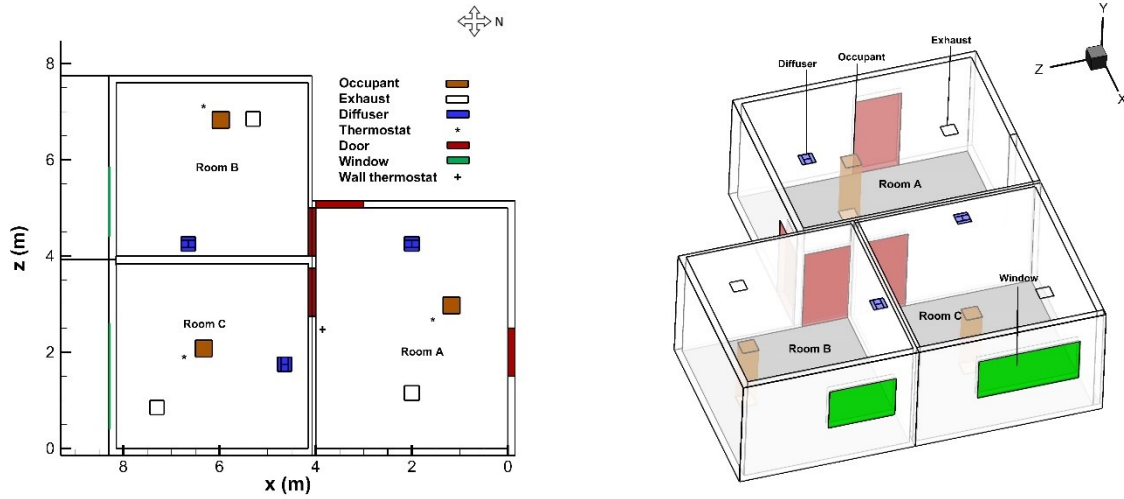
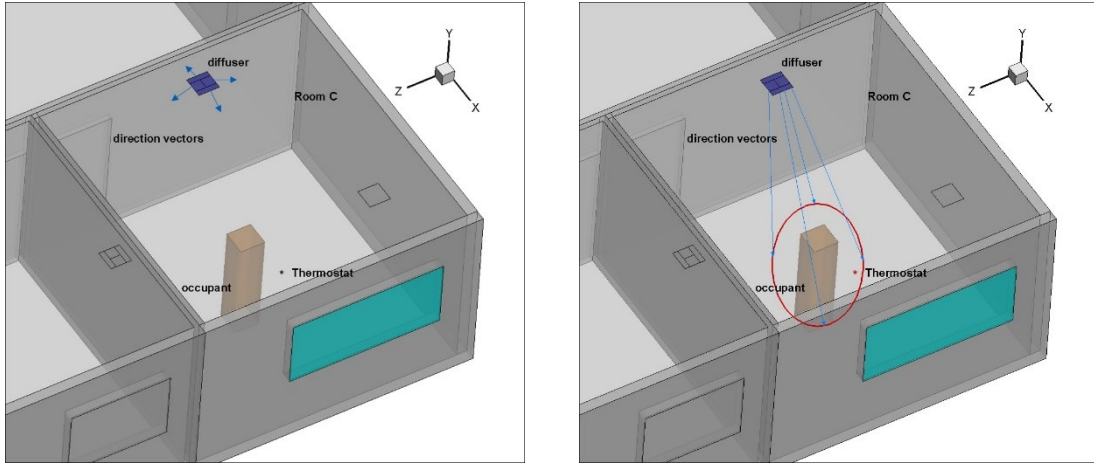


Figure 2. The layout of the simulated thermal zone and its characteristics



(a) Uniform air flow for conventional diffusers

(b) Directional air flow for active diffusers

Figure 3. Schematic of the air distribution through uniform and directional diffusers in room C.

3.2. CFD Simulation Details

The CFD simulations were performed using the commercial software ANSYS Fluent (18.0) [66] and its user-defined function capabilities. We have modeled the time-dependent behavior of air flow using the governing equations for mass, momentum, and energy. The Boussinesq approximation was used to model natural convection, which treats density as a constant value except for the force term in the momentum equation. The realizable $k-\epsilon$ model [67] was employed for turbulence modeling and the discrete ordinate model with solar ray tracing was used to solve for the incident solar radiation.

The segregated pressure-based Navier-Stokes (PBNS) solver was used to numerically solve the incompressible system of equations, and pressure-velocity coupling was solved using the semi-implicit method for pressure-linked equation (SIMPLE) algorithm. Furthermore, the least squares cell based (LSCB) and the pressure staggering option (PRESTO!) schemes were employed for spatially discretizing gradients and pressure, respectively. The momentum, energy, turbulent kinetic energy and dissipation rates, and

discrete ordinate were discretized using second-order upwind methods. A first-order implicit method was employed for time marching with a constant time step size of 0.05 s, for which the Courant Friedrichs-Levy (CFL) number was between 0.5 and 1.

As illustrated in Figure 2, the computational domain was extended 1 m beyond the exterior (southern) wall to represent the outdoor environment and model the effect of solar radiation on the exterior wall. Windows in rooms B and C were 1.5 m and 2.2 m wide, respectively, and 1 m high. The occupants were modeled as parallelepipeds with a height of 1.5 m (considering a seated position) and a width of 0.35 m on each side. The human thermal load was 75 W heat release from each individual in Rooms B and C, and 150 W for Room A, representing two occupants [68]. Diffusers and exhausts have dimensions of 0.3 m by 0.3 m.

In all scenarios, air at 13°C (~55°F) was supplied through the diffusers at a rate of 0.0567 m³/s (or 120 cfm). For uniform diffusion, the conditioned air was uniformly supplied in all directions with an angle of 30° from the ceiling. For active diffusers, the flow was directed by a vector from the diffuser towards the occupant location (75 cm from the floor). Exhausts had a return duct gauge pressure of -24.88 Pa. The boundary conditions for the outdoor boundaries were set to an ambient pressure of 1 atm and temperature of 27°C to consider a summer day conditions. The solar radiation was modeled on the walls and through the windows. The solar intensity was calculated using the direct solar irradiance data provided by NREL [69]. The solar irradiance, for the location of the simulated thermal zone, ranged between 4.5 – 5.5 kWh/m². The longest summer day of 14 hours with a constant solar intensity of 350 W/m² on the south-facing windows were used. The shades at the windows were assumed to transmit only 80% of the incident solar radiation into the rooms. Given the buildings materials, dolomite was considered for the exterior wall. All the interior walls were modeled adiabatic assuming negligible conduction through the interior walls with no-slip condition for fluid-wall interactions. Characteristics of the boundary conditions are summarized in Table 1.

Table 1. Characteristics of model boundary conditions

Boundaries (Materials)	Radiation Parameters*	Thermal conductivity (k) (W/m-K)	Boundary condition values
Outside environment	n/a	-	Temp: 27°C Pressure: 1 atm
Diffusers	n/a	-	Flow: 0.0567 m ³ /s (or 120 cfm) Temp: 13°C (~55°F)
Exhausts	n/a	-	Pressure: -24.88 Pa
Internal walls/ceiling (N/A)	n/a	-	No-slip Zero heat transfer (Adiabatic)
Outside walls (Dolomite)	$\alpha = 0.5$ $e = 0.5$ $\tau = 0$	1.5	No-slip Coupled
Windows (Glass)	$\alpha = 0.1$ $e = 0.9$ $\tau = 0.1$	1.15	No-slip Coupled
Doors (N/A)	n/a	-	No-slip Zero heat transfer (Adiabatic)
Floors	$\alpha = 0.15$ $e = 0.6$ $\tau = 0$	-	No-slip Zero heat transfer (Adiabatic)
Occupants (per person)	n/a	-	No-slip Heat flux = 612.25 W/m ²

* e: Emissivity | τ : Transmissivity | α : Absorptivity

3.3. Control Strategy Modeling

We implemented user-defined functions (UDFs) to simulate different control logics. Each scenario was evaluated over 60 minutes for energy efficiency that was measured based on the energy use for achieving comfort. All the doors were assumed closed, allowing no interaction between the rooms – a reflection of actual operation in the testbed. The thermal comfort was achieved by adjusting the ambient temperature until it reached a setpoint in the vicinity of the thermostat. In commercial settings, a temperature deadband (i.e., upper and lower setpoints) is set to keep the temperature within a comfortable range. Similarly, in our analysis, the temperature was controlled by using a temperature deadband (following the logic of thermostats) of 21.6–23.3°C (71–74°F).

3.4. Grid Sensitivity and CFD Validation

A grid resolution sensitivity assessment was conducted using the grid convergence index (GCI) to determine the discretization error for grid-independent solutions [70]. Room A was simulated using four meshes with varying numbers of cells, i.e., 38 k (mesh 4), 98 k (mesh 3), 164 k (mesh 2) and 663 k (mesh 1), and the average room temperature was used to compute the GCI. Figure 4 shows the temperature changes for each mesh when the diffuser turns off at approximately 275 s. Using the numerical methodology described in [70], the GCI was below 0.1 % for each pair of consecutive meshes, which indicates extremely small discretization error. Therefore, a moderate mesh size (mesh 3) was adopted to model each room, and further cell refinement was applied in the vicinity of the occupants, diffusers, and exhausts; the entire domain utilized 300 k cells.

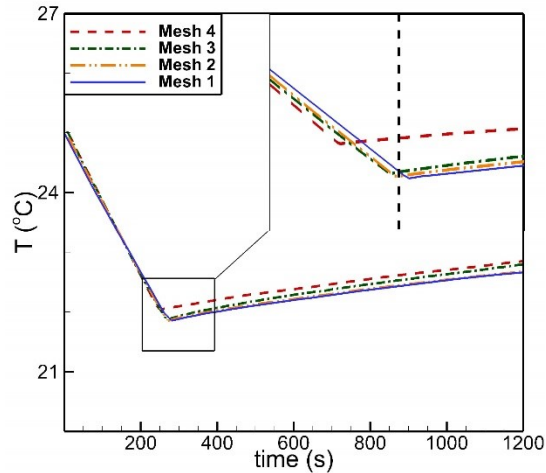


Figure 4. Comparing average temperature of Room A for different mesh resolutions

The experiments by Loomans [71] for supply airflow in a climate chamber, representing an office room was modeled and simulated to further validate the efficacy of the proposed CFD modeling. Figure 5 shows the 3D model that replicates the experiments with an air-supply below a desk ($0.047 \text{ m}^3/\text{s}$ at 19.8°C), two computers (61.5 W each), a personal light source (10.9 W), ceiling lights (18.1 W per light), and an exhaust. Walls, floor, and ceiling are maintained at constant temperatures ($22.2\text{--}23.2^\circ\text{C}$). The occupant has a surface area of 1.6 m^2 and releases 59.8 W of heat. The only subtle difference is our parallelepiped occupant modeling. Loomans [71] collected temperature and velocity data at various locations within the room, and select data are presented here. The temperatures measurements (using T thermocouples with an accuracy of $\pm 0.1^\circ\text{C}$) were compared with CFD in Figure 6(a) at $z = 1.93 \text{ m}$ at three x -locations. The velocity measurements (using a hot sphere anemometer, reliable for velocities greater than 0.1 m/s with an accuracy of $\pm 0.025 \text{ m/s}$) were compared with CFD in Figure 6(b) at $z = 2.3 \text{ m}$. There is a lack of experimental velocity data below 1 m where the air motion was very small. Overall, there is very good agreement between the experiments and CFD predictions, validating our approach to model the HVAC system of an office. It is

worth noting that Stamou and Katsiris [72] also verified their CFD models with the data of Loomans and demonstrated similar agreement.

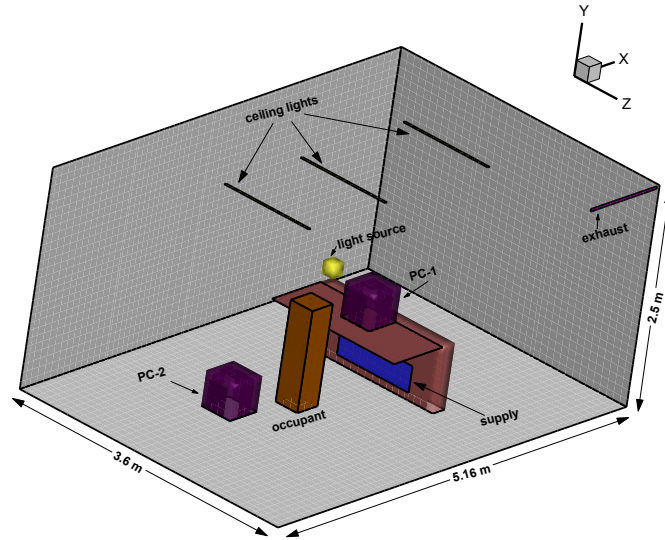


Figure 5. CFD model replicating the experiments of Loomans [71]

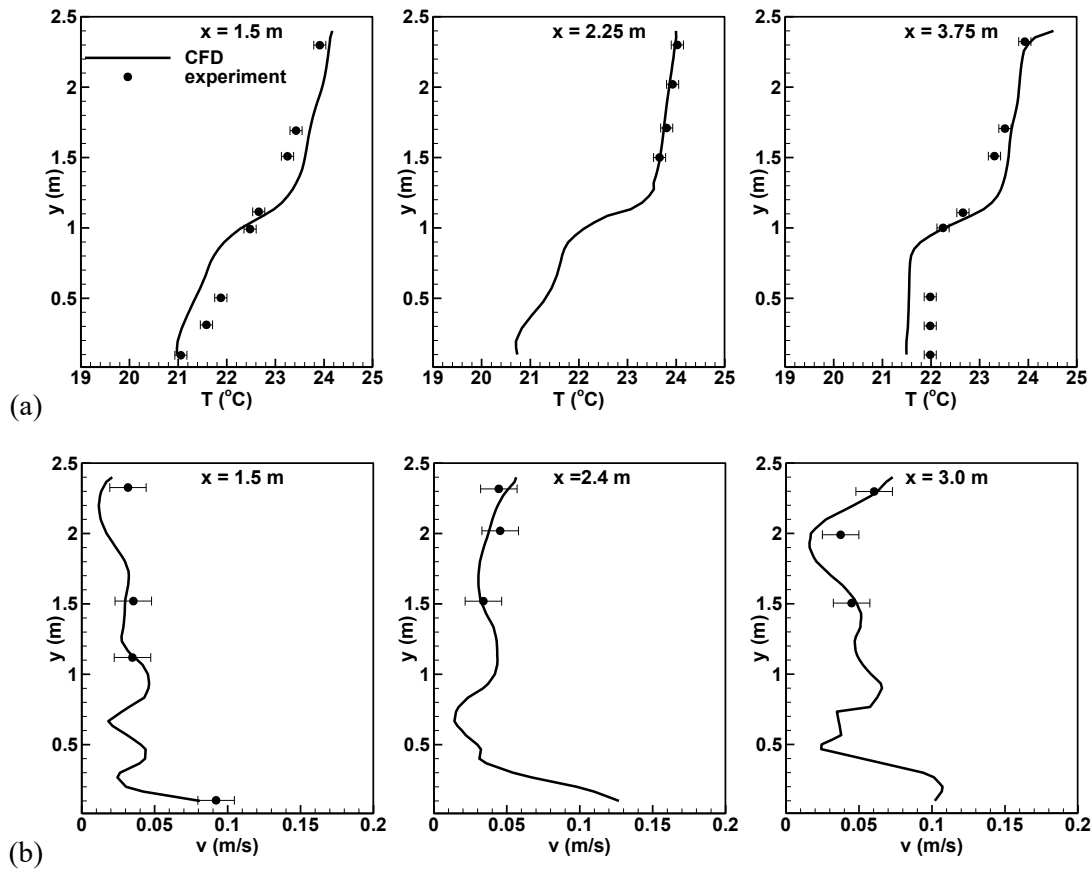


Figure 6. Profiles comparing the experiments of Loomans [71] and CFD predictions for (a) temperature at $z = 1.93$ m and (b) velocity at $z = 2.3$ m

4. Results and Discussion

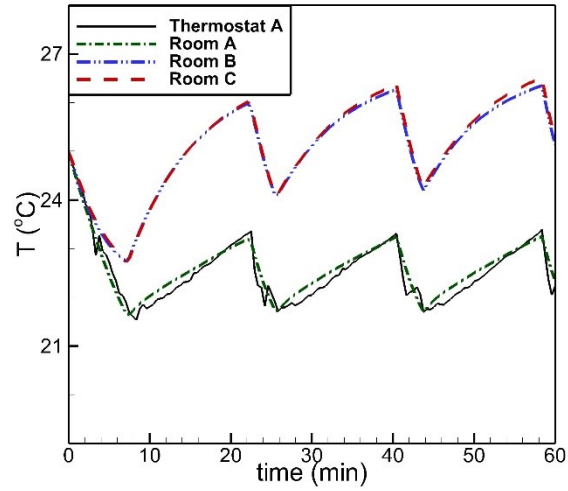
The simulation scenarios, including the sensing and actuation conditions are in Table 2.

Table 2. Summary of the conditions for simulation scenarios

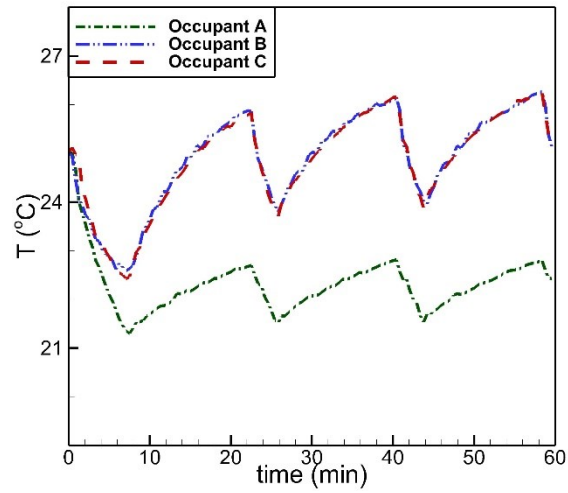
Simulation Scenario	Sensing	Actuation
Scenario 1	Zone Thermostat	• Binary at VAV box (all diffusers at once) • Uniform diffuser flow
Scenario 2	Distributed Personal Thermostats (average reading)	• Binary at VAV box • Uniform diffuser flow
Scenario 3	Distributed Personal Thermostats (average reading)	• Binary at VAV box • Directional diffuser flow
Scenario 4	Distributed Personal Thermostats (independent reading)	• Binary at individual diffusers • Uniform diffuser flow
Scenario 5	Distributed Personal Thermostats (independent reading)	• Binary at individual diffusers • Directional diffuser flow

4.1. Scenario 1: Uniform air distribution controlled by thermostat in Room A (baseline)

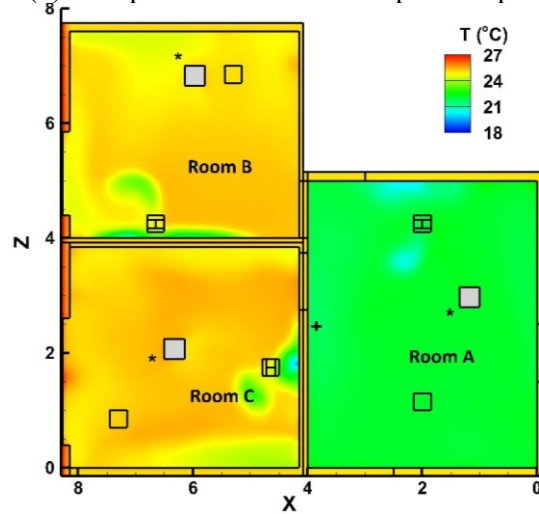
Figure 7(a) shows the temporal variation of average room temperatures controlled by the thermostat in Room A and Figure 7(c) presents the temperature contours at neck height (1.25 m) and at $t=60$ mins. The temperature across all the rooms was initially 25°C when conditioning started from an HVAC off state. Therefore, the initial drop in temperature and its rate of change were higher compared to the next cycles. The temperature decreased steadily with a lower rate in Rooms B and C due to heat gain through exterior windows and walls. The air conditioning initially turned off at 7 min-21 s when the thermostat in Room A reached the cutoff temperature of 21.6°C even though temperatures in Rooms B and C were far above the thermal comfort range. Note that the temperatures in Rooms B and C rise above the initial conditions after the initial drop. The temperatures in Rooms B and C continue to rise to uncomfortable states with additional conditioning cycles demonstrating that the HVAC cannot meet the required cooling load due to the control logic of receiving feedback in Room A resulting in a bias in the control loop. The off-cycle duration is relatively long compared to the on-cycle duration because of the small heat gain in Room A. This observation reflects the actual daily operations in the zone, in which acceptable temperatures in Rooms B and C require a setpoint of 20°C . The average temperature of Room A is fairly close to the thermostat temperature because the room is completely isolated from the exterior environment and the doors to Room A are closed. The average temperatures in Rooms B and C are almost the same, however, a difference in the temperature near the occupants (averaged around neck and ankle) can be seen in Figure 7(b), where the surrounding temperature of occupant B, who is located farther from the window, is cooler. Cooler regions can be noticed in each room under the diffusers. The average time of the air supply (i.e., on time) per cycle for all diffusers was approximately 5 minutes and 30 seconds.



(a) Temporal variation of average room temperature

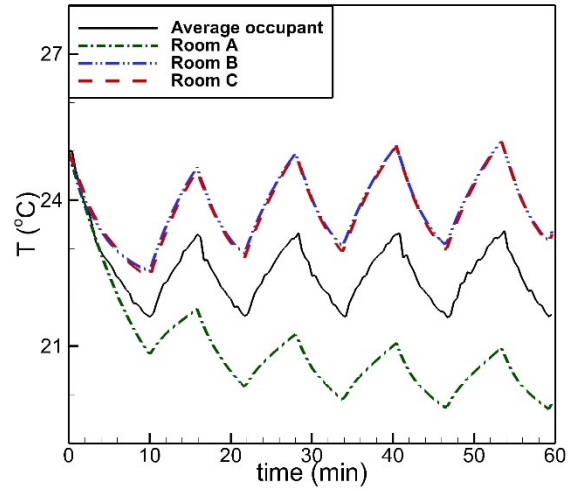


(b) Temporal variation of occupant temperature

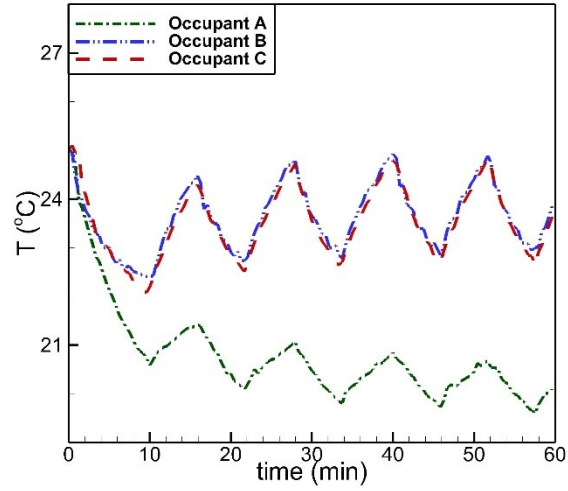


(c) Temperature contour at neck height at $t=60$ mins

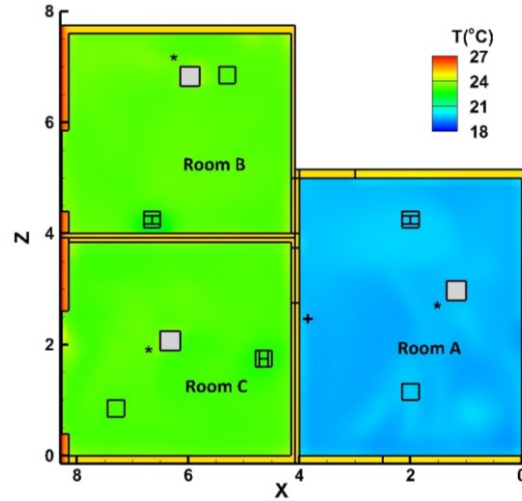
Figure 7. Temperature plots for binary control at VAV box using wall thermostat in Room A with uniform flow from diffusers (Scenario 1 – baseline legacy control)



(a) Temporal variation of average room temperature



(b) Temporal variation of occupant temperature



(c) Temperature contour at neck height at t=60 mins

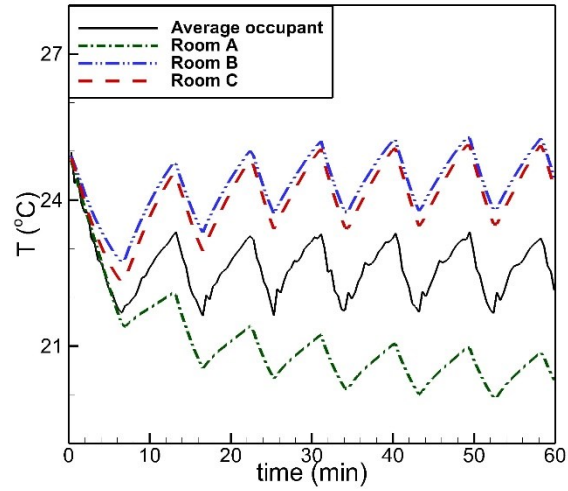
Figure 8. Temperature plots for binary control at VAV box using average temperature at the vicinity of occupants in all rooms with uniform flow from diffusers (Scenario 2 – baseline control by using distributed feedback)

4.2. Scenario 2: Uniform air distribution controlled by average temperature in the vicinity of occupants

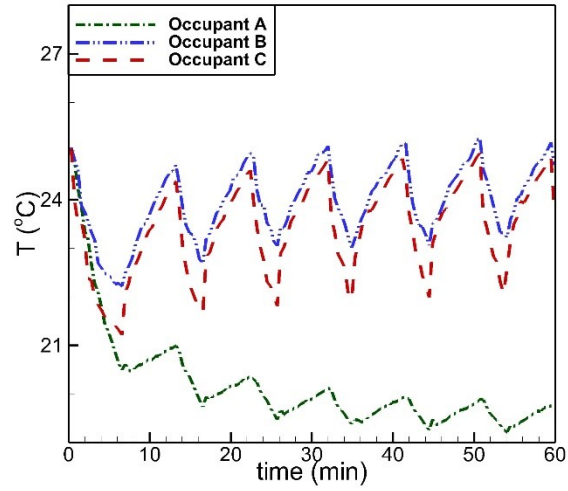
To eliminate the bias of measuring temperature in only one sub-space, the combined average temperatures of the occupant surroundings in each room was used for context-aware control. As noted, this distributed feedback could be obtained through portable thermostat (similar to ecobee) or mobile wearable devices. Figure 8(a) shows the temporal variation of average room temperatures. The solid lines indicate the average temperature close to the occupants, which was used as the control feedback. This approach improved the thermal condition in Rooms B and C, but resulted in a drop of temperature in Room A considering that higher cooling load are needed in Rooms B and C. This is the pattern that is observed in reality where occupants keep adjusting the temperature setpoint on the thermostat for comfort. Since thermal comfort ranges, in Rooms B and C, were effective in driving the control signal, the initial cooling duration (from HVAC off state and initial temperature of 25°C) is longer for Scenario 2 (~10 minutes) compared to Scenario 1. The temperatures, in Rooms B and C, ranged from 22.5°C to 25°C within the cycles, which are closer to thermal comfort ranges compared to Scenario 1, where temperatures reach 25°C after two cycles. However, the temperatures increase slightly in Rooms B and C as the cycles continue, but drop below 20°C in Room A, which may cause discomfort especially for a room without sunlight. Figure 8(b) shows the difference in temperatures at occupants' neck height after 1 hour when the cooling cycle ends. The temperatures in Rooms B and C are close to 23°C, which shows that these rooms could not be cooled below this limit. The average time of air supply (HVAC on) per cycle was 7 min 22 s, higher than Scenario 1, reflecting higher need for cooling load and thus higher energy consumption. Nonetheless, this increase in energy consumption does not assure simultaneous conditioning of all rooms to thermal comfort. This is an indicator of lack of flexibility in control of the HVAC system. In other words, accounting for personal comfort in a centrally controlled HVAC system, resulted in an increased energy use with no guarantee of satisfactory indoor conditions for all occupants.

4.3. Scenario 3: Directional air distribution controlled by average temperature in the vicinity of occupants

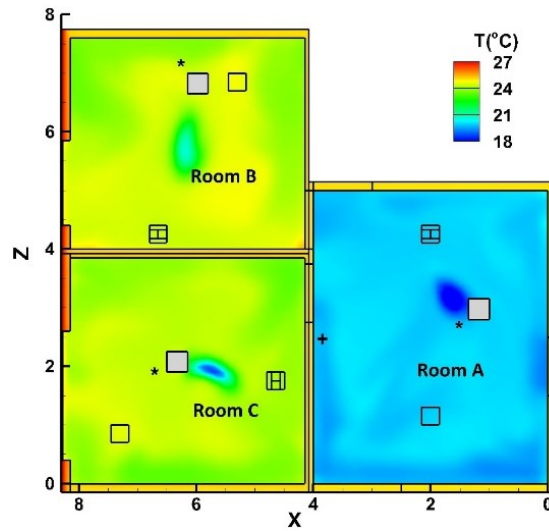
This scenario examines how directional air flow could contribute to achieving energy efficiency. In the envisioned system, active diffusers communicate with the distributed sensors for information on occupants' locations and surrounding temperatures. The locations of the distributed sensors are used to determine the direction for the air supply. Figure 9 shows the temperature variations. We observed increased number of cycles and decreased duration of cycles (six cycles compared to four for Scenario 2). Through directional flow, HVAC only provides conditioning for the occupants' surroundings instead of the entire space, and thus, the durations of cycles decrease. Moreover, temperatures close to occupants are lower compared to the previous scenarios (Figure 9(b)), demonstrating the potential of directional flow in providing personal thermal comfort even in a warm environment. It is also seen that demand targeting can still provide conditioning for the entire space that is important for temporary occupants. The initial cooling time of 6 minutes-24 seconds is nearly 34% lower compared to 9 minutes-43 seconds in Scenario 2 with a shorter average cooling time per cycle of 3 minutes-11 seconds (a total of 23 minutes-43 seconds) – showing energy saving potentials of directional flow through active diffusers. Considering energy use correlation with the volume of supplied air, the reduced durations (71.1 mins compared to 96.3 mins in Scenario 2) leads to reduced energy use. However, occupants' thermal needs were not sufficiently satisfied. While occupants in Rooms A and C are experiencing cool regions, occupant in Room B is not completely affected by conditioned air. This may be due to farther distance between diffuser and occupant in Room B and the impact of the air circulation. In addition to temperature, an important factor for thermal comfort is the air speed close to occupants and it is discussed in Section 4.6.



(a) Temporal variation of average room temperature

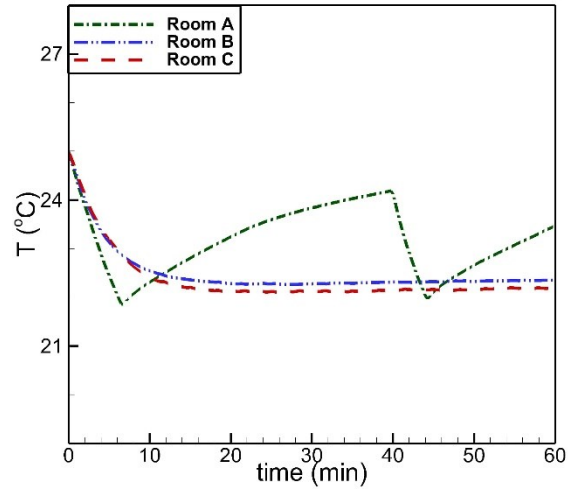


(b) Temporal variation of occupant temperature

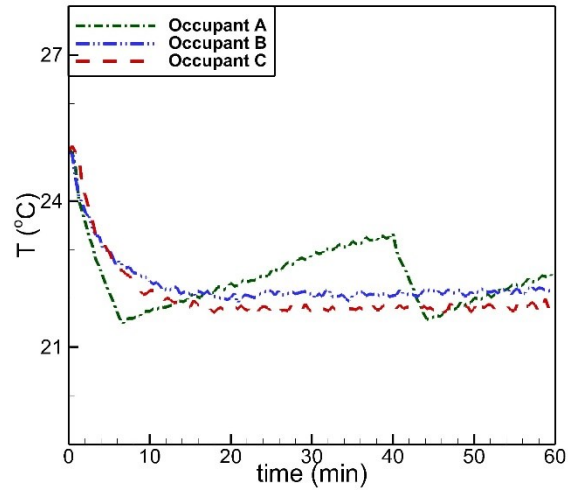


(c) Temperature contour at neck height at t=60 mins

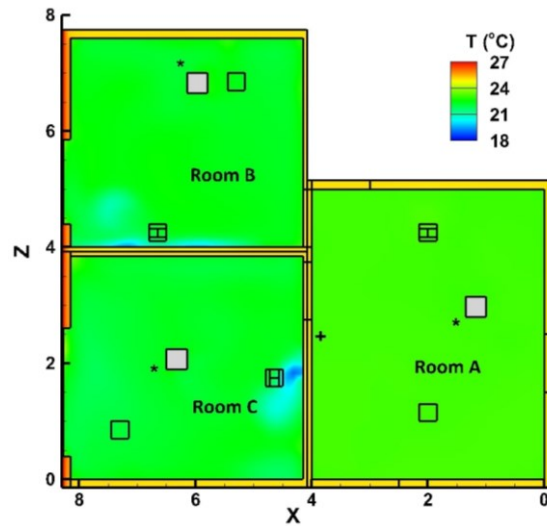
Figure 9. Temperature plots for binary control at VAV box using average temperature at the vicinity of occupants in all rooms with directional flow from diffusers (Scenario 3)



(a) Temporal variation of average room temperature



(b) Temporal variation of occupant temperature



(c) Temperature contour at neck height at t=60 mins

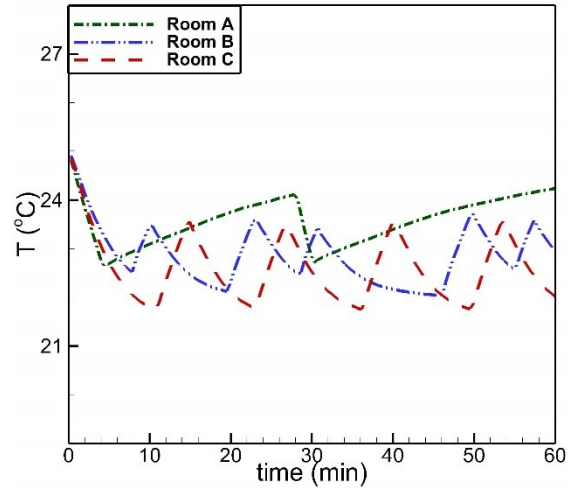
Figure 10. Temperature plots for binary control at VAV box using average temperature at the vicinity of occupants in all rooms with directional flow from diffusers (Scenario 4)

4.4. Scenario 4: Uniform air distribution controlled at individual diffuser level by independent temperature feedback from distributed sensors

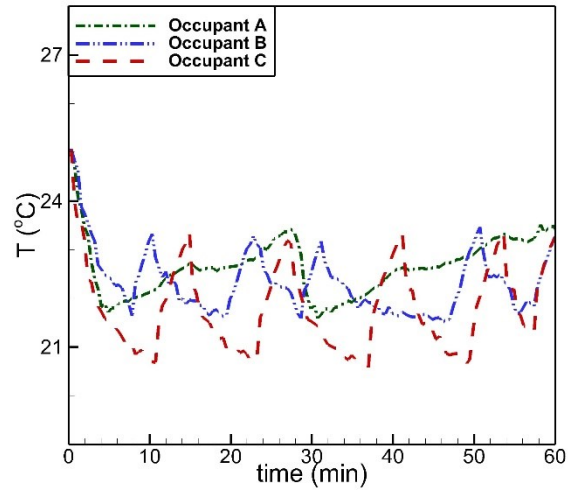
The previous cases showed the lack of flexibility (i.e., adaptation capacity) in providing comfortable temperature ranges for occupants. This rigidity stems from binary control of air supply on a centralized unit. All diffusers simultaneously cycle on and off regardless of the need in sub-spaces. However, these rooms are subjected to different thermal loads, hence, require different thermal conditioning. To achieve independent sub-space control of air supply, Scenario 4 simulates binary air flow control at diffuser level using legacy diffusers for uniform air supply – i.e., turning diffusers off in each room based on feedback from distributed sensors. Figure 10(b) shows the capability of this approach in satisfying expected thermal comfort ranges ($21.6^{\circ}\text{C} - 23.3^{\circ}\text{C}$) in each room. However, to achieve this objective, diffusers in Rooms B and C remain on for the entire time. Rooms B and C were maintained at 22.3°C and 22.1°C with occupant temperatures reaching 21.75°C and 21.95°C , respectively. Given the cut-off bound of 21.6°C , the diffusers in these rooms did not cycle off. The constant temperatures in Rooms B and C indicate an equilibrium between the heat gained from radiation and heat extracted by air conditioning - showing the need for additional conditioned air. In a full control loop, which engages the VAV box, cutting off air to one diffuser could direct the air discharge to other diffusers for increased cooling load to rooms B and C. The temperature contours show similarity across the zone with occupant temperatures within the thermal comfort range ($21.6^{\circ}\text{C} - 23.3^{\circ}\text{C}$). The conditioned air directed towards the wall (Figure 10(c)), could be directed towards the occupant to extract the excess heat received from solar radiation in Rooms B and C and provide comfort without excessive energy use as described in Scenario 5.

4.5. Scenario 5: Directional air distribution controlled at individual diffuser level by independent temperature feedback from distributed sensors

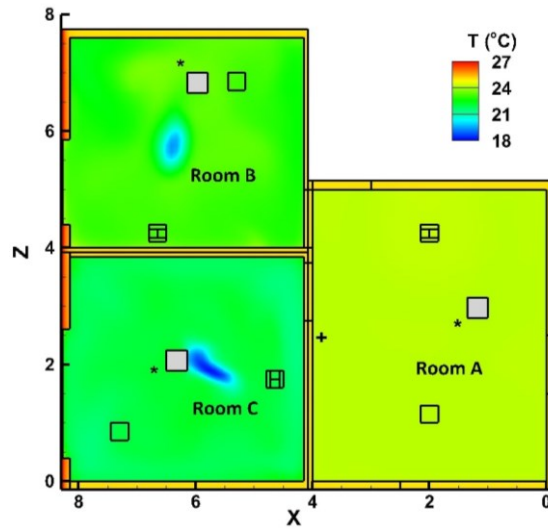
Compared to Scenario 4, achieving higher levels of flexibility is feasible by augmenting the diffusers with directional flow. Scenario 3 demonstrated that directional air flow improves thermal satisfaction while consuming less energy. Combining these two approaches, in this scenario, we evaluated directional air flow with independent control in each sub-space. The direction of flow remains fixed for the entire simulation as occupants are stationary. As Figure 11(a) presents, Room A requires longer off cycles and shorter cooling time compared to Rooms B and C. Room C requires longest initial cooling time as the distributed sensor is subjected to solar heat flux. The average cooling time per cycle for Room C with a larger window (~9 minutes) was more than Room B (~8 minutes). Figure 11(a) and (b) show that the average room temperature in Room A is higher than the occupant temperature at any given time, which implies the personalized conditioning of the air surrounding the occupant in Room A. In Room B, the cooling time per cycle decreases as time progresses indicating a highly transient behavior. Figure 11(c) presents the temperature contour at neck height ($y=1.25\text{ m}$) after 1 hour. The average temperature of room A is higher than Rooms B and C because the diffuser is at the end of the off cycle (approximately off for 30 minutes). Blue regions in rooms B and C represent cooler air, directed towards occupants, showing the increased efficiency of cooling. The initial cooling time in Room A decreased from 7 minutes to 4.5 minutes compared to Scenario 4, where conditioned air is lost near the walls due to the uniform supply of air.



(a) Temporal variation of average room temperature



(b) Temporal variation of occupant temperature



(c) Temperature contour at neck height at t=60 mins

Figure 11. Temperature plots for binary control at individual diffusers using temperature at the vicinity of occupants in each room with directional flow from diffusers (Scenario 5)

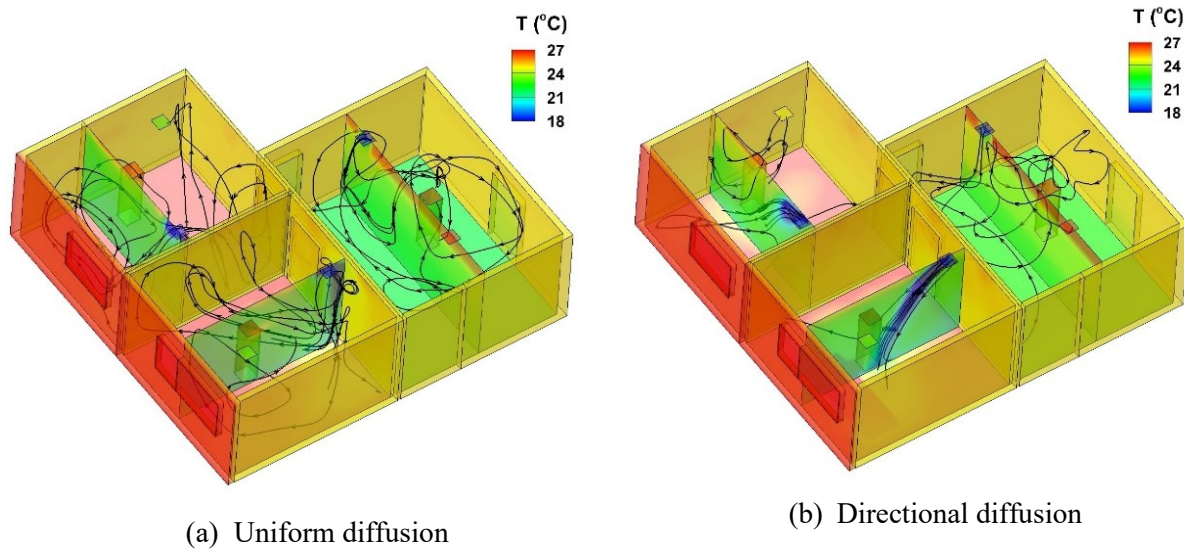


Figure 12. 3D streamlines and temperature contours for uniform (Scenario 4) and directional flows from diffusers (Scenario 5).

The three-dimensional view for uniform (Scenario 4) and directional (Scenario 5) flows are shown in Figure 12 at $t = 60$ min. In each view, streamlines are superimposed with temperature contours to investigate the velocity-temperature coupling. There is a vertical plane shown in each room located at the center of each diffuser to provide an additional visualization of the airflow patterns and corresponding temperatures. Note that the diffuser in Room A is off for both cases at this instance. Therefore, the observed streamlines in Room A are due to natural convection. The temperature contours present the detailed thermal profile in each case:

- Low temperature regions in Figure 12(a) – i.e., darker areas on the planes near the walls of Rooms B and C – confirm that part of the conditioned air is consumed to adjust the wall temperature due to uniform diffusion. The streamlines in Room C show that air moves downward along the wall due to buoyancy. Streamlines in Room B show a portion of air moving towards the window and door. Although distribution of air in all directions provides overall better circulation, it does not guarantee thermal comfort.
- Figure 12(b) clearly shows air directed towards the occupants in Rooms B and C. The diffuser in Room A is off as the setpoint was satisfied; hence, no directional flow is observed. The streamlines of the air jet leaving the diffusers elucidate the low temperature zones (blue region) on the middle planes of Rooms B and C. The cooler air leaving the diffuser does not follow a linear path, moves in the downward direction, most likely due to buoyancy. Additionally, as it is not subjected to solar radiation, the floor in Room A (in both cases) is at a lower temperature than the other rooms. As expected, a vertical temperature gradient is seen in the plane of Room A as the layer of warm air becomes more prominent as time progresses.

4.6. Thermal comfort implications

Thermal comfort is affected by factors such as ambient temperature, relative humidity, radiant temperature, and air speed. We assessed the performance of different scenarios according to thermal comfort requirements by ASHRAE [73]. This is important given that directional flow could increase air speed in the vicinity of occupants. The ASHARE acceptable air speed is determined according to a number of factors including access to control, thermal conditions, and human related variable such as clothing insulation and

metabolic rate. For occupants with control of air flow, there is no recommendation upper air speed limit. We assumed no occupant control, and therefore, the maximum acceptable air speed for typical office activities and clothing level in summer is:

$$\left\{ \begin{array}{ll} t_o > 25.5^\circ\text{C} & \rightarrow V_a = 0.8 \text{ m/s} \\ 23^\circ\text{C} < t_o < 25.5^\circ\text{C} & \rightarrow V_a = 50.49 - 4.4047t_o + 0.096425 t_o^2 \text{ m/s} \\ t_o < 23^\circ\text{C} & \rightarrow V_a = 0.2 \text{ m/s} \end{array} \right. \quad (1)$$

in which, t_o is the operative temperature and V_a is the average air speed around an occupant. Operative temperature could be calculated from average ambient temperature (t_a) and radiant temperature around an occupant [74]. For cases that occupants are not under direct solar radiation (as is the case in this study), the difference between average ambient temperature and radiant temperature is negligible [75], rendering the t_o to be considered equal to t_a .

Table 3. Temperature and air speed near occupants for the last cooling cycle, and the acceptable max air speed recommended by ASHRAE

Occupant(s) in Room	Parameter	Scenarios									
		Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5	
		on	off	on	off	on	off	on	off	on	off
Room A	Temperature ($^\circ\text{C}$)	21.6	22.8	19.7	20.6	19.3	19.8	21.7	23.3	21.7	23.2
	Speed (m/s)	0.12	0.02	0.11	0.03	0.13	0.01	0.1	0.01	0.15	0.01
	Max Recommended Air Speed (m/s)	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.21	0.2	0.2
Room B	Temperature ($^\circ\text{C}$)	24	26.3	22.8	24.9	23.3	25.2	22	-	21.7	23.3
	Speed (m/s)	0.11	0.05	0.12	0.06	0.19	0.07	0.12	-	0.22	0.07
	Max Recommended Air Speed (m/s)	0.31	0.8	0.2	0.58	0.21	0.73	0.2	-	0.2	0.21
Room C	Temperature ($^\circ\text{C}$)	23.9	26.3	22.6	24.9	22.2	25	21.9	-	20.7	23.4
	Speed (m/s)	0.12	0.06	0.11	0.05	0.26	0.07	0.13	-	0.27	0.07
	Max Recommended Air Speed (m/s)	0.30	0.8	0.2	0.58	0.2	0.62	0.2	-	0.2	0.22

Table 3 shows temporal average temperature and speed around occupants for the last cycle before and after thermal conditioning, as well as the acceptable maximum air speed. Four points around the neck and four points around the ankle were averaged to determine the average temperature and speed for an occupant. Based on the temperatures and velocities, the following can be gleaned:

- In Scenario 1, occupants in Room A experienced thermal comfort during the on-off cycles unlike occupants in Rooms B and C with temperatures higher than the initial indoor condition of 25°C .
- In Scenarios 2 and 3, occupants in Rooms B and C experienced lower temperatures compared to Scenario 1. However, in room A, temperature reaches near 20°C below the acceptable range.
- All occupants are within comfort range for Scenarios 4 and 5 with better performance for Scenario 5. As expected, the speed at occupant location is higher for directional flow. In Scenarios 3 and 5, the air speeds around the occupants surpass the acceptable maximum, specifically for Room C. Equation 1 shows that thermal comfort is driven by operative temperature and the air speed around the occupants. Therefore, as a potential adaptive capacity, active diffusers could adjust the directional flow to opt for higher temperatures with higher air speed near occupants for thermal

comfort with lower energy use. Alternatively, the angle of directional flow with respect to the ceiling could be constrained to avoid direct air flow towards occupants. These are some of the potential modifications that will be part of the future research directions.

4.7. Energy consumption

The primary goal of using directional flow is energy conservation while maintaining comfort. Table 4 presents the total duration of supplying conditioned air during the 60-minute simulated operations.

Table 4. Total cooling time (in minutes) per diffuser in each room over a 60-min duration

Rooms	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
A	17.5	32.1	23.7	10.8	8.8
B	17.5	32.1	23.7	60	39
C	17.5	32.1	23.7	60	49.7
Thermal Zone	52.5	96.3	71.1	130.8	97.5

To compare energy consumption of different operational scenarios, we have used total volume of conditioned air, supplied to the thermal zone, during the one-hour simulation as the indicator of the energy consumption in Table 5. It has been shown that the air flow to thermal zones is linearly correlated with energy consumption of HVAC systems [56]. The supply air temperature is also an important factor in driving the energy consumption; however, since this temperature was constant across all scenarios, we only used air flow for comparisons. The total volume of air was calculated by multiplying the air supply durations in Table 4 by the air flow rate at each diffuser. Although the total cooling time for Scenarios 4 and 5 is more than Scenarios 1-3, thermal comfort was only achieved for Scenarios 4 and 5. We used the following formula to measure how effective each scenario was in keeping the temperature close to preferred temperature (i.e., setpoint):

$$\Delta c = \sum |T_i - T_r|$$

Δc is the discrepancy between occupants' temperature and the setpoint of 22.3°C (T_r), and T_i is the average occupant's temperature through an on-off cycle (we used the average of lowest and highest temperatures around occupants during one cycle). The room-level and zone-level values for Δc have been presented in Table 5.

- In Scenario 1, the legacy control logic does not provide comfort in Rooms B and C, thus, the lower energy demand is not representative of the real-world operation. The outcome was similar to having a thermal conditioning system only in Room A as the Δc values in Rooms B and C indicate. Therefore, in the following assessments, we have considered the second scenario as the baseline.
- By integration of distributed feedback, Scenarios 2 and 3 yielded better Δc across all rooms although the overall Δc is similar to Scenario 1. In other words, these scenarios help improve the fairness across the thermal zone. However, Scenario 3 (which uses the envisioned directional flow) has resulted in reduced energy demand.
- Through binary control augmentation at the diffuser level, we could see considerable improvements in thermal comfort experience. Considerable higher energy demand in Scenario 4 is associated with the insufficiency of the cooling load for the high thermal demand in Rooms B and C that resulted in an hour-long on cycle (see Figure 10). On the other hand, Scenario 5 shows similar cooling demand compared to the baseline (Scenario 2) with much improved thermal comfort experience. This is a demonstration of the benefits from integration of the proposed active diffusers. Integration of VAV box control could further reduce the energy demand due to distribution of air discharge.

- The last row of Table 5 shows the cooling demand corrected/normalized for comfort discrepancy. In these calculations, we have scaled the cooling demands by $\Delta c_k/\Delta c_2$, where Δc_k is Δc from scenario k – e.g., $\Delta c_4/\Delta c_2$ is 0.9/515. This is interpreted as energy efficiency – the effective use of energy for thermal satisfaction. As the values show, Scenarios 4 and 5 have resulted in considerable improvement in effective use of energy for comfort. The addition of directional flow shows further improvement over binary control in active diffusers.

Table 5. Energy efficiency comparison analysis

Energy consumption and comfort proxies	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Δc – Room A	0.1	2.15	2.75	0.2	0.15
Δc – Room B	2.85	1.55	1.95	0.3	0.2
Δc – Room C	2.8	1.45	1.3	0.4	0.25
Δc	5.75	5.15	6.0	0.9	0.6
Total Supplied Conditioned Air (m ³) - TSCA	178	327	242	444	331
TSCA Normalized for Comfort Discrepancy	N/A	327	282	78	39

4.8. Discussion

The proposed concept of active diffusers with adaptation capabilities was shown to result in flexible performances in thermal zones for increased energy efficiency (effective energy use for thermal comfort). However, reaching a significant conclusion on the overall efficacy and energy saving potentials (i.e., formalization of adaptation capacities) calls for a comprehensive study that accounts for different thermal zone configurations, occupancy patterns, thermal comfort ranges of occupants, climate conditions, and control parameters such as ramping the conditioning loads. For example, occupancy patterns of individual rooms play a significant role in energy efficiency. The scenarios that use binary control at the VAV box level, are far less flexible when the thermal zone is partially occupied. In those scenarios, the continued supply of air in unoccupied zones could result in a considerable increase in energy consumption compared to cases with independent diffusers. Considering the computational cost of combinatorial analyses, the formalization studies require computational tools with higher efficiency such as Fast Fluid Dynamics and leveraging GPU computing. Another limitation of our study was the disconnection between control at the diffuser level and the VAV box level. Binary control at one diffuser (i.e., turning off the flow) will change the flow for other diffusers, which should be managed at the VAV box level control. Further studies into the flow distribution between different diffusers could provide a better insight into the efficiency of highly adaptative diffusers.

Further investigation on the impact of the space and building system configurations (e.g., multi-occupancy and open-space offices) is also necessary. In open space scenarios, zoning and multi-VAV configuration could support targeting sub areas, covered by individual diffusers. Equipping the diffusers for detecting activities and number of occupants [3, 12], the control algorithms could account for multi-occupancy scenarios using alternative strategies, such as targeting a group of occupants, alternating between different occupant locations, or switching between directional and uniform diffusion. The energy efficiency implications of such scenarios under the uncertainty of occupancy patterns could lead to quantifying the whole building adaptation capacity and load flexibility [76].

5. Conclusion

To investigate flexibility potentials of HVAC systems for introducing new adaptive capacities, we investigated the impact of alternative control strategies by accounting for (1) distributed feedback from the indoor environment, and (2) adaptation in control loop by introducing a new perspective for active diffusers. Active diffusers could change their actions (i.e., turning air supply on or off and adjusting the direction of the air flow) according to the dynamics of occupants and environments. To this end, we adopted a case study approach by creating a CFD simulation of a real-world thermal zone with imbalanced behavior and

evaluated five scenarios of operational strategies. At a high level, these scenarios included legacy control, control by measuring feedback at the locations of individual occupants, and control by flexibility augmentation at the diffuser level. The results of simulations were interpreted in terms of effective energy use for thermal comfort provision. The integration of distributed feedback showed to improve the fairness in thermal comfort across the thermal zone although individual occupants' comfort requirements might not be satisfied. However, the integration of diffuser-level adaptive (binary and directional) actuation showed improvements in thermal comfort satisfaction while reducing energy demand – by $\sim 25\%$ compared to sole use of binary actuation. This study showed the potentials of new dimensions in adaptive operation of HVAC systems. Given these potentials, the future of this research will focus on developing control frameworks that use artificial intelligence for inference of occupancy and thermal preferences, as well as intelligent control for the indoor condition and energy optimization. Therefore, formalizing the adaptive capacities of these new dimensions for diverse contextual conditions, experimental evaluation of the proposed new adaptive capacities, and investigating intelligent and context-aware algorithmic frameworks for autonomous operation of diffusers are among the future directions of this research.

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