LEVERAGING DIVERGENCES:
BUILDING CONTROL, PERSONAL COMFORT AND INDOOR CLIMATE

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ABSTRACT

LEVERAGING DIVERGENCES: BUILDING CONTROL, PERSONAL COMFORT AND INDOOR CLIMATE

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Over the last two decades, major advances in technology have allowed researchers to develop strategies for automating the operational tasks in buildings to improve the overall system efficiency. However, the stochastic nature of human needs and standardized, one-size-fits-all configurations in current control approaches lead to disharmony in human-automation coexistence in buildings. Although well-established interaction between control systems and occupants is acknowledged as one of the core elements of intelligent buildings, defined borderlines of the prevailing automation modalities fail to satisfy this primary feature. To this end, this research conceptualizes a collaborative building control framework, which establishes a communication ground between people and buildings. To assess comfort and energy related implications of the proposed framework, a simulation based and data driven research was conducted in the thermal domain, considering the need for investigating the personalized dimensions of building control, human comfort, and indoor climate. A multi-occupancy office space shared by six occupants was adopted as a case study. Probabilistic personal comfort profiles were used to quantify the likelihood of each occupant being comfortable in diverse conditions. Thermal distribution characteristics of the space were investigated using computational fluid dynamics (CFD) simulations under varying supply airflow rates, supply airflow directions, and

occupancy settings. Through performing an optimization analysis, achievable comfort improvements and energy savings were presented. The results confirmed that considering the divergences in personal comfort and indoor climate with a dynamic control strategy, where occupants are kept in the loop, has great potential for providing comfortable indoor environmental conditions and improving energy efficiency.

Keywords: Building Control, Thermal Comfort, Energy Efficiency, Personal Comfort Models, Computational Fluid Dynamics, Occupant-Centric Building Operation

ÖZ

FARKLILIKLARDAN YARARLANMAK:
BİNA KONTROLÜ, KİŞİSEL KONFOR VE İÇ MEKÂN İKLİMİ

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Son yirmi yılda, teknolojideki büyük ilerlemeler araştırmacıların genel sistem verimliliğini artırmak için binalardaki operasyonel görevleri otomatikleştirmeye yönelik stratejiler geliştirmelerine olanak sağlamıştır. Bununla birlikte, insan ihtiyaçlarının stokastik doğası ve mevcut kontrol yaklaşımlarındaki standartlaştırılmış, herkese uyacağı düşünülen tek tip konfigürasyonlar, binalarda insan-otomasyon birlikteliğinde uyumsuzluğa yol açmaktadır. Kontrol sistemleri ve bina kullanıcıları arasında iyi kurulmuş etkileşim, akıllı binaların temel unsurlarından biri olarak kabul edilse de mevcut otomasyon yöntemlerinin tanımlanmış sınırları bu ana özelliği karşılamakta başarısız olmaktadır. Bu amaçla, bu araştırma, insanlar ve binalar arasında iletişim zemini oluşturan, ortaklaşmaya dayalı bir bina kontrol çerçevesini kavramsallaştırmaktadır. Önerilen çerçevenin konfor ve enerji ile ilgili getirilerini değerlendirmek için, bina kontrolü, insan konforu ve iç mekân ikliminin kişiselleştirilmiş boyutlarını araştırma ihtiyacı göz önünde bulundurularak termal alanda simülasyona ve veriye dayalı bir araştırma yürütülmüştür. Altı kişi tarafından paylaşılan çok kişilik bir ofis alanı, vaka çalışması olarak kabul edilmiştir. Her bir bina kullanıcısının farklı koşullarda konforlu olma ihtimallerini belirlemek için olasılıksal kişisel konfor profilleri kullanılmıştır. Seçilen mekânın termal dağılım özellikleri, farklı besleme hava akış hızları, besleme hava akış yönleri ve bina kullanıcısı doluluğu düzenlemeleri altında hesaplamalı akışkanlar dinamiği simülasyonları kullanılarak incelenmiştir. Optimizasyon analizi yapılarak, insan konforu ve enerji tasarrufu bakımından ulaşılabilir iyileştirmeler sunulmuştur. Sonuçlar, bina sakinlerinin kontrol döngüsüne dahil edildiği dinamik bir kontrol stratejisi çerçevesinde kişisel konfor ve iç mekân iklimi farklılıklarının dikkate alınmasının konforlu iç mekân koşulları sağlama ve enerji verimliliğini artırma konusunda büyük potansiyele sahip olduğunu doğrulamıştır.

Anahtar Kelimeler: Bina kontrolü, Termal Konfor, Enerji Verimliliği, Kişisel Konfor Modelleri, Hesaplamalı Akışkanlar Dinamiği, Kullanıcı Merkezli Bina İşletimi

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BAS	Building Automation System
BMS	Building Management System
CFD	Computational Fluid Dynamics
DB	Dry Bulb
IoT	Internet of Things
HVAC	Heating, Ventilation, and Air Conditioning
MRT	Mean Radiant Temperature
MSE	Mean Squared Error
RF	Random Forest
VAV	Variable Air Volume
VSD	Variable Speed Drive

CHAPTER 1

INTRODUCTION

Building control, personal comfort, and indoor climate are interdependent subjects that have received considerable attention in the building industry over the last two decades (Figure 1.1). Although the specific focus of research has been remarkably diverse amongst the scholars, they are all in pursuit of a common goal at a higher level, which is to provide a comfortable and healthy indoor climate for people while ensuring the efficient use of energy resources for lessening the negative impacts of buildings on the environment. As an overarching contribution to this common purpose, this research conceptualizes an occupant-centric building control framework and leverages its implementation for climatization systems by coupling the non-uniformity of individuals' comfort needs and the heterogeneity of thermal conditions in shared indoor spaces.

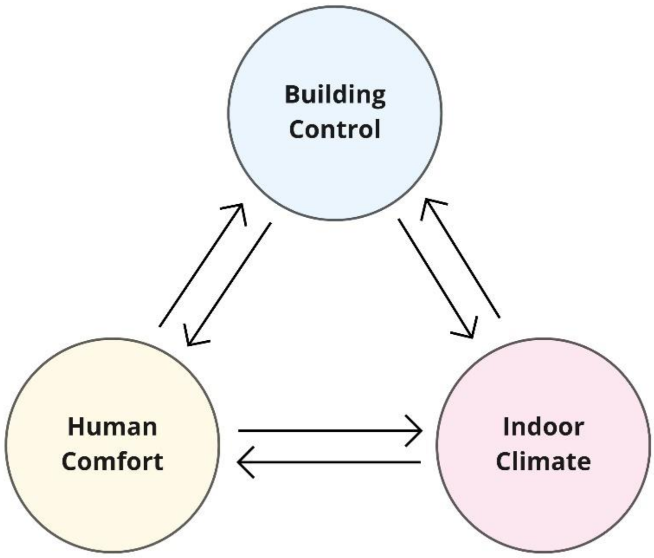


Figure 1.1. Three interdependent subjects in building practice

1.1 Research Motivations and Problem Statement

Divergences in Building Control

The energy demand of the building sector constitutes nearly 40% of total energy use globally, and energy is primarily utilized to satisfy occupants' comfort needs. Heating, ventilation, and air conditioning (HVAC) systems alone are accountable for nearly 75% of electricity consumption and 40% of total energy consumption in buildings in the United States (DOE, 2011). With the intention of reducing energy consumption and minimizing inefficacies in the operation of building systems, adopting a centralized automated control has been introduced as a possible technology aided solution (Wang, 2010). However, such approaches did not gain popularity and high acceptance levels amongst the occupants due to the decreased perceived control, ever-changing dynamic individual needs and standardized, one-size-fits-all approach in current automation systems. Depriving occupants completely of building control affects both energy efficiency and occupant comfort in a negative manner (Day and Heschong, 2016). It is crucial to note that occupants and their complex nature have significant impacts on building energy performance, and they are the major factors contributing to the excessive energy consumption of building systems (Hong *et al.*, 2017). Considering these, it can be claimed that maintaining efficient operation of building systems and human comfort simultaneously requires an inclusive approach, where both the control capacity of technology-powered methods and flexibility granted by incorporating occupants in the loop are ensured.

Divergences in Personal Comfort

Among various human dynamics, thermal comfort can be claimed as the paramount subject considering its effects on overall human satisfaction (Frontczak & Wargocki, 2011; Wagner *et al.*, 2007) and the account of HVAC systems on building energy use. Providing thermal comfort in buildings is quite a complex task, which is still unresolved and studied by many. Building researchers have concentrated on developing empirical models, which link the thermal variables (temperature, air velocity, etc.) of indoor environments and other factors with the comfort states of occupants. Two main models, namely the predicted mean vote (PMV) and adaptive models, underpin the current thermal comfort approaches and were adopted in international standards like ASHRAE 55 (2017) and ISO 7730 (2005). However, both are pre-defined aggregate models, and their prediction only demonstrates the average comfort of large populations. They fail to accurately predict individuals' thermal comfort in multi-occupancy indoor environments, where occupants with varying comfort profiles share the same thermal zones. In recent years, the developments in the Internet of Things (IoT) concept have enabled the collection and analysis of real-time personal data, and this paved the way for a new paradigm in thermal comfort modeling, called personal comfort models (Kim, Schiavon, *et al.*, 2018). Personal comfort models eliminate the over-simplified assumptions in PMV and adaptive models by demonstrating a highly granular, individualistic approach. Through directly making use of the data collected in everyday environments, it utilizes machine learning algorithms to learn individuals' comfort profiles and creates the base for occupant-centric building control (Jung & Jazizadeh, 2019a).

Divergences in Indoor Climate

One of the primary assumptions in current studies on occupant-centric building control is the uniform temperature distribution in the spaces under investigation, which does not take dynamic conditions specific to particular positions into consideration. Although a single thermostat or a local sensor is attributed to be representative for the entire room for assessing the thermal conditions, micro-thermal conditions may vary by location, especially in large offices with multiple occupants (Zhou *et al.*, 2015). Many parameters can affect micro-climate around different occupants, including proximity to windows, furniture layout, solar radiation, supply air inlet placement, and heat flux aroused from electronic appliances. These factors can lead to variations in indoor environmental parameter values within the same space, making occupant location an essential aspect for continuous comfort. In the absence of proper control strategies, occupants may have varying sensations (cold, warm, et.) in the same room caused by the uneven thermal distribution. The worst-case scenario would be not being able to provide comfort for any occupants while consuming an excessive amount of energy for conditioning the space. In that sense, just like regarding the nonuniformity in personal comfort, taking the heterogeneity of indoor climate conditions into consideration in building control holds great potential for improving occupant comfort and reducing energy consumption.

Nevertheless, limited research exists questioning the potential of incorporating micro-thermal condition data in control loops for system efficiency in buildings. The reason may be the high cost associated with acquiring controlled measurements and implementing complex sensor infrastructures to comprehensively analyze the patterns and distributions of thermal parameters in indoor environments. However, with advances in technology facilitating greater accessibility to high computational power, it is becoming increasingly feasible to leverage computational fluid dynamics (CFD) simulations as a more economical and efficient alternative for obtaining the necessary thermal variables. CFD simulation is a powerful tool that solves a set of partial differential equations for conservation of mass (the continuity equation), momentum (Navier-Stokes equations), and energy with applicable turbulence models. Although this simulation tool is extensively used to design and optimize HVAC systems in buildings (Duan & Wang, 2019; Shan *et al.*, 2019; Zhou *et al.*, 2014), its employment to elaborate occupant-centric control is relatively limited.

1.2 Objectives

This research argues that an occupant-centric building control framework, which allows bi-directional communication and control negotiation between building management systems and occupants, can increase human comfort while enhancing energy efficiency. To assess the potential benefits of the framework, a data driven investigation was conducted in the thermal domain. This investigation involved personalized evaluation of thermal comfort and dynamic operation of HVAC systems. The main objectives of this dissertation are identified as:

- Developing a collaborative building control framework enabling collaboration and communication between building occupants and the automation to respond to the drawbacks of prevailing building control approaches.
- Assessing the optimization of collective thermal comfort and efficient operation of conditioning systems, through leveraging nonuniformity of people's personal comfort preferences and distribution of thermal parameters in shared spaces.
- Demonstrating the influences of occupancy (number, position, etc.), supplied airflow parameters and potential human-building communication for improving collective thermal comfort and efficient system operation in multi-occupancy scenarios.

Accordingly, in pursuit of these aims:

- A building control framework that aims to enhance human-building communication was conceptualized through reviewing existing human and automation related system issues.
- Multiple personal comfort profiles were generated with Bayesian network modeling approach by employing available datasets collected from actual buildings in the literature.
- Heterogeneity of thermal conditions in shared indoor spaces were demonstrated under various conditioning and occupancy settings, by carrying out CFD simulations in ANSYS Fluent software.
- A data-driven optimization analysis within the scope of proposed framework was carried out using personal comfort profiles and thermal distribution datasets to present collective comfort and energy saving improvements.

1.3 Research Questions

The main question of this research is: How can we improve occupant comfort while ensuring the efficient use of energy in building operation?

In order to answer the main question, following sub-questions are formed:

- What are the comfort and energy affiliated problems in prevailing building control approaches and how can they be tackled?
- What are the implications of occupant comfort in shared indoor environments on building control?
- What are the characteristics of thermal distribution patterns in multi-occupancy office spaces?
- Can we leverage varying comfort preferences of occupants and heterogeneity of thermal conditions to improve collective comfort and energy efficiency?

1.4 Contribution

Jendritzky and de Dear (2009) reported that even making small adjustments on temperature set points (i.e., tuning a few degrees) may have profound impacts on energy consumption and greenhouse gas emissions. Despite the considerable amount of energy used to provide comfort in buildings, the lack of thermal comfort is still one of the most common occupant complaints. Based on what this research provides, it is expected to demonstrate how building energy can be effectively used for optimum thermal comfort provision in multi-occupancy indoor environments. In doing so, a collaborative building control framework enabling control flexibility and providing desired comfort conditions for building occupants is proposed. The applicability of the proposed approach was validated in the thermal domain, through examining the primary assumptions made in building control, which are the averageness of thermal comfort sensations and homogeneity of thermal conditions in indoor spaces. Within the scope of an optimization analysis, control strategies are elaborated to use the aroused potentials in favor of human comfort and energy efficiency.

Throughout the progression of this research, three journal articles (Topak & Pekeriçli, 2021; Topak & Pekeriçli, 2022; Topak *et al.*, 2023) were published, and the sections were partially presented in several conferences (Topak *et al.*, 2019; Topak & Pekeriçli, 2020; Topak *et al.*, 2022; Topak *et al.*, 2023), the exhaustive list of which is given in Appendix-A.

1.5 Research Structure and Disposition

The structure of this dissertation is composed of four main sections, which is demonstrated in Figure 1.2. Following the introduction section, Chapter 2 provides an overview of occupant and system related issues of building automation systems in the literature and presents the conceptualized collaborative building control framework, which proposes a mixed-initiative approach in system operation.

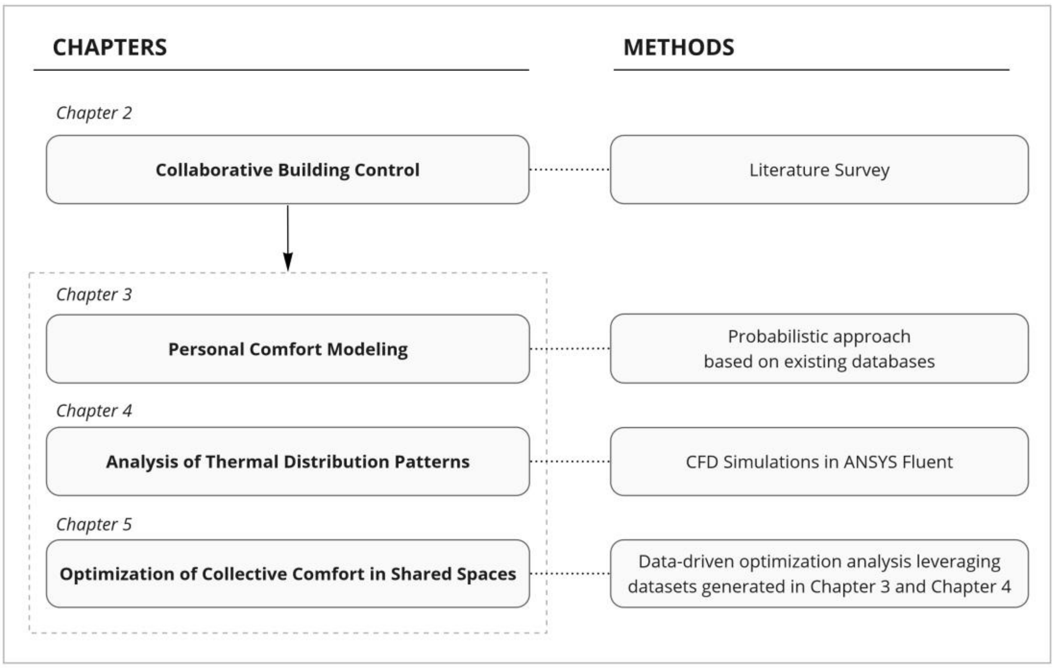


Figure 1.2. Overview of research structure

Chapter 3, Chapter 4, and Chapter 5 altogether constitute a dedicated workflow for demonstrating how the proposed framework may function for the thermal domain. In Chapter 3, the transition towards personal comfort models is explained, and multiple comfort profiles are presented, generated by applying Bayesian network modeling approach on existing real-world datasets in the literature to account for the individual differences in comfort needs and preferences.

Chapter 4 addresses the nonuniformity of thermal conditions in shared indoor spaces. The procedural process of running numerical CFD simulations, simulation-based assessment of independent variables, main simulation scenarios and corresponding results are presented, respectively. The impacts of occupancy, supplied airflow rate, and supplied airflow direction in thermal distribution patterns are illustrated.

Leveraging personal comfort profiles and indoor thermal distribution patterns datasets presented in Chapter 3 and Chapter 4, Chapter 5 elaborates a data-driven optimization assessment and analyzes the potential implications of human-building cooperation in the thermal domain. The range of achievable comfort improvement probabilities and energy-saving possibilities are demonstrated in comparison to the pre-determined baseline scenarios.

The dissertation is concluded in the last chapter with the overall discussion, revisiting of research questions, limitations of the study, and projections on future work.

CHAPTER 2

COLLABORATIVE BUILDING CONTROL

In this chapter, through reviewing current human and automation related system issues, a conceptual mixed-initiative framework that aims to enhance human-automation collaboration for the control of building systems was presented. The conceptualization is refined through analyzing related subjects, and the framework is elaborated upon the available evidence in the literature. The novelty of the proposed approach is to introduce “mixed-initiative” concept to the building control, which enables human-automation collaboration for achieving optimum efficiency-comfort balance. This proposal may help researchers comprehend the integral components of mixed-initiative building control and grasp the prospective research directions, enhancing more human-centric built environments. Following the conceptualization, the building control scheme was concretized for the indoor environments shared by multiple occupants, which presents a unique challenge for personalized operation in building control due to the potential variations in people’s behaviors, preferences and tolerance levels.

The chapter is structured as follows. First, the emergence of automation concept in buildings were reviewed and prevailing occupant-related building automation issues were introduced. Then, the concept of flexibility in automation was discussed by referring to the automation taxonomies in general. Subsequently, after critically reviewing the literature, the conceptualization of the mixed-initiative framework was demonstrated and the operational workflow was explained. Lastly, a potential application scenario of the proposed framework in the thermal domain was elaborated by structuring a simplified building control scheme and the chapter was finalized with some conclusive remarks and discussion.

2.1 Literature Review

2.1.1 Intelligent Buildings

Starting from the early 1980s, considerable advancements in computer, information, and communication technologies reflect themselves in the management and control of building services, evolving from simple function dedicated systems to today's computerized buildings. The integration of cutting-edge technological tools in built environments has been studied in the literature under the umbrella term of intelligent buildings, the concept of which was born with the purpose of creating energy-efficient, productive, and environmentally healthy spaces for people (Clements-Croome, 2013). The early definitions of the term "intelligent building" were almost entirely related to technology integration and building automation. Many of the examples of so-called intelligent buildings were only representing the incorporation of increasing quantities of information technology into buildings (Wigginton & Harris, 2002). Later on, the definition of the intelligent building concept was expanded to cover the linkage between occupants, building systems, and the environment. From seeking technology integration, the main focus of the concept gradually shifted towards responding to occupant expectations, comfort needs, and quality of life enhancement. One of the very first comprehensive definitions of intelligent buildings was presented by Clements-Croome (1997) through referring CIB Working Group W98's proceedings as:

> An intelligent building is a dynamic and responsive architecture that provides every occupant with productive, cost effective and environmentally approved conditions through a continuous interaction among its four basic elements: Places (fabric; structure; facilities); Processes (automation, control, systems); People (users, occupants) and Management (maintenance; performance) (p. 396).

In their intelligent environments manifesto, Augusto, Callaghan, Cook, Kameas, and Satoh (2013) defined intelligent buildings as the environments where intelligent software agents control networked controllers to ensure holistic functionality and comfort for inhabitants. From our perspective, an intelligent building can be described as a dynamic immersive living machine, which incorporates numerous processes flexibly to respond to the various needs of its occupants through enabling human-machine cooperation, data-systems integration and technological articulation. In fact, one of the most fundamental characteristics of intelligent environments is to minimize the burden of occupants on controlling different operational tasks in buildings through the employment of technology, providing them more free time to spare other activities (Cole *et al.*, 2012).

The main component of intelligent buildings satisfying this characteristic is called building automation (Wang, 2010). The state-of-the-art technological developments supporting automation in buildings in recent years includes but not limited to artificial intelligence algorithms, ubiquitous sensing, actuation systems, cloud computing, big data engineering and the Internet of Things (IoT) products (Jia *et al.*, 2019). These tools enable to collect and analyze data from both occupants and built environments, and assist decision making in the control of various building systems and operations including heating, ventilation and air conditioning (HVAC), lighting, shading, plugged-in appliances and so on.

Despite the advanced developments and wide-scale use of automation systems in various disciplines, the employment of automation in buildings has not gain popularity. This is mainly caused by the fact that automation has a low-acceptance level amongst the building occupants, which is the reflection of disharmony between human nature and the operation principles of current building automation systems (Brush *et al.*, 2011; Mayra *et al.*, 2006). Although well-established continuous interaction between building control systems and occupants is referred to as one of the core elements of intelligent environments (Clements-Croome, 1997), strictly-defined borderlines of the prevailing automation systems fail to satisfy this primary feature (Ahmadi-Karvigh *et al.*, 2017; E. S. Lee *et al.*, 2013).

2.1.2 Building Automation Systems

Building automation systems (also known as building management systems), refer to the installed technological infrastructure that monitor and administrate buildings' physical environments and operations, including heating, ventilation and air conditioning, lighting, shading, auxiliary energy, and water supply. Automating the building systems and creating centralized control is generally favored by many engineers, designers, and facility managers, with an intended goal of enhancing system efficiency. Although automation systems' capabilities have been extended in recent years (Aparicio-Ruiz *et al.*, 2018; Naylor *et al.*, 2018), their wide-scale employment by building occupants has remained unrealized (Meerbeek *et al.*, 2014), which can be grounded by several reasons.

First of all, people usually desire to have a control over their environments; they prefer manual adjustments rather than automated operation. An experimental study conducted by Luo *et al.* (2016) demonstrated that the feeling of being in charge, which is often referred to as perceived control in the literature, affects people's perception of comfort. Tamas, Ouf, and O'Brien (2019) reported that occupants are usually dissatisfied with building automation, and perceived comfort is correlated with perceived control. People accustomed to primitive building systems that are almost entirely transparent with their simple logic and physical interfaces (*i.e.*, a light switch) become relatively unenlightened in the existence of advanced logic of automation systems operating in the background with no intervention possibilities. When people do not understand fundamentals of a system, they do not trust it, and their sense of control and satisfaction decreases dramatically (Karjalainen, 2013).

Secondly, occupants' automation needs and preferences are dynamic, and the level of autonomy that they desire may change depending on their physical, psychological, and emotional states (Callaghan, 2013). Although there have been some research efforts for enabling occupants to vary the level of technical assistance in the built environments (Ball & Callaghan, 2012b; Bradshaw *et al.*, 2003), no widely-influential result or a comprehensive framework has been demonstrated so far, and current building automation systems still lack such flexibility.

Lastly, building automation systems usually provide standardized indoor environmental conditions that are the mean preference of many people, following a “one-size-fits-all” management approach. Park and Nagy (2018) asserted that the research on building automation systems mostly focuses on energy savings rather than incorporating human comfort, demonstrating the recent discrepancy between indeed very much related two subjects. Despite the ongoing progress in developing personalized comfort models to improve occupant comfort using technology (Jung & Jazizadeh, 2019a; Kim, Schiavon, *et al.*, 2018), most of them rely on physical sensor measurements and fail to centralize people in the control loop of their indoor habitats. Due to human beings’ stochastic nature, comfort is very individual and time-dependent, and standardized automation systems fail to fulfill occupants’ requirements.

People have certain comfort expectations of their environments, and when these expectations are not met, they perform actions to adjust their surroundings. In modern buildings, occupants have been allowed to interact with static building components to adjust the environment according to their comfort levels. For example, individually controlled window ventilation has been a universal consent, and it was demonstrated as a beneficial strategy for ensuring a relaxed state for occupants (Brager et al., 2004). In the last two decades, it is revealed by many researchers that such human-building interactions have crucial influences on building energy performance, indoor environmental conditions, and occupant comfort (Hong *et al.*, 2017). Building automation solutions were devised to overcome such impacts by dramatically decreasing the level of control handed over to occupants through centralizing the building controls and automating systems’ operation (Vasseur & Dunkels, 2010). However, recent researches demonstrated a high demand for direct personal control, which necessitates a change of perspective in the research agenda of building automation systems.

Since the unfamiliarity of occupants with the way automation works leads to inadequate human-building interactions, and resultantly, to system failures, human intervention could be considered a risky input for the proper functioning of building automation systems (Lazarova-Molnar & Mohamed, 2017). Occupants' awareness and knowledge of technology is an essential aspect for obtaining the desired benefits. Day and Heschong (2016) emphasized that both energy efficiency and occupant comfort were negatively affected when occupants are deprived of building control without any prior clarification. Considering the core of implementation barriers of building automation systems and the impacts of occupant behaviors, the main issue to be concentrated on can be identified as the lack of a mechanism providing coordination and communication between occupants and building automation systems. In order to enhance the system robustness, efficient operation of building systems, and human comfort simultaneously, benefiting from both control capacity of computer-powered methods and flexibility granted by incorporating occupants in the loop holds a substantial potential.

2.1.3 Flexibility in Automation

Incorporating a coordination and cooperation mechanism between people and automation systems requires a certain level of system adjustability on the machine end. Such flexibility has been initially led with different taxonomies proposing varying levels of automation (LOA) in the literature. Starting from late 1950s, intermediate levels between the two extremes of full manual operation and full automation have been assessed to find solutions for control conflicts in various human-machine interaction scenarios (Vagia *et al.*, 2016). Automation levels have been specified based on the discipline they are applied in, including avionics, advanced manufacturing, teleoperation, air traffic control, and piloting.

A comprehensive general human-machine interaction model with no specified application was introduced by Riley (1989) in order to assist the investigation of automation-related issues. Accordingly, the author proposed twelve levels, through combining automation degrees and system's intelligence sophistication. The former six levels were categorized based on system's information processing maturity and the level of displayed advising, while the latter six were collocated according to their ability of taking actions. Levels are labelled based on the system's functional capability limits, including information fuser, advisor, servant, assistant, partner, and supervisor. A more recent and refined taxonomy was proposed by Vagia *et al.* (2016), intending a wider range of usability (Table 1). LOA described in this taxonomy is also created considering how and when the system would notify the user, share responsibilities and take actions. Although these different levels show how the computerized systems can provide adjusted forms of aid to humans based on their needs, designating automation systems though using the identified levels brings out a static situation yet again, which lacks flexibility in operation. Considering the ever-changing requirements in built environments due to the stochastic nature of occupant behaviors, facilitating dynamic arrangements in the level of supplied machine assistance is of the utmost importance.

The possibility of dynamic shifts between different LOA has been studied under different key terms, including adaptive automation (Kaber & Endsley, 2004), adjustable (or adaptable) automation (Miller & Parasuraman, 2007), and mixed-initiative systems (Barnes *et al.*, 2015). Chen and Barnes (2014) explained that these three terms cover flexibility in automation and are differentiated depending on the delegation of authority between humans and machines on the management of the shifts between the automation levels. As depicted in Figure 2.1, which is elaborated upon the work of Ahmadi-Karvigh *et al.* (2017), automation modalities are categorized based on the trade-off between the amounts of human control and the automated operation. In adaptive systems, the automation is designated to invoke appropriate drifts between LOA based on analysis of the contextual and situational data. In adjustable systems, on the other hand, decisions of changing the automation levels are made by humans. Adaptive systems lack human involvement in the management of critical tasks and may lead to a reduced perceived control, whereas adjustable systems require certain human capabilities and result in an unbalanced mental work load for people (Hussein & Abbass, 2018).

Table 2.1. Levels of automation proposed by Vagia *et al.* (2016)

LOA	Description	Explanation
1	Manual Control	Computer offers no assistance
2	Decision Proposal	The computer offers some decisions to the operator. The operator is responsible to decide and execute.
3	Human decision select	The human selects one decision and the computer executes.
4	Computer decision select	The computer selects one decision and executes with human approval.
5	Computer execution and human information	The computer executes the selected decision and informs the human
6	Computer execution and on call human information	The computer executes the selected decision and informs the human only if asked
7	Computer execution and voluntarily human information	The computer executes the selected decision and informs the human only if it decides to
8	Autonomous control	The computer does everything without human notification, except if an error that is not into the specifications arrives. In that case, the computer needs to inform the operator.

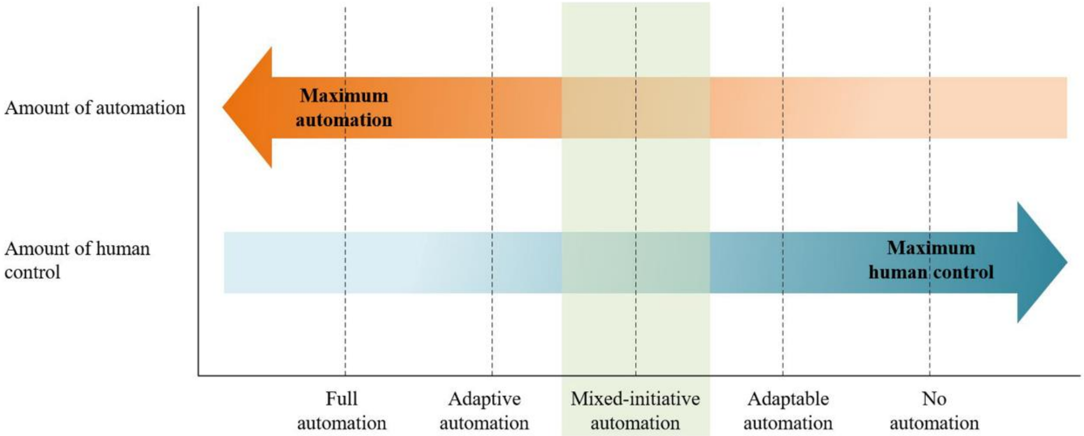


Figure 2.1. Comparison of different automation modalities

As an eclectic solution combining the advantages of adaptive and adjustable systems, mixed-initiative systems were proposed to allow a balanced responsibility distribution in decision-making. Allen (1999) defined these systems as: “Mixed-initiative refers to a flexible interaction strategy, where each agent (human or computer) can contribute to the task what it does best.” Accordingly, in the process of solving a problem, the roles are opportunistically negotiated between the agents to actualize the best possible solution. In some cases, one of the agents might have the full initiative as the other operates to assist it, while in some other, the roles might be reversed. The agents may also work independently in performing some tasks and dynamically adapt their interaction level based on the specifically asked assistance (Allen, 1999).

Mixed-initiative systems require dynamic and adaptive function allocation, which are usually delegated to the automation due to their complex challenges. These challenges were pointed out by Horvitz (2007) as; recognition and decomposition of problems, identification of sub-problems that may be best solved either by the human or the automation, the task of sequentially and symphonically interleaving human and automation contributions, and enhancement of coordination and communication during the reasoning and problem solving processes. Such collaboration may be predicated on pre-scripted operational codes, and task distribution can be adjusted according to particular conditions. Yet, if instant communication between the two sides can be provided where necessary, a more natural cooperation process for humans can be accomplished.

2.2 Conceptualization of Mixed-Initiative Building Control

The aforementioned researches in the previous section are mostly carried out to converge solutions to numerous problems in various disciplines where a certain level of automation is utilized. However, the achieved advances and developments were not fully reflected in building automation systems, which can be seen as a root cause of the fact that they are not widely adopted in the built environments. To the best of our knowledge, although studies focusing on LOA (Aryal *et al.*, 2021), adaptive automation (Ahmadi-Karvigh *et al.*, 2019) and adjustable autonomy (Ball & Callaghan, 2012a) in buildings exist, no previous research proposed a mixed-initiative framework for the operational management of built environments.

In intelligent buildings research, the focus is usually either on empowering the end-user for building control or developing fully autonomous agent-driven systems that minimize occupant inference. However, people generally prefer to be given the ability to control their environments and choose the tasks to be delegated to the automation (Ball & Callaghan, 2011). The study of Aryal *et al.* (2020) revealed that no single automation level could satisfy all users, and the authority of building control should be shared between the intelligent system and the users to be regulated where necessary. Ahmadi-Karvigh *et al.* (2017) indicated that LOA preferences of occupants change by context, and certain demographic variables and personality traits impact their inclinations. Likewise, the occupant's probable desire to vary the amount and the type of assistance they receive from intelligent building applications was predicated by Callaghan (2013) on two main reasons. First, the people's mental or physical states that change according to age, health, mood, ability, *etc.* may affect the desired level of technological assistance. The second reason is that the accuracy of intelligent assistance may not be as high as it should be depending on the repetitiveness of tasks and how spontaneous the occupant's persona is, which may be best solved with adjustability through enabling communication between humans and the automated systems. Pritchett and Feary (2011) asserted that team play between people and automation systems is well-grounded, where both are expected to contribute their strengths and work in harmony to ensure the effective operation of building systems. For this teamwork, the authors emphasized the significance of several features including communication, cooperation, giving of suggestions or feedbacks, consensus formation and reassurance. In addition, Röcker *et al.* (2005) showed that occupants would favor the automation system that is easy to manage and configurable to adjust personal preferences and control settings.

Although manual control has been shown to be energy inefficient and the automation is a need in the built environment, the level of user satisfaction dramatically decreases when the individual control is unavailable (Tabadkani *et al.*, 2020). Perceived control, which is characterized by occupant's awareness of available controls and the effectiveness of the feedback given by exercising control over the environment, is attributed as an essential factor for technology acceptance models and user satisfaction measures (Venkatesh *et al.*, 2003). Similarly, it has also appeared to be one of the significant concepts in automated building control studies (Lolli *et al.*, 2020). Researches have shown that both occupant comfort (Karjalainen, 2009) and energy consumption in buildings (Yun, 2018) are affected by the level of perceived control. Occupants with higher levels of perceived control were reported to be more tolerant to the deviations from the comfortable indoor environmental conditions (Luo *et al.*, 2016). On the contrary, when personal control is unavailable, or the complexity of the control interface leads to an inconvenience for usage, occupants become more likely to report discomfort or switch off the automated operation (Karjalainen & Koistinen, 2007; Meerbeek *et al.*, 2014). Hellwig (2015) provided a comprehensive review, where the concept of perceived control and its implications for the buildings have been analyzed in detail.

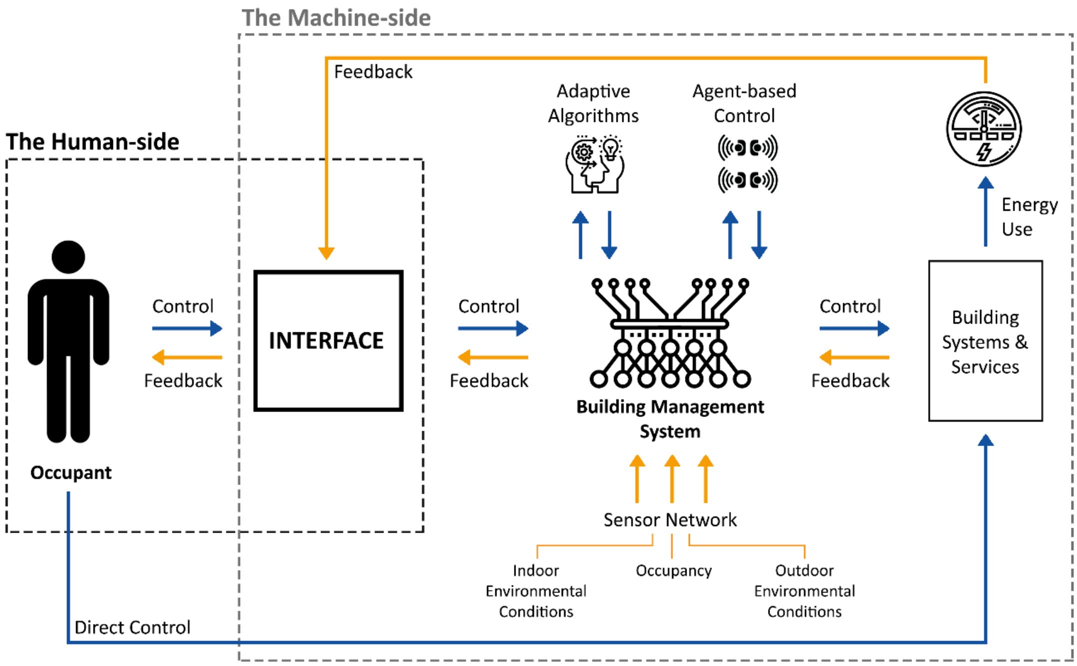


Figure 2.2. Conceptual model of the mixed-initiative building control framework

Considering the current evidence on the link between the automation and the occupant's comfort, perceived control, cognitive load, and energy efficiency, there is a need to establish a coordination and communication framework, which allows for mixed-initiative interaction and encourages control negotiation between buildings automation systems and occupants. The critical point here is to provide the occupants with a sense of continuous control while allocating operational responsibility to the system where applicable. Such a scenario could enact concurrent assessment of occupant comfort and energy efficiency while making automated applications more favorable for building inhabitants. Naturally, designing every detail of such a framework requires the contribution of various disciplines with specialized proficiencies. Accordingly, this study approaches the need for conceptualizing a novel building control framework from a general perspective and defines the borderlines of the mixed-initiative system. As demonstrated in Figure 2.2, this conceptual framework can be segregated and studied under two main sections, namely the machine side and the human side.

2.2.1 The Machine Side

The implementation of the proposed conceptual framework is predicated on the existence of a Building Management System (BMS), appropriate sensor network, and compatible building components. One of the core elements to be integrated into BMS is agent-based control. Human comfort in buildings is tied to three factors that are thermal comfort, visual comfort, and indoor air quality. Satisfying comfort needs requires multiple building systems and components to be operated simultaneously with optimal performance. In order to enhance energy efficiency, possible conflicts that could arise between building subsystems or between the occupant's needs and system operations should be avoided. One of the most advanced efforts towards ensuring the coordination in the operation of building systems has been agent-based control systems (Dounis & Caraiscos, 2009). Multi-agent based control, especially, is widely employed for sophisticated combined control of building systems in intelligent environments for achieving optimum performance under dynamic conditions (Qiao *et al.*, 2007). The design of multi-agent based systems varies, and adapted logic and agent attribution differ based on the approach (J. Lee, 2010; R. Yang & Wang, 2013). Intelligent agents can represent physical devices, particular building zones, specific user profiles, or concepts such as conflict resolution or energy management, and they can communicate with each other for sharing information, making requests, or checking objectives. The defined task assignments to the agents result in a hierarchical and layered organization, where some agents execute simple tasks like controlling illuminance levels in a room, while others have more complex functionalities like generating decisions for the best possible control action based on the occupant feedback (Hurtado *et al.*, 2014). Treado and Delgoshaei (2010) listed the possible benefits of utilizing agent-based building control as enabling subsystems to organize themselves for basic operation, optimizing building performance through an adaptive strategy based on dynamic human factors and environmental data, spontaneous fault detection and rectification, facilitating interactions with utility grids and city networks, allowing system upgradability and promoting the integration of innovative building systems. As it has been asserted as a viable solution for handling the complex problems of dynamic environments, agent-based control should be an integral part of the mixed-initiative framework.

The machine side of the proposed conceptual framework employs adaptive algorithms to assist building management system in analyzing the sensor data and adjusting operational setpoints. Ideally, an intelligent environment should have persistent awareness of human presence, activities, and personal comfort requirements and adjust indoor environment setpoints based on occupant preferences. In the last two decades, studies have focused on developing adaptive algorithms as predictive controls through recording and analyzing human actions in buildings (Haldi & Robinson, 2008; Mirakhorli & Dong, 2016). Predictive building control models usually utilize various machine learning algorithms, artificial neural networks, or fuzzy logic to learn patterns in occupant actions with regard to contextual parameters. Through continuously retraining themselves with new data to update control procedures, predictive control algorithms are to be incorporated in the mixed-initiative framework, for not only automating preference adjustments for adaptive system operation (Gunay *et al.*, 2014), but also allowing flexible and efficient management of energy usage (Kathirgamanathan *et al.*, 2021). Adaptive control algorithms assist building management through making use of the system inputs, state changes in building components, and collected environmental and human-related data. Evidently, configuring a compatible utilization of both agent-based control and adaptive control algorithms, when combined with the central logic defining the building management flow, is promising to assure a competent composition in the machine side of the defined framework.

2.2.2 The Human Side

The main component of the human-side in the framework is the interface, through which all building systems might be controlled. The interface element is ascribed as a meta-control intermediary, which could be either mobile or well-integrated with the building design, providing bidirectional feedback and communication between the occupants and the building systems. In conventional buildings, primitive building components that are almost entirely transparent with their simple logic and physical interfaces (i.e., light switches, operable windows) provided occupants sophisticated opportunities to regulate indoor environmental conditions, including temperature, lighting, and air quality. Traditional touch-input procedures will progressively be replaced with a common building interface that provides a cooperation ground between occupants and buildings and regulates interaction dynamics (Topak & Pekeriçli, 2021).

The transition in the control modalities and the importance of building interfaces are currently very hot research topics and were extensively reviewed by Day *et al.* (2020) and Tabadkani *et al.* (2020). Considering the fact that the sole intermediary for bi-directional communication and coordination between the automation and the human is the interface, which stands at the intersection of the sides (Figure 2.2), it is of the utmost importance to study the questions like "how do building interfaces, their context, and their underlying control logic affect behavior and perceived control?" and "what interface features and characteristics are most effective at delivering a comfortable environment, outstanding perceived control, and reductions in energy consumption?", which are pursued by IEA Annex 79 research group and outlined by O'Brien *et al.* (2020). The most prevalent technologies to be used as a communication tool between occupants and intelligent environments were listed by Marson and McAllister (2021) as mobile apps, screens, dashboards, biometrics, implantables, gait identification, and thought control. However, it is not easy to list possible intermediary tools explicitly due to the pace that technological developments have reached in recent years. As appropriately designed and understandable control interfaces in buildings are claimed to be an effective way of matching building operations to actual occupant needs (Cohen *et al.*, 1999), a common, user-friendly interface model enabling building occupants to have full control of their environments should be well-established within the demonstrated framework.

2.2.3 System Operation

In order to actualize the control flow that is suggested in the framework, building management system should be supplied with continuous spatial and temporal data from compatible tools and systems, allowing spontaneous connection, coordination, actuation, and data exchange. As the internet revolution has evolved into interconnecting objects surrounding everyday life to furnish intelligent built environments, IoT can be considered as a primary enabler for the proposed conceptual framework. In his book, Mukhopadhyay (2014) explained that the connectivity IoT provides through improving access to information can increase reliability, sustainability, and efficiency in any system. As pointed out by Moser, Harder, & Koo (2014), one of the paramount issues in intelligent buildings is the lack of interoperability between different sensors, devices, and building components. Internet-enabled communication can be considered as an effective solution to this interoperability problem. In the case where every building component, device or sensor, regardless of their vendors, is capable of communicating through the Internet, a smooth interaction and data exchange between systems and an integrated and coherent operational process could become possible. Moreover, IoT has been attributed to have human-related data collection functionality, including occupancy detection (Jeon *et al.* 2018), occupant monitoring (Akkaya *et al.* 2015), and activity recognition (Zou, Zhou, Yang, and Spanos 2018). Lilis *et al.* (2017) also asserted that the abundance of devices brought by the IoT extends the benefits of BAS with energy harvesting capabilities without the need for intervention, improved habit tracking, low-cost sensors for monitoring, and occupant-centric decision-making.

The proposed framework can be implemented once the necessary hardware and software platforms are available. Building systems' states, indoor and outdoor environmental conditions, and occupants can be monitored by installing the sensor network, the collected data of which is to be deployed in the central server. Agent-based control models and adaptive algorithms can be implemented using the platform and protocols utilized by building management system, to process both the sensor data and the event logs and control building systems and services. In order to hand over the overall control of the building to the occupants, a meta-interface should be provided that is connected to building management system, through which occupant requests, system suggestions, and bidirectional feedbacks are communicated. There exist continuous feedback-control loops between the interface, building management system, and the building services. The building systems and services (such as HVAC, lighting, or windows) could be controlled either directly by the occupant, ignoring system suggestions, or through consensus reached by the system and the occupant, depending on the personal inclination.

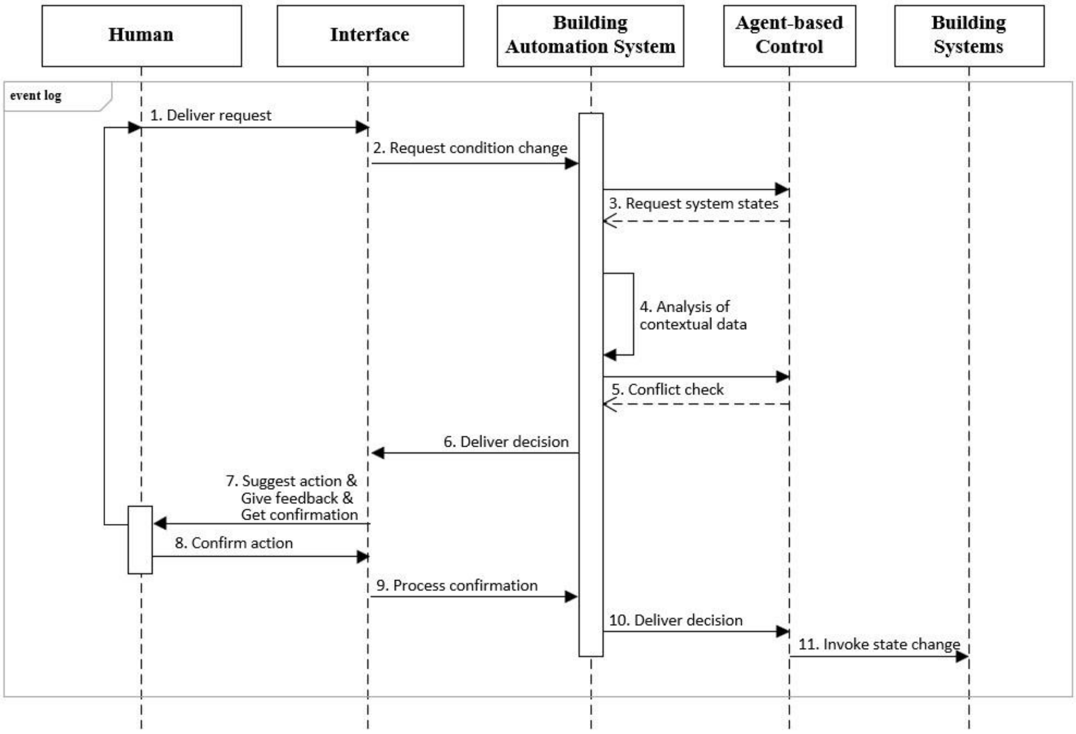


Figure 2.3. Workflow model of the proposed framework

An explanatory possible scenario model is presented in Figure 2.3, in order to clarify the intended workflow of the system. Accordingly, when an occupant desires a cooler indoor environment on a windy summer day and delivers this request to the building through the interface, the most convenient action to satisfy this request can be determined by the building using the collected data from the environment and the building systems. Instead of turning on the mechanical cooling, the building may decide or suggest opening the windows for cross-ventilation, which is a more energy-efficient solution satisfying the same requirement. In other words, the system may respond to the needs of its occupants by invoking the most effective and efficient action. If the occupant does not comply with the system's decision and desires to take a different action, the system can give related feedbacks through the interface and confirm the user's preferences regardless. Every request-analysis-action event can be saved as an event log in the system and used to train the control algorithms and the central management logic. Such a scenario could be a convenient way to simultaneously enhance personal comfort, perceived control, and energy efficiency, as it grants comprehensive controllability on the human-side and data-driven automation adjustability on the machine side.

2.3 Building Control in Shared Environments

It is foreseen that the abovementioned system operation could have a smooth flow in cases where the space is occupied by a single person, as it allows indoor environmental parameters to be controlled based on individual-specific characteristics and feedbacks. However, considering the potential variations in people's behaviors, preferences and tolerance levels, environments shared by multiple building occupants present a unique challenge for personalized operation in building control (Figure 2.4). Interaction patterns and feedback to BMS would differ based on each occupant's personal traits. In scenarios where occupants have conflicting choices, a control dispute may arise that could be solved with an optimization strategy.

In order to assess and study the control dispute in multi-occupancy environments under a manageable complexity and decrease the number of independent variables, the research scope was required to be narrowed down to a single domain. Considering thermal comfort's massive impact on overall human well-being and the amount of energy used by HVAC to satisfy comfort needs of building occupants, the research scope was determined as thermal domain. Although there are some studies proposing strategies for multi-occupancy comfort optimization in the literature (S. Lee *et al.*, 2019; Nagarathinam *et al.*, 2021), optimization of occupant comfort through utilizing personal comfort preferences in shared environments has still room for further investigation.

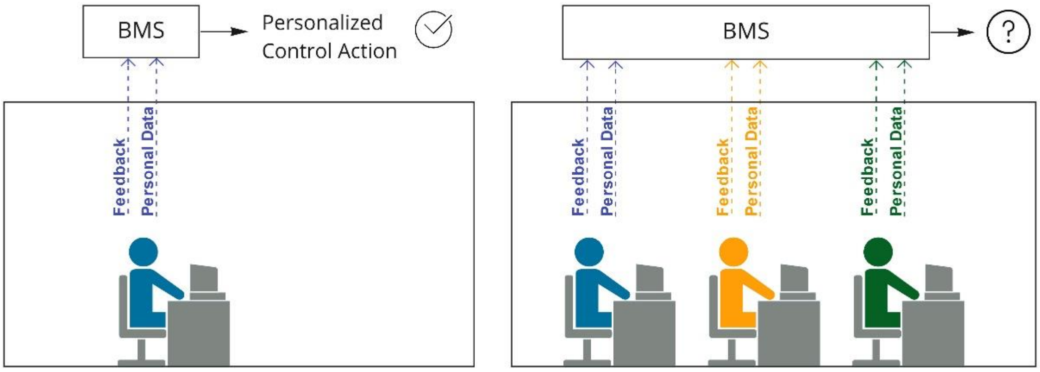


Figure 2.4. Flowchart of the proposed building control framework

The scope of the research in terms of building type is identified as office buildings, depending on the fact that commercial buildings is the leading sector in energy demand growth with a predicted increase rate of 1.6% per year from 2012 to 2040 (EIA, 2016). They are dynamic environments where the number and type of occupants are unpredictable, and require real-time feedback-response control systems for efficient system operations. Moreover, the motivation of occupants to regulate their behaviors towards enhancing energy efficiency is different in commercial buildings from that of residential ones. Since occupants are not responsible for building control and its costs in commercial buildings, they may not be aware of the consequences of their energy-related interactions (Zanjani, 2017).

2.3.1 Occupant-centric Approach

In modern buildings, indoor climate is generally controlled based on pre-defined setpoints and schedules that are determined in the design phase with limited knowledge about occupancy and user profiles. Regardless of the mismatch between the initial presumptions and the actual inputs during building operation, a defined set of control parameters are rarely updated or modified. This simplistic and conservative process was built upon the assumption that controlling buildings based on custom occupancy, average occupant characteristics, and so-called ideal conditions are adequate for improving energy efficiency and human comfort. However, certain suboptimal issues were demonstrated, including maximum occupancy assumption in spaces, continuous operation in unoccupied zones, and over-conditioning despite creating discomfort (Brager et al., 2015; Erickson et al., 2009). In recent years, occupant-centric building control has emerged as a novel approach, taking human dynamics such as presence, location, preferences, and behaviors as inputs to enhance overall occupant comfort and optimum system operation (Naylor *et al.*, 2018; O'Brien *et al.*, 2020). This approach has shifted the paradigm in indoor climate control from a one-size-fits-all perspective towards human-oriented merits.

Although occupant-centric building control has been studied since the early 2000s (Dounis & Caraiscos, 2009; Guillemin & Morel, 2001), there has been significant growth in the number of researches over the past decade along with technological developments (Park, Ouf, *et al.*, 2019; Wagner *et al.*, 2018). As there is not a standardized approach about the level of occupant-related data integration to control loops (Naghiyev *et al.*, 2014), various scopes have been defined by the researchers within the extent of occupant-centric building control depending on the utilized data characteristics. For example, Park *et al.* (2019) referred to systems that only use presence/absence states of occupants as occupancy-based controls, whereas defined the ones that employ data on occupant preferences as occupant behavior-based controls. Jung and Jazizadeh (2019b) used the term 'human-in-the-loop operation' to account for dynamics of occupants, including presence, count, position, and thermal comfort. To this end, a broader overview was presented by Naylor *et al.* (2018), categorizing occupant-centric control research into four based on implementation approaches, which are reactive response to occupancy in real-time, control to individual occupant preference, control catered to individual behaviors/activity types and control based on the prediction of future occupancy/behaviors. As a common practice in occupant-centric control studies, occupant-related data is coupled with the data representing indoor and outdoor environmental conditions (such as temperature, humidity, air quality, illuminance, etc.) to ensure both human comfort and system efficiency (Jung & Jazizadeh, 2019a; Park, Dougherty, *et al.*, 2019; Peng *et al.*, 2019). Xie *et al.* (2020) reported that occupant-centric control research offers improvements on both comfort and energy efficiency with a median of 29% and 22%, respectively.

The scope of occupant-centric control studies oftentimes extends to occupant-related building performance metrics, including indoor air quality, thermal comfort, visual comfort, and acoustics comfort (Antoniadou & Papadopoulos, 2017; Azar *et al.*, 2020). Kong *et al.* (2022) tested an occupancy-based control approach with side-by-side experiments to quantify perceived air quality and thermal comfort in commercial buildings. Park, Dougherty, *et al.* (2019) developed a reinforcement learning-based controller for lighting, which learns from and adapts to occupant behaviors and indoor conditions. Peng *et al.* (2019) proposed an adaptive operational strategy for climate control indoors, which considers dynamic aspects of occupant behaviors and environmental conditions. Acoustic comfort is usually assessed alongside other elements of personal comfort, providing a base for multi-sensory consideration in buildings (Bourikas *et al.*, 2021; W. Yang & Moon, 2019).

Among other occupant-related comfort aspects, thermal comfort attracted the attention of researchers the most due to its massive impact on overall human satisfaction and the account of HVAC systems on building energy use. Frontczak & Wargocki (2011) conducted a literature survey about the effects of indoor environmental quality (IEQ) on overall human comfort and reported that thermal comfort was the top ranked factor in most of the studies. Similarly, Leccese *et al.* (2021) revealed that thermal comfort was weighted as the most critical IEQ factor in more than half of the related studies published between 2002 to 2018. On the other hand, according to the Department of Energy (DOE, 2011), HVAC systems consume

75% of electricity and 40% of total energy in buildings in the United States. However, despite the high levels of energy used by HVAC systems to provide comfort in buildings, the lack of thermal comfort is still one of the most common occupant complaints (ASHRAE, 2017). According to the study by Karmann *et al.* (2018) analyzing thermal comfort votes from 52980 occupants in 351 office buildings, only 2% of buildings meet the targeted satisfied occupant rate, which was determined as 80% by ASHRAE (2017). They reported that 43% of occupants were thermally dissatisfied with their working environments, which might be correlated with the inadequate personalized conditioning or control provided by prevailing HVAC systems.

2.3.2 Proposed Structure for Thermal Domain

Ideally, an intelligent building control framework should account for human presence, activities, and personal comfort requirements to adjust indoor environment conditions in all domains based on occupant preferences. Once the physical requirements such as a central building management system, appropriate sensor network, and compatible building components are properly installed, the operational logic of the building subsystems should be established in coordination with each other. In the last two decades, multi-agent-based control have become a prominent strategy for coordinating tasks in complex environments to ensure conflict-free operation of different subsystems (Duan & Lin, 2008; Micolier *et al.*, 2019). This control strategy basically allocates individual tasks to autonomous entities, which are usually called as agents, and establishes a communication ground for agents' interaction. Each agent has its internal mechanism with specific inputs, objectives, and decision-making triggers for taking necessary actions to complete defined tasks (Dorri *et al.*, 2018). In multi-occupancy environments, the number of personal agents could be determined considering the room capacity to reflect the preferences of all individuals in building control.

In order to ground an optimization strategy for the operation of HVAC systems, we isolated the interaction between the HVAC agent and personal agents from the bigger multi-agent-based control scheme. In doing so, we outlined the data flow in agent interactions within the thermal domain to illustrate how building control can be framed in an occupant-centric manner (Figure 2.5). Accordingly, occupant-centric control framework requires data from both occupants and the environment. Utilizing Internet of Things (IoT) sensor network is a plausible strategy to collect real time data about indoor environmental conditions including temperature, air velocity, relative humidity, etc. and occupant characteristics such as behaviors, preferences and sensations. Together with information retrieval about personal factors such as age, gender, heart rate etc., collecting and leveraging such data in the building management system would allow the development of personal comfort models that would shape the base logic of personal agents. If continuous data flow with high granularity is enabled, developed models could be dynamically updated to account for the changes in occupant preferences in the long run. These models can be stored on the central database and retrained regularly with the dedicated machine learning algorithms.

Similarly, HVAC agent could be formed based on the generated data and iterative outcomes of parameter combinations. As demonstrated later in Chapter 4, thermal dynamics of a space can be assessed using CFD simulations, by setting environmental conditions, contextual factors and HVAC system components as boundary conditions. Once all representative variations are modeled and simulated, thermal distribution patterns data could be stored in the central database. The base logic of HVAC agent could then be fed with thermal distribution input to make optimum control decisions based on instantaneous requirements of the space prescribed by real-time data. It is also possible to substitute thermal distribution patterns data generated using CFD simulations with a comprehensive sensor infrastructure in place. In such a scenario, the granularity and placement of sensors should be properly arranged to account for spatial and temporal variations. Although a sensor-based system development has the potential to be more accurate and robust than a simulation-based approach, installation and maintenance of the infrastructure may be quite costly and complex to deal with. Regardless of the approach, machine learning algorithms could be employed for real-time processing and continuous learning based on the type and the quality of the data.

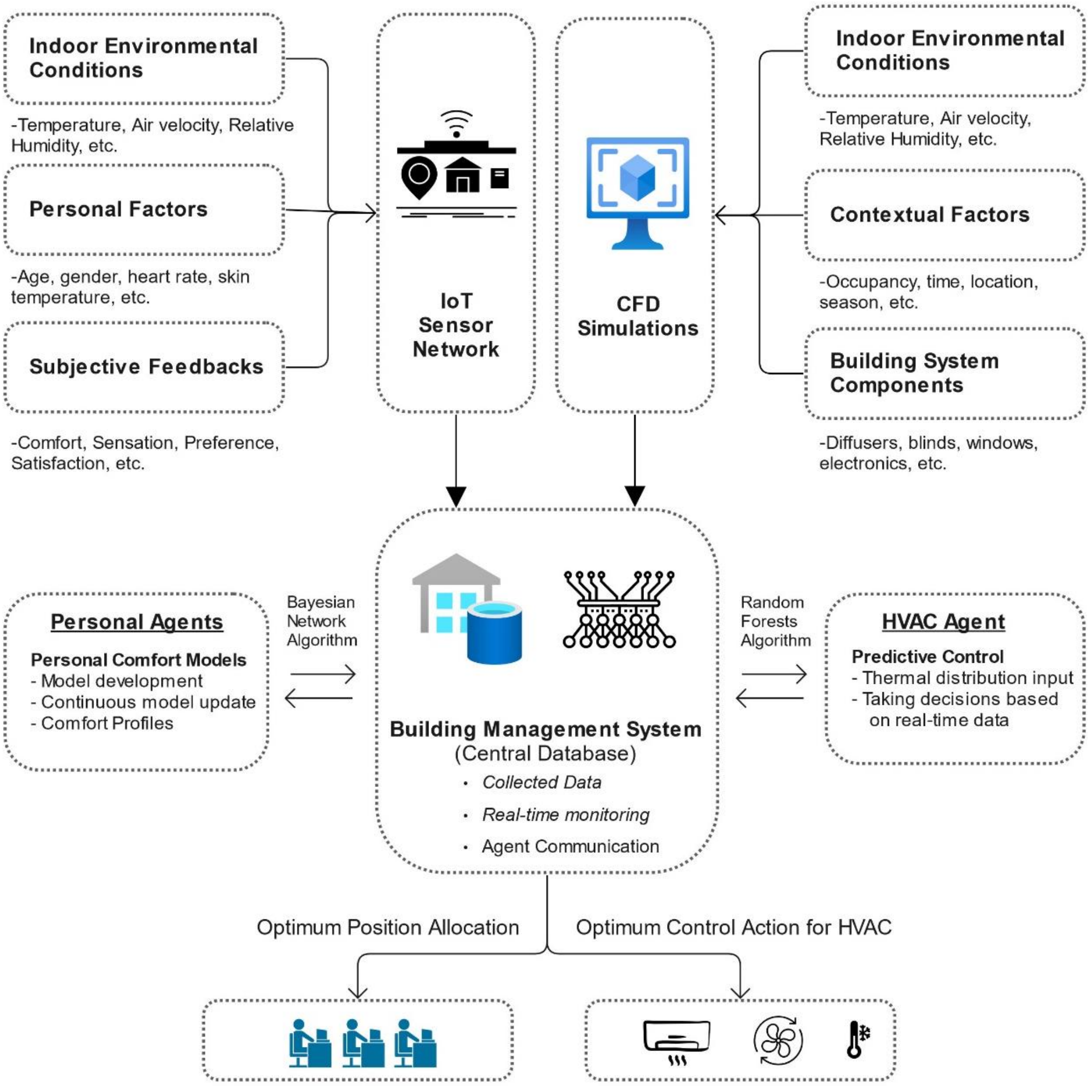


Figure 2.5. Data flow and control framework for thermal domain

Conventional design approaches aim to achieve relatively uniform thermal conditions at an average setpoint temperature throughout a space. This approach naturally implies that the thermal environment will likely be suboptimal for many of the building occupants. Individuals who are thermally uncomfortable would interact with building controls to adapt their environments to retrieve their comfortable states. However, this may disrupt other occupants, and resultantly, lead to an iterative control problem in shared space conditioning. Considering these, we hypothesized that collective comfort in multi-occupancy environments could be provided by explicitly influencing and leveraging the development of non-uniform thermal conditions, together with accounting for the differences in personal comfort preferences of individuals. The nonuniformity of both personal comfort levels and climatic conditions indoors can be interpreted as an optimization problem, and could be solved through setting up an intelligent system scheme. Accordingly, once the control structure shown in Figure 2.5 is well-established and real-time dataflow from both the indoor environment and the occupants are ensured, a simplified workflow (Figure 2.6) could be used to assess the potentials of the proposed framework for improving collective comfort in shared indoor spaces.

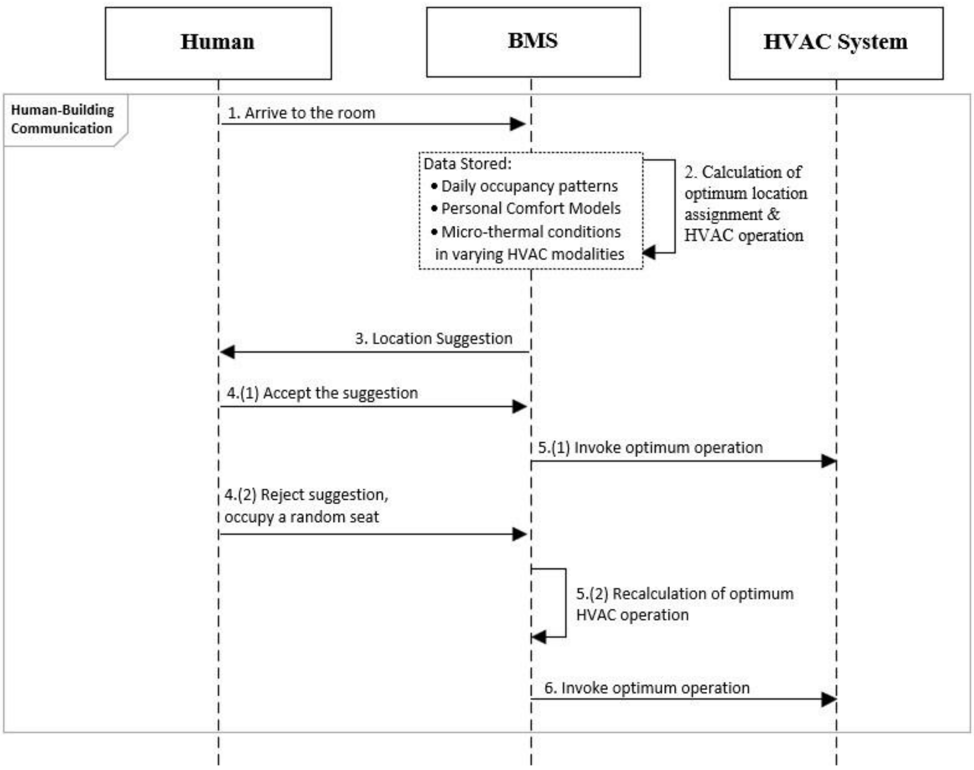


Figure 2.6. Workflow model for the thermal domain

The demonstrated workflow model in Figure 2.6 proposes that building occupants can be optimally assigned to micro-locations (i.e., workstation) at the start of each day, based on their personal comfort profiles stored in the central building system. Accordingly, once an occupant arrives to the room, BMS suggests an optimum location by processing multiple variables including individual's profile, occupancy patterns for the day and micro-thermal conditions. If the occupant accepts the seat assignment, conditioning system can use pre-calculated optimum operational settings. If the occupant decides not to comply with the suggestion, then the system can recalculate the optimum settings; this time by including the position and personal comfort profile of that occupant within the inputs. At this decision-making stage, the 'optimum operation' can be defined by setting the system priorities about energy use and occupant comfort. Since continuous relocation of occupants is neither practical, nor logical in real-life conditions, suggested flow assumes that occupants would not be relocated after they occupy a workstation for the day. As occupants have the initiative for complying with the system suggestions, BMS can adjust its operation to the optimum settings based on the given conditions and inputs, rather than enforcing the ideal scenario maximizing collective comfort or energy efficiency. It is worth mentioning that, the overall performance of the strategy would potentially improve over time, as the database on comfort preferences of the individuals expands and occupancy patterns are recognized by the system. For the initial employment, personal comfort models can be pre-trained by conducting comfort surveys.

2.3.3 Case Selection

In order to assess the viability of the proposed structure for thermal domain, a case study was described for carrying out a proof-of-concept analysis. An office space in the College of Engineering of Penn State University was selected, which houses workstations for six graduate students (as illustrated in Figure 2.7). The room is on the second floor of a three-story building located at University Park Campus in State College, the United States, the climatic zone of which can be described as cool-humid. It is surrounded by indoor spaces on three sides and it has five large windows on its wall facing outdoors.

The office space is approximately ~53 m^2. It has a conventional HVAC settling, where the fresh air is supplied through an inlet on the ceiling and return air is exhausted through an outlet on the west wall. The space use is not regular and occupancy pattern throughout the weekdays changes each academic term depending on students' weekly programs. Depending on the given space characteristics, a comprehensive analysis requires accounting for the personal preferences of six different individuals and examining the thermal distribution dynamics under varying occupancy and conditioning scenarios.

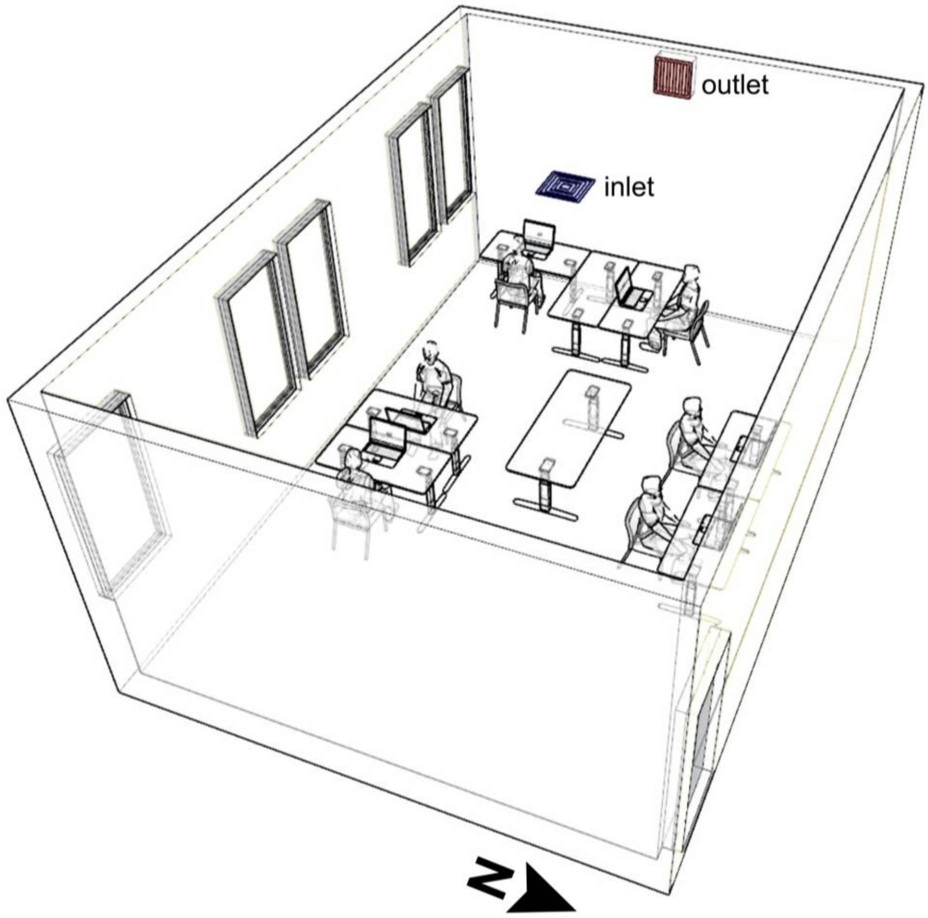


Figure 2.7. Three-dimensional model of the selected office space

Accordingly, Chapter 3, Chapter 4 and Chapter 5 were organized to (1) presenting dedicated personal comfort profiles, (2) composing the thermal distribution patterns dataset and (3) assessing the potentials for improving collective comfort through a data-driven analysis, respectively. Further details on the selected case are given in Chapter 4, where the geometric modeling process for simulations are provided.

2.4 Discussion

Technology has been continuously transforming the built environments, with changing magnitudes throughout the last century. Lately, this transformation has been accelerated and reached a considerable pace, with the developments in artificial intelligence, the Internet of Things concept, sensing, actuation, and information systems. In the built environment, building automation can be claimed as one of the primary concepts in terms of technology integration, which has been introduced to provide efficient management by centralizing building control and minimizing human intervention. However, researches have indicated a disharmony between the operating principles of prevalent building automation systems and people's instinctive desires, which have slowed down the employment of automation in buildings. In order to demonstrate a refined solution scenario, this research outlined a composition for the collaborative building control system and conceptualized the borderlines of a mixed-initiative framework.

According to the conceptual framework, the control of building systems is proposed to be managed through a human-automation collaboration, where occupant needs and preferences are prioritized. The most efficient and effective control action is invoked by the automation through analysis of occupant requests and feedbacks, as well as the collected environmental and human-related data. As it is an initial elaboration for speculating the need for a drastic shift in system operation, the study might help researchers comprehend the integral components of such a mixed-initiative control in buildings and grasp the prospective research directions. Considering the comprehensiveness of the subject, the detailed configuration of presented components can be achieved through compartmentalized analysis of the domains in buildings. To this end, thermal domain was identified for further investigation in the following sections of this research. The collaboration procedure was simplified for enabling a computationally applicable analysis in a multi-occupancy indoor environment, which is shared by occupants with possibly varying personal traits. It is anticipated that assessing the technological viability of the proposed collaborative control approach can be predicated on the demonstrated achievements in the specified domains, the results of which could help to compound the overall structure of the integrated framework.

CHAPTER 3

PERSONAL COMFORT MODELING

This chapter delves into the concept of thermal comfort in buildings and highlights the transition towards personalized models by reviewing the widely accepted approaches in the literature. It presents six personal thermal comfort profiles, which were used to represent six different individual occupants. These comfort profiles were designated to be used in collective comfort probability analysis in Chapter 5, to account for the individual differences in comfort needs and preferences of occupants. The presented unified probabilistic thermal comfort profiles were developed by processing available real-world datasets with Bayesian network modeling approach.

In this section, firstly, the basics of the PMV and adaptive models were explained and the emergence of the personal comfort modeling concept was presented. Then, the employed dataset was introduced and the probabilistic modeling process was illustrated. Lastly, generated personal comfort profiles were demonstrated with a comparison on their characteristics. The chapter was concluded with a discussion on the importance of personalized models for improving occupant comfort in the built environment and potentials revealed by this new approach in the field. The author would like to acknowledge that the methodology used in this chapter was built upon the study of Jung & Jazizadeh (2019a).

3.1 Literature Review

3.1.1 Thermal Comfort in Buildings

Thermal comfort is defined by ASHRAE (2017) as "that condition of mind which expresses satisfaction with the thermal environment". An individual who wishes to feel neither warmer nor cooler when asked about their thermal state can be deemed as thermally comfortable. Contrary to its simple definition, providing thermal comfort in buildings is not a trivial task, as it depends on many environmental and personal factors. Since what is accounted as comfortable changes from one place, time, and person to another (Chappells & Shove, 2005), developing knowledge on thermal comfort in buildings has been a critical research subject over the years (De Dear *et al.*, 2013).

The overarching aims of research efforts in thermal comfort field listed by Taleghani *et al.* (2013) in their review include improving occupant satisfaction, productivity and work performance in indoor environments, achieving energy savings, reducing the negative impacts of buildings on the environment, and improving standards. Wang *et al.* (2019) demonstrated how thermal comfort can affect occupants' productivity by influencing their mental workload. Lipczynska *et al.* (2018) explored the link between thermal comfort and self-reported productivity and indicated a direct correlation. Likewise, a field survey in an office building conducted by Tanabe *et al.* (2015) confirmed that improvements in work performance is closely related to individual thermal satisfaction. On the other hand, maintaining comfortable conditions for building occupants have great implications for energy consumption in buildings due to the proliferation of HVAC systems in most countries (Yang *et al.*, 2014). Although there have been many efforts to develop advanced intelligent building control systems that improve energy efficiency while maintaining thermally comfortable conditions, a completely satisfactory framework is yet to be achieved (Merabet *et al.*, 2021).

In modern buildings, the prevailing approach towards ensuring thermal comfort has been the development and optimization of proper mechanical systems. With the purpose of setting system requirements and control parameters for providing collectively acceptable conditions, the HVAC industry has defined comfort in terms of physical variables, i.e., temperature, airspeed, and humidity (Nicol & Roaf, 2017). Likewise, researchers have concentrated on developing empirical models that link such physical variables with the comfort states of building users to describe the boundaries of comfort for average users. Among other thermal indices, two major approaches, the PMV and adaptive models, have been dominant in the current practice and effective in international standards. In recent years, however, comfort assessment paradigm has shifted towards being more granular and individualistic, and resultantly, a new approach called personal comfort modeling has become a point of interest for building researchers (Figure 3.1).

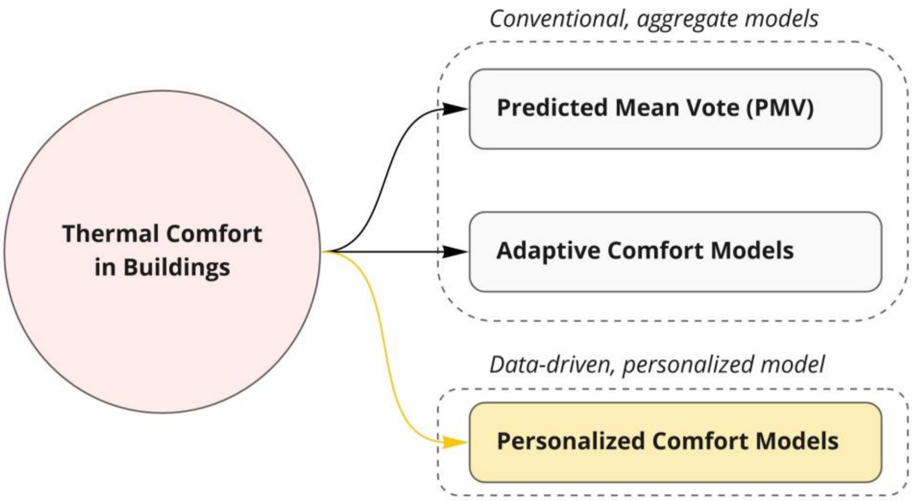


Figure 3.1. Prevalent thermal comfort approaches in buildings

3.1.2 The Predicted Mean Vote (PMV) and Adaptive Models

The PMV, which was established through a series of experiments in climate chambers by Fanger (1970), is the most widely accepted model, and it served as the basis of ASHRAE 55 (2017) and ISO 7730 (2005) standards. The PMV explains human thermal sensation as an outcome of the heat transfer between the human body and the ambient environment and proposes a quantitative assessment by combining environmental factors (air temperature, airspeed, mean radiant temperature, humidity) and personal factors (metabolic rate, clothing insulation). Based on a steady-state physiological model, it simply predicts the mean thermal sensation votes of a large group of building users for any given environmental and personal factors, on a scale ranging from -3 to +3, corresponding to the sensations of cold, cool, slightly cool, neutral, slightly warm, warm and hot (Van Hoof, 2008). Adaptive models, on the other hand, incorporate the assumption that building users would consciously react in ways to adapt their environments or themselves to changing conditions to retrieve their comfortable states. Developed through inferring a linear relationship between comfortable indoor temperature and prevalent outdoor temperature by analyzing field study data from naturally-ventilated buildings in different climate zones, adaptive model by de Dear & Brager (1998) was included in ASHRAE 55 (2017) standard and adaptive model by Nicol and Humphreys (2002) was placed in EN 15251 (2007) standard. Although the adaptive approach differs from the PMV in its underlying philosophy, both use simple linear scales to assess thermal comfort (Nicol & Roaf, 2017).

Although the PMV and adaptive models were adopted successfully in the aforementioned international standards, both models have some inherent limitations. Kim *et al.* (2018) listed the main drawbacks of these approaches as the burdensome acquirement of input variables and simplified assumptions, their static nature that lacks capabilities of calibration and relearning from new field data at particular settings, and their inability to be modified with new input factors (such as sex, age, body mass index, etc.) beyond models' pre-defined variables. Above all, both are aggregate models whose comfort predictions are applicable to a group of people or a large population. They fail to predict individuals' thermal comfort in shared environments, where occupants with varying comfort profiles share the same environment (Van Hoof, 2008). A recent study showed that a simple linear model is about 40% more accurate than the PMV at predicting individual comfort (Guenther & Sawodny, 2019). Similarly, the prediction accuracy of the adaptive model for thermal preferences was reported as 50%, which is almost the same as random guessing (Kim, Zhou, *et al.*, 2018). Moreover, André *et al.* (2020) noted that neither of these two approaches is suitable for evaluating the performance of personal comfort systems since they are designed for stable, uniform environments.

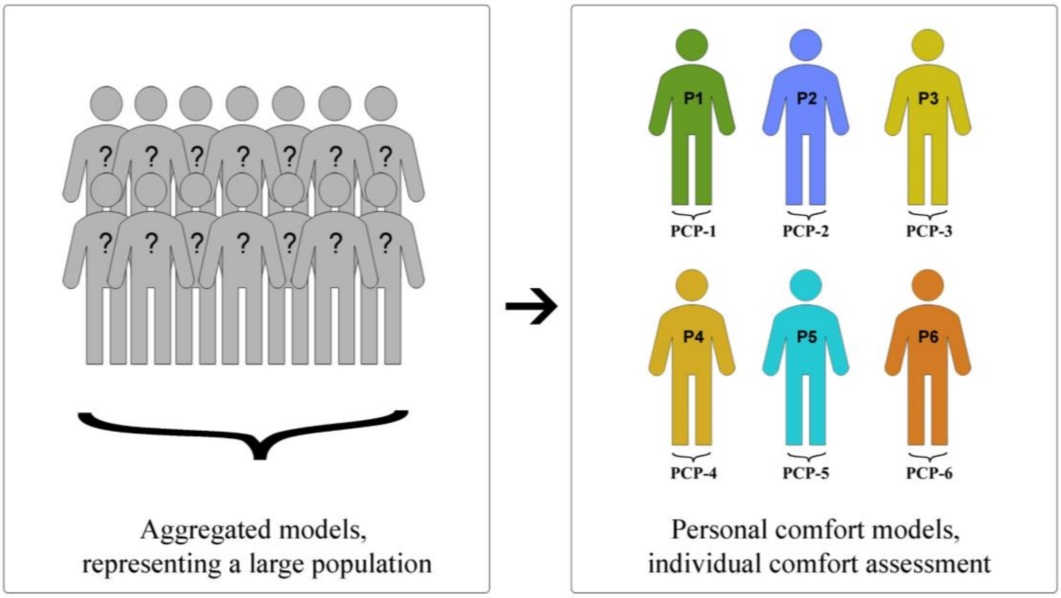


Figure 3.2. Aggregated models versus personal comfort models

In response to the deficiencies of the conventional approaches in thermal comfort management in buildings, a new paradigm named personal comfort modeling has been proposed (Kim, Schiavon, *et al.*, 2018). Benefiting from the developments in the data-driven technologies, personal comfort models eliminate the over-simplified assumptions in the PMV and adaptive models and suggest promising features for highly granular, individualistic, and context-relevant strategies in building control. Aggregated group models differs from personal models in the main comfort assessment approach (Figure 3.2), and Xie *et al.* (2020) emphasized that shifting from the former to the latter can help the practice of occupant-centric control, despite the recency of the latter.

3.1.3 Personal Comfort Models

The advancements in the Internet of Things (IoT) concept have enabled easy and low-cost collection and generation of personal data, which formed a foundation for more context-based, tailor-made approaches. Personal comfort modeling is a data-driven strategy that predicts an individual's thermal comfort based on direct feedback (e.g., thermal sensation, preference, pleasure) and specific data (e.g., personal, contextual) from a single person (Kim, Schiavon, *et al.*, 2018). Using the data collected in daily life environments, it utilizes machine learning algorithms to learn individuals' comfort responses, reveals variations between comfort needs of different occupants, and allows to achieve higher satisfaction rates and energy efficiency (André *et al.*, 2020). Contrary to the conventional approaches, personal comfort models are flexible, enabling the application of different modeling methods and having the capacity to adapt new input variables and additional data. According to the review by Martins *et al.* (2022), the most frequently used input variables in these models include environmental factors such as indoor temperature, airspeed, relative humidity, outdoor temperature, and personal features such as skin temperature, heart rate, activity level, clothing level, and metabolic rate. It has also been shown that thermal comfort prediction performance escalates when environmental and personal factors are combined as inputs in the model development (Aryal & Becerik-Gerber, 2019; Jung *et al.*, 2019).

Developing personal comfort models with high predictive performance has been a prominent objective for many researchers in the last two decades. The main prediction logic of developed models is predicated on correlating environmental and personal sensor data with the occupant feedbacks collected through various mediums (Daum *et al.*, 2011; Ghahramani *et al.*, 2015; Kim, Zhou, *et al.*, 2018; W. Liu *et al.*, 2007). Kim, Schiavon, *et al.* (2018) explained the process of developing personal comfort models in their pivotal work as data collection, data preparation, model selection, model evaluation, and continuous learning, respectively, as shown in Figure 3.3. Accordingly, once the model is established, it could be integrated into building control loops with the help of connected sensors, controllers, a local network, and a central server. However, both Kim, Schiavon, *et al.* (2018) and Martins *et al.* (2022) highlighted that there is still no consensus on a unified and systematic framework for personal comfort modeling in the field.

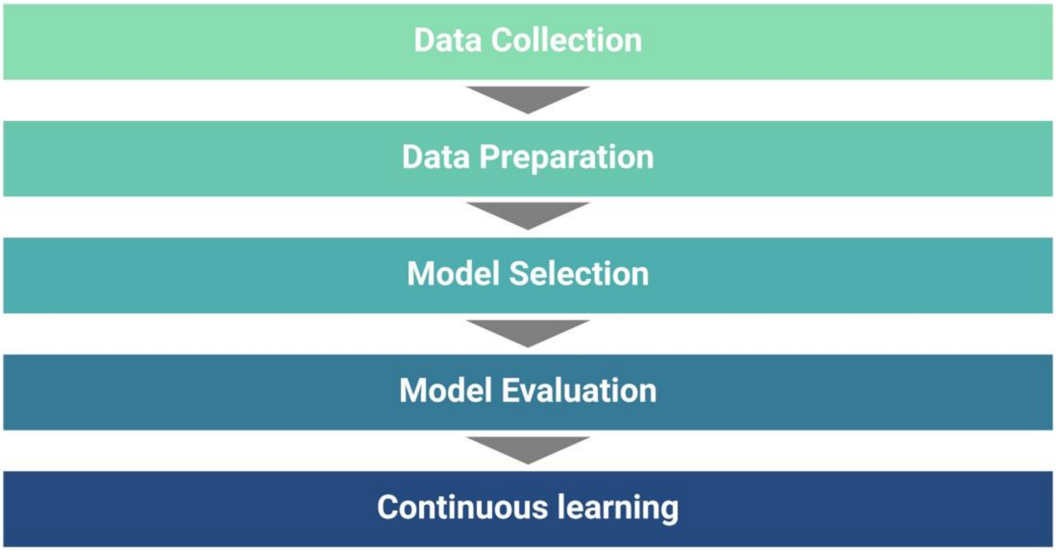


Figure 3.3. Development of personal comfort models
(adapted from Kim, Schiavon, *et al.*(2018))

In recent years, many researchers have developed personal comfort modelling strategies using various methods. Zhao *et al.* (2014) utilized a physical human-machine interface to model occupants' thermal complaints. Jazizadeh *et al.* (2014a) employed a participatory sensing application for smartphones to learn occupants' comfort preferences. Kim et al (2018) used occupants' heating and cooling behaviors as comfort feedback to establish personalized models with high accuracy. Feng *et al.* (2023) leveraged wearable sensors and smartphone applications to collect individualized comfort measurements from both occupants and their micro-environments. Regardless of the approach, the common practice at this field is to fuse occupants' comfort feedback and indoor environmental data, and apply machine learning algorithms to establish personalized comfort models.

One of the early studies for personal comfort modeling was published by Liu *et al.* (2007). They trained a neural network model with occupant responses at varying air temperature, humidity and air velocity values to predict individuals' thermal sensations under different thermal conditions and demonstrated a high prediction performance. From there on, various models were developed employing different machine learning algorithms. Some of the commonly employed machine learning algorithms in personal comfort models are random forest (Chaudhuri *et al.*, 2018), support vector machine (Jiang & Yao, 2016), fuzzy classification (Jazizadeh *et al.*, 2014a), neural networks (W. Liu *et al.*, 2007), Gaussian process (Guenther & Sawodny, 2019), Bayesian network (Ghahramani *et al.*, 2015) and logistic regression (Daum *et al.*, 2011). In a considerable number of studies, multiple machine learning algorithms were comparatively tested to achieve the best prediction performance and avoid algorithm-biased deviations (Aryal & Becerik-Gerber, 2019; Kim, Zhou, *et al.*, 2018; S. Liu *et al.*, 2019). Among others, random forest algorithm has been demonstrated to have a higher preference rate (Martins *et al.*, 2022) and better accuracy (Kim, Zhou, *et al.*, 2018; S. Liu *et al.*, 2019).

3.2 Material and Method

In order to capture the diversity in thermal preferences of six occupants within the selected case (described in section 2.3.3), six different personal comfort profiles were developed by utilizing available datasets in the literature. A probabilistic modeling approach was adopted and Bayesian network was employed as the machine learning algorithm to process the data. It is worth mentioning that since the main aim of generating personal comfort profiles in this section is to account for the differences in individuals' comfort preferences, some steps of developing personal comfort models such as model evaluation and continuous learning process were not considered within the research scope.

3.2.1 Dataset

In order to accurately evaluate the potential of occupants' having different thermal comfort preferences in multi-occupancy scenarios, considering actual human subjects and using realistic data is of utmost importance. In ideal conditions, the proposed framework in this research enhances real-time monitoring with continuous data collection for generating personal comfort models and flexibility augmentation by integrating numerical simulations for occupant-centric building control. However, since the outlined case methodology was designated to reveal the possible strategies towards these goals with an offline procedure, using an existing dataset for developing personal comfort models was deemed as a plausible option. To this end, we used several probabilistic personal thermal comfort profiles that represent the individual differences in thermal comfort perceptions. These profiles were generated using a probabilistic approach and data presented in previous studies. The approach used to generate the profiles is as follows. A personal comfort feedback dataset compiled through field measurements carried out for several months by Daum *et al.* (2011) has been utilized. They adopted a multinomial logistic regression model to separate three thermal perception vote types: uncomfortably cool, comfortable, and uncomfortably warm. Leveraging the data obtained from comfort profiles reported by Daum *et al.* (2011), together with actual thermal votes dataset extracted from previous studies (Jazizadeh *et al.*, 2014a; Pazhoohesh & Zhang, 2018), unique personal comfort profiles have been developed to represent different occupants. In this process, air temperature and thermal sensations were taken as input variables for calculating the probability distribution of comfort.

3.2.2 Probabilistic Modeling

As an individual could have both comfort and discomfort votes under the same thermal conditions in different occasions, a stochastic modeling approach were adopted to reflect the uncertainty of occupant sensations. A Bayesian network modeling process proposed by Ghahramani *et al.* (2015) was employed to create unified probabilistic thermal comfort profiles. This method leverages the Bayes rules and combines occupants' votes reported for being uncomfortably cool, comfortable and uncomfortably warm across different ranges of temperatures to calculate overall comfort probability for a given temperature (Figure 3.4).

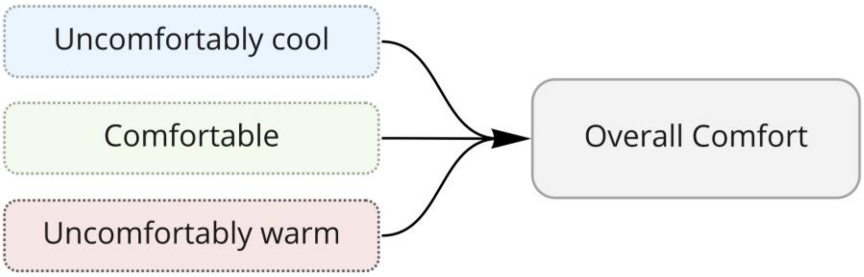


Figure 3.4. Graphical representation of the Bayesian network

In order to form the overall thermal comfort profiles, three probability distributions were created, representing reported comfort states of individuals within the defined spectrum (comfortable, uncomfortably cool and uncomfortably warm), using Equation (1), Equation (2) and Equation (3). Normal distribution was used for the probability distribution of comfortable votes to account for the variance in probability distributions of comfort, and two half-normal distributions were used for the probability distributions of uncomfortably cool and uncomfortably warm votes overlapping with comfortable votes. The mean value for half-normal distribution of uncomfortable cool votes denotes to minimum temperature that an occupant voted as comfortable ($\min(t_c)$), while the mean value for half-normal distribution of uncomfortable warm votes denotes to maximum temperature that an occupant voted as comfortable ($\max(t_c)$). Accordingly:

- Probability distribution of comfortable votes (*P(c|t))*:

$$P(c/t) = f(t_c : \sigma_c) = \frac{1}{\sigma_c \sqrt{2\pi}} \exp\left(-\frac{(t_c - \mu_c)^2}{2\sigma_c^2} \right) \quad (1)$$

, where t_c is any indoor temperature value that was voted as comfortable, μ_c and σ_c represents the mean and standard deviation of t_c values, respectively.

- Probability distribution of uncomfortably cool votes (*P(uc|t))*:

$$P(uc/t) = f(t_{uc}:\sigma_{uc}) = \frac{\sqrt{2}}{\sigma_{uc}\sqrt{\pi}}\exp\left(-\frac{(t_{uc}-\min(t_c))^2}{2\sigma_{uc}^2}\right)\ \forall\ t_{uc} \geq \min(t_c) \quad (2)$$

$$\sigma_{uc} = \sqrt{\frac{1}{n_{t_{uc}}}\sum_{1}^{n_{t_{uc}}}(t_{uc}-\max(t_c))^2}$$

, where t_{uc} is any indoor temperature value that were voted as uncomfortably cool within the comfortable temperature range, σ_{uc} represents standard deviation of t_{uc} with respect to $\min(t_c)$, and $n_{t_{uc}}$ denotes to the number of t_{uc}

- Probability distribution of uncomfortably warm votes (*P(uw*|t*))*:

$$P(uc/t) = f(t_{uw}:\sigma_{uw}) = \frac{\sqrt{2}}{\sigma_{uw}\sqrt{\pi}}\exp\left(-\frac{(t_{uw}-\min(t_c))^2}{2\sigma_{uw}^2}\right)\ \forall\ t_{uw} \geq \min(t_c) \quad (3)$$

$$\sigma_{uw} = \sqrt{\frac{1}{n_{t_{uw}}}\sum_{1}^{n_{t_{uw}}}(t_{uw}-\max(t_c))^2}$$

, where t_{uw} is any indoor temperature value that were voted as uncomfortably warm within the comfortable temperature range, σ_{uw} represents standard deviation of t_{uw} with respect to $\max(t_c)$, and $n_{t_{uw}}$ denotes to the number of t_{uw}.

Using the probability distributions for three thermal vote types and conditional probability rules, a joint probability distribution compiling comfort profile for each occupant were generated using Equation (4).

$$P(oc\,|\,t) = \frac{P(c\,|\,t)}{P(uc\,|\,t)\ +\ P(c\,|\,t)\ +\ P(uw\,|\,t)} \quad (4)$$

In Equation (4), *P(oc|t)* denotes to the probability of the overall comfort for a given temperature, *P(uc|t)* is the probability distribution of uncomfortably cool votes, *P(c|t)* refers to the probability distribution of comfortable votes and *P(uw|*t*)* indicates the probability distribution of uncomfortably warm votes. Having added a normalization step, each comfort profile employs a Gaussian distribution defined by the average and the standard deviation of corresponding temperatures for the votes.

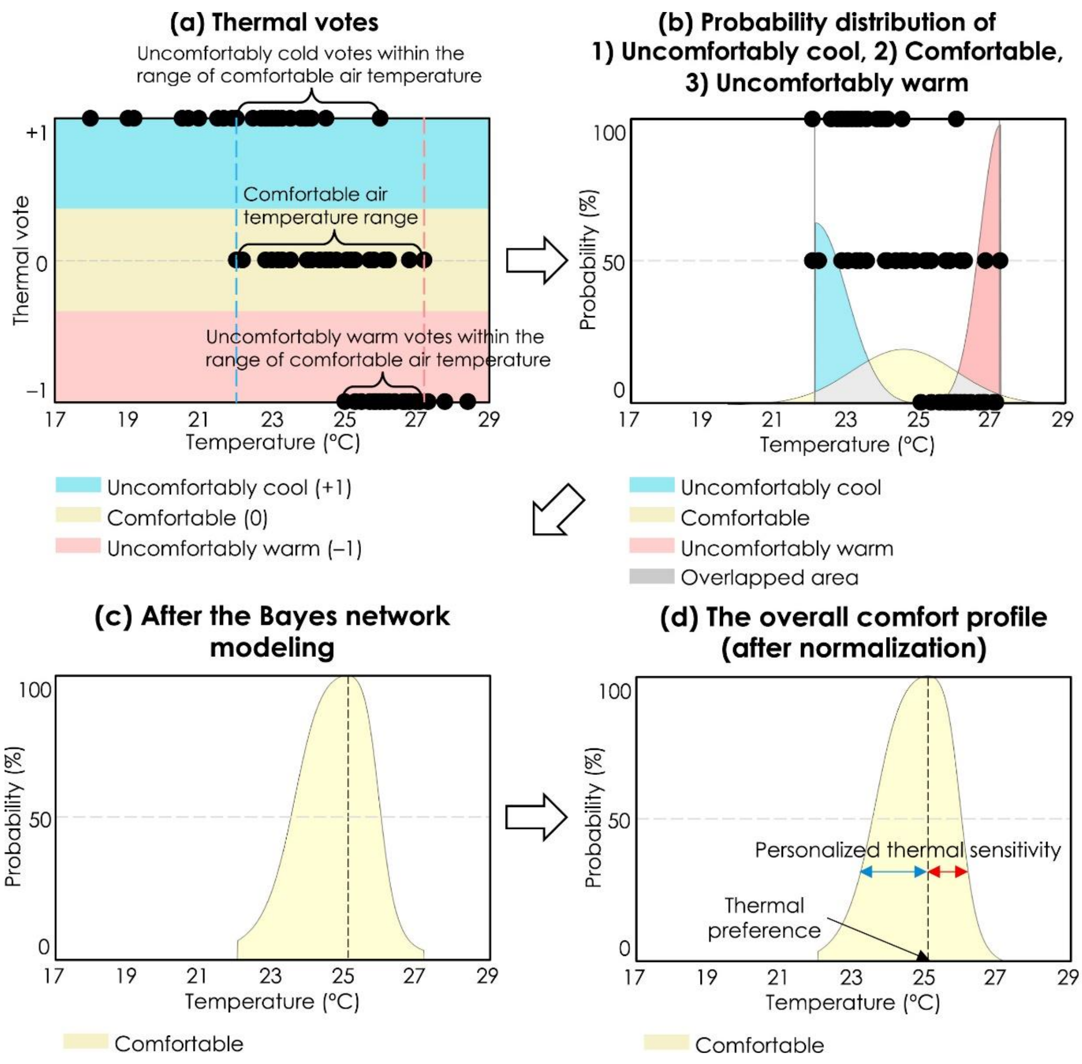


Figure 3.5. Graphical representation of the comfort profiling process
(Jung & Jazizadeh, 2019a)

The steps of creating thermal comfort profiles were established by Jung & Jazizadeh (2019a), which are compiling the thermal votes dataset, creating probability distributions for the defined comfort spectrum and Bayesian network modeling, as shown in Figure 3.5. Each personalized profile created using this method demonstrates how an occupant's thermal satisfaction probability changes with respect to the changes in room temperature.

3.3 Personal Comfort Profiles

As illustrated in Figure 3.6, six comfort profiles with different thermal behaviors were generated to assign a unique profile for each occupant within the scope of selected case. Each colored curve represents an occupant's thermal comfort probabilities across the given air temperature range. Occupants can be assumed to be most comfortable at the temperature where the curve reach its top point. Correspondingly, the temperature that each occupant is most comfortable at are 20.5°C, 24.2°C, 22.0°C, 24.4°C, 22.7°C, and 23.3°C, respectively.

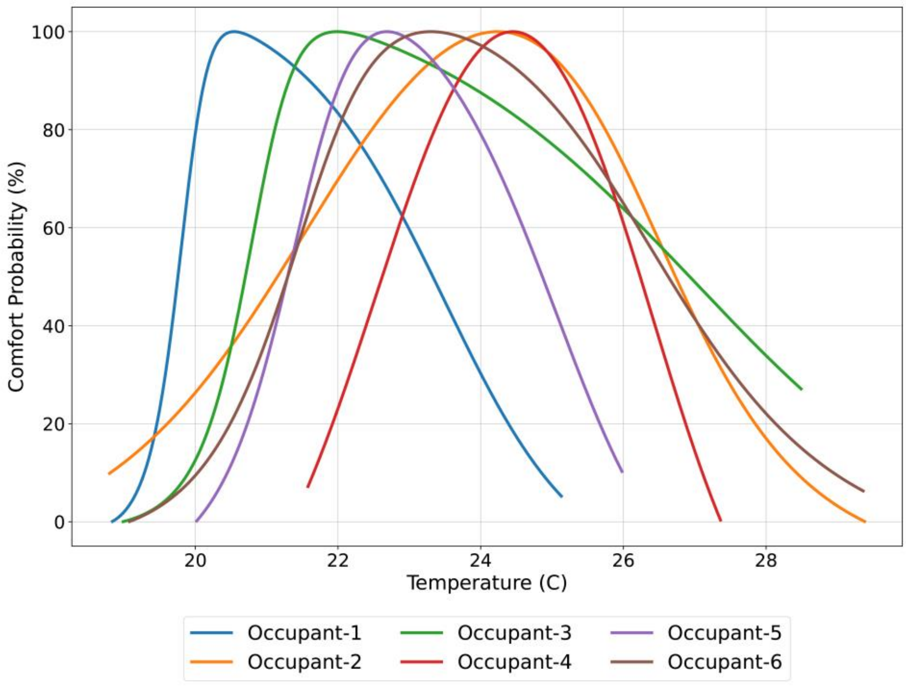


Figure 3.6. Personal comfort profiles for six occupants

Although some of the occupants have similar comfort preferences like occupant #2 and occupant #4, or occupant #5 and occupant #6, their thermal comfort sensitivities have appeared to be different. Occupant #2 had a better tolerance towards both lower and higher temperatures in comparison to occupant #4, whereas occupant #6 had a much better tolerance toward higher temperatures in contrast to occupant #5. This study assumes that these personal comfort profiles, which are generated by the models ideally developed over a certain period of time and have updateability features with continuous learning (Kim *et al.*, 2018), could reflect thermal comfort dynamics of occupants.

Interpreting ASHRAE (2017)'s required comfortable occupant rate indices which is 80%, comfort probability of 80% could be claimed as the lower boundary for defining each occupant's comfortable thermal range. Based on this assumption, thermal comfort sensitivities of occupants were illustrated in Figure 3.7. Accordingly, temperature range that Occupant #1, occupant #4 and occupant #5 are comfortable at is narrower when compared to those of the other three occupants. It is also notable that Occupant #3 has the highest tolerance level, while being more sensitive to lower temperatures. Temperature range meeting each occupant's comfort probability with a rate of at least 80% are 20.0°C - 22.2°C, 22.5°C - 25.8°C, 21.1°C - 24.7°C, 23.3°C - 25.5°C, 21.8°C - 24.0°C and 22.0°C - 25.3°C, respectively. This difference between occupants' comfort sensitivities can be leveraged to provide comfortable conditions for all individuals in shared environments by balancing gain and loss trade-offs between comfort probabilities. The importance of comfort sensitivity for improving collective comfort in buildings was asserted by (Jung & Jazizadeh, 2019a), who demonstrated its statistically crucial role for determining temperature setpoints in multi-occupancy indoor spaces.

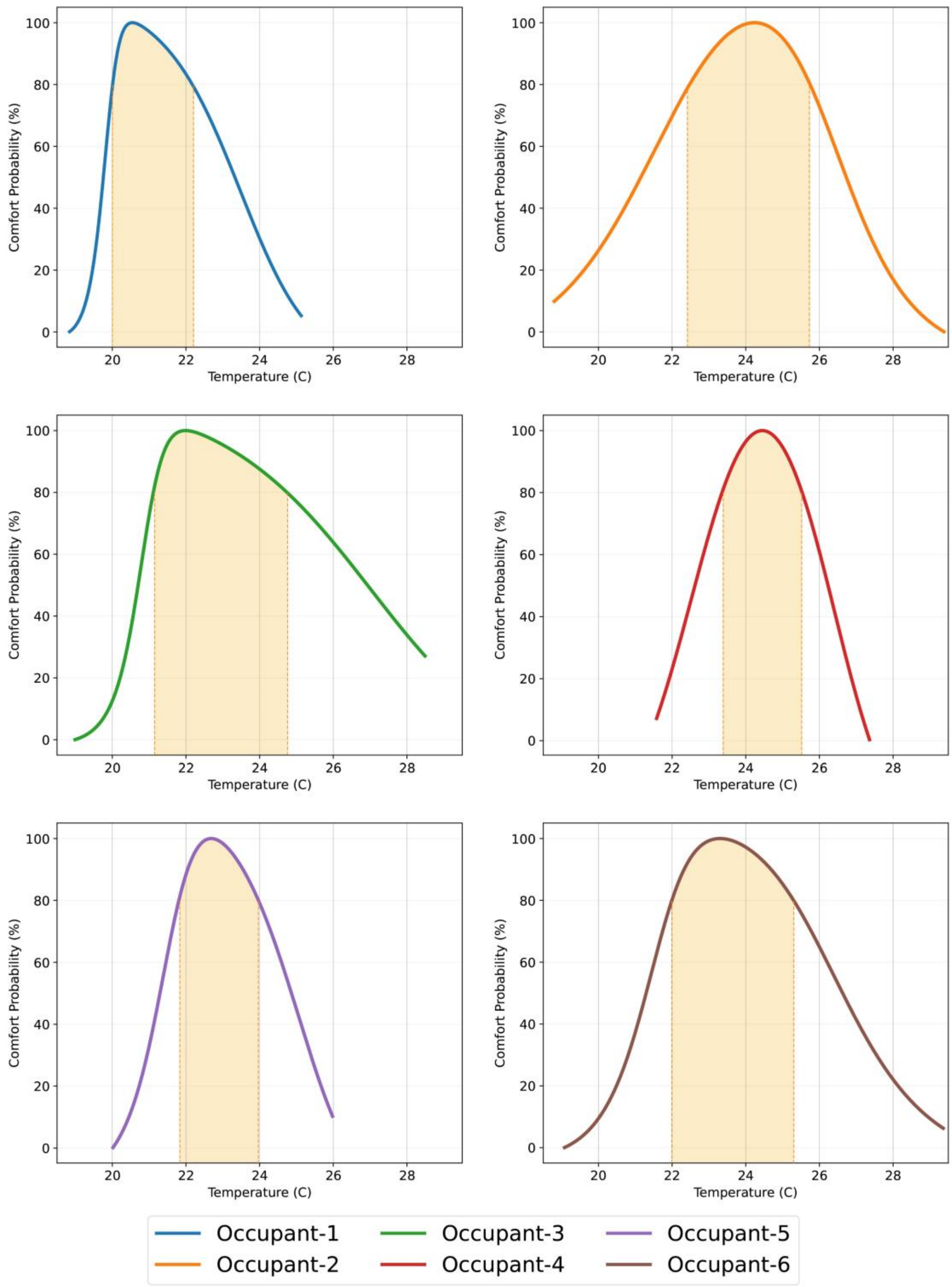


Figure 3.7. Thermal comfort sensitivity differences between the six occupants

3.4 Discussion

As individual differences result in variations in the comfort needs of occupants, shifting from centralized to personalized conditioning is a prime subject for providing comfort and energy efficiency in indoor built environments (Wang *et al.*, 2018). Personal comfort models have been a significant step forward in terms of leveraging more individual-specific data collection and utilization in comfort management.

In practice, the thermal comfort profiles for each occupant would need to be established ahead of time and dynamically fed into building control system. Lately, various personal comfort modelling approaches have appeared using various tools including physical human-machine interface (Zhao *et al.*, 2014), smartphones (Jazizadeh *et al.*, 2014a), and wearables (Feng *et al.*, 2023). With the advancing technology, tools used for collecting feedback from the occupants may transform into new forms. It is anticipated that thermal comfort profiles will be stored in personal devices in near future like a comfort fingerprint, readily available to be fed into the control system in any indoor space.

The time required for generating personal comfort profiles depend on the employed tools, modeling types, and training methods. These include different sensing (e.g., participatory sensing using mobile devices, ambient conditions sensing, and wearable sensing) and data analytics methods (e.g., probabilistic or supervised machine learning techniques). The key issue is the quality and quantity of the collected data. For example, Jazizadeh *et al.* (2014b) developed thermal comfort profiles with a data collection process of two weeks using participatory and ambient sensing. Similarly, Liu *et al.* (2019) defined the data collection duration as 14 days and stated that model performance is improved with more data. Another study by Feng *et al.* (2023) collected 300 data points in three to four weeks to generate thermal comfort profiles. On the other hand, in their pivotal study, Daum *et al.* (2011) demonstrated that an initial default profile can be generated with a few data points, and it can then be converged towards the real thermal comfort profile in time. They indicated that 90 data points would be sufficient for such a convergence. As pointed out, these data points could be obtained through wearable sensing, participatory sensing, or even smart thermostats, such as Google Nest. Once sufficient data points (composed of comfort feedback and environmental conditions data) are collected, they are processed with statistical or machine learning algorithms to generate personal comfort profiles. However, it is important to note that personal comfort profile development is not a static process. These profiles are supposed to be updated continuously with the incoming personal and environmental data, which will help maintain their predictive performance over time.

Previous research have demonstrated that integrating personal comfort models into HVAC control loops for a comfort-driven operation both improves human comfort and enhances efficient energy use by providing conditioning at the needed level (Jazizadeh *et al.*, 2014b; Li *et al.*, 2017; Z. Yang & Becerik-Gerber, 2014). In single-occupancy spaces, personal comfort models suggest huge benefits for ensuring the desired indoor climate with high sensitivity. However, although there are some studies proposing strategies for multi-occupancy comfort optimization in the literature (S. Lee *et al.*, 2019; Nagarathinam *et al.*, 2021), optimization of occupant comfort through utilizing personal comfort preferences in shared environments has still room for further investigation. Considering these, in this chapter, six personal comfort profiles representing comfort probabilities of six individuals across a range of temperature values were developed, using a Bayesian network modeling approach. Although conventional HVAC systems generally do not offer high granularity for individual-specific comfort assessment in multi-occupancy spaces, effective strategies and upgrades enabling the integration of personalized comfort data in building control have a huge potential to shift the current paradigm. Insightful research efforts in this field will encourage the building industry towards this transition to seek new paths for optimizing and transforming conventional mechanical systems in shared environments.

CHAPTER 4

ANALYSIS OF THERMAL DISTRIBUTION PATTERNS

This chapter focuses on the heterogeneity of thermal conditions in shared indoor spaces. Through studying the selected case study (presented in section 2.3.3) in depth, spatial variations in thermal parameters were analyzed. In doing so, CFD simulations were adopted to assess the influences of different parameters including supply airflow rate, supply airflow direction and occupancy. Following an initial analysis of the independent variables, a total number of 432 scenarios were defined and simulated to compile a dataset revealing thermal distribution characteristics in a multi-occupancy environment under varying occupancy and HVAC settings.

The chapter starts with introducing the importance of non-uniformity of thermal conditions in multi-occupancy environments. Then, CFD simulation framework, governing equations, grid independence study and initial parameter assessment were presented. After defining the scenarios created with parameter combinations, the thermal distribution patterns were visualized and temperature variations at occupant locations were illustrated. The importance of defined parameters was analyzed using Random Forest algorithm, and the section was concluded with a brief discussion on the results.

4.1 Literature Review

4.1.1 Spatial Heterogeneity in Shared Spaces

Thermal comfort in multi-occupancy spaces is a challenge as comfort optimization is usually limited by the granularity and flexibility of the existing building systems. In conventional HVAC control loops, when the thermostat is set to a specific temperature, conditioning adjustments are made based on the measurements from a single sensor placed at a pre-defined point. Yet, as thermal conditions are not homogenous in indoor spaces (Zhou *et al.*, 2014), temperature gradients may lead to a discrepancy between the temperature buildings occupants are subject to and the temperature setting on the thermostats (Du *et al.*, 2015). The dynamics of indoor environmental conditions affect both human comfort and energy use. Especially in large shared environments, many parameters can affect micro-climate around different occupants, including proximity to windows, furniture layout, solar radiation, supply air inlet placement, and heat flux aroused from electronic appliances. These factors lead to fluctuations in indoor environmental parameter values in the same space, making occupant location an essential aspect for continuous comfort. Due to the influencing factors around their immediate surroundings and resultant micro-climate, occupants may be subjected to different thermal conditions within the very same indoor environment (Figure 4.1).

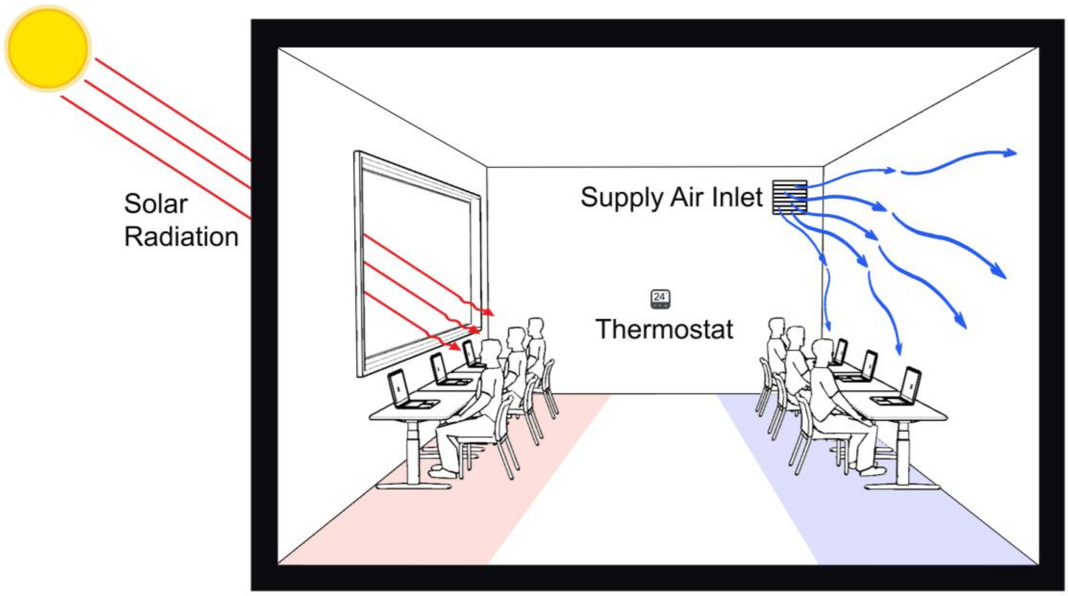


Figure 4.1. Factors causing micro-climate variations in shared spaces

Regardless, most of the current studies on occupant-centric building control are predicated on the assumption that temperature is uniformly distributed in the considered zones, ignoring the dynamic local conditions of particular positions. Although a single thermostat or a local sensor is attributed to be representative for the entire room for assessing the indoor environmental parameters, thermal conditions may vary by location (Zhou *et al.*, 2015). The spatial heterogeneity in buildings requires a high number of distributed measurements for making comfort implications based on occupant location.

In the absence of proper control strategies, individuals occupying the same room may experience diverse thermal sensations, such as cold or warmth, owing to uneven thermal distribution. The most unfavorable outcome of this scenario would be the inability to provide satisfactory comfort for any occupants, coupled with the excessive energy consumption to regulate the indoor environment. Hence, analogous to addressing the nonuniformity in personal comfort, accounting for the heterogeneity of indoor climatic conditions in building control holds a promising opportunity for enhancing occupant comfort and decreasing energy consumption. Moreover, flexible working hours and remote working have been a common practice for many firms since the beginning of the Covid-19 pandemic. As dynamic occupancy patterns are expected to remain in effect in large offices even in the post-pandemic era (Mantesi *et al.*, 2022), the operation of HVAC systems can be adjusted according to the demand to avoid conditioning unoccupied locations while ensuring comfort for the positions that are occupied.

Despite the potential benefits of using micro-thermal data to optimize building control systems for enhanced efficiency, the current body of research on this topic is relatively limited. The reason may be the costly requirement of controlled measurements with complex sensor infrastructures to understand the patterns and distributions of thermal parameters in indoor environments. As the high computational power gets more accessible with advanced technology, it has become more viable to utilize computational fluid dynamics (CFD) simulations to obtain the required thermal variables in an economical and efficient manner.

4.1.2 Computational Fluid Dynamics Simulations

Research efforts towards assessing thermal dynamics in indoor spaces are mainly conducted by on-site measurements and computer simulations. In recent years, due to the complex physical requirements and time-intensive nature of field studies, CFD simulation has been a very useful tool for understanding and visualizing the air distribution patterns of thermal parameters. When compared with field studies, which relies on a limited number of specific point measurements, it enables to capture indoor thermal parameters with a much higher granularity. Although its introduction in HVAC industry dates back to the 1970s, it has become widely popular in the last two decades (Nielsen, 2015).

Through solving a set of partial differential equations for conservation of mass, momentum, and energy with suitable turbulence models, CFD simulation allows to analyze and visualize airflow dynamics and temperature distribution within a defined environment. With the increasing availability and advancements in high-power computing and processing tools, CFD has become a prominent way of dealing with the complex flow problems within the built environment in the last decades (Nielsen, 2015). Building researchers adopted this approach for assessing various subjects. including indoor environmental factors Sevilgen and Kilic (2011), HVAC design (Duan & Wang, 2019), personalized systems (J. Liu *et al.*, 2019), occupant comfort (Hajdukiewicz *et al.*, 2013; Shan *et al.*, 2020) and energy use (Zhou *et al.*, 2014). The study by Buratti *et al.* (2017) demonstrated that spatial variations in thermal comfort can be accurately simulated using CFD tools. Other researchers employed CFD simulations to make thermal comfort predictions in various indoor environment typologies including lecture halls (Cheong *et al.*, 2003), stadiums (Stamou *et al.*, 2008), offices (Myhren & Holmberg, 2008; Semprini *et al.*, 2019) and residential spaces (Z. Chen *et al.*, 2020). A recent study by Jazizadeh *et al.* (2020) tested the applicability of adaptive HVAC operation using CFD simulations and demonstrated promising insights for employing this method for occupant-centric building control research.

4.2 Material and Method

In this section, CFD simulations were employed to analyze thermal distribution characteristics in a shared office space. Simulation procedure and setup components including solver settings, governing equations, and boundary conditions were explained in detail. In order to confirm the reliability and validity of the simulations, grid independence test and setting validation study were carried out. After simulating eight initial cases to understand the influence of the independent variables, 432 different scenarios were defined using the combinations of different supplied airflow rates, supplied airflow directions and occupancy cases. The variations of independent variables were intentionally kept at a manageable level, considering the cumulative increase in the number of combinations and computing time.

4.2.1 Simulation Framework

In this study, commercial software ANSYS Fluent (ANSYS Inc., 2021) is used for performing CFD simulations. It is one of the most popular software packages for assessing indoor air parameter distributions, with its user-friendly function allocations (Y. Zou *et al.*, 2018). The simulation process starts with developing three-dimensional geometry and mesh generation, which are then followed by simulation setup, grid independence study, mesh refinement, and running the simulations (Figure 4.2). The finite volume method embedded in the software is used to solve the governing equations by decomposing the fluid domain into small control volumes. The partial differential equations are discretized into algebraic equations at each point of the generated mesh grid, and these algebraic equations are solved through iterations to obtain thermal distribution and airflow patterns within the defined boundaries (Shan *et al.*, 2020). In this study, a steady-state simulation setup was employed, which provides a snapshot of the conditions within the defined space at a given time under selected boundary conditions.

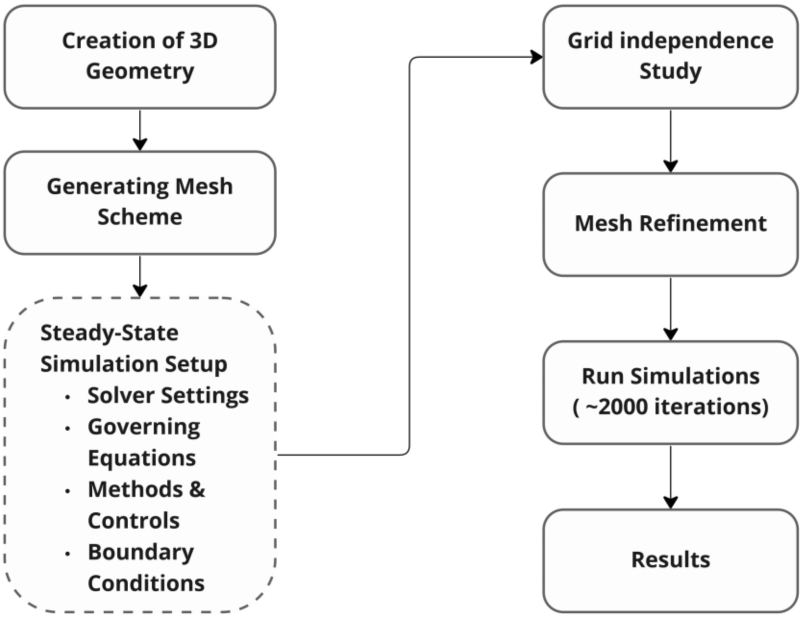


Figure 4.2. CFD simulation framework

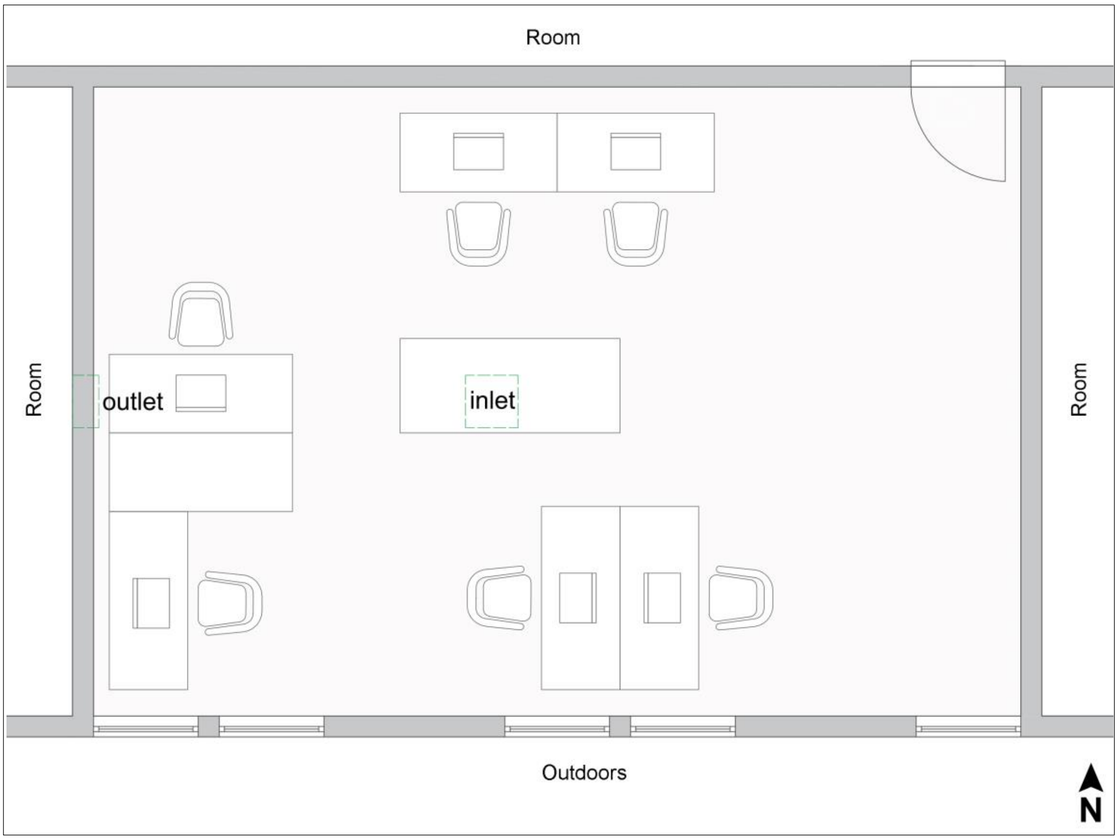


Figure 4.3. The architectural layout of the selected office space

An office space in the College of Engineering of Penn State University is selected as the simulation case (Figure 4.3). Shared by six occupants, space dimensions are 8.8m in length, 6m in width, and 4m in height. The room's only side subjected to the exterior conditions is the south wall, having five large windows. There is one supply air inlet and a return outlet in the room, both having dimensions of 0.5m x 0.5m.

4.2.2 Governing Equations and Boundary Conditions

Based on the real-world parameters of the selected space, a three-dimensional geometric model is developed using the SpaceClaim platform in ANSYS Fluent. Walls, windows, tables, computers, HVAC components, and occupants are abstracted in the model to reduce complexity and avoid irrelevant details in meshing (Figure 4.4). Occupant surface area is modeled as 1.8 m^2, representing an average human body (ASHRAE, 2017).

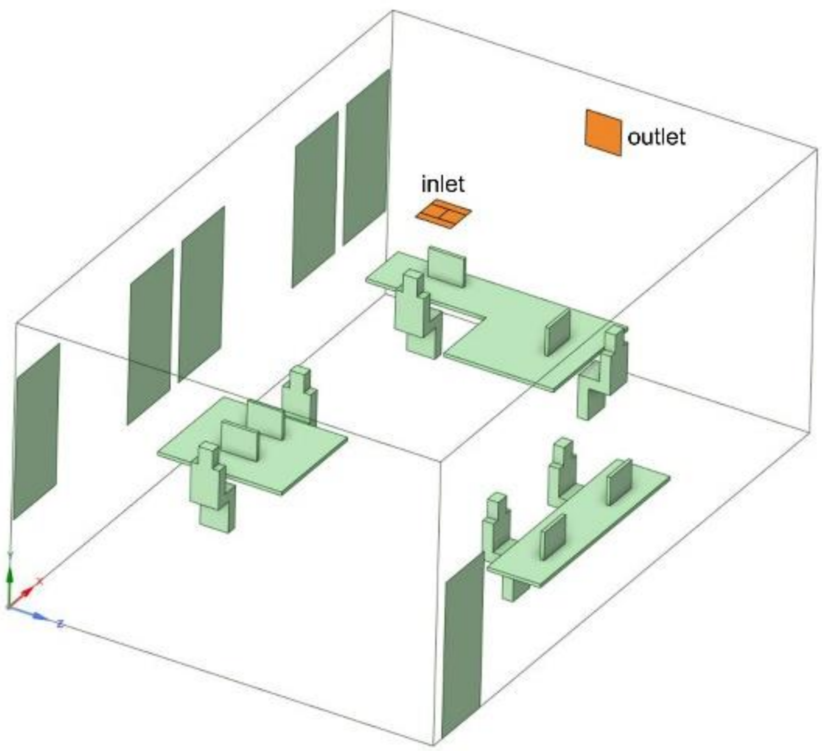


Figure 4.4. Simulated geometry and generated mesh in ANSYS Fluent

The governing equations used in simulations, which are conservation of mass (5), conservation of momentum (6a, 6b, 6c), and conservation of energy (7), were explained in detail by Versteeg and Malalasekera (2007). Referring to Duan & Wang (2019), equations can be written as:

Continuity equation (conservation of mass):

$$\frac{\partial \rho}{\partial t} + \nabla \cdot \left(\rho \vec{V} \right) = 0 \tag{5}$$

, where ρ is the density, $\vec{V}$ is the velocity, and ∇ resembles divergence.

Navier-Stokes equations (conservation of momentum):

$$\frac{\partial (\rho u)}{\partial t} + \nabla \cdot (\rho u \vec{V}) = -\frac{\partial P}{\partial x} + \frac{\partial \tau_{xx}}{\partial x} + \frac{\partial \tau_{yx}}{\partial y} + \frac{\partial \tau_{zx}}{\partial z} + \rho f_x \tag{6a}$$

$$\frac{\partial (\rho v)}{\partial t} + \nabla \cdot (\rho v \vec{V}) = -\frac{\partial P}{\partial y} + \frac{\partial \tau_{xy}}{\partial x} + \frac{\partial \tau_{yy}}{\partial y} + \frac{\partial \tau_{zy}}{\partial z} + \rho f_y \tag{6b}$$

$$\frac{\partial (\rho w)}{\partial t} + \nabla \cdot (\rho w \vec{V}) = -\frac{\partial P}{\partial z} + \frac{\partial \tau_{xz}}{\partial x} + \frac{\partial \tau_{yz}}{\partial y} + \frac{\partial \tau_{zz}}{\partial z} + \rho f_z \tag{6c}$$

, where *u, v, w* is the velocity in *x, y, z* directions, P is the pressure force per unit area, τ_{ij} stands for a stress in *j*-direction exerted on a plane perpendicular to the *i*-axis; ρf_i denotes the body force on the fluid element acting in the *i*-direction, respectively.

Conservation of energy equation:

$$
\begin{aligned}
&\frac{\partial}{\partial t}\left(\rho\,(e+\frac{V^2}{2})\right)+\nabla\cdot\left(\rho\,(e+\frac{V^2}{2}\vec{V})\right)\\
&=p\ddot{q}\frac{\partial}{\partial x}\left(k\frac{\partial T}{\partial x}\right)+\frac{\partial}{\partial y}\left(K\frac{\partial T}{\partial y}\right)+\frac{\partial}{\partial z}\left(K\frac{\partial T}{\partial z}\right)-\frac{\partial(up)}{\partial x}-\frac{\partial(vp)}{\partial y}-\frac{\partial(wp)}{\partial z}\\
&+\frac{\partial(u\tau_{xx})}{\partial x}+\frac{\partial(u\tau_{yx})}{\partial y}+\frac{\partial(u\tau_{zx})}{\partial z}+\frac{\partial(v\tau_{xy})}{\partial x}+\frac{\partial(v\tau_{yy})}{\partial y}+\frac{\partial(v\tau_{zy})}{\partial z}\\
&+\frac{\partial(w\tau_{xz})}{\partial x}+\frac{\partial(w\tau_{yz})}{\partial y}+\frac{\partial(w\tau_{zz})}{\partial z}+\rho\vec{f}\cdot\vec{V}
\end{aligned}
\tag{7}
$$

, where $(e+\frac{V^2}{2})$ is the total energy, k is the thermal conductivity, T is the local temperature, $\ddot{q}$ is the rate of volumetric heat addition per unit mass.

The pressure-based segregated solver is used for the incompressible flow equations, and the Boussinesq approximation is employed to model natural convection. The realizable k-ε model is used for turbulence modeling under full buoyancy effects, and solar radiation is solved using a surface-to-surface (S2S) model with solar ray tracing.

The semi-implicit method for pressure-linked equation (SIMPLE) is applied as the pressure-velocity coupling algorithm. Least squares cell based (LSCB) is used for discretizing gradients, and the pressure staggering option (PRESTO!) is selected for pressure. Second-order upwind methods are utilized for the discretization of momentum, turbulent kinetic energy, turbulent dissipation rate, and energy. The selection of these methods is predicated on the previous validations by Wang *et al.* (2017) and Jazizadeh *et al.* (2020).

Boundary conditions and material properties for the baseline scenario are defined, as shown in Table 3.1. Accordingly, air with a flow rate of 0.1625 m^3/s and a temperature of 13 degrees Celsius is supplied to the space from the inlet, uniformly in all directions with an angle of 30 degrees from the ceiling. The surface of walls, slabs, and tables are set as adiabatic, presuming no-slip conditions for fluid-surface interactions. The heat sources in the space are determined as occupants with a heat flux of 60 W/m^2 per individual, computers with a generated heat of 60 W/m^2 per device, and the windows exposed to the exterior temperature and radiation effects. The windows are designated with a heat transfer coefficient of 5.6 W/m^2 and a solar radiation transmittance feature of 80%. The global position of the selected office space is defined in the solar calculator of the S2S model to have accurate solar radiation effects applied on the windows. The exterior temperature is set as 28^{O}C, considering a hot summer day in the case location. The date and time were arranged as June 21st, 13:00. As indicated in Table 4.1, density, specific heat, and conductivity parameters are defined for a low-insulation window.

Table 4.1. Boundary conditions used in the baseline simulation

Boundary	**Properties**	**Conditions**
Supply Inlet	n/a	airflow rate=0.1625 m^3/s air temperature = 13˚C
Return Outlet	n/a	pressure outlet
Walls	n/a	adiabatic, no-slip condition
Windows	density = 2700 kg/m^3 specific heat = 840 J/kg.K conductivity = 0.14 W/m.K	heat transfer coeff.: 5.6W/m^2K exterior temperature: 28˚C transmittance: 80%
Occupants	density = 998 kg/m^3 specific heat = 4182 J/kg.K conductivity = 50 W/m.K	heat flux = 60 W/m^2
Computers	density = 115 kg/m^3 specific heat = 1810 J/kg.K conductivity = 0.181 W/m.K	heat flux = 60 W/m^2

4.2.3 Grid Independence Study and CFD Validation

As the quality of the generated mesh is quite critical for the accuracy of simulation results and the computational cost, determining a reasonable grid size is crucial. In order to ensure the robustness of the solution and determine the suitable mesh to be used in the simulations, a grid independence study is performed. Four different meshes are generated considering the grid refinement ratio, starting from coarse quality towards the fine.

$$r = \left(\frac{mesh_{fine}}{mesh_{coarse}} \right)^{\frac{1}{3}} \tag{8}$$

Table 4.2. Grid parameters for different mesh sizes

Mesh-1	Mesh-2	Mesh-3	Mesh-4	r_{43}	r_{32}	r_{21}
174 136	411 336	964 995	2 150 072	1.31	1.33	1.33

The grid refinement ratio (r) for three-dimensional meshes is calculated for two consecutive meshes (i.e., fine and medium, or medium and coarse), as defined in Equation (8). In order to assess the discretization error in isolation, the refinement ratio is required to be greater than 1.3 (Hajdukiewicz *et al.*, 2013). Accordingly, four successively refined meshes are created using unstructured elements, with the maximum element sizes of 0.17 m, 0.12 m, 0.08 m, and 0.06 m, respectively. The number of elements in each mesh and grid refinement ratios is shown in Table 4.2.

A qualitative grid independence assessment is conducted by comparing vertical temperature profiles along the room height at two random locations. As demonstrated in Figure 4.5 and Figure 4.6, profiles simulated with mesh-2, mesh-3, and mesh-4 are very close, implying a very small discretization error. Considering the trade-off between the number of elements and high computational cost with calculation time, mesh-2 (411 k elements) is adopted for simulations. The selected mesh size is further refined in the vicinity of the supply inlet, return outlet, and occupants.

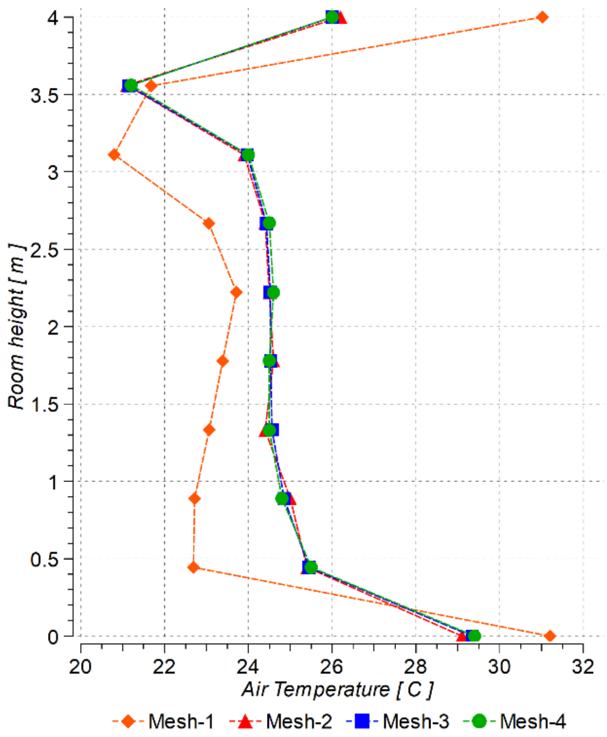


Figure 4.5. Vertical temperature profiles simulated with four meshes – random location-1

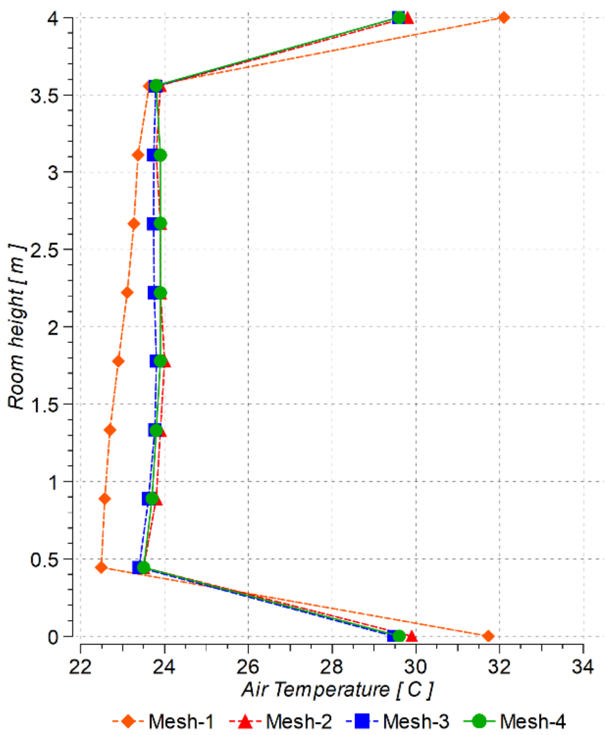


Figure 4.6. Vertical temperature profiles simulated with four meshes – random location-2

The convergence of the solution is checked through monitoring the residual root mean square error values for mass, momentum, and energy equations, together with relevant variables including average temperature, average velocity, and mass flow rate at inlet and outlet surfaces. The criterion for convergence is set as 1e-6 for energy and 1e-3 for x-velocity, y-velocity, z-velocity, k, and epsilon. The solutions are assumed to satisfactorily converge once the numerical results of the monitored variables between the consecutive iterations become negligibly small. After performing numerous initial simulations, it is acknowledged that the calculations in the defined case can be terminated after 2000 iterations, where the residuals reach converged values and the monitored variables have a steady solution.

In order to validate the effectiveness of CFD modeling approach adopted in this study, the experiments conducted in a climate chamber by Loomans (1998) was replicated by modeling and simulating the described office space. Loomans (1998) comprehensively documented the experiment characteristics and reported temperature and velocity measurements at certain locations within the test bed, for which researchers employed his work for verifying their CFD models (Jazizadeh *et al.*, 2020; Stamou & Katsiris, 2006). As shown in the developed 3D model for replicating the experiment in Figure 4.7, the space has an inlet under the desk table that supplies air with a rate of 0.047 m^3/s at 19.8°C and a return outlet on the upper corner just below the ceiling. As the heat sources, there are one occupant (59.8 W), two PC simulators (61.5W each), three ceiling lights (18.1W each) and a light source (10.9W). The temperatures of the walls, floor, and ceiling were set constant values between 22.2°C - 23.2°C.

Select experimental data recorded by Loomans (1998) was compared with the predictions made with our CFD simulations. CFD calculations were compared to the temperature values measured using T thermocouples (with an accuracy of ±0.1°C) at x = 1.5 m at three z-locations, and to the velocity values measured using a hot sphere anemometer (with an accuracy of ±0.0.25 m/s) at x = 2.40 at three z-locations. As demonstrated in Figure 4.8, a very satisfactory agreement between the experiment measurements and CFD calculations were achieved, which validates the modeling approach adopted in this study to simulate HVAC system of an office space.

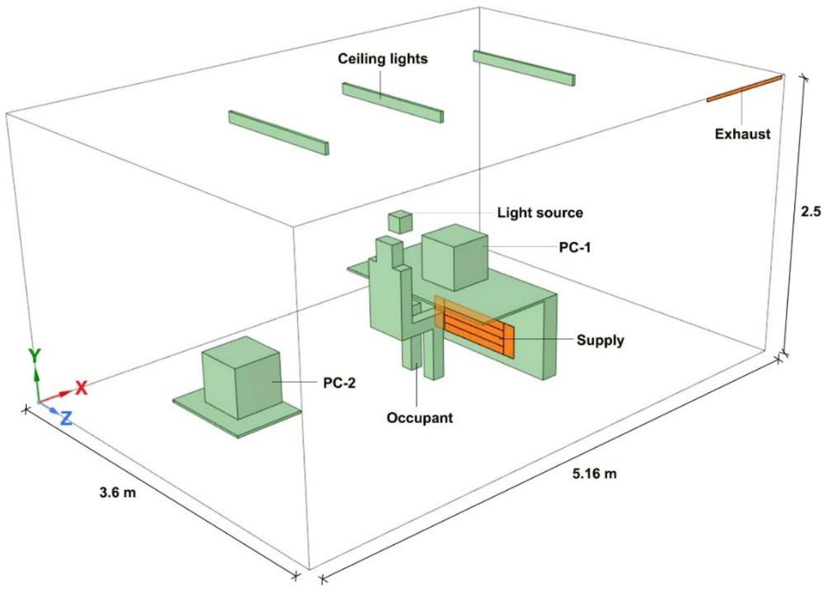


Figure 4.7. CFD model geometry created for simulating the experiments of Loomans (1998)

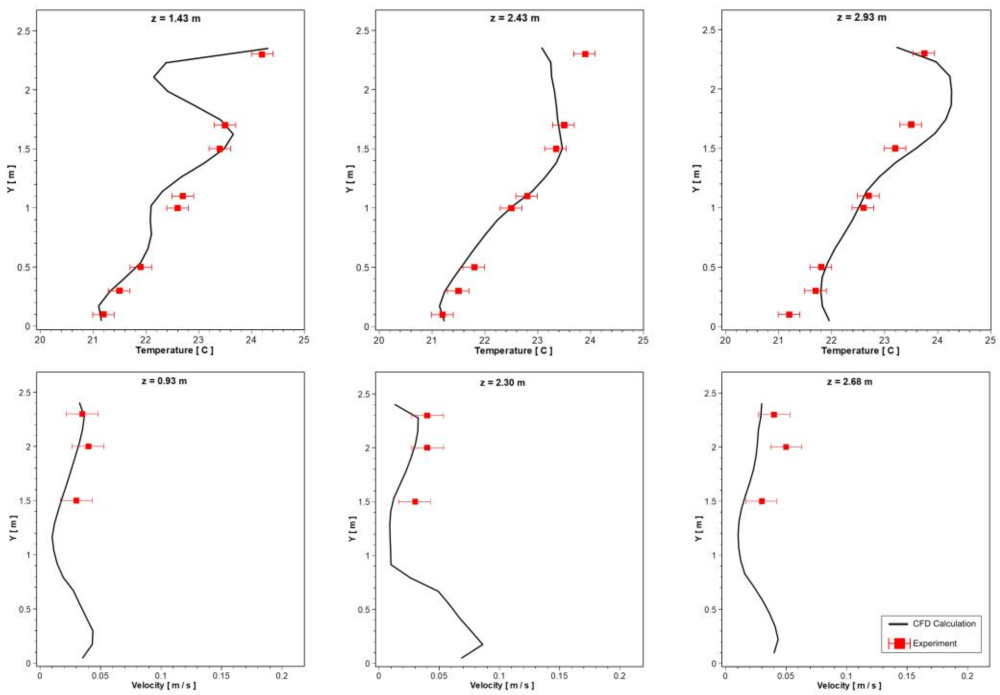


Figure 4.8. Vertical profiles comparing the measurement of (Loomans, 1998) and CFD calculations for temperature at x=1.50 m and velocity at x = 2.40 m

4.2.4 Initial Analysis for Independent Variables

Prior to proceeding to define scenarios, initial CFD simulations were performed to gain an overall perspective on how different independent variables affect the distribution of thermal parameters in shared environments. Airflow rate, airflow direction, and occupancy states were evaluated with comparative analysis.

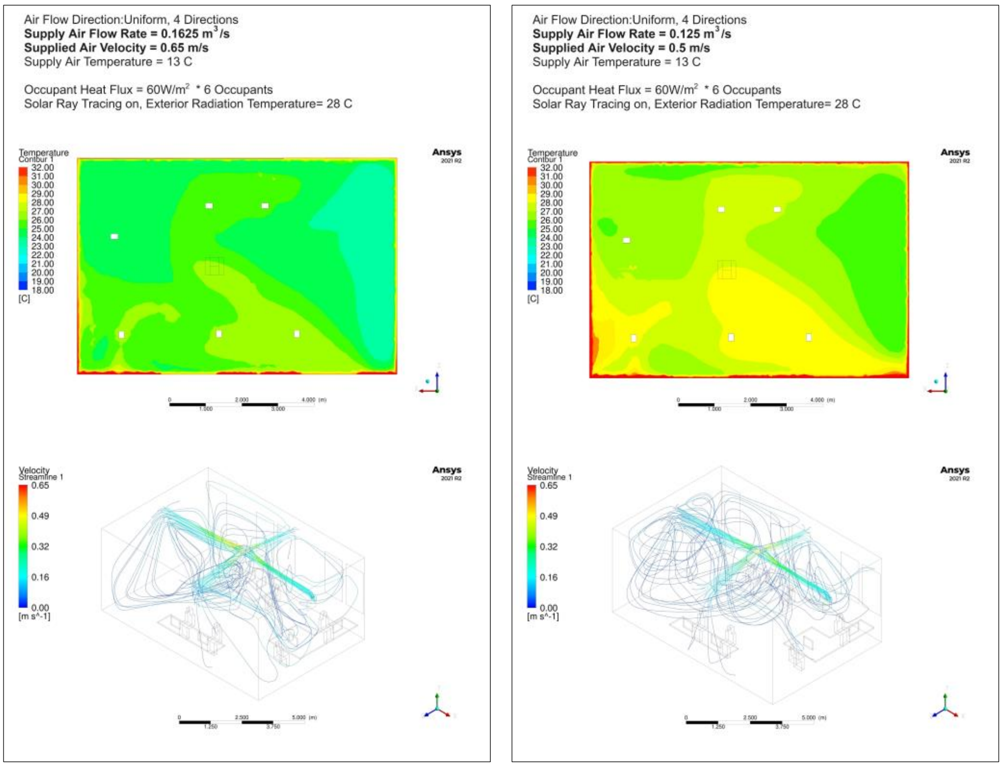


Figure 4.9. CFD simulations for supplied airflow rate variations

First, the impact of the supplied airflow rate was assessed by running two simulations cases created based on the baseline scenario. Airflow direction, supply air temperature, and occupancy were kept constant in both cases. In the first case, supplied-air velocity was defined as 0.65 m/s, which creates a flow rate of 0.1625m^3/s. In the second case, supplied-air velocity was decreased to 0.5 m/s, leading to an airflow rate of 0.125 m^3/s. While the average temperature of the room was 24.7°C in the first case, it increased to 26.8°C in the latter. Temperature gradients and air circulation were impacted as well, implying the influence of flow rate in thermal distribution patterns in indoor spaces. Figure 4.9 demonstrates the resultant plan views at neck-level and air velocity streamlines.

Secondly, we checked whether the occupant presence is an influential factor for the indoor environmental parameters. Keeping all other settings, boundary conditions, and variables as constants, we remodel the room as an unoccupied space. It was observed that the average temperature in the unoccupied case is dropped by four degrees Celsius compared to the baseline (Figure 4.10). These results were interpreted to be correlated with the heat flux created by the occupants. In addition, air circulation patterns were affected by the absence of human bodies. It was recognized that keeping the system operation static could lead to uncomfortable conditions in case of occupancy variations.

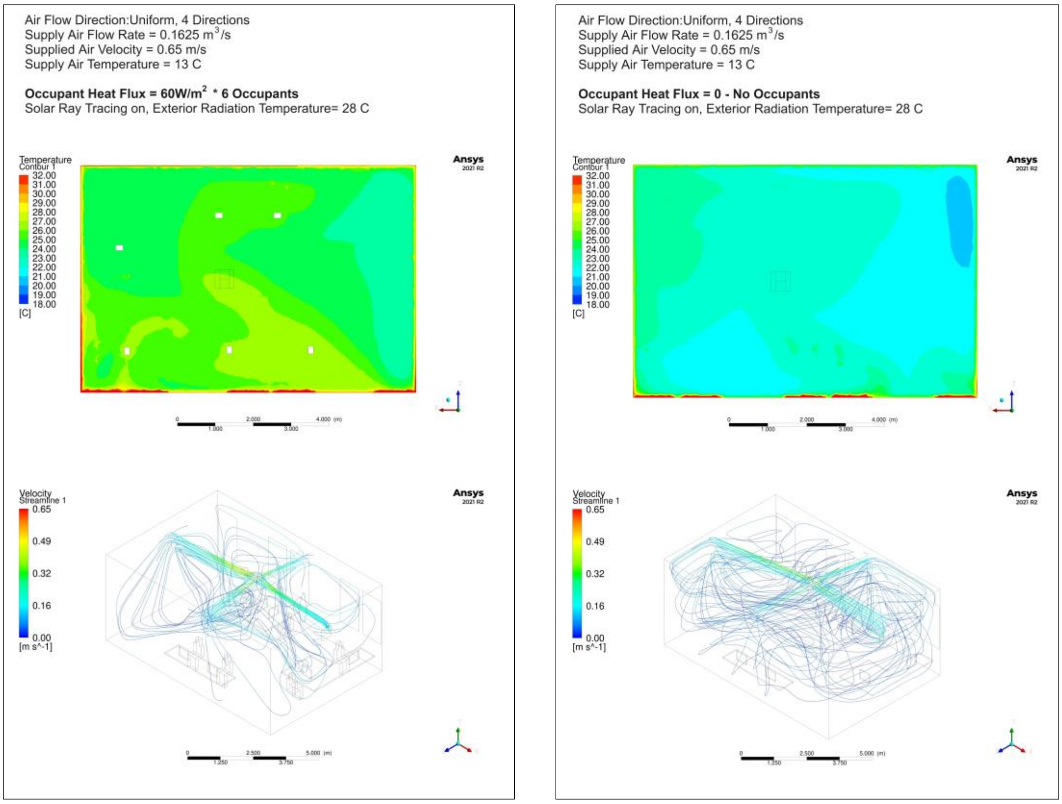


Figure 4.10. CFD simulations for occupancy variations

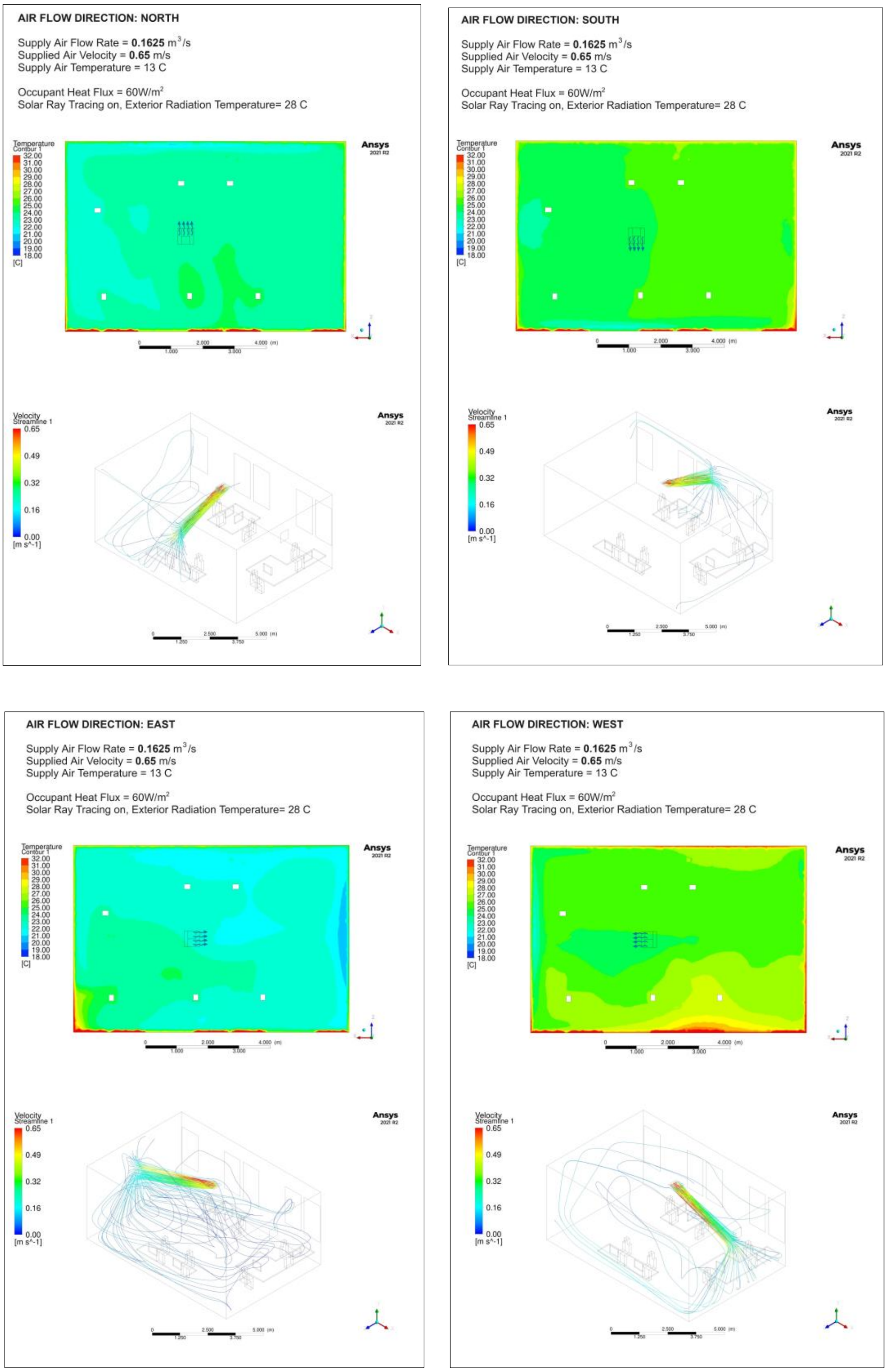


Figure 4.11. Comparative analysis of airflow direction variations

Lastly, alterations of supplied airflow direction were evaluated. As mentioned before, airflow is assumed to be uniformly distributed in all directions with an angle of 30 degrees from the ceiling in the baseline scenario. In order to determine the influence of airflow direction, four cases were created. Directed airflow is adopted towards only one direction in each case, north, south, east and west directions, respectively. Simulation results showed that airflow direction changes average temperature and distribution gradients. As illustrated in Figure 4.11, the longer the supplied cool air travel inside the space, the cooler the room becomes, depending on the placement of the pressure outlet. As the return outlet was placed on the upper part of the interior wall on the west side, directional airflow towards the east side creates the coolest conditions, while the one towards the west side leads to comparatively higher indoor temperature.

Initial CFD simulations have proven that spatial distributions of indoor environmental parameters are influenced by different independent variables, including supplied airflow rate, airflow direction, and occupancy. Results also verified the heterogeneity of thermal conditions in large shared spaces, endorsing the aforementioned research motivation towards discovering optimization strategies for more comfortable and efficient built environments.

4.2.5 Scenarios

In order to discover strategies for the optimization of collective comfort in shared environments and leverage occupant-centric HVAC control strategies, a total number of 432 scenarios were created using combinations of independent variables, as shown in Figure 4.12. Firstly, for the occupancy variable, we created 16 scenarios. While one of the scenarios was for the fully occupied state with six occupants, the rest were created with the assumption that only two occupants were present in the space. This assumption was made considering the fact that two is the minimum number creating the multi-occupancy state. The allocation probabilities of two occupants between 6 seats compose 15 scenarios, based on the combination theory (Figure 4.13, Figure 4.14).

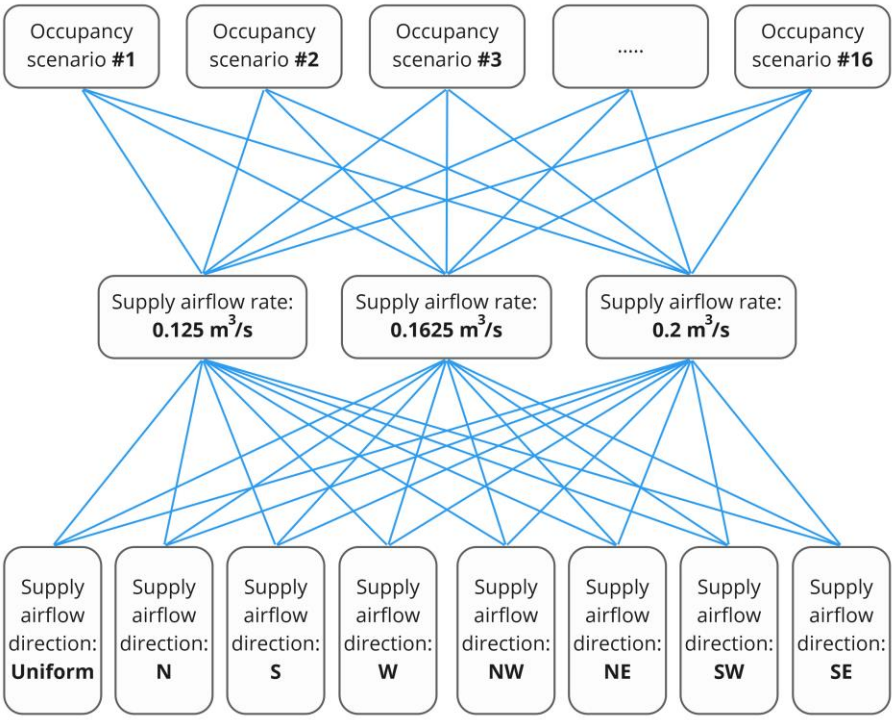


Figure 4.12. Variable combinations for simulation scenarios

Secondly, three different supply airflow rates were determined, keeping the simulated average room temperature within acceptable limits and satisfying the standard ventilation requirements. The airflow rates of 0.125 m^3/s, 0.1625 m^3/s, and 0.2 m^3/s, correspond to air change rates (ACH) of 2.31, 2.77, and 3.41, respectively, for this space. As the amount of supplied cold air can be directly correlated with the consumed energy, it is possible to assess the energy saving possibilities with these setting variations. The previous researches on ventilation rates in office spaces asserted that an airflow rate of 0.025 m^3/s per individual reduces the prevalence of sick-building-syndrome symptoms (Sundell *et al.*, 2011). Since reducing the amount of supplied air comes with the risk of decreased occupant well-being and low productivity, the range of airflow rates were defined considering the requirements to ensure a healthy environment for a maximum of six occupants.

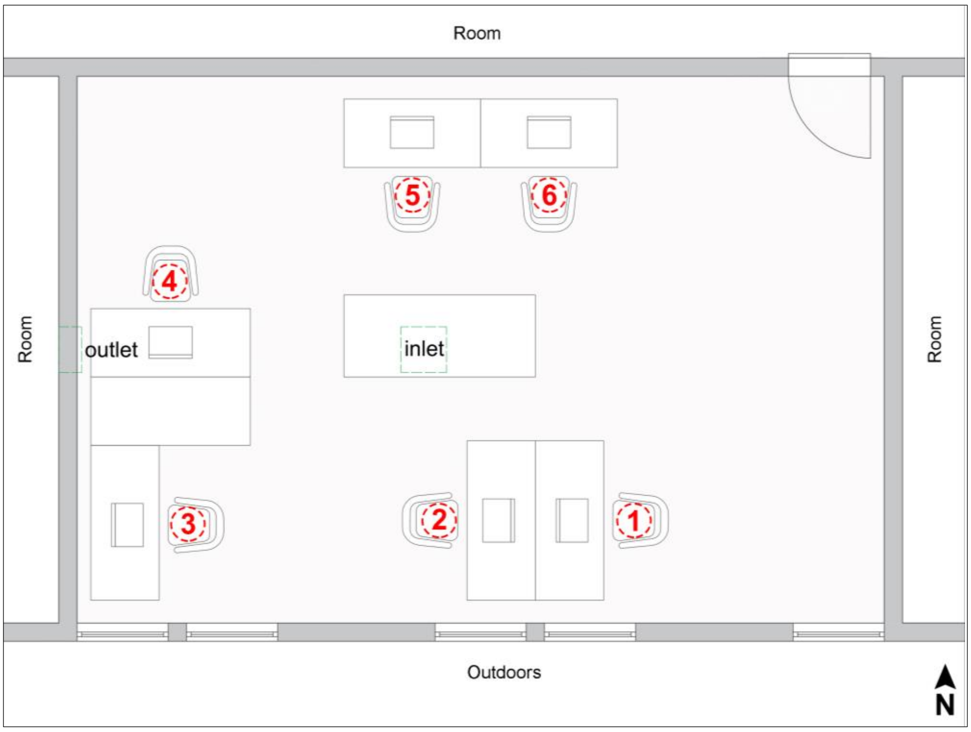


Figure 4.13. Six occupant locations in the multi-occupancy office space

Figure 4.14. Occupancy scenarios

Lastly, four cardinal directions: north, south, west, and east, four intermediate directions that are northwest, northeast, southwest, and southeast, and uniform distribution towards all directions were used as alternatives for the directional flow of supplied air. The combination of these three variables' options led to a total number of 432 scenarios. For each of 432 scenarios, CFD simulations will be performed by making related modifications in the geometric model and applying defined boundary conditions.

4.3 CFD Simulation Results

After compiling the results of the CFD simulations as a dataset, various analyses were performed. To start with, a density diagram was plotted in order to visualize how much variation there is across all of the simulation cases for each occupant location (Figure 4.15). The distributions are quite wide for all six locations, which demonstrates the sensitivity of temperatures at each location to the simulation settings. This result suggests that there should be some good opportunities in relocating occupants for optimization, provided that we have similar variation in occupant thermal comfort profiles.

While there is a wide distribution for each position, occupant locations near windows have clearly higher operative temperature values. Density of the temperature values for near-windows positions (loc-1, loc-2, loc-3) ranges between 18.5°C to 28°C and culminates at 22°C. On the other hand, the interval for loc-4, loc-5 and loc-6 is between 17.5°C to 27°C and 20.5°C has the highest density. This difference between two sets of occupant locations is in tune with the fact that positions near windows are affected more from the solar radiation and they are subjected to higher mean radiant temperatures.

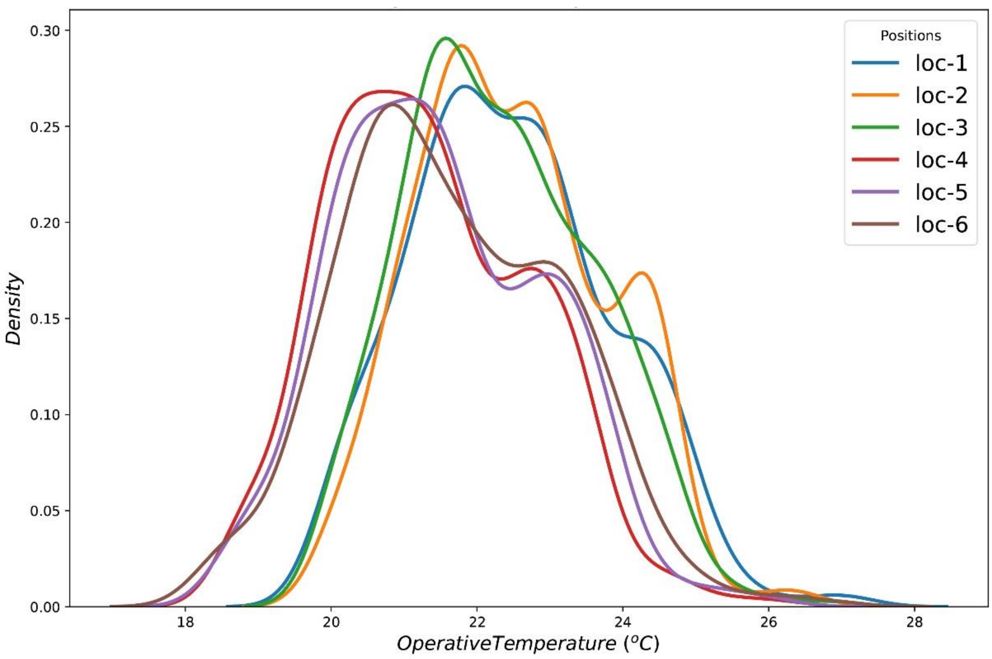


Figure 4.15. Density plot for all six occupant positions

4.3.1 Visualization of Thermal Distribution Patterns

In order to evaluate the spatial variation of temperature in the selected space, temperature contours at neck height (1.25m) in scenarios for maximum occupancy and minimum multi-occupancy baseline cases were visualized using ANSYS Fluent's post-processor. The colored temperature legends were kept same (between 18˚C – 32˚C) in each simulation case and all plan views were arranged together for an accurate and legible comparative analysis, as shown in Figure 4.16 and Figure 4.17.

Accordingly, higher supplied airflow rates create cooler conditions given that airflow direction and the occupancy case are constant. However, the average room temperature decreases by one to two degrees Celsius when the number of occupants drops from six (Figure 4.16) to two (Figure 4.17), even with the same supplied airflow characteristics. The observed difference could be explained with the fact that occupants are important heat sources in indoor environments with the heat flux released from their bodies. This result reflects the importance of occupancy and demonstrates how pre-defined static operation of climatization systems may lead to unintended thermal conditions in case of occupancy fluctuations in indoor spaces, which in return could affect human comfort and satisfaction. In addition, regardless of occupancy case, airflow rate or airflow direction, temperature is nonuniform in all of the cases. Temperature gradients do exist in this relatively small-scale office space with a conventional HVAC system, proving that people can be subjected to different thermal conditions in the very same environment, depending on desk positions.

As demonstrated in Figure 4.16 and Figure 4.17, the supplied airflow direction has a direct influence in thermal conditions and temperature distribution. The critical parameters here were considered to be the placement of supply air inlet and the return outlet. As illustrated in Figure 4.13, the outlet is located on the west wall whilst the inlet is in the center of the room with a small drift to the west. As a natural phenomenon, if the supplied airflow direction is towards to the opposite side of the return outlet, fresh cold air circulates more in the conditioned space and make it cooler. The changes in room temperatures in Figure 4.16 and Figure 4.17 for different airflow directions seem to be well in line with this. Accordingly, supplying air towards the east direction created the coldest conditions while adjusting the airflow direction to the west resulted in the highest room temperatures in all the cases with varying airflow rates and occupancy. Keeping the airflow rate constant (using same amount of energy), modifying the direction of supplied air has the potential to fluctuate the average room temperature up to two degrees Celsius. As expected, temperature contours were also affected with the airflow direction alterations due to air circulation shifts.

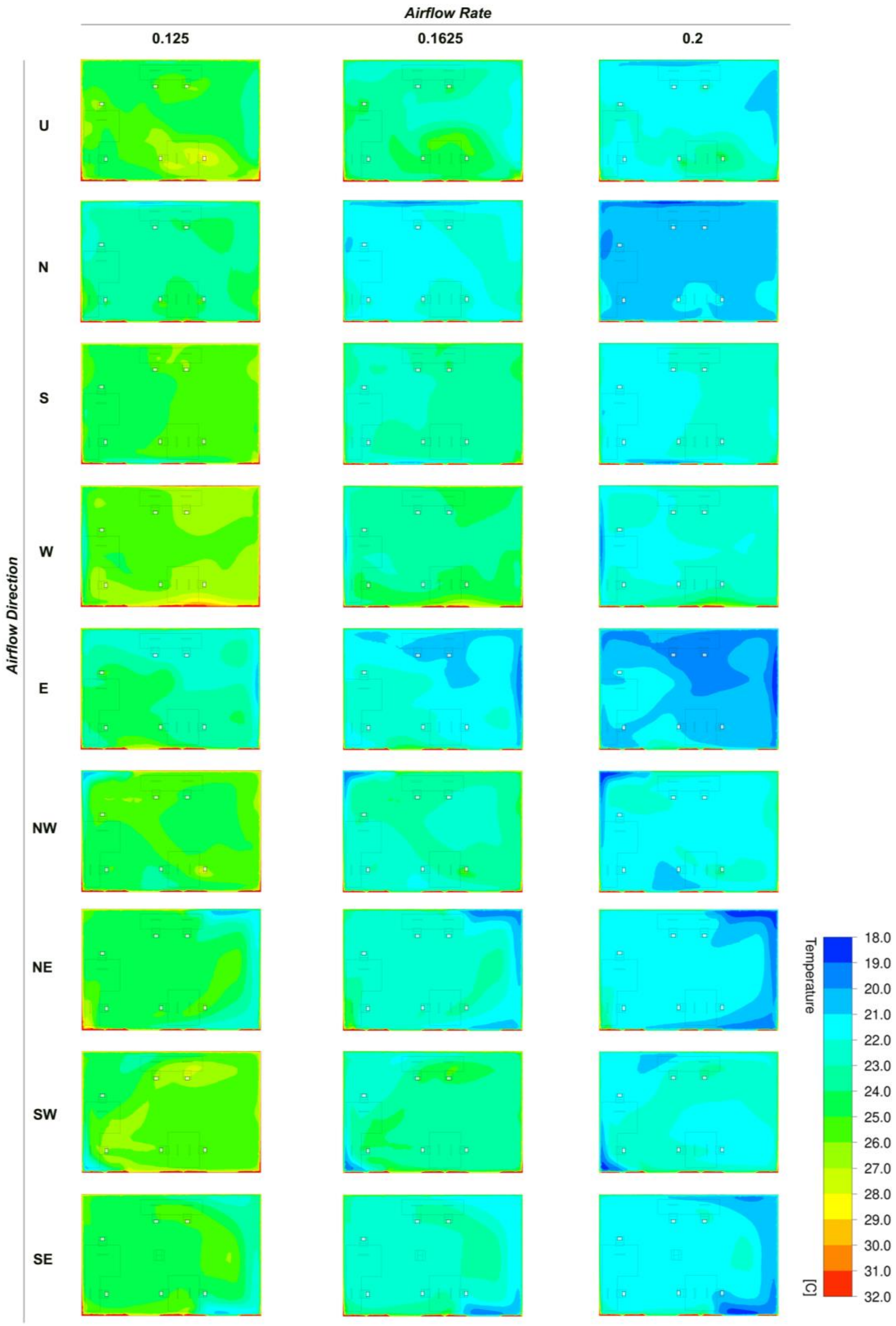


Figure 4.16. Temperature distribution gradients in scenarios for maximum occupancy

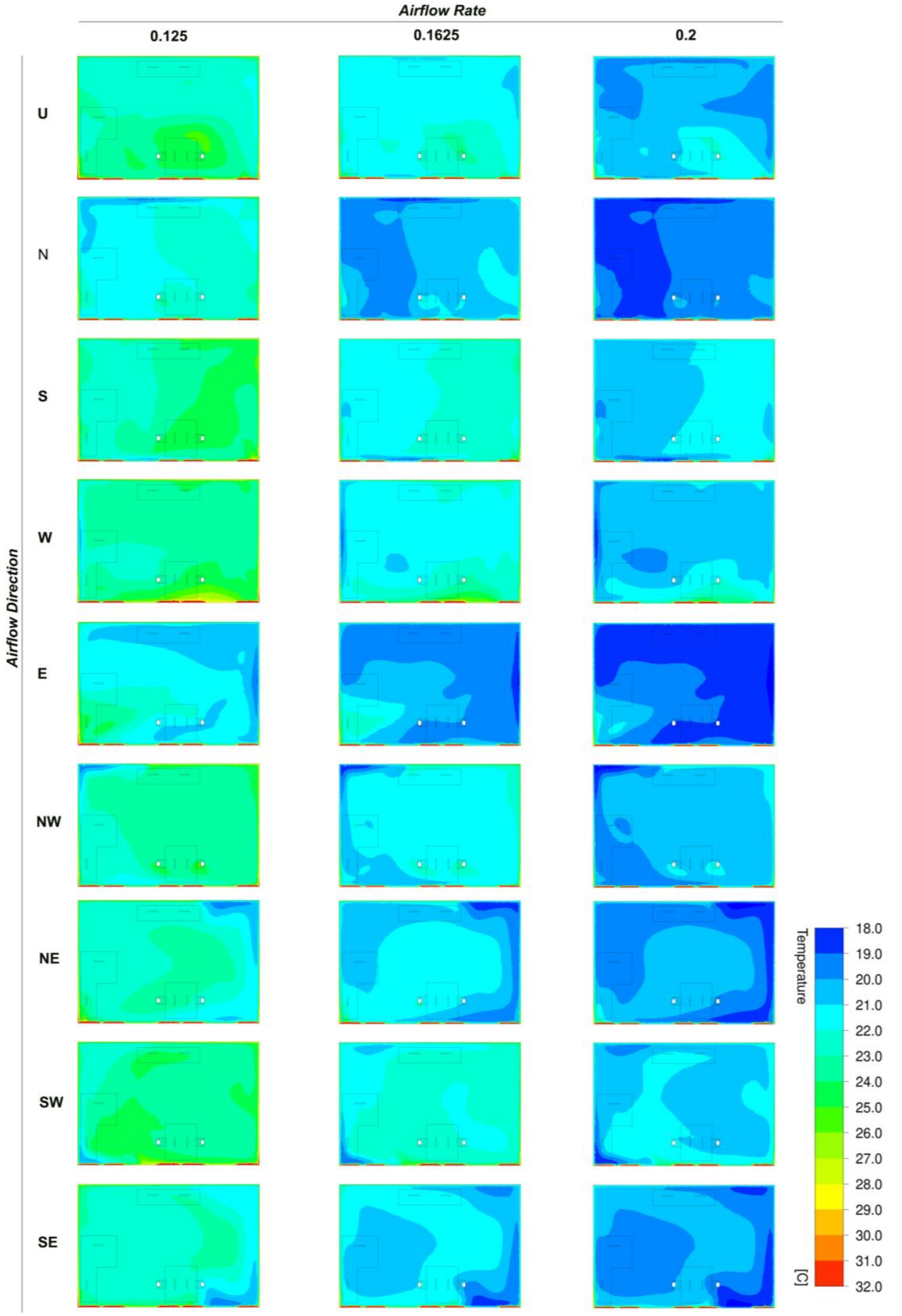


Figure 4.17. Temperature distribution gradients in scenarios for minimum multi-occupancy (one of the fifteen scenarios with two occupants)

4.3.2 Temperature Variations at Occupant Locations

In Figure 4.18, Figure 4.19 and Figure 4.20, operative temperature variations in minimum multi-occupancy scenarios at airflow rate=0.125m^3/s, airflow rate=0.1625m^3/s and airflow rate=0.2 m^3/s are presented, respectively. The temperature values at neck height (1.25 m) in fifteen occupancy cases with two occupants are illustrated in subplots, each of which is devoted to a certain airflow direction setting. The figure shows that thermal conditions are not uniform in the studied space in most of the cases, considering the temperature differences between two occupant positions and the average room temperatures. Despite the fact that average room temperatures do not show much fluctuation between different occupancy cases with constant airflow direction within each subplot, the temperature that each occupant is subjected to varies up to two degrees Celsius depending on their positions in the very same environment. Although this variance may pose a challenge for occupant-centric studies that assume homogenous thermal conditions in indoors, it also holds a great potential for improving collective comfort in multi-occupancy scenarios given the differences in occupants' thermal preferences.

In addition, the direct influence of the supply airflow direction on temperature variations is also observable in these figures, which is associated with the placement of supply air inlet and the return outlet.

As a natural phenomenon, if the supply airflow direction is towards to the opposite side of the return outlet, fresh cold air circulates more in the conditioned space and make it cooler. Accordingly, the cases in which the fresh air is supplied towards the east direction has the lowest temperature values, while the cases where airflow direction was set to the west has the highest. To this end, it can be claimed that changing the supply airflow direction, which do not require any additional energy at neither the cooling coil nor the fan levels, could be seen as a promising energy efficient strategy, instead of modifying the airflow rate to adjust the temperature.

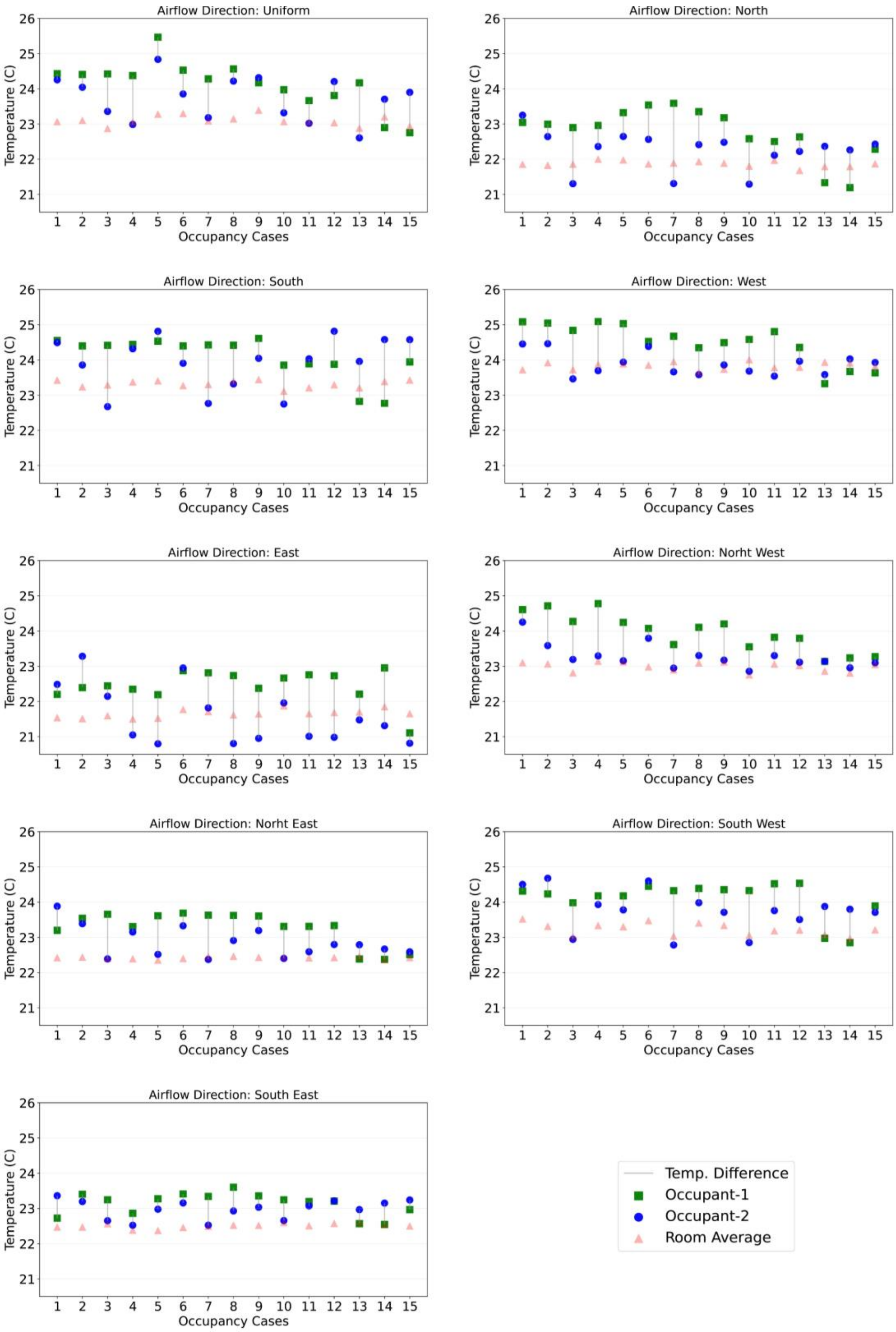


Figure 4.18. Operative temperature values in case of minimum multi-occupancy for different airflow direction and occupancy case scenarios (for airflow rate=0.125 m^3/s)

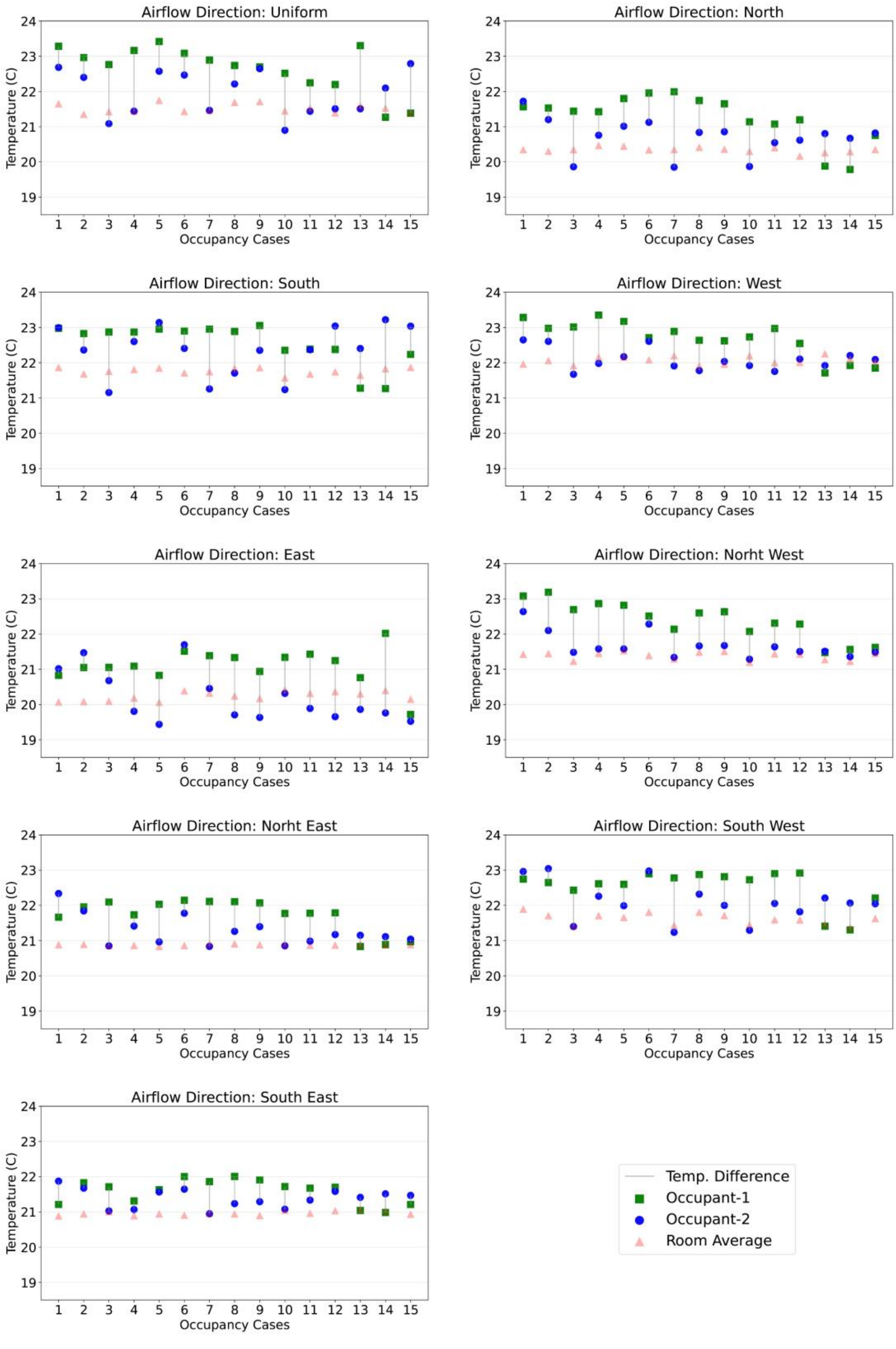


Figure 4.19. Operative temperature values in case of minimum multi-occupancy for different airflow direction and occupancy case scenarios (for airflow rate=0.1625 m^3/s)

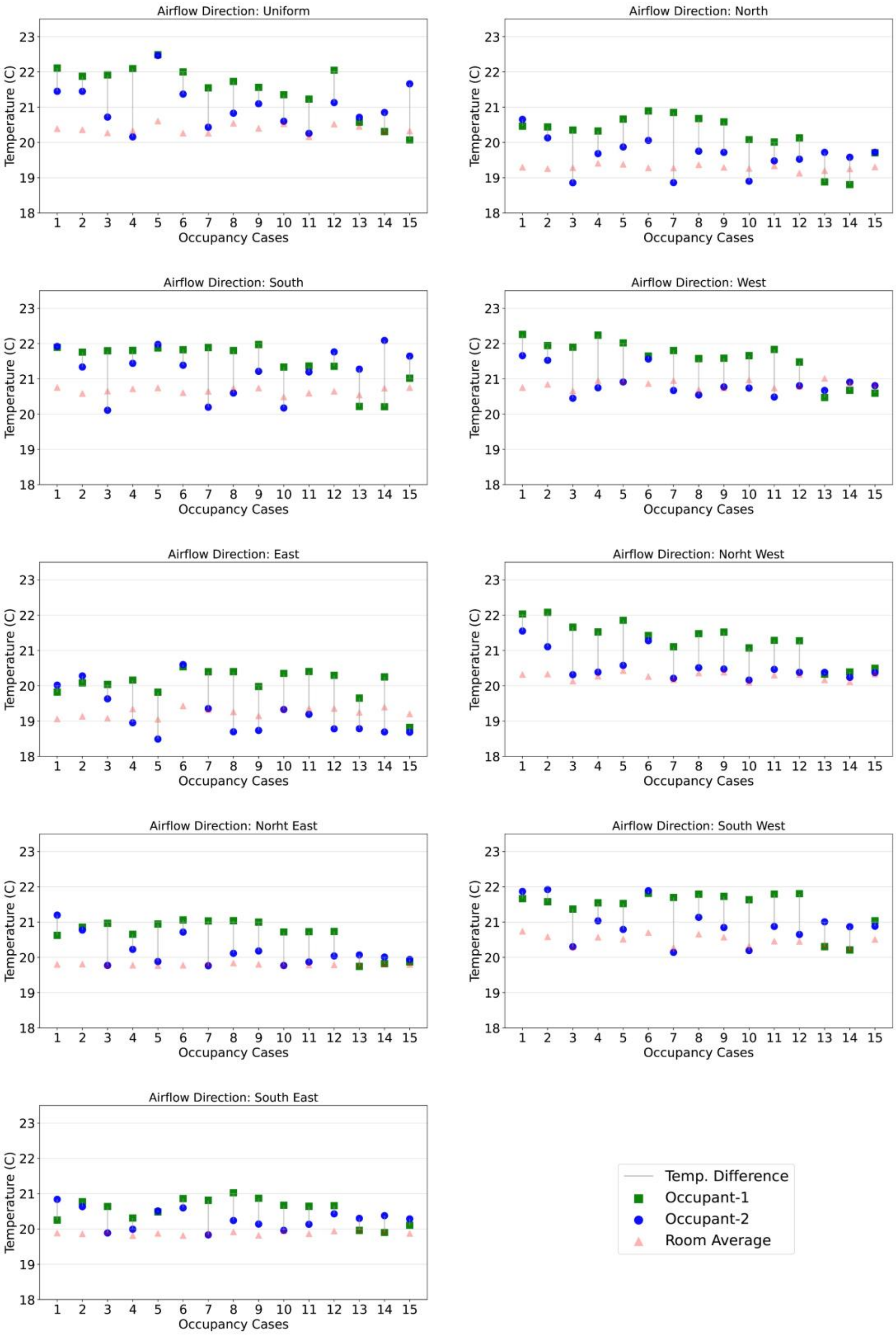


Figure 4.20. Operative temperature values in case of minimum multi-occupancy for different airflow direction and occupancy case scenarios (for airflow rate=0.2 m^3/s)

Comparing the temperature values in three figures reveals that higher supply airflow rates create cooler conditions as expected, given that airflow direction and occupancy positions are fixed. Yet, it also presents that supplying airflow at a higher level is not the only way for decreasing the room temperature, if the supply airflow direction is adjustable. Allowing a modest alteration possibility at diffuser level is shown have a promising potential in terms of ensuring occupant comfort without using more energy in multi-occupancy scenarios.

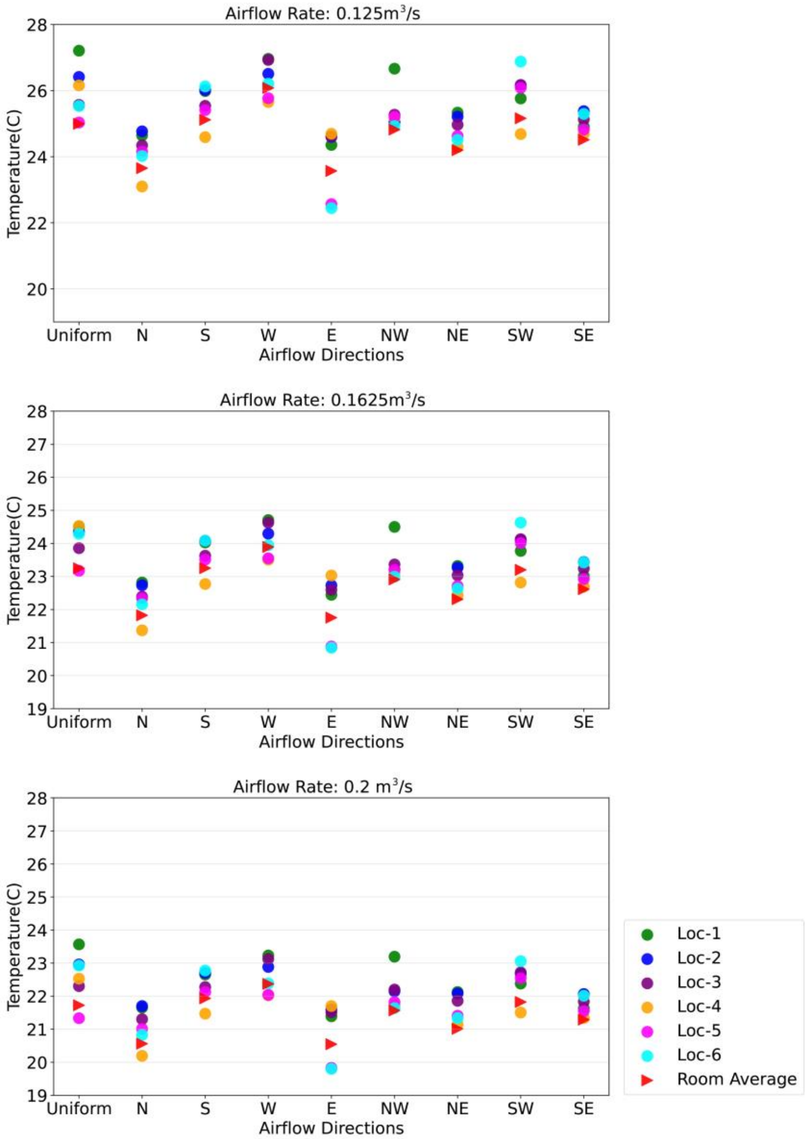


Figure 4.21. Operative temperature values in case of maximum multi-occupancy for six occupant locations

Similar to the minimum multi-occupancy scenarios, thermal conditions are not homogenous in maximum multi-occupancy scenario. Although temperature values are higher in maximum occupancy, the variances between the micro-thermal conditions that occupants are subjected to are almost the same with the minimum multi-occupancy cases. For example, average room temperature at airflow rate=0.1625 m^3/s and airflow direction=Uniform at minimum multi-occupancy is 21.5 degrees Celsius, whereas the same setting at maximum occupancy results in an average room temperature of 23.2 degrees Celsius. In both occupancy cases, however, the temperature difference between occupant locations goes up to two degrees Celsius. This similarity suggests that the indoor thermal conditions are non-uniform regardless of the number of occupants present in the space, while the temperature values on average naturally rises with the increasing number of occupants due to the heat release from their bodies. As shown in Figure 4.21, operative temperature values between six occupant locations varies up to two and a half degrees Celsius in different cases with constant supply airflow settings. As expected, supplying airflow at a higher level, which means using more energy, generally created cooler conditions when the airflow direction is fixed. However, the results also demonstrate that creating cooler conditions does not always require an increase in supply airflow rate. For example, average room temperature at airflow rate=0.2 m^3/s and airflow direction=Uniform, could also be achieved by setting airflow rate=0.1625 m^3/s and airflow direction=East. It is important to note that, regardless of the room averages, operative temperature at each occupant location varies depending on the defined supply airflow settings and adjustments at the diffuser level have the potential of altering the temperature that each occupant is subjected to. Accordingly, once the personal preferences are accounted for in building control, it could be possible to determine optimum settings in multi-occupancy scenarios to improve collective comfort. Depending on the relative thermal comfort characteristics of the occupants, wasting valuable energy could be prevented without sacrificing human well-being.

4.3.3 Analysis of Variable Importance

With the purpose of investigating the significance of defined parameters on CFD simulation results, we developed statistical models using Random Forest (RF) method, which is a machine learning algorithm. To account for the impact of occupant locations, separate models for each of the six locations were generated, together with the main model that employs data from all locations. These models could be considered as a proxy for assessing predictive building control potentials.

Given

S: Original Training sample dataset of size n

p: Number of input predictors

X: Test observation

Initially Determine

M: Number of Trees to be generated

v: Number of predictors to be selected as split candidates for each tree (usually $v \approx \sqrt{p}$)

for m ← 1 **to** M **do**

  Draw a random sample S* of size n with replacement from S (Bootstrap)

  Grow a tree T_m using S* through the following loop:

  while minimum node size $node_{min}$ is not reached **do**

    For the leave node of the tree

    Randomly select *v* predictors out of the *p* predictors

    Select the best pair of split candidates among the *v* predictors

    Split the node into two daughter nodes

  end while

  print Constructed tree $T_m(X)$

end for

print Prediction for a given new input X as per majority vote ← $\frac{1}{m}\sum_{m=1}^{M} Tm(X)$

{Note: $node_{min}$ is the minimum number of observations at each leaf node}

Figure 4.22. Pseudo code for Random Forest algorithm

RF algorithm (Breiman, 2001) is a method that is used for both classification and regression tasks. It uses Bootstrap and Aggregation technique, which is commonly known as bagging. Bootstrap is a resampling method, which involves repeatedly drawing samples from a training dataset and refitting a model on each sample. Bagging refers to drawing a number of bootstrap datasets, fitting each to a decision tree and averaging prediction of all trees. The algorithm basically generates multiple decision trees trained over the same data and determine the final output by averaging the results of each model. RF introduces two types of randomness: (1) to data so that each tree is fit to a somewhat different dataset and (2) to predictors when making a split at any point in a given tree. The former reduces variance and controls over-fitting, whereas the latter makes it robust and reliable against correlated predictors. The algorithm also enables to analyze the relative importance of the model inputs for the model predictions. RF procedure was implemented using Python software, the pseudo code of which is illustrated in Figure 4.22.

Table 4.3. Results of RF models for each location

	Random Forest Model for Each Location					
	Loc-1	**Loc-2**	**Loc-3**	**Loc-4**	**Loc-5**	**Loc-6**
Mean Squared Error	0.07	0.06	0.05	0.06	0.12	0.17
feature_importance: Airflow Rate	0.62	0.69	0.72	0.66	0.65	0.56
feature_importance: Airflow Direction	0.28	0.21	0.19	0.20	0.24	0.30
feature_importance: Occupancy Case	0.10	0.10	0.09	0.14	0.11	0.14

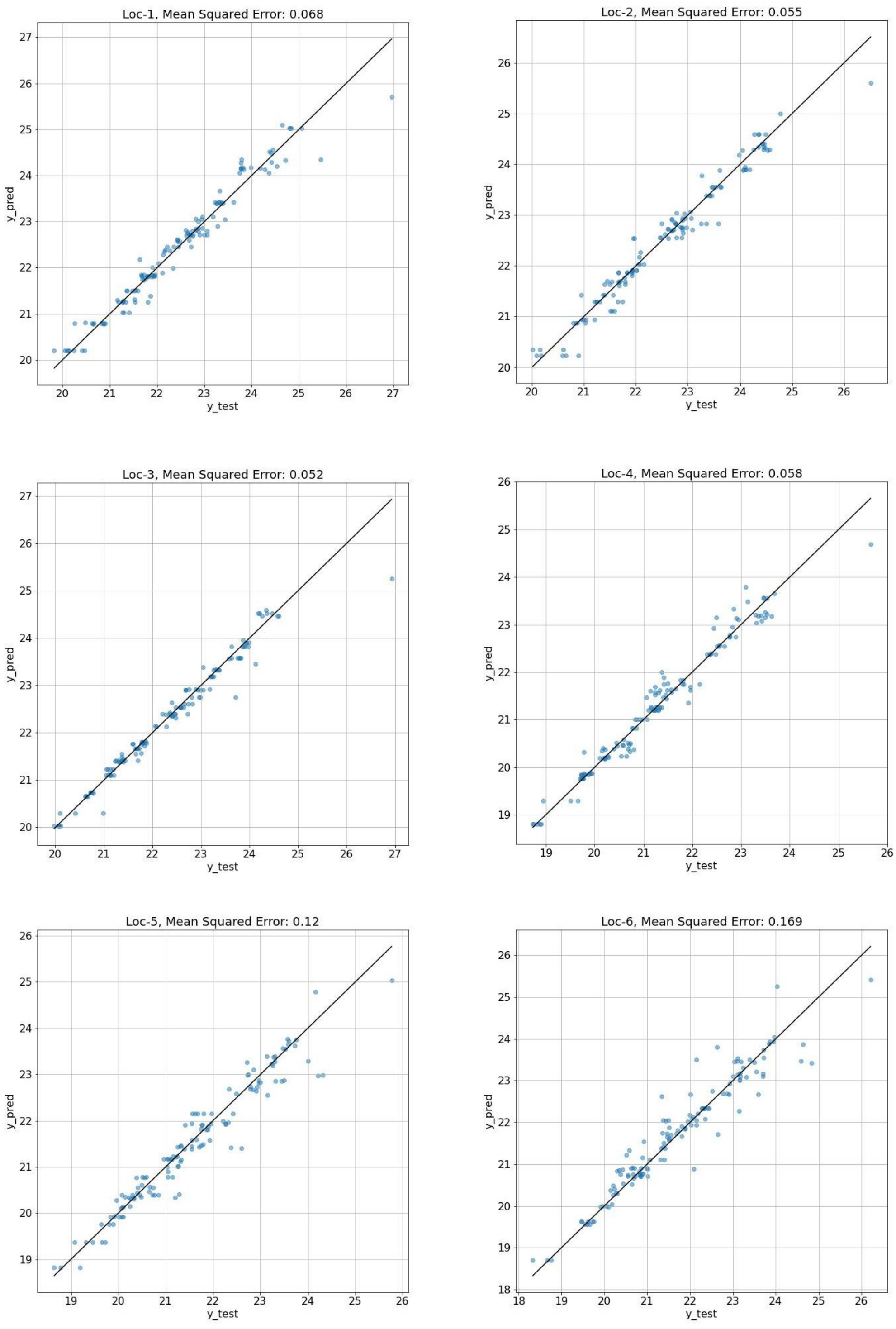


Figure 4.23. Predictive performance of Random Forest models, developed for each occupant location

We developed a dedicated multi-input-single-output prediction model using RF regressor for each occupant location in the defined space. In order to derive the temperature values as the predicted output, we used the independent variables that we've adopted in CFD simulations as model inputs, which are airflow rate, airflow direction and occupancy case. One-hot encoding was applied for occupancy case and all variables were treated as continuous. The Relative statistical importance of these features are given in Table 4.3. Accordingly, while all three inputs were found to be influential on predictions, airflow rate is clearly the dominant feature for all models.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - Y_i')^2 \tag{9}$$

To determine the amount of error in the generated models, mean squared error (MSE) values were also calculated. The MSE is simply an estimator measuring the average squared difference between the model predictions and the actual values, and can be formulated as in Equation (9). It refers to the empirical risk, and better accuracy is assessed by the closeness of MSE values to zero. Based on the results, MSE values demonstrates an acceptable accuracy for the models. However, to better interpret the accuracies, we created plots to visualize how the predictions of our models compare to the test values of perfect prediction models. As illustrated in Figure 4.23, each model has a good performance overall, indicating a promising potential for predictive building control.

After evaluating the models for each occupant location, we also developed a main RF model with available data from all six locations. The difference of the main model is the additional variable that is added to account for locations. Similar to the location-specific models, airflow rate was also found to be the most influential factor, followed by airflow direction, location and occupancy case (Table 4.4). Although the MSE value for the main model is somewhat higher than the previous ones, the fit could still be considered as good considering the model predictions versus test data plot illustrated in Figure 4.24.

Table 4.4. Results of the main RF model

	Random Forest Model for all locations *with additional 'Location' feature*
Mean Squared Error	0.086
feature_importance: Airflow Rate	0.57
feature_importance: Airflow Direction	0.2
feature_importance: Occupancy Case	0.1
feature_importance: Location	0.13

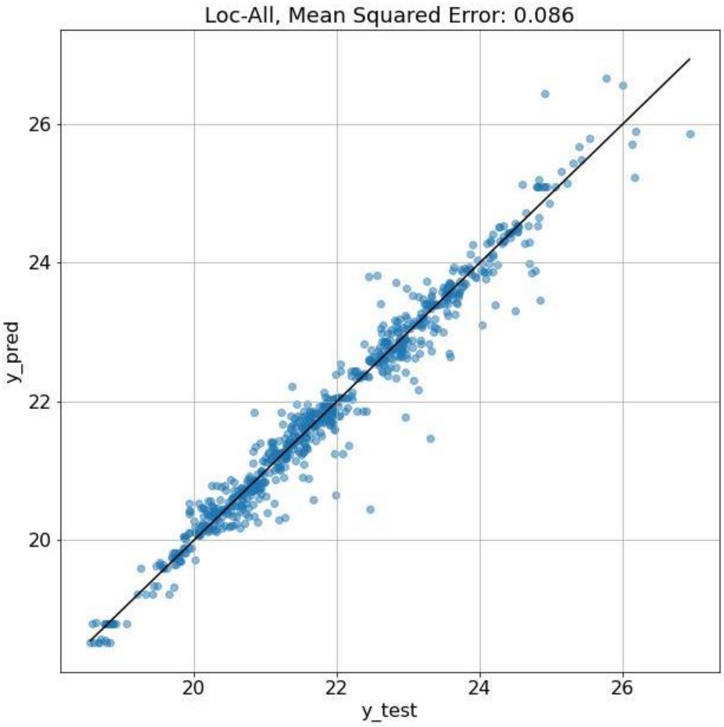


Figure 4.24. Predictive performance of Random Forest model, developed with data from all locations

4.4 Discussion

In the current practice, thermal zones are usually controlled using data from a single sensor, the reading of which is attributed to be representative of the entire zone for assessing indoor environmental parameters. However, the results of this study demonstrated that temperature is not uniform throughout the indoor environment and occupants may be subjected to different thermal conditions within the same space. The variance in thermal conditions were shown to be influenced by the studied independent variables, which are the supplied airflow rate, supplied airflow direction and occupancy. As expected, increasing the supplied airflow rate led to cooler conditions and the number of occupants was directly proportional to the room temperature. Interestingly, it was demonstrated that changing the supplied airflow direction could be adopted as an alternative strategy to adjust the indoor temperature. In contrast to the supplied airflow rate alteration, adjustments in the supplied airflow direction would not require consuming additional energy, making it an efficient strategy to provide desired indoor conditions. Moreover, placements of supply air inlet and return outlet were also found to be crucial, given their impact on the air circulation characteristics in the conditioned zones.

According to analysis conducted with Random Forest modeling, it can be claimed that once thermal distribution data under defined settings are compiled to a certain degree, machine learning algorithms could be leveraged to predict the relevant results for the settings that were not simulated. This kind of a strategy could lessen the need for simulating each and every possible variation in the boundary conditions, allowing for a more robust and efficient control mechanism. Moreover, the developed models have the potential to be continuously updated with new field data. This adaptability could be used to better account for the dynamics of airflow with changing conditions in indoor environments. In the literature, such approaches are studied under the term ‘predictive building control’, which were shown to have huge benefits in terms of comfort improvements and energy savings in buildings (Drgoňa *et al.*, 2020).

Considering the results of this chapter, it can be claimed that if the spatial heterogeneity was accounted for by having sensors at each desk location, or employing a type of thermal scanning sensor, building control system could seek to maintain a particular thermal asymmetry based on the personal comfort profiles to provide collectively acceptable thermal conditions in shared indoor spaces. Apart from providing desired conditions at where it is actually required, consuming energy unnecessarily for conditioning vacant spaces could also be prevented with such strategies.

CHAPTER 5

OPTIMIZATION OF COLLECTIVE COMFORT IN SHARED SPACES

In this chapter, through leveraging the personal comfort profiles and the thermal distribution patterns dataset that were created in Chapter 3 and Chapter 4, a data driven optimization analysis were conducted to reveal collective thermal comfort improvement potentials. Three control strategies with an incremental complexity were introduced to assess comfort and energy efficiency implications of adjustability at different degrees. Temporal impacts were analyzed through performing CFD simulations for additional 108 cases. Collective comfort probabilities for both minimum multi-occupancy and maximum occupancy conditions under varying settings were comparatively presented. This chapter may help researchers to fathom the potentials that lies in accounting for the nonuniformity of thermal conditions and personal preferences. It also underlines the importance of a communication ground between the building control and the occupants, by reporting the difference made by intelligent allocation of individuals to the workstations in a multi-occupancy indoor environment.

In this chapter, firstly, previous studies focusing on developing strategies for collective comfort improvement and energy efficiency were reviewed, and the position of this research in comparison to the existing approaches was demonstrated. After outlining thermal comfort assessment agenda, overall framework of the optimization analysis was described. Then, control strategies were introduced and related collective comfort probability analysis results were discussed. Collective comfort probability changes in one of the cases was visualized to further elaborate the results. Subsequently, details and results of the follow-up study, which was conducted to evaluate the implications of temporal variations on collective comfort probabilities, were illustrated. The chapter was concluded with a discussion on possible practical reflections of the research outcomes.

5.1 Literature Review

5.1.1 Comfort Improvement Strategies

In the pursuit of generating collectively comfortable indoor conditions, several operational strategies were proposed in the literature. Jung and Jazizadeh (2020) listed the four main strategies, which are the majority rule, error minimization, collective learning and thermal comfort sensitivity based optimization.

The majority rule strategy was proposed by Murakami *et al.* (2007), who referred it as ‘logic for building a consensus’. In a multi-occupancy office space with 50 occupants, they adopted an interactive system to collect thermal comfort feedback from the occupants, and determined the setpoint temperature in a way to respond to the requests of the majority. Although demonstrating a promising energy-saving potential of 20%, their strategy did not provide any improvement in terms of collective thermal comfort. The error minimization strategy, on the other hand, was used by Jazizadeh *et al.* (2014b), who identified the temperature preferences of occupants by adopting a participatory sensing approach through a user interface. Their strategy was to minimize the gap between desired temperature values and the setpoints and they reported 39% reduction in daily average airflow, which corresponds to a considerable energy saving. Despite demonstrating improvements in terms of both energy efficiency and occupant comfort, the proposed strategy was employed to identify separate setpoints for single-occupancy office spaces and did not cover the dynamics exist in shared spaces. Similarly, although collective learning strategy proposed by Erickson and Cerpa (2012) utilized collective thermal feedback for updating the PMV model and achieved setpoint improvements, it assumed homogeneous conditions in the considered spaces and did not account for individual differences.

In their overarching study, Jung and Jazizadeh (2020) proposed thermal comfort sensitivity based optimization and comparatively analyzed their approach with the majority rule and the error minimization strategies. They integrated personal comfort profiles into the control loop of HVAC systems and evaluated the energy implications of the control strategies. Accordingly, the majority rule strategy was demonstrated to achieve the best performance in terms of energy savings, followed by thermal comfort sensitivity based optimization. The error minimization strategy was shown to have the highest energy demand, due to the relatively higher conditioning loads brought by selecting the setpoint in between all the preferred temperatures.

Nonetheless, all of the abovementioned strategies were designated to optimize the setpoint temperatures, and they left the heterogeneity of indoor environmental parameters beyond their scopes. However, in recent years, assessing the differences in micro-climates within shared indoor spaces and variances in personal comfort preferences have attracted more attention from building researchers.

5.1.2 Strategies Accounting for Nonuniformity

Researchers introduced various solutions to minimize the potential negative impacts of uneven thermal distribution and optimize occupant comfort in indoor environments. Zhou *et al.* (2014) proposed a demand-driven control strategy to substitute the conventional HVAC control logic, building upon the developments in wireless sensors and occupant localization field (Topak *et al.*, 2018). The authors observed progress in energy savings through setting the temperature control based on the breathing level and avoiding to condition the unoccupied zones. Shan *et al.* (2020) indicated the improvements achieved by increasing the number of thermostats and separating setpoints in subzones to recognize thermal nonuniformity. Another approach adopted by the researchers is to provide micro-location-based solutions, such as directing the airflow towards occupant’s positions. Jazizadeh *et al.* (2020) investigated the implications of operating modalities, airflow direction, and individual-level feedback in HVAC system operation. They explained that integrating directed airflow and micro-location feedback-based control at the diffuser level results in a 25% reduction in energy demand and improvements in thermal comfort. Likewise, Hu *et al.* (2020) presented an intelligent air conditioning system configuration, employing multiple air vents to flexibly create desired micro-thermal conditions at target indoor positions. On the other hand, localized personal comfort systems have offered improvements in energy use and overall satisfaction by providing manageable micro-thermal settings (Shahzad *et al.*, 2018). Melikov (2016) argued that a paradigm shift from conventional systems designed for total volume climatization towards individually controlled distributed conditioning is a necessity for saving energy and improving comfort. However, the combined impact of employing personal comfort devices for individuals on the overall indoor climate is unforeseeable and requires exhaustive research. In addition, the wide-scale applicability and acceptability of personal comfort systems are questionable in terms of maintainability and cost-efficiency.

Research efforts also sought to explore the applicability of utilizing personal preferences in the presence of multiple thermal zone control loops. Z. Yang & Becerik-Gerber (2014) presented the potential improvements of assigning occupants with similar schedules to the rooms that are in the same mechanical zone. Nagarathinam *et al.*, (2021) assessed the same problem in an open-plan office without any partition walls, and they proposed clustering occupants into groups based on their thermal preferences and assigning them to the presumptive cells, each of which has a separate actuator and dynamic setpoint selection feature. Although demonstrating promising insights for optimized control in very large spaces with over hundred occupants, their approach lacks high sensitivity for personalized comfort and micro-climatic conditions, as temperature setpoints for defined cells are determined through averaging the profiles of a group of occupants. S. Lee *et al.* (2019) developed a method for personalized HVAC control in a shared open-plan office space by learning occupants' comfort preferences and operating a conditioning system with multiple control loops. However, their study employs a radiant-based floor cooling system and air-mixing and flow dynamics are not assessed.

Table 5.1. Comparison of previous studies in the literature

Study	*Research method*	*System controlled*	*Variables*	*Thermal comfort assessment*	*Thermal heterogeneity consideration*	*Occupant location assignment*
Zhou et al. (2014)	Simulation, Experiment	Room-level air diffusers	Supply airflow rate Occupancy	No	Yes	No
Yang & Becerik-Gerber (2014)	Simulation	Zone-level air diffusers	Occupancy	No	No	Yes - at room level
Ghahramani et al. (2014)	Experiment	Zone-level air diffusers	Supply airflow rate Occupancy	Personal comfort models	No	No
Jazizadeh et al. (2014)	Experiment	Zone-level air diffusers	Supply airflow rate Occupancy	Personal comfort models	No	No
Lee et al. (2019)	Experiment	Room-level radiant cooling	Occupancy	Personal comfort models	Yes	No
Jung & Jazizadeh (2019)	Simulation	Room-level air diffuser	Setpoint temperature resolution	Personal comfort models	No	No
Shan et al. (2019)	Simulation	Room-level air diffusers	Setpoint temperature	PMV Model	Yes	No
Jazizadeh et al. (2020)	Simulation	Room-level air diffuser	Supply airflow rate Supply airflow direction Control actuation logic	Predefined setpoint values	No	No
Nagarathinam et al. (2021)	Simulation	Room-level air diffusers	Occupancy	Personal comfort models	Yes	Yes - at subzone level
This study	Simulation	Room-level air diffuser	Supply airflow rate Supply airflow direction Occupancy	Personal comfort models	Yes	Yes - at workstation level

Although there are studies querying the optimization potentials in multi-occupancy spaces based on individual preferences (Ghahramani *et al.*, 2014; Jung & Jazizadeh, 2019a), the potentials of coupled utilization of personal comfort models and thermal distribution patterns in building control to maximize collective occupant satisfaction and enhance energy efficiency have not been systematically examined. Table 5.1 compares the previous studies focusing on improving human comfort while being cognizant of consumed energy in office buildings. As a direct correlation between individuals' positions and their satisfaction levels has already been demonstrated (Abdelrahman *et al.*, 2022), this study aims to further reveal possible strategies and potentials for collective comfort optimization in shared environments. Once the personal differences between occupants are accounted for with personal comfort models, they can be addressed at individual level with control alterations in room-level HVAC operation or allocating occupants to the adequate locations.

5.2 Material and Method

This research adopted a simulation-based quantitative approach for evaluating the potentials aroused from uneven temperature distribution and nonuniformity in individuals' thermal comfort preferences. The methodology in this section is complementary to the ones in Chapter 3 and Chapter 4. In this post-processing phase, a data-driven optimization analysis was conducted by leveraging the personal comfort profiles and thermal distribution patterns datasets created in Chapter 3 and Chapter 4 to generate occupant-centric strategy deductions and uncover collective comfort improvement potentials.

5.2.1 Thermal Comfort Assessment

Although thermal comfort is influenced by many factors, operative room temperature is considered as an acceptable proxy for comfort implications. Given the airflow direction and airflow rate manipulations in the simulated scenarios, air velocity values were also checked to confirm that air speed around occupants are within the comfortable limits (< 0.20m/s) defined by ASHRAE (2017), as shown in Figure 5.1.

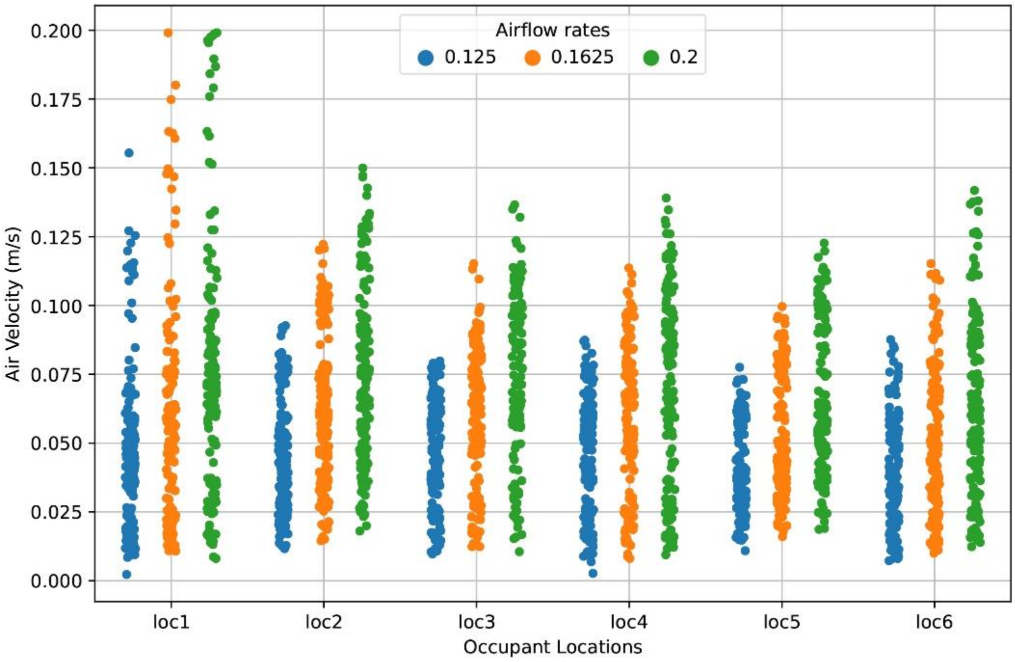


Figure 5.1. Air velocity values in all simulations

Operative temperature, which is defined as "*the uniform temperature of an imaginary black enclosure, where an occupant would exchange the same amount of heat by radiation and convection as in the actual non-uniform environment*", is calculated by combining ambient air temperature and mean radiant temperature (Djongyang *et al.*, 2010). For cases where there is no exposure to air velocities greater than 0.20m/s, the calculation oftentimes approximated as:

$$t_o = \frac{t_a + t_r}{2} \tag{10}$$

, where t_o , t_a and t_r represent operative temperature, ambient air temperature and mean radiant temperature, respectively.

In this study, ambient air temperature values were obtained by CFD simulations and mean radiant temperatures were calculated using a 3D mean radiant temperature (MRT) tool, developed by Center for Built the Environment (CBE) (Hoyt, 2016). The ambient temperatures at occupant locations were defined by averaging ten representative points at neck height (1.25 m) near each occupant, considering a similar approach used in Jazizadeh *et al.* (2020). Related boundary conditions and surface temperatures extracted from CFD simulation results for each case were used as inputs for MRT calculation using CBE's online tool (Figure 5.2). MRT is an important physical parameter that may vary spatially depending on the indoor environmental factors, just like ambient air temperature. In order to account for their joint impact on occupants' thermal comfort, operative temperature calculations were made through averaging these values at given occupant locations, using Equation (10).

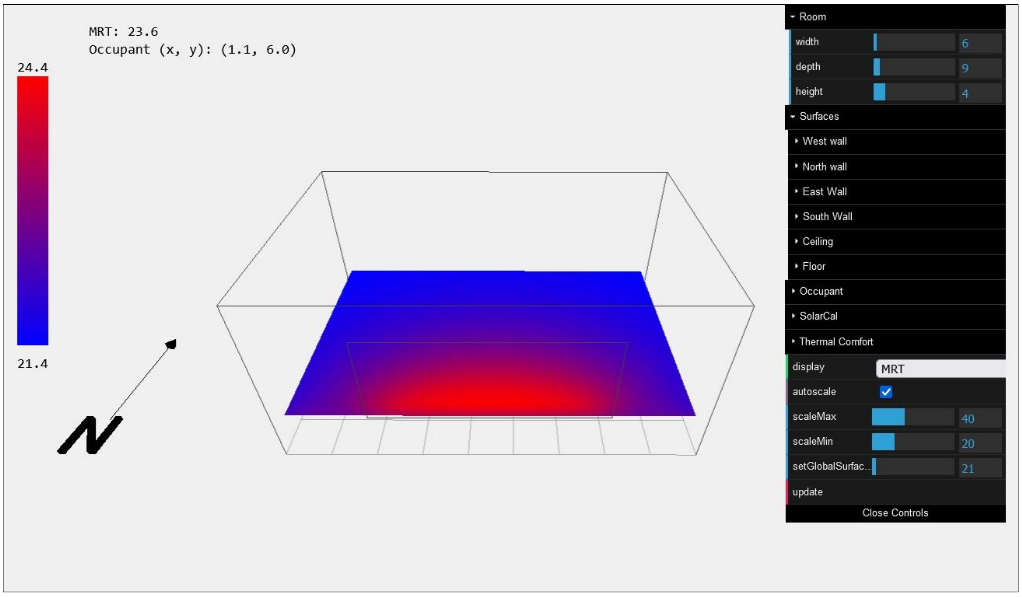


Figure 5.2. MRT tool developed by CBE (Hoyt, 2016)

5.2.2 Energy Saving Assessment

Energy performance changes brought by altering supply airflow rates were estimated by assuming a single-zone system with reference system parameters from ASHRAE

90.1-2022 Appendix L: Mechanical System Performance Rating Method (ASHRAE, 2022). Accordingly, following conditions were adopted:

- From 'Total System Performance Ratio (TSPR) Reference Building Design HVAC – Medium Office (cold)' table in ASHRAE (2022):
    - System type: Packaged VAV – Hydronic reheat
    - Fan control: VSD, no static pressure reset
    - Main fan power: (>MERV13 filter) 1.285 W/cfm
    - Cooling source: DX, multistage, $COP_{cooling}$ = 3.40
    - 30% minimum flow fraction
- From Fan and Pump Power Curve Coefficients table in ASHRAE (2022), the fan power curve coefficients for the 'VSD, no static pressure reset' are as in Equation (11).

$$\begin{gathered} ElecPowFrac = \\ 0.0013 + 0.147 * (FlowFrac) + 0.9506 * (FlowFrac)^2 - 0.0998 * (FlowFrac)^3 \end{gathered} \tag{11}$$

, where *ElecPowFrac* is the fraction of power at full flow and *FlowFrac* is the fraction of design flow.

- The Summer Design Conditions for University Park (725128), where the selected office space is located, are:
    - 0.4%: 31.4 °C DB
    - 1.0%: 29.9 °C DB
    - 2.0%: 28.0 °C DB
    - Climate Zone 5A (Cool-Humid), but near the border of 6A (Cold-Humid)

As illustrated earlier in table 4.1, CFD results were generated using an ambient dry bulb temperature of 28°C, occupant heat gain of 60 W/m^2, computer heat gain of 60 W/m^2, window heat transfer coefficient of 5.6 W/m^{2}K, and solar transmittance of

80%. The simulated airflow rates of 0.125 m^3/s, 0.1625 m^3/s, and 0.2 m^3/s all kept the average room temperature within the acceptable thermal comfort limits.

5.2.2.1 Maximum Fan Energy Change

The maximum change in fan energy across flow rates were estimated by assuming that the largest flow used in our simulation (0.2 m^3/s) is the design air flow rate (i.e., the fan is operating at max power at our highest flow rate). This was not completely inconceivable, since the 2.0% cooling design condition is equivalent to the ambient temperature used for our studies. This gave a design fan power of:

$$1.285 \text{ W/cfm} * 2118.88 \text{ cfm}\times\text{s/m}^3 * 0.2 \text{ m}^3\text{/s} = 545 \text{ W} \tag{12}$$

With 0.2 m^3/s as the design flow, the three flows of 0.125 m^3/s, 0.1625 m^3/s, and 0.2 give flow fractions of 0.625, 0.8125, and 1.0, respectively. The *ElecPowFrac* were then 0.44, 0.69, and 1.0, respectively, based on the fan curve in Equation-11. Thus, if 0.1625 m^3/s case were taken as the reference point, increasing to 0.2 m^3/s would result in 44% more fan energy and decreasing to 0.125 m^3/s would result in 37% less fan energy (assuming same runtime for the snapshot analyzed).

5.2.2.2 Low Fan Energy Change

In order to create a lower estimate for the change in fan energy, we assumed that the smallest flow used in our simulation (0.125 m^3/s) corresponds to the minimum 30% required flow rate, and that the fan is operating at a minimum flow fraction of 30%. The design flow rate in this case would be 0.417 m^3/s, with a design fan power of,

$$1.285 \text{ W/cfm} * 2118.88 \text{ cfm}\cdot\text{s/m}^3 * 0.417 \text{ m}^3\text{/s} = 1135 \text{ W} \tag{13}$$

(i.e., about twice as large). This represents the case where the fan is operating in its lowest part of the performance curve. The corresponding flow fractions would be

0.3, 0.39, and 0.48, with power fractions of, 0.13, 0.20, and 0.28, respectively. Again, taking 0.1625 m^3/s as the reference, results in the low flow rate would save 35% fan energy and the higher flow rate would lead to 42% more fan energy use.

We forgo analyzing a multi-zone case, as the results would be highly dependent on the size of the other zones relative to the zone of interest, the relative load diversity, and assumptions about multizone air-handler controls.

5.2.2.3 Cooling Coil Energy Savings

When airflow is reduced, the cooling coil energy would also be reduced. To estimate the change in energy, we assumed that the coil entering and leaving air conditions are the same so that the change in enthalpy of the air stream is the same for the three flow rate cases. With this assumption, the change in total cooling coil load is directly related to the change in mass flow rate (Equation (14)). Thus, reducing the flow to the lower flow rate would result in 23% energy savings, while increasing to the higher flow rate would require 23% more energy.

$$Q_{total} = \dot{m} * \Delta h \qquad (14)$$

(Q_{total} denotes to total load, $\dot{m}$ refers to mass flow rate and Δh is enthalpy)

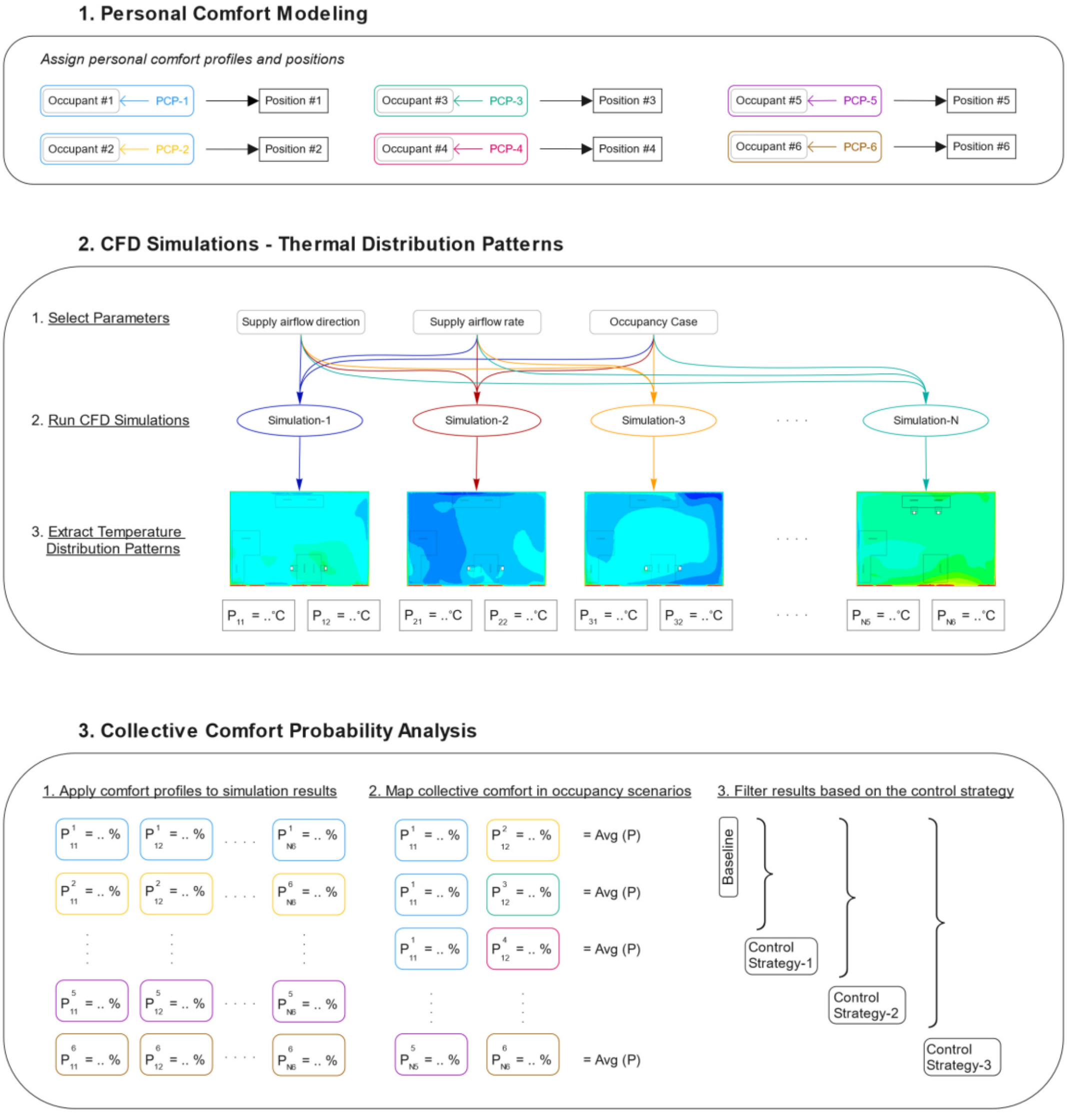
In these calculations, the assumption of constant enthalpy was an approximation. It is conceivable that the dry bulb temperature leaving the coil would be the same in all cases, if the coil were capacity controlled based on a supply air temperature setpoint. However, the humidity leaving the coil depends on the conditions of the air entering the coil and the latent performance of the coil at part load operating conditions. At the low flow rate, the average zone temperature would be higher and the temperature entering the coil would also be higher. Similarly, under the high flow scenario, the air would return to the air handler in a cooler state. Detailed modeling and analysis of coil latent performance and zone/AHU moisture balance is out of the scope of this work, as the intent is to generate approximate figures for relative changes in energy use. The calculations presented did capture the dominant variable that impacts coil energy use (i.e., the supply air flow rate.)

In summary, it was calculated that lowering the flow rate would save around 35% fan energy and 23% cooling coil energy. Raising the supply air flow rate would require around 44% more fan energy and 23% more cooling coil energy. It is worth mentioning that the calculations are made based on the aforementioned assumptions and the actual energy savings on fan and cooling coils need to be comprehensively analyzed for each individual flow rate supplied to the zone.

5.2.3 Compiled Datasets and Data Flow

As illustrated in Figure 5.3, the overall framework of the methodology consists of three parts. First, personalized thermal comfort profiles (PCP) were developed using a probabilistic modeling approach for six occupants, each of which was assigned to a fixed workstation in the baseline scenario regardless of room population (see Figure 4.13).

Secondly, possible combinations of the selected parameters were simulated using CFD and micro-thermal conditions at occupant locations were extracted for all cases. A prior grid independence test and verification study were also performed to demonstrate the reliability of the modeling approach. Lastly, a data-driven analysis was carried out to compute collective comfort probabilities under different conditioning (i.e., HVAC control) and occupancy settings. The first and the second parts were presented in Chapter 3 and Chapter 4, respectively. This chapter demonstrates the last part of the defined methodology, in which the compiled datasets were processed using a comparative analysis approach. Personalized comfort profiles were combined with micro-thermal conditions data for comfort probability calculations and the compiled data was filtered to contrast the baseline and proposed control strategies.



P_{XY}: Neck-level temperature (X: simulation case, Y: Occupant location #)
P_{XY}^{A}: Comfort probability (A: personal comfort profile #, X:simulation case, Y:occupant location #)

Figure 5.3. Overall framework of the comfort optimization analysis

5.2.4 Control Strategies for Data Analysis

Given the simulation scenarios, the baseline and three control strategies were established. The baseline scenarios represent conventional operational settings in office buildings, where every occupant has a fixed position and climatization is performed with a static airflow rate and uniform air distribution towards all directions. A dedicated baseline scenario for each occupancy case was defined to account for occupant location alterations, compiling sixteen baseline scenarios in total. In order to assess comfort and energy efficiency implications of adjustability in (1) airflow direction, (2) airflow direction and airflow rate and (3) airflow direction, airflow rate and occupant locations, three control strategies were defined with an incremental complexity (Figure 5.4).

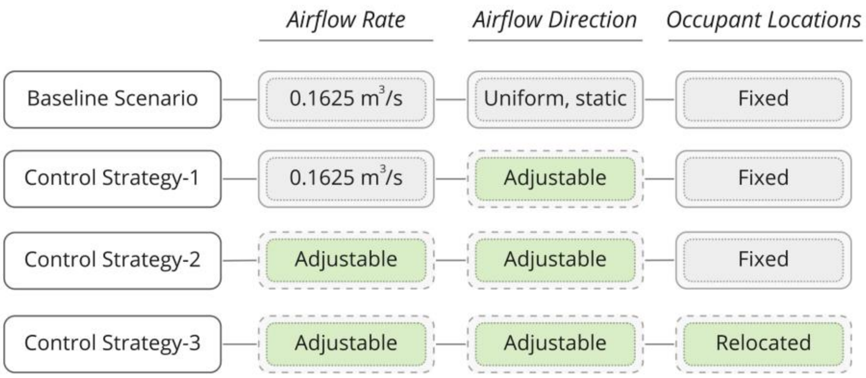


Figure 5.4. Characteristics of the baseline and control strategies

The number of strategies was determined considering the scope of the thermal distribution dataset such that an accumulative complexity was established between the strategies by enlarging the included extent of the simulation results at each consecutive strategy. While control strategy-1 and control strategy-2 were established to analyze how modest adjustments on HVAC operation like changing supply airflow rate or direction influence collective comfort probability, control strategy-3 was predicated on the intelligent allocation possibility of occupants between working desks. Recent studies on the interfaces enabling human-building communication creates a ground for generating such strategies and understanding the potentials of keeping the occupants in the loop for control efficiency (Day *et al.*, 2020; Marson & McAllister, 2021).

Collective comfort probabilities in each control strategy were calculated by averaging the comfort probabilities of occupants based on the assigned comfort profiles. To this end, we calculated the collective comfort probabilities for sixteen baseline scenarios considering the occupying individuals. We performed a data-driven analysis for assessing improvements achieved by the defined control strategies, through reorganizing the thermal distribution dataset constructed with CFD simulations based on given strategy characteristics.

5.3 Results

Determining a proper strategy to enhance collective comfort in multi-occupancy environments has been a key question for building researchers (Shin *et al.*, 2017). Many approaches have been proposed for collective comfort improvements over the years. Although proven to have diverse implications based on the contextual factors in different cases in the literature, many of the strategies have certain drawbacks, such as being designated to find an optimal setpoint temperature, assuming the uniformity of the thermal conditions indoors or disregarding the individual differences between building occupants.

To date, very few studies have assessed the implications of accounting for the nonuniformity of both personal preferences and indoor conditions for improving collective comfort and energy efficiency. According to the outcomes of the study presented in Chapter 4, it was demonstrated that temperature is not uniformly distributed in large multi-occupancy spaces, and thermal conditions that occupants are subjected to varies based on the contextual factors in their immediate surroundings. In order to leverage this condition in favor of collective thermal comfort, we concentrated on the temperature values at occupant locations rather than the room averages, and analyzed the potentials of coupling temperature distribution patterns and personal comfort profiles to improve occupant comfort while ensuring energy efficiency. In doing so, we assigned a unique comfort profile for each of the six occupants and assessed collective comfort probabilities in different occupancy scenarios considering the related operative temperatures at the occupied locations.

Table 5.1 presents the collective comfort probabilities at minimum multi-occupancy scenarios with two occupants. Accordingly, collective comfort probability at the baseline, where occupant positions are fixed and supply airflow rate is constant with uniform distribution towards all directions, was calculated as 68% on average. Introducing adjustability to the supply airflow direction at the diffuser level in control strategy-1 increased the probability of achieving collective comfort to 79%, while allowing alterations in both rate and direction of supplied airflow in control strategy-2 resulted in 91% probability on average.

In accordance with ASHRAE (2017), a building zone is considered to satisfy comfort requirements if the comfortable occupants compile at least 80% of the room population. Translating this to the approach adapted in this study, achieving collective comfort with a probability of at least 80% could be claimed as the targeted level. Although control strategy-1 and control strategy-2 provided collective comfort probability improvements, both failed to satisfy 80% comfort probability for all occupancy scenarios. This implies that, in some cases, occupants would be dissatisfied with the thermal conditions of the space regardless of the supply airflow settings. However, control strategy-3, which allows dynamic allocation of the occupants between six positions together with supply airflow alterations, offered substantial improvements in collective comfort probabilities and complied with the minimum comfort requirements in all scenarios. With a probability of 98% on average, utilizing control strategy-3 was shown to provide almost seamless operation for ensuring comfort in minimum multi-occupancy.

In Table 5.1, changes in supplied airflow rate were illustrated as changes in energy use, due to their correlation based on the cubic relationship between flow rate and fan power. Accordingly, control strategy-1 does not have any implications on energy use, in which the supplied airflow rate was fixed. Control strategy-2 offered energy savings in nine out of fifteen cases, while improving the collective comfort probabilities. A superior energy performance was suggested by control strategy-3, with which the collective comfort was shown to be improved while saving energy in twelve out of fifteen cases. There is one exceptional case for both control strategy-2 and control strategy-3, where the supplied airflow rate was increased.

Table 5.2. Collective comfort probabilities for the baseline and three control strategies (for minimum multi-occupancy, in cases of two occupants)

Occ. Case	O1	O2	Baseline (%)	CS -1 (%)	CS-2 (%)	Energy Use	CS-3 (%)	Energy Use
1	Occ-1	Occ-2	67	83	83	–	95	↓
2	Occ-1	Occ-3	79	95	95	–	99	↑
3	Occ-1	Occ-4	33	48	52	↓	90	↓
4	Occ-1	Occ-5	57	82	82	–	99	↓
5	Occ.-1	Occ-6	71	80	86	↑	97	↓
6	Occ-2	Occ-3	94	94	97	↓	98	↓
7	Occ-2	Occ-4	43	53	94	↓	99	↓
8	Occ-2	Occ-5	89	92	98	↓	99	↓
9	Occ-2	Occ-6	90	90	99	↓	99	↓
10	Occ-3	Occ-4	49	58	85	↓	98	↓
11	Occ-3	Occ-5	78	98	98	–	99	↓
12	Occ-3	Occ-6	79	99	99	–	99	–
13	Occ-4	Occ-5	70	70	99	↓	99	↓
14	Occ-4	Occ-6	40	53	93	↓	99	↓
15	Occ-5	Occ-6	76	97	99	↓	99	–
	Average:		*68*	*79*	*90*		*98*	

Although the priority was given to achieve the highest collective comfort probability in our calculations, the proposed strategies have offered considerable improvements in terms of energy efficiency. Considering the calculations in section 4.6.2.1 and the illustrated changes in energy use (i.e., the supplied airflow rate) in Table 5.1, the best performing strategy (control strategy-3) offered savings with a rate of 35% fan energy and 23% cooling energy in 80% of simulated scenarios with two occupants. This result confirmed that valuable energy could be wasted if HVAC systems are operated in a static manner with full occupancy assumption. Once the number of occupants decreases in an indoor environment, the load of conditioning system could be reactively lowered by adjusting the relevant parameters. On the other hand, in the maximum occupancy scenario, improving collective comfort probability led to an increase in fan energy by 44% and cooling coil energy by 23%. However, it should be noted that the proposed control strategies were designated to maximize the collective comfort and the energy saving was not prioritized, which could have an influence on this outcome.

To further elaborate the results, we visualized how temperature distributions and comfort probabilities changes under different control settings in one of the occupancy scenarios with two occupants (occupancy case-10 at Table 5.1). In the occupancy case illustrated in Figure 5.5, occupant-3 and occupant-4 are at their preassigned locations and air is supplied uniformly towards all directions with a rate of 0.1625 m^3/s in the baseline case. To this end, occupant-3 had a comfort probability of 98%, whereas thermal conditions that occupant-4 is subjected to were not within the acceptable limits considering the personal comfort profiles, resulting in an average comfort probability of 49%. Although allowing supply airflow direction alterations in control strategy-1 provided a slight improvement for occupant-4 while not diminishing the comfort probability of occupant-3, it did not suggest a satisfactory achievement on average.

On the other hand, enabling adjustability on both direction and rate of supplied cool air in control strategy-2 presented a dramatic collective comfort improvement for the two occupants. In the given case, reducing supplied airflow rate from 0.1625m^3/s to

$0.125m^3/s$ increased the collective comfort probability by 27%. This result implies that operating multi-occupancy spaces based on full-occupancy assumption settings may create uncomfortable conditions for occupants and occupant-centric strategies in HVAC control have a great potential for energy savings.

Although collective comfort probability that was calculated by averaging the comfort probabilities of the occupants increased to 85% in control strategy-2, the comfort probability of occupant-3 decreased from 97% to 81%, which is not desired. With control strategy-3, in which occupants are optimally assigned to workstations, a collective comfort probability of 98% was achieved. Accordingly, both occupants' locations were reassigned based on their thermal comfort profiles, occupant-4 is to location-1 and occupant-3 is to location-4. Desired non-uniform thermal conditions were achieved by adjusting the supply airflow direction towards the south wall while keeping the airflow rate at $0.125m^3/s$. It is assumed that occupant schedules were known at the start of the date. It is also worth noting that occupants are subjected to different operative temperature values in all cases with a variation ranging from 0.8°C to 1.7°C, illustrating how heterogenous thermal conditions can be in spaces of such scale.

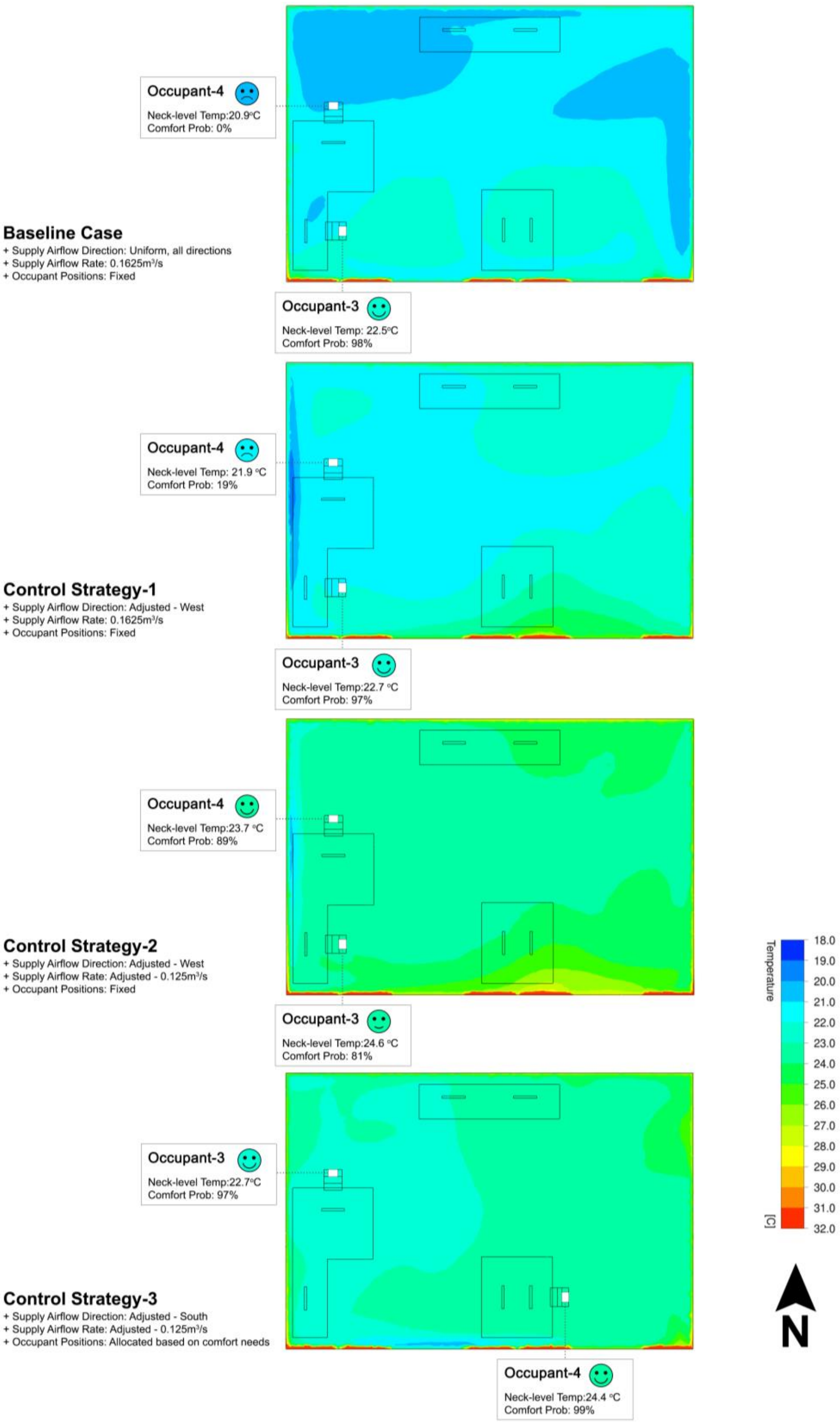


Figure 5.5. Temperature distributions (at plane y = 1.25 m) and comfort probabilities under the baseline and three control strategies settings (occupancy case-10)

The probability analysis for maximum occupancy produced parallel results to the ones in minimum multi-occupancy, as illustrated in Figure 5.6. As the initial supply airflow rate was designated for six occupants, collective comfort probability in the baseline at maximum occupancy was found as 82%, which is 14% higher in comparison to the minimum multi-occupancy scenarios. This result reflects the importance of occupancy and demonstrates how pre-defined static operation of climatization systems may lead to unintended thermal conditions in case of occupancy changes in indoor spaces. While control strategy-1 and control strategy-2 did not offer a considerable improvement at maximum occupancy, control strategy-3 increased the collective comfort probability of 12%, leading to the level of 94%.

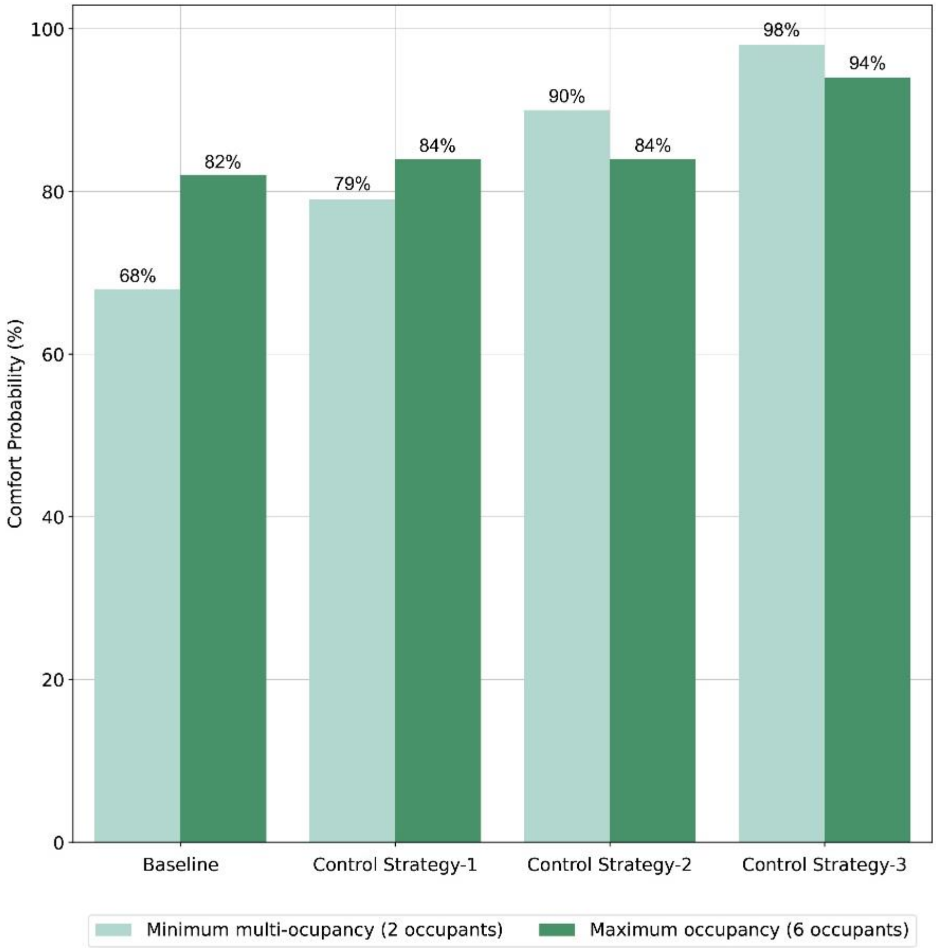


Figure 5.6. Collective comfort probabilities for the control strategies
(For minimum multi-occupancy (on average) and maximum occupancy)

Overall, these results confirms that collective comfort is enhanced if a control strategy where occupants are allocated to the positions considering both personal comfort preferences and micro-thermal conditions is employed in multi-occupancy spaces. In addition to comfort improvement, redundant HVAC energy use or waste due to conditioning vacant spaces can be avoided through dynamically determining operational shifts based on occupant data in buildings.

5.4 Follow-up Study for Assessing Temporal Variations

As mentioned earlier, CFD simulations were conducted using a steady-state mode, the result of which provides a snapshot of the thermal conditions in the defined space under given boundary conditions at a particular time. In order to confirm the applicability of the proposed control strategies under temporal variations, a follow-up study was designated. The primary intention here was to assess whether the collective comfort levels that were achieved with the proposed strategies at a certain time of the day (ToD) could be maintained throughout the working hours in any day. Within the defined borderlines of the proposed framework, it is expected that once the occupants are intelligently allocated to the workstations at the start of the day, the adjustability of the supplied airflow rate and supplied airflow direction should be sufficient to dynamically respond to occupants' comfort needs.

5.4.1 Additional Simulation Scenarios

The aforementioned 432 simulations were performed by setting the date and time as June 21st, 13:00. For the follow-up study, keeping the date as constant, ToD was introduced as a new variable and four different times of day, which are 09:00, 11:00, 15:00 and 17:00, were added as ToD alternatives. Considering the accumulative increase in the number of combinations and resultant computing time, including only the maximum occupancy case was deemed adequate. Alternatives for the supplied airflow rates (0.125 m^3/s, 0.1625 m^3/s, and 0.2 m^3/s) and the supplied airflow direction (uniform, north, south, west, and east, northwest, northeast, southwest and southeast) were used as they were defined in Chapter 4. Correspondingly, the combinations of three supplied airflow rates, nine supplied airflow directions and four out of five ToD alternatives (scenarios for ToD:13:00 were previously simulated) composed 108 additional scenarios, as illustrated in Figure 5.7.

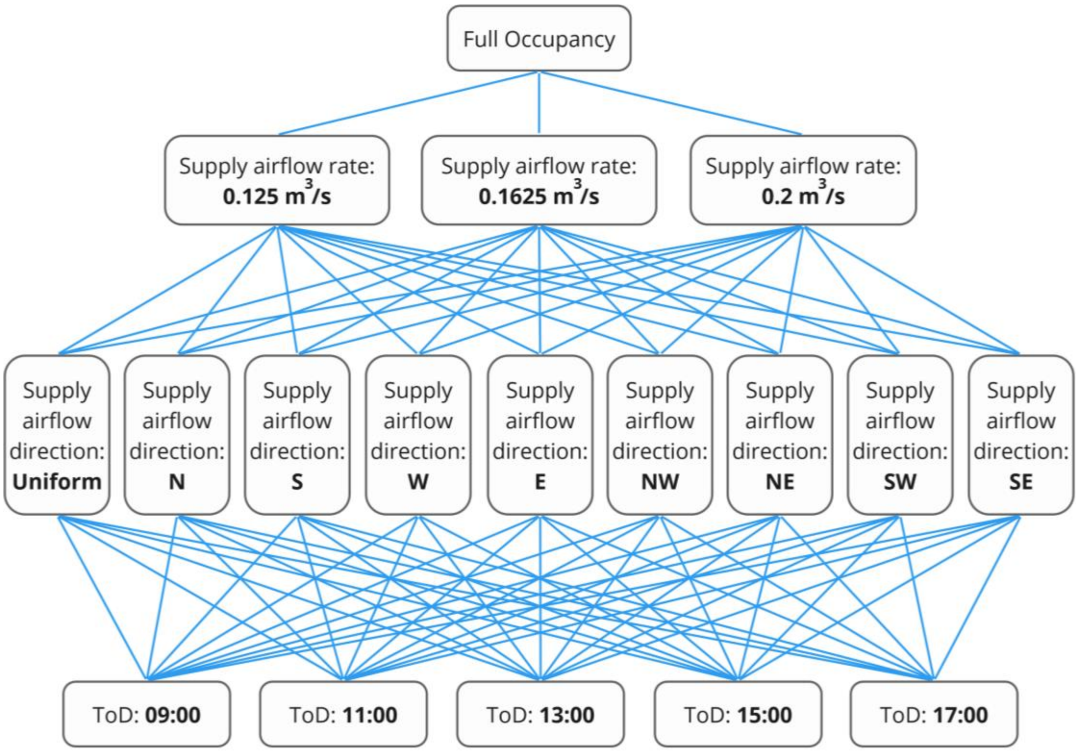


Figure 5.7. Simulation scenarios for temporal variation analysis

5.4.2 Analysis of Temporal Impacts

The control strategies defined in section 5.2.4 were used to evaluate collective comfort probability changes with respect to temporal variations. By averaging the comfort probabilities of occupants based on the assigned comfort profiles, comfort probabilities at ToD alternatives were calculated for the baseline and three control strategies. For control strategy-3, which was predicated on the relocation of occupants to the workstations based on their comfort profiles, the relevant calculations were not done through isolating each ToD alternative. Instead, the intelligent allocation was done through considering all five ToD cases to maximize the performance of the control strategy. Seat assignment was determined to be done at the start of the day, and the occupant locations were considered to be fixed afterwards. The seat allocation maximizing the collective comfort probability for the day was computed by averaging the comfort probabilities at all ToD alternatives.

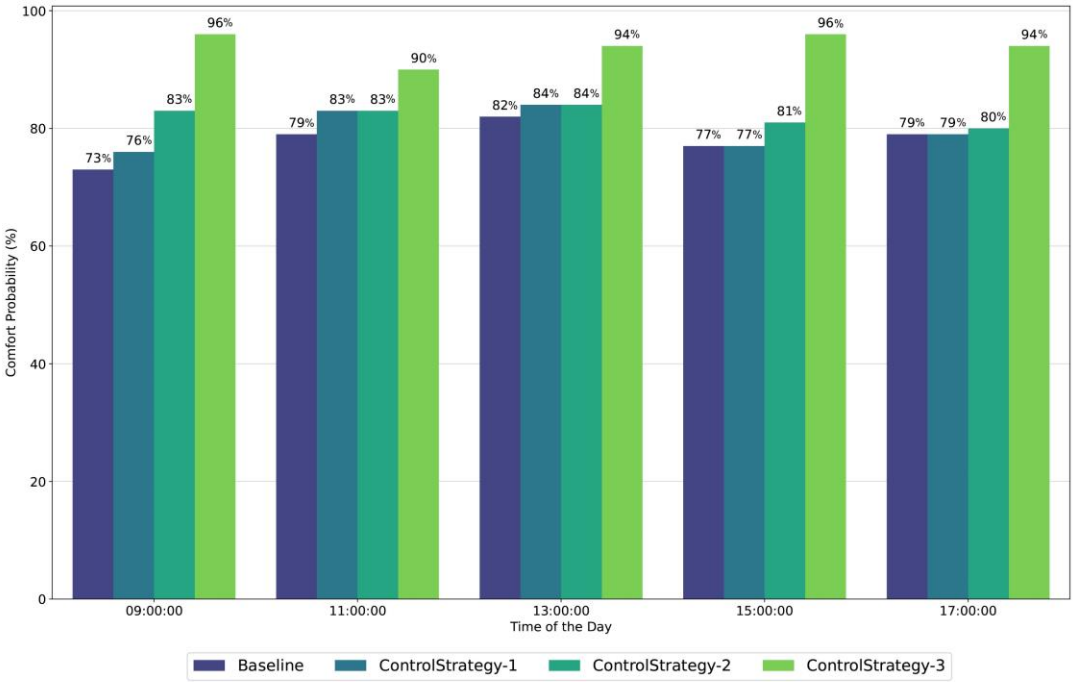


Figure 5.8. Temporal variations of collective comfort probabilities at baseline and three control strategies

Collective comfort probabilities in the baseline and three control strategies are illustrated in Figure 5.8. Accordingly, the calculated collective comfort probabilities for the baseline, in which the HVAC settings were fixed with static occupancy assumption, range between 73% to 82%. This result demonstrates that the baseline settings fail to maintain the minimum comfort range (80%, as mentioned earlier) throughout the day, owing to the variations in exterior conditions (i.e., solar radiation). Despite slightly increasing the probabilities granted by the baseline, improvement implications of control strategy-1 and control strategy-2 did not show a notable fluctuation between different times of the day. However, it was observed that the employment of control strategy-2, which implies adjustability in supplied airflow rate and direction, keeps the collective comfort level above the minimum required comfort threshold regardless of the time of the day.

What stands out in Figure 5.8 is that, with control strategy-3, seat assignment procedure performed by considering the changes brought by temporal variations increases the comfort probabilities dramatically and collective comfort could be maintained throughout the day with a probability range between 90% to 96%. This strategy, naturally, requires the compliance of the occupants with the seat assignment procedure. If occupants did not collaborate with the building control system and choose to have their workstations fixed, then the maximum achievable collective comfort would be provided with control strategy-2, with a probability between 80% to 84%. In an unlikely case where occupants randomly change their seats based on their likings, the building control system could take a reactive action and adjust HVAC settings providing the highest collective comfort probability, provided that the occupant comfort is prioritized in the system logic.

In order to further investigate the collective comfort improvement brought by control strategy-3, temperature values at occupant locations were comparatively analyzed. In this regard, operative temperature changes with respect to temporal variations in the baseline settings and control strategy-3 are depicted in Figure 5.9 and Figure 5.10, respectively. In the baseline settings, the difference between temperature values that occupants are subjected to fluctuates during the day and reaches up to 2.7 degrees Celsius at 11:00. This fluctuation is caused by the temporal impacts on operative temperatures at each occupant location. Accordingly, in the baseline settings, operative temperature values at six locations throughout the day range between 23.7°C to 25.2°C, 23.2°C to 24.6°C, 22.2°C to 23.9°C, 22.8°C to 24.5°C, 21.3°C to 23.2°C and 23.2°C to 24.2°C, respectively. The temporal variations were observed to influence the thermal conditions at all occupant locations, with the highest impact at location-5 (1.9 degrees Celsius) and the lowest impact at location-6 (1.0 degrees Celsius). Readers may refer to Figure 4.13 for occupant locations.

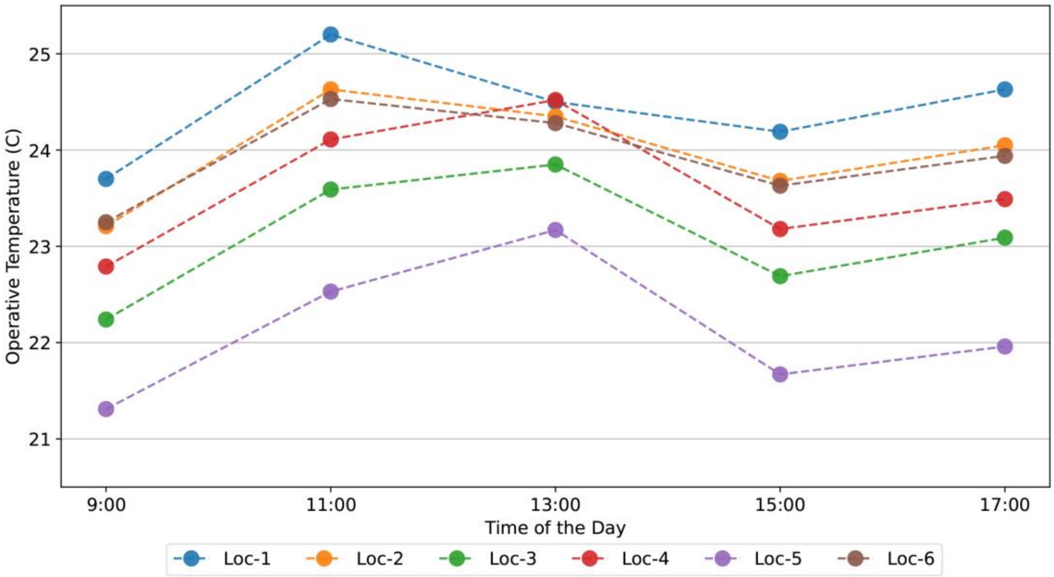


Figure 5.9. Temporal variations of operative temperature in baseline settings

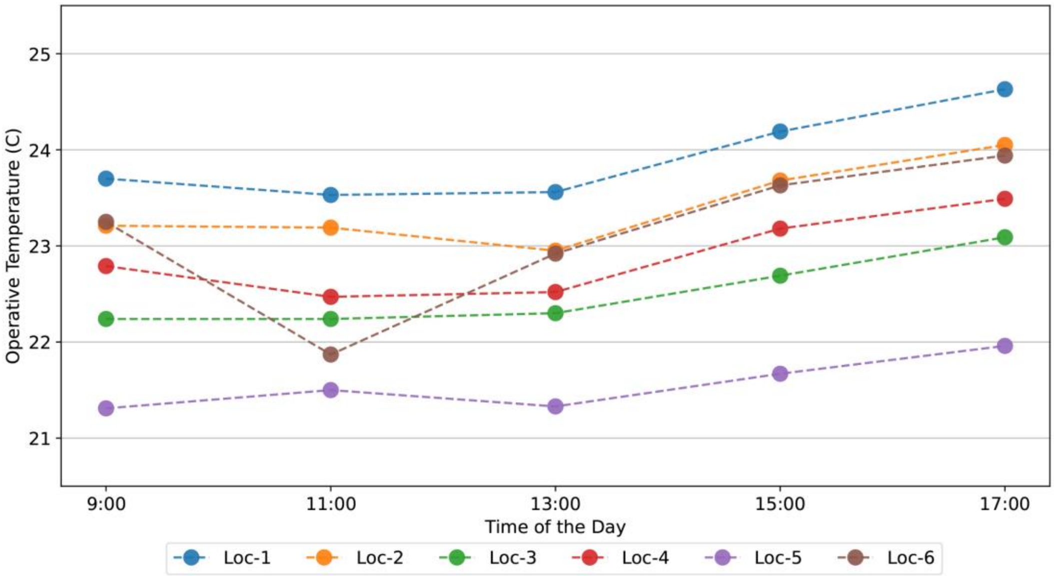


Figure 5.10. Temporal variations of operative temperature in Control Strategy-3

Apart from the relocation of occupants based on their personal comfort profiles (Figure 5.11), what control strategy-3 grants is to reduce the temporal impacts and minimize the operative temperature fluctuations to the extent possible at each occupant location. Compared to the baseline settings, in control strategy-3, operative temperature ranges at defined locations drop significantly, stretching between 23.5°C to 24.6°C, 23.0°C to 24.0°C, 22.3°C to 23.0°C, 22.5°C to 23.5°C, 21.3°C to 21.9°C and 21.9°C to 23.9°C, respectively. What can be clearly seen in Figure 5.10 is the sharp temperature drop at loc-6 at 11:00. This drop can be correlated with the airflow dynamics influenced by the increased supplied airflow rate, which is implied by the control action to flatten the rising temperature at 11:00.

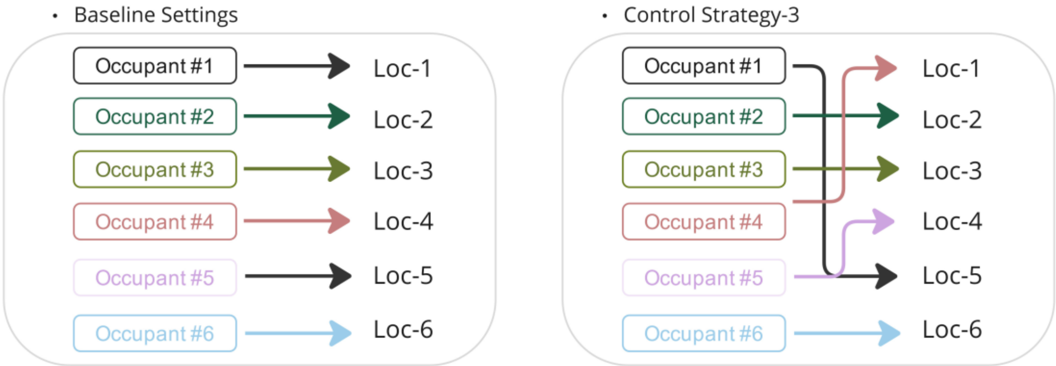


Figure 5.11. Relocation of occupants in control strategy-3

5.4.3 Individualistic Comfort Evaluation

As mentioned earlier, collective comfort probabilities were calculated by averaging the comfort probabilities of occupants based on their assigned comfort profiles. Although the averaged probability value could allow a plausible interpretation for overall comfort assessment in shared indoor environments, further analysis at individual level may reveal the personal implications of the proposed strategies. It may also provide insights for improving building control. Having analyzed the temporal impacts on operative temperature values at the defined locations, comfort probabilities of each occupant at five ToD alternatives were computed. The changes in personal thermal comfort levels in the baseline settings and control strategy-3 are demonstrated in Figure 5.12 and Figure 5.13, respectively. It is worth noting that the relocation of occupants (Figure 5.11) was taken into account while performing the calculations for the control strategy-3 in Figure 5.13.

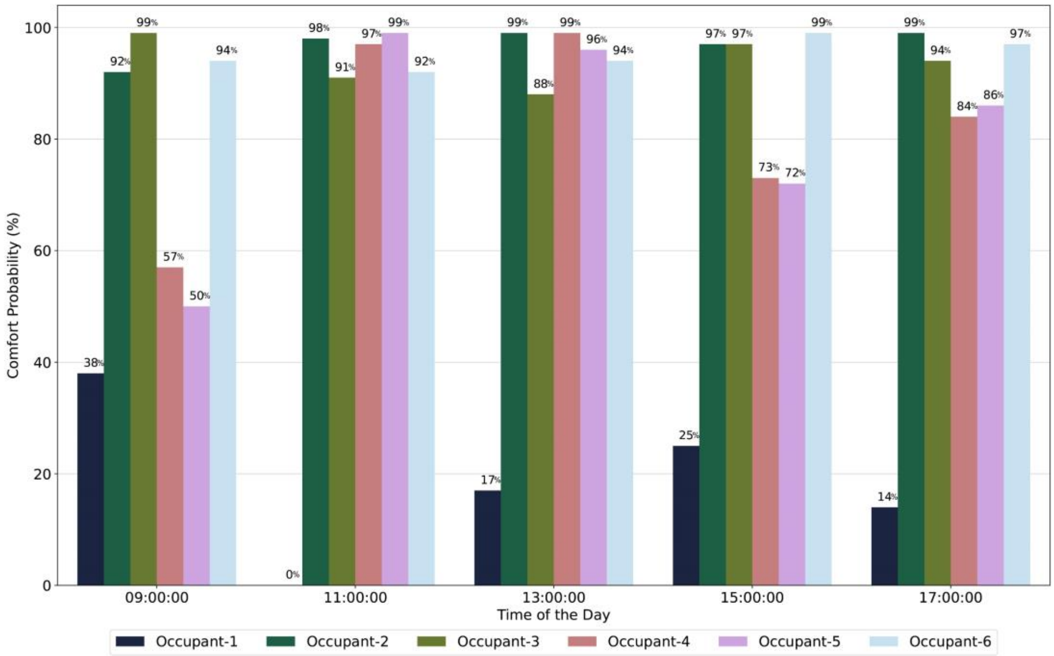


Figure 5.12. Occupants’ comfort probabilities in the baseline setting

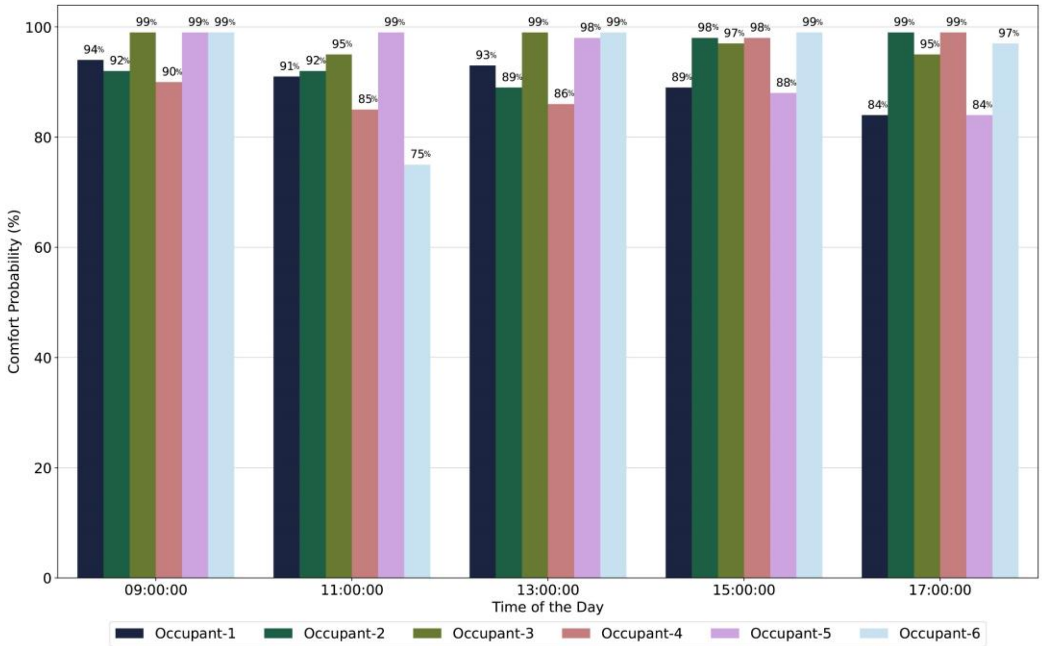


Figure 5.13. Occupants’ comfort probabilities in control strategy-3

What is striking in Figure 5.12 is the continuous discomfort of occupant-1 throughout the day in the baseline settings. Even at 13:00, when the collective comfort probability was reported as 82% that was considered to be above the minimum required comfort range, occupant-1 suffers from the lack of thermal comfort. Moreover, the comfort probabilities of occupant-4 and occupant-5 seem to fall below the minimum required range at 09:00 and 15:00, while other times their comfort levels are satisfactory. These results show that temporal variations have impacts on thermal comfort, and individual occupant assessment in building operation would decrease the risk of leaving out some occupants while providing comfortable conditions in shared environments.

Since neither control strategy-1 nor control strategy-2 demonstrate a remarkable improvement for the collective comfort (see Figure 5.8), analysis of individual comfort assessment for these strategies were not presented. Figure 5.13 demonstrates that control strategy-3 has some dramatic improvement implications for thermal comfort at an individual level. When compared with the baseline settings, the obvious improvement is achieved on the comfort probability of occupant-1, without sacrificing the remaining occupants' well-being. The only notable downside that is observable in control strategy-3 is that, the comfort level of occupant-6 falls slightly below the minimum comfort range at 11:00 with a probability of 75%. This can be related with the aforementioned unexpected drop of operative temperature at location-6 due to the airflow dynamics, as illustrated in Figure 5.10. Apart from that, the individual comfort probabilities are quite satisfactory with a range between 84% to 99% with a solid inclination towards the upper limit.

To wrap up, it can be argued that thermally comfortable conditions could be provided regardless of the temporal variations with the proposed building control strategy, if the occupants comply with the relocation procedure at the start of the day based on their personal comfort preferences. It is of utmost importance to take an additional step and include individual comfort assessment while determining the collectively comfortable conditions in multi-occupancy indoor spaces. Trusting solely on the collective comfort probability calculation may result in overlooking the discomfort of an individual in the studied space. Although not observed in our current analysis, considering occupants with different comfort profiles than reported in this work could have changed the situation, and may have led to this problem.

5.5 Discussion

In the conventional practice, offices have occupants assigned to certain workstations. In such settings, HVAC system operations could be configured to provide the comfortable conditions based on personal preferences of individuals. On the other hand, in recent years, with the boosting impact of Covid-19 pandemic, flexible working and hot-desking have become a popular space usage strategy for many offices. Instead of providing permanent offices, occupants are dynamically allocated to the workstations with the purpose of reducing operational costs, minimizing energy use and promoting work efficiency (Candido *et al.*, 2019; Sood *et al.*, 2020). This growing trend have the potential to both necessitate and enable adopting new operational strategies in buildings for maintaining comfort requirements and efficient use of resources. In this research, it was demonstrated that personal differences between individuals' comfort needs and natural spatial variations in thermal conditions can be leveraged in shared environments to establish novel building control strategies to overcome the limitations of conventional approaches and to meet the incurring operational needs without additional energy use. Both for the conventional office settings and the lately popular operational strategies, the proposed framework demonstrates more flexible, efficient and sustainable operational flow, without overlooking the personal needs of building inhabitans.

In the optimization analysis presented in this chapter, although the employed datasets and analysis procedure were carried out with an offline procedure, the primary intention was to establish the scientific base for an occupant-centric building control mechanism that would dynamically respond to the needs of all individuals within shared indoor environments. Based on what this section provides, further elaborations and interpretations that were discussed in Chapter 2 could be made to actualize an integrated building control framework.

In a practical application, it is anticipated that the supplied airflow rate and direction can be adjusted at the diffuser level, based on the required thermal asymmetry implied by the differences in occupants' personal comfort preferences. Personalized air conditioning has been getting attention in the past recent years as a method to provide more efficient energy management in buildings considering the diversity in individual preferences. The active diffusers providing flexibility of airflow adjustments (for both throughput and airflow direction) can be employed to create the desired temperature distribution. Active diffuser is a relatively new concept, the development of which received attention from both researchers (Jazizadeh *et al.*, 2020) and commercial initiatives (Lindinvent, 2023) in recent years. By controlling the rate and the direction of supplied fresh air, the required thermally heterogeneous environment could be achieved to respond to the comfort needs of all individuals in a shared space. In addition, such diffusers can shut themselves off if the space is detected to be vacant by the occupancy sensors. Various control techniques, from rule-based to reinforcement learning, could be developed to configure the indoor environment using such technologies.

CHAPTER 6

CONCLUSION

This research has focused on conceptualizing a building control framework and analyzing its applicability in the thermal domain, as an overarching contribution to the efforts of providing comfortable climatic conditions in buildings and being cognizant of consumed energy. Responding to the drawbacks of the one-size-fits-all approaches in the current practice, personalized dimensions of building control, thermal comfort, and indoor climate were investigated. Researches have shown that relying solely on automating the operation of building systems is not a very efficient control strategy, as the needs of occupants are not static, and standardized settings do not provide satisfactory indoor environmental conditions for every individual. It was also demonstrated that keeping the occupants completely out of the control loops leads to decreased perceived control, which impacts both energy consumption and human comfort in a negative manner. To this end, a collaborative control framework, which establishes a communication ground between people and buildings were conceptualized. In order to analyze how such a framework could enable improvements in human comfort and energy efficiency, a simulation-based and data-driven research was conducted in the thermal domain. Differences in personal comfort preferences and micro-climatic conditions in multi-occupancy indoor spaces are accounted for by developing personal thermal comfort profiles and investigating thermal distribution patterns. Through performing an optimization analysis, achievable comfort improvements and energy savings were presented in case of both occupants' incorporation and sole automation. The results of the data-driven analysis confirmed that considering the nonuniformity of personal comfort and indoor climate in a dynamic building control strategy where the occupants are kept in the loop have great potential for providing comfortable indoor environments without wasting valuable energy excessively.

6.1 Revisiting the Research Questions

The main research question that this research focused on was: How can we improve occupant comfort while ensuring the efficient use of energy in building operation?

To answer the main research question, the following sub-questions were addressed:

What are the comfort and energy affiliated problems in prevailing building control approaches and how can they be tackled?

With the aim of answering this question, a literature review was performed to investigate human and automation-related system issues in building control. It was revealed that the main focus of current approaches is either on empowering the occupants for building control or developing fully automated system operation minimizing human inference. While relying on manual control has been shown to be inefficient in terms of energy use, the full automation also has crucial disadvantages, such as decreased perceived control leading to lower satisfaction levels, and standardized operational assumptions. To address these drawbacks, a collaborative building control mechanism that provides a sense of continuous control for occupants and allocates operational decisions to the building management system was proposed, and system components were discussed. The outlined control framework was predicated on a communication ground between the occupants and the building, which would enable automation adjustability at the desired level and allow bidirectional feedbacks, suggestions and notifications.

What are the implications of occupant comfort in shared indoor environments on building control?

Satisfying occupant comfort needs in personal offices or single-occupancy spaces is achievable by configuring the building operation based on the individual specific preferences. However, providing comfortable conditions for all occupants in multi-occupancy indoor environments is a unique challenge for building control. In consideration of the possible differences in comfort preferences of occupants, available personal comfort feedback datasets were processed with Bayesian network modeling approach to generate personal comfort profiles of multiple individuals. The illustrated variations in the thermal comfort sensitivities of six people revealed that controlling the thermal domain in shared spaces based on generic and averaged assumptions will create suboptimal conditions for many of the occupants. Individuals sharing the same zone may have different thermal comfort preferences, and this imply personalized system configuration requirement for building control.

What are the characteristics of thermal distribution patterns in multi-occupancy office spaces?

This inquiry was addressed by performing CFD simulations in ANSYS Fluent software. Thermal distribution patterns in a multi-occupancy office space were investigated under varying climatization and occupancy settings. Based on the outcomes of the numerical and visual analysis, it was demonstrated that the temperature is not uniform in the selected office space and the distribution is influenced by the supplied airflow rate, the supplied airflow direction, the number and positions of occupants, and the placement of diffusers. In keeping with the anticipated outcome, the increase in the supplied airflow rate and the number of occupants led to higher room temperatures. It was also revealed that changing the supplied airflow direction has a direct impact on the indoor temperature, and setting the directional airflow configuration considering the inlet and outlet locations could be used as an alternative strategy for providing required thermal conditions.

Can we leverage varying comfort preferences of occupants and heterogeneity of thermal conditions to improve collective comfort and energy efficiency?

A data-driven optimization analysis was performed to test the potentials of leveraging the nonuniformities in personal comfort preferences and distribution of thermal parameters. A baseline setting and three control strategies were defined with an incremental complexity. The quantitative analysis performed demonstrated improvements in collective comfort probabilities for almost all occupancy cases, brought by the proposed control strategies compared to the baseline. While substantial energy saving potential was revealed for minimum multi-occupancy scenarios, a trade-off between collective comfort and energy consumption was observed for maximum occupancy. The results confirmed that if building management system can communicate with the occupants and the individuals cooperate by complying with its suggestions (i.e., seat assignment), achievable comfort and energy improvements are maximized. Without this communication ground, the optimization strategies that account for personal preferences and micro-climatic conditions still offered improvements but they were relatively limited.

6.2 Limitations and Future Work

This study also has several limitations. To start with, the proposed building control scheme was only assessed in the thermal domain with a simplified collaboration component, which is the assignment of occupants to the workstations. The communication between the building and the occupants may be configured in a more complex fashion by designating a dedicated interface in an experimental study. The field of human-building interaction could be investigated further to discover the different dimensions of bidirectional communication between buildings and occupants, including influential parameters, energy and comfort affiliated potentials and achievable improvements.

Although this work only focused on thermal comfort, other indoor environmental conditions such as lighting, acoustics, or privacy concerns can affect occupants' overall comfort levels and their seat selections. Other domains could also be studied in isolation to understand their specific implications first, and then multi-domain studies could be conducted to reveal the overall configuration requirements of the integrated control framework. Establishing a seamless flow and well-configured compatibility between various building systems serving different domains could enable BMS to take the most efficient and effective action in response to the feedback received from the building occupants.

Personal comfort profiles utilized in this research have a direct impact on the optimization results. Having different personal comfort profiles than the ones defined in the optimization analysis could lead to changes in the selected settings by the control strategies. Based on the available evidence in the literature (Wang *et al.*, 2018), it was assumed that occupants usually have different thermal comfort preferences and tolerances. However, it can be claimed that in the cases where thermal preferences of the individuals sharing the same environment are very similar, indoor thermal conditions may not be optimal for all occupants, given the heterogeneity in thermal conditions. For such a consideration, further research is required to reveal the strategies that would provide uniform thermal conditions in shared indoor spaces. Moreover, in order to confirm the inclusivity of the methodology, more personal characterictics such as age, sex, body mass index, etc. could be incorporated in personal comfort profiles. Having more personal traits embedded in personal comfort profiles could also lead to profound improvements on the predictive performance of the generated models, and decrease the required data collection time to reach accurate representations.

The methodology proposed in this research was validated in an office space at an educational facility, the scale and dimensions of which may have an influence on the numerical results. Accordingly, building type, location, defined space volume, selected time of the year and number of occupants can be variated in further studies to investigate the applicability of the methodology in the presence of different contextual factors.

In CFD simulations, due to the cumulative increase in the number of combinations and computing time, only minimum and maximum multi-occupancy cases with three supply airflow rates were modeled and analyzed. Incorporating all possible occupancy scenarios and increasing supply airflow rate resolution by adding more levels could reveal further explorations for ensuring collective comfort in an energy-efficient manner. Moreover, the positions of the supply air inlet and the return outlet were modeled considering the real-world parameters of the studied space, and they were kept constant. Considering their influence on air mixing and flow dynamics, the impact of the HVAC components' placement could be assessed to reveal possible design strategies. In addition, we have analyzed thermal distribution patterns through a steady state simulation setup, which provides a snapshot of the environment at a given time under defined boundary conditions. A further study with a transient simulation setup could make it possible to assess more granular time-dependent fluctuations of indoor environmental conditions, which was not viable within the scope of this research.

Applicability of the proposed control strategies under different conditions could be verified through longitudinal field studies enabling continuous data acquisition with adequate sensor infrastructure, which is anticipated as a future research direction for this study. For further investigation, we also plan to incorporate more parameters, including the time of the day at four seasons, the scale of the multi-occupancy spaces, the arrangement of venting components, and the positioning of the working desks to account for more contextual factors.

6.3 Conclusive Remarks

It is of the utmost importance for building researchers to consider the human dimension in any attempts leaning towards achieving technological improvements in buildings. As the most fundamental parameter of the built environment is the occupants, laying the bricks on a human-centered foundation would always be a good step forward for disposing of potential obstacles in integrating new advancements to buildings. Considering the interdependency between building control, indoor climate, and human comfort, operational codes of building systems should be configured with a comprehensive understanding.

In an effort to develop an occupant-centric building control framework enhancing human involvement, this study tackled with the challenges in the thermal domain, posed by the differences in personal comfort preferences and nonuniformity of micro-thermal conditions, and leveraged them for comfort provision at an individual level in shared environments. In doing so, an office space with six occupants was adopted as a case study, and a unique comfort profile was developed to be assigned to each individual within the defined environment. Thermal distribution characteristics of the space were investigated using CFD simulations under varying supply airflow rates, supply airflow direction, and occupancy settings. Three control strategies were proposed with an incremental complexity to delve into the potentials of adjustability in supply airflow direction, supply airflow direction, and supply airflow rate, and supply airflow direction, supply airflow rate, and occupant locations. Collective comfort probabilities were examined under three control strategies at the minimum and maximum multi-occupancy and assessed the findings in comparison to the defined baseline scenarios. Simulation results illustrated that temperature is not uniformly distributed in multi-occupancy spaces, and occupants are subjected to different thermal conditions depending on their locations and related contextual factors. Although adjustability of supply airflow direction and supply airflow rate implies comfort improvements in minimum multi-occupancy scenarios, their sole employment was ineffective in full occupancy. However, it was revealed that adjusting supply airflow direction could be used as an alternative strategy for adjusting thermal conditions in shared indoor environments instead of altering supply airflow rate, which typically implicates higher energy use due to the cubic relationship between flow rate and fan power. According to the analysis results, coupling personal comfort preferences and thermal distribution patterns in building control increases the probability of achieving collective comfort considerably, if individuals are intelligently allocated between six occupant positions.

This study showed that keeping occupants in the loop while determining the control actions in buildings has profound improvement potential. For the thermal domain, assuming the uniformity of thermal conditions in multi-occupancy spaces may be misleading for occupant-centric building control studies, and the comfort requirements of occupants should be assessed based on micro-conditions at their positions rather than representative room thermostat measurements.

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APPENDICES

A. Publications from This Thesis

Journal Articles

A.1. Topak, F., & Pekeriçli, M. K. (2021). Transformation of the Interface: Future of Human-Building Interactions. GRID - Journal of Architecture Planning and Design, 4(1), 38–52. https://doi.org/10.37246/grid.820370

A.2. Topak, F., & Pekeriçli, M. K. (2022). Collaborative building control: a conceptual mixed- initiative framework. Intelligent Buildings International, 14(4), 487–498. https://doi.org/10.1080/17508975.2021.1941731

A.3. Topak, F., Pavlak, G. S., Pekeriçli, M. K., Wang, J., & Jazizadeh, F. (2023). Collective comfort optimization in multi-occupancy environments by leveraging personal comfort models and thermal distribution patterns. Building and Environment, 239, 110401. https://doi.org/10.1016/j.buildenv.2023.110401

Conference Papers

C.1. Topak, F., Pekeriçli, M. K., & Tanyer, A. M. (2019). Human-Building Interactions in Intelligent Built Environments. II. International Conference and Exhibition on Digital Transformation & Smart Systems - DTSS 2019, 89-92. Ankara, Turkey

C.2. Topak, F., & Pekeriçli, M. K. (2020). Towards Using Human-Computer Interaction Research for Advancing Intelligent Built Environments : A Review. *6th International Project and Construction Management Conference*, 835–843. Istanbul, Turkey.

C.3. Topak, F., Pavlak, G. S., Pekeriçli, M. K., & Wang, J. (2022). Energy Efficiency and Comfort Optimization in Shared Indoor Spaces. Next Built - International Conference on Challenges for the Next Generation Built Environment. Bologna, Italy.

C.4. Topak, F., Pavlak, G. S., Pekeriçli, M. K., & Wang, J. (2023). Analysis of Thermal Distribution Patterns in Multi-Occupancy Environments. ASHRAE Annual Conference. Tampa, FL.

B. Temperature Distribution Patterns in All Occupancy Scenarios

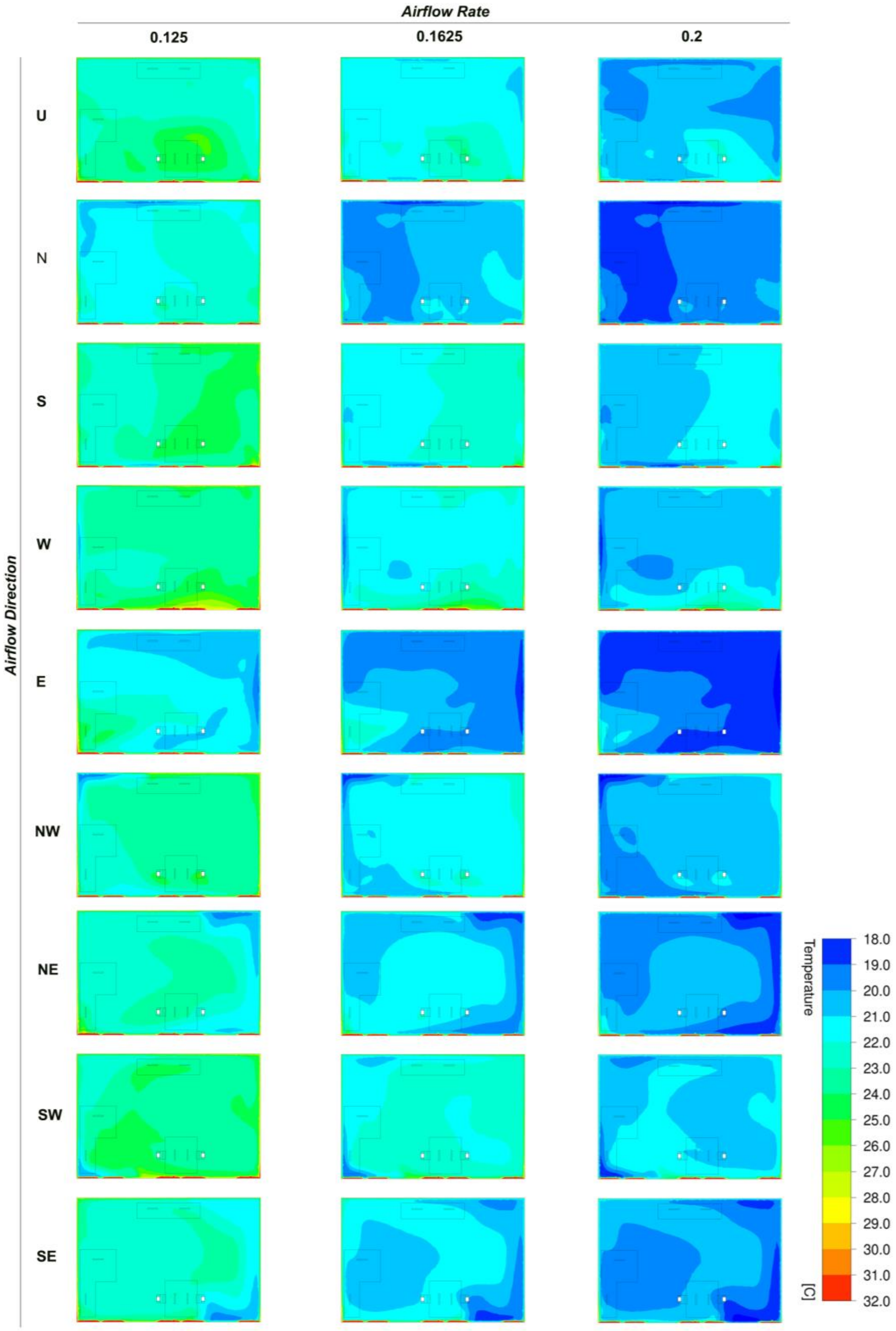

Figure A.1. Temperature distribution gradients in minimum multi-occupancy scenario-1

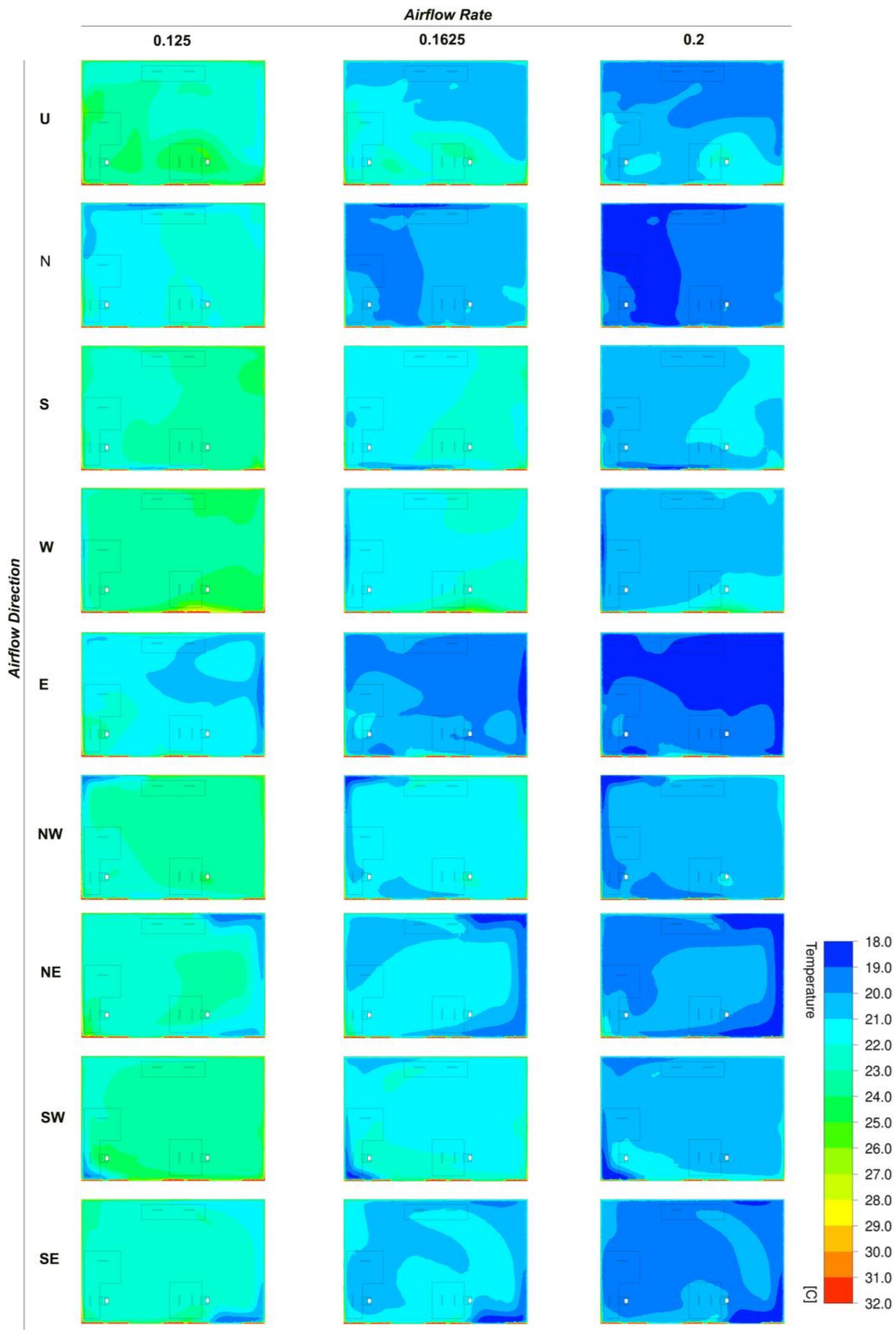

Figure A.2. Temperature distribution gradients in minimum multi-occupancy scenario-2

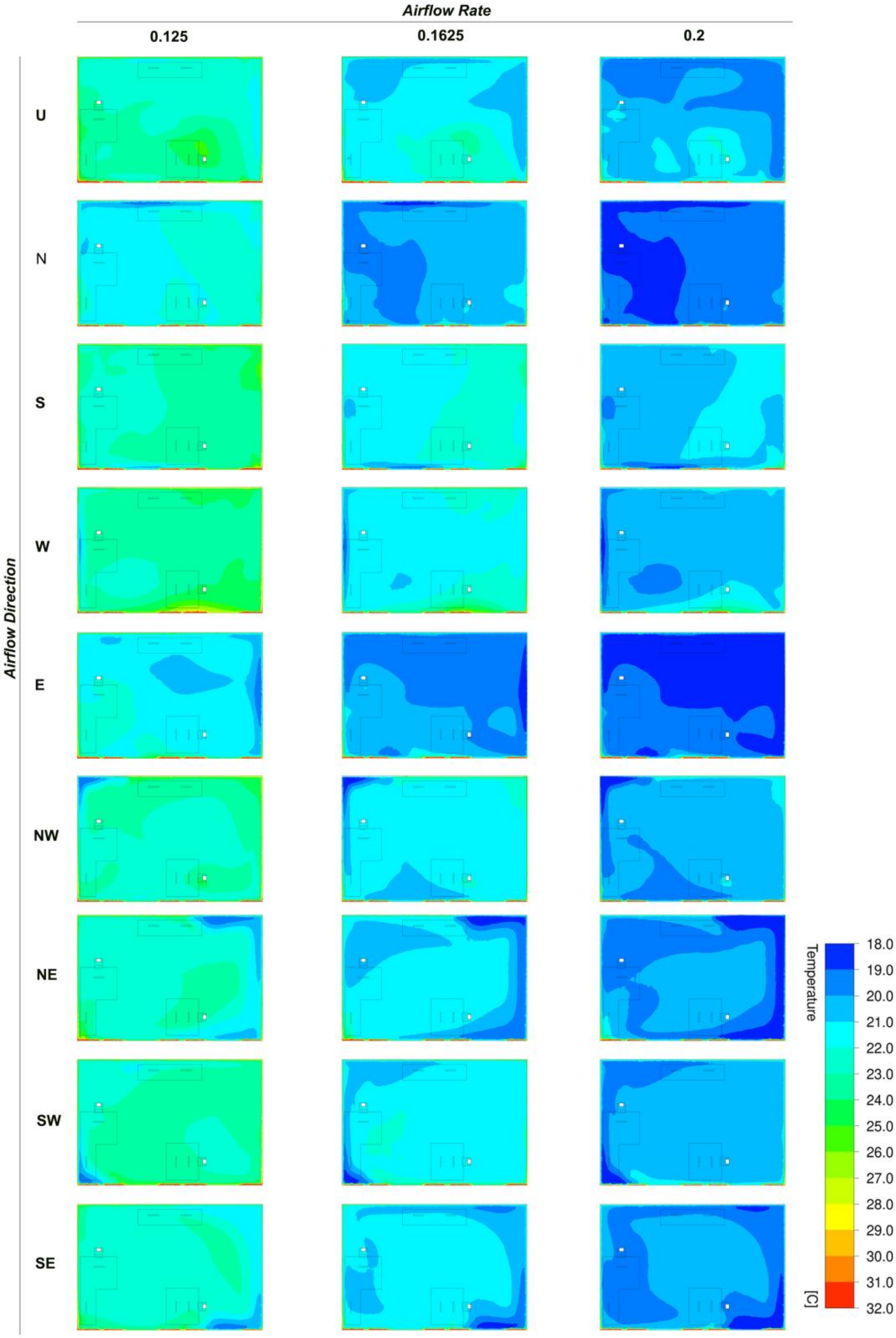

Figure A.3. Temperature distribution gradients in minimum multi-occupancy scenario-3

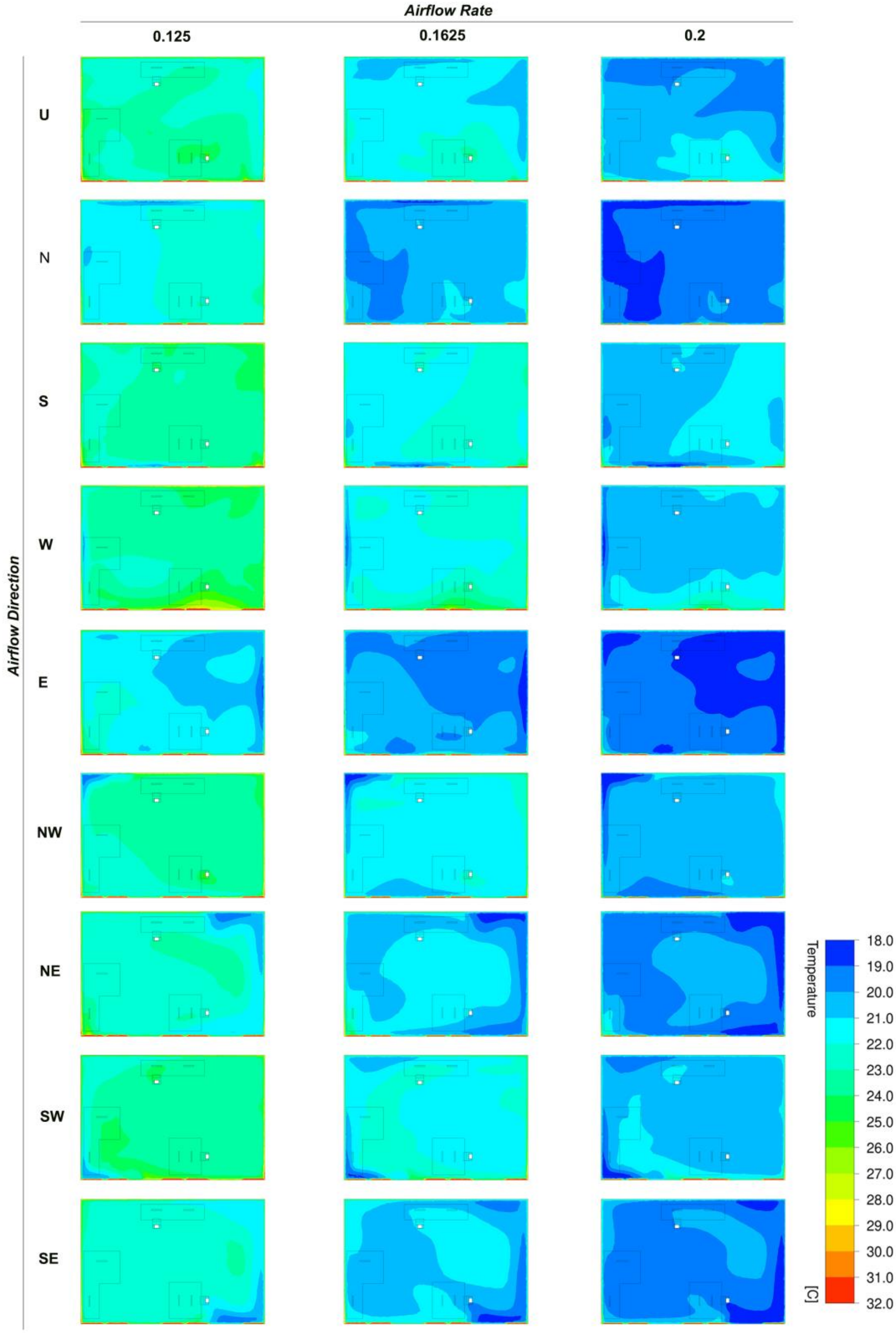

Figure A.4. Temperature distribution gradients in minimum multi-occupancy scenario-4

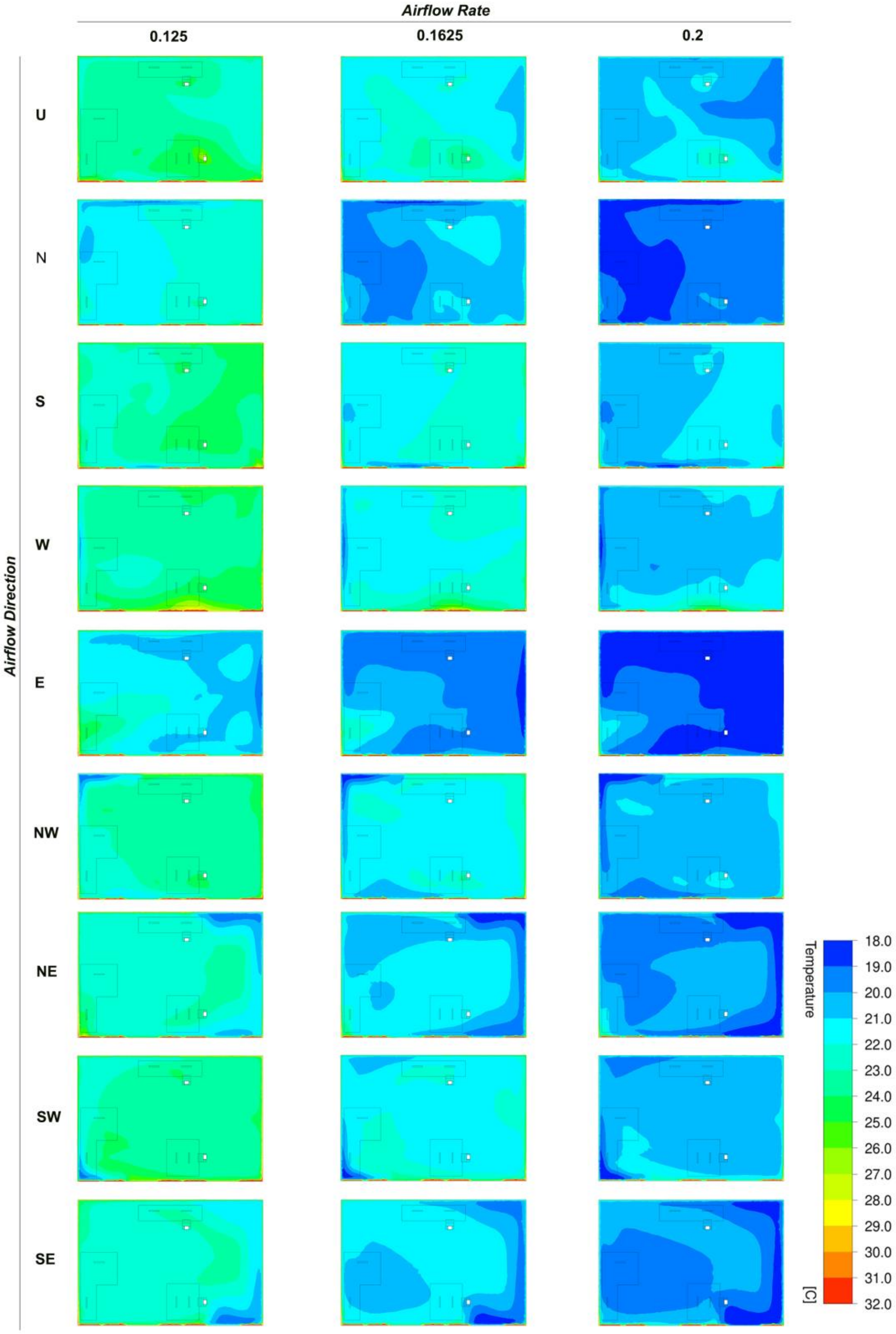

Figure A.5. Temperature distribution gradients in minimum multi-occupancy scenario-5

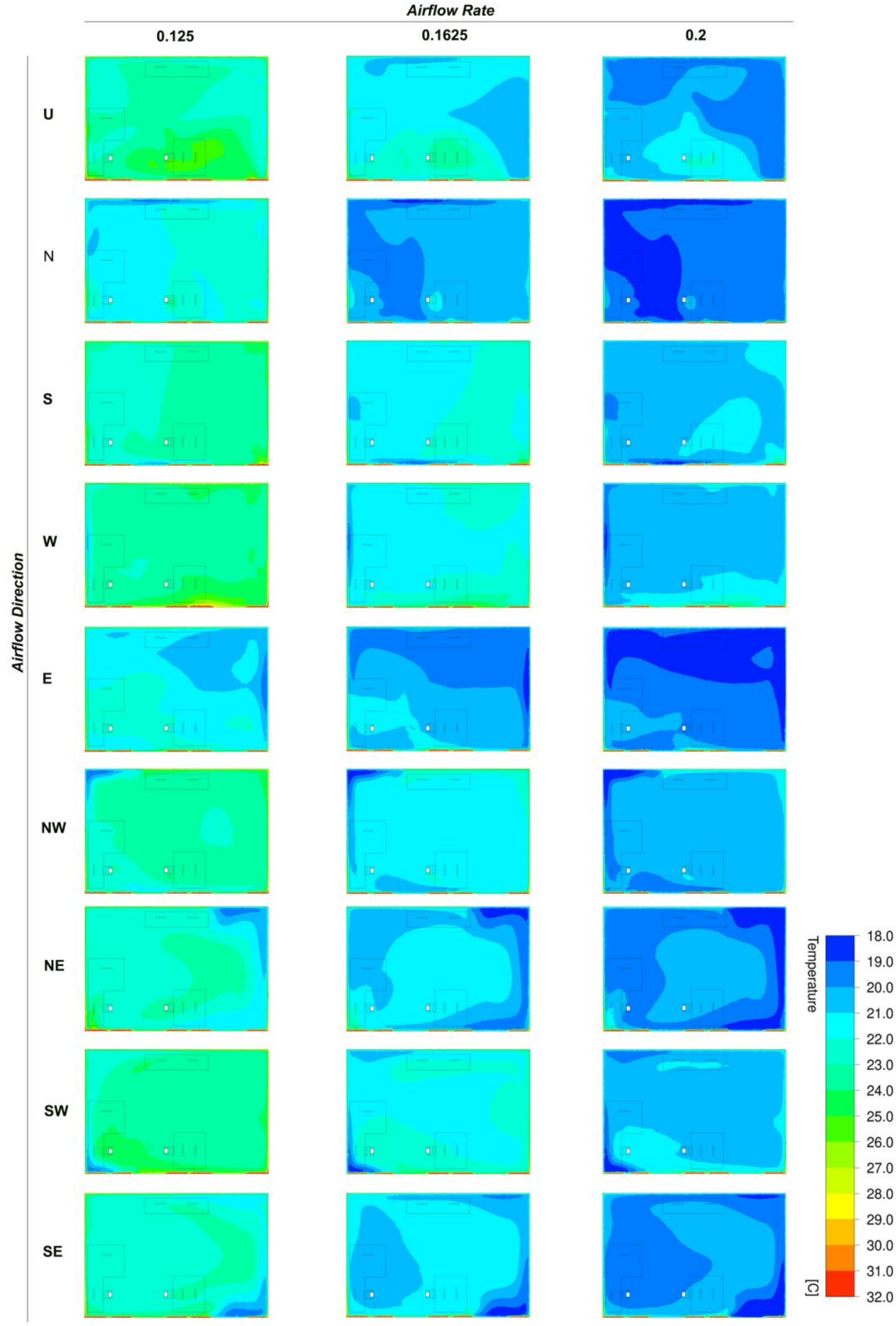

Figure A.6. Temperature distribution gradients in minimum multi-occupancy scenario-6

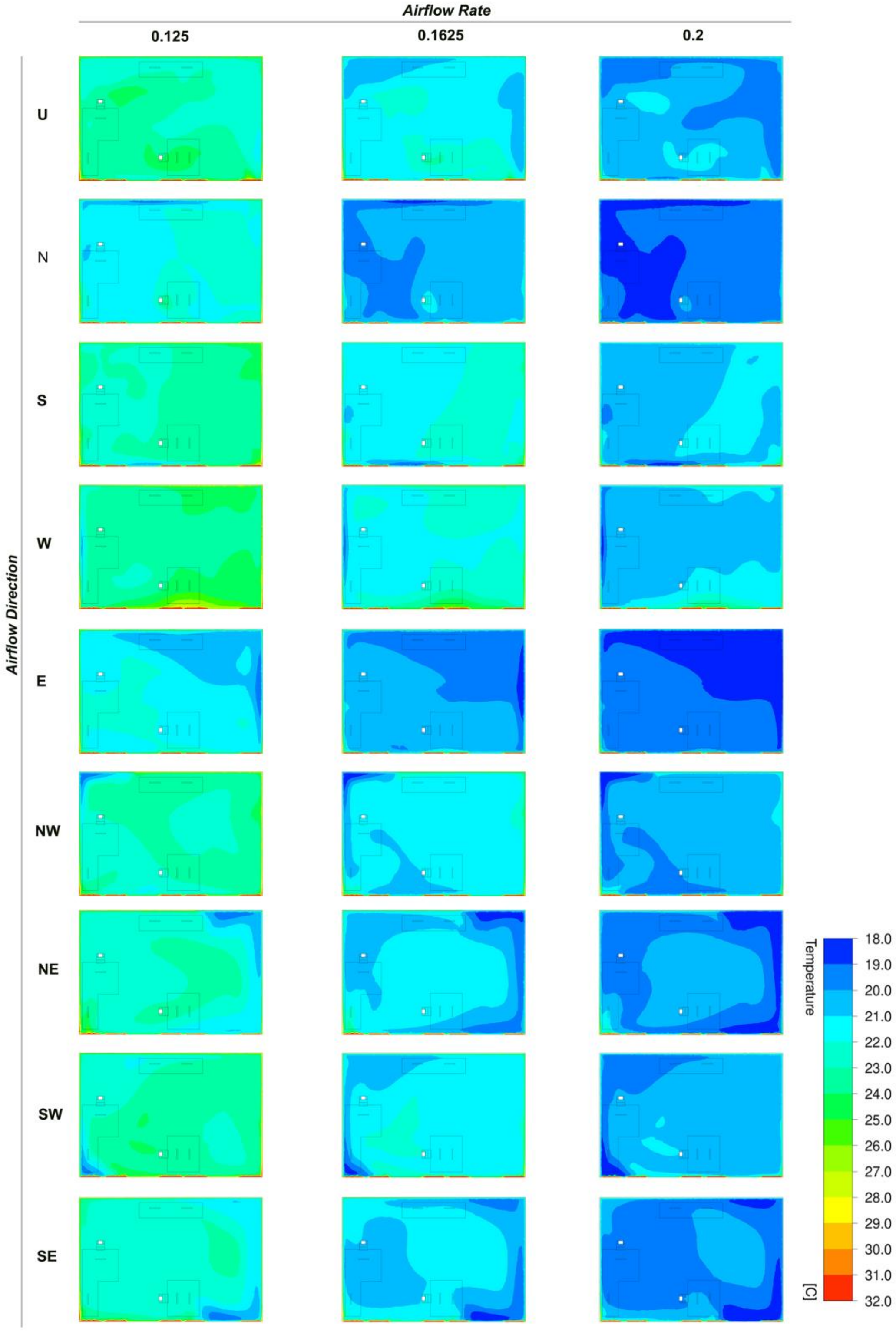

Figure A.7. Temperature distribution gradients in minimum multi-occupancy scenario-7

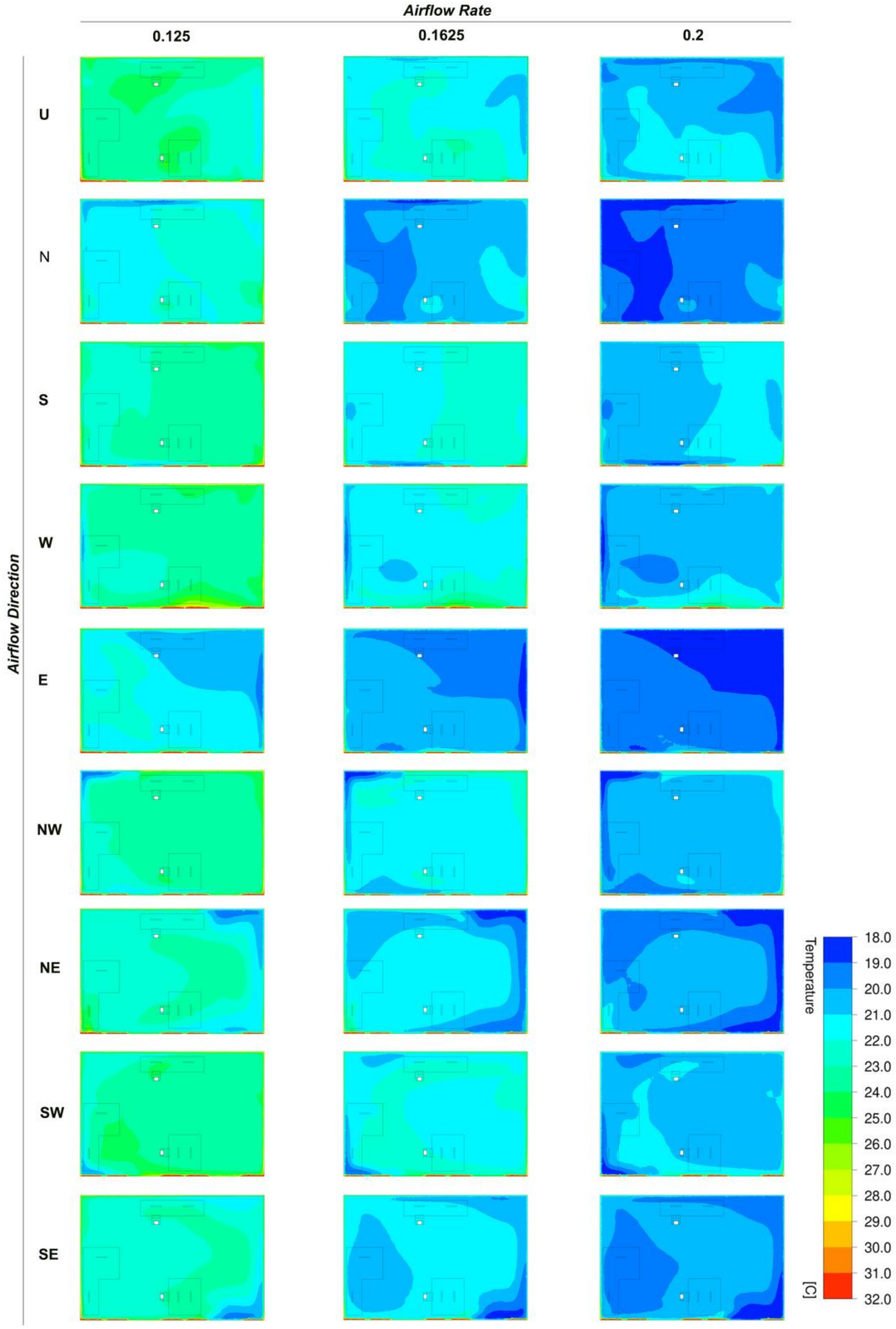

Figure A.8. Temperature distribution gradients in minimum multi-occupancy scenario-8

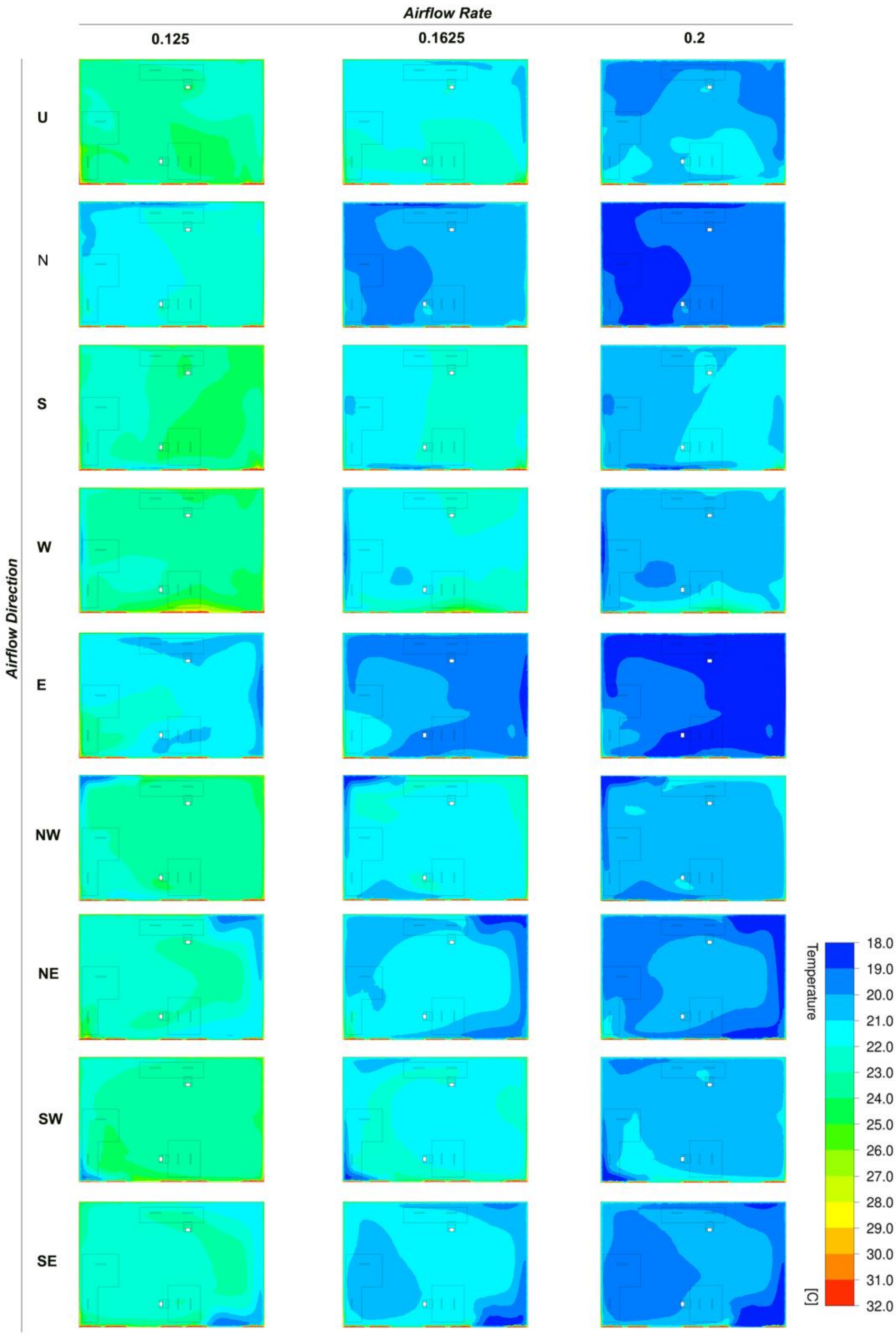

Figure A.9. Temperature distribution gradients in minimum multi-occupancy scenario-9

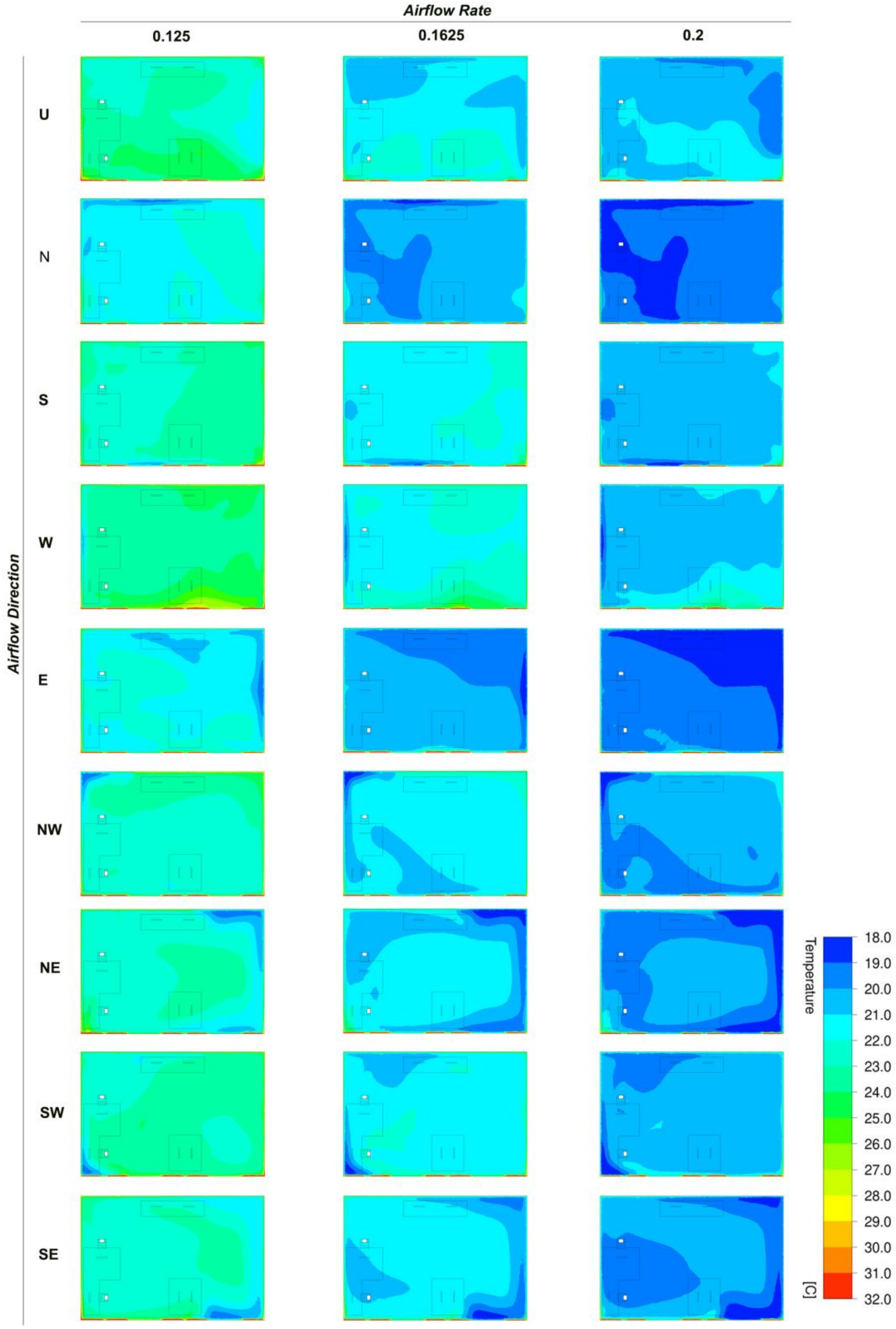

Figure A.10. Temperature distribution gradients in minimum multi-occupancy scenario-10

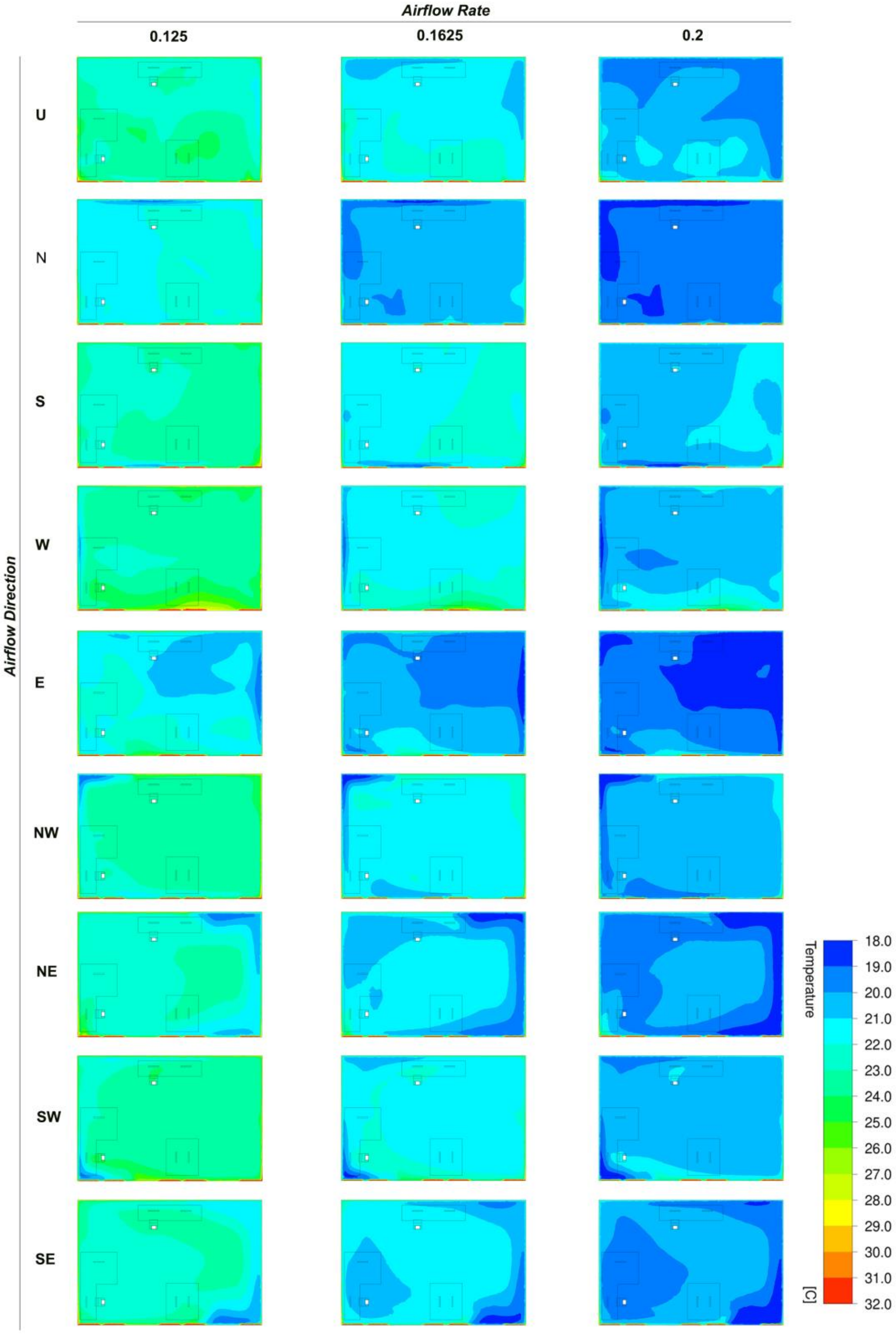

Figure A.11. Temperature distribution gradients in minimum multi-occupancy scenario-11

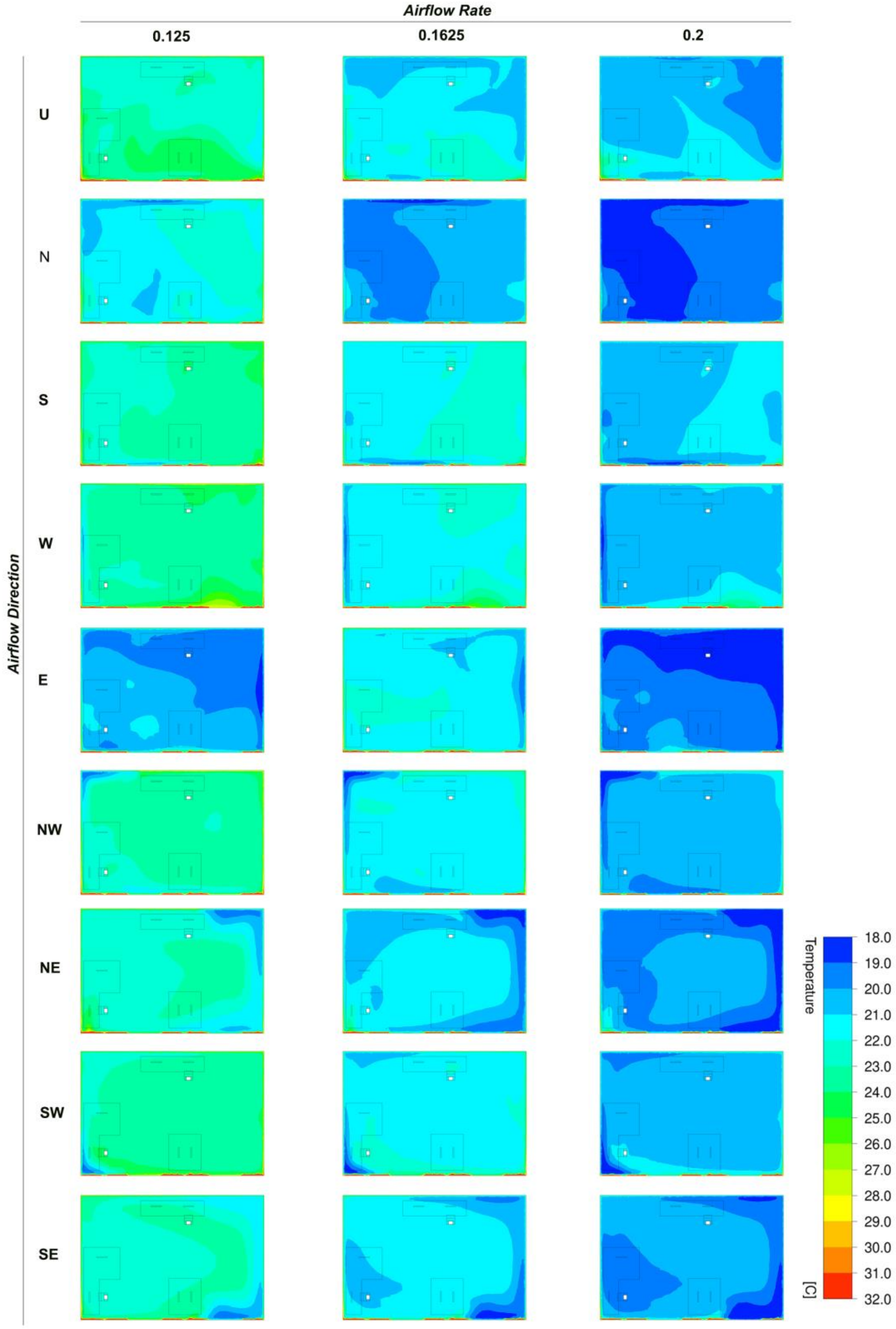

Figure A.12. Temperature distribution gradients in minimum multi-occupancy scenario-12

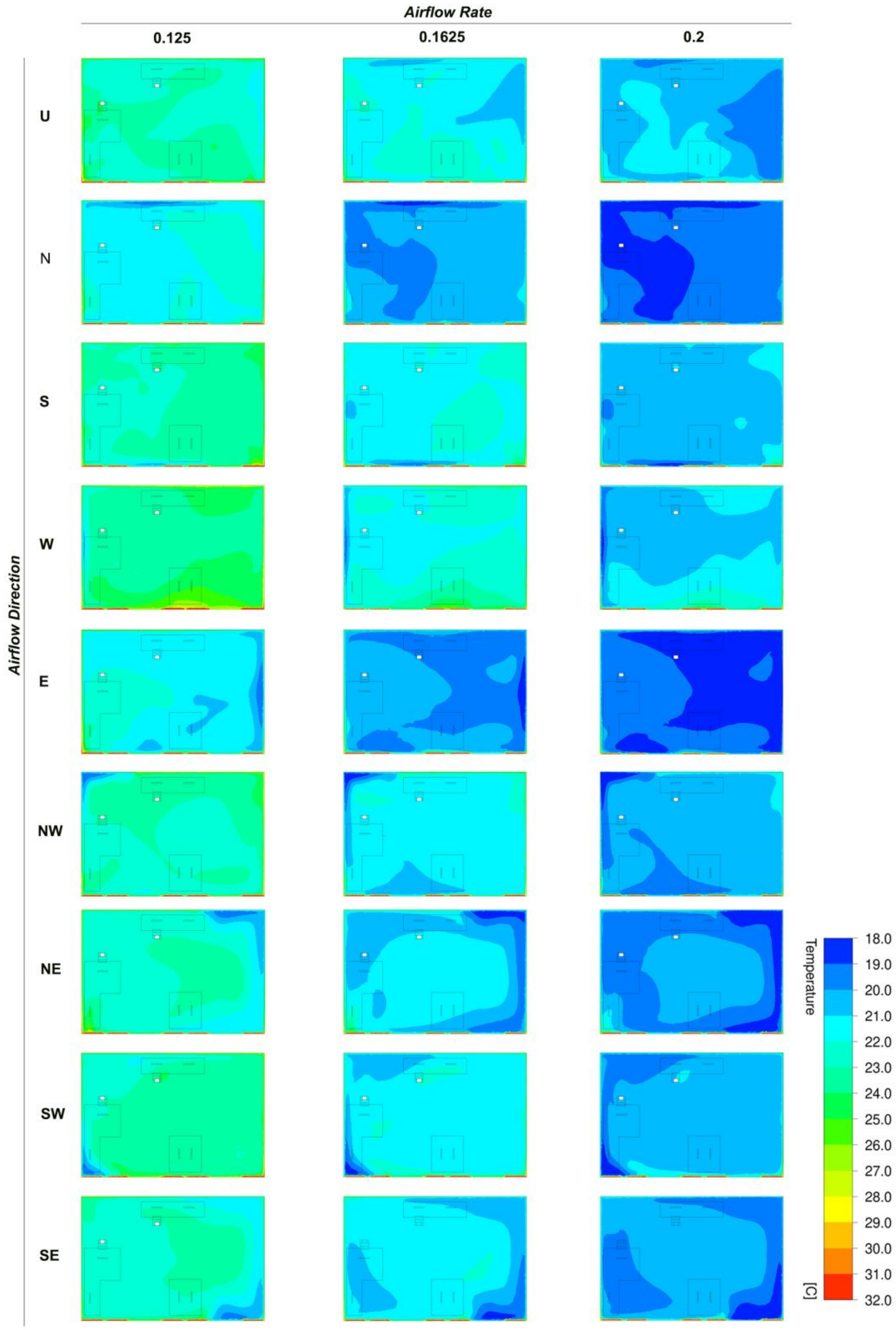

Figure A.13. Temperature distribution gradients in minimum multi-occupancy scenario-13

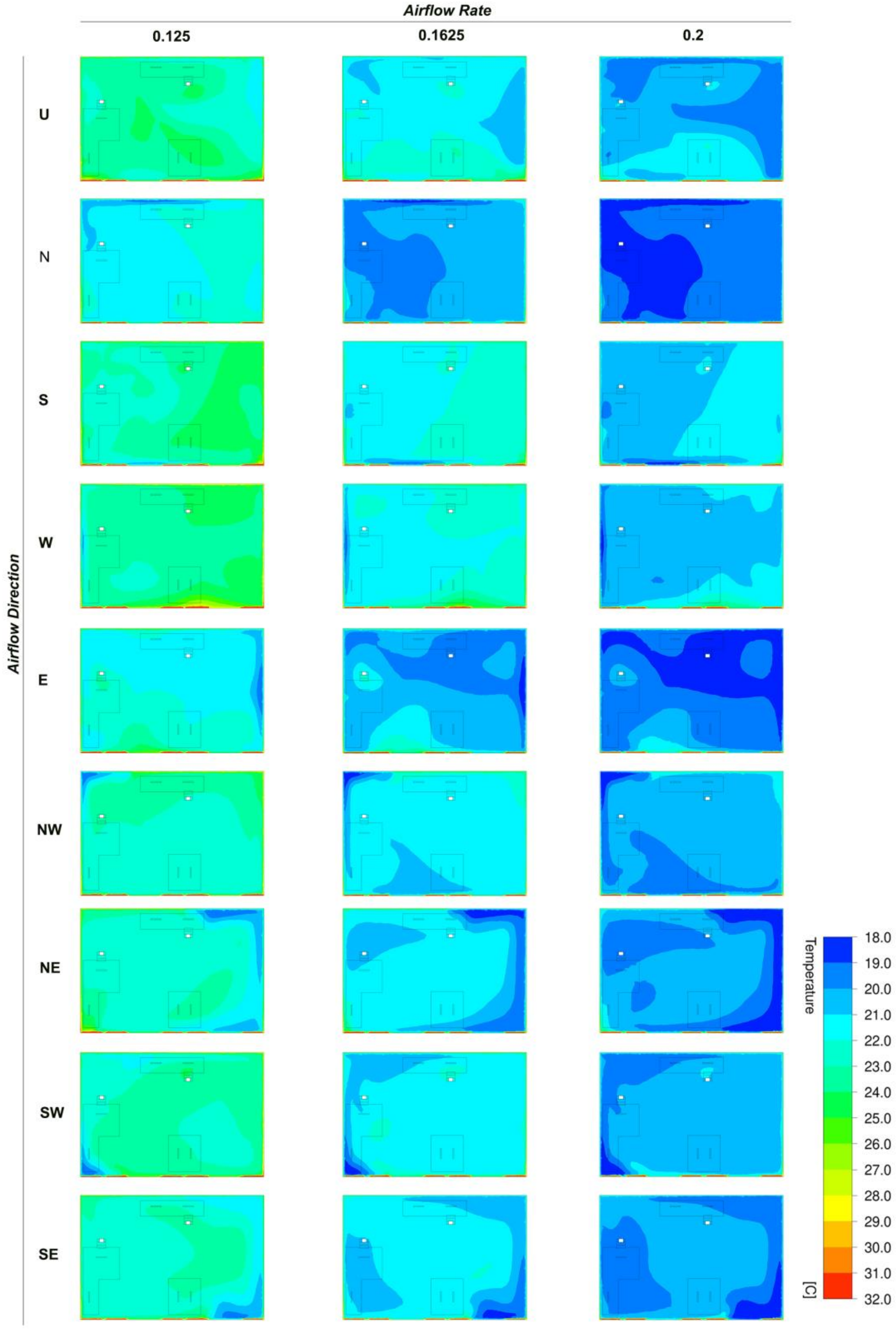

Figure A.14. Temperature distribution gradients in minimum multi-occupancy scenario-14

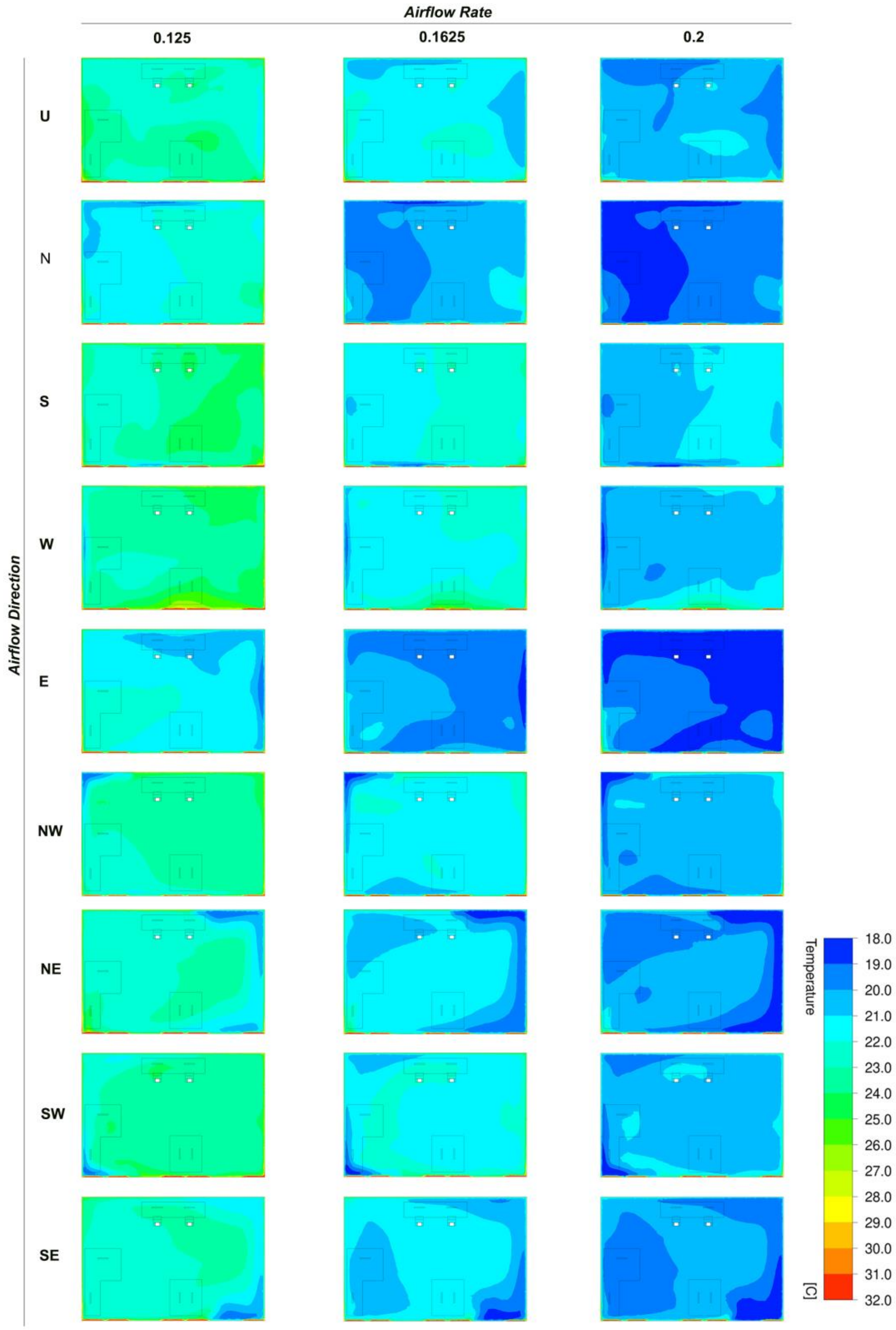

Figure A.15. Temperature distribution gradients in minimum multi-occupancy scenario-15

CURRICULUM VITAE

Surname, Name: Topak, Fatih

EDUCATION

Degree	Institution	Year of Graduation
M.Sc.	METU, Building Science	2016
B.Arch.	METU, Architecture	2013

RESEARCH INTERESTS

Energy efficiency, human comfort, occupant-centric building control, intelligent built environments, building automation systems, human-building interactions

PUBLICATIONS

Refereed Journal Articles

- **Topak, F.**, Pavlak, G. S., Pekeriçli, M. K., Wang, J., & Jazizadeh, F. (2023). Collective comfort optimization in multi-occupancy environments by leveraging personal comfort models and thermal distribution patterns. *Building and Environment*, 110401. https://doi.org/10.1016/j.buildenv.2023.110401.
- **Topak, F.,** & Pekeriçli, M. K. (2022). Collaborative Building Control: A Conceptual Mixed-Initiative Framework. *Intelligent Buildings International*, 14(4), 487–498. https://doi.org/10.1080/17508975.2021.1941731.
- **Topak, F.,** & Pekeriçli, M. K. (2021). Transformation of the Interface: Future Human-Building Interactions. *GRID - Journal of Architecture Planning and Design*, 4(1). https://doi.org/10.37246/grid.820370
- **Topak, F.**, Tokdemir, O. B., Pekeriçli, M. K., & Tanyer, A. M. (2019). Sustainable construction in Turkish higher education context. *Journal of Construction Engineering, Management and Innovation*, vol.2, 40-47. https://doi.org/10.31462/jcemi.2019.01040047

- **Topak, F.**, Pekericli M. K., Tanyer A. M. (2018). Technological Viability Assessment of Bluetooth Low Energy Technology for Indoor Localization. *ASCE Journal of Computing in Civil Engineering*, 32 (5), 04018034. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000778

Refereed Conference Papers

- **Topak, F.,** Pavlak, G.P., Pekericli, M.K., Wang, J. (2023). *Analysis of Thermal Distribution Patterns in Multi-occupancy Environments*. *ASHRAE 2023,* Tampa, FL, United States.

- **Topak, F.,** Pavlak, G.P., Pekericli, M.K., Wang, J. (2022). *Energy Efficiency and Comfort Optimization in Shared Indoor Spaces*. *Next Built - International Conference on Challenges for the Next Generation Built Environment*, Bologna, Italy.

- **Topak, F.**, & Pekeriçli, M. K. (2020). Towards Using Human-Computer Interaction Research for Advancing Intelligent Built Environments: A Review. *6th international Project and Construction Management Conference (IPCMC2020)*, İstanbul, Turkey.

- **Topak, F.**, Pekeriçli, M. K., & Tanyer, A. M., (2019). Human-Building Interactions in Intelligent Built Environments. *II. International Conference and Exhibition on Digital Transformation & Smart Systems - DTSS 2019*, Ankara, Turkey

- **Topak F.**, Tokdemir O. B., Pekericli M. K., Tanyer A. M. (2018). Turkish Architectural and Civil Engineering Education within the Scope of Sustainable Construction. *The 5th International Project and Construction Management Conference - IPCMC 2018 (pp.200-208)*. Girne, Cyprus.

- Kızılkaya Öksüz N., **Topak F.**, Pekericli M. K., Tanyer A. M. (2017). Integration of Fire Vulnerability and Indoor Localization in Built Environments. *MSTAS 2017 - 11th Computational Design in Architecture National Symposium (In Turkish)* (pp. 228-237). Middle East Technical University, Ankara, Turkey.

- **Topak F.**, Pekericli M. K., Tanyer A. M. (2016). An Assessment of Bluetooth Low Energy Technology for Indoor Localization. *International Council for Research and Innovation in Building and Construction - CIB W78 Conference,* Brisbane, Australia, (ISSN: 2706-6568), http://itc.scix.net/paper/w78-2016-paper-048.

- **Topak F.**, Pekericli M. K., Tanyer A. M. (2016). A Bluetooth Low Energy Based Framework Approach for Real-time Occupancy Detection. *Sustainable Built Environments 2016 – SBE16*, Istanbul, Turkey.

- **Topak F.**, Pekericli M. K., Tanyer A. M. (2016). A Review of Indoor Localization Use Cases in the Built Environment. *International Conference on Advanced Technology & Science (ICAT'16)*, Konya, Turkey.

- **Topak F.**, Pekericli M. K., Tanyer A. M. (2016). Kapalı Alanlarda Konum Bulma Teknolojilerinin Değerlendirilmesi. *The 4th Project and Construction Management Congress (In Turkish)*, Eskisehir, Turkey.

- **Topak F.**, Pekericli M. K., Tanyer A. M. (2016). Yapılı Çevre İçin Kapalı Alanlarda Konum Belirleme Kullanım Potansiyellerinin İncelenmesi. *The 3rd National Building Congress and Exhibition (In Turkish)*, Ankara, Turkey.

ACADEMIC EXPERIENCE

Healthy Buildings Europe 2023 Conference, Aachen, Germany 2023

International Scientific Committee Member

IEA EBC - Annex 87 - Personalized Environmental Control Systems 2022 – present

Research Associate

Penn State University, State College, United States 2021-2022

Visiting Scholar at Department of Architectural Engineering
Advisors: Dr. Gregory S. Pavlak and Dr. Julian Wang

IEA EBC - Annex 79 - Occupant-Centric Building Design and Operation 2021 – 2023

Research Associate

Middle East Technical University – Scientific Research Project 2017 – 2020

Researcher (*Project Title: Identifying performance of teams at construction sites using wearable technologies)*

Gesellschaft für Internationale Zusammenarbeit (GIZ), Germany July - August 2018

Participant (*Project Title: Energy Efficiency in Buildings)*

AWARDS AND HONORS

The Scientific and Technological Research Council of Turkey (TÜBİTAK) 2021 - 2022
Visiting Scholar Fellowship for PhD Research

The Scientific and Technological Research Council of Turkey (TÜBİTAK) October 2018
International Scientific Publication Incentive Award

METU Development Foundation September 2018
Scientific Publication Award, with SCI-Indexed Article

Gesellschaft für Internationale Zusammenarbeit (GIZ) July 2018
Full Scholarship for Summer School on Energy Efficiency

METU Graduate School of Natural and Applied Sciences June 2018
Course Performance Award – with highest ranking cumulative GPA

METU Faculty of Architecture 2009 – 2013
Dean's Honor & High Honor List

Solar Decathlon China 2013 2012
One of the 20 finalist (w/Team Turkey)

TECHNICAL SKILLS

BIM Tools: Revit, ArchiCAD, Autodesk Navisworks

Vector Drawing & Visualization: AutoCAD, SketchUp, Adobe Photoshop, Tableau

Language: Python (Libraries: NumPy, SciPy, Pandas, Scikit-Learn, Matplotlib, etc.)

Simulation: ANSYS Fluent, EnergyPlus

REVIEW ACTIVITY

Building and Environment 2023

Healthy Buildings Europe 2023 2023

Energy, Sustainability and Society 2021

The 4th International Conference on Computer Science and Application Engineering 2020