Simulating the Integrated Optimization of

Energy Costs and Occupants' Productivity in Offices

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Abstract

Simulating the Integrated Optimization of Energy Costs and Occupants' Productivity in Offices

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Environmental conditions of an indoor space have impacts on the mental and physical well-being of its occupants and subsequently influence their productivity. Occupants in a shared space may have varied thermal and visual preferences for the indoor environmental conditions. Moreover, their perceptions of the indoor environment, such as their thermal and visual sensations, depend on their positions inside the space. For energy management systems of office buildings, inability to acknowledge occupants' preferences may cause productivity losses. Salaries of office workers are many times higher than the costs of energy consumption in providing comfort in the working space, hence, improving the productivity of occupants in office buildings can offer significant economic benefits. While optimizing energy consumption costs, the energy management system of an office building can provide occupants with preferred indoor environmental conditions by making timely energy-related decisions for the indoor environment. Several continuously changing inputs including indoor and outdoor environmental parameters, energy exchange processes across the building, energy prices, occupants' presence, activities, and preferences, are required to make timely decisions.

The main objective of this research is to propose a method for personalized energy and comfort management in office buildings to simultaneously optimize energy consumption costs and the productivity of office workers. A simplified RC-network thermal model of a multi-zone office building, located in Montreal, Canada is developed and its annual energy performance simulation is studied. The method presents Pareto optimal solutions for the automated control of the indoor environment, by managing the level of indoor temperature, ventilation rate, natural illumination, and artificial lighting, in different zones of the office. Within a multi-objective optimization framework, several parameters are considered by the method, including (1) energy exchange processes across the zones, (2) sets of indoor and outdoor environmental parameters, (3) energy prices, (4) indoor air quality of the zones, and (5) occupants' positions, activities, personalized thermal and visual preferences, and adaptive behavior. Under different scenarios, occupants are considered to have distinct thermal and visual preferences and behavior. The flexibility of the method to perform personalized energy and comfort management, by managing the indoor environmental conditions according to occupants' personalized thermal and visual preferences, thermal and visual behavior, and positions are determined. Based on the provided results, the proposed method is capable of improving the productivity of occupants, by up to $1000 per year per person (assuming fixed productivity rate of 20 $/h), while simultaneously optimizing the energy consumption costs.

Keywords: Energy Management, Building Simulation, Integrated Building Control, Productivity, Energy Conservation, Multi-Objective Optimization, Occupant Behavior Modeling

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English Symbols

a_{cold}, a_{warm}, b_{cold}, b_{warm}	Thermal regression parameter [-]
a_{bright}, a_{dark}, b_{bright}, b_{dark}	Visual regression parameter [-]
A_s	Area of the surface [m^2]
c	Specific heat of the fluid [J/kg.K]
c_{zone}	Average specific heat of the zone [J/kg.K]
E	Energy consumption [kWh]
h_c	Heat transfer coefficient [$W/m^2.K$]
$ILL_{\text{maxcomfort}}$	The illuminance level of maximum visual comfort [lux]
$\dot{m}$	Mass flow rate [kg/s]
$Prob_{1^{st}\text{ category behavior}}$	Probability of 1^{st} category adaptive behavior [-]
$Prob_{2^{nd}\text{ category behavior}}$	Probability of 2^{nd} category adaptive behavior [-]
$Prob_{\text{Cold}}$	Probability of being cold [-]
$Prob_{\text{Thermal\_Comfort}}$	Probability of being thermally comfortable [-]
$Prob_{\text{Thermal\_Discomfort}}$	Probability of being thermally uncomfortable [-]
$Prob_{\text{Visual\_Comfort}}$	Probability of being visually comfortable [-]
$Prob_{\text{Visual\_Discomfort}}$	Probability of being visually uncomfortable [-]
$Prob_{\text{Warm}}$	Probability of being warm [-]
$q_{\text{in-zone}}$	Heat generated in the zone [W]
Q	Ventilation rate [m^3/s per m^2]
RP_{Behavior}	Situation-specific relatively productivity [-]
RP_{IAQ}	Relative productivity with respect to indoor air quality [-]
RP_{Overall}	Overall relative productivity [-]
RP_{thermal}	Relative productivity with respect to thermal conditions [-]

RP_{visual}	Relative productivity with respect to visual conditions [-]
t	Time [hour]
T	Indoor temperature [°C]
$T_{\text{maxcomfort}}$	Maximum comfort temperature [°C]
T_{s}	The surface temperature [K]
T_{zone}	Average temperature of the zone [K]
$Tolerance_{\text{thermal}}$	Tolerance range with respect to thermal conditions [K]
$Tolerance_{\text{visual}}$	Tolerance range with respect to visual conditions [K]
V_{zone}	Volume of the zone [m^3]

Greek Symbols

α	The curvature of the utility for the gains, in the prospect theory [-]
β	Productivity booster [-]
γ	A parameter, related to the weight function of a choice, in the prospect theory
δ	A parameter, related to the weight function of a choice, in the prospect theory
λ	Loss aversion coefficient, in the prospect theory [-]
$\lambda_{\text{adaptive}}$	Adaptive coefficient [-]
ρ_{zone}	Average density of the zone [kg/m^3]
τ	The curvature of the utility for the losses, in the prospect theory [-]

Abbreviations

ABM	Agent-Based Modeling
AI	Artificial Intelligence
AmI	Ambient Intelligence
ANN	Artificial Neural Network
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
CI	Computational Intelligence

CIBSE	Chartered Institution of Building Services Engineers
CO_2	Carbon Dioxide
EMCS	Energy Management and Control System
EMS	Energy Management System
GA	Genetic Algorithm
HVAC	Heating, Ventilation and Air Conditioning
IAQ	Indoor Air Quality
IEMS	Intelligent Energy Management System
IEQ	Indoor Environmental Quality
IoT	Internet of Things
LR	Likelihood Ratio
MABM	Multi-Agent-Based Modeling
MOOP	Multi-Objective Optimization
MRT	Mean Radiant Temperature
NEMS	National Energy Modeling System
P	Proportional
PI	Proportional-Integral
PID	Proportional-Integral-Derivative
PMV	Predicted Mean Vote
PPD	Predicted Percentage Dissatisfied
PSO	Particle Swarm Optimization
RP	Relative Productivity
SBS	Sick Building Syndrome
SOOP	Single-Objective Optimization
SS MOOP	Situation-Specific Multi-Objective Optimization
VAV	Variable Air Volume

1 Introduction

An energy intelligent building is taken as an independent entity, which is able to manage its operation to ensure its occupants comfort and minimize energy consumption [1]. Reducing energy consumption and improving occupants' comfort conditions are often in conflict with each other. Hence, energy management systems of energy intelligent buildings should have the capability to consider both of these objectives simultaneously, while making energy-related decisions for the indoor environment.

Paying excessive attention to energy conservation may have adverse impacts on the Indoor Environmental Quality (IEQ) of the buildings. Thermal, visual conditions, and Indoor Air Quality (IAQ) of an enclosed space, as IEQ parameters, could be influenced by energy conservation actions. Using computational intelligence techniques, or computational optimization methods, such as Multi-Objective Optimization (MOOP), two objectives of occupants' comfort conditions and energy consumption can be combined to find optimal solutions for the control of the indoor environment [2, 3].

Nowadays, energy consumption is an ever-increasing parameter in a global context, since climate change has become a real threat to the earth and its inhabitants, including billions of people living on it [4]. The building sector accounts for a large part of energy demands and can play a major role in mitigating the climate change threat. Reports show that in Canada, residential, commercial, and public buildings consume 46% of total energy produced [4].

Over the recent decades, there has been a continuous development of the building technologies with more efficient energy consumption, while energy efficiency programs and renewable energies have been presented as clean ways to decrease energy consumption [4]. One of the most promising approaches in building energy efficiency is to make buildings *energy intelligent*, by performing intelligent control of building facilities and communicating with occupants.

The National Energy Modeling System (NEMS) definition for commercial buildings, describes the commercial building as "the type of building, which is engaged in other businesses rather than industrial or transportation" [5]. Based on the NEMS data for the United States, commercial buildings account for 35% of total energy consumption. During the peak demand period, the share is increased to 45% [5]. Hence, the commercial building sector has been very appealing to intelligent building research [6].

The beginning of the 1980s was the starting point of research on making buildings intelligent [1]. Development of information technology and concerns about energy resources, supported the intention to provide a more comfortable living environment for the occupants while consuming less energy. Early intelligent building research only focused on the automated operation of building, ignoring occupants and building interactions. However, researchers discovered the adverse effects of this approach. Today, during the design and operation of intelligent buildings, productivity, morale, and satisfaction of occupants have the same importance as energy conservation objectives.

Considering main occupants' requirements and building facilities, intelligent buildings can be classified into *automated buildings*, *smart homes*, *green buildings*, *energy efficient buildings*, and *energy intelligent buildings* [1, 7]. Automated buildings concentrate on the automated operation of building electrical and mechanical facilities, while the focus of smart homes is on designing a user-friendly environment for occupants. Green or sustainable buildings research is mainly about creating an environmental-friendly process during the life cycle of the building; from its design, construction, and operation, to maintenance, renovation, and demolition. The energy efficient building area of research also focuses on the whole life cycle of the building, with the goal of minimizing energy consumption for that period.

The type of intelligent buildings, which is of interest to this research, is *energy intelligent buildings*. Energy intelligent buildings are able to contribute to the idea of demand engagement into energy supply chain, in order to maintain a balance between supply and demand, and ensure the reliability of electrical grid operation. The main objectives of an energy intelligent building are to provide its occupants' comfort conditions and minimize energy consumption. For these purposes, an energy intelligent building should (1) perceive its environment through indoor environment monitoring system; (2) acknowledge occupants' needs and communicate with them; (3) make energy-related decisions by its Energy Management System (EMS); (4) take energy-related actions through its Energy Management & Control Systems (EMCS), and (5) have a learning capability to improve its performance (Fig. 1).

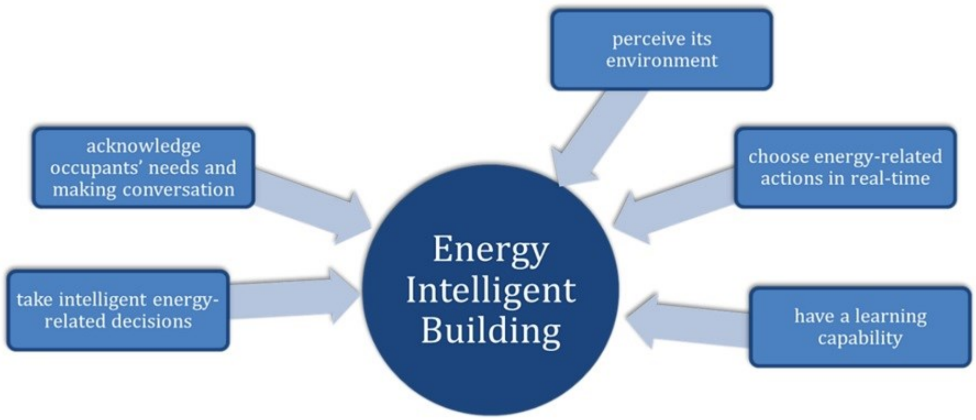

Fig. 1: Energy intelligent building requirements

1.1 Intelligent Energy Management

In commercial and residential buildings, providing occupants with satisfactory indoor environmental conditions is the main reason for energy consumption. At the same time, during the design and operation of the building, maintaining occupants' comfort conditions is of utmost importance. The overall comfort of an occupant represents his or her quality of life inside a building. Occupants interact with the indoor environment through their senses. They can see, touch, smell, and hear their environment, or they can find the environment warm or cold through their skin. These different sensations lead to a greater or lesser degree of comfort, which are independent of each other. Hence, there are several factors that have positive or negative impacts on occupants' overall satisfaction, including the level of thermal comfort, visual comfort, aural comfort, and IAQ. These factors together define IEQ, inside an enclosed space.

Inside an energy intelligent building, occupants and the indoor environment are the main factors for the energy-related decision-making of the Intelligent Energy Management System (IEMS). IEMS requires data from the indoor environmental parameters, before making decisions. The first requirement of a successful decision-making is to acquire sufficient information about the environment or to have the Ambient Intelligence (AmI), through building monitoring system.

Decisions made by energy management systems may not be acceptable to occupants, consequently, they might adjust their indoor environment to meet their personal comfort. Hence, IEMS should communicate with occupants to have up-to-date information on their preferred indoor environmental conditions.

Fig. 2 illustrates the simplified version of the interactions between IEMS, occupants, and indoor environment. Apart from indoor environmental parameters and occupants' preferences, external environmental parameters such as solar irradiance, outdoor temperature, and energy prices could play key roles in energy-related decisions. The acquired data should be processed and analyzed through intelligent processing and computational techniques, in order to make timely decisions for intelligent energy and comfort management.

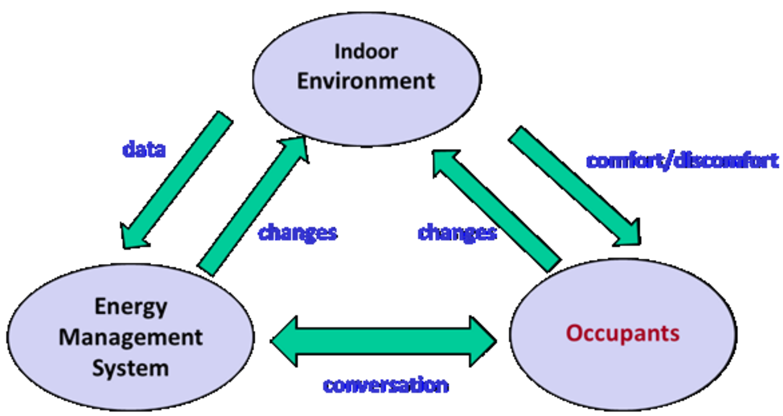

Fig. 2: Intelligent Energy Management System (IEMS) interactions with indoor environment and occupants

1.2 Problem Statement

In buildings, reducing energy consumption and improving occupants' comfort conditions are two sides of the same coin. Paying excessive attention to energy consumption reduction may have adverse impacts on IEQ of the buildings, since thermal and visual conditions, and IAQ of enclosed spaces could be influenced. Occupants' comfort conditions have impacts on their performances, hence, in office buildings, there is a direct relationship between IEQ and productivity of the office workers. Fisk et al. [8] estimated that economic benefits of 17 to 26 billion dollars are achievable annually, by improving IEQ of office buildings across the United States.

The typical approach for energy and comfort management in office buildings is to optimize building energy consumption costs, by considering occupants' comfort conditions as constraints on the indoor environmental parameters (e.g. temperature set-points, minimum ventilation rate, or minimum illumination level). This approach doesn't necessarily produce optimal indoor environmental conditions for occupants. In this research, methods for simultaneous optimization of energy costs and occupants' comfort are proposed. The proposed methods consider the combined effect of thermal conditions, visual conditions and IAQ on occupants' comfort and find optimal solutions for the control of the indoor environment.

Having energy consumption minimization and occupants' comfort maximization objectives, a problem arises when these two objectives are compared. IEMS of energy intelligent building should consider both objectives to make intelligent decisions for optimized building energy performance. Since energy consumption and occupants' comfort conditions cannot be expressed in the same unit, comparing these objectives is complicated. Hence, effective techniques, as well as computational methods, are required to combine and simultaneously optimize energy consumption and occupants' comfort conditions.

Intelligent energy management systems should consider interactions between different parameters of the indoor environment, as well as energy exchange processes across the building. Several continuously changing inputs are required to make intelligent energy-related decisions including energy prices, sets of indoor and outdoor environmental parameters, occupants' presence, preferences, and behavior inside the building. Because of the ever-changing nature of these parameters, the related problem formulation is being changed all the time. Therefore, a well-structured framework is required to reach the optimum conditions for energy consumption and occupants' comfort, under any circumstance. Here, by combing building energy performance simulation, occupant behavior modelling, and comfort conditions, a method to connect and simultaneously optimize energy consumption and occupants' productivity is developed.

Another challenge is related to occupants' integration into building energy performance decision-making systems. In order to provide satisfactory comfort conditions for occupants, IEMS should consider each individual's up-to-date preferences for indoor environmental conditions. Over time, each occupant's preference model should be developed, according to his or her feedback on the indoor environmental conditions. Each individual's overall comfort requirement is the combination of different criteria, such as thermal comfort, visual comfort, and IAQ. When making decisions, IEMS should consider all occupants' preferences to optimize indoor environmental conditions and energy consumption.

1.3 Research Objectives

The main interest of this research is to develop a method for personalized energy and comfort management in office buildings. The method performs Multi-Objective Optimization (MOOP) of energy consumption and occupants' comfort conditions, with the goal to simultaneously minimize energy costs and overall productivity losses of occupants (office workers). Indoor environmental conditions have impacts on the performances of occupants in certain tasks, which subsequently, influence their overall productivity. Using the level of productivity to represent occupants' comfort conditions, it would be possible to express both energy consumption costs, and occupants' comfort conditions in a monetary unit. Hence, making a comparison between these two objectives is possible.

In order to evaluate the capabilities of the proposed method for personalized energy and comfort management, the method is applied to the energy management system of a single-floor office building. The simulated multi-zone office is located in Montreal, Canada. A simplified RC-network thermal model of the office building is developed, using MATLAB software. In different zones of the office, the proposed method performs automated control of the indoor environment by managing the level of indoor temperature, ventilation rate, natural illumination, and artificial lighting, on an hourly basis. Within a well-structured framework, (1) energy exchange processes across the building, (2) energy prices, (3) sets of indoor and outdoor environmental parameters, (4) IAQ, occupants' (5) presence, (6) thermal and visual preferences, (7) behavior inside the building, are considered for decision-making.

The proposed method constructs and updates each occupant's thermal preference, and visual preference model, based on his or her feedback on the indoor environmental conditions. Occupants' preference models reveal both their preferences and behavior, inside enclosed spaces. The proposed method combines thermal preference model, visual preference model, and the level of IAQ to consider the overall comfort requirement of each individual. Each occupant's specific overall comfort requirement is introduced into the decision-making problem formulation, to perform *personalized energy and comfort management*.

In shared spaces, occupants may have varied thermal and visual preferences for the indoor environmental conditions. For energy management systems of office buildings, inability to acknowledge occupants' preferences may lead to significant productivity losses. The proposed method acknowledges all occupants' thermal and visual preferences to improve the collective productivity of occupants in a shared space.

An occupant's perception of the indoor environment, such as his or her thermal and visual sensations, depends on his or her position inside an enclosed space. To further improve the performance of the proposed method in optimizing occupants' productivity and energy consumption, positions of occupants are also considered in *position-based energy and comfort management*. Moreover, different activity types are also weighted, by considering varied hourly productivity for occupants.

The proposed method can offer *behavioral intelligence* by acknowledging occupants' energy-related behavior, while making energy-related decisions for the automated control of the indoor environment. In the proposed *situation-specific* energy and comfort management, adaptive behavior of an occupant varies according to the specific situation in the indoor environment. Hereby, alongside the environmental parameters, the influence of human-related parameters (e.g. moods and emotions) on the adaptive behavior of occupants, can also be considered.

To summarize, the proposed methods for personalized energy and comfort management in office buildings, have the following objectives:

Objective 1. Providing economic-optimum conditions for the operation of office buildings, by simultaneously reducing energy costs and improving overall productivity;

Objective 2. Performing personalized energy and comfort management, by acknowledging occupants' thermal and visual preferences from their feedback;

Objective 3. Performing position-based energy and comfort management, considering occupants' positions, as well as their thermal and visual preferences; and

Objective 4. Introducing behavioral intelligence into energy and comfort management, by acknowledging occupants' energy-related behavior in an indoor environment.

1.4 Structure of Thesis

In order to reach each research objective, multiple steps have been established. The objectives, related steps, and prerequisite, together form the structure of thesis.

Prerequisite: Modeling the Office Building & Control Systems (*Chapter 3 & Chapter 4*)

- *Step 1:* Develop a simplified RC-network thermal model of an office building, using MATLAB software, for building energy performance simulation.
- *Step 2:* Validate the RC-network thermal model of the office building, by comparing its annual energy performance, with the energy performance of an office building with the same characteristics simulated in e-Quest software.
- *Step 3:* Add integrated control of Heating, Ventilation and Air Conditioning (HVAC) systems, lighting systems, blinds, and natural ventilation to the office building model.
- *Step 4:* Perform Single-Objective Optimization (SOOP) of energy consumption costs in the office building, using the automated control system.
- *Step 5:* Simulate annual energy performance of the office building, using the SOOP method for energy management, to realize its potentials and limitations.

Objective 1: MOOP of Energy Costs & Occupants' Productivity (*Chapter 3 & Chapter 4*)

- *Step 1:* Construct the objective function of the proposed MOOP method to simultaneously optimize occupants' productivity and energy consumption costs.
- *Step 2:* Present a method for MOOP of energy costs and productivity losses, considering the thermal comfort of occupants.
- *Step 3:* Propose a method for MOOP of energy costs and productivity losses, considering the thermal comfort of occupants, and IAQ of the zones.

- *Step 4:* Evaluate the effectiveness of the methods, proposed in Step 2 and Step 3, by comparing their performances to the performance of the SOOP method, with respect to energy costs and occupants' comfort conditions.

Objective 2: Personalized MOOP of Energy Costs & Occupants' Productivity (*Chapter 3 & Chapter 5*)

- *Step 1:* Find an effective technique to construct and update thermal preference models of occupants, from their feedback on the indoor environmental conditions.
- *Step 2:* Identify occupants' thermal preferences and thermal tolerance, as personalized parameters, to construct their thermal preference models.
- *Step 3:* Propose a method for personalized optimization of energy costs and occupants' productivity, considering the thermal preferences of occupants and IAQ of the zones.

Objective 3: Position-Based MOOP of Energy Costs & Occupants' Productivity (*Chapter 3 & Chapter 6*)

- *Step 1:* Present a method to construct visual preference models of occupants.
- *Step 2:* Propose a method for personalized optimization of energy costs and occupants' productivity, based on the thermal and visual preferences of occupants, and IAQ.
- *Step 3:* Develop a method to evaluate the thermal and visual comfort of occupants, based on their positions inside enclosed spaces.
- *Step 4:* Perform position-based optimization of energy costs and occupants' productivity, considering thermal comfort, visual comfort, and IAQ.

Objective 4: Situation-Specific MOOP of Energy Costs & Occupants' Productivity (*Chapter 3 & Chapter 7*)

- *Step 1:* Identify human-related parameters that influence energy-related behavior of occupants inside enclosed spaces.
- *Step 2:* Develop a model, inspired by the fields of behavioral science and neuroeconomics, which simulates an occupant's decision-making process, prior to energy-related actions.

- *Step 3:* Insert the proposed model in Step 2, in energy costs and occupants' productivity optimization problem, to introduce behavioral intelligence to energy and comfort management.

1.5 Thesis Outline

In Chapter 2, a literature review related to the research objectives is presented. The topics covered in the literature review are: (1) Occupant comfort conditions, categorized into thermal comfort, visual comfort, and IAQ; (2) The relationship between occupants' comfort conditions and their productivity; (3) Comfort control strategies in buildings and the difference between conventional and intelligent control; (4) Computational methods for parallel optimization of energy and comfort; and (5) Personalized energy and comfort management, which also covers the studies on modeling occupants' behavior, and monitoring the indoor environment.

In Chapter 3, research methodologies are presented. First, developing a simplified RC-network thermal model of a single-floor office, with five zones, located in Montreal, Canada, is discussed. Simulating integrated control of the office for automated control of the indoor environment is described. Second, the general framework for the problem formulation of the proposed MOOP method, for energy and comfort management is provided. Subsequently, MOOP of energy costs and occupants' productivity, considering the thermal comfort of occupants, and IAQ is presented. The third part of Chapter 3, covers personalized energy and comfort management, based on MOOP of energy costs, thermal comfort, and IAQ, according to occupants' feedback. In the fourth part, a method for position-based energy and comfort management is presented. The techniques for position-based evaluations of the thermal and visual comfort of occupants are described, separately. Afterward, a method for position-based MOOP of energy costs and occupants' productivity, considering their thermal preferences, visual preferences, and IAQ is proposed. In the last part of Chapter 3, a technique to model occupant decision-making process is presented. Accordingly, occupants' energy-related behavior is introduced into MOOP of energy costs and productivity to enhance the behavioral intelligence of the method. The updated method is called *situation-specific* MOOP of energy costs and occupants' productivity.

Chapter 4 provides results of annual energy performance simulation of the office building, using the proposed method for MOOP of energy costs, thermal comfort, and IAQ. It is demonstrated that the proposed method generates Pareto optimal solutions for the automated control of the indoor environment. Thermal comfort of occupants and IAQ requirements in the office are studied. Using the MOOP method and the SOOP method (with the objective of energy costs minimization), the productivity of occupants and energy costs are compared. The last part of Chapter 4 concentrates on the need for personalized energy and comfort management, by analyzing the sensitivity of the proposed method to occupants' thermal preferences, their thermal behavior, and IAQ.

In Chapter 5, the proposed method for personalized MOOP of energy costs, thermal comfort, and IAQ is examined, by simulating its operation as the energy management system of the office building. From thermal comfort and IAQ evaluations in different zones of the office, the ability of the method to provide occupants' preferred indoor environmental conditions, while minimizing energy costs, is analyzed. Under varied occupancy scenarios of having single or multiple thermal preferences in the same space, indoor environmental conditions are evaluated. In the final part of Chapter 5, the importance of occupants' productivity rates and thermal behavior is indicated, by performing a sensitivity analysis on the performance of the method, with respect to varied productivity rates and thermal behavior of occupants.

Chapter 6 provides results of position-based MOOP of energy costs, thermal comfort, visual comfort, and IAQ. The performance of the position-based method, with respect to occupants' preferred thermal and visual conditions, and IAQ is studied. The same analysis is performed, with regard to productivity and energy costs optimization, by examining the hourly performance of the method in varied outdoor weather conditions. Moreover, capabilities of the position-based method to acknowledge occupants' productivity rates, positions, varied thermal and visual preferences, and varied thermal and visual behavior, are evaluated. Thereby, the suitability of the proposed position-based method for personalized energy and comfort management in offices is confirmed.

In Chapter 7, first, the proposed method for situation-specific energy and comfort management is discussed. If an occupant is not comfortable with any aspects of the indoor environment in an enclosed space, he or she might adjust the indoor environment to improve his or her personal comfort. The potential adjustments the occupant made, may be in conflict with the objective of energy costs minimization. While managing the indoor environment, the method should avoid energy-related actions of the occupants. By presenting a framework to model occupants' energy-related behavior, the situation-specific method has the behavioral intelligence to acknowledge occupants' situation-specific adaptive behavior, while making decisions for the automated control of the indoor environment. The proposed situation-specific method is studied in detail, by hourly energy performance simulation of the office building, and hourly thermal comfort, visual comfort, and IAQ evaluations of different zones of the office. Human-related parameters, such as occupants' mood, emotions, desire, self-control, willpower, deprivation of comfort, and short-term adaptation to the environment, can all influence their situation-specific adaptive behavior. It is claimed that the situation-specific method can acknowledge occupant behavior changes in different situations. This is examined by analyzing the sensitivity of the method to thermal and visual behavior changes of occupants.

Chapter 8 provides discussions and conclusions of the research, as well as directions for future work.

1.6 Application of the Research

In order to apply the proposed methods to an office building, the first requirement is to continuously measure the indoor environmental parameters that affect occupants' comfort conditions. Here, indoor temperature (°C), illuminance level (lux), and ventilation rate (m^3/s per m^2), are used to evaluate the overall productivity of each occupant. Hence, real-time data on the level of indoor temperature, air flow, and illuminance, are required in each zone of the office.

For real-time monitoring of the indoor environmental parameters, a wireless sensor network is required. A wireless sensor network consists of hardware and software infrastructures that are communicating, using communication protocol for personal area network monitoring and control. The main component of a wireless sensor network is a sensor module. The sensor module is responsible for collecting and transmitting environmental data [9, 10]. Each sensor module hosts a set of environmental sensors. Environmental sensors are chosen based on the type of data desired. For this research, a temperature sensor, a light sensor, and an air flow sensor are the environmental sensors, considered in each sensor module.

The second requirement is to have information on the preferences of occupants, and their relative productivity with respect to indoor environmental parameters. Generally, there are two approaches to collecting these data. The first approach is by performing a series of field studies on occupants' performances while modifying ambient parameters, such as indoor temperature or ventilation rate [11-14]. These field studies should be short-term (or often one-time) experiments, otherwise, they might be tedious. Moreover, they are not capable of simulating all aspects of office workers' daily jobs. Another approach is from continuous interaction with occupants, and collecting their feedback on indoor environmental conditions.

In order to apply the proposed methods to an office building, continuous interactions with occupants are considered to generate and update their comfort preference models. A smartphone application and/or a web-based application may be used as an intermediary to collect occupants' thermal and visual sensation votes. Any time of the day, occupants may voluntarily express their thermal and visual perceptions of the indoor environment through the application software. It is considered that real-time thermal and visual sensation votes of each occupant are correlated to real-time indoor temperature (°C) and indoor illuminance (lux), received from the sensor module of the occupant's zone, and are archived, and analyzed in the central server. The central server constructs each occupant's thermal and visual preference models, from the history of his or her thermal and visual sensation votes. By receiving fresh thermal and visual sensation votes, thermal and visual preference models of occupants can continuously be updated. From each occupant's thermal and visual preference models, his or her relative productivity with respect to indoor temperature (°C) and illuminance (lux), is derived. The methods, proposed for developing thermal and visual preference models of occupants from their feedback, and relating their relative productivity to indoor environmental conditions, are described in Chapter 3.

A scenario is considered, in which the proposed method is running on the central server. Under this scenario, the method makes energy-related decisions for the indoor environmental conditions of each zone, based on the indoor environmental parameters, occupants' comfort preferences, and real-time weather data from the local meteorological station. It is assumed that the decisions are transmitted to the building energy management system, through a standard communication protocol. Subsequently, they are translated into commands from the building energy management system, for the actuators and controllers across the zones.

In office buildings, there could be different situations of occupancy in each zone. If there is a single occupant in a zone, there is only one comfort preference to be considered for energy and comfort management. But if there are multiple occupants inside a zone, there might be varied comfort preferences. In the case of having multiple occupants in an enclosed space, there are two approaches to controlling indoor environmental conditions. Building energy management system can either perform zone-level (group-level) control or personalized control [10].

If the control of the indoor environment is at zone-level, occupants with varied indoor environmental preferences are subject to reduced relative performances, which cause overall productivity losses of occupants. Using the personalized method, proposed in Chapter 3 and analyzed in Chapter 5, the collective productivity of occupants and energy consumption costs are simultaneously optimized. Having occupants with varied thermal and visual preferences is studied, and the importance of their positions for personalized decision-making is discussed, in Chapter 6. The position-based energy and comfort management method makes energy-related decisions, according to occupants' comfort preferences, as well as their positions inside the zones.

2 Literature Review

Theoretical background, related to the subject of this research, is provided within five parts:

1. Occupant comfort conditions
2. Occupant productivity as the by-product of comfort conditions
3. Comfort control strategies
4. Computational optimization methods for energy and comfort management
5. The quest to personalize energy and comfort management

2.1 Occupant Comfort Conditions

There are several factors that affect occupants' overall comfort, including the level of thermal comfort, visual comfort, aural comfort, and IAQ. Energy management systems can provide occupants with acceptable thermal and visual conditions, and IAQ, by making proper energy-related decisions. In this section, theories related to these three aspects of occupants' comfort conditions, are described.

2.1.1 Thermal Comfort

Thermal comfort of an occupant is "that condition of mind which expresses his or her satisfaction with the thermal environment" [15, 16]. According to this definition, comfort is both a feeling through the skin and a condition of mind through a cognitive process. The human body has two types of sensors in the skin and in the brain, called skin sensors and hypothalamus sensors. The inner body's temperature is around 37 ºC. The skin sensors start sending impulses to the brain when the skin temperature is below 34 ºC. The hypothalamus sensors send signals when the body temperature exceeds 37 ºC [17]. A person is in the thermal neutral condition when the magnitude of these two signals is the same. One of the two conditions of being satisfied with the thermal conditions is being in the state of thermal neutral condition.

The human body is also in a continuous exchange of heat with its environment. Heat is lost through evaporation (e.g. sweating), and respiration. There are heat exchanges through convection and conduction, between the body, clothes, and the environment, and through radiation, between the body, clothes, and the environment surfaces. On the other hand, the human body generates heat through metabolism, by transforming energy to heat. The second condition of thermal comfort is satisfied, when the metabolic rate is in balance with the rate of heat lost from the human body.

Several indicators have been developed to represent thermal comfort conditions in a particular environment. The most popular one is Predicted Mean Vote index (PMV-index), introduced by Fanger, in the 1970s [18]. He attempted to formalize the subjective steady-state thermal sensation of a group of people in an environment, in where they were staying for a long period of time. According to this model, environmental parameters of indoor air temperature (ºC), air velocity (m/s), mean radiant temperature (ºC), relative humidity (%), as well as personal parameters of metabolic rate (met or W/m^2), clothing insulation (clo or m^2 ºC/W), are the main variables to predict the thermal comfort of occupants [16, 18]. Having these four environmental parameters, and two personal parameters available, PMV can be calculated [16]. PMV is in the range of -3 to +3, where -3 is being very cold, zero is neutral thermal sensation, and +3 is being very warm:

PMV	**Thermal Sensation**
-3	very cold
-2	cold
-1	slightly cold
0	neutral
1	slightly warm
2	warm
3	very warm

In order to maintain satisfactory thermal conditions in an environment, different standards recommend a PMV index equal to zero, with a tolerance range of ±0.5 [16, 19]. Another index, called the Predicted Percentage Dissatisfied (PPD), can also be derived from PMV. PPD value (%), predicts the percentage of people that are not satisfied with the thermal conditions of an indoor environment [16]:

$$PPD = 100 - 95 \, . \, exp \; [-(0.0335 \, PMV^4 \; + 0.218 \; PMV^2)] \tag{2.1}$$

During the last twenty-five years, different studies on finding additional influential parameters on the thermal sensation of occupants, have been conducted. Based on these studies, parameters such as age, gender, outdoor weather conditions, social dimensions, economical background, history of thermal sensations, perceived control over the environment, psychological and physiological adaptation to the environment, and behavioral adjustment, are identified as the parameters that influence the thermal sensations of occupants [16, 20]. Studies of different scientific groups on adaptive thermal comfort, resulted in the addition of a new standard of adaptive thermal comfort, ANSI/ASHRAE Standard 55-2004, to the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) standards [21].

Recently, Chinese scientists have been very active on the adaptive thermal comfort research. Based on the previous studies on adaptive thermal comfort, they presented a new adaptive thermal comfort index, called adaptive-PMV or αPMV, which is the combination of Fanger's PMV models, and personalization of thermal sensation. Based on their theory, Adaptive Predicted Mean Vote (αPMV) is calculated from:

$$\alpha PMV = \frac{PMV}{1 + \; \lambda_{\mathrm{adaptive}} \, . \, PMV} \tag{2.2}$$

In which, $\lambda_{\mathrm{adaptive}}$ is adaptive coefficient; $\lambda_{\mathrm{adaptive}}$ is composed of psychological adaptation, physiological adaptation, and behavioral adjustments parameters [20].

2.1.2 Indoor Air Quality

IAQ requirements of an enclosed space are met when the air is perceived as fresh and pleasant by occupants, and breathing the indoor air has no negative impact on their health [22]. Indoor air pollution can have adverse impacts on occupants' health and productivity. Over the last decades, the term Sick Building Syndrome (SBS) has been heard repeatedly. SBS means a general feeling of malaise that occupants experience as a result of poor IAQ. SBS reduces comfort levels and can cause poor general health [23].

Major sources of indoor air pollution are human activities, materials used in the building, microbiological organisms such as mold and dust, and outdoor pollution. Source control and air ventilation are the effective methods to control the level of indoor pollutants, and improve IAQ. Using ventilation systems, conditioned outdoor air, instead of already polluted air, can continuously be provided for occupants. The rate of fresh and filtered air introduction by a ventilation system is defined by the rate of air change in volume and time (l/s), or by a number of times the volume of air within that space is changed in one hour (ach) [23].

Occupants are addressed as the primary source of indoor pollution; hence, Carbon Dioxide (CO_2) is taken as the main indicator for IAQ analysis. CO_2 is the natural constituent of the air we breathe (0.04% of natural air). CO_2 is also a by-product of combustion of carbonic compounds and is generated from human breathing, with the rate of 20 l/h [23]. Although there could be many dangerous contaminants in the indoor environment, CO_2 is the most common gaseous contaminants for IAQ tests and assessments.

The minimum required ventilation rates have been drastically changed, during the last decades. The costs of energy resources, technology, and lifestyle advancements, and HVAC system design changes have been the main reasons behind these variations [24]. According to ASHRAE Ventilation Standard 62.1, the ventilation rate should not be less than 7.5 l/s (15 cfm) per person [23]. The size of a dwelling is another factor for designing a ventilation system; a room with larger floor area requires a higher rate of air change per hour.

2.1.3 Visual Comfort

According to the European Committee for Standardization, visual comfort can be specified as "a subjective condition of visual well-being, induced by the visual environment" [25]. The lighting system of a building should provide safety for its occupants, help them with their visual tasks, and provide an appropriate and pleasant visual environment for them [4].

Daylighting, artificial lighting, and blind usage, are the means to provide and control the visual comfort of occupants. Traditionally, the control of lighting system is based on a few numbers of laws. First, more important tasks require brighter visual conditions. Second, the contrast makes objects more visible and easier to see, and last but not least, glare should be forbidden, as it hurts occupant's visual perception [4]. These days, scientists are conducting research on human-centric lighting systems. Within these research studies, the influence of personalized and psychological parameters, such as affective processes, mood, environmental appraisal, and perceived control, on the visual perception of occupants, have been studied [26].

Illuminance level and its uniformity, glare, the color of light, color rendering, flicker rate, and the amount of daylight, are the parameters to evaluate the visual comfort of occupants. Based on the type of building (school, office, hospital, etc.), and the type of activities performed in each area, international standards define a minimum illuminance level to be provided for the occupants. According to the Chartered Institution of Building Services Engineers (CIBSE), the minimum required illuminance in an office, for typical office works, such as writing and reading, is 500 lux, while for more technical works, such as architectural drawing, the minimum required illuminance is 750 lux [4].

2.2 Occupant Productivity as the By-Product of Comfort Conditions

Comfort is related to an occupant's quality of life inside an environment. Comfort is the combination of an occupant's sensations and the health risks of an environment. The productivity of an occupant is defined as "the extent to which activities have provided performance in terms of system goals" [27]. During the last three decades, there have been several studies to quantify the relationships between occupants' productivity and their level of comfort [11, 12, 17, 28, 29].

Relative Productivity (*RP*) is a term to compare an occupant productivity with his or her maximum level of productivity. Relative productivity has a value between 0 and 1, and is also expressed in percentage (%). Normally, RP of 100% is assigned to the optimum thermal comfort. Some researchers found a single value of optimum comfort temperature, while some other studies found a temperature range, in which productivity is maximum [12, 28-30].

Kosenen et al. [12] conducted research on the relationship of thermal comfort and mental performances. They separated mental performances, by the lower cognitive operation of typing and the higher cognitive process of thinking, and derived a quantitative relationship between RP in these two tasks, and thermal sensation votes of occupants. In their analysis, fixed values of air velocity, metabolic rate, clothing, and relative humidity, were assumed in PMV calculation.

Accordingly, they conducted a parametric analysis on selected occupants to find relationships between their performances and thermal sensations. Derived relationships between *RP losses* (%) of performance, in typing and in thinking tasks, and thermal sensation votes (*PMV*) are:

$$RP\ Losses\ in\ Typing\ Task\ (\%) = -60.5\ (PMV)^6 + 198.4\ (PMV)^5 - 183.7(PMV)^4 - 8.1\ (PMV)^3 + 50.2\ (PMV)^2 + 32.1\ (PMV) + 4.9 \quad (2.3)$$

$$RP\ Losses\ in\ Thinking\ Task\ (\%) = 1.6\ (PMV)^5 - 1.5(PMV)^4 - 10.4\ (PMV)^3 + 19.2\ (PMV)^2 + 13.4\ (PMV) + 1.9 \quad (2.4)$$

Another attempt to find a relationship between thermal sensation votes and productivity was carried out by Jansen et al. [29]. Their conducted research was significant in two terms. First, they used data of 12000 buildings around the world, which shows the comprehensiveness of their research. Moreover, instead of using fixed values for parameters in PMV calculations, details of activity level, clothing, air velocity, and age (as a factor of metabolic rate), were used to calculate more accurate thermal sensation votes. According to their studies, the relationship between *PMV* and *RP* is:

$$RP = -0.007\ (PMV)^2 - 0.0012\ (PMV) + 0.99 \quad (2.5)$$

Jansen et al. model has its maximum mental productivity, at a temperature between 21-22 °C.

Seppanen et al. [28] conducted another valuable research on the impact of comfort on occupant productivity. They performed a meta-analysis of 26 studies that previously conducted on the relationship between indoor temperature and occupant performance. These studies were varied in the method used, the sample size, and the type of occupants' tasks. They categorized studies, based on the type of performances considered, varied from simple tasks, visual tasks, and complex tasks. Subsequently, they assigned a weight to each study, in a manner that studies that considered more complex tasks, received larger weights. Based on their work, the relationship between *RP* and indoor temperature (*T*, in °C) is:

$$RP = 0.16\,T - 0.0058\,T^2 + 0.000062\,T^3 - 0.47 \tag{2.6}$$

In their analysis, *RP* (maximum relative performance) is equal to 1 when the indoor temperature is 21.7 °C.

Seppanen et al. [31] developed a relationship between ventilation rate and occupant productivity. Their meta-analysis was over nine field studies, including schools, laboratories, and call centers, concluding that higher ventilation rates improve concentration and vigilance of occupants. They assumed a reference point of 6.5 l/s per person, and assigned it to the relative productivity of 1, and found the impact of improved ventilation rate on the performance of occupants. Based on their analysis, the relationship between ventilation rate (*Q*) and *RP* is:

$$RP = 0.021 \ln Q + 0.960 \quad 6.5 \text{ l/s per person} \leq Q \leq 45 \text{ l/s per person} \tag{2.7}$$

Where; *Q* is the ventilation rate in l/s per person. According to this study, ventilation rates above 45 l/s per person do not have any influence on the performance of occupants [31].

Another study was conducted by Lan et al. [14, 30]. This research is significant since the productivity definition is expanded to a larger number of parameters. They categorized occupant behavior into emotional, cognitive, and executive functions, and carried out field studies to find the impact of thermal satisfaction on each of these categories. Their results indicated that thermal satisfaction is directly connected to the mood, and positive and negative emotions of occupants, as well as their performance in cognitive tasks such as perception, learning, memory, expression, thinking, and executive functions. Results of their studies were demonstrated in terms of the relationship between thermal sensation (*PMV*) and relative productivity (*RP*):

$$RP = -0.035\,(PMV)^3 - 0.53\,(PMV)^2 - 0.22\,(PMV) + 0.99 \tag{2.8}$$

Where, *RP* is the relative performance with respect to the maximum performance, and *PMV* is the Fanger's thermal sensation vote, in the range of (−3, 3).

2.3 Comfort Control Strategies

Comfort control strategies in buildings are roughly classified into (1) Conventional Methods, (2) Intelligent Control, and (3) Multi-Agent-Based Modeling (MABM) Techniques. The three classifications are not mutually exclusive. For instance, an intelligent multi-agent-based system can use computational intelligence techniques, such as fuzzy logic, to make its agents intelligent.

2.3.1 Conventional Control Systems

Building control systems are the fundamental parts of building energy management, to optimize energy use and occupants' comfort conditions. Traditionally, the main goal of designing building control systems is to minimize energy consumption. On/off controllers, Proportional (P) controllers, Proportional-Integral (PI) controllers, and Proportional-Integral-Derivative (PID) controllers that are closed-loop/feedback controllers, have been widely used to control indoor environmental conditions. On/off controllers are not the optimal solutions to provide comfort and reduce energy consumption, due to their frequent energy consumption waste, instabilities, and overshoots of the set-points. P, PI, and PID controllers don't have a direct perception of the system they control, and are not fast enough for the dynamic operation of HVAC systems [32].

From the 1980s, a new wave of research on control strategies was started that considered comfort condition of occupants as important as energy consumption [33]. In order to cover limitations of conventional controllers, adaptive, optimal, and predictive control strategies were introduced. Each building has a particular non-linear thermal behavior, with respect to its location, orientation, materials, construction, and facilities. Predictive control methods consider a model for the disturbances of the controlled system. In the case of energy management system, these disturbances could be solar irradiance, or occupancy pattern [34, 35].

Adaptive controllers have the capability to self-regulate and adapt to their environment. The non-linearity and dynamic nature of building environment cause uncertainties in environmental parameters. Adaptive controllers try to keep the performance stable when facing these uncertainties [36]. Optimal controllers can also manage uncertainties in weather conditions, by using Dynamic Programming and considering the effects of weather conditions on control strategies [37].

2.3.2 Intelligent Control

With the rapid development of digital electronic, microprocessors, and wireless communication technologies, better, smaller, and cheaper sensors have been manufactured. Wireless sensor networks have been widely used to collect indoor environmental data in buildings. The process of data provides information, and knowledge is the product of analyzing the information, which leads to intelligent behavior or action:

$$data \rightarrow information \rightarrow knowledge \rightarrow intelligent\ behavior\ (action)$$

Artificial Intelligence (AI) techniques are the combination of mathematics and technology, helping the building to behave intelligently. Application of AI techniques to building control systems has been initiated from the 1990s. In building energy management, AI with rational thinking concentration, enables energy management systems to decide and act like humans [7].

Intelligence can also be added to data processing to generate information, or to generate knowledge database for the system. The simplest type of AI decision-making is performed by knowledge-based systems. A knowledge-based system receives facts (information from the environment) and contains linguistic rules that are generated continuously by its production memory. Doukas et al. [38] used knowledge-based systems in building energy management, to ensure occupants' comfort conditions, and minimize energy consumption. Two different rule-based expert systems were provided. One expert system contained energy consumption minimization rules while the other contained occupants' comfort conditions rules. Energy management decisions were made, based on these two rule sets. The knowledge-based system was proved to reduce the energy costs by 10%. However, knowledge-based systems are not dynamic enough to consider occupants' up-to-date preferences for the indoor environment.

The need to simultaneously optimize energy consumption and occupants' comfort conditions according to occupants' preferences, moved researchers towards the introduction of Computational Intelligence (CI) technologies. CI technologies, including techniques such as *Fuzzy Logic*, *Artificial Neural Network,* and *Generic Algorithm*, are used in different sub-systems of buildings, to enhance the performance of IEMSs. These intelligent techniques are alternatives to computational optimization methods (such as the one used in this research), for intelligent energy and comfort management in buildings. Hence, their applications in energy management systems are described, briefly.

Fuzzy logic is a form of many-valued logic that does approximate reasoning, instead of exact reasoning. The approximate reasoning is done by assigning a value between 0 to 1, instead of true or false (zero or one), as a degree of truth to a variable [39, 40]. The popularity of fuzzy logic techniques in IEMS is mainly due to their capability to model non-linear processes such as building energy performance, as well as complex building energy management control strategies. The main applications of fuzzy logic in building energy and comfort management system are (1) in relation to occupants' thermal and visual comfort, and IAQ, to describe the degree of comfort; and (2) for designing knowledge-based energy management systems, based on fuzzy linguistic rules. Eftekhari et al. [41] designed a rule-based fuzzy IAQ controller for a naturally ventilated room. Guillemin et al. [42] presented a system that automated the operation of shades, lighting, and heating systems, to provide the visual and thermal comfort of occupants. Dounis et al. [43] generated a set of 23 rules to control the thermal conditions of the indoor environment. The operation of auxiliary heating and cooling system, shading devices, artificial lighting, and window opening, were regulated with the outputs from the fuzzy logic rules.

The development of neural network technology, and evolutionary algorithms, such as Genetic Algorithm (GA), helped researchers to add the learning capability to building energy and comfort management systems. Artificial Neural Network (ANN) is a computing system, made of a number of simple, highly interconnected processing elements that process information by their dynamic state responses to external inputs [44]. An ANN consists of an input layer, a number of hidden layers, and an output layer. Layers are composed of nodes with activation functions. Nodes are interconnected with the weighted connections. Learning is accomplished by modifying the weights of the connections, according to the input patterns.

The PMV model for thermal comfort is non-linear and has complicated calculations. ANN can be used to approximate the thermal comfort model. Liu et al. [45] provided an ANN structure with an input layer, consists of four environmental and personal parameters, and one hidden layer with five parameters. One single-parameter output layer was constructed to predict each individual's thermal sensation. Neural Networks can be applied in HVAC systems to regulate the thermal comfort of occupants. Liang et al. [46] developed a direct ANN controller for an HVAC system, based on the PMV calculation.

In some intelligent control strategies, there is a need for tuning. For example, fuzzy logic controllers require tuning to find the optimal membership functions or the scaling factors that relate the inputs and outputs of a control system. GA performs tuning or optimization of fuzzy logic controllers. GA is a type of stochastic searching techniques, inspired by Darwin's theory of evolution. In GA, the solution to a problem is evolved in a process. Algorithm is started with an initial population, and solutions of each population are used to create a new population. This is achieved by keeping the part of solutions with better fitness and deleting the rest, with the hope that the survived population has a higher chance to reproduce better solutions. The procedure is continued until some conditions are satisfied (e.g. limit on the number of the population) [33].

Nassif et al. [47] used GA to optimize temperature set-points, with respect to PMV index, in a manner that thermal conditions were always kept satisfactory. Kolokotsa et al. [48] developed a fuzzy controller with GA optimization. The membership function of the fuzzy controller was modified and optimized by GA technique, according to user preferences. Alcala et al. [49] tuned and optimized fuzzy logic controllers that controlled HVAC systems of a building, with respect to energy consumption and occupants' comfort. By maintaining occupants' comfort conditions at satisfactory levels, and repetition of GA process, further energy consumption reduction was achieved (16% compared to non-optimized control).

2.3.3 Multi-Agent-Based Modeling Techniques

During the last decade, Agent-Based Modeling (ABM) has become a popular technique to model operation of IEMSs. According to Macal et al., a typical agent-based model has three elements: "(1) A set of agents, their attributes and behaviors; (2) A set of agent relationships and methods of interaction; and (3) An agents' environment" [50]. In IEMSs, the agents' environment is the building.

The most important characteristic of an intelligent agent is its ability to act autonomously, without external help or interference. Each agent has special attributes and behavior. With these attributes, the agent is capable of producing output, based on the available data. Agents can be goal-oriented. Each agent can have a special goal to fulfill, while cooperating and interacting with other agents, within the operation of the whole system. An intelligent agent consists of two parts; architecture and programming. In building control systems, the architecture could be a computer, intelligent controller, actuator, smart sensor, etc. The programming guides an agent's decision-making process, according to its applications.

Joumma et al. [51] presented a framework for a multi-agent system, integrated to a home automation system that was able to manage power consumption, according to utility prices and user preferences. Hagras et al. [52] provided an agent-based IEMS for a commercial building, which has the learning capability. Fuzzy logic, GA, and ANN were used together, to optimize energy and comfort, according to outdoor weather conditions, occupancy patterns, and occupants' requirements.

2.4 Computational Optimization Methods for Energy and Comfort Management

Optimization is the process of finding the best solutions for the given problems, while "optimization theory encompasses the quantitative study of optima and methods for finding them" [53]. In building energy management systems, the objective of optimization is related to at least one of these criteria: Energy efficiency, environmental impact, comfort, or productivity of occupants. The objective of optimization could be in the form of minimization or maximization, such as minimizing energy costs in the SOOP problem; or simultaneously minimizing energy costs and maximizing the productivity of office workers, in an office building.

According to Shaikh et al. [3], who studied optimized control systems for energy and comfort management in smart sustainable buildings until 2014, almost 60% of control systems reviewed, are based on the SOOP approach. The reason behind this popularity is the simplicity of the SOOP approach, and the availability of a single utopia point (the point, in which optimization problem goal is reached). Using the SOOP approach in building energy management systems, occupants' comfort conditions are mathematically secondary to energy consumption costs, hence, comfort conditions are featured as constraints on the indoor environmental parameters. For instance, consider the temperature of a room, as an indoor environmental parameter; two values of *heating* *set-point* and *cooling set-point* are chosen carefully, by the designer of energy management system, and serve as the lower and upper bounds of the indoor temperature, for the optimization problem. Accordingly, the indoor temperatures would never exceed these two values.

Using MOOP techniques for energy and comfort management, the two objectives of energy costs minimization and occupants' comfort maximization, could be in conflict with each other. Hence, a single optimal solution that optimizes both of these objectives is not always available. MOOP techniques consider a trade-off between these two (or more) objectives [2]. The task of optimization techniques is to find the best possible set of compromises between occupants' comfort and energy consumption. In MOOP problems, occupants' comfort is represented by at least one of the thermal, visual, or IAQ factors.

The major difference between MOOP methods can be found in how and when the preferences of the problem solver, or the designer of the optimization problem, are brought into the process. In methods with *a priori* articulation of preferences, the relative importance of two objectives (here energy consumption and occupants' comfort optimization) is assigned by the problem solver, before running the optimization algorithm. In contrast to *a priori* methods, in methods with *a posteriori* articulation of preferences, decision-making is performed after running the optimization algorithm, by selecting a single solution from a set of mathematically equivalent solutions [2].

Among all methods with *a priori* articulation of preference, *Weighted Sum Method* is the most popular one. Weighted sum method is also the most used MOOP method for energy and comfort management [3]. Weighted sum method is a type of classical MOOP methods. Generally said, how classical methods solve MOOP problems, is to convert them into a number of SOOP problems. This can be done by aggregating objective functions together while scaling them; or by optimizing one of the objectives while treating the others as constraints [2].

Dynamic Weighted Sum Method, Goal Programming, and ε-Constraint Method are the other types of classical methods. Dynamic weighted sum method is similar to weighted sum method, with the difference that the weights can be incrementally changed. In goal programming, the program seeks to find the minimum deviation from the pre-specified goals, for each of the objectives. The drawback of this method is the necessity to have sufficient information to predefine the goals. The ε-constraint method is designed, based on the optimization of one objective while treating the other objectives as the constraints bounds, by some allowable range, ε [2].

There have been several studies in the field of energy and comfort management that used weighted sum method. In weighted sum approach, constructing an objective function with energy consumption and occupants' comfort terms, is of utmost importance. Yang et al. [54], and Wang et al. [55] optimized energy consumption and overall comfort, using weighted sum method to construct the objective function. Dai et al. [56] introduced human performance, in terms of productivity of occupants, in MOOP of energy consumption and comfort conditions. The relative productivity of occupants was expressed, as a function of their thermal sensations (thermal comfort) and ventilation rate (IAQ).

Using weighted sum method, a problem arises when the energy consumption term and the occupants' comfort term in the objective function, are normalized to be treated similarly. If the energy consumption term and the occupants' comfort term are not expressed in the same unit, normalization affects the outcome. For instance, if the occupants' comfort term is expressed in terms of the deviation from the thermal satisfactory range (e.g. PMV index), and the energy consumption term is expressed in terms of energy costs ($), normalization is necessary. On the other hand, if two objectives are expressed in the same unit, they can be easily combined (and compared) in the objective function. Wright et al. [57] designed an HVAC system, using weighted sum method. Minimizing the operational costs and capital costs of the HVAC system, are considered as the two objectives of MOOP. The objectives can be easily combined and compared since operational costs and capital costs can be both expressed in terms of a monetary unit.

Another drawback of weighted sum method is its dependence on the choice of weight factors, and the fact that it only leads to one optimal solution, based on the weight factors chosen. In order to refine this limitation, *Pareto Optimality* concept is developed, and *Pareto Set* is defined. Pareto set can be constituted by an infinite number of Pareto points, or non-dominated solutions that are optimal points, found by varying weight factors. A solution belongs to the Pareto optimality set "if there is no other solution that can improve at least one of the objectives, without degradation any other objective" [58].

Multi-Objective Genetic Algorithm, Niched Pareto Genetic Algorithm, Strength Pareto Evolutionary Algorithm, and Multi-Objective Particle Swarm Optimization, are among the most popular types of Pareto-based approaches. Pareto-based approaches seek to find the *Pareto Front* for MOOP problems. Pareto-based approaches allow simultaneous exploration of different points on the Pareto front, and multiple solutions generation in a single run. The optimization can be performed without *a priori* information on the relative importance of the objectives. Brownlee et al. [59] used GA in MOOP of energy consumption and comfort, for optimal HVAC system design. The operational cost of HVAC system and maximum thermal discomfort of occupants were chosen as objectives to be minimized. The GA-based search method found non-dominated solutions to construct Pareto optimal set of solutions.

Yang et al. [54] combined weighted sum method, and Particle Swarm Optimization (PSO), to optimize energy consumption and comfort, in an agent-based energy management system, with a central controller, and a number of fuzzy-based local controllers. Wang et al. [60], and Dounis et al. [61] also used PSO algorithm to develop IEMSs, with central coordinator controllers, and local thermal, visual, and IAQ controllers. The central controller used PSO technique to develop a Pareto optimal set of solutions that demonstrated the trade-off between energy consumption and overall comfort of occupants.

2.5 The Quest to Personalize Energy and Comfort Management

The PMV-PPD model, established by Fanger [18] is a conventional representation of human thermal sensation, which is still very popular in thermal sensation calculations. However, this model has its own critiques. The main criticism of this model is its *one-size-fits-all* approach, which considers all occupants in any location, with any cultural and geographical background, the same. Calculating PMV and PPD values, from personal and environmental parameters, would result in the minimum and maximum thresholds for the indoor temperature. The main criticism of using PMV-PPD index for the thermal comfort evaluation is its lack of flexibility.

Fanger et al. [15] found 1.2 ºC standard deviation in the preferred temperature of different occupants in a shared environment, and 0.6 ºC standard deviation in the daily thermal sensations of a specific occupant, in a certain environment. During the last two decades, studies on adaptive thermal comfort have found additional influential parameters on the thermal sensations of occupants [62-68].

There are various parameters that influence thermal sensations of occupants. Humphreys et al. [64], and de Dear et al. [62] found relationships between the adaptive thermal comfort of occupants and outdoor temperature, considering occupants with different cultural background, in different outdoor weather conditions. Age, gender, social, cultural, and economic dimensions, are among the other parameters evaluated in multiple studies [63, 66, 68].

Furthermore, studies have indicated that history of thermal sensations, perceived control over the environment, and human-automation system interaction, have impacts on thermal comfort sensation [20, 67]. People who think they have a good control over their environment, or people who can easily interact with the automated control system, have relatively more tolerance ranges with respect to variations in indoor environmental conditions. The perceived control over the indoor environment, alongside the history of thermal sensations, influence the cognitive appraisal of the brain and alter the thermal discomfort boundaries [67].

The pro-environmental behavior of occupants is another factor in accepting indoor environmental conditions. It is observed that people with more environmental-friendly behavior are more forgiving in sacrificing their immediate satisfaction [69, 70]. Adjusting clothes to warmer or colder ones, relaxing cultural or social clothing norm, choosing alternative physical activities, and drinking beverages, are the most common adaptive behavior of pro-environmental occupants. There have been several studies on describing pro-environmental behavior, based on differences in individual people, their values, attitudes, and background [71-73]. Karp et al. [73] categorized people based on their level of openness to change or conservation, and their level of self-enhancement or self-transcendence, into four classes of green activist, good citizen, healthy consumer, or traditional consumer of energy. Stern et al. [71, 74] presented a model for environmental concern of people, and provided numerous parameters that are classified into their background, beliefs, attitudes, gender, and level of knowledge, to form a general model of environmental concern.

Occupants also have adaptive behavior in response to indoor environmental conditions. Adaptation could be psychological, physiological, or by behavioral adjustment, such as wearing more or fewer clothes when feeling uncomfortable [62]. Psychological and physiological forms of adaptation are self-adaptive behavior, while behavioral adjustment could be in the form of making changes to the indoor environmental conditions, as well. Physiological adaptation takes more time and is detectable in a long-term. Psychological adaptation is generally the change in occupant expectation of thermal comfort [62, 68, 75].

2.5.1.1 Modeling Occupants' Behavior

Modeling occupants' behavior in buildings, is categorized into stochastic and cognitive approaches. In stochastic modeling of occupants' preferences and behavior, their probabilities of satisfaction, or probabilities of taking energy-related actions, are expressed as a function of indoor environmental parameters, using statistical regression analysis. Nicol et al. [76] explored occupants' adaptive behavior in different geographical locations and formed probabilistic models of their thermal perceptions, based on indoor and outdoor temperatures. Rijal et al. [77], Haldi et al. [78], and Gunay et al. [79] used logistic regression techniques to predict occupants' thermal and visual comfort conditions, and developed probabilistic models to characterize their behavior, such as the use of window, blind and fan, based on indoor and outdoor environmental parameters. Daum et al. [80] proposed a technique to use an occupant's feedback on the thermal conditions of the indoor environment, to indicate his or her probability of being comfortable in a wide range of indoor temperatures.

Cognitive approaches to human behavior modeling consider human's sensation, perception, and cognition. In order to model energy-related decisions using cognitive approaches, a link between their comfort requirements and their actions is constructed. Up until now, *The Theory of Planned Behavior* and *Value-Belief-Norm Theory* are the most popular cognitive theories to explain occupants' energy-related behavior.

The theory of planned behavior considers behavior as a consequence of cost and benefit analysis of different factors. These factors are the subjective norm (social influence), perceived behavioral control (ease or difficulty of behavior), and attitude toward behavior (costs, profit, and effort) [81]. The theory of planned behavior is solely based on the rational decision-making process. Andrews et al. [82] used the theory of planned behavior inside a multi-agent-based modeling framework, to describe occupants' energy-related behavior, based on their beliefs, desires, and intentions. Lee et al. [83], and Kashif et al. [84] developed agent-based cognitive methods, influenced by the theory of planned behavior, to model occupants' energy-related behavior.

Compared to the theory of planned behavior, value-belief-norm theory has more capability to describe the altruistic behavior of occupants, such as their pro-environmental behavior. Self-enhancement, self-transcendence, openness to change, conservation of occupant, their level of awareness of consequences of their behavior, the ascription of responsibility, and personal norms, are the main factors included in value-belief-norm theory [72].

According to the definition of thermal comfort, provided by Fanger, comfort is both a feeling through the skin and a condition of mind through a cognitive process [18]. Several scientists in the fields of behavioral economics, psychology, and neuroscience have stated the strong relationship between emotions and cognition, and the significant influence of affective processes (emotion, mood, and feeling) on the decision-making process [85-87]. Energy-related decisions of an occupant can also be influenced by affective processes, alongside his or her beliefs, values, and preferences [88]. In order to consider the influence of affective processes on occupants' energy-related behavior, the first step is to construct a model that combine affective processes with other influential parameters.

2.5.1.2 Learning Occupants' Preferences

Generally, there are two approaches to learning the comfort preferences of occupants. The first approach is to execute experimental studies, and measure each person's performance in certain tasks while modifying environmental and personal parameters [11, 12, 14]. Experimental tasks are varied in terms of the level of mental work required. Another approach is to perform longitudinal studies on the comfort sensations of occupants. Within this approach, occupants, while doing their regular jobs, signal their sensation votes. Over time, comfort sensation votes of each occupant, in a wide range of each considered environmental parameter are collected. Based on the collected data, comfort preference model of each person can be constructed.

Haldi et al. [78] designed a web-based questionnaire, and collected thermal sensation votes of occupants within a long-term observational study, and subsequently, identified their thermal preference models using logistic regression techniques. Jazizadeh et al. [10] suggested collecting occupants' feedback through participatory sensing using smartphones or web-based applications.

The main requirement of the second approach is the real-time monitoring of indoor environmental parameters, through building environmental monitoring system. Indoor environmental parameters and occupants' comfort sensation votes should be continuously collected, through building monitoring systems, to be synchronized with occupants' sensation votes. Jang et al. [9], Noh et al. [89], and Qian et al. [90] proposed wireless sensor networks for building environmental monitoring systems, applicable to comfort studies. They developed sensor modules to collect data from the environment and transmit the environmental data towards a central server for further analysis, through wireless communication protocols. The main components of a sensor module are environmental sensors, such as temperature and light sensors, and a microcontroller for continuous sampling from the sensors, and transmitting data to a central server.

In recent years, different companies have manufactured smart or programmable thermostats that are able to acknowledge users' thermal preferences, and manage the thermal conditions of the controlled indoor environment, accordingly. Honeywell [91], Emerson [92], and Carrier [93] have manufactured programmable thermostats that control the thermal conditions, according to pre-set schedules. The schedules can be set by the users via smartphone applications, web interfaces, or voice commands. Containing built-in occupancy sensors, as well as indoor environmental sensors, programmable thermostats can have varied modes of operation, based on the given schedule. The manufactured programmable thermostats have been successful in reducing building energy consumption [91-93]. However, they cannot adapt their operation to continuously changing thermal preferences of occupants, since they lack the learning capability and only operate according to pre-set schedules.

Ecobee3 thermostat, manufactured by Ecobee, also operates based on a pre-set schedule [94]. This thermostat is able to monitor more than one place in a specific space since it has remote sensors, as well as built-in sensors. The remote sensors can be placed in any other location of the controlled space. Hereby, the thermostat manages the thermal conditions of the indoor environment, by averaging the temperatures of built-in sensors and remote sensors to improve the thermal conditions of occupants. Nest has manufactured smart thermostats with learning capabilities [95]. Nest thermostats have built-in occupancy sensors, as well as built-in indoor environmental sensors. Through built-in machine-learning algorithms, the smart thermostats can model the internal thermal dynamics of the controlled space to enhance their operations. Furthermore, Nest smart thermostats are able to continuously program themselves by learning the thermal preferences and habits of occupants. Users can communicate with Nest learning thermostats via smartphone applications, web interfaces, or voice commands [95].

2.6 Summary and Analysis

The general idea of this research is to propose methods for personalized energy and comfort management in office buildings. The main objective of the proposed methods is to provide occupants' comfort conditions while simultaneously optimizing energy consumption costs, by performing automated control of the indoor environment. In the first part of the literature review (Section 2.1), different aspects of occupants' comfort in enclosed spaces were described. By controlling indoor environmental parameters, energy management system can provide the thermal and visual comfort of occupants, as well as satisfactory IAQ. In reviewing comfort control strategies in buildings (Section 2.3), it was discussed that conventional control systems are not optimal solutions to simultaneously provide occupants' comfort and reduce building energy consumption. With the rapid development of digital electronic, microprocessors, wireless communication technologies, and the introduction of computational intelligence techniques, researchers have moved towards intelligent energy and comfort management in buildings.

MOOP method, as a computational optimization method, can be used for intelligent energy and comfort management in buildings (Section 2.4). The major difference between MOOP methods can be found in how and when the preferences of the problem solver, or the designer of the optimization problem, are brought into the process. In methods with *a priori* articulation of preferences, the relative importance of two objectives is assigned by the problem solver before running the optimization algorithm. In contrast, in methods with *a posteriori* articulation of preferences, decision-making is done after running the optimization algorithm by generating

Pareto optimal solutions. Between all methods with *a priori* articulation of preference, weighted sum method is the most popular one.

Using MOOP methods, such as weighted sum method, for energy and comfort management, a problem arises when the energy consumption term and the occupants' comfort term, in the objective function, are normalized to be treated similarly. Reviewing studies that used MOOP methods for energy and comfort management in buildings, it is observed that when the energy consumption term and the occupants' comfort conditions term are not expressed in the same unit, the normalization procedure affects the optimization outcome.

Here, in order to remove the dependency of the optimization outcome to the normalization procedure, the productivity of each occupant is introduced as a variable inside the MOOP problem formulation. Comfort conditions have impacts on the performances of occupants in certain tasks that influence their overall productivity (Section 2.2). The effects of thermal comfort and IAQ on the performances of occupants have been evaluated in multiple studies. Expressing occupants' comfort conditions by their level of productivity, both energy consumption costs and occupants' comfort conditions can be expressed in a monetary unit. Hence, making a comparison between these two objectives is possible, without further need for normalization.

Moreover, based on the relationship between occupants' comfort conditions and their productivity, a procedure for personalized decision-making for energy and comfort management is developed. Within this procedure, positive features of methods with *a priori* and *a posteriori* articulation of preferences are combined. Weighted sum method is used, while a set of Pareto optimal solutions are generated from each decision-making process (each hour of simulation). The final optimal solution for the automated control of the indoor environment can be chosen by learning influential factors such as energy prices, occupancy data, occupants' productivity rates, thermal and visual preferences, and adaptive behavior.

In Section 3.2, a method is proposed for integrated optimization of energy costs, thermal comfort, and IAQ. To express the relationship between thermal comfort and occupant productivity, as well as the relationship between IAQ and occupant productivity, results of studies by Seppanen et al. [28, 31] are used (Section 2.2). Using the results of these studies, occupants are assumed to have similar thermal and IAQ preferences.

Based on the studies on adaptive comfort, parameters such as age, gender, outdoor weather conditions, social dimensions, economical background, history of thermal and visual sensations, perceived control over the environment, psychological, physiological adaptation to the indoor environment, and behavioral adjustment, influence comfort sensation of occupants (Section 2.5). Thus, in shared spaces, occupants may have varied thermal and visual preferences for the indoor environmental conditions. Compared to the previous studies on personalized energy and comfort management, here, personalization is introduced in MOOP of energy costs and occupants' comfort conditions. A method is proposed (Section 3.3) to perform personalized energy and comfort management, by acknowledging occupants' thermal and visual preferences from their feedback.

Compared to the reviewed studies on energy and comfort management, here, positions of occupants are also accounted for thermal and visual comfort evaluations (Section 3.4). In the proposed position-based method, it is considered that occupants' perceptions of the indoor environmental conditions, specifically their thermal and visual sensations, depend on their positions inside enclosed spaces. Hence, their thermal comfort and visual comfort and consequently, their relative productivity with respect to indoor thermal and visual conditions, depend on their positions.

The approaches to modeling occupants' energy-related behavior in buildings are categorized into stochastic and cognitive approaches (Sub-Section 2.5.1). In stochastic modeling of occupants' energy-related behavior, by using statistical regression analysis, their probabilities of taking energy-related actions are expressed as functions of indoor environmental parameters. Meanwhile, in cognitive approaches to human behavior modeling, a link between their comfort requirements and their energy-related actions is constructed. Compared to the previous studies on modeling occupant behavior for energy and comfort management, here, occupant behavior modeling is expanded to MOOP of energy costs and comfort. Occupants' energy-related behavior are modeled, by proposing a method, inspired by the fields of behavioral economics and neuroscience (Section 3.5). The method considers the adaptive behavior of occupants, by computational modeling of their energy-related decision-making process.

In reviewed studies on modeling occupants' energy-related behavior, occupants are considered as rational decision-makers (e.g. in the theory of planned behavior, or in value-belief-norm theory). Several scientists in the fields of behavioral economics, psychology, and neuroscience, have stated the strong relationship between emotions and cognition, and the significant influence of affective processes (emotion, mood, and feeling) on the decision-making process (Section 2.5). The *Prospect Theory*, used here to model the decision-making process of occupants, is able to account for both rational and irrational aspects of decision-making. Accordingly, the proposed situation-specific method (Section 3.5) can consider both rational and irrational aspects of human behavior.

3 Methodologies

Different MOOP methods are proposed to simultaneously optimize energy consumption costs and occupants' productivity in office buildings (Fig. 3). The first MOOP method assumes a single relationship between productivity and IEQ, for all occupants. The second MOOP method (called the *personalized* MOOP method) is able to consider the diversity in the thermal preferences of occupants. The third method (called the *position-based* MOOP method) acknowledges the diversity in both thermal and visual preferences of occupants, and also evaluates the thermal and visual conditions of occupants, based on their positions inside an enclosed space. A model is developed to simulate the adaptive behavior of each occupant in each specific situation. Accordingly, the fourth MOOP method (called the *situation-specific* method) is proposed that is able to optimize energy costs and occupants' productivity, based on occupants' thermal and visual preferences and positions, as well as their situation-specific adaptive behavior. The performances of the methods are simulated, in a multi-zone office building, located in Montreal, Canada (modeled in Section 3.1). The methods automatically control the indoor environmental conditions of different zones of the office building.

In the first MOOP method, the effect of thermal conditions and IAQ on occupants' productivity is considered (Section 3.2). For all occupants, unique single relationship between their productivity and thermal conditions, and productivity and IAQ is assumed. Accordingly, in the simulated office, integrated MOOP of energy costs and productivity is carried out, and the results are compared with SOOP of energy costs (Chapter 4). Subsequently, the sensitivity of the developed MOOP method to occupants' thermal preferences is analyzed to identify the need for personalized energy and comfort management.

In the second MOOP method (*personalized* MOOP method), the thermal preference models of occupants are used in MOOP of energy costs and productivity, to manage the indoor environmental conditions of the office, based on occupants' thermal preference models, as well as IAQ (Section 3.3). It is proposed that the personalized thermal comfort of each occupant, can be modeled in the shape of a Gaussian function, with two personalized parameters that indicate the thermal preference and thermal tolerance of the occupant. Personalized MOOP of energy costs and productivity is performed to demonstrate the capability of the personalized method to improve the collective productivity of occupants while optimizing the energy costs (Chapter 5). Subsequently, the sensitivity of the personalized method to thermal preference and thermal tolerance of occupants is analyzed.

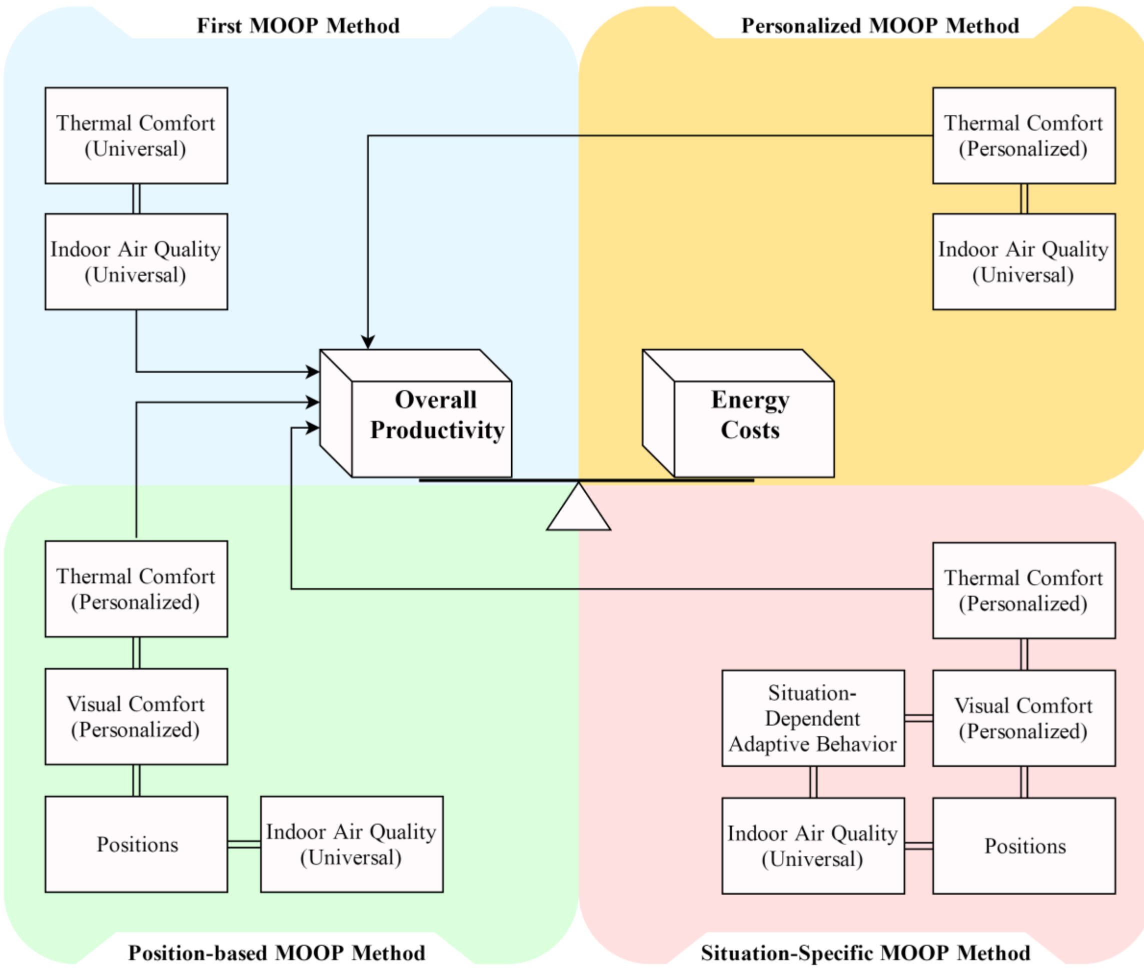

Fig. 3: The proposed MOOP methods and the parameters considered for occupants' productivity

It is also proposed that the personalized visual preference of each individual can be modeled, in the shape of a Gaussian function. In the third MOOP method (*position-based* method), both personalized thermal and visual models of occupants are used for MOOP of energy costs and productivity (Section 3.4). Moreover, in this method, the thermal and visual conditions of occupants are evaluated, based on their positions inside the zones. Accordingly, the optimal performance of the office building considering occupants' positions, personalized thermal and visual preferences, and IAQ, is simulated (Chapter 6). Afterward, the sensitivity of the method to occupants' thermal and visual tolerances is analyzed, to highlight the importance of occupants' thermal and visual behavior changes for personalized energy and comfort management.

Following the simulations of the sensitivity analysis of the position-based method to occupants' behavioral changes, a model is developed to simulate occupant decision-making process, prior to energy-related behavior (Section 3.5). Based on this model, occupants' potential responses to the indoor environmental conditions (their potential adaptive behavior), in each specific situation of the indoor environment are computationally modeled. This model is added to the position-based method to propose the fourth MOOP method (*situation-specific* method), described in Section 3.5. The situation-specific method is used to simulate the optimal performance of the office building, considering occupants' situation-dependent behavior, thermal and visual preferences, and positions (Chapter 7). Finally, the sensitivity of the situation-specific method to occupants' situation-dependent behavior is analyzed.

3.1 Building Model & Control Systems

3.1.1 Modeling the Office Building

A single-floor office with an overall area of 555 m^2, located in Montreal, Canada, is assumed, and its simplified RC-network thermal model is developed. The choice of the office building and RC-network model is in accordance with the objectives of this research. Alternatively, the proposed methods can be applied to other buildings, by developing their thermal models. In order to validate the developed model, the simulated annual energy consumption is compared with the simulations of eQuest and TRANSYS software; less than 5% difference is observed between the compared values (see App. A). For building energy performance simulation, typical meteorological year weather data of Montreal is used. Montreal has a warm and humid summer, a very cold winter, and is located in climate zone 6 in ASHRAE climate zones map [96]. The office has five zones: *north*, *east*, *central*, *south*, and *west*. In all the zones except central zone, the wall with a connection to the outside has a window-wall ratio of 0.4. The ceiling heights, in all the zones, are equal to 3 meters. In each zone, there could be up to ten office workers. Fig. 4 shows the plan of the office, and the thermal model of one of the zones.

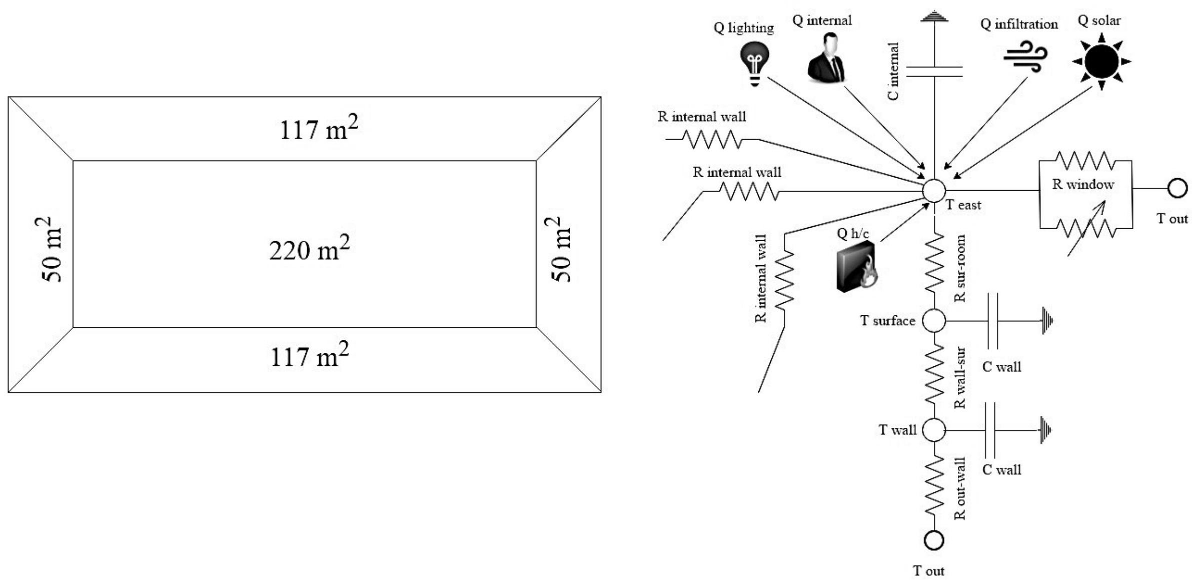

Fig. 4: Simulated office (left), RC-network thermal model of east zone (right)

Each node represents an area with similar environmental parameters (e.g. temperature, lighting, and air velocity), such as a single zone, or one of the layers of the walls. Heat is transferred between the nodes by convection, conduction, or radiation. Resistances express conduction and convection from one zone to the other, or from outside through the wall, while capacitances represent thermal storage. For each zone, a specific set of energy balance equations is derived, from various types of energy exchanges processes, including (1) solar gain through windows, (2) internal heat gain from occupants, systems, and equipment, (3) infiltration, (4) heat exchange between the zones, (5) the effect of thermal storage of external walls, (6) the influence of blinds position on the conductive heat transfer of the windows, (7) artificial lighting, and (8) heating and cooling systems. For each zone of the office (i), the governing equation, representing energy balances, are in the form of:

$$\rho\, V_i\, c_p\, \frac{\partial T_i}{\partial t} = \sum_{j=1}^{n} h_{c\, i-j} A_{sj}\, (T_{sj} - T_i) + \sum_{k=1}^{m} \dot{m}_{i-k}\, c_p\, (T_k - T_i) + q_{in} \tag{3.1}$$

The term $\rho\, V_i\, c_p$ represents the thermal capacitance of the fluid (air) inside the zone, in which ρ is the density of air (kg/m^3), V_i is the volume of the zone (m^3), c_p is the specific heat of air (J/kg.K), and T_i is the temperature of the zone (K). Forward difference scheme is applied to the partial derivative, over some finite time interval (an hour), in hourly building energy performance simulation: $\frac{\partial T_i}{\partial t} = \frac{T_i^{t+\Delta t} - T_i^t}{\Delta t}$. During the energy performance simulation, $T_i^{t+\Delta t}$ is the inside temperature of the zone, calculated during that hour, Δt is equal to one hour, and T_i^t is the inside temperature of that zone, calculated in the previous hour.

The term $h_{c\,i-j} A_{sj}\,(T_{sj} - T_i)$ in the governing equation expresses the convective heat transfer rate (W) between the zone (i) and the surrounded surfaces (j). T_{sj} is the surface temperature, A_{sj} is the contact area of the zone with the surface (m^2), and $h_{c\text{-}i\text{-}j}$ is the heat transfer coefficient ($W/m^2.K$). Here, surfaces' $h_{c\text{-}i\text{-}j}$ are replaced by *U-values* (thermal transmittance, including inside and outside film coefficients, $W/m^2.K$), stated in Table 1. The term $\sum_{k=1}^{m} \dot{m}_{i-k}\, c_p\, (T_k - T_i)$ describes the rate of energy exchange (W) due to the fluid flow between the zone and other zones, or between the zone and outdoor. In this equation, $\dot{m}_{i-k}$ is the pressure/temperature driven mass flow rate (kg/s) between the two volumes, c_p is the specific heat of air, transferred from another zone or from the outdoor, and T_k is one of the other zone's temperature or outdoor temperature. q_{in} represents the heat generated in the zone from occupants and appliances, or from artificial lighting, or heating/cooling system. There could be specific relations between variables that shape nonlinear constraints of the optimization problem, and should be respected while solving the problem. In this model, there are nonlinear constraints, based on the effect of thermal storage of external walls, and also the influence of blind position on the conductive heat transfer of windows. It is assumed that the simulated office is on the middle floor of a high-rise office building. Accordingly, all the ceilings and floors are adiabatic. Values of parameters, used in the thermal model, are stated in Table 1.

Table 1: Building parameters

Parameter	***Value***	***Parameter***	***Value***
Chiller COP	3.5	Exterior Wall Specific Heat (kJ/kg .K)	42
Electrical Heater Efficiency (n)	1	Exterior Wall Outdoor Surface Convection Heat Coefficient ($W/m^2.K$)	34
Open Shade Window U-Value ($W/m^2.K$)	2.3	Exterior Wall Indoor Surface Convection Heat Coefficient ($W/m^2.K$)	8.5
Close Shade Window U-Value ($W/m^2.K$)	1.4	Interior Wall U-Value ($W/m^2.K$)	1.5
Fluorescent Lamp Efficacy (lumens/W)	70	Fan Energy Consumption (W per m^3/s of air)	1760
Exterior Wall U-Value ($W/m^2.K$)	0.4	Maximum Lamp Power (W/m^2) [4]	15

3.1.2 Automated Control System

In each zone, four environmental parameters of *artificial lighting*, *natural illumination*, *indoor temperature*, and *ventilation rate* are automatically controlled, on an hourly basis. It is assumed that the office is occupied during weekdays from 9 am to 5 pm. Each zone is equipped with a Variable Air Volume (VAV) system that provides heating, cooling, and air ventilation. During the unoccupied hours, energy management and integrated control of the zones are based on the SOOP of energy consumption costs. The objective function of the SOOP method is only comprised of an energy costs term. For each zone, total energy consumption (E_{total}) in an hour is the sum of energy consumption of artificial lighting, chiller, boiler, and fan:

$$E_{\text{total}} = E_{\text{lighting}} + E_{\text{cooling}} + E_{\text{heating}} + E_{\text{fan}} \tag{3.2}$$

The energy costs term in the objective function of the SOOP method, is the product of electricity or gas prices and the associated hourly energy consumption. Fixed rates of 8 cents per kWh and 20 cents per m^3 are assumed as electricity and gas prices in Montreal. For each hour of simulation, the energy costs term, in the objective function is in the form of:

$$Energy\ costs\ = \left[ElecPrice\ .\sum_{z=1}^{5} E_z^{electricity}\ + GasPrice\ .\sum_{z=1}^{5} E_z^{gas}\right] \tag{3.3}$$

In which, E is the energy consumption in kWh; z is the number of the zone; *ElecPrice* and *GasPrice* are electricity and gas prices.

During the occupied hours, the proposed MOOP method automatically controls the indoor environmental conditions of the zones. In the objective function of the MOOP method, besides the energy costs term, an occupants' productivity term is introduced. The occupants' productivity term considers the overall productivity of occupants, with respect to indoor environmental conditions. Considering each occupant's comfort preference, the proposed method manages the indoor environment to simultaneously optimize energy costs and occupants' overall productivity.

Table 2 defines building schedule during the occupied and unoccupied hours.

Table 2: Building schedule

Schedule	***Occupied***	***Unoccupied***
Minimum Indoor Illuminance (lux) [4]	750 (always ≤ 2500 lux)	50
Occupancy Heat Generation (W/m^2)	12.6	1.6
Equipment Heat Generation (W/m^2)	10.7	3
Cooling Set-Point (°C)	-	26.6
Heating Set-Point (°C)	-	18.3
Minimum Conditioned Outdoor Air Flow Rate (m^3/s per m^2) [16]	0.0007 + 0.0003 (infiltration)	0.0003 (only infiltration)

3.2 Multi-Objective Optimization of Energy Costs and Comfort

3.2.1 Problem Formulation

"The process of optimizing systematically and simultaneously a collection of objective functions" is called multi-objective optimization [2]. The goal of an optimization problem is represented by an *objective function*, or *utility function*. Solving an optimization problem is the process of finding a set of design variables, under design constraints that suits the objective function of the optimization problem, the best. The general form of a MOOP problem is [2]:

$$\begin{aligned} &\text{minimize } F(x) = [F_1(x), F_2(x) \ldots F_k(x)]^T \\ &\text{subject to } g_i(x) \leq 0, j=1, 2 \ldots m, \\ &h_l(x) = 0, l=1, 2 \ldots e, \\ &x_{low} \leq x_c \leq x_{\text{high}}\ c=1, 2 \ldots n \end{aligned} \tag{3.4}$$

Where; $F(x)$ is a vector of objective functions; $h_l(x)$ and $g_i(x)$ are inequality and equality constraints; $X=X_1, X_2, \ldots X_n$ are design variables, in which n is the number of independent variables; x_{low} and x_{high} are constraints on design variables; k is the number of objective functions; m is the number of inequality constraints. Design constraints, design variables, and their relations typify the operation of the system, which the optimization problem is set upon.

There are different methods to introduce occupants' comfort into energy costs and comfort optimization problem. The easiest approach to introducing comfort conditions into optimization problem is taking them as the lower or upper bounds of design variables, or treating them as the constraints on indoor environmental parameters to constitute the problem of SOOP of energy costs. There are design variables that are directly related to occupants' comfort, such as temperature set-points, minimum ventilation rate, or minimum illumination level. SOOP problems do not offer sufficient flexibility to simultaneously optimize energy and comfort. Taking occupant comfort as a more flexible and important parameter, it is possible to transfer comfort conditions into the objective function, to construct MOOP of energy costs and comfort.

In the first proposed MOOP method, the overall comfort of occupants is considered to be the combination of their thermal comfort and IAQ. In the following proposed methods, occupants' visual conditions, positions and behavior are also considered for overall comfort evaluation. There is a strong relationship between occupants' comfort conditions and their performances [11, 12, 14]. Hence, occupants' performances in the office can be translated to their levels of *productivity*. Initially, relative productivity is expressed as a function of indoor temperature (representing thermal comfort), and ventilation rate (representing IAQ). In this manner, both initial energy costs and occupants' comfort conditions terms, are expressed in a monetary unit. Weighted sum method is used to combine the two terms. Accordingly, the objective function of the first proposed MOOP method is constructed from the energy costs term and the occupants' productivity losses term. The energy costs term, in the objective function of the MOOP method, is similar to the objective function of the SOOP method in (3.3). The productivity losses term (in the first proposed method) considers the productivity losses of each occupant with respect to the thermal conditions and IAQ.

3.2.2 Multi-Objective Optimization of Energy Costs, Thermal Comfort & Indoor Air Quality

Initially, to express the relationship between thermal comfort and productivity, results of a meta-analysis by Seppanen et al. [28] is used. Seppanen et al. performed a meta-analysis of 26 studies that previously conducted on the relationship between indoor temperature and occupants' performance. These studies were varied in the method used, the sample size, and the type of occupants' tasks. They categorized studies, based on the type of performances considered, varied from simple tasks, visual tasks, and complex tasks. Subsequently, they assigned a weight to each study, in a manner that studies that considered more complex tasks, received larger weights. The derived relationship between relative productivity with respect to thermal conditions (RP_{thermal}) and indoor temperature (T, in °C) is indicated in (3.5), and shown in Fig. 5. RP_{thermal} is a term to compare occupants' productivity with their maximum level of productivity:

$$RP_{\text{thermal}} = 0.16\,T - 0.0058\,T^2 + 0.000062\,T^3 - 0.47 \qquad (3.5)$$

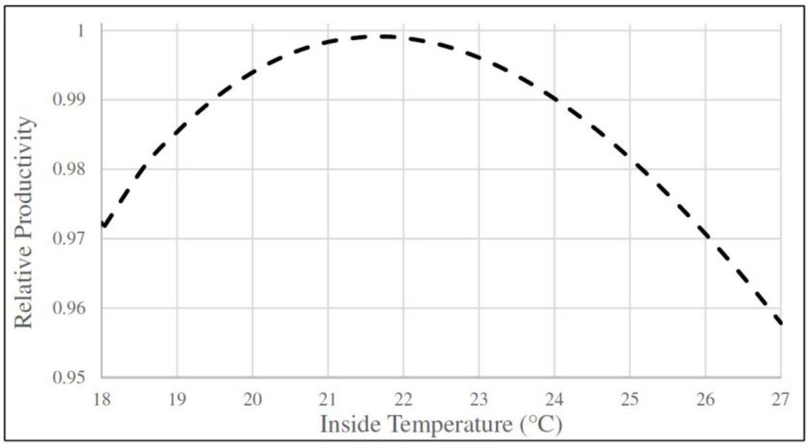

Fig. 5: Relative productivity of occupants with respect to inside temperature (ºC) [28]

In addition to the thermal comfort, IAQ of occupants are also considered in their overall comfort evaluations. Relative productivity with respect to IAQ (RP_{IAQ}) is derived from Seppanen et al. meta-analysis of nine field studies, previously conducted on the relationship between ventilation rate and relative productivity [31]. Based on Seppanen et al. study, higher ventilation rates improve concentration and vigilance of occupants. They assumed a reference point of 6.5 l/s per person, and assigned it to the relative productivity of 1, and found the impact of improved ventilation rate on the performance of occupants. The relationship between ventilation rate (Q, l/s per person) and RP_{IAQ} is presented in (3.6), and displayed in Fig. 6. Based on this assumption, the minimum value of RP_{IAQ} is equal to one (Fig. 6).

$$RP_{\text{IAQ}} = 0.021 \ln Q + 0.960 \quad 6.5 \text{ l/s per person} \leq Q \leq 45 \text{ l/s per person} \qquad (3.6)$$

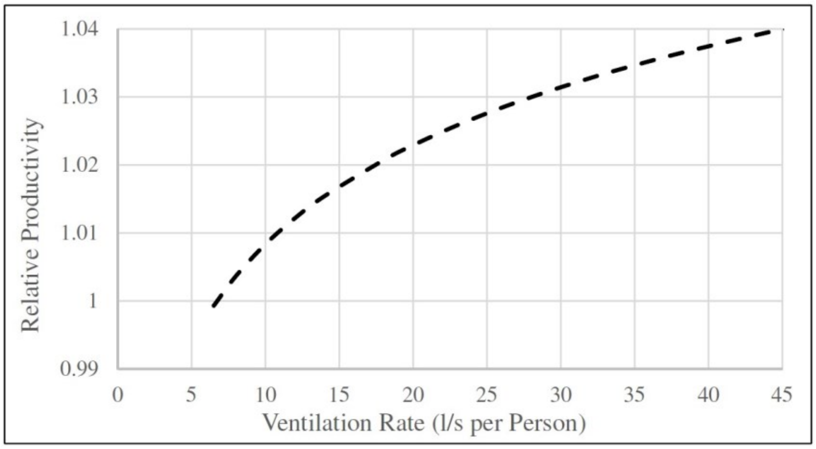

Fig. 6: Relative performance with respect to ventilation rate (l/s per person) [31]

Relative productivity with respect to indoor temperature (RP_{thermal}) and ventilation rate (RP_{IAQ}) are combined using a method suggested by Dai et al. [56]; it was stated that the combined effect of indoor air temperature and ventilation rate, on the overall productivity of occupants (RP_{overall}), can be assumed to be in the range of the average of RP_{thermal} and RP_{IAQ}, and the maximum value between the two. They justified their assumption by suggesting that the magnitude of the combined effect of two parameters (indoor air temperature and ventilation rate) should be at least the effect of the greater of the single parameters, but not more than the sum of two independent parameters [56]. Accordingly:

$$RP_{\text{overall}} = [\text{average}\ (RP_{\text{thermal}}, RP_{\text{IAQ}}) + \text{maximum}\ (RP_{\text{thermal}}, RP_{\text{IAQ}})] / 2 \tag{3.7}$$

RP_{overall} is a dimensionless quantity and can be expressed in percentage (%), or as a value within the range of 0 to 1. RP_{overall} equal to 1 is assigned to an occupant's maximum level of productivity.

Hourly productivity losses of each occupant (*Productivity losses*) are derived from the two parameters of *productivity per hour* (\$/h) and RP_{overall}:

$$\textit{Productivity losses}\ (\$/\text{h}) = \textit{productivity per hour}\ (\$/\text{h}).\ (1 - RP_{\text{overall}}) \tag{3.8}$$

Using weighted sum method, the objective function of the method, to be minimized on an hourly basis, is constructed in the form of:

$$Objective\ function\ (\$/h) = energy\ costs + \sum_{i=1}^{n} productivity\ losses_{\ i} \quad (3.9)$$

In which, n is the number of occupants.

The proposed method uses the solver *fmincon* of MATLAB. *fmincon* is able to handle non-linear MOOP problems with both linear and non-linear constraints (e.g., the proposed problem). For the optimization algorithm of *fmincon*, the interior-point method is used. Generally, in non-linear programming, there is no guarantee that the global optimum point can be reached. It is probable that the solver reaches local optimum instead of global optimum point. In the MOOP problems of this research, the fact that the ranges of variables are limited improves the probability of reaching global optimum. Moreover, in order to increase the degree of confidence in the procedure, optimizations were repeated with many different initial conditions, to make sure that similar (global) optimum point is reached.

Using the first proposed method, MOOP problem of energy costs and productivity is solved to provide economic-optimum conditions for the operation of the office building (*Objective 1* of the research). In each zone, the method performs the integrated control of the indoor environment, by managing the level of indoor temperature, ventilation rate, natural illumination, and artificial lighting (see App. B.1). Based on the level of occupants' productivity in each zone, the method can generate hourly Pareto optimal solutions for the automated control of the indoor environment.

It is considered that the shading systems of the zones are controlled with blind actuators, to manage the level of solar irradiance or natural illumination entering the zones, and provide the thermal and visual comfort of occupants. The artificial lighting system of a zone provides additional lighting if the level of natural illumination is not enough to fulfill the visual comfort of occupants. HVAC systems are controlled to ensure thermal comfort, as well as IAQ.

3.3 Personalized Energy and Comfort Management

Personalized energy and comfort management is to make energy-related decisions for the indoor environment, according to occupants' personalized preferences. The proposed personalized method acknowledges the diversity in the thermal preferences of occupants, and simultaneously optimizes energy consumption and occupants' overall productivity, considering occupants' personalized thermal preferences, as well as IAQ (*Objective 2* of the research).

3.3.1 Thermal Preference Modeling

To learn the personalized thermal preferences of occupants, their feedback on the thermal conditions of the indoor environment should be collected. Here, occupants and their thermal (and later visual) preferences are simulated, based on the results of a conducted field study. The results of a longitudinal field study [97], which was carried out over a three-year span in a building in Lausanne, Switzerland, is used to model the thermal preferences of occupants considered in this research. Participants in the field study were questioned randomly of their thermal sensations. Their feedback (their thermal sensation votes) were classified into feeling (1) warm, (2) comfortable, or (3) cold. Over time, each participant's thermal sensation feedback, across a wide range of indoor temperatures were collected.

Each participant's probability of being comfortable ($Prob_{\text{Thermal\_Comfort}}$) or uncomfortable ($Prob_{\text{Thermal\_Discomfort}}$), at a given indoor temperature, were expressed in the form of [80]:

$$Prob_{\text{Thermal\_Discomfort}} = Prob_{\text{Cold}} + Prob_{\text{Warm}} - Prob_{\text{Cold}}.\ Prob_{\text{Warm}} \tag{3.10}$$

$$Prob_{\text{Thermal\_Comfort}} = 1 - Prob_{\text{Thermal\_Discomfort}} = (1 - Prob_{\text{Cold}}).\ (1- Prob_{\text{Warm}})$$

Using multinomial logistic regression techniques in the field study, the probability of a participant satisfaction ($Prob_{\text{Thermal\_Comfort}}$) from the immediate thermal conditions (indoor temperature (T); °C), was expressed by specific unit-less regression parameters, a_{warm}, b_{warm}, a_{cold}, b_{cold} [97]:

$$Prob_{\text{Thermal\_Comfort}}\ (T) = \frac{1}{1+\exp(a_{warm} + b_{warm}\ .T)+\exp(a_{cold}+b_{cold}\ .T)} \tag{3.11}$$

Five arbitrary participants from the field study are selected, and their thermal sensation votes (their thermal regression parameters) are used to construct five *thermal preference models*. Five thermal preference models characterize the thermal preferences of five different occupants, simulated here. The thermal regression parameters of the selected participants and related thermal preference models are stated in Table 3.

Table 3: Thermal regression parameters extracted from [97] and related thermal preference models

Thermal Preference Model	Thermal Regression Parameters			
	a_{cold}	b_{cold}	a_{warm}	b_{warm}
Model #1	11.7	-0.6	-39.7	1.4
Model #2	12.6	-0.7	-21.4	0.8
Model #3	11.6	-0.8	-28.9	1.1
Model #4	8.8	-0.4	-16.4	0.6
Model #5	20.1	-1	-22.7	0.8

In this research, *two assumptions* are made to model the thermal (and visual) preferences of occupants. First, thermal (and visual) preference models are considered to be in the shape of *Gaussian functions*. Having each individual's thermal regression parameters (Table 3), $Prob_{\text{Thermal\_Comfort}}\ (T)$ is constructed from (3.11). Subsequently, constructed $Prob_{\text{Thermal\_Comfort}}\ (T)$ is fitted into a Gaussian function with a mean value of $T_{\text{maxcomfort}}$ and standard deviation of $Tolerance_{\text{thermal}}$ (see App. B.2):

$$Prob_{\text{Thermal\_Comfort}}\ (T) = \mathrm{e}^{\frac{-(T-T_{\text{maxcomfort}})^2}{2.(Tolerance_{\text{thermal}})^2}} \tag{3.12}$$

Based on the proposed shape for the thermal preferences of occupants, $T_{\text{maxcomfort}}$ and $Tolerance_{\text{thermal}}$ are two personalized variables that together characterize each thermal preference. $T_{\text{maxcomfort}}$ of a specific thermal preference model is the indoor temperature (T), in which an occupant with that thermal preference model has the highest probability of thermal comfort.

Second, when optimization is performed for thermal comfort, we assume that the relative productivity ($RP_{\text{thermal}}\ (T)$) is equal to the probability of thermal comfort ($Prob_{\text{Thermal\_Comfort}}$):

$$RP_{\text{thermal}}\ (T) = Prob_{\text{Thermal\_Comfort}}\ (T) \tag{3.13}$$

$RP_{\text{thermal}}\ (T)$ expresses the level of an occupant satisfaction from the immediate indoor environmental conditions.

$T_{\text{maxcomfort}}$ (°C) and $Tolerance_{\text{thermal}}$ (K) of five thermal preference models are stated in Table 4. $T_{\text{maxcomfort}}$ and $Tolerance_{\text{thermal}}$ are varied across the thermal preference models that indicate the diversity in the thermal preferences of occupants. These two personalized variables can be influenced by various parameters, such as seasonal changes, cultural and social norms, thermal expectations, history of thermal sensations, attitudes and beliefs, perceived control over the environment, and physiological and psychological adaptation [20, 62, 66, 67].

Table 4: $T_{\mathrm{maxcomfort}}$ and $Tolerance_{\mathrm{thermal}}$ of five thermal preference models

Thermal Preference Model	Model #1	Model #2	Model #3	Model #4	Model #5
$T_{\mathrm{maxcomfort}}$ (°C)	23.9	21.9	20.9	24.3	23.3
$Tolerance_{\mathrm{thermal}}$ (K)	6.2	5.1	5.2	7	4.3

For each thermal preference model, maximum RP_{thermal} is considered at $T_{\mathrm{maxcomfort}}$, in which RP_{thermal} is equal to 1. Based on the Gaussian function characteristics, higher values of $Tolerance_{\mathrm{thermal}}$ mean that the occupant is less sensitive to the indoor temperature changes. Moving away from $T_{\mathrm{maxcomfort}}$, RP_{thermal} decreases relatively slower, compared to an occupant with a similar $T_{\mathrm{maxcomfort}}$ but lower $Tolerance_{\mathrm{thermal}}$. In contrast, having low values of $Tolerance_{\mathrm{thermal}}$ implies that the occupant is more sensitive to the thermal conditions, and has relatively lower RP_{thermal}. $Tolerance_{\mathrm{thermal}}$ (K) only receives positive values.

3.3.2 Personalized Multi-Objective Optimization of Energy Costs, Thermal Comfort & Indoor Air Quality

Occupants' thermal preference models are introduced into the objective function of the MOOP problem to perform personalized energy and comfort management. The objective function of the personalized MOOP method consists of the energy costs term and the occupants' productivity losses term. Productivity losses term considers relative productivity losses of occupants with respect to the thermal conditions, and IAQ of the indoor environment. Having $T_{\mathrm{maxcomfort}}$ and $Tolerance_{\mathrm{thermal}}$ of five occupants (Table 4), RP_{thermal} of each occupant is constructed from (3.13). Relative productivity with respect to IAQ (RP_{IAQ}) is derived from Seppanen et al. meta-analysis [31], previously mentioned in (3.6) and demonstrated in Fig. 6.

Hourly productivity losses of each occupant (\$/h) are determined, using their *productivity per hour* (\$/h) and *RP*. Occupants' activities during a specific hour can be translated into their productivity per hour, and introduced in the MOOP problem formulation, as a variable parameter. Productivity losses associated with the thermal conditions ($productivity\ losses_{\mathrm{Thermal}}$) and IAQ

($productivity\ losses_{\text{IAQ}}$) of the indoor environment, are derived from the product of *productivity per hour* (\$/h) and *RP* losses:

$$\begin{aligned} &Productivity\ losses_{\text{Thermal}}\ (\$/\text{h}) = productivity\ per\ hour\ (\$/\text{h}).\ (1 - RP_{\text{Thermal}}) \\ &Productivity\ losses_{\text{IAQ}}\ (\$/\text{h}) = productivity\ per\ hour\ (\$/\text{h}).\ (1 - RP_{\text{IAQ}}) \end{aligned} \tag{3.14}$$

It is assumed that the overall productivity losses of each occupant ($productivity\ losses_{\text{Overall}}$) are in the range of the average of thermal ($productivity\ losses_{\text{Thermal}}$) and IAQ ($productivity\ losses_{\text{IAQ}}$) losses, and the maximum of these two values [56]:

$$\begin{aligned} &Productivity\ losses_{\text{Overall}} = [\text{average}\ (productivity\ losses_{\text{Thermal}}, productivity\ losses_{\text{IAQ}}) + \\ &\text{maximum}\ (productivity\ losses_{\text{Thermal}}, productivity\ losses_{\text{IAQ}})\ ]\ /\ 2 \end{aligned} \tag{3.15}$$

The objective function of the personalized MOOP method, to be minimized, is constructed using weighted sum method:

$$Objective\ function\ (\$/\text{h}) = energy\ costs + \sum_{i=1}^{n} productivity\ losses_{\text{Overall}}{}^{(i)} \tag{3.16}$$

In which, n is the number of occupants.

The automated control of the indoor environmental conditions is performed by managing the level of indoor temperature, ventilation rate, natural illumination, and artificial lighting. For each zone of the office, according to occupants' productivity rates, the personalized method can generate hourly Pareto optimal solutions for the economic-optimum building operation. Occupants' productivity rates can be measured, by the type of tasks they perform and the amount of time they spend on each task [98-100].

3.4 Position-based Energy & Comfort Management

Occupants' perceptions of the indoor environment, including their thermal and visual sensations, depend on their positions inside enclosed spaces. In the proposed position-based method, positions of occupants inside the zones, as well as their personalized thermal and visual preferences, are considered for personalized energy and comfort management (*Objective 3* of the research). Here, the inside plan of the single-floor office is changed from previous sections (Fig. 4), and the number of zones in the office are reduced to four. The central zone, existed in the previous plan of the office, is eliminated, since it doesn't have any window, and is not suitable for the visual comfort evaluation. The plan of the office with its four zones is demonstrated in Fig. 7.

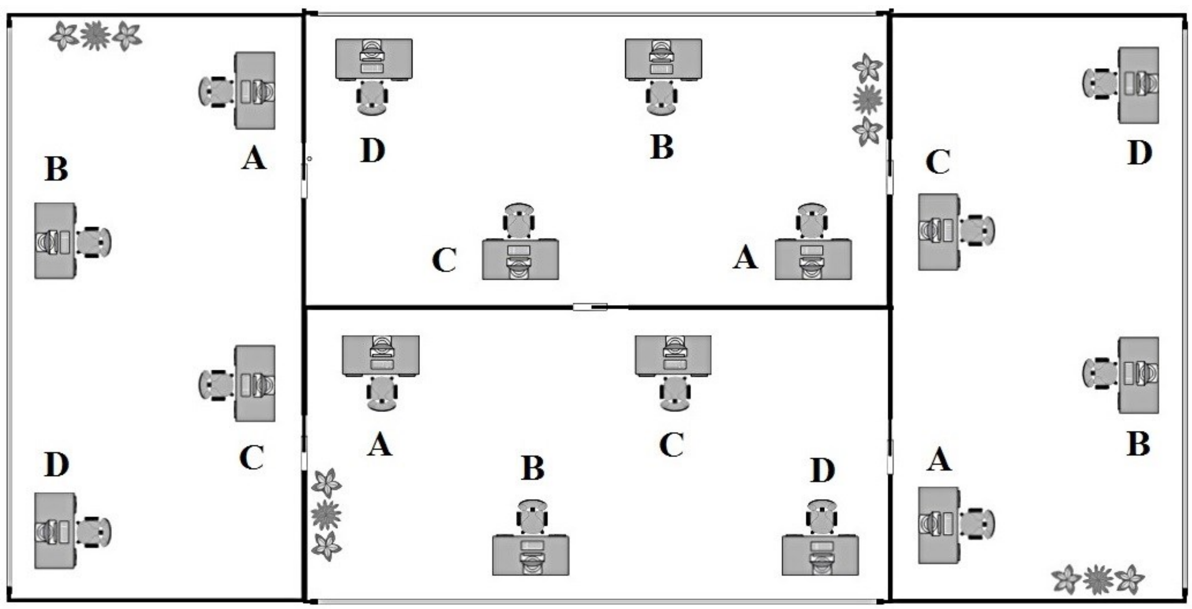

Fig. 7: Positions and their name in each zone of the office

In all the zones, the floor area is equal to 139 m^2 (16.66 m x 8.33 m), and the ceiling height is 3 meters. In all four zones, the wall with a connection to the outside has a window-wall ratio of 0.4. Each window (with 20 m^2 area) has the same width as the wall and is located in the middle of the wall. In each zone, four arbitrary positions for occupants are assumed, using this procedure; the floor area of each zone is divided into eight equal squares (4.16 m x 4.16 m), and the positions of occupants are adjusted to the middle of four of each square. In each zone, positions are called; *Position-A*, *Position-B*, *Position-C,* and *Position-D*. The positions of occupants inside each zone are illustrated in Fig. 7. For thermal and visual comfort analysis, the operative temperatures (°C) and illuminance levels (lux) in the positions are studied. Building parameters considered are similar to the building parameters, stated in Table 1.

Similar to the previous MOOP methods, in the position-based method, the level of artificial lighting, natural illumination, indoor temperature, and ventilation rate of each zone, are automatically controlled. These four indoor environmental parameters relate to the thermal and visual comfort of occupants, and IAQ of the zones. For these simulations, the office is assumed to be occupied all days, from 9 am to 5 pm. During the occupied and unoccupied hours, energy and comfort management are performed differently.

During the unoccupied hours, energy management is based on the SOOP of energy consumption costs. Energy consumption in each zone is the sum of energy consumption of artificial lighting, chiller, boiler, and fan. Fixed rates of 8 cents per kWh and 20 cents per m^3 are assumed as electricity and gas prices, respectively. In the SOOP of energy costs, occupants' comfort conditions are treated as the limits on the indoor environmental parameters. The constraints, related to visual comfort (indoor illuminance), thermal comfort (heating and cooling set-points), and IAQ (conditioned outdoor air flow rate) are demonstrated in Table 5. Building schedules, during the occupied and unoccupied hours, are compared in Table 5. The major difference between the proposed method and the SOOP method is the presence of thermal comfort, visual comfort, and IAQ parameters, inside the objective function of the position-based method.

Table 5: Building Schedule

Schedule	***Occupied***	***Unoccupied***
Minimum Indoor Illuminance (lux) [4]	750 (always ≤ 2500 lux)	50
Occupancy Heat Generation (W/m^2)	12.6	1.6
Equipment Heat Generation (W/m^2)	10.7	3
Cooling Set-Point (°C)	-	27
Heating Set-Point (°C)	-	21
Minimum Conditioned Outdoor Air Flow Rate (m^3/s per m^2) [16]	0.0006 + 0.0003 (infiltration)	0.0003 (only infiltration)
Maximum Conditioned Outdoor Air Flow Rate (m^3/s per m^2)	0.002	0.002

During the occupied hours, the position-based method provides economic-optimum conditions for the operation of the building, by managing the level of the mentioned indoor environmental parameters. The method has an energy costs term, as well as an occupants' productivity term, in its objective function. Indoor and outdoor weather conditions, energy prices, occupancy data, occupants' productivity rates, thermal and visual preferences, thermal and visual behavior, and positions, are the factors that influence the decision-making of the position-based method.

3.4.1 Position-based Thermal Comfort Evaluation

The operative temperature (°C) in each position, is assumed to be the average of indoor temperature and Mean Radiant Temperature (MRT). Indoor temperature in each zone is automatically controlled by the proposed method, and is assumed to be uniform throughout the zone. But, MRTs (°C) are varied and depend on the position of each occupant inside the zone. The procedure to find MRTs in different positions, is as follows:

1. For each zone, eight surfaces are considered. The wall with the window is divided into three surfaces; a window surface in between (with 1.2 m height), and two top and bottom sides of the window (with 0.9 m height). Five other surfaces are the three other interior walls, the floor, and the ceiling.
2. Configuration factors between occupants' positions (points) and each surface ($Configuration\ Factor_{\text{point-surface}}$), are calculated from (3.17), in which x, y, and z are the distances between the center of position and that surface in three-dimensional spaces [101].

$$f(x,y,z) = \frac{1}{2\pi}(\arctan\left(\frac{x}{z}\right) - \frac{z}{\sqrt{y^2+z^2}}\ .\arctan\ (\frac{x}{\sqrt{y^2+z^2}})) \tag{3.17}$$

3. For all positions, the workplace height is assumed to be 0.9 m.
4. The sum of configuration factors between a single point and all the surfaces should be equal to one.
5. Temperatures of all indoor surfaces (T_{surface}) are calculated (except floor and ceiling); T_{surface} is influenced by the level of solar radiation.
6. Floor and ceiling are considered as adiabatic surfaces, in the RC-network thermal modeling of the office, hence, their surface temperatures in each zone are assumed to be the same as the indoor temperature of that zone.
7. MRT calculations are in Kelvin (K), hence, should be transformed into Celsius (°C).
8. In each zone, MRT in Celsius (°C) in each point (position), is calculated from [101]:

$$(273 + MRT_{\text{point}})^4 = \sum_{k=1}^{8} (273 + T_{\text{surface } k})^4 . \, Configuration\ Factor_{\text{point-surface } k} \quad (3.18)$$

9. In each zone, for each point, the *Operative Temperature* (°C) is calculated from [16]:

$$Operative\ Temperature_{\text{point}} = \frac{Indoor\ Temperature + MRT_{\text{point}}}{2} \quad (3.19)$$

3.4.2 Position-based Visual Comfort Evaluation

Since the plan of all four zones and the positions inside the zones are similar, position-based visual comfort evaluation is discussed for only one of the zones. South zone is chosen to describe the position-based visual comfort evaluation in the office. South zone is divided into eight surfaces. The first five surfaces are the three interior walls that are west wall, east wall, and north wall in south zone, as well as the ceiling, and the floor. The wall with windows (south wall) contains three other surfaces; a window surface in between (with 1.2 m height), a surface above the window surface, and a surface below the window surface (each with 0.9 m height). From (3.20), a row number is assigned to each surface of south zone (e.g. west wall: one, window: six).

$$Surfaces = [\text{west wall, north wall, east wall, ceiling, floor, window, south wall-top, south wall-bottom}]^T \quad (3.20)$$

Both position-based thermal comfort and visual comfort evaluations require calculation of configuration factors. Calculating configuration factors is discussed, in the first 4 steps of position-based thermal comfort evaluation (Section 3.4.1). Configuration factors between each of the four positions and each surface from (3.20), are calculated using (3.17):

$$\begin{aligned}
Configuaration\ Factor_{\text{Position-A}} &= [0.129, 0.130, 0.002, 0.310, 0, 0.006, 0.212, 0.212]^T \\
Configuaration\ Factor_{\text{Position-B}} &= [0.016, 0.023, 0.004, 0.402, 0, 0.066, 0.245, 0.245]^T \\
Configuaration\ Factor_{\text{Position-C}} &= [0.004, 0.146, 0.016, 0.410, 0, 0.008, 0.208, 0.208]^T \\
Configuaration\ Factor_{\text{Position-D}} &= [0.002, 0.018, 0.129, 0.412, 0, 0.060, 0.190, 0.190]^T
\end{aligned} \quad (3.21)$$

For position-based visual comfort evaluation, apart from the configuration factors, the view factors between all surfaces of the zone, as well as each surface reflectance are required. For all parts of the wall, the reflectance of 0.7 is assumed, while for the window, floor, and ceiling the reflectances equal to 0.05, 0.3, and 0.8 are considered, respectively:

$$Reflectances = [0.7, 0.7, 0.7, 0.8, 0.3, 0.05, 0.7, 0.7]^T \quad (3.22)$$

Considering south zone's shape and dimensions and the size of the windows, the view factors between all surfaces of south zone are calculated, using the related equations in [101]. The *View Factor*$_{A \to B}$ is the portion of the radiation that leaves Surface A and strikes Surface B [101]. Considering eight surfaces and their assigned numbers in (3.20), the *View Factor*$_{i \to j}$, in which *i* and *j* are the surfaces' assigned numbers, is presented:

$$View\ Factor_{\,i \to j} = \begin{pmatrix} 0 & 0.139 & 0.026 & 0.354 & 0.352 & 0.059 & 0.039 & 0.039 \\ 0.069 & 0 & 0.070 & 0.380 & 0.377 & 0.049 & 0.036 & 0.036 \\ 0.026 & 0.139 & 0 & 0.352 & 0.354 & 0.059 & 0.040 & 0.040 \\ 0.064 & 0.137 & 0.063 & 0 & 0.609 & 0.052 & 0.051 & 0.032 \\ 0.063 & 0.136 & 0.064 & 0.609 & 0 & 0.052 & 0.032 & 0.053 \\ 0.074 & 0.124 & 0.074 & 0.364 & 0.364 & 0 & 0 & 0 \\ 0.066 & 0.121 & 0.066 & 0.475 & 0.296 & 0 & 0 & 0 \\ 0.066 & 0.121 & 0.066 & 0.296 & 0.475 & 0 & 0 & 0 \end{pmatrix} \quad (3.23)$$

Having the configuration factors in each position, the view factors between the surfaces, the surface reflectances, and the level of natural illumination (lux) entered the room from the window, *Natural Illuminance* (lux), in each of the four selected positions are calculated [101]:

$$Natural\ Illuminance_{\text{Position}-x} = Configuaration\ Factor_{\text{Position}-x} \,.\, (Identity\ (8) - Reflectances.\ View\ Factor)^{-1}.\ M_0 \quad (3.24)$$

In which M_0 is:

$$M_0 = [0, 0, 0, 0, 0, \textit{Transmitted light through the window}\ \text{(lux)}, 0, 0]^T \quad (3.25)$$

Here, the level of illuminance (lux) in each position, is the parameter to consider in visual comfort evaluation. Moreover, for avoiding glare, the minimum illuminance level (lux) and the maximum illuminance level (lux), should be respected as the constraints on the visual conditions (Table 5). The level of *Illuminance* (lux) in each position is the sum of *Natural Illuminance* (lux) and *Artificial Illuminance* (lux):

$$Illuminance_{\text{Position-x}} = Natural\ Illuminance_{\text{Position-x}} + Artificial\ Illuminance_{\text{Position-x}} \tag{3.26}$$

It is considered that illuminance from artificial lighting is uniform across the zone. Here, position-based visual comfort evaluation in south zone is discussed. The same approach is used for position-based visual comfort evaluation in alternative zones of the office.

3.4.3 Modeling Thermal Preferences

Occupants' feedback on the thermal and visual conditions of the indoor environment, or their thermal and visual sensation votes, should be collected to learn their preferences. Similar to Section 3.2, the results of the mentioned longitudinal field study [97], carried out from 2006 to 2009, in a building located in Lausanne, Switzerland, is used to construct the thermal and visual preference models of occupants, simulated here. In the field study, the participants were questioned randomly and on a daily basis, of their thermal and visual sensations and the type of actions they chose to restore their comfort. For each participant, thermal regression parameters, specific to thermal sensations of feeling warm and feeling cold, were found. Logistic regression techniques extracted these specific thermal regression parameters from their thermal sensation votes [97].

The methodologies used to simulate the thermal preference models of occupants (considered in this research), from the specific thermal regression parameters of the field study's participants, are already covered in Sub-Section 3.3.1. Using equations (3.10) and (3.11) and having personalized thermal regression parameters from [97], the probability of an occupant satisfaction ($Prob_{\text{Thermal\_Comfort}}$) from the thermal conditions of the indoor environment (temperature; T) can be defined.

From the longitudinal field study, four participants are selected. Thermal regression parameters of four selected participants, alongside the name assigned to them here, are shown in Table 6. Here, the set of chosen participants from the field study, is different from the set of chosen participants in personalized energy and comfort management (Section 3.3). It should be noted that the conclusions derived from these simulations are independent of the choice of occupancy scenario.

It is proposed that thermal (and visual) preference models of occupants are in the shape of a Gaussian function. Using equations (3.11) to (3.13) and Table 6, the thermal preference model (RP_{thermal}) of each of the four occupants is constructed, by fitting his or her probability of comfort ($Prob_{\text{Thermal\_Comfort}}$) into a Gaussian function, with a mean value of $T_{\text{maxcomfort}}$ and standard deviation of $Tolerance_{\text{thermal}}$.

Table 6: Occupants' names in this research and their thermal regression parameters in [97]

Occupant Name	Thermal Regression Parameters			
	a_{cold}	b_{cold}	a_{warm}	b_{warm}
Occupant #1	13.6	-0.6	-11.2	0.4
Occupant #2	20.1	-1	-22.7	0.8
Occupant #3	15.7	-0.8	-13.9	0.5
Occupant #4	11.3	-0.5	-13.2	0.5

According to the proposed approach, $T_{\text{maxcomfort}}$ and $Tolerance_{\text{thermal}}$ are two personalized variables that form the personalized thermal preference model (RP_{thermal}) of each occupant. RP_{thermal} (T) of each occupant indicates his or her immediate satisfaction from the thermal conditions of the indoor environment. For each occupant, the maximum thermal productivity (RP_{thermal}=1) is considered at $T_{\text{maxcomfort}}$. $Tolerance_{\text{thermal}}$ of an occupant expresses his or her level of sensitivity to the thermal conditions of the indoor environment. Based on the procedure described, the thermal preferences models of four considered occupants are constructed (Table 7).

Table 7: Occupants' personalized parameters – Thermal comfort

Thermal Preference Model	**Occupant #1**	**Occupant #2**	**Occupant #3**	**Occupant #4**
$\boldsymbol{T_{\text{maxcomfort}}}$ **(°C)**	25.5	23.4	24.3	23.9
$\boldsymbol{Tolerance_{\text{thermal}}}$ **(K)**	7.2	4.4	5.8	6.7

As it was discussed, from equations (3.11) to (3.13) and thermal regression parameters (Table 6), occupants' probability of comfort ($Prob_{\text{Thermal\_Comfort}}$) are fitted into Gaussian functions, in order to construct their RP_{thermal} (T). Fig. 8 demonstrates this procedure for two of the occupants. The dotted lines (not exactly Gaussian) show $Prob_{\text{Thermal\_Comfort}}$ (T) of two occupants, derived from (3.11), and the solid lines (Gaussian) indicate RP_{thermal} (T), derived from (3.13).

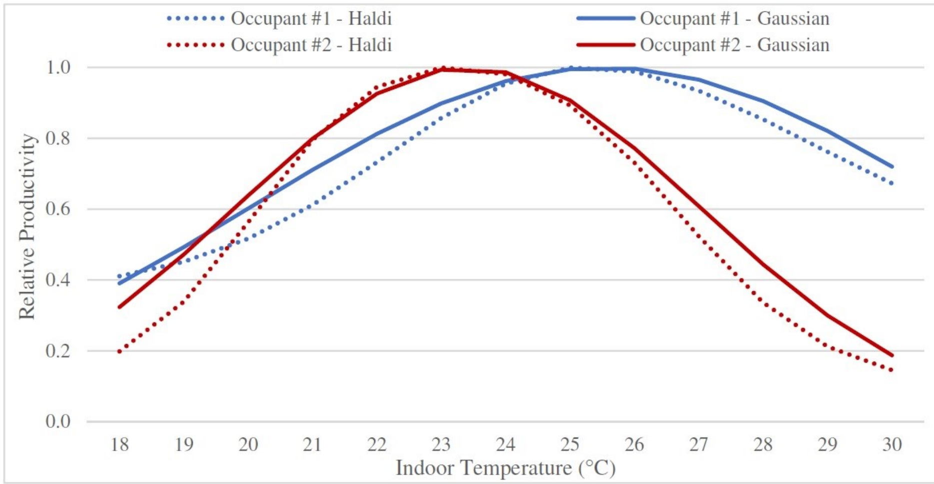

Fig. 8: Fitting the thermal sensation votes of occupants in Haldi research [97] to Gaussian functions

3.4.4 Modeling Visual Preferences

Through multinomial logistic regression, the regression parameters related to the visual comfort of participants of the field study, were derived in [97]. For the same four participants, selected in Section 3.4.3, the visual regression parameters a_{dark}, a_{bright}, b_{dark}, b_{bright} are presented in Table 8.

Table 8: Occupants and their visual regression parameters [97]

Occupant Name	Visual Regression Parameters			
	a_{dark}	b_{dark}	a_{bright}	b_{bright}
Occupant #1	5.9	-1.3	-10.9	0.006
Occupant #2	3.7	-0.8	-4.3	0.006
Occupant #3	1.6	-0.6	-3.3	0.003
Occupant #4	9.6	-1.8	-4.4	0.001

The *visual preference models* of four occupants, simulated here, are constructed from the visual regression parameters in Table 8. The level of illuminance (lux) is the parameter to evaluate the visual comfort. The probability of an occupant satisfaction ($Prob_{\text{Visual\_Comfort}}$) from the visual conditions of the indoor environment (indoor illuminance ($Illuminance$); lux), can be defined using specific unit-less regression parameters a_{bright}, b_{bright}, a_{dark}, b_{dark} [97]:

$$Prob_{\text{Visual\_Comfort}}(Illuminance) = \frac{1}{1 + \exp\left(a_{bright} + b_{bright} \,.\, Illuminance\right) + \exp\left(a_{dark} + b_{dark} \,.\, Illuminance\right)} \tag{3.27}$$

Here, it is suggested that for each occupant, the probability of visual comfort ($Prob_{\text{Visual\_Comfort}}$) with respect to the level of illuminance (lux) is fitted into a Gaussian function with a mean value of $ILL_{\text{maxcomfort}}$ and standard deviation of $Tolerance_{\text{visual}}$:

$$Prob_{\text{Visual\_Comfort}}\,(Illuminance) = \mathrm{e}^{\frac{-(Illuminance - ILL_{\text{maxcomfort}})^2}{2.(Tolerance_{\text{visual}})^2}} \tag{3.28}$$

$ILL_{\text{maxcomfort}}$ and $Tolerance_{\text{visual}}$ are two personalized variables, related to the visual comfort of occupants. For each occupant, if his or her specific $ILL_{\text{maxcomfort}}$ is provided in the occupant's position, he or she has the highest probability of visual comfort (RP_{Visual}=1). We assume that the relative productivity from the visual ambient (RP_{Visual}) is equal to the probability of visual comfort ($Prob_{\text{Thermal\_Comfort}}$):

$$RP_{\text{Visual}}\,(Illuminance) = Prob_{\text{Visual\_Comfort}}\,(Illuminance) \tag{3.29}$$

Accordingly, visual preference models of the simulated occupants are constructed by fitting their visual sensation votes into Gaussian functions. $ILL_{\text{maxcomfort}}$ and $Tolerance_{\text{visual}}$ of four occupants, derived from the fitting process, are demonstrated in Table 9.

Table 9: Occupants' personalized parameters - Visual comfort

Visual Preference Model	Occupant #1	Occupant #2	Occupant #3	Occupant #4
$ILL_{\text{maxcomfort}}$ (*Illuminance*) [lux]	937	1563	1569	1429
$Tolerance_{\text{visual}}$ (*Illuminance*) [lux]	667	1199	1203	1105

Personalization is only applied to the thermal comfort and visual comfort of occupants. However, a general relation between ventilation rate and productivity of occupants, provided in (3.6), is used to consider and improve IAQ of the zones.

3.4.5 Position-based Multi-Objective Optimization of Energy Costs, Thermal & Visual Comfort & Indoor Air Quality

Overall comfort conditions are considered to be the combination of thermal comfort, visual comfort, and IAQ. The strong relationship between occupants' comfort and their performances is discussed, in Section 2.2. In the problem formulation of the proposed position-based method, occupants' performances are expressed as their *productivity rates*. Hereby, the objective function consists of two terms: (1) the energy costs term, and (2) the occupants' productivity term. The occupants' productivity term considers the productivity of each occupant, with respect to his or her overall comfort conditions (RP_{Overall}).

RP_{Overall} is used to compare an occupant productivity with his or her maximum level of productivity. RP_{Overall} is a dimensionless quantity and can be expressed in percentage, or as a value in the range of 0 to 1. RP_{Overall}, equal to 1, is assigned to an occupant's maximum level of productivity. For each occupant, RP_{Overall} is assumed to be in the range of the average of RP_{Thermal}, RP_{Visual}, and RP_{IAQ}, and the maximum value between RP_{Thermal}, RP_{Visual}, and RP_{IAQ} [56]:

$$RP_{\text{Overall}} = [\text{average}\ (RP_{\text{Thermal}}, RP_{\text{Visual}}, RP_{\text{IAQ}}) + \max\ (RP_{\text{Thermal}}, RP_{\text{Visual}}, RP_{\text{IAQ}})]\ /\ 2 \tag{3.30}$$

Productivity losses of each occupant are equal to occupant's productivity during that hour (*productivity per hour*), multiplied by his or her overall relative productivity losses (1- RP_{Overall}):

$$\textit{Productivity losses}\ (\$/\text{h}) = \textit{productivity per hour}\ (\$/\text{h}).\ (1 - RP_{\text{Overall}}) \tag{3.31}$$

Using weighted sum method, the objective function of the position-based MOOP method to be minimized, is constructed:

$$\textit{Objective function}\ (\$/\text{h}) = \textit{energy costs} + \sum_{i=1}^{n} \textit{productivity losses}_{\ \text{i}} \tag{3.32}$$

In which, *energy costs* are derived from (3.3), and *n* is the number of occupants in the office.

In order to evaluate the performance of the proposed position-based method, different parametric simulations are performed (Chapter 6), where varied scenarios of occupancy in different zones of the office, are assumed. The selection of occupancy scenarios in the office building are arbitrary. Occupants and their thermal and visual preferences are selected from Table 7 and Table 9, respectively, and their positions are chosen from the assumed positions in Fig. 7. For each parametric simulation, the considered scenario of occupancy is stated at the beginning of the related section. It should be noted that the conclusions derived from the parametric simulations are independent of the choice of occupancy scenario.

3.5 Situation-specific Energy and Comfort Management

Within the position-based method, proposed in Section 3.4, different human-related parameters including occupants' thermal and visual preferences, thermal and visual tolerances, productivity rates, and positions are considered for personalized energy and comfort management. The position-based method is able to receive thermal and visual sensation votes of occupants, model their thermal and visual preferences, and control the indoor environment, accordingly. Here, the objective of the proposed *situation-specific* method is to offer *behavioral intelligence*, by acknowledging occupants' situation-specific adaptive behavior, while making energy-related decisions for the automated control of the indoor environment (*Objective 4* of the research).

3.5.1 Modeling Occupants' Sensations and Positions

Similar to Section 3.4, positions of occupants are considered for energy and comfort management, hence, position-based thermal comfort and visual comfort evaluations, described in Sub-Section 3.4.1 and Sub-Section 3.4.2, are applied here as well. In order to construct the thermal preference model (RP_{Thermal}) of each individual, from his or her thermal sensation votes, equations (3.10) to (3.13) are used. For each individual occupant, RP_{Visual} is derived from his or her visual sensation votes, using equations (3.27) to (3.29). Moreover, RP_{IAQ} of each occupant is considered, using (3.6). $RP_{\text{Sensation-Overall}}$ of each occupant is assumed to be in the range of the average of RP_{Thermal}, RP_{Visual}, and RP_{IAQ}, and the maximum value between the three [56]:

$$RP_{\text{Sensation-Overall}} = [\text{average}\ (RP_{\text{Thermal}}, RP_{\text{Visual}}, RP_{\text{IAQ}}) + \max\ (RP_{\text{Thermal}}, RP_{\text{Visual}}, RP_{\text{IAQ}})\ ] / 2 \tag{3.33}$$

The set of occupants considered here is similar to the set of occupants considered in Section 3.4. The personalized thermal and visual parameters of the four occupants are stated in Table 7 and Table 9, respectively. Each RP_{Thermal} and RP_{Visual} is comprised of two personalized thermal and visual parameters: $T_{\text{maxcomfort}}$ and $Tolerance_{\text{thermal}}$ and $ILL_{\text{maxcomfort}}$ and $Tolerance_{\text{visual}}$. $Tolerance_{\text{thermal}}$ and $Tolerance_{\text{visual}}$ represent the thermal tolerance and visual tolerance of an occupant. Having higher values of $Tolerance_{\text{thermal}}$ and $Tolerance_{\text{visual}}$, the occupant is less sensitive to the variations of the indoor thermal and visual conditions. On the contrary, lower values of $Tolerance_{\text{thermal}}$ and $Tolerance_{\text{visual}}$ express the higher sensitivity of the occupant to the indoor environmental conditions.

3.5.2 Occupants' Situation-Dependent Adaptive Behavior

In different situations inside an enclosed space, an occupant may have varied responses to the indoor environmental conditions [62, 68, 78, 97]. In the proposed situation-specific energy and comfort management, the thermal and visual behavior of an occupant is assumed to vary according to the specific situation in the indoor environment. When energy and comfort management of an enclosed space is at group-level or zone-level, occupants in a shared space may have varied thermal and visual preferences. Hence, there may have varied levels of satisfaction from the indoor environmental conditions of the space. Dissatisfied occupants in the space, might adjust the indoor environment to improve their personal comfort [62, 67, 68].

An occupant's responses to the indoor environmental conditions are categorized into (1) coping or choosing self-adaptive behavior to increase comfort level (here called *1st category behavior*), or (2) adjusting the indoor environment to elevate personal comfort level (here called *2nd category behavior*) [67, 68, 84]. First category behavior includes changing or adjusting clothes, drinking warm or cold beverage, changing physical activity level, and changing positions in the room. In contrast, second category behavior is energy-related actions, such as adjusting room's thermostat, adjusting the level of artificial lighting, and opening or closing the blinds.

Occupants' responses or their adaptive behavior are the product of their decisions, while decisions are generated in their brains [81, 85, 87]. Multiple studies in the fields of behavioral economics and neuroscience have provided computational models for the human brain operation while choosing between different alternatives [102-111].

In the proposed situation-specific energy and comfort management, it is assumed that for each occupant, a combination of *situation* and *sensation* shapes his or her decision-makings, and subsequently his or her adaptive behavior. The proposed situation-specific method, inspired by behavioral economics and neuroscience studies, computationally models each occupant's brain function while making decisions for the type of adaptive behavior.

Each occupant's $RP_{\text{Sensation-Overall}}$, derived from (3.33), is served as the basis to model his or her *situation-specific RP* or RP_{Behavior}. RP_{Behavior} expresses the relative productivity with respect to the probability of 2nd category adaptive behavior. RP_{Behavior} equal to 1 of an occupant, implies that the probability of adjusting the immediate indoor environment by the occupant is equal to zero. On the other hand, with the decrease in RP_{Behavior}, the probability of 2nd category behavior of the occupant increases.

The objective of the situation-specific method is to minimize the probability of occupants' 2nd category behavior, or to minimize the probability of occupants' dissatisfaction from the indoor environmental conditions while optimizing the energy consumption costs. Considering *n* occupants in a zone, the objective function of the situation-specific MOOP method, to be minimized, is in the form of:

$$objective\ function = energy\ costs + \sum_{i=1}^{n} productivity\ per\ hour\ (i).\ (1 - RP_{Behavior}(i)) \tag{3.34}$$

In which, *energy costs* are derived from (3.3), and *n* is the number of occupants in the office.

3.5.3 Modeling Occupants' Situation-Specific Responses to the Indoor Environment

From cognitive science and neuroscience studies, the neural basis of the brain response to sensory stimuli can be computationally modeled [104-107]. The human brain's response to sensory stimuli (e.g. indoor environmental parameters) shapes the decision-making process of that individual, in a particular situation.

Here, it is proposed that for an individual occupant, having (1) the knowledge of his or her prior comfort sensation probabilities, and (2) the benefits and costs associated with his or her 2nd category behavior, the relationship between his or her probability of 1st category behavior and the probability of 2nd category behavior, can be constructed.

Accordingly, *Likelihood Ratio* (*LR*) of the occupant's 2nd category behavior can be modeled. *LR* is used to model RP_{Behavior} in a specific situation. The general form of *LR* (*2nd Category Behavior*) formulation is derived from studies in the field of neuroscience [104, 105, 112]:

$$LR\ (2^{nd}\ Category\ Behavior) = \frac{Prob_{\ 2nd\ Category\ Behavior}}{Prob_{\ 1st\ Category\ Behavior}} = \frac{Prob_{Discomfort}}{Prob_{Comfort}} \cdot \frac{Value\ of\ Action}{Costs\ of\ Action} \tag{3.35}$$

Based on (3.35), in any situation, if *LR* (*2nd Category Behavior*) of the occupant is larger than 1, 2nd category behavior is more likely than 1st category behavior. The proposed situation-specific method models each occupant's decision-making process and avoids situations that *LR* (*2nd Category Behavior*) of any occupant is larger than 1.

Likelihood Ratio in (3.35), is unit-less and is comprised of two terms. Here, the first term ($\frac{Prob_{Discomfort}}{Prob_{Ccomfort}}$) is called *Discomfort Parameter*. *Discomfort Parameter* expresses the prior comfort sensation probabilities of each occupant, and can be derived from $RP_{\text{Sensation-Overall}}$ in (3.33):

$$Discomfort\ Parameter = \frac{Prob_{Discomfort}}{Prob_{Comfort}} = \frac{1 - Prob_{Comfort}}{Prob_{Comfort}} = \frac{1 - RP_{Sensation-Overall}}{RP_{Sensation-Overall}} \tag{3.36}$$

The second term of the proposed *Likelihood Ratio*, $\frac{Value\ of\ Action}{Costs\ of\ Action}$, is *Decision-Making Parameter*. *Decision-Making Parameter* of an occupant, itself, consists of two terms (*Value of Action* and *Costs of Action*) that relate the occupant to the specific situation in the indoor environment.

3.5.4 Using the Prospect Theory to Model Occupants' Decision-Making Process

To model occupants' situation-specific energy-related decision-making (and behavior), a theory from the field of behavioral economics is used. The *Prospect Theory*, developed by Economic Nobel Prize laureate, Daniel Kahneman, and Amos Tversky, provides a model for human decision-making process under risk [86, 109]. The model is also expandable to riskless decisions [111].

Using the prospect theory to model human decision-making process, (1) decision-making is based on *value* and *costs functions*, rather than the final outcome of the decision; (2) every choice is reference-dependent (Here, the reference is the combination of indoor environmental conditions and other influential human-related parameters); (3) people are more sensitive to their losses compared to their gains [86].

Based on the proposed approach for computational modeling of an occupant's decision-making process, his or her comfort losses are assumed to be equal to the value of his or her behavior (action), since the intention of adaptive behavior is to restore comfort losses (*Value of Action*).

Energy costs and other occupants' comfort losses are considered to be the expenses of the behavior (*Costs of Action*).

According to the prospect theory, subjective value/costs, $V(x, p)$, of each decision is described by [109]:

$$V(x, p) = \mathrm{v}(x).\ \mathrm{w}(p) \tag{3.37}$$

in which, x is the choice; $\mathrm{v}(x)$ is the value function that measures the subjective value (or costs) of the consequences of choosing x; p is the probability of consequences; and $\mathrm{w}(p)$ is the weighting function that represents the impact of probability p on the attractiveness of the consequences [113].

The Weighting function, used here, is suggested in [114]:

$$\mathrm{w}(p) = \frac{\delta\,.\,p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}} \tag{3.38}$$

in which, δ=0.84 and γ=0.68. $\mathrm{w}(p)$ indicates that people are relatively more risk averse with respect to their losses, and relatively less risk averse with respect to their gains.

Based on (3.38), when p is equal to 1, it implies that for that person, decision-making is not associated with any risk, and the person is totally aware of both positive and negative consequences of that decision. For a single decision (action), the value of p for positive or negative consequences of the decision (action) could be different. Throughout the simulations, fixed values of p equal to 1, for the value of actions (positive consequences), and p equal to 0.9, for the costs of actions (negative consequences), are assumed. Accordingly, it is considered that people are more confident of the positive consequences of their actions (increasing personal comfort), compared to the negative consequences of their actions (affecting other occupants' comfort and energy consumption).

The value function used here, $\mathrm{v}(x)$, for the subjective value/costs of decisions is in the shape of [86, 109, 110]:

$$\mathrm{V}(x) = \begin{cases} x^{\alpha}, x \geq 0 \\ -\lambda\,(-x)^{\tau},\ x < 0 \end{cases} \tag{3.39}$$

in which, α=0.88, τ=0.88, λ=2.25. The parameters α and τ determine the curvature of the utility for the gains and losses, respectively. The parameter λ is the *loss aversion coefficient* [86, 109, 110].

Based on the proposed method to model occupant situation-dependent behavior, x^{α} expresses an occupant's *costs of action*, if he or she adjusts the indoor environment to restore his or her comfort. Accordingly, the costs of an occupant's action include (1) the energy costs, and (2) the productivity losses of other occupants, associated with that action. Each occupant's action(s) is considered as the action(s) that fully restores his or her overall comfort.

Moreover, $-\lambda\,(-x)^{\tau}$ (where $x < 0$) represents the overall comfort losses, or the overall productivity losses of each occupant, while making decisions. λ larger than one (here, λ is assumed to be equal to 2.25) conveys that each occupant prefers his or her own comfort, rather than the other occupants' comfort. It is assumed that an occupant chooses an adaptive behavior, to increase his or her $RP_{\text{Sensation-Overall}}$ to its maximum level.

Based on the proposed approach to apply the prospect theory to model occupant situation-dependent behavior, the subjective value and costs of each occupant's 2nd category adaptive behavior, are estimated using (3.37), considering v(x) and w(p), from (3.38) and (3.39):

$$Value\ of\ Action = 2.25\,.\,(productivity\ gains\ associated)^{0.88}\,.\,\mathrm{w}(p) \tag{3.40}$$

$$Costs\ of\ Action = (productivity\ losses\ associated + energy\ costs\ associated)^{0.88}\,.\,\mathrm{w}(p)$$

Value of Action, and *Costs of Action* are introduced into (3.35), to derive the *Likelihood Ratio* of 2nd category adaptive behavior, from *Discomfort Parameter* and *Decision-Making Parameter*. Subsequently, RP_{Behavior} is calculated from *Likelihood Ratio* of 2nd category adaptive behavior:

$$RP_{Behavior} = \frac{1}{1 + Likelihood\ Ratio} \tag{3.41}$$

Maximum RP_{Behavior} of an occupant, in any situation in an indoor environment, is achieved when the *LR* (*2nd Category Behavior*) is equal to zero. With the increase in the likelihood of 2nd category adaptive behavior, RP_{Behavior} is decreased.

By performing various parametric simulations, the performance of the proposed situation-specific method is studied in Chapter 7. The same four occupants in Section 3.4 (and Chapter 6) and their thermal and visual preferences (Table 7 and Table 9), are considered for simulations. It should be noted that the choice of occupancy scenarios for the parametric simulations, are arbitrary. For different simulations, varied scenarios of occupancy in different zone(s) of the simulated office building, are assumed, to demonstrate the versatility of the proposed method. The occupants considered in each simulation and their positions inside the considered zone(s) are stated, at the beginning of the related section. The conclusions derived from the parametric simulations are independent of the choice of occupancy scenario.

4 Multi-Objective Optimization of Energy Costs, Thermal Comfort and Indoor Air Quality [1]

In this chapter, the capabilities of the method, proposed in Section 3.2, to perform simultaneous optimization of energy costs and productivity, are evaluated. The simplified R-C network thermal model of a single-floor office building, located in Montreal, Canada, is developed (Section 3.1.1), and the building integrated control system is modeled (Section 3.1.2). The proposed MOOP method performs automated control of the indoor environment, in different zones of the office.

Using the proposed method for energy and comfort management, energy costs, thermal conditions of occupants, and IAQ are simultaneously optimized. Thermal comfort of occupants and IAQ are expressed in terms of their relative productivity with respect to indoor environmental conditions. In order to express relative productivity with respect to thermal conditions (RP_{thermal}) and IAQ (RP_{IAQ}), results of previous studies on the relationship between productivity and comfort conditions, are used [28, 31]. RP_{thermal} and RP_{IAQ} are combined to construct RP_{Overall} of occupants.

Within the method presented (Section 3.2), thermal comfort and IAQ requirements of occupants are considered at group-level. Accordingly, for a group of occupants in a shared zone, same relationships between their relative productivity and thermal conditions, as well as, their relative productivity and IAQ of the zone, are assumed. Here, the performance of the proposed method, in terms of energy consumption reduction and overall productivity improvement, is analyzed.

First, the operation of the SOOP method, with only energy costs optimization objective, is studied. During the unoccupied hours of the office, the SOOP method performs automated control of the indoor environment in different zones, by managing the level of indoor temperature, ventilation rate, natural illumination, and artificial lighting, on an hourly basis.

A scenario of using the SOOP method for energy management, during both unoccupied and occupied hours, is considered as the *Base Case*. The performance of the proposed method, with

[1] A version of this chapter has been published in Journal of Energy and Buildings [121]:
Mofidi F. Akbari H., "Integrated optimization of energy costs and occupants' productivity in commercial buildings," *Energy and Buildings*, vol. 129, p. 247-260, 2016. http://dx.doi.org/10.1016/j.enbuild.2016.07.059

respect to energy costs and occupants' comfort conditions, is compared to the Base Case. Monthly indoor air temperatures, and monthly ventilation rates, chosen by MOOP and SOOP methods, in varied outdoor weather conditions, are compared and discussed. It is demonstrated that the MOOP method is capable of optimizing productivity losses and energy costs, simultaneously. Moreover, the construction of Pareto optimal solutions by the MOOP method is discussed. Energy and comfort management in different zones of the office is studied, to demonstrate the influence of external parameters (e.g. solar irradiance), on the operation of the MOOP method. Furthermore, the sensitivity of the proposed method to occupants' (1) thermal preferences and (2) tolerances, and (3) IAQ is analyzed to assess the suitability of the proposed method to perform personalized energy and comfort management.

4.1 The Base Case

A Base Case scenario is considered, in which, during both occupied and unoccupied hours, the indoor environmental conditions of the office are controlled, by the SOOP method. The SOOP method has only the energy costs term in its objective function. The objective function of the SOOP method to be minimized is provided in (3.3). Using the SOOP method, occupants' comfort conditions are featured as the constraints on the indoor environmental parameters. Building schedule is stated in Table 2. In the Base Case, two values of 21 ºC and 25.5 ºC are chosen as the heating and cooling set-points, during the occupied hours.

By simulating the annual energy performance of the office building, the operation of the SOOP method, with respect to energy costs and occupants' comfort conditions, is evaluated. For this purpose, the integrated control of the office using the SOOP method is compared to the schedule control scenario. Under schedule control scenario, inside temperature is kept at 23 ºC, ventilation rate is set at the minimum required level (0.0007 m^3/s per m^2), and window shades are kept closed all the time. Under both scenarios of energy management, the annual energy performance of the office building is simulated, to observe the energy consumption reduction potential of the integrated control scenario. Monthly energy costs ($\$/m^2$), associated with the operation of the office building (including all 5 zones), under the two considered scenarios of energy management, are demonstrated (Fig. 9). The integrated control, using the SOOP method, is associated with reduced monthly energy costs ($\$/m^2$), with reference to the schedule control.

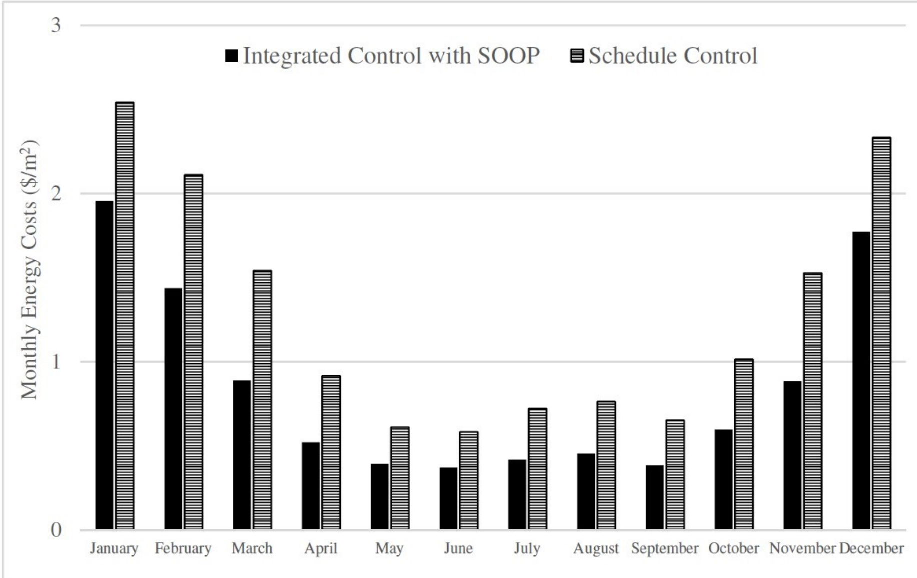

Fig. 9: Monthly energy costs ($\$/m^2$) using the SOOP method, and the schedule control for energy management

Subsequently, the operation of the SOOP method, with respect to the thermal comfort of occupants is evaluated. PMV index is used to represent the thermal sensations of occupants. For PMV calculations, occupants are considered seated, with the metabolic rate of 58 W/m^2 (1.0 Met unit) and with typical office clothes (1.0 in Clo unit). Moreover, 50% relative humidity, and 0.1 m/s air speed are assumed. Using the SOOP method for energy management, annual PMV values in north zone of the office are studied (Fig. 10).

Under the SOOP method energy management scenario, thermal sensation votes during the summer do not have variations (Fig. 10). During the winter, as well, the majority of PMV values are equal to -0.6, which is the minimum possible value, considering the heating set-point (21 °C). Consequently, the SOOP method is incapable of providing flexible indoor thermal conditions, according to occupants' thermal preferences. On the other hand, the proposed MOOP method manages the indoor environmental conditions, according to occupants' preferences, while optimizing the energy consumption costs. In other words, the proposed method provides economic-optimum conditions, considering the productivity of office workers and energy consumption costs, simultaneously (*Objective 1* of the research).

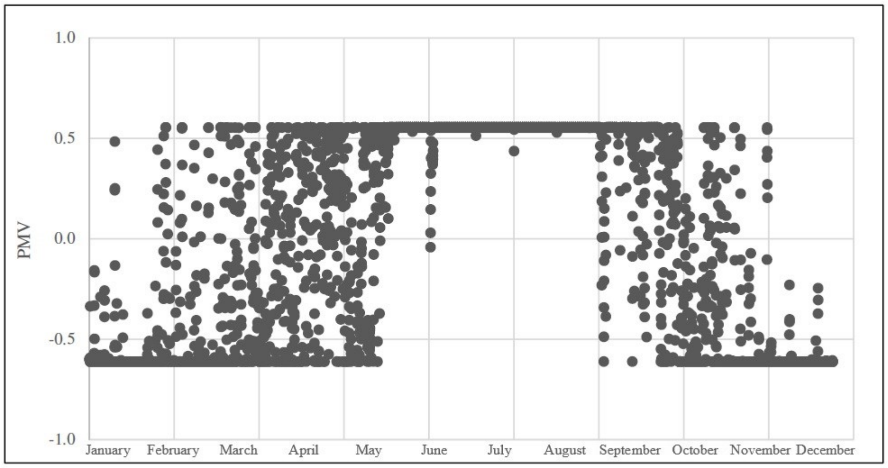

Fig. 10: Annual Predicted Mean Vote (PMV) variations in north zone, using the SOOP method

4.2 The Multi-Objective Optimization Method and Pareto Optimal Solutions

Based on the relationships between occupants' comfort conditions and their productivity, a method for energy costs and productivity optimization is developed. On an hourly basis, for each zone, a set of Pareto optimal solutions in generated for the automated control of the indoor environment. The final optimal solution can be chosen, by learning the influential parameters including energy prices, occupancy data, and occupants' productivity rates.

Occupancy data and occupants' tasks can indicate their productivity rates. It is assumed that occupants have conversations over different projects and their tasks, through a communication software, while each occupant is assigned to work on specific tasks within a project [98-100]. The minimum productivity of each office worker is assumed to be \$10/h. Based on the number of occupants and the importance of their tasks, ten values for the overall hourly productivity of occupants (\$10/h to \$100/h) are considered to construct Pareto optimal solutions. Considering real-time pricing, electricity prices can also be variable, with reference to signals received from the utility side. However, for avoiding complexity in analyzing the results, electricity and gas prices in Montreal, are assumed as fixed rates of 8 cents per kWh and 20 cents per m^3, respectively. Two objectives of energy consumption minimization and productivity maximization, are often in conflict with each other. This fact is illustrated in Fig. 11; Pareto optimal solutions, in one of the zones (east zone), in a single hour (10-11am, 1st of January) are illustrated. Negative values for the costs of discomfort indicate the level of occupants' satisfaction from the improved IEQ.

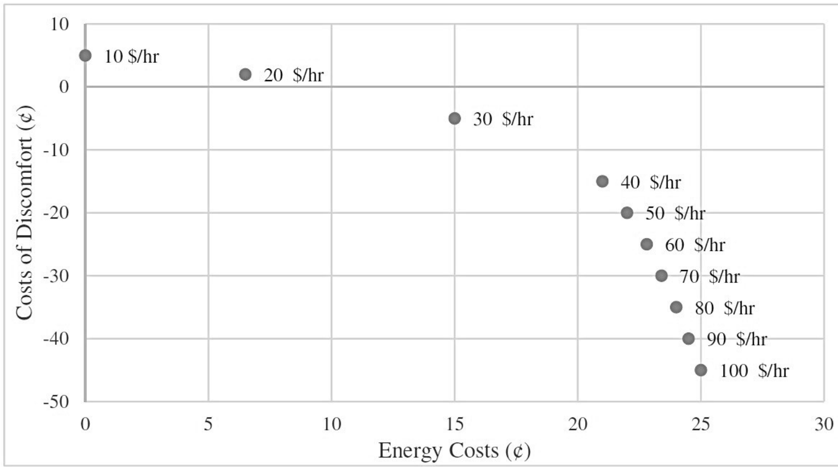

Fig. 11: Pareto optimal solutions: Energy costs vs. costs of discomfort - East zone, 10-11am, 1st of January

4.3 Thermal Comfort

The operation of the proposed MOOP method (*Proposed Case*) and the SOOP method (*Base Case*) are compared, with respect to thermal comfort of occupants. Indoor temperatures of single-hour simulations in January and July, chosen by the Proposed Case and the Base Case are compared (Fig. 12). Pareto optimal solutions are generated by varying the productivity rate ($/h).

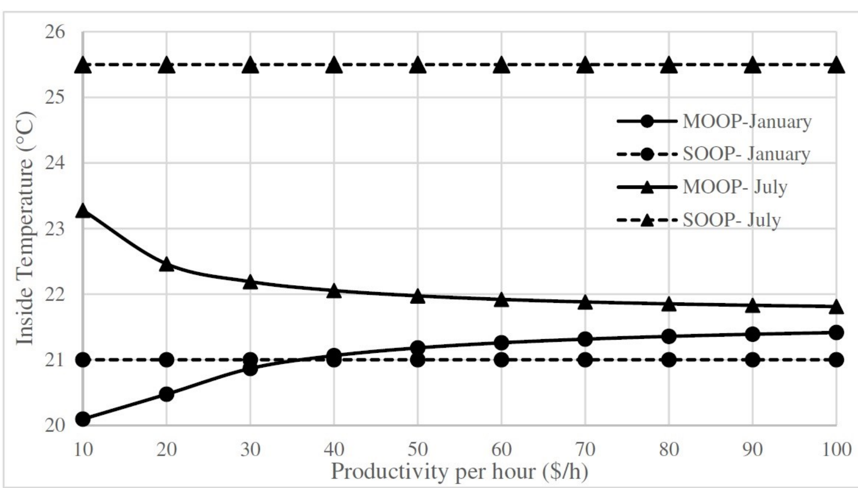

Fig. 12: Indoor temperatures (ºC), chosen by the Proposed Case & the Base Case in east zone, 10-11 am, 1st of January & July

The SOOP method only chooses the value of heating set-point (21 ºC) and cooling set-point (25.5 ºC), irrespective of the level of hourly productivity (Fig. 12). In contrast, the MOOP method (Proposed Case), chooses varied indoor temperatures with productivity per hour ($/h) variation. Furthermore, the proposed MOOP method pays relatively more attention to occupants' comfort, when the number of occupants is higher, or their tasks are more important. For both outdoor weather conditions, with the increase in hourly productivity ($/h), indoor temperatures (ºC) are crawled towards the maximum comfort temperature (21.7 ºC), by increasing in January and decreasing in July (Fig. 12). When the overall productivity rate, increases to a very high level, occupants' comfort supersede energy criterion, and the method prioritizes the former.

Subsequently, the operation of the MOOP method is studied, on a monthly basis. Two months of January and July, with mean outdoor temperatures of -10.2 ºC and 25.3 ºC, are chosen to represent the warm and cold seasons of Montreal. During each month, the proposed method controls hourly indoor temperature (as well as other indoor environmental parameters, stated in Section 3.1.2), by MOOP of energy costs and productivity. Monthly mean indoor temperature (ºC), inside three selected zones of the office (east zone, central zone, and south zone), during January and July, are presented (Fig. 13).

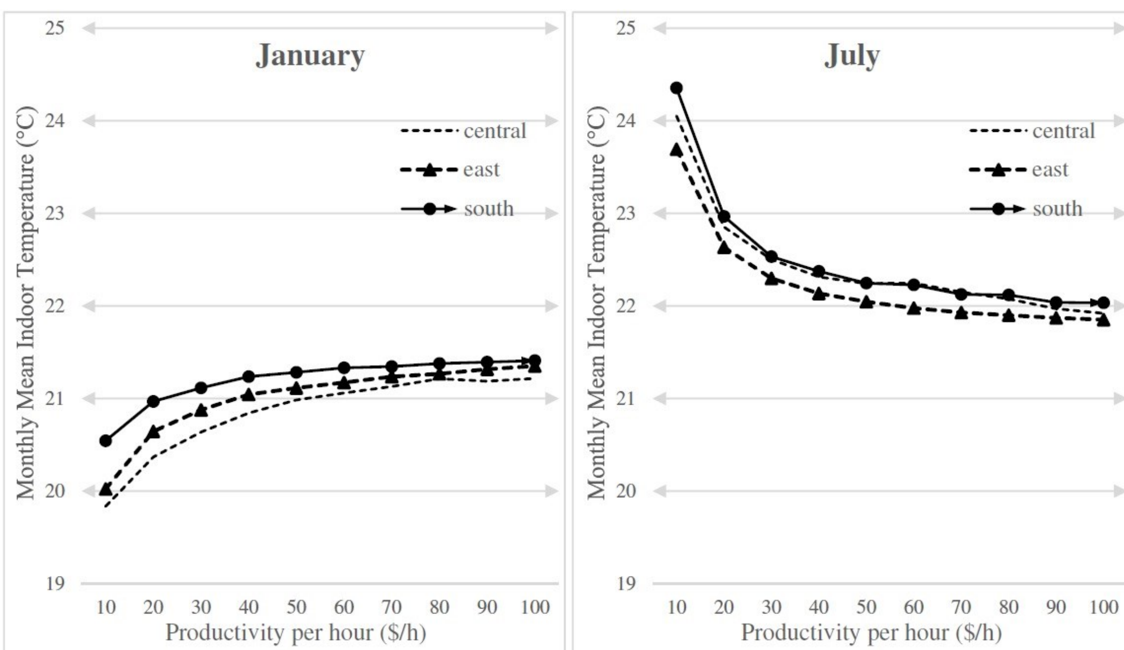

Fig. 13: Proposed Case- Monthly mean indoor temperatures (ºC) of 3 zones, under varied scenarios ($/h) - January (a) July (b)

In all three zones and for both outdoor weather conditions, with the increase in productivity per hour ($/h) of occupants, monthly mean indoor temperatures move towards the maximum comfort temperature (21.7 ºC). With the increase in collective productivity, the relative importance of occupants' productivity with respect to energy costs increases, hence, the method reduces relative productivity losses of occupants by approaching the maximum comfort temperature. Here, monthly mean indoor temperature (ºC) is chosen for thermal comfort evaluation. An alternative approach is to demonstrate the frequency distribution of thermal sensation votes, and calculate the number of hours that thermal sensation votes are inside the comfort range. This approach is convenient when thermal comfort indicators, such as PMV Index and PPD Index [16], are used to indicate the thermal sensation votes.

4.4 Indoor Air Quality

The performance of the proposed method, with respect to IAQ of different zones of the office, is studied. Similar to the thermal comfort analysis, January and July are chosen to represent the cold and warm seasons. Monthly mean ventilation rates (m^3/s per m^2), under varied productivity per hour scenarios, inside east zone, central zone, and south zone, are shown (Fig. 14).

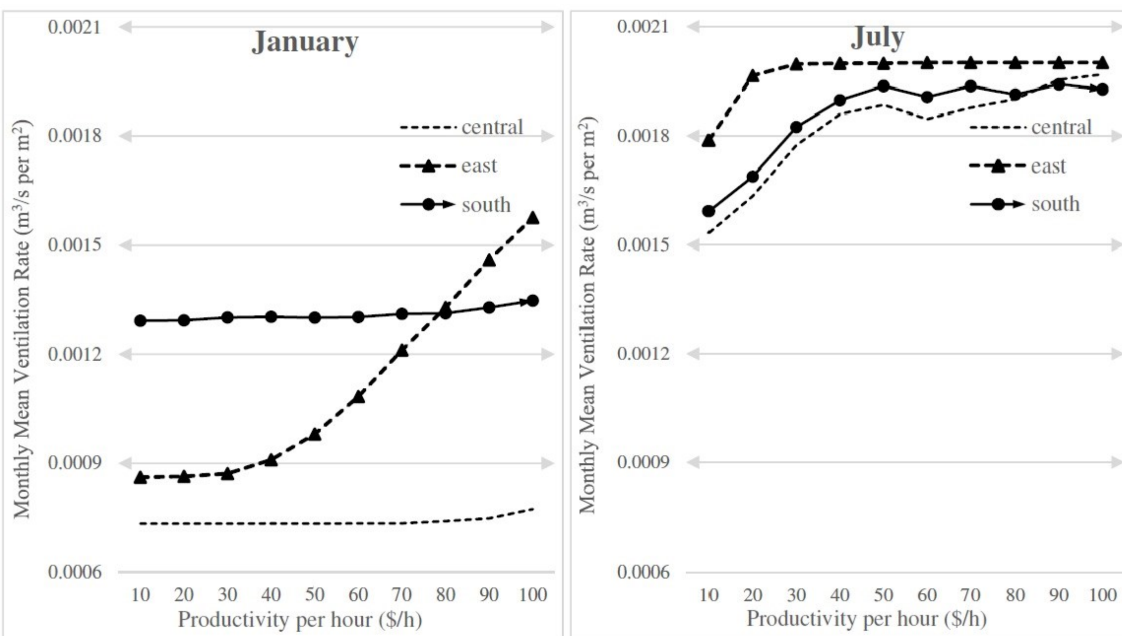

Fig. 14: Proposed Case- Monthly mean ventilation rates (m^3/s per m^2) of 3 zones - January (a) July (b)

Monthly mean ventilation rates are varied in different zones, and in different outdoor weather conditions. Nevertheless, the general tendency is to increase with the addition of productivity per hour ($/h). The level of ventilation rate in different zones is influenced by the solar irradiance. This subject will be discussed in detail, in Sub-Section 4.7.

4.5 Productivity Losses & Energy Costs

Overall costs associated with the operation of the office building, is the aggregation of energy consumption costs and productivity losses of occupants. For three different outdoor weather conditions, monthly overall costs, using the Proposed Case and the Base Case, are compared. April is chosen to represent the swing season of Montreal. During January, April, and July, monthly overall costs of the Base Case (Fig. 15), and the Proposed Case (Fig. 16) are assessed.

There are substantial differences between the overall costs in the Proposed Case, and in the Base Case; especially between their associated productivity losses. In contrast to the Proposed Case, in the Base Case, with the increase in hourly productivity of occupants ($/h), productivity losses ($), and subsequently overall costs ($) are increased significantly (especially during April and July). Replacing the SOOP method in the Base Case, with the MOOP method, significant productivity improvements are achievable during April and July (Fig. 15 and Fig. 16).

Results show the substantial potential to increase the productivity of occupants, by improving IEQ of the office. Considering a constant number of six office workers inside each zone (total 30 occupants in the office) during July, the proposed method can save up to $80 on the monthly productivity of each occupant. Improving productivity of occupants would directly benefit the institution, they are working for. In general, it is the society that benefits from having more productive citizens [115].

One of the positive features of the proposed method is its capability to receive dynamic influential parameters while making decisions for the automated control of the indoor environment. Dynamic influential parameters could be real-time electricity and gas prices, sets of indoor and outdoor environmental parameters, occupants' presence, productivity rates, and preferences. Here, for better clarification, most of these parameters are considered to be constant. However, the availability of these parameters significantly boosts energy consumption reduction and productivity improvement objectives. This requires hardware and software infrastructure to have sufficient information from the utility, and from the building environment.

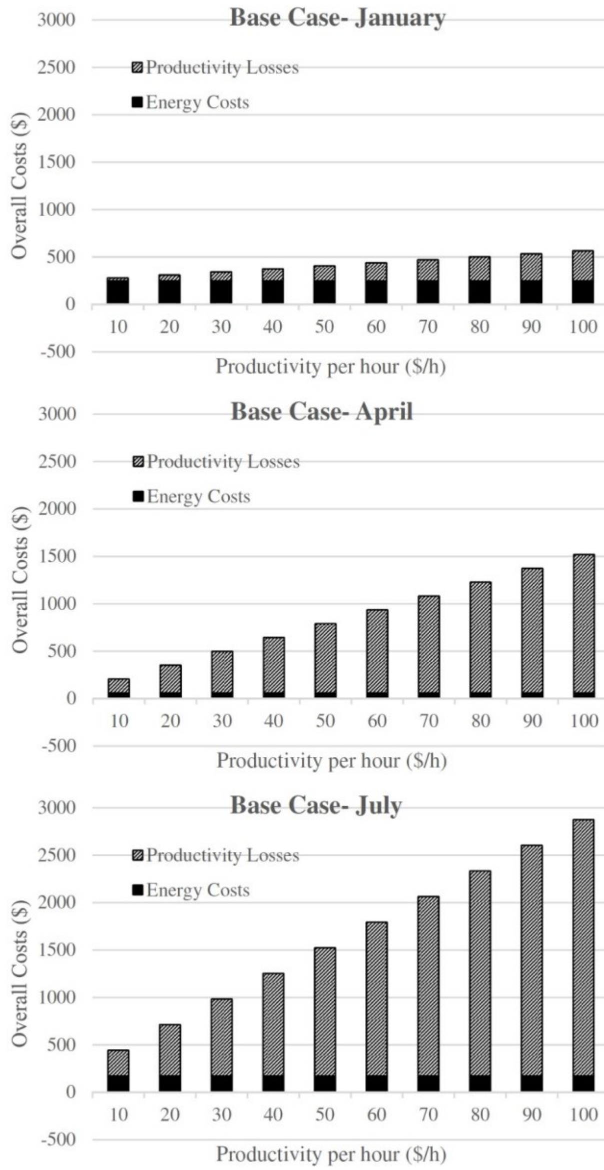

Fig. 15: Base Case- Monthly overall costs ($) during three months of January (a), April (b), and July (c)

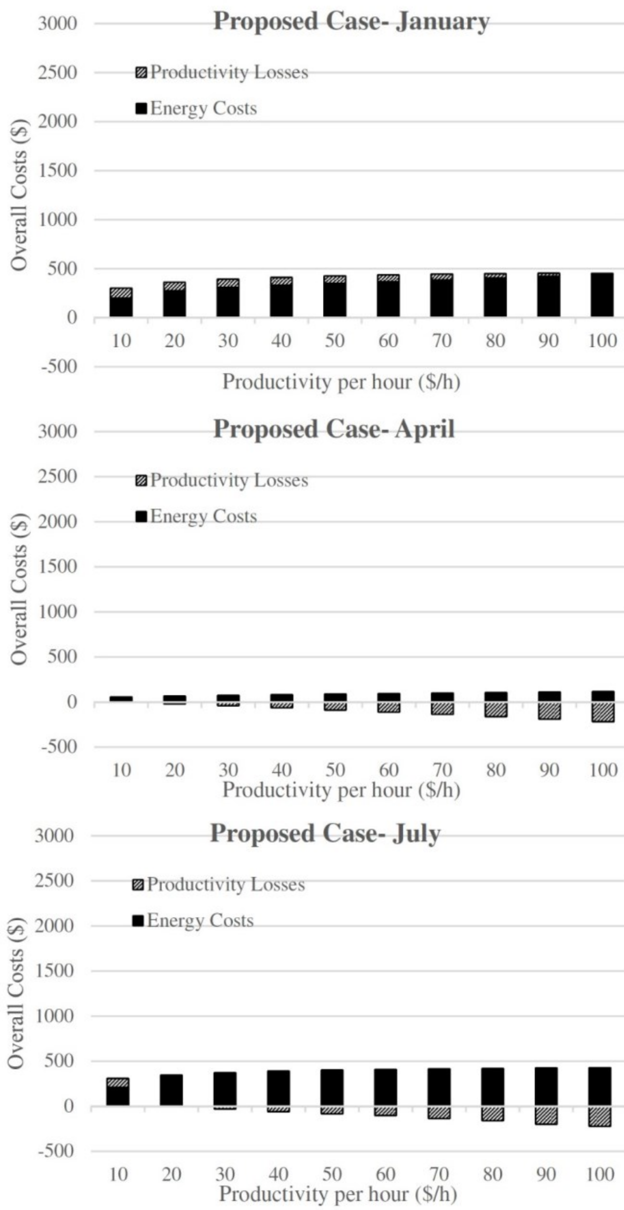

Fig. 16: Proposed Case- Monthly overall costs ($) during three months of January (a), April (b), and July (c)

4.6 Potentials for Productivity Improvement

The potentials for productivity improvement in five zones of the office, in varied outdoor weather conditions are evaluated. Three months are chosen to represent varied outdoor weather conditions of Montreal: February (cold), May (swing), and June (warm). Similar to Section 4.5, the SOOP method is considered as a Base Case. The capability of the proposed method to improve occupants' productivity, in all five zones is discussed, by making a comparison between the Proposed Case and the Base Case. To analyze the potentials for productivity improvement, *Productivity Booster* (β) parameter is defined. β compares the level of productivity improvement or productivity losses avoided ($), to the energy costs associated with this improvement ($), as a result of replacing the SOOP method with the proposed MOOP method, during a specific time:

$$Productivity\ Booster\ (\beta) = \frac{Productivity\ Losses_{\mathrm{SOOP}} - Productivity\ Losses_{\mathrm{MOOP}}}{Energy\ Costs_{\mathrm{MOOP}} - Energy\ Costs_{\mathrm{SOOP}}} \tag{4.1}$$

For instance, if $100 of productivity losses would be avoided ($Productivity\ Losses_{\mathrm{SOOP}} - Productivity\ Losses_{\mathrm{MOOP}}$) with the addition of $40 to energy costs ($Energy\ Costs_{\mathrm{MOOP}} - Energy\ Costs_{\mathrm{SOOP}}$), by replacing the SOOP method with the proposed method, β would be equal to 2.5. *Productivity Booster* (β) is unit-less and can be determined within any period of time. Here, β is calculated on a monthly basis. Monthly β values, during February, May, and June are provided, under five productivity per hour scenarios (Fig. 17).

In cold outdoor weather conditions of February, south zone, has the highest values of β, and consequently, the highest potential for productivity improvement (Fig. 17.a). The main reason is the higher level of solar irradiance in south zone, compared to the other zones. By automated control of the shades, the proposed method can take advantage of solar irradiance for zone heating. In contrast, β is very low for north zone, and even has negative values with productivity per hours of $10/h and $30/h.

During June, β has positive values, increasing consistently with the increase in productivity per hour (Fig. 17.c). In the Base Case, all zones of the building, during June, is associated with productivity losses. Monthly productivity losses of each zone, in the Base Case, are in the range of $50 to $500, depending on the level of hourly productivity. During warm outdoor weather conditions, there is an excellent potential to avoid productivity losses, and the proposed MOOP method is capable of doing exactly the same thing.

The highest values of β belong to May (Fig. 17.b). May is considered as a month in the swing season, with a monthly mean outdoor temperature of 14.1 °C. Alongside May, April and October are also considered as the months in the swing season of Montreal. April and October have monthly mean outdoor temperatures of 10.1 °C and 12 °C, respectively. Using the SOOP method for energy management, during these three months (May, April, and October), the office building is associated with only $210 energy consumption costs.

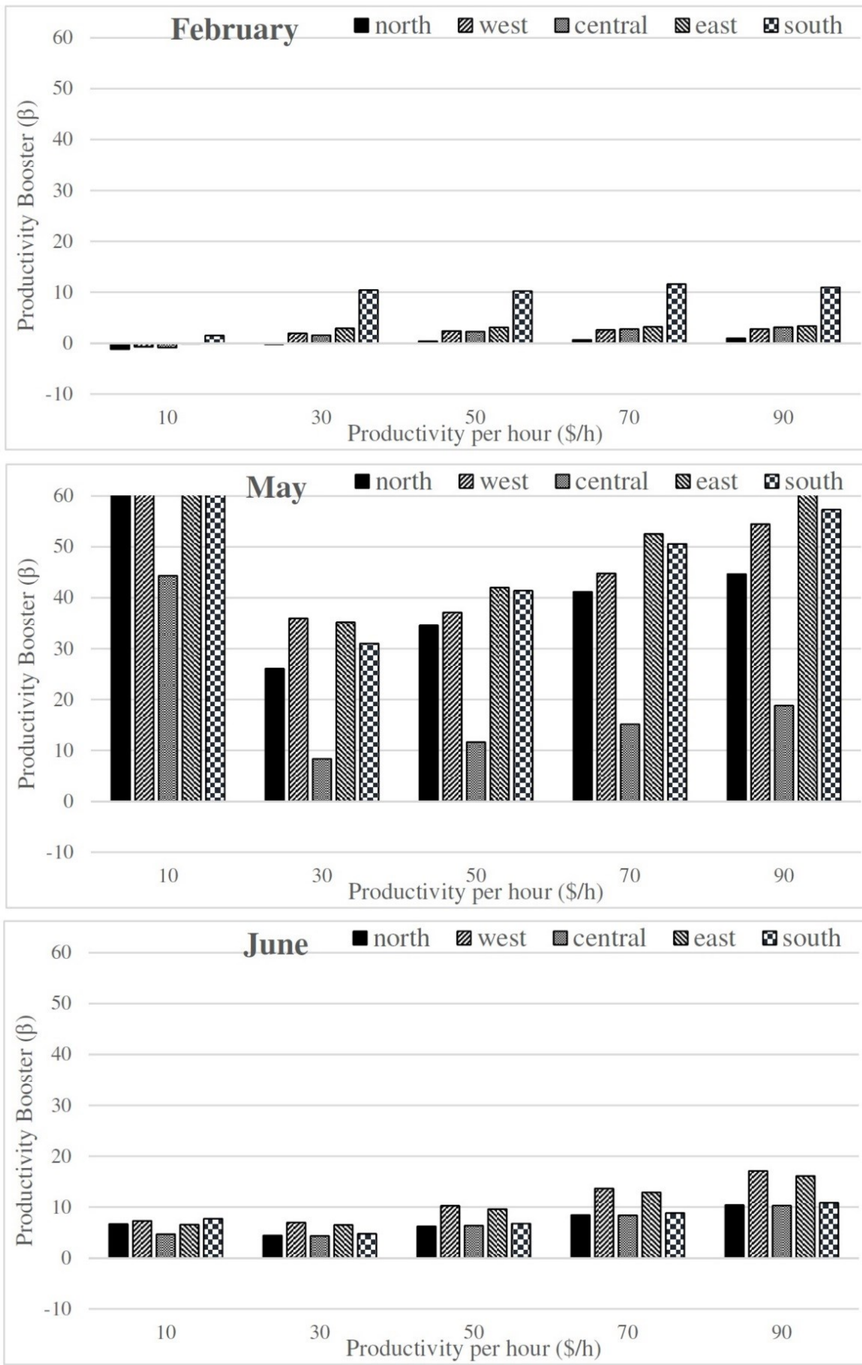

Fig. 17: Monthly mean Productivity Booster (β) during February (a), May (b), and June (c)

On the other hand, productivity losses across three months, are ranged from \$500 to \$5000, depending on the productivity per hour scenario. Hence, the swing season is very suitable for applying the proposed MOOP method, in order to reduce productivity losses of office workers. Consuming around \$50 more energy, across these three months, would avoid around \$1000 productivity losses. This is visible in Fig. 17.b, in which large values of β can be found in May.

4.7 Differences between the Zones

The operation of the method in different zones of the building, during the occupied hours, is evaluated. Monthly mean indoor temperatures (ºC) in south, west, north and east zones, chosen by the method, during January, are presented (Fig. 18). In all the zones, with the increase in productivity (\$/h), mean indoor temperatures (ºC) approach the maximum comfort temperature (21.7 ºC). Moreover, in south zone, monthly mean indoor temperatures (ºC) are closer to the maximum comfort temperature, compared to monthly mean indoor temperatures in the other zones (Fig. 18). Accordingly, during January and between all the zones, providing comfort in south zone requires less energy expenditures. Providing occupants' comfort in north zone is relatively the most expensive. During January, south zone has the highest value of monthly solar irradiance, with an average hourly solar irradiance of 382 W/m^2. East and west zones are second and third, with 183 W/m^2 and 158 W/m^2 average hourly solar irradiance, respectively.

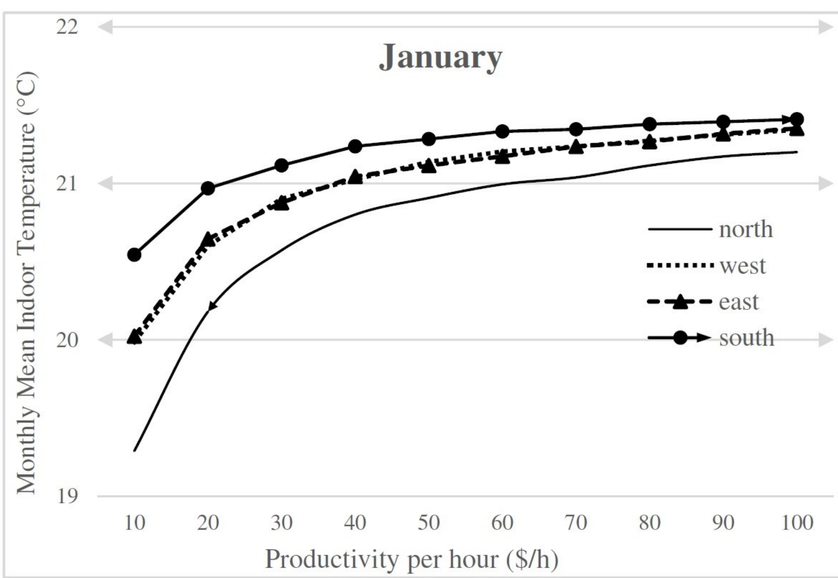

Fig. 18: Proposed Case- Monthly mean indoor temperatures (ºC) in different zones, under varied scenarios (\$/h) - January

North zone only has a mean hourly solar irradiance of 83 W/m^2 (central zone is not considered in this part since it doesn't have any window). During January, the MOOP method continuously benefits from the sun to provide the thermal comfort of occupants. South zone, the least expensive zone with respect to energy consumption, during January, becomes the most expensive with respect to providing occupants' comfort, during July. During July, the order of solar irradiance (W/m^2) is similar to January; with a mean hourly solar irradiance of 324 W/m^2 for south zone, 316 W/m^2 for east zone, 306 W/m^2 for west zone, and 195 W/m^2 for north zone. In south zone, during the cold season, having higher levels of solar irradiance helps the MOOP method to provide occupants' comfort with less energy expenditure. While, during the warm season, high levels of solar irradiance have negative effects on the comfort of occupants, hence, are avoided by the proposed method, with the automated control of the blind positions.

The importance of the sun is not solely associated with the thermal (and visual) comfort of occupants. IAQ of the zones is also influenced by the level of solar irradiance. Monthly mean ventilation rates (m^3/s per m^2) in different zones, during January, are demonstrated in Fig. 19. During January, south zone has the best IAQ. Having the highest level of solar irradiance allows the method to provide a higher level of conditioned outdoor air for the occupants (Fig. 19). The opposite applies to north zone. Compared to the other zones, occupants inside north zone are relatively more sensitive to ventilation rate.

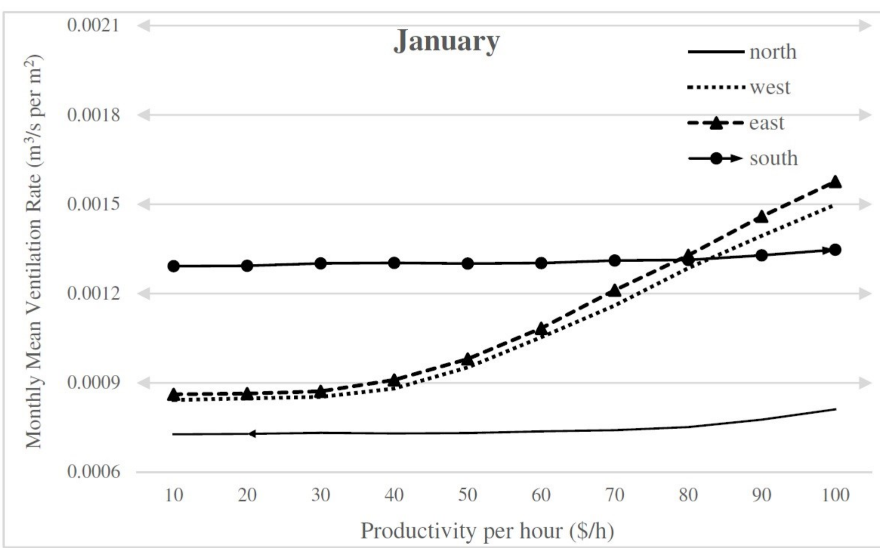

Fig. 19: Proposed Case- Monthly mean ventilation rates (m^3/s per m^2) in different zones, under varied scenarios ($/h) - January

Their higher sensitivity is due to the relatively lower levels of solar irradiance in north zone, compared to the other zones. The method keeps ventilation rates low, but still high enough to provide acceptable IAQ. Using the method during January (and during any other month), with the increase in productivity per hour ($/h), the level of monthly mean ventilation rates (m^3/s per m^2) increase, as well (Fig. 19). The annual operation of the SOOP method and the proposed MOOP method are compared, with respect to overall costs (Fig. 20). The proposed method is successful in improving the productivity of occupants. In contrast, using the SOOP method, productivity losses of occupants are increased to extreme levels, with the increase in productivity per hours (Fig. 20). The proposed method is capable of avoiding productivity losses of occupants, while simultaneously reducing associated energy costs (*Objective 1* of the research).

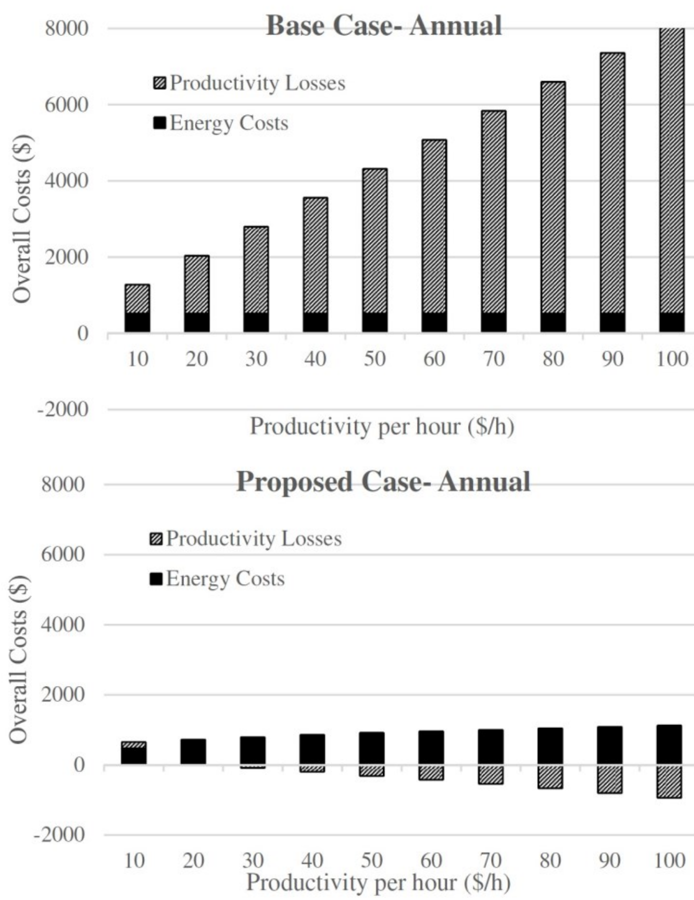

Fig. 20: Annual overall costs ($) of the Base Case (a) & the Proposed Case (b), under varied scenarios ($/h), divided into annual energy costs ($) & annual productivity losses ($)

4.8 Discussion

Several studies have focused on identifying influential parameters that affect occupants' comfort conditions. Humphreys et al. [64], and de Dear et al. [62] determined cultural background and outdoor weather conditions, as parameters that influence the thermal preferences of occupants. Age, gender, social dimensions, and economical background of occupants are further parameters, evaluated in other studies [63, 66, 68]. If these parameters are considered for occupants' thermal comfort evaluation, diverse thermal sensations among the occupants would result. Diverse thermal sensations have varied RP - Indoor Temperature (ºC) relationships.

4.8.1 Sensitivity of the Optimization to Occupants' Preferences

Here, the capability of the proposed method to manage diverse thermal sensations is studied. For the first step, the focus is on the maximum comfort temperature (ºC) of occupants, as one of the parameters that define their RP. So far, RP - Indoor Temperature (ºC) relationship has the maximum comfort temperature of 21.7 ºC (Fig. 5). The sensitivity of RP to the diversity in occupants' preferences is evaluated, by shifting the maximum comfort temperature, towards a higher value of 22.4 ºC, and a lower value of 21 ºC. Shifting RP - Indoor Temperature curve towards left and right creates two new curves (Fig. 21).

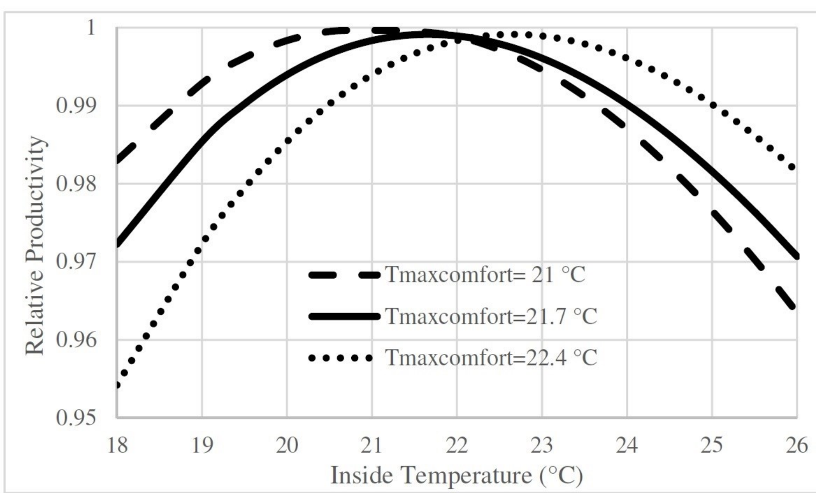

Fig. 21: Sensitivity analysis: Shifting the maximum comfort temperature (°C) of occupants

The operation of the method with the two new RP - Indoor Temperature curves is studied, and compared with a case that considers original RP- Indoor Temperature relationship (Fig. 5). Two months of January and July are chosen to represent the warm and cold seasons. Energy costs ($) of the office building, during January and July are calculated, in the three cases (Fig. 22). During the cold month of January, having RP curve with relatively higher maximum comfort temperature increases energy costs. In contrast, in warm outdoor weather conditions of July, having occupants with higher maximum comfort temperature reduces energy costs (Fig. 22).

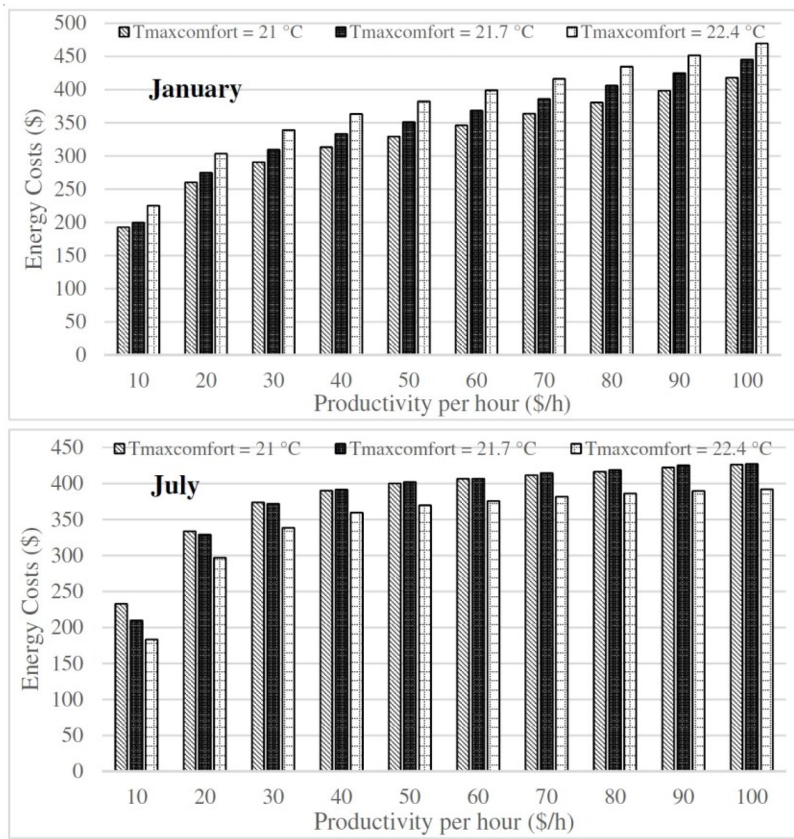

Fig. 22: Sensitivity of the energy costs ($) to the thermal preferences ($T_{maxcomfort}$- °C), during January (a) & July (b)

Here, the choice of 21 ºC and 22.4 ºC, as alternative maximum comfort temperature values are arbitrary. Having relatively lower values of maximum comfort temperature, during the cold season, or relatively higher values of maximum comfort temperature, during the warm season, would further reduce the associated energy costs. The objectives of the conducted sensitivity analysis are (1) demonstrating the fact that the proposed method performs the automated control of the indoor environment, according to the thermal preferences (maximum comfort temperatures) of occupants, (2) stating the need to treat *Maximum Comfort Temperature* as a dynamic variable, inside the MOOP problem formulation.

Under each occupancy scenario (productivity per hour, \$/h), according to occupants' preferences (RP curves), the proposed method provides particular indoor environmental conditions, by the automated control of HVAC system, lighting, and blinds. Monthly mean indoor temperature (°C) of three zones (north, south, and east), according to different RP curves, during January and July, are provided (Fig. 23). The difference between the zones are already covered in Section 4.7, hence, zones are not defined, to highlight the overall performance of the method, with respect to varied occupants' thermal preferences. It is observed that the proposed method is capable of following occupants' thermal preferences while optimizing energy consumption costs (Fig. 23).

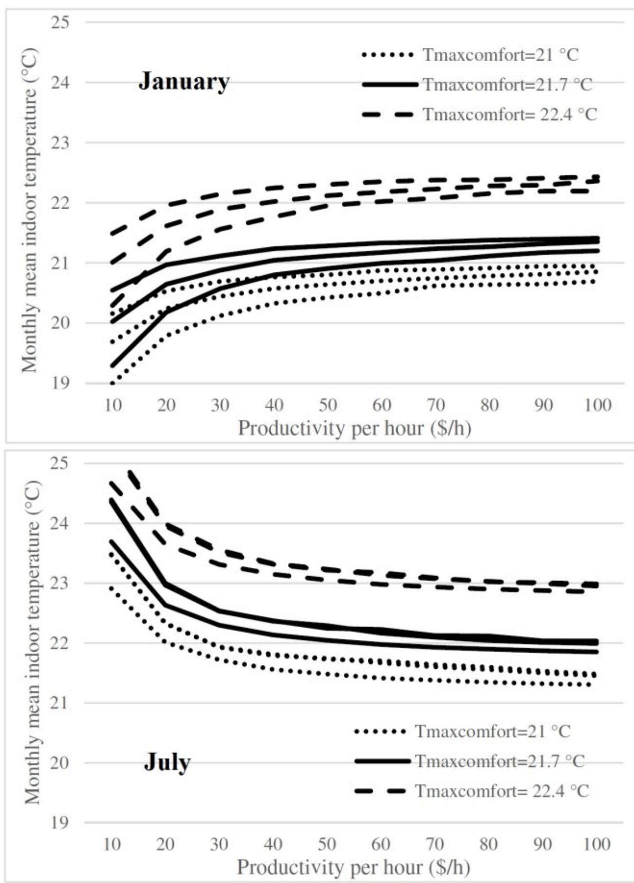

Fig. 23: Monthly mean temperatures (ºC) of three zones (north, south, and east), based on varied thermal preferences ($T_{maxcomfort}$-°C) during January (a) & July (b). Zones are not stated to highlight the influence of varied $T_{maxcomfort}$ on thermal conditions

4.8.2 Sensitivity of the Optimization to Occupants' Behavior

Most recent studies on occupants' comfort indicated that occupants' history of thermal sensations, perceived control over the environment, and human-automation system interaction, influence the thermal sensations of occupants [20, 67]. People who think they have a good control over their environment, or people who can easily interact with the automated system, have relatively more tolerance range, with respect to variations in indoor environmental parameters.

The pro-environmental behavior of an occupant is another factor that influences his or her tolerance range. People with more environmental-friendly behavior have relatively more tolerance ranges, with respect to variations in indoor environmental parameters [68-70]. Adjusting clothes to warmer or colder ones, relaxing cultural or social clothing norm, choosing alternative physical activities, and drinking beverages are among the most common types of self-adaptive behavior. These types of adaptive behavior are categorized as behavioral adjustments. There are also psychological and physiological forms of adaptation. Physiological adaptation takes more time and is detectable in a long-term. Psychological adaptation is generally the change in the occupant's expectation of thermal comfort [62]. Here, the sensitivity of RP to occupants' behavior is studied, to perceive the importance of their adaptive behavior for energy and comfort management. Two cases of lower tolerance and higher tolerance, besides a case of normal tolerance, are considered to account for occupants' behavior diversity (Fig. 24).

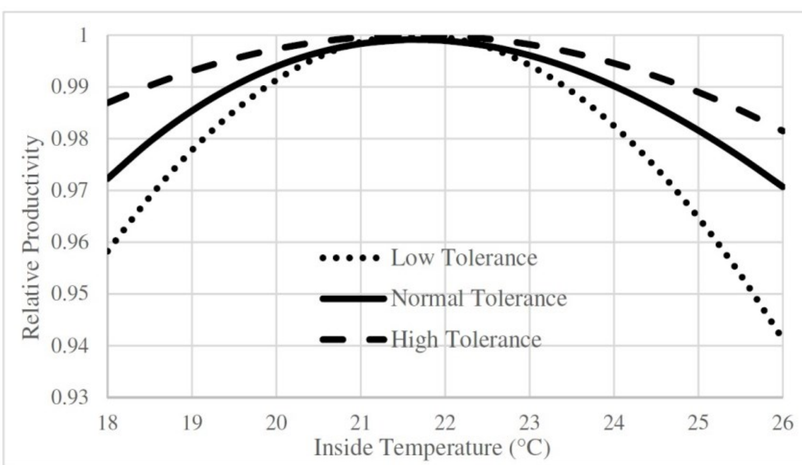

Fig. 24: Sensitivity Analysis: Considering varied tolerance ranges (°C)

The operation of the method with respect to the varied adaptive behavior of occupants is studied, during January and July. Monthly mean indoor temperatures (°C) of three zones (north, south, and east zone), chosen by the method, are demonstrated (Fig. 25). The proposed method is capable of managing the indoor environmental conditions, according to occupants' behavior. Having occupants with low tolerances, the proposed method provides indoor temperatures (°C) that are relatively closer to the maximum comfort temperature (21.7 °C). On the other hand, when occupants have high levels of tolerance, the method benefits from their more tolerance ranges to reduce the energy costs, by moving away from the maximum comfort temperature (Fig. 25). When tolerance ranges are very low, occupants' comfort is much more important than energy costs, hence, the method prioritizes occupants' comfort, without any compromise.

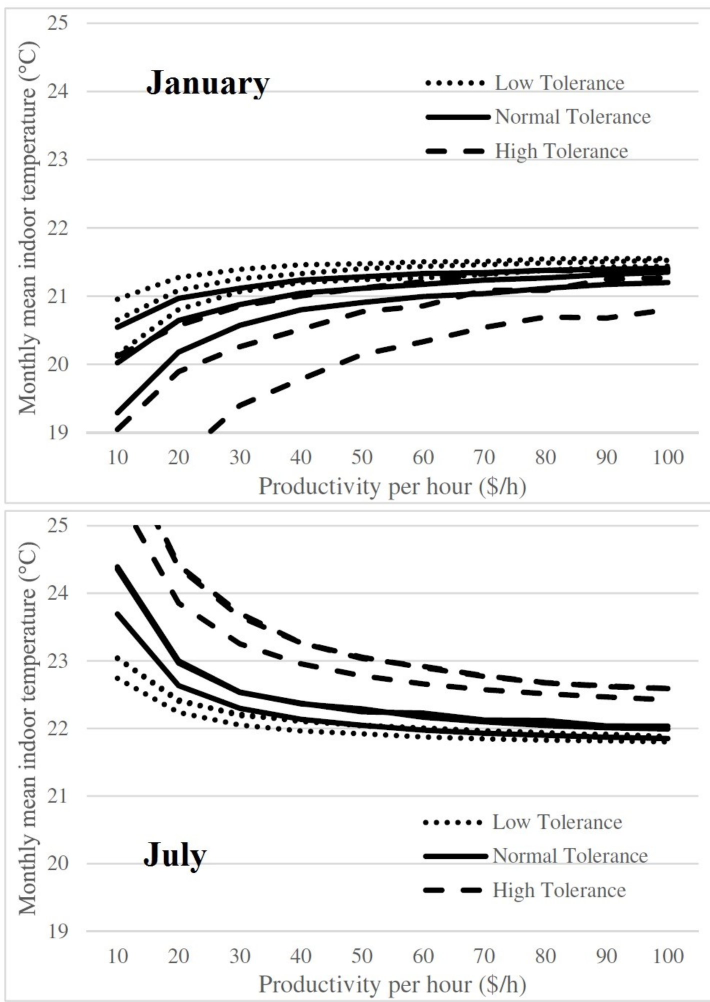

Fig. 25: Monthly mean indoor temperatures (°C), based on varied occupants' behavior (Tolerance, °C) during January (a) & July (b). Zones are not stated to highlight the influence of varied occupants' behavior on thermal conditions

4.8.3 Sensitivity of the Optimization to the Indoor Air Quality

The sensitivity of the overall productivity (RP_{Overall}) of occupants to ventilation rates is evaluated, and the operation of the proposed method, with respect to the diversity in IAQ importance is studied. In order to account for the diversity in IAQ importance, it is assumed that IAQ has relatively higher or lower influence on RP_{Overall}. These two cases are compared with the normal influence of IAQ, to observe the sensitivity of RP_{Overall} to ventilation rates (Fig. 26).

During January and July, the operation of the proposed method, considering the diversity in IAQ importance, is studied. The sensitivity of energy costs ($) to the influence of IAQ on RP_{Overall}, is analyzed (Fig. 27). For both outdoor weather conditions, having higher IAQ influence increases monthly energy costs of the office building.

Moreover, during the same months of January and July, the sensitivity of productivity losses ($) to the IAQ influence are assessed (Fig. 28). Monthly productivity losses ($) of occupants, considering the diversity in IAQ importance are compared. Monthly productivity losses during July, are generally lower than monthly productivity losses during January. Under most of the occupancy scenarios (varied productivity per hour), instead of productivity losses, productivity gains are observed. For both outdoor weather conditions, with the increase in the influence of IAQ on RP_{Overall}, productivity losses of occupants ($/h) are reduced (Fig. 28).

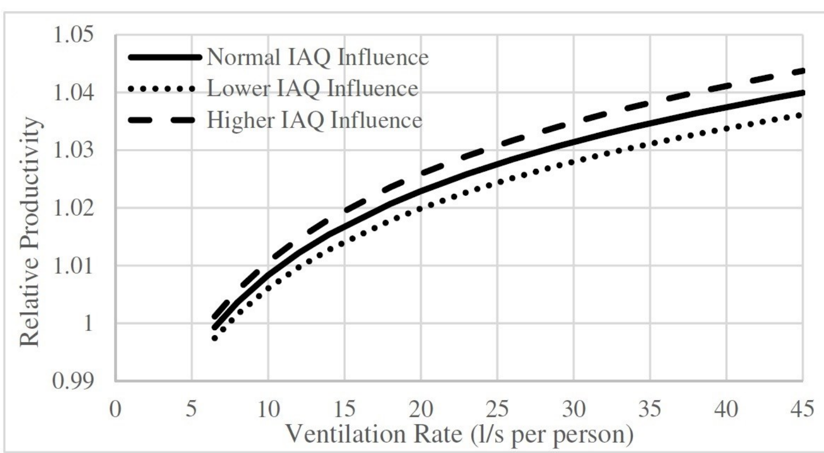

Fig. 26: Sensitivity Analysis: Considering varied levels of Indoor Air Quality (IAQ) influence on $RP_{Overall}$

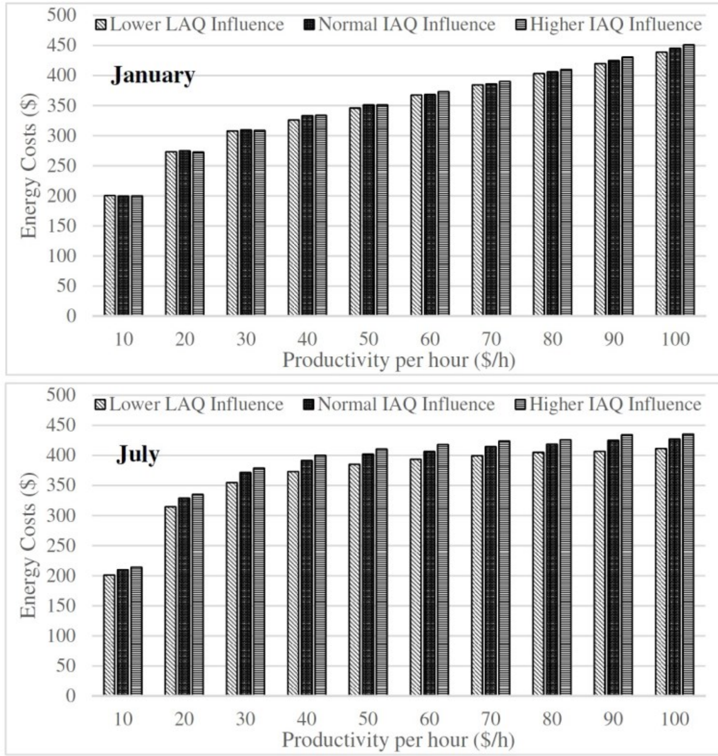

Fig. 27: Sensitivity of the energy costs ($) to the influence of Indoor Air Quality (IAQ) on $RP_{Overall}$, during January (a) & July (b)

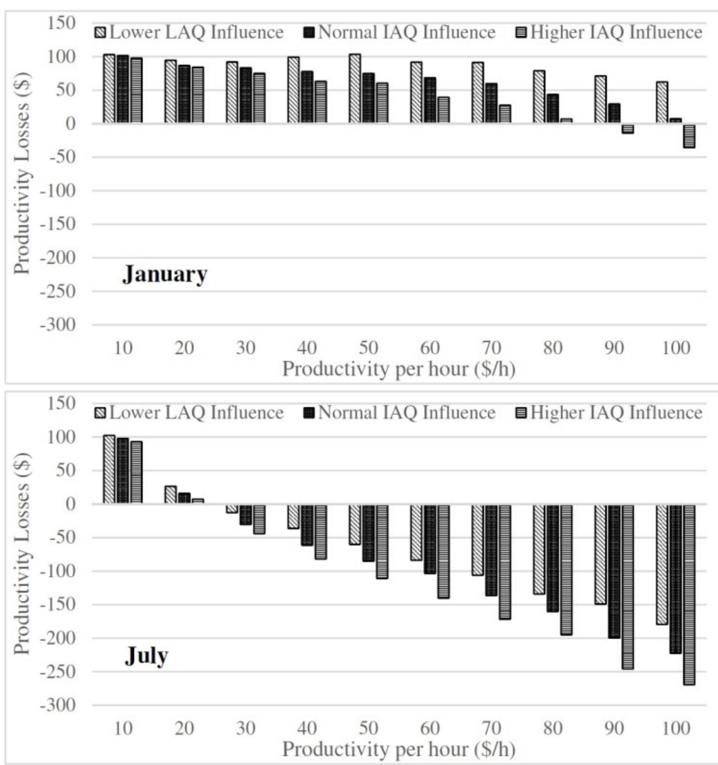

Fig. 28: Sensitivity of the productivity losses ($) to the influence of Indoor Air Quality (IAQ) on $RP_{Overall}$, January (a) & July (b)

The sensitivity of the overall comfort of occupants (RP_{Overall}) to three parameters of (1) thermal preferences (*Maximum Comfort Temperature*), (2) thermal behavior (*Tolerance Range*), and (3) the influence of IAQ on overall productivity (*IAQ Influence*) are analyzed. The objective of the sensitivity analysis is to demonstrate the capability of the proposed method to acknowledge the diversity in occupants' preferences, or to perform *personalized* energy and comfort management. This capability is essential for intelligent energy and comfort management.

Here, thermal preference models of occupants and the choice of two personalized variables, *Maximum Comfort Temperature* and *Tolerance Range,* was according to Seppanen et al. meta-analysis [28]. Based on the adaptive thermal comfort studies, there are different parameters that influence *Maximum Comfort Temperature* and *Tolerance Range* of occupants, such as age, gender, social dimensions, economical background, pro-environmental behavior, history of thermal sensations, adaptation to the environment, and perceived control over the environment [16, 62]. Accordingly, there are variations in occupants' thermal preferences. In the next chapters, having occupants with varied thermal and visual preferences will be studied. Moreover, the importance of their positions for thermal and visual comfort evaluations will be discussed.

4.9 Chapter Summary

The main interest of this chapter is to propose a method for energy management systems of office buildings, to simultaneously improve the productivity of occupants and reduce energy consumption costs (*Objective 1* of the research). Based on the provided results, the proposed MOOP method is capable of avoiding significant productivity losses, by providing a productive indoor environment for the occupants.

By evaluating *Productivity Booster* (β) values, it is indicated that the potential for productivity improvement in the office, compared to the additional energy consumption required, is substantial. The provided results also validate Fisk et al. claim of the significant potential for productivity improvement in office buildings. Fisk et al. [8] estimated the annual economic profit of 17 to 26 billion dollars, or \$ 700 per person, as a result of IEQ improvement in office buildings, across the United States.

Furthermore, the proposed method is capable of providing economic-optimum indoor environmental conditions, for each specific situation of occupancy. The focus of contemporary studies on thermal comfort is on the diversity among thermal sensations of occupants. There are various parameters that influence thermal sensations of occupants including age, gender, social dimensions, economical background, pro-environmental behavior, perceived control over the environment, history of thermal sensations, and adaptation to the environment. Intelligent energy and comfort management system should have the flexibility to acknowledge occupants' personalized thermal preferences.

The topic of Chapter 5 is to present a method to consider occupants' thermal sensations and their preferences to perform *personalized* energy and comfort management. For this purpose, personalized variables of *Maximum Comfort Temperature* and *Tolerance Range*, are introduced in the MOOP problem formulation. In addition, in Chapter 6, visual comfort of occupants, and their positions inside enclosed spaces, are considered to perform *position-based* personalized energy and comfort management.

5 Personalized Multi-Objective Optimization of Energy Costs, Thermal Comfort & Indoor Air Quality [2]

Occupants have varied thermal preferences for the indoor environmental conditions. Their thermal preferences are also subject to change over time [15, 20, 62, 65, 76]. In *personalized* energy and comfort management, the automated control of the indoor environment is according to occupants' comfort preferences. The method (presented in Section 3.3) performs personalized energy and comfort management, by acknowledging occupants' thermal preferences from the history of their thermal sensation votes. Here, the application of the personalized method on the office building model (discussed in Section 3.1) is simulated.

Two personalized variables of *Maximum Comfort Temperature* ($T_{\text{maxomfort}}$) and *Tolerance Range* ($Tolerance_{\text{thermal}}$) form the up-to-date *thermal preference model* (RP_{thermal}) of each occupant. RP_{thermal} (T) expresses the level of an occupant's satisfaction from the indoor temperature (T, °C). The construction of RP_{thermal} from the history of thermal sensation votes is explained, in Sub-Section 3.3.1. Thermal preference models of five occupants, considered during simulations, are stated in Table 4. The method explores optimal solutions for the automated control of the indoor environment, having two objectives of productivity improvement and energy costs minimization. Varied scenarios of occupancy are assumed. First, arbitrary scenarios of having a single thermal preference in the zones are studied. Under each scenario, the operation of the method with respect to its two objectives is evaluated. Subsequently, arbitrary scenarios of having varied thermal preferences in the same environment are compared with single thermal preference scenarios.

The effects of $T_{\text{maxcomfort}}$ and $Tolerance_{\text{thermal}}$ on energy consumption and indoor environmental conditions are also discussed, in detail. Subsequently, the importance of two parameters of *individual productivity* and $Tolerance_{\text{thermal}}$ is studied by analyzing the sensitivity of the personalized method to these parameters. The number of office workers in each zone is assumed to be five. For each zone, six values for overall productivity per hour, from \$20/h to \$120/h, are considered. Three months of January (cold season), April (swing season), and July (warm season)

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[2] A version of this chapter has been published in Journal of Energy and Buildings [122]:
Mofidi F. Akbari H., "Personalized energy costs and productivity optimization in offices," *Energy and Buildings*, vol. 143, p. 173-190, 2017. https://doi.org/10.1016/j.enbuild.2017.03.018

are selected to represent different outdoor weather conditions in Montreal. Monthly performance of the method is studied in varied outdoor weather conditions.

5.1 Single Comfort Preference Model

5.1.1 Thermal Comfort

For the start, having a unique thermal preference model, across the entire office building is examined. Two arbitrary scenarios are considered. Under the first scenario, Model #1 (from Table 4) is chosen as the thermal preference model of all occupants. Accordingly, all occupants have $T_{\mathrm{maxcomfort}}$ of 23.9 °C and $Tolerance_{\mathrm{thermal}}$ of 6.2 K. Under the second scenario, it is assumed that all occupants have $T_{\mathrm{maxcomfort}}$ of 21.9 °C and $Tolerance_{\mathrm{thermal}}$ of 5.1 K (similar to Model #2).

Under each scenario, in varied hourly productivity ($/h) situations, the proposed method constructs Pareto optimal solutions for the automated control of the indoor environment, from MOOP of energy costs and occupants' productivity. Each set of Pareto optimal solutions includes optimized values for the level of natural illumination, artificial lighting, indoor temperature, and ventilation rate, in each zone. Monthly mean indoor temperature (°C) and monthly mean ventilation rate (m^3/s per m^2) are considered as the parameters to evaluate the thermal comfort of occupants, and the IAQ of the zones, respectively. Fig. 29 and Fig. 30 demonstrate monthly mean indoor temperatures (°C) in different zones of the office, during January, April, and July, under two considered thermal model governance scenarios.

Inspecting Fig. 29 and Fig. 30, three important features of the personalized method are recognized. First, under both scenarios, the method controls the indoor environment, according to the thermal preferences of occupants, by providing indoor temperatures (°C) close to their $T_{\mathrm{maxcomfort}}$. Second, with the increase in productivity per hour ($/h) of occupants, in all three months, monthly mean indoor temperatures (°C) of all the zones approach their $T_{\mathrm{maxcomfort}}$. Third, there are differences between the indoor thermal conditions of the zones. During January, under both thermal model governance scenarios, monthly mean indoor temperatures (°C) are relatively higher in south zone than the other zones. In contrast, monthly mean indoor temperatures (°C) of north zone are farthest from $T_{\mathrm{maxcomfort}}$ of occupants (Fig. 29.a and Fig. 30.a).

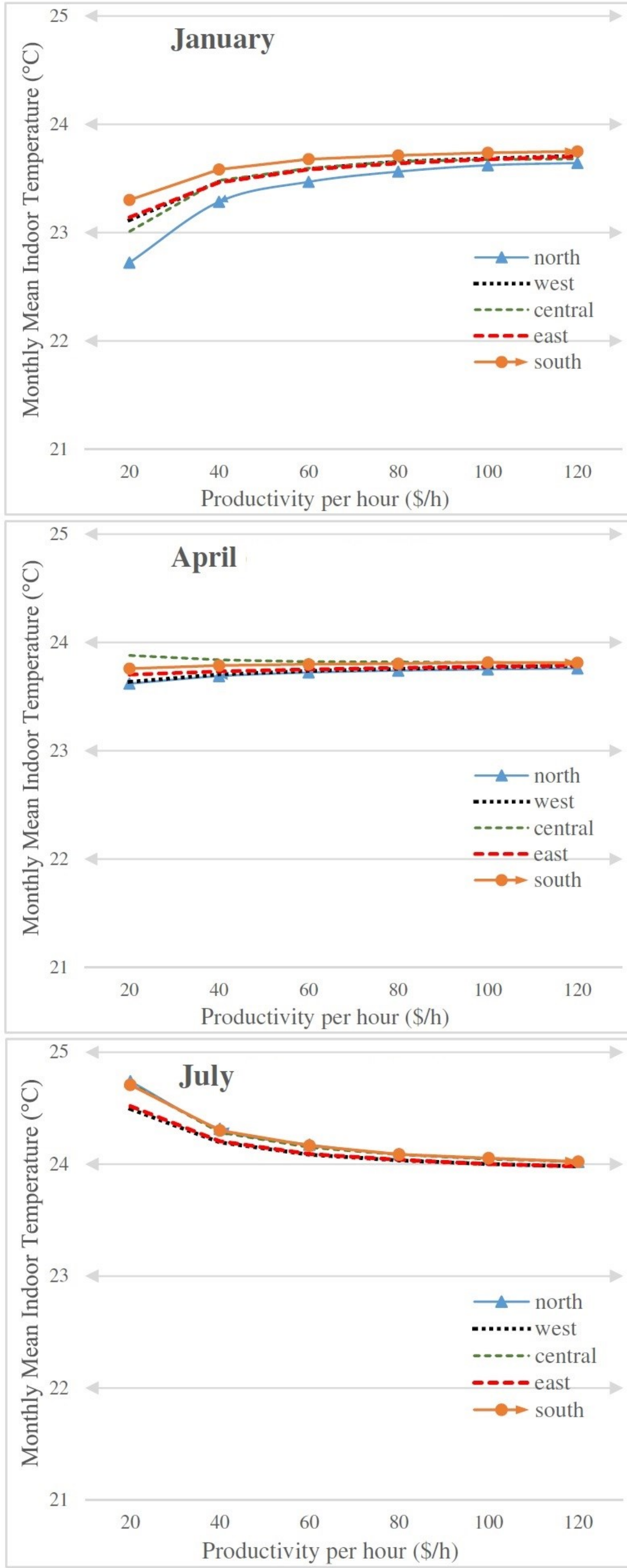

Fig. 29: Monthly mean indoor temperatures (°C) during January (a), April (b) & July (c) – Model #1 governance. With the increase in Productivity per hour ($/h), Monthly mean indoor temperatures (°C) approach $T_{maxcomfort}$ in Model #1 (23.9 °C)

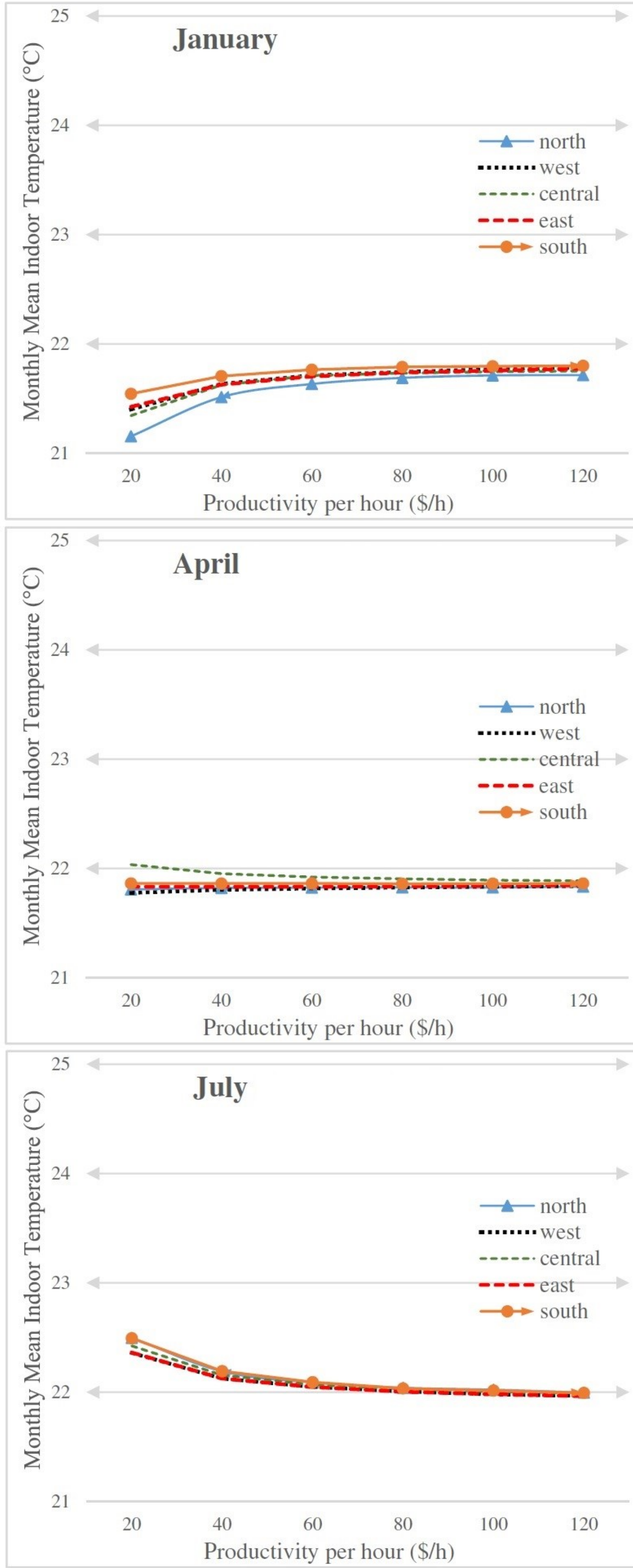

Fig. 30: Monthly mean indoor temperatures (°C) during January (a), April (b) & July (c) – Model #2 governance. With the increase in Productivity per hour ($/h), Monthly mean indoor temperatures (°C) approach $T_{maxcomfort}$ in Model #2 (21.9 °C)

During January, between all the zones with windows (all zones, excluding central zone), south zone has the highest level of monthly solar irradiance, with an average hourly level of 382 W/m^2. East and west zones are second and third, with 183 W/m^2 and 158 W/m^2 average hourly solar irradiance, while north zone only has an average hourly solar irradiance of 83 W/m^2.

The personalized method automatically controls the blind positions in all the zones. During the cold season, the method takes advantage of the solar irradiance to heat the zones. Having the highest level of monthly solar irradiance, south zone becomes the most thermally comfortable zone for the occupants during the cold season (Fig. 29.a and Fig. 30.a). The difference in the level of the zones' monthly solar irradiance explains the diversity in the thermal conditions of the zones in alternative outdoor weather conditions.

5.1.2 Indoor Air Quality

During the cold and swing seasons, the importance of the sun is not solely associated with the thermal comfort of occupants. IAQ is also influenced by the level of solar radiation, through variation of ventilation rate. In order to observe this effect, the operation of the method is studied, under two arbitrary thermal model governance scenarios. Model #3 or Model #4 are considered as the thermal preference model of all occupants in the office (Table 4). Model #3 represents occupants with $T_{\text{maxcomfort}}$ of 20.9 °C and $Tolerance_{\text{thermal}}$ of 5.2 K. Model #4 has a higher $T_{\text{maxcomfort}}$ of 24.3 °C (Table 4). Under the two considered models, monthly mean ventilation rates (m^3/s per m^2) in different zones, during January, April, and July are demonstrated (Fig. 31 and Fig. 32).

During January and April, between all the zones, south zone has the best IAQ (Fig. 31 and Fig. 32). Having occupants with either Model #3 or Model #4 thermal preferences, monthly mean ventilation rates (m^3/s per m^2) are relatively higher in south zone, compared to the other zones. The high levels of solar irradiance in south zone, during January and April, allows the personalized method to draw more outdoor air into the zone. The opposite applies to north zone and central zone. Central zone doesn't benefit from solar heating, while between the zones with window, north zone has the lowest level of monthly solar irradiance, during January and April.

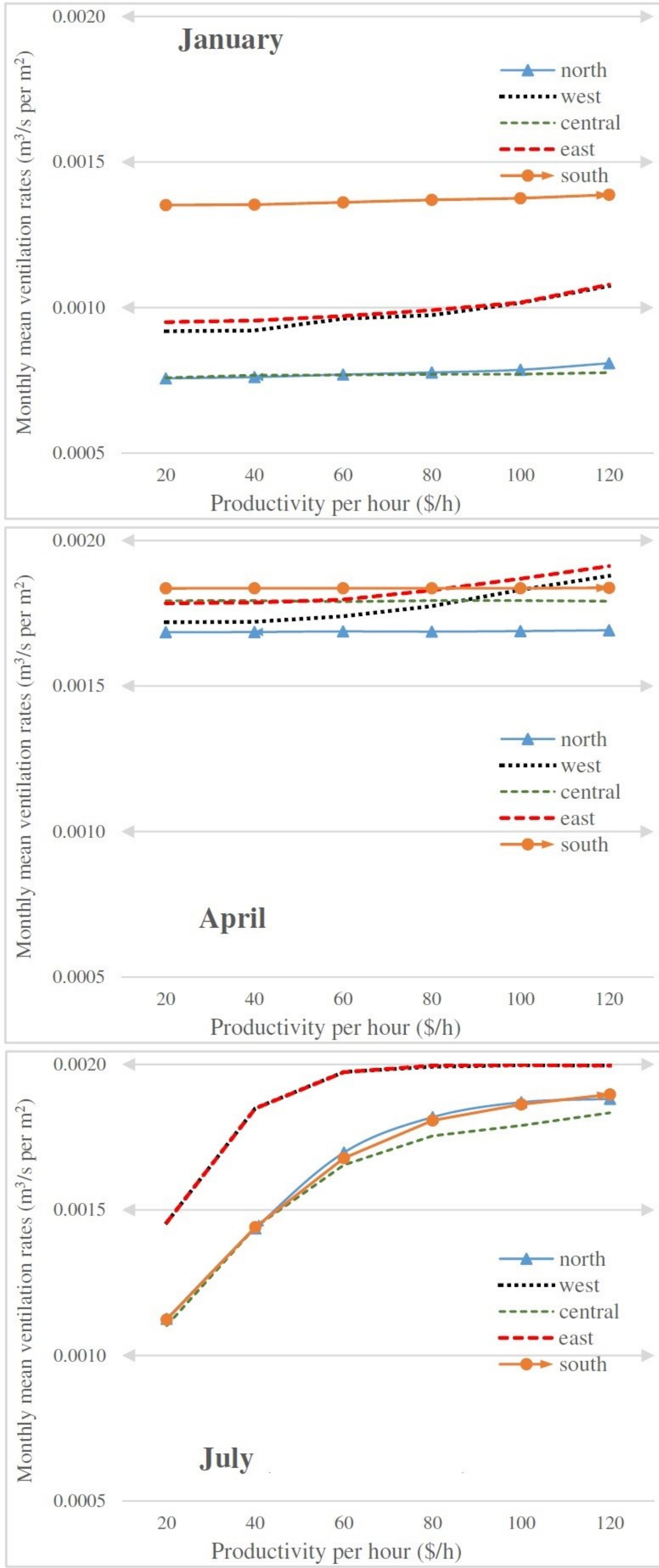

Fig. 31: Monthly mean ventilation rates (m^3/s per m^2) during January (a), April (b) & July (c) – Model #3 governance

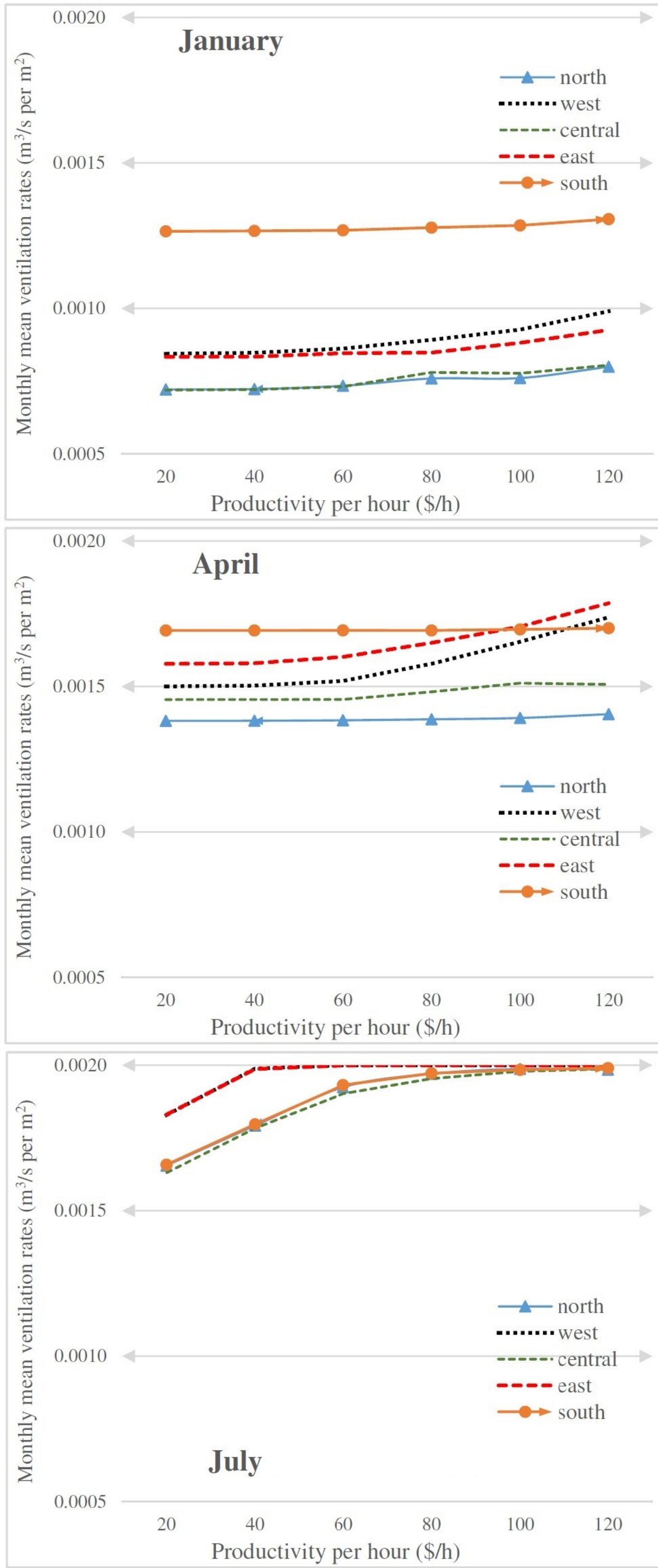

Fig. 32: Monthly mean ventilation rates (m^3/s per m^2) during January (a), April (b) & July (c) –Model #4 governance

The next observation is related to the sensitivity of ventilation rates to the outdoor weather conditions. Under both considered scenarios, with the increase in monthly mean outdoor temperature, monthly mean ventilation rates (m^3/s per m^2) are also increased (Fig. 31 and Fig. 32). Compared to January and April, during July, the personalized method improves IAQ of the office, by drawing relatively more outdoor air into the zones.

The thermal preferences of occupants also affect IAQ of the zones. During January and April, considering Model #3 and Model #4 governance scenarios, ventilation rates are slightly higher under Model #3 governance scenario (Fig. 31 and Fig. 32). Model #3 has relatively lower $T_{\text{maxcomfort}}$ (20.9 °C) compared to Model #4 (24.3 °C), hence, during the cold and swing seasons, more outdoor air can be introduced inside the zones.

On the other hand, under Model #4 governance scenario, IAQ of the zones in July are relatively better than the alternative occupancy scenario, since $T_{\text{maxcomfort}}$ of Model #4 (24.3 °C) is relatively closer to monthly outdoor temperatures, compared to $T_{\text{maxcomfort}}$ of Model #3 (20.9 °C). It can be concluded that external parameters, such as solar radiation and outdoor weather conditions, influence the automated control of the indoor environment by the personalized method.

5.1.3 Energy Costs

In order to evaluate the performance of the personalized method with respect to energy costs, five arbitrary scenarios are considered. Under each of the five scenarios, one of the thermal preference models in Table 4, is assumed as the thermal preference model of all the occupants in the office. During January, April, and July, energy consumption costs ($) of the entire office building (only occupied hours), under the five considered scenarios, are assessed (Fig. 33).

There is a direct relationship between productivity per hour ($/h) and energy costs ($). With the increase in hourly productivity of occupants ($/h) in all three months, monthly energy consumption costs ($) also rise (Fig. 33). Having relatively more productive occupants, the personalized method values the productivity of occupants relatively more important. The method considers a trade-off between energy costs and occupants' productivity. Assigning relatively more importance to the occupants' comfort conditions and their productivity, the energy costs associated with the operation of the office building also increase.

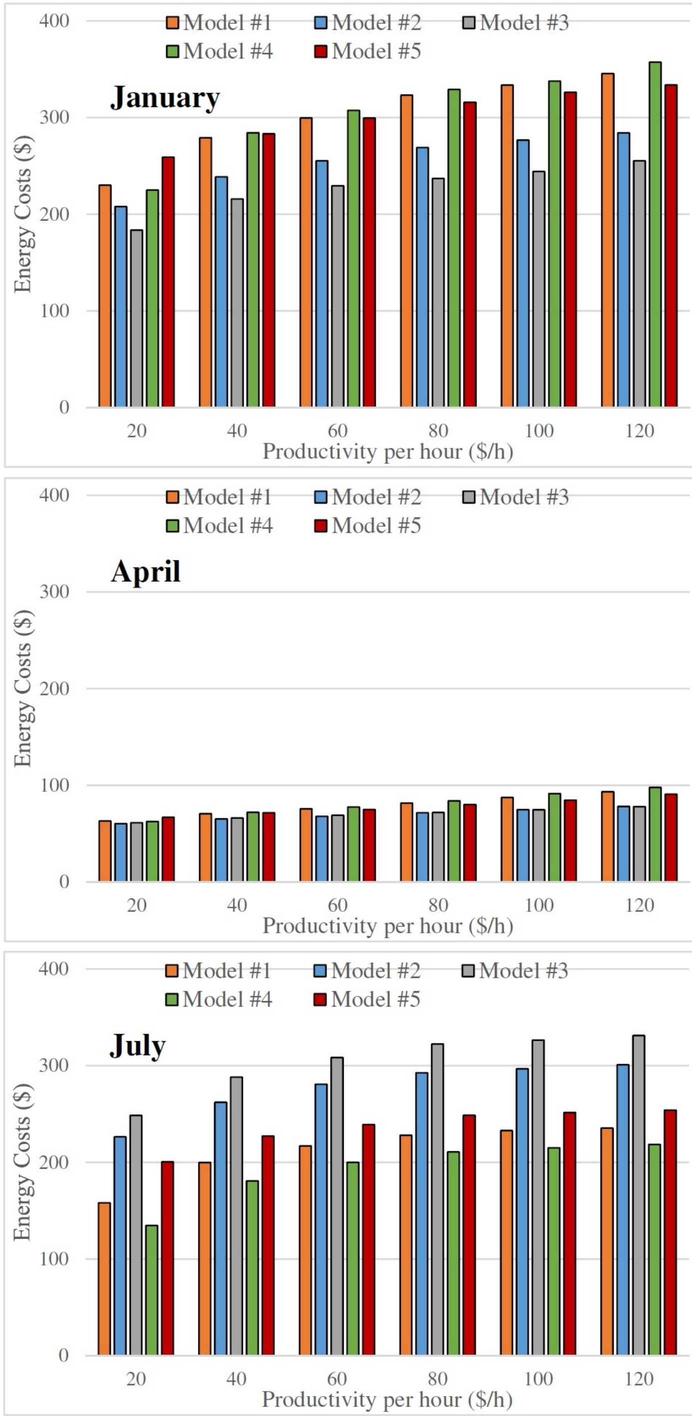

Fig. 33: Monthly energy costs ($) – 5 thermal model governance scenarios, during (a) January, (b) April & (c) July. Under all scenarios (Model #1 to Model #5 governance), it is assumed that all occupants have the same thermal preferences

Furthermore, a relationship is recognizable between the thermal preferences of occupants ($T_{\text{maxcomfort}}$; °C) and monthly energy costs ($). During January, the scenario of having occupants with Model #4 thermal preference (highest $T_{\text{maxcomfort}}$ in Table 4) is associated with the highest level of energy costs (Fig. 33.a). On the other hand, the scenario of having occupants with Model #3 thermal preference (with $T_{\text{maxcomfort}}$ of 20.9 °C) requires relatively less energy expenditures (Fig. 33.a). During July, providing the thermal comfort of occupants with Model #3 thermal preference, requires approximately $100 more monthly energy expenditures, compared to providing the thermal comfort of occupants with Model #4 thermal preference (Fig. 33.c).

5.1.4 Productivity Losses

If thermal conditions of an enclosed space are only controlled according to a single thermal preference model, occupants with alternative thermal preferences would experience productivity losses. To illustrate this point, the operation of the personalized method, under the governance of each of the five thermal preference models (Table 4), are studied and compared. Inside each zone, it is assumed that there are five occupants (Occupant #1 to Occupant #5), with five varied thermal preferences (Model #1 to Model #5). Occupants' names, their thermal preference models, and their personalized parameters are stated in Table 10. A similar hourly productivity of 20 $/h is assumed for each of the occupants.

Table 10: Occupants names and their thermal preference models, assumed in the productivity losses analysis

Occupant	**Occupant #1**	**Occupant #2**	**Occupant #3**	**Occupant #4**	**Occupant #5**
Thermal Preference Model	**Model #1**	**Model #2**	**Model #3**	**Model #4**	**Model #5**
$T_{\text{maxcomfort}}$ (°C)	23.9	21.9	20.9	24.3	23.3
$Tolerance_{\text{thermal}}$ (K)	6.2	5.1	5.2	7	4.3

During January, April, and July, productivity losses of all the occupants (Occupant #1 to Occupant #5), under five arbitrary thermal preference governance scenarios (Model #1 to Model #5), are compared (Fig. 34).

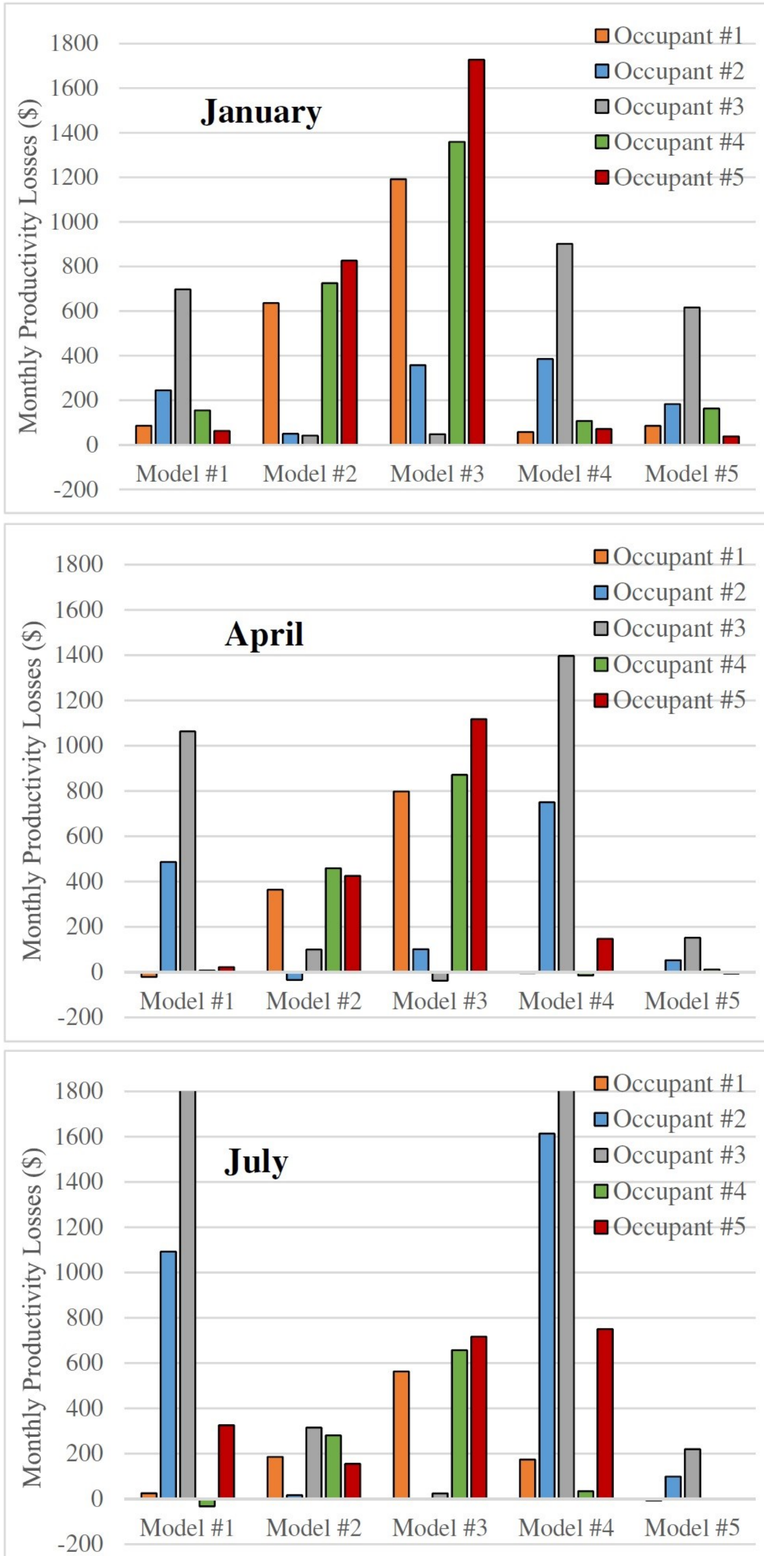

Fig. 34: Monthly productivity losses ($) of occupants (Occupant #1 to Occupant #5), under five thermal models (Model #1 to Model #5) governance scenarios, during (a) January, (b) April & (c) July

Very low or even negative values of productivity losses ($) are observed, when the indoor environment is controlled in accordance with occupants' thermal preferences. For instance, under the scenario of Model #1 governance, Occupant #1 with Model #1 thermal preference has very insignificant monthly productivity losses ($) during January and July (Fig. 34.a and Fig. 34.c); while during April, under the same scenario, Occupant #1 has productivity gains instead of productivity losses (Fig. 34.b).

On the other hand, the model predicts significant productivity losses ($), when occupants' workplace is managed according to a very different thermal preference. Under the scenarios of Model #1 ($T_{\text{maxcomfort}}$ of 23.9 °C) or Model #4 ($T_{\text{maxcomfort}}$ of 24.3 °C) governance, Occupant #2 (Model #2 with $T_{\text{maxcomfort}}$ of 21.9 °C) and Occupant #3 (Model #3 with $T_{\text{maxcomfort}}$ of 20.9 °C), experience significant monthly productivity losses (Fig. 34). This study demonstrates the significant potential to improve the productivity of occupants by acknowledging their thermal preferences while making energy-related decisions for their indoor environment.

5.2 Multiple Thermal Preference Models

When occupants' preferred thermal comfort conditions are neglected, they are subject to significant productivity losses (Fig. 34). The personalized method respects the thermal preference of any occupant who is present at the time of decision-making. $RP_{\text{thermal}}(T)$ of each occupant with respect to the indoor temperature, can be shaped as a Gaussian function with personalized parameters of $T_{\text{maxcomfort}}$ and $Tolerance_{\text{thermal}}$. Considering m occupants in the zone, $RP_{\text{thermal}}{}^{(1)}$ to $RP_{\text{thermal}}{}^{(m)}$ are constructed from their personalized thermal parameters. $Productivity\ losses_{\text{Thermal}}$ of m occupants, is in the form of:

$$Productivity\ losses_{\text{Thermal}}\ (\$/\text{h}) = \sum_{i=1}^{m} Productivity\ per\ hour\ (i) \,.\, (1 - RP_{thermal}{}^{(i)}) \qquad (5.1)$$

The objective function of the method is constructed, using equations (3.14) to (3.16).

An arbitrary occupancy scenario of having occupants with five different thermal preference models (Model #1 to Model #5 in Table 4), in each zone of the building is considered. This scenario is called *All Models Scenario*. Under All Models Scenario, it is assumed that each zone has five occupants with five different thermal preferences (Thermal Model #1 to Model #5). Under this scenario, for each zone, the collective productivity per hour of occupants are assumed to vary in the range of 20 $/h to 120 $/h (or 4 $/h to 24 $/h per person). Considering All Models Scenario, the performance of the personalized method, with respect to (1) thermal comfort of occupants, (2) IAQ, (3) energy costs, and (4) overall productivity is evaluated.

5.2.1 Thermal Comfort

Monthly mean indoor temperatures (°C) are considered to evaluate the indoor thermal conditions of the zones in varied outdoor weather conditions. January, April, and July are selected to represent varied outdoor weather conditions in Montreal. Monthly mean indoor temperatures (°C) for these three months are demonstrated (Fig. 35). During the three months and in all the zones, with the increase in the collective productivity of occupants, monthly mean indoor temperatures (°C) move towards a single optimal point.

In fact, the personalized method considers the diversity in the thermal preferences of occupants and finds optimal indoor temperatures (and optimal values for other indoor environmental parameters), in those the sum of the collective productivity losses of occupants and energy costs is minimized. Under All Models Scenario, variation of hourly productivity doesn't have notable effect on the monthly mean indoor temperatures of the zones (Fig. 35). The diversity in the thermal preferences of occupants limits the influence of productivity rate on the thermal conditions of the zones.

5.2.2 Indoor Air Quality

Under All Models Scenario, monthly mean ventilation rates, during January, April, and July, are evaluated to investigate the IAQ of the zones (Fig. 36). The personalized method controls hourly ventilation rate while managing the diversity in the thermal preferences of occupants. IAQ, as one of the parameters that define the overall comfort (RP_{Overall}), is controlled according to occupants' hourly productivity ($/h).

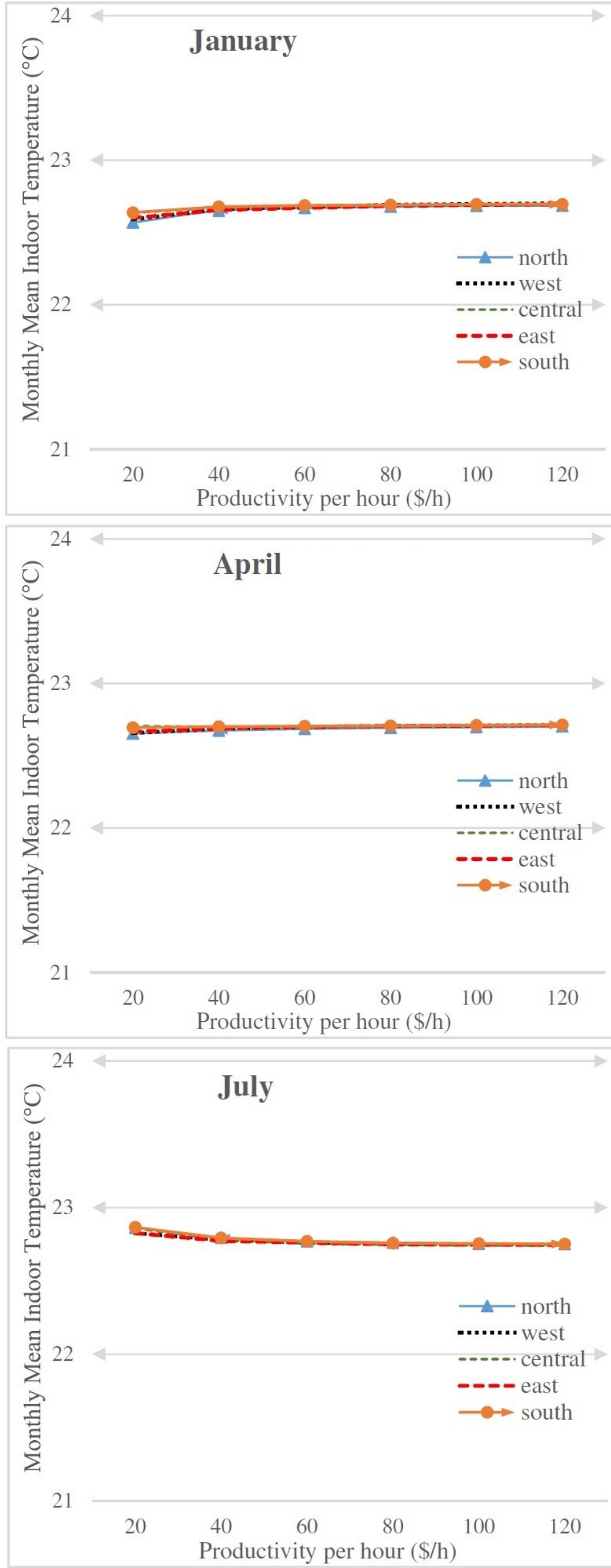

Fig. 35: Monthly mean indoor temperatures (°C) during January (a), April (b) & July (c) – All Models Scenario. Monthly mean indoor temperatures (°C) approach a single optimal point despite the diversity among occupants' thermal preferences

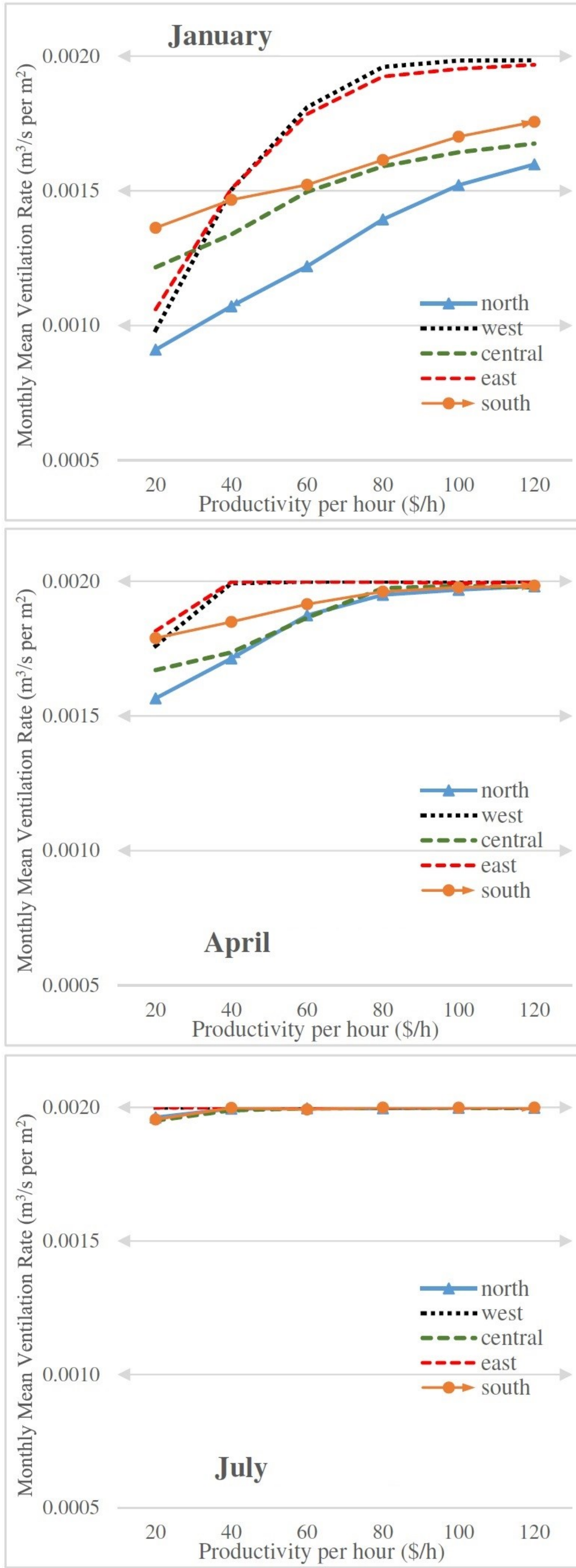

Fig. 36: Monthly mean ventilation rates (m^3/s per m^2) during January (a), April (b) & July (c) – All Models Scenario

Higher levels of ventilation rates provide a relatively more productive indoor environment for the occupants. In all three months and in all the zones, the increase in hourly productivity of occupants ($/h) results in the increase in monthly mean ventilation rates (m^3/s per m^2). Furthermore, with the increase in the monthly mean outdoor temperature, from January to April, to July, monthly mean ventilation rates are increased, as well. Observing monthly mean ventilation rates in July (Fig. 36.b), it can be perceived that hourly ventilation rates are most of the time kept at its maximum allowable level (0.002 m^3/s per m^2).

5.2.3 Energy Costs

Under All Models Scenario, monthly energy costs ($) associated with the office building, during January, April, and July are evaluated (Fig. 37). A comparison is made between the energy costs under the five single thermal preference scenarios and All Models Scenario. Under all considered scenarios, the collective hourly productivity of occupants in each zone, are assumed to vary in the range of 20 $/h to 120 $/h (4 $/h to 24 $/h per person).

During the cold month of January, monthly energy consumption costs ($) of the office building are lower, compared to the energy costs under Model #1, Model #4, or Model #5 governance scenarios (Fig. 37.a). Under these three single thermal preference scenarios, all occupants have $T_{\text{maxcomfort}}$ of 23.9 °C (Model #1), 24.3 °C (Model #4), or 23.3 °C (Model #5). Under All Models Scenario, with the increase in hourly productivity of occupants, monthly mean indoor temperatures (°C) in all zones move toward an optimum point of 22.8 °C (Fig. 37.a). The optimum indoor temperature, selected by the method, is lower than $T_{\text{maxcomfort}}$ of occupants with Model #1, Model #4, or Model #5 thermal preferences. Accordingly, the energy costs under All Models Scenario, are also less than the energy costs under the three single thermal preference scenarios. During January, monthly energy costs ($) under Model #2 and Model #3 governance scenarios, are relatively lower than monthly energy costs under All Models Scenario (Fig. 37.a). This is because of the relatively lower value of $T_{\text{maxcomfort}}$ of Model #2 (21.9 °C) and $T_{\text{maxcomfort}}$ of Model #3 (20.9 °C), compared to the optimum point, chosen by the method under All Models Scenario (22.8 °C).

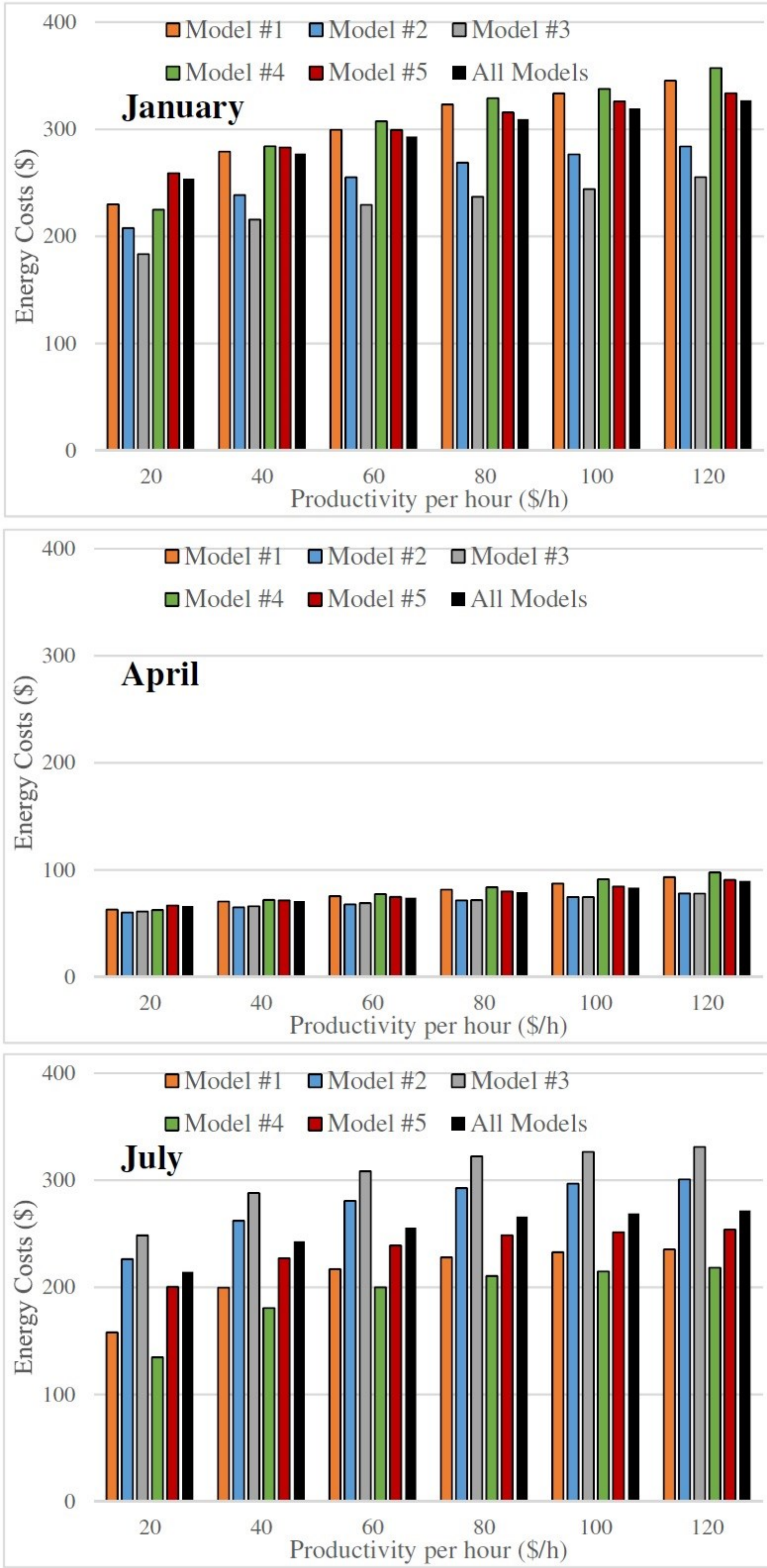

Fig. 37: Energy costs ($) under each of five single thermal model governance scenarios & All Models Scenario, during (a) January, (b) April & (c) July

The same discussion can also express the differences between the energy costs under varied scenarios of occupancy in April (Fig. 37.b). During July, due to the warm outdoor weather conditions, providing satisfactory indoor thermal conditions, for the occupants with relatively lower levels of $T_{\text{maxcomfort}}$, requires a relatively higher level of energy consumption. Hence, the energy costs associated with the office building, under All Models Scenario, are lower compared to the energy costs under Model #2 and Model #3 governance scenarios (Fig. 37.c). The optimum indoor temperature of All Models Scenario (22.8 °C) is lower than $T_{\text{maxcomfort}}$ of occupants with Model #1 (23.9 °C), Model #4 (24.3 °C), and Model #5 (23.3 °C) thermal preferences. Hence, during July, the energy costs, under the governance of these three thermal preferences, are lower, compared to the energy costs under All Models Scenario (Fig. 37.c).

5.2.4 Productivity Losses

It is observed that neglecting occupants' thermal preferences can cause significant productivity losses in the office (Fig. 34). In Section 5.1.4, it is considered that five occupants stay in each of the five zones. In each zone, five occupants (Occupant #1 to Occupant #5) are assumed to have five different thermal preferences (Model #1 to Model #5). Their thermal preference models are stated in Table 10. Here, under the same scenario of occupancy, the productivity of all five occupants are compared to their productivity when the office is controlled according to a single thermal preference. A fixed value of 20 $/h hourly productivity is considered for each of the occupants. Accordingly, overall hourly productivity of occupants in each zone is equal to 100 $/h. Monthly productivity losses of occupants ($) in all the zones, and in varied outdoor weather conditions, under different governance scenarios are demonstrated (Fig. 38).

Under five single thermal model governance scenarios (Model #1 to Model #5), productivity losses of occupants ($) are increased, when the indoor environmental conditions are controlled according to a very different thermal preference. For instance, under the governance of Model #1 or Model #4, during April and July, Occupant #2 and Occupant #3 experience significant monthly productivity losses (Fig. 38).

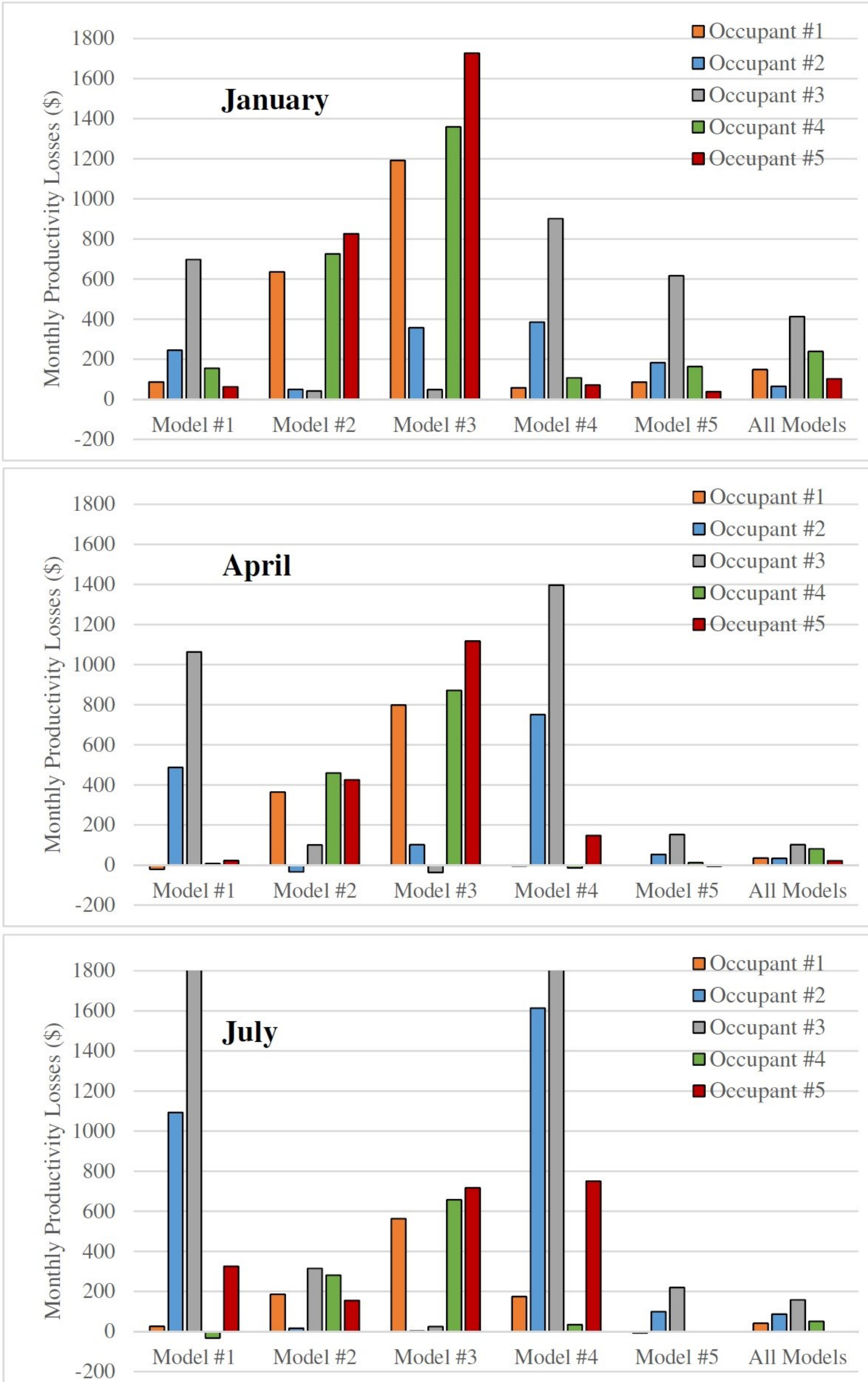

Fig. 38: Productivity losses ($) under each of five single thermal preference governance scenarios & All Models Scenario, during (a) January, (b) April & (c) July

The method acknowledges occupants' varied thermal preferences, introduces the thermal preferences of all occupants in the MOOP of energy costs and productivity, and improves the overall productivity of occupants. For all outdoor weather conditions, the personalized method (under All Models Scenario) avoids significant productivity losses (observed under the other scenarios) and keeps the productivity losses of occupants ($) relatively low (Fig. 38).

5.3 Discussion

So far, two features of the proposed personalized method have been discussed. First, it is observed that the method is capable of performing personalized energy and comfort management. The method controls the indoor environmental conditions according to occupants' thermal preferences, and at the same time minimizes the energy consumption costs. Second, analyzing the performance of the personalized method under All Models Scenario, it is determined that the method can manage the diversity in the occupants' thermal preferences and optimizes their collective productivity. In this section, the importance of two parameters of *individual productivity* and $Tolerance_{\text{thermal}}$ will be discussed, by analyzing the sensitivity of the personalized method to these two human-related parameters.

5.3.1 Importance of Individual Productivity

Under All Models Scenario (described in Section 5.2), it is assumed that each zone has five occupants with five different thermal preferences. The productivity of each occupant in the office is assumed to be equal and vary in the range of 4 $/h to 24 $/h. Here, the influence of the hourly productivity on the automated control of the indoor environment is examined, by assuming the diversity in the occupants' productivity rates.

Similar to All Models Scenario, an arbitrary scenario of having five occupants with five different thermal preferences (from Table 4), in each zone of the office, is considered. In each zone, an occupant with distinct thermal preference is considered to have higher hourly productivity rates, than the others. In other words, each zone is *dominated* by one of the thermal preference models, in terms of productivity. In Table 11, thermal preference models and dominated zones are stated.

Table 11: Thermal preference models & the zones they dominate – The productivity rate sensitivity analysis

Thermal Preference Model	**Model #1**	**Model #2**	**Model #3**	**Model #4**	**Model #5**
Dominated Zone	East	West	North	South	Central

The hourly productivity of occupants are considered to be similar and are ranged from 4 $/h to 24 $/h. To determine the dominance of an individual occupant in a particular zone, the hourly productivity of that occupant is assumed to be doubled in the dominated zone. For instance, in east zone, the occupant with thermal preference of Model #1 has the hourly productivity, in the range of 8 $/h to 48 $/h, while the other occupants (with thermal preferences of Model #2 to Model #5) have the hourly productivity of 4 $/h to 24 $/h.

Considering occupants' varied hourly productivity scenarios, monthly mean indoor temperatures (°C), during January, April, and July, are shown (Fig. 39). In all three months, monthly mean indoor temperatures (°C) in all the zones, are in the range of 22 °C to 23 °C. In west zone and north zone, having dominant occupants with relatively lower $T_{\text{maxcomfort}}$ of 21.9 °C and 20.9 °C (Model #2 and Model #3, respectively), monthly mean indoor temperatures (°C) are also lower than the other zones. In contrast, east zone, south zone, and central zone, under the dominance of occupants with Model #1, Model #4, or Model #5, have relatively higher monthly mean indoor temperatures (°C). The method prioritizes a more productive occupant while controlling the indoor environment according to all thermal preferences. This capability of the method is useful to perform personalized energy and comfort management in offices.

5.3.2 Importance of Occupants' Thermal Tolerances

The Gaussian representation of thermal preference consists of two personalized parameters; $T_{\text{maxcomfort}}$ and $Tolerance_{\text{thermal}}$. So far, the influence of $T_{\text{maxcomfort}}$ on the performance of the personalized method has been discussed. Here, the focus is on the role of $Tolerance_{\text{thermal}}$. An individual occupant signals his or her thermal sensation votes, by calling the indoor environmental conditions either acceptable or unacceptable. If an occupant has more tolerance and is less sensitive to the thermal conditions, his or her negative feedback are less, compared to a more sensitive occupant. Occupants' thermal sensation votes construct their thermal preference models, hence, a less sensitive occupant has higher $Tolerance_{\text{thermal}}$ than a more sensitive one.

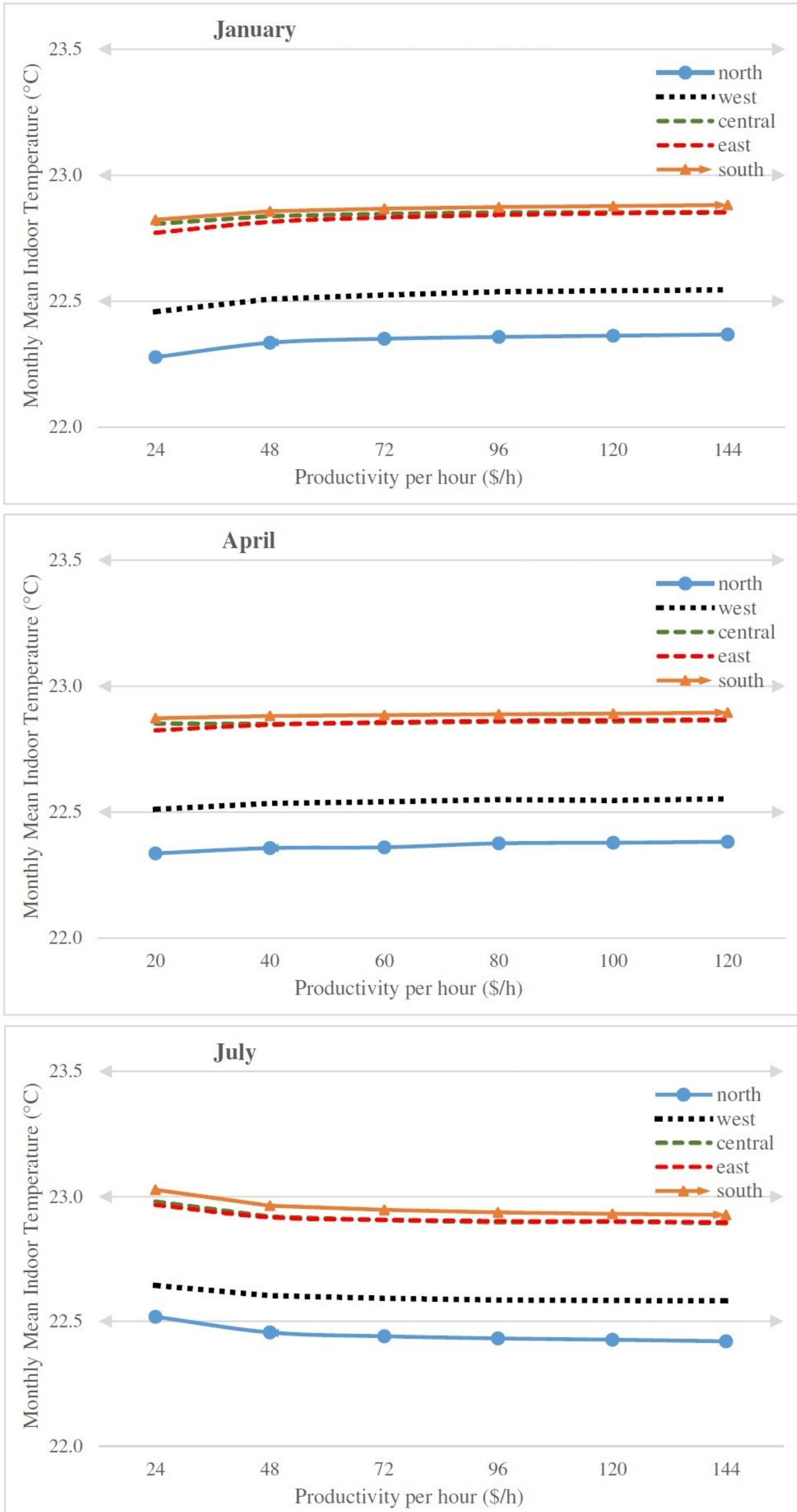

Fig. 39: Monthly mean indoor temperatures (°C) in the productivity rate sensitivity analysis, during (a) January, (b) April & (c) July

Considering $Tolerance_{thermal}$ variations, the sensitivity of the method to occupants' tolerance is analyzed. An occupancy scenario, similar to All Models Scenario is considered, in which each zone has five occupants with five varied thermal preferences. As an assumption, $Tolerance_{thermal}$ of occupants with thermal preferences of Model #1 and Model #5 are varied by 20%, during January. During July, 20% variation in $Tolerance_{thermal}$ of occupants with thermal preferences of Model #2 and Model #3, are assumed. Accordingly, two scenarios of occupants' high tolerance and occupants' low tolerance are created (Table 12). The operation of the method under these scenarios are compared to the scenario of normal tolerance, which is All Models Scenario.

Table 12: Scenarios with varied thermal tolerances, during January and July - Sensitivity analysis to thermal tolerance

Thermal Preference Model	Model #1	Model #2	Model #3	Model #4	Model #5
Normal Tolerance					
$T_{maxcomfort}$ (°C)	23.9	21.9	20.9	24.3	23.3
$Tolerance_{thermal}$ (K)	6.2	5.1	5.2	7	4.3
High Tolerance - January					
$Tolerance_{thermal}$ (K)	**7.5**	5.1	5.2	7	**5.2**
High Tolerance - July					
$Tolerance_{thermal}$ (K)	6.2	**6.1**	**6.3**	7	4.3
Low Tolerance - January					
$Tolerance_{thermal}$ (K)	**5**	5.1	5.2	7	**3.5**
Low Tolerance - July					
$Tolerance_{thermal}$ (K)	6.2	**4.1**	**4.2**	7	4.3

Monthly mean indoor temperatures (°C) and monthly mean ventilation rates (m^3/s per m^2), during January and July, considering occupants' tolerance variations (high tolerance +, low tolerance -) are demonstrated (Fig. 40 and Fig. 41). It is observed that the indoor thermal conditions of the zones are influenced by occupants' $Tolerance_{thermal}$ (σ) variations (Fig. 40).

From Fig. 40, it can be perceived that higher thermal tolerances of occupants ($Tolerance_{thermal}$) result in the lower levels of energy consumption, by decreasing monthly mean indoor temperatures (°C) in January, and increasing them in July. On the other hand, occupants' thermal tolerance variation do not have an impact on the IAQ of the zones (Fig. 41).

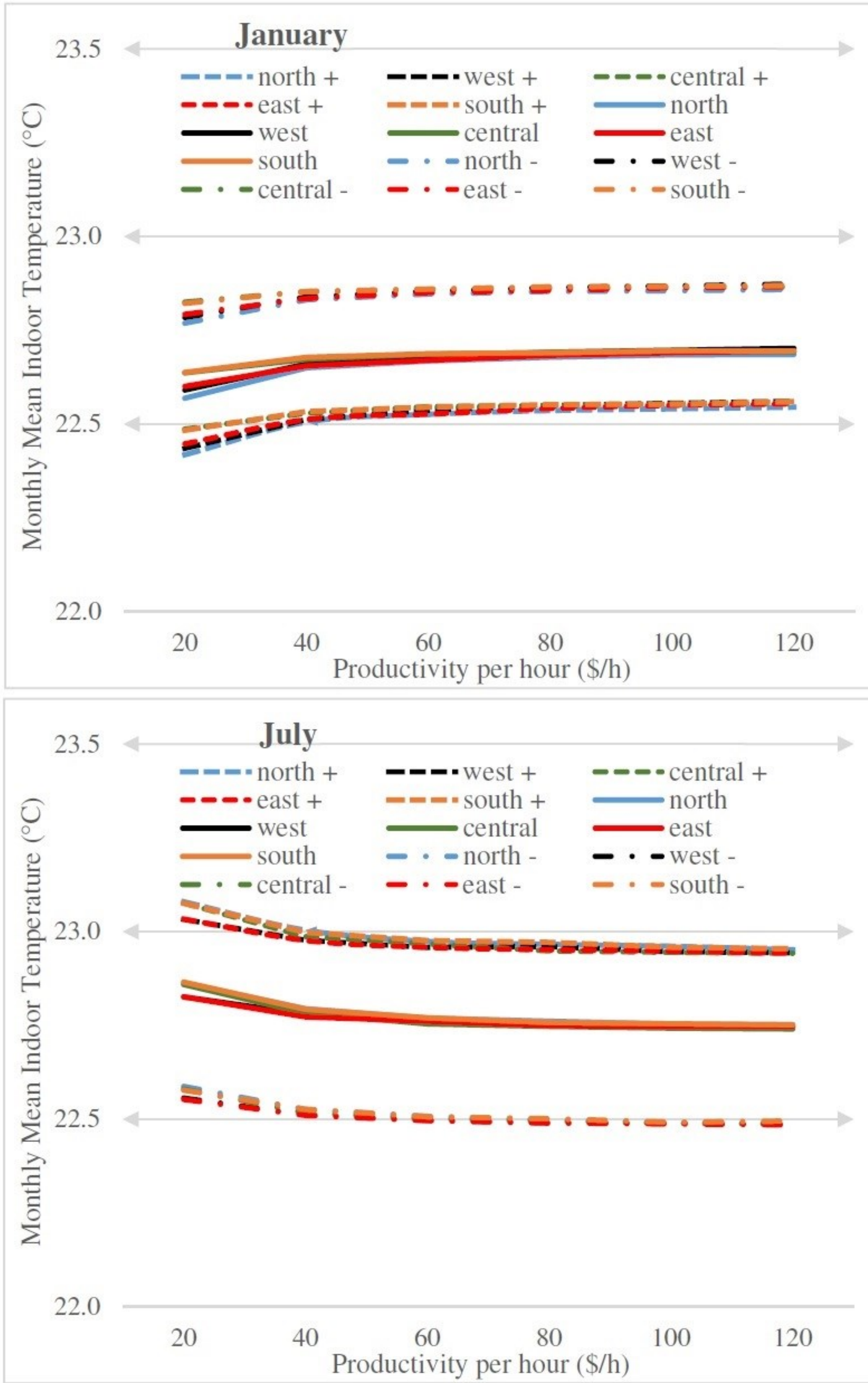

Fig. 40: Monthly mean indoor temperatures (°C) during (a) January & (b) July – Sensitivity analysis to Tolerance$_{thermal}$ (σ). Here, the focus is on the influence of occupants' tolerance variations (high tolerance +, low tolerance -) on the thermal conditions of each zone, rather than the difference between the zones

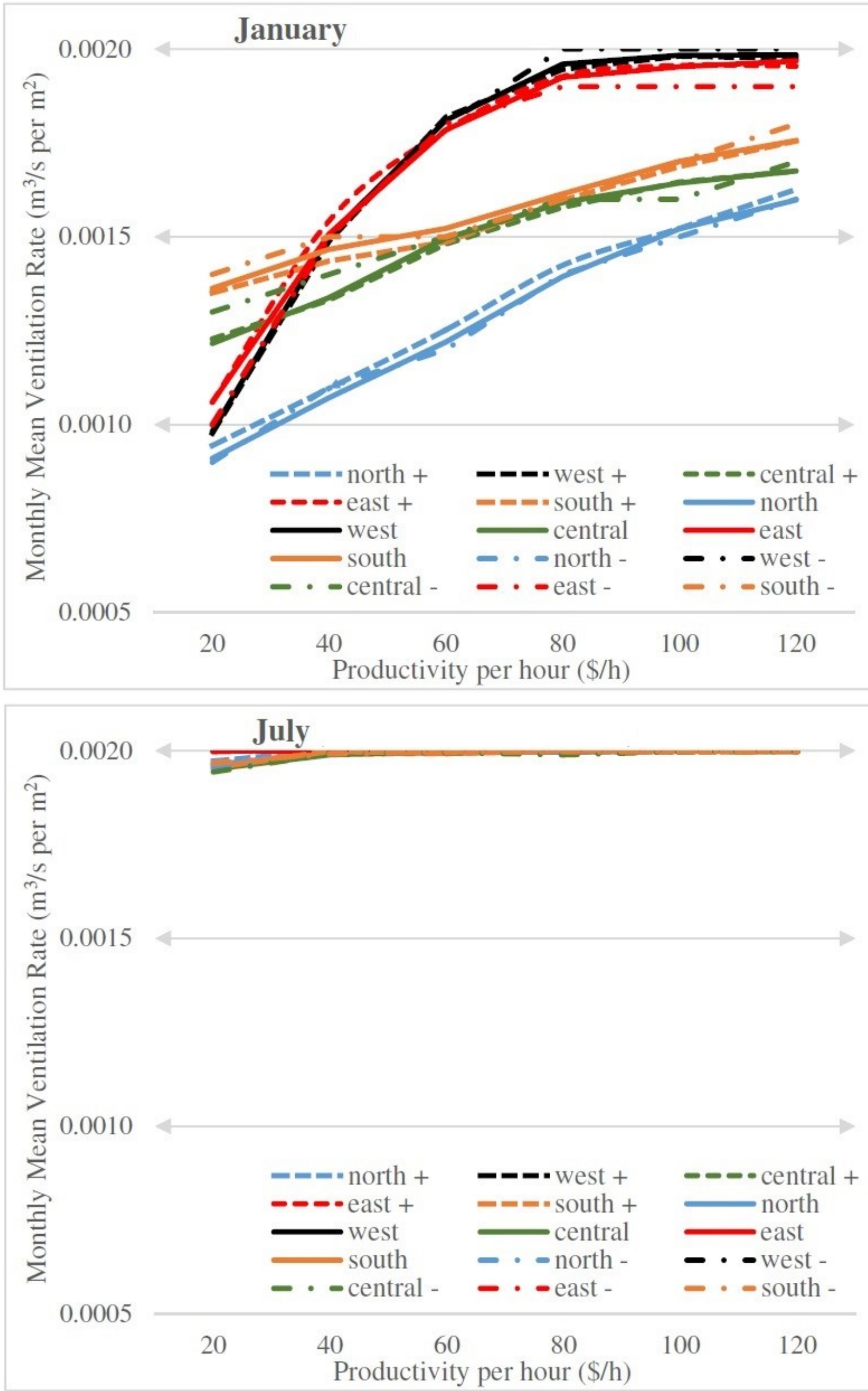

Fig. 41: Monthly mean ventilation rates (m^3/s per m^2) during (a) January & (b) July – Sensitivity analysis to Tolerance$_{thermal}$ (σ)

Finally, the effect of occupants' collective thermal tolerance variations, on the indoor temperature of the zones is studied. To consider the collective thermal tolerance variations of occupants, their $Tolerance_{\text{thermal}}$ is assumed to alter 30%. Values of $T_{\text{maxcomfort}}$ and $Tolerance_{\text{thermal}}$, under the new scenarios and the default scenario (All Models Scenario), are stated in Table 13.

Table 13: Scenarios of occupants' collective tolerance variations

Thermal Preference Model	**Model #1**	**Model #2**	**Model #3**	**Model #4**	**Model #5**
Normal Tolerance					
$T_{\text{maxcomfort}}$ (°C)	23.9	21.9	20.9	24.3	23.3
$Tolerance_{\text{thermal}}$ (K)	6.2	5.1	5.2	7	4.3
High Tolerance					
$Tolerance_{\text{thermal}}$ (K)	8.1	6.6	6.8	9.1	5.6
Low Tolerance					
$Tolerance_{\text{thermal}}$ (K)	4.4	3.6	3.7	4.9	3

Under the three considered scenarios of collective thermal tolerance, monthly mean indoor temperatures (°C), during the whole year, are demonstrated in Fig. 42. It is observed that the range of monthly mean indoor temperatures (°C) is wider, under high thermal tolerance scenario, compared to normal tolerance, and low tolerance scenarios. Accordingly, the personalized method benefits from the higher tolerance of occupants to optimize the energy costs, by providing lower indoor temperatures (°C) during the cold seasons, and higher indoor temperatures (°C) during the warm seasons.

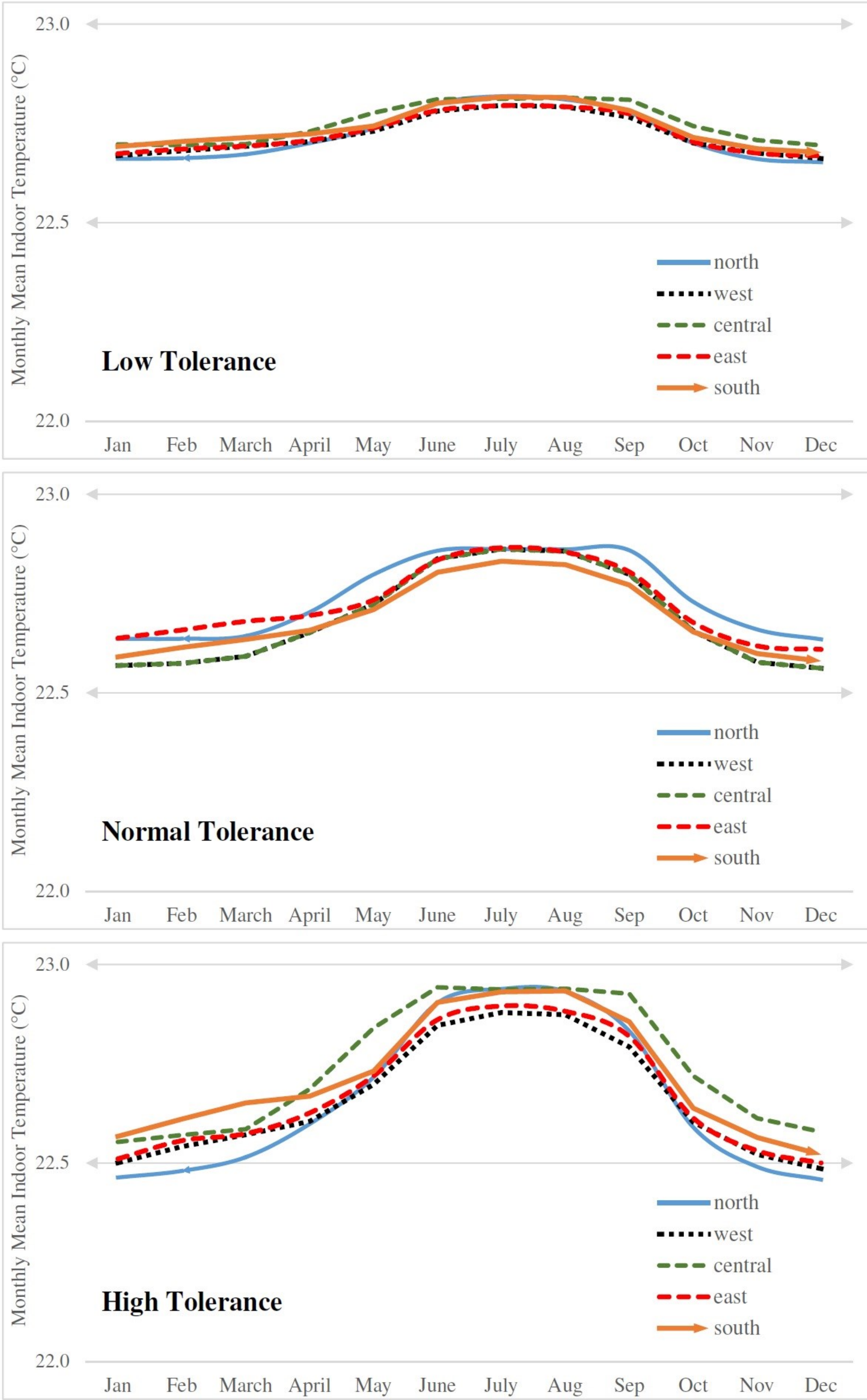

Fig. 42: Monthly mean indoor temperatures (°C) under three collective tolerance scenarios

5.4 Chapter Summary

In this chapter, the performance of the personalized method, proposed in Section 3.3, with respect to energy costs minimization and occupants' productivity maximization, is evaluated. The personalized method is able to construct the thermal preference models of occupants, from the history of their thermal sensation votes. Two personalized variables of $T_{\text{maxomfort}}$ and $Tolerance_{\text{thermal}}$ express the up-to-date thermal preference model (RP_{Overall}) of each occupant. The proposed method optimizes energy costs and productivity of occupants, considering occupants' thermal preferences and IAQ, by exploring optimal solutions for the automated control of the indoor environment. The method is used for energy and comfort management, in the office building model, discussed in Section 3.1. The performance of the personalized method, under varied occupancy scenarios, is studied. Based on the provided results, it is demonstrated that the personalized method is capable of simultaneously improving the productivity of office workers while minimizing the associated energy costs (*Objective 2* of the research).

In offices, it is possible to have office workers with varied thermal comfort preferences sharing the same enclosed space. In buildings where comfort conditions are controlled at a group-level or zone-level, neglecting occupants' thermal preferences may cause productivity losses. Based on the provided results, it is confirmed that the personalized method avoids significant economic losses, by improving the collecting productivity of office workers (*Objective 2* of the research). The sensitivity of the method to two parameters of *individual productivity* and *individual tolerance* is analyzed, in order to study capabilities of the method to perform personalized energy and comfort management. Considering varied hourly productivity for occupants, the personalized method prioritizes a more productive occupant, while simultaneously optimizing indoor environmental conditions, according to all comfort preferences. Furthermore, the method performs the automated control of the indoor environment, according to occupants' thermal tolerance ranges ($Tolerance_{\text{thermal}}$). Hereby, the personalized method can benefit from the higher tolerance of occupants to minimize energy consumption costs. The subject of Chapter 6 is to include the visual preferences of occupants, alongside their thermal preferences, to perform personalized energy and comfort management. In addition, the positions of occupants inside the zones are also considered to evaluate and optimize their thermal and visual conditions, under *position-based* MOOP of energy costs and comfort conditions.

6 Position-Based Multi-Objective Optimization of Energy Costs, Thermal & Visual Comfort & Indoor Air Quality

In *position-based* MOOP of energy costs and occupants' productivity, besides the thermal comfort of occupants (RP_{Thermal}) and IAQ of the zones (RP_{IAQ}), their visual comfort conditions (RP_{Visual}) are also considered to model their overall productivity (RP_{Overall}). Occupants' perceptions of the indoor environment (their thermal and visual sensations) depend on their positions inside enclosed spaces, as well as their environmental preferences [62]. In the proposed position-based energy and comfort management, thermal comfort and visual comfort are evaluated more accurately, by considering each occupant's position inside a zone (*Objective 3* of the research). During simulations, four arbitrary positions: *Position-A*, *Position-B*, *Position-C,* and *Position-D* are considered for office workers, inside each zone (Fig. 7).

Position-based thermal comfort evaluation is discussed, within nine steps, in Sub-Section 3.4.1. In the position-based consideration of indoor thermal conditions, operative temperature (°C) is the parameter to evaluate the thermal comfort of occupants. In each position, the operative temperature is the average of indoor temperature and MRT. The MRT directly depends on the position, as well as the enclosed space characteristics, such as its shape, dimensions, and window design. The indoor temperature (°C) in each zone is controlled by the position-based method, on an hourly basis, and is assumed to be uniform throughout the zone. In position-based energy and comfort management, the proposed method controls the indoor temperature (°C) inside each zone, in order to provide satisfactory operative temperatures (°C) for the occupants.

Position-based visual comfort evaluation is explained in Sub-Section 3.4.2. The level of illuminance (lux) in each position is the parameter to consider in visual comfort evaluation. Moreover, for avoiding glare, the minimum illuminance level (lux) and the maximum illuminance level (lux) should be respected as the constraints on the visual conditions (Table 5). The level of *Illuminance* (lux) in each position is the sum of *Natural Illuminance* (lux) and *Artificial Illuminance* (lux). It is considered that the illuminance from artificial lighting is uniform across the zone. *Natural Illuminance* (lux) in each position is calculated from (3.24) having (1) the configuration factors in that position, (2) the view factors between the surfaces, (3) the surface reflectances, and (4) the level of natural illumination (lux) entered the room from the window.

In Sub-Section 3.4.3 and Sub-Section 3.4.4, thermal and visual preference models of four arbitrary occupants were constructed. In order to construct their thermal and visual preference models, their thermal and visual regression parameters, from [97], are used. Occupants' thermal and visual regression parameters represent their thermal and visual sensation votes [97]. Here, thermal and visual sensation votes of occupants are fitted into Gaussian functions to express their relative productivity, with respect to the thermal and visual conditions of the indoor environment. Two personalized variables of $T_{\text{maxcomfort}}$ and $Tolerance_{\text{thermal}}$ declare relative productivity of an occupant, with regard to the thermal conditions (RP_{thermal}). Two other personalized variables of $ILL_{\text{maxcomfort}}$ and $Tolerance_{\text{visual}}$ express his or her RP_{visual}, or relative productivity with respect to the visual conditions of the indoor environment. Accordingly, occupants' thermal and visual preference models (RP_{thermal} and RP_{visual}) are constructed, and their personalized thermal and visual variables are derived (Table 7 and Table 9).

The problem formulation of the position-based MOOP method is discussed in Sub-Section 3.4.5. The office building schedule and building parameters are shown in Table 5 and Table 1. During the occupied hours, the position-based method acts as the decision-maker for energy and comfort management. In order to evaluate the capabilities of the position-based method, different parametric simulations are performed, where arbitrary scenarios of occupancy, inside different zones and during varied months of the year, are considered. First, the importance of personalized energy and comfort management is demonstrated, by making a comparison between performances of the position-based MOOP method and the SOOP method. The flexibility of the position-based method to make energy-related decisions, based on the personalized parameters of occupants' (1) hourly productivity rates, (2) thermal preferences, (3) visual preferences, and (4) positions, are evaluated in different parametric simulations. January, April, and July represent the cold, the swing, and the warm season of Montreal. Weekly results of simulations, in these three months, are analyzed to have a detailed view on the operation of the method and its decision-making capabilities.

6.1 Importance of Personalized Control

It is assumed that during the occupied hours, the energy and comfort management is performed using (1) the SOOP method and (2) the position-based method. Accordingly, the weekly performances of the position-based method and the SOOP method are compared with respect to (1) thermal comfort, (2) visual comfort, (3) IAQ, (4) overall productivity of occupants, and (5) energy costs.

The major difference between the position-based method and the SOOP method is the presence of thermal comfort, visual comfort, and IAQ parameters, inside the objective function of the former. On the other hand, in the SOOP of energy costs, occupants' comfort conditions are treated as constraints for optimization. The constraints, related to visual comfort (indoor illuminance) and IAQ (conditioned outdoor air flow rate), are demonstrated in Table 5. Moreover, two value of 21 ºC and 27 ºC are chosen as the heating and cooling set-points, during the occupied hours.

During January, April, and July, arbitrary scenarios of having two occupants in specific positions of the zones, are considered. Table 14 states the studied zones, occupants inside, and their positions in specific months. It is assumed that each occupant has a constant productivity rate of 8 $/h.

It should be noted that throughout this chapter, the choice of occupancy scenarios and occupants' productivity rates are arbitrary. Since the performance of the position-based method is independent of the choice of occupancy scenarios, for different studies, varied occupancy scenarios are assumed.

Table 14: Occupancy scenarios - Importance of personalization analysis

Month	Zone	Occupancy Scenarios			
		Position A	Position B	Position C	Position D
January	East	Occupant #1	Occupant #2		
April	North		Occupant #2	Occupant #3	
July	West		Occupant #2		Occupant #4

6.1.1 Thermal Comfort

During the first week of January, hourly operative temperatures (°C) in Position-A and Position-B of east zone are analyzed (Fig. 43). Under the scenario of using the SOOP method, hourly operative temperatures (°C) in Position-A (for Occupant #1) and in Position-B (for Occupant #2) are close to the heating set-point (21 °C). Occupant #1 has $T_{\text{maxcomfort}}$ of 25.5 °C and Occupant #2 has $T_{\text{maxcomfort}}$ of 23.4 °C (Table 7). Hence, under the SOOP-based energy management scenario, during the first week of January, the thermal conditions of east zone are not optimal for the two occupants. On the other hand, the MOOP method provides hourly operative temperatures (°C) within the range of $T_{\text{maxcomfort}}$ of two occupants (Fig. 43).

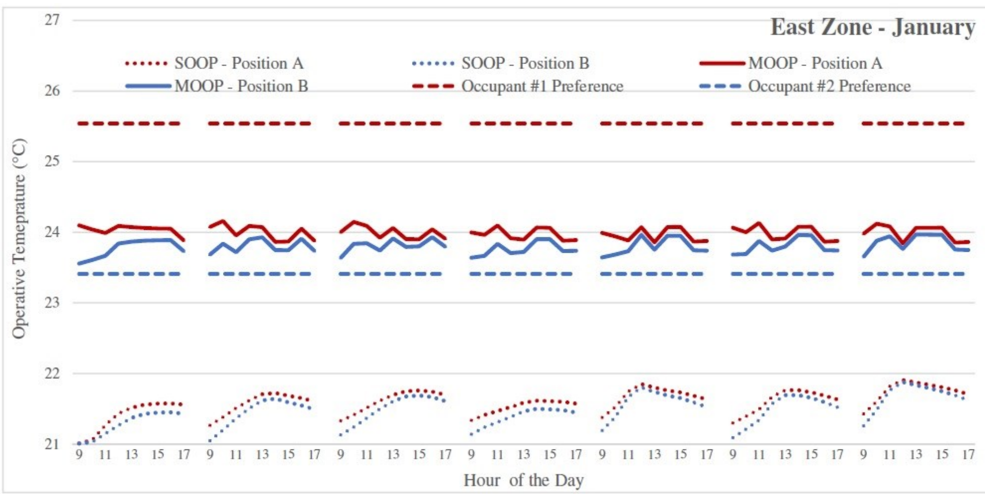

Fig. 43: Comparing position-based MOOP method & SOOP method – Weekly thermal comfort analysis in the cold season

During April, the performance of the proposed method and the SOOP method are compared for the north zone. Occupant #2 in Position-B has $T_{\text{maxcomfort}}$ of 23.4 °C, while Occupant #3 in Position-C has $T_{\text{maxcomfort}}$ of 24.3 °C (Table 7). The position-based method provides operative temperatures (°C) in the range of $T_{\text{maxcomfort}}$ of the two occupants. On the other hand, the SOOP method only pays attention to its energy costs minimization objective which results in relatively lower operative temperatures (Fig. 44). Using the SOOP method during the swing season, there are high variations in hourly operative temperatures (°C) of the zones, which demonstrate the sensitivity of the SOOP method to outdoor weather conditions.

Fig. 44: Comparing position-based MOOP method & SOOP method – Weekly thermal comfort analysis in the swing season

During the warm season analysis, Occupant #2 and Occupant #4 are considered as the office workers in west zone (Table 14). Occupant #2 in Position-B has $T_{\text{maxcomfort}}$ of 23.4 °C, while Occupant #4 in Position-D has $T_{\text{maxcomfort}}$ of 23.9 °C (Table 7). During July, using the SOOP method, hourly operative temperatures (°C) are close to the cooling set-point (27 °C). Using the position-based method, hourly operative temperatures (°C) in Position-B and Position-D are relatively closer to occupants' ideal temperatures (Fig. 45).

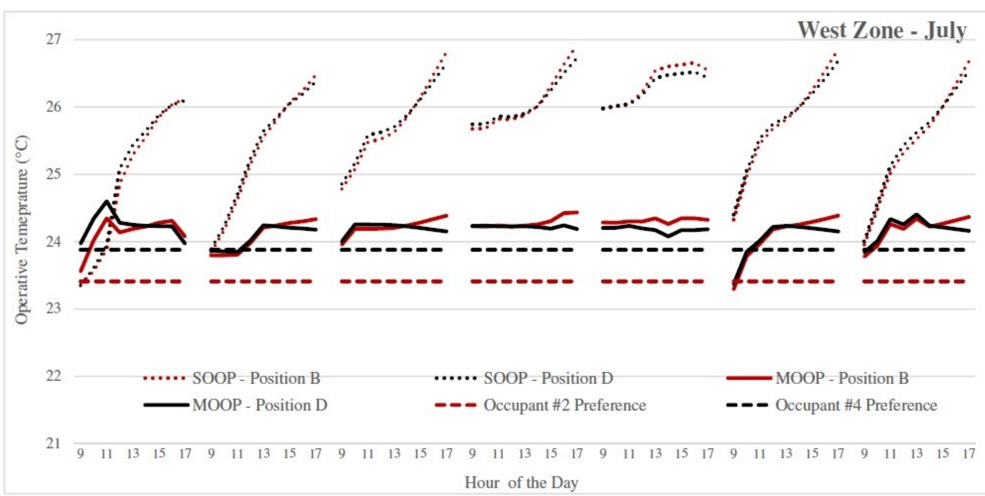

Fig. 45: Comparing position-based MOOP method & SOOP method – Weekly thermal comfort analysis in the warm season

Studying the thermal conditions of arbitrary sets of occupants, in different zones and in varied outdoor weather conditions, it can be concluded that the position-based method acknowledges the personalized thermal preferences of occupants, while making decisions for the automated control of the indoor environment.

6.1.2 Visual Comfort

Considering the arbitrary occupancy scenarios in Table 14, the weekly operation of the two methods, with respect to the visual comfort of occupants are compared (Fig. 46). During January, the assumed occupancy scenario is to have Occupant #1 with $ILL_{\mathrm{maxcomfort}}$ of 937 lux in Position-A, and Occupant #2 with $ILL_{\mathrm{maxcomfort}}$ of 1563 lux in Position-B of east zone. Using both methods, illuminance levels (lux) in two positions are within the range of minimum (750 lux) and maximum (2500 lux) acceptable levels (Table 5). However, the position-based method provides illuminance levels close to the occupants' preferred visual conditions (Fig. 46). Having the personalized visual comfort term inside its objective function, the proposed method is continuously paying attention to the visual preferences of occupants, while controlling the blind position and artificial lighting.

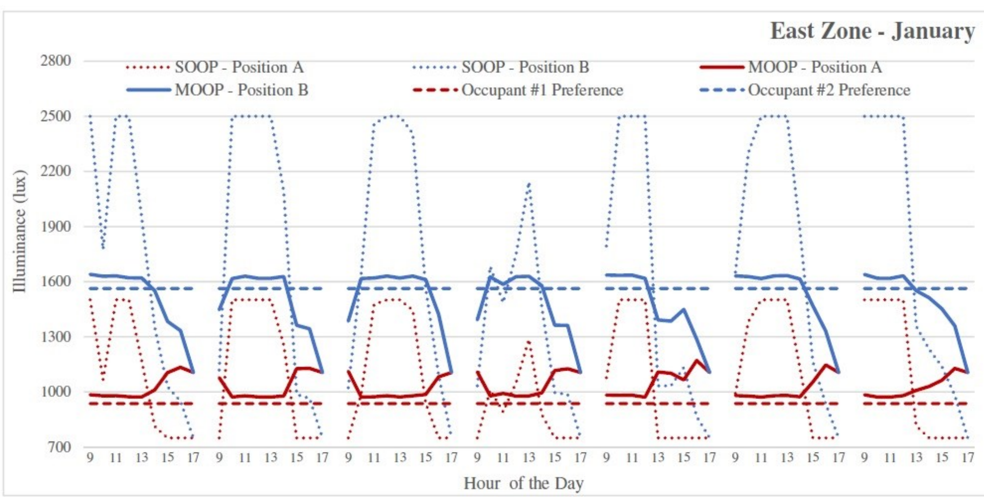

Fig. 46: Comparing position-based MOOP method & SOOP method – Weekly visual comfort analysis in the cold season

The performance of the position-based method, with respect to the visual comfort of occupants, is evaluated during July, as well. For this purpose, the weekly operation of the proposed method and the SOOP method are compared in west zone. Inside west zone, an arbitrary occupancy scenario of having Occupant #2 with $ILL_{\mathrm{maxcomfort}}$ of 1563 lux in Position-B, and Occupant #4 with

$ILL_{\text{maxcomfort}}$ of 1429 lux in Position-D are assumed (Table 9 and Table 14). Indoor illuminance (lux) in Position-B and Position-D, under both energy and comfort management scenarios, are demonstrated (Fig. 47). The position-based method performs the automated control of the indoor environment, in order to provide the preferred visual conditions of the occupants.

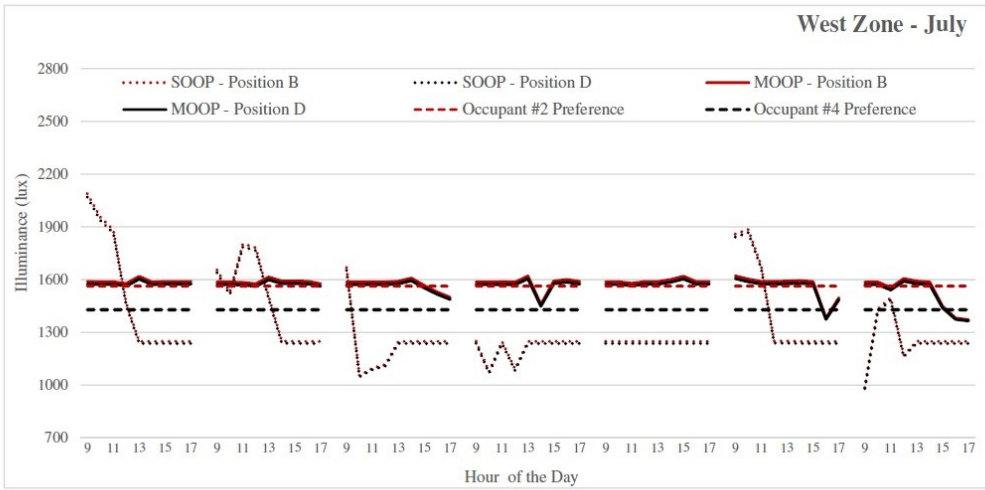

Fig. 47: Comparing position-based MOOP method & SOOP method – Weekly visual comfort analysis in the warm season

Studying the performance of the position-based method, under arbitrary occupancy scenarios, in varied outdoor weather conditions, it is confirmed that the method acknowledges the thermal and visual preferences of occupants, while making energy-related decisions for the automated control of the indoor environment.

6.1.3 Indoor Air Quality

The next step is to compare the performances of SOOP and MOOP methods, with respect to the IAQ of the office. By supplying higher levels of ventilation rates, a relatively more productive environment can be provided for occupants [31]. Under the same occupancy scenarios (Table 14), the level of ventilation rates, optimized by the two methods are compared. Ventilation rates (m^3/s per m^2), during weekly analysis in April and July, in north zone and west zone, are presented in Fig. 48 and Fig. 49.

During April, the SOOP method only supplies the minimum acceptable level of ventilation rate (0.0007 m^3/s per m^2) throughout the week. In Montreal, the outdoor air temperature in April is generally below the average inside air temperature, hence, increasing ventilation rate (m^3/s per m^2) above the minimum required level, and drawing additional outdoor air into the zone is in conflict with the energy costs minimization objective of the SOOP method. Compared to the SOOP method, the position-based method provides relatively higher levels of ventilation rates (Fig. 48).

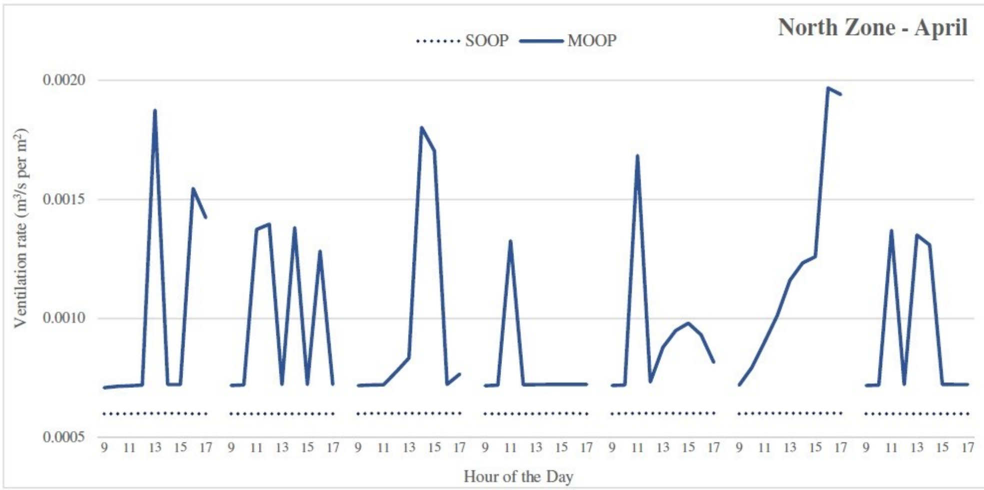

Fig. 48: Comparing position-based MOOP method & SOOP method – Weekly IAQ analysis in the swing season

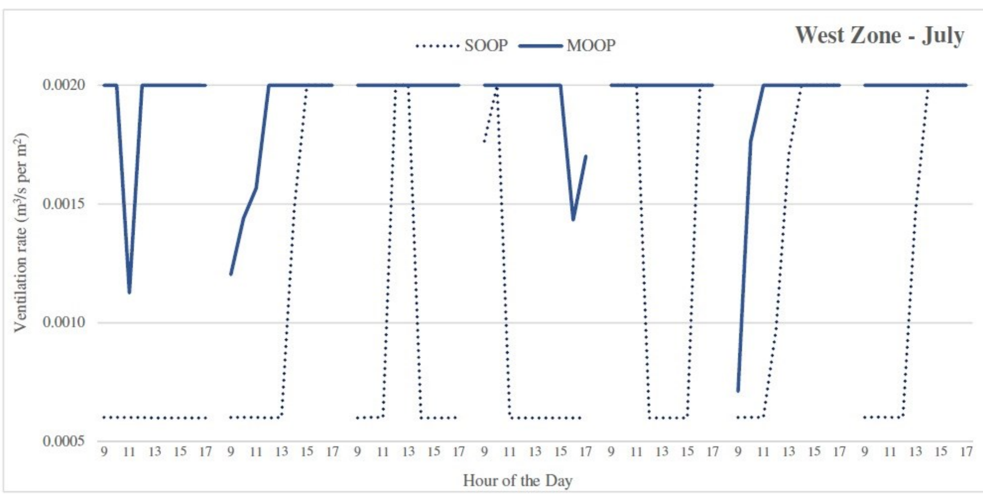

Fig. 49: Comparing position-based MOOP method & SOOP method – Weekly IAQ analysis in the warm season

During July, as well, the level of hourly ventilation rates (m^3/s per m^2) are higher using the position-based MOOP method, compared to the SOOP method (Fig. 49). In most hours of decision-making, the position-based method supplies the maximum acceptable level of ventilation rate (0.002 m^3/s per m^2) for the occupants in west zone. Making a comparison between the performances of the position-based method and the SOOP method, in both April and July (Fig. 48 and Fig. 49), the position-based method provides a relatively more productive environment for occupants, with respect to IAQ.

6.1.4 Productivity Losses & Energy Costs

Overall productivity of an occupant inside an enclosed space is relative to the level of thermal comfort, visual comfort, and IAQ [12, 22, 26]. It can be imagined that the productivity of occupants is higher, using the position-based method, compared to the SOOP method. On the other hand, it can be conceived that having a single energy costs minimization objective, the operation of the SOOP method is associated with less energy expenditure, compared to the operation of the position-based MOOP method. To check both arguments, productivity losses ($) and energy costs ($) associated with the weekly operation of the position-based method and the SOOP method, in January, April, and July are studied under arbitrary scenarios of occupancy. Occupancy scenarios in all the zones, during a week in January, April, and July are stated in Table 15. It is assumed that each occupant has an hourly productivity of 8 $/h. Using the two methods for energy and comfort management, the associated productivity losses ($) and energy costs ($) are shown for January (Fig. 50), April (Fig. 51), and July (Fig. 52).

Table 15: Occupant Scenarios – Comparing productivity losses & energy costs

Month	**Zone**	**Occupancy**			
		Position A	**Position B**	**Position C**	**Position D**
January	All 4 Zones	Occupant #1	Occupant #2		
April	All 4 Zones		Occupant #2	Occupant #3	
July	All 4 Zones		Occupant #2		Occupant #4

For all three outdoor weather conditions, using the SOOP method for energy management, significant amounts of productivity losses are observed. Productivity losses of each set of occupants (Table 15), during the occupied hours of a week in January, April, and July are increased to $723, $570 and $463, respectively. In contrast, the position-based method is successful in avoiding productivity losses of occupants, since the method is able to provide occupants' preferred indoor environmental conditions. Applying the position-based method for energy and comfort management, weekly productivity losses ($) of each set of occupants are decreased significantly to $78 in January, $75 in April, and $61 in July. These amounts of productivity losses are because of the diversity in thermal and visual preferences of occupants and the fact that they share the zones with each other.

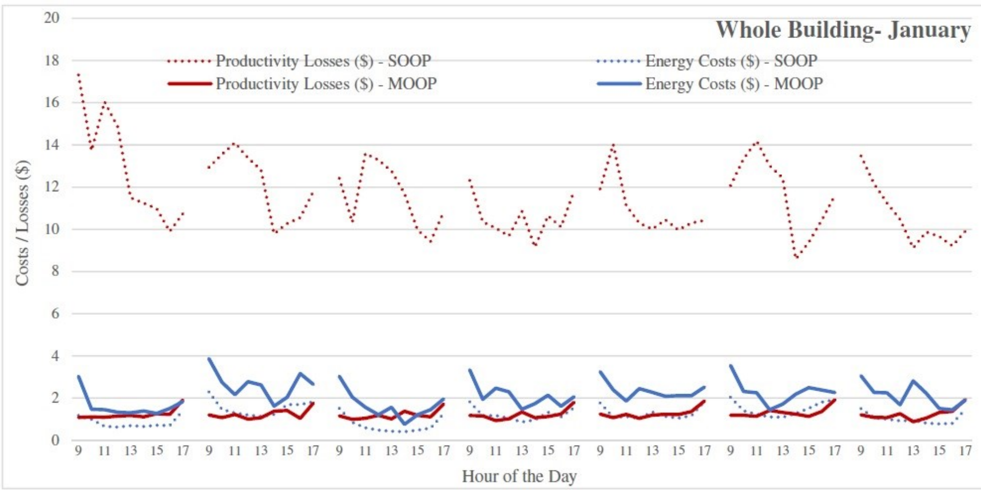

Fig. 50: Comparing position-based method & SOOP method – Weekly productivity losses ($) & energy costs ($) analysis, in the cold season

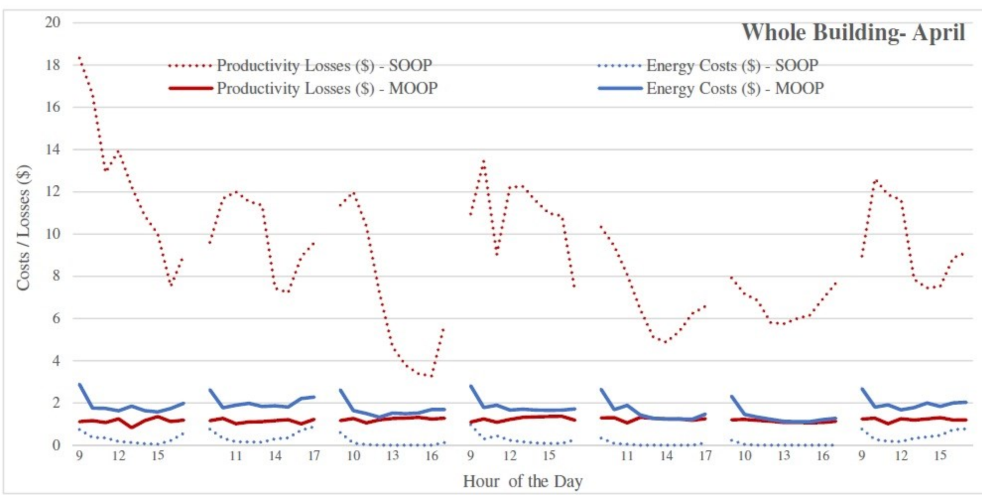

Fig. 51: Comparing position-based method & SOOP method – Weekly productivity losses ($) & energy costs ($) analysis, in the swing season

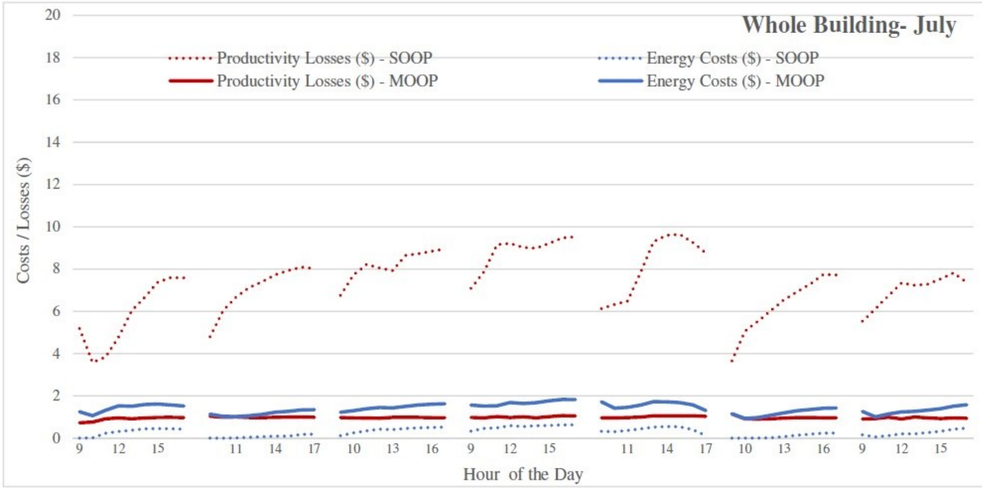

Fig. 52: Comparing position-based method & SOOP method – Weekly productivity losses ($) & energy costs ($) analysis, in the warm season

Moreover, the position-based method performs very well with respect to energy costs minimization objective. In all three months, the associated energy costs is slightly higher than the energy costs with the SOOP method.

6.2 Effect of Occupants' Productivity: Single Occupant

The hourly productivity of an office worker is defined from his or her type of activity. The hourly productivity of each occupant in the office is introduced as a personalized variable in the MOOP problem formulation. To have information on occupants' hourly productivity, occupancy data, and tasks distribution within the office workers are required. The amount of time office workers spend on each task is an important factor to define their productivity rates. The level of hourly productivity influences the method's decision-making. Here, the influence of hourly productivity variation on the thermal and visual comfort of occupants and IAQ are studied.

6.2.1 Thermal Comfort

An arbitrary situation of having a single occupant (Occupant #2 in Position-B) inside south zone is considered. To create varied productivity scenarios, hourly productivity of Occupant #2 is assumed to be (1) 4 $/h, (2) 8 $/h, and (3) 16 $/h. Considering varied hourly productivity scenarios, hourly operative temperatures (°C) in Position-B, during the occupied hours of a week in January (Fig. 53), April (Fig. 54), and July (Fig. 55) are observed.

Fig. 53: The influence of productivity per hour ($/h) on the thermal comfort of occupants– The cold season analysis

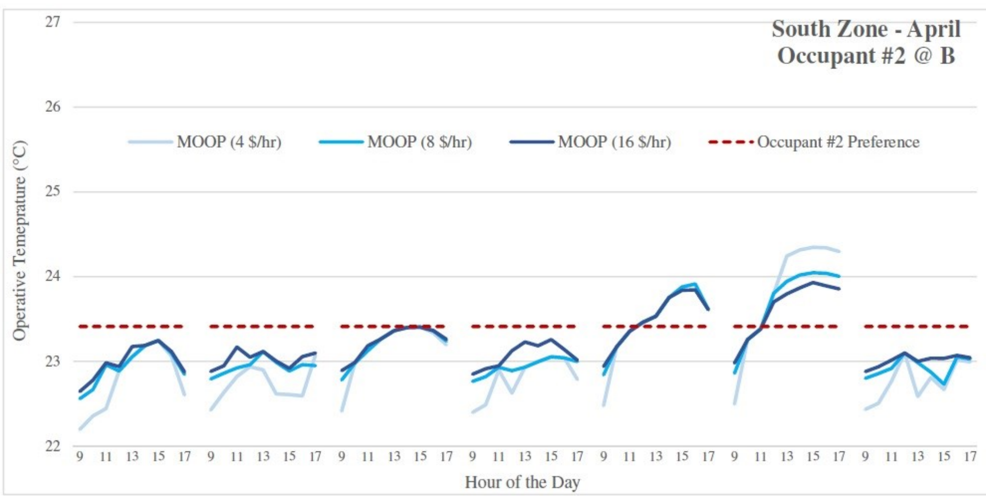

Fig. 54: The influence of productivity per hour ($/h) on the thermal comfort of occupants – The swing season analysis

In all three months, with the increase in hourly productivity ($/h) of Occupant #2, hourly operative temperatures (°C) in Position-B move closer to $T_{\mathrm{maxcomfort}}$ of the occupant (23.4 °C). When the productivity of an occupant increases, the position-based method ascribes a relatively more value to his or her thermal comfort. Accordingly, the operative temperatures (°C) in the occupant's position approach his or her $T_{\mathrm{maxcomfort}}$ (Fig. 53, Fig. 54, and Fig. 55).

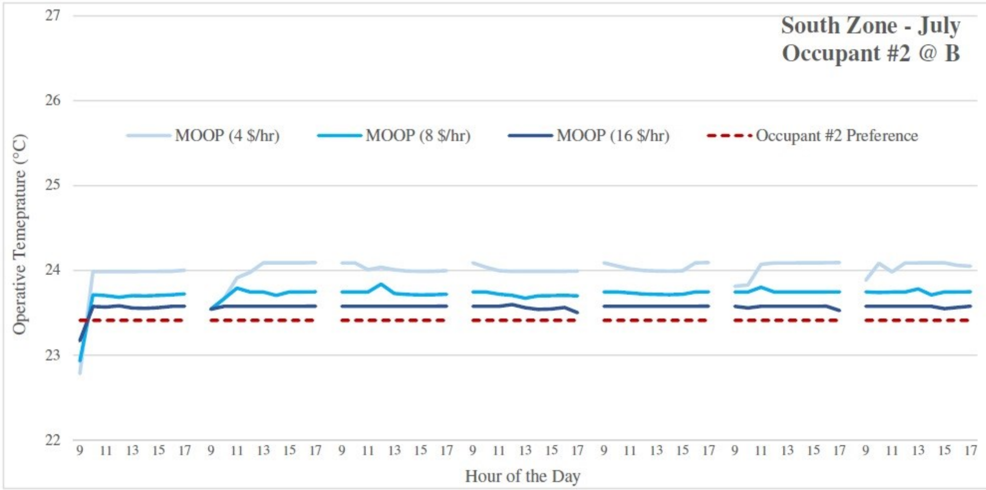

Fig. 55: The influence of productivity per hour ($/h) on the thermal comfort of occupants – The warm season analysis

6.2.2 Visual Comfort

For the same occupancy scenario, the influence of hourly productivity ($/h) variation on the operation of the position-based method are illustrated (Fig. 56 and Fig. 57). Occupant #2 has $ILL_{\text{maxcomfort}}$ of 1563 lux. For both outdoor weather conditions, with the increase in hourly productivity of Occupant #2, from 4 $/h to 16 $/h, provided illuminance levels (lux) in Position-B converge toward $ILL_{\text{maxcomfort}}$ of the occupant.

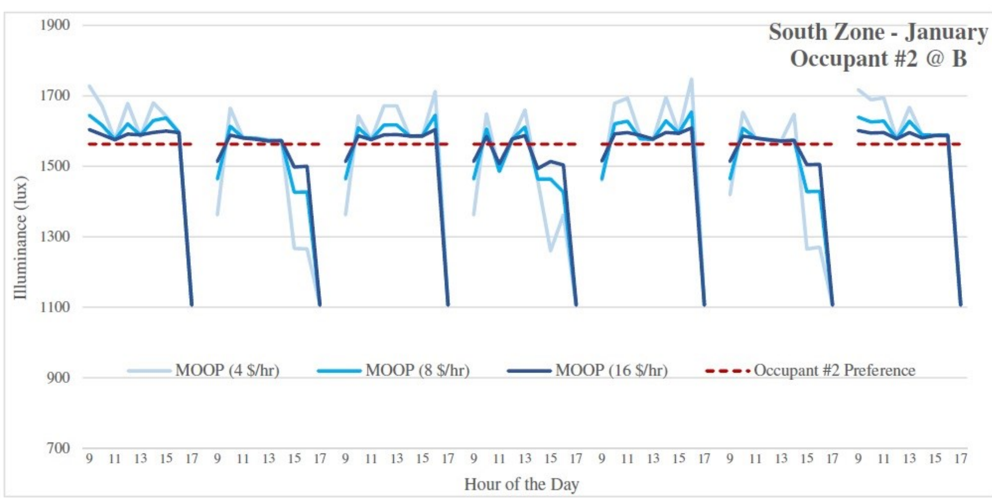

Fig. 56: The influence of productivity per hour ($/h) on the visual comfort of occupants – The cold season analysis

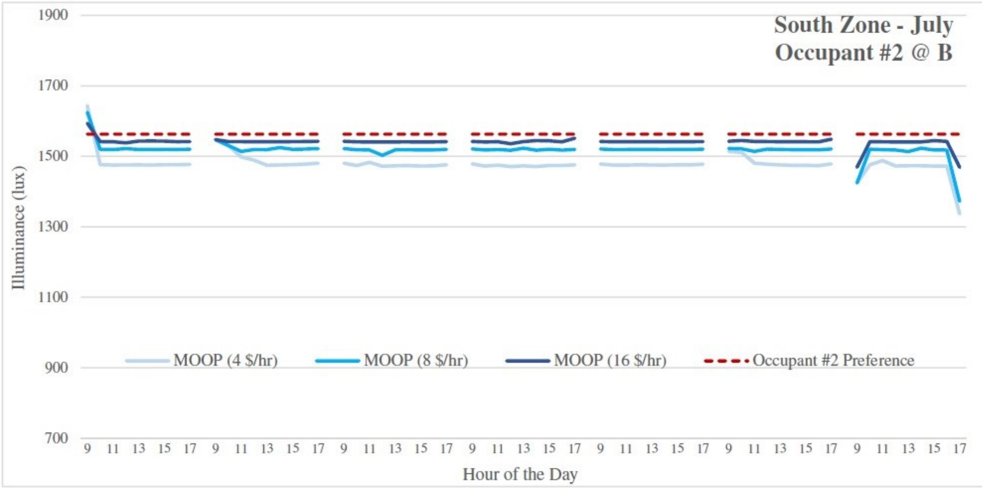

Fig. 57: The influence of productivity per hour ($/h) on the visual comfort of occupants– The warm season analysis

6.2.3 Indoor Air Quality

In order to study the influence of hourly productivity ($/h) variations on the IAQ, the same occupancy scenario as the thermal and visual comfort analysis is assumed (Occupant #2 in Position-B of south zone). Results are provided, for a week in January (Fig. 58), and a week in July (Fig. 59). It is observed that with the increase in hourly productivity ($/h) of the occupant, the level of ventilation rates (m^3/s per m^2) in south zone are also increased (Fig. 58 and Fig. 59).

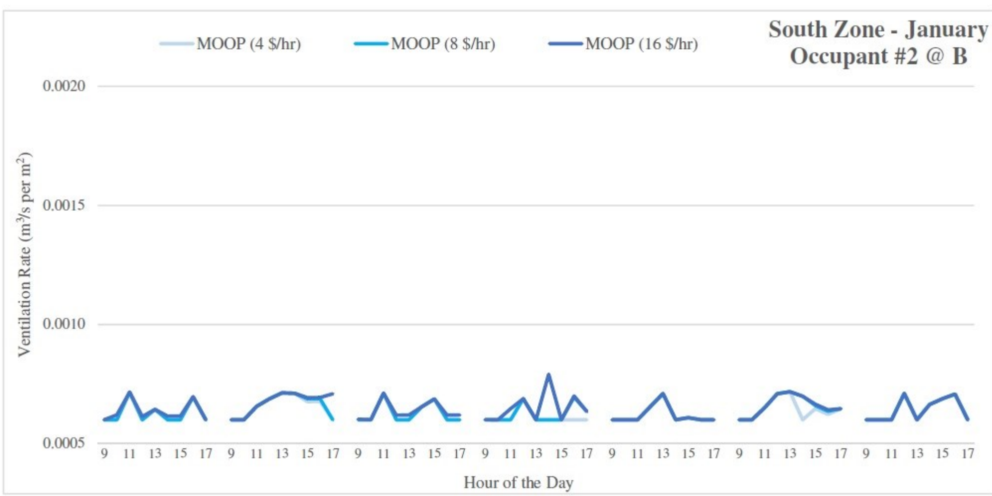

Fig. 58: The influence of productivity per hour ($/h) on the IAQ – The cold season analysis

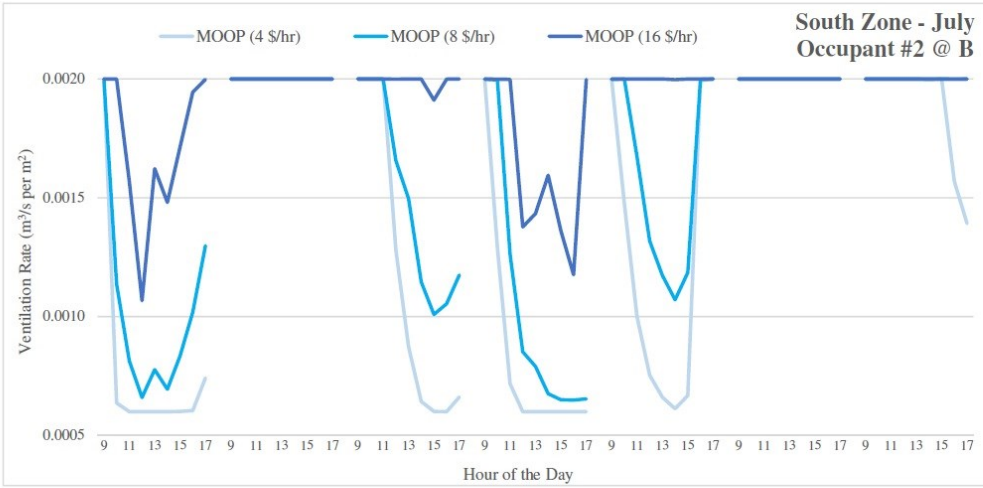

Fig. 59: The influence of productivity per hour ($/h) on the IAQ – The warm season analysis

6.3 Effect of Occupants' Preferences: Single Occupant vs. Multiple Occupants

Considering varied thermal and visual preferences among the occupants, the position-based method should have the capability to provide satisfactory indoor environmental conditions for all the occupants, while minimizing energy costs. To evaluate the capabilities of the method to acknowledge the diversity in preferences of occupants, the weekly energy performance of the office building under different scenarios of occupancy, in varied outdoor weather conditions is studied. In west zone, three arbitrary scenarios of having (1) Occupant #1 in Position-A, (2) Occupant #2 in Position-B, and (3) Occupant #1 in Position-A and Occupant #2 in Position-B, are considered. It is assumed that each occupant has a constant productivity rate of 8 $/h.

6.3.1 Thermal Preferences

Under the third scenario of occupancy, it is assumed that Occupant #1 and Occupant #2 are sharing west zone. There is a conflict between the thermal preferences of Occupant #1 and Occupant #2. Occupant #1 has $T_{\text{maxcomfort}}$ of 25.5 °C while Occupant #2 has $T_{\text{maxcomfort}}$ of 23.4 °C (Table 7). Hourly operative temperatures (°C) in Position-A and in Position-B, under three occupancy scenarios, are demonstrated for a week in January and April (Fig. 60 and Fig. 61).

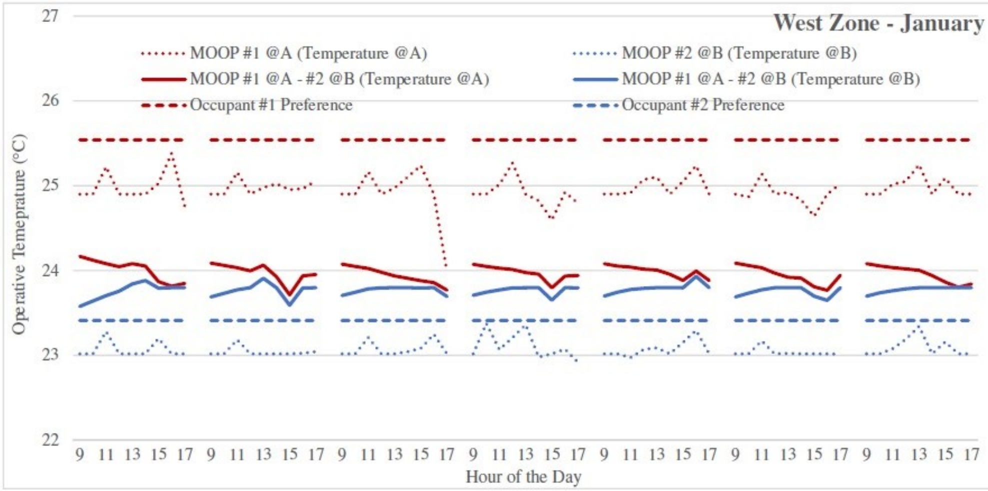

Fig. 60: Acknowledging occupants' thermal preferences – The cold season analysis

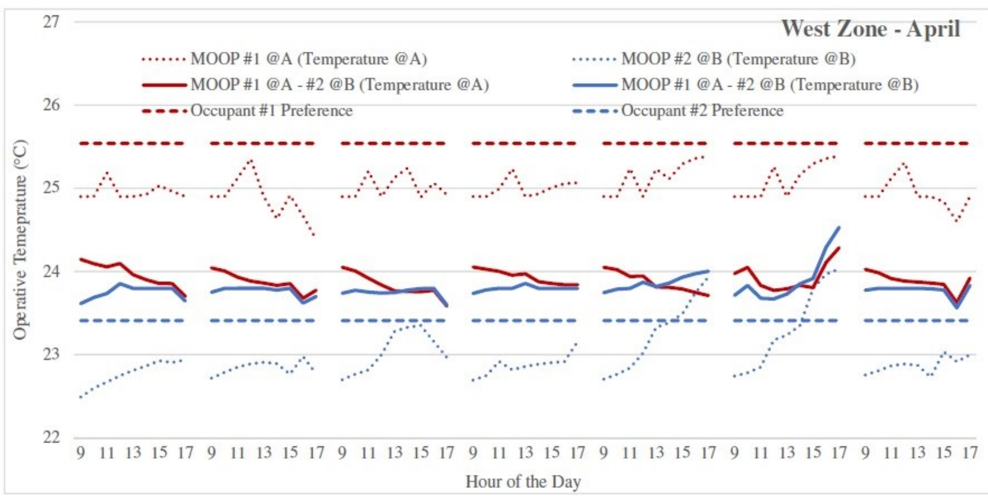

Fig. 61: Acknowledging occupants' thermal preferences – The swing season analysis

For both outdoor weather conditions, under the two single-occupancy scenarios (Occupant #1 in Position-A or Occupant #2 in Position-B), operative temperatures (°C) in Position-A and Position-B are not far away from the maximum comfort temperatures of the two occupants. These values are slightly lower than the maximum comfort temperatures of the occupants, because of the energy costs minimization objective of the method, during the cold and swing seasons. On the other hand, under the multiple-occupancy scenario, hourly operative temperatures (°C) in Position-A and in Position-B are within the range of Occupant #1's $T_{\text{maxcomfort}}$ (25.5 °C) and Occupant #2's $T_{\text{maxcomfort}}$ (23.4 °C). The position-based method controls the thermal conditions of west zone with the objective of improving the collective productivity of occupants while minimizing the energy costs as much as possible.

Under the multiple-occupancy scenario, operative temperatures (°C) are closer to $T_{\mathrm{maxcomfort}}$ of Occupant #2 (23.4 °C), than $T_{\mathrm{maxcomfort}}$ of Occupant #1 (25.5 °C). There are two reasons for this effect. First, the method also has the energy costs minimization objective. During the cold and swing seasons, having lower indoor temperatures reduces the energy consumption costs. Second, $Tolerance_{\mathrm{thermal}}$ of Occupant #2 (4.4 K) is lower than $Tolerance_{\mathrm{thermal}}$ of Occupant #1 (7.2 K), hence, Occupant #2 is more sensitive to the thermal conditions of the indoor environment, compared to Occupant #1. The method acknowledges the higher sensitivity (the lower thermal tolerance) of Occupant #2 by providing operative temperatures closer to $T_{\mathrm{maxcomfort}}$ of Occupant #2. During July, hourly operative temperatures (°C) in Position-A and in Position-B of west zone, under the three considered scenarios, are studied (Fig. 62). The same discussions can also describe the performance of the position-based method in warm outdoor weather conditions.

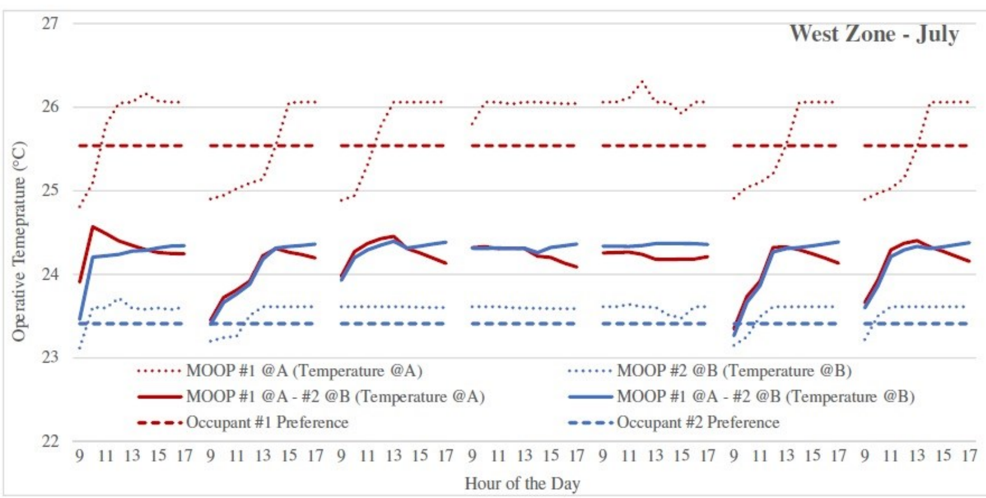

Fig. 62: Acknowledging occupants' thermal preferences – The warm season analysis

6.3.2 Visual Preferences

Under the three considered occupancy scenarios, hourly illuminance levels (lux) in Position-A and Position-B, during a week in January (Fig. 63) and July (Fig. 64), are presented. For both outdoor weather conditions, under the two single-occupancy scenarios, the position-based MOOP method manages the level of natural illumination (lux), and artificial lighting (lux) in order to provide satisfactory visual conditions for that specific occupant. Meanwhile, under the scenario of having both Occupant #1 and Occupant #2, the position-based method is still successful in managing the diversity in occupants' visual preferences.

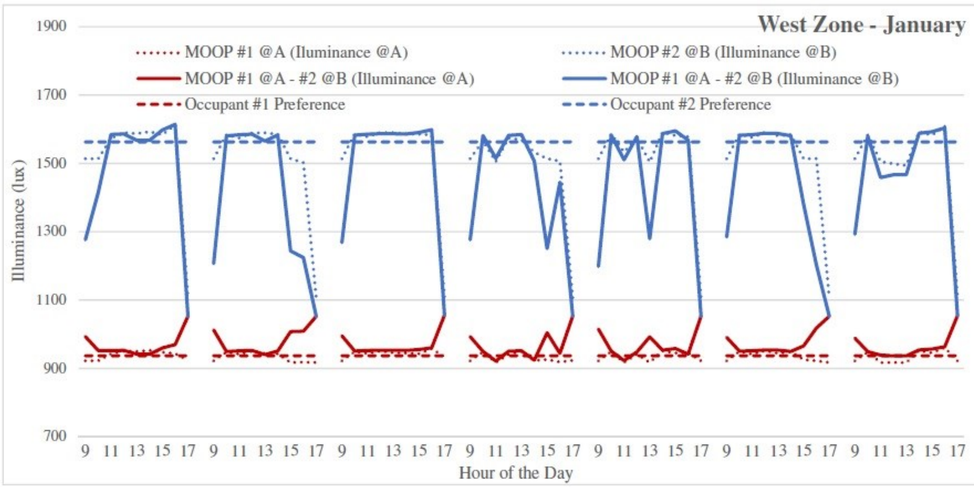

Fig. 63: Acknowledging occupants' visual preferences – The cold season analysis

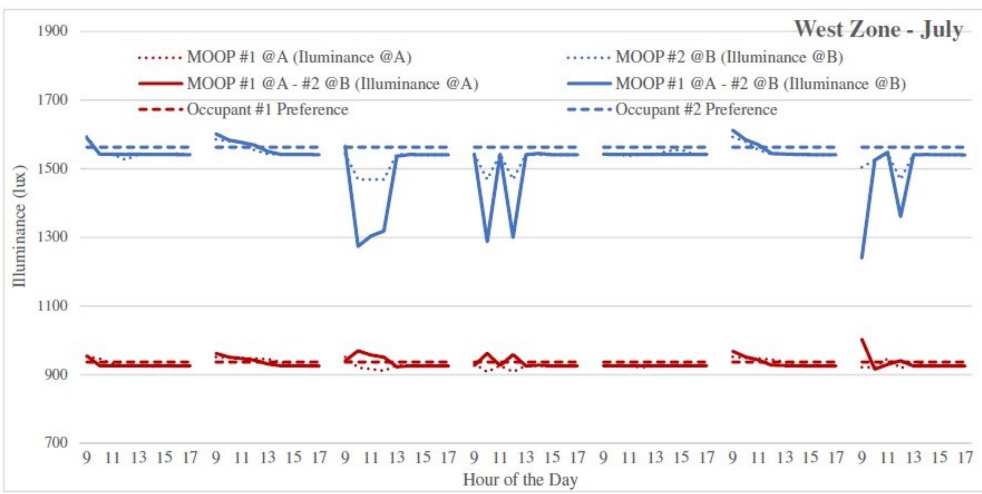

Fig. 64: Acknowledging occupants' visual preferences – The warm season analysis

The position-based method is also helped by the positions of the occupants since the position of Occupant #2 is near the window (Fig. 7). Occupant #2, with the preference of a brighter ambient, receives higher levels of natural illumination (lux), compared to Occupant #1 in Position-A. In the following section, the influence of occupants' positions is discussed in detail.

6.4 Effect of Occupants' Positions on Optimized Energy Use and Comfort

Here, the focus is on the importance of occupants' positions and the effect it has on the performance of the position-based method. Occupants with varied thermal and visual preferences are considered for the simulations. Occupant #1, with a relatively higher $T_{\mathrm{maxcomfort}}$ of 25.5 °C, prefers a warmer indoor environment, while Occupant #2 and Occupant #3 with $ILL_{\mathrm{maxcomfort}}$ of 1563 lux and 1569 lux, respectively, prefer a brighter ambient (Table 7 and Table 9). Two arbitrary occupancy scenarios of having (1) Occupant #1 in Position-A and Occupant #2 in Position-B, and (2) Occupant #2 in Position-A and Occupant #1 in Position-B of west zone, are considered. It is assumed that each occupant has a constant productivity rate of 8 \$/h.

Under these two scenarios, the operation of the method with respect to the visual comfort of two occupants, is studied for January and July. Subsequently, productivity losses (\$) and energy costs (\$) associated with the weekly operation of the office building are compared. The level of hourly illuminance (lux) in Position-A and Position-B of west zone, under the two considered scenarios of occupancy, during January (Fig. 65) and July (Fig. 66) are shown. For both outdoor weather conditions, under the 1st scenario of occupancy, the method is successful in providing occupants' preferred indoor visual conditions. However, under the 2nd scenario, hourly illuminance levels (lux) in both positions are very close to each other (Fig. 65 and Fig. 66).

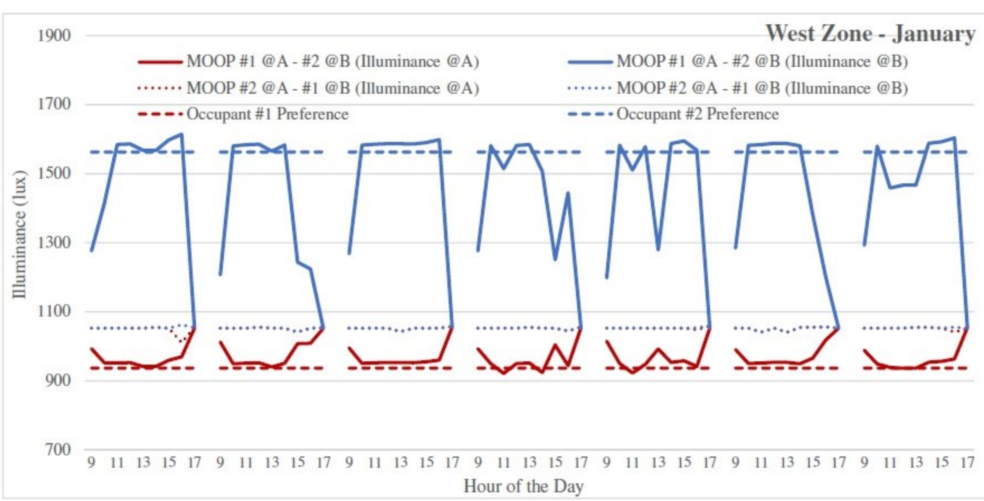

Fig. 65: The importance of occupants' positions for the visual comfort evaluation – The cold season analysis

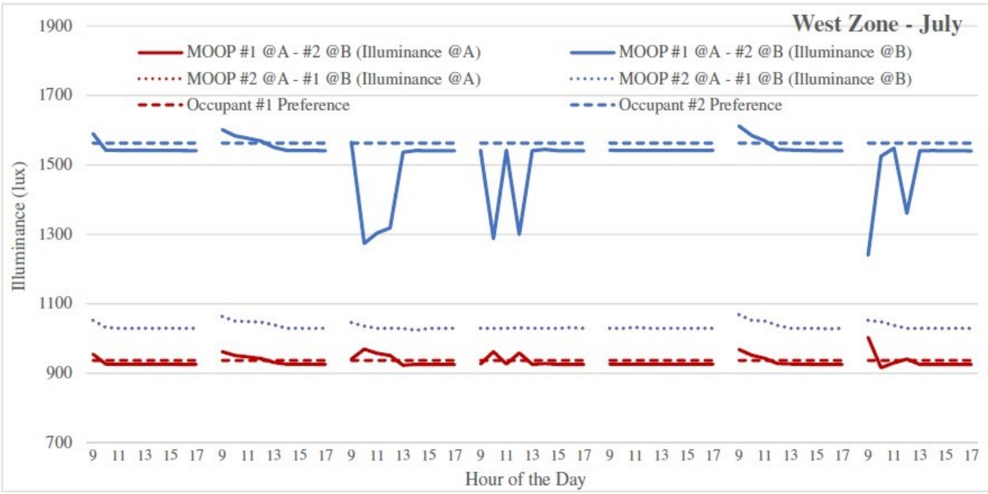

Fig. 66: The importance of occupants' positions for the visual comfort evaluation – The warm season analysis

The level of hourly artificial illuminance (lux) in west zone, under the two considered scenarios of occupancy, are compared for January and July (Fig. 67 and Fig. 68). For both outdoor weather conditions, under the scenario of having Occupant #2 (with a brighter ambient preference) in Position-B (near the window), the position-based method provides a significant portion of lighting demands from natural illumination. In contrast, having Occupant #1 in Position-B and Occupant #2 in Position-A, their visual preferences, and the energy costs minimization objective of the position-based method are in conflict with each other. Hence, the levels of natural illumination reduce, and consequently, the levels of artificial lighting increase.

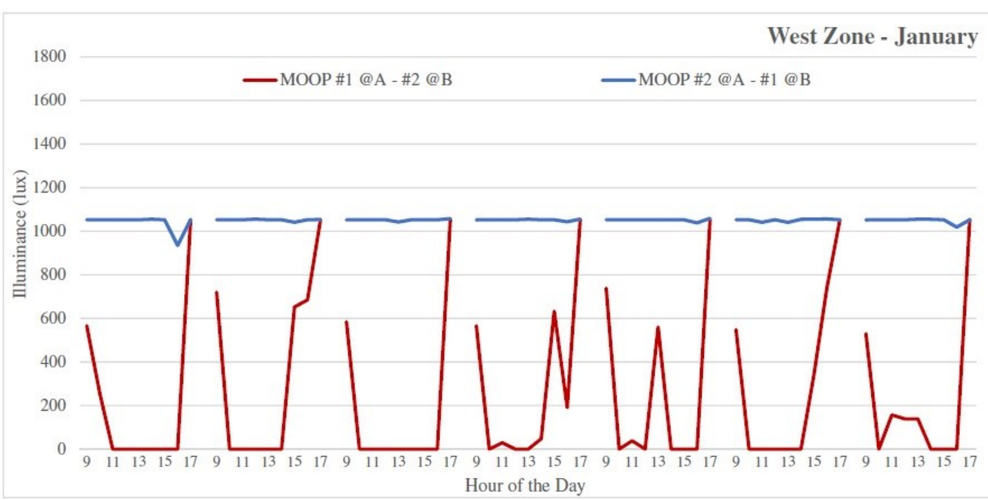

Fig. 67: Different occupancy scenarios and the level of artificial lighting (lux) – The cold season analysis

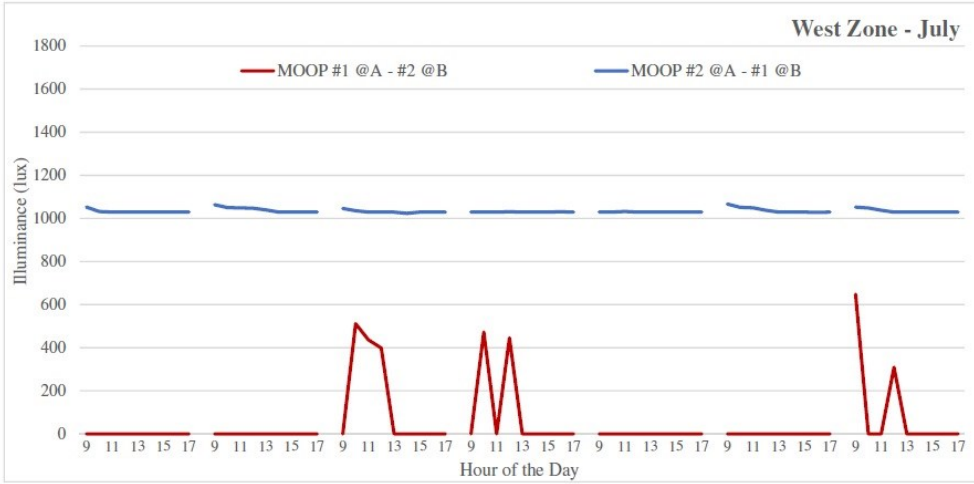

Fig. 68: Different occupancy scenarios and the level of artificial lighting (lux) – The warm season analysis

The diversity in occupants' preferences and positions have impacts on the automated control of the environment. To observe the influence of occupants' positions on the productivity of occupants and the energy costs associated, two previously considered scenarios of occupancy are expanded to all four zones. In all the zones, two arbitrary scenarios of having (1) an occupant with the same preferences as Occupant #1 in Position-A, and an occupant with similar preferences to Occupant #2 in Position-B; and (2) an occupant with the same preferences as Occupant #2 in Position-A, and an occupant with similar preferences to Occupant #1 in Position-B, are considered. During January and July, the weekly energy performance of the building with respect to productivity losses ($) and energy costs ($) is analyzed (Fig. 69 and Fig. 70).

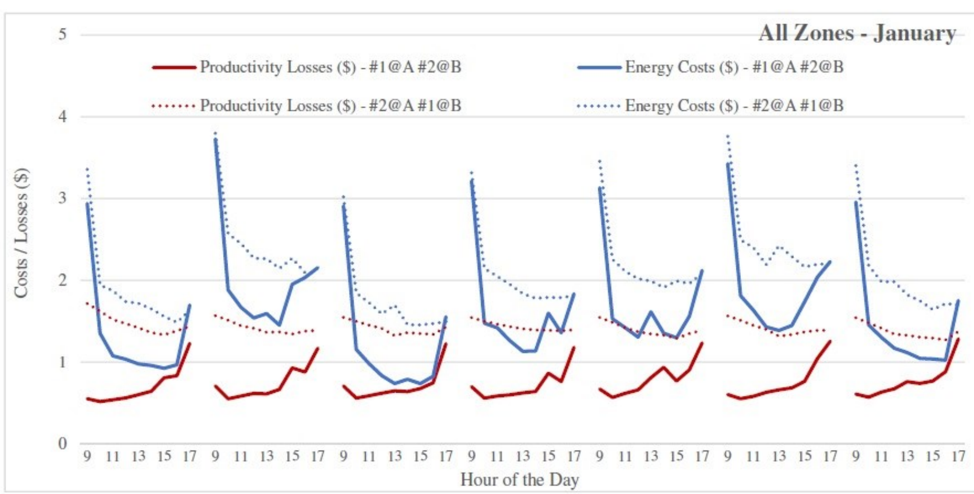

Fig. 69: The importance of occupants' positions for the productivity losses ($) and energy costs ($) - The cold season analysis

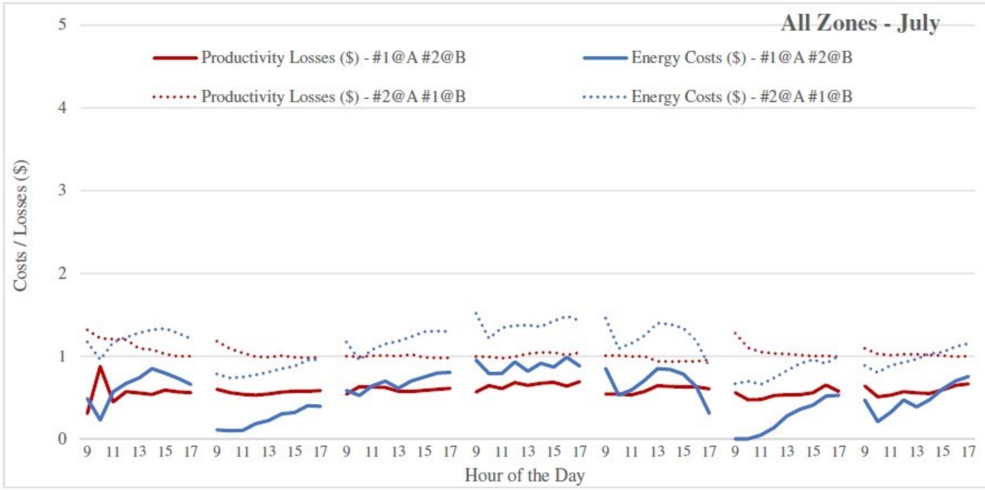

Fig. 70: The importance of occupants' positions for the productivity losses ($) and energy costs ($) - The warm season analysis

It is observed that in both months, under the 1st scenario of occupancy, both the weekly productivity losses of occupants ($) and the energy costs of the office ($) are relatively lower, compared to the alternative scenario of occupancy (Fig. 69 and Fig. 70).

6.5 Effect of an Occupant's Comfort Preferences on the Productivity of Other Occupants: Multiple Occupants

Here, the influence of the diversity in comfort preferences of occupants is studied, by inspecting the presence and absence of an individual occupant, and the impact it has on the productivity of other occupants. An arbitrary scenario is developed in which Occupant #1 is in Position-A, Occupant #2 is in Position-B, Occupant #3 is in Position-C, and Occupant #4 is in Position-D of the north zone. The absence/presence of Occupant #1, in each hour of decision-making is studied. Accordingly, two scenarios of having (1) four occupants and (2) three occupants are analyzed. The productivity of each occupant is considered to be at a constant rate of 8 $/h. Hourly operative temperatures (°C) in Position-B and Position-C, in the presence/absence of Occupant #1, during January (Fig. 71) and April (Fig. 72), are presented. For both outdoor weather conditions, the absence of Occupant #1 with the highest $T_{\text{maxcomfort}}$ (25.5 °C), has distinguished influence on the thermal conditions of other occupants. This influence is positive for Occupant #2 (with $T_{\text{maxcomfort}}$ of 23.4 °C) and negative for Occupant #3 (with $T_{\text{maxcomfort}}$ of 24.3 °C).

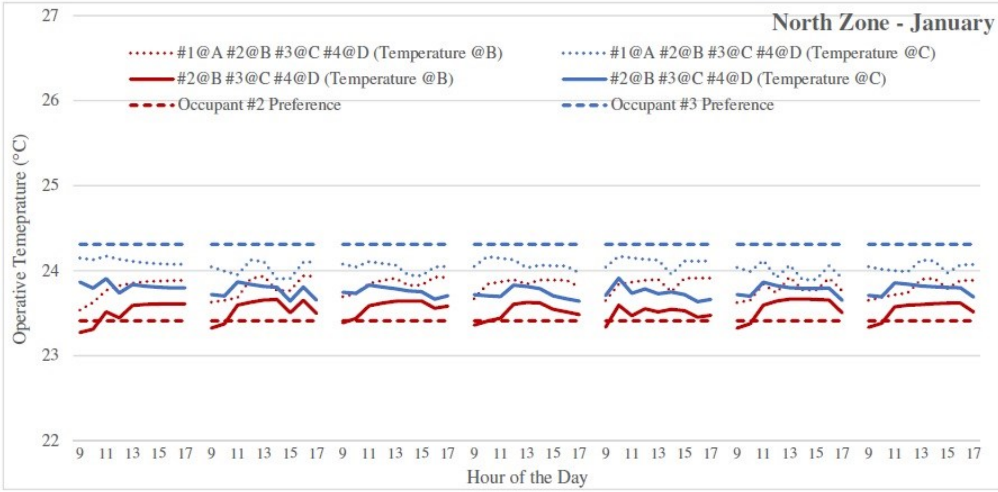

Fig. 71: The influence of an occupant's presence and absence on the thermal comfort of others- The cold season analysis

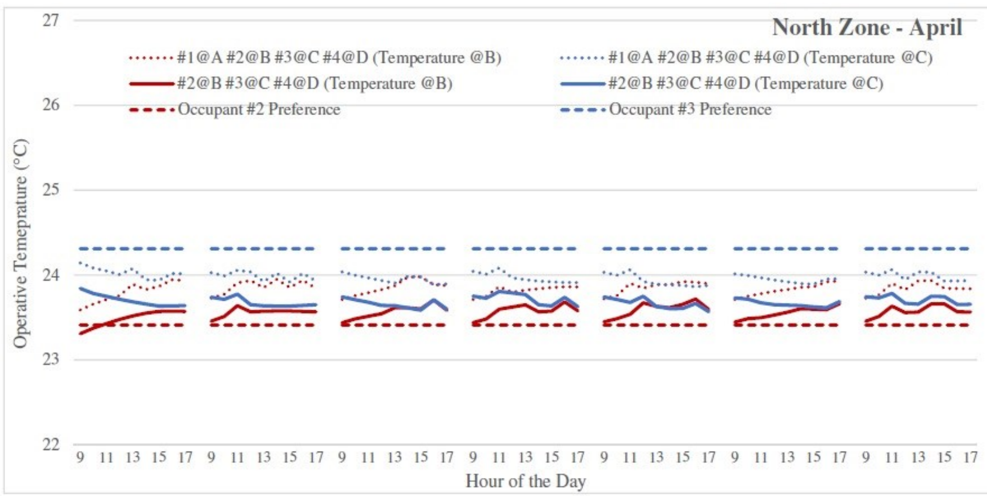

Fig. 72: The influence of an occupant's presence and absence on the thermal comfort of others- The swing season analysis

Under the same occupancy scenario and considering the presence/absence of Occupant #1, the visual comfort of remaining occupants are studied. Hourly illuminance levels (lux) in Position-B and Position-C, during April (Fig. 73) and July (Fig. 74) are demonstrated. For both outdoor weather conditions, the absence of Occupant #1 has a positive influence on the visual comfort of Occupant #2 and Occupant #3. It can be concluded that the position-based method is capable of making energy-related decisions for the automated control of the indoor environment, considering the presence and absence of each individual occupant.

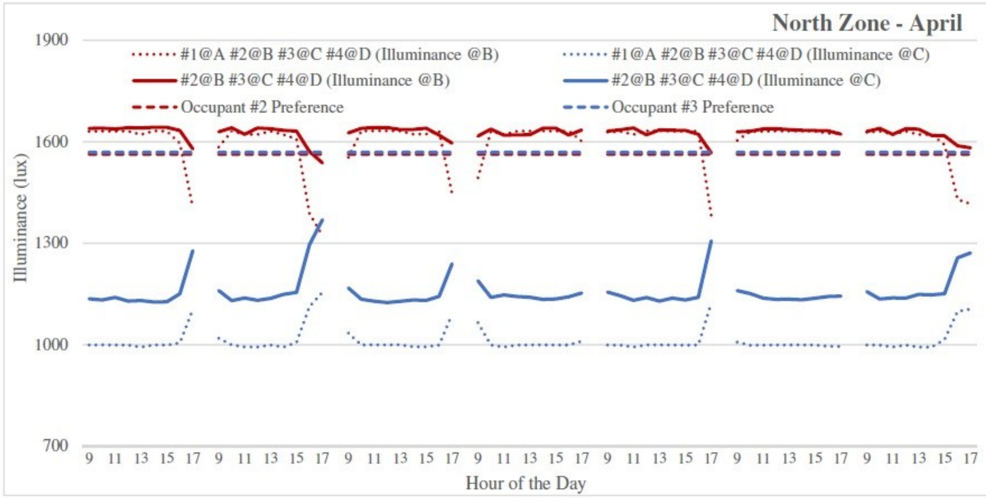

Fig. 73: The influence of an occupant's presence and absence on the visual comfort of others- The swing season analysis

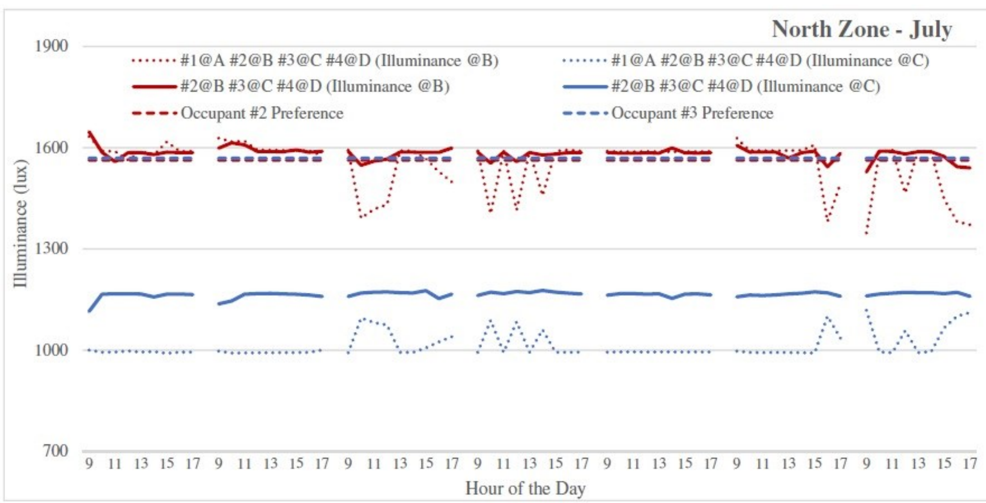

Fig. 74: The influence of an occupant's presence and absence on the visual comfort of others- The warm season analysis

6.6 Discussion

So far, the flexibility of the position-based method for the automated control of the indoor environment, according to different personalized parameters have been studied. These personalized parameters include occupants' (1) productivity rates, (2) thermal preferences, (3) visual preferences, and (4) positions inside the zones. From the Gaussian expressions of RP_{Thermal} and RP_{Visual} (proposed in this research), each occupant's $T_{\text{maxcomfort}}$, $Tolerance_{\text{thermal}}$, $ILL_{\text{maxcomfort}}$, and $Tolerance_{\text{visual}}$ are extracted as personalized parameters. $Tolerance_{\text{thermal}}$ and $Tolerance_{\text{visual}}$ of each occupant represent his or her thermal and visual behavior, respectively. Here, the sensitivity of the position-based method to the varied thermal and visual behavior of occupants is analyzed, by considering variations in their $Tolerance_{\text{thermal}}$ and $Tolerance_{\text{visual}}$.

6.6.1 Thermal Behavior Change

In north zone, during July, an arbitrary occupancy scenario of having Occupant #1 in Position-A, Occupant #2 in Position-B, Occupant #3 in Position-C, and Occupant #4 in Position-D is considered. Variations in the thermal behavior of Occupant #2 are studied. Within the sensitivity analysis, $Tolerance_{\text{thermal}}$ of Occupant #2, during the first week of July is assumed to variate 30%.

Accordingly, three arbitrary scenarios of (1) *Less Tolerance* of the occupant, (2) *Normal Behavior* of the occupant, and (3) *More Tolerance* of the occupant are created (Table 16). Under each of the three scenarios, the performance of the method, with respect to the thermal comfort of all occupants is studied. A constant productivity rate of 8 $/h is considered for each occupant.

Table 16: Scenarios for thermal behavior change analysis during July - North zone

Thermal Behavior Variation Scenarios		
Scenario 1	**Scenario 2**	**Scenario 3**
Occupant #2 Less Tolerant $Tolerance_{\text{thermal}} = 3.1$ K	Occupant #2 Normal $Tolerance_{\text{thermal}} = 4.4$ K	Occupant #2 More Tolerant $Tolerance_{\text{thermal}} = 5.7$ K

The variations of hourly operative temperatures (°C), in different positions of the north zone, during the occupied hours of the first week of July, are studied (Fig. 75, Fig. 76, Fig. 77, and Fig. 78). If Occupant #2 has less thermal tolerance, the position-based method provides operative temperatures (°C) relatively closer to $T_{\text{maxcomfort}}$ of Occupant #2, which is 23.4 °C (Fig. 75). It is observed that the thermal behavior variations of Occupant #2 influence the thermal conditions of Occupant #1 (Fig. 76), Occupant #3 (Fig. 77), and Occupant #4 (Fig. 78), as well.

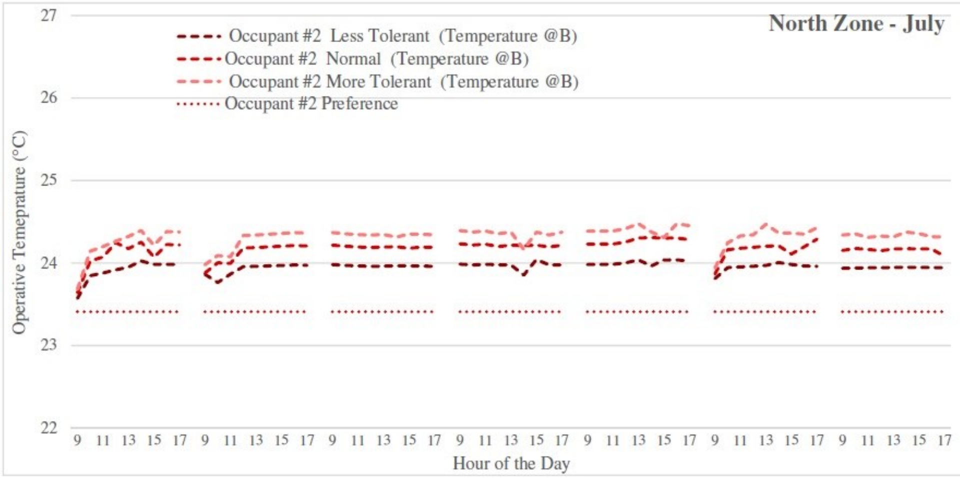

Fig. 75: Thermal conditions of Occupant #2, under thermal behavior change scenarios- The warm season analysis

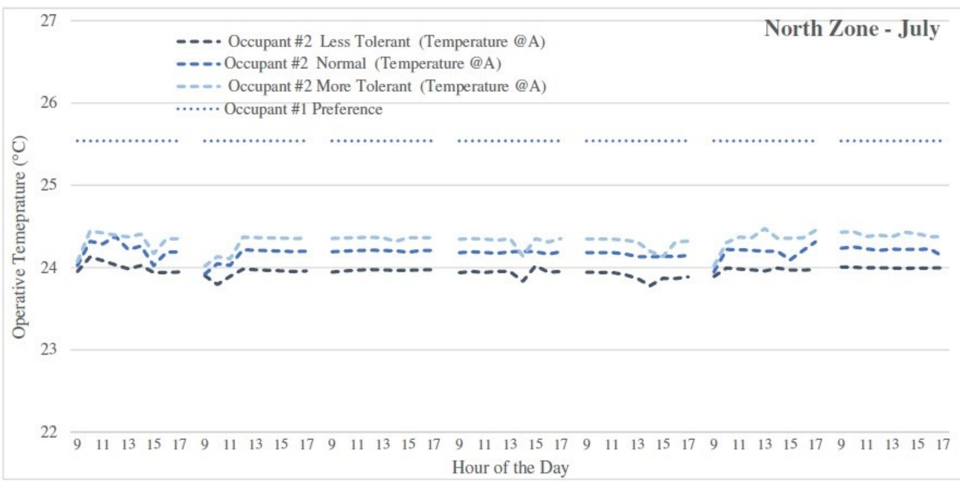

Fig. 76: Thermal conditions of Occupant #1, under thermal behavior change scenarios- The warm season analysis

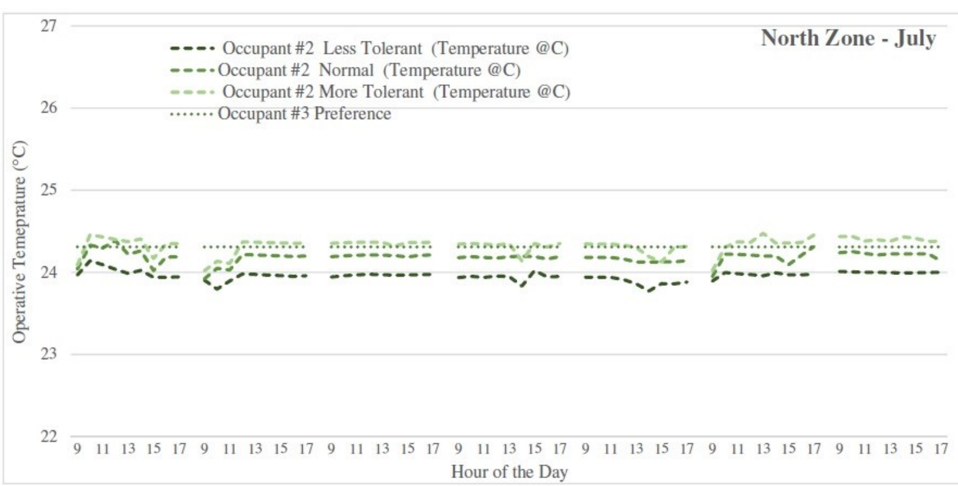

Fig. 77: Thermal conditions of Occupant #3, under thermal behavior change scenarios- The warm season analysis

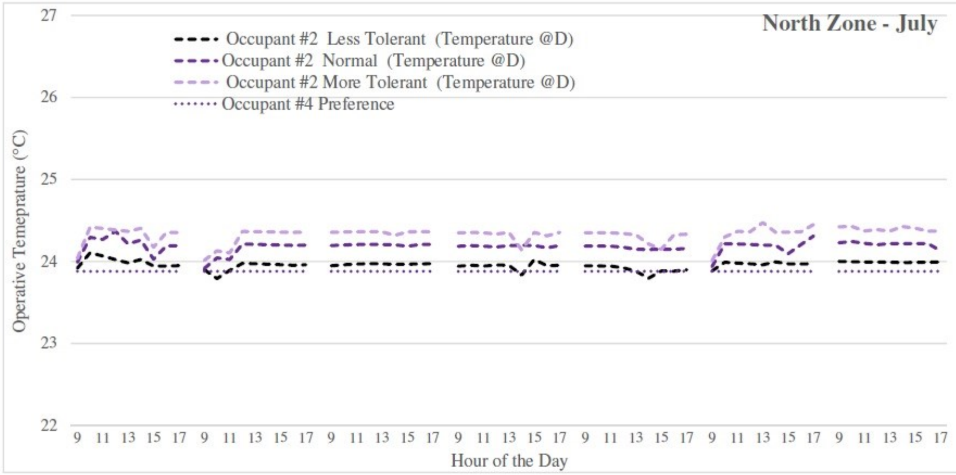

Fig. 78: Thermal conditions of Occupant #4, under thermal behavior change scenarios- The warm season analysis

6.6.2 Visual Behavioral Change

Here, the sensitivity of the position-based method to the visual behavior of an individual occupant is analyzed. In east zone, an arbitrary occupancy scenario of having Occupant #1 in Position-A, Occupant #2 in Position-B, Occupant #3 in Position-C, and Occupant #4 in Position-D is considered. It is assumed that each occupant has a constant hourly productivity of 8 $/h.

Among four occupants, Occupant #1 has the visual preference of a relatively least bright indoor environment (937 lux). During January, the visual behavior of Occupant #1 is chosen for the sensitivity analysis (Table 17). $Tolerance_{\mathrm{visual}}$ of Occupant #1 is assumed to vary 20%, from its normal value of 667 lux. Subsequently, the performance of the method with respect to the visual comfort of Occupant #1, as well as the visual comfort of other three occupants is studied.

Table 17: Scenarios for visual behavior change analysis during January – East zone

Visual Behavior Variation Scenarios		
Scenario 1	**Scenario 2**	**Scenario 3**
Occupant #1 Less Tolerant $Tolerance_{\mathrm{visual}}$ = 533 lux	Occupant #1 Normal $Tolerance_{\mathrm{visual}}$ = 667 lux	Occupant #1 More Tolerant $Tolerance_{\mathrm{visual}}$ = 800 lux

The levels of hourly illuminance (lux) in different positions of east zone are demonstrated for January (Fig. 79, Fig. 80, Fig. 81, and Fig. 82). In each hour, the position-based method considers the visual behavior of Occupant #1 and chooses the illuminance levels (lux), accordingly. When Occupant #1 has less visual tolerance, hourly illuminance (lux) in Position-A is relatively closer to $ILL_{maxcomfort}$ of Occupant #1 (937 lux). On the other hand, when Occupant #1 has more $Tolerance_{visual}$, illuminance (lux) in Position-A, can be further away from $ILL_{maxcomfort}$ of Occupant #1 (Fig. 79).

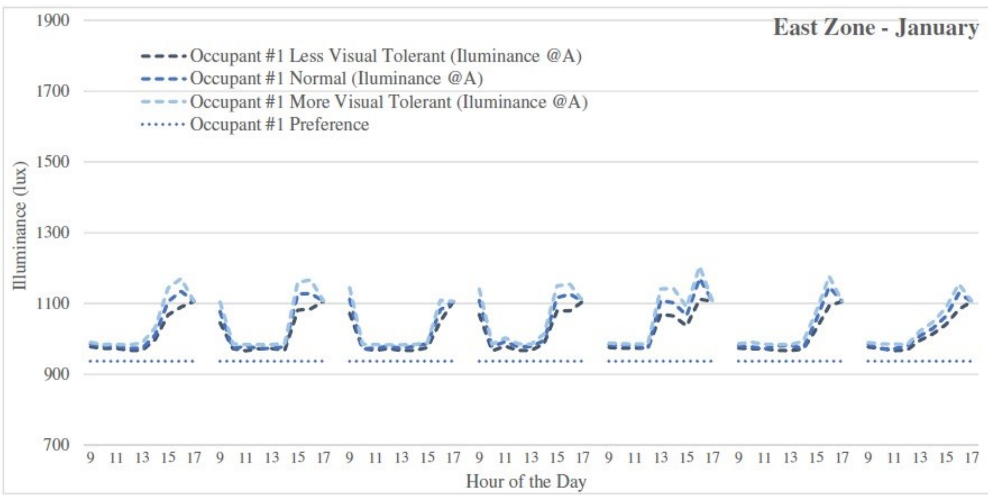

Fig. 79: Visual conditions of Occupant #1, under visual behavior change scenarios - The cold season analysis

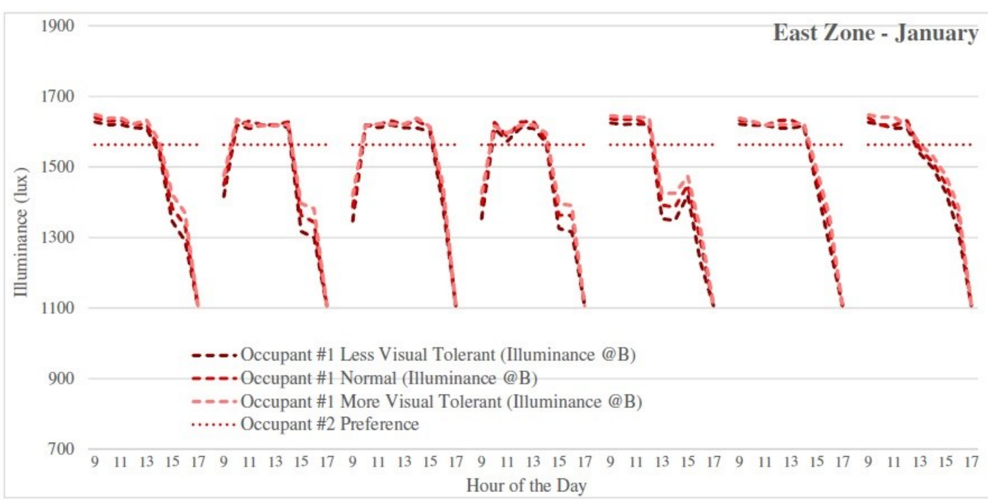

Fig. 80: Visual conditions of Occupant #2, under visual behavior change scenarios - The cold season analysis

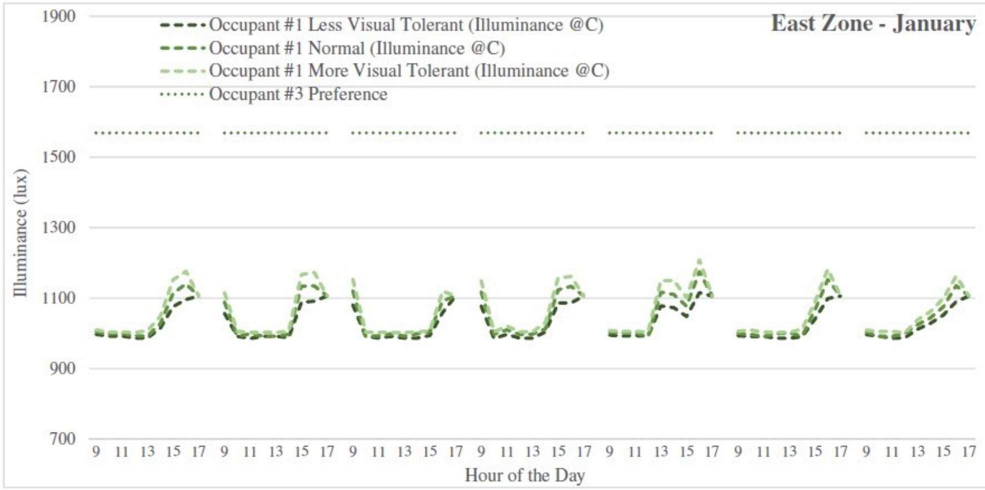

Fig. 81: Visual conditions of Occupant #3, under visual behavior change scenarios - The cold season analysis

Compared to Occupant #1, other three occupants of east zone prefer a brighter visual ambient (Table 9). Hence, they benefit from the higher visual tolerance of Occupant #1. Under the scenario of Occupant #1's higher visual tolerance, levels of hourly illuminance (lux) in Position-B (for Occupant #2), in Position-C (for Occupant #3), and in Position-D (for Occupant #4) are relatively closer to $ILL_{\text{maxcomfort}}$ of the occupants, compared to the alternative scenarios (Fig. 80, Fig. 81, and Fig. 82). The position-based method, wherever possible, can benefit from an individual's or a group of individuals' thermal and/or visual behavior variations, to reduce the associated energy consumption costs of the office building.

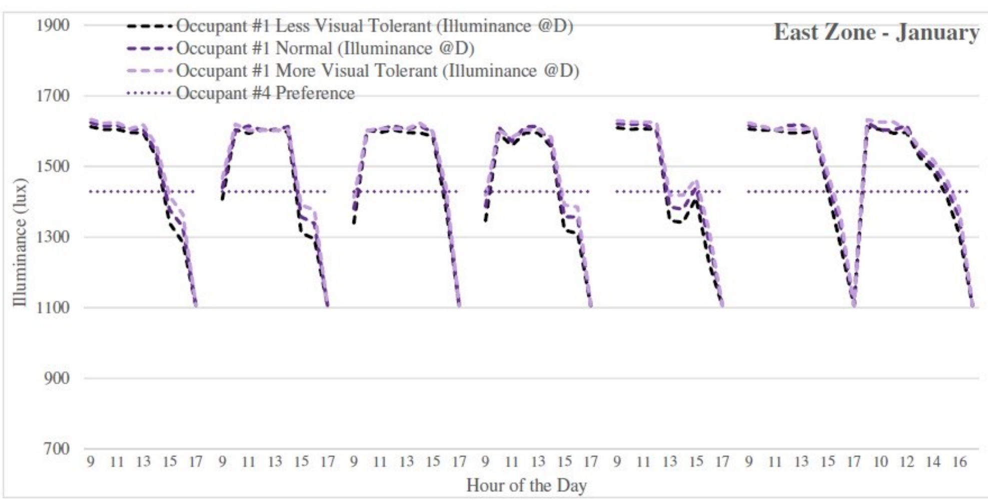

Fig. 82: Visual conditions of Occupant #4, under visual behavior change scenarios - The cold season analysis

6.7 Chapter Summary

In this chapter, the capabilities of the *position-based* MOOP method (proposed in Section 3.4) to perform personalized energy and comfort management are evaluated. The proposed position-based method performs the automated control of the indoor environment, by managing the level of indoor temperature, ventilation rate, natural illumination, and artificial lighting, in different zones of the considered office (Section 3.4).

Occupants of the buildings, as energy consumers, can significantly benefit from the personalized control of the indoor environment. Based on the provided results, the position-based method is capable of managing the indoor environmental conditions according to occupants' (1) thermal preferences, (2) visual preferences, (3) productivity rates, (4) positions, (5) thermal behavior, and (6) visual behavior. Furthermore, it is confirmed that the position-based method is successful in simultaneously improving occupants' productivity and optimizing energy consumption costs (*Objective 3* of the research).

It is observed that the position-based method can make energy-related decisions for the automated control of the indoor environment, according to the varied thermal and visual behavior of occupants. Hence, the proposed method has the potential to acknowledge additional human-related parameters that shape occupants' behavior, in different situations.

The additional human-related parameters are included but not limited to occupant's (1) varied behavior in the presence of other occupants, (2) mood and set of emotions, (3) desire and willpower, (4) deprivation of comfort, (5) and short-term adaptation to the environment. These human-related parameters, alongside already considered personalized parameters, can shape a *specific situation*, in an enclosed space. By acknowledging these parameters while making energy-related decisions, the proposed method can offer *behavioral intelligence*, and perform *situation-specific* energy and comfort management. This is the subject of the next chapter.

7 Situation-Specific Multi-Objective Optimization of Energy Costs, Thermal & Visual Comfort & Indoor Air Quality

The situation-specific method, proposed in Section 3.5, can offer *behavioral intelligence*, by acknowledging occupants' adaptive behavior while making energy-related decisions for the automated control of the indoor environment (*Objective 4* of the research). Here, the capabilities of the proposed method for *situation-specific* energy and comfort management are studied.

Occupants' adaptive behavior, or their responses to the indoor environmental conditions, are the product of their decisions, while decisions are generated in their brains [85, 86]. Here, it is considered that an occupant's adaptive behavior is the product of his or her sensations in that specific situation. There are behavioral parameters, such as mood and emotions that are *situation-specific* [85]. These behavioral parameters, as well as environmental parameters, influence decision-makings of occupants and subsequently their behavior in an enclosed space [88]. Accordingly, within the proposed situation-specific method, the adaptive behavior of an occupant in a particular situation, is considered to vary according to that specific situation.

Similar to the position-based method (Chapter 6), in the situation-specific method, thermal comfort and visual comfort evaluations are based on the positions of occupants (Sub-Section 3.4.1 and Sub-Section 3.4.2). Each occupant's personalized thermal and visual preference models are constructed, from his or her thermal and visual sensation votes, using equations (3.10) to (3.13) for thermal preference model (RP_{thermal}), and equations (3.27) to (3.29) for visual preference model (RP_{visual}). In this chapter, the same four occupants in Chapter 6 are considered for the simulations. The occupants' thermal and visual preference models and their personalized thermal and visual parameters are stated in Table 7 and Table 9. RP_{IAQ} is also considered from (3.6). From RP_{thermal}, RP_{visual}, and RP_{IAQ}, $RP_{\text{Sensation-Overall}}$ is constructed using (3.33). $RP_{\text{Sensation-Overall}}$ is considered as the basis to construct RP_{Behavior} or situation-specific relative productivity. Using the methodologies described in Section 3.5 and specifically, equations (3.35) to (3.41), RP_{Behavior} of each individual in each specific situation can be derived. RP_{Behavior} of each occupant is introduced into (3.34) to form the objective function of the situation-specific method. Accordingly, the objective of the situation-specific method is to simultaneously optimize energy consumption costs and occupants' productivity.

The performance of the situation-specific method is analyzed, by simulating its operation in a single-floor office, located in Montreal. The office plan is similar to the plan of the four-zone office, considered in Chapter 6. The office plan, and the positions of occupants are indicated in Section 3.4 (Fig. 7). The office building schedule, during the occupied and unoccupied hours, and the building parameters, are stated in Table 5 and Table 1, respectively. Within different parametric simulations, varied scenarios of occupancy in different zones of the office, are assumed to study the capabilities of the proposed method for situation-specific energy and comfort management. Similar to Chapter 6, weekly results are demonstrated to have a detailed view on the operation of the proposed method.

First, the performance of the proposed method is compared to the SOOP method to confirm that the proposed method performs personalized energy and comfort management. Using the SOOP method, occupants' comfort conditions are treated as the limits on indoor environmental parameters. The constraints related to visual comfort and IAQ are stated in Table 5. Moreover, two values of 21 °C and 27 °C are chosen as the heating and cooling set-points, during the occupied hours. Subsequently, making energy-related decisions, according to varied hourly productivity, and varied thermal and visual preferences of occupants, are studied. The main difference between the position-based method (Section 3.4 and Chapter 6) and the situation-specific method (Section 3.5 and this chapter) is discussed, by simulating the capability of the situation-specific method to consider the adaptive behavior of occupants. Finally, the sensitivity of the situation-specific method to occupants' behavior variation is analyzed.

7.1 Importance of Personalized Control

During January, an arbitrary occupancy scenario is considered in one of the zones of the office (east zone). The considered occupancy scenario is to have Occupant #1 in Position-A, and Occupant #2 in Position-B, during the first week of January. Thermal and visual preference models of these two occupants are stated in Table 7 and Table 9, respectively. For each occupant, a constant hourly productivity of 8 $/h is considered. Considering the proposed situation-specific method and the SOOP method for energy and comfort management, the thermal and visual conditions of the occupants, and IAQ of the zone are compared.

7.1.1 Thermal Comfort

Here, similar to the position-based method (Chapter 6), hourly operative temperature (°C) in each specific position is considered for thermal comfort evaluation. During the first week of January, hourly operative temperatures (°C) in Position-A and Position-B of east zone are investigated to study the thermal conditions of Occupant #1 and Occupant #2. The performance of the situation-specific MOOP method and the SOOP method, with respect to the thermal conditions of the two occupants, are compared (Fig. 83).

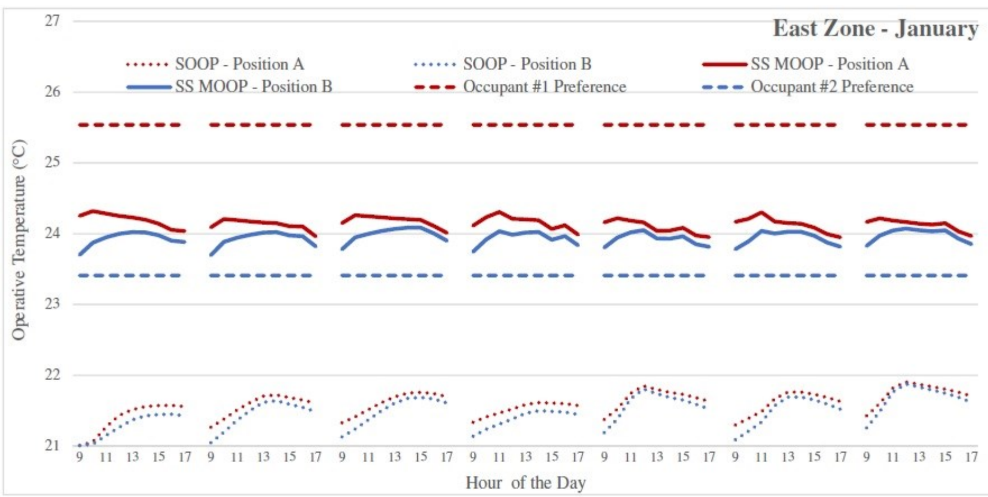

Fig. 83: Comparing situation-specific MOOP (SS MOOP) method & SOOP method – Weekly thermal comfort analysis in the cold season

The SOOP method manages the indoor environmental conditions of east zone irrespective of the thermal preferences of Occupant #1 ($T_{\text{maxcomfort}}$ of 25.5 °C) or Occupant #2 ($T_{\text{maxcomfort}}$ of 23.4 °C). The hourly operative temperatures (°C) in both positions under the scenario of SOOP energy management are slightly higher than the heating set-point (Fig. 83). On the other hand, the proposed situation-specific method acknowledges the thermal preferences of the two occupants, while making decisions for the indoor environmental conditions of the zone.

Because of the difference in the thermal preferences of Occupant #1 and Occupant #2, the proposed method provides hourly operative temperatures within the range of the two occupants' preferred thermal conditions (Fig. 83). Hourly temperatures in both positions are slightly closer to $T_{\text{maxcomfort}}$ of Occupant #2 (23.4 °C), compared to $T_{\text{maxcomfort}}$ of Occupant #1 (25.5 °C). This is as a result of (1) the relatively higher sensitivity of Occupant #2 to the thermal conditions of the indoor environment (with $Tolerance_{\text{thermal}}$ of 4.4 K) compared to Occupant #1 (with $Tolerance_{\text{thermal}}$ of 7.2 K), and (2) the energy costs minimization objective of the MOOP method.

7.1.2 Visual Comfort

Visual preference models of Occupant #1 and Occupant #2 are stated in Table 9. Occupant #1 has $ILL_{\text{maxcomfort}}$ of 937 lux, and Occupant #2 has $ILL_{\text{maxcomfort}}$ of 1563 lux. For the visual comfort analysis, Illuminance (lux) in each position is the parameter to investigate. The minimum and maximum acceptable illuminance levels, during the occupied hours, are 750 lux and 2500 lux, respectively (Table 5). Using the situation-specific method and the SOOP method for energy and comfort management, the levels of hourly Illuminance (lux) in Position-A and Position-B of east zone, during the occupied hours of the first week of January, are compared (Fig. 84).

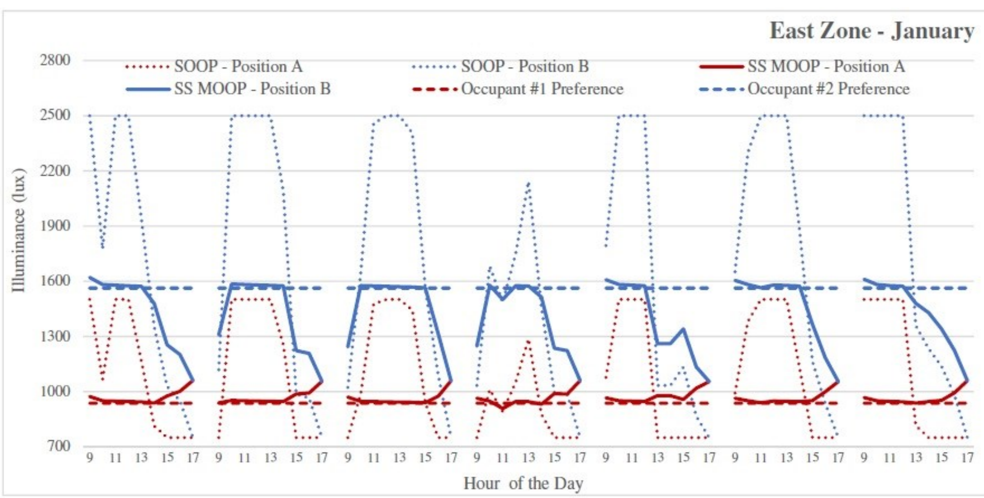

Fig. 84: Comparing situation-specific MOOP (SS MOOP) method & SOOP method – Weekly visual comfort analysis in the cold season

The visual preferences of Occupant #1 and Occupant #2 do not concern the SOOP method. The SOOP method only considers the constraints on the visual conditions, and provides hourly illuminance levels (lux), within the range of the minimum and maximum acceptable illuminance levels (Fig. 84). In contrast, under the scenario of situation-specific energy and comfort management, hourly illuminance levels (lux) in Position-A and Position-B are managed according to the visual preferences of Occupant #1 and Occupant #2, respectively (Fig. 84).

7.1.3 Indoor Air Quality

In contrast to the thermal and visual comfort of occupants, personalization is not applied to the IAQ of the zones. However, the situation-specific method includes IAQ inside its objective function, by considering the relationship between IAQ and productivity of occupants, discussed in (3.6) [31]. Hourly ventilation rates (m^3/s per m^2) in east zone, during the occupied hours of the first week of January, under the scenarios of the situation-specific method or the SOOP method energy and comfort management, are compared (Fig. 85). As long as it does not significantly influence its other objective (energy costs minimization), the situation-specific method increases hourly ventilation rates (m^3/s per m^2) to improve the productivity of the occupants.

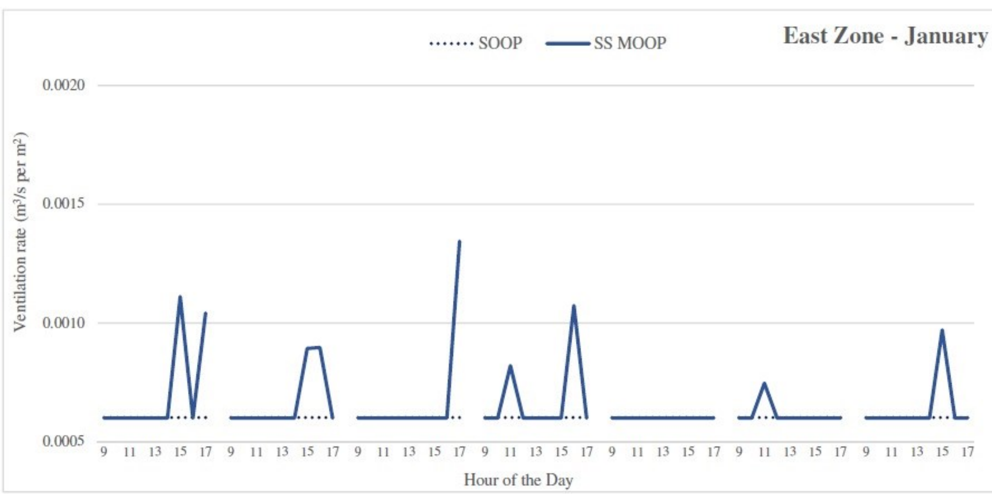

Fig. 85: Comparing situation-specific MOOP (SS MOOP) method & SOOP method – Weekly IAQ analysis in the cold season

During the first week of January, the SOOP method only provides the minimum acceptable level of ventilation rate (6×10^{-4} m^3/s per m^2) for the occupants of east zone (Fig. 85). Because of the energy costs minimization objective of the SOOP method, supplying higher levels of outdoor air, during the cold month of January, is in conflict with the objective of the SOOP method. Compared to the SOOP method, using the situation-specific method for energy and comfort management, a relatively more productive indoor environment with respect to IAQ, is provided for the occupants of east zone (Fig. 85).

7.1.4 Productivity Losses & Energy Costs

Thermal comfort, visual comfort, and IAQ of Occupant #1 and Occupant #2, under the scenarios of SOOP and situation-specific energy and comfort management, are compared. The proposed method is successful in providing personalized thermal and visual preferences of the two occupants. Furthermore, using the situation-specific method, IAQ of the zone is better. Accordingly, the productivity of Occupant #1 and Occupant #2 are higher, under the situation-specific energy and comfort management scenario, compared to the alternative SOOP.

In order to study the performance of the situation-specific method with respect to energy costs and occupants' productivity losses, an arbitrary occupancy scenario of having two occupants (with a constant productivity rate of 8 $/h) in each zone is considered. It is assumed that in each zone, an occupant with thermal and visual preferences similar to Occupant #1, sits in Position-A, while the other occupant in Position-B, has the thermal and visual preferences similar to Occupant #2. During the occupied hours of the first week of January, the operation of the SOOP method is associated with $723 productivity losses. On the other hand, using the situation-specific method, the productivity losses of occupants decreased significantly to $73 (Fig. 86).

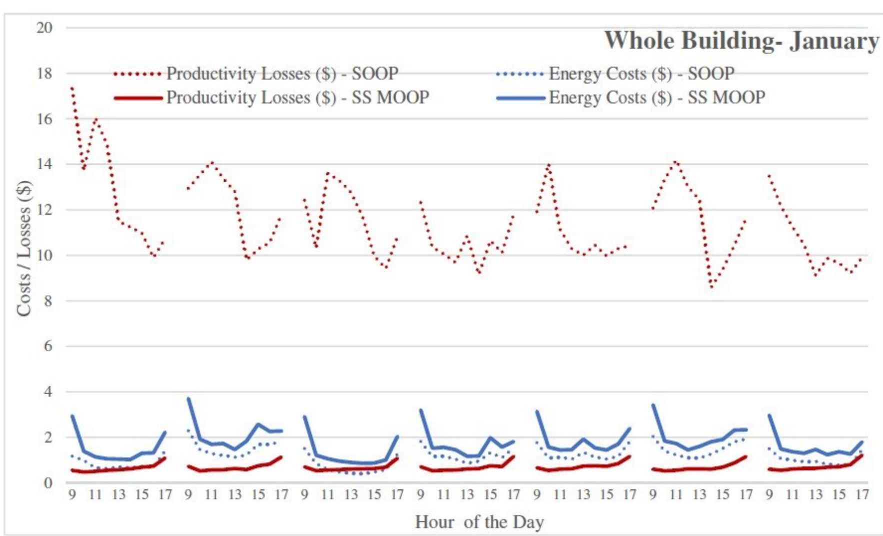

Fig. 86: Comparing situation-specific MOOP (SS MOOP) method & SOOP method – Weekly productivity losses ($) and energy costs ($) in the cold season

The difference between the weekly energy costs of the whole office, under the SOOP method and the situation-specific method is $57. Accordingly, it is confirmed that the situation-specific method manages to simultaneously optimize the productivity of occupants and energy costs.

7.2 Effect of Occupants' Productivity: Single Occupant

In order to observe the influence of the productivity rate on the performance of the situation-specific method, an arbitrary scenario of having Occupant #1 in Position-A of south zone, during the occupied hours of the first week of January and July is considered. Under three scenarios of productivity rate, hourly productivity ($/h) of Occupant #1 is assumed to be constant and equal to (1) 4 $/h, (2) 8 $/h, and (3) 16 $/h. The operative temperature (°C), illuminance (lux) in Position-A, and ventilation rate (m^3/s per m^2) of south zone are investigated to assess the thermal and visual conditions of Occupant #1, and the IAQ of the zone.

7.2.1 Thermal Comfort

Occupant #1 has the maximum RP_{thermal} when the operative temperature (°C) in Position-A is equal to 25.5 °C (Table 7). Hourly operative temperatures (°C) in Position-A of south zone, during a week in January and in July, are demonstrated in Fig. 87 and Fig. 88, respectively.

Fig. 87: The influence of productivity rate ($/h) on the thermal comfort of Occupant #1 - The cold season analysis

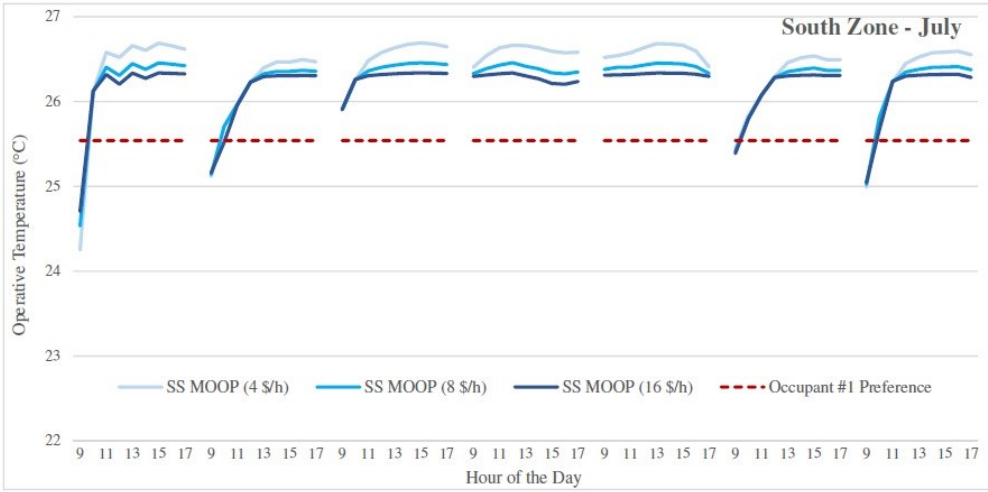

Fig. 88: The influence of productivity rate ($/h) on the thermal comfort of Occupant #1 - The warm season analysis

For both outdoor weather conditions, with the increase in hourly productivity ($/h) of Occupant #1, hourly operative temperatures (°C) in Position-A approach $T_{\text{maxcomfort}}$ of the occupant (25.5 °C). Hence, under the scenario of highest productivity rate (16 $/h), the situation-specific method provides relatively more satisfactory thermal conditions for the occupant, compared to the alternative scenarios.

7.2.2 Visual Comfort

Under the three productivity rate scenarios, during the occupied hours of the first week of January and July, hourly illuminance levels (lux) in Position-A are demonstrated in Fig. 89 and Fig. 90. Occupant #1 has the maximum satisfaction from the visual conditions of south zone ($ILL_{\text{maxcomfort}}$) when illuminance in Position-A is equal to 937 lux (Table 9).

The situation-specific method performs personalization of energy and comfort, by managing the visual conditions of the indoor environment, according to Occupant #1' preferences. For both outdoor weather conditions and under all three productivity rate scenarios, illuminance levels (lux) in Position-A are very close to $ILL_{\text{maxcomfort}}$ of Occupant #1. Meanwhile, with the increase in productivity rate ($/h) of Occupant #1, hourly illuminance levels (lux) in Position-A approach $ILL_{\text{maxcomfort}}$ of Occupant #1 (Fig. 89 and Fig. 90).

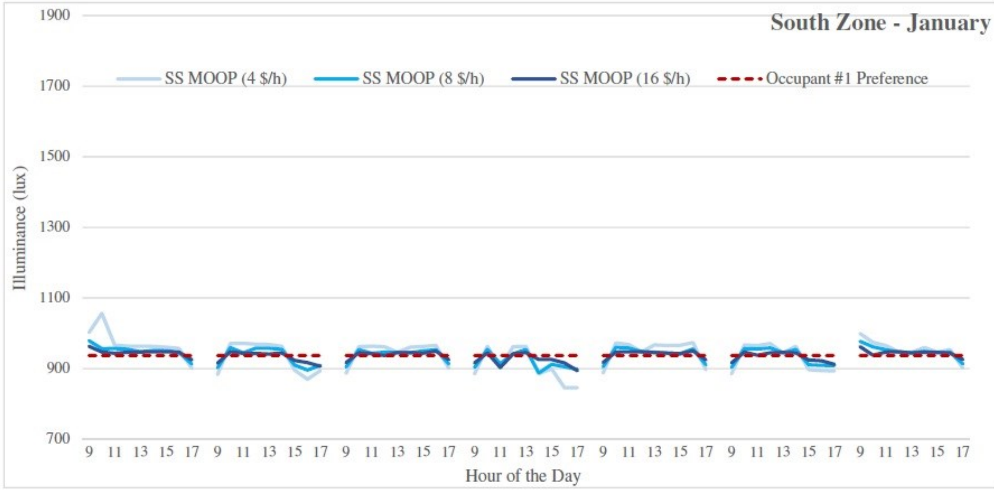

Fig. 89: The influence of productivity rate ($/h) on the visual comfort of Occupant #1 - The cold season analysis

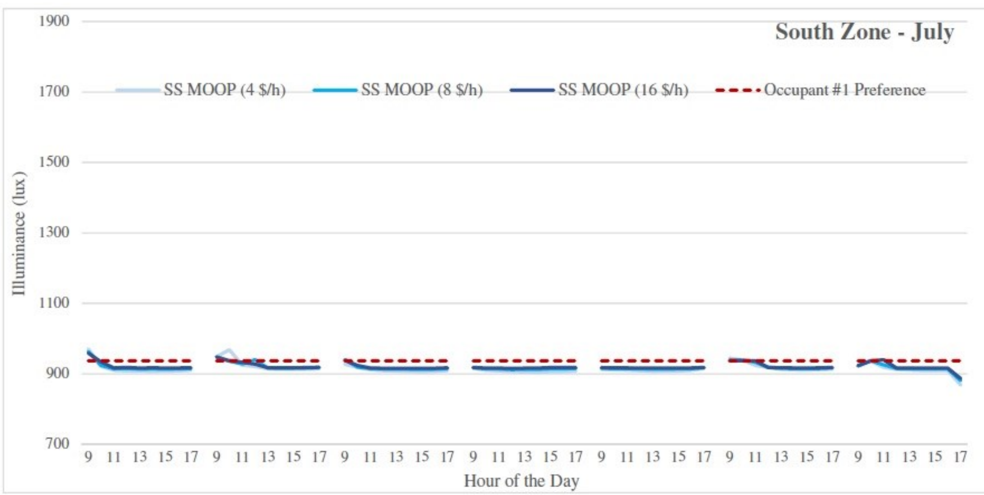

Fig. 90: The influence of productivity rate ($/h) on the visual comfort of Occupant #1 - The warm season analysis

7.2.3 Indoor Air Quality

During the first week of January and July, under the three productivity rate scenarios, hourly ventilation rates (m^3/s per m^2) in south zone are presented (Fig. 91 and Fig. 92). During the cold month of January, when the hourly productivity of Occupant #1 is the lowest (4 $/h), the situation-specific method provides ventilation rates equal to, or slightly higher than the minimum acceptable level (0.0006 m^3/s per m^2). With the increase in hourly productivity of Occupant #1, the level of ventilation rate increases (Fig. 91). During July as well, productivity rate of the occupant has a direct relationship with the ventilation rate of the zone. When the hourly productivity of Occupant #1 is the highest (16 $/h), ventilation rates are mostly equal to its maximum acceptable level of 0.002 m^3/s per m^2 (Fig. 92).

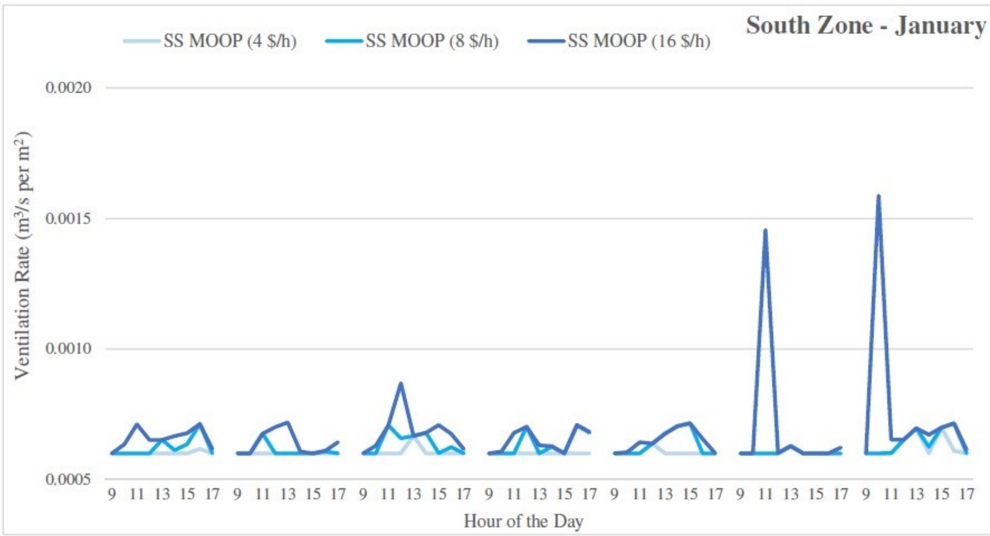

Fig. 91: The influence of productivity rate ($/h) on the IAQ of the zone- The cold season analysis

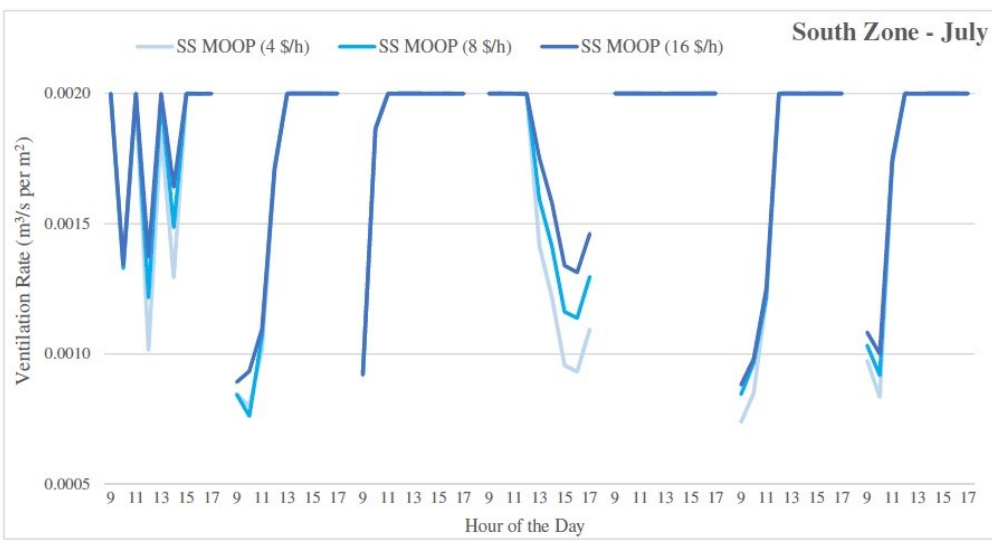

Fig. 92: The influence of productivity rate ($/h) on the IAQ of the zone- The warm season analysis

7.3 Effect of Occupants' Preferences: Single Occupant vs. Multiple Occupants

In order to study the performance of the situation-specific method with respect to the diversity of occupants' preferences, three arbitrary scenarios of occupancy, inside the west zone of the office are considered. Under the three scenarios, it is assumed that in west zone, during the occupied hours of the first week of July (1) Occupant #1 alone works in Position-A, (2) Occupant #2 alone works in Position-B, and (3) Occupant #1 works in Position-A and Occupant #2 works in Position-B. The performance of the proposed method, with respect to the diversity in thermal and visual preferences of occupants are analyzed, separately. It is assumed that under all three scenarios of occupancy, each occupant has a constant productivity rate of 8 $/h.

7.3.1 Thermal Preferences

The level of operative temperature (°C) in Position-A and Position-B are investigated to evaluate the thermal conditions of Occupant #1 and Occupant #2, respectively. Under the three considered scenario of occupancy, during the occupied hours of the first week of July, hourly operative temperatures (°C) in the occupants' positions are presented (Fig. 93). Occupant #1 has $T_{\text{maxcomfort}}$ of 25.5 °C while Occupant #2 has a relatively lower $T_{\text{maxcomfort}}$ of 23.4 °C. Under the two scenarios of having either Occupant #1 or Occupant #2 in west zone, the situation-specific method approaches the thermal preference of that occupant, by providing hourly operative temperatures (°C) close to the occupant's $T_{\text{maxcomfort}}$.

Under the scenario of having both Occupant #1 and Occupant #2, the method provides hourly operative temperatures (°C) within the range of the two occupants' preferred thermal conditions (Fig. 93). Occupant #2 with $Tolerance_{\text{thermal}}$ of 4.4 K is relatively more sensitive to the thermal conditions of the indoor environment, compared to Occupant #1 with $Tolerance_{\text{thermal}}$ of 7.2 K (Table 7). The method respects the relatively higher sensitivity of Occupant #2. Accordingly, hourly operative temperatures (°C) are relatively closer to the preferred temperature of Occupant #2 (23.4 °C), compared to $T_{\text{maxcomfort}}$ of Occupant #1 (25.5 °C).

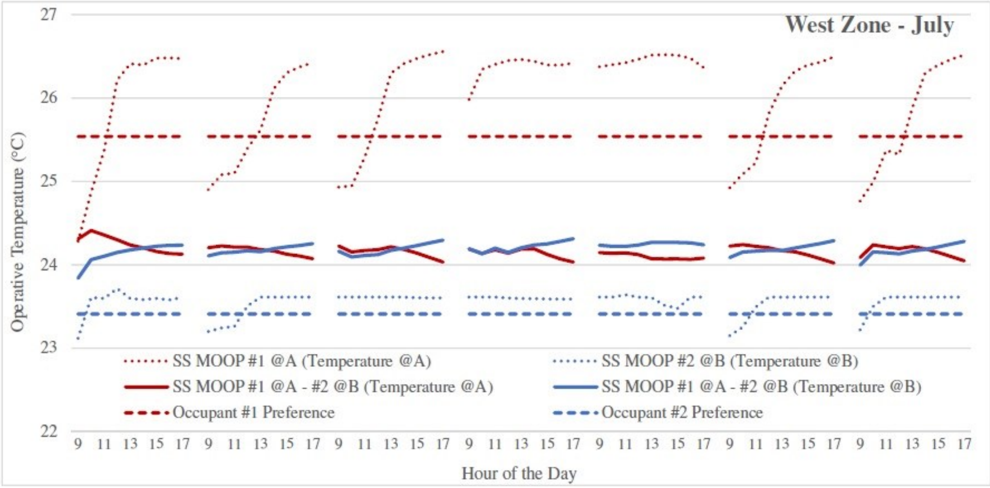

Fig. 93: Acknowledging the diversity in Occupants' thermal preferences- The warm season analysis

7.3.2 Visual Preferences

The two considered occupants have different visual preferences, as well. Occupant #1 has $ILL_{\text{maxcomfort}}$ of 937 lux while Occupant #2 has $ILL_{\text{maxcomfort}}$ of 1563 lux. Under the three considered scenarios of occupancy, illuminance levels (lux) in Position-A and Position-B are studied to evaluate the performance of the situation-specific method with respect to the diversity in the visual preferences of occupants. Hourly illuminance levels (lux) in both positions, during the occupied hours of the first week of July, under the three scenarios are shown in Fig. 94.

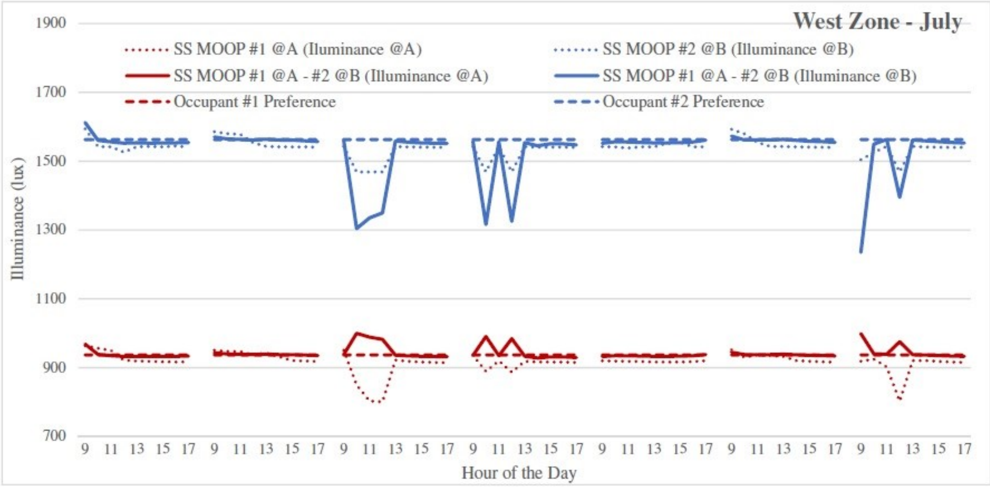

Fig. 94: Acknowledging the diversity in Occupants' visual preferences- The warm season analysis

Under two single-occupancy scenarios, the method controls the level of natural illumination (lux) and artificial lighting (lux) to provide the preferred visual conditions of the occupants. Under the multiple-occupancy scenario, although there is a diversity in the visual preferences of the occupants, the situation-specific method is still successful in providing satisfactory visual conditions for both of the occupants (Fig. 94). This is because of the positions of the two occupants. Occupant #2, with the preference of a brighter ambient, sits in Position-B, near the window, while Occupant #1 sits further away, close to the interior walls (Fig. 7).

7.4 Effect of Occupants' Behavior: Multiple Occupants

The major improvement in the situation-specific method, compared to the position-based method (Chapter 6) is its enhanced behavioral intelligence. Each occupant's dissatisfaction from the indoor environmental conditions might result in his or her adaptive behavior to improve his or her personal comfort. In the situation-specific method, each occupant's responses to the indoor environmental conditions are modeled (Section 3.5). Accordingly, the method optimizes the probability of occupants' *2nd category behavior* (adjusting the indoor environment to elevate personal comfort).

In Section 3.5, the likelihood ratio of an occupant's 2nd category behavior is introduced in (3.35). *LR* of 2nd category adaptive behavior of an occupant considers both the prior comfort sensation probabilities of the occupant (*Discomfort Parameter*) and his or her decision-making process in that specific situation (*Decision-Making Parameter*). *Discomfort Parameter* is presented in (3.36). *Decision-Making Parameter* is derived through the computational modeling of each occupant's decision-making process in a specific situation, from equations (3.37) to (3.40).

In each specific situation, if *LR* (*2nd Category Behavior*) of an occupant is larger than 1, it means that the occupant's 2nd category behavior is more probable than his or her self-adaptive behavior (*1st category behavior*). In (3.41), a relationship between RP_{Behavior} of an occupant, and his or her *LR* (*2nd Category Behavior*) is presented. Based on this relationship, RP_{Behavior} is maximum when *LR* (*2nd Category Behavior*) is equal to zero. RP_{Behavior} considers both sensations and the decision-making process. RP_{Behavior} of each occupant is introduced in the objective function of the situation-specific method, presented in (3.34).

In order to demonstrate the behavioral intelligence of the situation-specific method, the performance of the situation-specific method is compared to the position-based method from Chapter 6. Initially, an arbitrary occupancy scenario of having two occupants in the same zone during January, and subsequently, an arbitrary occupancy scenario of having four occupants in a shared zone during July, are considered. Using the situation-specific method and the position-based method, *LR* (*2nd Category Behavior*), RP_{Behavior} of occupants, as well as the environmental parameters of the considered zone, are compared.

7.4.1 Evaluating Behavioral Intelligence: A Scenario with Two Occupants

An arbitrary occupancy scenario of having Occupant #1 in Position-A, and Occupant #2 in Position-B of east zone (each with a constant productivity rate of 8 $/h), during the first week of January, is assumed. Values of *LR* (*2nd Category Behavior*) and RP_{Behavior}, associated with the operation of the position-based MOOP method and the situation-specific MOOP method are presented in Fig. 95 and Fig. 96, respectively.

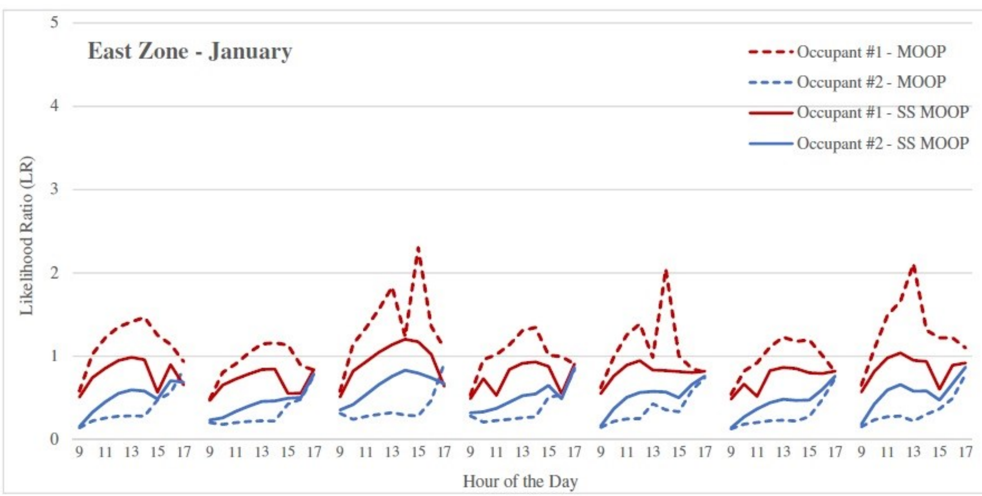

Fig. 95: Comparing LR (2nd Category Behavior) of two occupants, under the scenarios of position-based MOOP method (MOOP) and situation-specific MOOP method (SS MOOP) - The cold season analysis

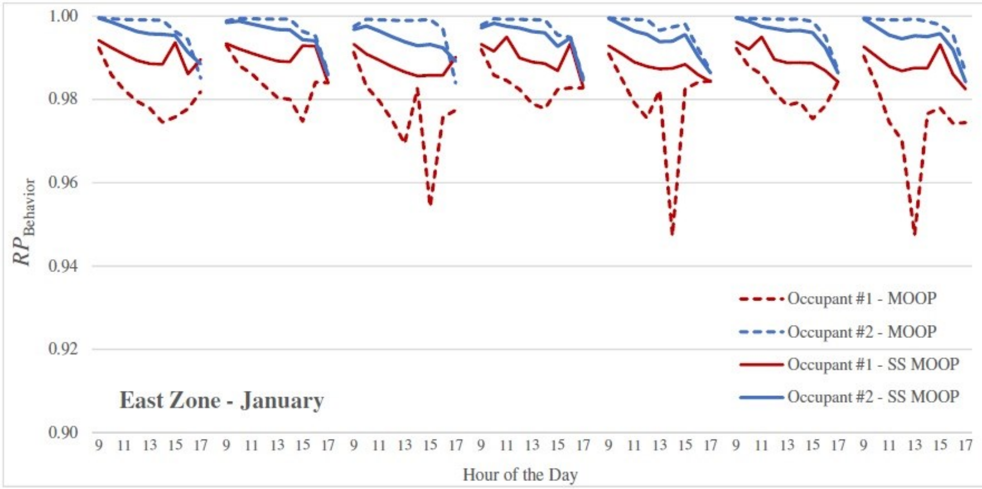

Fig. 96: Comparing $RP_{Behavior}$ of two occupants, under the scenarios of position-based MOOP method (MOOP) and situation-specific MOOP method (SS MOOP) - The cold season analysis

Under the position-based energy and comfort management scenario, *LR* (*2nd Category Behavior*) of Occupant #1 frequently exceeds 1 (Fig. 95). Accordingly, for Occupant #1 in that specific situation, the probability of 2nd category behavior (adjusting the indoor environment) is higher than the probability of 1st category behavior (self-adaptive behavior). *LR* (*2nd Category Behavior*) of Occupant #2 never exceeds 1.

On the other hand, under the situation-specific energy and comfort management scenario, the values of hourly *LR* (*2nd Category Behavior*) of Occupant #1 reduce significantly and rarely exceed 1 (Fig. 95). The situation-specific method keeps *LR* (*2nd Category Behavior*) of both Occupant #1 and Occupant #2 below 1 to optimize the probability of occupants' 2nd category behavior while optimizing energy costs. Furthermore, using the situation-specific method, RP_{Behavior} of Occupant #1 is remarkably improved, compared to the position-based method (Fig. 96).

Considering position-based and situation-specific energy and comfort management scenarios, hourly operative temperatures (°C) and hourly illuminance levels (lux) in Position-A and Position-B of east zone, are demonstrated (Fig. 97 and Fig. 98). Using the position-based method, the hourly operative temperatures (°C) provided for Occupant #1 in Position-A are low, relative to $T_{\text{maxcomfort}}$ of the occupant. Hence, 2nd category adaptive behavior of Occupant #1 (to improve personal comfort) is probable. The situation-specific method reduces this probability, by increasing the indoor temperature (°C) in the zone (Fig. 97).

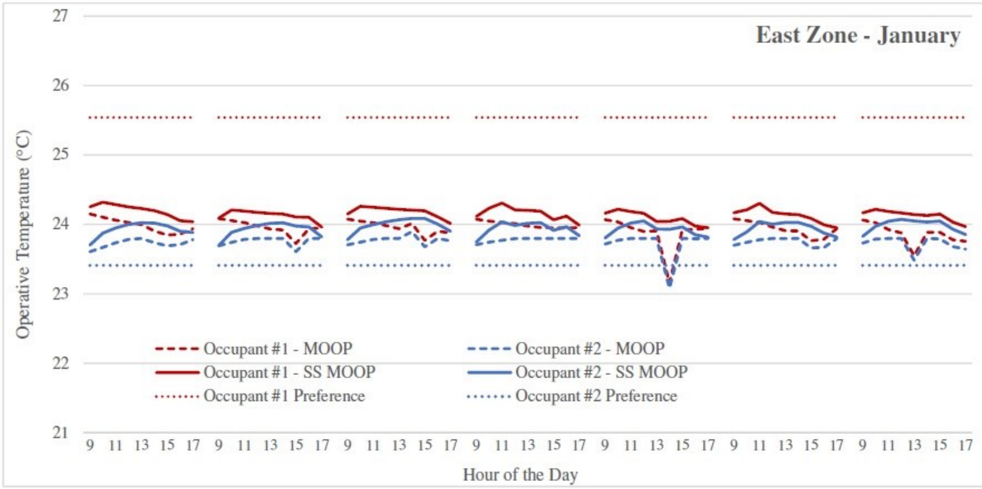

Fig. 97: Comparing the thermal comfort of two occupants, under the scenarios of position-based MOOP method (MOOP) and situation-specific MOOP method (SS MOOP) - The cold season analysis

Using the position-based and situation-specific methods, the visual conditions in Position-A and Position-B of east zone are very similar (Fig. 98).

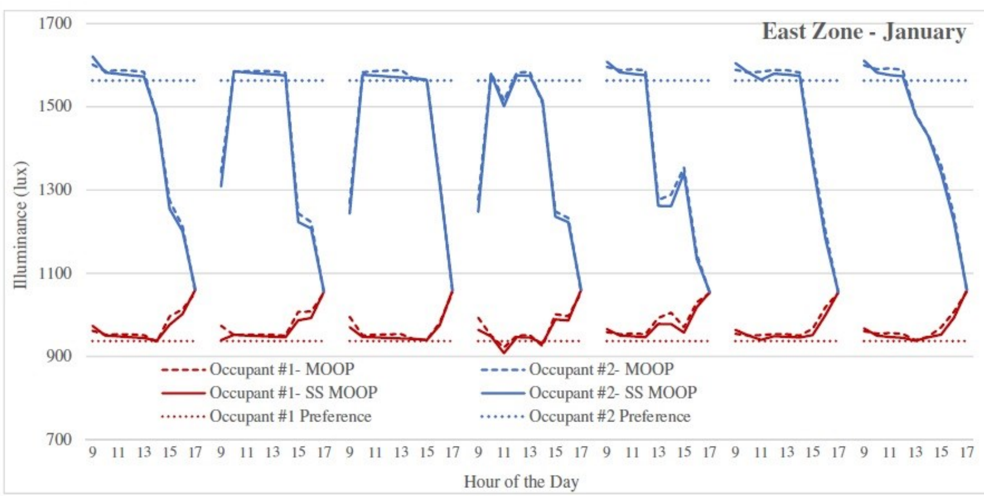

Fig. 98: Comparing the visual comfort of two occupants, under the scenarios of position-based MOOP method (MOOP) and situation-specific MOOP method (SS MOOP) - The cold season analysis

It is observed in Fig. 99 that under the considered scenario of having two occupants in the zone, both the situation-specific method (studied in this chapter) and the position-based method (studied in Chapter 6) are successful in keeping energy consumption costs ($) and productivity losses ($) at relatively low levels.

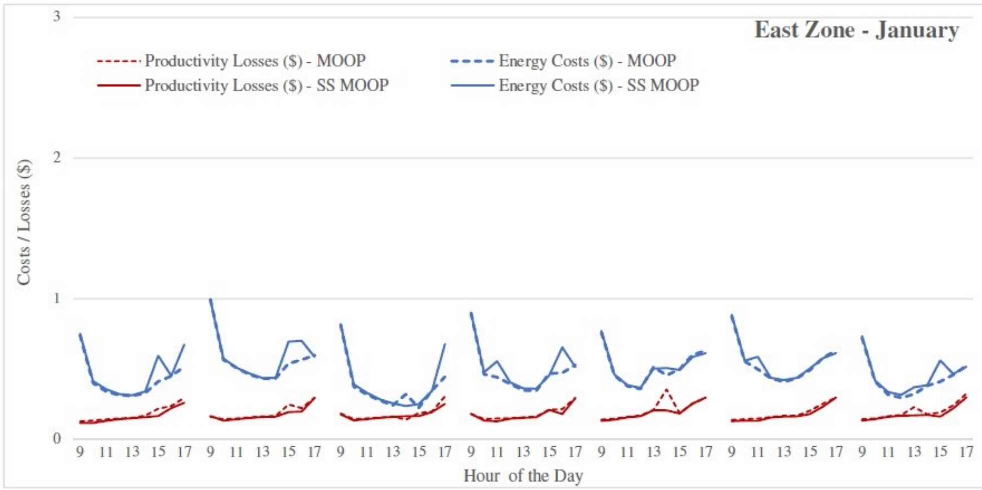

Fig. 99: Comparing energy costs ($) and productivity losses ($), under the scenarios of position-based MOOP method (MOOP) and situation-specific MOOP method (SS MOOP) - The cold season analysis

7.4.2 Evaluating Behavioral Intelligence: A Scenario with Four Occupants

Considering four occupants in a shared zone, the performances of the situation-specific method and the position-based method are compared. Under the considered occupancy scenario, Occupant #1 is in Position-A, Occupant #2 is in Position-B, Occupant #3 is in Position-C, and Occupant #4 is in Position-D of east zone. Each occupant is assumed to have a constant productivity rate of 8 $/h. During the occupied hours of the first week of July, the operations of the position-based method and the situation-specific method are compared. First, *LR* (*2^{nd} Category Behavior*) and RP_{Behavior} of the occupants, are assessed. *LR* (*2^{nd} Category Behavior*) of the four occupants, using the position-based MOOP method and the situation-specific MOOP method for energy and comfort management, are shown in Fig. 100 and Fig. 101.

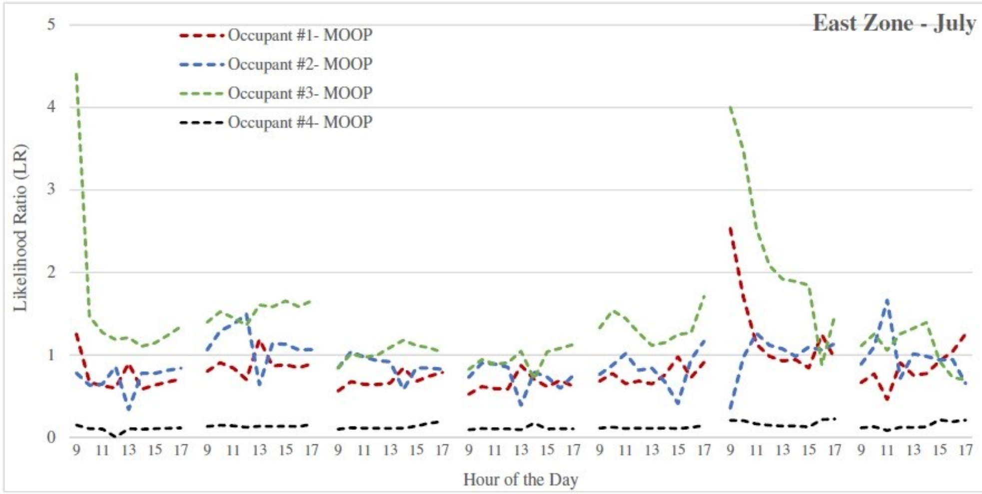

Fig. 100: LR of four occupants, using the position-based MOOP method (MOOP) - The warm season analysis

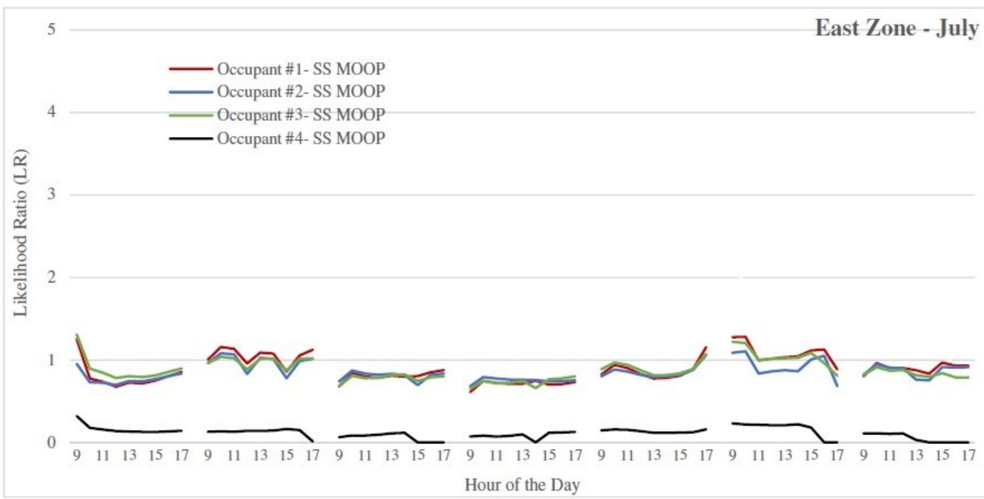

Fig. 101: LR of four occupants, using the situation-specific MOOP method (SS MOOP) - The warm season analysis

Using the position-based method, between the four occupants, Occupant #3 has the largest values of hourly *LR* (Fig. 100). Values of hourly *LR* (*2nd Category Behavior*) of Occupant #3 frequently exceed 1. The situation-specific method perceives the high values of *LR* (*2nd Category Behavior*) as the risk of 2nd category behavior (adjusting the indoor environment to improve the personal comfort). Hence, the situation-specific method performs the automated control of the indoor environment to reduce *LR* (*2nd Category Behavior*) of Occupant #3. Using the situation-specific method, *LR* (*2nd Category Behavior*) of Occupant #3 and other occupants are kept at relatively lower levels (Fig. 101).

The large values of *LR* (*2nd Category Behavior*) of Occupant #3 in position-based energy and comfort management is because of the visual conditions in Position-C, where Occupant #3 sits. Occupant #3 has $ILL_{\text{maxcomfort}}$ 1569 lux (Table 9). However, using the position-based method, hourly illuminance levels (lux) in Position-C are not acceptable to Occupant #3. During the warm month of July, the method welcomes relatively lower levels of solar irradiance to reduce the costs of cooling the office. Moreover, Occupant #1 in Position-A has a relatively low level of $ILL_{\text{maxcomfort}}$ (937 lux), compared to Occupant #3. Consequently, the position-based method does not provide high illuminance levels (lux) for Occupant #3 in Position-C (Fig. 102).

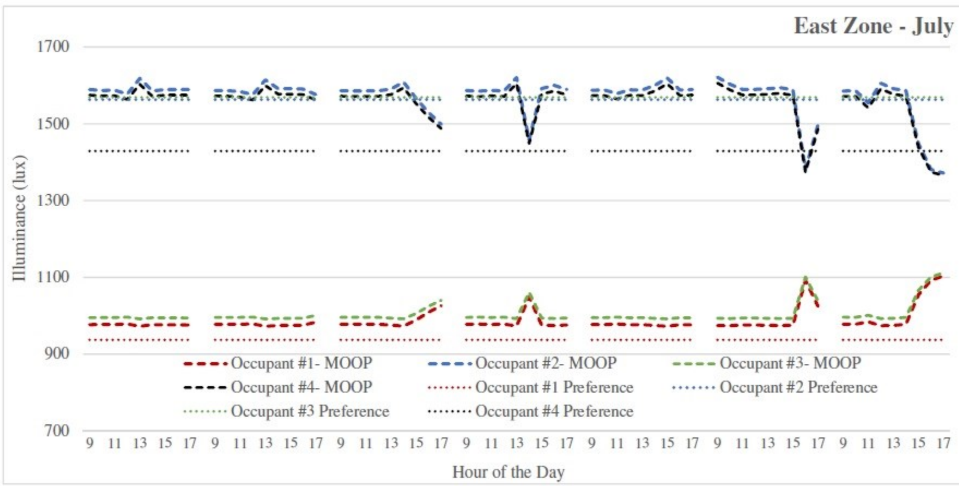

Fig. 102: The visual conditions of occupants, using the position-based MOOP method (MOOP) - The warm season analysis

When the situation-specific method performs the automated control of the indoor environment in east zone, the levels of hourly illuminance in Position-C are higher, compared to the operation of the position-based method (Fig. 103). Increasing illuminance levels (lux) in Position-C has an impact on the visual conditions of other occupants. Nevertheless, their *LR* (*2nd Category Behavior*) are still kept at low and acceptable levels (Fig. 101).

Considering position-based and situation-specific methods, under the considered scenario of having four occupants in east zone, RP_{Behavior} of the occupants are demonstrated (Fig. 104 and Fig. 105). The situation-specific method computationally models occupants' decision-making process and their adaptive behavior, and introduces the occupants' adaptive behavior into personalized energy and comfort management method, in order to offer behavioral intelligence.

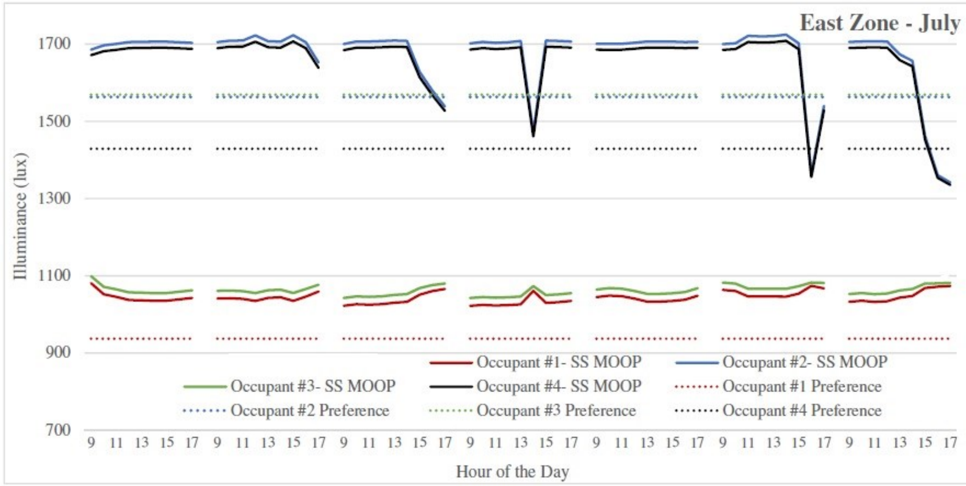

Fig. 103: The visual conditions of occupants, using the situation-specific method (SS MOOP) - The warm season analysis

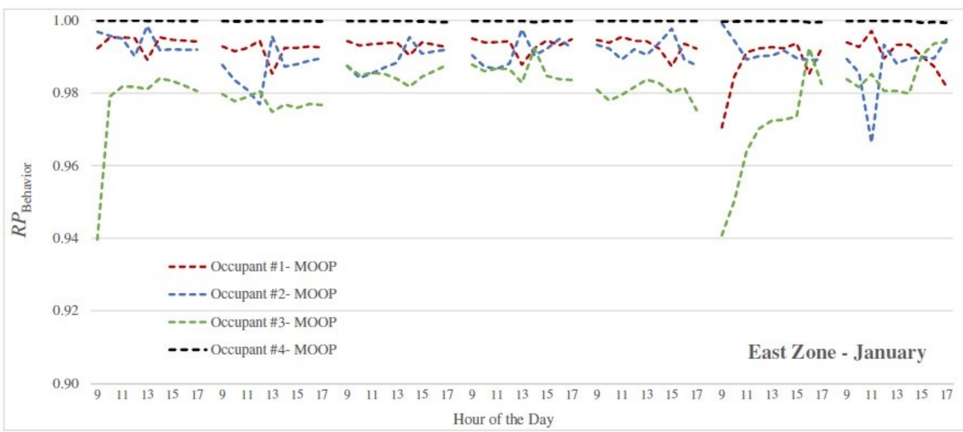

Fig. 104: $RP_{Behavior}$ of four occupants, using the position-based MOOP method (MOOP) - The warm season analysis

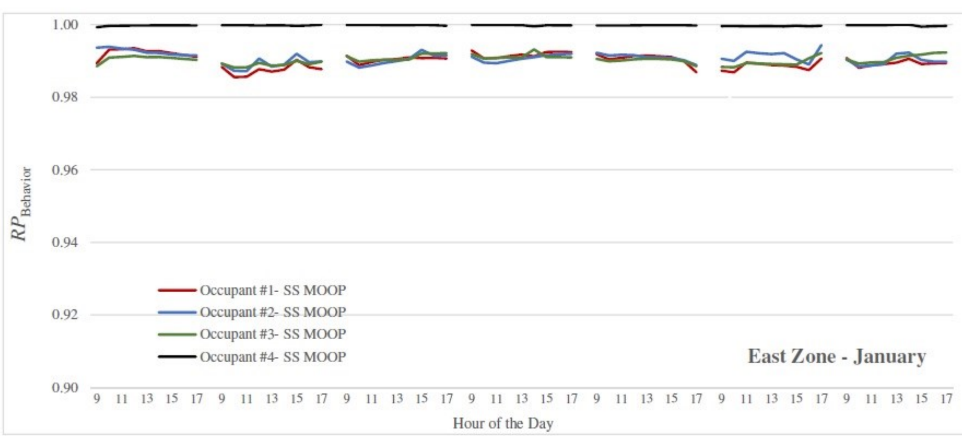

Fig. 105: $RP_{Behavior}$ of four occupants, using the situation-specific MOOP method (SS MOOP) - The warm season analysis

Under the considered scenario of having four occupants, the performance of the position-based method and the situation-specific method with respect to their two objectives, energy costs minimization and productivity maximization, are evaluated and compared (Fig. 106). It is observed that both proposed methods are successful in minimizing the associated energy consumption costs ($) and productivity losses ($) of occupants.

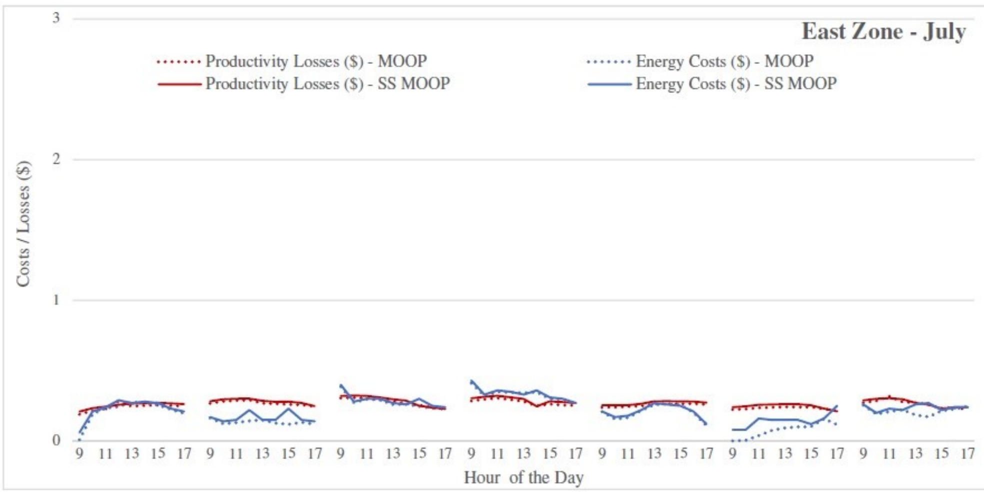

Fig. 106: Comparing energy costs ($) and productivity losses ($), under the scenarios of position-based MOOP method (MOOP) and situation-specific MOOP method (SS MOOP) - The warm season analysis

7.5 Discussion: Effect of Loss Aversion Coefficient (λ)

The likelihood ratio of an occupant's 2nd category behavior, or *LR* (*2nd Category Behavior*), is the product of *Discomfort Parameter* and *Decision-Making Parameter* (Section 3.5). *Discomfort Parameter* expresses the prior comfort sensation probabilities and is derived from $RP_{\text{Sensation-Overall}}$, indicated in (3.33). *Decision-Making Parameter* of an occupant in each situation consists of the value of action and the costs of action, associated with the 2nd category behavior (adjusting the indoor environment to restore personal comfort).

Using the prospect theory [86], the value of action and costs of action (associated the adaptive behavior of an occupant in a specific situation) are computationally modeled, through equations (3.37) to (3.40). Within the prospect theory, it is considered that people are more sensitive to their own losses, compared to their gains [110]. Accordingly, in (3.39), a loss aversion coefficient (λ)

value larger than one (λ equal to 2.25) is assumed to put more weight on losses, compared to gains in the decision-making process model [86].

However, different studies have found different values for loss aversion coefficient (λ), according to the parameters considered in the decision-making process [113]. Affective processes, such as mood and emotions, are among the parameters that can influence occupants' energy-related decisions and behavior [88]. Furthermore, the influence of moods and emotions of occupants on the shape of the decision-making process model, and specifically on the value of loss aversion coefficient (λ) has been discussed and computationally modeled [116, 117]. In fact, the main reason to use the prospect theory in the proposed situation-specific method to model the decision-making process, is the flexibility of the theory to accept human-related parameters, such as mood and emotions as the influential parameters.

Here, the flexibility of the situation-specific method, to accept varied values of loss aversion coefficient (λ) is discussed. Two occupancy scenarios of having "two occupants" and "four occupants" in a shared zone of the office are assumed, and the performance of the proposed situation-specific method with respect to λ variations is evaluated.

7.5.1 Effect of Loss Aversion Coefficient (λ): Two Occupants

During the occupied hours of the first week of January, Occupant #1 in Position-A, and Occupant #2 in Position-B are considered as the office workers in north zone. A constant productivity rate of 8 $/h is assumed for each of the office workers. $\lambda_{\text{Occupant\#2}}$ is assumed to be fixed and equal to its default value in (3.39) ($\lambda_{\text{Occupant\#2}}=2.25$). On the other hand, $\lambda_{\text{Occupant\#1}}$ is considered to vary. In three different situations, three different values of loss aversion coefficient is assumed for Occupant #1: (1) $\lambda_{\text{Occupant\#1}}=1$, (2) $\lambda_{\text{Occupant\#1}}=2.25$, and (3) $\lambda_{\text{Occupant\#1}}=5$.

Hourly operative temperatures (°C) in Position-A (Occupant #1) and Position-B (Occupant #2) of north zone are shown (Fig. 107 and Fig. 108). Occupant #1 and Occupant #2 have contrasting thermal preferences (Table 7). The increase in $\lambda_{\text{Occupant\#1}}$ would result in the increase in hourly operative temperatures (°C) in Position-A, towards $T_{\text{maxcomfort}}$ of Occupant #1 (Fig. 107). On the other hand, Occupant #2 would be most thermally satisfied when $\lambda_{\text{Occupant\#1}}$ is equal to one (Fig.

108). In this situation, Occupant #1 puts similar weight on his own comfort conditions and Occupant #2's comfort conditions.

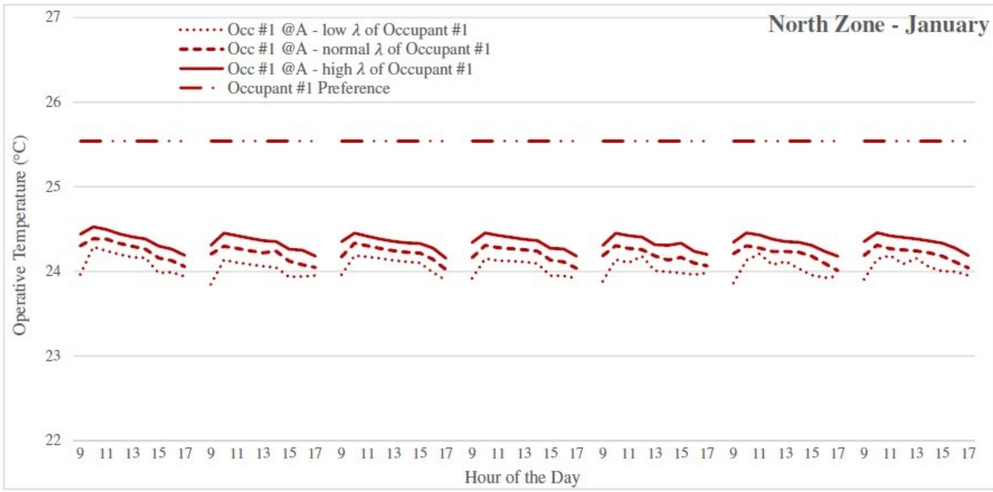

Fig. 107: The thermal conditions of Occupant #1 with respect to $\lambda_{Occupant\#1}$ variation in north zone- The cold season analysis

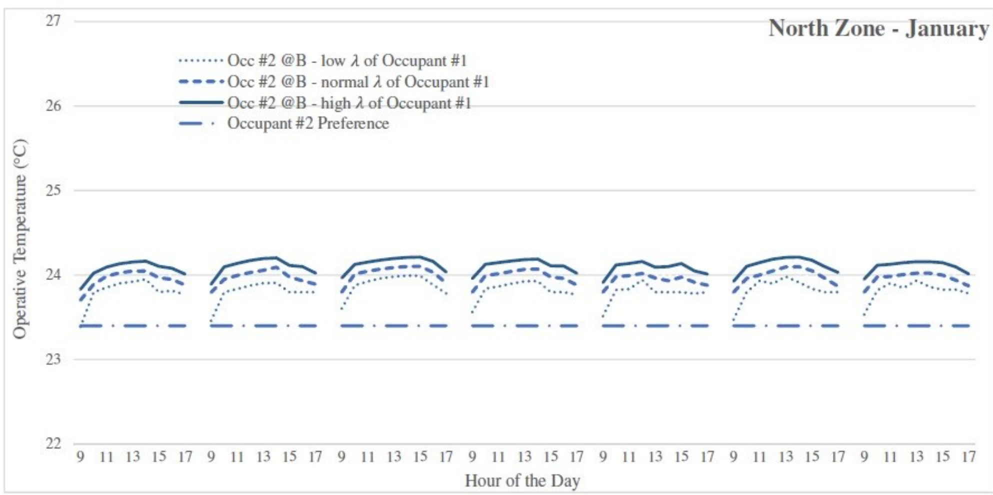

Fig. 108: The thermal conditions of Occupant #2 with respect to $\lambda_{Occupant\#1}$ variation in north zone - The cold season analysis

The levels of hourly illuminance (lux), provided for Occupant #1 and Occupant #2, in three different situations of $\lambda_{Occupant\#1}$ are demonstrated in Fig. 109 and Fig. 110, respectively. The same discussion explains the influence of Occupant #1's loss aversion coefficient ($\lambda_{Occupant\#1}$) on the visual conditions of Occupant #1 and Occupant #2 in north zone. Within the situation-specific energy and comfort management method, situation-specific behavioral parameters of each occupant influence all occupants' comfort conditions.

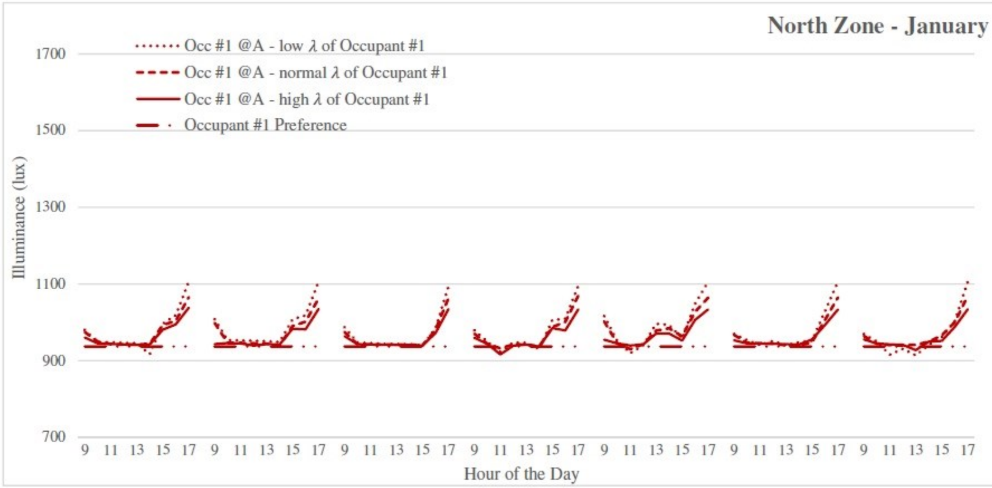

Fig. 109: The visual conditions of Occupant #1 with respect to $\lambda_{Occupant\#1}$ variation in north zone - The cold season analysis

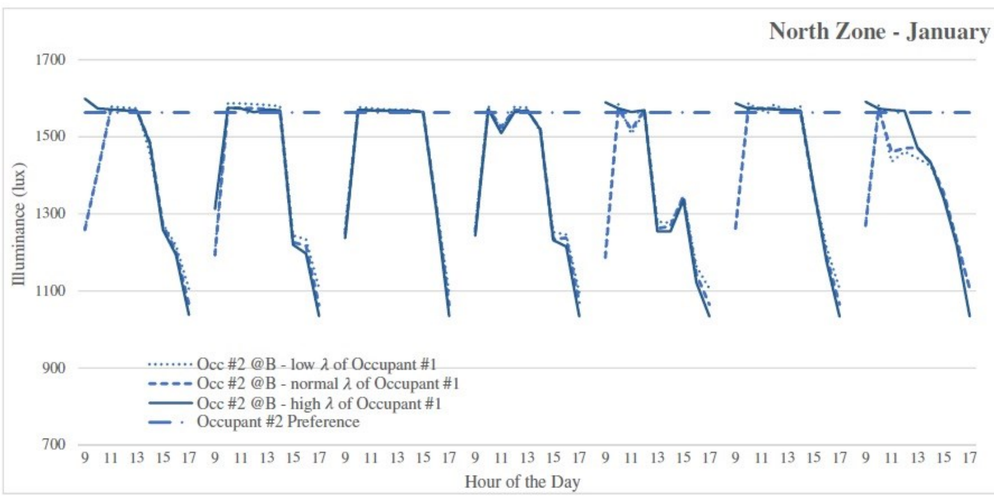

Fig. 110: The visual conditions of Occupant #2 with respect to $\lambda_{Occupant\#1}$ variation in north zone - The cold season analysis

In order to evaluate the behavioral intelligence of the situation-specific method in different outdoor weather conditions, an arbitrary scenario of having Occupant #1 and Occupant #2 in north zone, during the occupied hours of the first week of July, is studied. This time, $\lambda_{Occupant\#1}$ is assumed to be fixed ($\lambda_{Occupant\#1}$=2.25), and $\lambda_{Occupant\#2}$ is considered to vary. In three different situations, (1) $\lambda_{Occupant\#2}$=1, (2) $\lambda_{Occupant\#2}$=2.25, and (3) $\lambda_{Occupant\#2}$=5 are assigned. A constant productivity rate of 8 $/h is assumed for each of the occupants. Hourly operative temperatures (°C) in Position-A and Position-B of north zone, during the first week of July, are presented (Fig. 111 and Fig. 112). Occupant #1 in Position-A has $T_{maxcomfort}$ of 25.5 °C, while Occupant #2 in Position-B has a relatively lower $T_{maxcomfort}$ of 23.4 °C. The increase in $\lambda_{Occupant\#2}$ implies that for Occupant #2, the value of personal comfort is highest, compared to the alternative situations. Hence, in this situation, hourly operative temperatures (°C) are closer to $T_{maxcomfort}$ of Occupant #2, compared to low $\lambda_{Occupant\#2}$ and normal $\lambda_{Occupant\#2}$ situations (Fig. 112).

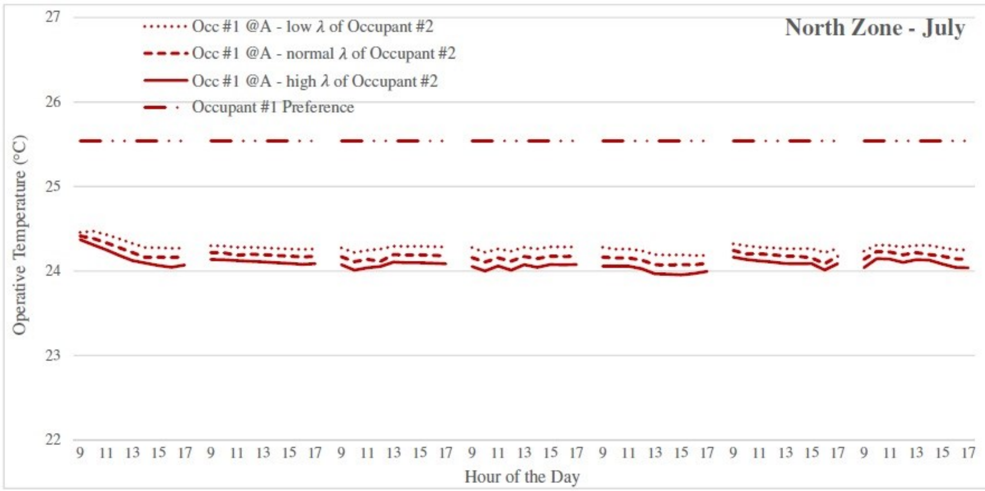

Fig. 111: The thermal conditions of Occupant #1 with respect to $\lambda_{Occupant\#2}$ variation in north zone - The warm season analysis

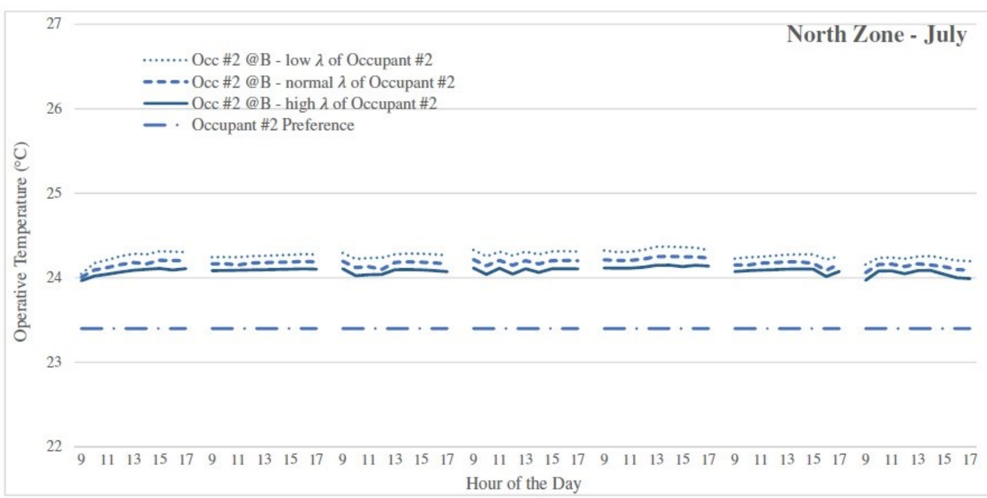

Fig. 112: The thermal conditions of Occupant #2 with respect to $\lambda_{Occupant\#2}$ variation in north zone - The warm season analysis

In three different situations of $\lambda_{Occupant\#2}$, hourly illuminance levels (lux), in Position-A (Occupant #1) and Position-B (Occupant #2) of north zone, during the occupied hours of the first week of July are demonstrated in Fig. 113 and Fig. 114, respectively. The influence of $\lambda_{Occupant\#2}$

variation on the visual conditions of the occupants is not as visible as its impact on their thermal conditions. The method is helped by the positions of the occupants, since Occupant #2 with visual preference of a brighter ambient sits close to the window, while Occupant #2 sits further away from the window (Fig. 7). Hence, behavioral changes of Occupant #2 does not have a noticeable impact on the decision-making of the situation-specific method, and subsequently the visual conditions of occupants.

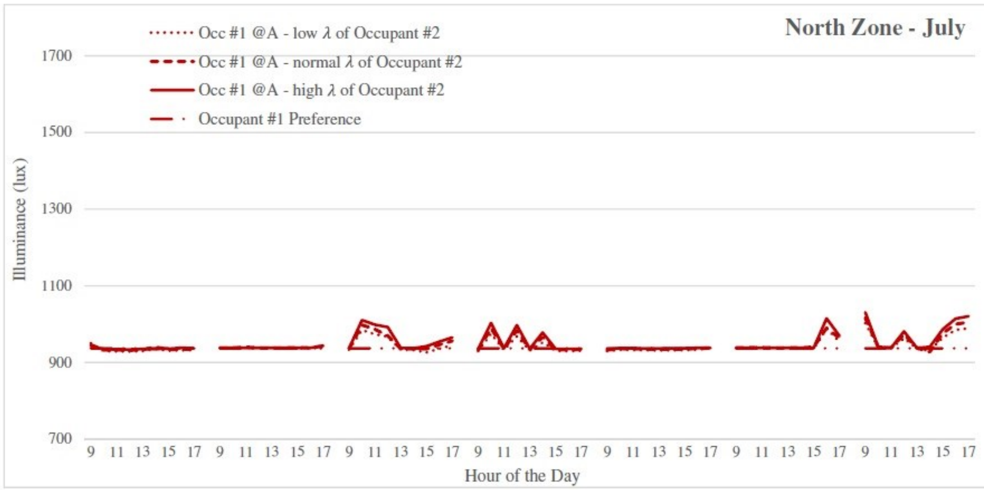

Fig. 113: The visual conditions of Occupant #1 with respect to $\lambda_{Occupant\#2}$ variation in north zone - The warm season analysis

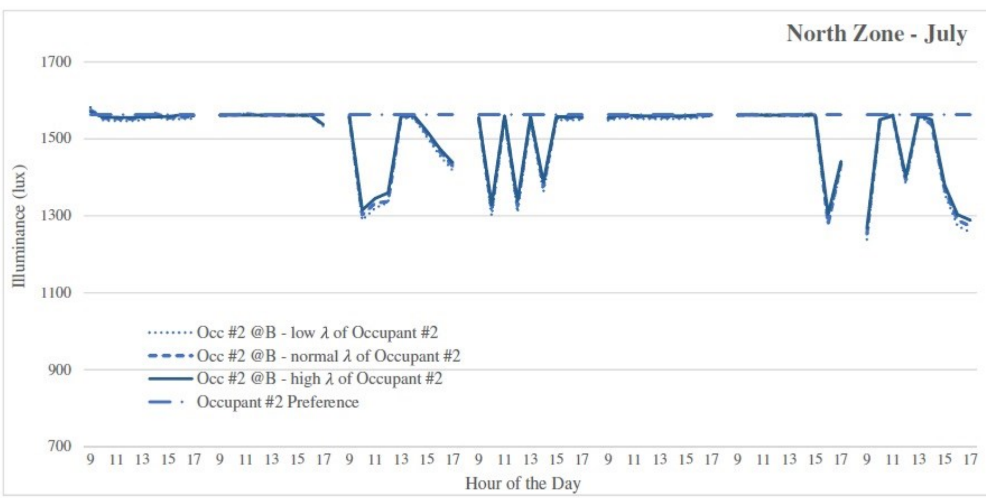

Fig. 114: The visual conditions of Occupant #2 with respect to $\lambda_{Occupant\#2}$ variation in north zone - The warm season analysis

7.5.2 Effect of Loss Aversion Coefficient (λ): Four Occupants

An arbitrary scenario of having four occupants in west zone, during the first week of January is considered. Under this scenario, it is assumed that Occupant #1 is in Position-A, Occupant #2 is in Position-B, Occupant #3 is in Position-C, and Occupant #4 is in Position-D (Fig. 7). A constant hourly productivity of 8 $/h is considered for each of the occupants, during the occupied hours. $\lambda_{\text{Occupant\#2}}$, $\lambda_{\text{Occupant\#3}}$, and $\lambda_{\text{Occupant\#4}}$ are assumed to be fixed and equal to 2.25, the default value in (3.39), while $\lambda_{\text{Occupant\#1}}$ varies. In three different situations, loss aversion coefficient of Occupant #1 is assumed to be: (1) $\lambda_{\text{Occupant\#1}}=1$, (2) $\lambda_{\text{Occupant\#1}}=2.25$, and (3) $\lambda_{\text{Occupant\#1}}=5$.

The behavioral intelligence of the situation-specific method is evaluated, in three different situations of Occupant #1 behavior. Accordingly, the performance of the situation-specific method, with respect to the thermal and visual conditions of all four occupants of west zone is analyzed. Hourly operative temperatures (°C) in each of the four positions, in different situations of Occupant #1 behavior are presented (Fig. 115, Fig. 116, Fig. 117, and Fig. 118). In the situations that Occupant #1 has a relatively higher loss aversion coefficient (e.g. $\lambda_{\text{Occupant\#1}}=5$), the occupant is more sensitive to the indoor environmental conditions. The situation-specific method respects the higher sensitivity of the occupant. Consequently, hourly operative temperatures (°C) are higher and closer to $T_{\text{maxcomfort}}$ of Occupant #1 (25.5 °C), compared to the alternative situations (Fig. 115).

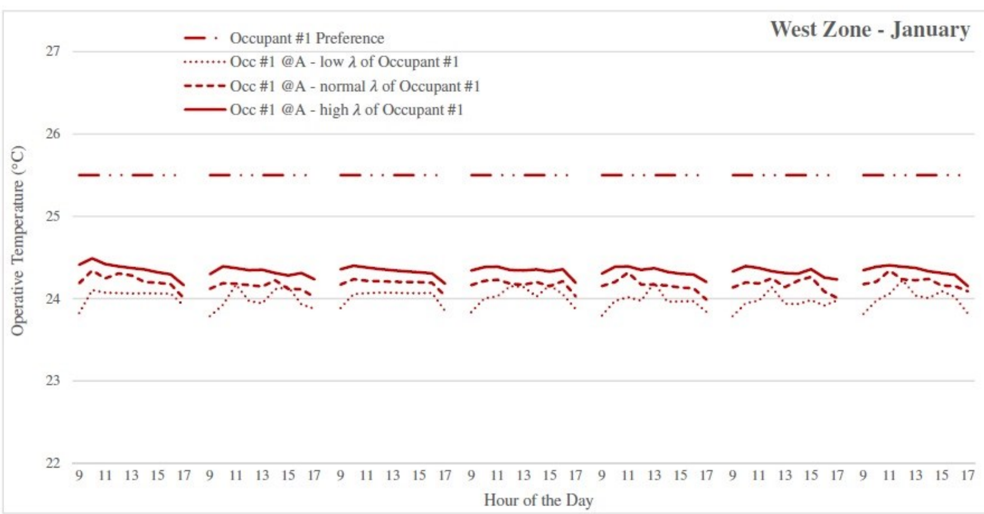

Fig. 115: The thermal conditions of Occupant #1 with respect to $\lambda_{\text{Occupant\#1}}$ variation in west zone – The cold season analysis

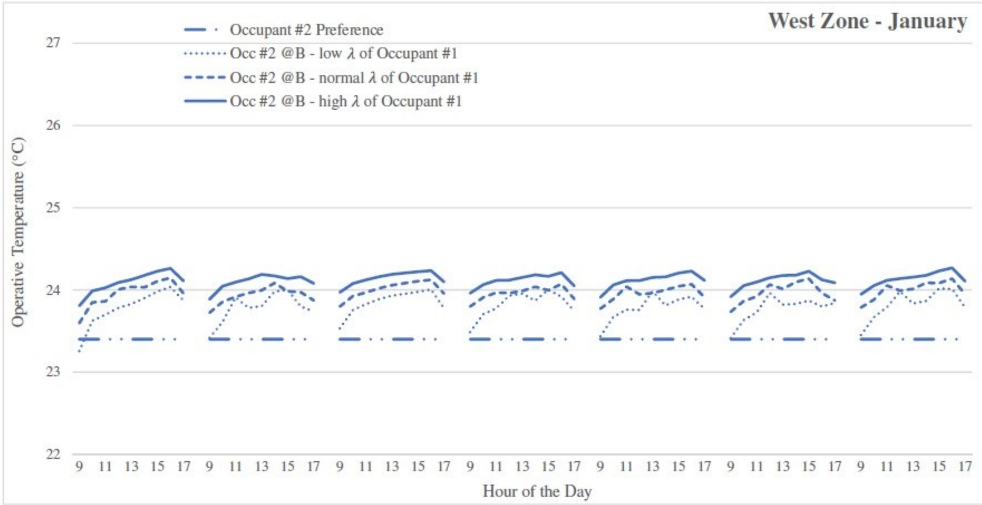

Fig. 116: The thermal conditions of Occupant #2 with respect to $\lambda_{Occupant\#1}$ variation in west zone – The cold season analysis

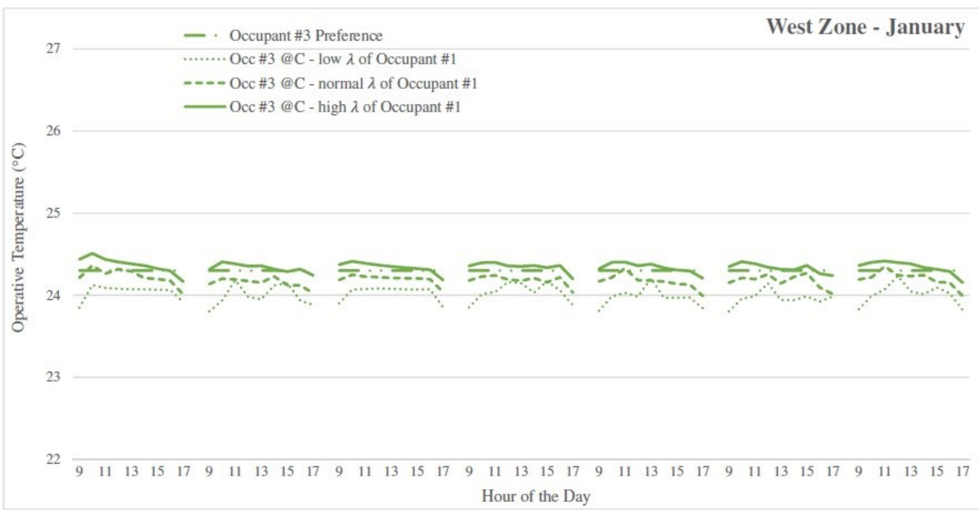

Fig. 117: The thermal conditions of Occupant #3 with respect to $\lambda_{Occupant\#1}$ variation in west zone – The cold season analysis

The variations in the loss aversion coefficient of Occupant #1 influence the thermal comfort of other occupants in west zone, as well. The higher sensitivity of Occupant #1 (higher λ) has negative impacts on the thermal conditions of Occupant #2 with $T_{\text{maxcomfort}}$ of 23.4 °C (Fig. 116) and Occupant #4 with $T_{\text{maxcomfort}}$ of 23.9 °C (Fig. 118). On the other hand, the thermal conditions of Occupant #3 in Position-C, with a relatively higher $T_{\text{maxcomfort}}$ of 24.3 °C, are improved with the increase in $\lambda_{\text{Occupant\#1}}$ (Fig. 117). Within the situation-specific method, behavioral change of each occupant has impacts on the thermal conditions of that occupant, as well as the thermal comfort of other occupants in the zone.

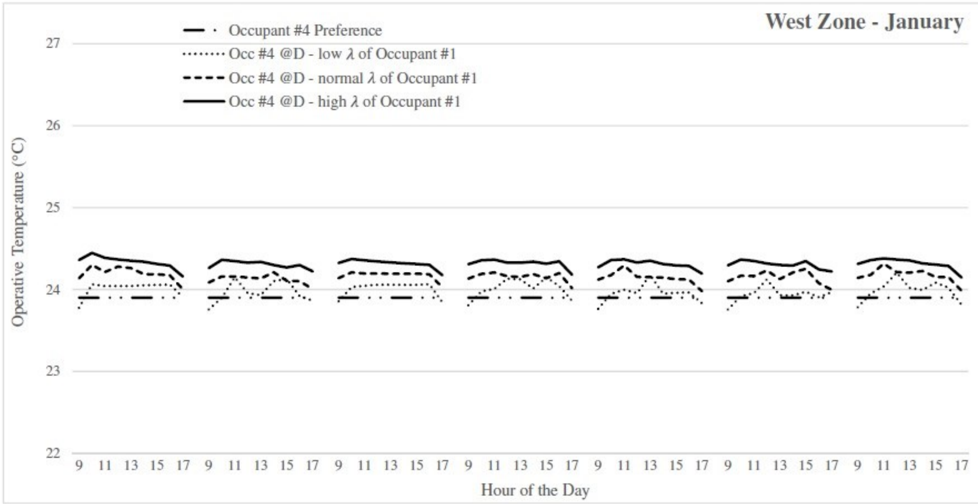

Fig. 118: The thermal conditions of Occupant #4 with respect to $\lambda_{Occupant\#1}$ variation in west zone – The cold season analysis

The influence of occupants' behavior is not limited to the thermal conditions of occupants. $\lambda_{\text{Occupant\#1}}$ variation would result in the change in the visual conditions of all occupants, as well. The levels of hourly illuminance (lux) in each position of west zone are investigated (Fig. 119, Fig. 120, Fig. 121, and Fig. 122). With the increase in $\lambda_{\text{Occupant\#1}}$, hourly illuminance levels (lux) in Position-A, approach $ILL_{\text{maxcomfort}}$ of Occupant #1 (937 lux), to acknowledge the relatively higher sensitivity of Occupant #1 to the indoor environmental conditions (Fig. 119).

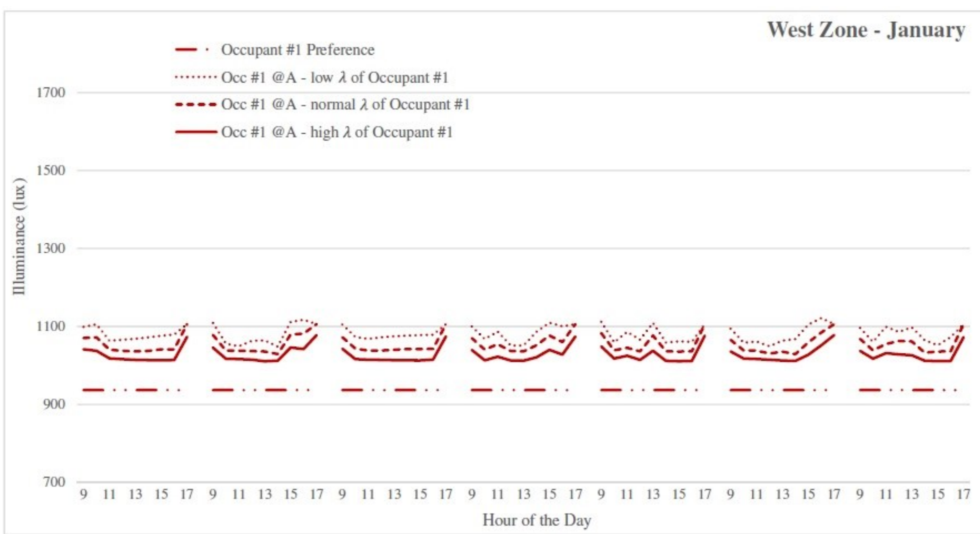

Fig. 119: The visual conditions of Occupant #1 with respect to $\lambda_{Occupant\#1}$ variation in west zone – The cold season analysis

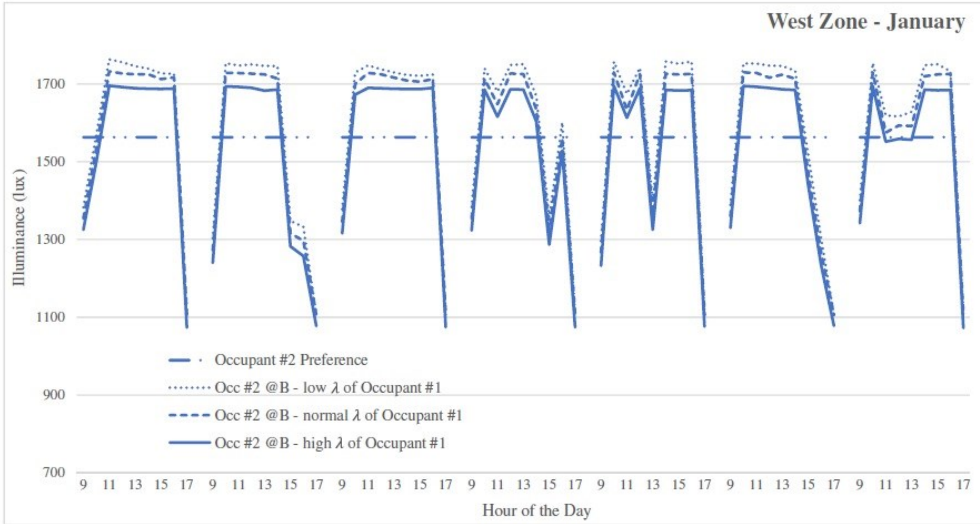

Fig. 120: The visual conditions of Occupant #2 with respect to $\lambda_{Occupant\#1}$ variation in west zone – The cold season analysis

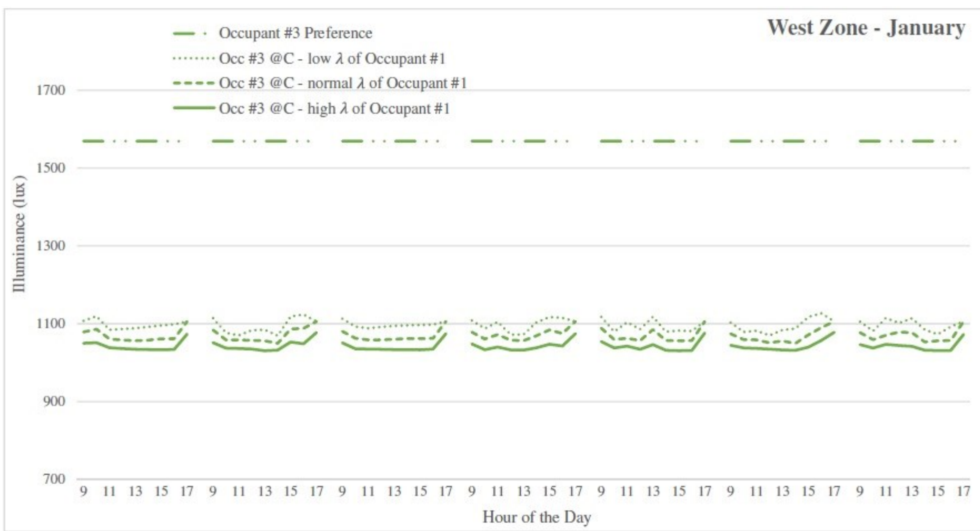

Fig. 121: The visual conditions of Occupant #3 with respect to $\lambda_{Occupant\#1}$ variation in west zone – The cold season analysis

In the situation of high $\lambda_{Occupant\#1}$, the visual conditions of Occupant #2 and Occupant #4 that are sitting near the window are also improved (Fig. 120 and Fig. 122). In fact, the situation-specific method improves the visual conditions of Occupant #2 and Occupant #4 to compensate the decline in their thermal comfort, when $\lambda_{Occupant\#1}$ increases (Fig. 116 and Fig. 118). On the other hand, the increase in $\lambda_{Occupant\#1}$ has a negative impact of the visual comfort of Occupant #3 (Fig. 121).

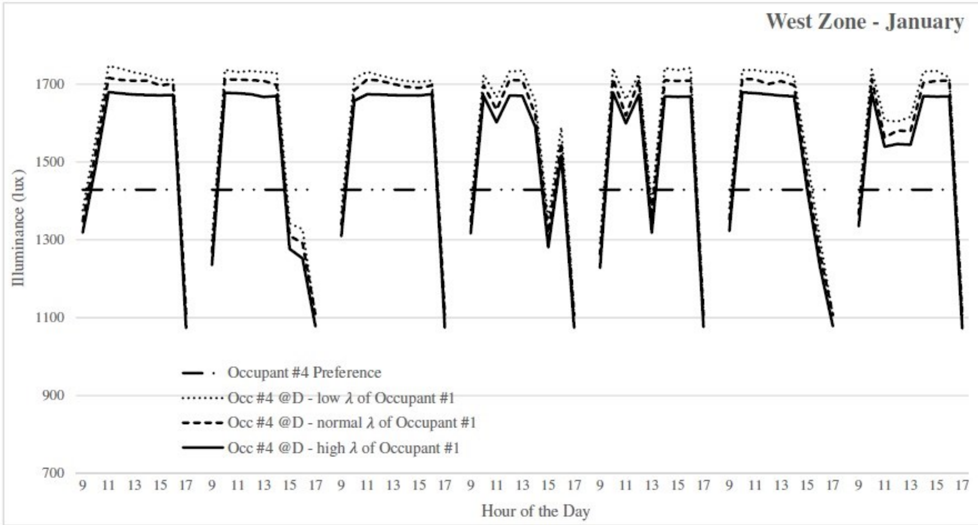

Fig. 122: The visual conditions of Occupant #4 with respect to $\lambda_{Occupant\#1}$ variation in west zone – The cold season analysis

7.6 Chapter Summary

In this chapter, the performance of the *situation-specific* method, proposed in Section 3.5, is evaluated. Within the situation-specific method, adaptive behavior of an occupant varies, according to the *specific situation* in the indoor environment. Hereby, alongside the environmental parameters, the influence of human-related parameters (e.g. mood and emotions) on the adaptive behavior of occupants can also be considered. Accordingly, the situation-specific method can offer *behavioral intelligence* by acknowledging occupants' behavior, while making energy-related decisions for the automated control of the indoor environment.

Similar to the proposed methods in previous chapters, the situation-specific method has the objective to simultaneously optimize energy costs and productivity of occupants. By simulating the operation of the situation-specific method, in different zones of the office, in varied outdoor weather conditions, it is demonstrated that the situation-specific method achieves its objective. The situation-specific method makes energy-related decisions, according to the varied thermal preferences, visual preferences, productivity rates, and positions of occupants. The sensitivity of the proposed method to these parameters is analyzed, by studying the performance of the method, under varied scenarios of occupancy.

Each occupant's energy-related behavior is computationally modeled, using the prospect theory [86, 109]. Accordingly, *LR* of *2nd category behavior* (adjusting the indoor environment to restore personal comfort) is derived. The large value of *LR* (*2nd Category Behavior*) of an occupant in a specific situation, reveals the risk of his or her 2nd category adaptive behavior. From *LR* of an occupant in each situation, his or her situation-specific relative productivity (RP_{Behavior}) is derived. In the situation-specific method, RP_{Behavior} of each occupant is introduced into the objective function of the MOOP problem, in order to optimize the probability of occupants' *2nd category behavior* (adjusting the indoor environment to elevate personal comfort).

By making a comparison between the operation of the position-based method (discussed in Section 3.4 and studied in Chapter 6), and the situation-specific method (discussed in Section 3.5 and studied in this chapter), the behavioral intelligence of the situation-specific method is evaluated. The situation-specific method, while making energy-related decisions for the automated control of the indoor environment, avoids the situations that *LR* (*2nd Category Behavior*) of any occupant is high, and simultaneously optimizes RP_{Behavior} of occupants and energy costs. This is the main improvement in the proposed situation-specific method, compared to the position-based method.

The *loss aversion coefficient* (λ) value, in the decision-making process model of the prospect theory, indicates that people put more weight on their losses, compared to their gains [111]. In different studies on the prospect theory, based on the behavioral parameters considered in the decision-making process, distinct values for the loss aversion coefficient have been found [113, 117]. The flexibility of the situation-specific method to accept different values of loss aversion coefficient (λ) of occupants is discussed. It is confirmed that the situation-specific method has the flexibility to acknowledge human-related parameters, such as mood and emotions, while making personalized decisions for the automated control of the indoor environment.

8 Conclusions and Recommendations for Future Work

There is a strong relationship between indoor environmental conditions of a building and the performances of its occupants; hence, in office buildings, there is a potential to increase the productivity of office workers by improving their comfort conditions. The salaries of office workers are many times higher than the costs of energy consumption; therefore, improving their comfort conditions have significant economic benefits. The common approach to manage energy and comfort in offices, is to consider uniform indoor environmental requirements for all the occupants in a shared enclosed space. However, this approach may lead to significant productivity losses, since it is very probable to have diversity among the environmental preferences of occupants, especially their thermal and visual preferences. In contrast to the common approach for energy and comfort management, the proposed methods in this research, acknowledge the personalized thermal and visual comfort of each occupant, by developing a model for his/her personalized thermal and visual preferences.

In this research, several Multi-Objective Optimization (MOOP) methods have been proposed to simultaneously optimize energy consumption costs and occupants' comfort conditions in office buildings. The objective functions of the MOOP methods are constructed, based on the relationship between occupants' productivity and their comfort conditions. Accordingly, the objectives of the proposed MOOP methods are to simultaneously optimize energy consumption costs and productivity of office workers. A single-floor, multi-zone office building, located in Montreal, Canada is considered and its simplified RC-network thermal model is developed, using MATLAB software. During the occupied hours of the office building, the proposed methods perform automated control of the indoor environment by managing the level of indoor temperature, ventilation rate, natural illumination, and artificial lighting, on an hourly basis, in different zones of the office.

The application of the proposed methods in this research were discussed in Section 1.6. For the proposed methods to be applicable to an office building, the first requirement is to have continuous and user-friendly interaction with occupants, to obtain up-to-date information on their environmental preferences. Recently, different smart phone applications have been built to communicate with occupants and receive their preferences for the indoor environment. However, additional quantitative studies are required to relate various aspects of occupants' comfort and their performances in different tasks. For this research, certain assumptions are made from the results of previously conducted field studies to relate occupants' comfort conditions and productivity, as well as to model thermal and visual preferences of occupants. Having information on the indoor environmental preferences of occupants, the proposed methods are applicable to any office (or more generally, commercial) building.

It should be noted that the proposed methods are able to accept energy prices as variables, and make energy-related decisions based on the price changes. Real-time prices can be transmitted from the utility side to the building gateways, through the smart grid. Accordingly, the office buildings and their occupants can participate in demand-side management programs, by adjusting their situation-dependent energy-related behavior.

Furthermore, in this research, the results of MOOP of energy costs and occupants' productivity, are demonstrated on an hourly basis. However, the ultimate goal of this research is to propose an adaptive personalized method that can make near real-time energy-related decisions, according to the changes in occupants' preferences and behavior, as well as in indoor and outdoor environmental parameters, and energy prices. For this purpose, an adaptive control system is required to timely respond to the changes in the influential human-related and environmental parameters.

In the proposed position-based method, as well as the situation-specific method, thermal and visual comfort of occupants are evaluated based on their positions in the zones. Indoor Air Quality (IAQ) requirements of occupants can also be assessed according to their positions in enclosed spaces. For this purpose, the first step is to model building ventilation system in the simplified thermal model of the office. Here, IAQ of the office building is evaluated by studying the level of ventilation rate (l/s per person) in each zone. Alternatively, Carbon Dioxide-level (CO2-level), which is a more common indicator, can be used for IAQ analysis in the building.

Moreover, in this research, the combined effect of thermal conditions, visual conditions and IAQ on the performance of the occupants are optimized. Alternatively, the effect of different aspects of indoor environmental conditions on occupants' productivity can be evaluated separately to more accurately identify the potentials for productivity improvement in office buildings.

Another point is related to the indoor environmental monitoring in offices. Inside an office building, various environmental sensors should be installed, depending on the plan of the office and the positions of occupants inside enclosed spaces. In this research, indoor temperature, mean-radiant temperature, ventilation rate, as well as illuminance level should be continuously measured; hence, in each enclosed space of an office, temperature sensors, light sensors, mean-radiant temperature sensors, and air flow sensors may be required. Moreover, a wireless sensor network is required to transmit environmental data and energy-related decisions (commands) across the office.

Recently, the use of Internet of Things (IoT) technologies for smart buildings have become popular. IoT technologies create open software translation layers for data communication, in order to connect several devices inside a building. For intelligent energy and comfort management of office buildings, the use of IoT technologies facilitate the communication between environmental sensors, the energy management system, controllers and actuators. Moreover, IoT technologies enable cloud-based intelligent energy and comfort management. The proposed methods are able to act as the *brain* behind the decision-making system of a cloud-based energy management platform. Consequently, the required hardware and software infrastructure for the implementation of the proposed methods would be reduced significantly. The application of the proposed methods for personalized energy and comfort management are yet to be studied in a real office building, with real occupants. However, the idea of this research is to study the application of personalized energy management system to simultaneously optimize office workers' productivity and energy costs, by considering human-related parameters that have not been considered in the previous studies.

8.1 Summary of Key Outcomes

First, based on the previous studies on the relationship between productivity and comfort conditions [28, 31], for all occupants, a unique relationship between their productivity and indoor thermal conditions and another relationship between their productivity and IAQ are considered.

Accordingly, a method for MOOP of energy costs and productivity, considering the thermal comfort of occupants and IAQ of the zones, was developed and studied. Based on the provided results in Chapter 4, it is concluded that:

- The proposed MOOP method can generate Pareto optimal solutions for the automated control of the indoor environment, in each zone, according to the level of *hourly productivity* ($/h) of occupants in the zone.
- With the increase in hourly productivity ($/h) of occupants in a zone, thermal conditions and IAQ of the zone are improved.
- While optimizing energy consumption costs of the office building, the MOOP method is able to avoid significant productivity losses ($), by providing occupants with their preferred thermal conditions and improving IAQ of the zones.
- The method can improve the productivity of occupants (with 20 $/h productivity rate) by up to $1000 per year per person, compared to the SOOP method (without occupants' comfort in its objective function).
- External parameters, including outdoor weather conditions and solar irradiance, influence the performance of the proposed method, and consequently, the thermal conditions of the occupants and IAQ of the zones.
- Occupants' thermal preferences and their tolerance ranges have impacts on the automated control of the indoor environment.

Based on the adaptive thermal comfort studies, parameters such as age, gender, outdoor weather conditions, social dimensions, economical background, history of thermal sensations, perceived control over the environment, psychological and physiological adaptation to the environment, and behavioral adjustment, influence the thermal sensations of occupants [16, 20]. Thus, occupants in a shared space may have varied thermal preferences for the indoor environment. A *personalized* method for energy and comfort management is developed to consider each occupant's personalized thermal preference and tolerance. The method performs MOOP of energy costs, thermal comfort and IAQ, in different zones of the office. By analyzing the performance of the personalized method with respect to thermal comfort of occupants, IAQ of the zones, and energy consumption costs, the following results are concluded:

- Occupants' thermal preference models can be introduced into the MOOP problem formulation to perform personalized energy and comfort management.
- If the indoor environmental conditions of the office building are managed according to a single thermal preference, occupants with alternative thermal preferences would experience significant productivity losses.
- In each zone of the office, thermal preferences of all occupants are respected by the personalized method, in order to maximize the collective productivity of occupants.
- Alongside thermal preferences, thermal behavior (tolerance range) of occupants also influence the performance of the personalized method.
- The personalized method can benefit from the higher thermal tolerances of occupants to optimize the energy consumption costs.

Occupants' perceptions of the indoor environment, specifically their thermal and visual sensations, depend on their positions inside enclosed spaces. Moreover, occupants in a shared space may have varied visual preferences for the indoor environment [26]. The proposed *position-based* method performs MOOP of energy costs and productivity, considering personalized thermal and visual preferences of occupants, their positions, and IAQ of the zones, as well as energy consumption costs. The performance of the position-based method in the office building is studied, under different occupancy scenarios, in varied outdoor weather conditions. Based on the provided results in Chapter 6, it is concluded that:

- The proposed position-based method is able to simultaneously optimize the productivity of occupants and energy consumption costs, by acknowledging thermal and visual preferences of occupants, and their positions inside the zones.
- Thermal and visual preferences of each occupant influence his or her own thermal and visual conditions, as well as those of other occupants.
- The position-based method can benefit from the varied thermal and visual behavior (higher tolerance ranges) of an occupant (or occupants), to improve other occupants' thermal and visual conditions and/or to reduce the energy consumption costs.

When the control of the indoor environment in an enclosed space is at group-level, there might be varied levels of satisfaction from the indoor environmental conditions. Dissatisfied occupants in the space might adjust the indoor environment to improve their personal comfort. Within the *situation-specific* method, occupants' potential responses to the indoor environmental conditions, in each specific situation of the indoor environment are modeled, in order to minimize the probability of their dissatisfaction. The prospect theory is used to model each occupant's decision-making process that might result in his or her *2nd category adaptive behavior* (which is adjusting the indoor environment to improve personal comfort). Accordingly, each occupant's situation-specific relative productivity is constructed (RP_{Behavior}) as the product of his or her thermal and visual sensations, and situation-dependent behavioral parameters. The objective of the situation-specific method is to simultaneously optimize energy costs and RP_{Behavior} of occupants. Based on the provided results of the operation of the method, under different occupancy scenarios, in varied outdoor weather conditions, it is concluded that:

- Compared to the position-based method, the situation-specific method further improves the productivity of occupants, by making energy-related decisions according to each specific situation in the indoor environment, as well as personalized thermal and visual preferences of occupants and their positions.
- Situation-specific behavior of each occupant has an impact on his or her thermal and visual conditions.
- Within the situation-specific method, the thermal and visual conditions of all other occupants in an enclosed space are influenced by the change in the situation-specific behavior of an individual.
- Having the *behavioral intelligence*, the situation-specific method can benefit from the variations in occupants' behavior, in order to reduce the energy consumption costs.
- The situation-specific method has the flexibility to accept additional human-related parameters (e.g. mood and emotions), as the influential parameters in energy-related decision-making.

8.2 Future Work

The proposed methods in this research are able to acknowledge a number of human-related parameters, including occupants' thermal and visual preferences, thermal and visual behavior, and positions, in order to make personalized decisions for energy and comfort management.

Furthermore, the situation-specific method can offer behavioral intelligence, by acknowledging situation-specific human-related parameters, while performing automated control of the indoor environment. The recommended future research work on the proposed personalized methods for energy and comfort management, follows from the advancements of the present research study, and the potential to further enhance the behavioral intelligence of the situation-specific method:

1. Using the prospect theory in the situation-specific method, to model the decision-making process, the method has the capability to acknowledge the influence of affective processes (emotion, mood, and feeling) on the decision-making process and adaptive behavior of occupants. A topic for future work is to propose an emotional intelligent energy and comfort management method, with the objective to simultaneously optimize occupants' productivity and energy costs. For this purpose, the studies on the influence of affective processes on the decision-making process should be reviewed [116-118].
2. Within the situation-specific method, an occupant's decision-making process, and consequently, his or her adaptive behavior, are represented by the two terms of *value of action* and *costs of action*. Using neuroeconomics studies [106, 107, 119, 120], dynamic value/costs can be assigned to each action. Accordingly, the influence of additional psychological and physiological parameters, including short-term adaptation and the level of deprivation, on the decision-making and behavior of occupants, can be modeled. For this purpose, the subjective value/costs of energy-related decisions, and the loss aversion coefficient (λ) can be considered as *situation-dependent* variables [106-108, 120]. Hereby, the behavioral intelligence of the proposed method would be further enhanced.
3. From the studies on the subject of values and their effect on pro-environmental behavior [72-74], the level of environmental concern of each occupant can be modeled. Accordingly, the proposed method can make energy-related decisions, based on the levels of environmental concern, alongside other influential human-related parameters.
4. The other direction for future work is to apply the proposed methods to a real office building with real occupants, in order to test and validate the methods. The main requirements to design the planned experiment are wireless sensor network for real-time monitoring of the indoor environmental parameters, and a smartphone application (or a web-based application) to have continuous interaction with the occupants. When the

proposed methods are applied to a real office building, additional sensitivity analysis would be beneficial to identify the impact of each specific parameter on productivity of occupants, as well as energy costs. Such an in-depth study on a real building can give more depth to the outcomes of this research and suggest new directions for further work on this topic.

5. This research was performed based on existing data and understanding of the relationships between relative productivity and indoor environmental conditions. Based on these relationships, selected parametric simulations were performed to demonstrate the application of the proposed methods. The relationship between relative productivity and indoor environmental conditions is the subject of many ongoing research studies. As our understanding is improved for such relationships, the optimization can be expanded to incorporate new information.

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Appendix A: Validating the Developed RC-Network Thermal Model

The RC-network thermal model of the office building (developed in MATLAB) is validated by comparing its annual energy consumption, with annual energy consumption of a building with the same plan and characteristics, in the same location, considered in eQuest and TRANSYS software. For this purpose, a single-floor building, with five zones (four perimeter zones and one core zone, separated by interior walls), is developed in eQuest and TRANSYS. The building has an overall area of 555 m^2, and is located in Montreal, Quebec, Canada. The input parameters, considered for building construction and operation, are similar in MATLAB, eQuest and TRANSYS. These input parameters (building characteristics, facilities, and schedule), are stated in Table A.1.

Table A. 1: The inputs parameters, considered in building energy performance simulation; similar for MATLAB, eQuest and TRANSYS

Input Parameter	***Value / Description***
Window-Wall Ratio	0.4
Ceiling Heights	3 meters
Wall Construction	Wood shingles, plywood, R-13 fiber insulation, gypsum board
Exterior Wall U-Value	0.4 $W/m^2.K$
Exterior Wall Specific Heat	42 kJ/kg.K
Roof	Adiabatic
Interior Wall U-Value	1.5 $W/m^2.K$
Window Glass	0.6 cm plate double pane
Door Glass	1.3 cm plate single pane
Window U-Value	1.4 $W/m^2.K$
Chiller	Reciprocating air cooled chiller
Chiller COP	3.5
Boiler	Gas fired hot water boiler
Electrical Heater Efficiency (n)	1

Input Parameter	*Value / Description*
Occupancy Heat Generation	12.6 W/m^2
Equipment Heat Generation	10.7 W/m^2
Lamp Power	15 W/m^2
Cooling Set-Point	26.6 °C
Heating Set-Point	18.3 °C
Infiltration	0.3 ACH
Minimum Indoor Illuminance	50 lux

Using the input parameters in Table A.1, annual energy consumption of the office building, developed in MATLAB, is compared with annual energy consumption of simulated buildings in eQuest and TRANSYS (Fig. A.1). Less than 5% difference is observed between the compared values. Accordingly, the developed building RC-network thermal model in MATLAB is validated.

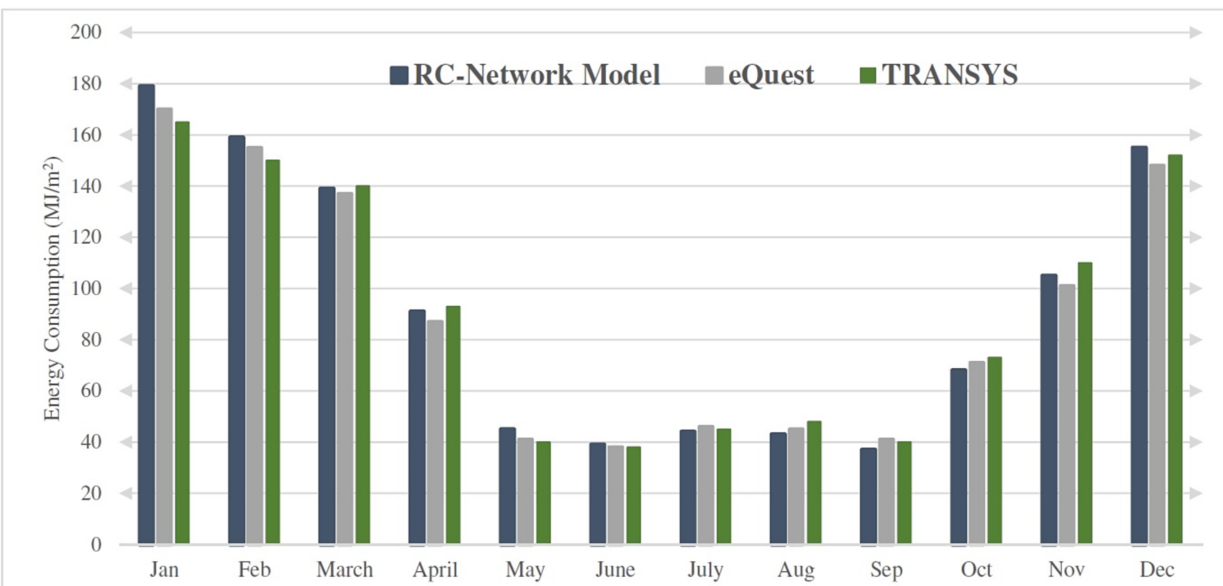

Fig. A.1: Validating the RC-network thermal model of the office building, by comparing its annual energy consumption, with annual energy consumption of the same building, simulated in eQuest and TRANSYS

Appendix B:

Appendix B.1: The code for multi-objective optimization of energy costs and productivity in the (RC-network thermal model of the) multi-zone office building, located in Montreal, Canada:

```
% Introducing Variables:
% [Artificial Lighting, Blind Position, Cooling Energy, Heating Energy,
% Inside Temeprature, Outside Air Flow Rate, Exterior Wall Inside Temperature,
% Exterior Wall Outside Temperature]


% Introducing Constraints on Variables including Controlled Environmental Parameters:

    if hr(i)<9 || hr(i)>17
        lb=[0 0 0 0 18.3 0 -Inf -Inf];
        ub=[1 1 Inf Inf 26.6 0.002 Inf Inf];
    else
        lb=[0 0 0 0 21 0.0007 -Inf -Inf];
        ub=[1 1 Inf Inf 25.5  0.002 Inf Inf];
    end

    if hr(i)<9 || hr(i)>17
        lb_dynamic=[0 0 0 0 18.3 0 -Inf -Inf];
        ub_dynamic=[1 1 Inf Inf 26.6 0.002 Inf Inf];
    else
        lb_dynamic=[0 0 0 0 -Inf 0.0007 -Inf -Inf];
        ub_dynamic=[1 1 Inf Inf Inf 0.002 Inf Inf];
    end


% Introducing Both Linear & Non-Linear Constraints:

    Aeqeast=[0 0 0 0 0 0 -0.005 1;0 0 0 0 -0.16 0 1 -0.008];
    Beqeast=[0.54*Texternaleast0+0.44*temp(i);0.82*Tsurfaceeast0];

    Aeqwest=[0 0 0 0 0 0 -0.005 1;0 0 0 0 -0.16 0 1 -0.008];
    Beqwest=[0.54*Texternalwest0+0.44*temp(i);0.82*Tsurfacewest0];

    Aeqnorth=[0 0 0 0 0 0 -0.005 1;0 0 0 0 -0.16 0 1 -0.008];
    Beqnorth=[0.54*Texternalnorth0+0.44*temp(i);0.82*Tsurfacenorth0];

    Aeqsouth=[0 0 0 0 0 0 -0.005 1;0 0 0 0 -0.16 0 1 -0.008];
    Beqsouth=[0.54*Texternalsouth0+0.44*temp(i);0.82*Tsurfacesouth0];


% Introducing Main Part of the Optimization Method:

       if hr(i)<9 || hr(i)>17

        [Y_east(:,i),q_east(i)] =fmincon(@totalenergy_east,XX_east,[],[],
```

```
    Aeqeast,Beqeast,lb,ub,@(X)confuneq_east(X,i,T_east,T_south,T_north,
    T_central,ILLsun_east,Qsolar_east,temp));
    XX_east=Y_east(:,i);
    T_east=Y_east(5,i);
    Tsurfaceeast0=Y_east(7,i);
    Texternaleast0=Y_east(8,i);

    [Y_west(:,i),q_west(i)] =fmincon(@totalenergy_west,XX_west,[],[],
    Aeqwest,Beqwest,lb,ub,@(X)confuneq_west(X,i,T_west,T_south,T_north,
    T_central,ILLsun_west,Qsolar_west,temp));
    XX_west=Y_west(:,i);
    T_west=Y_west(5,i);
    Tsurfacewest0=Y_west(7,i);
    Texternalwest0=Y_west(8,i);

    [Y_north(:,i),q_north(i)] =fmincon(@totalenergy_north,XX_north,[],
    [],Aeqnorth,Beqnorth,lb,ub,@(X)confuneq_north(X,i,T_north,T_east,
    T_west,T_central,ILLsun_north,Qsolar_north,temp));
    XX_north=Y_north(:,i);
    T_north=Y_north(5,i);
    Tsurfacenorth0=Y_north(7,i);
    Texternalnorth0=Y_north(8,i);

    [Y_south(:,i),q_south(i)] =fmincon(@totalenergy_south,XX_south,[],
    [],Aeqsouth,Beqsouth,lb,ub,@(X)confuneq_south(X,i,T_south,T_east,
    T_west,T_central,ILLsun_south,Qsolar_south,temp));
    XX_south=Y_south(:,i);
    T_south=Y_south(5,i);
    Tsurfacesouth0=Y_south(7,i);
    Texternalsouth0=Y_south(8,i);

    [Y_central(:,i),q_central(i)] =fmincon(@totalenergy_central,
    XX_central,[],[],[],[],lb,ub,@(X)confuneq_central(X,i,T_central,
    T_east,T_west,T_south,T_north,temp));
    XX_central=Y_central(:,i);
    T_central=Y_central(5,i);

else

    for k=1:1:10

        w2_east=k;
        w2_west=k;
        w2_north=k;
        w2_south=k;
        w2_central=k;

        [Y_east_occ(k,:,i),q_east(i)] =
        fmincon(@(X)totalenergycomfort_east(X,Tset_east(i),
        Pro_base_east(i),w2_east),XX_east,[],[],Aeqeast,Beqeast,
        lb_dynamic,ub_dynamic,@(X)confuneq_east(X,i,T_east,T_south,
        T_north,T_central,ILLsun_east,Qsolar_east,temp));

        [Y_west_occ(k,:,i),q_west(i)] =
```

```
            fmincon(@(X)totalenergycomfort_west(X,Tset_west(i),
            Pro_base_west(i),w2_west),XX_west,[],[],Aeqwest,Beqwest,
            lb_dynamic,ub_dynamic,@(X)confuneq_west(X,i,T_west,T_south,
            T_north,T_central,ILLsun_west,Qsolar_west,temp));

            [Y_north_occ(k,:,i),q_north(i)] =
            fmincon(@(X)totalenergycomfort_north(X,Tset_north(i),
            Pro_base_north(i),w2_north),XX_north,[],[],Aeqnorth,Beqnorth,
            lb_dynamic,ub_dynamic,@(X)confuneq_north(X,i,T_north,T_east,
            T_west,T_central,ILLsun_north,Qsolar_north,temp));

            [Y_south_occ(k,:,i),q_south(i)] =
            fmincon(@(X)totalenergycomfort_south(X,Tset_south(i),
            Pro_base_south(i),w2_south),XX_south,[],[],Aeqsouth,Beqsouth,
            lb_dynamic,ub_dynamic,@(X)confuneq_south(X,i,T_south,T_east,
            T_west,T_central,ILLsun_south,Qsolar_south,temp));

            [Y_central_occ(k,:,i),q_central(i)] =
            fmincon(@(X)totalenergycomfort_central(X,Tset_central(i),
            Pro_base_central(i),w2_central),XX_central,[],[],[],[],
            lb_dynamic,ub_dynamic,@(X)confuneq_central(X,i,T_central,
            T_east,T_west,T_south,T_north,temp));


        XX_central=Y_central_occ(1,:,i);
        T_central=Y_central_occ(1,5,i);

        XX_east=Y_east_occ(1,:,i);
        T_east=Y_east_occ(1,5,i);
        Tsurfaceeast0=Y_east_occ(1,7,i);
        Texternaleast0=Y_east_occ(1,8,i);

        XX_west=Y_west_occ(1,:,i);
        T_west=Y_west_occ(1,5,i);
        Tsurfacewest0=Y_west_occ(1,7,i);
        Texternalwest0=Y_west_occ(1,8,i);

        XX_north=Y_north_occ(1,:,i);
        T_north=Y_north_occ(1,5,i);
        Tsurfacenorth0=Y_north_occ(1,7,i);
        Texternalnorth0=Y_north_occ(1,8,i);

        XX_south=Y_south_occ(1,:,i);
        T_south=Y_south_occ(1,5,i);
        Tsurfacesouth0=Y_south_occ(1,7,i);
        Texternalsouth0=Y_south_occ(1,8,i);
    end


% Introducing Objective Function - East Zone as a Sample

function objfun = totalenergycomfort_east( X,Tset_east,w2_east,Pro_base_east)

Aroom_east=50.66;
```

```
Eh_eastin2=3600*(X(4)+0.1*X(4));
Ec_eastin2=3600*(X(3)/3.5+0.1*X(3));
El_eastin2=3600*(X(1)*15.8*Aroom_east);
Ef_eastin2=3600*(X(6)*1760);

Eh_eastin_kwh=Eh_eastin2/(3.6*10^6);
Ec_eastin_kwh=Ec_eastin2/(3.6*10^6);
El_eastin_kwh=El_eastin2/(3.6*10^6);
Ef_eastin_kwh=Ef_eastin2/(3.6*10^6);

Relative_Pro_east=max(0,(0.1647524*X(5)-0.0058274*X(5)^2+ 0.0000623*X(5)^3-0.4685328));
Relative_Pro_east_vent=0.021 * log(X(6)*9285)+0.960;

objfun=(0.05*(Eh_eastin_kwh)+0.08*(Ef_eastin_kwh+El_eastin_kwh)+...
    0.1*(Ec_eastin_kwh))+ ...
    w2_east*Pro_base_east*1/4*(1/2*((1-Relative_Pro_east)+...
    (1-Relative_Pro_east_vent))+...
     3*max((1-Relative_Pro_east),...
    (1-Relative_Pro_east_vent)));

end

% Introducing Energy Consumption Function - East Zone as a Sample

Aroom_east=50.66;

energyconsumption_east=zeros(8760,1);

Eh_east=zeros(8760,1);
Ec_east=zeros(8760,1);
El_east=zeros(8760,1);
Ef_east=zeros(8760,1);
Eh_east_kwh=zeros(8760,1);
Ec_east_kwh=zeros(8760,1);
El_east_kwh=zeros(8760,1);
Ef_east_kwh=zeros(8760,1);
totalcost_east=zeros(8760,1);

for i=1:8760

Eh_east(i)=3600*(Y_east(4,i)+0.1*Y_east(4,i));
Ec_east(i)=3600*(Y_east(3,i)/3.5+0.1*Y_east(3,i));
El_east(i)=3600*(Y_east(1,i)*15.8*Aroom_east);
Ef_east(i)=3600*(Y_east(6,i)*1760);

energyconsumption_east(i)= Eh_east(i)+Ec_east(i)+El_east(i)+Ef_east(i);

Eh_east_kwh(i)=Eh_east(i)/(3.6*10^6);
Ec_east_kwh(i)=Ec_east(i)/(3.6*10^6);
El_east_kwh(i)=El_east(i)/(3.6*10^6);
Ef_east_kwh(i)=Ef_east(i)/(3.6*10^6);

totalcost_east(i)=0.05*(Eh_east_kwh(i))+...
```

```
    0.08*(Ef_east_kwh(i)+El_east_kwh(i))+...
    0.1*(Ec_east_kwh(i));

end

% Introducing Constraints Function including RC-Network Thermal Modeling of the Building -
% East Zone as a Sample

function [ c, ceq ] =
confuneq_east(X,i,T_east,T_central,T_north,T_south,ILLsun_east,Qsolar_east,temp,w1,w2)

Toutdoor=temp;
Teast0=T_east;
Tnorth0=T_north;
Tsouth0=T_south;
Tcentral0=T_central;

Cint=1006;
dt=1;
Awin=22.1;
Urr=1.53;
Usr=8.5;
Awallin=23;
Awallinsmall=15;
Awall=22.2;
Aroomsur=95;


    if hr(i)<9 || hr(i)>17
        c= 430.5- ILLsun_east(i)*X(2)-1106*X(1);
        Qint=233;
    else
        c= 753.5- ILLsun_east(i)*X(2)-1106*X(1);
        Qint=1180;
    end


    ceq=(Cint/dt+1.4*Awin+Usr*Awall+0.0003*Aroomsur*Cint)*X(5)+...
        (0.9*Awin)*X(5)*X(2)-(0.9*Awin*Toutdoor(i))*X(2)+...
        Cint*X(6)*X(5)*Aroomsur-Aroomsur*Cint*X(6)*Toutdoor(i)...
        -Usr*Awall*X(7)-X(4)+X(3)-979.6*X(1)-Awin*...
        Qsolar_east(i)*X(2)*0.8-Qint-Cint*0.0003*Aroomsur*Toutdoor(i)-1.4*...
        Awin*Toutdoor(i)-Cint*Teast0/dt-...
        Urr*Awallin*Tcentral0+Urr*Awallin*X(5)-Urr*Awallinsmall*Tsouth0+...
        Urr*Awallinsmall*X(5)-Urr*Awallinsmall*Tnorth0+Urr*Awallinsmall*X(5);
```

Appendix B.2: Fitting $Prob_{\text{Thermal\_Comfort}}$ (T) into a Gaussian function with a mean value of $T_{\text{maxcomfort}}$ and standard deviation of $Tolerance_{\text{thermal}}$, for Thermal Model #1 to Thermal Model #5:

```
% Fitting "Probability of Thermal Comfort" into a "Gaussian Function" with
% a mean value of "Tmaxcomfort" & standard deviation of "Tolerance Thermal",
% for Thermal Model #1 to Thermal Model #5.

% Thermal Model #1

        Acold_1=11.70;
        Bcold_1=-0.635;
        Ahot_1=-39.72;
        Bhot_1=1.377;

        Tmaxcomfort_Model_1= Mean(Ahot_1,Bhot_1,Acold_1,Bcold_1);
        Tolerance_Model_1=Variance(Ahot_1,Bhot_1,Acold_1,Bcold_1);

% Thermal Model #2

        Acold_2=12.64;
        Bcold_2=-0.697;
        Ahot_2=-21.47;
        Bhot_2=0.839;

        Tmaxcomfort_Model_2= Mean(Ahot_2,Bhot_2,Acold_2,Bcold_2);
        Tolerance_Model_2=Variance(Ahot_2,Bhot_2,Acold_2,Bcold_2);

% Thermal Model #3

        Acold_3=11.64;
        Bcold_3=-0.77;
        Ahot_3=-28.88;
        Bhot_3=1.127;

        Tmaxcomfort_Model_3= Mean(Ahot_3,Bhot_3,Acold_3,Bcold_3);
        Tolerance_Model_3=Variance(Ahot_3,Bhot_3,Acold_3,Bcold_3);

% Thermal Model #4

        Acold_4=8.83;
        Bcold_4=-0.427;
        Ahot_4=-16.39;
        Bhot_4=0.581;

        Tmaxcomfort_Model_4= Mean(Ahot_4,Bhot_4,Acold_4,Bcold_4);
        Tolerance_Model_4=Variance(Ahot_4,Bhot_4,Acold_4,Bcold_4);

% Thermal Model #5

        Acold_Model_5=20.08;
        Bcold_Model_5=-0.999;
        Ahot_Model_5=-22.74;
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        Bhot_Model_5=0.856;

        Tmaxcomfort_Model_5= Mean(Ahot_5,Bhot_5,Acold_5,Bcold_5);
        Tolerance_Model_5=Variance(Ahot_5,Bhot_5,Acold_5,Bcold_5);

% Introducing Mean Function:

function q=Mean(Ahot,Bhot,Acold,Bcold)

ProbofComfort1=zeros(25,2);
ProbofComfort2=zeros(25,2);
Iside_Temperature=zeros(25,2);
Relative_Producticity=zeros(25,2);

Tin=17.5;

for i=1:25

Tin=Tin+1/2;

ProbofComfort1(i,1)=Tin;
ProbofComfort1(i,2)= 1/(1+ exp(Ahot +Bhot*Tin) + exp(Acold + Bcold*Tin));

end

y=max(ProbofComfort1(:,2));

difference=1-y;

for i=1:25

ProbofComfort2(i,2)=ProbofComfort1(i,2)+difference;
ProbofComfort2(i,1)=ProbofComfort1(i,1);
Iside_Temperature(i,1)=ProbofComfort2(i,1);
Relative_Producticity(i,1)=ProbofComfort2(i,2);

end

MyCoeffs=coeffvalues(createFit(Iside_Temperature, Relative_Producticity));

q=MyCoeffs(2);

end

% Introducing Variance Function:

function q=Variance(Ahot,Bhot,Acold,Bcold)

ProbofComfort1=zeros(25,2);
ProbofComfort2=zeros(25,2);
Iside_Temperature=zeros(25,2);
Relative_Producticity=zeros(25,2);

Tin=17.5;
```

```
for i=1:25

Tin=Tin+1/2;

ProbofComfort1(i,1)=Tin;
ProbofComfort1(i,2)= 1/(1+ exp(Ahot +Bhot*Tin) + exp(Acold + Bcold*Tin));

end

y=max(ProbofComfort1(:,2));

difference=1-y;

for i=1:25

ProbofComfort2(i,2)=ProbofComfort1(i,2)+difference;
ProbofComfort2(i,1)=ProbofComfort1(i,1);
Iside_Temperature(i,1)=ProbofComfort2(i,1);
Relative_Producticity(i,1)=ProbofComfort2(i,2);

end

MyCoeffs=coeffvalues(createFit(Iside_Temperature, Relative_Producticity));

q=MyCoeffs(3);

end
```