INVESTIGATION OF HYBRID VENTILATION POTENTIAL OF COMMERCIAL BUILDINGS IN US

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INVESTIGATION OF HYBRID VENTILATION POTENTIAL OF COMMERCIAL BUILDINGS IN US

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To my family who always support me

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TABLE OF CONTENTS

LIST OF TABLES **ixx**

LIST OF FIGURES **xi**

LIST OF SYMBOLS AND ABBREVIATIONS **xiv**

SUMMARY **xiv**

CHAPTER 1. INTRODUCTION **1**
1.1 Background **2**
1.1.1 Naturally Ventilated Building 2
1.1.2 Hybrid Ventilation (Mixed Mode) Building 5
1.2 Literature Review for Natural Ventilation/Hybrid Ventilation Research **8**
1.2.1 Simulation of Natural Ventilation 8
1.2.2 Thermal Comfort in Natural Ventilation 12
1.2.3 Thermal Comfort in Mixed Mode Building 18
1.2.4 Air Quality Influence on Natural Ventilation 20
1.2.5 Control of Hybrid Ventilation 24
1.2.6 Potential of Natural/Hybrid Ventilation 29
1.3 Motivation **30**
1.4 Research Question, Goal and Scope **31**
1.5 Impacts of Natural/Hybrid Ventilation on Building Stakeholders **33**
1.5.1 General Impacts 33
1.5.2 Broader Impacts 45
1.6 Research Framework **47**

CHAPTER 2. UNCERTAINTIES IN BUILDING SIMULATION **50**
2.1 Introduction of Uncertainties in Building Simulation **52**
2.2 Uncertainty Quantification and Propagation **55**
2.2.1 Uncertainty Quantification 56
2.2.2 Uncertainty Propagation 61
2.3 Sensitivity Analysis **63**

CHAPTER 3. DEVELOPMENT OF INTELLIGENT CONTROL FOR HYBRID VENTILATION **65**
3.1 Model Predictive Control (MPC) Development **65**
3.1.1 MPC Development Process 65
3.1.2 Candidate Models and Variables 67
3.1.3 Model and Variable Selection Process 71
3.1.4 Model and Variable Selection Result 76
3.1.5 Central Model Training Result 79
3.1.6 Cost Function and Constraint 83

3.1.7 MPC Verification 83
3.1.8 Developed MPC Overview 85
3.2 Comparison with Rule-Based Control 87

CHAPTER 4. HYBRID VENTILATION USAGE POTENTIAL UNDER BUILDING INTELLIGENCE AND UNCERNTAINTY 91
4.1 Hybrid Ventilation Potential Investigation Process 91
4.2 Hybrid Ventilation Potential Investigation With Uncertainties And Building Intelligence 92
4.2.1 US Climate Zones and Representative Cities 93
4.2.2 Baseline Building 95
4.2.3 Generality of Results 96
4.2.4 Stage 1 Preliminary Investigation 99
4.2.5 Sensitivity Analysis 102
4.2.6 Building Intelligence Development 103
4.2.7 Stage 2 Investigation Results 105
4.3 Influence of Building Intelligence and Uncertainties on Hybrid Ventilation 107

CHAPTER 5. INFLUENCE OF OUTDOOR AIR QUALITY ON NATURAL VENTILATION 109
5.1 Investigation Process of Influence of Outdoor Air Pollutants on Natural Ventilation 109
5.2 Experiment Settings 111
5.3 Investigation Procedures 111
5.3.1 Data Collection and Cleaning 111
5.3.2 Descriptive Statistical Analysis on Air Pollutant Data 113
5.3.3 Representative Air Pollutant Data Selection 122
5.3.4 Air Pollutant Modeling 124
5.4 Emulator Establishment 128
5.5 Scenarios of Investigation 129
5.6 Result Analysis 131

CHAPTER 6. DETERMINISTIC SIMULATION VS. UNCERTAINTY ANALYSIS IN NATURAL VENTILATION DESIGN 138
6.1 Experiment Settings 138
6.1.1 Baseline Building Establishment 138
6.1.2 Thermal Comfort Criteria 140
6.1.3 Applied Uncertainties and Uncertainty Propagation 141
6.2 Thermal Comfort Evaluation Comparison 141
6.2.1 Comparison Result 141
6.3 Design Scenario Tests 143
6.3.1 Shading Design 143
6.3.2 Construction Type 145
6.3.3 Insulation Level 146
6.3.4 Orientation 147
6.4 Conclusion on Deterministic Simulation VS. Uncertainty Analysis 147

6.5 Sensitivity Analysis and Discussion 150

CHAPTER 7. SUMMARY AND CONCLUSIONS 155
7.1 Summary 155
7.2 Contribution 157
7.3 Limitation and Future Research 158

REFERENCES 161

LIST OF TABLES

Table 2.1	-	Urban Settings in Uncertainty Analysis	57
Table 2.2	-	Applied Uncertainties	60
Table 3.1	-	Prediction of Air Temperature	73
Table 3.2	-	Prediction of Operative Temperature	73
Table 3.3	-	Prediction of Energy	74
Table 3.4	-	Adding Variable Sequence	77
Table 3.5	-	Detailed Building Information	80
Table 3.6	-	Building System Configuration	80
Table 3.7	-	Statistical Measures of the Established Prediction Models	81
Table 3.8	-	Performance of MPC	84
Table 3.9	-	Performance Comparison of MPC with RB control	89
Table 4.1	-	Climate Zones and Representative Cities	94
Table 4.2	-	Detailed Baseline Building Information	96
	-		
Table 4.3	-	Comparison Results for Ventilation Mechanism	97
Table 4.4	-	Comparison Results for Building Shapes	98
Table 4.5	-	Comparison Results for Window Wall Ratio	98
Table 4.6	-	Uncertainty Analysis Results using TMY	100
Table 4.7	-	Uncertainty Analysis Results using HMY	101
Table 4.8	-	Hybrid Ventilation Potential Investigation Results	106
Table 4.9	-	Standard Variance of the Energy Saving Percentage	108
Table 5.1	-	Outdoor Air Pollutant in Different Cities	116
Table 5.2	-	Outdoor Air Pollutant in Different Climate Zones	117
Table 5.3	-	Summary of Descriptive Statistical Analysis Result	122

Table 5.4	-	Test Result of Predictions for Three Candidate Model	128
Table 5.5	-	Summary for Outdoor Air Pollutants on Natural Ventilation Usage	132
Table 5.6	-	Influence of Outdoor Air Pollutants on Natural Ventilation Usage in Urban Area	134
Table 5.7	-	Influence of Outdoor Air Pollutants on Natural Ventilation Usage in Suburban Area	135
Table 5.8	-	Influence of Outdoor Air Pollutants on Natural Ventilation Usage in Rural Area	135
Table 6.1	-	Building Information Summary	139
Table 6.2	-	Design Scenario Test Result of roof canopy with overhangs	144
Table 6.3	-	Design Scenario Test Result of only attaching west shading	144
Table 6.4	-	Design Scenario Test Result of different Construction type with wall	146
Table 6.5	-	Design Scenario Test Result of Different wall insulation level	146
Table 6.6	-	Design Scenario Test Result with Influence of orientation	147

LIST OF FIGURES

Figure 1.1	-	Natural Ventilation Principles	3
Figure 1.2	-	GSW Headquarter Center	4
Figure 1.3	-	Principles of Hybrid Ventilation	7
Figure 1.4	-	Macerata building, Italy	8
Figure 1.5	-	PMV – PPD Curve	14
Figure 1.6	-	Adaptive Thermal Comfort Model Comfort Zone (ASHRAE 55)	15
Figure 1.7	-	Rule-based Control Example	26
Figure 1.8	-	Hybrid Ventilation Building Development Process	37
Figure 1.9	-	Average Score of Mixed Mode Building	43
Figure 1.10	-	Score Distribution of Mixed Mode Building	44
Figure 1.11	-	Research Framework	48
Figure 2.1	-	Predicted and measured EUI of LEED buildings	50
Figure 2.2	-	EER Diagram for Physical Model Uncertainty	54
Figure 2.3	-	EER Diagram for Scenario	55
Figure 2.4	-	PDF of quantified ground reflectance	58
Figure 2.5	-	GURA-W Working Process	62
Figure 3.1	-	MPC Development Process	66
Figure 3.2	-	Neural Network Model	71
Figure 3.3	-	Statistical Measures for Different Models with Variables	74
Figure 3.4	-	Baseline Building Configurations	80
Figure 3.5	-	Residual Plots for three phase NN model Training (LA)	82
Figure 3.6	-	Example of MPC Control	85
Figure 3.7	-	MPC Control Process	87
Figure 3.8	-	Detailed Components of Developed MPC	87

Figure 4.1	-	Hybrid Ventilation Potential Investigation Process	92
Figure 4.2	-	Climate Zones in US	94
Figure 4.3	-	Sensitivity Analysis Result	103
Figure 4.4	-	Framework of the Model Predictive Control	105
Figure 4.5	-	Histograms of Energy Saving Percentage	108
Figure 5.1	-	Research Procedures	110
Figure 5.2	-	Air Pollutant Fluctuation Trend	112
Figure 5.3	-	Box Plots for Outdoor Air Pollutions in Different Climate Zones	115
Figure 5.4	-	Box Plots for Outdoor Air Pollutions in Different Cities	116
Figure 5.5	-	FS Statistics for Air Pollutant Difference Between Different Location Settings	120
Figure 5.6	-	Correlation for Air Pollutant Between Different Location Settings	121
Figure 5.7	-	FS Statistics for Representative Pollutant Data Selection	124
Figure 5.8	-	Verification of Air Pollutant Modeling	127
Figure 5.9	-	Residual Plots in Model Training (PM2.5)	129
Figure 5.10	-	Configuration of Co-simulation in BCVTB	130
Figure 5.11	-	Verification of Natural Ventilation Considering Air Pollutants	131
Figure 5.12	-	Summary of Outdoor Air Pollutant Influence on Natural Ventilation Usage	136
Figure 6.1	-	Baseline Building Model	139
Figure 6.2	-	Uncertainty Analysis results considering all the uncertainties for baseline	142
Figure 6.3	-	Layout of most risky zones	142
Figure 6.4	-	Sensitivity Analysis results	151
Figure 6.5	-	Uncertainty Analysis Results After Applying UHI effect only	153
Figure 6.6	-	Uncertainty Analysis Results After Applying Local Wind Uncertainty only	154

Figure 6.7 - Uncertainty Analysis Results After Applying Ground Reflectance Uncertainty only 154

LIST OF SYMBOLS AND ABBREVIATIONS

NV	Natural Ventilation/Naturally Ventilated
AC	Air Conditioning
MPC	Model Predictive Control
HV	Hybrid Ventilation
CFD	Computational Fluid Dynamics
TMY	Typical Meteorological Year
HMY	Historical Meteorological Year
DOE	Department of Energy
EPA	Environmental Protection Agency
EER	Enhanced Entity Relationship
PDF	Probability Distribution Function
CDF	Cumulative Distribution Function
MAE	Mean Absolute Error
MSE	Mean Square Error
RMSE	Root Mean Square Error
SHGC	Solar Heat Gain Coefficient
NAAQS	National Ambient Air Quality Standard

SUMMARY

Commercial buildings, as one of the largest energy consumers in US, account for more than 20% of energy consumption in US. To improve its energy efficiency, employing the natural cooling for the air conditioning is considered as an amiable measure to reduce the energy consumption during the building operation. However, how much natural cooling potential could be utilized and how to better exploit it are key questions to answer to provide more insight into the usage of natural cooling. Hence, in this dissertation, we propose two major questions to address in this study:

1. What are the potential of energy saving in different climates of US by using the natural cooling considering uncertainties, building intelligence and outdoor air pollutant?
2. How to reduce thermal comfort risks of natural cooling during the building design?

To address the first question, we firstly quantified the uncertainties in different levels such that they could be applied in the analysis later. The model predictive control for employing the natural cooling was then developed and compared with the traditional rule-based control to investigate the influence of building intelligence on the natural cooling usage. Also, the outdoor air pollutant records were collected and analyzed to study the relative influence of natural ventilation with the premise of ensuring the occupant health. Then to answer the second question, we have compared the uncertainty analysis with the deterministic simulation to better uncover the thermal comfort risk

during natural cooling. Design scenario tests were also conducted for a detailed comparison.

Through the whole study, the dissertation concluded that the Climate Zone 3B and 3C are most suitable for natural cooling usage if only outdoor meteorology is considered while the rest of climate zones share the same cooling energy saving potential of 15% to 25%. The developed model predictive control is better at maintaining the thermal comfort for occupants while sacrificing some energy saving potential at certain climate zones. If the outdoor air pollutant is taken into account in the natural ventilation operation, the reduction of natural cooling usage could reach up to 80% in Los Angeles (Climate Zone 3B), 30% to 40% in Atlanta (3A), Chicago (5A) and San Francisco (3C) while 10% to 20% in the major cities of other climate zones. The urban/suburban areas are typically more polluted compared to the rural area. Furthermore, PM2.5 is always the most significant air pollutant to consider to maintain the acceptable level of indoor air pollutants. Finally, as the last part of the study, the comparison between the uncertainty analysis and deterministic simulation showed that the uncertainty analysis was better at uncovering the thermal comfort risk during natural cooling while the deterministic simulation was efficient to use when conducting the comparative analysis based on our case study.

1. INTRODUCTION

Commercial building, which represent a group of buildings such as office buildings, warehouse or retail stores, play an important role in our lives and constitutes a large area of floor space in most countries (Nguyen & Aiello, 2013). In US, as one of the largest energy consumers in our society, commercial buildings take up approximately 20% of total energy consumption based on the data from Department of Energy (DOE) (Dept. of Energy, 2010). In a recent report from U.S. Energy Information Administration, this energy consumption from the commercial sector is projected to increase with more than 30% from 2015 to 2040 (Conti et al, 2016). Among the high energy consumption of commercial buildings, nearly half is consumed by HVAC (Heating, ventilation, and air conditioning) systems, which commonly exists in most of commercial buildings in US for maintaining a comfortable thermal environment for building occupants (Guo and Zhou, 2009). Despite this high energy consumption, complains of thermal comfort and health problems still commonly exist in air-conditioned buildings. The mean building satisfaction rate was only reported as 59% based on a large survey of building occupants (Huizenga et al, 2006), which is far below the minimum thermal comfort requirement in ASHRAE standard 55 (ASHRAE, 2010). Too hot or too cold has also been reported as the most commonly encountered complaints for facility managers during the building operation (Booty, 2009). Meanwhile, in addition to thermal comfort issues, there also exist health problems in air-conditioned buildings. These health problems contain both building related diseases (typically caused by specific exposure to infectious indoor source) and sick building syndrome, which describes a group of general symptoms including eye or throat irritation, shortness of breath, visual disturbance etc. (Redlich et al, 1997), (Burge, 2004). With another large study including 4000 office workers (Burge et al, 1987), air-conditioned (AC) buildings usually have more building symptoms per worker compared to naturally ventilated (NV) buildings.

In these years, with the increasing awareness of sustainability, the prevalence of more sustainable buildings has attracted more attentions from both academia and industry. Out of numerous options of moving towards green buildings, the natural ventilation that utilizes the freely available outdoor air and wind for both ventilation and cooling is favorable among building designers considering its low life-cycle cost and the additional amenity to nature for building occupants. Hence, with the elaborate design to fully employ the benefits of natural ventilation, naturally ventilated buildings and hybrid ventilated buildings have arisen as increasingly popular options for building owners. In the next section, the details of naturally ventilated building and hybrid ventilation building will be introduced.

1.1 Background

1.1.1 Naturally Ventilated Building

The naturally ventilated building is the type of building in which the building air exchange is driven by the natural force of wind or temperature (Liddament et al, 2006). Based on ventilation principles, there exist mainly three ventilation types for natural ventilation – single-side ventilation, cross-ventilation and stack ventilation (Kleiven, 2003). As shown in Figure 1.1 (left) below, the single side ventilation occurs when the windows of the ventilation zone only locate in one side of the wall. With the relatively weak effect of wind, the single side ventilation could only be used in zones with depth of

2 – 2.5 times the floor to ceiling height to ensure enough ventilation rate for occupants. Meanwhile, the cross ventilation, which happens when two or more openings are on the opposite side of walls, is shown in the middle of Figure 1.1 below. Cross ventilation is capable of providing much larger wind effect compared to the single side ventilation thus serving the ventilation of larger zones. Lastly, the stack ventilation is driven by the difference of air density that is caused by the air temperature difference. In the natural ventilated building that utilizes stack ventilation for air exchange, typically a thermal chimney will be designed to optimize the effect of natural ventilation. It is worthy to mention that the wind effect will also have significant influence on the stack ventilation (Gładyszewska-Fiedoruk & Gajewski, 2012). The pressure difference caused by the wind will result in unexpected ventilation performance such as the reverse draft. In the practice, the ventilation principles are usually combined to provide enough ventilation for a naturally ventilation building.

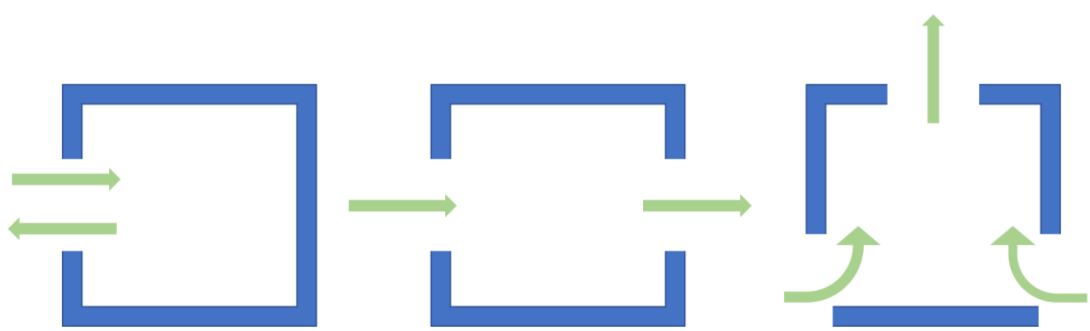


Figure 1.1 Natural Ventilation Principles (Left: Single-Side Ventilation, Middle: Cross Ventilation, Right: Stack Ventilation)

These years, with the development of sophisticated simulation techniques to aid the building design, an increasing number of naturally ventilated building were built around the world. One good example is the GSW Headquarters in Germany (Lee et al, 2018). The building is a 22-storey building with 11 meters wide. Cross ventilation is the main ventilation principle that is utilized for the air exchange of the building. Meanwhile, the building is equipped with a double skin façade such that the stack ventilation could also be employed to increase the ventilation rate during building operation. The building configuration is shown in Figure 1.2 below. Similarly, combining the cross ventilation with the stack ventilation as the alternative, Building Research Establishment is a low-rise naturally ventilated building with the capability of accommodating more than 100 office workers (Edwards & Naboni, 2013). Instead of the double façade skin used in GSW Headquarters, a vertical chimney was designed to draw hot air through ducts and windows such that it can be efficiently exhausted from the building. In addition to these two most commonly used natural ventilation strategy, the single-side ventilation was applied on cellular offices on the north side of the building.

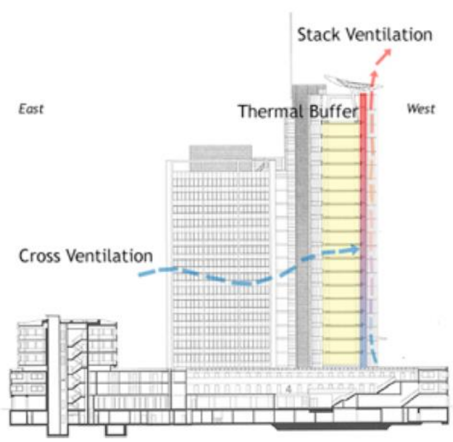


Figure 1.2 GSW Headquarter Center

Naturally ventilated buildings could bring many benefits for building occupants. One of the most prominent benefits is the healthy indoor environment due to the high air exchange rate when windows are opened (Seppanen, 2002). The lower CO_2 and VOCs (volatile organic compounds) accumulation in naturally ventilated buildings is also reported to be beneficial for occupant productivity. In a study of investigating the influence of CO_2 and VOCs accumulation on occupants, the occupant cognitive function scores significantly increased in “Green building” days compared to “conventional building” days (air conditioning on) (Allen et al, 2016). In spite of these benefits, naturally ventilated buildings have several drawbacks as well. One of the biggest shortcomings is its susceptibility to its outdoor environment climate, which often leads to inconsistent performance in maintaining the thermal comfort for building occupants. Thus, in the realization of naturally ventilated buildings, strict weather constraint should be applied to guarantee the performance of these buildings. In most of climate zones, purely relying on natural ventilation is impossible to maintain a consistently acceptable indoor environment for building occupants.

1.1.2 Hybrid Ventilation (Mixed Mode) Building

By definition, a hybrid ventilation building is defined to be the building equipped with a hybrid ventilation system, which is a two-mode system capable of providing a comfortable indoor environment using natural and mechanical forces according to the dynamic indoor and outdoor environment (Heinonen & Kosonen, 2000). Coupling natural ventilation with mechanical ventilation, hybrid ventilated buildings have the potential to minimize energy bills for owners without compromising the thermal comfort need of building occupants. Compared to the mechanical ventilation building, the hybrid ventilation system allows to open the window when the outdoor environment is favorable, which provides occupants with amenity to nature and a significant amount of saving of both fan and cooling energy in the building operation (Lim et al, 2015). Compared to the naturally ventilated building, the hybrid ventilation building could protect the building occupants from unfavorable outdoor environment with air conditioners on. It helps to resolve an important issue, i.e. the uncertainty of thermal comfort status, in a naturally ventilated building and promotes the natural ventilation to be utilized without suffering from severe climate constraints (Karava et al, 2012).

The main hybrid ventilation principles fall into three categories, including natural and mechanical ventilation, fan-assisted natural ventilation and stack and wind assisted mechanical ventilation (Heiselberg, 2002), as shown in Figure 1.3 below. Among these, the natural and mechanical ventilation is the most commonly existed strategy for hybrid ventilation (shown in Figure 1.3 left). Basically, this principle is based on two autonomous system that can switch their modes in different periods of a day. This type of hybrid ventilation building is also called mixed mode building, which is defined to use a hybrid approach with a combination of natural ventilation and mechanical ventilation to distribute air and maintain the comfort of building indoor environment. Typical control strategies, classified based on spatial and temporal characteristics, exist for the optimal control of this type of building. The details of them will be introduced later in the Section 1.2. In addition to the improved thermal comfort and reduced energy consumption as mentioned above (CBE, 2018), mixed mode building is also highly tunable with redundancy in cooling and flexibility in personalized control thus a potentially longer building life with higher occupant satisfaction rate. Besides, the fan-assisted natural ventilation (shown in Figure

1.3 middle) describes a natural ventilation system to serve the building demand with the aid of fans. The fan will be turned on when the pressure caused by local wind effect is insufficient to provide enough ventilation for different zones of the building. Lastly, the third type is the stack and wind assisted mechanical ventilation. Actually, the ventilation in this type of hybrid ventilation building is purely based on a mechanical ventilation system. But the air inlet of the building is typically designed to make the optimal use of natural wind during the ventilation period.

Figure 1.3 Principles of Hybrid Ventilation (Heinonen & Kosonen, 2000)

The design of hybrid ventilation building is more complicated compared to the traditional air-conditioned buildings considering the automatic or manual control strategies used in the building operation. However, with its foreseen benefits, an increasing number of hybrid ventilation buildings were built in different places these years. A good example of this is the Macerata building in Italy (Delsante & Vik, 2002), as shown in the Figure 1.4 below. The building is a 4-floor office building with a central atrium for air circulation. Openable panels were installed on the south and north of facades and the roof to facilitate the natural ventilation within the building. Meanwhile, each room is equipped with a fan coil unit to maintain the stable indoor thermal comfort environment if necessary. Another example of the application of hybrid ventilation on high-rise buildings is the San Francisco

Federal Building, which is a LEED Silver certificated building with floor 6 to 18 using natural ventilation while the other floors using mechanical ventilation. A combination of wind-driven and stack-driven ventilation was utilized to provide enough ventilation rate with both occupant-operable windows and automatically-controlled windows (McConahey et al, 2002), (Fowler, 2010). The automatic windows adjust the window opening position based on the pressure difference of the indoor and outdoor environment.

Figure 1.4 Macerata building, Italy

1.2 Literature Review for Natural Ventilation/Hybrid Ventilation Research

In this section, a brief literature review of the aspects in natural ventilation and hybrid ventilation that are related to our research in the dissertation will be presented. The covered topics include the simulation and thermal comfort of natural ventilation, the influence of outdoor air quality on the natural ventilation, the control for the hybrid ventilation operation and the potential investigation on the natural ventilation/hybrid ventilation.

1.2.1 Simulation of Natural Ventilation

Accurately simulating the airflow during the natural ventilation is one of the most significant issues to address to establish a naturally ventilated building with robust performance. Considering the complicated turbulence characteristics and unpredictability of airflow, how to simulate the airflow during natural ventilation in a fast and correct manner is always a harassment for building designers. Currently, there mainly exist three most popular models to simulate the airflow in natural ventilation, i.e. analytical and empirical models, multi-zone airflow models and Computational Fluid Dynamics (CFD). Starting from the simplest approach, the analytical and empirical models for the airflow prediction are usually derived from fundamental equations in fluid dynamics and heat transfer (Chen, 2009). With the straightforward computation, they are effective in approximating the airflow rate in a fast and rough way for engineers to use in the design. However, these models are often limited in specific scenarios where they were derived such that it is not easy to widely apply them in different cases without modification. Thus, they mainly serve as good indicators for the estimated ventilation performance in the practical design process (Chen et al, 2010). A more sophisticated modeling is the multi-zone airflow modeling. In the multi-zone airflow modeling, the whole building is idealized as a set of zones that the airflow path connects with (Axley, 2007). The airflow between different zones are either driven by the wind pressure difference or temperature variation. As to the method of building simplification, the nodal approach, which represent each zone as a node associated with pressure and temperature, is currently dominant on the market (Lorenzetti, 2002). It is tempting to use nodal approach for the zone representation due to the much fewer system variables exist in the model, which makes it fast in computation, especially when the building is complicated. A variety of multizone network models have already been developed in the market, such as MIX (Li et al, 2000), CONTAM (Walton, 1997), COMIS (Feustel, 1999), ESP (Clarke & Hensen, 1991) etc. When using the multizone airflow models in predicting the airflow rate of natural ventilation, the treatment of airflow typically contains two assumptions, i.e. (1) the air momentum dissipated quickly after entering one zone such that it is negligible, (2) the air property is assumed to be uniform in each zone (Johnson et al, 2012). Modelers should pay careful attention to these two assumptions for an accurate estimation of airflow when employing the multizone airflow models in practice. Except for the multi-zone airflow simulation, with the advancement of computing powers, Computational Fluid Dynamics (CFD) has also been frequently applied to study the air movement and temperature distribution in the ventilation prediction (Sørensen & Nielsen, 2003). Solving a set of partial differential equations based on the principles of conservation of mass, momentum and energy and numerical methods, the CFD is capable of providing results with respect to pressure, temperature and in a spatial and temporal resolution that is much fined compared to other approaches (Chen, 2009). Despite its versatility in modeling different types of airflow and complicated scenarios of ventilation, the CFD models are typically complex and delicate with its accuracy being strongly influenced by settings during the model establishment process, such as the specification of boundary conditions etc (Norton et al, 2007). Hence, for the quality control purpose, the CFD models needs to be carefully validated in practice based on the three principles, i.e. (1) confirm the abilities of the turbulence model and other auxiliary models for the prediction of all physical phenomena in the indoor environment; (2) confirm the discretization method, grid resolution, and numerical algorithm are suitable to be applied in the airflow simulation; (3) confirm the modeler's ability to use CFD to conduct the analyses (Malkawi & Augenbroe, 2004).

With the potential of using different models for the airflow prediction, building engineers and researchers have conducted many studies to improve the performance and design of a naturally ventilated building through the simulation. For example, Mora et al (2004) have compared three zonal simulation models to investigate the influence of the absorption/desorption of building materials on the indoor air conditions for zones with natural ventilation. They have concluded that this influence was not significant to consider in the design of natural ventilation in the hot and humid climate. Similarly, Axley et al (2002) have presented an approach based on a climate suitability analysis tool, in which the loop equation design method and multizone thermal-airflow analysis tool were used to facilitate the natural and hybrid ventilation systems design in early phases of a project. As an advanced tool with more superior capability, Computational Fluid Dynamics (CFD) has also been heavily used in different research projects to aid and optimize the design of natural ventilation. Wong and Heryanto (2004) have conducted more than 30 CFD simulations to comparatively study different design scenarios in order to improve natural ventilation performance using active stack. Also, Guo et al (2015) have presented the methodology and a case study to optimize the natural ventilation design with respect to the site planning, building shape and building envelope based on CFD simulation results. The ventilation status of the building greatly improved after adjustments. Lastly, employing CFD-based air quality model, Tong et al (2016) have investigated the influence of traffic-related air pollution on indoor air quality of a naturally ventilated building near the road. They concluded that with an obviously observed increase of indoor air pollutant concentrations, it would be significant to consider the size and location of window openings and the indoor layout if natural ventilation is to be adopted in the building adjacent to the roads.

In my study, I have applied multi-zone airflow modeling to simulate the indoor airflow condition considering the required resolution and computation speed for my purpose. Since only a general estimate of airflow rate for each zone is necessary, using CFD is definitely an over-shoot for this purpose. The over-complicated model of CFD without validation could also possibly cause bias in the results. On the other hand, the analytical and empirical model is too simple here and expected to provide results with less accuracy compared to the multi-zone airflow models.

1.2.2 Thermal Comfort in Natural Ventilation

As one of the most significant aspect in the evaluation of the building performance, thermal comfort, which represents the perception of occupants on the thermal status of surrounding environment, has been proven to be strongly connected with occupant health and productivity (Huizenga et al, 2006), (Seppanen et al, 2006). Medical studies have already shown that either too hot or too cold will increase the risk of cardiovascular diseases or respiratory issues (Ormandy & Ezratty, 2016), (Mendell et al, 2002). Meanwhile, the thermal discomfort is also reported to lead to decrease of productivity (Huizenga et al, 2006). Based on a summary research with respect to the impact of room temperature on the productivity of building occupants, one-degree increase of temperature above 25℃ is expected to cause a decrease productivity of 2% (Seppanen et al, 2005). In addition to its impact on the health and productivity, the other significance of the occupant thermal comfort is that it often serves as the main driver for many occupant behaviors. According to the adaptive principle, the occupants will react to restore the thermal comfort if any change occurs to arise thermal discomfort (Nicol & Humphreys, 2002).

Occupant thermal comfort will be influenced by both physical and psychological factors. Out of numerous models for the evaluation of occupant thermal comfort in buildings, the PMV/PPD (Predicted Mean Vote/Predicted Percentage of Dissatisfied) model developed by Fanger (1970) has been most widely used and served as the guidance to appropriately adjust the indoor thermal comfort status. The PMV/PPD model was established based on the heat balance between the human body and its surrounding environment in the laboratory setting. In the model, six factors, including the air temperature, radiant temperature, relative humidity, air velocity, clothing insulation and metabolic rate, were finally evaluated to determine the indoor thermal comfort status, which is represented by predictive mean vote. It ranges from -3 to 3 to depict the states from cold to hot. Each PMV value is also associated with a PPD value to predict the percentage of dissatisfactory among occupants. Figure 1.5 below shows their corresponding relationships. PMV range of -0.5 to 0.5, which corresponds to the PPD of less than 10% is recommended by ASHRAE 55 (ASHRAE, 2010) to guide the operation of buildings.

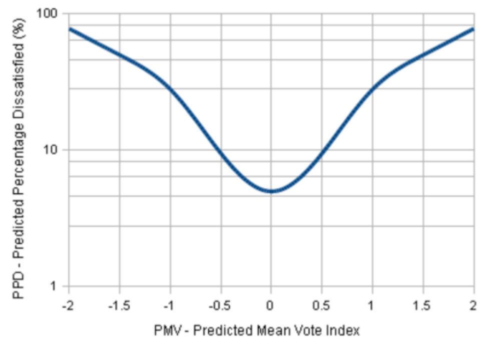


Figure 1.5 PMV – PPD Curve

In addition to the long-existing PMV/PPD model, the adaptive thermal comfort model, which is newly included in ASHRAE Standard 55 in 2002, is considered the best model for the evaluation of occupant thermal comfort in naturally ventilated buildings (De Dear & Brager, 2002). The model was developed based on the principle that the occupants are more tolerant in naturally ventilated buildings compared to air-conditioned buildings where the indoor thermal condition is strictly constrained (Brager & de Dear, 2000). The researchers collect a large of amount of survey data about the thermal comfort votes of a descriptive scale in naturally ventilated buildings first. Then the statistical analysis was conducted to generate thermal comfort zones for natural ventilation (De Dear & Brager, 2002). According to the adaptive thermal comfort model, the thermal comfort zones is determined based on the running mean outdoor temperature, as described in the Figure 1.6 below. The running mean outdoor temperature was calculated based on weights for several consecutive days first. Then the thermal comfort zone was calculated based on the running mean temperature and the regression models from the statistical analysis.

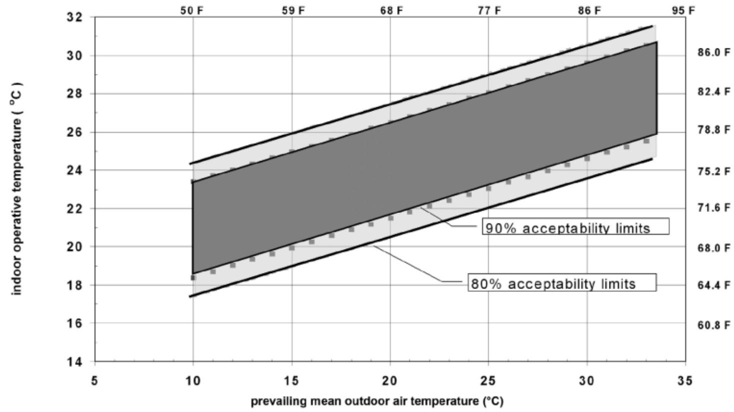


Figure 1.6 Adaptive Thermal Comfort Model Comfort Zone (ASHRAE 55)

Although occupants have been proven to be more tolerant in naturally ventilated buildings, the overall thermal comfort status in natural ventilation is still not satisfactory with unexpected thermal performance based on several studies with respect to occupant thermal comfort satisfaction in naturally ventilated buildings. One of the largest studies for the thermal comfort evaluation is done by Yang and Zhang (2007). In their survey, more than 120 responses were collected from occupants in naturally ventilated buildings. ASHRAE sensation scale of -3 to 3 was used in the study for occupants to self-assess their sensation of thermal environments. The results showed that the mean vote from occupants is 1.29, which means the occupants tend to feel hot in naturally ventilated buildings. Only 58% of occupants deemed their thermal environment acceptable. Also, in the San Francisco Federal Building introduced above where natural ventilation was utilized to provide ventilation from floor 6 to 18, occupants also frequently complained about their thermal environment based on a post-occupancy survey (Fowler, 2010). In Germany, Wagner et al (2007) have conducted a field study on the thermal comfort status of a naturally ventilated office building and found that more than 20% of occupants were at least slightly unsatisfied with their thermal environment. Similarly, in Andreasi's work (Andreasi, 2010) where the occupant feedbacks of thermal conditions were collected from naturally ventilated buildings spread in three cities at April and November, the responses showed that occupants in different buildings tend to have significantly different thermal feelings, ranging from 31% thermally satisfactory rate as the lowest to 86% as the highest. But they rarely exceed the 80% threshold defined in the ASHRAE thermal comfort standard (ASHRAE, 2010).

Thus, to establish a naturally ventilated building with better thermal performance, researchers have endeavored to optimize the naturally ventilated building design through simulation techniques. Mukhtar et al (2018) have established two Response Surface Methodology (RSM) based on sets of Computational Fluid Dynamics models to optimize the position of the ventilation shaft to provide enough ventilation rate for natural ventilation. Ahmed and Wongpanyathaworn (2012) have performed airflow simulation in IES (2018) to investigate the most effective and economical design for ventilation opening configurations and size. Also, Longo et al. (2011) performed deterministic simulation in EnergyPlus to test different window areas and operation strategies in order to improve thermal conditions within the experiment building. Ledo et al. (2012) tested the effectiveness of a range of energy conservation measures (ECMs) that have potential to enhance a building's thermal performance based on the deterministic simulation. Although it's convenient to just run one deterministic simulation, there are underlying risks when decision makers only consider results from that one-time simulation as a reference, considering assumptions of certain input parametersthat could potentially have significant impacts on the results.

To improve the performance of thermal comfort in naturally ventilated buildings, the uncertainty analysis, which provides probabilistic probes into building performance indicators considering different forms of uncertainties, has been proposed for the evaluation of thermal comfort conditions in naturally ventilated buildings. Yun et al have developed a probabilistic occupant behavior program and integrated it with a simulation tool to investigate the impact of occupant behavior on natural ventilation (Yun et al, 2009). The results concluded that up to 2.6 ℃ can be observed between the office with active window users and inactive window users. Hyun et al (2007) have quantified the uncertainties of many model parameters such as meteorological data, building leakage areas and performed the uncertainty analysis of airflow in natural ventilation. It was shown that the impact of uncertainties was non-negligible in the prediction of airflow rates. Also, Hopfe et al. (2007) have applied material uncertainties to test their influence on the thermal comfort prediction of a simple building. The estimate of weighted overheating hours ranges from 300 to 420 in the uncertainty analysis. Parys et al. (2012) have utlized uncertainty analysis to assess the feasibility of passive cooling for an office building in Belgium. Various design scenarios with different insulation level, glazing-to-wall ratio and glazing types were tested. The study showed that the building could be sufficiently cooled simply by manual window operation. Also, a decision-making scenario in a naturally ventilated building design was assumed and tested using uncertainty analysis. With different preference of risks, the role of uncertainty analysis in the decision-making process was explicitly shown (De Wit & Augenbroe, 2002). Lastly, as one of the most thorough work done by Breesch and Janssens (2010), a small office with two rooms was modelled with the single side ventilation, stack ventilation and cross ventilation. The uncertainty analysis showed that the uncertainty of thermal comfort increased significantly when a weather data set with consecutive warm years was applied. The authors also tested several design scenarios and concluded that the reliability of natural ventilation could be increased with an increase of ventilation rate, attachment of top cooling and increase of thermal mass.

In spite of efforts mentioned above using the uncertainty analysis for the thermal comfort evaluation in naturally ventilated buildings, all these works are still incomplete by neglecting the influence of building microclimate and other building uncertainties such as convective heat transfer uncertainty. Meanwhile, how to better utilize the uncertainty analysis and the deterministic simulation in the naturally ventilated building design is still unclear as well. More works in related fields are necessary for a more thorough application of uncertainty analysis to aid the development of natural ventilation.

1.2.3 Thermal Comfort in Mixed Mode Building

The mixed mode building is different from a fully naturally ventilated building in a way that it has a mechanical ventilation system with air conditioner installed. As a result, this difference leads to the controversy that whether the mixed mode building should be classified as a naturally ventilated building or a mechanically ventilated building in the evaluation of indoor thermal comfort status, i.e. it is more appropriate to use the adaptive thermal comfort model or PMV/PPD model for the thermal comfort evaluation. Interestingly, two thermal comfort standards, i.e. ASHRAE 55 (2010) in US and EN 15251 (2007) in Europe, classify the mixed mode building into different categories. In ASHRAE 55, the standard specifies that the building should be classified as the air-conditioned building such that the PMV/PPD model should be used to determine the indoor thermal comfort status as long as a mechanical cooling system is presented in the building. In contrast, EN 15251 dictates that the adaptive thermal comfort model could be used for the thermal comfort evaluation if two criteria (1) the building has operable windows (2) no clothing protocol are enforced, are met.

Although this controversy is still ongoing, an increasing number of recent researches have supported that the adaptive model is more appropriate for the thermal comfort evaluation in mixed mode buildings. For example, in a longitudinal field study of thermal comfort status of a mixed mode building in Sydney, more than 1300 subjective comfort questionnaires from were collected. The results showed that the adaptive model is more suitable for the thermal comfort evaluation in the mixed mode building (Deuble & de Dear, 2012). This result is also supported by another study, in which the thermal comfort temperature range of a mixed mode building was measured in summer and compared with both adaptive comfort model and PMV model (Fu & Wu 2015). Lastly, Luo et al have conducted another longitudinal study in a mixed-mode office building in subtropical climate conditions. The study explicitly showed that the occupants in the mixed mode building have the shift of thermal sensation when the building switch between air conditioning mode and natural ventilation mode. During the natural ventilation, occupants become more tolerant with their thermal comfort. Thus, the adaptive thermal comfort model is considered a better fit of thermal comfort evaluation in the mixed mode building (Luo et al, 2015).

Consequently, in this dissertation, the adaptive thermal comfort is employed to guide the natural ventilation operation and determine the indoor thermal comfort status of a mixed mode building during natural ventilation based on recommendations from former researches.

1.2.4 Air Quality Influence on Natural Ventilation

Natural ventilation has become an increasing adorable feature for occupants with its much higher ventilation rate compared to the traditional mechanical ventilation. This high ventilation rate could bring in many benefits such as the improvement of indoor air quality with less carbon dioxide and volatile organic compounds (VOC), the improvement of occupant productivity (Allen et al, 2016) etc. However, there also exists issues associating with the high ventilation rate, the most significant one of which is the increase of outdoor air pollutants exposure for occupants, especially when the outdoor air pollutant concentrations are high. In a fully air-conditioned building, the outdoor fresh air is provided by one or several central Heating, ventilating, and air conditioning (HVAC) systems, in which filters could be easily installed to filter out not only the outdoor air pollutant, but also the air pollutants generated from indoor environment when the air is recirculated. Nevertheless, since occupants typically adjust operable windows that are widely spread and freely controllable in natural ventilation for both ventilation and cooling, it is hard to install a central filter system such that the indoor air pollutants could be sufficiently controlled from the influence of outdoor air pollutants. Researchers have shown that the median indoor/outdoor (I/O) ratios of PM2.5 were 1.2, 2.2 and 6.3 higher in the analogous natural ventilation compared to the mechanical ventilation with MERV 8, 11, and 16 filters installed (Ben-David & Waring, 2016). Hence, to avoid the excessive exposure of outdoor air pollutants and the associated health impacts on occupants (Filliger et al, 2010), (Schwartz et al, 1996), the natural ventilation operation should be adjusted according to the fluctuation of outdoor air pollutant concentration.

With the diversity of nature and influence of anthropic activities such as plant generation and transportation, in our daily lives, numerous categories of outdoor air pollutants exist, including particulates, Ozone, Carbon Monoxide (CO), Sulfur oxides (SO2, SO3), hydrogen sulfide (H2S), acid gases (HF, HCl), Nitrogen oxides (NO2 and others), Lead, Volatile organics (VOC's) (Curtis et al, 2006) etc. Out of all these pollutants with different sources and influence, avoiding the excessive exposure of Particulate Matter (PM2.5, PM10) and ozone is of most significance considering their potential impacts on human health (US EPA, 1999).

Particulate Matter (PM) is a complex mixture of small particles and droplets that are formed chemically or physically with various sizes in the air (US EPA, 2018a). Particulate Matter could be further classified as PM10 and PM2.5 based on the aerodynamic diameter of particles. PM10 includes all the inhalable particles with diameters of equal or less than 10 micrometers while PM2.5 contains all find particles with diameters of equal or less than 2.5 micrometers (Monn et al, 1997). As both a primary and secondary pollutant, PM2.5 can be directly emitted from pollutant sources or formed from reactions or oxidation of precursor pollutants, such as Nitrogen oxides, acid products etc. Thus, the combustion related activities, such as the combustion in engines during transportation, the combustion of fossil fuels in power plant or fires, are the main contributors of PM2.5 pollution. On the other hand, PM10 is a primary pollutant, which is mainly contributed by fugitive dust in the construction, transportation or other anthropic activities (US EPA, 2014 & 2017). Particulate Matter has been confirmed to increase the morbidity of various diseases, such as respiratory symptoms, asthma, Cardiovascular system problems, and also the mortality of children and adults (Barnett et al, 2005), (Zanobetti & Schwartz, 2005), (Meister et al, 2012).

In addition to the Particulate Matter, medical studies have also shown that ozone was associated with adverse health impacts on human health, including the respiratory symptoms, central nervous system effects and total mortality (Lippmann, 1989), (Brown & Bowman, 2013) etc. The formation of ground level ozone is mainly driven by the sunlight to stimulate the reactions between nitrogen oxides (NOx) and volatile organic compounds (VOC) (US EPA, 2018b). Thus, it has strong daily patterns, which typically peaks in the afternoon. Since the operation of power plants and transportation emit a huge amount of nitrogen oxides, they constitute the main sources of ground level ozone pollution. The excessive indoor ozone concentration is extremely harmful for occupants since it will further generate other oxidation products such as formaldehyde, hydroperoxides, fine and ultrafine particles (Weschler, 2006) etc.

Considering their detrimental effects on occupant health, several studies have investigated their influence on the natural ventilation usage around the world. One of the most recent studies was done by Tong et al (2016), in which the influence of outdoor air pollutants on the natural ventilation across China was investigated. In the study, they have estimated the natural ventilation usage potential across all major Chinese cities according to local weather conditions and outdoor air quality that is represented by AQI (Air Quality Index) as the aggregate indicator for the air quality. The results revealed that 8 – 78% of cooling energy saving could be achieved in different cities of China even though the air quality is not satisfactory now. Kunming is the city with most energy saving potential using natural ventilation while Beijing is the city with most potential improvement in energy saving due to its large area of office buildings and unfavorable ambient air quality. Also, using similar method, Martins and da Graça (2017a, 2017b, 2018) have investigated the impact of PM2.5 on the natural ventilation in three megacities of Asia (Beijing, Shanghai and New Delhi), California, US and nine European cities (Antwerp (Belgium), Krakow (Poland), Lisbon (Portugal), London (United Kingdom), Madrid (Spain), Paris (France), Prague (Czech Republic), Skopje (the Former Yugoslav Republic of Macedonia) and Strasbourg (France)). In their investigation of the influence of PM2.5 on natural ventilation in three megacities of Asia, they have studied the benefits of using personal comfort system to improve natural ventilation usability first. 15% increase of natural ventilation usage associated with 13% - 42% HVAC energy consumption reduction was reported. Then, the influence of outdoor air pollutant on natural ventilation is studied in the second stage. Authors concluded that Shanghai is the best cities for natural ventilation with appropriate temperature and low PM2.5 concentrations. Then authors have utilized a multi-year database containing both weather data and PM2.5 concentration data to research on the impact of airborne particle on natural ventilation usability of office buildings in California. The research was also composed of two stages. In stage 1, authors have conducted a statistical analysis to study the coincidence between outdoor weather and PM2.5. The results showed that in some cities the pollutant concentrations are highly correlated with weather while in other cities the connection is not obvious. In the stage 2 of analysis, a detailed building simulation was performed to calculate the possible reduction in energy savings. Based on the investigation results, limiting the natural ventilation usage only when the outdoor PM2.5 concentration is less than 12 μg/m3 could lead to the energy saving reduction of 20% - 60% in California. Finally, applying the same approach, in the nine European cities studied, the authors concluded that most of time suitable for natural ventilation in these cities occurred when the outdoor PM2.5 concentration level is high. Antwerp, Lisbon and Paris are three cities that have the highest energy saving potential using natural ventilation considering the influence of outdoor air pollutants.

With the efforts to uncover the impact of outdoor air pollutants on the natural ventilation usage, researches now are still incomplete considering the following two aspects. Firstly, most of current researches still just focus on the influence of PM2.5 while neglecting the influence of the other two important outdoor air pollutants – ozone and PM10, which leads to the underestimate of the influence. Also, current studies didn't distinguish the possible difference of the outdoor air pollutant influence in different location settings of a city. Hence, improvement from former works are still necessary to more explicitly present the influence of outdoor air pollutants on natural ventilation.

1.2.5 Control of Hybrid Ventilation

The control of hybrid ventilation is crucial for ensuring the success of hybrid ventilation buildings in terms of achieving energy saving and maintaining thermal comfort of occupants. Overall, based on the recommendation from Brager et al (2007), the hybrid ventilation control can be categorized according to the temporal and spatial difference of running air conditioning or natural ventilation within one building. First and foremost, if different conditioning modes are allowed in different zones of the building at the same time, this strategy is called zoned control strategy. Typically, the zoned strategy is suitable for hybrid ventilation buildings with deep floor plans, in which the mechanical ventilation system will be always in the running mode to provide enough ventilation for core zones of the building while the ventilation mode will be switched in the building boundary zones based on indoor and outdoor environment. Another important application of the zoned strategy is for high-rise hybrid ventilation buildings. The lower floors should run in fully mechanical ventilation mode due to the security reasons while the upper floors are allowed to use natural ventilation in appropriate time. This is based on the spatial difference of using different ventilation mode. In addition to the zoned control, the other category of control strategies is the complimentary control. Based on the temporal difference of ventilation mode operation, the complimentary control strategy could be further distinguished into three sub-categories - concurrent, changeover and alternate, based on whether the natural ventilation and mechanical ventilation are allowed to run at the same time within the same space or not. The concurrent control allows natural ventilation and mechanical ventilation to run at the same time such that the cooling provided by natural ventilation is considered as a complimentary to the mechanical cooling. In the changeover strategy, the natural ventilation and mechanical cooling have interlock such that only one mode is allowed at a time. Lastly, in the alternate strategy, one mode will run infinitely until being switched to the other. The control strategy for a hybrid ventilation building in practice could belong to multiple categories of control strategies mentioned above.

With its easiness of implementation and understand, in the current practice of hybrid ventilation building control, currently, almost all the hybrid ventilation buildings operate based on simple heuristics rules (rule-based control). In the rule-based control, the window operation schedule is typically determined based on the outdoor air temperature, wind speed, relative humidity or indoor environment factors such as CO2 accumulation etc

(Brager et al, 2007). An example of typical rule-based control is as shown in Figure 1.7 below. To provide sufficient ventilation of the building while maintaining the occupant comfort, the louver location is adjusted based on both temperature and local wind speed. Although the rule-based control is simple to implement and easy to understand by the occupants, it has drawbacks as well, including the thermal comfort problems that occasionally occurred and the unoptimized energy.

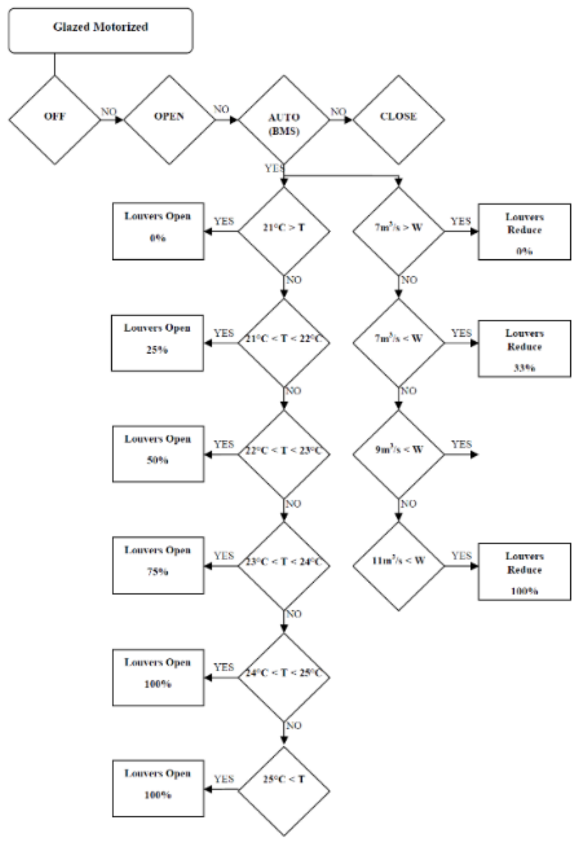


Figure 1.7 Rule-based Control Example

Thus, with the advancement of control techniques and computation power these years, the model predictive control (MPC) has emerged and attracted more attention from building researchers for the hybrid ventilation control. With a model to predict the future system status when different control sequences are applied, the model predictive control is expected to provide a more robust solution for the hybrid ventilation building operation since the control outcomes are well accounted for in the planning horizon and the control sequence is optimized based on defined control objectives. The core of the model predictive control is its central model for prediction, which directly determines the performance of the developed model predictive control. Based on types of central model, the model predictive control could be divided into three categories - white box approach, grey box approach and black box approach when it is used for helping hybrid ventilation control.

As the most frequently used approach, several works about the model predictive control with a white box (physical) model as the central model were developed these years. For example, Hu and Karava (2014) have developed a model predictive control for hybrid ventilation based on the prediction of energy and indoor environment using a transient thermal and airflow network. The comparison with a rule-based control showed that the model predictive control could help achieve better thermal performance in the hybrid ventilation operation. To aid in the operation of mixed-mode buildings, May-Ostendorp et al (2011) have utilized logistic regression to extract rules from optimal control sequence generated by the model predictive control using the EnergyPlus model as central model. As an extension work, three algorithms, including the generalized linear models (GLM), classification and regression trees (CART) and adaptive boosting were also compared to achieve the performance of the model predictive control through the rule extraction (May-Ostendorp et al, 2013). In addition, the model predictive control with white box model was exploited to help achieve better building operation as well. Zhao et al (2015) have proposed a design-build-operate energy information modeling infrastructure that incorporate using calibrated EnergyPlus model as the central model for the model predictive control of building operation. Similarly, Corbin et al (2013) have utilized EnergyPlus and Matlab to develop a model predictive control strategy to adjust the building operation and achieve energy saving. Henze et al (2005) have demonstrated a novel model predictive controller based on short-term weather forecast and a calibrated TRNSYS model for the active and passaive building thermal storage control. Although the results are not ideal considering the insufficient thermal mass in the test building, the utility cost saving compared to conventional control strategy is still substantial.

On the other hand, the gray-box or black-box MPC has also become an attractive option for the hybrid ventilation operation with the surge of data these years. Unlike using white box (physical) model as the central model in MPC, the gray-box or black-box MPC is developed based on partially or fully data-driven models. Typically, it is faster in computation compared to the white box approach. However, the central model might carry implicit meaning, which makes it hard to be clearly understood, especially in the black-box approach. A good example of this work was done by Spindler and Norford (2009a, b). Based on the linear method, they have established a combination of linear zonal models for the prediction of indoor environment. Various indoor and outdoor environment variables (e.g. indoor and outdoor air temperature, the wind speed etc.) with their lagged terms were incorporated into the prediction. The genetic algorithm is proposed for the optimization of building control considering its complicatedness.

In summary, researchers and building engineers have endeavored to improve the building control intelligence for better hybrid ventilation operation with higher energy efficiency and increased robustness of maintaining the comfortable thermal environment for occupants. Nowadays, more and more sensor data were generated from the building operation. How to better integrate these data to further aid the intelligent control of building systems is an interesting direction to pursue in the future. These data are precious to help not only the black-box control of the building, but also the white-box approach of control with a more accurate physical model in usage.

1.2.6 Potential of Natural/Hybrid Ventilation

As an important step to further popularize the hybrid ventilation technique, a reliable hybrid ventilation potential investigation is necessary to provide guidance on establishing hybrid ventilation buildings in different climates across US. Related to the investigation of hybrid ventilation potential, one of the most recent works was done by Ezzeldin and Rees (2007), in which the hybrid potential in the arid climate was investigated. In the research, they have selected a single floor office building as the baseline building and tested different combinations of energy saving strategies to see the most effective way to save energy. The results concluded that the energy saving of hybrid ventilation is approximately 50% compared to a fully air-conditioned building in the arid climate (it can reach up to 90% if all the most effective energy saving measures were used). Emmerich (2006) have modelled a low to mid-rise commercial building for the hybrid ventilation potential investigation using the multi-zone simulation. The investigation was done in five representative cities and showed that a hybrid system could provide reliable ventilation and maintain acceptable thermal comfort in US climates. Also, Spindler has simulated a single floor small office building in more than 40 cities in US for the hybrid ventilation potential investigation (Spindler & Norford, 2009a). The results concluded that possible energy savings could range from 2% to approximately 30% in different climates with the climate in San

Francisco most suitable for implementing the hybrid ventilation. Except for US, Yao et al (Yao et al, 2009) have investigated the natural ventilation potential for office buildings in China based on a simplified thermal and airflow model. Using the adaptive thermal comfort model ASHARE Standard 55 (2010) as reference, the dynamic simulations showed that an efficient ventilation strategy (cross ventilation) could provide more than 30% of energy saving in all the tested cities (Harbin, Beijing, Shanghai, Kunming, GuangZhou), which are representatives of corresponding climate zones in China. Lastly, in addition to the works that are the investigation of natural ventilation potential horizontally, Tong et al (2017) have quantitatively estimate the vertical profile of natural ventilation for high-rise buildings in US. An in-house boundary layer meteorological model was employed in the analysis the characterize the vertical temperature profiles in six major US cities – Miami, Houston, Los Angeles, New York, Chicago and Minneapolis. The analysis showed that Los Angeles is the best city for natural ventilation, followed by New York.

1.3 Motivation

Despite the efforts in the hybrid ventilation potential investigation, all these results were still generated based on deterministic building simulations, by which large uncertainties were neglected with the potential investigation results being biased. Hence, a reliable uncertainty analysis that provides probabilistic probes into the interested outcomes could help better uncover the hybrid ventilation potential in different climates with the confidence interval of energy saving. Meanwhile, in all the hybrid potential investigation works mentioned above, only simple building operation control strategies (the rule-based control) were implemented. With the advancement of hybrid ventilation building control these years, different intelligent building control technologies are expected to be capable of imposing large impacts on the hybrid ventilation usage. More advanced hybrid ventilation control should be developed and incorporated to see its influence. Finally, in addition to these, as another influential factor on assessing the potential of natural cooling usage, the impact of the outdoor air pollutant is non-negligible for an accurate assessment as well. However, studies related to the influence of outdoor air quality on the natural ventilation across different climates in US are still lacking. With higher exposure to the outdoor environment, the hybrid ventilation building should shield the building occupants from detrimental effects of outdoor pollutants thus to maintain a healthy indoor environment. Consequently, a more thorough work of hybrid ventilation potential investigation and a study of their impacts in US climates are necessary.

Besides, due to the common use of one-time deterministic simulation and a variety of existing uncertainties in the simulation and building operation, it would also be worthwhile to give more attentions about how to deal with the risks of fully relying on deterministic simulation in the natural ventilation design. A complete comparison between uncertainty analysis and deterministic simulation is necessary to provide building designers and engineers with deeper insight about the usage of the deterministic simulation and uncertainty analysis in the practice.

1.4 Research Question, Goal and Scope

The goals of this research consist of two aspects: (1) the dissertation aim to more thoroughly investigate the hybrid ventilation potential across different US climates considering the influence of different levels of uncertainties, ventilation control with different intelligence and the outdoor air quality and their respective impacts, (2) the dissertation aims to compare the difference between the deterministic simulation and uncertainty analysis to find out how to better use the deterministic simulation and uncertainty analysis in the design of a naturally ventilated building.

Thus, by fulfilling the goal of this research, the detailed research questions answered by the dissertation include

(1) What are the hybrid ventilation potential in different climate zones across US considering different influential factors?

(2) How will the uncertainties, building intelligence and outdoor air quality affect the usage of hybrid ventilation across different climates?

(3) Is the deterministic simulation sufficient to evaluate the thermal comfort risks of natural ventilation?

(4) If not, how to make better use of the deterministic simulation and uncertainty analysis to help the design of a building during natural ventilation?

Overall, the dissertation is developed to provide decision makers with general guideline about the potential natural cooling benefits of small to medium commercial building in different climates of US considering the impacts of different influential factors (uncertainties, building intelligence, outdoor air pollutant). The dissertation also describes how to better evaluate the thermal comfort risk during natural ventilation by comparing different method (i.e. uncertainty analysis and deterministic simulation) used for the natural ventilation design. The excessively detailed simulation of airflow in the building (such as using CFD) and a detailed study for comparing different measures with respect to the natural ventilation design are out of the scope of this study considering the purpose of the dissertation.

1.5 Impacts of Natural/Hybrid Ventilation on Building Stakeholders

1.5.1 General Impacts

Building Owners

With the improvement of sustainability awareness and the advancement of the capability to design more innovative system, hybrid ventilation has become an attractive option for building owners these years. The hybrid ventilated building could bring building owners with the direct cost saving due to more energy-efficient operations, including the reduction of fan power, the reduction of refrigeration load and system load from building operation such as lighting and appliance. Also, the direct cost saving of hybrid ventilation could come from the reduced capital cost of establishing hybrid ventilation building (Brager et al, 2007). Currently, almost all commercial buildings in US utilize mechanical ventilation for provide fresh air for occupants in both interior and exterior building zones. The cost associated with the central HVAC system, ductworks, diffusers is expensive and sometimes could account for more than 30% of the initial cost of a new building (Price Industry, 2011). Utilizing the cooling potential from natural ventilation could cause potentially substantial downsize of HVAC system, thus a much lower capital cost spent on HVAC equipment, ductworks etc. Despite the necessary additional investment in the natural ventilation control, the benefit will still be over the cost if the hybrid ventilation building is designed properly. In addition to this direct cost reduction, hybrid ventilation buildings also bring more values in the market to owners with sustainable features compared to traditional air-conditioned buildings. The occupants in hybrid ventilation buildings are usually more satisfied with their indoor environment compared to air-conditioned buildings (Brager & Baker, 2009). In a better ventilated building with improved indoor air quality, occupants will have higher productivity at work thus generating more values for owners. These are all underlying advantages that could provide substantial benefits for building owners.

Despite its benefits, the hybrid ventilation building could also bring issues for owners such as more initial investment with sophisticated features (e.g. ventilation control) added to the building and a possible higher operation cost due to unexpected performance or the over-complicated building control. Also, in the building development, many owners/occupiers now like to rent or procure the building in joint ventures with developers and then sell the building later. The adaptive feature of hybrid ventilation building is expected to be a plus in the selling market. However, in the practice, the design of hybrid ventilation approach is typically too slow to catch on in the speculative market, which could make it hard to sell (CIBSE, 1999). Meanwhile, the establishment a successful hybrid ventilation building with expected performance also requires the early involvement of owners and a close collaboration with design teams. These all pose great challenges for owners to adopt the hybrid ventilation in the new building design.

Designers

As to the design of hybrid ventilation building, the designers also face significant difference compared to the design of traditionally air-conditioned buildings. The main difference between the air-conditioned building design and the hybrid ventilation building design are two-folds, (1) the design of hybrid ventilation building is a much more integrated process during the design phase with many influential factors, such as the location and size of operable windows, the thermal mass in the structure etc. All these require a close collaboration between design teams of different aspects to ensure the successful implementation of hybrid ventilation. (2) Unlike the traditional approach of ventilation design that is close to "mass production" following simple rules and fitting in available systems, the design of hybrid ventilation is "tailored" for special needs and the optimization of performance (Heiselberg, 2002). These differences hinder the development of hybrid ventilation in some degree due to the difficulty and extra efforts to achieve a successful design in practice, although surveys have indicated that it is possible to design a performance-robust hybrid ventilation building based on simpler approaches (CIBSE, 1999).

The whole development process of a hybrid ventilation building is shown in Figure 1.8 below. As the first step, the programme phase, which could also be considered as the planning phase, is the phase where the basis and the targets of the project are defined. These targets include but not limited to the requirement of indoor air quality, thermal comfort, energy usage and budget limits etc. Then, based on the defined targets in the programme phase, the designers begin the conceptual design phase, in which general building parameters (building form, size, location etc.) are determined. The analysis based on former experience and guidelines for the hybrid ventilation building design was conducted. Also importantly, the ventilation principles as mentioned in Section 1.1 above associated with the design of mechanical ventilation system was determined in this phase. After the conceptual design, the next step is to do the basic design. The main task in the basic design phase is to estimate the performance of hybrid ventilation building, including the possible building heat and contaminant loads, the airflow rate in ventilation and the annual energy consumption and corresponding peak powers. The hybrid ventilation settings will be adjusted in this phase to ensure the expected performance of the building. Then the building comes to the detailed design phase, where the design of the hybrid ventilation building is optimized with respect to the building energy saving, contaminant control and location of ventilation system components. In this phase, instead of the estimate of annual energy consumption from the last phase, the hourly calculation is typically performed for the optimization and analysis purpose. Finally, the last phase of a hybrid ventilation building design is the design evaluation phase. In the design evaluation, a detailed check will be conducted to see whether the design can meet the requirements of the project (Heiselberg, 2002). Overall, the process of a hybrid ventilation or mixed mode building design is much more complicated compared to the design of traditional air-conditioned buildings (CBE, 2018).

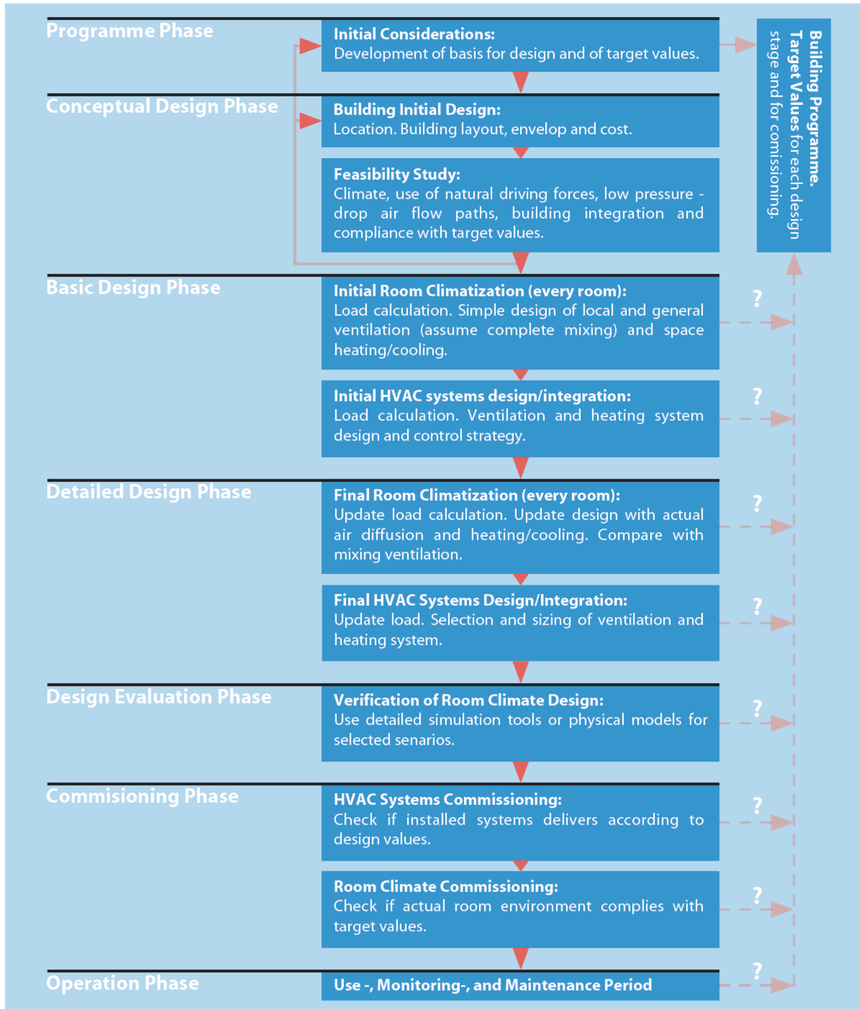


Figure 1.8 Hybrid Ventilation Building Development Process (Heiselberg, 2002)

Establishing a successful hybrid ventilation building is certainly challenging in design. In short, the barriers in design mainly arise from four aspects (Delsante & Vik, 2002). Firstly, one of big concerns for designers to design a hybrid ventilation building is from the economy consideration. In the design of hybrid ventilation building, the design fee is typically based on the investment cost of ventilation components. Also, the budget for the project is also constrained from owners such that the design team should also strictly control the investment cost, which could sometimes be unexpectable. Secondly, lack of former experiences, detailed documentations and helpful guidelines for the design of this type of building also put a lot of pressure on the design team to ensure the success of hybrid ventilation buildings. Hence, design teams usually need to spend significant efforts on meeting objectives and required performance during the design of a hybrid ventilation building. Designers also found that there was a lack of suitable design tools to facilitate the design process. Thirdly, the regulations of fire and noise also put a lot constrains for design options in ventilation. Meeting requirements of these regulations with respect to fire compartmentation and noise reduction will lead to inevitably increased cost for establishing a hybrid ventilation building. Fourthly, the designers are also concerned with impacts of some special ventilation design, such as chimneys, towers etc. on the overall aesthetics of the building. Overcoming these barriers in design would greatly help the more widespread of hybrid ventilation buildings.

Construction team

As the important step of making a hybrid ventilation building from design blueprints to a physically-existing object, the construction plays a key role in the success of a hybrid ventilation building. The ignorance during the construction could lead to severe problems of building performance such as overheating etc (Liddament et al, 2006). It happened before that the construction team has left a fan out of the construction, which led to the insufficient ventilation in one building zone of the hybrid ventilation building and overheating accordingly.

Although the challenges and requirements for the construction team are not as many as the design team, a successful implementation of a hybrid ventilation building also put new requirements of construction, the most significant of which is the early involvement in the project. Similar as owners who should be incorporated early into the project to help more clearly define the objectives and limits, the early involvement of a construction team would greatly aid the design team to come up with solutions with better constructability thus avoiding significant changes in the future implementation of the building. As recommended by National Renewable Energy Lab as the best practice (Pless & Torcellini, 2012), involving the key mechanical and electrical subcontractors in the design phase is necessary for the cost control of novel or possibly untested building design. This early involvement will not only help avoid the constructability issues, but also reduce the construction cost if the subcontractor has former experiences with related construction. It is important for the subcontractors to have a clear understanding of the project intents, requirements and scopes such that the risks associated with unexperienced constructors could be eliminated. Also, this early involvement of construction teams could help the project run a continuous value engineering process such that the schedule, scope, budget and building performance could be better balanced and optimized in the project.

Additionally, another best practice for successfully implementing a hybrid/natural ventilation building is to use the modular construction as much as possible. The construction of modular components is done offsite with a strict quality control process, which is important especially if the building is equipped advanced features that require a delicate construction. Not only limited to the high quality they have, these components are typically much easier to deploy such that the quality of construction could be guaranteed. The benefits associated with the modular construction will make the project be constructed in a better way that the design intent is fully realized and the construction process is optimized to save values for building owners.

Facility manager

Considering the building operation constitutes the most significant span of a building lifecycle, the investigation of possible impacts of hybrid ventilation and natural ventilation on facility managers in the building operation is important as well. Compared to the fully mechanically-ventilated buildings, facility managers could typically run a building with natural ventilation components using a reduced operation cost and workload. The first reason is that the ventilation system for the natural ventilation is usually easier to inspect and clean since ventilation components are much simpler for natural ventilation compared to the traditional mechanical ventilation system that needs not only a central sophisticated air handling unit for air processing, supply and return ducts spread in different zones for air transport but also other components such as Variable Airflow Volume box to work. Sometimes, the natural ventilation system is even maintenance free (Heiselberg, 2002). Using the natural ventilation system could also prevent the intrusion of snow and rain that could possibly cause maintenance issues in the central HVAC system. The other important reason for the reduced operation cost and workload for facility management team is the durable feature of natural ventilation system. In the operation of a mechanically ventilated building, the central mechanical plant will require a significant refurbishment and even a complete replacement after 20 years of operation (Price Industry, 2011). However, the natural ventilation components, such as waterproof louvers, shafts etc., could typically last longer. Thus, from these aspects, facility managers are capable of running a building with natural ventilation features more easily, especially for a fully naturally ventilated building.

However, there also exist a lot of potential issues of running the building with natural ventilation (either hybrid ventilation or fully mechanical ventilation) for facility managers, which might not be experienced in running a fully mechanical ventilation building (Delsante & Vik, 2002). First and foremost, since the hybrid ventilation system typically requires more sophisticated control and other mechanism such that the natural ventilation could be properly used, facility managers may sometimes face the failure of automation of components and controls that are difficult to address, especially when a huge amount of novel and complex features are added to the building. This is actually a barrier for the spread of hybrid ventilation building since facility managers concern with these maintenance requirements they are not familiar with (CBE, 2018). Other than these possibly higher maintenance requirements when the design of building is complex, secondly, facility managers also need to help occupants to resolve the indoor air quality and thermal comfort issues that might happen more frequently during the building operation if the building is not properly designed. Due to the high susceptibility of indoor environment to outdoor environment during natural ventilation and stochastic nature of building operation, building occupants are more likely to suffer from a much significant indoor temperature fluctuation compared to the mechanical ventilation building, thus leading to possibly over-heating problems in summer. Other issues with respect to the indoor air quality and thermal comfort that facility managers worry about include the possible ventilation short-circuit or obstructed airflow, the risks of draught when the local wind speed is high, the under-performance of ventilation system caused by inappropriate operation of occupants and risks of unacceptably high concentration of indoor air pollutants due to air pollutant sources such as traffic, manufacturers etc. Thirdly, the acoustics issues that might not be expected in the building design but experienced in the building operation are also necessary to address to ensure the satisfactory performance of the hybrid/natural building. Although the system operation noise in either hybrid ventilation or natural ventilation is typically lower than a fully mechanical ventilated system due to the reduced system size and fan power usage, the excessive noise from the ventilation openings in natural ventilation might be a serious concern especially if the building is located at the dense urban area. To address this issue, special components might be necessary for the ventilation system such that the max noise level could be kept under requirements. Lastly, there also other issues such as monitoring for the building performance in terms of air supply and indoor air quality and safety issues especially if operable ventilation components (e.g. operable windows) are installed.

Occupants

Serving the occupants well is the most significant objective that a successful building should achieve. To compare the performance of traditional air-conditioned building with that of mixed mode building, a large survey was conducted by Center for the Built Environment in UC Berkeley (Brager and Baker, 2008). In the survey, more than 40000 responses from 370 buildings were collected online, which also contains 520 responses from 12 mixed mode buildings. The influence of mixed mode buildings on building occupants are always positive. As shown in Figure 1.9 below, the mixed mode buildings outperform air-conditioned buildings in all aspects, especially with respect to general building satisfaction, the thermal comfort and the air quality. Using the 7-points satisfaction scale in the evaluation (-3 is very dissatisfied and 3 is very satisfied), the mixed mode buildings have a median of 0.34 in thermal comfort and 1.9 in air quality while the air-conditioned building only get -0.13 and 0.28 in these two aspects. The high score of thermal comfort in mixed mode buildings is mainly caused by the flexibility of indoor thermal environment control while the high score of air quality is caused by high ventilation rate such that the building zones are not stuffy. From Figure 1.10, we can observe that the mixed mode buildings mostly rank on the top quantile with respect to thermal comfort and air quality compared to other buildings. It is also surprising to see that the mixed mode building even received a high mean score compared to air-conditioned buildings in terms of acoustics, although the plot of acoustics score of mixed mode buildings against air-conditioned buildings showed that mixed mode buildings covered the full range of distribution.

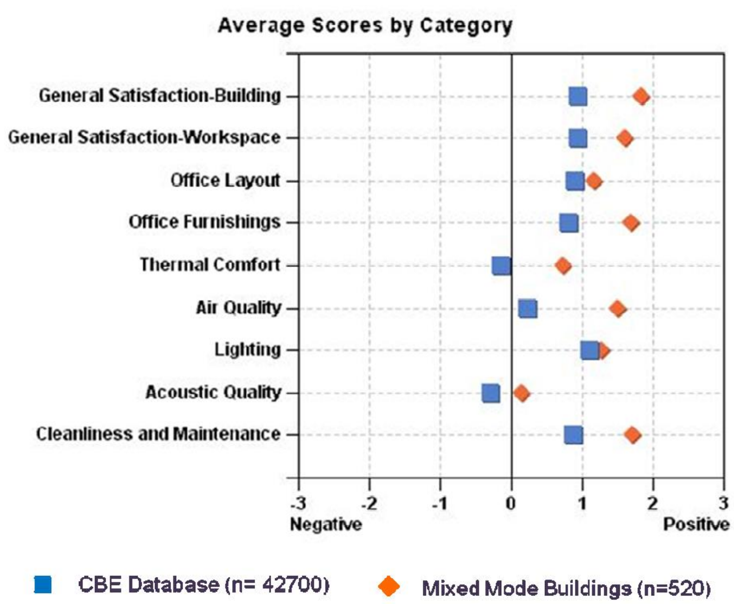


Figure 1.9 Average Score of Mixed Mode Building (Brager and Baker, 2008)

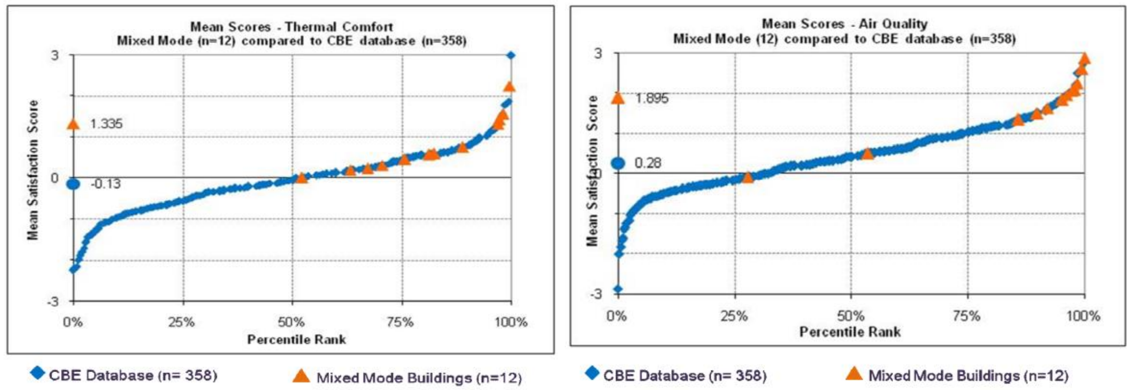


Figure 1.10 Score Distribution of Mixed Mode Building (Brager and Baker, 2008)

This increased performance in hybrid/natural ventilation building could bring in many benefits, out of which the most significant are improved productivity and less sick building syndrome. Based on the results from studies of relationship between improved air quality and productivity, decreasing the indoor air pollutions and increasing outdoor air supply are statistically-positive related with the productivity of office works, such as text-typing, proof-reading etc., and the overall cognitive scores when handling problems (Wargocki et al, 2000a), (Allen et al, 2016). Meanwhile, it has been perceived that the increased air quality could also reduce the sick building syndromes such as dryness of mouth and throat, difficulty in thinking, stuffiness etc (Wargocki et al, 2000b), (Jaakkol et al, 1991). On the other hand, as mentioned before, many issues such as the unexpected thermal performance due to the large fluctuation of outdoor environment, the unacceptable noise level and the increased occupant exposure to outdoor air pollutant are worthy of attentions and accounted in the building design to ensure the performance of hybrid/natural ventilation buildings as well. In the operation of hybrid ventilation strategy, the potential pitfalls that might cause the dissatisfaction among occupants include (1) the operation strategy is unclear to occupants such that the occupants don't have the intuition about when and how the system makes decisions, (2) the deprivation of occupant control and override right in the mixed mode operation, which constrains the flexibility of occupants to control their indoor environment thus losing one of the biggest benefits in mixed mode buildings.

1.5.2 Broader Impact

As to impacts of this dissertation on building stakeholders, firstly, this diisertation work is a good reference for building owners to use when evalating the financial benefits of adopting natural ventilation in establishing a sustainable building. With an estimate of cooling energy consumption in the area where the building is located, the building owner could use the energy saving potential in different climates of US from this dissertation and the electricity tarrif in that area to calculate the economic benefits of adopting natural ventilation. If they have informed designers and engineers to include the air pollutant control in the control design, the further reduction caused by air pollutant should also be accounted for in the benefit evaluation. Then if owners could get an estimate of construction cost of a natural ventilation system, the payback period of adopting natural ventilation (through installment of operable windows) could directly be estimated such that the owners will have a concrete number at hand, which facilitate the decision making process. The possible variance of the energy saving potential in different climates will also help owners to generate a conservative estimate and optimistic estimate of the associated economic benefits so that they can evaluate the risks of investing in natural ventilation.

Meanwhile, this dissertation work will help design and engineer teams in the building design across all the conceptual design, basic design and detailed design phases. Similarly, for the designers and engineers who are involved in the design of a naturally ventilated building, they could also use the estimated energy saving potential and its variance like owners to better define the performance goal in the building conceptual design. This dissertation work will alleviate the burden of designers and engineers in helping owners for the evaluation of project performance. No complicated simulation of energy saving potential from natural ventilation is necessary any more in the conceptual design stage. With a general estimate of this energy saving potentials and requirements of owners, the design and engineer team could focus on optimizing the building performance in the basic and detailed design stage later. Then, in the basic and detailed design phase, by using the general guidelines provided by this dissertation about the usage of deterministic simulation and uncertainty analysis, the design and engineer team could better utilize these techniques to improve the building performance with reduced risks in terms of both energy saving and thermal comfort. As recommended in the dissertation, the simulation results from the uncertainty analysis could be utilized as the baseline while the determinisic simulation is used in the comparative study to save the computation time. Finally, if the design team wants to employ the model predictive control for ventilation operation, the team could consider using the simulation results as the training data and developing a black-box control as presented later (Chapter 3) in this dissertation. The neural network model with its correspondingly best set of indoor and outdoor variables should be considered as the first option to try in the central model development process.

Last but not least, the developed model predictive control in this dissertation also has the potential to help facility managers to maintain better thermal comfort for building occupants. By considering the building operation and seasonality in the control design, the developed control outperforms the traditional rule-based control, which is the mostly widely used control strategy now for the hybrid ventilation control, based on our comparison results. Overall, by benefiting different stakehodlers, this dissertation promotes the widespread of natural ventilation/hybrid ventilation across the US.

1.6 Research Framework

To fulfill our purpose mentioned above, Figure 1.11 below shows the whole research framework of this study. As the first step, we have quantified the uncertainties in different levels as the foundation of this study. Later, based on these quantified uncertainties, we have developed the model predictive control for hybrid ventilation building operation. Then, accounting for these quantified uncertainties, the different building intelligence (using advanced model predictive control and rule based control) and the collected outdoor air pollutant data, we firstly investigated the potential benefits of natural ventilation usage in different US climates. For the second part, the uncertainty analysis was compared with the deterministic simulation to illustrate their usage in evaluating the thermal comfort risks of natural ventilation.

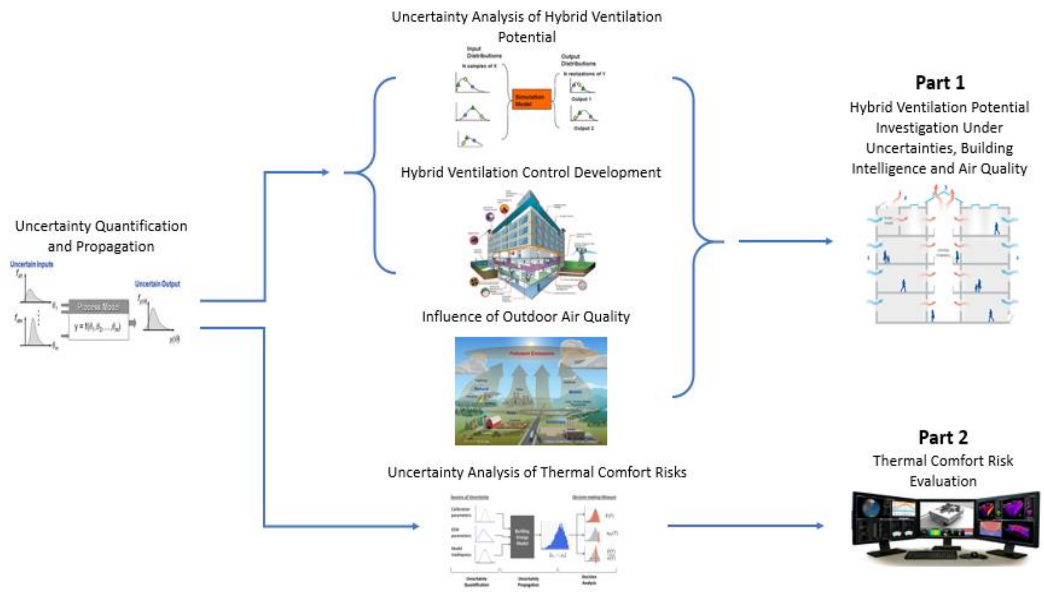


Figure 1.11 Research Framework

In the dissertation, the Chapter 1 describes the background of the research with the motivation and research questions to address in this work. Then serving as the core of this study, the Chapter 2 presents the uncertainty quantification, uncertainty propagation and sensitivity analysis methods used in the analysis. As another part that is influential on the performance of hybrid ventilation, the Chapter 3 describes thorough procedures to develop the black-box model predictive control for hybrid ventilation operation. Then, the hybrid ventilation potential across different climate zones in US was investigated in the Chapter 4 accounting for both uncertainties and building intelligence. As a further step, the Chapter 5 describes the influence of another important factor, i.e. the outdoor air pollutants, on the usage of natural ventilation. The Chapter 6 utilizes a case study to investigate how to better use the uncertainty analysis and the deterministic simulation to help uncover the thermal comfort risk in the natural ventilation design. Lastly, the Chapter 7 provides the summary and conclusions of this dissertation. The limitation of current works and recommendation for future works will also be discussed.

2. UNCERTAINTIES IN BUILDING SIMULATION

Despite the advancement of building simulation, the so-called “performance gap”, which describes the difference between the prediction of building simulation and measured performance, still commonly exists in the building simulation practice. One of the most prominent examples of the performance gap is from the New Building Institute (NBI), in which the predicted EUI (energy use intensity) for more than 100 LEED buildings were compared with measured values (NBI, 2008), as shown in Figure 2.1 below. The left figure presents the ratio of measured to predicted EUI according to the EUI value while the right figure classifies buildings based on their LEED ratings. Both figures clearly show that the discrepancy between predicted values and measured values is significant, especially when the energy saving is intended to be aggressive. These mismatch between prediction and measurements are explained by various causes, which could mainly be grouped into three categories – the causes related to the design, the causes rooted from the construction, the causes related to the building operation (De Wilde, 2014). As emphasized by many studies (Ryan & Sanquist, 2012) (Turner et al, 2008), the deterministic simulation result with one-point estimate could hardly present with enough confidence in the prediction of building performance.

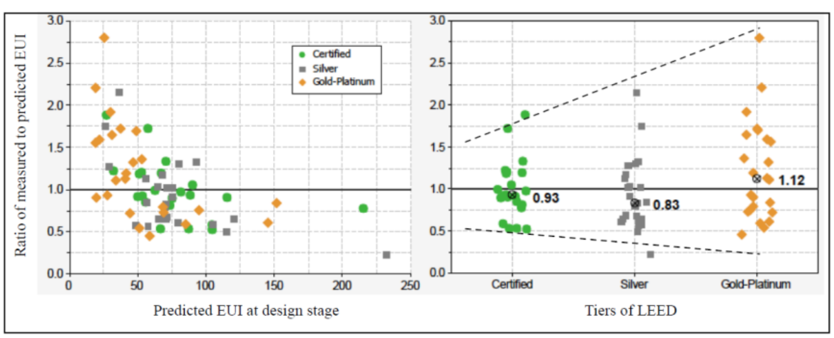


Figure 2.1 Predicted and measured EUI of LEED buildings (NBI 2008)

As one of the major endeavors to close this performance gap, uncertainty analysis arises as an important approach to produce a probabilistic probe into the gap between the predicted and measured data. Several recent studies have shown the capability and significance of using uncertainty analysis to provide better predictions in the building simulation. One of the most recent studies was done by Sun (2014), in which substantial improvements of building energy consumption prediction compared to the deterministic simulation for six case buildings on Georgia Tech campus were shown using the uncertainty analysis. Being capable of covering more possible scenarios using sampling techniques, uncertainty analysis is also beneficial in evaluating risks thus to help decision making. By enabling decision makers to see the confidence interval in making decisions, the probabilistic results from uncertainty analysis provide the decision makers a way to explicitly evaluate the fitness of decisions and choose options based on their own preference. As an example, Heo et al (2013) have also shown the importance of applying uncertainties in evaluating the energy conservation measures (ECM) in retrofit projects.

With the capability of better mimicking the real building operation scenarios and better evaluating the risks, the uncertainty analysis is expected to play a significant role in evaluating the thermal comfort environment in a naturally ventilated building, which sometimes is highly uncertain due to its susceptibility to the dynamic outdoor environment. As one of the earliest works in this aspect, de Wit has conducted an uncertainty analysis on the thermal comfort of a naturally ventilated building (2001, 2002). The uncertainty analysis result shows significant difference of the TO indicator, which is the adaptive comfort performance indicator describing the annual number of hours with more than 10% dissatisfaction of the occupants in the building, compared to the deterministic simulation.

Later, a decision-making scenario with two different decision makers was established to see the possible influence of uncertainty analysis on the decision making. In addition to this work, another relevant work was done by Breesch and Janssens (2010), in which a small naturally ventilated office was simulated with different ventilation mechanisms. In the investigation, the uncertainty analysis clearly uncovered the possible risks of warming climate on the thermal comfort of the baseline building. The authors concluded that the reliability of a naturally ventilated building could be increased with an increase of ventilation rate, thermal mass, and an attachment of top cooling. Overall, the uncertainty analysis has shown its significance in evaluating the thermal comfort risks of a naturally ventilated building.

2.1 Introduction of Uncertainties Analysis in Building Simulation

The uncertainty analysis of building performance consists of two steps – the uncertainty quantification and uncertainty propagation. In the uncertainty quantification stage, the uncertainties from different sources are quantified first based on statistical methods or empirical experiments. Then these quantified uncertainties are propagated into the simulation using different sampling techniques, such as Monte Carlo sampling, Latin Hypercude Sampling etc.

To get a better world view of uncertainties in building simulation and model uncertainties to bridge the gaps between predicted and realized performance, the uncertainties in building simulation could be separated into two parts – the uncertainties from physical model and uncertainties from scenario.

Firstly, the EER diagram, which describes the conceptual model of entity types and their corresponding relationships, for the physical model uncertainty, is shown in Figure 2.2 below. Overall, the physical model uncertainties depict the gaps between design specifications in the building simulation and the physically realized buildings. It consists of five detailed categories of uncertainties – specification uncertainty, realization uncertainty, uncertainty from randomness, model simplification uncertainty and modeler's bias. More specifically, the specification uncertainty arises from the lack of granularity and accuracy when specifying the physically realized buildings in the simulation program, such as an inaccurate specification of thermal properties for the construction material. Also, the realization uncertainty happens in the process of transforming what is on the design documents to the real buildings, including the workmanship uncertainty and interpretation uncertainty from construction team. Then the uncertainty from randomness is related to the variability of known "knowns", e.g. the randomness of events happens in the manufacturing process of building materials. The model simplification uncertainty represents the deviation caused by the simplification of simulation models, such as the simplification of control strategy, the simplification of some weather models etc. Lastly, the modeler's bias is straightforward. It is caused by inaccurate speculation of building modelers in the simulation process.

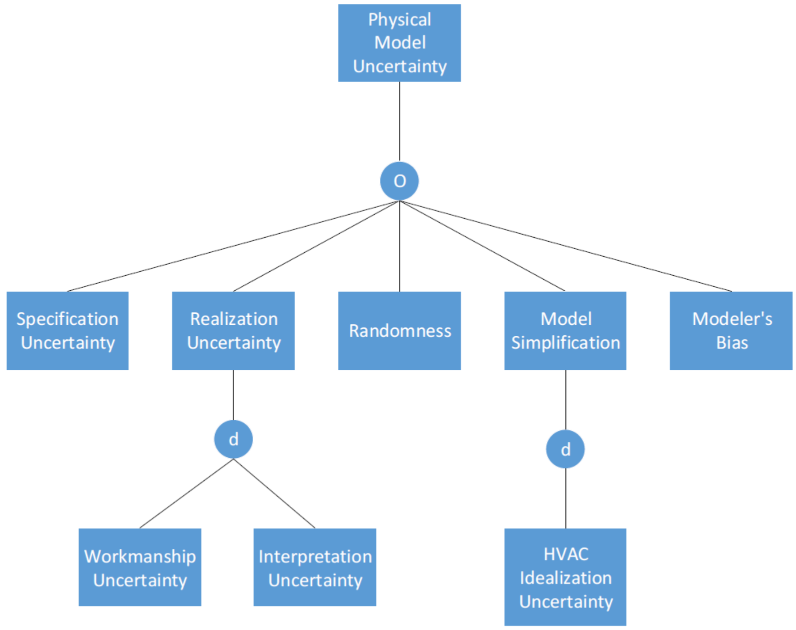


Figure 2.2 EER Diagram for Physical Model Uncertainty (Wang, 2016)

In addition to the physical model uncertainties, the EER diagram in Figure 2.3 shows the uncertainties from "scenario" in the building simulation. The first category is the usage scenario uncertainty in the building simulation, which springs from the stochastic nature of building indoor and outdoor environment. The examples of these uncertainties include the variability of occupant presence, the lighting and electric equipment consumption and occupant behaviors (such as the change of thermostat) in the building. Then the second category is the critical scenario uncertainty, which describes the possible building operation outside the normal conditions, e.g. extreme heat wave, power, outage etc. Thirdly, the last branch is the normative scenario uncertainty, which could be an uncertainty source if the building simulation is evaluated against normative scenarios.

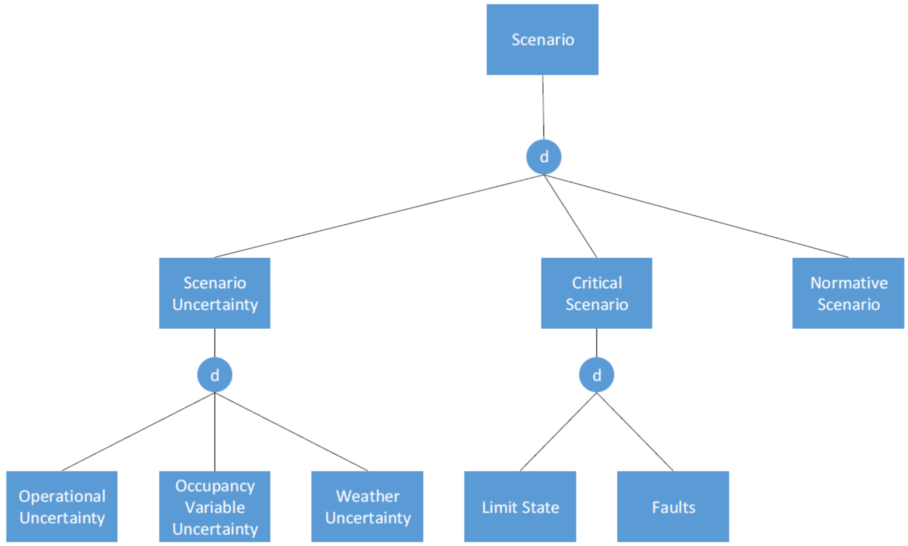


Figure 2.3 EER Diagram for Scenario (Wang, 2016)

Besides the typology above, the other categorization of uncertainties in the building simulation is to divide the uncertainties into model form uncertainty and parametric uncertainty. The model form uncertainty represents the insufficiency of using simplified physical modeling process to describe the physical behaviors. The model form uncertainty could be further categorized into the exposable model form uncertainty, in which we can use explicitly quantified uncertainty on model parameters as proxies of model discrepancy, and un-exposable model formed uncertainties for which the uncertainties are not easily quantified. On the other hand, the parameter uncertainty comes mostly from the lack of exact information for properties of simulated building before the building is established. In our uncertainty quantifications later, we quantify both model form uncertainties and parameter uncertainties into four levels based on scales, i.e., meteorological uncertainty, urban uncertainty, building uncertainty and operation uncertainty. All these are used in our uncertainty analysis later in the research.

2.2 Uncertainty Quantification and Propagation

2.2.1 Uncertainty Quantification

Firstly, the meteorological uncertainty depicts the uncertainty spring from the stochastic weather fluctuation or possible climate change. In the current practice of building simulation, the Typical Meteorological Year (TMY) or Test Reference Year (TRY) is frequently utilized by building modelers as the weather input. However, the generation of all these reference years typically represent the possible significant meteorological variability in the climate of an area insufficiently. Thus, the meteorological uncertainty has been proven with its potential large impacts on the building performance prediction (Bhandari et al, 2012). As to its quantification, we can either do sampling to choose a random historical meteorological year as the simulation input or study the past weather patterns and generate stochastic representations of them. In our study, for each city, 20 historical meteorological years were chosen as the sampling pool to represent the meteorological uncertainty.

In addition to the meteorological uncertainty, the microclimate uncertainty springs from the difference between building microclimate and the place of recorded weather data (typically in the airport, which is a rural area). In the study, we have considered mainly three aspects of microclimate uncertainty, i.e. urban heat island effect, the local wind uncertainty and the ground reflectance uncertainty. Firstly, to quantify the impact of the urban heat island effect, the TEB model (town energy budget) (Masson et al, 2002) was utilized as the high-fidelity model in the uncertainty quantification process. Using different geometric settings (Canyon Height (H), Canyon Ratio (H/W), pervious road and building roof fraction) and weather conditions (short-wave and long-wave solar radiation, air temperature, wind speed, atmospheric pressure, specific humidity) to characterize different scenarios, the results from one run for the rural area and one run for the urban area were compared to calculate the hourly temperature difference triggered by the urban heat island effect. After these temperature differences were generated, linear regression was used to model these differences under each setting. At last, the Gaussian Process (Rasmussen & Williams, 2006) and Inverse Distance Interpolator (IDI) (Joseph and Kang, 2011) were further used to relate these coefficients with their corresponding geometric settings.

Similar to the temperature difference between the recorded weather station data and building microclimate, the local wind speed uncertainty is the uncertainty related to the difference of outdoor wind speed in these two locations. To quantify the local wind speed uncertainty, the CLM (Community Land Model) (Oleson et al, 2010) was used as the high-fidelity model to calculate the average wind speed difference between urban and rural settings. Later, the variation of wind with respect to the height z was quantified using the piecewise linear regression, as shown in formula (1) below. R^2 of more than 95% were achieved in all our regressions.

$$\Delta_W = \begin{cases} \beta_{01} + \beta_{11} z + \xi & \xi \in N(0, \sigma^2) \quad when\, z < \tau \\ \beta_{02} + \beta_{12} z + \xi & \xi \in N(0, \sigma^2) \quad when\, z \geq \tau \end{cases} \quad (1)$$

For the quantification of both urban heat island effect and local wind speed uncertainty, the input related to geometric settings for high fidelity models were all derived from a global database that has information for typical scenarios of urban and rural areas around the world (Jackson et al, 2010). The detailed geometric settings parameters are listed in Table 1 below.

Table 2.1 Urban Settings in Uncertainty Analysis

Parameter Name	Parameter Range
Canyon Height	Uniform Distribution (10, 30)
Canyon Ratio	Uniform Distribution (0.5, 2)
Pervious Road Fraction	Uniform Distribution (0.2, 0.8)
Building Roof Area Fraction	Uniform Distribution (0.2, 0.8)

As the last part of microclimate uncertainty, the ground reflectance uncertainty was quantified using the formula (2) below.

$$\rho_{ground} = \rho_{pervious} f_{pervious} + \rho_{impervious} f_{impervious}$$

In the formula, ρ_{ground} is the ground reflectance. In the uncertainty quantification, the Monte-Carlo sampling is used to generate samples for all these variables ($\rho_{pervious}$, $f_{pervious}$, $f_{impervious}$, $\rho_{impervious}$) based on the same global database mentioned above. Then for each sampling run, the ground reflectance value was calculated. Figure 2.4 below shows the calculation results for the ground reflectance values.

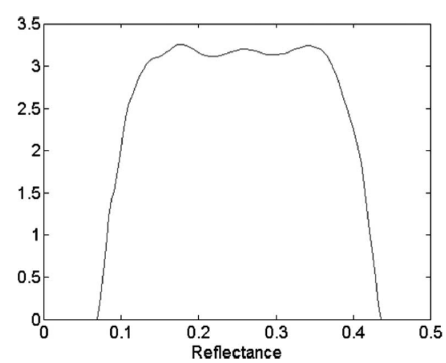


Figure 2.4 PDF of quantified ground reflectance (Sun, 2014)

After quantifying the microclimate uncertainty, in our study, mainly two building level uncertainties were quantified. First and foremost, the convection coefficients (exterior and interior) play important roles in determining the building heat balance thus to generate accurate building performance prediction results. The basic procedures for quantifying both exterior and interior convection coefficients are the same. Below shows the quantification of exterior convection uncertainty as an example. Firstly, the external convection coefficient was expressed as the formula (3) shown below,

$$h_c = aV_z + b \quad (3)$$

in which h_c is the exterior convection coefficient, V_z is the wind speed and a and b are the corresponding coefficients. Then to quantify the uncertainties of exterior convection coefficient (h_c), the uncertainties of a and b were quantified. A thorough search of related researches and lab experiments was conducted to model these two coefficients. Equal weight was applied for findings from all these literatures. And a bi-normal distribution was then assumed to be enough for the uncertainty quantification (modeling) purpose. Finally, using the kernel density estimator, the bi-normal distribution was modelled based on the observations of a and b from found literatures.

Besides the convection uncertainty, the uncertainties of construction material properties are also significant for an accurate prediction of building performance. Several experiments were done before for investigations of possible variation of mainstream construction materials. Based on one of the most thorough works from Domínguez-Muñoz et al (2010), a relative normal distribution with 10% variance was applied for the window conductivity, density of major construction materials (e.g. brick, concrete) and the corresponding specific heat capacity. Meanwhile, a relative normal distribution with 5% variance was applied for the other window properties such as solar transmittance etc.

Lastly, as to the operation uncertainty, with a "vanilla" version of uncertainty quantification due to limited available data, a relative uniform distribution with 70% as lower bound and 130% as upper bound was applied for the occupant presence, lighting consumption and electric equipment consumption as illustrative purposes according to (Sun et al, 2014a).

This section just briefly presents examples about how each category of uncertainties were quantified in our analysis. More detailed works about all these uncertainty quantification process could be found from former works (Sun, 2014a, b). All the detailed settings of applied uncertainties are presented in Table 2.2 below. In our analysis, no context information was assumed to be known for our investigated building. Thus, a general version of uncertainties was applied.

Table 2.2 Applied Uncertainties

Phenomena/Parameter	**Uncertainty Quantification**
Microclimate Level	
Canyon Height	Uniform (10,30)
Canyon Ratio	Uniform (0.5,2)
Pervious Road Fraction	Uniform (0.2,0.8)
Building Roof Fraction	Uniform (0.2,0.8)
Ground Reflectance	Uniform (0.15,0.35)
Building Level	
External Convective Heat Transfer $h_{c,ext} = aV_z + b$	Bivariate Normal [a,b] ~ $N(\mu, \sum)$
Internal Convective Heat Transfer $h_{c,int} = m_w\lvert\Delta_T\rvert^{n_w}$	Bivariate Normal $[m_w, n_w]$ ~ $N(\mu_w, \sum_w)$

Floor Convective Heat Transfer $h_{c,floor} = m_f\|\Delta_T\|^{n_f}$	Bivariate Normal $[m_f, n_f] \sim N(\mu_f, \sum_f)$
Ceiling Convective Heat Transfer $h_{c,ceil} = m_c\|\Delta_T\|^{n_c}$	Bivariate Normal $[m_c, n_c] \sim N(\mu_c, \sum_c)$
Conductivity	Relative Normal (1, 5%)
Density	Relative Normal (1, 10%)
Specific Heat Capacity	Relative Normal (1, 10%)
Solar Absorptance	Relative Normal (1, 10%)
Glazing Conductivity	Relative Normal (1, 10%)
Glazing Front Side Solar Reflectance	Relative Normal (1, 5%)
Glazing Vack Side Solar Reflectance	Relative Normal (1, 5%)
Glazing Solar Transmittance	Relative Normal (1, 5%)
System and Occupant Level	
Lighting Consumption	Relative Uniform (0.7,1.3)
Electric Equipment Consumption	Relative Uniform (0.7,1.3)
Occupants Density	Relative Uniform (0.7,1.3)

2.2.2 Uncertainty Propagation

To propagate the quantified into the simulation, we utilized the GURA-W (Georgia Tech Uncertainty and Risk Analysis Workbench) (Lee et al, 2013), which was developed to help more flexibly uncertainty analysis for the building simulation. The complete working procedures of GURA-W are shown in Figure 2.5 below. Firstly, a UQ (Uncertainty Quantification) repository that describes the distributions of each uncertain parameters should be defined. Then the sampling module will sample from these defined distributions using Latin hypercube sampling (LHS) and then distribute these sampled values into the building module and weather module for further processing. The building module will deal with the sampled parameters related to the building level uncertainty while the weather module will process the sampled parameters related to the microclimate level uncertainty. After processing, all these variables will then be distributed into the simulation module, which utilizes EnergyPlus as the core simulation engine and conduct the simulation. Finally, the post-processing module will process the simulation results based on user needs.

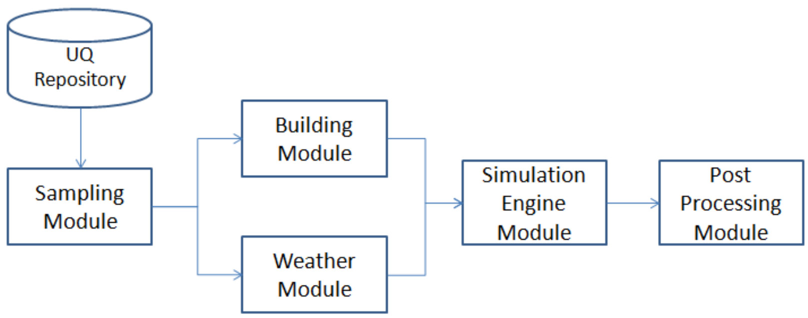


Figure 2.5 GURA-W Working Process

As to how these samples are propagated into the simulation models, typically, they are distributed into simulation in the building level, i.e. one sample for each uncertainty analysis run and represents the value of this parameter for the whole building. The only exception for the sample distribution are the sampled values for presence, lighting consumption and electric equipment consumption. In each uncertainty analysis run, one value will be sampled from the defined distribution for each building and then distributed into the simulation model. Thus, one sampled value will only represent the corresponding parameter in a zone level. This is designed to consider the spatial variability of operation uncertainty in each building zone.

2.3 Sensitivity Analysis

Increasingly becoming an important couple to the uncertainty analysis, the sensitivity analysis helps to identify the most significant variables that will affect our interested output in the uncertainty analysis. Overall, the sensitivity analysis methods could be divided into two major categories – local sensitivity analysis method and global sensitivity method (Tian, 2013). In the local sensitivity analysis method, the sensitivity measure was calculated by changing one variable at a time. Thus, although it is straightforward to interpret the results, the local sensitivity analysis has drawbacks including lack of variable interaction consideration, no self-verification etc. On the other hand, the global sensitivity analysis method attempts to investigate how sensitive are the sensitivity measures to the uncertain parameters as a whole. The global sensitivity analysis method could be further categorized as regression method (Standardized Regression Coefficients, Partial Correlation Coefficients, stepwise method etc.), screening-based method (Morris method), variance based method (Fourier Amplitude Sensitivity Test, Sobol method) and Meta-model based method.

In the sensitivity analysis later, the Multivariate Adaptive Regression Splines (MARS) (Milborrow, 2016) is employed, which is a meta-model based method as mentioned above (also variance-based method). Taking the form as follows,

$$\hat{f}(x) = \sum_{i=0}^{k} \beta_i B_i(x)$$

$x = (x_1, .., x_n)$ are the n dimensional inputs, $B_i(x)$ is the basis function, which could be a constant value 1, a hinge function $\max(0, x_{\mathrm{i}} - const)$ or a product of multiple hinge functions, and β_i are corresponding coefficients. Multivariate Adaptive Regression Splines offers the advantage of dealing with high-dimensional nonlinear data in a flexible and efficient manner. Based on the complexity of thermal comfort data and energy consumption data from simulation, in the sensitivity analysis, only considering the first order hinge function has already been able to provide a satisfactory performance. During the model and variable selection process, the Generalized Cross Validation error (GVC) with stepwise procedures was utilized. Finally, based on the fitted model, all the parameters were ranked using their relative importance of explaining the variance of responses in the sensitivity analysis. The formula for calculating the relative importance score is shown below (RSS is the sum of residual sum of square),

$$Relative\ Importance\ Score\ of\ variable\ j$$
$$= \frac{\sum_{i=1}^{k} Decrease\ of\ RSS\ of\ Sub-Models\ with\ variable\ j}{\sum_{i=1}^{n} Decrease\ of\ RSS\ of\ all\ the\ Sub-Models}$$

The relative importance score calculation process is based on the model establishment process before with stepwise selection. The relative importance score for one variable j is calculated by dividing the sum of residual sum of square (RSS) decrease for all the sub-models contain variable j by the total sum of RSS decrease for all the sub-models in the model and variable selection process.

3. DEVELOPMENT OF INTELLIGENT CONTROL FOR HYBRID VENTILATION

The control strategy of a hybrid ventilation building is crucial component to ensure the robust performance of a hybrid ventilation building. An over-optimistic or over-conservative control strategy will lead to different problems such as unexpected thermal performance or unoptimized energy efficiency. In this chapter, we firstly present the detailed development process of our model predictive control. The developed model predictive control strategy for the hybrid ventilation building operation is a black-box approach with the verification of control performance under uncertainties. Then its comparison with a traditional rule-based control is conducted to illustrate the potential impact of building intelligence on the hybrid ventilation building performance.

3.1 Model Predictive Control (MPC) Development

3.1.1 MPC Development Process

As one of the key factors in determining the performance of hybrid ventilation building, establishing a robust control is significant in the practice of running hybrid ventilation. Figure 3.1 below shows the whole process of developing the model predictive control (MPC) in this study. The first step of developing the MPC is to identify a set of variables and models as candidates for the central model establishment. Then, four statistical measures are defined to facilitate the model and variable selection. We have used the brute-force approach with the stepwise selection in this step. Based on the Bayesian Information Criterion, the best performance of each candidate model in predictions were compared with each other in terms of both temperature and energy consumption. To help better interpret the selection results, we have also plotted the figures about how different statistical measures change in the variable selection process. Then, once we have determined the atomic central model with corresponding variables, as the third step, three clusters of neural network models were established for the prediction of building operation status in natural ventilation, air conditioning and transition between two modes. To improve the central model training, the meteorological uncertainty and microclimate uncertainty were also applied to broaden the training set by generating more realistic weather scenarios that a building could experience in practice. Finally, the developed model predictive control was verified under all uncertainties, including the meteorological uncertainty, microclimate uncertainty, building uncertainty and operation uncertainty. 30 simulation runs were performed to ensure the correctness of the developed control.

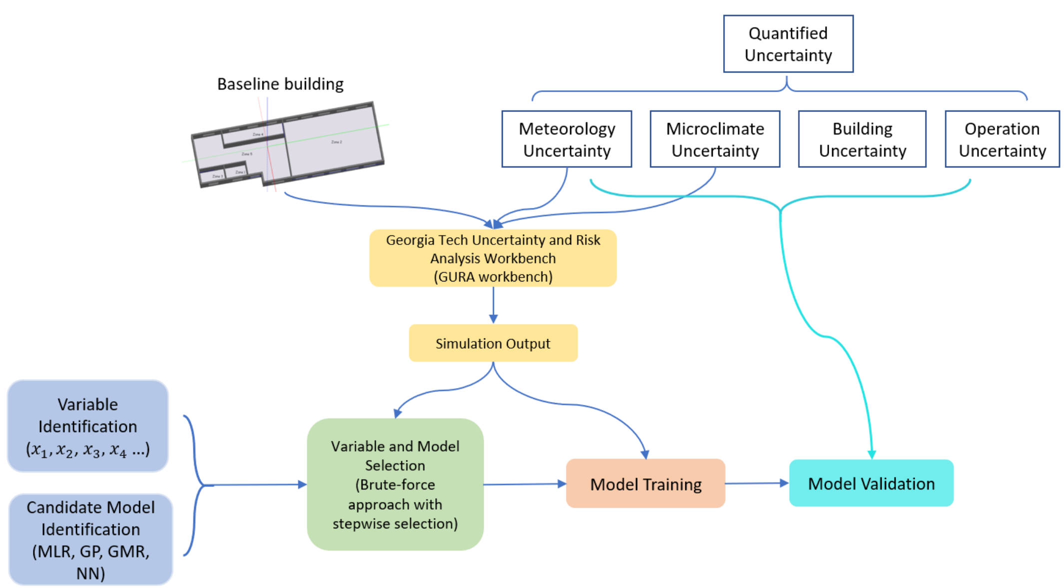


Figure 3.1 MPC Development Process

3.1.2 Candidate Models and Variables

To ensure the performance of our central model with respect to both computational accuracy and speed, we have identified four candidate models as the potential atomic central model, ranging from linear to nonlinear and parametric to non-parametric.

The first model we have considered is the multiple linear regression (Aiken et al, 2003), which is one of the most widely used methods in practice to extract patterns from the data. In the multiple linear regression, the relationship between the response variable and multiple independent variables is modelled linearly as shown in the form below,

$$y = \beta_0 + \sum_{p=1}^{k} \beta_p * x_{ip}$$

Here, the coefficients ($\beta_1 \dots \beta_p$) are the coefficients for each of our predictors ($x_1 \dots x_p$) while β_0 is the constant in the model to adjust the predictions. All these coefficients are typically estimated using the least square method.

Secondly, in addition to the linear method such as the multiple linear regression, nonlinear methods were chosen and tested in the model selection process as well. As a parametric method for nonlinear data regression, the Gaussian Mixture Regression (GMR) (Sung, 2004) predicts the response of new incoming data based on the weighted sum of estimates from different fitted Gaussian models in the model training process. It is a generative approach that models both predictors and responses as a whole. In the training process, we assume all underlying data follow Gaussian distribution first. Then, the Expectation-Maximization (EM) (Moon, 1996) algorithm is used to infer the parameters of fitted Gaussian distribution, which will be used to predict the response of new coming data later. Being efficient in the data processing, only the parameters of each fitted Gaussian distribution are necessary to be kept and later utilized in the prediction. The brief procedures of deriving the predicted responses are shown as below. First of all, the data are assumed to follow the joint distribution,

$$p(x, y) = \sum_{k=1}^{k} \pi_k p(x, y|\mu_k, \Sigma_k)$$

In which $\sum_{k=1}^{k} \pi_k = 1$, μ_k and $\sum_k$ are the mean and covariance of kth fitted Gaussian distribution in the Gaussian Mixture Model. Then,

$$p(x, y) = \sum_{k=1}^{k} p(x, y|\mu_k, \Sigma_k) = \sum_{k=1}^{k} \pi_k p(y|h_k(x), \sigma_k^2)\, p(x|\mu_{kX}, \Sigma_{kXX})$$

Where $h_k(x) = \mu_{kY} + \Sigma_{kYX}(\Sigma_{kXX})^{-1}(x - \mu_{kX})$ and $\sigma_k^2 = \Sigma_{kYY} - \Sigma_{kYX}(\Sigma_{kXX})^{-1}\Sigma_{kXY}$.

For which we can get

$$p(y|x) = \frac{p(x, y)}{p(x)} = \frac{p(x, y)}{\int p(x, y)dy} = \frac{p(x, y)}{\sum_{k=1}^{k} \pi_k p(x|\mu_{kX}, \Sigma_{kXX})}$$

Then based on equation (2) and (3) above, we can derive

$$h(x) = E(Y|X = x) = \sum_{k=1}^{k} \omega_k(x) h_k(x)$$

where $\omega_k(x) = \frac{\pi_k p(x|\mu_{kX}, \Sigma_{kXX})}{\sum_{k=1}^{k} \pi_k p(x|\mu_{kX}, \Sigma_{kXX})}$ and $h_k(x)$ as shown above.

Finally, the corresponding conditional variance could be calculated as

$$v(x) = V(Y|X = x) = \sum_{k=1}^{k} \omega_k(x)(h_k^2(x) + \sigma_k^2) - (\sum_{k=1}^{k} \omega_k(x)h_k(x))^2$$

In our training process, as one of the key factors that determine the performance of Gaussian Mixture Model prediction, the number of components in the Gaussian Mixture Model was estimated using the Bayesian Information Criterion (BIC) as the criteria.

Thirdly, the Gaussian Process Regression (Rasmussen, 2006), which is a kernel-based regression model, was considered as an option for our central model establishment as well. As a nonparametric model, all training data points are treated as a random variable such that the joint of them follows a multivariate normal distribution overall. Then, the covariance matrix $k(x, x')$ is specified in the training to establish Gaussian Process Regression model. Finally, to predict the response for the new coming data point, the similarity between the new coming data and the stored training data is calculated. The procedures below show the prediction process with new data coming. Assuming $D = \{x^{(i)}, y^{(i)}\}_{i=1}^{m}$ are the training set with m data points, the Gaussian process regression model could be represented as

$$y^{(i)} = g\left(x^{(i)}\right) + \varepsilon^{(i)}$$

in which $g(\cdot) \sim GP(0, k(\cdot,\cdot))$ where $k(\cdot,\cdot)$ is covariance function, and $\varepsilon^{(i)} \sim N(0, \sigma^2)$ are the i.i.d. errors. Thus, with new predictors x^*,

$$\begin{bmatrix} \vec{g} \\ \vec{g^*} \end{bmatrix} |x, x^* \sim N(\vec{0}, \begin{bmatrix} k(x,x) & k(x,x^*) \\ k(x,x^*) & k(x^*,x^*) \end{bmatrix}) \text{ and } \begin{bmatrix} \vec{\varepsilon} \\ \vec{\varepsilon^*} \end{bmatrix} \sim N(\vec{0}, \begin{bmatrix} \sigma^2 I & \vec{0} \\ \vec{0}^T & \sigma^2 I \end{bmatrix}).$$

Then, based on the equation (1) above, it is not hard to infer that

$$y^*|y, x, x^* \sim N(\mu^*, \textstyle\sum^*)$$

In which

$$\mu^* = k(x^*, x)(k(x,x) + \sigma^2 I)^{-1}\vec{y}$$

$$\sum^{*} = k(x^{*}, x^{*}) + \sigma^{2}I - k(x^{*}, x)(k(x, x) + \sigma^{2}I)^{-1}k(x, x^{*})$$

Lastly, in addition to three models mentioned above, the artificial neural network (Fausett, 1994) was also tested in this study for the hybrid ventilation building operation status prediction. Deriving from the way how natural neurons communicate and work with each other, the Neural Network algorithm is one of the most famous machine learning algorithms that is widely used for different purposes, such as energy prediction, decision making improvement in the context of building related (Kalogirou, 2000). For example, Biswas et al (2016) have utilized neural network for the energy consumption of residential houses. Similarly, Deb et al (2016) have also employed neural network to forecast the diurnal cooling energy load for institutional buildings. Overall, the Neural Network algorithm not only provides good accuracy in the prediction, but also fast computation and flexibility in the establishment of the model. As shown in Figure 3.2 below, the Neural Network model consists of three layers, the input layer, hidden layer and output layer. Serving as the core of Neural Network, the hidden layer can incorporate multiple layers and utilize different structures (e.g. as Logistic or tanh) to achieve the better prediction performance. Each neuron in one layer is connected with the neurons in the layers before or after them in different weights. In this study, we have used the Levenberg–Marquardt algorithm (Moré, 1978) for the Neural Network model training.

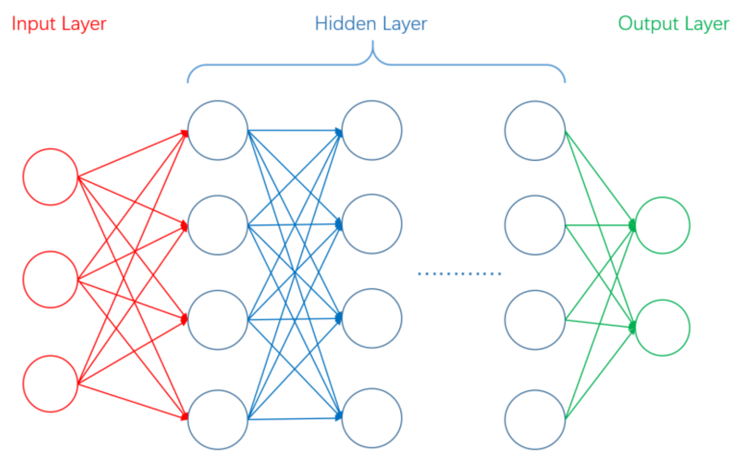


Figure 3.2 Neural Network Model

After identifying all the candidate models to test, we have also identified ten variables with respect to building indoor environment and operation status (average air temperature, indoor dew temperature at the last time step, office hour index) and outdoor environment (outdoor air temperature, dew temperature, relative humidity, wind speed, total solar radiation, horizontal infrared intensity, season index) to achieve the prediction of hybrid ventilation building operation status, including the indoor air temperature, indoor operative temperature and the energy consumption we are interested in. All these variables were selected based on the recommendations from different related literatures (Zhao et al, 2012), (Kusiak et al, 2010), (Kalogirou, 2006). Most of these variables are numeric variables with only the season index (1~4 represents from Spring to Winter) and the office hour index (1~12 represents the office hour from 7am to 7pm) as the categorical variables.

3.1.3 Model and Variable Selection Process

To run through a thorough model and variable selection process, we have defined four statistical measures, including R^2, MAE (mean absolute error), RMSE (root mean square error) and BIC (Bayesian information criterion), to evaluate the performance of each candidate model and variable in the prediction.

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

$$MAE = \frac{\sum_{i=1}^{n} AE(y_i - \hat{y}_i)}{n}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}$$

$$BIC = -2\ln(\hat{L}) + \ln(n)k$$

As shown in the formulas above, R^2, which is the coefficient of determination, is one of the most popular statistical measures to assess the performance of model fitting. In the formula, the $\hat{y}_i$ represents the predicted value of i-th data while the $\bar{y}$ represents the mean of all data points such that it can be interpreted as how much variance of the data was explained by the fitted regression line. Except for the coefficient of determination, the MAE (mean square error) and RMSE (root mean square error) are also good indicators of how much the predictions deviate from the measured values. The most significant differences between these two measures are that the RMSE is more sensitive to the outliers in the prediction while MAE just averages all the prediction errors. Finally, the Bayesian information criterion (BIC) calculated by the combination of likelihood and the punishment of including predictors was employed in the variable selection process and avoid overfit of the model.

With all these statistical measures defined to aid the model and variable selection, we have employed the brute-force approach with the forward selection, in which each variable is added into the tested candidate model one by one for the performance evaluation. To aid the formulation of our objective function in the model predictive control later, we have defined the indoor air temperature, indoor operative temperature and the building HVAC energy consumption as the interested responses. Table 3.1 – 3.3 below list the best prediction performance of all interested responses for each candidate model and its associated predictors based on BIC as criteria (1 is indoor air temperature, 2 is office hour index, 3 is outdoor air temperature, 4 is outdoor dew temperature, 5 is outdoor relative humidity, 6 is local wind speed, 7 is horizontal infrared intensity, 8 is season index, 9 is indoor dew temperature, 10 is total solar intensity and the sequence in the [] represents the sequence of adding it into the model).

Table 3.1 Prediction of Air Temperature

	Variable Set	Root Mean Square Error	Mean Absolute Error	R Square	BIC
Multiple Linear Regression	[3,1,10,2,7,6,9,4,8,5]	0.3487	0.2491	0.9901	51260.03
Gaussian Process	[3,1,2,10,6,8,4,5,9]	0.1271	0.0892	0.9987	-8922.2
Gaussian Mixture Regression	[3,1,10,2,5,6,7,9]	0.1365	0.0943	0.9985	-8848.7
Neural Network	[3,1,10,2,6,8]	0.1009	0.0741	0.9992	-81761.2

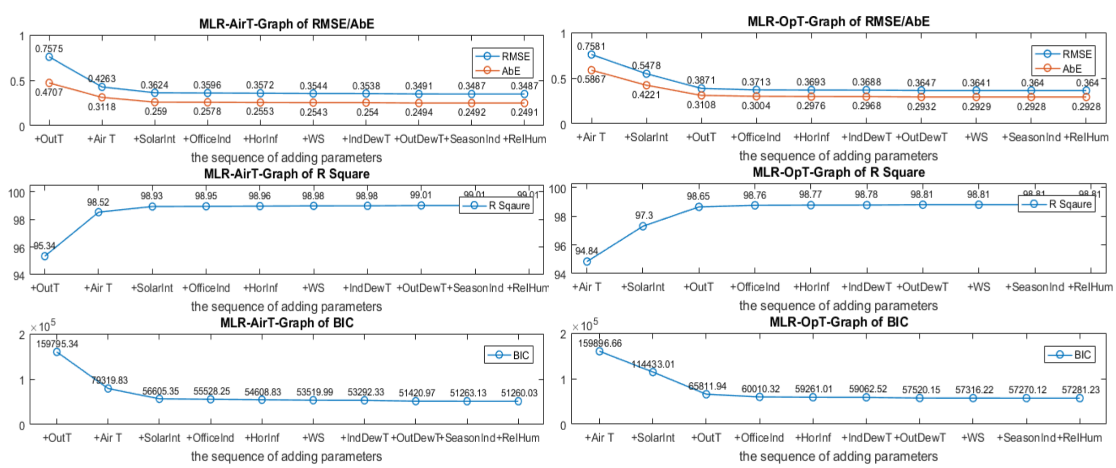
Table 3.2 Prediction of Operative Temperature

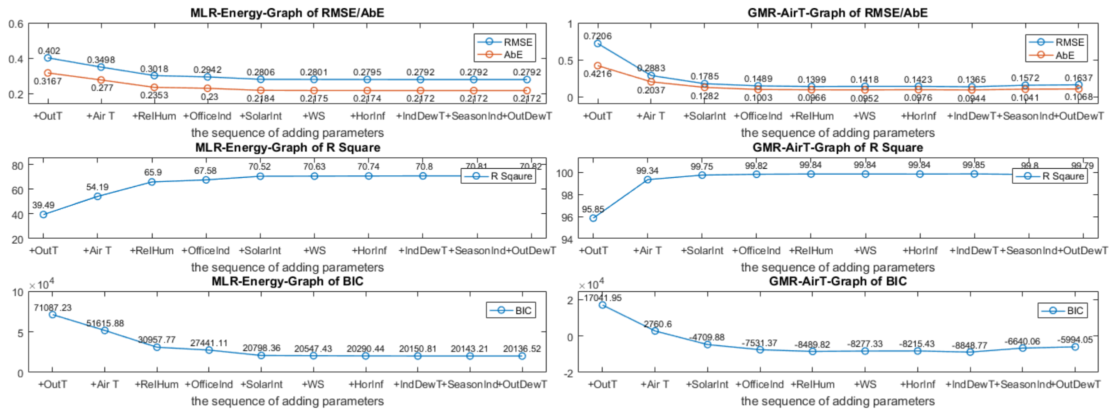
	Variable Set	Root Mean Square Error	Mean Absolute Error	R Square	BIC
Multiple Linear Regression	[1,10,3,2,7,9,4,6,8]	0.3640	0.2928	0.9881	57270.1
Gaussian Process	[1,10,3,2,8,6,4,7,9]	0.1677	0.1296	0.9975	-5041.9
Gaussian Mixture Regression	[1,10,3,2,6,7]	0.1949	0.1495	0.9965	-3310.6
Neural Network	[1,10,3,2,8,6,7,9,4,5]	0.1703	0.1313	0.9974	-32763.2

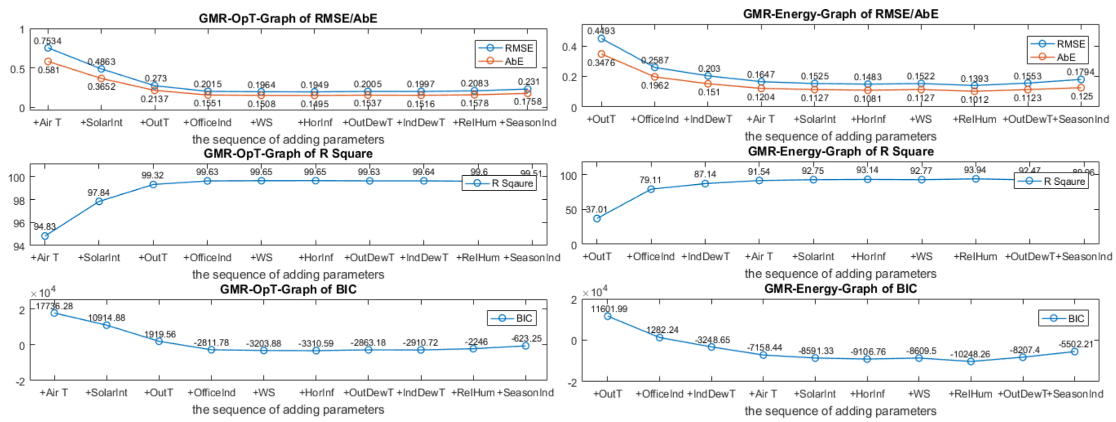
Table 3.3 Prediction of Energy

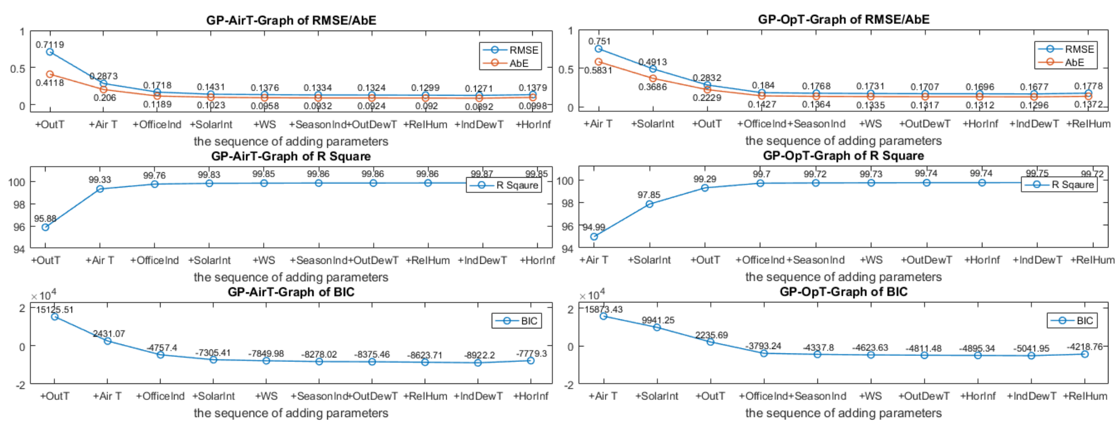
	Variable Set	Root Mean Square Error	Mean Absolute Error	R Square	BIC
Multiple Linear Regression	[3,1,5,2,10,6,7,9,8,4]	0.2791	0.2172	0.7082	20136.5
Gaussian Process	[3,2,1,4,8,9,6]	0.1204	0.0888	0.9553	-16909.4
Gaussian Mixture Regression	[3,2,9,1,10,7,6,5]	0.1393	0.1012	0.9394	-10248.3
Neural Network	[3,2,5,1,10,4,8,9,6]	0.0996	0.0743	0.9635	-193731.6

Meanwhile, to help better interpret the model and variable selection process, for the prediction of each interested response, we have plotted how each statistical measure changes after adding one variable that reduces BIC most, as shown in Figure 3.3 below. In the figure, the X axis shows the sequence of adding each candidate variable while the Y axis presents the change of statistical measures. For illustrative purpose, the figures for the model and variable selection when we use the weather of Los Angeles in the training. The results are similar across the city.




MLR-Energy-Graph of RMSE/AbE
RMSE
AbE
+OutT +Air T +RelHum +OfficeInd +SolarInt +WS +HorInf +IndDewT+SeasonInd+OutDewT
the sequence of adding parameters
MLR-Energy-Graph of R Square
R Sqaure
the sequence of adding parameters
MLR-Energy-Graph of BIC
BIC
the sequence of adding parameters
GMR-AirT-Graph of RMSE/AbE
RMSE
AbE
+OutT +Air T +SolarInt +OfficeInd +RelHum +WS +HorInf +IndDewT+SeasonInd+OutDewT
the sequence of adding parameters
GMR-AirT-Graph of R Square
R Sqaure
the sequence of adding parameters
GMR-AirT-Graph of BIC
BIC
the sequence of adding parameters


GMR-OpT-Graph of RMSE/AbE
RMSE
AbE
+Air T +SolarInt +OutT +OfficeInd +WS +HorInf +OutDewT +IndDewT +RelHum +SeasonInd
the sequence of adding parameters
GMR-OpT-Graph of R Square
R Sqaure
the sequence of adding parameters
GMR-OpT-Graph of BIC
BIC
the sequence of adding parameters
GMR-Energy-Graph of RMSE/AbE
RMSE
AbE
+OutT +OfficeInd +IndDewT +Air T +SolarInt +HorInf +WS +RelHum +OutDewT+SeasonInd
the sequence of adding parameters
GMR-Energy-Graph of R Square
R Sqaure
the sequence of adding parameters
GMR-Energy-Graph of BIC
BIC
the sequence of adding parameters


GP-AirT-Graph of RMSE/AbE
RMSE
AbE
+OutT +Air T +OfficeInd +SolarInt +WS +SeasonInd+OutDewT +RelHum +IndDewT +HorInf
the sequence of adding parameters
GP-AirT-Graph of R Square
R Sqaure
the sequence of adding parameters
GP-AirT-Graph of BIC
BIC
the sequence of adding parameters
GP-OpT-Graph of RMSE/AbE
RMSE
AbE
+Air T +SolarInt +OutT +OfficeInd+SeasonInd +WS +OutDewT +HorInf +IndDewT +RelHum
the sequence of adding parameters
GP-OpT-Graph of R Square
R Sqaure
the sequence of adding parameters
GP-OpT-Graph of BIC
BIC
the sequence of adding parameters

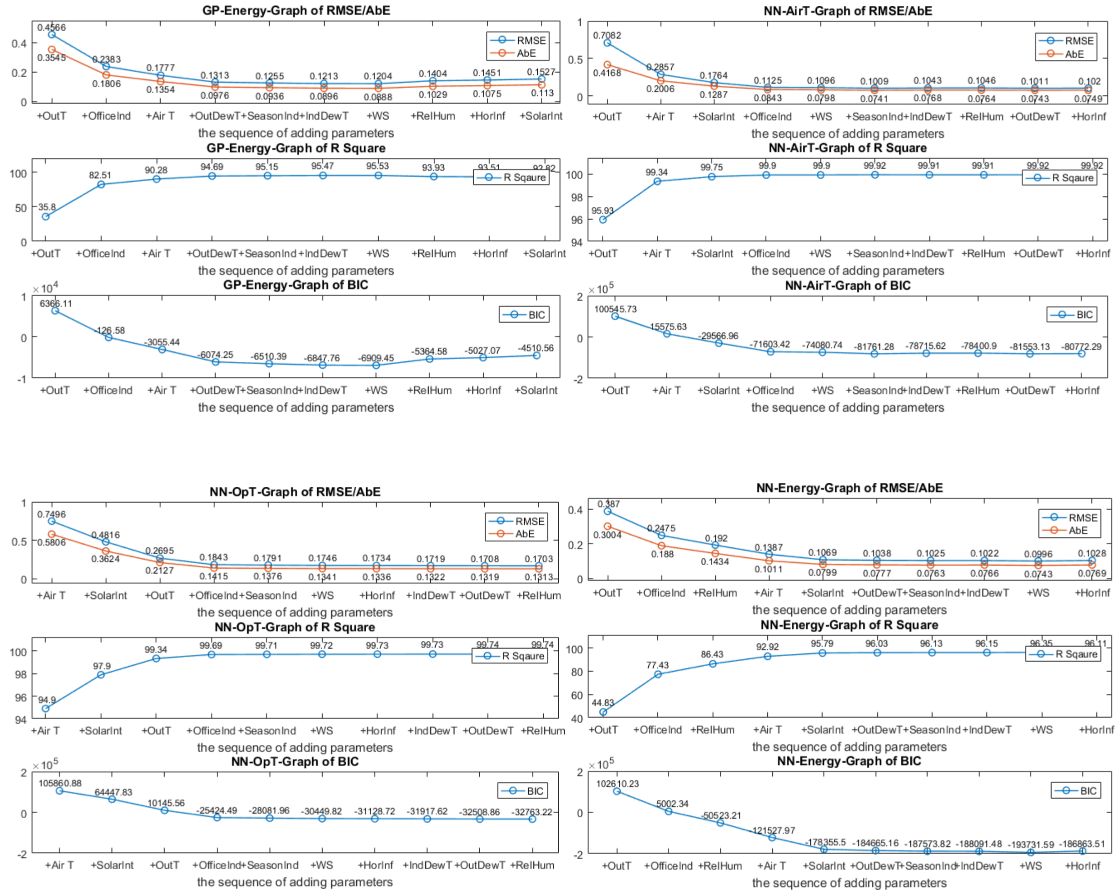


Figure 3.3. Statistical Measures for Different Models with Variables (Abbreviation: Air T = Air Temperature, OutT = Outdoor Temperature, SolarInt = Solar Intensity, OfficeInd = Office Index, SeasonInd = Season Index, WS = Wind Speed, HorInf = Horizontal Infrared Intensity, IndDewT = Indoor Dew Temperature, OutDewT = Outdoor Dew Temperature, RelHum = Outdoor Relative Humidity)

3.1.4 Model and Variable Selection Result

Based on the model and variable selection process as described above, we firstly eliminate the multiple linear regression as our option for the central model establishment due to its poor performance in terms of both indoor environment (indoor air and operative temperature) and energy consumption prediction compared to the other nonlinear approaches. Then, as to other nonlinear approaches, according to the statistical measures we have defined, the Neural Network models show consistently better performance compared to other methods in all predictions. In the model and variable selection process, we have only found that occasionally the Gaussian process could outperform Neural Network in predicting the indoor operative temperature with slightly improved accuracy. However, the excessive computational burden brought by the Gaussian process as a nonparametric method further hinders it to be chosen as the atomic central model. The necessity of storing all the training data in the model establishment and response prediction will lead to severe computational problems especially when the building is complex with indispensably large amount of training data. Consequently, the Neural Network with its flexibility, fast computation and good accuracy was chosen as the atomic model in the central model establishment of our model predictive control.

Then after choosing the appropriate central model, the next step is to choose the combination of variables that could achieve the best performance. For each of our interested response, the significance of each variable in the forward selection process slightly differs, as shown in Table 3.4 below. The sequence of listing the variables below reflect the sequence of adding each variable into the model during the model and variable selection process.

Table 3.4 Adding Variable Sequence

Interested Response	Sequence of Adding Variables
Indoor Air Temperature	the outdoor temperature, indoor air temperature, total solar intensity, office hour index, local wind speed and season index

Indoor Operative Temperature	indoor air temperature, total solar intensity, outdoor air temperature, office hour index, season index, local wind speed, horizontal infrared intensity, indoor dew temperature, outdoor dew temperature and outdoor relative humidity
Energy Consumption	the outdoor air temperature, office hour index, outdoor relative humidity, indoor air temperature, total solar intensity, outdoor dew temperature, season index, indoor dew temperature and local wind speed

Accordingly, to ensure the consistency of the prediction while maintaining enough accuracy, we have selected the indoor and outdoor air temperature, the outdoor relative humidity, the wind speed, the season and office hour index for the prediction of all interested responses. As to the parameters excluded as predictors, the most significant variable is the total solar intensity, which is ranked as 3rd, 2nd and 5th for the prediction of the indoor air temperature, operative temperature and energy consumption in the model and variable selection process. Nevertheless, it is still neglected in the prediction due to the applicability reasons. In the real practice, achieving the building level prediction of solar intensity is typically hard with a lot of uncertainties from the building microclimate and weather conditions. Also, the solar intensity prediction is not easily available from the normal weather forecast service. All these increase the difficulty and instability of applying our developed model predictive control in practice. Thus, it is neglected in the final prediction model. Except for the total solar intensity, the other excluded predictors, including the horizontal infrared intensity, the indoor dew temperature and outdoor dew temperature, are either insignificant in the prediction or highly correlated with predictors that are already in the model thus providing no additional values in the prediction.

3.1.5 Central Model Training Result

After determining the central atomic model with the best set of variables for the prediction, we started the central model training process for each of our tested cities – Los Angeles, San Francisco, Seattle and Atlanta. In this step, the meteorological uncertainty (randomly choose 10 years from the past 20 years historical meteorological year data) and microclimate uncertainty (urban heat island effect, local wind speed uncertainty) were incorporated to expand the training data set. The central model was trained in three clusters to predict the indoor air temperature, operative temperature and energy consumption when the hybrid ventilation building is in transition (from air conditioning to natural ventilation and from natural ventilation to air conditioning), continuous natural ventilation and continuous air conditioning.

To better illustrate the capability of the developed model predictive control, the baseline building that we have developed the control for a two-story building in the Georgia Tech campus. The building is composed of diverse types of zones, including lobby, individual offices, open spaces etc., such that it could be a representative commercial building. Figure 3.4 below shows the basic configuration of the baseline building. The construction details of the baseline building were adapted to different climate zones of tested cities according to the DOE reference commercial building (Deru et al, 2011), as shown in Table 3.5 below. Also, as recommended from the DOE reference commercial building, the baseline building is equipped with a Variable Air Volume system with reheat for air conditioning. The system configurations are listed in Table 3.6 below. Meanwhile, a motorized window control system is assumed to be installed for window control of the building.

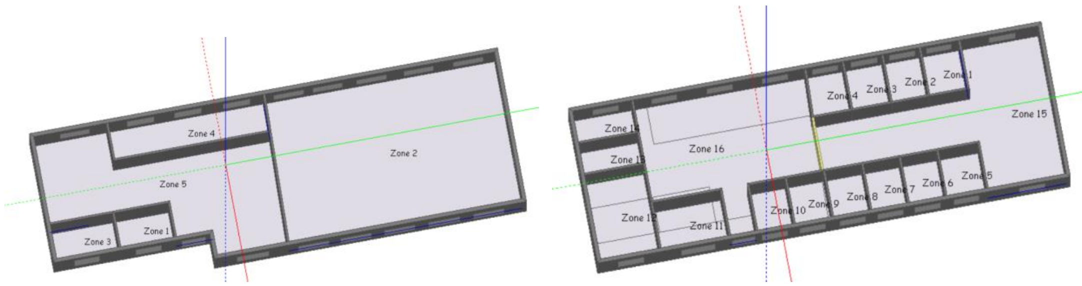


Figure 3.4 Baseline Building Configurations

Table 3.5 Detailed Building Information

	U value (W/m2*K)				SHGC	Operation Related Parameters		
Cities	Roof	Floor	Exterior Wall	Window	Window	Occupancy (m2/person)	Lighting (W/m2)	Electric Equipment (W/m2)
Atlanta	0.358	1.862	0.704	3.24	0.25	18.58	10.76	10.76
Los Angeles	0.358	1.862	0.704	3.24	0.25	18.58	10.76	10.76
San Francisco	0.358	1.862	0.704	5.84	0.39	18.58	10.76	10.76
Seattle	0.358	1.862	0.704	3.24	0.39	18.58	10.76	10.76

Table 3.6 Building System Configuration

System Type	Multizone VAV System with Reheat
Cooling COP	3.2
Heating Efficiency (Gas)	0.8
Supply Air temperature (Air handling Unit)	12.8 ℃
Air Economizer Operation	On when outdoor dry bulb temperature < 28 ℃
Heating Setpoint	21 ℃ 15.6 ℃ setback
Cooling Setpoint	24 ℃ 26.7 ℃ setback
Fan Efficiency	0.6

The central model (clusters of neural network models) training results of our baseline building are listed in the Table 3.7 below. For each of interested responses, we have listed the RMSE (root mean square error), MAE (mean absolute error) and R^2 (coefficient of determination) in the training. The training results present that the neural network model is capable of predicting all interested responses with coefficient of determination all ranges from 90% to 99%, both MAE and RMSE from 0.1 ℃ to 0.5 ℃ for both indoor air temperature and operative temperature prediction, 0.05 to 0.15 for the energy prediction (log scale).

Table 3.7 Statistical Measures of the Established Prediction Models (Air T is the air temperature; Op T is the operative temperature, 1 and 2 represents the first and second floor)

				Los Angeles			San Francisco			Seattle			Atlanta		
				RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2
AC Mode	Energy		1	0.133	0.097	0.934	0.180	0.135	0.905	0.193	0.143	0.929	0.193	0.140	0.935
			2	0.153	0.119	0.920	0.168	0.128	0.915	0.163	0.125	0.946	0.192	0.149	0.946
NV Mode	Op T		1	0.317	0.241	0.991	0.413	0.319	0.988	0.422	0.327	0.995	0.412	0.327	0.996
			2	0.327	0.248	0.992	0.398	0.312	0.991	0.408	0.317	0.996	0.421	0.329	0.997
	Air T		1	0.186	0.128	0.997	0.175	0.131	0.998	0.181	0.139	0.999	0.270	0.203	0.998
			2	0.160	0.114	0.998	0.175	0.131	0.998	0.174	0.133	0.999	0.214	0.160	0.999
Transition Mode	NV to AC	Energy	1	0.128	0.093	0.937	0.140	0.103	0.862	0.107	0.076	0.918	0.109	0.078	0.954
			2	0.129	0.101	0.948	0.133	0.101	0.895	0.106	0.081	0.932	0.116	0.086	0.956

		Op T	1	0.346	0.268	0.962	0.516	0.393	0.947	0.583	0.453	0.977	0.480	0.364	0.990
			2	0.381	0.294	0.963	0.505	0.390	0.954	0.519	0.408	0.982	0.529	0.406	0.989
		Air T	1	0.220	0.168	0.967	0.311	0.232	0.952	0.454	0.337	0.978	0.376	0.273	0.992
			2	0.216	0.155	0.957	0.248	0.191	0.950	0.355	0.269	0.978	0.409	0.299	0.987
	AC to NV	Op T	1	0.211	0.161	0.992	0.304	0.232	0.989	0.299	0.231	0.995	0.302	0.231	0.997
			2	0.315	0.242	0.985	0.374	0.293	0.985	0.337	0.265	0.995	0.361	0.279	0.996
		Air T	1	0.128	0.092	0.998	0.172	0.124	0.997	0.164	0.122	0.999	0.224	0.164	0.999
			2	0.144	0.108	0.997	0.155	0.118	0.997	0.152	0.113	0.999	0.241	0.169	0.998

In addition, the residual plots of training the central model in terms of the prediction of air temperature, operative temperature and energy were also generated. Figure 3.5 below shows the training result in Los Angeles as an example. The residuals from the model prediction are reasonable and evenly distributed after training.

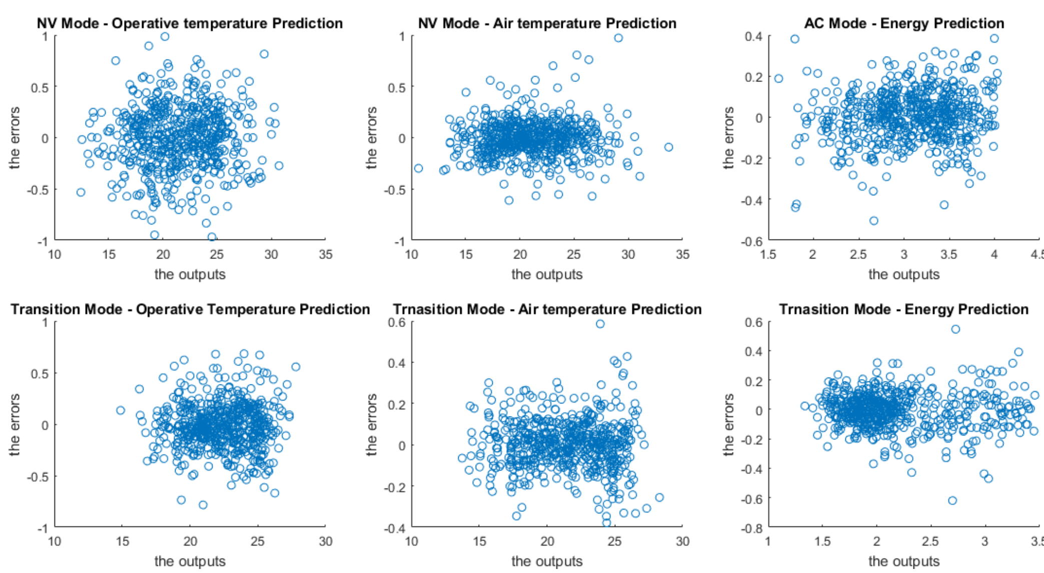


Figure 3.5. Residual Plots for three phase NN model Training (LA)

3.1.6 Cost Function and Constraint

As the last step of the model predictive control development, the objective function was formulated as below.

$$\min_{\vec{w}_{win},\vec{w}_{HVAC}} Energy(\vec{w}_{win}, \vec{w}_{HVAC})$$

$$\text{subject to: } \vec{w}_{win}, \vec{w}_{HVAC} \in \{0,1\},$$

$$v_{speed} < 7.5\ m/s\ ,$$

$$T_{opt}\ within\ adaptive\ model\ comfort\ bound\ in\ NV\ office\ hours,$$

$$\vec{w}_i = 0\ if\ outdoor\ tempersature > 24℃ \text{ and relative } humidity > 85\%$$

In which $\vec{w}_{win}$ and $\vec{w}_{HVAC}$ is the window and HVAC operation status that is either 1 or 0 and interlock with each other. Overall, the objective function was formulated in a way such that the average indoor operative is controlled within the comfort bound during natural ventilation while minimizing the HVAC consumption (ASHRAE, 2010). In addition, to avoid the local draught in different building zones, the window is set to be closed if the outdoor wind speed is larger than 7.5 m/s (Aggerholm, 2002). Meanwhile, the window will also be set to closed if the outdoor relative humidity is larger than 85% when the outdoor air temperature is larger than 24 ℃ to avoid excessive indoor humidity (Seppänen & Kurnitski, 2009).

3.1.7 MPC Verification

Since the developed model predictive control aims to minimize the energy consumption while maintaining the thermal comfort for building occupants in natural ventilation, to verify our developed model predictive control strategy, we have compared the building average and max/min operative temperature when the building is in natural ventilation with the thermal comfort bound to see whether the control effectively maintain the occupant thermal comfort. The verification was done by applying all the uncertainties (meteorological, microclimate, building uncertainty, operation uncertainty) to mimic possible scenarios a hybrid ventilation building could experience. Table 3.8 below lists the mean window opening percentage, building average temperature out of bound and building max/min temperature out of bound. All these percentage were calculated out of total numbers of office hours, which is 3120 hours per run. Hence, 2.5% to 5% of max/min temperature out of bound means that there will exist less than 150 hours of overheating/overcooling happening in the building (one or several zones) per year. We could conclude that the developed MPC is capable of maintaining a thermally comfortable indoor environment during hybrid ventilation building operation.

Table 3.8 Performance of MPC

	Mean window opening percentage	Average Temperature out of Bound	Max/min temperature out of bound
Los Angeles	29.10%	0.40%	3.90%
San Francisco	22.20%	0.70%	5.10%
Seattle	14.90%	0.40%	3.70%
Atlanta	9.80%	0.50%	2.50%

Meanwhile, as an illustrative example of control performance, Figure 3.6 below shows the control of hybrid ventilation building in each of our tested cities. In the figure, the X axis is the index of natural ventilation hours and the Y axis is the temperature in Celsius. The red and blue lines represent the calculated upper and lower thermal comfort bound from the adaptive thermal comfort model respectively. Also, the green line depicts the indoor average operative temperature while the yellow line depicts the fluctuation of outdoor air temperature. From the figure, we can observe that the building average operative temperature is almost always controlled within the bounds.

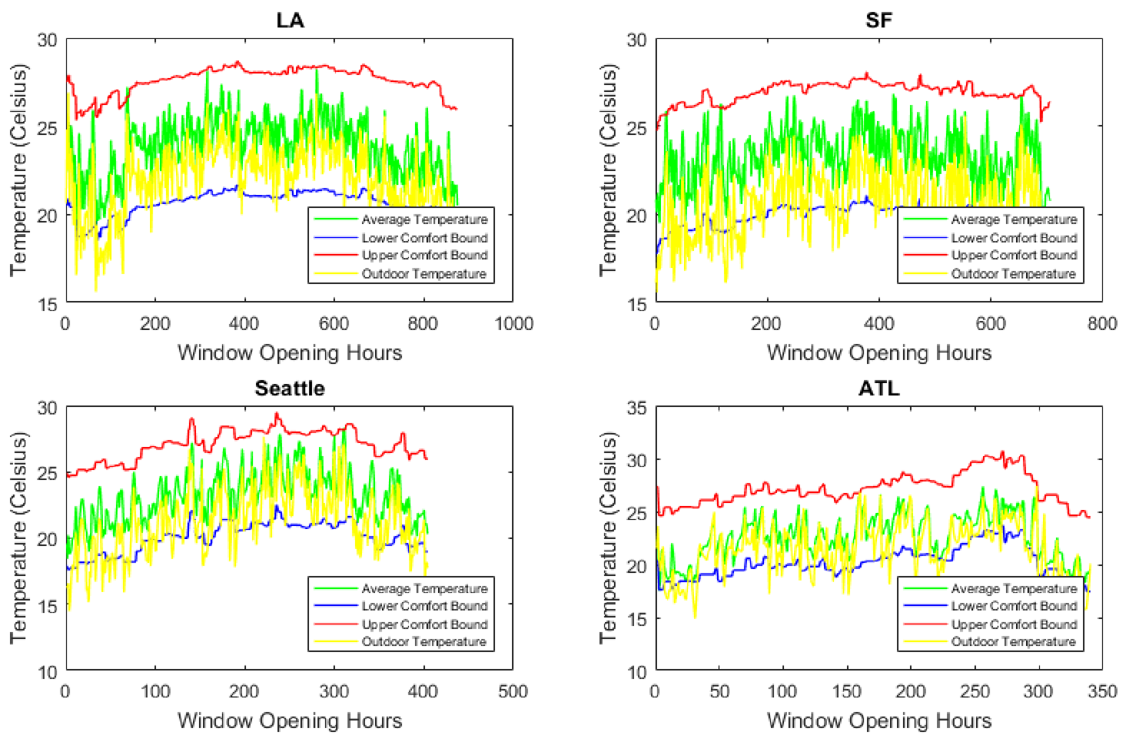


Figure 3.6. Example of MPC Control

3.1.8 Developed MPC Overview

For the better control of hybrid ventilation operation, we have developed a prototype light-weighted three phases model predictive control with clusters of neural network models as the central model. Figure 3.7 below shows the flowchart of detailed control process of the developed model predictive control. Firstly, based on the input signal in the planning horizon, the developed MPC will determine the appropriate cluster of neural network models for predictions. Basically, the central model of the developed MPC consists of three clusters of neural network models. The first cluster of neural network models are for the prediction of energy consumption in each floor when it is in air conditioning mode. Both indoor and outdoor environmental variables (the indoor and outdoor air temperature, relative humidity, office and season index and wind speed) will be used in the prediction. Then, the second cluster of neural network models are developed for the prediction of indoor operative temperature in each floor when the it is in natural ventilation mode. Lastly, the third cluster of neural network models are developed for the prediction of energy consumption and indoor operative temperature when it transits from natural ventilation to air conditioning or from air conditioning to natural ventilation. After all predictions are generated for the input signal, its penalty will be calculated based on the energy consumption and indoor operative temperature. The Particle Swarm Optimization (Kennedy, 2011) will be used to select the input signal that optimizes the control objective function. The detailed components of three phases neural network models for the developed MPC is shown in Figure 3.8 below. For each baseline building in the corresponding climate zone, one set of NN model clusters is established in the model predictive control development and test process.

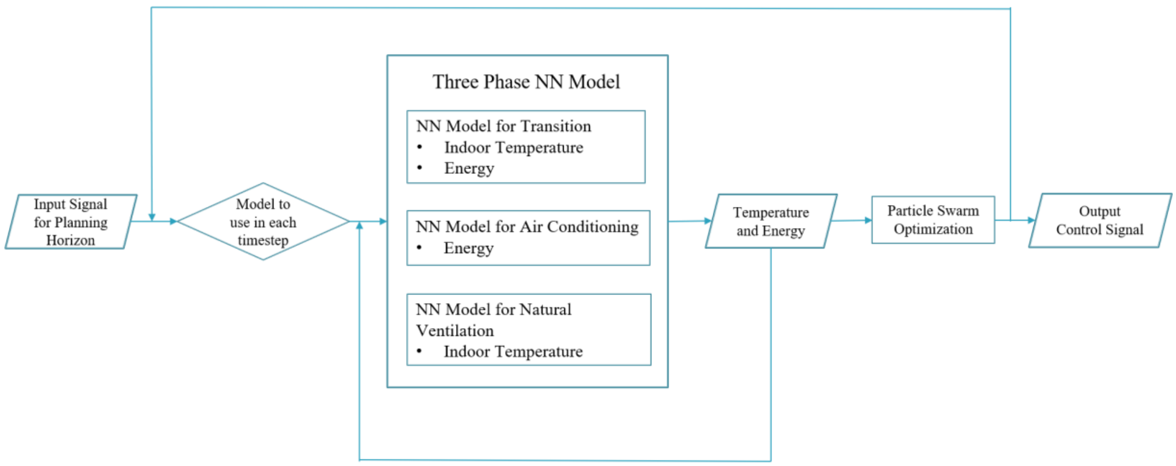


Figure 3.7 MPC Control Process

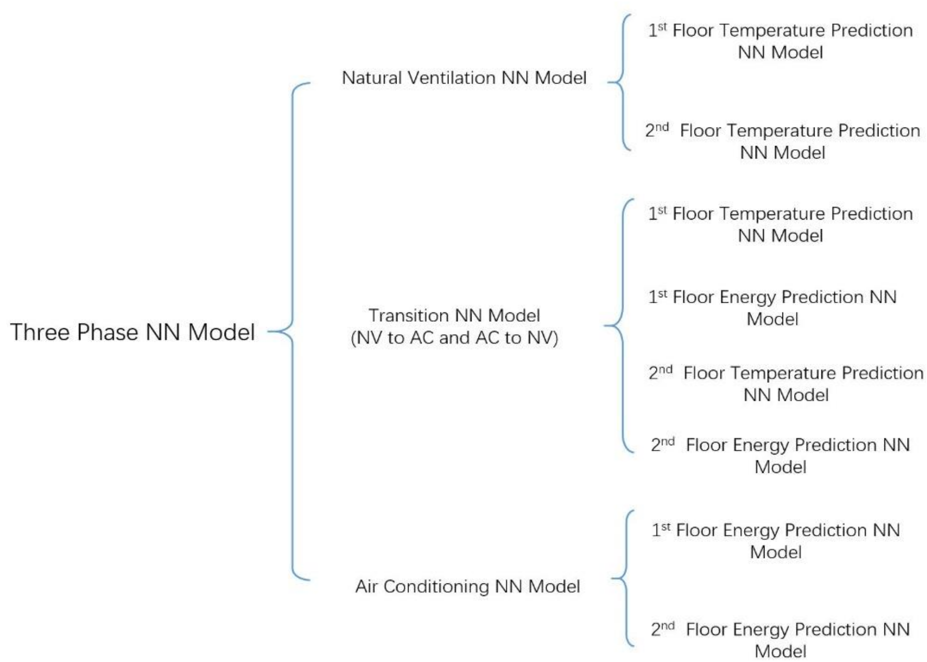


Figure 3.8 Detailed Components of Developed MPC

3.2 Comparison with Rule-based Control

To investigate the impact of applying model predictive control on the hybrid ventilation building operation, we have developed a baseline rule-based control for comparison. The rule-based control is currently the most widely used control for the hybrid ventilation building operation. In the rule-based control, the hybrid ventilation building operation schedule is typically set according to certain pre-defined rules related to both indoor and outdoor environment. In this study, we have set the appropriate window opening hour as 20 ℃ to 26 ℃ based on the adaptive thermal comfort model. For a fair comparison, the same constraints related to the local draught and indoor humidity apply to the rule-based control as well, i.e. the window is set to be closed if the outdoor wind speed is larger than 7.5 m/s and if the temperature is larger than 24 ℃ when the outdoor relative humidity larger than 85%. Applying the same uncertainties (meteorological, microclimate, building uncertainty, operation uncertainty) as in the model predictive control verification, Table 3.9 below lists the performance comparison between the developed MPC and the defined rule based control in terms of both energy saving and ability to maintain the thermal comfort. In the table, the energy saving was calculated based on the case in which the air conditioning runs continuously all through a year. Then the mean window opening percentage, average temperature out of bound and percentage of window opening with max/min out of bound were all calculated according to the total office hours. Finally, the percentage of window opening with uncomfortable hours was calculated out of the total natural ventilation hour such that it serves as a good indicator for comparing the ability of adjusting thermal comfort for occupants.

From the results, we could observe that the baseline rule-based control typically outperforms the model predictive control in terms of energy saving. In the test, the rule-based control on average achieves 5% - 10% more energy saving with more window opening percentages across our tested cities except for Seattle, in which the model predictive control achieves higher energy saving compared to the rule-based control. However, with respect to the ability to control the indoor thermal comfort, the developed model predictive control performs much better compared to the rule-based control. This is explicitly illustrated by observing the percentage of window opening with uncomfortable hours in the table. This finding clearly shows that the developed control can effectively maintain the thermal comfort in the hybrid ventilation building by predicting building indoor environment.

Table 3.9 Performance Comparison of MPC with RB control

	Los Angeles		San Francisco		Seattle		Atlanta	
	MPC	RB	MPC	RB	MPC	RB	MPC	RB
Energy Saving	37.60%	48.60%	29.70%	33.40%	17.60%	15.70%	13.10%	18.90%
Mean window opening percentage	29.10%	39.30%	22.20%	23.60%	14.90%	13.90%	9.80%	17.40%
Percentage of Window Opening with Uncomfortable hours	13.20%	18.30%	23.10%	26.40%	24.90%	33.80%	24.90%	36.40%
Average Temperature out of bound	0.40%	1%	0.70%	0.80%	0.40%	1%	0.50%	1.70%
Percentage of window opening with max/min out of bound	3.90%	7.20%	5.10%	6.20%	3.70%	4.80%	2.50%	6.40%

These results demonstrate that the developed model predictive control is more cautious in opening the windows with a more delicate modeling of indoor environment (thus less energy saving with better thermal comfort). The main reason is that the developed model predictive control adjusts the window operation based on the building operation and seasonal basis. Unlike the rule based control that determines the window operation purely based on air temperature, the developed model predictive control predicts the building operative temperature, which actually determines the occupant thermal comfort, and intrinsically models the impact of building operation and solar intensity the building could experience by including the office hour index in the central establishment. Thus, it provides a more direct way for determining the window operation status. In addition, the developed model predictive control also accounts for the season variation, which is an important factor to consider in the operation of hybrid ventilation buildings. In different seasons, the solar intensity could differ significantly from other seasons, thus impacting the estimate of indoor operative temperature. Meanwhile, the occupants will also wear different levels of clothes across seasons, which makes it not appropriate to use the constant threshold for the hybrid ventilation building operation all through a year. All these lead to the better performance of the model predictive control in maintaining the thermal comfort for occupants.

4. HYBRID VENTILATION USAGE POTENTIAL UNDER BUILDING INTELLIGENCE AND UNCERNTAINTIES

The influence of both building intelligence and uncertainties on the hybrid ventilation is expected to be significant considering the high variability of possible building indoor and outdoor environment. In this chapter, we will introduce the detailed process of investigating the hybrid ventilation potential across different climates in US considering the influence of building intelligence and uncertainties. This investigation process will be mainly composed of two stages. We assumed the ideal control of natural ventilation was used in the first stage while the developed optimal natural ventilation control was used in the second stage. Hence, the presented potentials represent the ideal energy benefits in the stage 1 and achievable energy benefits associated with certain thermal comfort risks under the defined control in the stage 2. The actual benefits of energy saving will vary if hybrid ventilation building is utilized in practice with different control targets, the influence of occupant behaviors and so on. Through the application of different building intelligence and different levels of uncertainties on the hybrid ventilation building operation, we will later present the energy saving potential with possible variance in running hybrid ventilation under the influence of these two aspects.

4.1 Hybrid Ventilation Potential Investigation Process

To investigate the influence of building intelligence and uncertainty on the hybrid ventilation and the energy saving potential of hybrid ventilation accounting for these two aspects, the whole process of investigation is composed of 5 steps, as shown in Figure 4.1 below. As the first step, we established a baseline building and propagated general uncertainties, as shown in Table 2.2, into our baseline building model. Then in the next step, we conducted a preliminary investigation of hybrid ventilation potential across all US climate zones using TMY (typical meteorological year) as the weather input and the free-running baseline building as the input model. The adaptive thermal comfort model was used as the thermal comfort evaluation criteria to identify the office hours that are suitable for natural ventilation. After the preliminary investigation, a sensitivity analysis was then applied to filter out some insignificant uncertainties to save computation time in later uncertainty analysis. Then using the developed model predictive control and the applied uncertainties, we generate the hybrid ventilation potential with confidence interval of energy saving across different US climates through co-simulation. The influence of building intelligence and uncertainties was determine based on the simulation results.

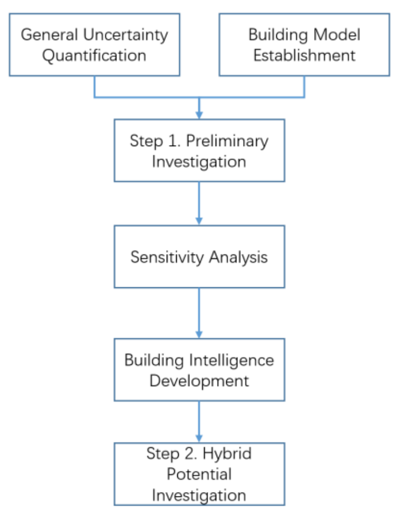


Figure 4.1 Hybrid Ventilation Potential Investigation Process

4.2 Hybrid Ventilation Potential Investigation with Uncertainties and Building Intelligence

4.2.1 US Climate Zones and Representative Cities

The United States has 9.8 million km2 in area and consist of 50 states, a federal district and five major self-governing territories. With such a large area, the United States has diverse types of climate zones that potentially have different potential of running hybrid ventilation across the country. In this study, we classified the different climate zones in US according to the IECC (International Energy Conservation Code) map (Baechler et al, 2010), in which the temperature and humidity are the main criteria for the classification. Table 4.1 below lists the main climate regions in US with its corresponding representative cities while Figure 4.2 below shows the map of climate zone classification.

According to the classification, for the hot-humid climate (zone 1A), it describes the regions that has more than 3000 hours with the wet bulb temperature >= 19.5 ℃ or more than 1500 hours with the wet bulb temperature >= 23 ℃ in the warmest consecutive six months. For the hot-dry (zone 2B) climate, the region is said to have more than 7 ℃ monthly average temperature and less than 50cm annual precipitation through the year. Then, in the mixed humid climate (zone 3A, 4A), the region is defined to have more than 50cm annual precipitation with more than 5400 heating degree days while the mixed dry region (zone 4B) should have less than 50cm annual precipitation with the same heating degree day. Moving to the north, the cold region (zone 5 - 6) is defined as the region with 5400 – 9000 heating degree days. Finally, as a special type of climate, the region in the marine climate (zone 3C, 4C) should meet all the following criteria, i.e. (1) the coldest monthly mean temperature is from -3℃ to 18℃, (2) the warmest monthly mean temperature is less than 22℃, (3) at least has monthly mean temperature of 10℃ with more than 4 months, (4) dry in summer.

Table 4.1 Climate Zones and Representative Cities

Climate Zone	Description	Representative City
Zone 1A	Hot-Humid	Miami, FL
Zone 2A	Hot-Humid	Houston, TX
Zone 2B	Hot-Dry	Phoenix, AZ
Zone 3A	Mixed-Humid	Atlanta, GA
Zone 3B	Hot-Dry, Coast	Las Vegas, NV; Los Angeles, CA
Zone 3C	Marine	San Francisco, CA
Zone 4A	Mixed-Humid	Baltimore, MD
Zone 4B	Mixed-Dry	Albuquerque, NM
Zone 4C	Marine	Seattle, WA
Zone 5A	Cold-Humid	Chicago, IL
Zone 5B	Cold-Dry	Denver, CO
Zone 6A	Cold-Humid	Minneapolis, MN
Zone 6B	Cold-Dry	Helena, MO

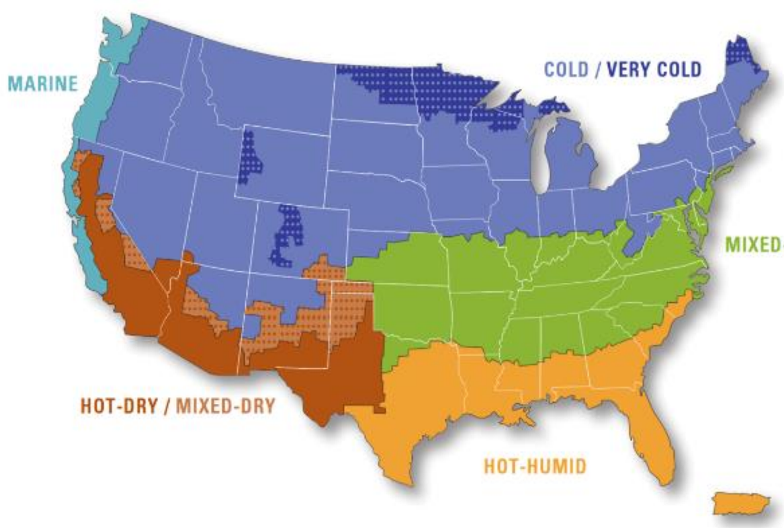


Figure 4.2 Climate Zones in US

4.2.2 Baseline Building

The configuration of baseline building used in the hybrid ventilation potential investigation is the same as what was shown in Figure 3.4 in the Chapter 3 above. The building is a campus building with diversity of zones such that it could be a representative for a small to medium commercial building. To ensure the correctness of the hybrid ventilation potential across all climate zones in US, we have adapted the baseline building construction according to the recommendations from DOE (Deru et al, 2011), as shown in the Table 4.2 below. Except for the U value of exterior wall and window and SHGC that vary across different climate zones, the roof U value (0.358 W/m^2*K), floor U value (1.862 W/m^2*K) and all the building operation parameters (occupancy as 18.58 m2/person, Lighting and Electric Equipment as 10.76 W/m2) are kept the same across all the climates. The window wall ratio of our baseline building is 0.3 in all cases. Also, the building system used in the baseline building is the same with the configuration shown in Table 3.6 above.

In the analysis, the airflow network module in the EnergyPlus (Crawley et al, 2001) was used to simulate the multizone airflow within the building. In establishing our baseline models, the AirflowNetwork:MultiZone:Component:DetailedOpening objects were used to define the windows and doors in the airflow network. The wind pressure coefficients of the building were calculated by Surface Average Calculation method (DOE, 2010) that is built-in in the EnergyPlus. Finally, the window opening ratio was calculated using the logistics regression as shown in the formula below. For simplification, the outdoor temperature is the only predictor in the model that determines the window opening ratio (p in the formula).

$$\log\left(\frac{p}{1-p}\right) = -2.31 + 0.104 * T$$

Table 4.2 Detailed Baseline Building Information

Cities	U value (W/m2*K)		SHGC
	Exterior Wall	Window	Window
Miami	0.704	5.84	0.25
Houston	0.704	5.84	0.25
Phoenix	0.704	5.84	0.25
Atlanta	0.704	3.24	0.25
Los Angeles	0.704	3.24	0.25
Las Vegas	0.704	3.24	0.34
San Francisco	0.704	5.84	0.39
Baltimore	0.704	3.24	0.39
Albuquerque	0.704	3.24	0.39
Seattle	0.704	3.24	0.39
Chicago	0.477	3.24	0.39
Denver	0.477	3.24	0.39
Minneapolis	0.477	3.24	0.39
Helena	0.477	3.24	0.39
Duluth	0.363	3.24	0.49

4.2.3 Generality of Results

Although the selected baseline building is considered as a good representative of small to medium commercial buildings in the US, to verify the generality of results based on the baseline building, we have further tested the influence of building configuration, building shapes and window-wall ratio on the natural ventilation performance compared to the settings in this baseline building. In this generality test, we think indoor temperature is the most relevant measure to determine the difference of natural ventilation performance since it will be directly used to determine the natural ventilation suitability and thermally uncomfortable hours in later studies. In addition, we have calculated the difference of air exchange rate in ACH as the other complementary measure of natural ventilation performance as well. We utilized the airflow network module with the thermal modelling in EnergyPlus for this airflow test. The tested buildings were in natural ventilation mode during office hours (8:00am to 6:00pm). The indoor temperature difference was calculated in these office hours.

First and foremost, we have tested the influence of building configuration on the natural ventilation performance by the comparison between our baseline case and the case that is in completely single-side ventilation and completely cross ventilation, respectively. In our baseline case, there exists a combination of single-side ventilation (in individual spaces) and cross ventilation (in the open spaces). Then for the comparison, we have further divided all zones to be single-side ventilated while making the back door of each individual zone completely open to establish the completely cross ventilation case. The comparison results are shown in the Table 4.3 below. Although significant difference of airflow exchange rate (in ACH) is observed in the test, the average indoor temperature difference is only mild (less than 0.6 ℃) in the comparison.

Table 4.3 Comparison Results for Ventilation Mechanism

	Airflow Difference in ACH	**Average Indoor Temperature difference in Celsius**
Single vs. Mixed	16	0.4
Single vs. Cross	36	0.6
Mixed vs. Cross	25	0.2

Additionally, we have also tested the influence of building shapes on the natural ventilation performance. The baseline building has rectangular layout. In our comparison cases, we have established a corresponding building in both T shape and H shape with the same design features. Table 4.4 below shows the comparison results. Similar as before, the indoor temperature difference is only moderate (less than 0.4 ℃). The difference of air exchange rate is also small (2 - 5.5 ACH) this time.

Table 4.4 Comparison Results for Building Shapes

	Airflow Difference in ACH	**Average Indoor Temperature difference in Celsius**
H vs. Baseline	5.3	0.36
H vs. T	1.9	0.27
Baseline vs. T	4.7	0.31

Lastly, we have also investigated the influence of window-wall ratio on the natural ventilation performance. The window wall ratio in our baseline case is 30%. We modified the window ratio to 5%, 10%, 20% and 40% additionally in the generality study. Table 4.5 below shows the comparison results. Obviously, we observe large difference of indoor air temperature (larger than 1 ℃) when we compared our baseline with the cases with only 5% or 10% window-wall ratio. However, if the window wall ratio is larger than 20%, this difference drops significantly to only 0.1 ℃ to 0.2 ℃.

Table 4.5 Comparison Results for Window Wall Ratio

	Airflow Difference in ACH	**Average Indoor Temperature difference in Celsius**
5% - 10%	2.5	0.6
5% - 30%	12	1.8
10% - 30%	10	1.2

20% - 30%	10	0.1
20% - 40%	13	0.2
30% - 40%	9	0.1

Overall, in this generality study, we found that the window-wall ratio is an important design parameter that could affect the natural ventilation performance of the baseline building. However, its impacts will degrade significantly once this window-wall ratio is above a threshold, which is approximately 15% to 20% in our tested cases. Hence, if the naturally ventilated building is properly designed with a reasonable window wall ratio, this design parameter won't affect the usage of our investigation results in the application. Furthermore, as shown in the comparison above, the impacts of different ventilation mechanism (single-side or cross ventilation) and building shapes are only moderate on the natural ventilation performance. Consequently, we concluded that the investigation results should be mostly generalizable as long as the hybrid ventilated/naturally ventilated building is reasonably designed since the natural ventilation performance doesn't shift significantly in different tested cases. However, this can't be completely confirmed without running the full set of experiments in the potential investigation again.

4.2.4 Stage 1 Preliminary Investigation

Then, after quantifying all uncertainties (as shown in Table 2.2 in Chapter 2 above) and establishing our baseline buildings, the next step is the stage 1 preliminary investigation, in which we firstly estimated the natural ventilation potential usage by calculating the percentage of suitable window opening hours based on the free-running baseline building and adaptive thermal comfort model. In this step, the Typical Meteorological Years were used on the first place.

As a factor that is highly related to the energy saving in one area, the mean annual natural ventilation suitable hour percentage, which was calculated by counting the hours that has indoor operative temperature falling within the adaptive thermal comfort range with less than 75% indoor relative humidity, was presented in Table 4.3 below to show the preliminary analysis result for the hybrid ventilation potential investigation of that area. From the table, we can observe that the climate zone 3B and 3C (Los Angeles and San Francisco) has the most hybrid ventilation potential across US. On average, the windows could be expected to be opened in 20% to 35% of time if the hybrid ventilation building is established in these two climate zones. Besides, the rest of climate zones all share the similar potential of energy saving. 10% - 15% mean annual natural ventilation suitable hour percentage is presented based on our uncertainty analysis results. Also, by observing the difference of mean annual NV (natural ventilation) suitable hours percentage in the investigation, we could see that the applied uncertainties are possible to impose large impacts on the hybrid ventilation usage in practice by shifting the mean of our interested indicators. The average difference of mean annual NV suitable hours is 0 to 5% across different climates.

Table 4.6 Uncertainty Analysis Results using TMY

Climate Zone	Uncertainty Analysis				Annual NV Suitable Hours Percentage (Deterministic Simulation)	Difference of Mean Annual NV Suitable Hours Percentage
	Best Three Months for Natural Ventilation	Number of months with more than 30% NV suitable hours	Number of months with less than 10% NV suitable hours	Mean Annual NV Suitable Hours Percentage		
Zone 1A - Mia	Dec, Jan, Feb	1(31%)	7	12.10%	17.70%	-5.60%

Zone 2A - Hou	Mar, Apr, Oct	0(24%)	5	11.20%	13.30%	-2.10%
Zone 2B - Phe	Jan, Mar, Nov	1 (35%)	5	13.90%	14.20%	-0.30%
Zone 3A- Atl	Mar, Apr, Oct	0 (27%)	6	12.50%	15.30%	-2.80%
Zone 3B - Veg	Mar, Pro, Nov	2 (40%)	4	15.10%	13.20%	1.90%
Zone 3B - LA	May - Jul	10(63%)	0	40.90%	36.60%	4.30%
Zone 3C - SF	Jul - Sep	6(52%)	2	28.90%	22.30%	6.60%
Zone 4A- Bal	Apr, May, Sep	1(39%)	6	10.40%	10.80%	-0.40%
Zone 4B - Alb	Mar, Apr, Oct	0(29%)	4	14.70%	12.30%	2.40%
Zone 4C -Sea	Jun - Aug	4(40%)	5	16.80%	13.40%	3.40%
Zone 5A - Chi	May, Aug, Sep	1(33%)	7	11.30%	11.80%	-0.50%
Zone 5B - Den	May, Jul, Aug	0(27%)	6	10.80%	10.50%	0.30%
Zone 6A- Min	May, Jun, Aug	0(28%)	7	11.10%	11.30%	-0.20%
Zone 6B - Hel	Jun-Aug	0(27%)	7	11.80%	11%	0.80%
Zone 7A- Dul	Jun-Aug	0(25%)	7	8.80%	9.60%	-0.80%

In addition to using the Typical Meteorological Year (TMY) in the former analysis, to further investigate the possible impacts of uncertainties, the Historical Meteorological Year (HMY) from four cities (represent climate zone 3A, 3B, 3C and 4C) instead of the Typical Meteorological Year (TMY) were also applied in this study. Table 4.4 below lists the results of using HMYs as the weather input and the comparison between HMY results and TMY results. The standard deviation of annual NV suitable hour percentage increase significantly (from 1% to 4% on average) across these representative cities. The mean annual NV suitable hour percentage also shifted compared to using TMY (difference ranges from 0.5% to 5%).

Table 4.7 Uncertainty Analysis Results using HMY

Climate Zone	Mean Annual NV Suitable Hours Percentage		Standard Deviation of Annual NV Suitable Hours Percentage		Difference of Mean Annual NV Suitable Hours Percentage
	TMY	HMY	TMY	HMY	
Zone 3A- Atl	12.5%	8.3%	0.7%	2.9%	4.3%
Zone 3B - LA	40.9%	36.5%	1%	4.8%	4.4%
Zone 3C - SF	28.9%	29.9%	1.1%	4.1%	-1%
Zone 4C -Sea	16.8%	16.1%	0.6%	1.5%	-0.7%

4.2.5 Sensitivity Analysis

Using the MARS (Multivariate Adaptive Regression Splines) method presented in Section 2.3 for the sensitivity analysis, we intended to filter out some unnecessary uncertainties to be applied in the stage 2 investigation. As one of the best indicator of natural ventilation potential, the annual percentage of NV suitable hour was selected as the response variable in the analysis. Figure 4.3 (x axis is the importance score) below shows the sensitivity analysis results based on applied uncertainties. The whole sensitivity analysis was composed of three steps. In the first step, we included all the applied uncertainties (shown in Figure 4.3 left). The result shows that including HMYs in the uncertainty analysis is most significant. However, mixing the scenario uncertainty with other uncertainties might cause deviation of the results in the sensitivity analysis based on our former experience. Thus, in the second step, we excluded the HMYs and applied all the other uncertainties and ran the sensitivity analysis again. This sensitivity analysis (shown in Figure 10 right) showed that the microclimate uncertainties (Canyon Height and Canyon Ratio), external convection uncertainties (OutAHext and OutBHext), material uncertainties (Conductivity, ThermalAbs, SpecHeat and Density) and operation uncertainties (ElectricEquip and Lighting) were all important in predicting the hybrid ventilation potential. Lastly, to further distinguish whether it is the local wind effect or urban heat island effect that caused CanyonHeight and CanyonRatio to rank top, two separate uncertainty analyses with their respective effects only were executed as the third step. The results revealed that the urban heat island effect could lead to much large mean annual NV suitable hour percentage shift and its standard variance (approximately 2% shift of mean annual percentage of NV suitable hour with 0.4% standard variance by applying urban heat island effect while only 0.2% shift for the mean annual percentage of NV suitable hour with 0.1% standard variance by applying local wind effect).

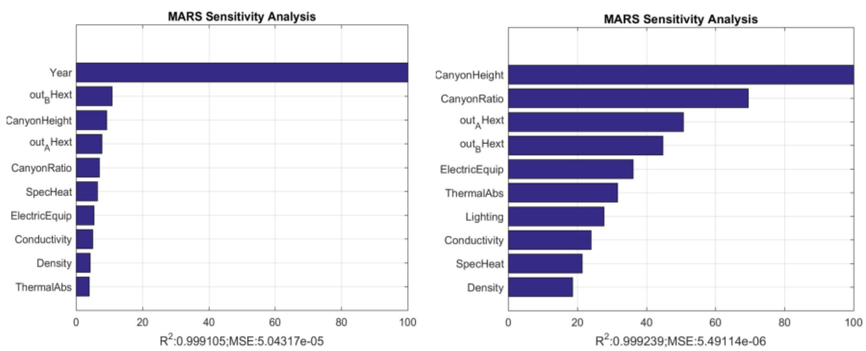


Figure 4.3 Sensitivity Analysis Result

Consequently, based on sensitivity analysis results shown above, the uncertainties applied in the stage 2 investigation included the meteorological uncertainty, urban heat island effect, external convection uncertainty, material uncertainty, electric equipment consumption uncertainty and lighting consumption uncertainty.

4.2.6 Building Intelligence Development

Before getting into the stage 2 investigation, we firstly defined three building intelligence levels to thoroughly investigate its impact on the hybrid ventilation usage. As the most commonly used control for the hybrid ventilation operation, the rule-based control with changeover strategy is set as our building intelligence level 1. The rule-based control is set to control the building using simple heuristics rules considering the building indoor and outdoor environment. In our study, the rule-based control is set to be the same as the strategy defined in Chapter 3, i.e. the windows of our baseline building are set to be closed if the outdoor temperature is lower than 20℃ or higher than 26℃ and if the outdoor relative humidity is higher than 85% when the temperature is higher than 24℃. For the building intelligence level 2, we used the model predictive control with changeover as developed in Chapter 3 above. In the developed model predictive control, the three-phase neural network models are used as the central model prediction and the objective function is formulated to minimize the energy consumption while maintaining the occupant thermal comfort. Finally, as the building intelligence level 3, instead of constraining the whole building into the same operation mode (natural ventilation or air conditioning), the model predictive control with zoned strategy is used. The zoned strategy here means that two floors could operate in different modes during the building operation. One optimization process will be established for each floor such that the decision is made separately.

Furthermore, to improve the optimization process thus to make the computational burden manageable, we have implemented the Dynamic Programming (Bellman, 2013) instead of the Particle Swarm Optimization (Kennedy, 2011) as the optimization method. Unlike the Particle Swarm Optimization that uses the heuristics approach to search for the optimal results, the dynamic programming breaks the problem into a collection of subproblems and then find the optimal solution for each subproblem thus to attain the optimal solution of the whole problem by back-tracing. To ensure the robustness of the developed MPC in the hybrid ventilation potential investigation, 10 years out of 20 historical meteorological years were randomly selected and the urban heat island effect were also applied to aid the central model training by broadening the training data set. 50 simulation runs with 50 different weather files were used during the training process. Figure 4.4 below shows the whole control process of improved model predictive control.

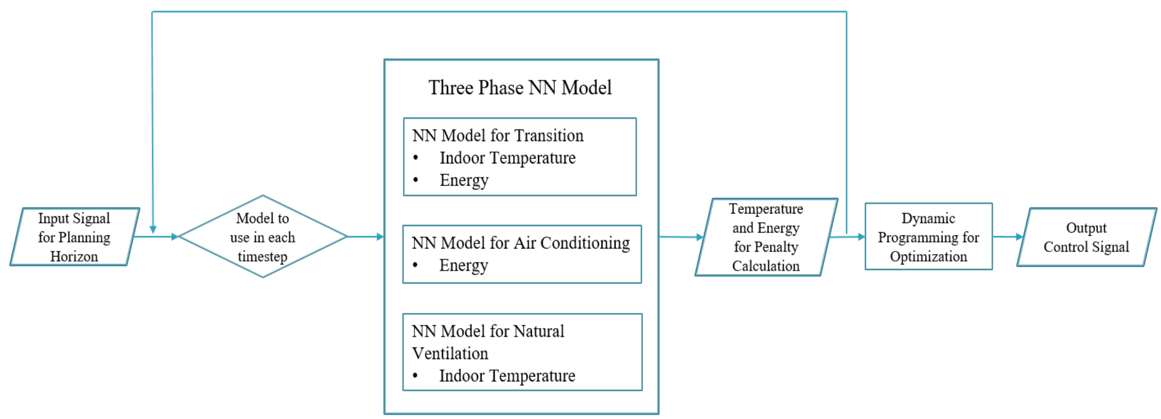


Figure 4.4 Framework of the Model Predictive Control

4.2.7 Stage 2 Investigation Results

Finally, in the stage 2 investigation, we applied all filtered uncertainties and the developed hybrid ventilation building intelligent control presented above to conduct a thorough investigation of hybrid ventilation potential across different US climates.

The investigation results were shown in Table 4.5 below. In the table, the mean percentage of energy saving is calculated by comparing the simulation results in the uncertainty analysis with its baseline case (AC on for the whole year under the same weather condition). The mean window opening percentage, average temperature out of bound, Max/Min building zone temperature out of bound are all calculated out of office hours (3120 hours in total for a year) with only the percentage of window opening with uncomfortable hours calculated out of total natural ventilation hours. Also, the percentages of time of temperature out of bound (last 3 columns) are all determined based on the adaptive thermal comfort model. The I1 to I3 represents the building intelligence level as defined in Section 4.2.5 above.

Clearly, the results dictate that both climate zone 3B-Coast Los Angeles and 3C San Francisco have the most hybrid ventilation potential to utilize considering the temperature and humidity. An energy saving of 40% to 55% could be achieved in Los Angeles while 30% to 40% could be achieved in San Francisco, associating with 20% to 40% of suitable window opening hours respectively. While for the Seattle and Atlanta, 15% to 25% of energy saving could be expected under different building intelligence levels, associating with 15% to 20% of window opening hours. All these echoes well with our preliminary investigation results (Stage 1).

Table 4.8 Hybrid Ventilation Potential Investigation Results

City	Intelligence Level	Mean percentage of Energy Saving	Mean of Window Opening Percentage	Percentage of Window Opening with Uncomfortable hours	Average T out of Bound	Max/Min Building Zone T Out of Bound
LA	I1	47.50%	39.30%	18.80%	1.10%	7.60%
	I2	39.20%	31.30%	9.60%	0.10%	3%
	I3	52.30%	36.20%	12.30%	0.20%	4.50%
SF	I1	32.80%	23.50%	27.60%	0.80%	6.50%
	I2	33.20%	24.70%	15.20%	0.10%	3.80%
	I3	41.30%	27.80%	17.80%	0.40%	4.95%
Seattle	I1	15.90%	13.90%	33.50%	1%	4.70%
	I2	17.40%	15%	18.60%	0.20%	2.80%
	I3	22.50%	16.30%	20.70%	0.40%	3.40%

Atlanta	I1	18.10%	17.40%	36.10%	1.80%	6.30%
	I2	17.90%	14.90%	24.40%	0.30%	3.50%
	I3	23.30%	17%	24.90%	0.50%	4.20%

4.3 Influence of Building Intelligence and Uncertainties on the Hybrid Ventilation

As to the impact of building intelligence on the hybrid ventilation, from the Table 4.5 above, we could firstly observe that different building intelligence usually leads to 5% ~ 15% difference of the average energy saving in different climates. Even using the same model predictive control strategy, constraining the whole building operation mode or not could give rise to up to 10% difference in terms of energy saving. Using the zoned strategy that allows different building zones to run in different modes helps to better employ the free cooling from the outdoor environment thus to achieve higher energy saving. These results confirm the building intelligence as a significant factor to consider when evaluating the performance of a hybrid ventilation building.

In addition to the influence of building intelligence, Figure 4.5 below presents the histograms of energy saving percentage across our representative cities when all uncertainties were applied in the analysis. In each figure, the X axis represents the energy saving percentage while the Y axis shows the frequency it happens in our study. From the figure, we can find that the energy saving in a good year (suitable for natural ventilation) deviates significantly from an unsuitable year (20% to 30% difference). The standard variance of energy saving in different building intelligence levels is listed in the Table 4.6 below. Considering the uncertainties in a hybrid ventilation building operation, the performance difference usually ranges from 10% to 20% (but up to 35%) across different operation scenarios.

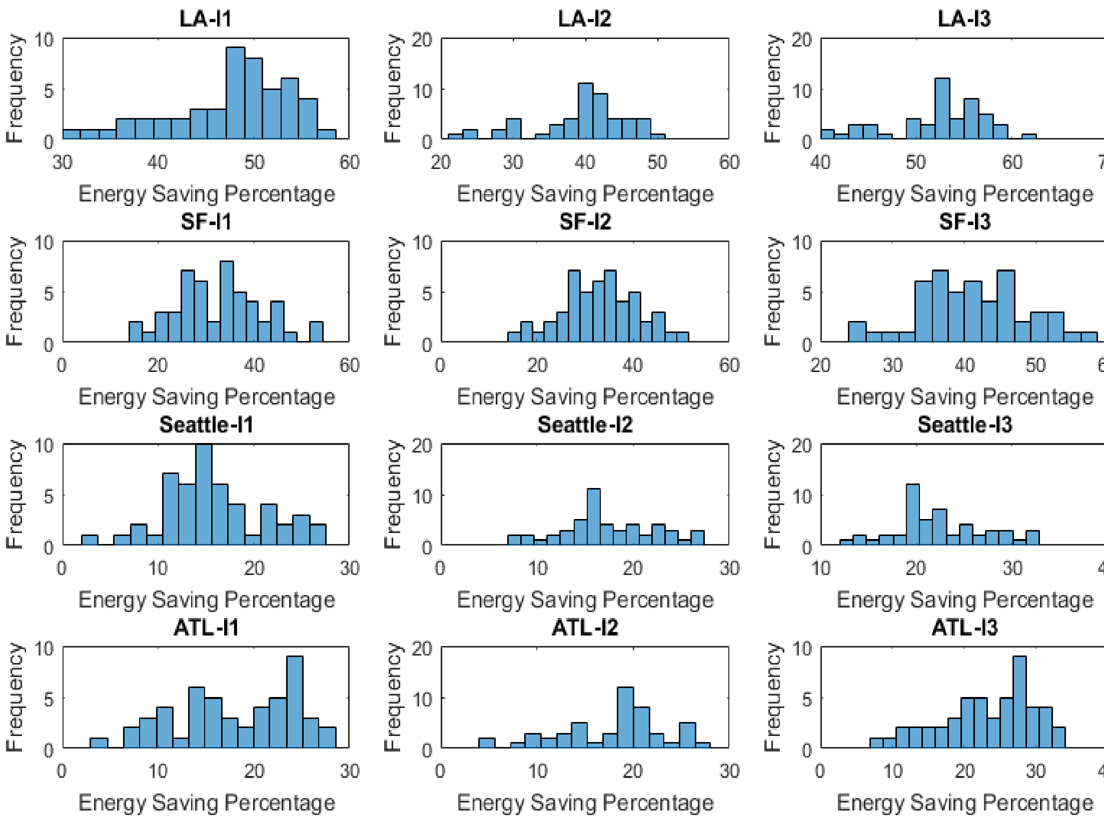


Figure 4.5 Histograms of Energy Saving Percentage

Table 4.9 Standard Variance of the Energy Saving Percentage

	I1	I2	I3
LA	6.39%	6.63%	5.13%
SF	9.11%	7.92%	7.46%
Seattle	5.32%	4.91%	4.85%
Atlanta	6.13%	5.46%	6.46%

5. INFLUENCE OF OUTDOOR AIR QUALITY ON NATURAL VENTILATION

Using natural ventilation in the building operation is proven to be capable of saving building energy consumption, improving the occupant thermal comfort and providing occupants with amenity to nature. In addition, the increase of air exchange rate provided by natural ventilation has the potential of enhancing the occupant productivity based on several research studies before. However, on the other hand, this increase of air exchange rate could also bring in issues, the most significant one of which is the increased outdoor air pollutant exposure in the indoor space. In this chapter, we will investigate the influence of outdoor air pollutants on the natural ventilation usability in large representative cities of each US climate zone. As will be presented later, major outdoor air pollutants will be identified with their respective influence on the natural ventilation usability in different location settings of a city (urban, suburban and rural areas).

5.1 Investigation Process of Influence of Outdoor Air Pollutants on Natural Ventilation

Aiming to better quantify the influence of outdoor air pollutants on the natural ventilation potential in different climate zones of US, we have developed thorough procedures for the investigation, as shown in the Figure 5.1 below. In the investigation, we identified large representative cities for each climate zone and the major interested outdoor air pollutants (PM2.5, PM10 and ozone in this study) on the first place. Based on these identified large cities and interested pollutants, we then began to collect data from US Environmental Protection Agency (EPA)'s website. A data cleaning process is necessary here to ensure the data quality for its investigation usage later. Following the data pre-processing process, a descriptive statistical study was implemented to provide some intuition on the collected air pollutant data. Meanwhile, for each air pollutant in investigated cities, we selected the representative air pollutant data in each month and concatenated them into the representative year of outdoor air pollutant concentration. Then, the air pollutant modeling was also conducted to aid the establishment of emulator, which utilizes machine learning approach to quantify the influence of outdoor air pollutant on the indoor environment using air pollutant modeling results from the last step as the training data. Finally, through the comparison between two scenarios of running two different controls, i.e. one of which adjusts the window operation considering the influence of outdoor air pollutant while the other one not, we clearly present the influence of outdoor air pollutants on the usage of natural ventilation across the selected large cities in US.

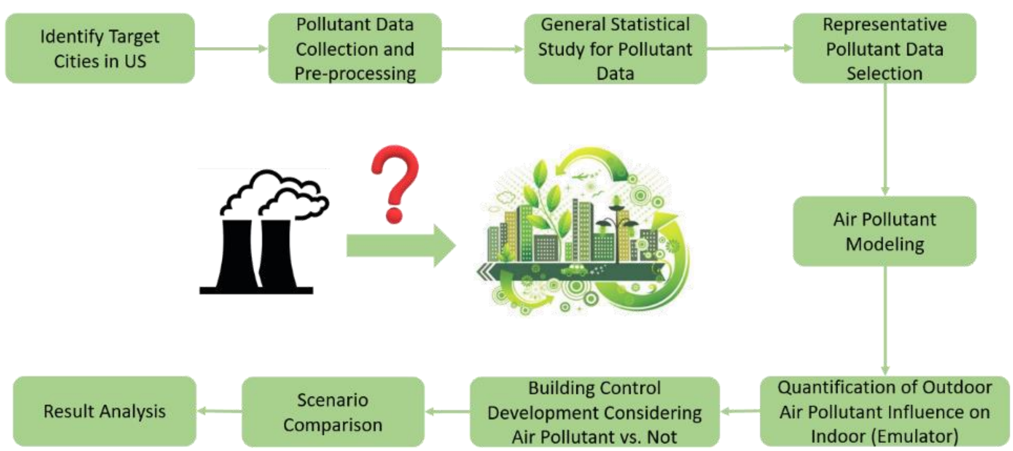


Figure 5.1 Research Procedures

5.2 Experiment Settings

In this study, to ensure the consistency with our former investigation about the hybrid ventilation potential in US, we have used the same classification of climate zones with the same representative cities as presented in Section 4.2.1 above. Similarly, Alaska was emitted from our analysis due to its special weather condition. Meanwhile, the baseline building in this study is the DOE small commercial reference building, which have 5 zones with 4 perimeter zones with the window wall ratio as 21%. The window opening ratio is determined using the same formula as shown in Section 4.2.2 above. As to the system side, each building zone is equipped with a constant air volume system. The total air exchange change of the zone is 4 ACH in total, in which 0.6 ACH is supplied as the outdoor air.

For the weather of each of our test cities in the analysis, we used the Typical Meteorological Year (TMY) since it can serve as the representative weather in that area thus providing a general estimate of natural ventilation potential usage accurately. Finally, the U.S. National Ambient Air Quality Standards (NAAQS) (US EPA, 2018c) was selected as the criteria to determine the acceptability of outdoor pollutant concentrations considering the long-term exposure of occupants to the air pollutant using natural ventilation. More specifically, the PM2.5 is not acceptable if the daily average concentration is higher than 12 $\mu g/m^3$ while the thresholds for PM10 and ozone are 150 $\mu g/m^3$ and 0.07 ppm respectively.

5.3 Investigation Procedures

5.3.1 Data Collection and Cleaning

After we have identified our interested places and air pollutants in the investigation, the first step is to collect the related data and further clean them to ensure their quality in the later usage. In this study, all the outdoor air pollutant data, including PM2.5, PM10 and ozone, are all collected from Environmental Protection Agency (EPA) website (US EPA, 2018d). Since the fluctuation of outdoor air pollutant data (shown in Figure 5.2 below) illustrates a continuously decreasing trend over the past 20 years but with relatively stable concentration in most recent years, we only collected the air pollutant data records of past 5 years in the analysis and considered them representative enough in our influence investigation.

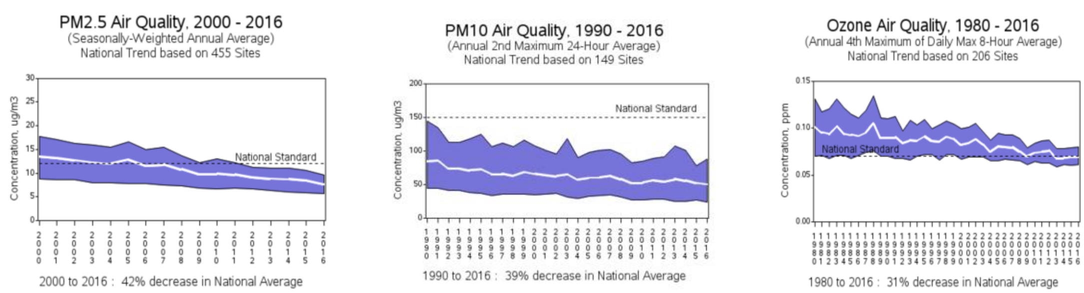


Figure 5.2 Air Pollutant Fluctuation Trend (US EPA, 2018e)

As to the data cleaning, we have divided the process into two steps – data filtering and data interpolation. In the data filtering, the data were eliminated if either of these two strict rules, i.e. (1) the missing records are more than 5% of total records in a month, (2) more than 12 consecutive missing records are detected in a month, were met such that we would get good quality data after this step. This is also important to ensure the performance of data interpolation in the second step. Then after we have the filtered data, the next step is to interpolate the missing data. In the current practice, there exist numerous methods for interpolating the missing air pollutant data, such as nearest neighbor interpolation, regression-based method, multi-layer perceptron interpolation and hybrid method etc. In this study, since the missing data will be in simple patterns (less than 10% missing data with 1/3 data missing of less than 6 hrs and the other 2/3 missing of less than 24 hrs) after the data filtering process, we have adopted the linear interpolation due to its satisfactory performance with fast computation, as suggested from former literatures (Junninen et al, 2004). By putting the collected outdoor air pollutant data through the data cleaning process as mentioned above, the data is guaranteed to have good quality, which provides solid basis for our investigation and analysis about the influence of outdoor air pollutants on the natural ventilation.

5.3.2 Descriptive Statistical Analysis on Air Pollutant Data

Following the clean air pollutant data after the data filtering and interpolation, we have conducted a descriptive statistical analysis on the collected data first to attain the intuition of the investigated data. More specifically, as the first step, we plotted the box plot for each pollutant data in our investigated cities. Then, to provide further insight into the data, the difference and correlation of outdoor air pollutant data between different location settings (urban, suburban, rural) were also generated.

During the descriptive statistical analysis on the air pollutant data, one of the largest problems we encountered in the investigation is the missing pollutant data. Since the study requires to further group the collected air pollutant data by location settings (urban, suburban, rural), we found that for certain cities, part of air pollutant data is missing, especially for PM10 and also rural areas. In the analysis, the PM2.5 data are the most complete data across different location settings of investigated cities. It turned out that only the urban data of Atlanta and rural data of Houston, Los Angeles and Minneapolis are missing (urban data of Chicago missing for one month). As to the ozone, most of the data are complete as well. For the urban area, the data of Atlanta, Baltimore, Helena and Chicago are missing. Meanwhile, the ozone concentration data of Helena and Seattle in the suburban area and the data of Los Angeles, Atlanta, Baltimore, Seattle and Minneapolis in the rural area are missing or partially missing. At last, the most severe data missing happens with respect to PM10. In Houston, San Francisco, Baltimore, Seattle and Helena, the PM10 data in all location settings of other cities are missing. In addition, the PM10 data are missing in Atlanta and Chicago for two location settings while the data of Los Angeles and Minneapolis are missing in the rural areas.

The box plots of the remaining PM2.5, PM10 and ozone data in all our tested climate zones and cities are shown in Figure 5.3 and 5.4 below. In these figures, the X axis displays the climate zone or cities while the Y axis presents the concentration level in log10 scale. If the air pollutant is PM2.5 or PM10, the unit of Y axis is $\mu g/m^3$ while the unit is ppm if it is ozone. Table 5.1 and 5.2 more clearly show the average and the standard deviation of outdoor air pollutant concentration in both climate level and city level.

Basically, as to the concentration of PM2.5, the most polluted climate zones with highest mean concentration level is 3B, 5A and 3A with their representative cities as the most polluted cities. Typically, the concentrations of PM2.5 for different cities and climate zones range from 7 $\mu g/m^3$ to 10 $\mu g/m^3$ with Los Angeles having 13.60 $\mu g/m^3$ PM2.5 concentration on average as the most pollute area. As to PM10, the most polluted climate zones are zone 2B and 3B, where the concentration level is about 37 $\mu g/m^3$ and 28 $\mu g/m^3$. The PM10 concentrations of their corresponding representative cities are 33 $\mu g/m^3$ and 27 $\mu g/m^3$ respectively. Except for those, the average PM10 concentration for the rest of US ranges from 17 $\mu g/m^3$ to 20 $\mu g/m^3$. What is also worthy to mention is the large deviation of PM10 concentration in climate zone 6B as shown in Table 5.2 below. From the box plots, we can also observe that the PM10 concentration in climate zone 6B is unstable and sometimes magnitude-higher compared to normal situations. Last of all, the average ozone concentration ranges from are from 0.025 ppm to 0.036 ppm with the standard deviation ranging from 0.015 to 0.02 ppm in different climate zones and cities. Using the average concentration as the metrics, the most polluted cities for ozone are Chicago, Baltimore and Phoenix (0.036, 0.034, 0.033 ppm respectively) while least polluted cities are Houston and Albuquerque (0.024 ppm for both).

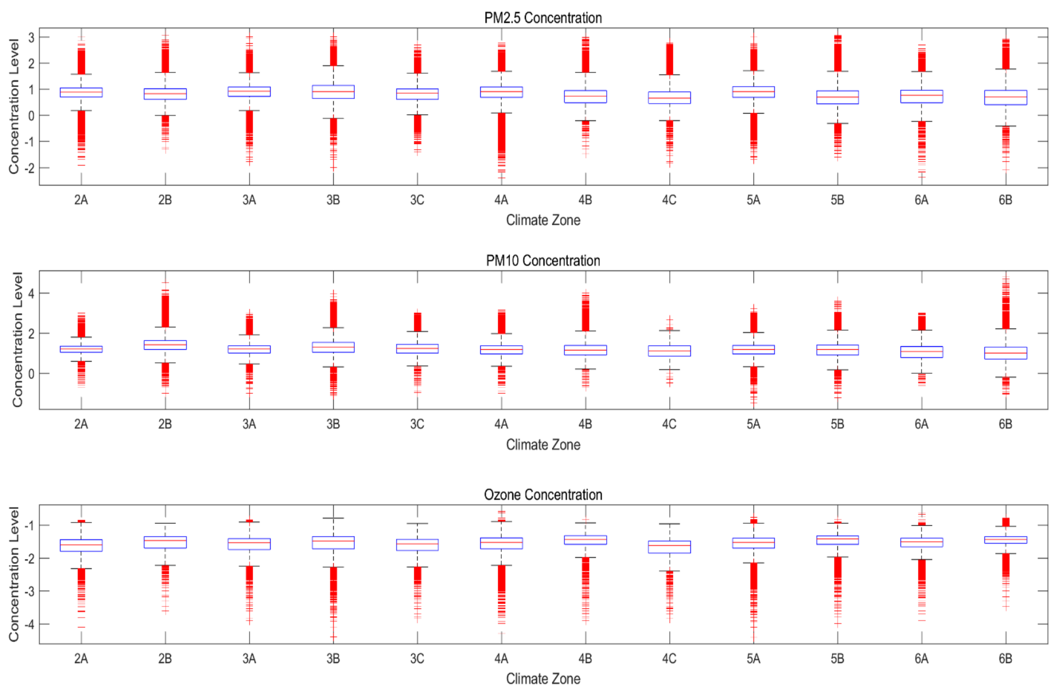


Figure 5.3 Box Plots for Outdoor Air Pollutions in Different Climate Zones

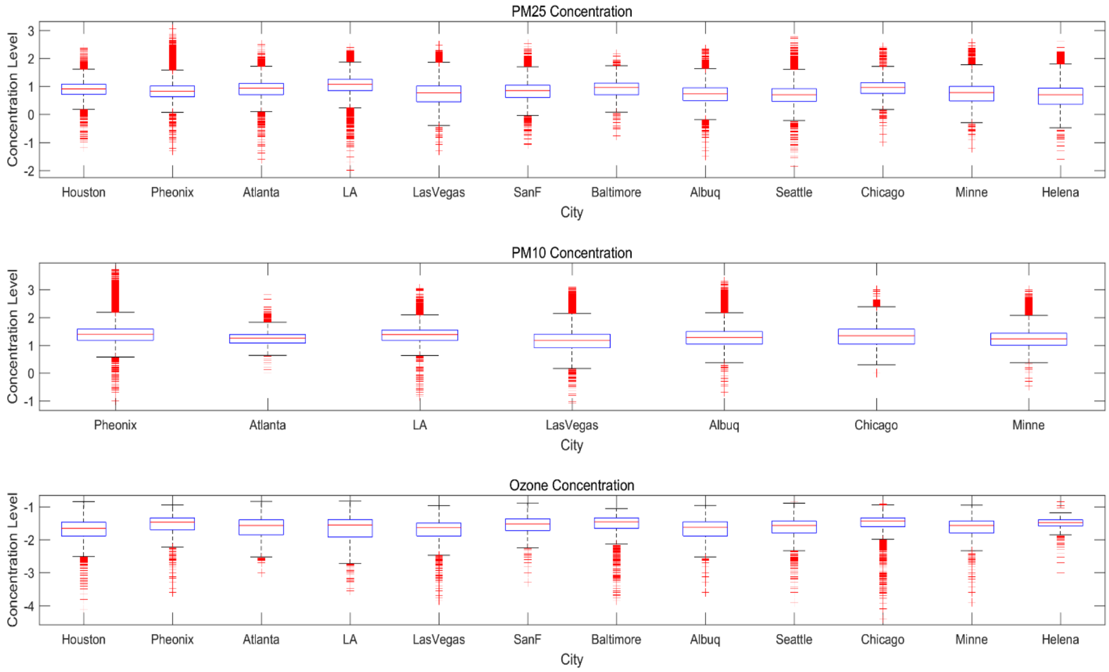


Figure 5.4 Box Plots for Outdoor Air Pollutions in Different Cities

Table 5.1 Outdoor Air Pollutant in Different Cities

Cities	PM2.5		PM10		ozone	
	Mean	Std	Mean	Std	Mean	Std
Houston	9.25	5.99	NA	NA	0.024	0.016
Phoenix	8.59	9.93	32.62	49.49	0.033	0.018
Atlanta	9.52	6.66	18.63	10.64	0.028	0.017
Los Angeles	13.60	10.22	26.91	21.94	0.029	0.020
Las Vegas	7.60	7.71	19.95	25.55	0.023	0.014
San Francisco	8.36	7.23	NA	NA	0.031	0.017
Baltimore	9.96	6.79	NA	NA	0.034	0.017
Albuquerque	7.10	6.93	28.21	42.32	0.024	0.014
Seattle	6.74	6.83	NA	NA	0.027	0.016

Chicago	10.19	6.95	28.54	28.80	0.036	0.017
Minneapolis	7.49	6.71	22.38	23.00	0.027	0.014
Helena	7.02	8.93	NA	NA	0.033	0.010

Table 5.2 Outdoor Air Pollutant in Different Climate Zones

Cities	PM2.5		PM10		ozone	
	Mean	Std	Mean	Std	Mean	Std
2A	8.70	6.08	17.98	12.87	0.026	0.015
2B	8.51	9.81	37.29	77.34	0.033	0.017
3A	9.19	6.62	18.57	15.69	0.029	0.015
3B	10.60	10.50	27.82	39.54	0.033	0.019
3C	7.96	7.15	21.60	25.26	0.027	0.014
4A	9.11	6.57	18.55	18.23	0.030	0.016
4B	7.46	12.50	21.91	53.84	0.036	0.016
4C	6.50	7.65	16.92	14.25	0.024	0.013
5A	9.38	7.22	19.84	21.89	0.030	0.015
5B	7.40	10.92	20.88	36.63	0.036	0.016
6A	6.94	6.40	17.53	20.98	0.031	0.014
6B	7.44	11.07	17.92	138.83	0.036	0.013

In addition to the mean and standard deviation of the collected air pollutant data of different cities and climate zones, we have also probed into the difference and correlation of air pollutants between different location settings to further provide insight into these air pollutant data. First of all, to quantify the difference between two sets of data, the Finkelstein - Schafer (FS) statistics (Finkelstein & Schafer, 1971), which measures the deviation of cumulative distribution function, was employed in this study as an indicator. The formula to calculate the FS statistics is shown below,

$$FS = (\frac{1}{n})\sum_{i=1}^{n}\delta_i$$

in which we have divided the cumulative distribution function of each set of data into n pieces and calculated the δ_i as the absolute difference between two CDFs at point x_i. Hence, the FS statistics represents the average difference between two cumulative distribution functions.

Secondly, as part of the descriptive statistical analysis on the air pollutant data, we utilized the Spearman's rank correlation coefficient (Pirie, 1988) to measure the correlation of outdoor air pollutant in different location settings as well. The formula of calculating Spearman's rank correlation coefficient is shown below,

$$\gamma_s = \rho_{rk_X,rk_Y} = \frac{cov(rk_X, rk_Y)}{\sigma_{rk_X}\sigma_{rk_Y}}$$

As a non-parametric approach that is capable of measuring the correlation even though it is nonlinear, the ρ denotes the Pearson correlation coefficient with rk_X and rk_Y as the rank for variable X and Y. The cov in the formula means the covariance and the σ_{rk_X}, σ_{rk_Y} are the standard deviations for the rank variables. In calculating the Spearman's rank correlation coefficient, all data from two groups will be sorted first with the covariance calculated then. In this study, since formation of air pollutant in different location settings is complex such that the correlation could be nonlinear, we considered that using the Spearman's rank correlation coefficient is more suitable for our purpose compared to the

Pearson correlation coefficient (Benesty et al, 2009) that can only measure the linear relationship between two sets of variables.

Then, after we have defined these two statistical measures, we have continued the descriptive statistical study based on them. In the analysis, the cumulative distribution function of each air pollutant in different location settings was extracted first in monthly basis. The FS statistics was then calculated between different locations settings for comparison. Meanwhile, the correlation of air pollutant between different location settings was also calculated monthly based on the hourly average air pollutant data. Then an aggerate value for measuring the correlation of air pollutant between different location settings was computed by taking the average of the 12 months. Figure 5.5 and 5.6 below show the FS statistics and the pollutant correlation for all the outdoor pollutant between different location settings respectively. From the plot of FS statistics, we could firstly observe that the difference between different location settings is about 5% ~ 15%. Overall, the difference of PM10 and ozone between different location settings is larger compared to PM2.5. In the cold climate (e.g. climate zone 6A and 6B), the difference of PM10 between urban/suburban and rural areas is always significant (usually 15% to 20% difference using the FS statistics). Similarly, the difference of ozone between urban and rural area is also obvious almost across all climate zones we have investigated. Up to 20% difference happens in climate zone 3B, 3C and 5B based on the data we have collected. In addition, based on the Spearman's rank correlation coefficient as the metric, the ozone always achieves strong correlation between different location settings regardless of the existing significant difference regardless of climate zones. Following ozone are PM2.5 and PM10. In the analysis, the PM10 and ozone data in Climate Zone 1A and 4C (Seattle) are left out in the calculation of FS statistics while the Climate Zone 1A data are left out in the calculation of correlation due to insufficient data records after the filtering process.

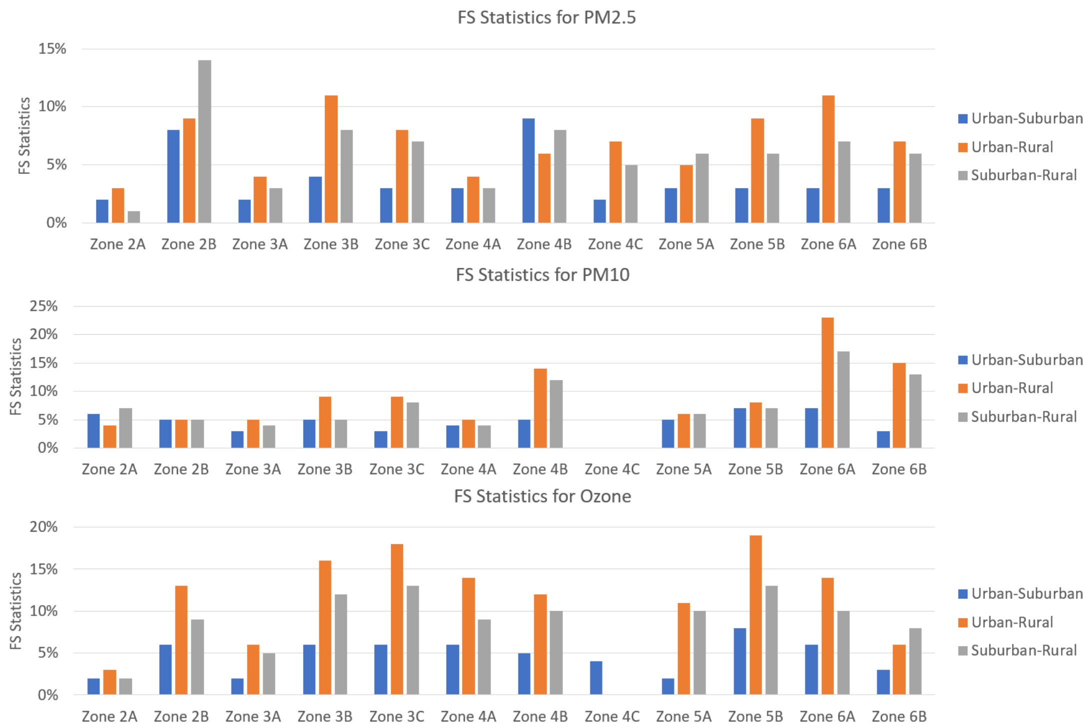


Figure 5.5 FS Statistics for Air Pollutant Difference Between Different Location Settings

Figure 5.6 Correlation for Air Pollutant Between Different Location Settings

Lastly, to more clearly present the difference and correlation of each air pollutant between different location settings, Table 5.3 below lists the aggregate statistical measures for Urban-Suburban, Urban-Rural and Suburban-Rural comparison. Overall, the concentration difference of all air pollutants between location settings is not large (4% - 5% on average). This gradually increase from Suburban-Rural comparison to Urban-Rural. The largest difference is the ozone difference between urban and rural areas, which is 12% on average based on FS statistics. On the other hand, with respect to the correlation, the ozone is always highly correlated between different location setting with the Spearman's rank correlation coefficient from 0.87 to 0.91 since its formation is mainly driven by sun. Then, both PM2.5 and PM10 are only moderately correlated (0.4 to 0.7) with the correlation of PM10 less than PM2.5. The main reason is that the Particulate Matter is harder to be transported within the atmosphere with gravity, especially for PM10. All these values help to provide a general estimate of the air pollutant difference and correlation between different location settings when there is no easily available data for the analysis.

Table 5.3 Summary of Descriptive Statistical Analysis Result

	Urban-Suburban		Urban-Rural		Suburban-Rural	
	FS	Correlation	FS	Correlation	FS	Correlation
PM2.5	0.04	0.75	0.07	0.66	0.06	0.67
PM10	0.05	0.59	0.09	0.42	0.08	0.47
Ozone	0.05	0.89	0.12	0.87	0.09	0.91

5.3.3 Representative Air Pollutant Data Selection

After running through a thorough descriptive data analysis, the next step is to select the representative air pollutant data out of past 5 historical records such that it can be integrated with the TMY of each city and generate a reasonable estimate of the influence of air pollutant on the natural ventilation. To select the monthly records that are representative enough for the long-term trend of the weather in that area, we have implemented the Sandia method (Hall et al, 1978), which was formerly developed by by Sandia National Laboratories to generate the Typical Meteorological Years data. By comparing the cumulative distributed function and the trend of data fluctuation, the Sandia method has been proven to be reliable in extracting the representative data. In this research, the implemented Sandia method was modified by a small amount since we only one variable (the concentration level) to consider in the selection. Thus, the main steps of the implemented Sandia method are listed below, (1) based on the FS statistics as the metric, the five candidate months that have the cumulative distribution function most similar to the long-term cumulative distributed function of the interested variable are taken out first, (2) these five selected months are then ranked according to their closeness of mean and median to the mean and median of the long-term CDF, (3) count the frequency and run length of consecutive days with the concentrations level above 67^{th} percent and below 33^{rd} percent are determined for each candidate, then the candidate months with the longest runs, most runs and zeros run are excluded, (4) the remaining month with the highest rank in step 2 is selected. Finally, the 12 selected months are concatenated into to be the representative air pollutant concentration level of the whole year.

The selected outcomes of our representative air pollutant year are shown in Figure 5.7 below. In the figure, the x axis lists the cities we have extracted the representative air pollutant data for while the y axis is the difference based on the calculated FS statistics between the selected data and the cumulated long-term data. From the figure, we can observe that the difference is almost always less than 5% for all air pollutants we have chosen. The only exception for this happens when we select the PM2.5 data in the rural area of San Francisco and Las Vegas since only limited data records exist in the rural areas of these cities. The results show that the selected air pollutant data could be representative enough for the concentration of major air pollutants in one area. Also, as mentioned in the Section 5.3.2 above, part of the air pollutant data is missing in the analysis.

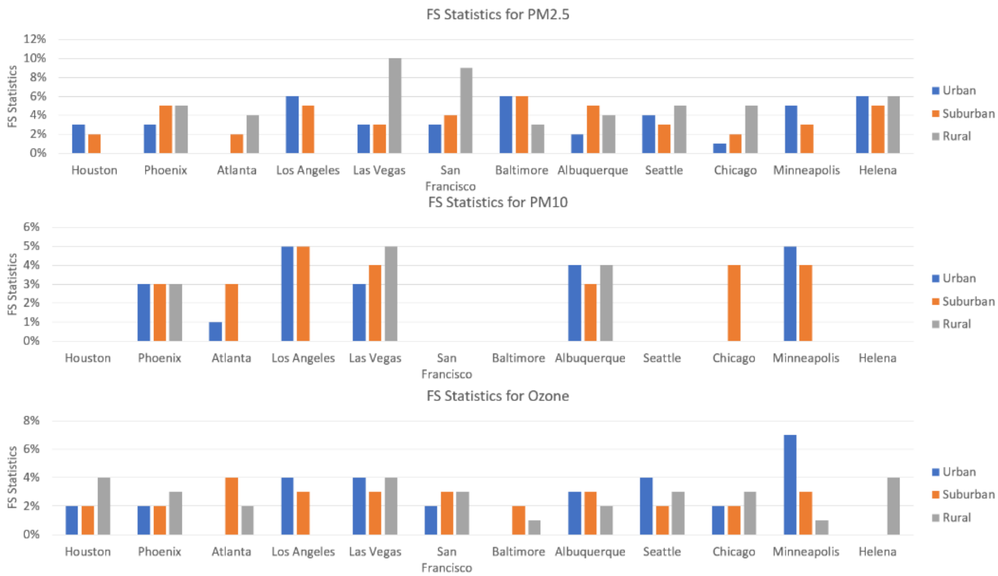


Figure 5.7 FS Statistics for Representative Pollutant Data Selection

5.3.4 Air Pollutant Modelling

To quantify the influence of outdoor air pollutant on the indoor air pollutant concentration, establishing a valid air pollutant modelling process is important. In this study, the conservation of mass principle was utilized as the basis for the air pollutant modelling, as shown in the formula below.

$$\frac{dC_{t,i}^{k}}{dt} = \sum S_i - \sum L_i * C_{t,i}^{k}$$

Basically, it describes that the change of indoor air pollutant concentration level is determined by summing the gain from all sources and loss due to all sinks. In the formula, $C_{t,i}^{k}$ $(unit\ is\ \mu g/m^3\ or\ ppm)$ represents the concentration level of pollutant i in building zone k at time step t, $\sum S_i$ is the sum of all sources for the air pollutant i while $\sum L_i$ (in the unit of h^{-1}) is the sum of all loss sources for the air pollutant i. In the air pollutant modeling of this study, the indoor sources (especially for ozone) and the reactions between different indoor air pollutants are neglected considering that our aim is to investigate the influence of outdoor air pollutants on the indoor environment. Also, all the source generation rate, loss rate and the zonal average concentration are all assumed to be constant within each time step. Hence, by accounting for all these, the formula above could be expanded into the formula as,

$$\frac{dC_{t,i}^{k}}{dt} = \sum_{i=1}^{n} C_{t,i}^{k} * \lambda_{i-k} + C_{t}^{out} * \lambda_{t}^{out-k} + C_{t}^{out} * (1-\eta_{fil}) * \lambda_{out} - \eta_{dep} * C_{t,i}^{k} - \sum_{i=1}^{n} C_{t,i}^{k} * \lambda_{k-i} - C_{t,i}^{k} * \lambda_{t}^{k-out} - C_{t,i}^{k} * \eta_{fil} * \lambda_{re}$$

In which $C_{t,i}^{k}$ is the concentration level of pollutant i in building zone k,

$\sum_{i=1}^{n} C_{t,i}^{k} * \lambda_{i-k}$ – the term describes the air pollutant transport from neighborhood zones the air pollutant i transported into zone k from all the neighborhood zones with λ_{i-k} as the airflow rate

$C_{t}^{out} * \lambda_{t}^{out-k}$ – the term describes the air pollutant transport from outside environment, air pollutant i transported into zone k from outdoor environment through windows with λ_{t}^{out-k} as the airflow rate, C_{t}^{out} is the concentration of outdoor pollutant i at time step t

$C_{t}^{out} * (1-\eta_{fil}) * \lambda_{out}$ – the term describes the air pollutant transport into the zone by mechanical ventilation, air pollutant i transported into zone k from the mechanical ventilation system with η_{fil} as the filter efficiency and λ_{out} as the outdoor airflow rate, C_{t}^{out} is the concentration of outdoor pollutant i at time step t

$\eta_{dep} * C_{t,i}^{k}$ – the term describes the air pollutant deposition loss, the deposition of air pollutant i with the deposition rate as η_{dep} in the unit of h^{-1}

$\sum_{i=1}^{n} C_{t,i}^{k} * \lambda_{k-i}$ – the term describes the air pollutant transport to neighborhood zones, the air pollutant i transport from zone k to all the neighborhood zones with λ_{k-i} as the airflow exchange rate

$C_{t,i}^{k} * \lambda_{t}^{k-out}$ – the term describes the air pollutant transport through windows to outside, air pollutant i transport from zone k to outdoor environment through windows

$C_{t,i}^{k} * \eta_{fil} * \lambda_{re}$ – the term describes the recirculation loss, air pollutant i filtered by the mechanical ventilation system with η_{fil} as the filter efficiency, λ_{re} is the recirculation airflow rate of the mechanical ventilation system

To solve the equation presented above, firstly, all the airflow related parameters (λ) are calculated using the Airflow Network modules in EnergyPlus (Crawley et al, 2001) except for the λ_{re} (recirculation airflow rate) and λ_{out} (outdoor airflow rate of mechanical ventilation) that are constant according to the baseline building system setting. In the airflow network, each zone is simulated as a node with the temperature, humidity and pressure associated with it while the windows and doors are defined as flow path. Besides, the deposition rate η_{dep} for PM2.5, PM10 and ozone were set to be 0.2, 2.2 and 1.5 h^{-1} based on recommendations from past literatures (Long et al, 2014), (Rackes & Waring, 2013), (Gao & Niu, 2007), (Reiss et al, 1994). A various of factors, including the deposition surface size, orientation, roughness and airflow condition etc., could all impact on these values such that we only provide a general estimate of these. Finally, for the system filtering efficiency, 24%, 70% and 40% were set as the nominal filtering efficiency for PM2.5, PM10 and ozone respectively (Azimi et al, 2014), (Zhao et al, 2007). These were set based on the requirement and recommendation of pollutant filtering in commercial buildings. The MERV (Minimum Efficiency Reporting Value) 8 filter was assumed to be installed in the system of our baseline building.

With all these rules established for the air pollutant modelling, the verification of the air pollutant modelling was done by comparing the indoor pollutant concentration fluctuation with the outdoor air pollutant. An illustrative example of the simulated indoor PM2.5, PM10 and ozone concentrated is shown in Figure 5.8 below. In the figure, the orange line presents the fluctuation of outdoor pollutant concentration while the blue line depicts the corresponding average indoor air pollutant in the building level. The x axis is the hour index while the Y axis shows the concentration level ($\mu g/m^3$ for PM2.5 and PM10 while ppm for ozone). Based on the comparison, the indoor average air pollutant concentration follows closely with the outdoor air pollutant fluctuation as expected, which verifies the correctness of the air pollutant modeling.

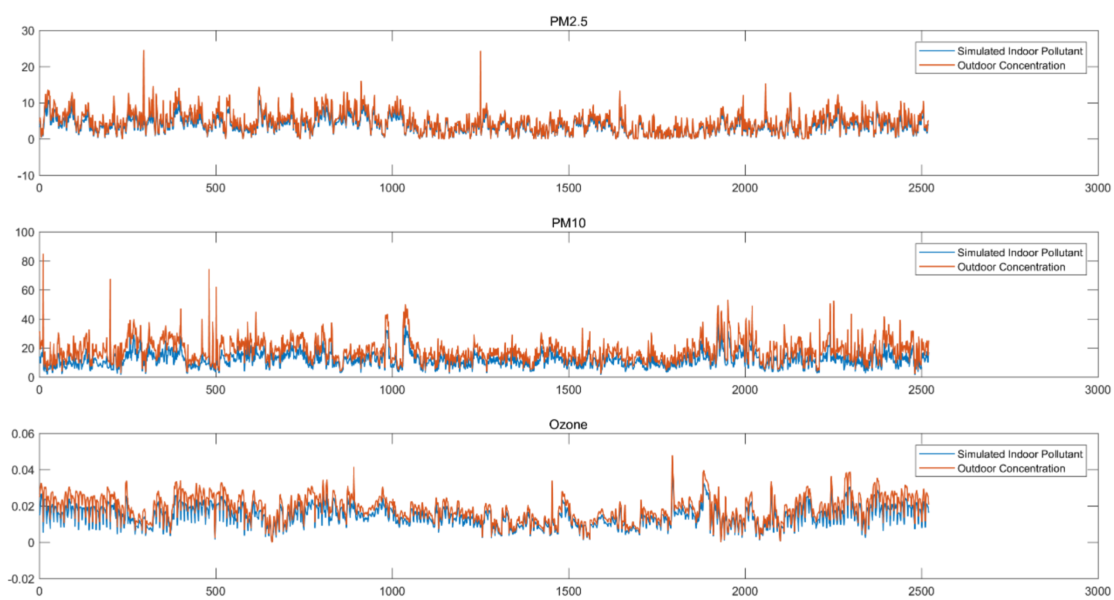


Figure 5.8 Verification of Air Pollutant Modeling

5.4 Emulator Establishment

To help the control of indoor air pollutant concentration, we have built an emulator to estimate the indoor air pollutant concentration using the outdoor air pollutant concentration level, wind speed and indoor air pollutant concentration level at last time step as predictors. The training data of the emulator is generated from the air pollutant modeling results. Two mathematical models, including the multiple linear regression and neural network, were selected as candidates for the emulator establishment. Both the multiple linear regression and neural network are already introduced in the Section 3.1.2 above thus no further introduction is provided here.

After selecting the three candidate models, three statistical measures, i.e. R^2 (coefficient of determination), MAE (mean absolute error), RMSE (root mean square error), were defined as the metrics in the model selection. Table 5.4 below shows the prediction performance of two candidate models in terms of indoor air pollutant fluctuation. From the table, we could see that the linear regression consistently underperforms than neural network with respect to all PM2.5, PM10 and Ozone prediction. Also, the residual plots show that using linear regression could occasionally generate outliers in the prediction of indoor air pollutant concentration, as shown in Figure 5.9 below. Hence, the neural network was finally selected to establish the emulator for the indoor air pollutant concentration level prediction.

Table 5.4 Test Result of Predictions for Three Candidate Model

	PM2.5			PM10			Ozone		
	MAE	RMSE	R^2	MAE	RMSE	R^2	MAE	RMSE	R^2

Linear Regression	0.2611	0.441	97.38	4.1	5.5	86.7	0.0017	0.0020	96.1
Neural Network	0.2174	0.3991	99.03	2.4	3.7	88.7	0.0016	0.0019	97.1

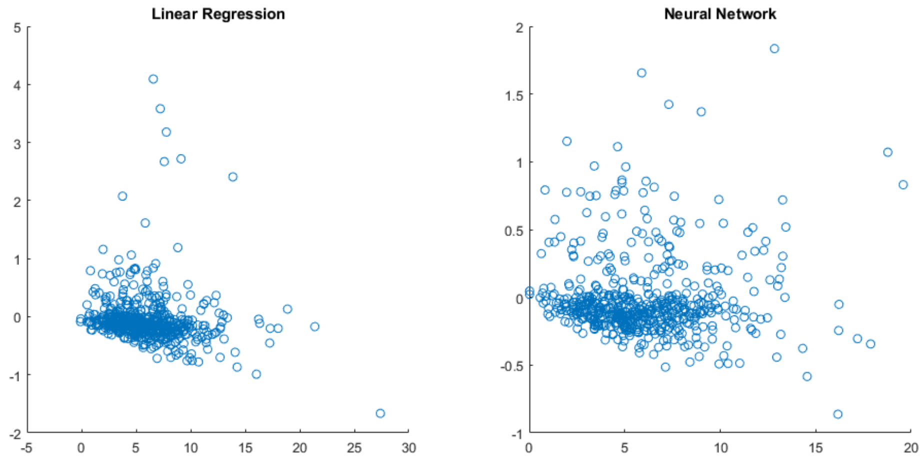


Figure 5.9 Residual Plots in Model Training (PM2.5)

5.5 Scenarios of Investigation

In this study, finally, with all steps done before, we have defined two scenarios – considering the outdoor air pollutant in the hybrid ventilation building operation vs. not, to quantify the potential impact of outdoor air pollutant on the natural ventilation usage. The baseline control strategy for hybrid ventilation building operation is the rule-based control strategy, which is most commonly used strategy in the current practice. In the baseline rule-based control strategy (Scenario 1), the windows of the hybrid ventilation building will be opened if all three criteria are met, i.e. (1) the outdoor temperature is between 19℃ and 26℃, (2) the outdoor wind speed is less than 7 m/s, (3) the outdoor relative humidity is less than 85% when the temperature is higher than 24℃. Then, in Scenario 2, the baseline control used in Scenario 1 is expanded with the emulator established above for the indoor air pollutant prediction such to shield the occupants from excessive exposure of outdoor air pollutants. The window will be closed if the predicted indoor air pollutant concentration exceeds the threshold defined in Section 5.2 above. Both of these control strategies were implemented using co-simulation through the BCVTB (Building Control Virtual Test Bed) (Wetter, 2009) platform. The configuration of BCVTB is presented in Figure 5.10 below. As shown, the implemented control in Matlab communicates with EnergyPlus for the data exchange in the co-simulation process.

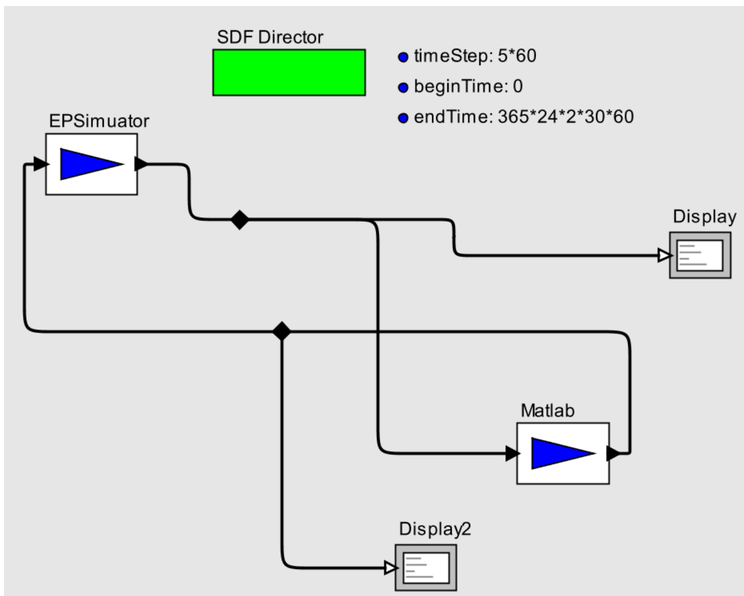


Figure 5.10. Configuration of Co-simulation in BCVTB

Lastly, to ensure the correctness of the hybrid ventilation control strategy considering the air pollutant, we verify the developed control strategy by comparing the average and max indoor air pollutant concentration level with the defined thresholds of PM2.5, PM10 and ozone. Figure 5.11 below presents an illustrative comparison result. In the figure, the x axis is the hour index for the window opening hours while the y axis depicts the concentration level. The threshold for each air pollutant is also plotted for better comparison. In our tests, it is clear that the developed control is capable of maintaining both mean and max indoor air pollutant concentration within the bound during natural ventilation.

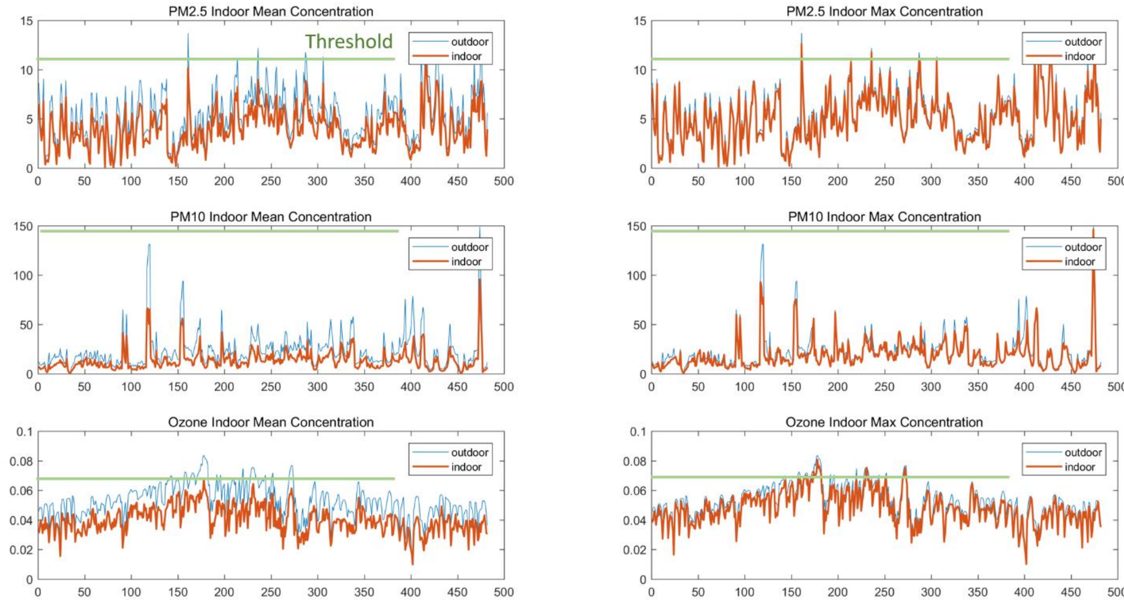


Figure 5.11 Verification of Natural Ventilation Considering Air Pollutants

5.6 Result Analysis

With the scenarios defined thus to quantify the influence of outdoor air pollutant on the natural ventilation usage, Table 5.5 below lists all the results we have generated for the natural ventilation reduction caused by outdoor air pollutants in different location settings of tested cities. In the table, the total NV hours are the naturally ventilated hours that account for both outdoor meteorology and air pollutant in window control while the Reduction due to Air Quality presents the hours in which the windows should be opened if only outdoor meteorology is considered but closed to avoid excessive outdoor air pollutant. Then, the percentage of these reduction hours in different location settings is calculated by dividing the reduction hours due to air pollutant by the number of natural ventilation hours if only outdoor meteorology is considered in the window control. Also, the subscript (1), (2) and (3) in the table serve as the indicator describing that whether that number in the table is calculated when PM2.5 data, PM10 data and ozone data are missing or partially missing, respectively. The rule of thumb of viewing the results from the table is that the number with subscript of (1) should be used with more attentions while the number subscript with (2) or (3) could be considered as a good estimate. From the table, we can firstly observe that the urban areas are typically most polluted followed by the suburban then rural areas. The reduction of natural ventilation in the urban areas usually ranges from 10% to 30% while both suburban and rural areas are from 5% to 20%. Considering the natural ventilation reduction in urban and suburban areas, the most polluted cities in US are Los Angeles, Chicago, then Atlanta and San Francisco. More than 60%, 30% and 20% (for both Atlanta and San Francisco) natural ventilation cut should be expected for these cities, respectively. Meanwhile, the natural ventilation reduction is similar in different location settings in Phoenix, Atlanta, Albuquerque, Chicago and Helena.

Table 5.5 Summary for Outdoor Air Pollutants on Natural Ventilation Usage

	Urban		Suburban		Rural		Reduction of NV usage in Urban Area	Reduction of NV usage in Suburban Area	Reduction of NV usage in Rural Area
	Total NV hours	Reduction due to Air Quality	Total NV hours	Reduction due to Air Quality	Total NV hours	Reduction due to Air Quality			
Houston	$502^{(2)}$	$132^{(2)}$	$534^{(2)}$	$100^{(2)}$	$626^{(1,2)}$	$8^{(1,2)}$	$20.8\%^{(2)}$	$15.8\%^{(2)}$	$1.3\%^{(1,2)}$
Phoenix	460	42	480	22	462	40	8.4%	4.4%	8.8%
Atlanta	$610^{(1,2,3)}$	NA	470	140	$420^{(2,3)}$	$190^{(2,3)}$	NA	23.0%	$31.1\%^{(2,3)}$
Los Angeles	186	930	360	756	NA	NA	83.3%	67.7%	NA
Las Vegas	342	46	360	28	376	12	11.9%	7.2%	3.1%
San Francisco	$494^{(2)}$	$140^{(2)}$	$490^{(2)}$	$144^{(2)}$	$610^{(2)}$	$24^{(2)}$	$22.1\%^{(2)}$	$22.7\%^{(2)}$	$3.8\%^{(2)}$

Baltimore	$378^{(1)}$	$94^{(1)}$	$422^{(2,3)}$	$50^{(2,3)}$	$436^{(2,3)}$	$36^{(2,3)}$	$19.9\%^{(1)}$	$10.6\%^{(2,3)}$	$7.6\%^{(2,3)}$
Albuquerque	394	36	366	64	372	58	8.4%	14.9%	13.5%
Seattle	$370^{(2)}$	$20^{(2)}$	$352^{(2,3)}$	$38^{(2,3)}$	$372^{(2,3)}$	$18^{(2,3)}$	$5.1\%^{(2)}$	$9.7\%^{(2,3)}$	$4.6\%^{(2,3)}$
Chicago	$348^{(2,3)}$	$152^{(2,3)}$	308	192	$288^{(2)}$	$212^{(2)}$	$30.4\%^{(3)}$	38.4%	$42.4\%^{(2)}$
Minneapolis	338	60	372	26	$398^{(2,3)}$	$0^{(1,2,3)}$	15.1%	6.5%	$0\%^{(1,2,3)}$
Helena	$276^{(2,3)}$	$40^{(2,3)}$	$286^{(2,3)}$	$30^{(2,3)}$	$272^{(2)}$	$44^{(2)}$	$12.7\%^{(2,3)}$	$9.5\%^{(2,3)}$	$13.9\%^{(2)}$

In addition to the table for providing the overall reduction of natural ventilation across different cities, for each location setting of these cities, we also present a table to better distinguish the influence of each outdoor air pollutant on the natural ventilation reduction, shown from Table 5.6 to 5.8 below. Similar to the Table 5.5 shown above, the subscript (1), (2), (3) means that the PM2.5, PM10 and ozone data is missing respectively while the subscript (p) dictates that the data is partially missing. From all three tables, we firstly observe that the PM2.5 usually accounts for the most significant amount of natural ventilation reduction across different location settings followed by ozone. In most of urban and suburban areas, the PM2.5 could lead to 10% to 30% reduction while both ozone and PM10 usually only account for less than 5% reduction together. The only exception is the suburban area of Albuquerque where the PM10 and ozone together account for almost 10% of natural ventilation reduction. As to PM10, its impact on the natural ventilation reduction is almost trivial across different location settings of all tested cities. There exist only two cases – the urban area of Minneapolis and the suburban area of Albuquerque that the PM10 contributes to more than 3% of natural ventilation reduction. Thus, it is an insignificant source to consider in terms of using natural ventilation. Lastly, with respect to ozone, it is typically not a significant source for the natural ventilation reduction as well. However, it is interesting to observe that its significance gradually increases as we move from the urban area to the rural area, such as the suburban area of Los Angeles (17.2%) and Albuquerque (4.7%) and the rural area of Chicago (7.2%). This increased level of significance is caused by the shift of balance in the ozone formation. Shown in the reaction below,

$$NO_2 + O_2 + hv \leftrightarrow NO + O_3$$

The ground level ozone concentration is determined by the balance of this reaction in which NO_2 reacted with O_2 on one side while NO absorbed O_3 on the other side. The concentration of O_3 in the ground level is the concentration of ozone when reaction reaches the equilibrium. In our daily lives, the larger amount of NO emitted by vehicles and other human activities (Kirchstetter et al, 1999) will lead the equilibrium to shift to the left in urban areas. Furthermore, the produced NO_2 will then be transported to the suburban and rural areas, which causes the equilibrium in these areas to shift to the right thus generating more O_3. Thus, the O_3 will become increasingly a problem in suburban and rural areas compared to the urban area. To more clearly visualize the impact of different air pollutants on the natural ventilation reduction, Figure 5.12 below shows the investigation results of natural ventilation reduction in the suburban areas as illustration.

Table 5.6 Influence of Outdoor Air Pollutants on Natural Ventilation Usage in Urban Area

	Urban								
	Close due to weather	Total win open hrs	Close due to pm25	Close due to pm10	Close due to ozone	Overall close due to air pol	Reduction Due to PM25	Reduction Due to PM10	Reduction Due to Ozone
Houston	1886	$502^{(2)}$	128	NA	4	$132^{(2)}$	20.2%	NA	0.60%
Phoenix	2018	460	40	4	0	42	8%	0.8%	0%
Atlanta	1910	$610^{(1,2,3)}$	NA	$0^{(p)}$	NA	NA	NA	0.0%	NA

Los Angeles	1404	186	924	10	12	930	82.8%	0.9%	1.1%
Las Vegas	2132	342	44	0	2	46	11.3%	0.00%	0.5%
San Francisco	1886	$494^{(2)}$	140	NA	0	$140^{(2)}$	22.1%	NA	0%
Baltimore	2048	$378^{(1)}$	$94^{(p)}$	NA	NA	$94^{(1)}$	19.9%	NA	NA
Albuquerque	2090	394	28	6	4	36	6.5%	1.4%	0.9%
Seattle	2130	$370^{(2)}$	20	NA	0	$20^{(2)}$	5.1%	NA	0%
Chicago	2020	$348^{(2,3)}$	148	NA	$18^{(p)}$	$152^{(2,3)}$	29.6%	NA	3.6%
Minneapolis	2122	338	46	14	0	60	11.6%	3.5%	0%
Helena	2204	$276^{(2,3)}$	40	NA	NA	$40^{(2,3)}$	12.7%	NA	NA

Table 5.7 Influence of Outdoor Air Pollutants on Natural Ventilation Usage in Suburban Area

	Suburban								
	Close due to weather	Total win open hrs	Close due to pm25	Close due to pm10	Close due to ozone	Overall close due to air pol	Reduction Due to PM25	Reduction Due to PM10	Reduction Due to Ozone
Houston	1886	$534^{(2)}$	100	NA	0	$100^{(2)}$	15.8%	NA	0%
Phoenix	2018	480	18	2	2	2	3.6%	0.4%	0.4%
Atlanta	1910	470	136	0	4	140	22.3%	0%	0.7%
Los Angeles	1404	360	684	2	192	756	61.3%	0.2%	17.2%
Las Vegas	2132	360	28	0	0	28	7.2%	0%	0%
San Francisco	1886	$490^{(2)}$	144	NA	0	$144^{(2)}$	22.7%	NA	0%
Baltimore	2048	$422^{(2,3)}$	44	NA	6	$50^{(2,3)}$	9.3%	NA	NA
Albuquerque	2090	366	40	20	20	64	9.3%	4.7%	4.7%
Seattle	2130	$346^{(2,3)}$	44	NA	$0^{(p)}$	$44^{(2,3)}$	11.30%	NA	0.00%
Chicago	2020	308	188	2	18	192	37.6%	0.4%	3.6%
Minneapolis	2122	372	26	0	0	26	6.5%	0%	0%
Helena	2204	$286^{(2,3)}$	30	NA	NA	$30^{(2,3)}$	9.5%	NA	NA

Table 5.8 Influence of Outdoor Air Pollutants on Natural Ventilation Usage in Rural Area

	Rural								
	Close due to weather	Total win open hrs	Close due to pm25	Close due to pm10	Close due to ozone	Overall close due to air pol	Reduction Due to PM25	Reduction Due to PM10	Reduction Due to Ozone
Houston	1886	$626^{(1,2)}$	NA	NA	8	$8^{(1,2)}$	0%	NA	1.3%
Phoenix	2018	462	34	6	4	40	6.8%	1.2%	0.8%
Atlanta	1910	$420^{(2,3)}$	184	NA	$10^{(p)}$	$190^{(2,3)}$	30.2%	NA	1.6%
Los Angeles	1404	NA	NA	NA	NA	NA	NA	NA	NA
Las Vegas	2132	376	12	0	0	12	3.1%	0%	0%
San Francisco	1886	$610^{(2)}$	24	NA	0	$24^{(2)}$	3.8%	NA	0%
Baltimore	2048	$436^{(2,3)}$	36	NA	$0^{(p)}$	$36^{(2,3)}$	7.6%	NA	0%
Albuquerque	2090	372	48	12	0	58	11.2%	2.8%	0%
Seattle	2130	$372^{(2,3)}$	18	NA	$0^{(p)}$	$18^{(2,3)}$	4.6%	NA	0%
Chicago	2020	$288^{(2)}$	180	NA	36	$212^{(2)}$	36.0%	NA	7.2%
Minneapolis	2122	$398^{(2,3)}$	NA	NA	$0^{(p)}$	$0^{(1,2,3)}$	0%	NA	0%
Helena	2204	$272^{(2)}$	44	NA	0	$44^{(2)}$	13.9%	NA	0%

Figure 5.12 Summary of Outdoor Air Pollutant Influence on Natural Ventilation Usage

(Suburban area, in the pie chart, Blue presents reduction because of temperature, humidity and wind speed, Green presents natural ventilation suitable hour considering both outdoor meteorology and air pollutant, Yellow presents reduction due to PM2.5, Dark Green presents reduction due to PM10, Dark Blue presents reduction due to ozone)

6. DETERMINISTIC SIMULATION VS. UNCERTAINTY ANALYSIS IN NATURAL VENTILATION DESIGN

By providing probabilistic probes into prediction outcomes, the uncertainty analysis has shown its power in closing performance gaps of building simulation. Several studies were conducted to show the application of uncertainty analysis for the thermal comfort evaluation in natural ventilation. However, it is still unclear that how the uncertainty analysis could help naturally ventilated building design compared to the deterministic simulation. Also, how to more effectively reduce thermal comfort risks in natural ventilation is another important problem to address to ensure the robust design of a naturally ventilated building. In this chapter, we will provide a detailed comparison between the uncertainty analysis result and deterministic simulation result for the evaluation of thermal comfort risks in naturally ventilated buildings using a case study. Meanwhile, the design scenario tests will also be implemented to investigate how to more appropriately utilize the uncertainty analysis to help the decision making in designing a naturally ventilated building and how to effectively reduce thermal comfort risks during natural ventilation. Finally, a sensitivity analysis was conducted to identify the most significant uncertainties to consider in natural ventilation design.

6.1 Experiment Settings

6.1.1 Baseline Building Establishment

To explicitly show the difference when evaluating the thermal comfort risks during natural ventilation, a baseline building has to be established first. Similar as before, the baseline building in our uncertainty analysis is a campus building with the actual configuration of zones (shown in Figure 6.1 below). To maintain sufficient air exchange rate in all building zones, at least one window (2.1m * 2.4m) is attached for each zone such that the ASHRAE Standard 62.1 ventilation for acceptable indoor air quality requirement (ASHRAE, 2007) is met. The window wall ratio for the whole building is kept 30% as the DOE medium commercial reference building. Table 6.1 below lists all the construction details of the baseline building. As to the operation related parameters, the occupancy density is set as 0.05 person/m^2 with the electric equipment consumption as 11 W/m^2 and lighting consumption as 7 W/m^2 based on the recommendation from ASHRAE (2009). TMY3 (typical meteorological year 3) of San Francisco is utilized in the analysis considering its appropriateness for natural ventilation. The simulation is conducted in the hottest season in San Francisco (June to Sep). No night ventilation is allowed for security reason during unoccupied hours (from 7 P.M. to 7 A.M.) in the current analysis.

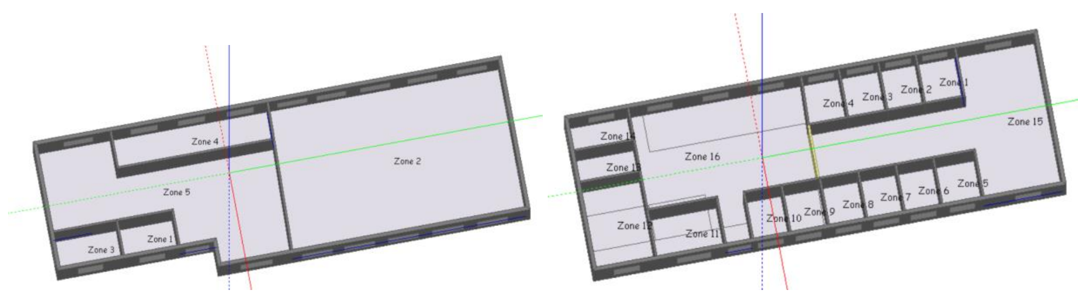


Figure 6.1 Baseline Building Model

Table 6.1 Building Information Summary

Exterior Wall	U Value: 0.55 $W/m^2 - K$ Brick: 5 cm, Concrete Block: 10 cm, Rigid Insulation: 5cm, Gypsum Plasterboard: 1.3cm
Ground Floor	U Value: 1.96 $W/m^2 - K$ Concrete Slab: 15 cm
Roof	U Value: 0.73 $W/m^2 - K$ Bitumen Layer: 1 cm, Rigid Insulation: 4 cm, Cast Concrete: 12 cm, Plasterboard: 1.3 cm
Window	U Value: 2 $W/m^2 - K$ SHGC: 0.55

6.1.2 Thermal Comfort Criteria

In the comparison study, two thermal comfort criteria are used to determine the thermal comfort status during natural ventilation. The first criteria is the adaptive thermal comfort model in the ASHRAE Standard 55 - Thermal Environmental Conditions for Human Occupancy (ASHRAE, 2010). In addition to the adaptive thermal comfort model, to more clearly identify the thermal comfort risks during natural ventilation, the EN15251 (2007) (Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics) is combined with TM52 (The Limits of Thermal Comfort: Avoiding Overheating in European Buildings) (CIBSE, 2013) to work as second criteria for thermal comfort evaluation as well. In TM52, the naturally ventilated building is considered to have thermal comfort risks if two of the following three criteria are met, (1) Indoor operative temperature exceeding the threshold of a thermal comfort zone should be no longer than 3% of occupied hours, (2) Daily weighted exceedance (degree hours), which is calculate as a combination of hourly exceeding hours and degree, shouldn't be more than 6 for any day of a year, and (3) Temperature shouldn't exceed an upper limit for 4K.

6.1.3 Applied Uncertainties and Uncertainty Propagation

As to the applied uncertainties in this test, we have applied the microclimate uncertainty (urban heat island effect, local wind speed, ground reflectance), the building level uncertainty (exterior and interior convection uncertainty, material uncertainty) and the operation uncertainty (occupant presence, electric equipment and lighting consumption). All details of these uncertainties settings are shown in the Table 2.2 above. Then, after we have quantified and defined all the uncertainties to apply, the GURA-W was utilized to propagate these uncertainties into the simulation model for the uncertainty analysis. The Latin Hypercube Sampling approach was used due to its higher efficiency in covering all possible values in sampling thus reducing the computational burden of the uncertainty analysis.

6.2 Thermal Comfort Evaluation Comparison

6.2.1 Comparison Result

To explicitly show the difference between uncertainty analysis and deterministic simulation, we firstly ran the thermal comfort evaluation on the baseline building using the deterministic simulation. The deterministic simulation result showed that the mean indoor operative temperature was out of comfort bound in 4.08% of the occupied hours with a range from 0% to 5.96% in different zones based on adaptive thermal comfort model in ASHRAE Standard 55 (ASHRAE, 2010). The TM52 check indicated that no building zone would suffer from overheating risks during the simulation period. On the other hand, the uncertainty analysis (200 runs) was performed with all applied uncertainties presented in Table 6.2. The results showed that the average percentage of indoor operative temperature out of bound shifted from 4.09% in the deterministic simulation to 6.69%. In addition, the TM52 check dictated that there existed 13, 11, 4 and 4 buildings suffering from 5%, 15%, 30% and 50% probability of overheating. The histogram about the fraction of unsatisfactory hours was shown in Figure 6.2 below. Furthermore, Figure 6.3 showed that all most risky zones of thermal comfort (more than 50% of overheating risks) were located in the west side of the building.

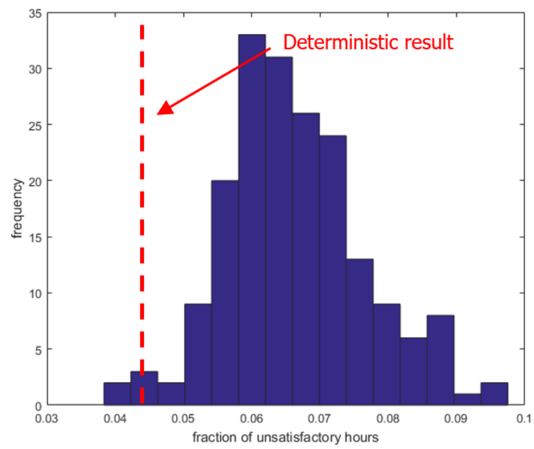


Figure 6.2 Uncertainty Analysis results considering all the uncertainties for baseline

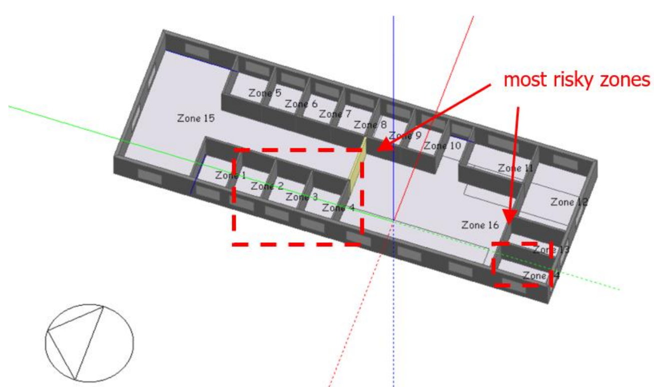


Figure 6.3 Layout of most risky zones

6.3 Design Scenario Tests

In addition to comparing baseline cases in terms of the thermal comfort evaluation of natural ventilation using the uncertainty analysis and deterministic simulation, we have tested several design scenarios including various shading designs, construction types, wall designs and the orientation of building using the uncertainty analysis, in order to further compare the deterministic simulation result with the uncertainty analysis thus providing meaningful guidance for building designers when designing a naturally ventilated building. The results of design scenario tests are shown from Section 6.3.1 to Section 6.3.4 below.

6.3.1 Shading Design

The first design scenario we have tested is the roof canopy with different shading designs. As one of the most important components in the building design, the roof canopy, which is typically composed of metal covering or fabric, is attached to the building not only to improve the building aesthetics but also to shield the building and its occupants from excessive solar influence, which might result in higher HVAC load in summer and potential thermal discomfort due to high radiant temperature. Hence, as the first step, we have tested five scenarios – the roof canopy with 10 ft overhang on all sides of the building, the roof canopy with 10 ft overhang on west side of the building, the roof canopy with 5 ft overhang on all sides of the building, the roof canopy with 5 ft overhang on west side of the building and green roof, using both uncertainty analysis and the deterministic simulation to see how effectively they can reduce the thermal comfort risk in a naturally ventilated building. From the Table 6.2, we can see that the number of building zones in different probability of overheating is reduced significantly in all the tested scenarios (the number of building zones with more than 50%, 30%, 15% overheating probability larger were 4, 4 and 11 in the baseline uncertainty analysis). Additionally, we have further tested the impact of shading by only adding the overhangs without the roof canopy, as shown in Table 6.3 below. Even with 6 ft overhang on the west side of the building could reduce the number of zones with more than 50%, 30%, 15% overheating probability to 0, 0 and 1. It is noticeable that the roof canopy with overhang is very effective in improving the robustness of thermal performance of natural ventilation. Actually, the tested green roof demonstrates the worst performance in terms of reducing the thermal comfort risks in natural ventilation compared to other tested scenarios.

Table 6.2 Design Scenario Test Result of roof canopy with overhangs

Design Scenarios (Roof Canopy)	**Deterministic result with new design**	**Compare to baseline deterministic run result**	**Uncertainty analysis result with new design**	**Compare to baseline uncertainty analysis result**	**Total number of zones suffer from overheating risks with probability (TM52)**			
					>50%	**>30%**	**>15%**	**>5%**
10ft overhang on all sides	1.41%	-2.67%	2.95%	-3.68%	0	0	0	0
10ft overhang on west side	2.12%	-1.96%	4.26%	-2.37%	0	0	0	0
5ft overhang on all sides	2.52%	-1.56%	4.61%	-2.02%	0	0	0	1
5ft overhang on west side	2.79%	-1.29%	4.97%	-1.66%	0	0	1	3
Green Roof	3.57%	-0.51%	6.2%	-0.43%	1	2	4	6

Table 6.3 Design Scenario Test Result of only attaching west shading

Design Scenarios	**Deterministic result with new design**	**Compare to baseline deterministic run result**	**Uncertainty analysis result with new design**	**Compare to baseline uncertainty analysis result**	**Total number of zones suffer from overheating risks with probability (TM52)**			
					>50%	**>30%**	**>15%**	**>5%**
6ft west overhang	3.48%	-0.6%	5.48%	-1.15%	0	0	1	10

10ft west overhang	3.15%	-0.93%	5.13%	-1.5%	0	0	0	10
14ft west overhang	2.96%	-1.12%	4.95%	-1.68%	0	0	0	9
20ft West Shading	2.78%	-1.3%	4.54%	-2.09%	0	0	0	6

6.3.2 Construction Type

In addition to the roof canopy with shading, we have also tested the impact of using different construction types on the thermal comfort risk evaluation in a naturally ventilated building. In our baseline scenario, the medium weight construction was employed. Thus, we further used the heavy and light weight concrete for the roof, wall and floor such that the building is set to heavy and light construction. Table 6.4 below lists all the results of the tests. Using TM52 as the reference, the number of building zones with different probability of overheating in a heavy construction building was significantly larger than the corresponding cases in a light construction building. By using the heavy and medium weight construction, the number of building zones with more than 50% of overheating probability reduces from 16 to 4 and 0 out of 21 zones in total in the baseline building. As an extreme case of building thermal mass in the building design, if the curtain wall is used in our baseline building, only by attaching the roof canopy with 10ft overhang on all sides of the building could help the building to achieve s similar thermal performance compared to the baseline case. Hence, by providing buffer thus more stability of indoor thermal comfort environment, the impact of utilizing thermal mass is significant in the design of a naturally ventilated building as well.

Table 6.4 Design Scenario Test Result of different Construction type with wall

Design Scenarios	Deterministic result with new design	Compare to baseline deterministic run result	Uncertainty analysis result with new design	Compare to baseline uncertainty analysis result	Total number of zones suffer from overheating risks with probability (TM52)			
					>50%	>30%	>15%	>5%
Heavy Construction	2.79%	-1.29%	4.41%	-2.22%	0	1	1	4
Light Construction	5.8%	+1.72%	9.67%	+3.04%	16	17	18	18
Curtain Wall with Roof Canopy	4.7%	+0.62%	7.74%	+1.11%	4	8	8	10

6.3.3 Insulation Level

Thirdly, we have also compared the scenarios when different insulation levels are employed in the natural ventilation design. The baseline building is composed with R10 wall while R15 and R5 wall are tested as new design scenarios. In the tests, only the thickness of insulation was changed thus to minimize the impact of the changing thermal mass on the thermal comfort performance of the building. As shown in Table 6.5 below, it is obvious that the wall insulation would only have trivial impacts on the thermal comfort risk of the building. Only using R15 could reduce the number of zones with more than 50% probability from 4 to 0. However, these zones will still suffer from more than 30% probability of overheating in natural ventilation.

Table 6.5 Design Scenario Test Result of Different wall insulation level

Design Scenarios (Roof Canopy)	Deterministic result with new design	Compare to baseline deterministic run result	Uncertainty analysis result with new design	Compare to baseline uncertainty analysis result	Total number of zones suffer from overheating risks with probability (TM52)			
					>50%	>30%	>15%	>5%
R15 Wall	4.09%	+0.01%	6.85%	+0.22%	0	4	6	13

R5 Wall	4.05%	-0.03%	6.44%	-0.19%	4	4	11	12

6.3.4 Orientation

Lastly, the influence of building orientation on the thermal performance of a building in natural ventilation was also investigated. In the test cases, we have rotated the baseline building to +/- 45 degrees and also 90 degrees (the shorter side of the wall will face west in this case). From Table 6.6, we can see that the number of building zones with different overheating probability decreases in all tested cases. Hence, choosing the right building orientation (e.g. avoid the building zone facing directly to the west directly) is also important in maintaining the thermal comfort of occupants in the natural ventilation.

Table 6.6 Design Scenario Test Result with Influence of orientation

Design Scenarios	Deterministic result with new design	Compare to baseline deterministic run result	Uncertainty analysis result with new design	Compare to baseline uncertainty analysis result	Total number of zones suffer from overheating risks with probability (TM52)			
					>50%	>30%	>15%	>5%
Rotate 90	1.97%	-2.11%	3.69%	-2.94%	1	1	1	2
Rotate 45	3.28%	-0.8%	5.66%	-0.97%	1	5	5	6
Rotate -45	3.44%	-0.64%	5.44%	-1.19%	1	2	9	10

6.4 Conclusion on Deterministic Simulation VS. Uncertainty Analysis

Clearly shown in Section 6.1.3 above, there exists large discrepancy between the deterministic simulation result and uncertainty analysis result, no matter it is using ASHRAE 55 adaptive thermal comfort model to check mean fraction of unsatisfactory hours or TM52 to identify the overheating risks in different building zones. In the test, the deterministic simulation results showed that no building zone will suffer from the overheating risk while the uncertainty analysis concluded that four west zones of the building will have more than 50% probability of overheating. This indicated that using deterministic simulation to evaluate thermal comfort risks could potentially neglect considerable overheating risks during design, thus leading to unexpected thermal comfort performance when running the naturally ventilated building in practice with significant uncertainties presented.

Continuing with design scenario tests to compare the effectiveness of deterministic simulation and uncertainty analysis in evaluating the naturally ventilated building design, we can observe that both deterministic simulation and uncertainty analysis give out results with similar trends, no matter it is the comparison of relative effectiveness between different design measures (e.g. compare the effectiveness of attaching shading with increase insulation) or the comparison of relative effectiveness within one measure (e.g. compare the effectiveness of different construction types in reducing the thermal comfort risks). More specifically, as to the comparison within one design scenario test, the percentage of reduction/increase of thermally uncomfortable hours are always similar between the uncertainty analysis and the deterministic simulation regardless of what design measures we have tested (e.g. the percentage of thermally uncomfortable hour decrease approximately 30% when changing from medium weight construction to heavy construction while increasing approximately 45% from medium weight construction to light weight construction in both deterministic simulation and uncertainty). On the other hand, for comparing the effectiveness between different measures, the uncertainty analysis and the deterministic simulation also gives out the same rank, i.e. roof canopy with shading

> construction type > orientation > wall insulation based on the reduced number of zones in different levels of overheating risks. Thus, to help the decision making, the deterministic simulation provides reliable results when comparing the relative effectiveness of different building designs. However, without reliable baseline case in the evaluation of thermal comfort risks during natural ventilation, fully relying on deterministic simulation in a naturally ventilated building design is hardly sufficient to uncover all potential risks of overheating, which makes it infeasible to guarantee the building thermal comfort performance in the building operation.

Lastly, based on the results from both uncertainty analysis and deterministic simulation in this case study, the most effective measures to reduce thermal comfort risks of a naturally ventilated building is to attach a shading or overhang to the building. This is easily observable with the most significant drop in fraction of unsatisfactory hours and the total number of zones suffer from different levels of thermal comfort risks in natural ventilation. Secondly, increasing the thermal mass of the building is also effective in maintaining a stable indoor environment of a naturally ventilated building. By using heavy construction in establishing a naturally ventilated building, the total number of zones that suffer from different levels (5%, 15%, 30% and 50%) of thermal comfort risks reduces to 0,1,1 and 4 compared to the light construction, in which 16, 17, 18 and 18 zones would suffer from thermal comfort risks. Thirdly, in our analysis, choosing the right orientation of the building also helps to improve the thermal comfort robustness of a naturally ventilated building since building zones with most severe thermal comfort risks are typically located on the western or southern side of the building. These zones suffer from the largest sun exposure when the outdoor temperature is high in the afternoon. Finally, the analysis indicated that changing the building insulation level will have only trivial impact on the thermal comfort robustness of a naturally ventilated building.

In summary, the uncertainty analysis could help better uncover the thermal comfort risks that are neglected in the deterministic simulation. When designing a naturally ventilated building, the deterministic simulation is capable of providing insight into the relative effectiveness of different design measures. However, without a reliable baseline case, fully relying on deterministic simulation in the design practice is not sufficient to guarantee the thermal comfort robustness of the building. Using uncertainty analysis is still considered to be necessary if decision makers intend to strictly control the potential thermal comfort risks of the naturally ventilated building. Finally, based on our case study, attaching shading and overhang is the most effective measures to reduce thermal comfort risks, then come with the increase of building thermal mass and choose of appropriate building orientation. The adjustment of insulation level has trivial impact on the thermal comfort performance of a naturally ventilated building.

6.5 Sensitivity Analysis and Discussion

As the last step in this study, the sensitivity analysis was conducted to further recognize the most significant uncertainties associated with the overheating risk in the natural ventilation design. The Multivariate Adaptive Regression Splines (MARS) was employed as the sensitivity analysis method considering its flexibility in dealing with high-dimensional nonlinear data. The thermally unsatisfactory percentage of time in each run was selected as the response while the sampled uncertain parameters were used as the independent variables in the sensitivity analysis. Figure 6.4 below shows the result of sensitivity analysis. Overall, the R square achieved in the Multivariate Adaptive Regression Splines was 99%, which means that almost all variance of our response variable explained.

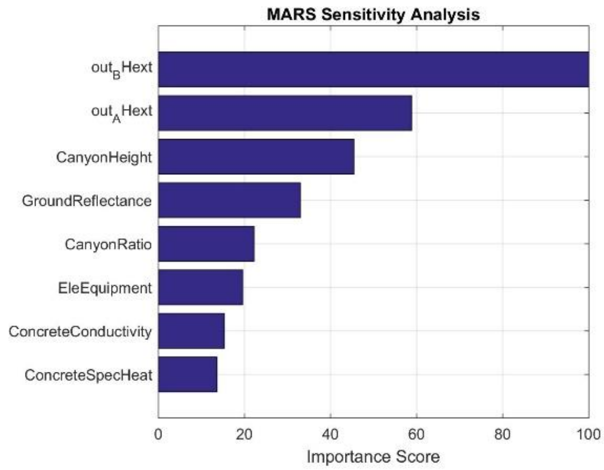


Figure 6.4 Sensitivity Analysis results

As shown in the figure above, in this study, the building exterior convection coefficients uncertainty (represented by outBHext and outAHext) was ranked as the most significant uncertainty associated with overheating risks in natural ventilation. The detailed analysis of the building convection later demonstrated that the convection actually constituted the largest part of energy loss of the tested building. Also, as shown in the Chapter 2 above, the exterior convection coefficients could suffer from large uncertainties (5 to 10 times difference), especially when the outdoor wind speed is large. Hence, if the exterior convection coefficients are overestimated in the simulation, the excessive decrease of convection heat loss typically can't be compensated by the increase of radiant heat loss (due to the higher exterior wall surface temperature) such that the heat will more easily accumulate within the building. Consequently, the uncertainty of the exterior convection is one of the most important source of uncertainties that needs more attention in designing a naturally ventilated building, especially when the local outdoor wind speed is large.

Besides the convection uncertainty, the microclimate uncertainty also plays an important role based on the sensitivity analysis result. As shown in Figure 6.4 above, three out of eight parameters, including Canyon Ratio, GroundReflectance and Canyon Height, all belong to this category of uncertainty. They are ranked as third, fourth and fifth respectively. However, since the Canyon Ratio and Canyon Height are related to both the urban heat island effect and local wind speed uncertainty, a further investigation is necessary to distinguish which uncertainty makes these two parameters rank high in the sensitivity analysis. Hence, to provide insight into how each microclimate uncertainty could impact on our result, we have applied each of these uncertainties separately to see how the percentage of thermally unsatisfactory hours changes. Figure 6.5 to 6.7 below show the results.

Firstly, applying the urban heat island shifted the mean unsatisfied percentage of time from 4.08% in the baseline deterministic simulation to 6.33% in the uncertainty analysis with standard variance of 0.6%. This significant shift of mean unsatisfied percentage with large standard deviation clearly illustrates its impact on the thermal comfort risk evaluation of natural ventilation. Some literatures (Hassid et al, 2000), (Chan, 2011) also confirmed the significance of considering the urban heat island effect in the estimate of the building energy consumption. However, in the current practice, most modelers only simply use the TMY as the simulation weather input without considering the potential influence of urban heat island effect. This should be improved in the future to help design a naturally ventilated building with more robust thermal performance considering its significance in the analysis. Secondly, the applied local wind speed uncertainty changed the mean percentage of unsatisfied hour to 4.87% with 0.4% standard variance. This test demonstrates that the weather file used in simulation overestimate the local wind speed in the urban/suburban areas, in which the wind could be severely blocked or weakened by surrounding objects such as buildings nearby. Thirdly, the applied ground reflectance uncertainty has caused the mean percentage of unsatisfied hour to move to 4.48% with 0.4% standard variance in the analysis. Although several studies (Thevenard & Haddad, 2006), (Purdy & Beausoleil, 2001) have already presented the importance of accurately estimating ground reflectance in terms of building energy consumption prediction, no study exists to demonstrate its impact on the thermal comfort evaluation in natural ventilation. The test here shows that the impact of the ground reflectance is also not trivial in the thermal comfort risk evaluation of natural ventilation.

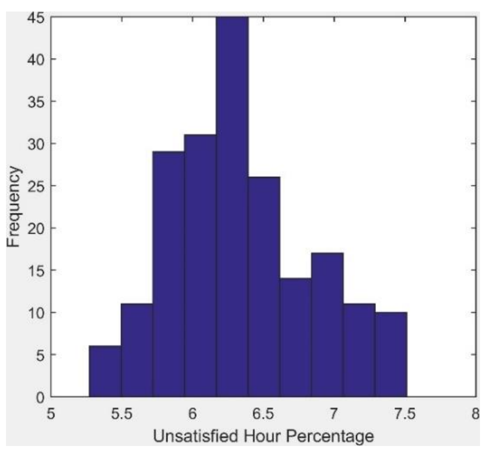


Figure 6.5 Uncertainty Analysis Results After Applying UHI effect only

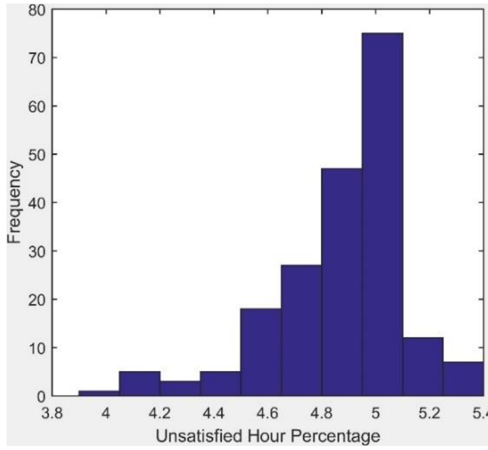


Figure 6.6 Uncertainty Analysis Results After Applying Local Wind Uncertainty only

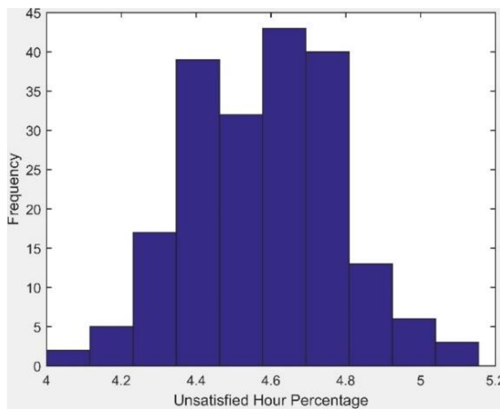


Figure 6.7 Uncertainty Analysis Results After Applying Ground Reflectance Uncertainty only

Lastly, in addition to the exterior convection uncertainty and microclimate uncertainty as mentioned above, the uncertainties related to the internal gain (electric equipment consumption) and the material uncertainties (concrete conductivity and specific heat) are also shown with certain impacts on the thermal comfort risk of natural ventilation based on the sensitivity analysis result. Designers should pay special attention to the zones that might have large amounts of electric devices or lightings running at the same time.

7 SUMMARY AND CONCLUSIONS

7.1 Summary

In spite of efforts in investigating the usage of natural cooling for commercial buildings in US, currently, all studies still utilized the deterministic simulation without accounting for the uncertainties in terms of meteorology, building microclimate, building own properties and operation in the investigation. Also, other significant factors such as the ventilation control intelligence and outdoor air pollutant were neglected in the studies. Finally, to further popularize the usage of hybrid/natural ventilation in the current practice, how to better utilize the deterministic simulation and uncertainty analysis to aid the design of a NV/HV building with more reliable thermal performance during natural ventilation is an important issue to address as well.

Consequently, to deal with these problems, this dissertation has thoroughly investigated the potential of natural ventilation accounting for all levels of uncertainties, building intelligence and the influence outdoor air quality. Meanwhile, a detailed comparison with scenario tests between the uncertainty analysis and the deterministic was conducted to provide insights into the better utilization of uncertainty analysis to reduce the thermal comfort risks during natural ventilation.

Until now, all questions mentioned in the Chapter 1 of the dissertation have been resolved. The conclusions are mainly composed of three parts. (1) Firstly, The Climate Zone 3B – Coast and Climate Zone 3C have the most energy saving potential of using natural ventilation in US. The expected energy saving is about 40% ~ 50% in the Climate Zone 3B – Coast (Los Angeles) and 30% ~ 40% in Climate Zone 3C (San Francisco). Except for these two climate zones, the other climate zones all share the similar energy saving potential for using the natural ventilation, which is about 15% ~ 25% under our experiment settings. (2) Secondly, as to the influence of uncertainties, building intelligence and outdoor air quality on the natural ventilation usage, we found that the standard variance of energy saving across years is usually 5% ~ 10% in different climates accounting for the uncertainties in hybrid ventilation usage. By applying different building intelligence levels on the hybrid ventilation control, the difference of energy saving could reach up to 13% on average, which proves the influence of building intelligence in terms of natural ventilation usage. Comparing the traditional rule-based control with the developed model predictive control, we also found the tradeoff between the occupant thermal comfort and the energy saving, i.e. the rule-based control could be better at achieving the energy saving while the developed model predictive control is better at maintaining the thermal comfort for occupants. With some potential improvements for the model predictive control strategy, it is promising to achieve better hybrid ventilation control performance in the future with improved energy saving and satisfactory occupant comfort. Meanwhile, the influence of outdoor air pollutants is significant as well. In the investigation, the most polluted cities are Los Angeles (60% ~ 80% reduction in natural ventilation), Chicago (30% ~ 40% reduction), then come with Atlanta and San Francisco (20% ~ 30% reduction for both) using NAAQS as the standard. In the other cities, the natural ventilation cut is expected to range from 10% to 20% in different location settings. The urban area is typically more polluted than the rural areas of a city. Also, PM2.5 is always the most important outdoor air pollutant to consider when using natural ventilation. Only when we move to suburban and rural areas, the ozone and PM10 becomes increasingly important to consider occasionally. (3) Thirdly, based on the case study in Chapter 6, deterministic simulation could significantly underestimate the thermal comfort risks during natural ventilation compared to uncertainty analysis. Through the detailed comparison between deterministic simulation and uncertainty analysis in the design scenario tests, the deterministic simulation has shown its ability to provide good insight in conducting comparative design studies. However, due to the lack of a valid baseline case when using deterministic simulation, the uncertainty analysis is still considered to be necessary at least when establishing the baseline case in natural ventilation design. Finally, the roof canopy and shading are tested as the most effective design measure to reduce the thermal comfort risk during natural ventilation in the case study. All these conclude our research.

We argue that by drawing all these conclusions and addressing these questions, we add significant knowledge to help better utilize the hybrid/natural ventilation in the current practice.

7.2 Contribution

This dissertation work was expected to provide a thorough investigation of hybrid ventilation potential across US considering different influential factors and their respective influence for the hybrid ventilation operation. By considering various uncertainties in the simulation process, we could better mimic the real building operation scenarios thus to have a better estimate of energy saving potential as a range with confidence intervals in different climates. Also, the developed black-box hybrid ventilation control purely based on the machine learning algorithm with fast computation and robust performance provided a new and interesting perspective on developing more advanced controls for the hybrid ventilation operation. The developed algorithm could be further integrated with other sensing techniques to become smarter. The influence of outdoor air quality on the natural cooling usage across different location settings (urban, suburban, rural) of major US cities was explicitly shown as well. This arised a more serious consideration of outdoor air quality in the building design (especially control design) for appropriately running a healthy hybrid ventilation building. Finally, the comparison study provided a good example and insights about how to better utilize uncertainty analysis and deterministic simulation to improve the robustness of building thermal performance during natural ventilation.

7.3 Limitation and Future Research

As to the limitation of this research, one of the biggest weakness in the current research is that the occupant behavior uncertainty is not sufficiently dealt with in current works. Considering that most of buildings are typically controlled by occupants during natural ventilation, the occupant behavior is expected to have large impacts on the performance of hybrid ventilation building operation as well. Certain behaviors of occupants, e.g. forgetting to close windows when the outdoor weather is not appropriate, in operating building windows might lead to severely adverse effect of energy saving, especially when the hybrid ventilation building utilizes the concurrent strategy in building operation. Thus, it is an important aspect to consider in this work. However, due to the insufficiency of data from occupants of hybrid ventilation building, the uncertainties associated with them are hard to quantify.

In addition to the uncertainty of occupant behavior, we also need to further verify the generality of these potential investigation results by running full sets of potential investigation experiments again using different building configurations tested in the generality study. Also, it is best that these results could be validated by real performance data from hybrid ventilation buildings in different climates. The applied uncertainties need to be validated for its effectiveness in the thermal comfort evaluation as well, although our former studies have proven its correctness in term of closing the prediction gap in the energy consumption. If we can have a naturally ventilated building with monitored indoor temperature, we can compare the simulated indoor temperature from uncertainty analysis with the monitored temperature of that building to ensure the validity of applied uncertainties in the thermal comfort evaluation during natural ventilation.

Lastly, the energy saving from utilization of night ventilation is not taken into accounted in this work as well. The main reason is that currently, this dissertation still focuses on the energy saving potential of using hybrid ventilation in small to medium office building. For this type of building, using night ventilation might cause security concerns since these buildings are low-rise. But in certain climates, night ventilation is proven to be capable of providing the potential of energy saving by pre-cooling buildings. How to better utilize this potential in small to medium office buildings is worthy of attentions in the future.

To continue from current works, firstly, a thorough investigation of occupant behaviors in hybrid ventilation buildings is recommended for future works. With the flexibility to control their own thermal environments in hybrid ventilation buildings, building occupants play a central role in the successful operation of this type of building. Hence, how to motivate occupants to better control the windows and reduce the uncertainties and risks associated with their behaviors is a key question to answer in the research. The system and control in hybrid ventilation buildings could also be designed to balance the energy saving with the flexibility of occupant control to ensure the performance of building. Besides, all potential investigation in current works are based on the representative weather of an area in the past. The weather projection of future years could be incorporated into this research to better estimate the benefits of using hybrid ventilation in different areas in the future.

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