Natural Ventilation Control Strategies and Their Effectiveness in Different Climates

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Accessibility
NATURAL VENTILATION CONTROL STRATEGIES
AND THEIR EFFECTIVENESS IN DIFFERENT CLIMATES

A dissertation presented

by

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to
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in partial fulfillment of the requirements

for the degree of

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Natural Ventilation Control Strategies and Their Effectiveness in Different Climates

Abstract

Natural ventilation (NV) is a sustainable building strategy that improves building energy efficiency, indoor thermal environment, and air quality. The successful implementation of natural ventilation relies on various factors, such as local climate, ambient air quality, floorplan, adjacent urban environment, window configuration, and urban noise. Among these factors, climate is the most influential one that determines the potential for natural ventilation, whereas the control of the heating, ventilation, and air conditioning (HVAC) system along with the window system becomes the most critical element for the successful natural ventilation in a given case, when only a few features are feasible to change.

This dissertation investigates global natural ventilation potential through NV hours and cooling energy saving percentage and estimates China’s natural ventilation potential by taking into account the additional factor of ambient air pollution. The aggregated energy savings and carbon reductions were estimated at the city level across 35 major Chinese cities. This dissertation then focuses on developing optimal NV control strategies to coordinate window operations with HVAC systems, aiming for an optimized synergy to achieve minimal energy consumption and maximum thermal comfort. A reinforcement learning control strategy is proposed, which demonstrates better performance compared
to the rule-based heuristic control in accommodating stochastic internal heat gain, maintaining steady indoor thermal comfort, and reducing HVAC system operation. Finally, the effectiveness of different levels of automation in NV control is tested in a variety of distinct climates. Specifically, spontaneous occupant manual control, informed occupant manual control, and fully automatic control (including rule-based heuristic control and model predictive control [MPC]) are evaluated. The results demonstrated the superiority of fully automatic control with MPC, which significantly enhances building energy efficiency and thermal performance. The findings from this dissertation provide information for architects, building owners, and policymakers to realize the potential for natural ventilation in buildings.
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Chapter 1: Introduction

The United Nations has estimated that by 2050 more than two-thirds of the world's population will be residing in cities (UN 2014). Such rapid urbanization has led to a significant increase in the energy consumption of buildings mostly due to population growth, climate change, and increased demand for thermal comfort (Ghiaus et al. 2006; UNEP 2009). Studies have shown that the building sector accounts for 23–47% of the total primary energy consumption in developed and developing countries worldwide (Pérez-Lombard, Ortiz, and Pout 2008; Zhang et al. 2015). The heating, ventilation, and air conditioning system (HVAC) that provides heating, cooling, and ventilation is the largest single end user of energy in both commercial and residential buildings, being responsible for 33% (EIA 2012) and 48% (EIA 2009) of electricity consumption, respectively. In this century, the worldwide demand for cooling is projected to strongly grow due to global warming and urbanization in developing countries (Davis and Gertler 2015). Given this enormous amount of energy consumption, many advanced technologies have been developed to achieve high energy efficiency in buildings. Among them, natural ventilation (NV), which supplies and removes air to and from an indoor space using natural forces of wind and buoyancy, shows great potential in terms of reducing the

The design strategy for buildings with natural ventilation systems heavily relies on the characteristics of the local climate, which varies considerably from region to region across the globe. Researchers in the past have investigated various aspects with respect to naturally ventilated buildings across different climate zones in the world (Table 1-1 summarizes existing studies on natural ventilation by location). For example, the potential for natural ventilation in Chinese residential buildings was studied through a simple prediction model using pressure difference Pascal hours (PDPH) as a metric (Yang et al. 2005). The potential for natural ventilation in Chinese office buildings in five climate zones was also investigated using the Thermal Resistance Ventilation model to illustrate the dependence of natural ventilation cooling on climate, building thermal characteristics and internal heat gains (Yao et al. 2009). The feasibility of adopting natural ventilation in a tropical climate has also been explored over the years. A study conducted in Bangkok, Thailand (Tantasavasdi, Srebric, and Chen 2001) suggested that natural ventilation can provide a thermally comfortable indoor environment for 20% of the year. This study derived the threshold of indoor air velocity in naturally ventilated buildings from the analysis of climate and thermal comfort. Furthermore, studies investigating the physics behind the design of wind towers, and how they can be utilized
to improve natural ventilation in the Middle East and North Africa, both of which have an arid and hot desert climate, were also conducted by several groups of researchers (Bahadori 1994; Bouchahm, Bourbia, and Belhamri 2011; Calautit, Hughes, and Ghani 2013). Europe boasts of widely adopting natural ventilation in various types of buildings, thanks to its mild climate. A study of the passive cooling of buildings by analyzing climatic data at 259 stations in Europe (Artmann, Manz, and Heiselberg 2007) demonstrated a high potential for night time natural ventilation cooling over Northern Europe, in Central and Eastern Europe, and certain areas in Southern Europe. In Denmark, 90% of the hours for which mechanical ventilation is used can be potentially reduced by using natural ventilation during summer, according to the study (Oropeza-Perez and Østergaard 2014b). A coupled CFD (Computational Fluid Dynamics) modeling approach was used to study urban wind flow and indoor natural ventilation, and was applied to study a large semi-enclosed stadium in the Netherlands (Van Hooff and Blocken 2010). This study demonstrated the importance of meteorological conditions and the surrounding urban environment for analyzing natural ventilation at the building scale. In America, the maps of target air change rate of 60 cities in the United States were provided (Hiyama and Glicksman 2015) for designing buildings with natural ventilation features. It has been estimated that 54% of air-conditioning demands in Mexican dwellings can be reduced through natural ventilation (Oropeza-Perez and Østergaard 2014a). Furthermore, guidelines for creating naturally ventilated buildings in Brazil have been proposed (Cândido et al. 2011) by considering occupants' adaptive potential as well
as thermal and air movement acceptability. These guidelines were based on results from field experiments in different climatic zones and existing studies. In Oceania, the effect of mixed-mode ventilation on occupant comfort in an academic office building in Sydney, Australia was studied using 1,359 subjective comfort questionnaires (Deuble and de Dear 2012). The findings of this study suggested that the building's mode of operation, such as air-conditioned and naturally-ventilated modes, has a more significant impact on thermal perceptions than the real indoor climate conditions.

Table 1-1: Summary of past studies on natural ventilation sorted by method and location

<table>
<thead>
<tr>
<th>Author and Year</th>
<th>Location</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yang et al. (2005)</td>
<td>China</td>
<td>Simulation</td>
</tr>
<tr>
<td>Luo et al. (2007)</td>
<td>China</td>
<td>Simulation</td>
</tr>
<tr>
<td>Yao et al. (2009)</td>
<td>China</td>
<td>Simulation</td>
</tr>
<tr>
<td>Yin et al. (2010)</td>
<td>China</td>
<td>Simulation</td>
</tr>
<tr>
<td>Indraganti (2010)</td>
<td>India</td>
<td>Survey &amp; experiment</td>
</tr>
<tr>
<td>Tantasavasdi et al. (2001)</td>
<td>Thailand</td>
<td>Simulation</td>
</tr>
<tr>
<td>Liping et al. (2007)</td>
<td>Singapore</td>
<td>Data analysis</td>
</tr>
<tr>
<td>Kubota (2009)</td>
<td>Malaysia</td>
<td>Survey &amp; Experiment</td>
</tr>
<tr>
<td>Bahadori et al. (1994)</td>
<td>Middle East</td>
<td>Review</td>
</tr>
<tr>
<td>Ayata et al. (2006)</td>
<td>Middle East</td>
<td>Simulation</td>
</tr>
</tbody>
</table>
Table 1-1 (Continued)

<table>
<thead>
<tr>
<th>Author and Year</th>
<th>Location</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calautit et al. (2013)</td>
<td>Middle East</td>
<td>Simulation</td>
</tr>
<tr>
<td>Mathews (1986)</td>
<td>South Africa</td>
<td>Simulation &amp; Experiment</td>
</tr>
<tr>
<td>Bouchahm (2011)</td>
<td>Algeria</td>
<td>Simulation &amp; Experiment</td>
</tr>
<tr>
<td>Artmann et al. (2007)</td>
<td>Europe</td>
<td>Data analysis</td>
</tr>
<tr>
<td>Kolokotroni and Aronis (1999)</td>
<td>U.K.</td>
<td>Simulation</td>
</tr>
<tr>
<td>Pasquay (2004)</td>
<td>Germany</td>
<td>Experiment</td>
</tr>
<tr>
<td>van Hooff and Blocken (2010)</td>
<td>Netherlands</td>
<td>Simulation &amp; Experiment</td>
</tr>
<tr>
<td>Oropeza-Pereza and Østergaardb (2014)</td>
<td>Denmark</td>
<td>Simulation</td>
</tr>
<tr>
<td>Germano (2007)</td>
<td>Switzerland</td>
<td>Data analysis</td>
</tr>
<tr>
<td>Ballestinia et al. (2005)</td>
<td>Italy</td>
<td>Simulation</td>
</tr>
<tr>
<td>Santamouris et al. (2008)</td>
<td>Greece</td>
<td>Experiment &amp; Simulation</td>
</tr>
<tr>
<td>Dutton et al. (2013)</td>
<td>The U.S.</td>
<td>Experiment</td>
</tr>
<tr>
<td>Oropeza-Pereza and Østergaardb (2014)</td>
<td>Mexico</td>
<td>Simulation</td>
</tr>
<tr>
<td>Cândido et al. (2011)</td>
<td>Brazil</td>
<td>Experiment &amp; Survey</td>
</tr>
<tr>
<td>Deuble and de Dear (2012)</td>
<td>Australia</td>
<td>Experiment &amp; Survey</td>
</tr>
</tbody>
</table>
The objective of this research is to develop optimal control strategies for natural ventilation and its coordination with HVAC systems in the buildings. The main challenges of studying natural ventilation lie on the nature that it is a nonlinear and chaotic process; hence no analytical solutions are readily available. To avoid classical control failures such as oscillation or overshooting and to improve the performance on energy efficiency, two paths arise as possible solutions: model-based approach and model-free approach, as illustrated in Figure 1.1. Both of which can achieve optimality if properly designed and implemented. The details are presented in this research, along with experiments to demonstrate their effectiveness in different climates.

Figure 1.1 Framework of optimal NV control strategies

This dissertation is organized as follows: Chapter 2 reveals the potential for natural ventilation across the world, evaluated by metrics including natural ventilation hour and energy saving percentage. Chapter 3 introduces models for simulating buildings with
natural ventilation, including a simplified empirical physics-based model, and a data-driven neutral network model, along with its validation on real building data. Chapter 4 provides an overview of various control strategies and introduces a reinforcement learning control for optimal control of natural ventilation and HVAC system. The performance is evaluated against the baseline control strategy in two studied cities. Chapter 5 discusses different levels of automation for implementing natural ventilation control strategies, including the characteristics of operations and performance on thermal comfort and energy efficiency. The effectiveness is evaluated in five Chinese cities with distinct climates. Chapter 6 summarizes the research and presents discussion and future studies.
Chapter 2: Potential for Natural Ventilation

Climate significantly impacts the energy usage of most commercial and residential buildings. In this context, it should be noted that the local climate is influenced by several factors, such as latitude, elevation, ocean currents, topography, vegetation, prevailing winds, etc. The primary evaluation of global natural ventilation potential is introduced in this chapter via the metrics of both NV Hour and expected energy savings.

2.1 Global Climatic Classification and Data Sources

Climate varies greatly over the Earth's surface. It is assessed by patterns of variations in temperature, humidity, atmospheric pressure, wind, precipitation, and other meteorological parameters at any given location over long periods. The typical meteorological year data of 1854 locations worldwide were used in this study. These climate data come from several sources. The data for Typical Meteorological Year 3 (TMY3) is available for locations in the U.S. and was derived from the record of the 1991–2005 period. TMY3 represents typical rather than extreme conditions, in the format of hourly values of meteorological elements for a one-year period. The Solar and Wind Energy Resource Assessment (SWERA), funded by the United Nations Environment Program (UNEP), includes typical year hourly data for 156 locations in Belize, Brazil,
Cuba, El Salvador, Ethiopia, Ghana, Guatemala, Honduras, Kenya, Maldives, Nicaragua, and Sri Lanka. International Weather for Energy Calculations (IWEC) comprises typical weather files suitable for use with building energy simulation programs for 227 locations outside the U.S. and Canada. The records for 18 years (1982–1999 for most stations) of hourly weather data were provided. Chinese Standard Weather Data (CSWD) includes 269 typical hourly weather files developed by Tsinghua University and China Meteorological Bureau. However, in many parts of the world especially Africa and South America, meteorological data are unavailable. Combining surface and satellite-derived meteorological measurements could be a promising means to overcome this issue, but this should be analyzed by future studies.

Current energy codes and standards contain various requirements based on global climate classification. The Köppen-Geiger classification is one of the most widely used climate classification systems; it is based on temperature and precipitation indices (Kottek et al. 2006), which divides the world’s climate into five major groups, namely, tropical, arid, temperate, continental, and polar. Each major group is subcategorized into different types and subtypes. The climate designations from the Köppen-Geiger system are descriptive and thus have been used in this study to describe climatic variations around the world. For the building energy simulation (BES), we employed a statistical climate classification scheme introduced by Briggs et al. in ASHRAE Standard 169–2006 (2003a, b), which is based on the grouping of similarities of different locations. Table 2-1 classifies the
various climate zones according to ASHRAE Standard 90.1–2007 based on cooling degree days (CDD) and heating degree days (HDD).

Table 2-1: Climate zone classification

<table>
<thead>
<tr>
<th>Zone Number</th>
<th>Zone Name</th>
<th>Thermal Criteria (SI Units)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1A and 1B</td>
<td>Very Hot – Humid (1A) Dry (1B)</td>
<td>5000 &lt; CDD10 °C</td>
</tr>
<tr>
<td>2A and 2B</td>
<td>Hot-Humid (2A) Dry (2B)</td>
<td>3500 &lt; CDD10 °C ≤ 5000</td>
</tr>
<tr>
<td>3A and 3B</td>
<td>Warm – Humid (3A) Dry (3B)</td>
<td>2500 &lt; CDD10 °C ≤ 3500</td>
</tr>
<tr>
<td>3C</td>
<td>Warm – Marine (3C)</td>
<td>CDD10 °C ≤ 2500 AND HDD 18 °C ≤ 2000</td>
</tr>
<tr>
<td>4A and 4B</td>
<td>Mixed-Humid (4A) Dry (4B)</td>
<td>CDD10 °C ≤ 2500 AND HDD 18 °C ≤ 3000</td>
</tr>
<tr>
<td>4C</td>
<td>Mixed – Marine (4C)</td>
<td>2000 &lt; HDD18 °C ≤ 3000</td>
</tr>
<tr>
<td>5A, 5B, and 5C</td>
<td>Cool-Humid (5A) Dry (5B)</td>
<td>3000 &lt; HDD18 °C ≤ 4000</td>
</tr>
<tr>
<td></td>
<td>Marine (5C)</td>
<td></td>
</tr>
<tr>
<td>6A and 6B</td>
<td>Cold – Humid (6A) Dry (6B)</td>
<td>4000 &lt; HDD18 °C ≤ 5000</td>
</tr>
<tr>
<td>7</td>
<td>Very Cold</td>
<td>5000 &lt; HDD18 °C ≤ 7000</td>
</tr>
<tr>
<td>8</td>
<td>Subarctic</td>
<td>7000 &lt; HDD18 °C</td>
</tr>
</tbody>
</table>
2.2 NV Hour

The natural ventilation hour (NV Hour) is employed as an indicator to measure the maximum natural ventilation potential for each location. It is defined as the number of hours in a typical year (out of 8760 h) when outdoor weather conditions (e.g., wind speed, temperature, humidity) is suitable for utilizing natural ventilation. As NV hour is derived from outdoor meteorological data alone, it measures the maximum number of hours when outdoor weather is favorable for natural ventilation. Mechanical ventilation can take place during NV hours if natural ventilation alone cannot meet satisfactory thermal comfort due to high building internal load. Instead of using a fixed upper-temperature threshold throughout the year, adaptive comfort models can be applied. The adaptive thermal comfort models are based on the idea that outdoor climate affects indoor comfort because humans can adapt to various temperatures during different times of the year.

Various ways to define NV hour can be found in the literature based on the data availability and purpose of the research (Artmann, Manz, and Heiselberg 2007; Tong, Chen, and Malkawi 2017; Yang et al. 2005). The NV hour employed in this study is described here. The upper threshold of temperature $T_{up}$ varies by month, and is calculated using Equation (1) where $T_{out}$ is the monthly average outdoor temperature determined from TMY weather data, and $\Delta T$ is the comfort zone temperature band. For 80% acceptability, $\Delta T_{80\%}$ is equal to 7 °C. The temperature thresholds are chosen when the
outdoor dry-bulb temperature is below the upper threshold, $T_{up}$ and greater than $T_{low} = 12.8 \, ^\circ C$ (the lowest supply air temperature specified in ASHRAE 55 and ASHRAE Handbook–Fundamentals to avoid unpleasant draft to occupants). The upper threshold for dew point temperature is 17 °C for the sake of humidity control by combining the ASHRAE winter and summer comfort zones.

$$T_{up} = 0.31T_{out} + 17.8 + \frac{1}{2}\Delta T_{80\%}$$

(1)

The maximum allowable indoor air velocity, $u_{in,max}$, is chosen at 0.8 m/s, according to ASHRAE Standard 55. The corresponding outdoor wind velocity, $u_{out}$, is calculated based on an empirical relationship Equation (2) (Phaff et al. 1980), which considers the combined effect of wind, temperature, and turbulence on natural ventilation.

$$u_{in,max} = \sqrt{C_1 u_{out,up}^2 + C_2 h \Delta T_{max} + C_3}$$

(2)

In the above equation, $h$ presents the vertical height of the opening; $\Delta T_{max}$ is the hourly maximum temperature difference between the outdoor temperature and indoor temperature during NV hours. Here, we approximated $\Delta T_{max}$ by taking the difference between the upper temperature threshold $T_{up}$, which was determined from the adaptive comfort model, and the lowest supply air temperature $T_{low}$; $C_1$ is the wind speed coefficient; $C_2$ is the buoyancy coefficient, and $C_3$ is the turbulence coefficient. Their
values are determined from the study by Phaff et al. (1980) in which $C_1 = 0.001$, $C_2 = 0.0035 \ [m \cdot s^{-2} \cdot K^{-1}]$, and $C_3 = 0.01 \ [m^2 \cdot s^{-2}]$. The outdoor wind velocity threshold $u_{out, up}$ is then calculated by solving Equation (2). The vertical variation of wind speed as a function of height is not considered here due to the lack of certain meteorological data (e.g., surface roughness length, atmospheric stability, and upper air weather data) in many cities across the world. Although NV hour is independent of building type and does not consider building-scale details, it provides valuable information that can conveniently assist architects and energy policy makers in evaluating the feasibility of using natural ventilation on a large scale without conducting building energy simulation for each building during the early design stage. In this study, NV hour across the world is evaluated in R environment (R Core Team 2013), and results are visualized through Tableau (TABLEAU Desktop, 2003-2019).

2.3 Global Potentials for Natural Ventilation

Many regions around the world are found to have great potential for utilizing natural ventilation, as shown in Figure 2.1. In particular, the subtropical highland climate, with spring-like weather year-round with little variation in temperature and almost no snowfall, shows a significantly large number of NV hours. This climate type can be found in Mexico City, Mexico (7161 h), Nairobi, Kenya (8435 h), Bahir Dar, Ethiopia (8136 h), and Kunming, China (5566 h). The other climate type that is favorable for utilizing natural ventilation is the Mediterranean climate. This climate type is not only found around the Mediterranean Sea, but also in California, Western Australia, Portugal,
and Central Chile. Representative cities include Los Angeles, California (7197 h), Perth, Australia (6094 h), Faro, Portugal (5673 h), and Antofagasta, Chile (8204 h). Moreover, cities with desert climate display greater-than-expected natural ventilation potentials, ranging from 3000 to 4000 NV hours. Although it is hot during summer days, the temperature drops considerably at night due to radiation loss under clear skies. As a result, night-purge ventilation can be largely employed in these regions including some parts of the Middle East and Central Australia. Another explanation for the potential of such places is the use of the adaptive thermal comfort model that is based on the theory that humans can adapt to different temperatures during different times of the year. Raising the upper-temperature threshold by a few degrees could result in significant increases in the number of NV hours. However, this increase varies from region to region.

The additional NV hours gained by using the adaptive thermal comfort model are shown in Figure 2.2. Cities in the polar climate zone show almost no increase, whereas cities associated with desert and semi-arid climates (e.g., Central Australia, Central East Africa, Middle East) display significant increases in NV hours, going over 1000. The histogram of global NV hour distribution over 1854 studied locations has been displayed in Figure 2.3. The distribution is left-skewed with a peak at around 2500 NV hours. The right tail goes all the way up to 8565 h while the left tail goes down to zero. Among the studied locations, the median number of NV hours is 2598 h with a standard deviation of 1296 h.
There are 108 locations (6%) with NV hours greater than 5000, and 44 locations (2.5%) with less than 100 NV hours, such as Kuala Lumpur, Malaysia, and Salvador, Brazil.
Figure 2.1: Geographic map of NY hours in 1854 locations.
Figure 2.2: Geographic map of additional NY hours gained by using adaptive thermal comfort mode.
Boxplots of NV hours in each continent are presented in Figure 2.3. Africa has not been plotted due to the lack of sufficient climate data in many African countries. Cities in Oceania demonstrate the largest natural ventilation potentials with median NV hours of 4630. Due to their diverse climate, cities in South America display the widest range of NV hours from nearly zero in the Amazon Rainforest to over 8000 NV hours in Central Chile. The distribution of NV hours across Asia and North America shares many similarities. For example, they both have median NV hours of approximately 2500 as a result of similar latitude. In general, cities in Europe have slightly greater NV hours (median is 3002) than Asia and North America, as Europe mostly lies in the temperate climate zone.
2.3.1 Africa

Africa mostly lies in the intertropical climate zone. A variety of warm and hot climates prevails over the whole continent except in the northernmost and southernmost fringes, and in places at very high elevations. Many parts of Africa display a considerable number of NV hours, especially those with a Mediterranean climate (dry summers and mild winters). For example, Bahir Dar in Ethiopia is estimated to have 8136 NV hours, Nairobi, Kenya is estimated to have 8435 NV hours, and Cape Town in South Africa (southernmost fringe) is estimated to have 6477 NV hours.

2.3.1.1 Egypt

In general, Egypt has a desert climate. Although the climate is moderate along the coast, temperatures can exceed 40 °C during summer in the central and southern part of the country. Cairo has 4886 NV hours, and Alexandria has 4739 NV hours.

2.3.1.2 Kenya

The climate in Kenya varies from a tropical climate along the coast to a temperate inland climate on the plateau. The variation in elevation of cities is a key factor in determining the potential for natural ventilation. For example, cities with higher altitudes have a much cooler temperature than those along the coast. As a result, there are cites with an insignificant number of NV hours, such as Mombasa (117 h), as well as places that are able to greatly utilize natural ventilation year-round, such as Nairobi (8435 h) and Nakuru (7606 h).
2.3.1.3 Ethiopia

Ethiopia lies in the tropical zone. Ethiopian Highlands cover most of the country, resulting in a cooler climate than other regions on the equator. Most major cities are located in elevated regions over 2000 m with a mild climate throughout the year. For example, Addis Ababa, the capital city, is estimated to have 7204 NV hours, and Bahir Dar in the northwest displays more favorable weather for natural ventilation (8136 h).

2.3.2 Asia

Asia, the world's largest and most populous continent, has a mix of different climates. The northeastern parts such as Siberia have short summers and long and freezing winters, while the climate in Southeast Asia is mainly tropical with hot and humid weather throughout the year. With respect to humidity, it is mostly dry across the inland and humid across the southeast. The number of NV hours varies from region to region in Asia. For example, countries in Southeast Asia such as Indonesia and Malaysia show nearly no potential for natural ventilation. In contrast, places in Southwest China display a significant number of NV hours.

2.3.2.1 China

China has a great diversity of climates due to its extensive land coverage and varied terrain conditions. The northeastern region has freezing cold winters and hot dry summers. Representative cities in this region include Shenyang (2182 h), Changchun (2352 h) and Harbin (2356 h). North China has a continental climate with large seasonal
temperature differences, in which summers are warm and hot, and the winters are cold. Such cities include Hohhot (2943 h), Shijiazhuang (2651 h), and Taiyuan (2949 h). Southeast China generally features a warm humid temperate climate with distinct seasons. Representative cities in this region include Shanghai (2302 h), Hangzhou (2193 NV hours), Nanjing (2246 h), Fuzhou (2924 h), and Guangzhou (2434 h). The Qinghai-Tibet plateau has cold winters and cool dry summers (e.g., Lhasa with 2689 h). The southwestern region has a mild climate and little variation in temperature throughout the year.

2.3.2.2 India

India comprises a wide variety of climates, ranging from a desert climate in the west, to a humid tropical climate in the south, to alpine tundra in the north. For most of India, summer is very hot, except in the alpine zone. The humidity level in the northeast is generally high except during the winter season. In terms of natural ventilation potential, New Delhi, the capital city of India, has a subtropical climate. The number of NV hours there is considerably high (3331 h) due to its mild and dry winters. Mumbai lies on the west coast of the country and demonstrates only 1373 NV hours due to its high temperature and humidity for most of the year.

2.3.3 Europe

Most of Europe lies in the temperate climate zone. Cold weather can be experienced in Russia and Scandinavia, with daily highs around 0 °C in the winter, whereas mild winters
can be experienced in Southern Spain and Southern Italy with an average temperature of approximately 15 °C during the day. Hot summers often occur in Southern Spain, while warm summers can be found north of the Mediterranean Sea. As a result, the number of NV hours is approximately 2000 in cities located in Northern Europe [e.g., Oslo, Norway (2360 h), Stockholm, Sweden (2229 h), Helsinki, Finland (1930 h), Copenhagen, Denmark (2459 h), St. Petersburg, Russia (2164 h), Moscow, Russia (2378 h)]. In contrast, significantly more NV hours are available in warm climate zones in Southern Europe [e.g., Faro, Portugal (5673 h), Valencia, Spain (4534 h), Barcelona, Spain (3803 h), Palermo, Italy (4731 h), Athens, Greece (4942 h), Izmir, Turkey (4646 h)]. For the rest of Europe, the average number of NV hours is approximately 3000 [e.g., Geneva, Switzerland (3065 h), Brussels, Belgium (2978 h), Amsterdam, Netherland (2845 h), Vienna, Austria (3294 h), Prague, Czech Republic (2733 h)].

2.3.3.1 United Kingdom

The climate in the United Kingdom is categorized as temperate oceanic with warm summers and cool winters. The variation in temperature throughout the year in this part of the world is moderate, with average annual temperature ranging from 8.5 °C to 11 °C. The average number of NV hours is approximately 2000 with slightly higher NV hours in the south (e.g., London, 2885 h) and slightly lower NV hour in the north (e.g., Aberdeen, 1756 h).
2.3.3.2 France

In general, France shares the same climate classification as the United Kingdom. In particular, the western part of the country has a temperate oceanic climate with moderate annual temperature variations (Brest, 3111 h). On the other hand, the central and eastern parts have a continental climate with cold winters and hot summers (Paris, 3451 h), whereas the southeastern part has a Mediterranean climate with warm dry summers and mild wet winters (Nice, 3909 h).

2.3.3.3 Germany

Germany has a temperate climate for the most part with cold winters and moderately warm summers. In the northwest, the climate is oceanic. The winters are mild, and summers are warm. In the east of Germany, the climate is more continental, where winters can be freezing and summers very warm. Specifically, Berlin located in the east is one of the most favorable cities in the country in terms of natural ventilation with 3130 NV hours, followed by Frankfurt (3126 h), Stuttgart (2822 h), Hamburg (2645 h), and Munich (2533 h).

2.3.4 North America

2.3.4.1 United States

The climate of the United States varies from region to region due to its massive expanse of land and complicated terrain. As shown in Figure 2.1, the number of available weather stations in the U.S. is the largest around the world, followed by China and Australia. The
California coast has a Mediterranean climate, with daily highs ranging from 21 to 27 °C in the dry summer and 10 to 16 °C in the wet winter. Cities in this region generally have high NV hours, such as Los Angeles (7197 h), San Diego (6864 h), and San Francisco (5337 h). Cities in the southwest, such as Phoenix and Las Vegas, have a desert climate with average highs over 38 °C during summers and average highs from 10 to 16 °C during winters. Northern Arizona, New Mexico, Central and Northern Nevada, and most of Utah have a semi-arid climate with cold winters. Dry air in these regions results in large temperature differences between day and night. Despite high temperature during the daytime, the temperature and humidity at night are often suitable for night-purge natural ventilation, especially in office buildings. Cities in these regions have a considerable number of NV hours, such as Phoenix (4591 h) and Las Vegas (4295 h). The Gulf Coast and South Atlantic states feature a humid subtropical climate with hot and humid summers and mostly mild winters. Representative cities include Houston (2248 h) and New Orleans (2622 h). The region from the southern states of the Great Plains, to the lower Midwest, eastward to the Central East Coast has a temperate climate. Cities in this region include Pittsburgh (2801 h) and Washington, D.C. (2601 h). The Northern Midwest, Great Lakes, and most of New England share a humid continental climate with four distinct seasons. The summers are warm to hot and often associated with high humidity. The winters are long and cold. Therefore, the cities in these regions have a moderate number of NV hours. Cities in this climate zone include Boston (2745 h), Minneapolis (2468 h), and Chicago (2608 h).
2.3.4.2 Canada

Canada borders the United States and constitutes 41% of the continent's area. Most of Central and Northern Canada lies in subarctic and Arctic climates. The summer is short, and winter is long, with temperature often below −20 °C. Most Canadian cities are within 300 km of the southern border of the country where the climate is continental with warm summers. Among the major cities, Vancouver located in the southwest corner of the coastal province of British Columbia has a Mediterranean climate with warm summers and mild winters. It is estimated to have 2959 NV hours. Other cities include Toronto (2489 h), Montreal (2480 h), and Ottawa (2473 h).

2.3.4.3 Mexico

The climate of Mexico varies depending on the region. The northern region experiences either an arid or a semi-arid climate, and winters can be cold with some snowfall. South of the Tropic of Cancer, the climate is tropical, and hot and humid year-round, particularly along the coastal plains. The capital, Mexico City, is located on the high plateaus in the center of Mexico at an altitude of 2240 m. It has a subtropical highland climate, which generally features mild weather nearly all year. Therefore, it is a city with one of the greatest potentials for natural ventilation in North America (7161 h).
2.3.5 Oceania

2.3.5.1 Australia

Most of Australia experiences a desert or semi-arid climate. The northern part of Australia has a tropical climate while the southeast and southwest corners have a temperate climate. As shown in Figure 2.1, the potential for natural ventilation is generally abundant in this country, even in cities with a desert climate. For example, Alice Springs is situated in the central desert region. During the summer, the average temperature is nearly 28 °C, and the dew point is approximately 8.6 °C. During winter, the average temperature is about 12 °C, and the dew point is about 2 °C. The number of NV hours is 4952, which greatly benefits from the proper outdoor conditions for night-purge ventilation in summer and from mild weather in winter. The largest city by population in Oceania is Sydney, Australia, which is located on the country's east coast. The climate is temperate with an average temperature of nearly 22 °C during summer and a dew point of about 15 °C. Winters are mild with an average temperature of approximately 14 °C and a dew point of about 5.5 °C. Sydney has the highest NV hours (5816 h). Other major cities, including Melbourne (5025 h), Adelaide (5477 h), and Brisbane (5002 h), generally have significant potential for natural ventilation as well.

2.3.5.2 New Zealand

New Zealand is an island country, mainly consisting of two islands. The country mostly has an oceanic climate that is similar to the southeast corner of Australia. The summers are warm, and the winters are mild. Generally, the number of NV hours is greater in
northern cities than in southern cities. Auckland, on the North Island, is the largest city in the country and is estimated to have 5995 NV hours.

2.3.6 South America

2.3.6.1 Brazil

Brazil covers nearly half of the area of South America. Most of this country, except the temperate southern regions, has a tropical climate with warm temperatures throughout the year. Most major cities, including Sao Paulo, Rio de Janeiro, and Belo Horizonte, are located in the southeastern region of the country. For example, Sao Paulo, the most populous city in Brazil, is located on a plateau with an average elevation of nearly 800 m above sea level. It experiences a temperate climate with moderately warm summers and mild winters. Similar to many cities with the same climate type, the natural ventilation potential of Sao Paulo is substantial with 5164 NV hours. Rio de Janeiro is the largest coastal city in Brazil with a tropical savanna climate. Unlike Sao Paulo, natural ventilation is only available for a small portion of the year (1518 h) due to its hot and humid weather nearly all year.

2.3.6.2 Argentina

Argentina is located in the southern part of the continent and shares a long border with Chile. The country has diverse climates, although the most populous cities are located in the temperate climatic zone. The capital city and the largest city of Argentina, Buenos Aires, is located on South America's southeastern coast. This city experiences a
temperate climate and is mild year-round with no major extreme temperatures. As a result, it has significant potential for natural ventilation with 4514 NV hours.

2.3.6.3 Chile

Chile lies between latitudes 17° S and 56° S and occupies a long strip of land between the Andean Mountains and the Pacific Ocean. Therefore, the climate in Chile is diverse, ranging from an arid desert climate in the north to a Mediterranean climate in the center, to alpine tundra in the south. Santiago, the capital city of the country, has a Mediterranean climate. Like many other cities with this climate, summers are dry with an average temperature of approximately 20 °C, while winters are mild with an average temperature of about 10 °C. Natural ventilation can be a practical option in this region, given that it has 4297 NV hours.

2.3.7 Summary

According to this analysis, subtropical highland climates show a significant number of NV hours due to their year-around mild weather. Such a climate type can be found in Mexico City, Mexico (7161 h), Nairobi, Kenya (8435 h), and Bahir Dar, Ethiopia (8136 h). Furthermore, the Mediterranean climate greatly favors natural ventilation. Characterized by dry summers and mild winters, this climate is not only found around the Mediterranean Sea but also in California, Western Australia, Portugal, and Central Chile. Representative cities include Los Angeles, United States (7197 h), Perth, Australia (6094 h), Faro, Portugal (5673 h), and Antofagasta, Chile (8204 h). Moreover, greater-than-
expected natural ventilation potentials, ranging from 3000 to 4000 NV hours, are displayed in regions with a desert climate, such as the Middle East, Central Australia, and Egypt. Despite high heat during summer days, the temperature can drop considerably to a comfortable level at night due to radiant sky cooling. For example, a good ventilation strategy in this region is to shade and insulate the house against the heat of the day and flush out any stored heat during the cooler nights. The region with the least natural ventilation potential is Southeast Asia (e.g., Singapore, Malaysia, and Indonesia), which display practically no NV hours, as a result of hot and humid weather throughout the year.

2.4 Energy Saving Potentials

Figure 2.4 presents NV hours, non-NV hours that result from hot temperature and high humidity ($NonNV\ hour_{hot\&humid}$), energy saving hour percentages NV% of the world's 60 largest cities (DWUA 2017) (based on urban land area and population) among 1854 locations, and corresponding energy savings percentage by natural ventilation ES%. 
Figure 2.4: NV hours (out of 8760 h), non-NV hours due to hot temperature and high humidity (out of 8760 h), energy saving hour percentages NV% of the world’s 60 largest cities, and corresponding energy savings ES% calculated with BES.

- Cities without typical weather data are excluded from the list.

Cities listed include Berlin, Beijing, Chengdu, London, Paris, Tokyo, and others.

The figure illustrates NV hours and non-NV hours for various cities, showing the percentage of hours that natural ventilation is feasible and the corresponding energy savings.
Energy saving percentage, or ES%, is calculated with EnergyPlus on a generic office building created by U.S. Department of Energy (Field, Deru, and Studer 2010)

\[
ES\% = \frac{E_{\text{mech}} - E_{\text{mixed}}}{E_{\text{mech}}}
\]

(3)

In the above equation, \(E_{\text{mech}}\) represents the total cooling energy consumption of mechanical ventilation, which also includes fan and pump electricity usage, whereas \(E_{\text{mixed}}\) represents the total cooling energy consumption of mixed-mode ventilation. 

A NonNV hour\(_{\text{hot\&humid}}\) is defined as an hour when outdoor temperature and humidity exceed the upper thresholds. We introduced this term here because it denotes the time period when cooling energy must be consumed. Energy saving hour percentage NV% is defined as follows:

\[
NV\% = \frac{\text{NV hour}}{\text{NV hour} + \text{NonNV hour}_{\text{hot\&humid}}}
\]

(4)

In addition to NonNV hour\(_{\text{hot\&humid}}\), the sum of NV hour and NonNV hour\(_{\text{hot\&humid}}\) represents the maximum time period when cooling energy consumption can occur, as mechanical ventilation can take place during NV hours if natural ventilation alone cannot meet satisfactory thermal comfort due to high building internal load. The ratio between
NV hour and the sum of NV hour and $NonNV\ hour_{\text{hot\&humid}}$ therefore indicates the maximum time fraction when cooling energy savings can occur.

In Figure 2.4, places with a tropical climate such as Manila, Bangkok, Chennai, Kuala Lumpur, and Singapore show both nearly zero NV hour and ES%, due to the hot and humid climate year-round. In contrast, cities with a cold climate such as Moscow and St. Petersburg still display moderate NV hours but high ES% over 30% due to favorable weather during summer. Large cities with a temperate climate including Mexico City, Los Angeles, and Johannesburg, display substantial NV hours greater than 6000 and ES% higher than 30%. For the rest of the cities on the list such as Tokyo, New York, and Beijing, NV hours typically range from 2000 to 3000, and ES% ranges between 20% and 30%.

The analysis demonstrates a strong correlation between ES% and NV% among the 60 cities with a correlation coefficient (r) of 0.93. Thus, the advantage of the NV hour approach is that it can assess maximum energy saving potentials without running detailed BES, which is especially useful in the early design stage.

2.5 Natural Ventilation and Air Quality in China

The building sector is a critical contributor to China’s energy consumption, and the sector’s life-cycle energy consumption accounts for over 40% of China's total energy use (Cao et al. 2014; Zhang et al. 2015). HVAC systems that heat, cool, and ventilate buildings comprise approximately 47% of operational energy consumption in buildings
across China. The operation of natural ventilation in an urban environment is influenced by various factors, such as outdoor ambient air pollution and noise (Nicol and Wilson 2004; Tong, Chen, Malkawi, et al. 2016b; Tong et al. 2012). In particular, outdoor ambient air pollution is an urgent challenge facing China’s development. Several cities in China suffer from degrading air quality and associated health risks, such as respiratory symptoms and cardiovascular diseases (Chan and Yao 2008; Gong et al. 2012; Seaton et al. 1995; Tong, Baldauf, et al. 2016; Zhang, Wu, Hu, et al. 2014; Zhang, Wu, Liu, et al. 2014). In the year 2014/2015, only 25 out of 190 Chinese cities were able to meet the National Ambient Air Quality Standards (Zhang and Cao 2015). Air pollution clearly impacts the operation of natural ventilation significantly. A few studies have estimated that natural ventilation can be implemented at several representative cities in China through simplified building models (Yang et al. 2005; Yao et al. 2009; Zhang et al. 2010), but they did not consider the pressing impact of air pollution.

2.5.1 Data Source

2.5.1.1 Climate Data

The climate in China varies from region to region due to its massive expanse of land and complicated terrain. According to the Standard on Division of Climate Zones for Buildings (GB50178-93 1993), the country is categorized into five climate zones: Severe Cold, Cold, Hot Summer/Cold Winter (HSCW), Hot Summer/Warm Winter (HSWW), and Mild. In particular, the northern part of China is characterized into Severe Cold and Cold zones where space heating dominates energy consumption in buildings. In the
central part of China, which falls under the category of the HSCW zone, both space heating and cooling are required in buildings. Southern China is mostly categorized into the HSWW zone where space cooling is needed during summer. The hourly Chinese Standard Weather Data (CSWD) developed by China Meteorological Bureau and Tsinghua University are employed for Building Energy Simulation (2005).

2.5.1.2 Air Quality Data

The Air quality index (AQI) is used to inform the public about air pollution levels and associated health risks. The AQI approach is based on the maximum value of individual pollutants in China. In general, as AQI increases, a larger percentage of the population is likely to experience adverse health effects. In this study, hourly AQI data are downloaded from the China National Environmental Monitoring Center website (http://113.108.142.147:20035/emcpublish/). Data from Aug. 2014 to Aug. 2015 was chosen. This particular year was selected because it provides data for a large number of Chinese cities (76 cities). According to the health effects defined in each AQI level (Table 2-2, and Table 2-3), the ambient air pollution results in negative health effects for sensitive groups when AQI is greater than 100 (GB3095 2012). The AQI threshold for allowing natural ventilation is therefore chosen to be 100.

In this analysis, the spatial variation of AQI within each city is not considered due to limited data availability. The AQI defined by the Ministry of Environmental Protection of the People’s Republic of China is based on the following equation:
\[ IAQI_p = \frac{IAQI_{Hi} - IAQI_{Lo}}{BP_{Hi} - BP_{Lo}} (C_p - BP_{Lo}) + IAQI_{Lo} \]  

(5)

In the above equation, IAQI\(_p\) is the index for pollutant \(p\); \(C_p\) is the rounded concentration of pollutant \(p\); \(BP_{Hi}\) is the breakpoint that is greater than or equal to \(C_p\); \(BP_{Lo}\) is the breakpoint that is less than or equal to \(C_p\); \(IAQI_{Hi}\) is the AQI value that corresponds to \(BP_{Hi}\), and \(IAQI_{Lo}\) is the AQI value that corresponds to \(BP_{Lo}\). IAQI and corresponding thresholds of each pollutant are displayed in Table 2-2. The overall AQI represents the maximum of all individual AQIs.

\[ AQI = \max\{IAQI_1, IAQI_2, IAQI_3, \ldots, IAQI_n\}, \quad n = 1, 2, \ldots, 6 \]  

(6)
Table 2-2: Individual AQI and corresponding thresholds of six pollutants

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<th>24-hour</th>
<th>1-hour</th>
<th>8-hour</th>
<th>1-hour</th>
<th>24-hour</th>
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<th>24-hour</th>
<th>1-hour</th>
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<td>100</td>
<td>150</td>
<td>250</td>
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</tr>
</tbody>
</table>

1) 1-hour concentration of SO2, NO2, CO is only used for hourly report. 24-hour concentration should be used in daily report.
2) If 1-hour SO2 concentration exceeds 800 μg/m³, 24-hour concentration should be used instead.
3) If 8-hour O3 concentration exceeds 800 μg/m³, 1-hour concentration should be used instead.
<table>
<thead>
<tr>
<th>AQI</th>
<th>Health Risk Category</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-50</td>
<td>Good</td>
<td>Air quality is considered satisfactory, and air pollution poses little or no risk.</td>
</tr>
<tr>
<td>50-100</td>
<td>Moderate</td>
<td>Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.</td>
</tr>
<tr>
<td>101-150</td>
<td>Unhealthy for sensitive groups</td>
<td>Children, older adults, and people with lung and heart disease are likely to be affected.</td>
</tr>
<tr>
<td>151-200</td>
<td>Unhealthy</td>
<td>Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects.</td>
</tr>
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<td>201-300</td>
<td>Very unhealthy</td>
<td>Health warnings of emergency conditions. The entire population is more likely to be affected.</td>
</tr>
<tr>
<td>301-500</td>
<td>Hazardous</td>
<td>Health alert: everyone may experience more serious health effects.</td>
</tr>
</tbody>
</table>
2.5.2 Method

2.5.2.1 Building Model

In our EnergyPlus model, a five-story office building with a gross floor area of 5000 m² (1000 m² each floor) is created based on the Chinese Building Design Standard as shown in Table 2-4 which specified the thermal characteristics (e.g., U value) of buildings in each climate zone (PGB50189 2015).

Table 2-4: Building thermal characteristics of each climate zone in China; U value and solar heat-gain coefficient are obtained from the Chinese Design Standard for Energy Efficiency of Public Buildings

<table>
<thead>
<tr>
<th>Climate Zone</th>
<th>Roof U [W/m²·K]</th>
<th>Wall U [W/m²·K]</th>
<th>Ground Floor U [W/m²·K]</th>
<th>Window U [W/m²·K]</th>
<th>Window SHGC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Severe Cold</td>
<td>0.25</td>
<td>0.35</td>
<td>0.25</td>
<td>1.76</td>
<td>0.68</td>
</tr>
<tr>
<td>Cold</td>
<td>0.39</td>
<td>0.46</td>
<td>0.46</td>
<td>1.77</td>
<td>0.37</td>
</tr>
<tr>
<td>Cold Winter Hot Summer</td>
<td>0.39</td>
<td>0.54</td>
<td>0.46</td>
<td>2.3</td>
<td>0.32</td>
</tr>
<tr>
<td>Warm Winter Hot Summer</td>
<td>0.44</td>
<td>0.72</td>
<td>1.32</td>
<td>2.4</td>
<td>0.2</td>
</tr>
<tr>
<td>Temperate</td>
<td>0.44</td>
<td>0.72</td>
<td>1.32</td>
<td>2.4</td>
<td>0.2</td>
</tr>
</tbody>
</table>
The percentages of the different types of HVAC systems installed in office buildings of major Chinese cities are unavailable. We assumed that the modeled building is served by a fan coil unit (FCU) due to its popularity in China; an FCU consumes much less energy than the variable air volume (VAV) system, thereby suiting the energy structure in China (Han 2010). While investigating cooling energy consumption, consumption by auxiliary systems such as fans and pumps was also looked into. The overall window-to-wall ratio is set as 50% and the operable window ratio is 30%. The plug load is 15 W/m² and lighting power density is 9 W/m². The fresh air rate is set as 8.3 L/s-person. The cooling and heating set-point temperatures for mechanical ventilation are 26 °C and 20 °C, respectively. The operation schedule of the HVAC system is set as 7:00 - 18:00 from Monday to Friday. The coefficient of performance (COP) in the simulation complies with the Chinese Building Design Standard (PGB50189 2015). For mixed-mode ventilation where both mechanical and natural ventilation are used, the thermal comfort thresholds for natural ventilation are determined according to the adaptive thermal comfort model that was established by de Dear and Brager (2002). Given the fact that not the entire Chinese building stock is suitable for natural ventilation and the difficulty to retrofit existing buildings, in this study we only used the floor area of a one-year newly constructed office building to estimate the potential for natural ventilation. The cooling energy savings of each city is approximated by multiplying the per-square-meter saving by the 10-year-averaged floor area of an annual newly constructed office building in each
city according to the National Bureau of Statistics of the People's Republic of China (2014).

2.5.2.2 Carbon Emission Calculation

The CO₂ emission factor of the power grids of each province is derived according to Equation (7) (National Development and Reform Commission (NDRC) 2013), which has been illustrated as follows:

\[
EF_p = \frac{Em_p + \sum_n (EF_n \times E_{imp,n,p}) + \sum_k (EF_k \times E_{imp,k,p}) + (EF_{grid,i} \times E_{imp,i,p})}{E_p + \sum_n E_{imp,n,p} + \sum_k E_{imp,k,p} + E_{imp,i,p}}
\]

(7)

In the above equation, \( EF_p \) is the CO₂ emission factor of province \( p \) in kgCO₂/kWh; \( Em_p \) represents direct CO₂ emission from electricity generation of province \( p \) given by Equation (8) in tonCO₂; \( EF_n \) is the average CO₂ emission factor of \( n \) provinces that have net electricity export to province \( p \) in kgCO₂/kWh; \( E_{imp,n,p} \) is the net electricity that is exported from \( n \) provinces to province \( p \) in MWh; \( EF_k \) is the average CO₂ emission factor of \( k \) countries that have net electricity export to province \( p \) in kgCO₂/kWh; \( E_{imp,k,p} \) is the net electricity that is exported from \( k \) countries to province \( p \), MWh; \( EF_{grid,i} \) is the CO₂ emission factor of regional grid \( i \) in kgCO₂/kWh, and \( E_p \) is the annual electricity generation of province \( p \) in MWh.
\[ Em_p = \sum_m (FC_m \times NCV_m \times EF_m / 1000) \]

(8)

In the above equation, \( FC_m \) represents the consumption of fossil fuel for electricity generation in province \( p \) in ton or m\(^3\); \( NCV_m \) is the net calorific value of fossil fuel \( m \) in GJ/ton or GJ/m\(^3\). Finally, \( E_{imp,i,p} \) is the net electricity that is exported from regional grid \( i \) to province \( p \) in MWh; it can be represented as follows:

\[ E_{imp,i,p} = \max((E_{u,p} - E_p - \sum_n E_{imp,n,p} - \sum_k E_{imp,k,p}),0) \]

(9)

In the above equation, \( E_{u,p} \) is the annual electricity consumption of province \( p \) in MWh, and \( EF_m \) is the CO\(_2\) emission factor of fossil fuel \( m \) in tonCO\(_2\)/TJ; it can be represented as follows:

\[ EF_m = CC_m \times OF_m \times \frac{44}{12} \]

(10)

In the above equation, \( CC_m \) is the carbon content factor of fossil fuel \( m \) in tonC/TJ; \( OF_m \) is the oxidation factor of fossil fuel \( m \) in percentage. \( CC_m \) and \( OF_m \) have been estimated based on previous studies (Liu et al. 2015).
2.5.3 Results

2.5.3.1 NV Hour

The air quality threshold is chosen to be AQI = 100, according to China National Ambient Air Quality Standards (GB3095 2012). Although NV hour does not consider specific information at building scale, it is intended to provide a straightforward method to assist architects and energy policymakers in evaluating the regional feasibility of implementing natural ventilation on a large scale without conducting a detailed simulation. As NV hour derived from meteorology and air quality data is independent of building types, it can be applied to both office and residential buildings. Figure 2.5 presents the air-pollution-adjusted NV hours of five climate zones in the year 2015 through a box plot. The national average NV hours is 2,324 (out of 8760 hours/year), with a standard deviation of 778. Clear differences in NV hour are observed across five climate zones. The Mild climate zone includes cities with the most number of NV hours. Furthermore, it is the most favorable climate for utilizing natural ventilation mainly due to its suitable outdoor temperature throughout the year. On the other hand, Hot Summer/Cold Winter (HSCW) is the least favorable climate for natural ventilation due to long hot/humid summers and cold/humid winters.
Figure 2.5: NV hour in five climate zones

Figure 2.6 displays the NV hours of 76 major cities based on weather and ambient air pollution data. The red wedge in the pie chart represents a reduction in NV hours due to ambient air pollution. The southwest region of China includes cities with the highest potential for natural ventilation. For instance, Kunming, the capital city of Yunnan province, has 5913 NV hours. The city is located in the Mild climate zone with an annual average temperature of 15.5°C and little variation in temperature throughout the year. The cities with the least potential for natural ventilation are located in South-Central China that fall within the hot-summer-cold-winter zones. In Northern China where an enormous amount of coal is consumed to generate power, NV hours are significantly reduced due to ambient air pollution (Chan and Yao 2008). As highlighted in Figure 2.6,
Zhengzhou, the capital of Henan province, displays the most significant loss of NV hours (1655) among the studied cities due to air pollution. In contrast, NV hours are reduced little by air pollution in the northeast region (i.e., Liaoning, Jilin, Heilongjiang) that falls into the Severe Cold climate zone, mainly due to the long and extremely cold winter seasons that prohibit natural ventilation regardless of the serious ambient air pollution from coal-fired heat generation. Compared to the HSCW zone, the smaller loss in NV hours due to air pollution in Northeast China does not necessarily imply better ambient air quality.
Figure 2.6: NV hours affected by ambient air pollution in 76 Chinese cities. Beijing, Zhengzhou, and Kunming are highlighted, and the corresponding NV hours and loss of NV hours due to air pollution are displayed. The unit is in hours per year. The area of the scale bars in the legend represents NV hours.
Seasonally, spring and fall show the largest mean and smallest deviation in NV hours across China as shown in Figure 2.7. The national average of NV hours is 794 in spring and 207 in winter. During summer, most cities located in the south of the Yangtze River experience hot and humid weather, which generates little potential for natural ventilation. Cities in the north offer much greater potential for cooling energy savings during the summer months. During winter, the northern part of China generally has almost no potential for natural ventilation due to cold weather, and the NV hours increase gradually with decreasing latitude from north to south.

Figure 2.7: Seasonal variation of air-pollution-adjusted NV hours in China. The unit is in hours per year.
2.5.3.2 Energy Savings and Carbon Dioxide Reduction

In this section, the per-square-meter cooling energy savings and carbon reduction potential are estimated using available floor area data of newly constructed office buildings in 35 major Chinese cities. This section will primarily focus on office buildings where energy saving potentials can be quantified. Residents in China typically ventilate their homes based on personal behavior and thermal comfort preference rather than using fixed set points and schedules. Therefore, there is not enough information to estimate the natural ventilation potential of residential buildings due to difficulties in collecting such datasets across major cities in China. Ten-year-averaged annual floor area data of office buildings from 2005 to 2014 is used to eliminate large yearly fluctuations in each city. Figure 2.8 shows the per-square-meter cooling energy consumption and savings potential for office buildings. The red wedge indicates the potential cooling energy savings by natural ventilation, whereas the yellow wedge indicates the additional cooling energy savings if air quality is improved (i.e., AQI remains below 100 for a majority of the time). The per-square-meter cooling consumption is generally larger in cities that are located in the south of the Yangtze River due to hot weather during summer. Among the 35 studied cities, Kunming was found to be the most favorable for natural ventilation in terms of both weather and ambient air quality. It has a per-square-meter cooling consumption of 20.7 kWh/m², and 78% of it could be saved with natural ventilation. The city with the least per-square-meter energy savings potential (2.4 kWh/m²) was found to be Chongqing, which is a major city in Southwestern China. Chongqing has hot and
humid weather in the summer months, with an average temperature of 27.1°C and relative humidity of 79%, which make the city unfavorable for utilizing natural ventilation.

Figure 2.8: Cooling energy consumption per-square-meter of office building in 35 major Chinese cities in kWh/m². The red wedge represents the cooling energy savings potentials by natural ventilation. The yellow wedge indicates the additional cooling energy savings if air quality is improved. The blue wedge indicates the remaining cooling energy consumption with natural ventilation. Beijing, Chongqing, and Kunming are highlighted, and the corresponding energy savings and additional energy savings if air quality is improved are displayed.
Figure 2.9: (Top) energy savings potential and additional cooling energy savings (if air quality is improved) in GWh for office buildings of 35 major Chinese cities, ranked from high to low; (Bottom) carbon dioxide reduction potential in thousand tons and the additional cooling energy saving (if air quality is improved) for office buildings in 35 major Chinese cities.

The total savings in cooling energy by a city presented in Figure 2.9 (Top) considers the total floor area at each city in the estimation. The aggregated energy savings potential of the 35 cities in the year of 2015 is 112 GWh, after a loss of 43 GWh due to air pollution. Beijing, the capital city of China, shows limited per-square-meter savings potential due to the unfavorable weather and air quality for natural ventilation. However, Beijing has the largest floor area of office buildings, and this creates an enormous energy saving...
opportunity. As shown in Figure 2.9, Beijing shows the largest potential for total energy savings (25 GWh) among 35 major cities in China, followed by Shanghai, Kunming, and Tianjin. These cities (except Kunming) are the most economically developed cities in China, with a large amount of government and private office space, although the per-square-meter savings from them are not among the top. For cities in northern China, the potential for savings is reduced dramatically. For instance, Beijing shows the largest additional energy savings potential of 12 GWh (if air quality is improved), which is equivalent to the sum of the energy savings potential of the bottom ten cities.

In Figure 2.9 (bottom), the top four cities with the greatest potential for carbon dioxide reduction are Beijing, Shanghai, Tianjin, and Hangzhou. The potential for aggregated carbon dioxide reduction by utilizing natural ventilation in office buildings across 35 major Chinese cities is estimated to be 79,000 tons, with a potential to reach 112,000 tons if AQI remains below 100 for a majority of the time. Wuhan and Chengdu are located in the provinces with abundant hydro resources and, therefore, they have a smaller reduction in CO₂ emissions per kWh of electricity saved.
2.5.4 Summary

As one of the most important features of green building, natural ventilation has become an increasingly attractive design option that provides a comfortable working environment and promising potential for energy savings. According to our analysis, ambient air quality and the total floor area in each city must be considered when evaluating the reality of natural ventilation’s overall energy savings potential. The aggregated energy savings potential of office buildings in 35 major Chinese cities was 112 GWh in the year 2015, even after allowing for a 43 GWh loss due to severe air quality problems, especially in North China. Beijing shows limited per-square-meter savings potential as a result of unfavorable weather and air quality for natural ventilation. However, it is the city with the most promising energy-saving potential in China (25 GWh), as it has the largest total floor area of office buildings. Based on provincial emission factors in China, the aggregated carbon dioxide reduction is 79,000 metric tons. It can reach 112,000 metric tons if AQI remains below 100 during non-air-pollution-adjusted NV hours, indicating the substantial impact air pollution has on this issue.

The utilization of natural ventilation creates tremendous energy saving potential, reducing emissions associated with coal-fired power generation, especially in North China. Contrary to case studies that focus on a particular building or site, the methodology presented here cannot fully consider neighborhood-scale characteristics such as surroundings, building configurations, and variation of AQI within each city due to limited data availability. However, the purpose of this study is to estimate the potential
for natural ventilation at a national level and, therefore, contribute to the development of energy and environmental policies in China. The results of this study demonstrate the co-benefits of natural ventilation in terms of energy saving and mitigating carbon emission to reduce outdoor air pollution. While air pollution is currently a severe environmental issue in China, human-induced climate change driven by carbon emissions is a global problem facing mankind. Therefore, the potential for natural ventilation estimated in this study will be valuable to architects and building operators, helping them to better implement different ventilation strategies to reduce building energy consumptions based on local climate and air quality conditions throughout China.
Chapter 3: Building Model for Control and Simulation

This chapter introduces building models for advanced natural ventilation control.

Building models are crucial to the development of NV control strategies. In model-based control, the performance of the derived control policy largely relies on the quality of its internal predictive model. In the case when a significant discrepancy exists between the model and the real building, the control policy that is developed and optimized on the model will become suboptimal on the real building. In model-free control, although theoretically the building model is not required, a representative model can be used to shorten the training phase of the controller significantly.

3.1 Physics-based Model

The Physics-based model (or white box model) simulates building thermal comfort and energy load based on detailed physics-based equations for building components, sub-systems, and systems. EnergyPlus (including DesignBuilder, OpenStudio) are widely used white box software for building simulation. However, the white box model has certain downsides: (1) the time-consuming task of gathering building information, such as construction, material, occupancy, internal load, and HVAC system specifications. Sometimes, comprehensive building information is extremely difficult to get; (2) the
calibration process is highly manual, usually requiring domain expertise or parametric study and grid searching.

Furthermore, implementing advanced control strategies on the white box model is cumbersome and has several limitations. The Energy Management System (EMS) embedded into EnergyPlus allows custom control of natural ventilation and the HVAC system through sensor components and actuator components, following a simple program written in EnergyPlus Runtime Language. However, such an approach can hardly aid in implementing any advanced control that is more complex than rule-based heuristic control. The Building Controls Virtual Test Bed (BCVTB) developed by Lawrence Berkeley National Lab, is another option that can enable more advanced and versatile control in white box models. It allows for co-simulation of software such as EnergyPlus, TRNSYS, and Modelica with more flexible and potent control coded in MATLAB/Simulink and Python (Wetter, Haves, and Coffey 2008).

3.1.1 Simplified Empirical Building Model

The building system can be simplified into the following heat balance equation (ASHRAE 2017)

$$\dot{Q}_{total} = \dot{Q}_{en} + \dot{Q}_r + \dot{Q}_{in} + \dot{Q}_{AC} + \dot{Q}_{NV}$$

(11)

In the above equation,
\(\dot{Q}_{total}\) is the total heat gain;

\(\dot{Q}_{en}\) is the heat gain through building envelope;

\(\dot{Q}_r\) is the heat gain from solar radiation;

\(\dot{Q}_{in}\) is the internal heat gain from people and equipment;

\(\dot{Q}_{AC}\) is the heat gain from the HVAC system;

\(\dot{Q}_{NV}\) is the heat gain through natural ventilation;

The heat gain through the building envelope depends on the surface heat transfer coefficient \(h_i\) and surface area \(A_i\) of each external surface \(i\), as well as the temperature difference between inside and outside environment (ASHRAE 2017), as in the equation below:

\[
\dot{Q}_{en} = \sum_{i=1}^{n} h_i A_i (T_{out} - T_{in})
\]  

(12)

The heat gain through natural ventilation depends on the rate of natural ventilation \(\dot{V}_{nv}\) and temperature difference. \(\rho\) is air density, and \(c_p\) is the specific heat of air (ASHRAE 2017), as in the equation below:
\[
\dot{Q}_{NV} = \rho c_p \dot{V}_{nv} (T_{out} - T_{in})
\]

(13)

The natural ventilation rate is a function of wind-driven and buoyancy-driven effect (ASHRAE 2017), which can be represented as follows:

\[
\dot{V}_{nv} = \sqrt{(\dot{V}_{wind})^2 + (\dot{V}_{stack})^2}
\]

(14)

The wind-driven effect is a function of opening effectiveness coefficient \( C_o \), window opening area \( A_{opening} \), and local wind speed \( u \) (ASHRAE 2017), as in the equation below:

\[
\dot{V}_{wind} = C_o A_{opening} u
\]

(15)

The buoyancy-driven effect is a function of discharge coefficient \( C_d \), window opening area, the height from the midpoint of lower opening to the neutral pressure level \( \Delta H_{NPL} \), and indoor and outdoor temperature (ASHRAE 2017), as in the equation below:

\[
\dot{V}_{stack} = C_d A_{opening} \sqrt{\frac{2g \Delta H_{NPL}}{T_{out} - T_{in}} \frac{|T_{out} - T_{in}|}{T_{in}}}
\]

(16)

The energy balance of the zone can be described as follows:
\[ \rho c_p V \frac{dT}{dt} = \dot{Q}_{total} \]

(17)

In the above equation, \( V \) is the zone volume.

The humidity ratio balance can be represented as follow (ASHRAE 2017):

\[ \rho V \Delta W = \sum k g_{load} + \dot{m}_{NV} (W_{out} - W) + \dot{m}_{AC} (W_{sup} - W) \]

(18)

In the above equation, \( \sum k g_{load} \) is the internal moisture load, and \( W_{out} \) and \( W_{sup} \) are outside humidity ratio and supply air humidity ratio respectively. The humidity ratio of supply air is the saturated humidity ratio at supply air temperature. The conversion between relative humidity and humidity ratio is given below:

\[ RH = 100 \frac{w}{w_s} \]

(19)

In the above equation, \( w_s \) is the saturation mixing ratio.

3.2 Artificial Neural Network Model

Artificial neural network (NN or ANN) is a bio-inspired machine learning technique that is very versatile for different tasks such as image recognition, classification, and regression (Hassoun 1995). The structure is comprised of an input layer, hidden layer(s),
and an output layer. There may be multiple hidden layers, and each hidden layer can have a different number of neurons.

A single neuron network, or a perceptron, is comprised of an affine function and an activation function. The Affine function is the linear combination of inputs plus bias:

\[ h = W^T X + \text{bias} \]  

(20)

The activation function can be chosen from a variety of options such as sigmoid \( f(x) = \frac{1}{1+e^{-x}} \), tanh \( f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \), ReLU \( f(x) = \max(0, x) \), and many more. The interpretation of the activation function in a perceptron is to decide whether to fire the signal or not, and the contribution of activation functions to a neural network is to introduce non-linearity.

In the case of simulating building thermal dynamics, \( X \) is the input matrix, and \( Y \) is the output matrix. Each row of the matrices is a sample; each column of the \( X \) matrix is a feature, including environmental conditions, AC/NV operations, and starting room conditions; each column of the \( Y \) matrix is a predicted variable, such as future room temperature and relative humidity. Each node in the hidden layer comprise an affine function and an activation function, and each hidden layer has multiple nodes.

The NN is trained through back propagation (Hecht-Nielsen 1992), the steps of which are listed as follows: (1) make a forward pass from \( X \) to \( Y \), (2) calculate the error using the
loss function, and (3) make a backward pass to update weights through stochastic gradient descent

$$\omega_{ij}(t + 1) = \omega_{ij}(t) + \eta \frac{\partial L}{\partial \omega_{ij}}$$

(21)

In the above equation, $\omega$ represents each weight, $\eta$ the learning rate, and $L$ the loss function.

3.2.1 Validation of Neural Network Model on Simulation Data

A $4\text{m} \times 4\text{m} \times 3.5\text{m}$ box model with a south-facing window was created in DesignBuilder with default construction materials, no heating system, a split air conditioner (no fresh air) for cooling, and the randomly operated window for natural ventilation, simulated under San Francisco weather. The purpose of the random operation is to explore as many different conditions as possible to train our neural network model. A neural network is constructed in Python with Keras package using TensorFlow backend (Chollet 2015), with three hidden layers (with 32, 16 and 10 nodes in each layer), using mean squared error as loss function, ReLU as activation function, and AdaDelta as optimizer, is able to predict indoor temperature and relative humidity based on environment conditions and AC/NV operations with a high accuracy of hourly $R^2=0.994$, as shown in Figure 3.1. In this figure, the X-axis indicates the true hourly-averaged indoor air temperature of the simulated period, and the Y-axis indicates the predicted hourly-averaged indoor air temperature.
3.2.2 Validation of Neural Network Model on Measured Building Data

Experiments were conducted on a real building (Harvard House Zero) located in the Northeastern U.S. in the summer of 2018 and winter of 2019. This building is a three-story, heavily insulated, wood-structured building with a basement. This building is equipped with a ground-source heat pump powered radiant floor for cooling and heating. The fresh air is supplied with natural ventilation through windows that can be both automatically and manually operated. The measurement of weather onsite (outdoor air temperature, dew point, relative humidity, solar radiation, wind direction, and wind speed) and indoor thermal conditions (indoor air temperature, relative humidity, concrete floor temperature, CO₂ concentration, window status) in the rooms on the third floor were recorded. The summer data spans across four segments: July 27-30th, August 3-5th,
August 10-14th, and September 7-10th. The winter data, on the other hand, is continuous from January 2nd to January 10th.

The critical measurements, including outside air temperature, indoor air temperature, slab temperature, and window status of summer experiment, are displayed in Figure 3.2, whereas the winter data is shown in Figure 3.3. In these plots, the indoor air temperature is plotted in red lines, concrete slab temperature in green lines, outdoor air temperature in blue lines, and the window-open period in light red shades. During the summer period, the mean indoor-outdoor temperature difference was 3.02 °C with a standard deviation of 2.99 °C, and the maximum temperature difference was 10.43 °C. During the winter period, the mean indoor-outdoor temperature difference was 15.62 °C with a standard deviation of 3.30 °C, and the maximum temperature difference was 25.38 °C. The window was kept open for the entire period of September 7-10. In the winter experiments, the window was opened intermittently for 15 min to 2 h intervals.
Figure 3.2 Summer experiment data

Figure 3.3 Winter experiment data
A neural network architecture was created in Python with Keras package using TensorFlow backend (Chollet 2015), to simulate the thermodynamics of the tested rooms. This NN structure comprises four hidden layers. The input layer has a dimension of 13 for input data (hour of the day, weekday, outdoor air temperature, dew point, relative humidity, solar radiation, wind direction, wind speed, indoor air temperature, relative humidity, concrete floor temperature, CO₂ concentration, window status). The output layer has a dimension of one for either the predicted indoor temperature or indoor relative humidity at a future timestep (same NN structure but trained separately). The visualization of this NN model is shown in Figure 3.4. The first hidden layer has 26 nodes (plus bias), the second layer has 13 nodes (plus bias), the third layer has 7 nodes (plus bias), and the fourth layer has 4 nodes (plus bias).
This neural network model demonstrates impressive performance in terms of predicting the future indoor temperature and relative humidity. The details of the summer and winter experiment are illustrated as follows. As shown in Table 3-1, the R-square scores are above 0.99 for all look-ahead time steps from 30 min to 120 min. The predicted indoor air temperature shows high accuracy with the middle 95 percentile errors within a very narrow range of 0.56 – 0.74 °C. The predicted indoor air temperature plotted against the true indoor air temperature is shown in Figure 3.5. As demonstrated, the predictions are very close to the true data. The model predictive capacity is also corroborated by the time series overlay shown in Figure 3.6. The predictions on indoor relative humidity are also
highly accurate, as illustrated in Figure 3.7 and Figure 3.8 that compare the true data with the predicted results.

Table 3-1 Summer data fitting metrics

<table>
<thead>
<tr>
<th>Time Ahead</th>
<th>30 min</th>
<th>60 min</th>
<th>120 min</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>0.99814</td>
<td>0.99780</td>
<td>0.99672</td>
</tr>
<tr>
<td>2.5 percentile error [°C]</td>
<td>-0.35643</td>
<td>-0.24401</td>
<td>-0.46796</td>
</tr>
<tr>
<td>97.5 percentile error [°C]</td>
<td>0.20565</td>
<td>0.33020</td>
<td>0.27047</td>
</tr>
<tr>
<td>95th range [°C]</td>
<td>0.56</td>
<td>0.57</td>
<td>0.74</td>
</tr>
</tbody>
</table>

Figure 3.5 Scatter plot of true test set data vs. predicted indoor T, summer experiment
Figure 3.6 Overlay of sensor data (training and test set combined) and predicted results, indoor air temperature, summer experiment

Figure 3.7 Scatter plot of true test set data vs. predicted indoor relative humidity, summer experiment
Summer data are relatively easier to fit by the model, as the indoor-outdoor temperature difference is moderate, and the window status is continuous. Winter data, on the other hand, imposes more challenge to our model. The indoor-outdoor temperature difference is strikingly large, and the window status was modified at a much higher frequency and shorter duration. Given the intrinsic characteristics of the winter experiment data, the model was only trained on a 10 min look-ahead time step. The R-square score is above 0.94 and shows satisfactorily high accuracy. The middle 95 percent of prediction errors on indoor air temperature is within a narrow range of 0.48 °C (Table 3-2).
Table 3-2 Winter data fitting metrics

<table>
<thead>
<tr>
<th>Time Ahead</th>
<th>10 min</th>
</tr>
</thead>
<tbody>
<tr>
<td>R2</td>
<td>0.9406</td>
</tr>
<tr>
<td>2.5 percentile error [°C]</td>
<td>-0.2517</td>
</tr>
<tr>
<td>97.5 percentile error [°C]</td>
<td>0.2334</td>
</tr>
<tr>
<td>95th range [°C]</td>
<td>0.48</td>
</tr>
</tbody>
</table>

Figure 3.9 Scatter plot of true test set data vs. predicted results, indoor temperature, winter experiment

As shown in Figure 3.9, Figure 3.10, and Figure 3.11 which compare the predicted results with both the test set data and entire data set, this neural network model is able to
accurately predict both indoor air temperature and relative humidity in very challenging conditions.

Figure 3.10 Overlay of sensor data (training and test set combined) and predicted results, indoor air temperature, winter experiment
Figure 3.11 Overlay of sensor data (training and test set combined) and predicted results, indoor relative humidity, winter experiment

One of the prominent advantages of using neural network model for the simulation of building thermal dynamics with natural ventilation is the high transferability. Unlike physics-based generative models (e.g., EnergyPlus or CFD) that involve tremendous man-hours in the process of collecting building-specific information and manual calibration, neural networks of the same structure can be trained separately for different buildings, and the training process is automatic. For model-based control, this NN model can be plugged in as the internal predictive model for control optimization; for model-free control, this NN model can be used for training the controller to a satisfactory level of performance before launching it into the real building to significantly shorten the commissioning period.
Chapter 4: Control of Natural Ventilation

This Chapter briefly overviews different types of control strategies, including spontaneous control, heuristic control, model-based control, and model-free control. A reinforcement learning control using model-free Q-learning is developed for the control of HVAC and window system. The experiment in two cities illustrates the effectiveness of this control strategy, compared against the baseline case using heuristic control.

4.1 Types of Control Strategies

Building ventilation strategies are highly dependent on climatic conditions at the location of interest. As climate varies from region to region in the world, it is critical to understand the variation between regions in order to utilize natural ventilation more effectively. Other than the local climate, the successful implementation of natural ventilation relies on numerous factors, such as immediate urban context (Ghiaus et al. 2006; Tong, Chen, and Malkawi 2016, 2017) (Sanaieian et al. 2014), building type (Wu et al. 2012), floor plan (Tantasavasdi, Srebric, and Chen 2001), ambient air quality (Tong, Chen, Malkawi, et al. 2016a; Tong, Chen, Malkawi, Liu, et al. 2016), (Kwok et al. 2016), window position and shape (Gao and Lee 2011; Shetabivash 2015), and noise level (Laurent, Samuelson, and Chen 2017; Nicol and Wilson 2004), just to mention a few.
However, in a given case, only a few features are subject to change, and the most critical element is the control of the HVAC and window system. In practice, natural ventilation is usually combined with mechanical heating and cooling system to achieve lower energy consumption and higher thermal comfort. This mixed-mode operation is commonly classified into categories of “concurrent” (HVAC and natural ventilation operate in the same space at the same time), “change-over” (HVAC and natural ventilation operate in the same space at different times) and “zoned” (HVAC and natural ventilation operate in different spaces at the same time) (Brager 2006). In these cases, the control of the operable windows and the synergy with the HVAC system becomes an important topic to be studied when discussing the implementation of natural ventilation.

4.1.1 Spontaneous Occupant Control

The manual control of natural ventilation by occupants is the dominant control strategies found in most naturally ventilated and mixed-mode buildings. Stemming from long-term surveys and monitoring the data of significant samples of occupants around the world, some shared behavior patterns have been revealed. For example, the window-open periods were much longer in the summer than in the winter (Rijal et al. 2007; Yao and Zhao 2017), the window-operation frequency was higher in non-heating seasons (Jeong, Jeong, and Park 2016), and people were more likely to open windows in the afternoon (Rijal et al. 2008). Zhao (2016) collected monitored window states data from 19 residences in Beijing and summarized the manually controlled natural ventilation pattern in each of the seasons, and found that window operations showing higher frequency
during the morning and night hours. Raja’s study (2001) on 15 UK offices showed that most windows were open when the outdoor temperature was above 25 °C and very few windows were open when the outdoor temperature was below 15°C. Statistical models, such as logistic regression (Equation (22) or (23)), have been established to predict window-operation behavior based on environmental and temporal factors that include season, time of the day, indoor and outdoor air temperature, indoor CO₂ concentration, wind speed, humidity, noise level, rain, and outdoor particulate matter (PM2.5) concentration (Andersen, Fabi, and Corgnati 2016; Andersen, Olesen, and Toftum 2011; Haldi et al. 2017; Herkel, Knapp, and Pfafferott 2008; Martins and Carrilho da Graça 2017; Schweiker et al. 2012; Shi and Zhao 2016; Zhang and Barrett 2012).

\[
\text{logit}(p) = \log \left( \frac{p}{1-p} \right) = b_0 + b_1\theta_1 + b_2\theta_2 + \cdots + b_n\theta_n \tag{22}
\]

or

\[
p = \frac{1}{1 + e^{-(b_0+b_1\theta_1+b_2\theta_2+\cdots+b_n\theta_n)}} \tag{23}
\]

Anderson et al. (2011) employed logistic regression models based on long-term monitoring data. This revealed that outdoor temperature, indoor temperature, solar radiation, and indoor CO₂ concentration were the most important variables influencing window open/close behaviors. Laurent et al. (2017) investigated occupant window control behaviors in dormitory buildings and fitted multiple logistic regression models on
variables including indoor temperature, outdoor temperature, CO₂ concentration, and
time of the day. Haldi and Robinson (2009) argued that the probability of a window
being open increases with decreasing indoor temperature, based on the logistic regression
model fitted to 7 years of measurement data from Switzerland. They also proposed that
since a logistic regression model is more suitable for predicting the window states, a
Markov Chain model is more appropriate to predict the probability of taking action to
open or close the window. A Markov process model is comprised of a collection of
distinctive states and the transition probabilities between each pair of states. As shown in
Figure 4.1 below, the windows have two states: open and closed. The change of states
happens when an action is taken by the occupant, either open a closed window, or close
an opened window. The probabilities associated are P00 (keep the window closed), P01
(open a closed window), P11 (keep the window open), and P10 (close an opened
window). Haldi and Robinson also differentiate the scenarios when occupants arrived in
the room, were staying in the room, and left the room.

![Markov Chain Model of window status](image)

\[
\begin{bmatrix}
  P_{00} & P_{01} \\
  P_{10} & P_{11}
\end{bmatrix}
\]

Figure 4.1: Markov Chain Model of window status
Although spontaneous manual control is an alluring option because of its simplicity and low maintenance, it may not respond appropriately to complicated and dynamic external circumstances or the internal activities of occupants due to its inherent limitations. Because spontaneous occupant control generally shows sub-optimal performance in energy savings and thermal comfort, advanced control strategies have been proposed to better realize the natural ventilation potential in buildings.

Haldi and Robinson (2009) developed a series of logistic models for the prediction of actions on windows based on seven years of measurements of 14 south-facing cellular rooms. Among these models, which included univariate and multivariate models with transformed or untransformed variables, the model with outdoor air temperature $T_{out}$ and indoor air temperature $T_{in}$ had the highest statistical significance and was the model that best fit the data,

$$\text{logit}(p) = \log \left( \frac{p}{1-p} \right) = a + b_1 T_{out} + b_2 T_{in}$$

(24)

In the above equation, $p$ is the probability for using the natural ventilation, $a = 1.459$, $b_1 = 0.14477$, $b_2 = -0.1814$, $T_{out}$ is outdoor air temperature, and $T_{in}$ is the indoor air temperature (in °C).

To ensure the applicability of the above derived equation, extreme conditions were excluded when the outside dry bulb air temperature was $<10^\circ C$ or $>30^\circ C$ (Jeong, Jeong,
and Park 2016; Raja et al. 2001; Yao, Liu, and Li 2010) (in these conditions the windows were closed regardless of the p value). In addition, spontaneous control was only valid 7am-11pm daily, which excluded bedtime when occupants were considered unresponsive.

4.1.2 Rule-Based Heuristic Control

One of the standard control strategies for operable windows and HVAC system is the rule-based heuristic control. This category of methods can be generalized into the decision tree model, where each parameter is compared to a value threshold, and the action is chosen when the circumstance falls into one specific leaf node, as illustrated in Figure 4.2. Koinakis (2005) compared the impact on thermal load and zone air temperature of several natural ventilation schedules based on the operation seasons (winter, summer) and time of the day (24h NV, noon NV, night NV). Eftekhari and Marjanovic (2003) developed fuzzy rule-based control strategies with wind velocity, rain, outside temperature and inside temperature as criteria to choose the action under each pre-defined circumstance. Breesch, Bossaer, and Janssens (2005) described a rule-based night natural ventilation control based on the temperature on the previous day, the current inside and outside temperature, relative humidity, rain, and wind velocity.
The heuristic control strategy is based on the outdoor and indoor environments, such as air temperature, relative humidity, rain, wind, and time of day (Chen et al. 2018; Chen, Tong, and Malkawi 2017). The room ventilation switched to natural ventilation mode by opening the window and turning off the AC when the specific indoor/outdoor requirements were met. In general, the operation switches to natural ventilation mode when the indoor air temperature was higher than the lower bound of the thermal comfort range, the outdoor air temperature was higher than a not-too-cold temperature and lower than the upper bound of the thermal comfort range, and the dew point temperature was
lower than a chosen degree for the sake of humidity control. Whenever the windows are
opened, the mechanical ventilation and air conditioning system turn off temporarily. If
any of the criteria are not met, the windows are closed, and the mechanical system
reactivated.

The rule-based heuristic control is the most common strategy seen in natural ventilation.
It has a fairly low technical barrier when implemented in real system hardware. Although
optimality is usually not an inherent attribute, adequate performance is typically
expected.

4.1.3 Model Predictive Control

More advanced control strategies that optimize actions by simulating the system using a
physical/empirical model on a finite time-horizon have been widely studied (Afram et al.
2017; Li and Wen 2014a, b, 2016). This model-based control approach can be
generalized into model predictive control (MPC) as shown in Figure 4.3. Mahdavi and
Pröglhöf (2008) developed a nonlinear data-driven model for the prediction of ACH in
the case of wind-driven natural ventilation. Lee and Braun (2008) employed a simple
inverse building models trained with short-term data to make estimations on peak cooling
demand under different building temperature setpoints. Homod et al. (2014) developed
model guide for comparison (MGFC) to predict system performance and integrated
control optimization for both natural ventilation and HVAC systems. Yuan and Perez
(2006) employed multi-zone MPC to optimize the outside air volume in VAV systems to avoid overventilation (leads to wasted energy) and underventilation (leads to poor IAQ). Their results showed better performance compared to conventional PID controllers. Similarly, Freire et al. (2008) studied thermal comfort optimization and energy savings through MPC by manipulating the signals to the HVAC system. Kolokotsa et al. (2009) expanded the MPC to the HVAC system, windows, shadings, and electric lighting to maintain satisfactory indoor temperature, relative humidity, CO₂ concentration, and illuminance level.

![Figure 4.3: Model predictive control](image)

A well-designed MPC is guaranteed to outperform the heuristic control in terms of both thermal quality and energy saving. However, MPC is a more complicated strategy that requires an accurate mathematical model of the building system for prediction and optimization. This is not a trivial task, either by traditional system identification or
modern machine learning techniques. In addition, high demands for computational resources will also be required for the entire operation period.

4.1.4 Model-Free Control

Model-free control is able to find an optimal action policy without requiring a model of the building system. While treating the environment as an unknown black box, the algorithm is able to learn from the interaction with the environment. Reinforcement learning (RL) control, as shown in Figure 4.4, is an example of model-free control, and exhibits crucial advantages over heuristic control and MPC. Previous studies (Cheng et al. 2016; Dalamagkidis et al. 2007; Liu and Henze 2006a, b; Yang et al. 2015) have shown successful progress in the control of a variety of building systems through reinforcement learning. Dalamagkidis et al. (2007) performed an early investigation on the heating and cooling control in buildings through reinforcement learning and found that the RL controller is as good as the traditional fuzzy-PD controller. Yang et al. (2015) used the Q-learning method for the control of photovoltaic-thermal modules, which outperforms rule-based control over 10% in terms of meeting the heating demand and maintaining the optimal operating temperature. Cheng et al. (2016) also employed Q-learning to control blinds and lights to improve the building energy efficiency. This study will expand the reinforcement learning control in order to advance the control strategy of natural ventilation and achieve better comfort and energy efficiency.
4.2 Reinforcement Learning Control

4.2.1 Method

Q-learning is one popular method of model-free reinforcement learning. It maintains a Q-value table storing all state-action values $Q(s, a)$, which is the expected utility of taking a given action $a$ at the state $s$ and following the optimal policy thereafter (Sutton and Barto 2018). In this study, the reinforcement learning is implemented in Python using the simplified empirical building model of the building with single thermal zone and single-sided natural ventilation, as introduced in Chapter 3. The natural ventilation control problem is mapped into the Q-learning algorithm as follows:

States

States, $S$, represent the measured environment known to the agent at each specific time steps. The agent evaluates the states and makes decisions on which action to take.
accordingly. Each state is a vector of outside weather conditions and inside thermal conditions. The internal heat gain is treated as an unknown disturbance to the system.

Actions

In this natural ventilation control problem, the set of actions, \( A \), contains five possible actions \( a \), including [window open, AC on] (concurrent operation), [window open, AC off] and [window closed, AC on] (change-over operation), [window closed, AC off], and [window closed, heating on].

Reward

Reward \( r \) is the sum of weighted discomfort and electricity load at a certain state and choosing a certain action. The weight can be customized to reflect the priority of the user, either preferring minimized electricity consumption or thermal discomfort.

The algorithm purely learns from samples (Sutton and Barto 2018), namely

\[
Q(s, a) \leftarrow (1 - \alpha) Q(s, a) + \alpha [r + \gamma \max_{a' \in A} Q(s', a')] 
\]

(25)

\( Q \) value is the value for each state-action pair. The \( Q \) value of taking action \( a \) at state \( s \) is updated using the current \( Q \) value \( Q(s, a) \) and the sample data \([r + \gamma \max_{a' \in A} Q(s', a')]\), where \( r \) is the reward of this time step, \( \max_{a' \in A} Q(s', a') \) is the \( Q \) value of the resulting next state \( s' \) and taking the optimal action \( a' \). \( \alpha \in (0, 1) \) is the learning rate that determines to
what extent the newly acquired information will override the old information. In extreme cases, when \( \alpha = 0 \), the agent is not learning anything from the newly acquired samples; when \( \alpha = 1 \), the agent only considers the most recent information and has no memory of past experience. In the Q-learning algorithm, the learning rate starts from a non-zero value and gradually decreases to zero in order to reach convergence. \( \gamma \in [0,1] \) is the discount factor that determines the importance of future rewards. A low \( \gamma \) indicates the preference on current rewards, while a high \( \gamma \) focuses on long-term rewards. The algorithm is shown below in Figure 4.5, where each episode is the simulation period, and each step is the time step of the simulation. The \( \epsilon - greedy \) policy chooses the optimal action \( a = \arg \max_{a \in A} Q(s,a) \) with a high probability \( 1 - \epsilon \) and chooses a random action with a low probability \( \epsilon \). This is to balance exploitation (make the best decision given current information) and exploration (gather more information) (Sutton and Barto 2018).

**Q-Learning**

- Initialize Q(s,a) table
- for each episode do:
  - Initialize s
  - for each step of episode do:
    - Choose a from s using policy derived from Q (\( \epsilon \)-greedy)
    - Take action a, observe r, s'
    - \( Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a')] \)
    - \( s \leftarrow s' \)
- end for
- end for

Figure 4.5: Q-learning
4.2.2 Results

To test the performance of this reinforcement learning control algorithm, the advanced control strategy is applied to two representative climates, the hot and humid Miami, and the mild-to-warm Los Angeles. The control goal is to maintain an indoor temperature close to the constant optimal temperature of 24.5 °C and an indoor relative humidity under 70% day and night, all year round. According to the International Energy Conservation Code (IECC), local climates can be categorized into Zone 1 to Zone 8 based on cooling degree days and heating degree days, where Zone 1 is the hottest, and Zone 8 is the coldest. Under each zone, the climate can be further categorized into subzones A (Moist), B (Dry) or C (Marine), based on moisture content. In the United States, Miami, Florida falls into Zone 1A, and Los Angeles, California falls into Zone 3B.

As shown in Figure 4.6, Miami has hot and humid summers and short and warm winters. The wet season’s monthly average temperatures from May to October are above 25°C; the winter is mild with the monthly average temperature generally above 20°C, but with low-temperature events. The monthly average relative humidity all year round is close to or above 70%, with times of lower relative humidity during winter seasons. The extreme temperatures are 5°C as the coldest and 36°C as the hottest, and relative humidity ranges from 20% to 100%. Comparatively, Los Angeles has a much milder climate. The monthly average temperatures of the three hottest months, July, August, and September, are around 20°C, and the coldest months, December to March, are close to 14°C.
Although summer is the dry season and rainfall events are rare, the weather is usually moist and the relative humidity in Los Angeles is close to or above 70% all year round. The extreme temperatures are 6°C as the coldest and 32°C as the hottest, and relative humidity ranges from 10% to 100%.

![Figure 4.6: Temperature and relative humidity of Miami and Los Angeles](image)

The solar radiation and wind velocity summaries of two cities are shown in Figure 4.7. Direct normal radiation is used as the metric to illustrate the level of solar radiation. Miami has 1.45 MWh/m2 total direct normal radiation throughout the year. The average
monthly solar radiation is similar in each month, with a slightly lower level in November, December, and January, and a slightly higher level in March, April, and May. Los Angeles has 1.76 MWh/m² total direct normal radiation throughout the year. Average monthly solar radiation is lower in November, December, and January, and higher in months from April to August. As for wind velocity, Miami has a sea breeze and hurricane season, while Los Angeles experiences Santa Ana winds that are strong and dry. The central 50% of wind velocity in Miami spans from 2.6 m/s to 5.7 m/s, and the central 50% of wind velocity in Los Angeles spans from 2.1 m/s to 4.6 m/s.
Figure 4.7: Solar radiation and wind speed of Miami and Los Angeles

The simulation period is an entire year with hourly weather data. The time step is 20 mins as is the minimum HVAC and window operation interval. The HVAC systems are sized to meet the different cooling loads in two cities, while other building parameters remain the same. Both rule-based heuristic control and reinforcement learning control are simulated for comparison. The details of heuristic control are listed in Table 4-1.
<table>
<thead>
<tr>
<th>Table 4-1 Heuristic control rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>HVAC operation</td>
</tr>
<tr>
<td>Cooling</td>
</tr>
<tr>
<td>Heating</td>
</tr>
<tr>
<td>Off</td>
</tr>
<tr>
<td>Window operation</td>
</tr>
<tr>
<td>Open</td>
</tr>
<tr>
<td>Close</td>
</tr>
</tbody>
</table>

The heuristic control makes decisions on HVAC and window operation based on outdoor and indoor environmental conditions at each time step. The HVAC system will provide cooling when the indoor temperature $T_{in}$ is higher than the target temperature $T_{optimal}$, or when the indoor relative humidity $RH_{in}$ is higher than the relative humidity limit $RH_{limit}$, the HVAC system will provide heating when the indoor temperature $T_{in}$ is cooler than the lower bound of comfort range $T_{low}$, and the HVAC system will be turned off if the indoor temperature is within the comfort range and the indoor relative humidity is below the humidity threshold. The window control rules allow natural ventilation only when outside weather conditions are suitable. Specifically, the window will be opened if the outside temperature $T_{out}$ at that time step is lower than the target indoor temperature $T_{optimal}$, and higher than the cold air temperature limit $T_{cold}$ to avoid the uncomfortable draft. In addition, the outdoor dew point temperature $T_{dew}$ needs to be lower than dew point.
temperature limit $T_{limit}$ for humidity control. In the case study, $T_{optimal}$ is set to 24.5°C, $RH_{limit}$ is set to 70%, $T_{low}$ is set to 21°C, $T_{cold}$ is set to 18°C, and $T_{limit}$ is set to 17°C.

Two 24-hour periods are analyzed in detail to show the effects of reinforcement learning and heuristic control strategies. Figure 4.8 shows the outdoor temperature and relative humidity of a 24-hour period in February, in Miami. The daily temperature range is 13.3°C to 26.1°C; the daily relative humidity range is 22% to 97%.

![Figure 4.8: Miami 24-hour temperature and humidity graph](image)

The indoor temperature and relative humidity under both heuristic and reinforcement learning control strategies are shown in Figure 4.9. The indoor temperature under heuristic control shows wider variation and more extremes, with high of 28.3°C and low of 20.6°C. The relative humidity also rises above 70% for a fraction of time. On the
contrary, the indoor temperature under reinforcement learning shows a more moderate trend in general, with no incidence out of the comfort range of 21°C to 27°C. The relative humidity is also well maintained under the humidity limit of 70%.

The reinforcement learning control results in 19% energy savings from the HVAC system compared to heuristic control. As illustrated in Figure 4.9, heuristic control leads to some events of heating-cooling conflict (hour 2 and hour 24) when the system is trying to reach both the desired temperature and humidity goal. In addition, the heuristic control takes less advantage of natural ventilation to help with cooling when the outside temperature is higher than the NV threshold but lower than the indoor temperature (hour 10-15), and it over-exploits natural ventilation (hour 17-19) which leads to sharp indoor temperature drop and cold incidences below the comfort range.
Figure 4.9: Indoor temperature and relative humidity by two control strategies, Miami 24-hour period
The outdoor temperature and relative humidity of a 24-hour period in September, Los Angeles is illustrated in Figure 4.10. The daily temperature range is 18.9°C to 24.4°C; the daily relative humidity range is 64% to 93%.

![Figure 4.10: LA 24-hour](image)

The Los Angeles 24-hour period analysis is shown in Figure 4.11. The indoor temperature under heuristic control shows clear diurnal swings, with highs of 28.1°C and low of 20.5°C. The relative humidity is close to the humidity limit of 70% before hour 7 and hour 18. On the contrary, the indoor temperature under reinforcement learning is well maintained between 23.2°C and 26.6°C, with no incidence out of the comfort range. The relative humidity is well maintained under the humidity limit of 70% for the entire 24-hour period.
The reinforcement learning control leads to 23% less energy consumption of the HVAC system compared to heuristic control. As illustrated in Figure 4.11, the heuristic control takes less advantage of natural ventilation to help with cooling when the outside temperature is higher than the NV threshold but lower than the indoor temperature (hour 10-17), and it over-exploits natural ventilation in the night which leads to a sharp indoor temperature drop and cold incidences below the comfort range.
Figure 4.11: Indoor temperature and relative humidity by two control strategies, LA 24-hour period
The annual simulation results of Miami using reinforcement learning control is shown in Figure 4.12. As illustrated, the indoor temperature is well maintained within the comfort range all year round, and the relative humidity is below the humidity limit most of the time, except for a few instances during winter. These are due to the fact that dehumidification is achieved through cooling, which is not operated in the winter.

![Image of annual simulation results](image)

**Figure 4.12: Miami annual simulation results by RL**

In comparison, the annual simulation results of Miami using heuristic control are shown in Figure 4.13. In general, the indoor temperature is also maintained within an acceptable range, but not as well as the case using reinforcement learning control. More frequent cold incidences are spotted in the winter season, as well as several hot incidences in the summer when the system fails to maintain optimal indoor thermal comfort. In addition, there are more humid events in the cooler season when the relative humidity is above the humidity limit.
The annual simulation results of Los Angeles using reinforcement learning control is illustrated in Figure 4.14. The indoor temperature is well maintained within the comfort range all year round. The relative humidity is also below the humidity limit for most of the time.

Figure 4.14: LA annual simulation results by RL
Figure 4.15 shows the annual simulation results of Los Angeles using heuristic control. As demonstrated, there are more substantial hot events during spring, summer and autumn, when the indoor temperature is noticeably higher than the optimal indoor temperature when HVAC system fails to fully maintain the indoor environment.

Moreover, over-cooling is spotted during the summer when the indoor temperature is too cold due to the HVAC system trying to lower the humidity, which is above the threshold.

Figure 4.15: LA annual simulation results by heuristic control

The summarized comparison of results through heuristic control and reinforcement learning control is shown in Figure 4.16. As demonstrated, RL leads to fewer HVAC operation hours in both Miami and Los Angeles. In Miami, heuristic control leads to 4796 hours of cooling and heating hours, while RL control results in 4189 hours of cooling and heating, which is 607 hours, or 13% fewer. In Los Angeles, heuristic control
leads to 3994 hours of cooling and heating, while RL control results in 3095 hours of cooling and heating, which is 899 hours, or 23% fewer.

The reinforcement learning control also shows superior results in maintaining the indoor temperature within the comfort range. The heuristic control of the Miami case results in 325 discomfort degree hours when the indoor temperature is either higher than 27°C or lower than 21°C. On the contrary, there are only 124 discomfort degree hours under reinforcement learning control, which is 62% less. The Los Angeles case shows 328 discomfort degree hours when the indoor temperature is beyond 21°C and 27°C under heuristic control. The reinforcement learning control reduces the discomfort degree hours to only 64, which is 80% fewer.

Reinforcement learning also shows better results on indoor humidity control. In Miami, there are 150 hours annually when the indoor relative humidity is higher than 70%, while there are only 56 hours of high humidity under reinforcement learning control, which is 63% lower. In Los Angeles, there are 310 hours annually when indoor relative humidity is higher than 70%, while there are only 71 hours of high humidity under reinforcement learning control, 77% lower.
The reinforcement learning control demonstrated significant improvement over heuristic control in the two case studies presented, that reduces the cooling and heating energy by 13% and 23%, lowers the discomfort degree hours by 62% and 80%, and decreases the high humidity hours by 63% and 77%.

The weight of energy consumption and thermal discomfort in reinforcement learning control can be adjusted to reflect the user’s priority and preference thus is flexible and able to further reduce the HVAC system energy consumption or thermal discomfort. The control target in this study is to maintain constant thermal comfort 24/7. The adaptive thermal comfort that varies seasonally or diurnally is subject to future study.

4.2.3 Discussion

The heuristic control algorithm adopted in this study is only a common rule-based control scheme without guaranteed optimality. There may exist a fine-tuned heuristic control that
performs better in each of these two specific cases. However, the search for such an
optimal rule-based control is a significant endeavor that usually required looking at the
option on a case-by-case basis, with a growing decision tree that takes many parameters
and conditions into consideration, which eventually develops into numerous specific
scenario-decision pairs. Reinforcement learning control, on the contrary, is a model-free
algorithm and is able to find the optimal control by only specifying the desired goal and
cost function.

The reinforcement learning control only needs a little knowledge for decision makings,
such as outside temperature, solar radiation level, wind speed, and indoor temperature in
this study. It maintains the indoor thermal comfort without requiring internal gain data as
an input. Reinforcement learning control has several other advantages that outperform the
traditional rule-based heuristic control. The reinforcement learning control can be applied
to different buildings and various climates by self-tuning over simulation or real-world
operation. It is usually guaranteed to achieve optimal control through constant self-
advancement. In addition, the reinforcement learning control also adapts to stochastic
occupancy and occupant behaviors, which is hard to accommodate by heuristic control.
Reinforcement learning control is an intelligent approach that continuously tunes its
control behaviors. The controller better learns about the occupant’s preference over time,
thus leading to a much better relationship between human and machine and higher
occupant satisfaction.
The limitation of reinforcement learning control is that it requires a sufficiently long learning period before it can make optimal decisions under various conditions. This prerequisite may cause difficulty in real-world practice, but it can be alleviated by the assistance of building simulations.
Optimal control of natural ventilation consists of two essential components: algorithm and implementation. Chapter 3 and Chapter 4 have discussed how to develop an optimal control algorithm, and this Chapter investigates the issues related to the implementation of control algorithms in practice. Specifically, the effectiveness of different levels of automation is evaluated under distinct climates. The characteristics and performance of each scheme are also presented in the Chapter, along with the discussion of the implications on the building system selections.

5.1 Manual, Hybrid, Automatic

Multiple levels of automation can be found in practice, which ranges from the most common spontaneous manual control to very advanced fully automatic systems. Details regarding spontaneous manual control have been discussed in Chapter 4.1. Although manual control is an alluring option because of its simplicity and low maintenance, it may not respond appropriately to complicated and dynamic external circumstances or internal activities of occupants due to its inherent limitations. Because spontaneous occupant control generally shows sub-optimal performance in energy savings and thermal
comfort, advanced control strategies have been proposed to better realize the natural ventilation potential in buildings.

Implementing an advanced window-control strategy requires either informed occupant control or fully automatic window systems. With an informed occupant control system, the signal to either open or close windows notifies the corresponding occupant to take appropriate action. Ackerly and Brager (2013) proposed and conducted an experiment using signaling systems to inform occupants when to open and close the windows to achieve better utilization of natural ventilation. In their experiment conducted in several office buildings in California, several types of signaling system were installed to inform occupants of the right actions to take on window control. From their findings, it was found that there was a substantial number of people who were unwilling to following the signals regularly, and in worst cases, ignored the signals altogether.

The advanced natural ventilation control can also be implemented by fully automatic window systems. With fully automatic window systems, occupants still have the right to override the control, but they will not need to take any action during daily operation. Theoretically, the fully automatic window/HVAC control system should be the best option to maximize the potential for natural ventilation. However, in real-world projects, the extra initial cost and high maintenance of the system are major hurdles that stall wide adoption of the technology. In addition, there is no easily accessible comparison to show building owners and developers how much of a performance boost they can expect from
the advanced technology to justify their investment. Therefore, it is an open question to investigate the effectiveness of automatic window control systems compared with spontaneous occupant manual control and informed occupant control.

5.2 Model Predictive Control

Model Predictive Control (MPC) (Rawlings and Mayne 2009) optimizes the operation of natural ventilation by finding the best immediate action in a series of exhaustive testing scenarios [(open window, turn on AC), (open window, turn off AC), (close window, turn on AC), (close window, turn off AC)] through parallel simulations. The best action at each time step balanced both the short-term and long-term thermal comfort with energy consumption by simulating the physics model of the dynamic system on a multiple-step time horizon from the current state. In this case study, thermal comfort was given higher priority than energy consumption. If multiple actions all led to a comfortable indoor temperature, the action that resulted in minimum energy consumption was preferred.

\[
\bar{a}_t = \arg\min_{\bar{a} \in A} (J_t)
\]

(26)

given

\[
J_t = \sum_{i=t}^{t+n} \omega_d \max\{T_{in,i} - T_{up}, 0, T_{low} - T_{in,i}\} + \sum_{i=t}^{t+n} \omega_e C_i
\]

(27)
and

\[ T_{in,t+1} = f(T_{in,t}, \overline{a_t}, \Phi_t) \]  

(28)

In the above equations describing this specific control strategy, \( \overline{a_t} \) is the action selected for timestep \( t \), \( A \) is the set of all possible actions, \( J \) is the cost function to be minimized, \( \omega_d \) is the weighting coefficient penalizing discomfort, \( \omega_e \) is the weighting coefficient for energy consumption, \( T_{in,t} \) is the indoor air temperature at time \( t \), \( T_{up} \) and \( T_{low} \) are the upper and lower threshold of the comfort range, respectively, \( C_t \) is the operation status of HVAC at time \( t \), and \( \Phi_t \) is the comprehensive building and weather conditions at time \( t \).

5.3 Climates for Case Study

To study the effectiveness of different levels of automation in NV control, the experiment is conducted in five Chinese cities from very distinct climates: Harbin (Severe Cold), Beijing (Cold), Shanghai (Hot Summer, Cold Winter), Guangzhou (Hot Summer, Warm Winter), and Kunming (Mild) (Figure 5.1). The annual discomfort degree hours accumulated when the indoor temperature dropped below 19˚C (as cold degree hour) or rose above 26˚C (as hot degree hour).
Figure 5.1: Monthly average, daily low, and daily high temperature of the five cities

The computational environment is Python, and the target building is the generic building with single thermal zone and single-sided natural ventilation simulated with the neural network model, as discussed in Chapter 3. Measured information included the duration of natural ventilation throughout the year, the total daily operation frequency, and the point of time when actions were taken. The performance of the studied control strategies was quantified through the cumulative distribution of the indoor air temperature, the total annual discomfort degree hours (>26°C or <19°C), and the cooling energy saving percentage compared to the Non-NV baseline case.

5.4 Automatic Compared with Spontaneous

The duration of natural ventilation and window operations are analyzed in this section for fully automatic control cases (MPC and heuristic control) and spontaneous occupant control cases.
5.4.1 The Duration of Natural Ventilation

The duration of natural ventilation of a fully automatic MPC and heuristic control, along with the spontaneous control in the five studied cities are illustrated in Figure 5.2. In the severely cold (Harbin) and cold (Beijing) climates, the opportunities for natural ventilation were prohibited in the winter, under all three control strategies. In the summer of the cold-winter-hot-summer (Shanghai), and warm-winter-hot-summer (Guangzhou) climates, nearly zero NV was allowed by the heuristic control, while occasional NV was instructed by MPC depending on the weather of the day, and consistently substantial duration of natural ventilation under spontaneous control. In the temperate climate (Kunming), the presence of natural ventilation could be found throughout the year under spontaneous control, but it was almost none or very limited in the winter by the heuristic control and MPC, respectively.

In general, MPC showed more granularity when compared to the spontaneous control and a wider span of natural ventilation seasons when compared to the heuristic control. The MPC also took advantage of the natural ventilation more conservatively, as compared to the heuristic control and spontaneous control in which 10+ hours per day of natural ventilation was common during natural ventilation seasons. The logic behind MPC’s shorter daily natural ventilation durations was to avoid over-ventilation while taking full advantage of free cooling by allowing just an adequate amount of natural ventilation.
Figure 5.2: The daily duration of natural ventilation throughout the year in the five cities
5.4.2 The Frequency of System Operation

The daily system operation frequencies of MPC, heuristic control, and spontaneous control in the five studied cities are illustrated in Figure 5.3. The occurrences of zero daily operation when the natural ventilation was prohibited by inclement weather (either too hot or too cold) are not shown in the figure. The total number of window operations in five cities over the course of an entire year was 3394 – 6996 with MPC, 560 - 1636 with heuristic control, and 1380 - 2728 with spontaneous control.

Compared to heuristic and spontaneous control, MPC had a much higher frequency of window-HVAC control operations. The median daily operation frequencies were 18, 18, 21, 20, and 19 for Harbin, Beijing, Shanghai, Guangzhou, and Kunming, respectively, and the 80th percentile daily operation frequencies were 27, 25, 34, 33, and 28 for the same five cities in the corresponding order. Such high daily operating frequencies implied a very low possibility for sufficiently functional manual control by occupants who needed to follow the MPC signals.

In general, the observed frequencies of window-HVAC control operations that followed the heuristic control strategy demanded a fairly light duty on the mechanical actuation system compared to MPC. Excluding the zero-operation days, more than one-third of the time only two daily operations were expected in all five cities. The median daily operation frequencies were 3, 3, 4, 2 and 4 for Harbin, Beijing, Shanghai, Guangzhou,
and Kunming, respectively, and the 80th percentile daily operation frequencies were 6, 6, 9, 7, and 12 for the same five cities in the corresponding order.

In spontaneous control cases, the frequency of daily window operations was ≤14 for all five cities. The median daily operation frequencies were 8, 6, 8, 8, and 8 for Harbin, Beijing, Shanghai, Guangzhou, and Kunming, respectively. The 80th percentile daily operation frequency was 10 for all five cities. These frequencies were consistent with reasonable human behavior patterns.

Figure 5.3: The daily frequency of system operations by MPC, heuristic control, and spontaneous control in the five cities

5.4.3 The Daily Distribution of System Operation

Figure 5.4 illustrates when the window-HVAC operations take actions on radar charts. A day is divided into six blocks of four-hour-duration periods: the morning (6am-10am), noon (10am-2pm), afternoon (2pm-6pm), evening (6pm-10pm), night (10pm-2am), and late night (2am-6am). The higher rate of occurrence shows further towards the edge,
while the center represents zero operations. Under MPC, most of the window-HVAC control actions were taken during the daytime, and almost none were taken during the sleeping time from 10 pm to 6 am. This was advantageous for minimal occupant disturbance, maintenance, and troubleshooting. The spontaneous control scheme showed a uniformly dominant pattern of a higher rate of the window opening in the early morning and window closing at night, which agreed with routine habits of occupants. Compared to MPC and spontaneous control, the heuristic control was more heterogeneous across the five cities, and with the substantial occurrence of operations during the night. The cities in colder climates employed natural ventilation mostly during the warmer season, and Harbin and Beijing demonstrated a higher rate of the window opening in the early morning and a higher rate of window closing at night. This was mainly due to the diurnal temperature swings to take advantage of the warmer daytime air and to avoid the chilling night air. For cities in warmer climates, a higher occurrence of operations occurred late at night to benefit from the breezy, cool air. The city in a hot climate where natural ventilation in the winter was possible, Guangzhou, showed a high rate of window opening during noon to capture the warmth from the winter sun. For the city in a temperate climate, Kunming, the particularly high operation rate during the late night was due to the slight fluctuation in outside air temperature around the borderline threshold set in the heuristic control, which led to repetitive opening and closing. This is one of the major weaknesses of rule-based control schemes with hard-cut criteria.
Figure 5.4: Time of the day for system operations by MPC, heuristic control, and spontaneous control in the five cities
5.4.4 Detailed Investigation

To better understand the difference among three control schemes, the 24h period of May 27th in Kunming was selected for closer observation. The outside air temperature was 15-21°C during this period, the indoor air temperature was within the comfort range of 20-25°C under both MPC and heuristic control, and the indoor air temperature dropped below 20°C for 5h in the morning under spontaneous control (Figure 5.5). Specifically, MPC instructed pulse natural ventilation to occur at different times during the day, which maintained indoor thermal comfort effectively. The heuristic control instructed mechanical cooling to occur around noon to keep the indoor air temperature below the upper bound of the comfort range, while the outside air temperature was cool but below the 18°C threshold indicated by the heuristic control criteria. During the night, due to prolonged natural ventilation periods, the indoor air temperature dropped below the lower bound of the comfort range, which triggered the mechanical heating system. For the spontaneous control, the long duration of natural ventilation in the morning resulted in cold indoor air temperature that triggered the heating system, which ran for 5h concurrently with opened windows.
The limitation of the heuristic control in this study was that it had no ability to consider future weather conditions and predicted indoor thermal conditions. For example, the threshold of 18°C to allow natural ventilation aimed to prevent over-cooling by extended periods of natural ventilation when it was cold outside, but at the same time, it lost some opportunities for natural ventilation. Although the heuristic control can be improved to cover such scenarios with more sophisticated criteria, it almost certainly will lead to more complicated case-by-case algorithms that are difficult to manage and to debug. For the spontaneous control, the concurrent heating and natural ventilation are commonly seen in the real world, as reported by Laurent et al (2017).
5.5 Automatic, Informed, and Spontaneous Control

The indoor air temperature, thermal discomfort degree hours, and energy saving performance of fully automatic control cases, spontaneous occupant control case, and informed occupant control cases are analyzed in this section.

5.5.1 Indoor Air Temperature

The cumulative distribution of indoor air temperature under each control schemes was shown in Figure 5.6. A steep slope of the curve indicates a high occurrence of the indoor air temperature within that corresponding temperature range on the x-axis, and a flat slope of the curve indicates a low occurrence of the indoor air temperature within that range on the x-axis. The target temperature range of 20-25°C is shaded in gray, and the one-degree leeway (i.e., 19-20°C and 25-26°C) is shown in a lighter shade of gray. The portion of the curve that is outside of the gray area implicates uncomfortable thermal conditions.

For the Non-NV baseline case, the plot shows that most of the time the indoor air temperature was around the lower bound (20°C) and higher bound (25°C) of the target range, with very steep curves around two ends and a flat section in-between. For the fully automatic cases, the indoor temperature was well maintained within the comfort range by both MPC and heuristic control in all five cities, which resulted in zero discomfort degree hours.
For spontaneous control, indoor air temperature fluctuated. A significant amount of discomfort time was observed in all five cities. Occurrences of hot temperature were seen in Harbin, Beijing, Shanghai, and Guangzhou with indoor temperatures that exceeded the upper limit of the comfort range but were generally below 28°C. Occurrences of cold temperature incidences prevailed in all five cities with indoor air temperatures below the lower limit of the comfort range, and there were several instances when the indoor temperature dropped to 15°C.

The four-time fixed-schedule daily operations that followed the signals from either MPC or the heuristic control were insufficient to maintain an acceptable indoor temperature. Specifically, the indoor air temperature was above 26°C for 10-30% of the time in the five cities. Even worse, the excessive heat incidences when indoor air temperature rose above 30°C were also seen in all five cities (i.e., read from the plot that the curves did not reach 100% cumulative frequency at 30°C).

The stochastic occupant response cases also resulted in poorly maintained indoor air temperatures with undesirable hot and cold occurrences. In general, for both heuristic control signal and MPC signal cases, the ability to maintain a desirable indoor temperature decreased with the diminishing probability of occupants’ compliance with the signals. Therefore, cases where the occupants only had a 20% probability of following a system control signal led to the worst performance, which resulted in a significant number of hot conditions and occasional excessive heat occurrences above 30°C.
Figure 5.6: The cumulative distribution of indoor air temperature under all 12 control schemes in the five cities
5.5.2 Discomfort Degree Hours

The number of total discomfort degree hours of each city under various control schemes is illustrated in Figure 5.7. As already mentioned, the indoor air temperature was maintained perfectly in the Non-NV and two fully automatic control cases (MPC and heuristic) and, therefore, no discomfort degree hours were seen in any of the cities.

Unlike the perfectly maintained indoor temperature in fully automatic cases, spontaneous control resulted in a significant number of discomfort degree hours. The number of hot degree hours when the indoor temperature was above 26°C were 199, 362, 519, 417, and 19 for Harbin, Beijing, Shanghai, Guangzhou, and Kunming, respectively. The cold degree hours when the indoor temperature was below 19°C were 643, 767, 1121, 1077, and 1158 for the cities in that same order.

Similarly, due to its poor performance in indoor temperature control, both fixed schedule cases (the heuristic control signals and MPC signals) led to a considerable number of discomfort degree hours, especially hot degree hours, in all five cities. For the MPC signal case, Harbin had >1000 hot degree hours, Beijing, Shanghai, and Kunming had approximately 2000 hot degree hours, and Guangzhou had >3000 hot degree hours. For the heuristic control signal case, Harbin had >1000 hot degree hours, Beijing and Kunming had approximately 2000 hot degree hours, Shanghai had >3000 hot degree hours, and Guangzhou had >4000 hot degree hours.
For the stochastic occupant response cases, performance decreased with the diminishing probability of the occupants following the signals and taking actions in both MPC and heuristic signal cases; this was especially true when a dramatic plunge in the performance of thermal comfort and energy saving occurred when the chance of compliance dropped from 50% to 20%. The tested cases with total annual discomfort degree hours <500 were R_MPC_80% (stochastic informed control with 80% of chance following MPC signals) in Beijing, R_MPC_80% and R_MPC_50% in Harbin, and for all probability cases except for R_Heu_20% (stochastic informed control with 20% of chance following heuristic signals) in Kunming. With a more lenient threshold of 1000 discomfort degree hours, the cases that met the standard were all probability cases except for R_Heu_20% in Harbin and Kunming, R_MPC_80% and R_MPC_50% in Beijing and Shanghai. All test cases in Guangzhou showed extensive warm periods with 1147-2989 hot degree hours.

Figure 5.8 illustrates the annual percentage of total discomfort time in each city under 12 control schemes. Except for Non-NV and fully automatic cases (both MPC and heuristic control) where no discomfort time was found, Guangzhou showed the highest percentage of discomfort time (9-29%), followed by Shanghai (6-21%), and Beijing (3-20%). Harbin and Kunming showed the lowest percentage of discomfort time, 1-12% and 0.1-14%, respectively.
Figure 5.7: Discomfort degree hours under all 12 control schemes in the five cities

Figure 5.8: Annual percentage of total discomfort time under all 12 control schemes in the five cities
5.5.3 Energy Consumption

The cooling energy saving percentage of each city under all studied control schemes are summarized in Figure 5.9. Compared against the Non-NV baseline, the fully automatic system with either MPC or heuristic control showed significant energy savings. In all five cities, MPC demonstrated superior performance with 5-17% more energy saving compared with the heuristic control. Kunming, the city located in a temperate climate showed the highest cooling energy saving of 66% with heuristic control and 80% with MPC. Harbin, the city located in a severe cold climate showed a high energy savings of 38% with heuristic control and 50% with MPC. Beijing (cold climate), and Shanghai (hot-summer, cold-winter) showed a moderate cooling energy savings of 22% and 13% with heuristic control, and 27% and 31% with MPC, respectively. Guangzhou, the city located in the hot-summer-warm-winter climate showed a 10% cooling energy savings by heuristic control and 17% with MPC.

The spontaneous control showed inferior energy performance compared with fully automatic cases. It resulted in 17.9%, 17.5%, 18.6%, 17.2%, and 15.7% less energy saving compared to MPC in the five cities respectively, and 5.9%, 12.4%, 1.3%, 9.8%, and 1.6% less compared to the heuristic control for the same corresponding cities. The energy performance of spontaneous control was particularly unsatisfactory in Guangzhou, where there was 0% energy saved.
Compared to fully automatic cases, the four-time daily operation that followed the heuristic control or MPC signals showed a dramatic decrease in cooling energy saving. The fixed schedule operation that followed the MPC signal resulted in 15%, 19%, 13%, 15%, and 11% reduction in energy savings in Harbin, Beijing, Shanghai, Guangzhou, and Kunming, respectively, compared with its fully automatic counterpart. The fixed schedule operation that followed the heuristic control signal resulted in 10%, 12%, 13%, 12%, and 18% reduction in energy saving compared to its fully automatic counterpart for the same corresponding cities. Specifically, the four-time daily operation that followed the heuristic control signal resulted in almost no cooling energy saving in Shanghai and even higher energy consumption in Guangzhou compared to the Non-NV baseline case.

The energy saving performance of the stochastic occupant response control decreased with the diminishing probability of following the signals in all five cities. All stochastic cases (R_Heu_80%, R_Heu_50%, and R_Heu_20%) that followed the heuristic control signal in Guangzhou resulted in more energy consumption than the Non-NV case. The same was true for Shanghai R_Heu_20% case.
5.6 Summary

The fully automatic control with mechanical window actuators and coordinated window-HVAC control system demonstrated substantial cooling energy savings and maintained the indoor temperature in all five studied cities. Specifically, the control system instructed by the heuristic criteria resulted in energy savings of 10%-66%. The control system instructed by the model predictive control algorithms showed higher energy savings of 17%-80%. The indoor air temperature was within the comfort range year-round. No thermal discomfort degree hours were found in any of the studied cities with the fully automatic control systems.
The total number of window operations annually was approximately 5,000 for MPC cases and approximately 1,000 for the heuristic control cases. The most common daily operation frequencies were 2-30 in MPC cases, and twice-daily for the heuristic cases. The operation time was mostly during the day in the MPC cases and during the morning, evening, and late night in the heuristic control cases. Consequently, the model pre-dive control could only be realized by an automatic actuation system due to its high operating frequency. Similarly, the heuristic control also provided little opportunity for full manual control due to the inconvenient time of day when operations were necessary.

The spontaneous occupant control that was driven by thermal comfort was not able to maintain the indoor temperature within the comfort range at all times. Both hot and cold occurrences were seen in all five cities. Compared to the fully automatic control, the spontaneous occupant control showed lower cooling energy savings by 1%-12% and 16%-18% compared with the heuristic control cases and MPC cases, respectively.

Two types of informed occupant control were explored in this study. For the four-times-daily fixed-schedule control, both cases that followed the heuristic control signals or MPC signals showed unsatisfactory results in indoor thermal comfort and energy performance. Hot conditions, especially when indoor air temperature rose above 30°C were not rare in all five cities regardless of the type of signals sent, which resulted in a large number of discomfort degree hours. In addition, the fixed schedule operation also led to 10% - 19% lower energy saving compared to the fully automatic cases. In
Shanghai and Guangzhou, it resulted in near zero energy savings or even higher energy consumption.

For the stochastic occupant response cases, performance decreased with the diminishing probability of following the signals in both the heuristic control and MPC cases. In particular, there was a dramatic plunge in the performance of thermal comfort and energy saving when the chance of compliance dropped from 50% to 20%. Overall, the MPC signal cases showed better performance in thermal comfort and energy saving compared with the heuristic cases. The higher energy consumptions compared to Non-NV baseline were seen in all three stochastic scenarios following heuristic signals in Guangzhou, and the case of 20% chance following the heuristic signals in Shanghai.

Although the stochastic occupant control with a high probability of occupant compliance showed a better performance than the fixed-schedule control, 80% and 50% stochastic control that followed the MPC signals still resulted in a very high frequency of daily operations that were required of the occupants. Both forms of informed occupant control, either with the fixed schedule or with a probability of proper response, inevitably produced a considerable number of discomfort degree hours. In real-world practice, this could bring increased frustration and distrust towards the system by the occupants, which could lead to a growing reluctance to respond and, eventually, to ignore the signals altogether and to convert to 100% mechanical ventilation instead.
Chapter 6: Conclusion and Discussion

Buildings that rely on either natural ventilation or mixed-mode ventilation have demonstrated significant potential for energy savings and improvements of indoor environmental quality in favorable climatic conditions. As climate varies widely from region to region in the world, this research estimates the natural ventilation potentials across Africa, Asia, Europe, North America, Oceania, and South America, using the approach of NV hour and expected energy savings. According to this analysis, subtropical highland climates show a significant number of NV hours due to year-round mild weather. The Mediterranean climate also greatly favors natural ventilation. In addition, greater-than-expected natural ventilation potentials are displayed in the desert climate, such as in the Middle East and Central Australia. Despite high heat during summer days, the temperature can drop considerably to a comfortable level at night due to radiant sky cooling. For example, a good ventilation strategy in this region is to shade and insulate the house against the heat of the day and flush out any stored heat during the cooler nights. The region with the least natural ventilation potential is Southeast Asia, which displays practically no NV hours, as a result of hot and humid weather throughout the year. As different climates pose different environmental challenges, the design of
natural ventilation systems can be customized to accommodate local climatic features with the goal of reducing energy consumption and improving indoor environmental quality. The results here provide valuable information to architects and policymakers seeking effective ventilation designs that meet local climatic conditions. The analysis of natural ventilation potential in China integrated the factors of ambient air quality and the total floor area of office buildings in each city into the evaluation of energy savings and carbon emission reductions. The results revealed that the utilization of natural ventilation had been hindered by air quality issues associated with the emissions from coal-fired power generation and the manufacturing industry, especially in North China.

The successful implementation of natural ventilation relies on numerous factors. However, in a given case, only a few features are subject to change, and the most critical element is the control of the HVAC and window system. In practice, natural ventilation is usually combined with mechanical heating and cooling system to achieve lower energy consumption and higher thermal comfort. In these cases, the control of the operable windows and the synergy with the HVAC system becomes an important topic to be studied when discussing the implementation of natural ventilation. The reinforcement learning control introduced in this study demonstrates significant improvement over heuristic control in two case studies, which is able to dramatically reduce the energy requirement for cooling and heating, lower the discomfort degree hours, and decrease the high humidity hours. Reinforcement learning control has several other advantages that outperform the traditional rule-based heuristic control. The reinforcement learning
control can be applied to different buildings and various climates by self-tuning through simulation or real-world operation. It is usually guaranteed to achieve optimal control through constant self-advancement. In addition, the reinforcement learning control also adapts to stochastic occupancy and occupant behaviors, which is hard to accommodate by heuristic control. The limitation of reinforcement learning control is that it requires a sufficiently long learning period before it can make the optimal decision under various conditions. In real-world practice, this prerequisite may cause difficulty but can be alleviated by the assistance of building simulations.

In terms of levels of automation regarding the control of natural ventilation, different strategies were evaluated in various climates. The superior performance of the fully automatic natural ventilation control system was confirmed by the study, especially in challenging climates where improper control of windows would induce discomfort and excessive energy consumption. Nevertheless, the informed occupant manual control instructed by the signals failed to show significant improvement compared with the spontaneous occupant control. The overall goal of advanced natural ventilation control is to balance initial investment, maintenance cost, annual energy saving, and occupant satisfaction. This research illustrates that fully automatic window-HVAC actuation system equipped with a computational backend is beneficial to the building energy and thermal performance.
A variety of detailed aspects of this study can be further investigated and are subject to future work. For example, the global natural ventilation potential can be re-evaluated under different scenarios, including various NV control strategies and levels of automation. Regarding the data-driven model for simulating natural ventilation process, further experiments can be conducted to analyze the relative importance of input variables. The findings can be useful to the decision makings on the minimum numbers and types of sensors to be installed in a building to provide sufficient information for modeling. In addition to the feed-forward neural network, other NNs such as recurrent neural network (including gated recurrent units and long short-term memory) are worth investigating, especially for buildings with a substantive amount of thermal mass, in which cases thermal responses may take a longer time and expected behavior could be delayed. Further improvement can be also made on the model-free reinforcement learning control. In this study, the Q values for each state-action pair are stored in the tabular form. In future studies, when state space and action space become high dimensional and continuous values are preferred, value function can be estimated through deep learning (for example neural networks). In such cases, the reinforcement learning control may equip with better capacity for more complicated and more granular control tasks.
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