Towards Comfortable and Walkable Cities:
Spatially Resolved Outdoor Thermal Comfort Analysis Linked to
Travel Survey-based Human Activity Schedules

by

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Submitted to the Department of Architecture
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Abstract

Outdoor thermal comfort can influence human powered mobility choices, namely walking and biking. As more people are living in cities than ever before in human history, the urban environments we erect and populate are unfortunately contributing to phenomena such as climate change, which is negatively affecting urban life. Our understanding and creation of comfortable environments that are conducive to human powered transport can significantly influence carbon emissions, energy efficiency, and human health, as well as have considerable economic and time saving impacts. With the continuous integration of computer-based decision support systems in design processes, there is a need for developing simulation frameworks that aid architects, urban designers and planners in making informed sustainable design decisions. The focus of this work, therefore, is the development of computer tools and workflows that promote the design of walkable and bikeable cities through comfortable outdoor spaces. This dissertation presents firstly, a simulation methodology, verified through a validation experiment conducted on the MIT campus, for spatially and temporally resolved Mean Radiant Temperature (MRT) simulation and consequent outdoor thermal comfort assessment. Secondly, Building Performance Simulation (BPS) occupancy and trip schedules generation through data clustering techniques applied to activity-based travel surveys. An office modeling case study is presented through extracted occupancy scenarios, to compare simulation accuracy against current practice standards. Finally, an assimilation of both workflows is presented to generate “Trip Comfort” metrics for human powered mobility assessment, in the context of existing or newly designed urban structures.

Thesis supervisor: Christoph F. Reinhart

Title: Associate Professor of Building Technology
I dedicate this work to my companion, best friend, and serenity, Nadia.
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Chapter 1. *Introduction*

Man builds machines to save time and effort. The advent of automobiles came with these two particular aims; traveling time distances from point A to point B. However, the expense of convenience in leading an automobile-centric lifestyle causes hazardous airborne pollution and an increase in Green House Gas (GHG) emissions (Chertok, Voukelatos, Sheppeard, & Rissel, 2004), as well as wasting non-renewable energy and financial resources on fuel and maintenance. In addition, even though the goal was to save time and effort, driving can waste time through traffic congestion in urban areas, which leads to less productivity and negative economic impacts (Calfee & Winston, 1998) along with an increase in urban noise pollution (Jakovljević, Belojević, Paunović, & Stojanov, 2006). With this myriad of undesirable effects caused by automobile-dependency, practices of sustainable urban transportation have shifted focus back to public transport as well as human-powered transportation. Adopting walking and biking in personal mobility counters most, if not all, previously mentioned negative effects of being car-centric, with the addition of contributing to better human health (Lawrence, et al., 2006). As one goes about daily activities curtailed by life in the city using human-powered means of transportation, the prevailing microclimate starts to have a vital role in personal mobility choices. A recent study that surveyed a nationally representative sample found that the primary smart phone application utilized in the United States is the weather forecast (Online Publishers Association, 2012). Urban dwellers check the weather daily to decide on clothing options, as well as mobility choices. If architects, urban designers and planners understand what activity patterns inhabitants engage in when living in cities, as well as how the built environment contributes to better outdoor thermal comfort conditions and microclimates that promotes active, human-powered mobility, then they would help in the creation of sustainable, walkable and bikeable neighborhoods and cities.

This introductory chapter sheds light on how cities are growing across the globe, and motivates the need of using computer simulation as an aid for designers in making informed design and planning decisions. Focus is then given to transportation energy and its relationship to thermal comfort and human powered mobility.
The chapter concludes by stating the research goal, hypothesis, objectives and questions, followed by a layout of the dissertation structure and research methods used.

1.1 Global Population, Urban Growth and Modeling Urban Energy Flows

Continuous urban growth, manifested through the development of new cities and neighborhoods, is constantly changing urban landscapes in many parts of the world. Rapid global population increase in tandem with migration to cities has amplified urbanization over time: the world’s urban population is expected to reach 4 billion between 2015 and 2020 (BBC News, 2015). The United Nations’ latest figures demonstrate that by the year 2050, the world population is expected to increase by 2.5 billion people. Around the globe more people live in urban areas than in rural areas, with 54% of the world’s population residing in urban areas in 2014. Thirty percent of the world’s population was urban in 1950. By 2050, 66% of the world’s population is projected to be urban, demonstrating the continuous increase of urbanization over time (United Nations, 2014). To accommodate this growth, cities are growing exponentially across the globe. Studies report that the cumulative change in urban expansion for the period of 1970 to 2000 was 58,000 km², which is approximately in the order of 2% of the global urban land area in 2000 (Seto, Fragkias, Güneralp, & Reilly, 2011). Numerous urban development projects happen ad hoc which contributes to carbon emissions due to the resulting uncoordinated concentration of people, vehicles and industrial activities (Svirejeva-Hopkins, Schellnhuber, & Pomaz, 2004). New neighborhoods are being built every day; pushing the definition and boundaries of cities, and contributing considerably to carbon emissions (Hutyra, Byungman, Hepinstall-Cymerman, & Alberti, 2011). Emissions increase due to limited knowledge of the long-term environmental impact of street grid layouts and land use planning decisions. The stakes for planners are high since a road network, once in place, tends to be remarkably resistant to change as exemplified by a comparison of part of El Muiz Street in Cairo, Egypt, almost 800 years apart (Figure 1).

The frequent absence of a larger planning framework is partly due to the absence of suitable simulation tools for urban designers and city planners. The purpose of such tools would be to enable the evaluation of multiple design iterations and optimization of certain performance criteria, such as resource efficiency, residents’ health and comfort. In this day and age, computation has become ubiquitous throughout the design world and is being used from small scale offices to multinational firms. Given the ever growing power of personal computers and the increasing use of cloud computing, workflows based on such technologies can thus help design teams throughout the world to develop low-tech urban solutions using high-tech design tools. While building energy simulations have become well established in practice, partially due to the proliferation of green building rating systems (such as LEED), recently an emerging trend among researchers and leading consulting firms is to model the performance of groups of buildings.
(neighborhoods, campuses etc.). When departing from one to several buildings, transportation and its associated energy uses necessarily become dimensions to consider in conjunction with operational building energy (Rakha & Reinhart, 2013).

Figure 1: A comparison between minimally changed structures of El Muiz Street in Islamic Cairo, Egypt. (Left) Mamluk Cairo street structure from the year 1250 (Raymond, 2002). (Right) Current street structure (Wikimedia, 2008).
Efforts are now being made to develop environmental performance simulation software for the design of cities and neighborhoods. The intention is to evaluate and analyze urban design principles and assumptions, and to bring reliable, accurate and rigorous tools to the practice of urban design and planning (Besserud & Hussey, 2011). The author is part of the Sustainable Design Lab at MIT, which is developing an overall urban modeling platform called UMI to enable urban planners and architects to examine multiple performance aspects of their urban proposals, including operational and embodied energy use, outdoor comfort and neighborhood walkability (Figure 2) (Reinhart, Dogan, Jakubiec, Rakha, & Sang, 2013). This dissertation specifically focuses on the UMI outdoor comfort module, which concentrates on microclimate simulation, and occupancy modeling on an urban scale, and its relevance to sustainable urban transport choices.

Figure 2: UMI Mobility module developed by the author, showing walkscores for fictional neighborhood.

1.2 Transportation Energy, Human Powered Mobility and Thermal Comfort

Transportation energy currently represents 25% of the world’s carbon emissions and it is growing rapidly. In the developing world, two-thirds of such energy demands are directed towards personal mobility, and are expected to remain the same for the next 50 years (Zegras, Chen, & Jürg, 2009). These estimations, along with accompanying health problems resulting from poor air quality (Wassener, 2012), pertain to why
numerous cities around the world have realized the consequences of accommodating driving at the expense of walking, biking and efficient utilization of public transit. Sustainable planning of the built environment influences health, reduction of pollution, fuel savings and leads to reduced carbon emissions through the promotion of physical activity. Today, sustainable urban environments promote active transportation through the manifestation of policy instruments and land use planning tactics.

Assessment of neighborhood walkability has long been considered a distance function with an acceptable range of a quarter mile to one and a half mile walking from housing units to vital amenities. This idea has been adapted by many walkability evaluation schemes in different forms, and is widely thought off as being a good indicator of “walking environments.” Popular indices such as the “Walkscore” (Walkscore, 2015) have been positively correlated to neighborhood walkability and health (Duncan, Aldstadt, Whalen, Melly, & Gortmaker, 2011) as well as real estate prices (Rauterkus, Thrall, & Hangen, 2010). However, to date it has not been demonstrated that walkscore-type evaluations are capable of predicting the probability that a population of a certain urban area are actually more likely to walk than a comparable population in a neighborhood with a lower mean Walkscore rating. The reason for this may be that the evaluation of walkability is subjective and depends on many interfacing parameters that are currently not included in these models. Other factors include pedestrian thermal comfort, climatic conditions and pleasantness of routes, to name a few. In order to be able to predict whether a given future urban development is not only going to provide access to active modes of transportation but also whether residents will actually choose to walk, modeling the aforementioned factors is a key requirement for a predictive urban mobility modeling tool.

1.3 Thesis Objectives and Structure

This dissertation presents simulation workflows for thermal comfort-based mobility evaluation of cities. The focus is on spatially resolved outdoor thermal comfort simulation, with links to human activity schedules extracted from travel survey analysis. The following section details the research hypotheses, objectives, questions and target audience focus.

Research Goal

To develop and validate simulation workflows for architects and planners to assess the likelihood of a population to walk / bike in a given neighborhood based on outdoor thermal comfort considerations.

Research Hypotheses

The premise of this dissertation is that outdoor thermal comfort can influence human powered travel decisions. This vision is based on three sets of assumptions:
1. **Feasibility:**
   a. The development of a simulation tool that predicts outdoor thermal comfort annually is both feasible and useful for design communities.
   b. Travel survey databases can be analyzed to produce representative city dweller activity schedules for simulation purposes.
   c. Linking of outdoor thermal comfort and citizen activity patterns can be used to conceptualize the probability of people’s human powered mobility choices.

2. **Effort:**
   a. The effort needed to produce annual outdoor thermal comfort metrics can be justified by the spatiotemporally resolved insight gained, which would influence informed urban design and planning decisions to create comfortable outdoor spaces.
   b. The required work to analyze activity-based travel surveys can be necessitated by the travel patterns’ influence on occupancy representation in building energy simulation based on travel behavior, which would differ significantly from traditional occupancy schedules for simulation.

3. **Significance:**
   Simulating outdoor thermal comfort and linking it to human activity patterns in cities aids in the creation of built environments more conducive to sustainable, energy efficient, environmentally friendly and healthy human powered mobility in cities.

**Research Objectives**

- Identify literature gaps in outdoor thermal comfort simulation and human activity analysis.
- Develop an outdoor thermal comfort simulation tool, and validate it through a field experiment.
- Demonstrate the use of computational clustering to generate travel-based simulation schedules.
- Link outdoor thermal comfort simulation with human activity pattern analysis in cities.
- Outline future research efforts based on limitations faced throughout the study.

**Research Questions:**

i. How can a computer model simulate outdoor thermal comfort and spatially map it?
ii. Can travel behavior be used to comprehend mobility and building occupancy patterns?
iii. How could outdoor thermal comfort conceptually influence travel behavior?

**Target Audience**

These simulation workflows are not expected to replace existing transportation engineering workflows or simulation engines which generally operate at the city block scale and beyond. Instead, these workflows
are meant to be complementary to the larger models and be used by architects, urban designers and planners on a finer scale than typical transportation forecast studies.

Dissertation Overview

Chapter 1 introduces the dissertation. Chapter 2 answers questions (i) by presenting an outdoor thermal comfort simulation workflow using a new Rhino3D/Grasshopper plug-in developed by the author, as well as a validation experiment to produce spatially resolved Mean Radiant Temperature (MRT) and consequent comfort metrics in urban areas. Chapter 3 introduces a methodology for clustering patterns in activity-based travel surveys to generate building occupancy schedules and consequent travel trips, which is suited for question (ii). Chapter 4 links the previous two topics, travel behavior and outdoor thermal comfort, to address question (iii) through conceptualizing links between both fields. An example case study is presented for Copley Square in Cambridge, MA. Chapter 5 concludes this work by revisiting the hypotheses and testing successful implementation, while also showing potential areas of development and limitations of the workflows along with recommendations for future directions. Figure 3 demonstrates the dissertation breakdown and relevant research methods used.
Figure 3: Research process flowchart.

Goal
To develop and validate simulation workflows for architects and planners to assess the likelihood of a population to walk/bike in a given neighborhood based on outdoor thermal comfort considerations.

Objectives
- Identify literature gaps
- Develop and validate comfort workflows
- Analyze activity patterns for sim. schedules
- Link comfort and activity patterns
- Recommend future research

Methods
- Research overview
- Building physics simulation and validation
- Data clustering applied to travel surveys
- Case study demonstration
- Exploratory investigation

Dissertation
- Chapter 1: Introduction
- Chapter 2: Outdoor Thermal Comfort
- Chapter 3: Activity Patterns
- Chapter 4: Comfort and Travel
- Chapter 5: Conclusion
1.4 References


*Wikimedia*. (2008, 04 10). Retrieved from Muiz Street:
http://commons.wikimedia.org/wiki/File:Muizz_Street.GIF

Chapter 2: *Outdoor Thermal Comfort:*

Spatially Resolved Simulation and Mapping

The form and function of the ever growing cities that humankind erects and inhabits influence various microclimatic aspects within built environments. If parameters that affect urban microclimates were better understood and properly manipulated, then urban dwellers’ quality of life could be improved dramatically (Erell, Pearlmutter, & Williamson, 2011), given that local governments would implement change through lessons learned. Designers strive to create spaces that encourage outdoor activities, and so outdoor thermal comfort becomes a critical characteristic of how inhabitants use public spaces for day-to-day interactions and enjoyment (Brown, 2010). Activities such as walking and cycling are influenced by people’s comfort in, and consequent satisfaction with, outdoor environments. That is why measures for evaluating pedestrian environmental comfort and computer-based design tools are gaining gradual interest in the practice of architecture and urban design. The goal is to test the performance of buildings and their influence on various public spaces (Robinson, 2011). The need to incorporate design-decision support tools in robust and reliable workflows has become essential. There are a number of tools available to model outdoor thermal comfort conditions. However, these tools may not be validated, require advanced expertise to simulate microclimatic aspects and are only capable of modeling a few moments in time, as opposed to a full year.

Hence, this chapter presents a new simulation methodology for spatially and temporally resolved outdoor thermal comfort assessment. The tool is developed as an integration within the 3D Computer Aided Design (CAD) software Rhinoceros (typically shortened to “Rhino”) which is a popular design and computer modeling environment (Robert McNeel & Associates, 2015). The tool was programmed via a visual scripting plugin for Rhino called “Grasshopper,” which allows for the development of computer tools within its environment in different languages, and in this case the C# programming language was used. The workflow is broken down into 3D modeling as a first step to produce what is called an “Urban Surfaces” model. Surface temperature simulation takes place then, borrowing from the field of computational
“rayracing” to calculate annual radiation falling on all subdivisions of Urban Surfaces, to become an input for Heat Diffusion Equations used to calculate surface temperatures. The tabulated results for every hour of the year are then recalled as part of a workflow to calculate Mean Radiant Temperature (MRT) through analysis nodes. MRT is an important phenomenon that explains how human beings “feel” radiation from their environment, and is typically a challenging component to predict for outdoor thermal comfort metrics. To compute MRT, the analysis nodes also use raytracing for surface temperatures, as well as short-wave/long-wave sun and sky radiation. MRT simulation outcomes are then validated against data collected from two sites on the MIT campus. This is based on Dry Bulb Temperature and Relative Humidity collected from a weather station on site, as well as Globe Temperature (Tg) readings from “grey globe” thermometers, and wind speed data collected using anemometers. The previous inputs are used to calculate comparable MRT. The sites are modeled in Rhino, and the simulation workflow used to predict comfort is validated against the measured data. The resultant simulation for MRT is used as part of comfort indices calculations that include dry bulb temperature and relative humidity from weather data files, and assumption of wind speed. The comfort metric used in the study is the Universal Thermal Climate Index (UTCI). The validation process is discussed, and a metric that was developed called “Annual Thermal Comfort Percentage” is presented as a measure for assessing outdoor space comfort throughout the year. This metric differs from previous work in the literature by giving value to the adaptive behavior human beings undertake when being in a situation of thermal discomfort. The details of the entire research work is presented next.

2.1 Literature Review

Thermal comfort is a longstanding research field in building science. It is defined as the condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation (ANSI/ASHRAE , 2013). It is generally understood that there are six primary factors that influence the sensation of thermal comfort:

Environmental parameters include –

1. **Air Temperature**, typically given in degree Celsius or Fahrenheit.
2. **Humidity**, which is the amount of water vapor present in the air.
3. **Radiant Temperature**, present with the existence of any heat sources in the environment that the human body interacts with. The Mean Radiant Temperature (MRT) is defined as the uniform temperature of an imaginary enclosure in which the radiant heat transfer from the human body is equal to the radiant heat transfer in the actual non-uniform enclosure.
4. **Wind Speed**, which is convective heat transfer through air velocity, measured in distance travelled by air per unit time.
On the other hand, personal factors encompass –

5. **Metabolic Rate**, which is the heat produced by human bodies, depending on the type of activity is undertaken. It is measured in watt per meters squared.

6. **Clothing Insulation**, which is an interference to the human body's ability to lose heat to the environment through clothing.

Researcher have longed tried to express thermal comfort as a function of these factors, and standards were developed to provide indices that quantify thermal sensation to predict the mean thermal sensation and satisfaction of a group of people (ISO 7730, 2005).

Human bioclimatic conditions were studied extensively, with more than 100 evaluative indices were developed over the past century (Krzysztof, Epstein, Jendritzky, Staiger, & Tinz, 2012). While the majority of these indices are used for specific purposes, three thermal comfort indices are commonly used to evaluate of thermal environments:

1. **The Predicted Mean Vote (PMV)** is a one-node heat transfer model that assumes constant skin temperature of 34 °C. It solves a heat balance equation that relies on human body heat generation, clothing insulation, respiratory heat loss, and sensible and latent heat loss from the skin. It was developed for controlled spaces in the context of the heating, ventilation and air-conditioning (HVAC) industry practice (Fanger, 1970). PMV doesn’t account for regulatory responses, such as sweating and shivering, and so it was found limited in certain indoor evaluations, and especially assessment of comfort in outdoor environments (Höppe, 2002).

2. **The Standard Effective Temperature (SET)** is based on a two-node heat transfer model (Gagge, Fobelets, & Berglund, 1986). It divides a person into body core and peripheries. SET is an extension of the New Effective Temperature (Gagge, Stolwijk, & Nishi, 1971), and it is an equivalent temperature from a standard environment in which a subject would experience the same skin wettedness and mean skin temperature. However, it cannot be used outdoors without modification, which was presented later as OUT_SET (Pickup & de Dear, 2000).

3. **The Universal Thermal Climate Index (UTCI)** is defined as the effective temperature of a reference environment for a person with a constant metabolic rate of 2.3 MET (135 W/ m²) walking at 4 km per hour (Bröde, et al., 2012). At the time of writing this dissertation, it was the latest outdoor thermal comfort index that used a multi-node model of thermal regulation (Fiala, Havenith, Bröde, Kampmann, & Jendritzky, 2012), and a dynamic clothing model that mimics human behavior based on air temperature inputs (Havenith, et al., 2012). While there was involvement of 45 scientists from 23 countries with the support of the European Cooperation in Science and Technology (COST),
development and validation studies were conducted mostly in Europe, and so further validation is needed in order for the model to be acceptable in other climates and cultures around the world.

So the question now is, which thermal comfort metric should be used? The standards provided by different entities, including ASHRAE and ISO, will favor the PMV in indoor comfort assessment. However, it is not usable in the context of outdoor thermal comfort as previously discussed. OUT_SET is based on steady state energy-balance models of the human body, and its use is, therefore, confined to situations when people stay outdoors for a long time (Höppe, 2002). This makes UTCI the most promising metric to be used, as it was designed specifically for interpreting thermoregulatory human responses in outdoor environments (Jendritzky, de Dear, & Havenith, 2012). The three (and many more) thermal comfort metrics are available as products within different simulation packages to aid designers in making informed design decisions using computers.

A number of simulation tools have been previously developed to simulate urban microclimates, with a specific focus on the MRT, since it has a considerable influence on man’s heat loss (Fanger, 1970). MRT specifically is challenging to model, since it relies on heat transfer principles to produce surface temperatures for the required period of analysis in the examined space. It also needs geometric analysis capabilities in order to create accurate form factors for the analysis nodes to trace how much each node “sees” from all surrounding surfaces in the environment, as well as the sun and sky. The most recent relevant development to model MRT accurately is CityComfort+, which presented a method to simulate the spatial variation of MRT in dense urban environments (Huang, Cedeno-Laurent, & Spengler, 2014). The method is rigorous and has found good agreement between simulated and measured data. However, the workflow assumes that urban surfaces fall within four categorizations of sunlit and shaded walls and ground, with no spatial resolution. This creates a lack in variations that urban surfaces exhibit in reality through change in short-wave and long-wave radiation values in an open space, which could be modeled explicitly to get finer and more reliable representation, more suited for nuanced urban design interventions. ENVI-met is an open source, freely available software package that focuses on urban microclimates (Toudert-Ali, 2005). It is constantly under development, and it can compute MRT in various urban situations, as well as other microclimate aspects such as wind speed and directions and comprehensive comfort metrics such as PMV. Unfortunately it cannot process vector-based geometries, and works through pixel-based modeling. This makes the workflow tedious, as buildings, topography and vegetation are modeled over raster images. It is also a computationally expensive workflow, where a 24 hour simulation can take 24 hours to simulate, with limitations of predicting long-wave radiation fluxes. The RayMan model is a simulation platform that aims to calculate radiation flux densities, sunshine duration, shadow spaces and thermo-physiologically relevant assessment indices using only a low number of meteorological and other input data (Matzarakis, Rutz, &
Mayer, 2010). The model’s limitations are lack of compatibility with low solar angels, and its inability to account for reflected short-wave radiation. Another development is the SOLWEIG model (Lindberg, Holmer, & Thorsson, 2008), which uses Digital Elevation Models as a GIS compatible pixel-based geometry input. This method uses simplified workflows for 3D geometry and microclimate elements such as diffused and reflected solar radiation, and it is also limited with density simulated. A summary of these relevant computer software is presented in Table 1. There are multiple other methods that were developed and were either not scientifically validated against measured data, or are not available for public use. The available packages do not produce reliable outcomes within a design environment thus far. Hence, there is a need for simulation tools that aid designers in exploring their design decision impacts on various aspects of outdoor microclimates, in a relatively robust and timely manner, which is the focus of this work.

Table 1: Limitations summary of available Mean Radiant Temperature simulation tools.

<table>
<thead>
<tr>
<th>Software Package</th>
<th>CityComfort+</th>
<th>ENVI-met</th>
<th>RayMan</th>
<th>SOLWEIG</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRT Simulation Limitations</td>
<td>No variation through surface shading categorization with no spatial resolution</td>
<td>Pixel based, no vector geometry</td>
<td>Limited with low sun angles</td>
<td>- Simplified 3D geometry. Limited with density.</td>
</tr>
</tbody>
</table>

2.2 Simulation Method

A simulation methodology for spatially and temporally resolved outdoor thermal comfort assessment is presented in this chapter. The tool is developed for the Rhinoceros 3D modeling environment to compute various comfort indices and map it in modeled outdoor spaces. To accurately predict comfort metrics in urban environments, the module combines multiple approaches that include Radiance-based backwards raytracing, and a custom admittance model to estimate mean radiant temperatures over time. The following sections detail the components of the presented simulation methodology, focusing on urban surface temperature simulation and consequent MRT calculations.

Façade / Ground Thermodynamics and Simulation

A three dimensional model in Rhinoceros 3D is used to model the outdoor urban environment. The simulation workflow utilizes a custom module in Grasshopper that meshes each building and ground surface for surface temperature simulations. The Radiance-based (Ward, 1994) Daysim (Reinhart & Walkenhorst, 2001) program is used to calculate hourly radiation values on a grid of outward facing sensors that are laid across all urban surfaces in the model. Exterior radiation values are then used to compute
surface temperature using the thermal admittance method (Heat Diffusion Equation) (Lienhard V &
Lienhard IV, 2011). The admittance method (façade and ground) includes several components that
comprise solar radiation, outdoor convection, conduction through surfaces and indoor convection.
Conduction presents a challenge through its three dimensionality. However, conduction through urban
surfaces can be simplified as one dimensional heat transfer through the heat diffusion equation. The
simplified heat transfer process of the façade is shown in Figure 4. Based on this model, heat balance
equations of the façade are as follows:

\[
\frac{\partial T}{\partial \tau} = \frac{a \partial^2 T}{\partial x^2} + \frac{-\lambda}{\partial x} \left|_{x=\delta} \right. \left. - h_{in} \left( t_{in} - T \right) + Q \right.
\]

\[
\frac{-\lambda}{\partial x} \left|_{x=0} \right. = h_{out} \left( t_{out} - T \right) + Q
\]

\[
\frac{-\lambda}{\partial x} \left|_{x=\delta} \right. = h_{in} \left( t_{in} - T \right) + Q
\]

Figure 4: Exterior façade backwards raytracing workflow and heat diffusion calculations.

Where:

\[Q = \text{Solar Radiation (W/m}^2\text{)}\]
\[h = \text{convection coefficient (W/m}^2\text{.K)}\]
\[t_{out} = \text{External Temperature (°C)}\]
\[t_{in} = \text{Internal Temperature (°C)}\]
\[\tau = \text{Time (Minutes)}\]
\[\lambda = \text{Conductivity (W/m.K)}\]
\[a = \text{Diffusivity (s/m}^2\text{)}\]
\[x = \text{Depth (m)}\]

Figure 4 shows three equations that define heat transfer inside the wall, external boundary conditions and
internal boundary conditions. They translate into the heat transfer equation below, which calculates
temperature within each wall layer for simulation purposes. The façade depth is discretized into a number
of layers \((k)\) with a thickness of \(\Delta x\), and temporal temperature change is also discretized into \(\Delta \tau\). For each layer a heat balance equation is built up:

\[
h(t^k_f - t^k_1) - \lambda \frac{t^k_1 - t^k_2}{\Delta x} = \rho c \frac{t^{k+1}_1 - t^k_1}{\Delta \tau} \frac{\Delta x}{2}
\]

Where:

\(\rho = \) density \((\text{kg/m}^3)\)

\(c = \) specific heat capacity \((\text{J/K})\)

The resultant surface temperatures are then tabulated with reference to the meshing geometry in a database to be recalled for temporal MRT calculations.

**Mean Radiant Temperature (MRT)**

An important microclimate parameter is MRT, which sums up all short and long wave radiation fluxes (both direct and reflected) to which the human body is exposed to (Thorsson, Lindberg, Eliasson, & Holmer, 2007). Figure 5 shows the main factors influencing MRT, which are broken down to short-wave radiation (direct, diffuse and reflected solar radiation) and long-wave radiation (sky and urban surfaces).

*Figure 5: Built Environment and Environmental Parameters influencing MRT in an urban canyon.*
For a 3D model a number of sensor nodes are generated to compute MRT as a step to simulate thermal comfort. The workflow is threefold:

1. **Solar Radiation**: Radiation coming from the sun has the strongest influence on MRT. To be accurately represented, three elements need to be simulated: direct, diffused and reflected short-wave solar radiation. The analysis nodes are used as input for radiance to raytrace these components using Daysim's hourly irradiation method. Daysim uses solar radiation data input from a weather station, which is typically reported as global horizontal radiation that is split into direct normal irradiance and diffuse horizontal irradiance using the Reindl method (Reindl, Beckman, & Duffie, 1990). The output is hourly radiation data for each analysis node as it is affected by the surrounding environment. With the short-wave solar radiation simulated, the MRT component is then calculated for each hour of the year using the Stefan-Boltzman law:

\[
MRT = \sqrt[4]{\frac{S_{str}}{(\varepsilon_p \sigma)}} - 273.15
\]

Where:

- \(\varepsilon_p\) is the emissivity of the human body. According to Kirchhoff's laws, \(\varepsilon_p\) is equal to the absorption coefficient of the emissivity for long-wave radiation (standard value 0.97).
- \(\sigma\) is the Stefan–Boltzmann constant \((5.67 \times 10^{-8} \text{ Wm}^{-2} \text{K}^{-4})\)
- \(S_{str}\) is the mean radiant flux density. It is equal to the product of multiplying the standard absorption coefficient for short-wave radiation \(\alpha_k = 0.7\) and short-wave radiation fluxes.

2. **Sky Radiation**: Long-wave radiation coming from the sky is challenging to simulate, and so it can be estimated as a function of dry bulb temperature (Swinbank, 1963).

\[
T_{sky} = 0.0552(T_{air})^{1.5}
\]

Where:

- \(T_{sky}\) = Temperature of the sky (°K)
- \(T_{air}\) = Dry bulb temperature (°K)

2. **Long-Wave Radiation**: Sensors are used as input for Radiance to send spherical rays out from each sensor to raytrace with 0 bounces all surrounding surfaces. This means that the sensor is attempting to detect the first surface each ray hits. A database is created in reference to each node and the number of surfaces
traced. Using this database view factors are computed based on the number of rays that hit each surface, which is controlled by the user as an accuracy level input, and the temperature of the traced surface is looked up in the surface temperature database previously simulated (Figure 6).

![Diagram of sensor nodes and view factor raytracing workflow in an urban model.](image)

*Figure 6: Sensor nodes and view factor raytracing workflow in an urban model.*

For each node and time step the long-wave MRT is then calculated using the following formula:

\[
MRT = \sqrt[4]{T_1^4F_{p-1} + T_2^4F_{p-2} + \cdots + T_n^4F_{p-n}}
\]

Where:

\(MRT\) = Mean Radiant Temperature

\(T_n\) = Surface Temperature for surface “n” (Kelvin)

\(F_{p-n}\) = angle factor between sensor node and surface “n”

MRT is computed by adding the short-wave and long-wave MRT components, and calculation of various comfort metrics such as PMV, Universal Thermal Climate Index (UTCI) and the like becomes achievable. Other parameters needed such as dry bulb temperature and relative humidity are extracted from weather data files, and wind speed, metabolic rates and clothing are assumed (shown in Appendix). An example case of Copley Square in Boston is presented in Figure 7 to demonstrate the entire methodology’s workflow, from 3D model creation, to surface temperature simulation and MRT calculations and mapping.
01: Existing Case Modeling – Copley Square, Boston, MA digital model in Rhino 3D

02: Surface Temperature Simulation – Cumulative Annual Surface Temperature Mapping

03: Mean Radiant Temperature Calculation – Mapping through Raytracing

Figure 7: MRT simulation workflow, from digital modeling to surface temperature simulation and MRT mapping.
2.3 Validation Experiment

To validate the above described simulation workflow, two locations were chosen on the MIT campus to represent an exposed and a shaded urban canyon (Figure 8) to collect metrological data for verification.

![Figure 8: Outdoor thermal comfort validation experiment in two on campus locations at MIT.](image)

For each location, a grey globe thermometer (Figure 9) was used to collect Globe Temperature ($T_g$) data for a certain period of time. The 40mm Grey Globes are made of copper and painted grey, with albedo = 0.3 and emissivity = 0.95. An Onset temperature sensor (type TMC6-HA) is placed inside the globe, with readings recorded on a data logger (type U12-006) in 15 minute intervals. They were placed at a height of 1.1m on tripods, and MRT is then calculated by combining wind speed data from either a local anemometer or from the anemometer installed specifically with that globe (type S-WCA_M003). An Onset weather station on site was collecting data for temperature. Two experiments to collect data have been conducted, one for a cold day on April 1st and for a warmer period between June 9th-13th 2014.
MRT is calculated in the case of measurements using this formula driven from a detailed study on the theory of globe thermometers (Kuehn, R. A., & Weaver, 1970):

\[
MRT = \left[ \left( T_g + 273 \right)^4 + \frac{1.1 \times 10^8 V_a^{0.6}}{\varepsilon D^{0.4}} * (T_g - T_a) \right]^{1/4} - 273
\]

Where:

\( T_g \) = Globe Temperature (°C)

\( V_a \) = Air Velocity (m/s)

\( T_a \) = Air Temperature (°C)

\( D \) = Globe Diameter (mm)

\( \varepsilon \) = Globe Emessivity

Figure 10 demonstrates the data collected dry bulb temperature, and Figure 11 shows concurrent Globe Temperatures. MRT was consequently calculated, which is shows in Figure 12.
Figure 10: Collected data for Dry Bulb Temperature.

Figure 11: Measured Globe Temperature.

Figure 12: Calculated Mean Radiant Temperature.
A 3D Model of the courtyard was created in Rhino 3D, and then translated into an urban surfaces model for MRT simulation (Figure 13). The building structure is reinforced concrete with a masonry envelope, and the windows are all single glazings of clear 6 mm glass with steel frames. Table 2 demonstrates simulation inputs. Surface temperature simulations ran first using weather data that was modified to include measured solar radiation at the date and time of the conducted experiments, and tabulated annual results were used to compute MRT without including the direct and diffuse solar components. DIVA for Rhino (Jakubiec & Reinhart, 2011) was used to generate analysis nodes and simulate solar radiation through Daysim. MRT was consequently computed, and validated against the measured data.

![Courtyard 3D Model](image1)
![Courtyard Urban Surfaces Model](image2)

Figure 13: Courtyard 3D model in Rhino and its conversion to an Urban Surfaces Model.

Table 2: Urban Surfaces Model simulation inputs.

<table>
<thead>
<tr>
<th>MATERIAL PROPERTY</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wall Thickness</td>
<td>0.3 m</td>
</tr>
<tr>
<td>Density</td>
<td>1700 kg/m³</td>
</tr>
<tr>
<td>Heat Capacity</td>
<td>840 J/K</td>
</tr>
<tr>
<td>Heat Conductivity</td>
<td>0.84 W/m.K</td>
</tr>
<tr>
<td>Glazing Thickness</td>
<td>0.06 m</td>
</tr>
<tr>
<td>Density</td>
<td>3000 kg/m³</td>
</tr>
<tr>
<td>Heat Conductivity</td>
<td>0.9 W/m.K</td>
</tr>
<tr>
<td>Indoor Temperature</td>
<td>26 °C</td>
</tr>
<tr>
<td>Indoor Convective Efficiency</td>
<td>8 W/m².K</td>
</tr>
<tr>
<td>Outdoor Convective Efficiency</td>
<td>25 W/m².K</td>
</tr>
<tr>
<td>Ground Temperature</td>
<td>10 °C</td>
</tr>
</tbody>
</table>
Figure 14 and Figure 15 demonstrate the validation experiment output for the two experiments. MRT trends are in close agreement in both locations. The limitations within the workflow validation are twofold: inherent measurement errors from instrumentation used coupled with underestimation of short-wave radiation. The combined grey globe and anemometer errors account for ±3.9°C, and given that error range, the simulation outcome trends match closely with measurements. In most cases, there is close agreement within a 18% error range between measured and simulated MRT, and relative Mean Bias Error (MBE)\(^1\) between 0% and 3%, and relative Root Mean Square Error (RMSE)\(^2\) between 1% and 2% (Table 3). However, the error range was more evident in the exposed situation on the cold day. There is underestimation for the direct solar contribution. This could be explained as an issue of emissivity assumptions for the grey globe thermometers, cleanliness of the device or human error. Nevertheless, most other simulation outputs lie within an acceptable margin of error, with room for future improvements specific to the short-wave radiation contribution to the MRT simulations.

### Table 3: Statistical analysis of validation experiment outcomes

<table>
<thead>
<tr>
<th>EXPERIMENT</th>
<th>MBE</th>
<th>RMSE</th>
<th>AVERAGE ERROR</th>
</tr>
</thead>
<tbody>
<tr>
<td>June 9-13th</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shaded</td>
<td>2%</td>
<td>2%</td>
<td>18%</td>
</tr>
<tr>
<td>Exposed</td>
<td>0%</td>
<td>2%</td>
<td>15%</td>
</tr>
<tr>
<td>April 1st</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shaded</td>
<td>3%</td>
<td>1%</td>
<td>18%</td>
</tr>
<tr>
<td>Exposed</td>
<td>0%</td>
<td>1%</td>
<td>28%</td>
</tr>
</tbody>
</table>

\(^1\) The relative Mean Bias Error (MBE) is a statistical measure to describe the similarity of two data series. It characterizes the relative size of the elements of a data series with respect to a reference data series, in this case it's the simulated and measured MRT. A positive / negative MBE indicates that the considered data series tends to lie above / below the reference data series. A vanishing MBE shows that the considered data series is scattered around the reference data series. It is defined as:

\[
\text{rel. MBE} = \frac{1}{n} \sum_{i=1}^{n} \frac{(x_{\text{sim},i} - x_{\text{mea},i})}{x_{\text{mea},i}}
\]

\(^2\) The relative Root Mean Square Error (RMSE) is a statistical measure to describe the similarity of two data series. It characterizes the average variance of the elements of a data series with respect to a reference data series, in this case, the simulated and measured MRT. A small relative RMSE indicates that the considered data series lie close together. It is defined as:

\[
\text{rel. RMSE} = \frac{1}{n} \sqrt{\sum_{i=1}^{n} \left(\frac{x_{\text{sim},i} - x_{\text{mea},i}}{x_{\text{mea},i}}\right)^2}
\]
Figure 14: Validation experiment results for the warmer period in June.
Figure 15: Validation experiment results for the cold day in April.
2.4 Discussion

This section will discuss the workflow, MRT simulation potentials and its use to produce outdoor thermal comfort metrics as an annual assessment metric.

**Workflow**

Outdoor thermal comfort is vital for public spaces. A walk down a comfortable street, or activities taking place in a public park require suitable microclimates for such undertakings, and designers have a say in the creation of these spaces. Human perception of the radiant environment is an important component in our sensation of comfort. Previously, architects and planners used design intuition, manual calculations, or computer tools that were not fully integrated in the design process to make informed outdoor comfort design decisions. The outcome maybe inaccurate due to the outdated workflows, or cumbersome to interpret due to the technical know-how required to run such tools. Therefore, the simulation workflow presented in this chapter was developed as a novel, robust method to calculate surface temperature and consequent MRT in urban spaces, with integration in the design environment of Rhino 3D and the Grasshopper plugin. While the use of raytracing significantly reduces simulation time, there is still development needed to produce reliable integration of short-wave radiation simulation, as previously presented in certain cases of the validation experiment. There is also a need to develop a more holistic approach that would include other climatic factors such as wind speed, and its effect on comfort sensation. A longer period of data collections is therefore needed as future work, with testing of multiple urban canyon environment configurations.

**Simulation Outcome and Comfort Metrics**

The outcome of this simulation workflow is spatially resolved MRT, which translates to daily MRT values mapped in urban spaces, as demonstrated in Figure 16. While such an outcome is specifically interesting for seasonal design interventions, annual visualization of 8760 hours of an entire year is needed in order to understand impacts over different seasons and time. The Ladybug for Grasshopper (Roudsari, Pak, & Smith, 2013) module was used to visualize this annual MRT map for the shaded node, and is presented in Figure 17. It becomes evident in this visualization that hours of sunlight have most influence on the increase of MRT values.

MRT is a phenomenon that is typically a challenging component of outdoor thermal comfort to simulate on a yearly basis. The methodology presented allows for the creation of an entire year’s outdoor comfort data. Beyond MRT, Figure 17 presents temporal mapping of the UTCI outdoor thermal comfort metric, with annual climate data assumed as inputs from Typical Meteorological Year (TMY) weather data files. A TMY file is defined as a set of measured hourly meteorological quantities. The data is kept in true sequence within each month. The most important input variables for building design are: dry bulb
temperature, relative humidity and wind speed, which in this case are input assumptions to the model. Annual temporal comfort maps can aid designers in visually identifying problematic time periods that would require design interventions on a daily, monthly and seasonal basis. Visualizing temporal maps is important when concentrating on individual nodes separately. However, comparing such maps for different points within a space is tedious, as the number of analysis nodes increase. There is a need to rapidly identify uncomfortable and problematic areas spatially, as well as temporally.

Figure 16: Simulated Mean Radiant Temperature visualization for the courtyard at representative dates and times.
Figure 17: Simulated annual MRT and UTCI of the exposed node in the courtyard.
Annual Thermal Comfort Metrics

While thermal comfort metrics are typically static, and can be considered a potential prediction of a snapshot in time, our human sensations and perceptions are spatiotemporal. There is a need for dynamic interpretations of thermal comfort that comprehends diurnal, weekly and seasonal patterns. A concept named “Thermal Autonomy” was previously presented, both as a metric and design process, for indoor environment assessments of thermal comfort. Thermal Autonomy is defined as “the percent of occupied time over a year where a thermal zone meets or exceeds a given set of thermal comfort acceptability criteria through passive means only.” Its graphical approach and numeric summary as a percentage provides a clear overview of an indoor thermal zones’ performance (Levitt, Ubbelohde, Loisos, & Brown, 2013). The concept, however, was not applied to explore spatial variations within one space, and was focused on indoor thermal performance. For an outdoor thermal comfort perspective on dynamic metrics, based on a time series of thermal comfort values, a recent study proposed three measures. 1) Thermal Comfort Autonomy, which is defined as the percentage of active time of a year that a specific space is within thermal comfort zone. 2) Heat Sensation Hours (HSH), which measures the exposure to heat stress during a designated time series and 3) Cold Sensation Hours (CSH), which conversely measures the exposure to cold stress during a designated time series. Both HSH and CSH are hourly aggregations of thermal sensation, based on ASHRAE’s 7-point thermal sensation scale. The produced spatially resolved maps aim to aid design and planning decisions, specific to annual assessment of outdoor thermal comfort (Jianxiang, 2013). The tri-part approach is comprehensive, but needs a mechanism for crediting analysis nodes that do not fully meet comfort conditions. The presented simulation workflow is capable of integration with the concepts behind dynamic thermal comfort metrics. Through the use of the temporal mapping of annual thermal comfort, a new metric, which builds on previous efforts, is proposed:

Annual Thermal Comfort Percentage (TCPa), which is defined as –

“The percentage of active time of a year that a person in a certain space is experiencing thermal comfort, with linear partial credit as comfort decreases.”

Figure 18 shows spatial mapping of TCPa in the courtyard used in the validation study, based on the UTCI metric. For this case, active time of a year was defined to be potential lunch hour (11 AM to 1 PM). Full score was given to UTCI “no thermal stress” (+9 to +26 °C), and partial credit that decreases linearly was given to cases of “moderate heat stress” (+26 to +32 °C) and “slight cold stress” (+9 to 0 °C). The partial credit is given as an interpretation of the adaptive nature of human thermal comfort. Annual comfort metrics assume a harsh cutoff, where if a person is not comfortable then there is nothing that can be done about it. However, adaptive interpretations suggest that behavior adjustments, such as adding or removing an article of clothing, change in physiological responses, or an altered perception / psychological reaction mean that
in an uncomfortable situation, humans react (de Dear & Brager, 1998). With that reaction, there should be a wider range of what we consider to be uncomfortable.

The proposed metric is only available in the context of using simulation software. It follows the logic behind major developments in assessment measures in other environmental performance fields, such as Climate-based Daylighting Metrics (Reinhart & Walkenhorst, 2001). TCPa allows for direct interpretations of outdoor thermal comfort annually, without referring to multiple maps of temporal comfort annually. This proposal takes advantage of the year-long MRT simulation workflow, and translates it into meaningful spatiotemporal interpretation of outdoor thermal comfort, as a direct enforcement for the making of better informed design decisions for spaces between buildings.

Figure 18: Annual Thermal Comfort Percentage mapped in the courtyard.

2.5 Conclusion

This chapter presented a simulation workflow for Mean Radiant Temperature and consequent outdoor thermal comfort metrics. The goal was to implement an integrated design decision support tool to aid architects and planners in the creation of comfortable outdoor spaces. The workflow amalgamated building physics through heat transfer equations and computational raytracing to generate urban surface
temperatures and mapping MRT in outdoor spaces. An experiment for validation in two locations on the MIT campus showed potentials and limitations within the simulation framework, and direct applications were shown in the context of spatiotemporal mapping of MRT and the UTCI comfort metric. A new dynamic thermal comfort metric, Annual Thermal Comfort Percentage, was presented and discussed. Future studies should focus on further validation of the simulation framework in different urban canyon configuration through multiple sites over longer periods of time. Further development of dynamic outdoor thermal comfort metrics and representations of spatial and temporally resolved outdoor comfort data is recommended.

2.6 References


Chapter 3: *Activity Patterns:*

Urban Occupancy Profiles and Trip Simulation

The current human world is, and will continue to be, mostly urbanized; with cities being planned, build and inhabited at an unprecedented rate (World Health Organization, 2015). In order for this urbanization process to be as sustainable as possible, architects and planners should apply measures of energy efficiency and carbon emissions reduction at an urban scale. The employment of Building Performance Simulation (BPS) tools supports such methods by predicting the annual energy use of buildings using mathematical representation of thermal and luminous environments, within an acceptable margin of error (Fabi, Andersen, Corgnati, & Olesen, 2013). These programs use complex models of occupant behavior within buildings to predict the control of various components, such as window opening (Fritsch, Kohler, Nygård-Ferguson, & Scartezzini, 1990), lighting controls and blind adjustments (Reinhart, 2004) and space heating/cooling demands (Hoes, Hensen, Loomans, de Vries, & Bourgeois, 2009). However, examining occupant behavior on a building by building basis becomes insufficient when whole districts or neighborhoods are being investigated. At that scale simulation needs to consider that people spend much of their time outside of buildings, living Gehl’s proverbial “life between buildings” (Gehl, 1986). In an urban context, occupants’ movements between buildings during daily activities affect transportation energy. This makes the simulation of activities in urban areas critical to the assessment of trips made for local transportation and consequent mode choices (walking, biking, automobile, etc.) based on proximity and other parameters.

This chapter presents a methodology for the generation of building occupancy and trip schedules in urban areas based on regional activity-based travel surveys. The chapter begins with a literature review that covers research relevant to occupancy behavior in buildings, followed by its connection to BPS. The review concludes by presenting travel behavior studies that aim to quantify the relationship between land-use
planning and urban mobility in relevance to the built environment. The research method is then introduced, which uses spectral clustering algorithms and eigendecomposition-based Principal Component Analysis (PCA) with k-means clustering. The latter was recommended as the data clustering methods used to identify activities as well as city resident types from travel survey analysis. The outputs of the analysis are typical occupancy schedules for building performance simulation, and activity profiles for mobility modeling in urban-scale simulation. As a proof of concept, the method is applied to the 2010/2011 Massachusetts Department of Transportation (MassDOT) travel survey. Several clusters of occupants were identified, and an example building occupancy schedule and complementary activity distributions were determined. A discussion is presented, in which these activity profiles were used to generate composite occupancy schedules for whole building energy simulation, and an example case study was developed using a simple office space modeled in Design Builder/Energy Plus.

3.1 Literature Review

Various factors affect energy use in buildings, where space occupancy and human behavior are primary aspects of influence. Research efforts were made to identify the specific effect occupant behavior has on building energy consumption. Yu et al. propose a systematic procedure for the investigation of occupant behavior on building energy performance using clustering techniques. By clustering similar buildings into groups of similar properties (climate, building construction, etc.) irrelevant of occupancy, the effect occupant behavior has on energy use can be identified accurately (Yu, Fung, Haghighat, Yoshino, & Morofsky, 2011). Another study by Santin, Itard and Visscher aimed at gaining insight into the effect of occupant behavior on energy consumption for space heating. Through the use of an existing Dutch building database, the investigation showed that occupant characteristics and behavior affect energy use by 4.2%, which was considered significant. However, building properties still determined 42% of the variance, which is a large portion of the energy consumed in a residential building (Santin, Itard, & Visscher, 2009). In that study, a comparison was made to an earlier investigation by Sonderegger’s examination of 205 dwellings over a period of 6 months in the USA, where the physical features of residential spaces explained 29% of energy use whereas 71% were attributed to different occupant-related consumption patterns (Sonderegger, 1978-1979). Research by Gill et al. presented a methodology to quantify the effect of occupant behavior on measured heating, electricity, and water consumption. The process showed how much of the measured energy/water consumption variation can be quantified as due to occupant behavior. A total of 51%, 37%, and 11% of the variation in heating, electrical, and water consumption, respectively, were explained by occupant actions (Gill, Tierney, Pegg, & Allan, 2010). While these earlier studies pertaining to the determining the influence of occupancy on energy use in buildings were not conclusive, since there are variations between different building situations and user types, they all concluded that the impact of
occupant behavior on building energy use is significant. Efforts were accordingly made to model these effects within various BPS tools.

In the field of BPS, a standard schedule is used for occupancy patterns in spaces. This creates what is typically known as an “occupancy schedule” or “occupancy profile,” which forms an input for human presence in spaces modeled within building energy simulation tools. Such schedules have been examined and questioned in terms of accuracy and relevancy to observed occupancy patterns in various building types. For an in-depth reference on the role occupancy has in BPS, the reader is referred to a book chapter by Mahdavi (Mahdavi, 2011). Davis and Nutter developed a method to predict occupancy diversity factors for classroom-type university buildings (Davis III & Nutter, 2010). A three-step data mining technique proposed by D'Oca and Hong uses a decision tree model to predict presence based on existing occupancy data, followed by an induction algorithm to learn a set of rules to be finally clustered in order to obtain consist occupancy schedules (D'Oca & Hong, 2015). A complementing effort by Duarte, Van Den Wymelenberg and Rieger attempted to reveal occupancy patterns through the use of occupancy sensor data. Diversity factors were presented for multiple building types using a 23-month dataset from an office building. The research found significant differences in comparison to the ASHRAE 90.1 2004 standard, where 46% reduction in average day profile peaks for private office occupancy and about 12% for open plan office where observed (Duarte, Van Den Wymelenberg, & Rieger, 2013). A study by Oldewurtel, Sturzenegger and Morari showed that simulation of an office building with Integrated Room Automation (IRA) has up to 34% and 50% energy saving potential in the case of homogeneous and alternating occupancy patterns, respectively (Oldewurtel, Morari, & Sturzenegger, 2013). Stoppel and Leite presented a method to describe building energy performance using probabilistic methods for occupants known long vacancy activities, and other building underutilization aspects. The simulation of a LEED certified building resulted in 612 MJ/m², which when compared to 590 MJ/m² actual annual energy consumption, indicates a modest improvement from the original energy model’s prediction of 691 MJ/m² Energy Use Intensity (EUI). However, the researchers highlight that the results also show significant limitations within the approach for assumptions of constant thermal set points for heating and cooling sensors regardless of occupancy rates, as well as the deterministic occupant schedules (Stoppel & Leite, 2014).

The use of a deterministic occupancy schedules was challenged in the literature by explorations of stochastic and probabilistic modeling approaches. Deterministic conversion of empirical Time of Use Data (TUD) was done by Widén, Molinb and Ellegård into a complete thermal load model, which encompassed both occupancy and various end-uses such as household electricity and domestic hot water. A Markov-chain approach for the generation of synthetic TUD sequences was then also implemented, to include a model for probabilistic load management, which proved more realistic and diverse than a deterministic
behavior model (Widén, Molin, & Ellegård, 2012). A methodology was developed by Aerts et al. to identify seven significantly different occupancy patterns from Belgian TUD using hierarchical clustering. A probabilistic model to reproduce individual daily and yearly occupancy patterns was developed, where calibration of the probabilistic model allows for the management of simulated occupancy sequences (Aerts, Minnen, Glorieux, Wouters, & Descamps, 2014). Research pursued by Virotea and Neves-Silva presented a stochastic Markov model for occupant behavior simulation, with focus was on energy consumption modeling (Virote & Neves-Silva, 2012). Page et al. described an algorithm for the simulation of occupant presence specific to BPS. The model generated a time series of state of presence of occupants by considering them as a heterogeneous Markov chain, interrupted by occasional periods of long absence. The model was validated against occupancy data from private offices, and was found reliable (Page, Robinson, Morel, & Scartezzini, 2008). Comprehensive models of occupant’s presence, opening and closing of windows and raising and lowering blinds have been developed by Haldi and Robinson. The models were developed using extensive field survey data acquired over 8 years in a lab building in Switzerland. Both deterministic and stochastic models were presented in a study that integrated them in an urban energy modeling tool called CitySim (Haldi & Robinson, 2011). However, such urban modeling approaches were applied on a building in a singular state, and didn’t take into account movement of occupants between various buildings.

Travel behavior and forecasting is a topic of interest for urban planners and transportation engineers, and links to the built environment have been established in the literature. The relationship between land use and travel behavior based on utility-based and activity-based theory of transportation was discussed by Maat, van Wee and Stead. They presented an argument to previous explorations that concluded that land use has limited or virtually no effect on travel behavior. Their study explained how trip-based approaches fail to address behavioral responses to compact urban design, and that utility-based and activity-based theory of transportation better explains complex travel behavior (Maat, van Wee, & Stead, 2005). The impacts the built environment has on travel behavior have been presented by Handy and Krizek. This effect was discussed in terms of Vehicle Miles Traveled (VMT) and consequent Green House Gas (GHG) emission reduction (Handy & Krizek, 2009). Microsimulation of activity-based travel patterns was developed for travel forecasting (Kitamura, Chen, Pendyala, & Narayanan, 2000). However, BPS has not benefited from the relationship between urban mobility and occupants travel. This work argues that understanding travel behavior in urban areas can enhance simulation of energy flows in and around groups of buildings in BPS. As the simulation focus expands from one to several buildings, consistent behavior models that account for individual occupants being in different buildings at different times, as well as travelling between those buildings.
3.2 Methodology

Figure 19 demonstrates the developed framework. An activity based mobility database is analyzed in order to identify what kind of activities exists in the chosen urban area, as well as to derive occupant behavior archetypes. Schedules and behavior profiles for different occupants are then generated. The details of each stage are described next.

Figure 19: Presented occupancy schedules and activity distribution generation framework.

Input: Activity Based Mobility Database - Travel Survey

In order to understand complex activities that occur in urban areas and the dynamics of its inhabitants, an activity-based travel database is used. The use of cell phone traces (Calabrese, Diao, Di Lorenzo, Ferreira Jr., & Ratti, 2013), online social media check-ins (Noulas, Scellato, Mascolo, & Pontil, 2011) and position tracking (Gonzalez, Hidalgo, & Barabasi, 2008) to comprehend human mobility and associated activities are emerging urban sensing techniques. It is foreseen that the future of activity-based mobility databases to be used in this workflow will be based on such technologies, but at the time of writing this dissertation, they were still being developed and access to existing data sets was limited due to privacy restrictions. In contrast, traditional travel surveys are often publically available and are the standard means of understanding mobility in cities. In this chapter, the MassDOT Travel survey is used as the database that will be analyzed in order to understand trends and patterns in urban mobility.

The activity survey data used included 15,000 households and was collected between June 2010 and November 2011. Participants were asked to identify where and how they traveled on a specific, designated travel day (24 hours). The sample was carefully chosen to represent the Massachusetts population by asking each participating household a series of detailed questions about their socioeconomic characteristics and access to transportation. Data mining techniques used to analyze this database are presented in the following section. Note that the only survey travel days assigned were weekdays, so the analysis excludes weekends.
The analysis also excludes Friday reports, as Friday travel behavior tends to substantially differ from that on other weekdays.

**Relevance to Occupancy Schedules**

An EnergyPlus daily occupancy schedule is simply a table of values ranging from 0 to 1, a value less than 1 indicating that only a fraction of all possible occupants are present. Each entry in the table corresponds to a simulation time step. For example, if the time step is one hour long, there will be 24 schedule entries. The value of the schedule at time step \( t \) indicates the portion of the maximum normal building occupancy present at time \( t \). If the building is a commercial building, the occupancy schedule describes the portion of the building’s worker population that is present at any given time.

In order to derive a useful individual building occupancy schedule from citywide data, a procedure for deriving a representative worker population from such data is needed. There are multiple plausible ways of doing this. An example might be to examine the building occupancy schedules of similar building types, for some measure of similarity in occupancy behavior; another might be to correlate demographic information. However, in this chapter, the focus is on citywide worker schedules. The aim is to identify clusters of real activity schedules, from which representative building occupancy schedules can be derived. A cluster of schedules is a group of schedules that are “similar” to each other and “dissimilar” to schedules in other clusters. These might be worker schedules (for commercial building occupancy), residence schedules (for household occupancy), student attendance schedules (for school occupancy), or some other subpopulation. Furthermore, capturing variations in schedule types; for example, identifying a “daytime worker” group as distinct from an “evening worker” group. This allows a representative occupancy schedule to be selected based on the expected commercial use of a building. In this specific application of data clustering techniques there is a degree of subjectivity which is why it is necessary to deliberately pick a similarity criterion that is relevant for the subsequent use of the clustered data.

**Preliminaries to Data Clustering**

Before an explanation of the clustering methods used is presented, some preliminaries are discussed.

*Survey Schedule Encoding:* Each response in the data set is encoded as a 96-number string, where each number corresponds to a 15-minute chunk of the survey day, and represents the activity that the respondent was participating in at the beginning of that period. The activity categories are shown in Table 4.
Table 4: Aggregated activities and original trips.

<table>
<thead>
<tr>
<th>ACTIVITY</th>
<th>ORIGINAL PRIMARY TRIP PURPOSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home</td>
<td>- Working at home (for pay)</td>
</tr>
<tr>
<td></td>
<td>- All other activities at home</td>
</tr>
<tr>
<td>Work</td>
<td>- Work/job</td>
</tr>
<tr>
<td></td>
<td>- All other activities at work</td>
</tr>
<tr>
<td></td>
<td>- Volunteer work/activities</td>
</tr>
<tr>
<td></td>
<td>- Work business related</td>
</tr>
<tr>
<td>School</td>
<td>- Attending class</td>
</tr>
<tr>
<td></td>
<td>- All other school activities</td>
</tr>
<tr>
<td>Transit</td>
<td>- Changed type of transportation</td>
</tr>
<tr>
<td></td>
<td>- Drop off passenger from car</td>
</tr>
<tr>
<td></td>
<td>- Pick up passenger from car</td>
</tr>
<tr>
<td></td>
<td>- Loop trip</td>
</tr>
<tr>
<td>Shopping/Errands</td>
<td>- Service private vehicle (gas, oil lube, etc.)</td>
</tr>
<tr>
<td></td>
<td>- Routine shopping (groceries, clothing, convenience store, HH maintenance)</td>
</tr>
<tr>
<td></td>
<td>- Shopping for major purchases or specialty items (appliance, electronics, new vehicle, major HH repairs)</td>
</tr>
<tr>
<td></td>
<td>- Household errands (bank, dry cleaning)</td>
</tr>
<tr>
<td>Personal</td>
<td>- Personal business (visit government office, attorney, accountant)</td>
</tr>
<tr>
<td></td>
<td>- Health care (doctor, dentist)</td>
</tr>
<tr>
<td>Recreation/Entertainment</td>
<td>- Eat meal outside of home</td>
</tr>
<tr>
<td></td>
<td>- Outdoor recreation/entertainment</td>
</tr>
<tr>
<td></td>
<td>- Indoor recreation/entertainment</td>
</tr>
<tr>
<td></td>
<td>- Visit friends/relatives</td>
</tr>
<tr>
<td>Civic/Religious</td>
<td>- Civic/religious activities</td>
</tr>
<tr>
<td>Other</td>
<td>- While traveling – other</td>
</tr>
<tr>
<td></td>
<td>- Other</td>
</tr>
</tbody>
</table>

**Embedding:** Spectral clustering, the second method used in this chapter, requires that data points be embedded into a “Euclidean space,” expressed in spatial relationships of distance and angles between points as vectors. The method used for this, which was specifically developed for human activity analysis (Eagle & Pentland, 2009), is a two-step process that converts a schedule $s$ encoded as above into a point in $\{0,1\}^{864}$. 
1. For each available activity a, generate a vector \( v \) in \( \{0,1\}^96 \) where \( v_i = 1 \) if \( s_i \) is \( a \) and 0 otherwise.

2. Concatenate all such generated vectors.

**Hamming Distance:** A metric of distance between two equal-length strings (Hamming, 1950). It is simply the number of entries that differ between the strings. For example, the Hamming distance between “0001” and “0111” is 2, the Hamming distance between “0100” and “1000” is 2, and the Hamming distance between “0000” and “0123” is 3. Identical strings have Hamming distance 0.

**K-Means Clustering:** A k-means clustering of some set of Euclidean points \( D \) assigns each to a cluster such that the distance from each point to its cluster’s mean is smaller than the distance to each other cluster’s mean (MacQueen, 1967). This method has two known limitations: the first is that it generates only convex clusters, which may not be a correct organization of the data. The second is that in the general case, finding a globally optimal solution is computationally intractable using known tools, especially when the “correct” number of clusters is not known beforehand. As such, standard implementations of k-means use iterative, heuristic algorithms that find local optima, and restart the algorithms multiple times in attempt to find the best one.

**Data Clustering Methods:**

The travel survey data was analyzed using two clustering techniques: principal component analysis with k-means and spectral clustering.

**Principal component analysis with k-means:** The first clustering approach was developed by (Jiang, Ferreira, & González, 2012) as an extension to previous work by Eagle and Pentland (Eagle & Pentland, 2009). Before describing its operation, a discussion of its motivations is presented.

Given a way to embed survey schedules into Euclidean space, and a simple way to cluster points in Euclidean space (k-means), it would seem straightforward to embed the points and then cluster them. However, Jiang et al. used a five-minute time step, which yields (with nine activity groups) a space of 2592 dimensions. Although the data occupies only an 864-dimensional space (because of the use of 15-minute time steps) the computational cost of applying k-means here is still high. However, if the dimensionality could be reduced, k-means could then be applied in a straightforward manner. One way to do this would be to represent each of the original 864-dimensional vectors as a linear combination of some \( m \) fixed, other 864-dimensional vectors. Each of these other vectors will be a “typical schedule part”. For example, one might indicate being at work from 9 AM to 5 PM, and other might indicate being at school from noon to 4 PM and also recreating from 7 PM to 10 PM. Ideally, each of these other “typical schedule parts” will be
completely uncorrelated with each other, to maximize the variety of information that can be expressed with them. The data points will now have dimensionality $m$. The greater $m$, the better the approximations will be, although the aim is to keep it well below 864.

This is the exact way in which principal component analysis (PCA) operates. There are multiple equivalent ways to perform the calculations necessary for applying PCA, and the covariance method is the one used:

1. Calculate the mean schedule vector.
2. Center each schedule by subtracting the mean schedule from it.
3. Create the matrix $D$ that has the centered schedule vectors as its rows.
4. Calculate the sample covariance matrix $C = \frac{1}{n-1} D D'$, where $n$ is the number of observations.
5. Calculate the eigenvalues and eigenvectors of $C$. Order the eigenvectors such that the first corresponds to the largest eigenvalue, the second corresponds to the second eigenvalue, and so forth.

The eigenvectors of $C$ are "typical schedule parts," and are called eigenactivities. By expressing each original (centered) schedule as a linear combination of the first $m$ eigenvectors, input data can be dimensionally reduce to $\mathbb{R}^m$. This is accomplished by treating the first $m$ eigenvectors as columns of a transformation matrix $E$. Right-multiplying an original centered schedule by $E$ projects it into the lower-dimensional space, suitable for clustering.

In order to choose $m$, the method devised by Jiang et al is followed. Note that left-multiplying a projected schedule by $E$ returns it to the original-dimensional space, although if $m$ is less than the original number of dimensions, some error will have been introduced. In this case, elements of the returned schedule (plus the mean schedule) will not be exactly 0 or 1. Consider now how a reconstructed schedule can be created in $\{0,1\}^n$ from such an approximated schedule. First, note that, for each time step $t$, there is a group of entries within the approximate vector that correspond to $t$; for example, entries 1,97,193,...,769 correspond to $t = 1$, with each entry in the set corresponding to a particular activity at that time. For each timestep, we can identify this corresponding group, find the maximum value, and set the corresponding entry in the reconstructed vector to 1. All other reconstructed entries corresponding to the approximated entries in the group are set to 0.

For each original schedule a corresponding reconstructed schedule is made. The reconstruction error is simply the Hamming distance between the two, normalized by the vector length, and will decrease as $m$ increases. $M$ is chosen such that the average reconstruction error across the data set is < 0.01. In this case, $m = 32$. Once the projected points are established, they can be clustered via k-means. To answer the question of how many clusters should be used, a visual method called Cluster Silhouettes (Rousseeuw, 1987) is used.
Given a clustered data point $i$, let $a(i)$ be the average squared Euclidean distance between $i$ and all other data points within the same cluster. For each other cluster, calculate the average squared Euclidean distance between $i$ and all points in that cluster; let $b(i)$ be the minimum of these. The silhouette of $i$ is defined as:

$$s(i) = \begin{cases} 
1 - \frac{a(i)}{b(i)}, & a(i) < b(i) \\
0, & a(i) = b(i) \\
\frac{b(i)}{a(i)} - 1, & a(i) > b(i)
\end{cases}$$

When $i$ is nearer to other points in its cluster than it is to points in other clusters, $s(i)$ is positive, and $i$ is probably appropriately clustered; when $i$ is nearer to points in some other cluster than it is to points in its own cluster, $s(i)$ is negative, and $i$ is probably mis-clustered. By examining the silhouettes generated, the performance of various cluster counts can be evaluated.

**Spectral Clustering:** Is a family of algorithms, and the particular algorithm used in this study was developed by (Ng, Jordan, & Weiss, 2002) and summarized in a spectral clustering overview provided by Von Luxburg (Von Luxburg, 2007).

In order to describe it, the premise should be setup using case-specific explanations from graph theory. A graph is a collection of vertices and edges which connect those vertices. Each edge connects exactly two vertices, and there can be no more than one edge between any two vertices. If an edge exists, it has a weight $> 0$. Two vertices are connected if each is “reachable” from the other by traversing some sequence of edges.

A connected component of a graph is a maximal set of the graph’s vertices such that each vertex in the set is connected to each other vertex in the set; intuitively, it is a “group” of vertices that are all connected to each other.

A graph so described with $n$ vertices can be completely described by an $n \times n$ symmetric matrix $W$; each matrix element $wij = wji$ is equal to the weight of the edge between vertex $i$ and vertex $j$, or 0 if there is no such edge. A diagonal matrix $D$ can then be generated, where each entry is equal to the sum of the corresponding row in $W$, and after that calculate $L = I - D^{-\frac{1}{2}}WD^{-\frac{1}{2}}$ (where $I$ is the $n \times n$ identity matrix). $L$ has the significant property that it has eigenvalue 0 with multiplicity equal to the number of connected components of the graph represented by $W$. Furthermore, each eigenvector corresponding to a 0 eigenvalue is an indicator vector for one of these connected components; that is, each of its entries corresponds to a graph vertex, where a nonzero entry means that the vertex is in this eigenvector’s connected component, and a zero entry means that it is not. If the eigenvectors are taken as columns of a matrix $T$, then each row corresponds to a graph vertex, with a nonzero entry in the column corresponding to the vertex’s connected component, and zeros in all other columns. Interested readers should refer to von Luxburg for a proof.
Clustering Procedure:

Consider now the effect of representing some data set $S$ with the matrix $W$. If each graph vertex corresponds to a data point, the edge weights can be used to represent the similarities between data points; that is, $w_{ij} = w_{ji} = \text{similarity}(S_i, S_j)$. In the ideal case, data points that belong in different clusters have zero similarity, and an examination of the eigenvalues and eigenvectors of $L$ as described above will trivially cluster the data (because a cluster corresponds perfectly to a connected component in the graph). However, if there was a similarity metric that returns 0 exactly when data points should not be clustered together, there would not be a need for a clustering algorithm; the data would be simply be categorized based on the metric used. What is more likely is that a similarity metric that approaches zero is used as data points become more dissimilar, but does not describe a hard boundary between clusters.

Two such similarity metrics are going to be introduced. First, Gaussian Hamming Similarity (GHS) (based on Hamming distance previously described in the preliminaries) between two schedule strings $a$ and $b$ (encoded as described in the preliminaries) as follows:

$$\text{sim}(a, b) = e^{-\frac{\text{hamming}(a, b)}{2\sigma^2}}$$

This maps Hamming distances to the interval $[0,1]$, where infinitely dissimilar strings have a similarity of 0, and identical strings have a similarity of 1. By modulating the parameter $\sigma$, the shape of the similarity decay is controlled. GHS is a metric of distance between two schedules defined using the nine classes of activities that were introduced earlier. When using this metric, there are effects on the eigenvalues and eigenvectors of $L$. If $W$ is perturbed slightly away from the ideal case to $W'$ (i.e. dissimilar data points receive similarities slightly above zero instead of zero exactly), there is still an initial set of (small) eigenvalues of the perturbed $L$, separated by a large gap from the rest of the (large) eigenvalues. The small eigenvalues are just not exactly zero. The difference between the last small eigenvalue and the first large one is called the eigengap. As $W'$ is perturbed more and more, the eigengap closes, until the first few eigenvalues cease to be cleanly separated from the rest of them, and the clusters smear together. The size and location of the eigengap can therefore be used to identify, for a given data set and similarity metric, the best number of clusters, and the relative quality of the clustering produced. Von Luxburg refers to this as the eigengap heuristic and provides an introduction to the mathematical formalisms behind it (Von Luxburg, 2007). By examining the eigengap characteristics of the data for a variety of values of $\sigma$, a big picture can be perceived of the data's clustering behavior.

To recover actual cluster assignments of data points in the perturbed case, some formal observations about the ideal case need to be made. Given $n$ data points and $m$ clusters, recall that the matrix $T$ will have $n$ rows and $m$ columns. The $i$th row of $T$ corresponds to the $i$th data point $d_i$. Each row of $T$ contains exactly one
non-zero entry in position $j$; this means that $d_i$ lies in cluster $j$. Consider the rows of $T$ as points in $\mathbb{R}^m$. Note that they all lie on an axis of $\mathbb{R}^m$ and on the same side of the origin. Now, normalize each row of $T$ to 1. This is equivalent to projecting each point in $P$ onto the unit hypersphere in $\mathbb{R}^m$. However, since each cluster’s points lie on the same axis and the same side of the origin, they will all be projected onto the same point on the hypersphere. The cluster of $d_i$ can therefore be recovered by examining the location of the projection of $p_I$; if the projections are coincident, the original data points are in the same cluster.

In the perturbed case, each row of the perturbed $\tilde{T}$ no longer has a single non-zero value. As a result, the points defined by the rows of $\tilde{T}$ no longer lie strictly on the space axes; they now lie only near the axes. Therefore, they no longer are coincident when projected onto the unit hypersphere. If the perturbation is small, i.e. the clustering pattern is still readily discoverable, the projections will form tight, distinct clusters on the hypersphere, and these clusters can be easily recovered by application of k-means to the projections. If the projections of two points $p_i$ and $p_j$ share a hypersphere cluster, then the original data points $d_i$ and $d_j$ share a cluster. This concludes the determination of the clusters.

**Output: Occupant Schedules and Behavior Profiles**

Two outputs are created through the previous data mining workflows. First, a typical at-work BPS occupancy schedule based on a “Worker” cluster, where an office building occupancy percentage of each timestep is the percentage of respondents in the cluster who are at work during that timestep. Second, an activity distribution profile for each of the clustered users. This sets the basis for modeling mobility in an urban area by identifying the type of activities people engage in and their expected activity-based travel within the city. The framework was applied to the State of Massachusetts, and results are detailed next.

3.3 Results

Two clustering algorithms were applied to analyze the Boston travel survey dataset. The first, principal component analysis with k-means, has been previously used by Jiang et al. for this type of study by previous work and also yields eigenactivities, which are an interesting way to analyze population behavior. The second approach, spectral clustering, has the benefit of carrying a built-in method for exploring the similarity metric parameter space and comparing cluster counts. The following section presents results of applying these algorithms.

**Principal component analysis with k-means**

The application of PCA with k-means requires the cluster count ($k$) to be selected beforehand. Figure 20 shows the use of cluster silhouettes (previously described in the preliminaries) as average data point silhouettes for various values of $k$. By using this metric, the best performing clustering is at $k=3$, followed
up by clusterings occurring at $k=4$, 2, and 6. To further analyze a particular clustering, we can examine a silhouette plot for that clustering; the silhouette plot for $k=3$, 4 and 6 is shown in Figure 21. Each row represents a particular data point, and its horizontal length corresponds to its particular silhouette. A silhouette ranges from -1 to 1, and the higher a silhouette value, the more likely that a point has been correctly clustered. A silhouette of 0 indicates a point that is right on the cusp of being improperly clustered. The silhouette plot shows that most of the points are correctly clustered, and also shows the relative sizes of the three clusters.

By examining the aggregate schedules generated from the clustering, each cluster can have informal characterizations specifically inferred. Such aggregate schedules are shown in Figure 22. Cluster 2 is called “standard-schedule workers” and cluster 3 is “students,” with everyone else in cluster 1. It is important to note that cluster 1 contains a number of workers, but their work hours are generally later than the workers in cluster 2. For this reason, a single “worker” cluster is insufficient for the generation of distinct worker profiles that can be used to generate BPS schedules for a variety of workplace categories. Clusters generated by larger values of $k$ are hypothesized to be corresponding to different working schedules.

Figure 23 and Figure 24 show the cluster schedules generated for $k=4$ and $k=6$. When $k=4$, the “new” cluster seems to be characterized by respondents who do not maintain a regular work or school schedule yet still generally leave the house, but the members of this new cluster appear to be difficult to cluster properly. When $k=6$, clusters 2 and 4 are distinct “typical” and “early” worker clusters, and clusters 1 and 5 are more difficult to characterize. The members of this latter pair of clusters are also likely improperly clustered, according to the silhouette plot.

![Figure 20: Average data point silhouette, number of clusters against average silhouette.](image)
Figure 21: Silhouette plot for cluster count \((k) = 3, 4 \text{ and } 6\) respectively.

Figure 22: Best performing clusters \((k=3)\) with primary groups (from left): stay-at-home, worker and student.
Figure 23: Clusters generated for (k=4) with the primary groups similar to fig. 3, with an adventurer cluster.

Figure 24: Clusters generated for (k=6) with emergence of early worker and late worker clusters.
Spectral clustering

Like PCA with k-means, spectral clustering requires the selection of a desired cluster count. The eigengap heuristic was used to evaluate particular cluster counts, and the similarity metric used, Gaussian Hamming similarity, is parameterized by $\sigma$, which informally controls the “neighborhood” size within the data. Figure 25 shows both the eigengap location (indicating optimal cluster count) and the eigengap size (indicating clustering quality) for a range of values of $\sigma$. The best clustering is $k=1$ as $\sigma$ goes to $\infty$, but the second-best is at $\sigma=3.55$, with $k=3$. Figure 26 shows the three cluster profiles generated in this case. A “normal-schedule worker”, “student”, and “other” cluster. In fact, the clustering is almost (but not exactly) identical to the clustering generated for $k=3$ by PCA/k-means; only 94 samples (out of 1900) are clustered differently by the two methods. If, as before, explorations of more granular clusters are needed, this can be done by looking for large eigengaps corresponding to other values of $k$. The next two largest eigengaps occur at $\sigma=3.03$ with $k=4$ and $\sigma=2.43$ with $k=8$. These clusterings are shown in Figure 27 and Figure 28.

Figure 25: Eigengap heuristic and Gaussian Hamming similarity, parameterized by $\sigma$. 
Figure 26: Clusters generated at $\sigma=3.55$, with $k=3$ with primary three clusters, similar to Figure 22.

Figure 27: Clusters generated at $\sigma=3.03$ with $k=4$, which show a late worker cluster.
Occupancy Schedules and Behavior Profiles

Through the presented analysis of activity patterns in the city, two outputs are extracted to be used in the field of BPS, occupancy schedules and behavior profiles. Both PCA with k-means clustering and Spectral clustering produced similar, but not identical, outputs for the purposes of BPS. In order to demonstrate the relevancy, the focus will be on the results of Principal component analysis, since Jiang et al (Jiang, Ferreira, & González, 2012) devised their methods on it, with k-means at k=3, which was the best performing output as it had the highest average silhouette value.

Occupancy Schedules: Typical schedules used for energy simulation use diversity factors for weekday and weekend patterns in using buildings. Such diversity factors were extracted from the Worker cluster (k=3) to demonstrate the pattern of office building types weekday according to analysis of the MassDOT survey, and are presented in Figure 29. The schedule starts at 7 AM, where 12% of occupants are expected to arrive at their work place, with a linear increase until 11 AM, where 98% of the users are present, and an expected decrease around noon takes place for lunch time, but it is only a change of 1%. A steady decline then of
workers leaving the work place takes place until 6 PM, where only 25% of the occupants remain and decrease to 6% 8 PM to reach 1% at 10 PM.

Figure 29: Office building occupancy schedule as extracted from the Worker cluster.

Behavior Profiles: For the simulation of activities taking place in urban areas, behavior distribution profiles are also extracted from the clusters. Figure 30 demonstrates the distribution of urban activities for the Worker cluster. While members of this cluster spend most of their time either at home or at work, other activities present themselves temporally, which gives a better understanding of the kind of activities this cluster would engage in a city. The Worker cluster activity profile gradually replaces staying at home temporally with work, with the rise of time specific activities mainly represented in transit from home in the morning and to home in the afternoon. A significant portion of other activities goes to recreation starting 4 PM up to 10 PM.
Once the profiles of individual “eigenusers” are identified based on clustering, a design team can now assume various mixtures and scenarios. Such activity time series for individual clusters are translated into a BPS occupancy schedule by mixing clusters for different building types. Through such combinations occupancy patterns emerge that differ with change in building use. Figure 31 shows an example occupancy schedule for a single family house composed of a “Worker,” a “Stay at Home” and two “Students.” Since this schedule focuses on “home” all other activities were disregarded, and the produced profile represents the basis for a residential building type schedule aggregated from a variety of clusters through their activity patterns. If one then assigns to which school and workplace three members of the household go, complementary building occupancy schedules for these buildings can also be generated.
3.4 Discussion

This section will discuss the framework, potentials in generating activity-based occupancy schedules and will speculate on the use of complete behavior profiles for urban modeling.

Framework

The presented framework demonstrates the relevance of analyzing human mobility to understand building performance. The procedure links between the two domains of knowledge: BPS and activity-based transportation analysis. While the workflow is not intended to replace any practice standards, it attempts to create common grounds for architects, planners and transportation engineers innovatively by utilizing activity-based travel surveys and databases to produce useful occupancy information for energy modelers. It is applicable to any urban area around the world, and will aid significantly in representing realistic occupancy patterns in neighborhoods and cities. The field of urban modeling and simulation is currently growing, and that is why having an approach, such as the presented framework, that addresses people as both building occupants and as travelers is becoming essential.
Occupancy Schedules

Occupancy schedules are a crucial input for whole building energy simulation. Numerous models have been previously developed based on occupancy monitoring, which is plausible when a building is erect, and simulation is being done for that structure specifically. However, the presented method aims to understand occupant behavior as part of a time-series of activities in the city. This makes the traditional occupancy schedule part of a bigger scope for urban simulations based on clusters of users. For example, an office building in an “innovation district” may have 50% workers and 50% adventurers. A more traditional office has a mix of 90% workers and 10% adventurers. By mixing the clusters for different spaces new occupancy patterns emerge, since simulation software do not place emphasis on what type of users are in a space at a point in time, just the number of occupants.

Office Building Schedule Example

To demonstrate the impact of creating occupancy schedules based on travel behavior, a typical office building environment was modeled in Design Builder/EnergyPlus (DesignBuilder Software Ltd, 2015), based on the reference office case (Reinhart, Jakubiec, & Ibarra, 2013). For the base case, internal walls and ceiling were considered adiabatic, and the south facing wall had an R-value of 4 m²·K/W. Window-to-wall ratio was 40% with 80% VLT single pane glazing. The HVAC system was modeled as Variable Air Volume (VAV) with Heat Recovery that assumed natural ventilation when outdoor conditions were suitable, and lighting system had a load of 10 W/m² with a linear / off control system. Occupancy was modeled to match the ASHRAE standard 90.1 (ASHRAE, 2007), and whole energy simulation was performed using Energy Plus (US-DOE, 2015). Figure 32 shows the geometry of the office space within the Design Builder modeling interface.

Five occupancy scenarios were created, based on the results of Principal component analysis with k-means at k=6. (Figure 24). Although the best performing clustering was at k=3, diversity explored through high numbers of clusters is needed in the particular case, in order to demonstrate the use of eigenusers in the context of BPS. With focus on worker profiles, three worker schemes are observed. Early-bird workers that start their work day at 5 AM and peak at 10 AM, then gradually decrease and end around 5 PM. Normal workers are similar to the work profile presented earlier in Figure 22. Finally, Late Night workers follow the “adventurer” type profile, with work typically starting around 10 AM and then continuing on sporadically until midnight. The five scenarios start with all workers being Early Bird, followed by a mix of 50% Early and 50% typical (normal), then a mix between the three types, followed by a 50% mix of Early and 50% Late, and concluding with all Late Night workers. The result of the simulation runs for the base case and the five occupancy scenarios is demonstrated in Figure 33.
Figure 32: 8.2 x 3.6 m office space designed to fit six occupants.

Figure 33: Office space occupancy patterns and corresponding Energy Use Intensity (EUI) for fuel breakdown with total EUI percentage change from the base case.

Table 1: Base Case (ASHRAE) Early Birds Cooling (kWh/m²) Heating (kWh/m²) Lighting (kWh/m²) Early+Normal Early Normal Late Night Equipment (kWh/m²) Difference (%)
Simulation results show how occupancy patterns significantly affect energy-use in buildings, with Early Bird occupancy patterns showing change from 146 kWh/m² to 131 kWh/m², a -10% change in EUI from the base case. As occupancy patterns change to include more daily activities away from daylit hours, EUI increase to reach 6.6% increase in the case of all workers arriving late to work. This result shows how users' reliance on natural lighting, as opposed to artificial lighting, affects energy flows in a range of 16%. To demonstrate this, Figure 34 shows change trends in energy consumption per load-type, with lighting reaching a 188% increase in the case of late night workers, and cooling and heating loads actually decreasing in certain cases, but in a relatively-less impactful manner.

Figure 34: Office space occupancy patterns and percent change in heating, cooling and lighting, in comparison to the base case.

With the presentation of these results, it becomes clear that examining buildings in the context of simulation as singular, devoid of relevancy to actual human travel patterns, and using typical occupancy schedule, may not reflect correctly on actual energy use in buildings. Ideal case scenarios do not represent real patterns of staying at work late, or coming to work early, which are trends that the clustering workflows showed. By
building occupancy schedules that better reflect actual human activity patterns, simulated energy use in buildings should better represent what is likely to happen: sporadic patterns that require more aware users, such as early bird workers, to consume less energy in the workplace. On a larger scale, when comparing energy uses across the city, adopting the standard ASHRAE schedule for all workers (a total 1620 worker respondents) yielded marginally higher EUIs when compared to a virtual population composed of the three types of workers previously discussed. As presented in Figure 35, when considering the populace as a divide between different types of workers, the number of late night workers is actually impactful as a percentage of the population (210 respondents, 13%), so electric lighting consumption difference is significant (16% higher). However, the inclusion of a working force that goes to work early made savings in heating (4%), cooling (5%) and equipment (3%), which evened out the comparison. This analysis suggests that further investigation of the impact each eigenuser has on the overall energy consumption of an urban area is needed, as a direct multiplication calculation doesn’t reflect on the expected variability on a larger scale.

Figure 35: EUI comparison of ASHRAE Standard schedule population (1620 respondents) and a composition of early (640), normal (825) and late (210) worker cluster schedules.
3.5 Conclusion

This chapter presented a framework for the generation of occupancy profiles based on activity-based travel behavior analysis. The aim was to approach the issue of human behavior modeling for BPS based on patterns of activity in cities. The use of clustering algorithms, such as PCA with k-means and Spectral clustering, contributes to our understanding of human activity patterns in cities. Applicability was shown in the context of BPS through the creation of detailed and more representative occupancy schedules for energy modeling. Assuming that more detailed data sets than travel surveys will soon be a reality, the clustering method presented in this chapter along with the conversion of these clusters into “eigenuser” profiles can yield consistent occupancy patterns and trips within cities. Future research should address the shortcomings of using travel surveys such as weekday and weekend patterns, and progress in urban sensing technologies and its reflection on simulation workflows should be observed as a means to support such an interdisciplinary approach.

3.6 References


Chapter 4: *Linking Comfort and Travel Behavior*

The past century has seen a steady decline in human powered transportation in urban areas. Throughout history, towns and cities were planned around how humans traveled to resources such as water and market places. Urban form followed the transportation technology available, and where a horse or donkey could take you was the limit for growth (Muller, 2004). However, each step forward in the field of transport technology development tended to worsen the pedestrian environment. The degradation of the walkability and bikeability of cities was strongly related to the loss of intimate scales in streets, as it became a separator between the people and the automobile. City officials engineered roads for cars, and became fully automobile-oriented in codes and standards. These include discontinuous loops as opposed to interconnected paths, large block sizes and widely spaced land uses that are segregated by type, and lastly over-scaled streets that are not equipped with basic pedestrian facilities such as sidewalks. With the awareness of such auto-dependency, interested researchers, governmental agencies and activists recently started to address such issues simultaneously. The concept of “walkable cities” as the foundation for a sustainable development was reborn. As populations switch to alternative modes of transportation (namely walking, biking and public transit), the benefits show in different aspects and scales, such as reduction in congestion, lower carbon footprint, energy efficiency and lower noise and air pollution (Forsyth and Southworth 2008). The evaluation of walkability in neighborhoods and cities is subjective, and depends on many interfacing parameters that include access to amenities, pedestrian thermal comfort, and pleasantness of routes, to name a few. In order to be able to predict if future urban interventions or developments are going to accommodate and encourage active, human powered transportation, modelling the aforementioned factors is key.

This chapter presents concepts for how one could link travel behavior based on human activity analysis and outdoor thermal comfort simulation. The goal is to provide designers with tools that can predict the potential walkability and bikeability of routes at certain times of the year based on the human perception of thermal
comfort conditions along these routes. The framework is attractive for design, but is presented as a blueprint for future work that requires validation. The chapter is divided into three sections. The first section focuses on translating activity patterns and schedules, previously presented in Chapter 3, into inputs for Agent Based Modeling (ABM) simulations. The aim is to provide designers with a more realistic representation of human movement patterns, and consequent mode choices for travel, than current building occupancy schedules. The second presents conceptual methods for linking outdoor thermal comfort analysis, previously presented in Chapter 2, to actual routes in order to quantify the likelihood that somebody will walk or bike along these routes at a given time. “Trip Comfort” metrics, specific to pedestrians and cyclists are then presented through a case study in Copley Square, Boston MA. The third section concludes the chapter through a discussion of the presented measures, and introduces a novel field called “Comfort in Motion” as a continuation to the assessment of thermal comfort in the context of active transportation.

4.1 Activity-centered Mobility Modeling Basis

A number of urbanization concepts that promote human powered transportation emerged as a reaction to the aggressive motorization of cities. These include neo-traditional planning, Transit Oriented Development (TOD), New Urbanism and Smart Growth. They share the same objective of creating a community that depends mainly on walking. However, each of them have “checklists” that comprehend different features between what is essential and what is desirable (Ewing 1999), and it is not guaranteed that the desired effects will be achieved. This is because design elements if applied improperly may actually have a counter effect on congestion and auto-use. For example, having an orthogonal grid for planning purposes is meant to facilitate walking because trips become closer, but without proper land-use mix and traffic calming it may actually increase auto-use (Crane, 1996). In the case of TODs, the success in part depends on the capacity of transit users to access key activities once they reach their destination. Therefore, walkability is strongly linked with TODs through pedestrian accessibility at transit stations (Schlossberg 2003).

The question of how much urban form has influence on travel behavior became quintessential for urban planners and designers interested in walkability. The idea of reducing Vehicle Miles Traveled (VMT) by switching travel modes as influenced by urban design strategies is attractive, but links to many factors such as density and land use mix to name a few. This is why applying a number of features may not be the most effective immediate solution. Comprehensive studies conducted to measure the effect urban form has on travel behavior use either simulation (hypothetical studies), descriptive studies and/or multivariate statistical approaches, which were reviewed extensively (Crane, 2000). In theory, the utilization of high density and diversity in land-use is an effective strategy that decreases VMT and contributes to more sustainable modes of transportation, as a short proximity between amenities encourages active, human powered transportation. There are formal approaches to applying such a strategy through well-known
schools of thought in urban planning practice. New Urbanism is an urban design movement that encourages walkability through density. A study that compared a New Urbanist neighborhood with conventional suburbs in Chapel Hill-Carrboro, NC showed that physical activity increased in the New Urbanist neighborhood due to accessibility to different amenities at close proximity. The total number of walking and cycling trips per day was 2.4 times higher for a single-family household in the New Urbanist neighborhood than in the conventional neighborhoods (Rodriguez, Khattak, & Evenson, 2007). Smart Growth advocates for compact, transit-oriented developments (Handy 2005). An example of an area that adapted some of Smart Growth’s principles is Standish Corner, a town of 10,000 citizens 18 miles west of Portland, ME. Through a number of community workshops, the town established form based codes relevant to their land-use that preserve its rural character and promote walkability (GrowSmartMaine 2012). These two examples show that even though they are given different names, New Urbanism and Smart Growth share the goal of having more walkable/bikeable and healthier communities. It is important to note that increase in density on its own is not sufficient; creating walkable destinations in tandem is critical to ensure significant reductions in automobile use. A comprehensive study concerned with density and climate change concluded that increasing residential density on its own does not significantly affect reductions in VMT. Doubling current density levels would account for 5% reductions in vehicular traffic. If this was combined with land-use diversity, aspects of neighborhood design and access to transit, VMT would be reduced to about 25-30% (Burnett, et al. 2010). The underlying hypothesis of these design movements is that – if given the choice and external weather condition allow for it – the majority of people choose walking over alternative modes of transportation. This means that the creation of many walkable destinations within a neighborhood internalizes trips within the neighborhood, and thus reduces reliance on driving and reduces related carbon emissions and pollution.

To quantify the impact of applying such principles, the integration of simulation tools that evaluate cities’ “walking friendless” in the design process is becoming significant. This reduction in car dependence makes the accurate estimation for the proportion of trips that are internalized through walking, biking or transit trips an important, albeit complex, task for existing cities or future developments. The ITE Trip Generation report (Institute of Transportation Engineering, 2008) although seemingly objective, logical and fast, is far from accurate due to the various limitations in the estimation assumptions that oversimplify travel behavior, as it was not designed to focus on human powered mobility. Previous relevant research presented a method which utilized hierarchal models that were validated against in-field traffic counts. The study first showed the impact of mixed-use developments in internalizing walking and transit mode share percentages in cities as high as Seattle (18.0%) and as low as Portland (15.9%). The model then varies “D” variables (density, diversity, design, destination accessibility, distance to transit and development scale) to predict trips generated (Ewing, et al., 2010). Another recent investigation demonstrated a model that uses annual non-
motorized count data to estimate mode share changes and avoided VMT (Rasmussen, Rousseau, & Lyons, 2013). However, both models approach the research question on a macro scale and pay minimum attention to micro interactions between individual buildings and surrounding activities.

In a study conducted by the author, a simulation module to model and examine the performance of active travel behavior and land-use planning interventions on a microscopic scale was presented. This is to assess urban form parameters for walkability. The tool aims to help answer questions such as: How likely is it that people will walk or bike in different neighbourhoods? What urban design parameters contribute to more walkable/bikeable cities? The tool forms part of an urban modelling platform called umi, developed at the Sustainable Design Lab at MIT, that also simulates operational energy use in buildings, embodied carbon and daylighting potential. The tool specifically investigated choices regarding the mode of transportation chosen by residents over the course of a year. The underlying model combines trip choices to multiple destinations (such as grocery, shopping, entertainment, etc.) based on Walkscore calculations (Walkscore, 2015). The choice to walk, bike, take public transport or drive is then simulated based on distances to destinations and climatic conditions. Next, the output was tabulated and converted into a carbon emissions balance. As a proof of concept for this simulation workflow, the study focused on VMT averted as a result of occupants walking to destinations in various simulated weather conditions. This was illustrated through a comparison of carbon emissions due to operational energy use and transportation energy in a fictional mixed use neighborhood in Boston, MA, USA. The investigation highlighted that even the most energy efficient of neighborhoods in terms of construction standards is estimated to consume as much as (if not more than) its annual operational energy use in personal transportation trips if it is not planned with human mobility in mind.

Residents’ travel behavior in the case study was assumed to be binary: if one does not walk, one drives. This is an assumption that is oversimplifying the reality in many places where alternative modes of transportation are available. For application in realistic situations, data has to be drawn from reliable sources such as detailed travel diaries and travel survey, as previously presented in Chapter 3. The uncertainty of occupancy behavior has long been an issue in BPS (Hoes P., Hensen, Loomans, de Vries, & Bourgeois, 2009), but has evolved over time, so this constraint of suitable behavior templates is needed. Another aspect to be tackled is the logic behind trip generation. People do not plan their trips discretely, they are usually in chains. The model that was previously presented dealt with trips between origins and destinations separately, however modelling of trip chains should also be considered (Rakha & Reinhart, 2013). A proposal was therefore developed to address these limitations, and is presented next.

Previously in Chapter 3, behavior distribution profiles that were extracted from clusters were discussed as an output of travel survey analysis. A demonstration of urban activities distributions for the Worker cluster

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was presented, which gave a better understanding of the kind of activities that certain clusters would engage in a city. Behavior profiles are an activity-based approach to visualize the type of activities clusters undergo temporally. The Worker cluster activity profile gradually replaced staying at home temporally with work, with the rise of time specific activities mainly represented in transit from home in the morning and to home in the afternoon. This is a useful output for mobility-based simulations in urban modeling, as a previous challenge to this type of simulations was the unavailability of a workflow that addresses “trip chaining” in relevance to simulation on the building and neighborhood scale. With the cluster-based profiles each activity is not considered a “trip” on its own, activities are now linked to each other temporally. However, it is presented in this framework as a deterministic output, while simulating occupant behavior and user activities in the city are better addressed using a stochastic process capable of producing probabilistic outcomes that are more in-line with real human behavior (Wang, Yan, & Jiang, 2011).

Figure 36 shows how this approach can be used as part of a Markov transition matrix, where each activity is linked to the previous not just temporally, but also probabilistically based on characteristics of the cluster and expected behavior. For example, as the workday comes to an end, occupants leave their building with probabilities of various activities. While this is of little value to building scale simulations, as modelers are only interested in when occupants arrive and leave, for urban modeling this approach allows for realistic micro simulation of mobility behavior based on the analysis of real human activity patterns. This sets the basis for a probabilistic workflow, where a stochastic process, such as Markov Chains, could be used as a generator for agent-based activities for urban mobility simulations. The probabilistic nature of the desired output and its employment in assessing mobility behavior lends itself perfectly to Agent Based Modeling (ABM) of human systems. Interactions between people (agents) and activities sought after in the city are heterogeneous, as the clustering process creates agents that deviate from average expected behavior (Bonabeau, 2002).

The presented framework draws its validity from the activity-based mobility database used, and it is not expected to be used as a tool that will accurately predict travel behavior. However, it is expected that the mobility patterns produced are going to be reliable, and will reflect on meaningful outcomes in terms of agent’s interactions with activities modeled, as well as trips internalized through proximity as walking and biking modes of transportation. Many aspects influence people’s mobility choices, and one of which is weather and microclimate, and their effect on outdoor thermal comfort in built environments, which is addressed next.
At 4 PM Workers start to change their work activity gradually to being in transit to home or other activities. As 6 PM is reached, most workers have shifted their activity to being at home.

4.2 Trip Comfort Workflows and Metrics

Although it is a relatively nascent field, in contrast to indoor thermal comfort, there is a plethora of research studies that were conducted to understand behavior and activity in relevance to outdoor thermal comfort, which were thoroughly reviewed (Chen & Ng, 2012). Research instrumentation and methods were also reviewed, to call for a unified standard for outdoor thermal comfort studies (Johansson, Thorsson, Emmanuel, & Krüger, 2014). The importance of understanding and enhancing outdoor thermal comfort is evident in the literature. The numerous motives for such investigations include alleviating the Urban Heat Island (UHI) effect, control of microclimatic effects and pedestrian thermal comfort to motivate outdoor activities and human powered mobility, to name a few (Hong & Lin, 2015). Studies continue their focus on various pedestrian comfort topics, such as sensation (Pantavou, Theoharatos, Santamouris, & Asimakopoulos, 2013), design intervention using shading (Paolini, Mainini, Poli, & Vercesi, 2014) assessment through simulation (Borong, Li, Zhu, & Qin, 2008), or thermal comfort analysis on the pedestrian level (Akashi & Lun, 2008). However, the concentration is typically specific to outdoor comfort as discrete states that represent spatiotemporal variations, similar to the work previously presented in Chapter 2. There are several methods to model energy exchange between pedestrians and their environment.
(David, Berliner, & Shaviv, 2007) (Soligo, Irwin, Williams, & Schuyler, 1998), yet such methods do not consider modeling for human movement, such as walking or cycling, or link them to built environment influences. While previous research findings suggest a strong correlation between weather and physical activity choices (Tucker & Gilliland, 2007) as well as decision cycling travel and commute decisions (Brandenburg, Matzarakis, & Arnberger, 2007), analysis of thermal comfort for human powered activity is typically only conducted for athletic and sports related activities (Pezzoli, Cristofori, Gozzini, Marchisio, & Padoan, 2012). There is a lack in connectivity between microclimate, outdoor thermal comfort and human powered mobility simulation. As a pedestrian makes a trip in an urban area, from point A to point B, the built environment affects his or her experience of outdoor thermal comfort.

**Trip Comfort Metrics**

To quantify the relationship between outdoor thermal comfort and human powered mobility, a new method is introduced in this section. The underlying premise is that, if provided with comfortable environments that are suitable for walking and biking, people will choose this option over alternative modes of transportation. The aim is to aid architects, urban designers and planners in creating built environments that are walkable and bikeable through the design of comfortable outdoor spaces. The workflow is threefold:

1. **Outdoor Thermal Comfort Simulation:**
   
   Outdoor thermal comfort metrics can be explored in existing or hypothetical cases through the use of any reliable simulation tool. Digital urban fabric models are created, and environmental parameters such as air temperature and relative humidity are extracted from weather data files, simulated or assumed. With inputs for urban surface material properties and geometry (for existing cases or proposed designs), MRT and wind speed are simulated. If needed, personal factors such as clothing and metabolic rate are assumed. A calculation for a chosen outdoor thermal comfort metric, such as UTCI, OUT_SET, etc. is then done to produce spatiotemporally resolved outdoor thermal comfort, mapped through digital urban space. Tabulated annual outdoor thermal comfort would be the final outcome of this stage.

2. **Human Activity Patterns Analysis:**
   
   An activity-based urban mobility database is needed as an input for data mining. This maybe a travel survey, cell-phone traces and/or social media check-ins. A computational data clustering technique is then applied on the mobility database to identify urban dweller archetypes (eigenusers) based on the type of activities they engage in through representative days, an extended period of time or an entire year. Depending on the clustering technique, a complementing method would be needed to identify the number of clusters. The produced clusters will display two outputs, time series to be used for BPS, and activity profiles that would be translated to Agent Based Modeling inputs. A route logic would be used (shortest distance, pleasantness,
etc.) to identify how agents would interact with the built environment to perform activities. Agents would follow the logic to perform activities as identified by land-use inputs to the digital model. A timestamp is created for each trip undertaken by an agent.

3. Trip Comfort Metrics:

With annual comfort computed, and as ABM logic identifies origins, destinations and timestamps within the simulated urban environment, trips are identified throughout the year. The workflow starts with the identification of origin and destination (A to B). The route is then discretized based on the needed resolution for thermal comfort simulation at a suitable height, and travel mode is chosen based on proximity. Comfort is recalled from simulations for each analysis node, where it is translated into a score between 0 and 100% that represented how travel distance is perceived based on the human experience of outdoor thermal comfort. Figure 37 shows a hypothetical “perceived travel time” based on the UTCI metric. For example, if the node was at “no thermal stress” between 0 and +9 °C UTCI, then a full score would be given, equals 100% and translates to a perception of walking speed = 4 km/hr. If the node is experiencing “very strong heat stress” between +38 and +46 °C UTCI then a score between 50 and 10% would be given. This is based on the concept that travel time perceived would increase dramatically when experiencing such discomfort.

![Outdoor Thermal Comfort and Perceived Travel Time](image)

*Figure 37: Perceived travel time according to the UTCI metric.*

The experience of outdoor thermal comfort is translated to a percentage decrease that explains how human beings perceive travel time based on their thermal comfort range. If perceived time traveled is 40%, this means that the traveler experiences discomfort that makes the perceived distance traveled increase by 60%, and the score given is 1.8 km/hr for this point.
Trip comfort is then calculated as the cumulative time of the entire trip. The workflow is presented in Figure 38. The analysis metric proposed is named:

Trip Comfort (TC), which is defined as –

“The cumulative perceived travel time of a human-powered transport trip, from a defined origin to a destination, based on a person’s experiences of outdoor thermal comfort.”

\[ TC = \frac{1}{n} \sum_{i=1}^{n} PTT_n \]

Where:

\( n \) = number of analysis nodes along a route

\( PTT \) = perceived travel time (seconds).

An example case study is presented in Figure 39. A situation is hypothesized in Copley square, where a city dweller is making a trip from point A to point B. There are three possible routes in that scenario for the trip. Route 1 (4 minutes) is mostly shaded by trees, as well as shade provided from the adjacent John Hancock Tower. Route 2 (3 minutes) crosses the streets and mostly unshaded except for shade by the tower, and a trip on Route 3 (4 minutes) is an experience that mixes solar exposure and urban shade. Thermal comfort was simulated using the workflow presented in Chapter 2, and UTCI values were simulated for the entire year. Figure 40 shows the route start options for the trip to be made for the 21st of June at noon. Even though Route 2 is the shortest in terms of distance, Route 1 is a paved path with recurring trees that provide a shaded route, which is more comfortable during the summer, and so TC favors route 1 over route 2 or 3, which involve crossing the street. Perceived travel time is approximated as equal to the actual time needed to make the trip (4 minutes) in Route 1, while in Route 2 and 3 it is 5 and 6 minutes, respectively. However,
as shown in Figure 41 in the winter route 2 and 3 are better performing, which suggests that human logic to get from point 1 to 2 should be changing over seasons, in order to perceive the fastest route experience during different climatic conditions.

*Figure 39: Case study example area in Copley Square, Boston MA.*

*Figure 40: Displaying an example Trip Comfort simulation June, 21st at noon.*
TRIP COMFORT ALONG THE ROUTES IN SUMMER AND WINTER

Perceived Time (Winter)  Perceived Time (Summer)  Travel Distance

Minutes

Route Choice

1  2  3

Figure 41: A comparison between different TC along routes from point A to B in presented case study.

4.3 Discussion: “Comfort in Motion”

The presented framework contextualizes outdoor thermal comfort analysis for pedestrians through analysis of human behavior in cities and linking it to outdoor thermal comfort simulation. Directionality from an origin point to a destination on a trip influence comfort sensation analysis, as the nodes are now connected through a movement vector, based on where an agent would go. The author, therefore, is recommending further research on a new concept called “Comfort in Motion” to be a new field of future studies. In order for the field to be a comprehensive framework, a number of limitations should be addressed in future research, to present a more comprehensive workflow.

1. Route Choice: While the simulation workflow helps in understanding route choices and consequent human powered mobility trips, it is clear that seasonal differences are not taken into account in the logic for trip choices. For example, a trip that would be comfortable in the winter due to solar exposure, would probably be uncomfortable in the summer for the same reason. The first way to address this is by presenting the workflow in a decision-making setting. This would be in the form of cell phone application (app) that could aid city inhabitants in making route-choice decisions based on outdoor comfort. Figure 42 shows a mockup for the integration of an App called “Comfort in Motion” to Google Maps. Figure 42 shows a mockup for the integration of an App called “Comfort in Motion” to Google Maps. A second way is through

3 https://maps.google.com accessed 04/29/2015
the integration of a stochastic logic in the simulation workflow. ABM that allows the agent to assess possible Trip Comfort for each route and consequently choose a comfortable trip, rather than an uncomfortable one that is short in distance, should significantly increase trip comfort on an annual scale. The annual performance would then be based on the number of trips in comfort, with lower perceived travel time, rather than the discomfort of a specific route choice.

Figure 42: Comfort in Motion app mockup for decision making support as a user moves from point A to point B. The focus is on the Copley Square case study previously presented.

2. Thermal Inertia: Running simulations for outdoor thermal comfort is typically discrete in terms of relationship between analysis nodes. However, Trip Comfort is specifically experimenting with the relationship between these nodes, in terms of a human being moving through them as a series, to get from an origin to a destination. There is a need to develop outdoor thermal comfort metrics that take
into account temporal change of boundary conditions, the human physiological state and clothing insulation. As one experiences thermal stress, for example, shading does not alleviate the stress immediately. The nature of our human experience of thermal environments is spatiotemporal, as exhibited by the Dynamic Thermal Sensation (DTS) model (Fiala & Lomas, 2001), as shown in Figure 43. Interpreting the effect walking and cycling has on thermal comfort sensation through space and time is critical. Each analysis node, therefore, should have a data input in relevance to the thermal comfort conditions of the prior node in the direction of movement. That dynamic relationship would address shortcomings of the discontinuity of the analysis nodes.

![Graph showing PMV and DTS indices with local thermal sensation vote on a manikin's surface](image)

*Figure 43: Virtual thermal manikin exposed to transient conditions and subject to changes of the ambient conditions and clothing insulation over time. The graph shows the respective PMV and DTS indices together with the local thermal sensation vote on the manikin's surface. Image: (Van Treeck, 2012)*

3. **Mode Choice:** Walking and cycling share the human-powered aspect of mobility, but they are different in terms of speed, metabolic rates, required infrastructure, state of mind, etc. An agent’s choice to walk or bike at this point is determined by the users’ input. This is a limitation because choice for routes differ, due to the inherent difference between the two modes. It is recommended that further cases are studied to incorporate bicycling in the context of Trip Comfort.
4.4 Conclusion

This chapter presented a novel approach to the assessment of outdoor thermal comfort in cities. The integration of Agent Based Modeling in Building Performance Simulation was introduced through human activity pattern analysis, as a means to simulate trip internalization for walking and biking in sustainable urban areas. Consequently, a set of methods were proposed, called “Trip Comfort,” to link outdoor thermal comfort analysis with activity patterns in cities. A case study presented the Trip Comfort metric in Copley Square, Boston MA. The results highlighted potential agent choices for routes to experience thermal comfort. Limitation of the workflow were presented, which included ABM logic flaws, integration of time and space in thermal comfort simulation, as well as mode choice limitations in the presented model. A new field called “Comfort in Motion” was introduced as a potential continuation for the field in future studies.

4.5 References


Chapter 5: Conclusion

As the dissertation concludes, we revisit the introductory objectives for a discussion about the findings, original contributions and an outlook for future directions.

1. Feasibility:

In Chapter 2, the MRT workflow was developed and verified against measured data and consequent outdoor thermal comfort simulation was presented. The outcome addressed shortcomings in comparable tools, and annual thermal comfort maps and metrics were consequently demonstrated as tools for designers to make informed design decisions about urban space geometry and materiality.

The development of a simulation tool that predicts outdoor thermal comfort annually was shown to be both feasible and useful for design communities.

In Chapter 3, the use of computational clustering techniques, such as Principal Components Analysis with K-means Clustering and Spectral Clustering, demonstrated two outcomes in the context of BPS, occupancy schedules and activity distributions.

Travel survey databases were analyzed to produce representative city dweller activity schedules for simulation purposes.

They were used to generate office occupancy schedules and were compared in terms of energy performance against ASHRAE standard schedules.

In Chapter 4, the concept of “perceived travel time” based on outdoor thermal comfort was presented, and the resulting “Trip Comfort” metric was used to demonstrate comfort along routes. In concept, the use of Agent Based Modeling, conceptual links between outdoor thermal comfort and active mobility choices were shown.
Linking of outdoor thermal comfort and citizen activity patterns was used to conceptualize the probability of people's human powered mobility choices.

2. **Effort:**

Representation models used for renderings and presentations by designers and planners are typically time consuming, but can be easily translated to urban surfaces model in CAD environments. This makes the effort most needed in outdoor thermal comfort simulation is proper input of thermal properties for material data. With the geometric and material input, microclimatic insight about what is happening between modeled buildings is defensible.

The effort needed to produce annual outdoor thermal comfort metrics was justified by the spatiotemporally resolved insight gained, which could influence informed urban design and planning decisions to create comfortable outdoor spaces.

The analysis of a mobility database, while computationally inexpensive, requires technical expertise with data clustering techniques. Once the methods are implemented, the use of occupant archetypes showed a significant difference in energy use, when compared to a standard ASHRAE occupancy schedule. Realistic representation of building occupancy and travel behavior on an urban scale is therefore justified, to demonstrate accurate energy performance in buildings, as well as potential active mobility trips made.

The required work to analyze activity-based travel surveys can be necessitated by the travel patterns' influence on occupancy representation in building energy simulation based on travel behavior, which would differ significantly from traditional occupancy schedules for simulation.

3. **Significance:**

According to Chapter 4, there are substantial variations in how a traveler would experience comfort from a hypothetical point A to B according to material properties and shading across the seasons. One route can be significantly more comfortable in comparison to another, and that would motivate human powered mobility. This insight was previously unquantifiable, and was more enforced through design intuition. This work gives designers tools for a more informed design decision that benefits sustainable urban mobility.

Simulating outdoor thermal comfort and linking it to human activity patterns in cities aids in the creation of built environments more conducive to sustainable, energy efficient, environmentally friendly and healthy human powered mobility in cities.
Outlook

This work presented a number of advances in a multidisciplinary approach to the assessment of built environments, and there are various directions for future research, which are summed up next.

Comprehensive Outdoor Comfort: The presented simulation method for MRT is robust, and a reliable cornerstone for outdoor thermal comfort analysis. However, further validation is needed, since the collected data for verification was specific only to one urban canyon geometry, as well as limited amount of days which are not comprehensively representative to annual performance across the seasons. Furthermore, assumptions for wind speed from weather data files should be replaced with real performance measures for wind speed. The incorporation of fast calculations, or advanced Computational Fluid Dynamics models in the workflow would yield more reliable results.

Advanced Human Mobility Analysis: Using activity-based traveled surveys demonstrated applicability in the context of computational data clustering for BPS. Therefore, in-depth investigations are needed to address the limitations of such surveys. One of which is exclusion of weekend patterns, and only working with a limited number of weekdays. This problem lends itself to advanced human sensing techniques, such as analysis of cell phone traces, use of wifi data and/or social media check-ins. This deeper understanding of human mobility patterns will help shape activity profiles that are more representative for the communities being tested.

Comfort in Motion: The novelty of linking outdoor thermal comfort metrics with human powered mobility creates conceptual space for an exciting new field. To implement further analysis in particular focus on the study of active mobility, further research into the sensation of comfort in motion is needed. Hence, future research should focus on modeling of outdoor thermal comfort sensation while people are in motion. Also adaptability in cases of discomfort should be taken into consideration, including psychological, physiological and physical adaptations.

Finally, if a computer tool can analyze different aspects of the built environment to present its readiness for human-powered mobility tactics, these models will qualify their employment to promote sustainable urban transportation. However, similar to most planning efforts, the suggested strategies uses terminology that is oriented towards drivers (such as reduction of VMT, rather than promotion of walkability for example). If planners, engineers and policy makers were given new metrics to understand how the built environment affects active transportation, this would promote a sustainable approach to the design and governing of our streets. Land-use planning at this instance becomes a tactic to provide accessibility to citizens, and driving then becomes the “alternative means” of mobility, as walking and biking are accepted as the truly sustainable way of human transportation.
Appendix

The screenshots below demonstrate the MRT simulation workflow using the Grasshopper plugin for Rhino.

Model parameters are set for each component of the urban surfaces model. The output is annual surface temperatures to be used as part of the MRT calculation next.
After identifying the simulation folder, surface temperatures are used as an input for MRT calculations. 8760 values of MRT are computed for the analysis nodes.

The output is used as an input for the Ladybug plugin for Grasshopper to compute UTCI. Assumptions for temperature, relative humidity, and wind are taken from weather files.