MULTI-MODAL TRANSPORTATION AND MULTI-CRITERIA WALKING (MMT-MCW) FOR WAYFINDING AND NAVIGATION SERVICES

by

Monsak Socharoentum

Survey Engineering, Chulalongkorn University, Thailand, 1999

M.Eng. Survey Engineering, Chulalongkorn University, Thailand, 2005
M.Sc. Information Technology, King Mongkut's University of Technology Thonburi, Thailand, 2004

Submitted to the Graduate Faculty of

School of Information Sciences in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

University of Pittsburgh

2014

UNIVERSITY OF PITTSBURGH

SCHOOL OF INFORMATION SCIENCES

This dissertation was presented

by

Monsak Socharoentum

It was defended on

July 22, 2014

and approved by

Janice C. Zgibor, Associate Professor, Department of Epidemiology, School of Public Health

Marek J. Druzdzel, Associate Professor, School of Information Sciences

Paul W. Munro, Associate Professor, School of Information Sciences

Dissertation Advisor: Hassan A. Karimi, Professor, School of Information Sciences

MULTI-MODAL TRANSPORTATION AND MULTI-CRITERIA WALKING (MMT-MCW) FOR WAYFINDING AND NAVIGATION SERVICES

Monsak Socharoentum, M.Sc., M.Eng.

University of Pittsburgh, 2014

Existing wayfinding and navigation services are primarily designed to support driving and riding modes of transportation. They do not provide walking as one mode of transportation in multi-modal transportation routes. To address this gap, this dissertation introduces the concept of Multi-Modal Transportation and Multi-Criteria Walking (MMT-MCW). The premise of MMT-MCW is based on the observations that: walking can be performed for other purposes in addition to travelling to a destination, such as maintaining or improving health; and traveler's characteristics and preferences play an important role in determining optimal route choices. MMT finds candidate routes that include walking plus other modes of transportation such as driving or riding public transit. MCW recommends a route among those suggested by MMT whose walking mode of transportation is optimal with respect to a set of criteria. An example criterion is fastest walking time, for which flat and short routes typically take priority over steep and longer routes. Another example is exercise, for which steeper and/or longer routes may take priority.

Methodologies and algorithms for MMT-MCW are developed, discussed, and analyzed. A prototype wayfinding service and a simulation methodology based on MMT-MCW are described. The benefits of MMT-MCW are demonstrated through the prototype and the results of simulating various trip scenarios.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

PREFACE

First, I would like to express my sincere gratitude to my advisor Dr. Hassan A. Karimi for his encouragement and mentoring over the years of my studies at the University of Pittsburgh. As a Ph.D. student, I really enjoyed discussing my research ideas with him. Over the past few years, he shared a lot of knowledge and ideas, and I used that guidance to improve my research skills including problem and hypothesis formulation, literature review, experiment design, critical thinking and discussion, technical writing, and publication. I really appreciate his mentoring.

Dr. Janice C. Zgibor, Dr. Marek Druzdzel, and Dr. Paul Munro, my committee members, were very kind. They were very prompt and cooperative when I contacted for appointments and discussions. They provided constructive criticism and guidance that really helped me construct my thoughts and ultimately, the dissertation.

I would like to also take this opportunity to thank my labmates: Duangduen Roongpiboonsopit, Jessica Benner, Mahdi Hashemi, Ming Ren, Monir Sharker, Piyawan Kasemsuppakorn, and Qiulei Guo for their critical discussions, encouragement, support, and friendship. I really had wonderful experiences with you guys.

I am very fortunate for the love and support from my parents, my wife, and my child. I would like to express my gratitude to the invaluable sacrifices of my father Yongsak and my mother Patchanee as I was living away and could not take care of them during my study. I am very grateful to my wife Pasanee for her love, encouragement, help, and understanding

throughout my study. And, the little and irreplaceable thing in my life, I am really fond of my daughter BhongBhan who always turns my stress and tiredness into bliss and strength.

I would also like to express my gratitude to the Office of Educational Affairs and Ministry of Science and Technology in Thailand for funding and fellowship support throughout my study.

Finally, the most admirable thing I learned was Buddha's teachings. Buddha's teachings are logical, being true and unbound by space and time. The dramatic change in living environments was a very challenging experience, especially with a whole family. However, with Buddha's teachings, we did overcome all the challenging situations and difficulties. It was extremely fortunate that we had the chance to explore and attain insights to Buddha's teachings. From this point on, my family and I will never be intimidated by any situations and difficulties that come to along.

1.0 INTRODUCTION

In this dissertation, we define wayfinding as a computational task that finds an optimal route given a set of criteria and navigation as a computational task that provides instructions for following a chosen route in real time. Today, wayfinding and navigation services are widely available and accessible through various platforms (desktop and mobile). Google, Microsoft, Yahoo, Apple, and other major IT enterprises are heavily investing in wayfinding and navigation services. Example wayfinding services are Google Maps[1], Bing Maps[2], and Yahoo Maps[3], and example wayfinding and navigation services for mobile devices are Google Maps for Android[4], Apple Maps for iOS[5], and Maps for Windows Phone[6]. Wayfinding and navigation services are also available through stand-alone software on PCs, Web applications, in-car navigation devices, and, more recently, as mobile applications. Despite much advances, current wayfinding and navigation services do not provide routes with walking, performed for other purposes (such as to maintain or improve health) besides merely reaching destinations, plus other modes of transportation. To enhance the capabilities of current wayfinding and navigation services, the Multi-Modal Transportation and Multi-Criteria Walking (MMT-MCW) concept, where walking is one mode and is optimized based on traveler's characteristics and criteria, is proposed.

[1] http://maps.google.com
[2] http://bing.com/maps/
[3] http://maps.yahoo.com/
[4] http://google.com/mobile/maps/
[5] http://apple.com/ios/maps/
[6] http://www.windowsphone.com/en-us/store/app/maps/763581b5-5c70-4009-99ce-39d49991039d

MMT-MCW is a new and advanced wayfinding capability that can be used in current wayfinding and navigation services. In this dissertation, we distinguish between two modes of wayfinding: real-time mode and simulation mode. Real-time mode is used when routes are planned for immediate trips. In this mode, all candidate routes are found and one that best satisfies the environmental and individual criteria is recommended. Simulation mode is for evaluating route options by simulating trip scenarios using various origins, destinations, criteria, preferences, and travelers' characteristics. The contributions, potential applications, beneficiaries, and organization of this dissertation are outlined as follows.

1.1 CONTRIBUTIONS

Contributions of this dissertation include:

1.1.1 Development of new wayfinding algorithms that can assist travelers in finding routes with walking, optimized with respect to various criteria and travelers' characteristics, plus other modes of transportation.

1.1.2 Development of a simulation methodology that can assist urban planners, among others, to evaluate transportation infrastructures in urban areas.

1.2 APPLICATIONS

Potential applications based on the results of this research can be categorized into two groups: (a) real-time wayfinding services and (b) multi-modal transportation simulations. Example applications of real-time wayfinding services are those that recommend optimal personalized routes, such as for physical activity, and those that address the mobility needs and preferences of people with disabilities. Example applications of multi-modal transportation simulations are evaluation of cities' transportation infrastructures for various transportation needs and for walkability of the built environment.

1.3 BENEFICIARIES

The results of this research will benefit:

- Navigation service developers and providers for implementing and deploying MMT-MCW into new generation of navigation services
- Transportation/traffic engineers for simulating MMT-MCW scenarios to study the relation between walking and other modes of transportation
- Urban planners for simulating MMT-MCW scenarios to study walkability of new urban areas and to design appropriate transportation infrastructures (such as sidewalks, bus stops, and parking locations) that can better serve various travelers' characteristics and preferences
- Travelers for finding personalized routes, such as those for physical activity purposes, based on MMT-MCW

1.4 ORGANIZATION

The rest of this dissertation is organized as follows. Chapter 2 describes MMT-MCW foundation. Chapter 3 discusses MMT-MCW routing. Chapter 4 outlines related works. Chapter 5 describes a prototype MMT-MCW service. Chapter 6 presents and discusses MMT-MCW simulation. A summary of the dissertation and suggestions for future research are discussed in Chapter 7.

2.0 MMT-MCW FOUNDATION

2.1 DEFINITIONS

In general, transportation refers to a means for carrying passengers or goods from one location to another. In the context of this dissertation, transportation refers to the traveling of people between locations by vehicles or on foot. Transportation can be classified into uni-modal, where only one mode of transportation (e.g., walking, driving) is involved, or multi-modal, where more than one mode of transportation (e.g., driving and walking) are involved. Trip refers to traveling from an origin to a destination. Trip can be uni-modal or multi-modal. Path is a possible physical connection between origin and destination for the purpose of traversing by uni-modal or multi-modal transportation. There could be multiple possible paths for a trip, and travellers usually choose the one they consider optimal based on one or more criteria. Finding an optimal path requires a network which, in addition to geometry of the infrastructure, contains topology of the transportation infrastructure (e.g., road, bridge, tunnel, intersection, and sidewalk).

Transportation networks are usually modelled as graphs of nodes and links. Each node represents a location where travellers must make a traversing decision (e.g., turn left/right, get on/off vehicle, and switch between modes) and a link connects two nodes representing traversable passage (e.g., road segment, sidewalk segment). Usually each link is assigned a cost between its start and end nodes. Example costs are distance, time, expense, air pollution, and slope. Transportation networks suitable only for one mode of transportation are uni-modal, and a multi-modal network is formed by combining different uni-modal networks with designated existing or new nodes or links for switching between them.

In this dissertation, a multi-modal network is formed by combining a non-vehicular network (pedestrian network) and a vehicular network. A pedestrian network is a type of transportation network involving only walking modality. A vehicular network is a type of transportation network associated with vehicular modalities which include personal cars and buses. Example vehicular networks are road networks (for personal cars) and bus networks. A MMT network is modeled by a directed graph $= (V, A)$, where V is the set of nodes and A is the set of directed links *(i, j)* connecting node *i* to node *j*; $i \in V$ and $j \in V$. The directed graph G is composed of two sub-graphs, one representing a pedestrian network, another representing vehicular network, and expressed as:

$$= G_W \cup G_H = (V_W, A_W) \cup (V_H, A_H) \tag{2.1}$$

where $_W$ and $_H$ are the graphs of the pedestrian network and the vehicular network, respectively; V_W and V_H are the nodes of $_W$ and $_H$, and A_W and A_H are the links between the nodes that can be traveled on foot and by vehicles, respectively.

To support passage between $_W$ and $_H$, additional nodes (called transfer nodes) that must exist in both graphs are needed. In case transfer nodes do not exist in $_W$ and $_H$, one or more transfer nodes must be created in both graphs so that they are connected. Figure 2.1 (a) illustrates two independent graphs $_W$ and $_H$. In Figure 2.1 (b), two transfer nodes (nodes 9 and 10) are added to both graphs. Figure 2.1 (c) shows two transfer nodes connecting a number of existing nodes in each graph. Depicted in Figure 2.1 (d), two additional links (represented by the dotted double headed arrows) are created to connect between the transfer nodes in $_W$ and $_H$, respectively. The additional links are called transfer links where they facilitate transfer between the two graphs. A transfer link can be a directed link, where passage is allowed only in a certain direction, and an undirected link, where passage is allowed in either direction with the same cost. Double-headed arrows represent two directed links and indicate that the cost of each direction (from $_W$ to $_H$, and vice versa) can be independent from each other. If only one direction is allowed, a one-headed arrow is used instead. In this dissertation, bi-directional links are assumed. Once transfer nodes and transfer links are added, $_W$ and $_H$ are combined, connecting the two graphs.

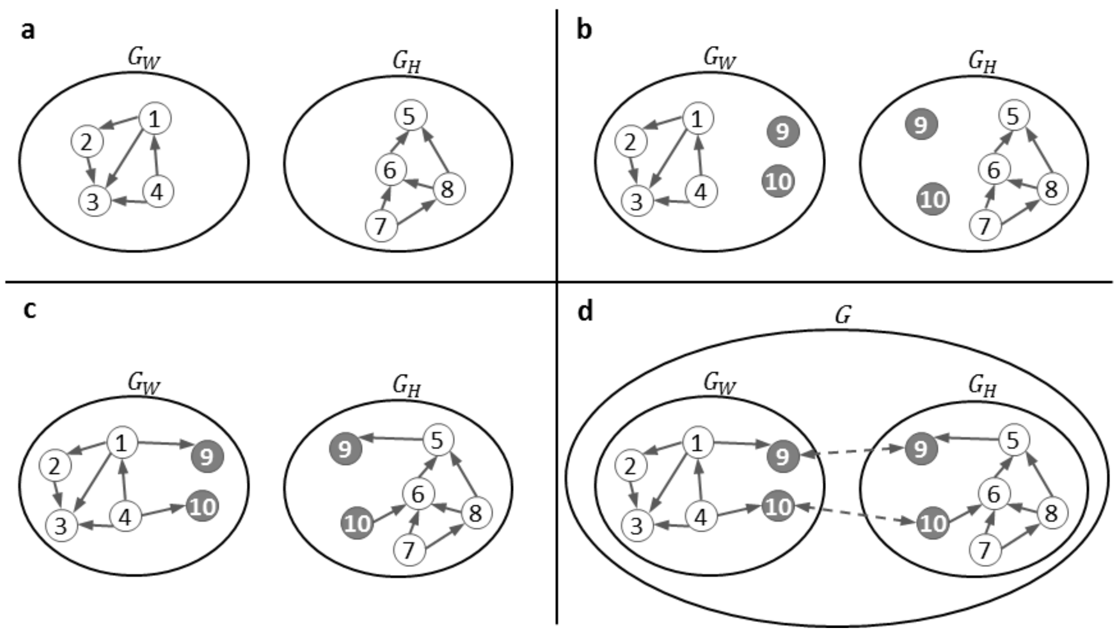


Figure 2.1. Combined multiple graphs

We define "walking transfer node" as a node representing the location where travelers switch from a pedestrian network to a vehicular network, or vice versa. In multi-modal trips, walking transfer nodes play an important role as they influence the solution space. For example, change of one parking lot (as a walking transfer node) to another may result in a different (and desired) solution. With respect to public transportation, the choice of a bus stop (as a walking transfer node) determines a specific bus route. A walking transfer node can be expressed as:

$$\exists_v (v \in V_H \wedge v \in V_W) \tag{2.2}$$

where V_H is the set of nodes in a vehicular network

V_W is the set of nodes in the pedestrian network

v is the walking transfer node

The expression (2.2) implies that v is considered as a walking transfer node only if it can be accessed by both walking and the vehicular mode of interest. For example, suppose a traveler wants to travel from home to a meeting location in downtown by taking three modes of transportation: driving, walking, and riding. The traveler can drive from home to a parking lot and then walk to a bus stop to take a bus to the meeting location (assuming walking from the bus stop to the meeting location is feasible). For driving-walking transfer, a node (v_i) representing a parking lot (which can be reached by car and on foot) is required. For walking-riding transfer, a node (v_j) representing a bus stop (which can be reached on foot and by bus) is required.

2.2 TOPOLOGY BETWEEN NETWORKS

In Section 2.1, transfer nodes and transfer links, which connect the two graphs, were discussed. This section discusses the connectivity between walking mode and vehicular modes at the transportation network level. Transfer nodes and transfer links are referred to as inter-modal nodes and inter-modal links, respectively. Inter-modal nodes represent real-world locations where travelers switch between different modes of transportation, for example, bus stops for switching between walking and riding, and parking lots for switching between walking and driving. Inter-modal links connect between inter-modal nodes located in different transportation networks. As this dissertation is mainly concerned with the interchange between walking and vehicular modes, inter-modal nodes and inter-modal links are referred to as walking transfer nodes and walking transfer links, respectively.

Figure 2.2 illustrates three uni-modal networks: road network (for private car), transit network (for bus), and pedestrian network. Figure 2.2 (a) shows real-world transportation features, namely road segments, road intersections, and bus stops. Figure 2.2 (b) shows topology among road intersections of a road network. Road intersections are modeled as nodes and are connected to each other by directed links. A directed link represents a road segment and relevant traffic direction of the road segment. A one-way directed link is used to represent one-way traffic direction. Two-way traffic directions can be represented by either two separate one-way directed links or a two-way directed link. For simplification, this dissertation uses two-way directed links to represent two-way traffic directions. Note that in a two-way directed link the cost for each direction does not have to be the same. Figure 2.2 (c) shows a transit network that represents four bus routes (B1, B2, B3, and B4) and their associated bus stops. A bus route is a series of a particular set of links (or bus stops) through which the bus runs. A bus stop is a fixed location where buses regularly stop for passengers to board or leave. When forming links for a bus route, the sequence of links and the connected bus stops must be consistent with the direction of the bus route, and a bus stop may belong to one or more bus routes. Figure 2.2 (d) shows a pedestrian network that represents the topology between sidewalk intersections. In this example, roads are assumed to have sidewalks on both sides, and sidewalk segments on different sides are assumed to be independent. A link either represents a sidewalk segment or a crosswalk at an intersection.

All links in a pedestrian network are two-way directed links because pedestrians can walk in either direction.

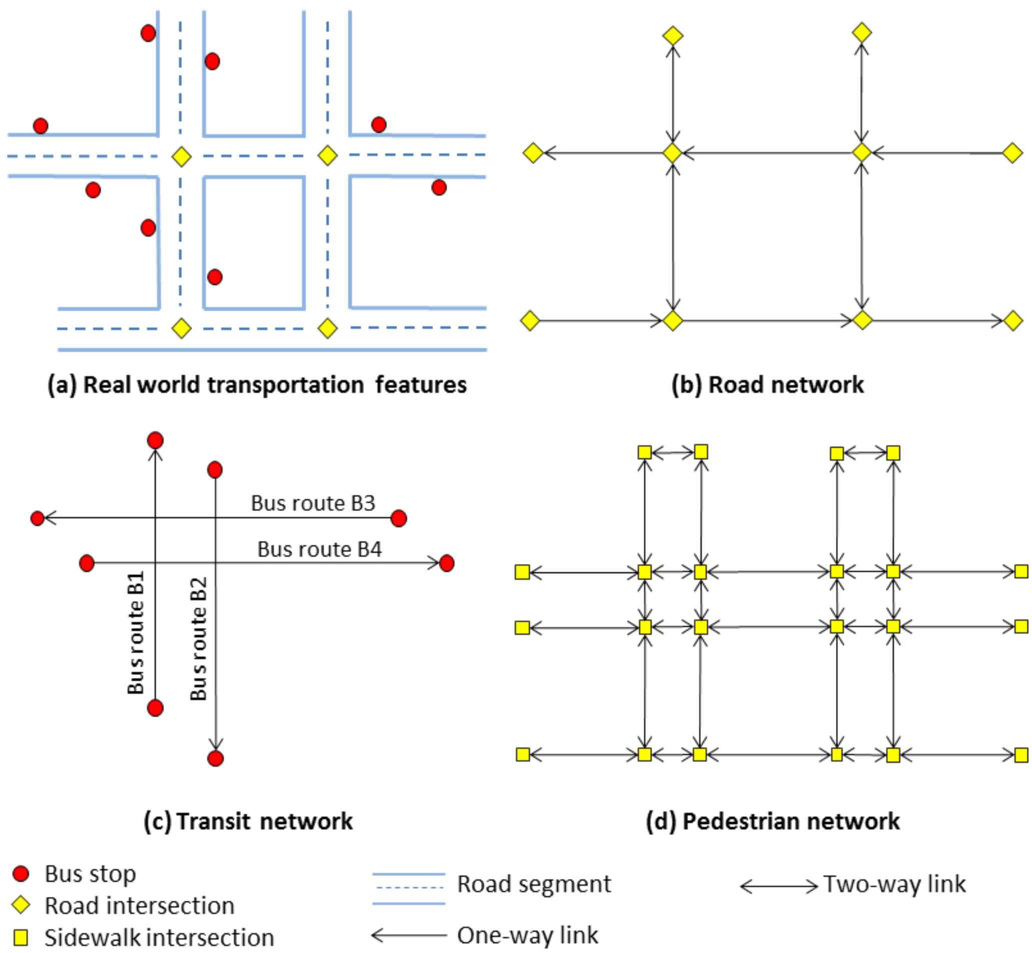


Figure 2.2. Modeling of uni-modal networks

Walking transfer nodes and waking transfer links are used to combine multiple uni-modal networks. Figure 2.3 shows example walking transfer nodes and walking transfer links. Initially, the three uni-modal networks (road network, transit network, and pedestrian network) are independent. The road network contains road intersections (nodes) and road segments (links).

The transit network contains bus routes. Each bus route is composed of certain nodes and links that represent a certain sequence of bus stops and their topology. The pedestrian network contains sidewalk intersections (nodes) and sidewalk segments (links). The three uni-modal networks are combined into a multi-modal network. In the new network, parking location nodes must be part of both the pedestrian network and the road network, and bus stop nodes must be part of both the pedestrian network and the transit network. Considering the road network in Figure 2.3, three walking transfer nodes (three parking location nodes) are added along with additional links that connect between the three parking location nodes and the original nodes (road intersections). An additional link in the road network refers to a traversable connection (by car) between a parking location and nearby road intersections such as those that bound the road segment on which the parking location is located. Similarly, a set of parking location nodes is also added to the pedestrian network, and additional links that connect between the parking location nodes and the original nodes (sidewalk intersections) of the pedestrian network are also created. An additional link in the pedestrian network refers to a traversable connection (on foot) between a parking location and nearby sidewalk intersections such as those that bound the sidewalk segment on which the parking location is located. Once the parking location nodes are added to the road network and the pedestrian network, the two uni-modal networks will be connected to each other through walking transfer links associated with the parking location nodes.

Similar to the case of parking locations discussed above, bus stops are required to create the connectivity between the transit network and the pedestrian network. For the transit network, bus stop nodes are already part of the network. To connect the pedestrian network to the bus stop nodes of the transit network, all the bus stop nodes (as walking transfer nodes) have to be added into the pedestrian network. For every bus stop node, one or more additional links have to be created to connect with nearby sidewalk intersections such as those that bound the sidewalk segment on which the bus stop node is located. Besides sidewalk intersections, in case a walkway between the parking location and the bus stop is available, such as a park-and-ride, an additional link may also be created to represent a direct connection between the parking location and the bus stop. After the bus stop nodes are added to the pedestrian network, walking transfer links that connect between the two sets of the bus stop nodes (one in the transit network and another in the pedestrian network) are created. Once all walking transfer nodes and walking transfer links are created for the road network, the transit network, and the pedestrian network, they can be combined into a multi-modal network.

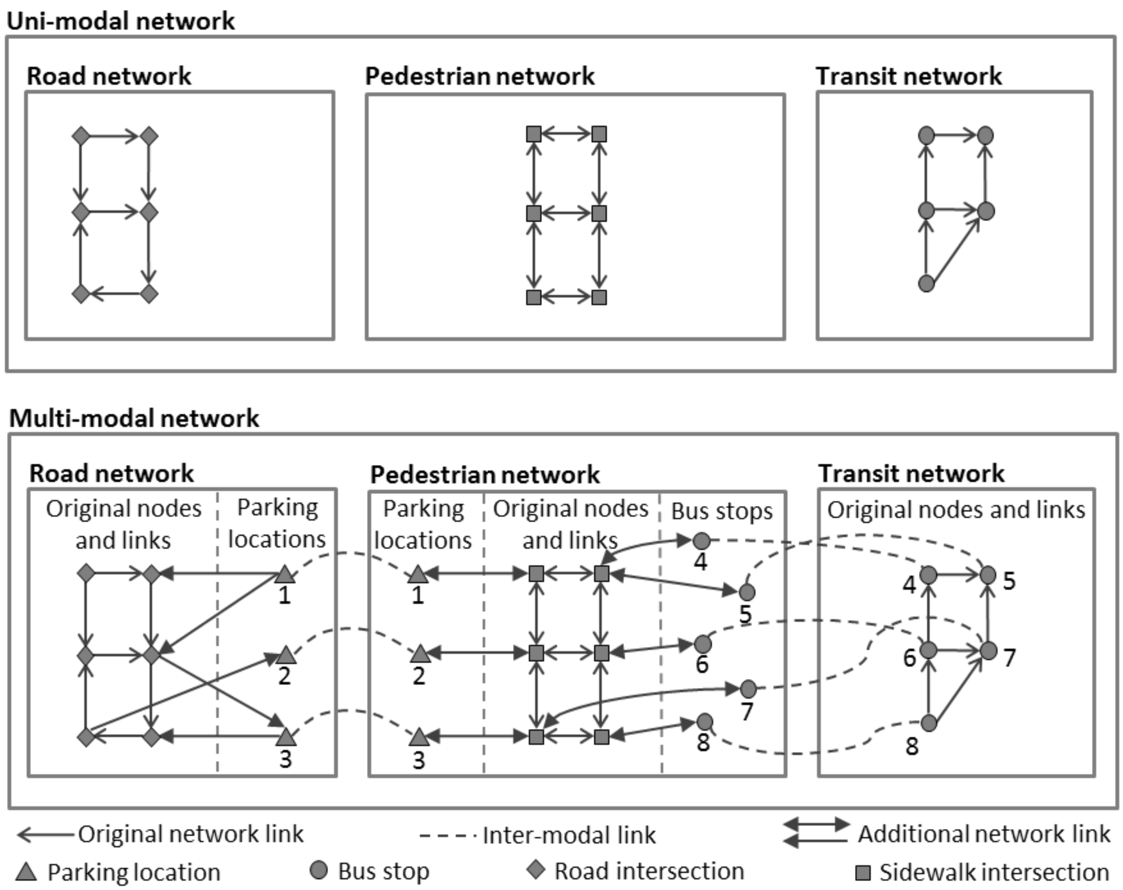


Figure 2.3. Example uni-modal and multi-modal networks

A multi-modal network can also be created based on the combination of two uni-modal networks. Figure 2.4 illustrates three multi-modal networks that are created based on all possible combinations of two uni-modal networks. Multi-modal network A is composed of a pedestrian network and a transit network. Multi-modal network B is composed of a pedestrian network and a road network. Multi-modal network C is composed of a transit network and a road network. The pedestrian networks (in multi-modal networks A and B) contain additional nodes and links which represent the traversable walkways that connect between sidewalk intersections and walking transfer nodes (bus stops for multimodal network A and parking locations for multi-modal network B). In multi-modal network C, as there is no pedestrian network involved, a new network (called transfer network) is introduced to contain the two groups of walking transfer nodes (bus stops and parking locations) and the connection between them. A connection (link) between a bus stop and a parking location refers to a walkway that allows travelers to commute between a bus stop and a parking location. Example walkways are sidewalk, road crossing, and pedestrian bridge.

A multi-modal network may be formed by combining two or three uni-modal networks as described above. Each combination supports certain modes of transportation and requires additional nodes and links to be added to the networks. Table 2.1 summarizes possible combinations and their characteristics.

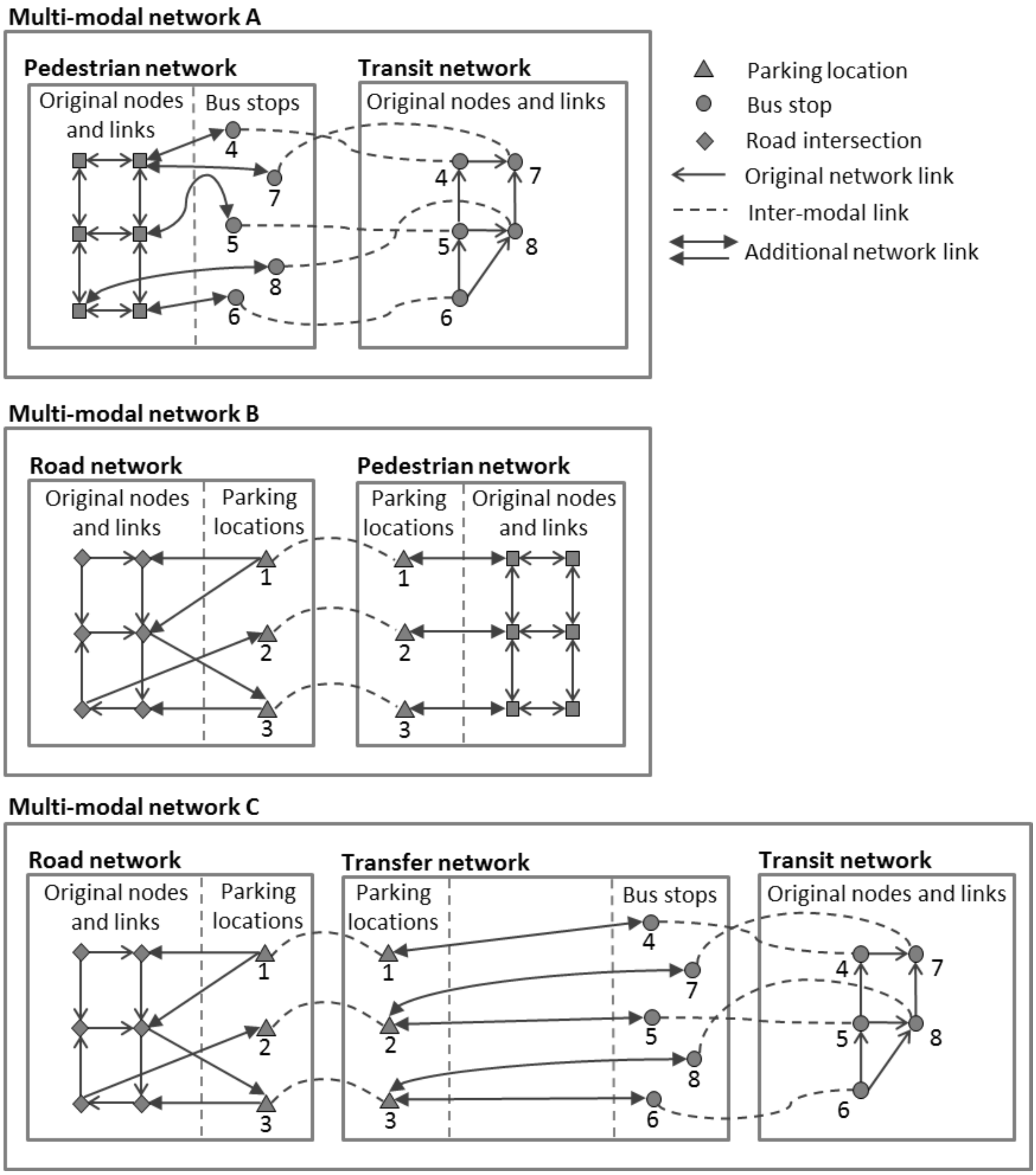


Figure 2.4. Multi-modal network based on two uni-modal networks

Table 2.1. Combination of uni-modal networks and their characteristics

Characteristics	Multi-modal networks (Pedestrian: P; Road: R; Transit: T)			
	P & T	**P & R**	**R & T**	**P & R & T**
Mode of transportation	Walking and riding	Walking and driving	Driving and riding	Walking, riding, and driving
Type of walking transfer node	Bus stops	Parking locations*	Bus stops and parking locations*	Bus stops and parking locations*
Links added to vehicular network	No	Yes	Yes (road network)	Yes (road network)
Links added to pedestrian network	Yes	Yes	No	Yes
Nodes added to vehicular network	No	Yes	Yes (road network)	Yes (road network)
Nodes added to pedestrian network	Yes	Yes	No	Yes

**parking locations may include (but are not limited to) parking garages, parking lots, and curbside parking spaces*

Parking locations influence the connectivity between road networks and pedestrian networks. In general, parking spaces are either private or public. In this dissertation, only public parking spaces are considered and parking garages and parking lots are represented by polygons (areas) and curbside parking spaces are represented by lines. Considering that a transportation network only contains nodes and links, objects represented as areas and lines must be converted to points. Figure 2.5 illustrates a conversion from a parking lot (area) to a point. The entrance and exit points of a parking lot are represented by two distinct nodes (shown as triangles). The two nodes are included into the road network by introducing additional links to connect them to the relevant road intersection nodes (shown as diamonds). The entrance node is a decision location where the traveler can decide to drive through and park in the parking lot. The exit node is a decision location where the traveler can exit the parking lot. Similar to the parking lot, a curbside parking space also requires a conversion. Unlike parking lots and parking garages, a curbside parking space usually covers a section of the curbside of a road. Figure 2.6 shows a conversion from a curbside parking space to a node in a road network. Figure 2.6 (left) shows a two-way traffic road segment that is bounded by two road intersections and a curbside parking space (hatched area) which appears on the right hand side of the road segment. In Figure 2.6 (right), the curbside parking space is converted to a node (curbside parking node), shown as pentagon, and four new links are created to connect the curbside parking node to the two road intersection nodes (shown as diamonds). Connection between a curbside parking node and road intersection nodes implies that a decision to drive or park can be made at the curbside parking node. Furthermore, because the road segment has two-way traffic and has no median divider island, it is assumed that cars from both intersections (directions) are allowed to stop and park at the curbside parking space. To reflect the topological connection between road intersections and the curbside parking space, new links from both road intersection nodes to the curbside parking node can be created. However, if a median divider island exists, the link that represents the traffic across from the curbside would not be connected to the curbside parking node. Note that traffic regulations are not considered in this example, though they must be taken into account when creating links between nearby road intersections and a curbside parking node.

Parking locations, as areas and lines, must also be converted to nodes to make connection between road networks and pedestrian networks. Figure 2.7 shows the conversion of a parking lot and curbside parking spaces into nodes. The parking lot is converted to an entrance and an exit node, and the curbside parking spaces are converted to curbside parking nodes. The entrance and exit nodes are connected to the sidewalk intersection nodes that bound the sidewalk segment on which the entrance and exit nodes are located. The new links are illustrated by a double-headed arrow (two-way directed link) to indicate that travelers can walk in either direction.

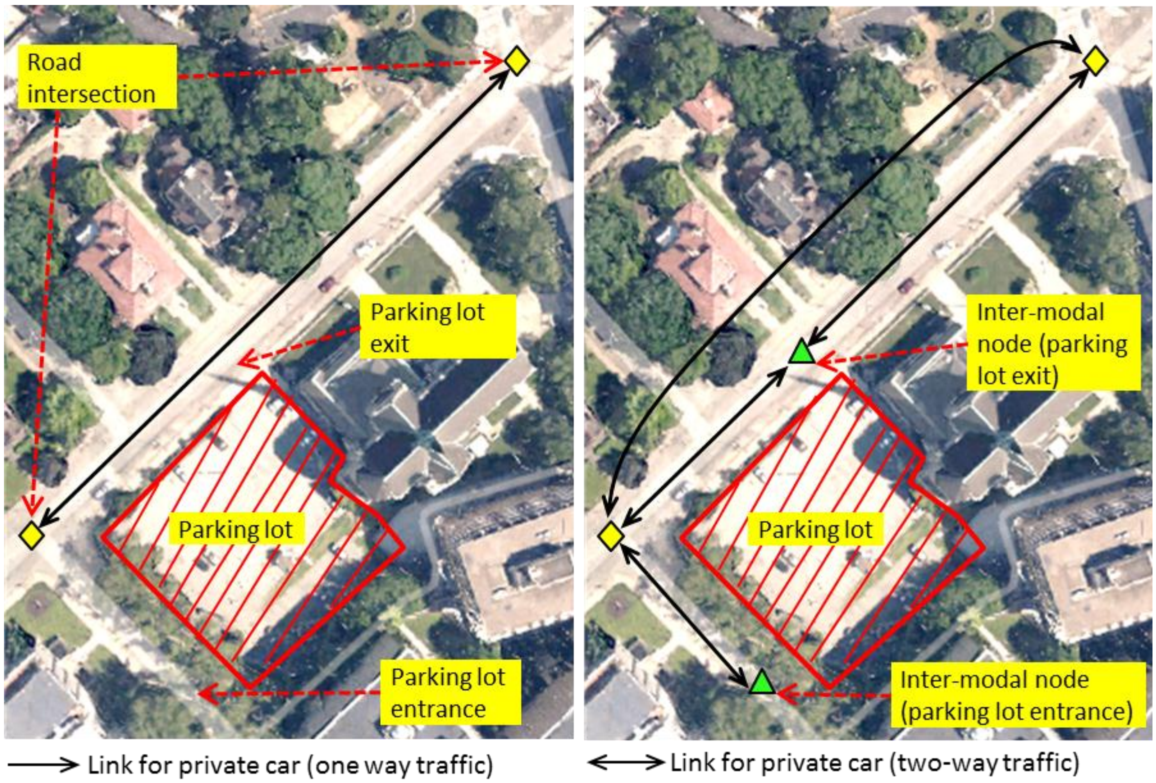


Figure 2.5. Conversion from parking lot locations to network nodes

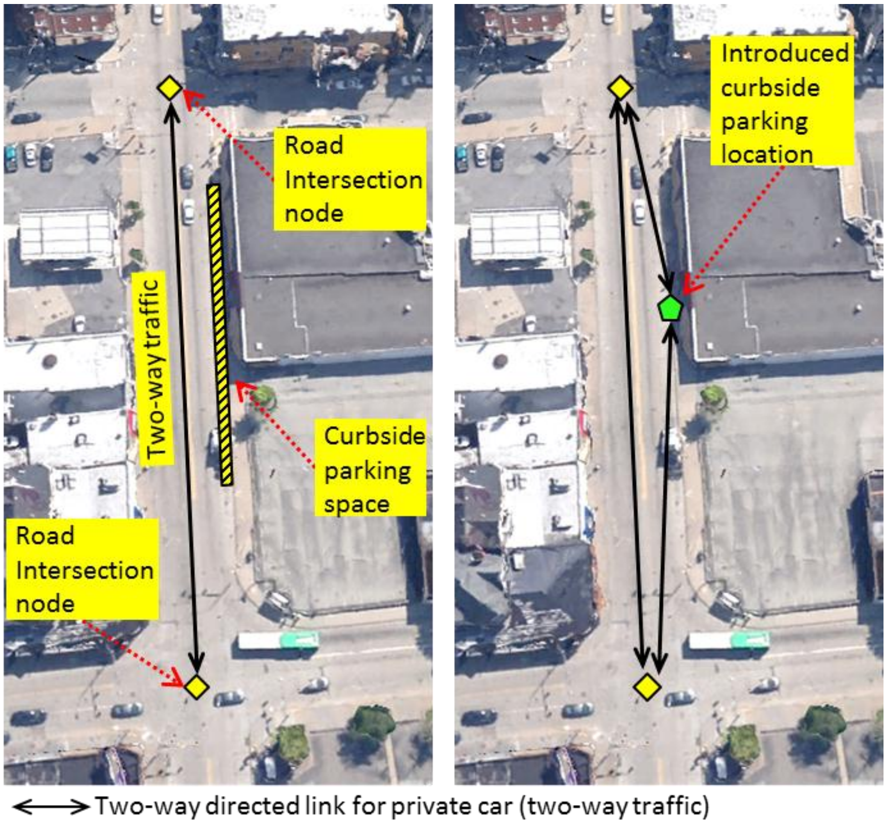


Figure 2.6. Conversion from a curbside parking space to a network node

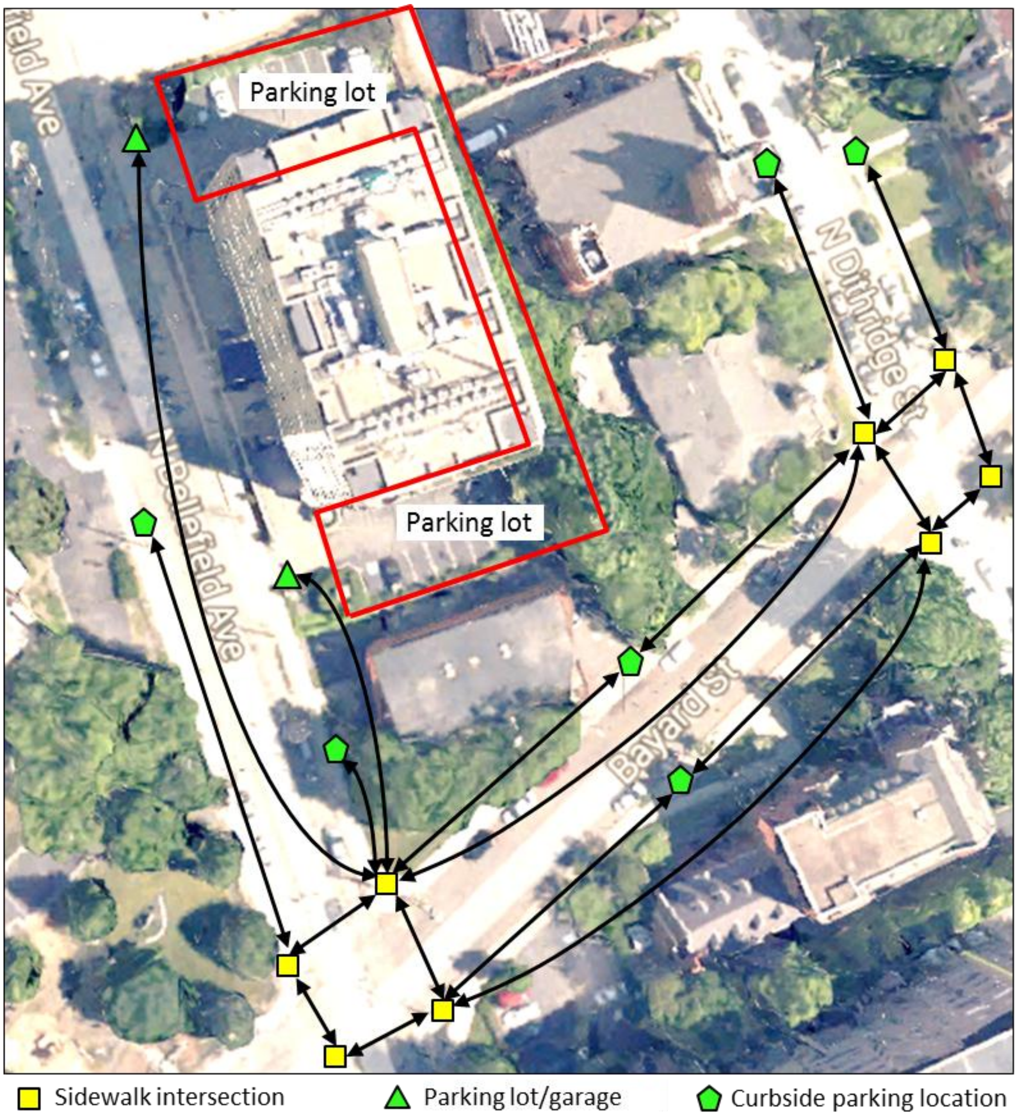


Figure 2.7. Conversion from a parking lot location and curbside parking spaces to network nodes

Connectivity between transit networks and pedestrian networks is mainly facilitated by bus stops since a bus stop is a designated location that buses regularly stop for travelers to get on/off buses. Figure 2.8 shows an example of transit network that contains three bus routes and their associated bus stops. To combine a transit network with a pedestrian network, bus stop nodes has to be added and connected to the pedestrian network. For example, in Figure 2.8, the bus stops of the transit network are included into the pedestrian network. To include the topology between the sidewalk intersection nodes and the bus stop nodes, each bus stop node (using two-way directed links, see Figure 2.9) is connected to the sidewalk intersection nodes that bound the sidewalk segment on which the bus stop node is located.

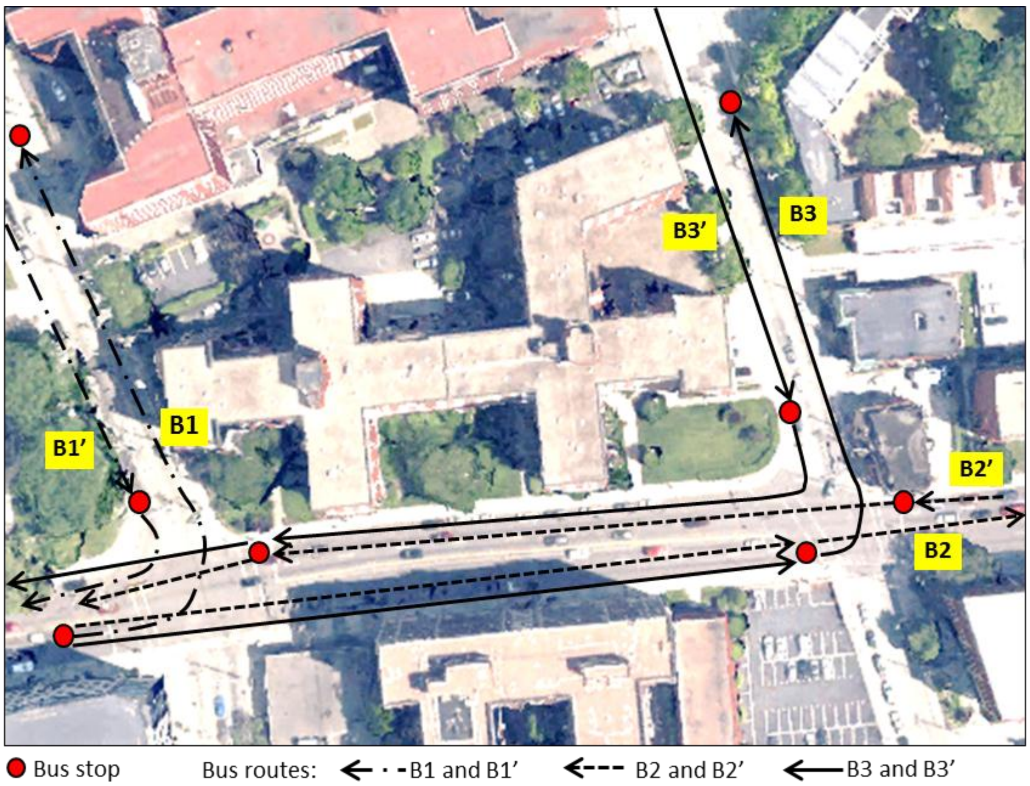


Figure 2.8. A transit network

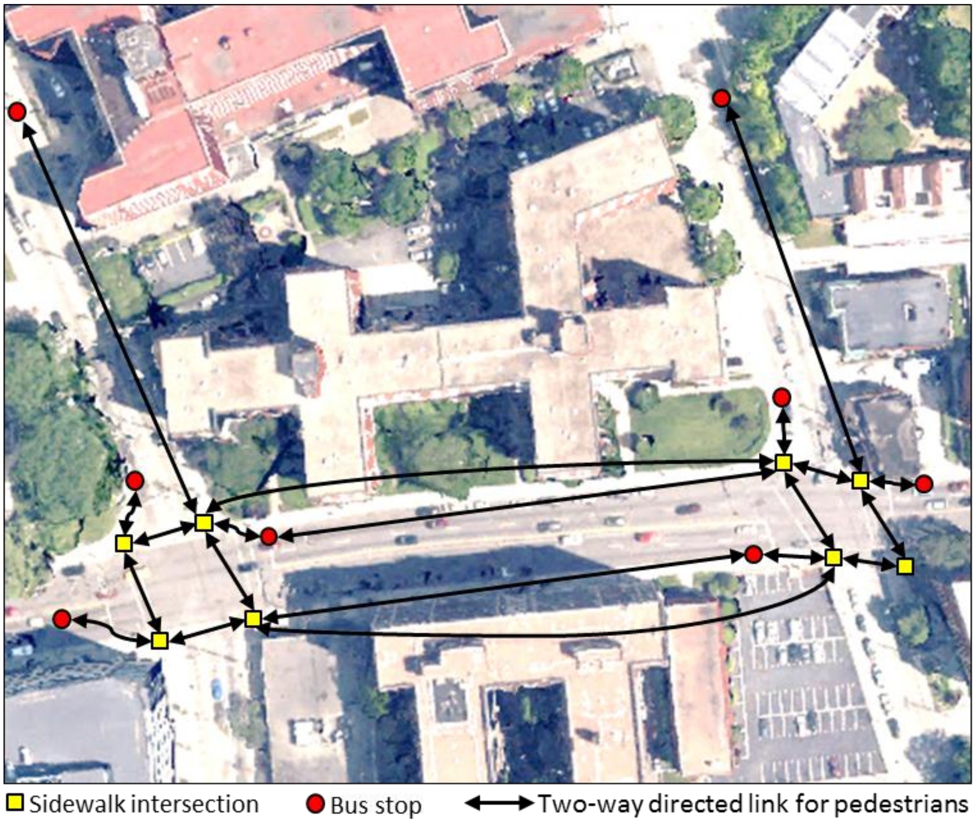


Figure 2.9. Integrating bus stops into a pedestrian network

The outcome of combining multiple uni-modal networks is a multi-modal network. Considering MMT-MCW, an optimal route can be a walking route (if feasible) or a multi-modal route with walking as one of the modes. Consider three modes (walking, riding, and driving), Figure 2.10 shows three basic cases of a route based on MMT-MCW, namely walking, walking and riding, and walking and driving. Based on the three basic cases, more complicated cases can be formed, such as two buses (Figure 2.11 upper diagram) and all three modes combined (Figure 2.11 lower diagram). Two observations about walking for the three basic cases and the complicated case are made: (1) type of walking transfer node (parking location and bus stop) is tightly coupled with mode of transportation and (2) walking typically occurs when approaching or leaving a walking transfer node. These observations confirm the claim that walking transfer node plays an important role in MMT-MCW.

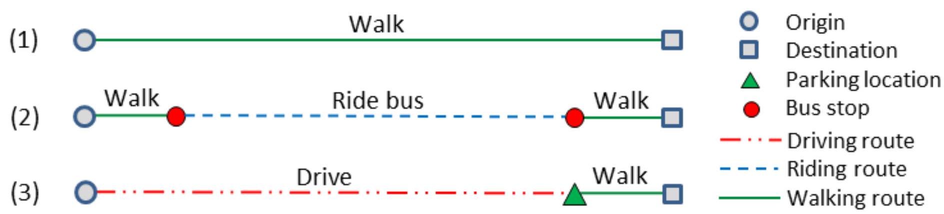


Figure 2.10. The three cases of a route

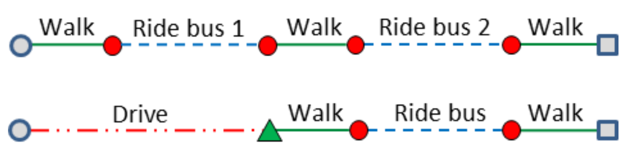


Figure 2.11. Two complicated cases formulated using the three cases

2.3 MULTI-CRITERIA OPTIMIZATION

Multi-criteria optimization has been researched for a long time and used in many areas, such as economics and engineering. Multi-criteria optimization (also known as multi-objective optimization) is "*the process of optimizing systematically and simultaneously a collection of objective functions*" (Marler & Arora 2004). Objective functions are formulated to quantify the solution of a decision problem based upon the objectives set forth. For example, a traveler may want an optimal walking route such that it: (1) burns around 40 kilocalories; (2) has no downhill slopes with a grade greater than 5%; (3) allows a walking pace of 2 to 2.5 miles per hour (54–67 meters per minute); and (4) ensures minimum air pollution exposure. In this example, there are four objective functions: one for calories burn, one for slope calculation, one for walking speed, and one for air pollution exposure. The values from these four objective functions will be used to find and recommend a suitable route. In case of conflict among criteria, a trade-off between the criteria is made. There are three terms associated with multi-criteria optimization: *alternative*, *decision space,* and *objective function* (Ehrgott 2010). This section describes those terms and discusses the way in which multi-criteria optimization is adopted for MMT-MCW.

Alternative is a reference to a feasible solution for a decision problem and does not have to be optimal in all circumstances. *Decision space* contains all alternatives for a decision problem. For instance, all possible routes from an origin to a destination are considered to be members of the decision space. Based on traveler's criteria, *objective functions* are defined to quantitatively measure the quality of alternatives. In this dissertation, these three multi-criteria optimization terms refer respectively to a candidate route, a set of candidate routes, and objective function, expressed as follows. Route (p) is a sequence of consecutive links in a graph ($G = (V, A)$):

$$p = (v_1, v_2, \ldots, v_n)\ ;\ v_i \in V \tag{2.3}$$

where node v_i is adjacent to node v_{i+1} for $1 \leq i < n$ and $n \in \mathbb{Z}$; $\mathbb{Z}$ is the set of positive integers.

The set of candidate walking routes ($\boldsymbol{P}$) from a start node (s) to an end node (e) is:

$$\boldsymbol{P} = \{p \in \mathbb{P} \mid s = v_1 \wedge e = v_n\} \tag{2.4}$$

where $\mathbb{P}$ contains all the routes that connect any two of the network's nodes.

Finally, the route optimization that uses the objective functions f_i follows the form:

$$\min_{p \in \boldsymbol{P}} \big(f_1(p), f_2(p), \ldots, f_n(p)\big) \tag{2.5}$$

$f_i(p)$ is the i^{th} objective function; $i = \{1,2, \ldots n\}$; $n \in \mathbb{Z}$ and $n > 1$

The above expression indicates that among all the candidate walking routes (in the set $\boldsymbol{P}$), the optimal route is the one which minimally fulfills the objective functions $f_1(p)$ to $f_n(p)$. Note that in case of conflict among criteria, the optimal route may change, depending on the trade-off made. Such a trade-off can be controlled using the *weighted-sum method*, which allows users to control the contribution of each objective function (criterion) through the weight factors. In the weighted-sum method, each criterion is assigned a weight factor value, and the sum of all weight factors must be a constant (usually 1). The larger the weight factor value, the more it contributes to the final weighted-sum value. When the weighted-sum method is integrated, the optimization problem can be formulated as:

$$\min_{p\in\boldsymbol{P}} \sum_{i=1}^{n} \; {}_i \cdot \Omega_i(f_i(p)) \tag{2.6}$$

where $\boldsymbol{P}$ is the set of candidate routes, f_i is the i^{th} objective function, λ_i is the i^{th} weight factor for the objective function f_i, ${}_i$ is the i^{th} normalization function, and $i = \{1,2,\dots,n\}$; $n \in \mathbb{Z}$ and $n > 1$. Candidate routes are optimized through expression (2.6). Note that the normalization function is used here to homogeneously combine various objective functions. A detailed discussion of the normalization function is provided in the Objective Functions Normalization section (Section 3.4).

3.0 MMT-MCW ROUTING

Wayfinding and navigation services based on MMT-MCW will be able to (a) find multi-modal transportation routes with walking as one component and (b) find an optimal walking component by considering multiple criteria. This chapter discusses the details of MMT-MCW routing including selection of walking transfer nodes, route computation complexity, context-aware walking segment, objective function normalization, and MCW algorithm.

3.1 SELECTION OF WALKING TRANSFER NODES

Travelers typically specify an origin and a destination for their trips, whereas the optimal walking transfer node is generally unknown and will be identified during route optimization. Traveler's preferences are the criteria for choosing walking transfer nodes. Example criteria are low parking fees, preference for parking garages over surface parking locations, distance between a parking facility and destination, overall safety of the area, and flexible parking hours. If the traveler wants to avoid paying expensive parking fees in a downtown area and less expensive parking locations are available just outside of that area, then a parking location outside of the downtown area should be selected based on the criterion that the total sum of the parking fee and the bus fare should be less than the downtown parking fee. Furthermore, the criteria for choosing the parking location and the bus stop may vary depending on the context. For instance, the same traveler may want to get some exercise by taking a brisk walk. In this case, walking transfer nodes that increase walking distance between the parking location and the bus stop (and/or between the bus stop and the destination) will be given high priorities. Finding appropriate walking transfer nodes will become more difficult if the traveler wants to minimize both parking fees and bus fares.

Walking transfer node selection criteria may conflict with route optimization criteria. For instance, a traveler who prefers low parking rates and shortest walking routes between parking facilities and the destination may find that parking facilities with a shorter walking route are the ones that also have high parking rates, and vice versa. Likewise, a traveler who prefers parking in a garage and then walking to get some exercise may find that reaching to outdoor parking locations can result in a more vigorous walk to the destination. Despite the inherent trade-offs between walking transfer nodes selection criteria and walking route computation criteria, the associated walking route can be computed only after a walking transfer node is selected. Therefore, considering both groups of criteria simultaneously is infeasible. In this dissertation, the inherent trade-offs are addressed by considering walking distance separately from all other criteria. To identify a candidate walking transfer node, traveler's desired walking distance is separated into estimated upper and lower limits. The upper limit excludes walking transfer nodes that are located beyond a traveler's maximum preferred distance. The lower limit excludes walking transfer nodes that are located closer than the desired minimum walking distance. As a result, one or more walking transfer nodes located within the limits can be selected. All other walking transfer node selection criteria (besides distance) are included as part of the route optimization criteria.

3.1.1 Buffering

Figure 3.1 illustrates examples of upper limit and lower limit of desired walking distance, as well as the use of walking distance in the walking transfer node selection. In Figure 3.1, the upper limit and lower limit are used to create two types of buffer: relaxed and restricted. The relaxed buffer (top left) uses the origin or the destination as a center (the blue shaded point in the center of the figure) and creates a circle buffer using the upper limit as its radius. The non-shaded points inside the buffer are the walking transfer nodes that can be selected for route computation, and non-shaded points outside the buffer are disregarded. The restricted buffer is a ring buffer (lower left) created with both an upper limit (for the outer radius) and a lower limit (for the inner radius). This restricted buffer is more constrained than the relaxed buffer in that the walking transfer nodes within the inner radius are disregarded. The boundaries of the two buffers on the left assume the lower and upper limits to be the Euclidean distance measured from the center. However, for more accurate results, buffer boundaries can also be generated based on the shortest distance from the center, measured along the sidewalk network (see the two buffers on the right).

After suitable walking transfer nodes are selected, vehicular and walking routes that connect the origin, the walking transfer nodes, and the final destination are computed. Figure 3.2 illustrates an example when traveler’s desired area for walking transfer nodes is near destination, which leads to a solution where vehicular transportation is expected to occur between an origin point and the walking transfer nodes. From the origin to each walking transfer node, one or more vehicular routes are computed, and the output vehicular routes (vehicular candidate routes) are all viable options for a particular trip. For a vehicular route computation, a basic criterion (such as shortest distance) can be used but if the traveler prefers more route choices, a different criterion (such as multiple shortest routes or route similarity) can be used. Similarly, from each walking transfer node to the destination, one or more walking routes are also computed. The vehicular routes and the walking routes are shown in Figure 3.2, using solid lines and dashed lines, respectively.

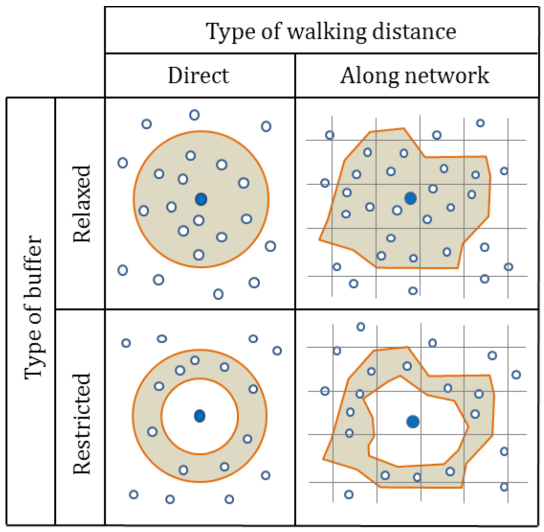


Figure 3.1. Type of buffer coupled with type of walking distance

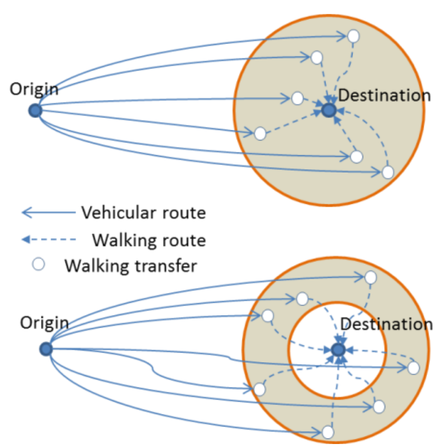


Figure 3.2. Vehicular routes, walking transfer nodes, and walking routes

To formalize the use of a lower limit and an upper limit for walking transfer node selection, the symbols used to represent transportation conditions and elements are summarized in Table 3.1. These symbols are also used to describe the walking transfer selection rules in Table 3.2.

Table 3.1. Symbols of transportation conditions and elements

Transportation conditions and elements	Value	Symbol
Walking and driving are preferred	T/F	S_1
Walking and riding are preferred	T/F	S_2
Walking, driving, and riding are preferred	T/F	S_3
Only walking is preferred	T/F	S_4
Walking is preferred near an origin	T/F	S_5
Walking is preferred near a destination	T/F	S_6
Walking is preferred in the middle of the trip	T/F	S_7
Upper limit walking distance	$\mathbb{R}^+$	d^{up}
Lower limit walking distance	$\mathbb{R}^+$	d^{lo}
Walking distance between nodes v_1 and v_2	$\mathbb{R}^+$	$d(v_1, v_2)$
Bus route number passing the bus stop node v	$\mathbb{Z}$	$BN(v)$
Set of nodes representing parking locations	N/A	$V(pk)$
Set of nodes representing bus stops	N/A	$V(bs)$
Origin node of the trip	N/A	*ori*
Destination node of the trip	N/A	*dest*
A walking transfer node	N/A	v

Table 3.2. Walking transfer selection rules

Case	Scenarios	Walking transfer selection rule
1	$S_1 \wedge S_5$	No parking location selection is required
2	$S_2 \wedge S_5$	$v \in V(bs) \wedge d^{lo} \leq d(v, ori) \leq d^{up}$
3	$S_1 \wedge S_6$	$v \in V(pk) \wedge d^{lo} \leq d(v, dest) \leq d^{up}$
4	$S_2 \wedge S_6$	$v \in V(bs) \wedge d^{lo} \leq d(v, dest) \leq d^{up}$
5	$S_2 \wedge S_7$	$v_1 \in V(bs) \wedge v_2 \in V(bs) \wedge v_1 \neq v_2 \wedge BN(v_1) \neq BN(v_2) \wedge d^{lo} \leq d(v_1, v_2) \leq d^{up}$
6	$S_1 \wedge S_7$	Not possible
7	S_3	Apply the proper combination of case 1 to 4
8	S_4	No walking transfer node is required

The first four cases in Table 3.2 represent combined driving-walking, riding-walking, and where walking is preferred near origin or destination. Among the four cases, only Case 1 does not require a walking transfer node selection, as walking to a fixed parking location is expected. Case 5 is for riding-walking, in which walking is preferred between two different bus routes and bus stops. Case 6 is not a possible case as it refers to the following sequence: driving to a parking location, walking from the parking location to another, and then driving to the destination. Case 7 represents the combinations of driving, riding, and walking, and Table 3.3 further describes the case. Case 8 does not require a walking transfer node, as walking is the only mode involved. In Table 3.3, six possible subcases of Case 7 in Table 3.2 are shown. Two of the possible sequences are driving-riding and riding-driving. For driving-riding, parking locations and bus stops, as walking transfer nodes, are required because when driving is the initial mode of transportation, the traveler has the flexibility to choose a parking location or a bus stop. For riding-driving, the choice of bus stop is flexible but a fixed parking location is required as it is expected that the traveler has already left his/her car at a parking location for the return trip.

Table 3.3. Walking transfer selection rules for combining driving and riding

Case	Mode sequence	Walking is preferred	Walking transfer selection rule
1	Driving→ Riding	Near origin	No parking location selection is required
2	Driving→ Riding	Near destination	Apply case 4 of Table 3.2
3	Driving→ Riding	Between walking transfer nodes	$v_1 \in V(pk) \wedge v_2 \in V(bs) \wedge$ $d^{lo} \leq d(v_1, v_2) \leq d^{up}$
4	Riding→ Driving	Near origin	Apply case 2 of Table 3.2
5	Riding→ Driving	Near destination	No parking location selection is required
6	Riding→ Driving	Between walking transfer nodes	$v_1 \in V(bs) \wedge v_2 \in V(pk) \wedge$ $d^{lo} \leq d(v_1, v_2) \leq d^{up}$

3.1.2 Soft Boundary Method

As an alternative to buffers to identify suitable walking transfer nodes, a metric function can be used to assign each walking transfer node a value representing the suitability value. Walking transfer nodes with higher suitability values will have more chances of selection. We define the metric function, Equation (3.1), which takes distance between the origin/destination and the walking transfer node of interest as input, and returns a suitability value.

$$ {}_i = \exp\left(-\left(\frac{(d_i - d)^2}{\delta^2}\right)\right) \tag{3.1}$$

where d is the goal distance (measured in a metric space such as Euclidian space) from the origin or destination location

d_i is the distance (measured in a metric space such as Euclidian space) between the i^{th} walking transfer node and the origin or destination

Z_i is the suitability value of the i^{th} walking transfer node

δ is the exponential decay factor; lower value results in faster decreasing rate of Z_i

Equation (3.1) can be used to calculate the suitability value; 0 and 1 are the minimum and the maximum values, respectively. To illustrate the patterns of the suitability value returned by the function, Figure 3.3 shows two surfaces rendered using d=1.5 and two exponential decay values (upper surface: δ = 0.6 and lower surface: δ = 1.5). These two exponential decay values were selected arbitrary and mainly for the purpose of visualizing the results of the technique. The color maps are provided with the accompanying numerical scale of suitability value; a lighter color represents a higher suitability value. The image on the right of each surface is the two dimensional projection (bird's eye view) of the surface. The surfaces and the two dimensional projections show a lower rate of change of suitability value when δ increases. The origin/destination is assumed to be at the coordinates (0,0,0), the goal distance (d) is set to one kilometer, and d_i is measured in all directions from the coordinates (0,0,0). The upper surface in the figure shows rapid change of suitability value as the difference between d_i and d increases. The two dimensional projection (upper right) also shows that the intensity of the shaded area changes rapidly from light to dark at the edges of the inner and outer radius. As for the lower surface, a higher value of δ was used, and the surface shows slow gradual change of suitability value. The two dimensional projection (lower right) shows larger coverage of lighter shaded area, and the intensity of the shaded area changes slowly from light to dark at the edges of the inner and outer radius.

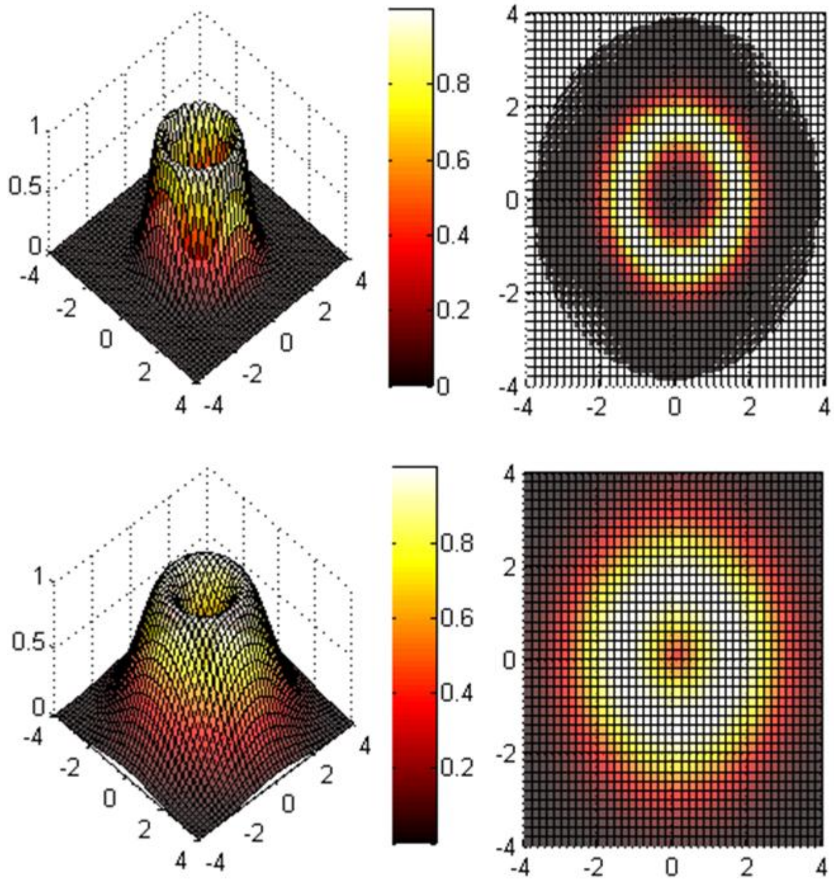


Figure 3.3. Surfaces of suitability values (upper surface: δ =0.6 and lower surface: δ = 1.5)

3.2 ROUTE COMPUTATION COMPLEXITY

Route computation in MMT-MCW involves three parts: modes of transportation, vehicular and walking routes, and walking transfer nodes. For a pair of input origin-destination, multiple modes of transportation must be considered in terms of both possible sequence and possible combination. Multiple candidate walking transfer nodes must be identified and considered, and accordingly, multiple candidate routes must be computed and evaluated. According to the facts described above, a request for an optimal MMT-MCW based route results in multiple times of route computations associated with various trip scenarios. This section discusses the possible trip scenarios influencing the route computation complexity.

Possible trip scenarios can be conducted based on possible sequence and combination of modes of transportation. Possible trip scenarios are categorized based on three characteristics: type of trip, combination of transportation modes, and walking locations. Type of trip is either one-way (OW) or roundtrip (RT). RT contains outgoing (OUT) and return trip (BACK). Three modes of transportation (walking, driving, and riding) are considered for the combinations of transportation modes, that is walking (WA), walking-driving (WD), walking-riding (WR), and walking-riding-driving (WRD). Walking locations can be near origin (NR), near destination (ND), between two walking transfer nodes (NW), not required (NQ), and walking is the only mode between origin and destination (NB). Note that walking may not be required for BACK if it is already included in OUT, and vice versa. Table 3.4 summarizes the trip characteristics, possible values, and their abbreviations. Figure 3.4 shows a tree diagram depicting the organization of the possible trip scenarios. The numbers in the parentheses in the figure refer to the numbers of possible trip scenario. The total number of possible trip scenarios is 78 in which 12 are one-way and 66 are roundtrip. Both one-way trip and roundtrip contain all four combinations of transportation modes: WA, WR, WD, and WRD. The WR under RT has 49 trip scenarios because both OUT and BACK are considered as two independent WR (7 trip scenarios), therefore the total number of combinations is 49. Example descriptions of the trip scenarios are shown in Table 3.5.

Figure 3.4 also indicates the number of trip scenarios to be considered. For example, if a traveler request for an optimal route for a walking-riding one-way trip, there will be 7 trip scenarios to be considered in the MMT-MCW simulation. The extreme case is when the traveler does not indicate type of trip, mode of transportation, and walking location, in which case all 78 trip scenarios have to be simulated, and routes being relevant to the scenarios have to be computed.

Table 3.4. Trip characteristics and abbreviations

Characteristics	**Possible values**	**Abbreviations**
Mode of transportation preferred	Walking	WA
	Walking-Riding	WR
	Walking-Driving	WD
	Walking-Riding-Driving	WRD
Types of trip	One-way	OW
	Round-trip	RT
	Out-going trip (origin to destination)	OUT
	Return trip (destination back to origin)	BACK
Walking location	Near origin	NR
	Near destination	ND
	Between two walking transfer nodes	NW
	Walking is the only mode between origin and destination	NB
	Walking is not required	NQ

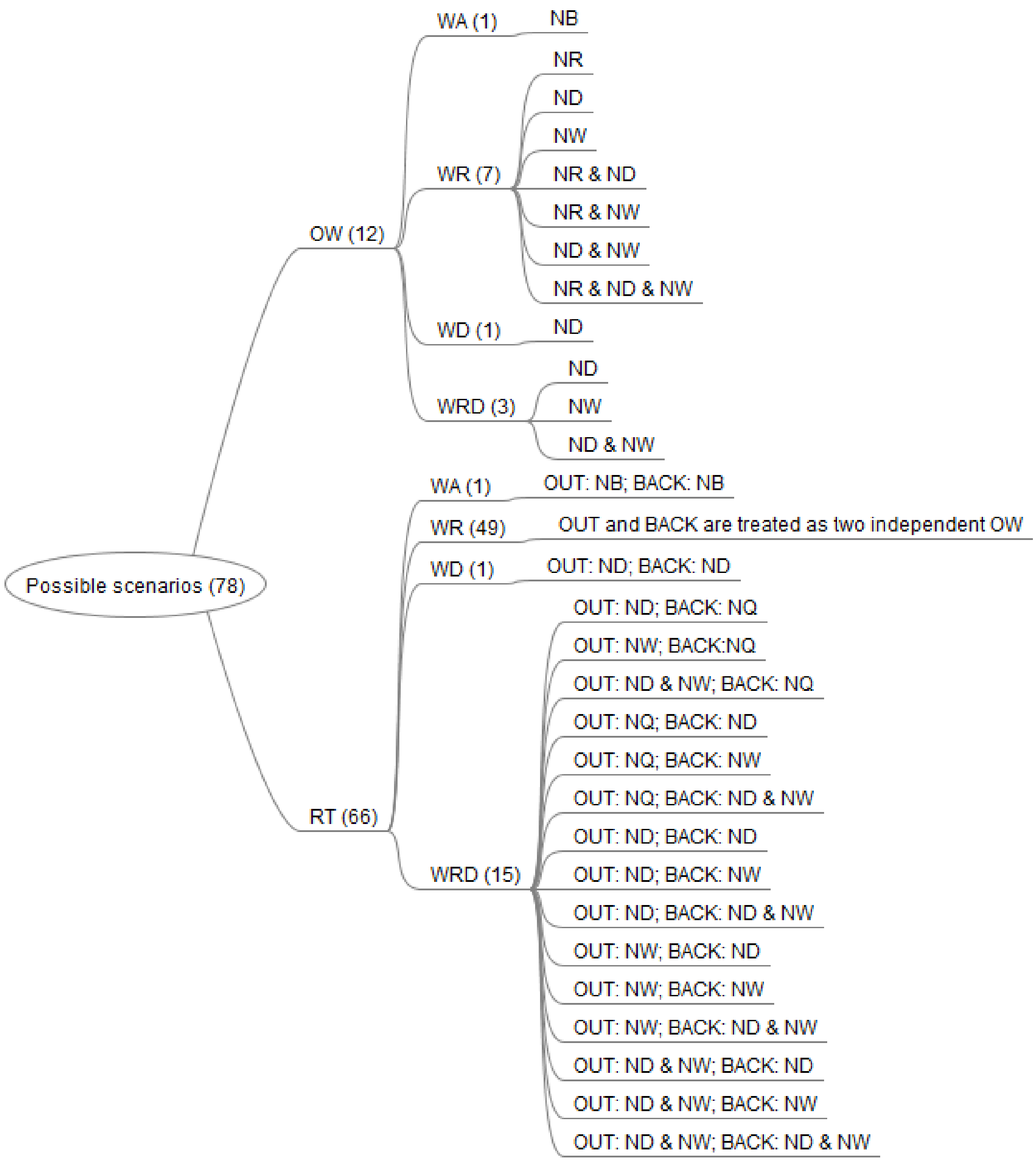


Figure 3.4. Numbers of possible trip scenarios

Table 3.5. Example description of trip scenarios

Trip	Mode	Preferred walking	Description for the preferred walking
OW	WA	NB	the only mode between O and D
OW	WR	NR	near O
OW	WR	NW	between walking transfer nodes
OW	WR	NR & NW	Near O and between two walking transfer nodes
RT	WD	OUT: ND; BACK:ND	near D for the outgoing; the return trip must begin with walking
RT	WRD	OUT: ND; BACK:NQ	near D for the outgoing; does not require walking for the return trip
RT	WRD	OUT: ND; BACK: ND	near D for the outgoing; the return trip must begin with walking
RT	WRD	OUT: NQ; BACK: NW	does not require walking for the outgoing trip; preferred between two walking transfer nodes for the return trip
RT	WRD	OUT: NW; BACK: NW	preferred between two walking transfer nodes for both the outgoing trip and the return trip

Number of possible trip scenarios is closely related to number of routes that must be computed. Route computation finds one or more optimal routes to travel from one location to another. In this dissertation, the two locations can be origin and destination, origin and walking transfer node, walking transfer node and destination, or two walking transfer nodes. The number of optimal routes depends on the routing algorithm being used. For example, the k-shortest path algorithm will return k shortest routes (Eppstein 1998) for a pair of locations. Dijkstra's algorithm returns shortest routes from one location to all other locations (Dijkstra 1959). In this dissertation it is assumed that only one route is returned for a pair of locations.

A trip can be uni-modal or multi-modal. A multi-modal trip is composed of two or more uni-modal trips connecting an origin, a walking transfer node, and a destination. Each uni-modal trip has a start location and an end location and may be associated with riding, driving, or walking. Finding an optimal route from the start to the end location of a uni-modal trip requires one time of route computation, and a route computation could be associated with a riding route, a driving route, or a walking route. Figure 3.5 shows five example trips and their number of route computations. The number in the parenthesis at the end of each example represents the total number of route computations for the example. Ex.1 requires only one computation as only one walking route is involved. Ex.3 requires the highest number of computations. An equation to estimate the number of route computations for a trip is expressed as:

$$N = 2R^{0,1}\beta + D^{0,1} + 1 \tag{3.2}$$

where N is the number of route computations

$R^{0,1}$ is the indicator of riding mode (0: no riding; 1: riding exists)

β is the number of buses to be taken (1, 2, 3, …)

$D^{0,1}$ is the indicator of driving mode (0: no driving; 1: driving exists)

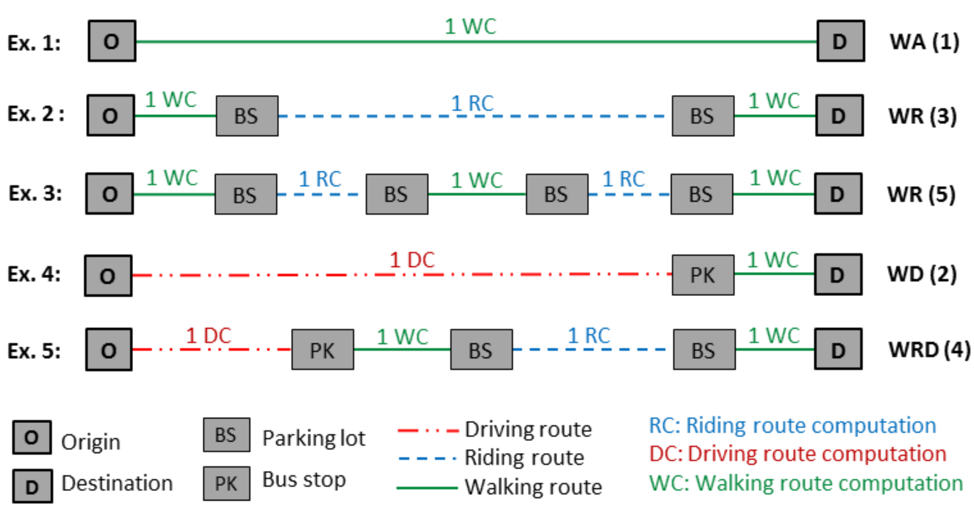


Figure 3.5. Route computation counting

There are no candidate routes and candidate walking transfer nodes in the examples shown Figure 3.5. Even though uni-modal routes that connect each pair of locations are optimal, those routes are only suitable for a certain pair of locations. To have candidate optional routes and walking transfer nodes, candidate start and/or end locations have to be considered. Figure 3.6 shows an example multi-modal trip with multiple candidate routes and multiple candidate walking transfer nodes. The multi-modal trip has five candidate multi-modal routes connecting A to B. Five walking transfer nodes (parking locations) are considered, and, accordingly, five candidate multi-modal routes are computed and presented. A candidate multi-modal route, composed of a driving route, a parking location, and a walking route, is formed. As a driving route must connect to a walking route at a walking transfer node, the number of candidate walking transfer nodes is expected to be equal to the number of driving routes and to the number of walking routes. Based on the relationship between walking transfer node, walking route, and vehicular route, Equation (3.3) to Equation (3.5) are used to estimate the number of route computations for a trip as follows:

$$N^r = \sum_{i=1}^{b}\left(b_i^s b_i^f\right) \quad (3.3)$$

$$N^w = N_x^{nr} + N_x^{nw\_1} N_x^{nw\_2} + N_x^{nd} \quad (3.4)$$

$$N = N^r + N^w + N^d \quad (3.5)$$

where N^r is the number of riding route computations

N^w is the number of walking route computations

N^d is the number of driving route computations and equal to number of candidate parking locations

N is the total number of route computations for the trip

b_i^s is the number of candidate start bus stops for bus *i*

b_i^f is the number of candidate final bus stops for bus *i*

N_x^{nr} is the number of candidate walking transfer nodes near the origin; this is for the case when walking is requested to be near origin

$N_x^{nw\_1}$ is the number of candidate walking transfer nodes at which a walking route starts; this is for the case when walking is requested to be between two walking transfer nodes

$N_x^{nw\_2}$ is the number of candidate walking transfer nodes at which a walking route ends; this is for the case when walking is requested to be between two walking transfer nodes

N_x^{nd} is the number of candidate walking transfer nodes near the destination; this is for the case when walking is requested to be near destination

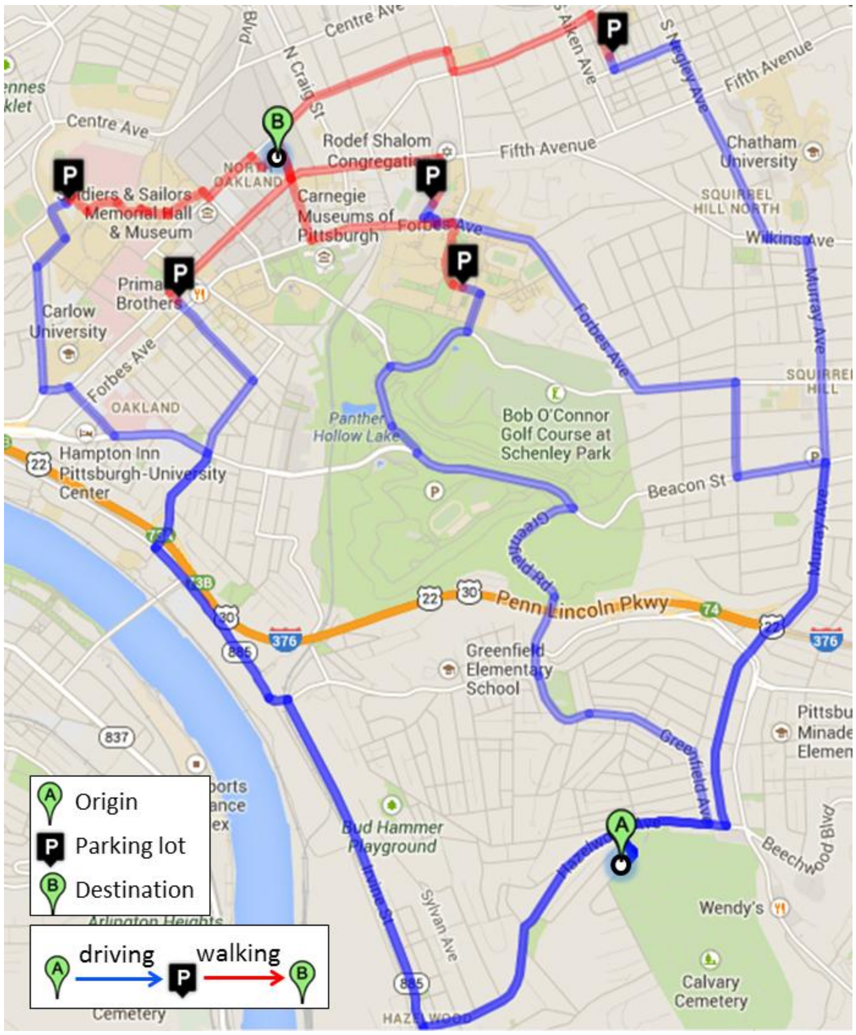


Figure 3.6. Example candidate multi-modal route

Figure 3.7 shows 13 cases computed based on Equation (3.2), which covers the possibilities of the number of route computations of the 78 possible trip scenarios. In these 13 cases, the number of candidate walking transfer nodes (bus stops and parking locations) is fixed at the value of 20, and the candidate walking transfer nodes will be considered only if walking is preferred (NR, ND, and NW). Only one walking transfer node is considered otherwise. For instance, Case 2 considers 20 candidate bus stops to be near origin as the case is WR:NR. Case 4

(WR:NW) considers 20 candidate bus stops as start locations of the candidate walking routes and another 20 candidate bus stops as end locations of the candidate walking routes. Two sets of candidate bus stops are considered because the case involves two buses, and walking is preferred between the two bus stops. Case 13 (WRD:NQ) refers to a situation when no walking is preferred, thus no candidate walking transfer nodes are considered, and only four route computations (1DC, 2 WC, and 1 RC) are required. The total number of route computations is in the parenthesis at the end of each fundamental case. All route computation counts match the results from Equation (3.2).

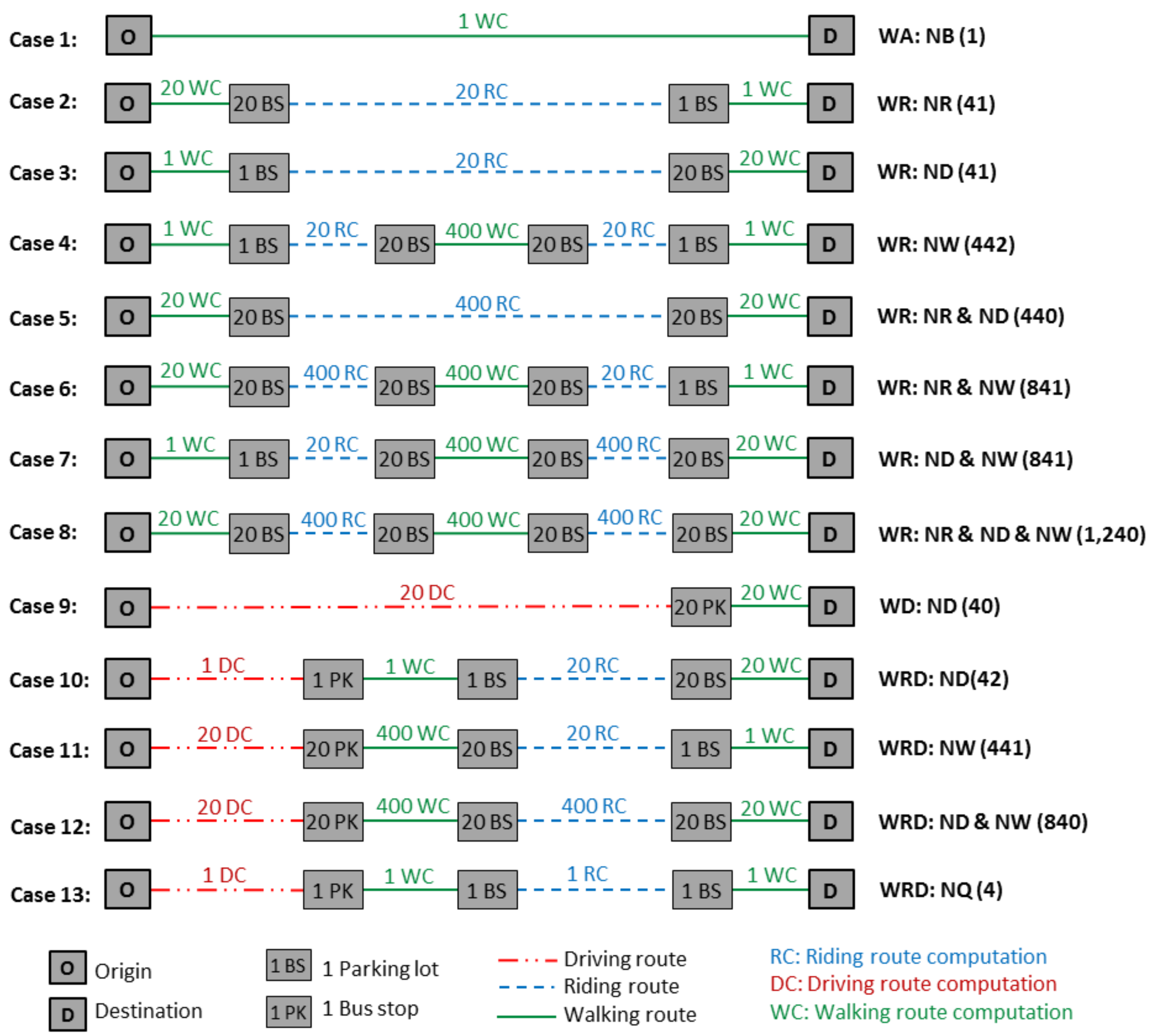


Figure 3.7. Enumeration of route computation counts

Routes computed for all the possible trip scenarios are analyzed next. Figure 3.8 enumerates the number of route computations (shown in the parenthesis) for each possible trip scenario. A possible trip scenario is composed of one or two of the 13 cases in Figure 3.7. For example, the trip scenario OUT:ND; BACK:NQ under WRD and RT (see Figure 3.8) is composed of Case 10 (WRD:ND; 46 route computations) and Case 13 (WRD:NQ; 4 route computations). Therefore, the number of route computations for the trip scenario is 42+4=46. To describe the interpretation of route computations, two examples are provided as follows. First, if the traveler prefers walking-riding for one-way trip without explicitly specifying the walking location (this matches the scenario WR under OW) then all seven scenarios under it will have to be considered. The number of route computations of the seven scenarios is 3,886. In case the traveler wants MMT-MCW to consider optimal routes for all possible trip scenarios, a total of 23,710 route computations must be performed. Note that the number of candidate bus stops and the number of parking locations are still fixed at the value of 20. The total number of route computations will be less if a lower number of candidate walking transfer nodes is considered.

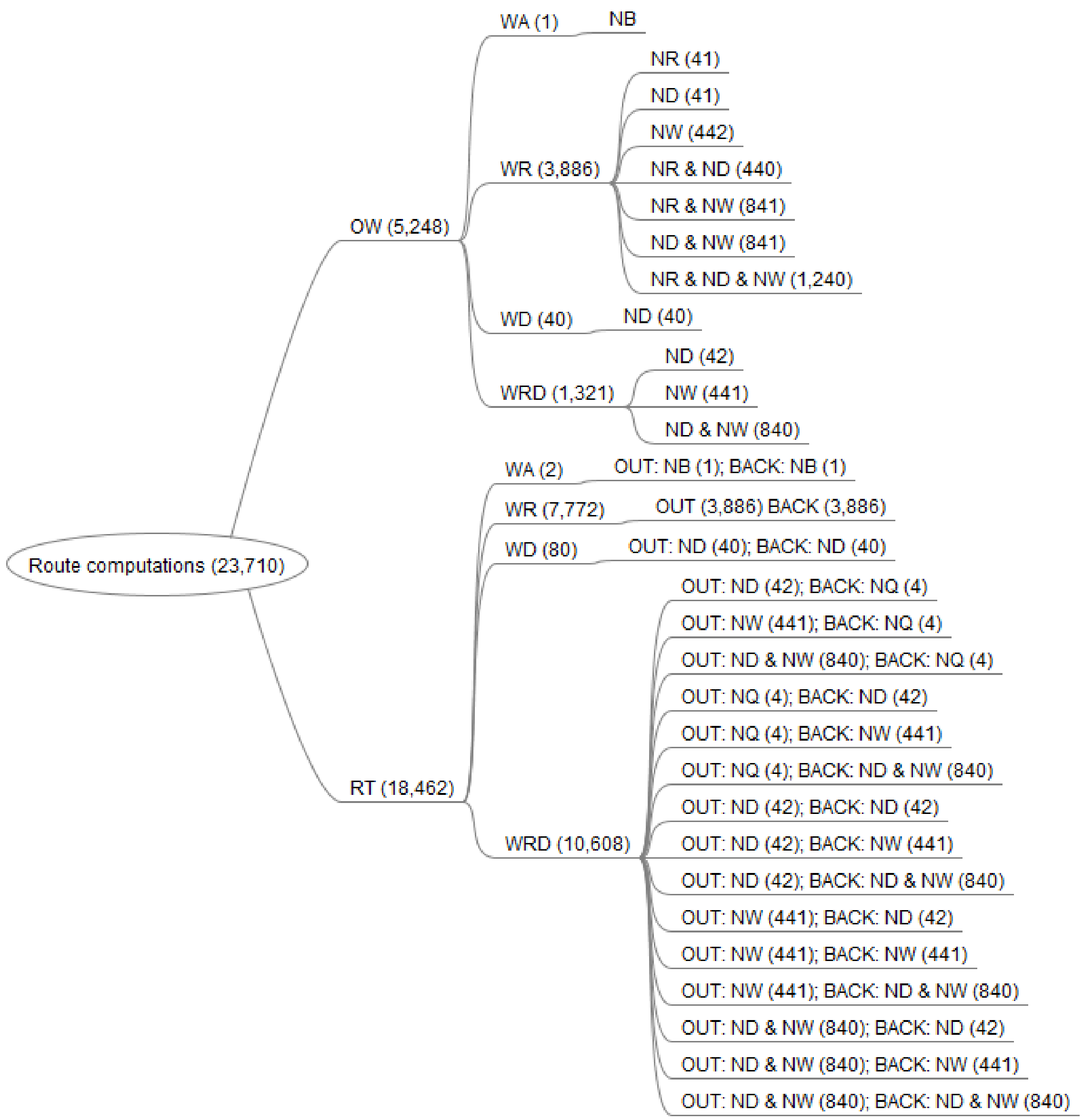


Figure 3.8. Number of route computations

The number of route computations has major influence on the computing performance of MMT-MCW, especially when travelers do not specify their scenario of interest. This is because a large number of possible trip scenarios and their relevant route computations will have to be considered. To elaborate influence of route computations on the computing performance of

MMT-MCW, a numerical example is provided as follows. Assuming a computation time of 0.1 second per route, the total computation time for 23,710 route computations is about 40 minutes, which is not acceptable for real-time mode.

3.3 CONTEXT-AWARE WALKING SEGMENT

Multiple criteria optimal walking requires various contexts of route evaluation. Examples criteria are shortest travel distance, shortest travel time, specified level of calories to burn, minimum traffic related air pollution exposure, and minimum slope variation. For each criterion, relevant attributes will need to be identified. For example, the relevant attribute for minimum slope variation criterion is slope variation, and each walking route must be evaluated in terms of slope variation. Multiple criteria will require multiple attributes, and a walking route must be evaluated with respect to various attributes. Figure 3.9 shows four examples of a walking route with respect to four attributes, i.e., amount of sun exposure, amount of traffic-related air pollution, slope, and distance. The criteria related to the four attributes can be minimum sun exposure, minimum traffic-related air pollution, minimum slope variation, and shortest distance. The four examples share the same origin (circle shape) and destination (square shape). The turning points (diamond shape) represent locations where attribute values change and can be independent of sidewalk intersections. For instance, for sun exposure, turning points represent transition locations of sun exposure levels (fully exposed, moderate, and shady). Transition locations can be identified using boundary of surface materials such as sidewalk canopies and shady plants. Three levels of traffic-related air pollution (low, moderate, and high), which may be influenced by wind flow direction, topography, surrounding buildings, and amount of road traffic, are assumed. Slope is calculated based on elevations along the walking route together with turning points that represent locations where slope changes between uphill, downhill, and flat. Distance is the summation of distances of all the relevant sidewalk segments (d_1+d_2+d_3+d_4).

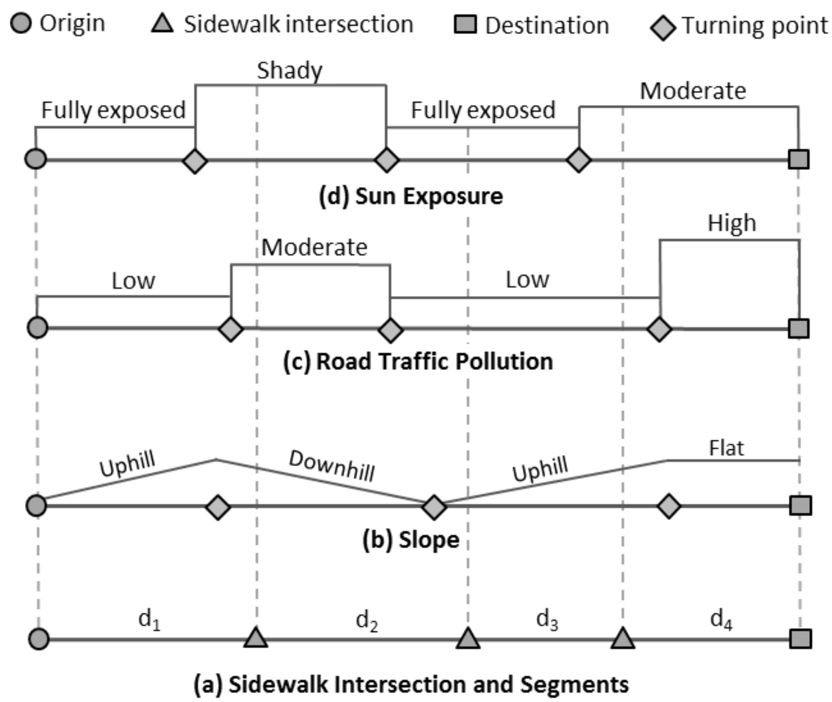


Figure 3.9. Four context examples of a walking route

When an objective function is used to quantify and evaluate a candidate route, there could be cases where the function requires homogeneous attributes within the route such as the examples described above. In some cases where the context of interest (such as slope) does not fit physical separation of sidewalk intersections and walking segments, it may not be accurate to rely on sidewalk intersections and segments. To address this problem, the concept of a "context-aware walking segment" is introduced. The concept is illustrated through the application of a specific example related to the estimation of calories burn on walking routes as follows.

The American College of Sports Medicine (1986) has investigated the amount of calories burn (energy expenditure) for several activities (such as walking, running, and stepping). The result of this investigation was an equation for a comfortable walking speed that ranges from 1.9 to 3.7 miles per hour (51–99 meters per minute) (Glass et al. 2007). The ACSM walking equation (Tharrett et al. 2012) expresses walking energy expenditure as:

$$EE = (0.1 \cdot S + 1.8 \cdot S \cdot G + 3.5) \cdot BM \cdot t \cdot 0.005 \quad (3.6)$$

where EE is walking energy expenditure (kilocalories)

S is walking speed (meters/minute)

G is grade (slope) in decimal form; e.g., 0.02 for 2% grade

BM is traveler's body weight (kilograms)

t is walking time (minutes)

Equation (3.6) is based on the assumption that the traveler walks at a constant speed during the time *t*, and the slope *G* is homogeneous. In order to maintain a homogeneous slope over a distance, a walking route may be split into *n* walking segments, where each segment has a homogeneous slope. This will result in the total energy expenditure (EE_{total}) for all the walking segments expressed as:

$$EE_{total} = \sum_{i=1}^{n} EE_i \quad (3.7)$$

where EE_i is the energy expenditure of the i^{th} walking segment, which can be estimated by using Equation (3.6). The *i* subscript in Equation (3.7) indicates that each segment may have a different walking speed, walking time, and slope.

To properly apply Equation (3.6) and Equation (3.7), walking segments must have homogeneous slope, in which case it is reasonable to assume that the traveler walks with a constant speed throughout the segment. A pedestrian network is composed of segments and nodes to represent topology between pedestrian route elements, and attribute information (such as segment length and slope) is incorporated to fit with the topology among segments (Kasemsuppakorn & Karimi 2009). However, the concept of segments and nodes of the pedestrian network is not suitable for this example as homogeneous slope is required. For this, regular segments are converted to context-aware walking segments. Figure 3.9 illustrates such a conversion. In the figure, sidewalk intersections are disregarded, and new nodes (contextual nodes) are created to represent the slope turning points. As a result, new segments (context-aware walking segments) are considered such that each context-aware walking segment has a homogeneous slope. Equation (3.6) can be applied to estimate calories burn for each context-aware walking segment, and the total energy expenditure of the entire walking route can be achieved through the application of Equation (3.7).

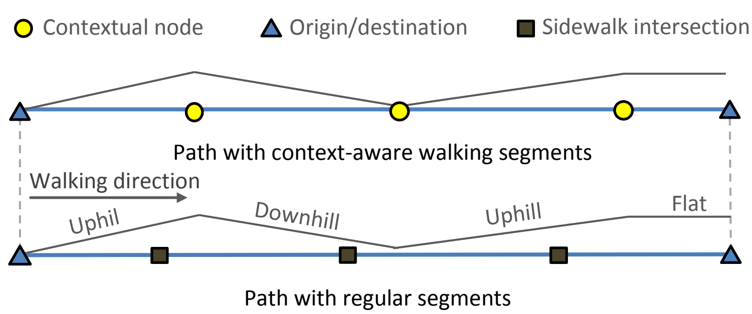


Figure 3.10. Conversion of regular segments into context-aware walking segments

Further examples regarding applications of context-aware walking segments are illustrated in Figures 3.10 (a) and (b). Figure 3.10 (a) shows a number of contextual nodes that represent the sun exposure turning points (between fully, moderate, and shady) which can be located based on the boundary of surface materials such as sidewalk canopies and shady plants. When the shadiest walking route is preferred, candidate walking routes will be evaluated with respect to the levels of sun exposure, and the relevant criterion for this is finding a walking route with minimum sun exposure. Figure 3.10 (b) shows another set of contextual nodes that represent the turning points of walkway surface (between paved or unpaved) of which the traveler is concerned about the surface quality of the walking route. It is also worth noting that type of walkway surface is static, whereas sun exposure is dynamic. For example, a walking segment may be shady in the morning, but becomes fully exposed to sunlight in the afternoon. Despite dynamic sun exposure, the context-aware walking segment concept is still applicable because the contextual nodes and the context-aware walking segments can be created dynamically, as the environment changes.

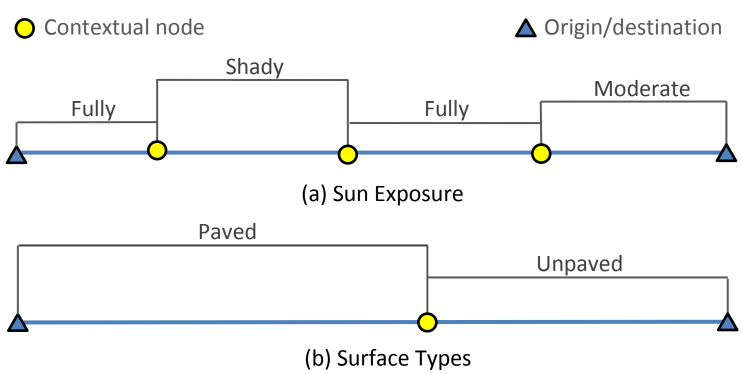


Figure 3.11. Various context-aware walking segments

As MMT-MCW is associated with multiple criteria (contexts), multiple sets of context-aware walking segments are expected. Each context would have an associated objective function to quantify the quality of a walking route with respect to the criterion of interest, and thus, multiple contexts result in multiple related objective function outputs (called context-aware scores) for the walking route. Figure 3.11 shows an algorithm that uses context-aware walking segments to evaluate candidate walking routes. The evaluation outputs are used for finding the optimal walking route.

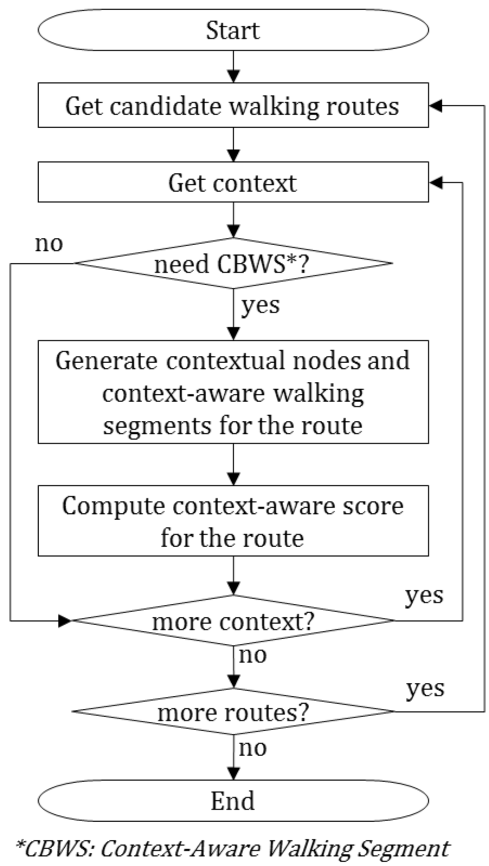


Figure 3.12. An algorithm for evaluating candidate walking routes

3.4 OBJECTIVE FUNCTION NORMALIZATION

Objective functions usually produce results in different numerical magnitudes. In the weighted-sum optimization method, when multiple objective functions are simultaneously optimized, normalization should be used to harmonize the magnitudes. As objective functions are usually formulated based on their context of interest, the term context-aware score (CS) is used to represent the numerical outputs from the objective functions. CS for MCW is normalized by using two methods: (1) maximize difference value between CS and the goal provided by the user; and (2) individual behavior. Equation (3.8) expresses the first methods and Equation (3.9) provides two examples of the second method. The normalized CS is called a context- aware index (CI).

$$CI_i^{p_k} = \frac{\left|CS_i^{p_k} - g_i\right|}{\max\limits_{p_j}\left(\left|CS_i^{p_j} - g_i\right|\right)} \tag{3.8}$$

$$CI_i^{p_k} = \begin{cases} \dfrac{\exp\left(\delta_i(x_k - avgX)\right)}{1 + \exp\left(\delta_i(x_k - avgX)\right)} & \text{, if goal is not defined} \\ 1 - \exp\left(\dfrac{-1(g_i - x_k)^2}{\delta_i}\right) & \text{, if goal is defined} \end{cases} \tag{3.9}$$

where $CS_i^{p_k}$ is the CS of the k^{th} route (p_k), with the i^{th} objective function

$CI_i^{p_k}$ is the context-aware index of route p_k (based on the i^{th} objective function)

$0 \leq CI_i^{p_k} \leq 1$; 0 is the most preferred and 1 is the most adverse

g_i is the goal value (≥ 0) for the CS of the i^{th} objective function

δ_i is the curve inclination factor of the i^{th} normalization curve

$x_k = CS_i^{p_k}$ and $avgX = \frac{\sum_{j=1}^{n} CS_i^{p_j}}{n}$

The two normalization examples in Equation (3.9) provide smooth transition of *CI* values from 0 to 1, support continuous context-aware scores, and allow travelers to control the rate of change of CI, with respect to CS, through the curve inclination factor. A higher rate of CI change implies that the traveler is more sensitive to the deviation of the CS value from its goal value. To illustrate this, a set of CSs was simulated and plotted using the two conditional functions (g_i is and is not defined) in Equation (3.9) (see Figure 3.12, left and right graphs). The left graph is generated by assuming that the goal value (g_i) is 600 and using two inclination factors (1300 and 400). The right graph is for a goal value of 0. In the left graph, if the CS of the route is 600, it is considered a perfect score, because the score exactly matches the goal, and hence its CI is 0; the CI increases as the score deviates from 600. In comparing the curve inclination factors 400 and 1300, even though both inclination factors share the same goal value, the inclination factor of 1300 (the dotted line graph) implies that the user is more flexible in relation to the goal, while the inclination factor of 400 (the solid line graph) reflects more a restrictive goal with less flexibility. In the right graph, the dotted line (δ =0.2) reflects a more restricted goal, while the solid line (δ =0.06) is more flexible. Therefore, by controlling the inclination values, a user can control the goal relaxation for normalization; the normalizing functions in Equation (3.9) are subject to individuals.

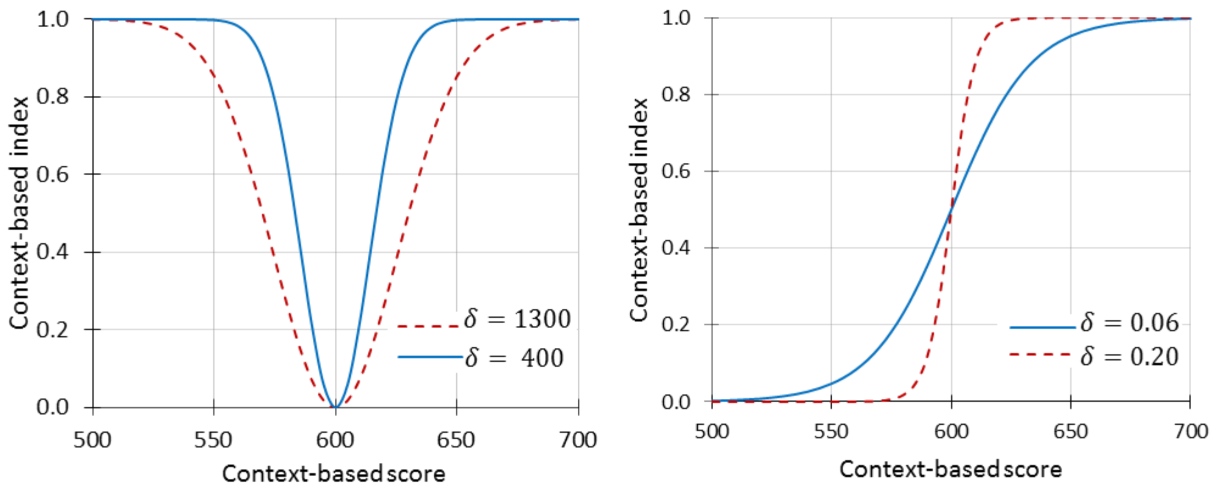


Figure 3.13. Normalization curves

Despite the differences bwteen the two approaches, i.e., the objective approach in Equation (3.8) and the subjective approach in Equation (3.9), both can be adopted in the same time by separating the objective functions. One group of objective functions may be more suitable when the objective approach is taken, while the other group is more suitable when the subjective approach is taken. One reason for this could be that the user may only be able (or willing) to identify the curve inclination factors for some of the objective functions, while the rest of the functions must rely on the objective approach. To justify the proper approach for a particular context, various factors, such as system requirements and user behavior, should be considred.

3.5 MCW ALGORITHM

A routing algorithm for MCW was developed. The inputs to the algorithm are origin, destination, and criteria given by the traveler, and the output is a set of one or more optimal routes. This section describes two versions of the MCW algorithm: the special version (which is for MMT-MCW real-time mode) and the general version (which is for MMT-MCW simulation mode).

Figure 3.13 describes the special version of MCW algorithm. To begin, the algorithm requires an origin (O), a destination (D), and a set of criteria from the traveler. Then the algorithm will examine whether or not the traveler is making a query for a return trip. If it is not a return trip, or if the return trip does not require driving, then the algorithm selects a number of suitable walking transfer nodes (depending on the criteria) either for all possible modes, or only for a number of specified modes. If suitable walking transfer nodes are found, vehicular routes and walking routes associated with the walking transfer nodes will be computed and combined into all possible multi-modal routes. If there is no suitable walking transfer node, the algorithm will only compute feasible walking routes that directly connect the origin and the destination. If the traveler indicates a need for a return trip in driving mode (e.g., if the traveler's car is parked in a particular parking location), the algorithm will check to see if the traveler prefers a different walking route than the one taken for the departure trip. If this is the case, the algorithm will compute all feasible walking routes from the destination back to the parking location.

Vehicular routes and walking routes are separated from each other by walking transfer nodes, so that they can be independently computed. The selection of walking transfer nodes is tightly coupled with walking distance limits. The details of using walking distance limits to select walking transfer nodes were discussed in the section "Selection of Walking Transfer Nodes (section 3.1)." When computing walking routes, it is possible to have multiple walking routes that connect to the same walking transfer node, as well as to multiple walking transfer nodes. This implies that the MCW algorithm must compute a much larger number of routes, as compared to regular route computations, such as shortest-path computation. A number of studies (such as Akgun et al. 2000; Beknor and Prato 2009) claim that computing multiple k-shortest path usually ends up with multiple spatially similar routes. However, in regard to vehicular route computation, there are many existing techniques in the literature that address computation of candidate vehicular routes for drivers, such as Prato et al. (2006); Ben-Akiva et al. (1984); Azevedo et al. (1993); De la Barra et al. (1993); Sheffi and Powell (1982); Ruphail et al. 1995; Park and Rilett 1997; and Friedrich et al. (2001). Generally, they all try to resolve the route similarity problem by introducing penalty on the links that are already part of a route. In some studies, an index to measure route similarity has been attempted where it is used to filter out undesired routes. Detail discussion of these techniques is beyond of the scope of this dissertation.

Once vehicular routes and walking routes are computed, they will be combined using their relevant walking transfer nodes, and a set of candidate routes will be the outputs. A candidate route refers to a possible walking route (i.e., a uni-modal route) or a combination of walking routes and vehicular routes (i.e., a multi-modal route). There could be multiple candidate routes for a pair of OD. For each walking route of each candidate route, the algorithm will compute a CS considering a certain criterion (context). The CS of the candidate routes are then used for optimization. The details of CS were discussed in the section "Context-aware Walking Segment (section 3.3)." The details of objective functions and their optimization are not described in the algorithm since they were discussed in the sections "Multi-Criteria Optimization (section 2.3)" and "Objective Function Normalization (section 3.4)." Finally, the algorithm will return the optimal route (s). Note that the optimization can be run for many times with respect to different sets of optimal parameters resulting in multiple optimal routes.

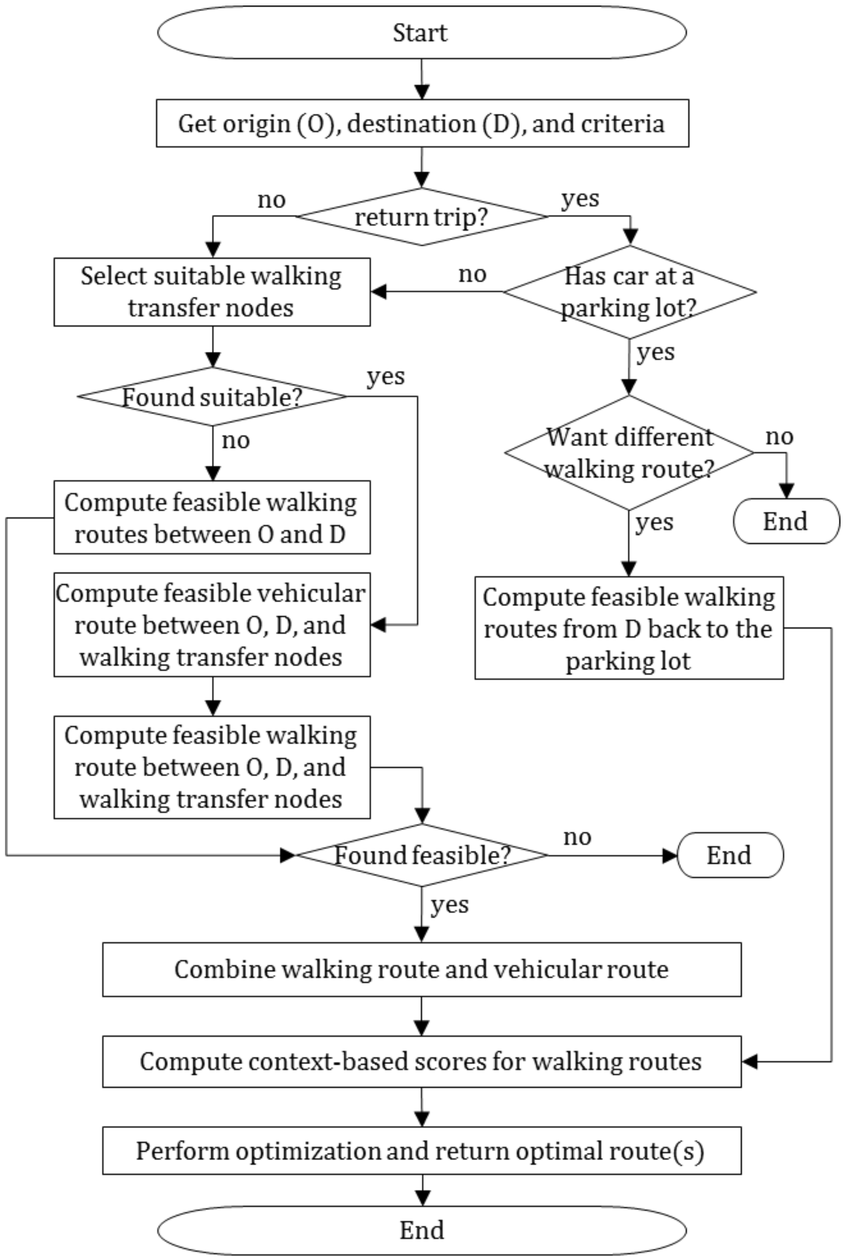


Figure 3.14. Special MCW algorithm

The general MCW algorithm is modified from the special version, in order to support MMT-MCW simulation. Three conditions are considered in modifying the special version: (1) the traveler may not know (or specify) a desired trip scenario and prefers the simulation to recommend a suitable one (see Section 3.2 for details of possible trip scenarios); (2) the real values of relevant environmental variables (such as weather condition) may be unknown by the time the traveler makes a trip request; and (3) different criteria may be considered as a result of travel plan changes. The general MCW algorithm is described in Figure 3.14. The algorithm takes as input an origin, a destination, traveler's criteria, and desired trip scenarios. Walking transfer nodes will be selected based on trip scenarios. If suitable walking transfer nodes are found, feasible walking routes and feasible vehicular routes will be computed; only feasible walking routes will be computed otherwise. Then the walking routes are combined with their relevant vehicular routes, so that complete candidate routes are obtained. Once the candidate routes are prepared, the most up-to-date values for the relevant environmental variables are considered. Next, a route score for each context is computed for all candidate routes. The route scores are normalized and optimized to find an optimal route, and then the optimal route together with its suitable trip scenario are returned. Once the optimal route is computed, the algorithm will keep monitoring the change of environmental variables and traveler's criteria to update the optimal route as needed. New route scores will be recomputed based on the updated environmental variables and traveler's criteria. If the values of the environmental variables are finalized or the traveler expresses a desire for termination, the algorithm will stop. It is also worth noting that the implementation of the algorithm does not have to completely contain all the components of the algorithm. For example, the example simulation in Chapter 6 was focused on data analysis, not for route recommendation so that the simulation did not include the modules for monitoring the change of environmental variables and for optimization.

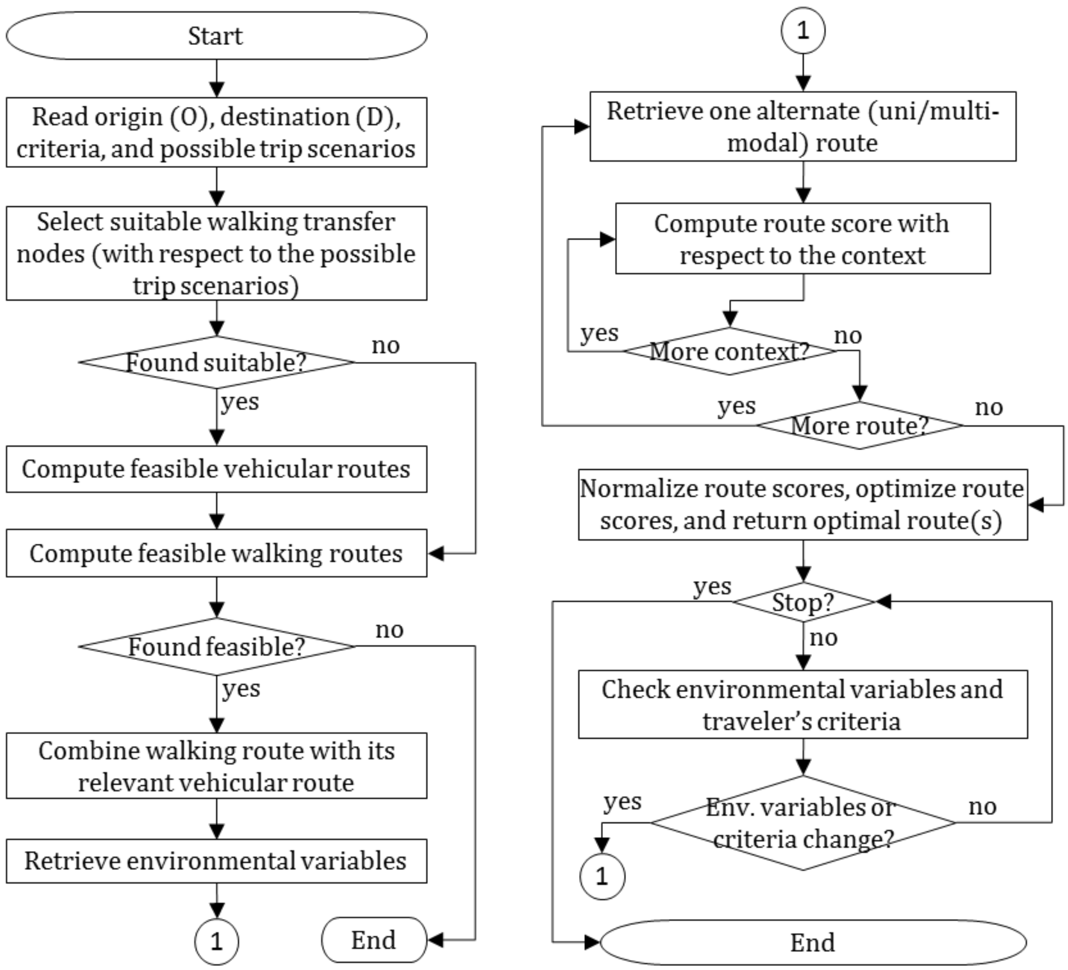


Figure 3.15. General MCW algorithm

4.0 RELATED WORKS

In this chapter, four areas of related works are described in the four sub-sections: (4.1) multi-modal network data model, (4.2) multi-criteria routing, (4.3) public transit and MMT planning, and (4.4) transportation simulation. Each sub-section is related to topics and/or parts of MMT-MCW as follows. Multi-modal network data model is related to topology between networks (Section 2.2) and context-aware walking segment (Section 3.3). Multi-criteria routing is related to multi-criteria optimization (Section 2.3), selection of walking transfer nodes (Section 3.1), and MCW algorithm (Section 3.5). Public transit and MMT planning is related to topology between networks (Section 2.2), route computation complexity (Section 3.2), and MCW algorithm (Section 3.5). Transportation simulation is related to MMT-MCW simulation (Chapter 6).

4.1 MULTI-MODAL NETWORK DATA MODEL

Walking is not only an independent mode of transportation, but it is also used as an intermediate mode in multi-modal transportation to switch between different vehicular modes such as riding and driving. This section outlines current multi-modal network data models related to MMT-MCW.

A multi-modal network data model represents the real-world transportation infrastructures (such as roads, intersections, bus stops, and parking lots) along with their geometries, topologies, and properties. Multi-modal network data models have been investigated in several studies to better capture the properties of transportation infrastructures, as well as to improve the computing performance of multi-modal networks. Huang et al. (2002) introduced an object-oriented Geographic Information System (GIS) data model to handle the dynamic nature of transit systems, particularly for Internet-based trip-planning applications. The entire transit network and its components are modeled as space-time entities (objects) with start times, end times, and life spans. With the addition of temporal constraints, only active components (such as routes that have available transit services) are factored into the network topology, leading to enhanced network search efficiency. Carlier et al. (2003) presented an architecture for MMT modeling. They proposed combining multiple uni-modal networks into a multi-modal network, called a supernetwork. A supernetwork includes the necessary components for the generation of (route) choice-sets and dynamic traffic assigned to the network. Bielli et al. (2006) proposed a methodology to combine national and urban networks through a multi-modal hierarchical graph model. Their goal was to provide a framework to model transportation networks and to address the algorithmic approach for solving the multi-modal shortest-path problem. They illustrated the advantages of merging graph concepts and the object-oriented paradigm to describe the existing multi-modal network data models. The resultant multi-modal network data models try to improve network computation performance and correctness by including routing and dynamic properties (such as traffic), but fall short of addressing walking as a transportation choice in the context of MMT trip planning.

4.2 MULTI-CRITERIA ROUTING

MCW is a type of multi-criteria routing. Multi-criteria routing research is focused on finding optimal transportation paths by considering multiple criteria (objectives) simultaneously. Bit et al. (1992) combined fuzzy set theory and linear multi-criteria programming to address multi-objective transportation problems. Their fuzzy programming approach has been claimed to be able to address problems with a large number of objectives and to be applicable to both minimum and maximum optimization problems. Modesti et al. (1998) proposed a utility measure that takes into account the overall travel expense, travel time, and bus crowded with passengers on public transport during rush hour. The utility values from the measure are then used as costs to find optimum paths using Dijkstra's algorithm. Das et al. (1999) proposed a solution to multi-objective transportation problems by expressing objective functions as interval degradation allowance values and then applying a fuzzy programming technique. Li et al. (2000) introduced a multi-objective linear programming model for transit itinerary planning and used it in a two-phase heuristic algorithm. The first phase is to generate all feasible paths with the objective of minimizing total travel time. The second phase is to evaluate the feasible paths by taking into account such decision criteria as number of transfer points, bus headway or frequency, and total travel expense, among other criteria. However, existing studies do not consider MCW in their exploration and discussion. For example, they do not suggest whether or not the criteria for walking and vehicular modes should be taken into account separately or simultaneously. They do not discuss how criteria related to the selection of transfer locations between walking and vehicular modes should be considered. Transfer locations are very important as they are used to define feasible modes of transportation and associated routes.

4.3 PUBLIC TRANSIT AND MMT PLANNING

Walking is inherent in public transit as it usually requires on-foot accessible locations where travelers get on/off transit vehicles (such as bus). Walking is also used to connect between different public transits. Current public transit and MMT planning only use walking to fulfill a public transit trip where walking is usually minimized. Karimi et al. (2004) developed an Internet-based application for bus route planning with minimum number of bus-to-bus transfers. Rehrl et al. (2007) designed a mobile application that provides personalized multi-modal trip planning, navigation assistance for transferring between buildings, and pedestrian routes in outdoors. Li et al. (2010) introduced a multi-modal trip planning system that incorporated real-time transit data into park-and-ride recommendations. Their system uses a prediction model (based on the regression analysis and historical data) to estimate the real-time arrival time. Tsolkas et al. (2012) described an architecture for a personalized mobile application and a multi-modal dynamic routing algorithm which takes into account real-time traffic information and individual routing preferences.

4.4 NEIGHBORHOOD WALKABILITY

Some studies explored walking for recreation and health. Leslie et al. (2005) and Cerin et al. (2008) investigated participants' perceptions of walkability to the participants' neighborhood areas. Frank et al. (2006) evaluated the association between a walkability index (incorporating land use mix, street connectivity, residential density, and retail floor area ratios) with health-related outcomes (physical activity, body mass index, and air pollutants). Leslie et al. (2007)

proposed an objective approach to assess walkability of cities by using spatial data (such as road network and transit stops). Forsyth & Southworth (2008) discussed the relationship between walkability and urban design. Smith et al. (2008) explored logistic regressions of a number of established predictors and body mass index, and found that levels of walkability have an inverse relationship with the risks of excess weight. Weinstein et al. (2008) reported a survey of pedestrian trips to transit focused on trip lengths and route choices. Brown et al. (2009) compared and reported relationships between body mass index and four types of diversity measures: equal distributions of walkable land use categories, distances to parks and transit stops, walk to work measures and neighborhood housing ages, and land use categories. Van Dyck et al. (2009) studied the differences in physical activity between adults living in high versus low walkable neighborhoods. Marshall et al. (2009) evaluated interactions between neighborhood walkability and air pollution exposure. Frank et al. (2010) developed a methodology to compute walkability index of a neighborhood built environment. Carr et al. (2010) explored the relationship between Walk Score™ (www.walkscore.com) and objective/subjective measures of the physical activity environment for a number of areas in Rhode Island State, USA. Duncann et al. (2011) extended the Walk Score™ to support multiple buffer distances and validated the Walk Score™ for four US metropolitan areas. King et al. (2011) explored the relationship between neighborhood design and health factors specifically related to older adults.

Neighborhood walkability studies mainly focus on trips in which origins and destinations are close within walkable distance; they do not address MCW as part of MMT.

4.5 TRANSPORTATION SIMULATION

Transportation simulation is another area related to this research. TRANSIMS is an open-source software package that is used to simulate and study regional transportation systems (Smith et al. 1995). It can be used to simulate travelers and their uses of multi-modal transportation, based on synthetic populations and their activities. A sample implementation of multi-modal transportation using TRANSIMS was presented by Nagel (2001). The process starts with generation of a plan for individuals (expressing where and when people do their activities), and then runs the simulation to simulate traffic representing people traveling in multi-modal transportation networks, based on the generated plan.

There are other software tools besides TRANSIMS that can simulate transportation activities. Krajzewicz et al. (2002) developed an open-source multi-modal microscopic traffic simulation software called SUMO (Simulation of Urban MObility). Traffic flow is simulated microscopically, such that every vehicle moving within the network is modeled independently and has a certain location and speed. DynaMIT (Milkovits et al. 2010) is another traffic simulation software tool designed for real-time traffic simulation analysis. The software tool can be used to estimate the current state of transportation network based on real-time traffic collected by traffic sensors simulate installed on real-world road networks, and can also be used to predict future states of the transportation network. CORSIM is another well-known traffic simulation software package, with claims of a solid foundation of traffic engineering modeling and analysis capabilities (Owen and McHale 2000).

Existing transportation simulations and software packages are mainly focused on analyzing behaviors of travelers in vehicles, including the traffic generated by the users themselves. The simulation software packages outlined above are designed for transportation engineers or urban planners to help them analyze road traffic and make decision about and developing transportation systems. The simulation in this dissertation can help transportation engineers improve the MMT needs of travelers and help urban planners analyze the built environment and design transportation friendly urban cities. The simulation can also help end users (travelers) in planning trips by considering walking as the primary choice in the context of MCW. Software developers can utilize the results of various MMT-MCW simulations to develop new wayfinding and navigation services or integrate the MMT-MCW simulation modules with existing wayfinding and navigation services to provide personalized routes.

5.0 A PROTOTYPE MMT-MCW SERVICE

This section discusses a prototype implementation of MMT-MCW real-time mode. The implementation was focused on a wayfinding service for promoting physical activity called Route2Health. Route2Health (Karimi and Socharoentum, 2014) recommends walking sessions, if feasible, for any trip. By taking as input origin, destination, and traveler's individual conditions, Route2Health recommends a sequence of transportation modes along with specific details about each mode that is most optimal (personalized). This chapter is organized as follows. A general implementation guideline is discussed in Section 5.1. Routeth2Health and its algorithm are described in Section 5.2 and Section 5.3. Routeth2Health implementation and example results are discussed in Section 5.4.

5.1 A GENERAL IMPLEMENTATION GUIDELINE

The implementation guideline discussed in this section is generalized so that it fits with any MMT-MCW based application. The later sections mainly focus on a particular application, Route2Health, and rely on the general implementation guideline.

MMT-MCW can be implemented as a service with the following capabilities. First, MMT-MCW service should support both uni-modal transportation and multi-modal transportation in which if walking is feasible for uni-modal transportation, it will be selected as the most desirable mode. Second, MMT-MCW service should be able to provide solutions where, as time passes, changes in the variables that affect the initial solutions are continuously monitored and in case of significant changes, the initial solutions are updated. Figure 3.15 shows the architecture of MMT-MCW service, which has seven components: (1) a walking transfer selector; (2) an candidate vehicular route generator; (3) an candidate walking route generator; (4) a route combiner; (5) a route evaluator; (6) an objective function normalizer; and (7) a multi-criteria optimizer.

The walking transfer selector is the component that takes as input origin-destination (OD) and the estimated walking distance upon which the walking transfer selector would identify a number of feasible walking transfer nodes. Then, based on the OD and the identified walking transfer nodes, candidate walking routes and candidate vehicular routes are computed by the candidate walking route generator and the candidate vehicular route generator, respectively. The candidate routes of the two modes are then combined into a complete candidate route by the route combiner. All the candidate routes are evaluated by the route evaluator by using the objective functions that are formulated with respect to traveler's criteria. The route evaluator also monitors environmental variables (such as traffic and weather conditions) and updates its outputs (route scores) as those variables change. In the objective function normalizer, the route scores are normalized so that route scores from different contexts (objective functions) can be combined into a single value. The normalized route scores are then optimized by the multi-criteria optimizer to obtain the final solution (the optimal route).

The origin, the destination, and the walking transfer nodes are used by the candidate walking route generator and the candidate vehicular route generator to compute the candidate routes, such that they cover most of the *feasible routes*. "Feasible route" is a reference to a route that is not longer than a pre-defined distance threshold for the related mode of interest. With this, walking routes that are longer than reasonable walking distance would be disregarded. The overall value of reasonable walking distance should be more flexible (longer) than that of the individual acceptable walking distance. Similarly, driving routes longer than a certain percentage of the Euclidean distance between the origin and the destination might be considered infeasible (the true distance should be investigated for practical implementation). A longer distance threshold would logically lead to a larger number of feasible candidate routes. Distance is used because it is the most fundamental and universal property and does not change over context and time.

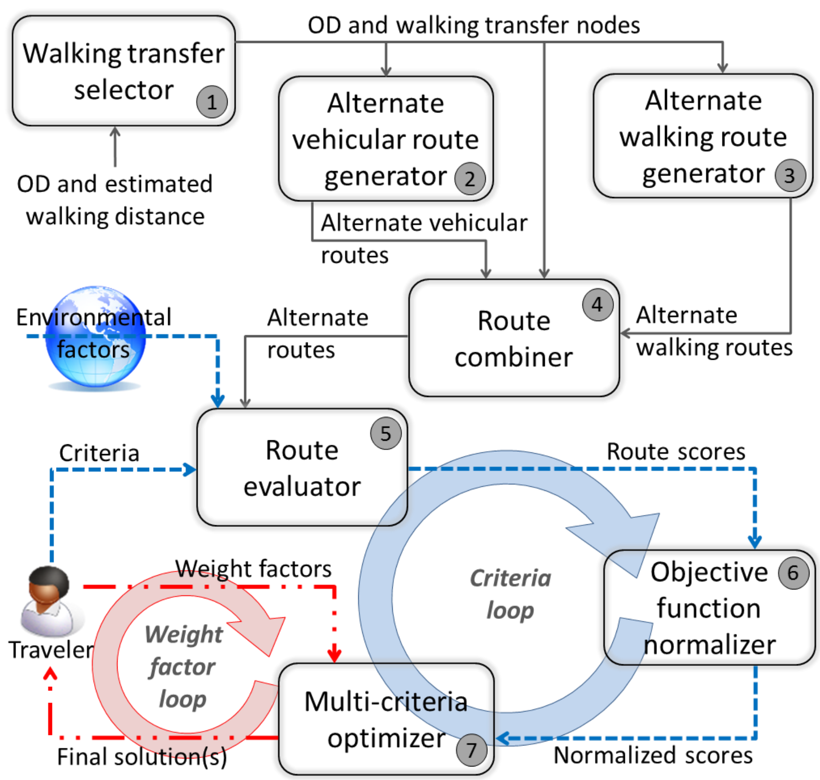


Figure 5.1. MMT-MCW service architecture

As discussed in Section 3.2, the number of route computations for all possible trip scenarios is very large. As part of MMT-MCW service, route computation must be programmed to be performed frequently to compute candidate routes for all possible trip scenarios when environmental variables and/or traveler's criteria change. To enhance the route computation performance, the architecture includes two iteration loops: the criteria loop and the weight factor loop. The criteria loop is formed by an external entity (the traveler), the route evaluator, and the objective function normalizer. The weight factor loop is formed by the traveler and the multi-criteria optimizer. The criteria loop is introduced to separate the traveler's criteria customization (adding, updating, or removing) from the candidate route computations, thus, candidate route computations are only required one time for an OD pair. The candidate routes should cover most of the feasible routes (as described above), and when the traveler customizes the criteria (with no changes on OD), the route evaluator can perform route evaluation on the same set of candidate routes. Based on the fact that changes to the weight factors only impact the optimization score and not the route scores, the weight factor loop is included to separate weight factor customization from criteria customization. If no traveler criteria are added, it is not necessary to update the route scores and the normalization. If a criterion is removed, its weight factor will be set to zero and the optimization score must be recomputed. Therefore, travelers may change the weight factors multiple times to find the most desirable routing solutions without influencing the computation of the route scores.

5.2 ROUTE2HEALTH

Walking is an essential mode of transportation, independent of vehicles or parking locations, and does not rely on specific service routes or schedules. Roads in urban and residential areas usually include sidewalks to connect building entrances and other locations that can be reached on foot. Walking plays an important role in multi-modal transportation planning. For example, when a person drives from home (origin) to another location (destination), walking may be required between a parking lot and the location of destination. In the case of public transit, walking may be from an origin to a particular transit stop, from a transit stop to the destination, and between transit stops.

Besides serving as a transportation mode, walking can offer interesting and desired benefits to travelers. For example, walking is considered as a physical activity that can be performed by many people regardless of geographic locations. It is recommended by the United States Department of Health and Human Services (1996) that moderate intense activities such as 30 minutes of brisk walking can lead to health benefits in adults. Numerous studies (e.g., see Sallis et al. 2004; Besser et al. 2005; Edwards 2008; and MacDonald et al. 2010) suggest that walking should be promoted as part of daily public transportation to prevent or mitigate various health conditions such as heart disease and obesity. Morabia et al. (2010) conducted a study and found that switching from private car to public transportation when commuting to work increased energy expenditure (more than 124 kilocalories/day) which is equivalent to the loss of 1 pound of body fat per 6 weeks. In an analysis of cross-sectional health and travel data at country, state, and city levels, Pucher et al. (2010) found negative relationships between active travel (waking and cycling) and self-reported obesity and negative relationships between active travels and diabetes. As a national agenda, walking is also promoted in Healthy People 2020[7] project which sets a goal to increase walking by at least 10%.

There is considerable variability in walking. For example, some people usually choose to walk up to a certain threshold, beyond which they will turn to other means of transportation. The threshold varies according to individual characteristics, e.g., weight, gender, behavior, health, and age. Younger people with good health may be able to walk farther. Older people may prefer shorter distances, lower uphill slope, and better sidewalk surface conditions than younger people. For instance, Weinstein et al. (2008) surveyed a group of pedestrians and found that they were willing to walk an average of half a mile to the rail station, and shortest distance was the most important factor influencing their route choice. Himann et al. (1988) reported a negative relationship between age and speed of walking. Sun et al. (1996) found that people's step lengths tend to decrease as the declination angle of the walkway surface increases. People who have an active lifestyle tend to walk faster, longer and more often compared to those who are less active. For example, a study by Bassett et al. (2008) shows that in Europe, North America, and Australia obesity rates have a negative correlation with percentage of trips taken by active transportations (walking, bicycling, and public transit). Malatesta et al. (2009) reported that obese adults tend to walk slower than adults of healthier weights. Traveler's behavior must also be taken into account, for example health conscious and active people may accept longer and more intense walking routes than others. Given that walking is essential, highly susceptible to individual differences, and desirable for good health, a new service that can recommend a feasible route for walking, for any of their regular or new trips is needed and beneficial. Finding optimal walking routes using multiple conditions through such a service is a challenging task. Current wayfinding

[7] http://www.healthypeople.gov/2020/

services, such as Google Maps, only consider common transportation criteria, for example, shortest travel time, shortest travel distance, fewest bus transfers, or minimum walking; none of the existing services takes into account individual physical activity preference.

5.3 ROUTE2HEALTH ALGORITHM

The outcome of Route2Health for each trip is a route, where walking is either the only mode or one of the two modes of transportation. Based on the special MCW algorithm (Section 3.5), a new algorithm was developed to compute health optimal walking routes (see Figure 5.2).

The algorithm requires an origin, a destination, body weight, desired walking distance and speed, and desired mode of transportation (driving or riding). Walking transfer nodes, located within a desired walking distance, are used for vehicular and walking route computation. If walking transfer nodes (parking locations or bus stops) are found, the appropriate transportation mode (driving or riding) is computed. In the absence of walking transfer nodes that satisfy the requested walking distance, the algorithm computes only walking routes that connect the origin and the destination. In the current version of the prototype, walking close to destination is considered. This means that driving-walking refers to driving from origin to a parking location then walking to the destination, and riding-walking refers to riding (bus) from origin to a bus stop then walking to the destination.

Once vehicular and walking route components for a trip are computed, the results (walking routes and vehicular routes) are combined to form multi-modal routes to link origin, walking transfer nodes, and destination, where the number of walking transfer nodes indicates the total number of candidate walking routes. For each candidate walking route, Equation (3.6) is used to estimate the calories burn for walking. Regarding the equation, slope of each segment of a walking route is estimated by using elevation data from high-resolution Digital Elevation Model (DEM). Walking speed is provided by the traveler, or could be calculated based on walking route distance and estimated time of walking. Finally, route geometry, travel distance, travel time, and estimated calories burn of the optimal routes are presented to the traveler.

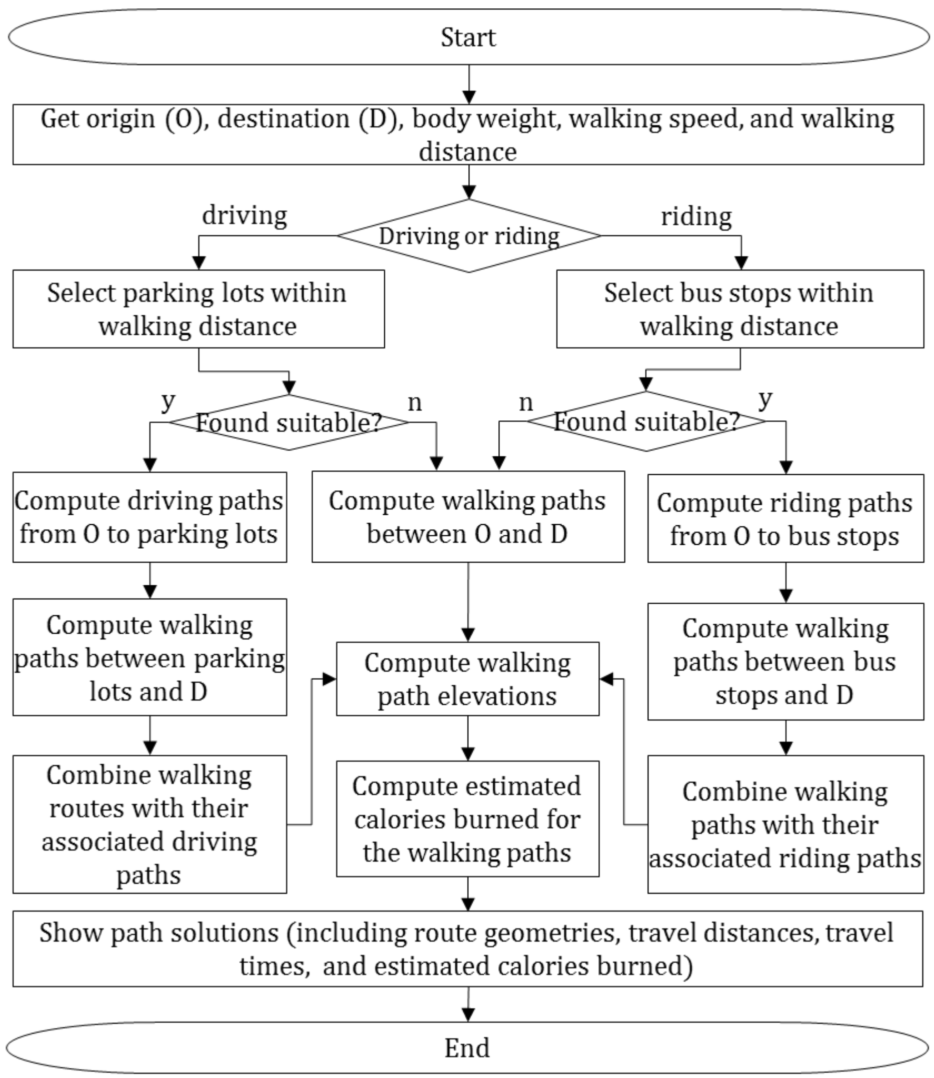


Figure 5.2. Route2Health algorithm

5.4 PROTOTYPE AND RESULTS

Route2Health is based on several external data and services (listed in Table 5.1) for its computation. Google Directions API is used to compute vehicular routes and walking routes. Google Directions API provides up to three candidate routes (other numbers would be possible) to a routing request. Google Elevation API is used to retrieve elevations along the walking route to calculate slope of walking segments. Google Places API is used to search for parking lots and bus stops.

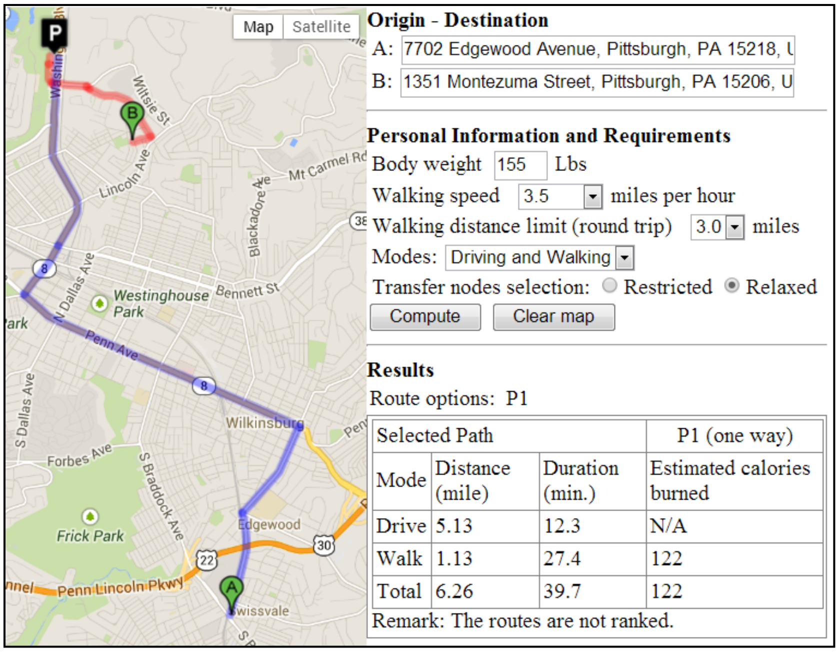
Table 5.1. External data and services used by Route2Health.

Information retrieved	Services
Base map	Google Maps API
Street address of a location	Google Geocoding API
Parking lot and bus stop locations	Google Places API
Driving and riding routes	Google Directions API
Walking routes	Google Directions API
Elevations along walking route	Google Elevation API

A web-based wayfinding service was developed to demonstrate the Route2Health concept. The service's interface (Figure 5.3) features two panels: map panel (the left panel) and input panel (the right panel). Through the input panel, the traveler specifies profile and preferences including body weight, walking speed, walking distance limit (round trip), and preferred transportation modes (i.e., driving-walking or riding-walking). If the traveler does not specify walking speed, the service will calculate one based on the walking route distance and time, both retrieved from Google Directions Service. Based on walking distance limit, either parking locations or bus stops (depending on the preferred mode) within a walking distance limit will be selected (using the buffering method discussed in Section 3.1.1) and used for candidate route computation. Once all parameters are included, candidate routes (up to 20 in the current version of the prototype) are computed and listed. For each candidate route, a link to detailed information, such as travel distance, travel time, and estimated calories burn, is provided.

Figure 5.4 shows two optimal driving-walking routes (P1 and P2) and Figure 5.5 shows two riding-walking routes (P3 and P4) between origin (A) and destination (B). The travel distance, travel time, and estimated calories burn for each route are summarized in Table 5.2. In these examples, the round trip walking distance limit is set to 3.0 miles (around 1.5 miles each way). For driving-walking, P2 contains a better one-way walking distance than P1 (1.45 miles versus 1.14 miles) and requires only one minute longer than P1 (44.6 minutes versus 45.5 minutes) to travel. For riding-walking, P3 and P4 require almost the same total travel time (75.0 minutes and 75.8 minutes), but P3 can help burn 170 kilocalories for 1.58 miles walking distance which is much better than P4 which helps burn 111 kilocalories for 1.09 miles.

Another scenario is when the origin and destination are close to each other. Figure 5.6 shows a traveler's request for a riding-walking route (with walking distance limit set at 3.0 miles), but since Route2Health found that the walking route is only 1.2 miles long, the walking route is recommended instead of a riding-walking route.



Selected Path			P1 (one way)
Mode	Distance (mile)	Duration (min.)	Estimated calories burned
Drive	5.13	12.3	N/A
Walk	1.13	27.4	122
Total	6.26	39.7	122

Figure 5.3. Route2Health user interface

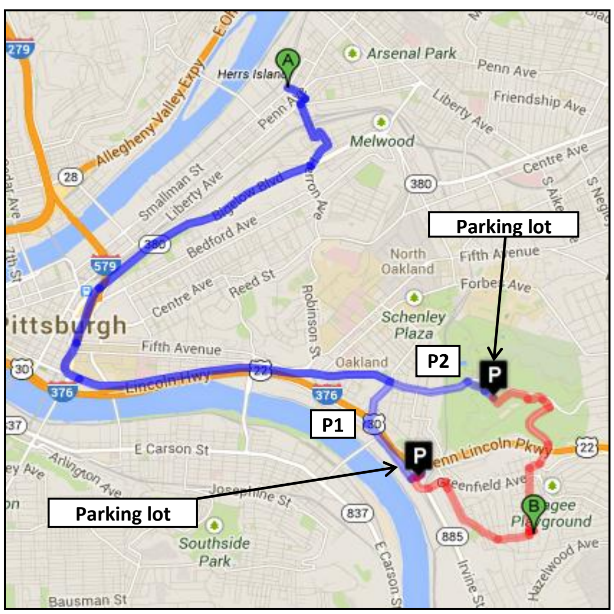


Figure 5.4. Driving-walking routes from A to B

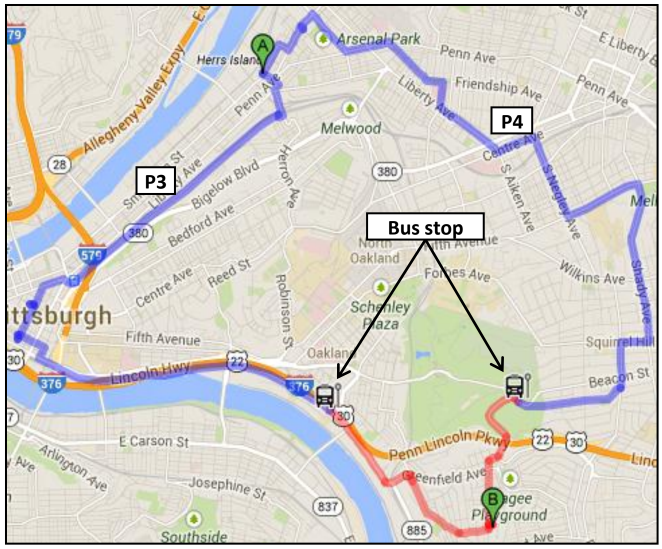


Figure 5.5. Riding-walking routes from A to B

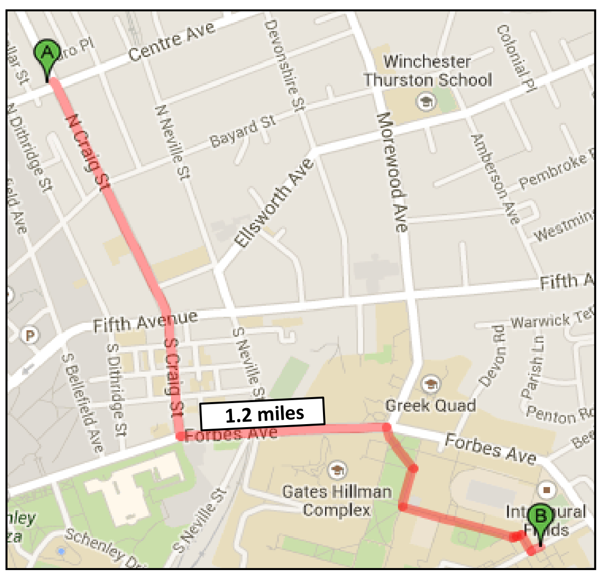


Figure 5.6. Walking route for a destination close to origin

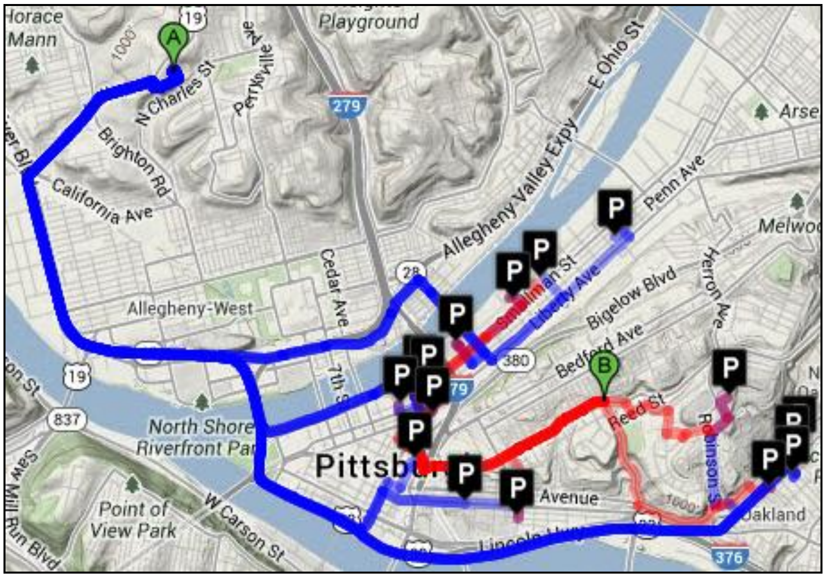


Figure 5.7. Multiple candidate parking lots in the downtown Pittsburgh area

Table 5.2. Candidate routes summary

Route	Mode	Distance (miles)	Duration (minutes)	Calories burn (kilocalories)
P1	Drive	5.90	15.2	N/A
	Walk	1.14	29.4	131
	Total	7.04	44.6	131
P2	Drive	5.73	13.4	N/A
	Walk	1.45	32.1	143
	Total	7.18	45.5	143
P3	Ride	5.19	36.9	N/A
	Walk	1.58	38.1	170
	Total	6.77	75.0	170
P4	Ride	5.97	50.9	N/A
	Walk	1.09	24.9	111
	Total	7.06	75.8	111

When a destination is located within a downtown area (which usually has a high road density and a large number of parking lots), a large number of candidate driving-walking routes would be expected. However, in a hilly area, like downtown in Pittsburgh, the computed candidate routes are not very different. In Figure 5.7, there are 16 parking lots suggested by

Route2Health, but the walking routes from the 16 parking lots merge into only three routes close to the destination which is located in downtown Pittsburgh. The reason for this may be alluded to the fact that the walking routes, computed by Google Directions Service, are chosen based on their flatness. The background terrain map in Figure 5.7 shows least variation in elevation on the routes in the north-east direction. The flat walking routes seem to be reasonable in general, but, as discussed in the previous section, some people may prefer more challenging (hilly) routes than flat routes. The example also confirms the claim that existing routing services do not support the concept of Route2Health.

For driving-walking, when the destination is close to an area with a large number of parking location options (such as a downtown area), the selected parking locations may spatially cluster together within the area. Figure 5.8 (upper map) shows an example of the aforementioned scenario. One problem with clustered parking lots is the possibility of computing impractical routes. In Figure 5.8 (lower map), the parking lots cluster on one side of the river, while the origin and destination are both located on the other side. This means that regardless of the routes the traveler chooses, the traveler must drives from the origin to the other side of the river, park the car, and then crosses the river on foot to destination. Similar situations also happen with bus stops. In Figure 5.9, as the area of interest has a large number of bus stops, most of the candidate bus stops linearly cluster just right next to each other on the same road. From the traveler's perspective, the linear sequence of bus stops represents the same riding route. The two examples (Figure 5.8 and Figure 5.9) support the claim (discussed in Section 3.1) that walking transfer node plays an important role in multi-modal transportation trip planning.

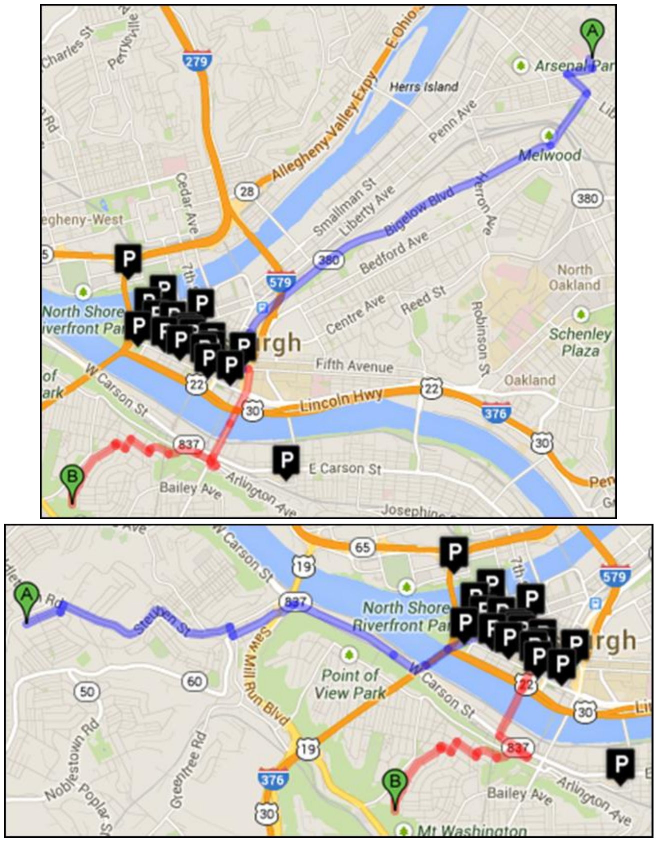


Figure 5.8. Parking lots clustered in a downtown area

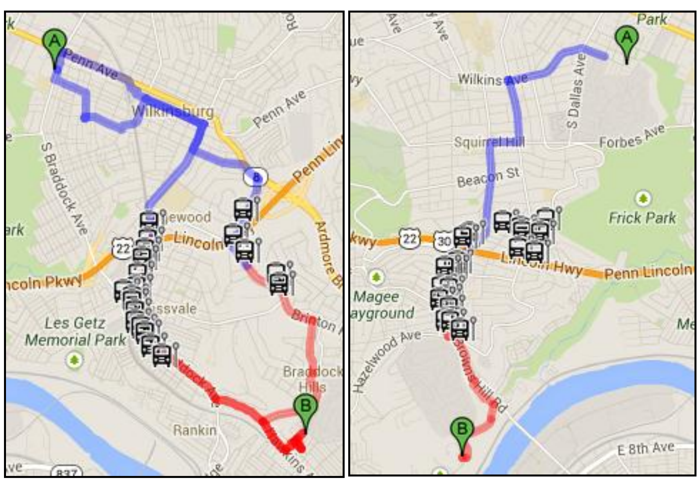


Figure 5.9. Clusters of selected bus stops along roads

6.0 MMT-MCW SIMULATION

This section presents an implementation of MMT-MCW simulation mode. Route finding scenarios for some cities in the United States were simulated for which relevant data from various sources were retrieved. The chapter is structured as follows. In the first two sections, an origin-destination selection methodology and a study area selection methodology for MMT-MCW simulation are described. In the third section, the inputs, data and the set of parameters used in the simulation are outlined. Simulation results are discussed in the final section.

6.1 ORIGIN AND DESTINATION SELECTION METHODOLOGY

Origin and destination in a routing request influence all major components of a trip including transportation modes and routes. This section discusses three methods to simulate origins and destinations: (1) random selection in Euclidean space; (2) selection with rectangular grid; and (3) random selection among points of interest (POI). In the first method, geographic coordinates are randomly selected within the study area, see Figure 6.1 (left). In the second method, a particular distance interval is used to create a rectangular grid, and then geographic coordinates are selected using the grid, see Figure 6.1 (middle). In the third method, origins and destinations are randomly selected from POIs (such as hotels, office buildings, and household addresses), see Figure 6.1 (right). The pros and cons of each method are summarized in Table 6.1. The third method is the only method that considers the spatial distribution of POIs which are common destinations. Since the results that most reflect common trips in cities were sought, the third method was used for the simulation.

Table 6.1. Pros and cons of different methods for origin/destination selection

Method	Pros	Cons
Random selection in Euclidean space	1. All geographic coordinates are treated equally 2. No extra thematic maps/data required 3. Number of selected geographic coordinates can be controlled, e.g., randomly selecting 100 points	1. Does not consider the spatial distribution of POIs which are common destinations 2. Categorization for origin and destination is not possible since semantic of positions are not considered 3. Some selected geographic coordinates may not be meaningful such as those located in the river
Rectangular Grid	1. Selected positions are evenly distributed 2. Point spacing can be controlled and customized to fit best with study areas (e.g., smaller spacing for urban area and larger spacing for rural area)	1. Does not consider the spatial distribution of POIs which are common destinations 2. Categorization for origin and destination is not possible since semantic of positions are not considered
Random POIs	1. Consider the spatial distribution of POIs which are common destinations 2. Typical destinations (i.e., POI) are selected 3. Specific locations can be filtered (e.g., only bank locations are taken) to explore specific type of POIs	1. Require extra thematic maps/data such as POI positions 2. Selected positions are influenced by spatial distribution of the thematic maps/data such that some regions of the study area are not covered 3. The reliability of selected positions depends on the quality (correctness and completeness) of the thematic maps/data used

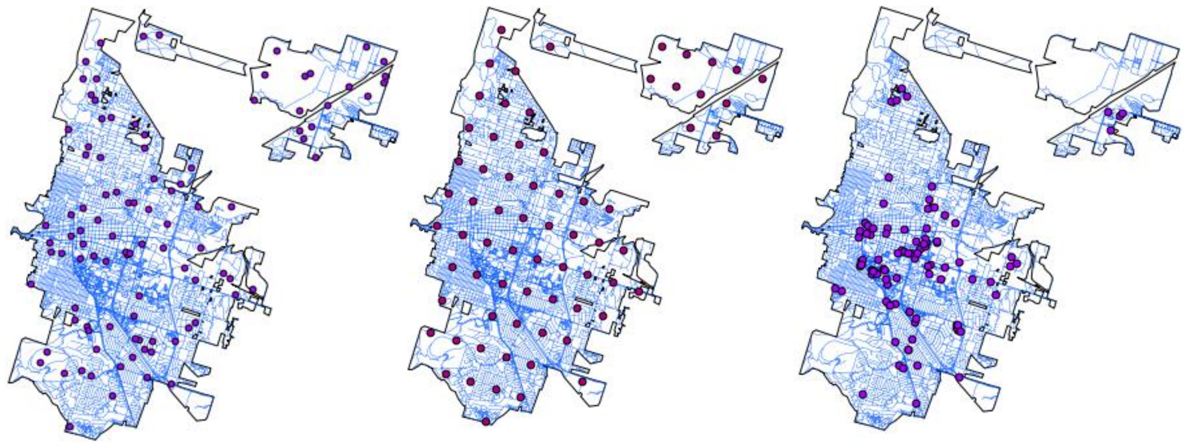


Figure 6.1. Random selection in Euclidean space (left), Rectangular grid selection (middle), and Random POI selection (right)

6.2 STUDY AREA SELECTION

Several cities within the United States were used in the simulation. Twelve cities were selected based on three attributes: population, body mass index (BMI), and elevation range. The US Office of Management and Budget uses population to define a statistical area. A statistical area contains one or more cities (and/or counties) and can be classified as metropolitan (high-density population) or micropolitan (low-density population). Metropolitan has population greater than 50,000 and micropolitan has population between 10,000 and 50,000. The Center for Disease Control and Prevention's (CDC; http://www.cdc.gov/) definitions and categories were considered for normal weight (18.5<BMI<24.9) and obese (BMI>30.0) where individual's BMI is calculated by dividing the individual's weight (kilogram) by the square of the individual's height (meter); BMI=weight/(height)^2. BMI statistics are from the year 2012 provided by the CDC (for details, refer to Appendix B). Elevation range was classified into hilly (elevation range

≥100 meters) and flat (elevation range ≤ 50 meters); elevation range = max. elevation - min. elevation, and elevations of 100 randomly selected positions within the city of interest were used to calculate the elevation range. The two threshold values (50 and 100 meters) were chosen for separating between hilly and flat terrains. For detailed statistics of the elevations, refer to Appendix A. The purpose of using the three attributes (population, BMI, and elevation range) is also to explore their influence on walking routes and walking transfer nodes.

To select cities for the simulation, statistical areas were ranked (in descending order) based on the BMI statistics (percentage of normal weight and obese people). To have strong representatives for each BMI category, priority in city selection is determined by their rank; a higher rank has a higher priority. To cover more number of states, if the second city is located in the same state as the first then the next available that is located in a different state will be used instead. The selected cities are shown in Figure 6.2. Figure 6.3 shows the maximum, minimum, and average elevations of the selected cities, and the following abbreviations are used: Micropolitan (Mi), Metropolitan (Me), Obese (O), Normal weight (N), Hilly (H), and Flat (F). There are six possible combinations based on the three mentioned attributes, and up to two cities were selected for each combination.

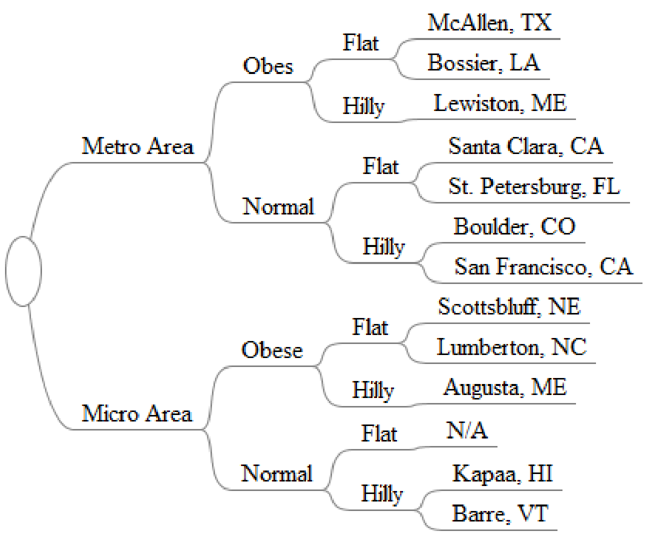


Figure 6.2. City and State selected for each category

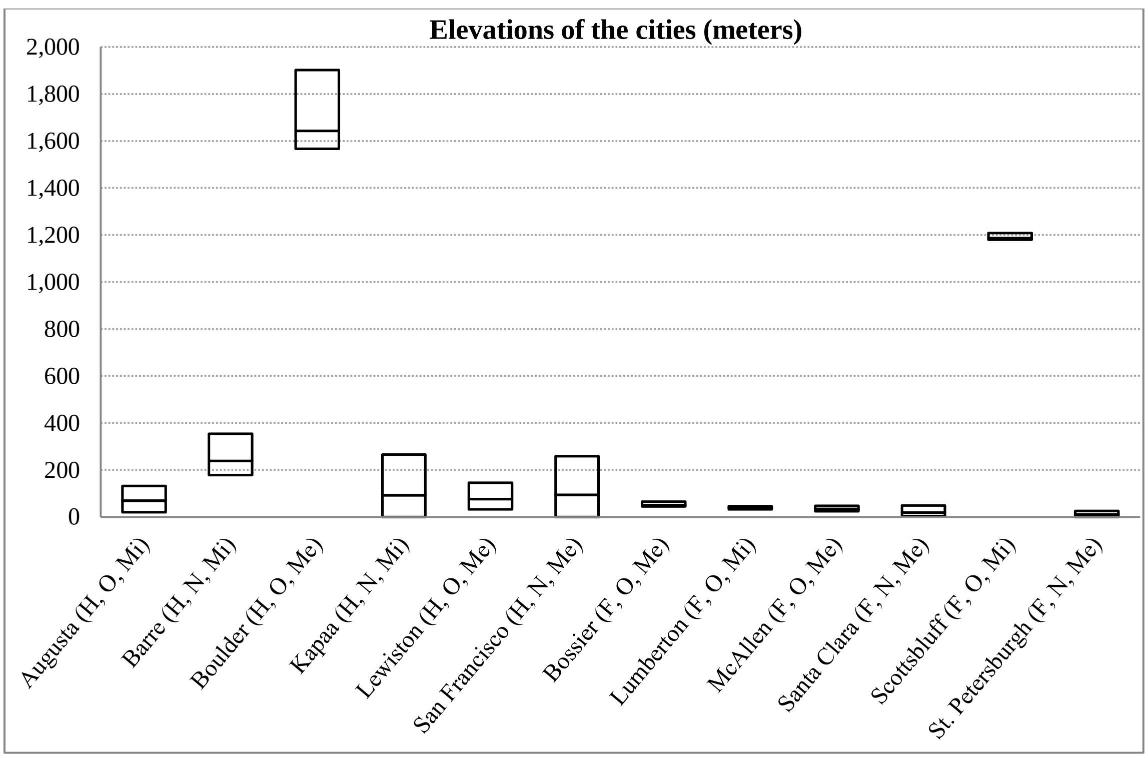


Figure 6.3. Maximum, minimum, and average elevations of the selected cities

6.3 DATA, PROGRAMS, AND SIMULATION PARAMETERS

Driving-walking and riding-walking using MMT-MCW were simulated. A driving-walking trip usually comprises (in sequence) driving, parking, and then walking, and the return trip is usually in the reverse sequence. Unlike driving-walking, travellers do not have to begin with vehicular mode in riding-walking trips. A trip may start by walking from origin to a nearby bus stop then taking bus to destination. Walking can also be in the middle connecting two different bus routes, and the return trip can be in any sequence. For simplicity, the return trips were not considered in the simulation, and walking was assumed as the mode to connect the walking transfer nodes and the destination. The vehicular route computation between origin and walking transfer node was not considered since it is not the MMT-MCW's main contribution. Accordingly, walking transfer nodes and walking routes were the focus in the simulation. Data associated with MCW included parking lots, bus stops, walking routes, sidewalk slopes, and POIs. A number of external programs were used for route and geometrical computations. A set of parameters for various travellers' characteristics was assumed. The details of data, programs, and parameters are described below.

The desired walking distance between walking transfer node and destination was assumed to be one kilometer. POI locations were selected from OpenStreetMap (Benner and Karimi, 2013), and 100 destinations within each city were randomly selected (if the number of POI of the city is less than 100, all the POIs are used). For detailed locations and distributions of the selected POIs, refer to Appendix C. A buffer (inner radius: 0.5 kilometer; outer radius: 1.5 kilometer) around the destinations was created to identify suitable parking lots and suitable bus stops. For each destination, up to 20 parking lots within a buffer were selected as walking transfer nodes (note that 20 here is an arbitrary number). Bus stops and bus routes data were collected from Google Transit Feed Specification (http://www.gtfs-data-exchange.com/). For each suitable parking lot and bus stop, up to three candidate walking routes were generated (ordered by their travel time). Parking lot locations and walking routes were retrieved from Google Places API and Google Directions API, respectively. Once all candidate routes were computed, elevation of points along the walking route of interest is retrieved from Google Elevation API, and then Equation (3.6) and Equation (3.7) were used to find calories burn for each candidate walking route. Walking surface roughness was also calculated using elevations. Walking surface roughness refers to the standard deviation of elevations along an entire walking route. The standard deviation of a flat walking route is zero, and the higher value of walking surface roughness refers to higher variation of elevations along the walking route. To simulate multiple traveller's characteristics, four body weights (60, 80, 100, and 120 kilograms) and three walking speeds (60, 80, and 100 meters/minute) were used. Tables 6.2 and 6.3 summarize the data, external programs, and parameters used.

Table 6.2. Data, external programs, and purposes

Data/Computation	Sources	Purposes
1. POI	OpenStreetMap	Destination selection
2. Parking lot locations	Google Places API	Walking transfer nodes selection
3. Bus stop locations	General Transit Feed Specification	Walking transfer nodes selection
4. Bus routes		Find number of available bus routes
5. Walking route computation	Google Directions API	Compute walking routes
6. Elevation information	Google Elevation API	Compute slope along walking routes

Table 6.3. Simulation parameters

Parameter Names	Values	Units
1. Desired walking distance	1.0	kilometer
2. Inner radius	0.5	kilometer
3. Outer radius	1.5	kilometer
4. Maximum number of suitable parking lot locations	20	-
5. Maximum number of suitable bus stop locations	No limit	-
6. Body weight trial values	60, 80, 100, 120	kilogram
7. Walking speed trial values	60, 80, 100	meters/minute

6.4 SIMULATION RESULTS

The simulation results are related to four entities: suitable parking lots, suitable bus stops, walking routes that connect parking lots and destination (PK routes), and walking routes that connect bus stops and destinations (BS routes). The buffering method discussed in Section 3.1.1 was used to identify suitable parking lots and suitable bus stops such that suitable parking lots and suitable bus stops are the parking lots and bus stops that are located within a buffer (inner radius: 0.5 kilometer; outer radius: 1.5 kilometer) around each destination. Results associated with suitable parking lots and acceptable PK routes are available for all twelve cities. Results associated with suitable bus stops and acceptable BS routes are only available for two cities (San Francisco and Santa Clara) which were the only two cities (among the selected cities) that publish their transit data. The acceptable PK and BS routes refer to PK and BS routes that have their distance fall within 0.9 and 1.1 kilometers (±10% of the 1 kilometer desired walking distance). Based on these four entities, result discussions are separated into three sub-sections: (6.4.1) suitable parking lots and acceptable PK routes, (6.4.2) suitable bus stops and acceptable BS routes, and (6.4.3) acceptable PK routes vs acceptable BS routes.

6.4.1 Suitable Parking lots and Acceptable PK Routes

Figure 6.4 shows the selected cities (on x-axis), the numbers of destinations (on y-axis), and the counts of destinations that have suitable parking lots (on Y-axis). The following abbreviations are used in the figure: Micropolitan (Mi), Metropolitan (Me), Obese (O), Normal weight (N), Hilly (H), and Flat (F). Most cities in metropolitan areas have a large number of destinations with suitable parking lots except Bossier (1 out of 72) and McAllen (4 out of 99). Four cities (Barre, Kappa, Scottsbluff, and Bossier) have zero or only one destination with at least one suitable parking lot, which are considered outliers and excluded from the analysis. From the figure, both obese and normal weight groups fall within cities with both small and large number of destinations with suitable parking lots. This indicates that there is no obvious separation between the two groups with respect to the number of destinations.

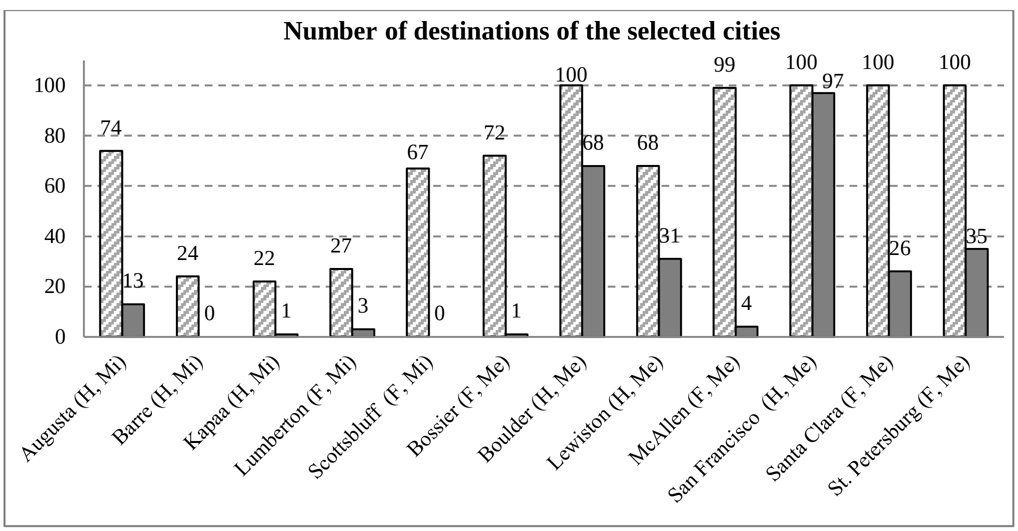


Figure 6.4. Number of destinations and the counts of destinations that have ≥ 1 suitable parking lots.

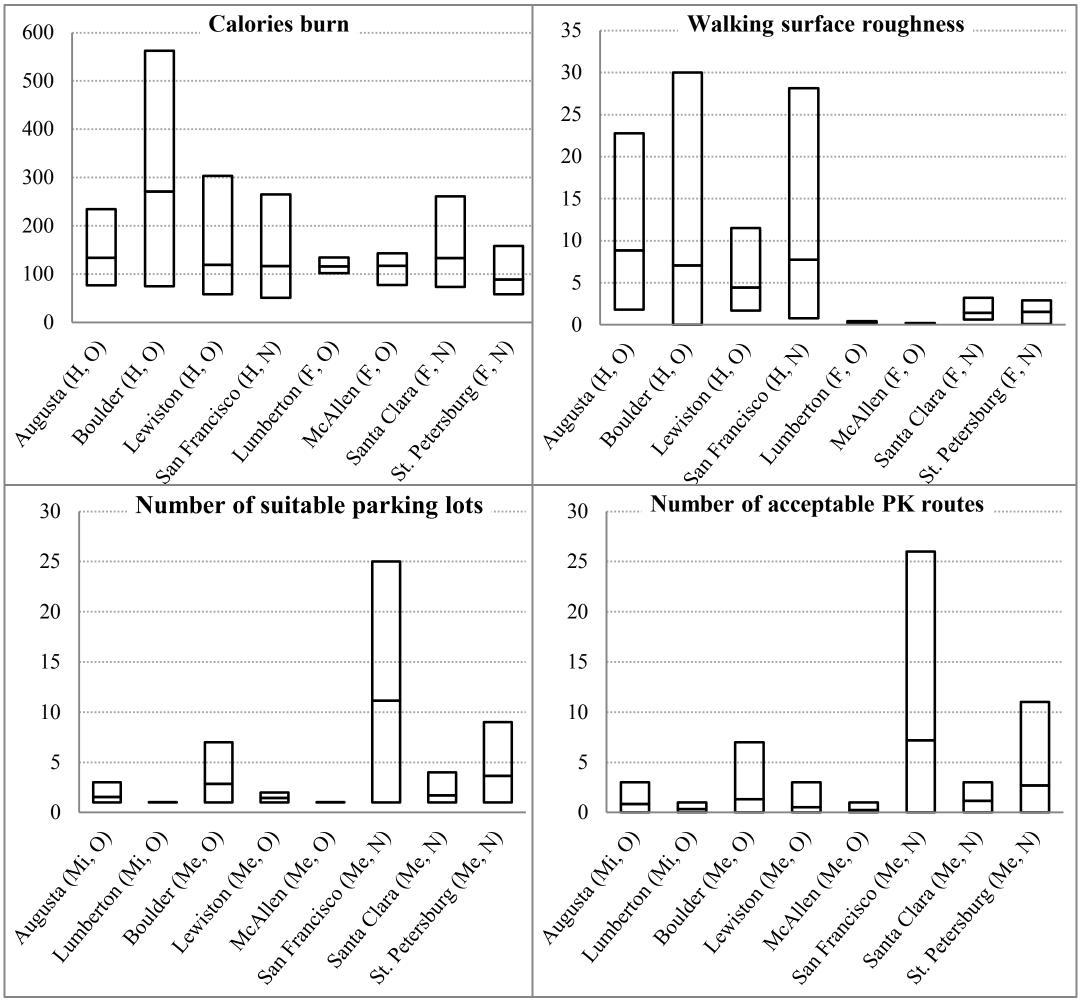


Figure 6.5. Comparisons of attributes between the selected cities

Figure 6.5 shows maximum, minimum, and average of calories burn (upper left), of walking surface roughness (upper right), of number of suitable parking lots (lower left), and of number of acceptable PK routes (lower right). On the x-axis of the two upper graphs in Figure 6.5, the first four cities are hilly and the latter four are flat. The graphs indicate that hilly cities have wider ranges of both calories burn and walking surface roughness since they are directly related to elevation ranges of the hilly cities. An interesting observation is that most cities (except Boulder) in the left figure have a similar average calories burn regardless of the elevation range. Although Boulder has a similar walking surface roughness compared to other hilly cities, its average calories burn is significantly higher than the others. This indicates that walking routes in Boulder is more efficient for burning calories. Regarding average number of suitable parking lots (Figure 6.5, lower left) and the associated PK routes (Figure 6.5, lower right), San Francisco has the highest value for both (11.16 suitable parking lots and 7.2 acceptable PK routes in average). The graphs also show that San Francisco has the largest range on both attributes, which is reasonable for a city with dense population where transportation infrastructures are usually dense. Note that San Francisco is the 13^{th} most populous city in the United States (US Census, 2010).

Figure 6.6 shows spatial distribution of destinations for the top five cities (Augusta, Boulder, San Francisco, Santa Clara, and St. Petersburg) with respect to the range of number of suitable parking lots. The destinations are classified into two groups: (1) destinations that have at least one suitable parking lot (circle shape) and (2) destinations that have no suitable parking lots (triangle shape). Augusta has obvious spatial separation between the two groups (located in the lower and upper region). Santa Clara, Boulder and St. Petersburg have both groups scattering across their area. Most destinations in San Francisco have at least one parking lot.

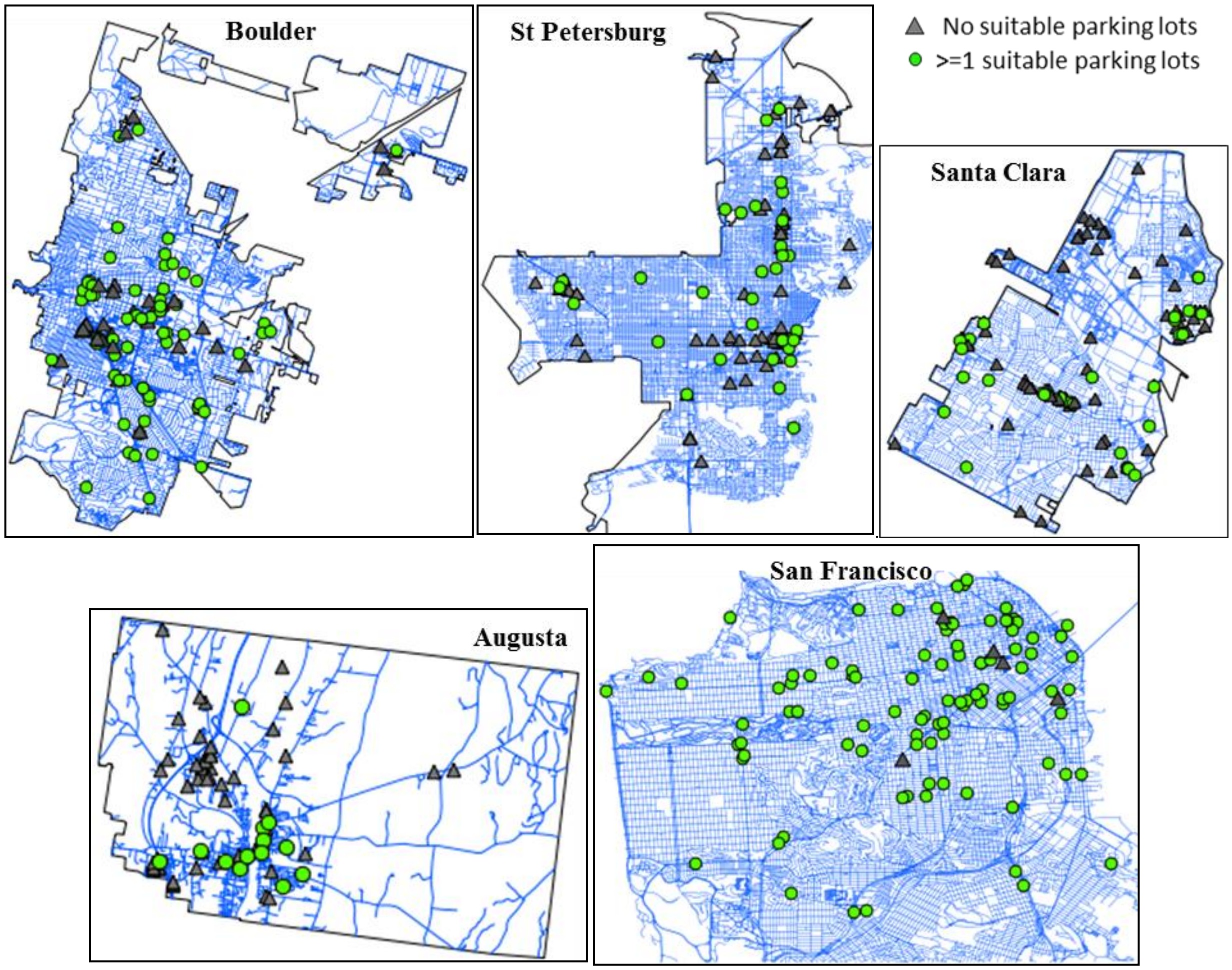


Figure 6.6. Destination distributions and parking lots availability

Figure 6.7 shows spatial distribution of destinations that have acceptable PK routes. Destinations in Augusta and Santa Clara have a very small number (between 1 and 3) of acceptable PK routes. St. Petersburg reveals a road (north-south direction) that has destinations with a high number of acceptable PK routes. The destinations in Boulder spatially spread across the city and do not show an explicit pattern. San Francisco has most of its destinations with a large number of acceptable PK routes. Most destinations in San Francisco cluster together in the north-east region of the city because most of the POIs (which are used as destinations) in San Francisco are also located in the north-east region.

Figure 6.7. Destination distributions with number of acceptable PK routes

Figure 6.8 shows averages calories burn of the acceptable PK routes grouped by destinations. Each map has legends showing the minimum and maximum values with circle sizes. All the cities (except Boulder) have their average and maximum value lower than 200.

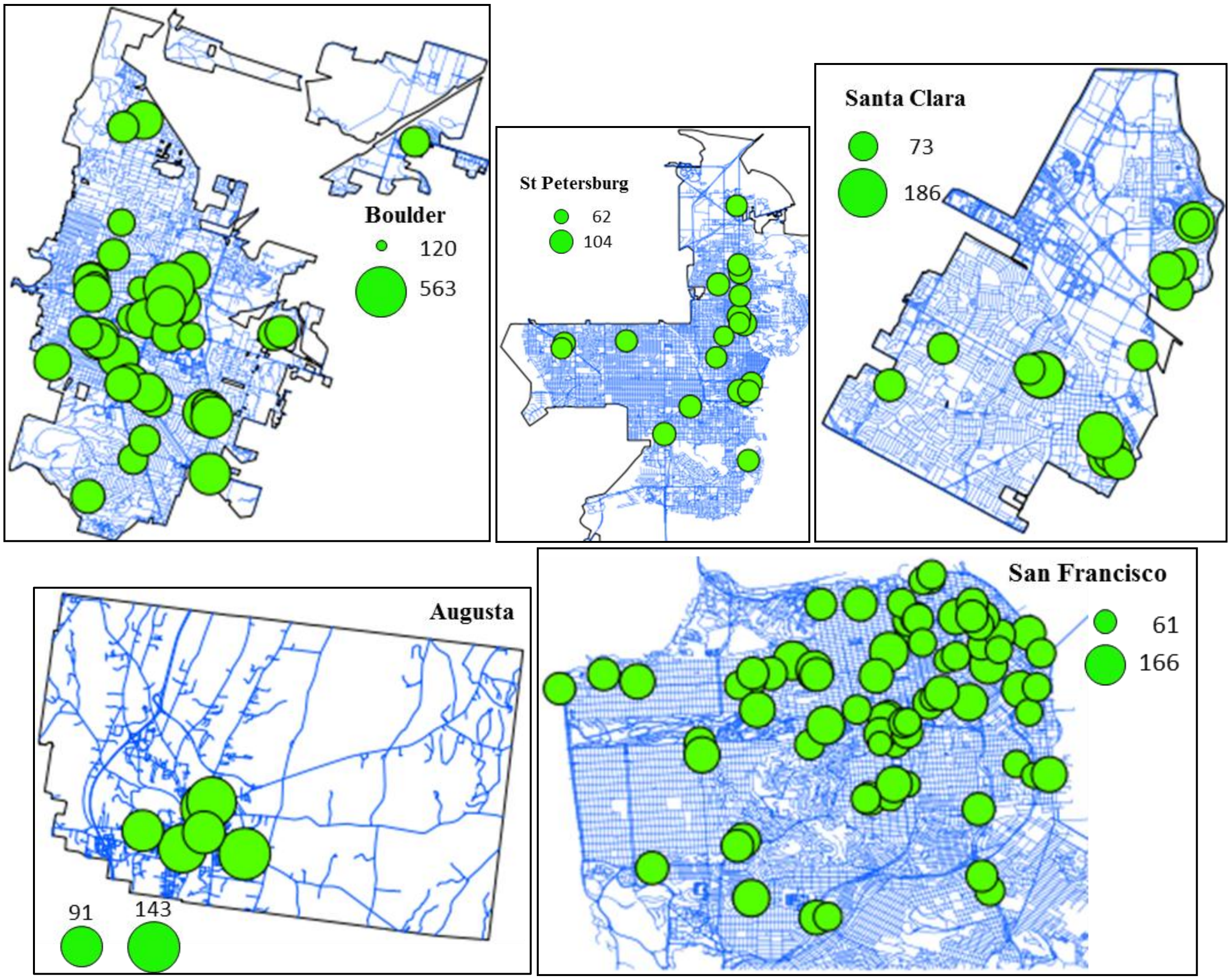


Figure 6.8. Destination distributions with calories burn for acceptable PK routes

This sub-section discusses and compares suitable parking lots and acceptable PK routes in five cities: Augusta, Boulder, San Francisco, Santa Clara, and St. Petersburg. San Francisco has the highest average numbers for both suitable parking lots, 11.16, and acceptable PK routes, 7.2. With similar walking distance and time, Boulder offers the best environment in terms of calories burn. Augusta has a high amount of calories burn only for destinations within the city's inner area which has dense road network. Even though Santa Clara is classified as a metropolitan city, it does not provide a large number of suitable parking lots. Santa Clara has 1.70 suitable parking lots on average, while Augusta (a micropolitan city) has 1.54.

6.4.2 Suitable Bus Stops and Acceptable BS Routes

Figure 6.9 shows spatial distribution of destinations in San Francisco and Santa Clara. The destinations are classified into two groups: (1) destinations that have suitable bus stops (circle shape) and (2) destinations that have no suitable bus stops (triangle shape). According to Figure 6.9 (left), there is a clear distinction between the two groups in San Francisco. The first group densely clusters within the north-east region of the city, while the second group is surrounding the first group. All of the destinations in Santa Clara have at least one suitable bus stop.

Figure 6.10 shows spatial distribution of destinations with number of suitable bus stops. None of the destinations in San Francisco has more than four suitable bus stops, while the destinations in Santa Clara have much larger number of suitable bus stops. Figure 6.11 shows spatial distribution of destinations with number of acceptable BS routes. None of the destinations in San Francisco has more than five acceptable BS routes, while the destinations in Santa Clara have wider range of number of acceptable BS routes. Most destinations with large number of acceptable BS routes in Santa Clara cluster within the inner region of the city. A counter intuitive observation is that despite denser road network (which imply more road segment connections and route choices), the destinations in San Francisco still have fewer number of acceptable BS routes compared to Santa Clara. Average number of BS routes is 2.41 for San Francisco and is 9.29 for Santa Clara. Note that destinations that do not have an acceptable BS route were not included in calculating the averages. An interesting observation related to suitable bus stops and acceptable BS routes in Santa Clara is that destinations in the lower region of the city have larger number of bus stops but have less number of BS routes, while destinations in the upper region have the opposite behavior.

Figure 6.12 shows spatial distribution of destinations with number of bus routes. All destinations that have a suitable bus stop in San Francisco have four bus routes. Two and seventeen are the minimum and maximum numbers of bus routes for destinations in Santa Clara, and destinations in the northern region tend to have larger number of bus routes than the others.

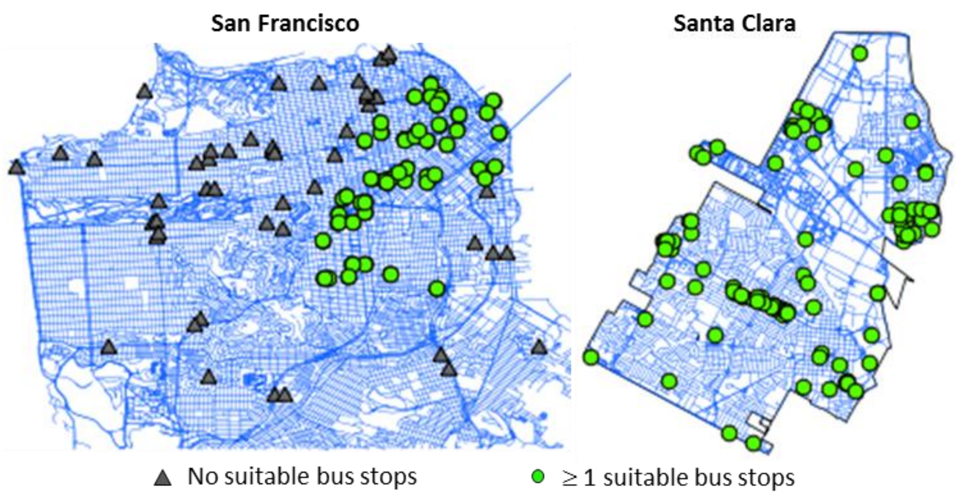


Figure 6.9. Suitable bus stops availability

Figure 6.10. Number of suitable bus stops

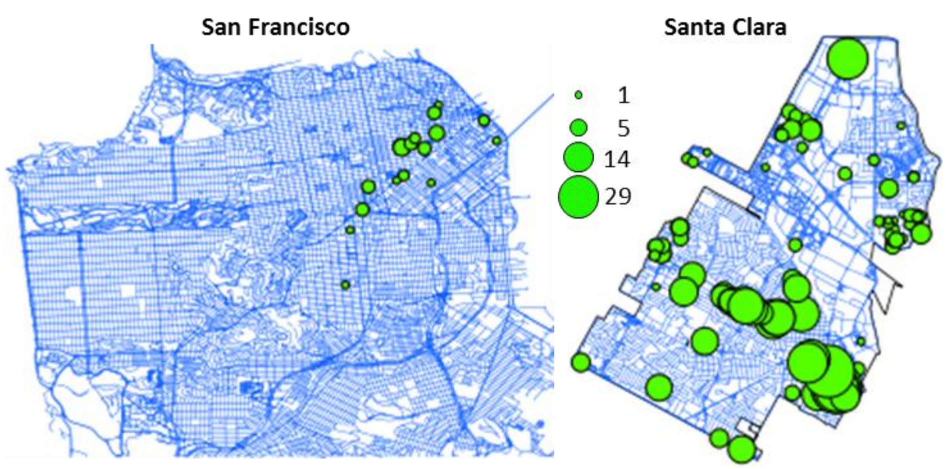


Figure 6.11. Number of acceptable BS routes

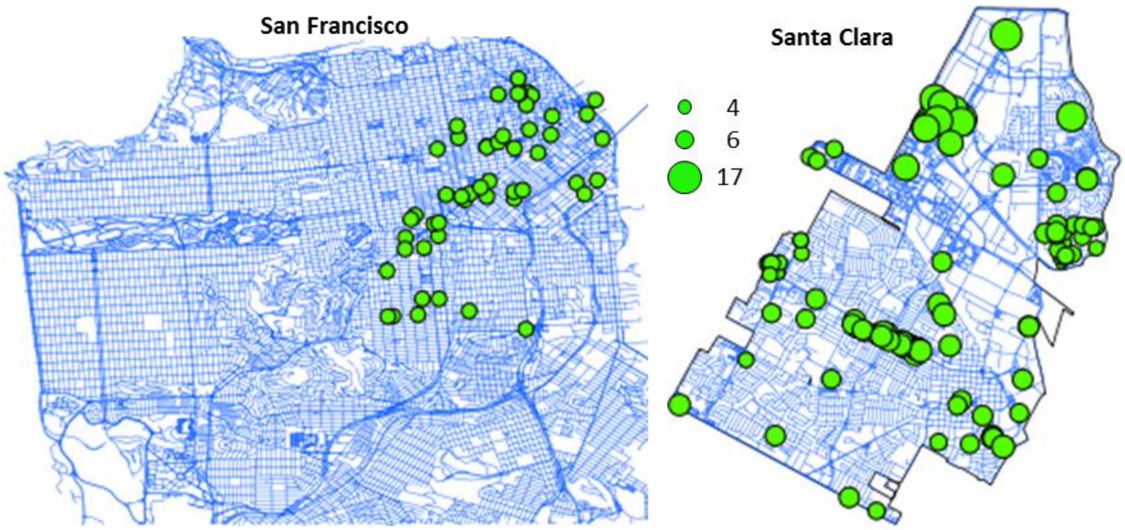


Figure 6.12. Number of bus routes

This sub-section discusses and compares suitable bus stops and acceptable BS routes in San Francisco and Santa Clara. Only destinations in the north-east region of San Francisco have suitable bus stops, while all destinations in Santa Clara have suitable bus stops. Assuming a direct relationship between road and sidewalk densities, San Francisco which has a denser road network should also provide a higher average number of BS routes, however, the results show otherwise. This indicates that road network density does not necessarily correlate with the number of acceptable BS routes.

6.4.3 Acceptable PK Routes VS Acceptable BS Routes

Figures 6.13 and 6.14 show the comparisons between acceptable PK routes and acceptable BS routes in San Francisco and Santa Clara which were the only two cities (among the selected cities) that publish their transit data. Each bar graph represents maximum, minimum, and average values. In San Francisco, the PK routes have higher average values than the BS routes, while, in Santa Clara, the opposite behavior is revealed. This indicates that PK routes and BS routes are not necessarily correlated. Considering walking surface roughness, BS routes in San Francisco have narrower range than PK routes, meaning that BS routes are generally flatter than PK routes. This can be inferred that the acceptable BS routes are available mostly in the flat areas. However, an interesting observation is that BS routes in Santa Clara show opposite behavior such that PK routes are flatter than BS routes. It should also be noted that both PK and BS routes in San Francisco have much larger walking surface roughness (by around 10 times) than their counterparts in Santa Clara, meaning that PK and BS routes in Santa Clara are much flatter. A counter intuitive observation from calories bar graphs in both Figures 6.13 and 6.14 is that despite different elevation range (San Francisco: Hilly; Santa Clara: Flat) and large different walking surface roughness, both PK and BS routes in San Francisco still have average calories close to their counterparts in Santa Clara (~120 calories for PK routes; ~140 calories for BS routes). This is because the amount of calories burn was estimated using the same walking speed (60 meters/minute) in both cities. Therefore, despite the close amounts of estimated calories burn, walking routes in San Francisco help burn more calories within the same period of time when compared to the walking routes in Santa Clara.

Figures 6.15 and 6.16 show the spatial distribution of destinations and the spatial coverage of PK and BS routes in San Francisco and Santa Clara overlaid on the cities' road network. The maps indicate the inverse behavior between the two cities such that PK routes have more coverage than BS routes in San Francisco, and vice versa for Santa Clara. Figure 6.17 shows the comparisons of destination distributions with number of acceptable PK and BS routes.

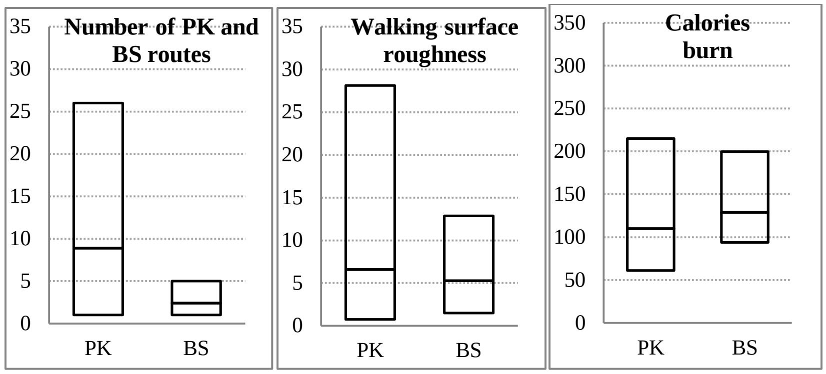


Figure 6.13. Comparisons between PK routes and BS routes for San Francisco

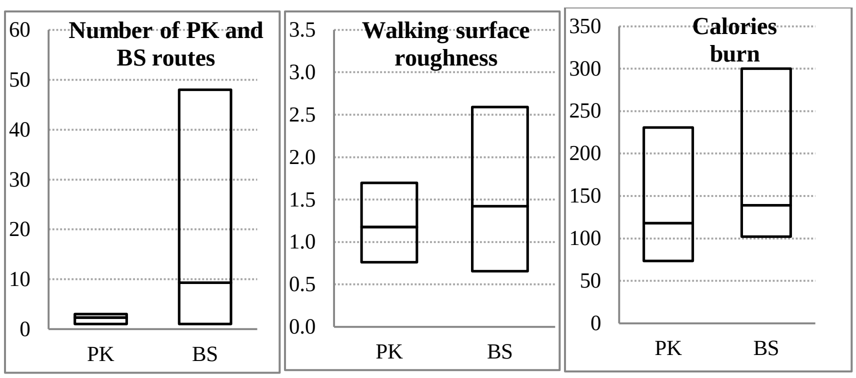


Figure 6.14. Comparisons between PK routes and BS routes for Santa Clara

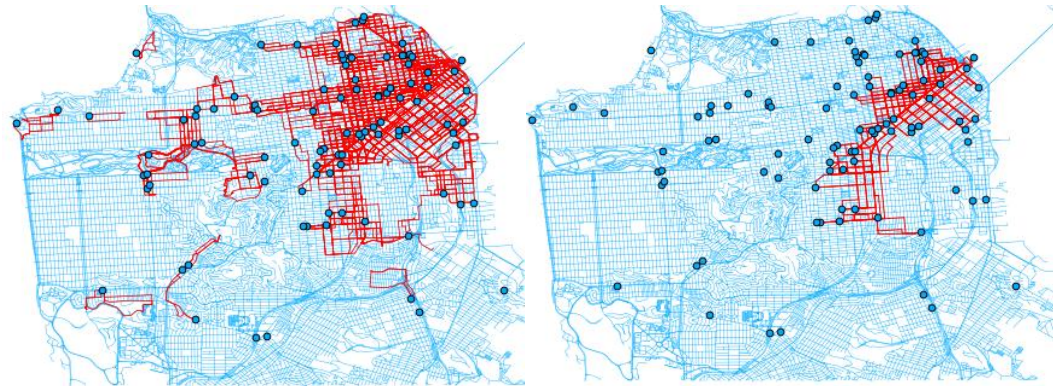


Figure 6.15. San Francisco: PK routes (left) and BS routes (right)

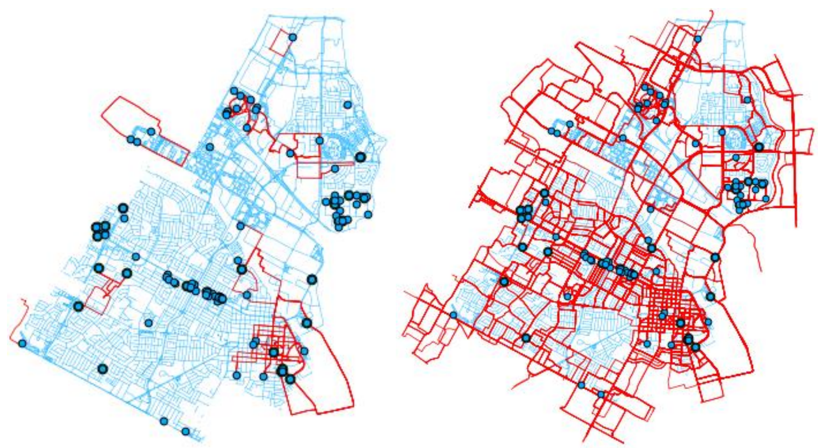


Figure 6.16. Santa Clara: PK routes (left) and BS routes (right)

Figure 6.17. Comparisons between destination distributions with number of acceptable PK and BS routes

In this sub-section, PK routes and BS routes of San Francisco and Santa Clara are compared. The results show that PK routes and BS routes are not necessarily correlated. For driving-walking mode, San Francisco has much more parking lots and acceptable PK routes than Santa Clara. For riding-walking mode, Santa Clara has much more bus stops and acceptable BS routes than San Francisco. Both PK and BS routes in San Francisco have much larger walking surface roughness (by around 10 times) than their counterparts in Santa Clara, meaning that PK and BS routes in San Francisco have much higher elevation variation.

7.0 SUMMARY, SHORTCOMING, AND FUTURE RESEARCH

In this dissertation, MMT-MCW is proposed as a new wayfinding option that provides multi-modal transportation routes with optimal walking components by considering various criteria. In MMT-MCW, walking is always one mode of transportation and is optimized based on traveler's characteristics and criteria. The MMT-MCW concept, foundation, and algorithms are presented. MMT-MCW can be used in two wayfinding modes: real-time mode and simulation mode. Real-time mode is used when routes are planned for immediate trips. In this mode, all candidate routes are found and one that best satisfies the environmental and individual criteria is recommended. Simulation mode is for evaluating routes based on scenarios that include environmental and individual criteria, preferences, and characteristics. We have shown that each wayfinding mode can be implemented differently for different purposes. One way of implementing the real-time mode is as a new wayfinding service for individuals interested in finding routes that include walking mode of transportation, and one example (Route2Health) is discussed in this dissertation. An example implementation of the simulation mode, also presented and discussed in this dissertation, is a simulation for evaluating cities for different purposes including walkability.

While this dissertation has established the foundation of MMT-MCW and provided some insights into how the MMMT-MCW concept may be used, there are limitations at various levels (theoretical, model, and implementation). Most important of these limitations are:

- The context-aware walking segment technique is only suitable for non-continuous attributes (such as elevation) and is not suitable for continuous attributes (such as air and noise pollutions); non-continuous attributes cannot easily be used to determine turning points.

- The walking transfer nodes selection methods do not differentiate between the bus stops located on different sides of a road. This means that all the bus stops on a road, en route to and away from the destination, are considered in finding optimal routes.

- The current prototype and simulation rely on vehicular routes, walking routes, and parking lot locations retrieved through Google's APIs. If Google modifies or terminates its APIs, the prototype and simulation will not work.

- The current prototype and simulation rely on Google Directions API and since Google does not disclose the routing algorithm and parameters it uses in its services, developers are not able to adjust routing criteria (such as shortest or fastest).

As far as future research, below is a list of some initial research ideas based on the findings in this dissertation that could be addressed:

- Investigating and developing other MCW optimization algorithms for travelers such as people with disabilities (e.g., wheelchair users and people who are blind or visually impaired), people with special physical conditions (e.g., aging and joint problems), and people with health conditions (e.g., an individual who must be less exposed to air pollution or sun light).

- Investigating and developing a predictive MMT-MCW methodology that allows route request well in advance and can monitor the recommended route up to minutes before the route is taken and update the recommendation based on changes of environmental and individual factors.

- Investigating and developing methodologies and algorithms for incorporating MMT-MCW, both modes, into a social navigation network system, such as SoNavNet (Karimi et al. 2009). MMT-MCW in SoNavNet allows sharing and exchanging multi-modal transportation route experiences among its members.

- Investigating and developing a MMT-MCW simulation platform that can be used for different purposes and applications such as those described above.

- Investigating and developing MMT-MCW, both modes, on clouds.

APPENDIX A: STATISTICS ON ELEVATION OF THE CITIES USED IN MMT-MCW SIMULATION

Table A.1. Statistics on elevation of the cities used in MMT-MCW simulation

City	Elevation statistics (meters)					Type
	Max.	Average	Min.	SD	Range	
Augusta, ME	131.54	68.92	20.13	20.65	111.41	Hilly
Barre, VT	354.13	237.56	178.25	43.40	175.88	Hilly
Bossier City, LA	64.51	50.58	44.71	2.41	19.8	Flat
Boulder, CO	1,901.37	1,642.92	1,567.37	66.02	334	Hilly
Kapaa, HI	265.57	91.77	0.15	61.08	265.42	Hilly
Lewiston, ME	145.24	76.36	32.87	20.73	112.37	Hilly
Lumberton, NC	45.47	39.23	32.42	3.33	13.05	Flat
McAllen, TX	46.89	34.23	24.27	3.92	22.62	Flat
Santa Clara, CA	49.33	19.21	3.55	12.40	45.78	Flat
San Francisco, CA	171.17	6.41	-87.96	41.31	259.13	Hilly
Scottsbluff, NE	1,207.97	1,186.50	1,179.47	6.17	28.5	Flat
St. Petersburgh, FL	15.35	0.3425	-10.63	5.75	25.98	Flat

APPENDIX B: BMI STATISTICS FROM CENTER FOR DISEASE CONTROL

Center for Disease Control and Prevention (CDC; http://www.cdc.gov/) classifies BMI into four ranges for adults: underweight (BMI<18.5), normal (18.5<BMI<24.9), overweight (25.0<BMI<29.9), and obese (BMI>30.0). The statistics of BMI that were used in MMT-MCW simulation were retrieved from CDC's website; http://apps.nccd.cdc.gov/BRFSS-SMART/SelMMSAPrevData.asp. The statistics were for the year 2012 which is the latest available by the time of retrieval. This appendix shows two tables containing top 25 statistical areas based on the percentages of normal weight and obese people, respectively.

Table B.1. Top 25 normal weight statistical areas

Metropolitan/Micropolitan Area	% Underweight	% Normal Weight	% Overweight	% Obese
Boulder, CO Metropolitan Statistical Area	N/A	50.6	31.5	14.8
San Jose-Sunnyvale-Santa Clara, CA Metropolitan Statistical Area	N/A	49.8	33	15.9
Kapaa, HI Micropolitan Statistical Area	N/A	48.1	27.9	21
San Francisco-San Mateo-Redwood City, CA	N/A	48.1	30.6	19.1
Logan, UT-ID Metropolitan Statistical Area	N/A	47.2	31.3	18.7
Fort Collins-Loveland, CO Metropolitan Statistical Area	N/A	46	32.7	18.3
Provo-Orem, UT Metropolitan Statistical Area	1.5	44.5	31.5	22.4
Bellingham, WA Metropolitan Statistical Area	N/A	43.9	33.2	20.5
Santa Fe, NM Metropolitan Statistical Area	2.2	43.2	37	17.6
Barnstable Town, MA Metropolitan Statistical Area	N/A	43	37.2	18
Colorado Springs, CO Metropolitan Statistical Area	2.2	42.3	34.4	21.1
Denver-Aurora, CO Metropolitan Statistical Area	2.4	42	35.5	20.1
Atlantic City, NJ Metropolitan Statistical Area	N/A	41.8	30.1	26.5
Tampa-St. Petersburg-Clearwater, FL Metropolitan Statistical Area	N/A	41.3	32.5	25.1
Urban Honolulu, HI Metropolitan Statistical Area	2.9	41.3	32	23.8
Boston, MA Metropolitan Division	2.6	41.2	35.1	21.1
Silver Spring-Frederick-Rockville, MD Metropolitan Division	1.9	41.2	35.8	21.1
Cambridge-Newton-Framingham, MA Metropolitan Division	2.3	40.6	37.1	20.1
Fairbanks, AK Metropolitan Statistical Area	N/A	40.5	35.9	23.5
Hilo, HI Micropolitan Statistical Area	1.7	40.2	33.3	24.9
Asheville, NC Metropolitan Statistical Area	N/A	40.2	39.3	19.4
Barre, VT Micropolitan Statistical Area	N/A	40.1	36	23.1
Kahului-Wailuku, HI Micropolitan Statistical Area	2.6	40	36.1	21.3
Salt Lake City, UT Metropolitan Statistical Area	2.1	39.7	34	24.3

Table B.2. Top 25 obese statistical areas

Metropolitan/Micropolitan Area	% Underweight	% Normal Weight	% Overweight	% Obese
McAllen-Edinburg-Mission, TX Metropolitan Statistical Area	N/A	23.1	31.2	44.5
Scottsbluff, NE Micropolitan Statistical Area	N/A	25.6	34.4	39.2
Lumberton, NC Micropolitan Statistical Area	N/A	23.8	32.5	38.8
Shreveport-Bossier City, LA Metropolitan Statistical Area	N/A	27.3	33.3	38.5
Sioux City, IA-NE-SD Metropolitan Statistical Area	N/A	27.4	34.9	35.9
Baton Rouge, LA Metropolitan Statistical Area	N/A	29.8	33.1	35.6
Huntington-Ashland, WV-KY-OH Metropolitan Statistical Area	1.7	30	33.2	35.1
Memphis, TN-MS-AR Metropolitan Statistical Area	N/A	30.3	33.6	35.1
Tuscaloosa, AL Metropolitan Statistical Area	N/A	31.2	33.4	34.8
Hagerstown-Martinsburg, MD-WV Metropolitan Statistical Area	N/A	27	36.8	34.4
Birmingham-Hoover, AL Metropolitan Statistical Area	1	31.3	33.4	34.3
Topeka, KS Metropolitan Statistical Area	2	29.2	34.5	34.3
Detroit-Livonia-Dearborn, MI Metropolitan Division	1.2	32.1	32.5	34.2
Mobile, AL Metropolitan Statistical Area	N/A	30.5	34	34.2
Laconia, NH Micropolitan Statistical Area	N/A	34.2	30.2	34
Augusta-Waterville, ME Micropolitan Statistical Area	N/A	27.7	38	33.7
Lewiston-Auburn, ME Metropolitan Statistical Area	N/A	30.8	33.5	33.7
Vineland-Millville-Bridgeton, NJ Metropolitan Statistical Area	N/A	26.3	38.8	33.7
Jackson, MS Metropolitan Statistical Area	N/A	31.9	33.5	33.6
Sayre, PA Micropolitan Statistical Area	0.9	24.6	40.8	33.6
Fort Wayne, IN Metropolitan Statistical Area	N/A	34.3	30.7	33.5
Harrisburg-Carlisle, PA Metropolitan Statistical Area	N/A	31.3	34.1	33.2
Montgomery, AL Metropolitan Statistical Area	N/A	31	34.4	33.2
Grand Island, NE Micropolitan Statistical Area	N/A	30	35.2	33.1

APPENDIX C: DESTINATIONS IN AND TOPOGRAPHY OF THE CITIES USED IN MMT-MCW SIMULATION

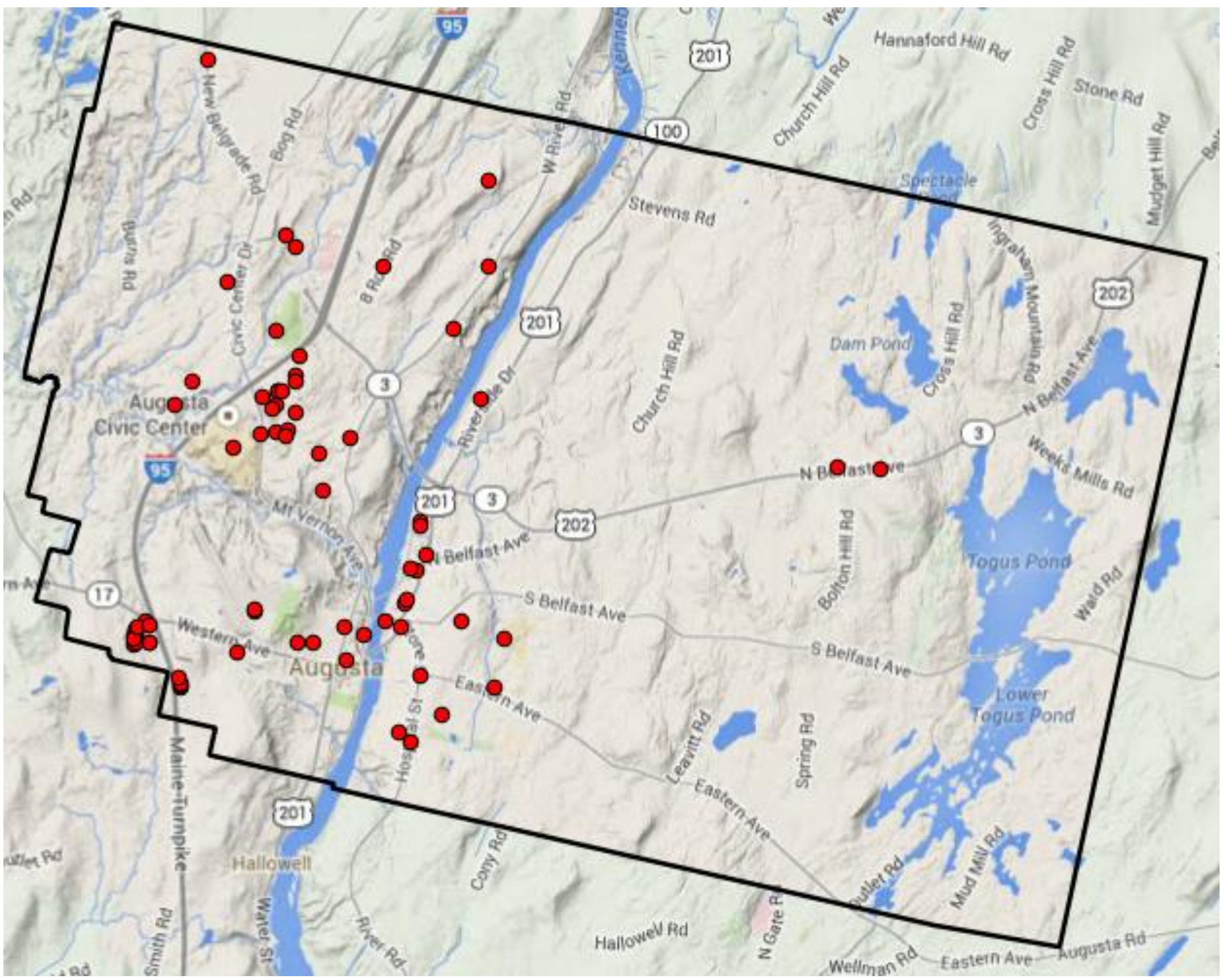


Figure C.1. Destinations in and topography of Augusta, ME

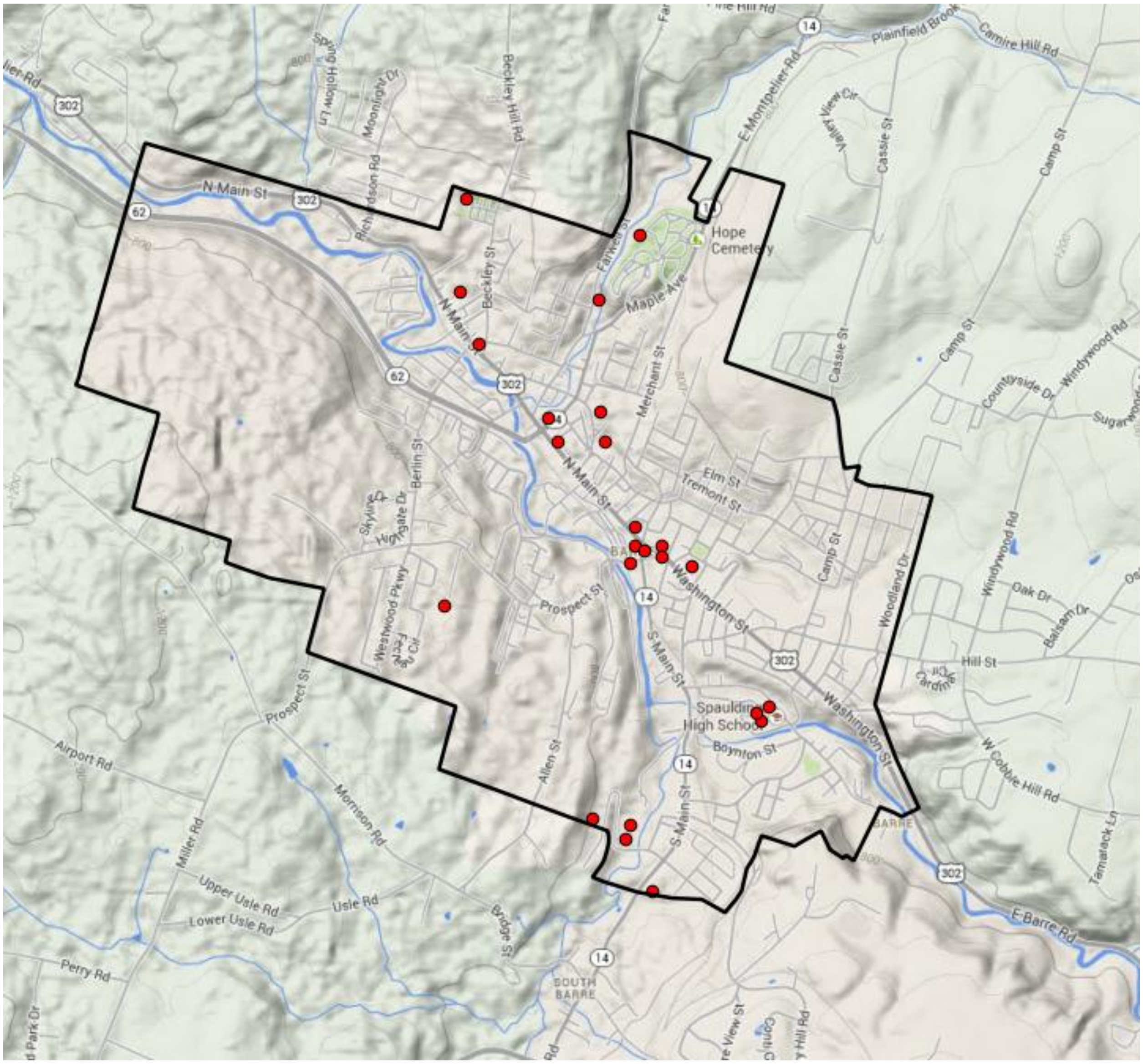


Figure C.2. Destinations in and topography of Barre, VT

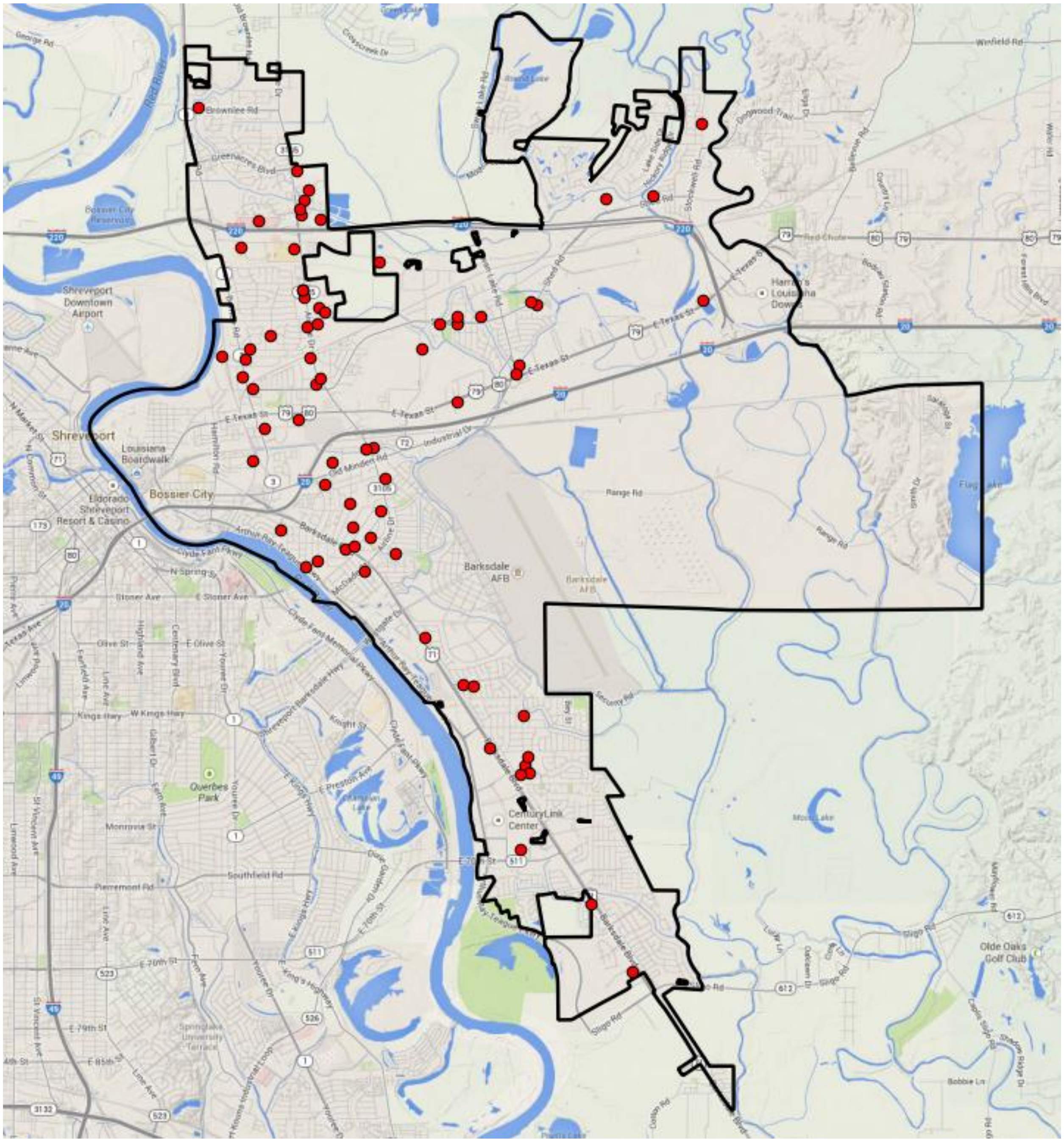


Figure C.3. Destinations in and topography of Bossier, LA

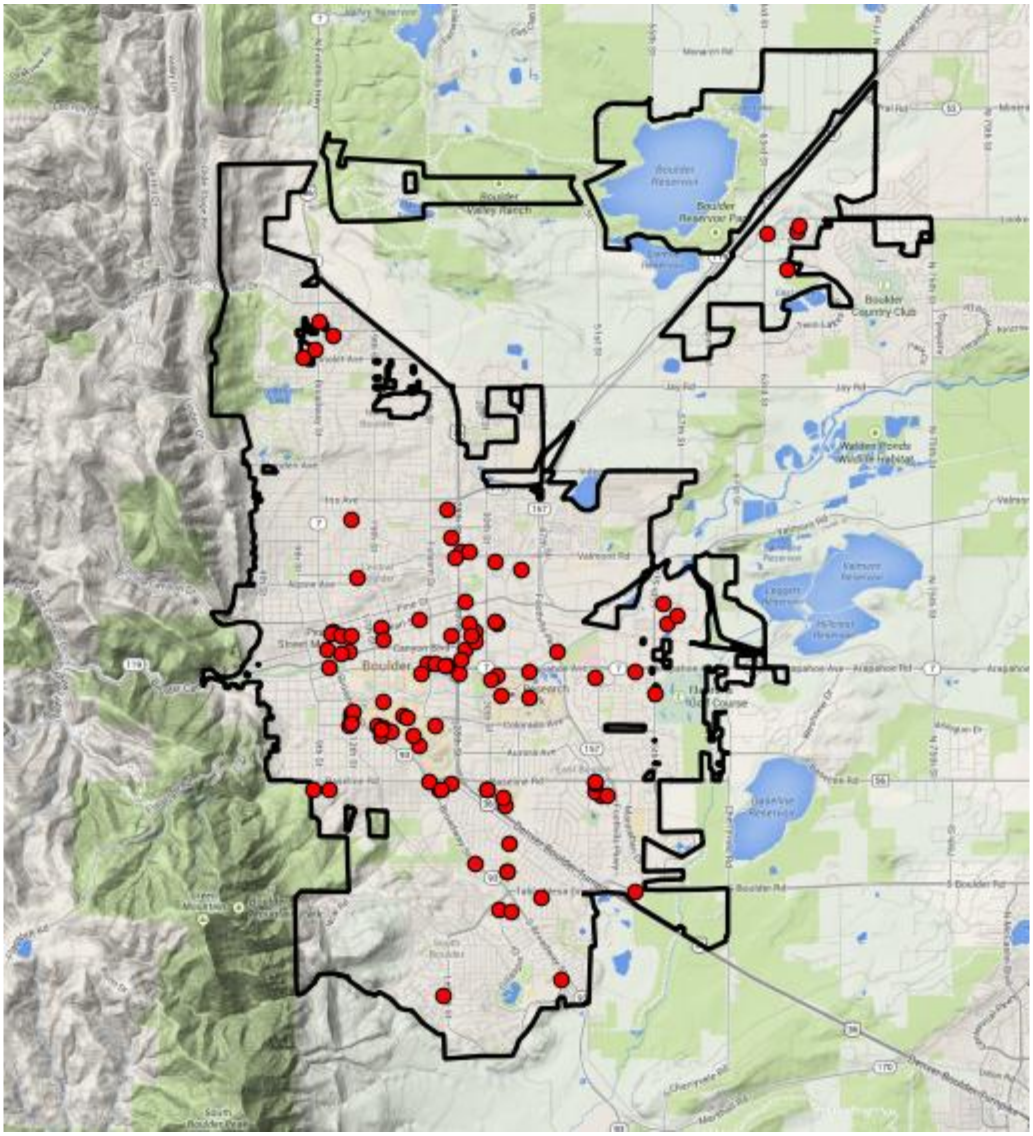


Figure C.4. Destinations in and topography of Boulder, CO

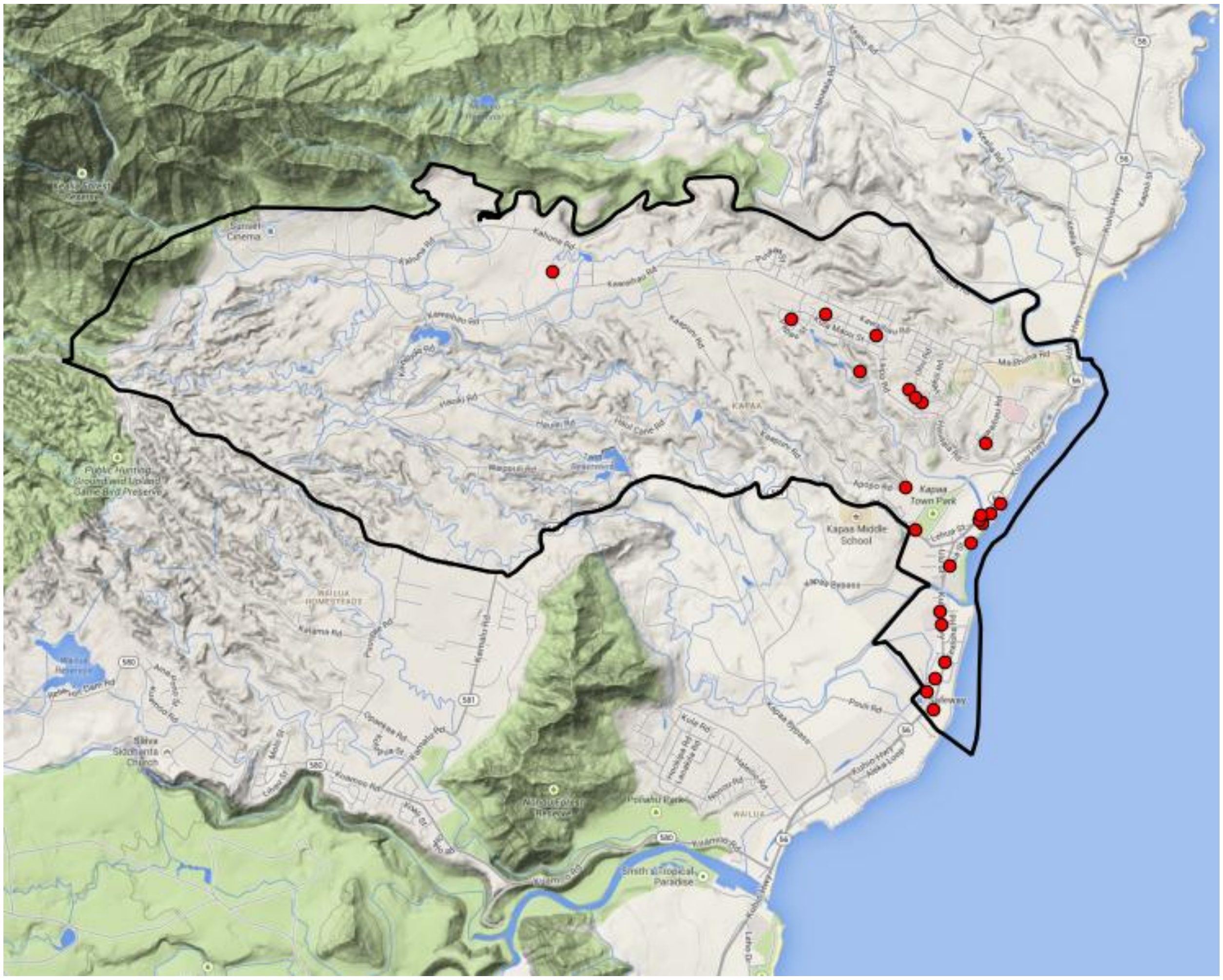


Figure C.5. Destinations in and topography of Kapaa, HI

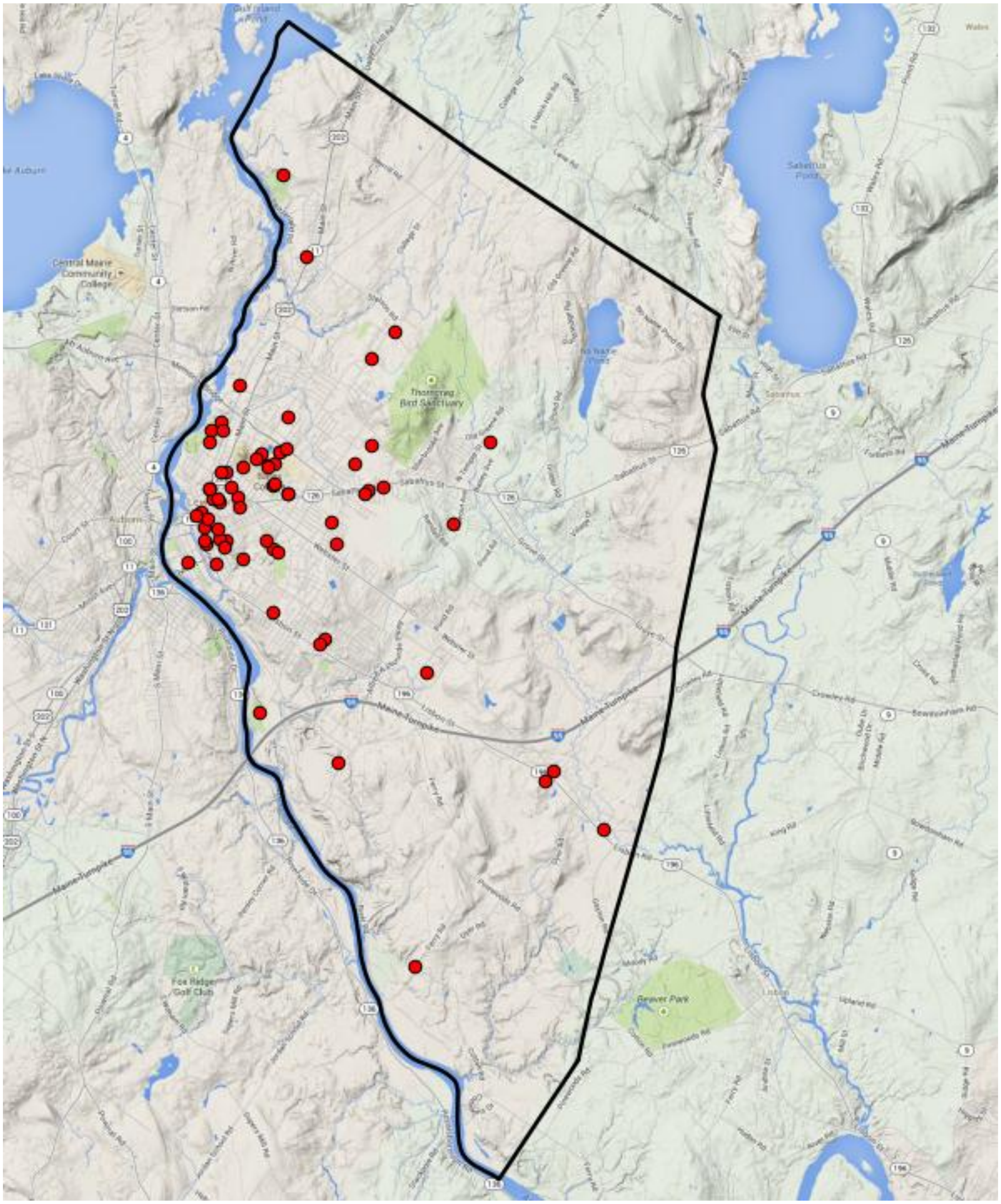


Figure C.6. Destinations in and topography of Lewiston, ME

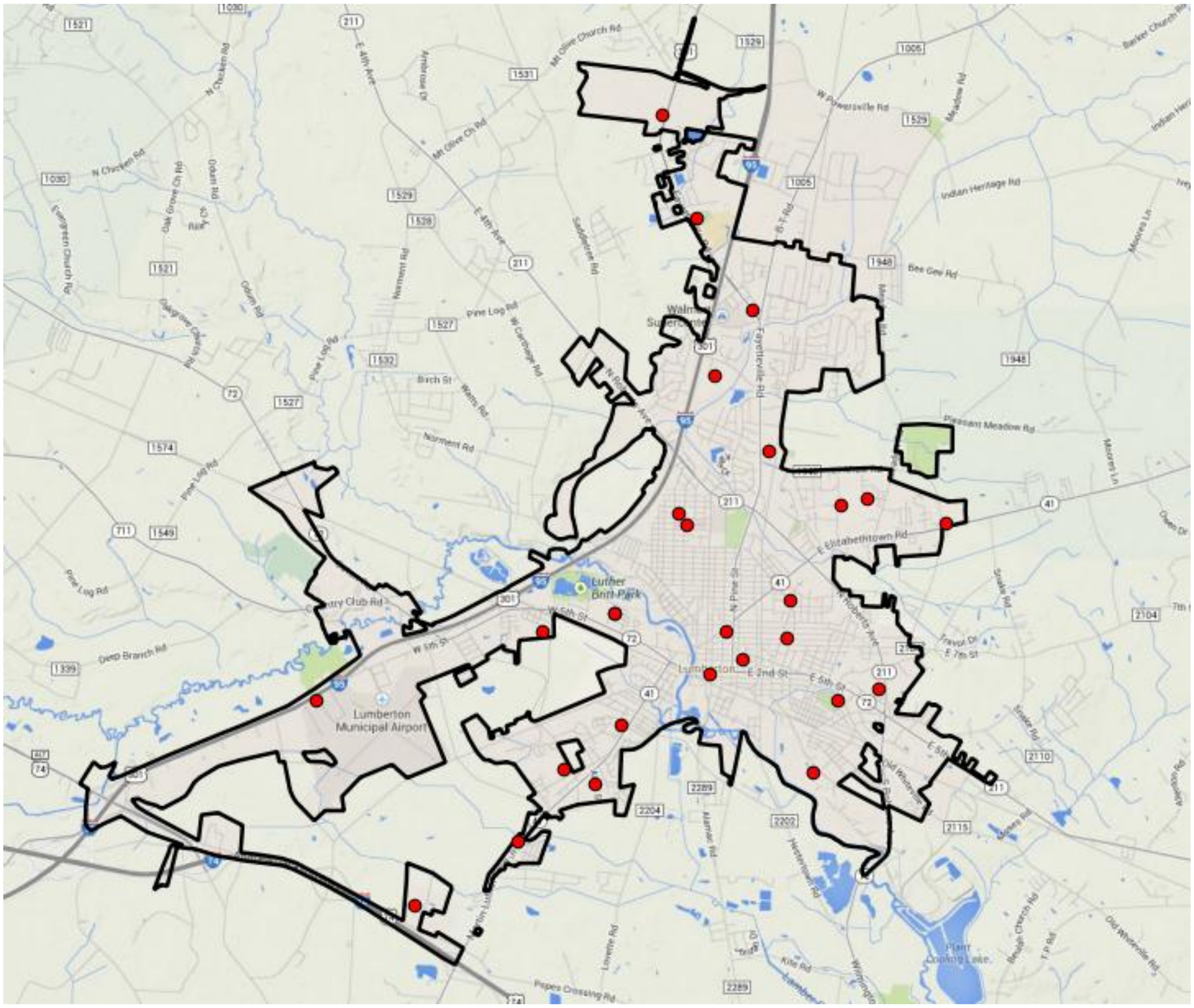


Figure C.7. Destinations in and topography of Lumberton, NC

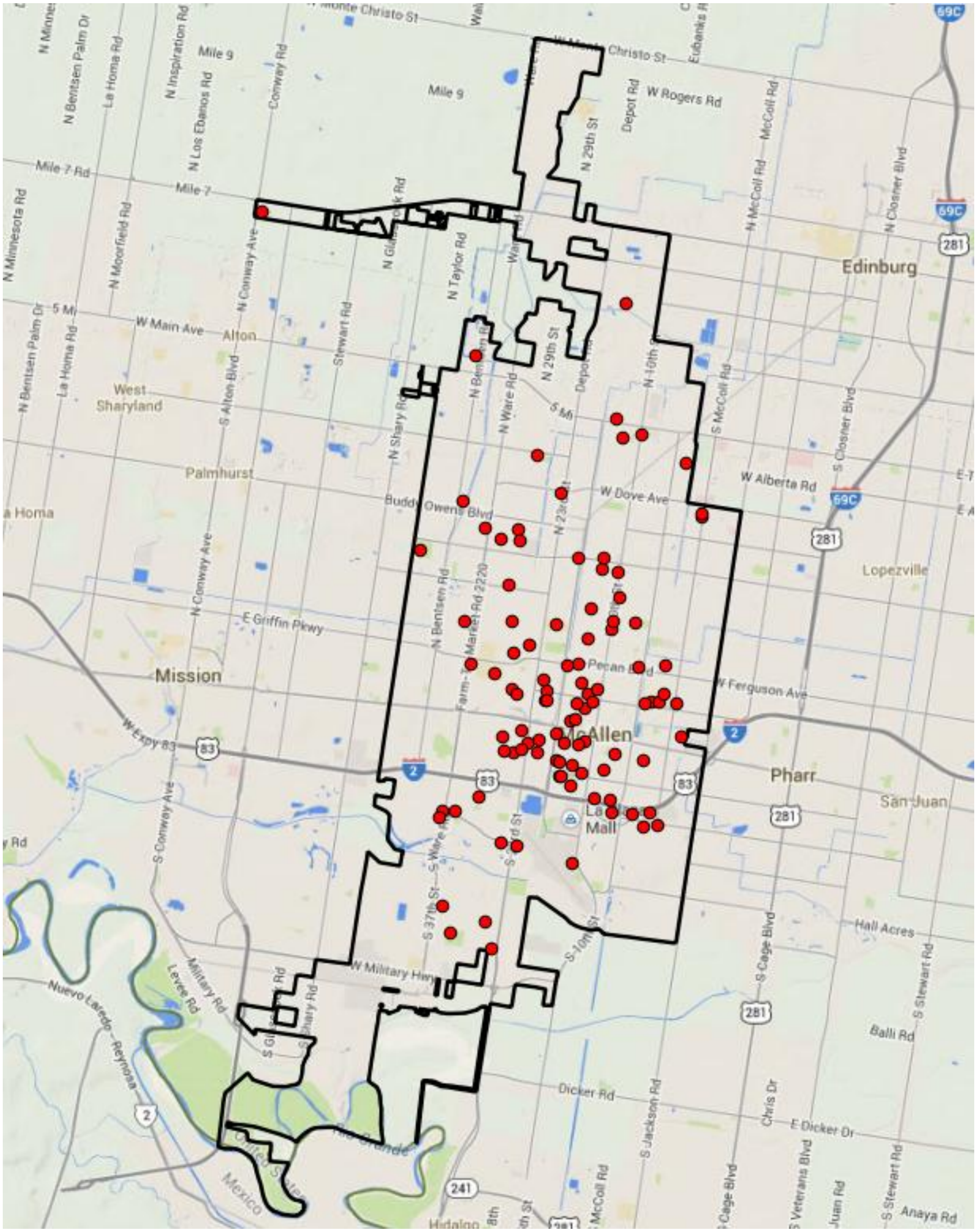


Figure C.8. Destinations in and topography of McAllen, TX

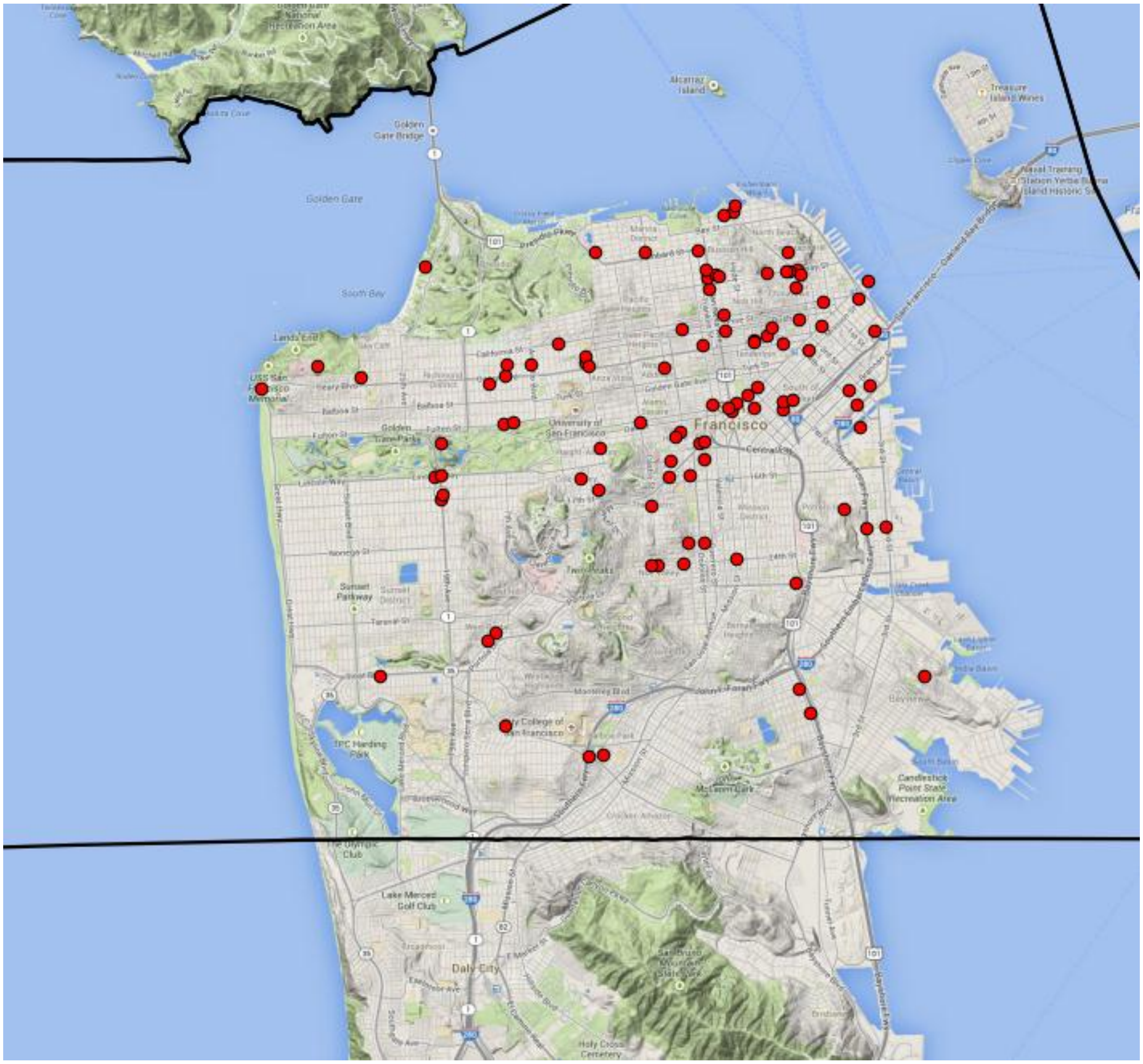


Figure C.9. Destinations in and topography of San Francisco, CA

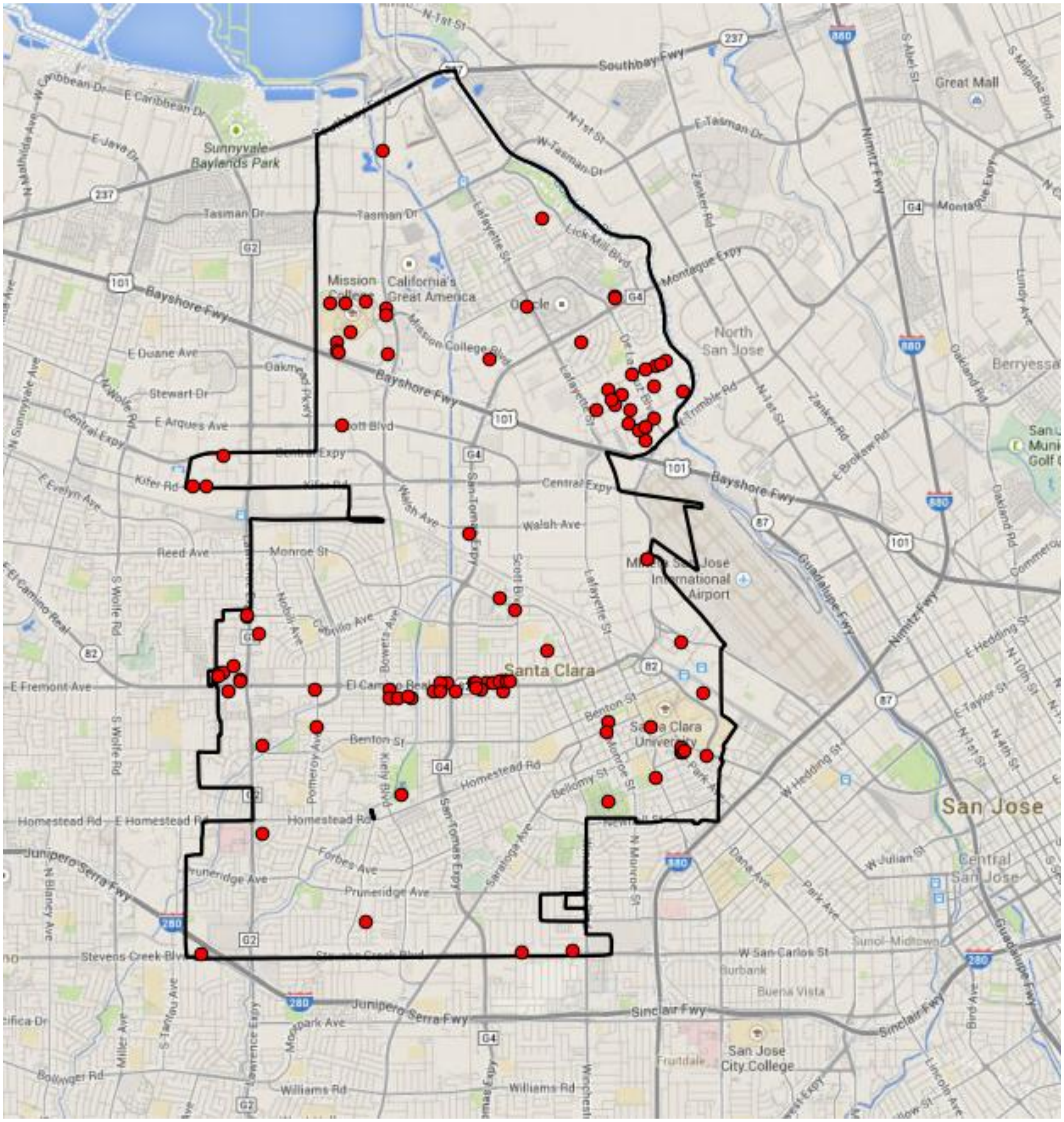


Figure C.10. Destinations in and topography of Santa Clara, CA

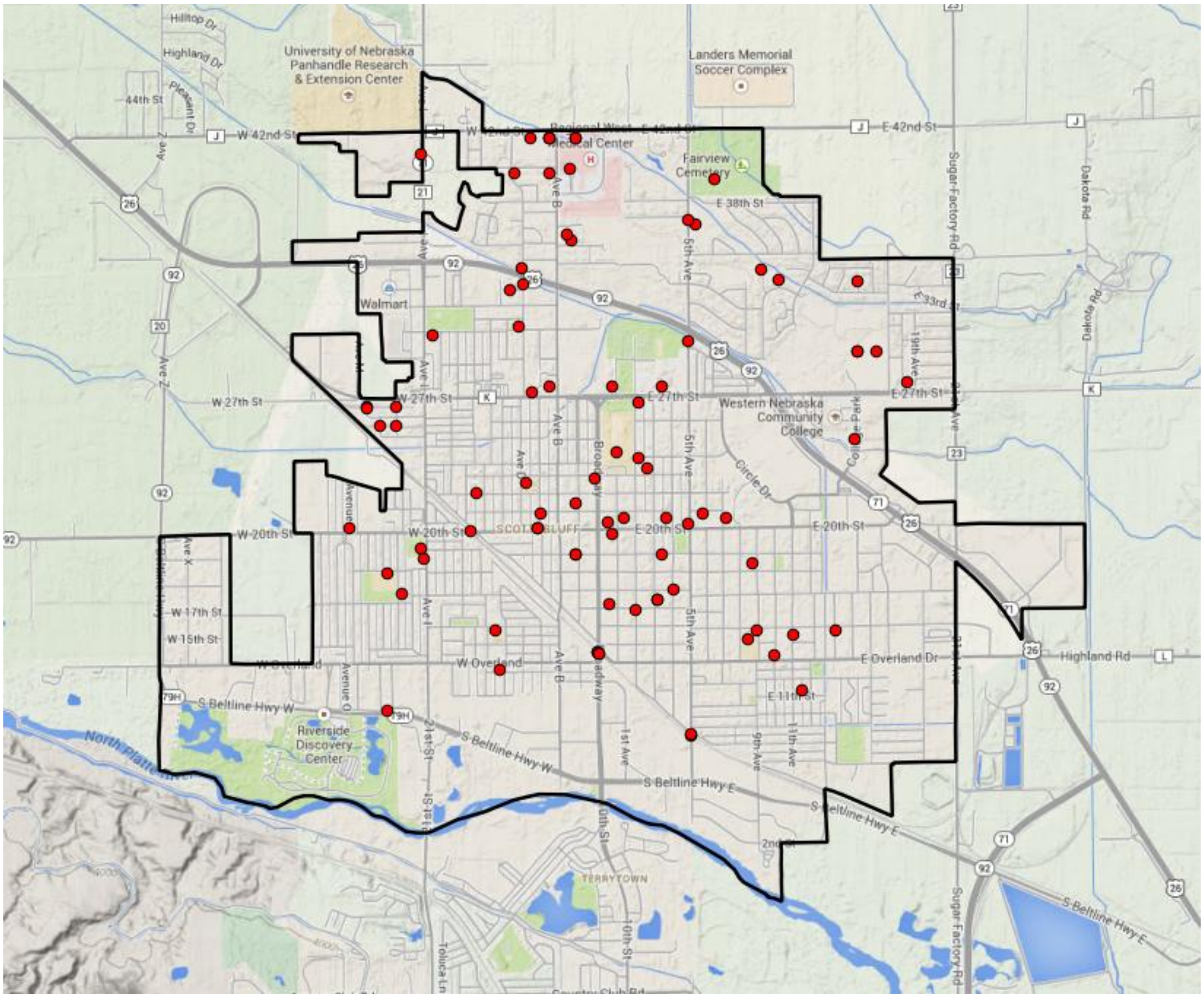


Figure C.11. Destinations in and topography of Scottsbluff, NE

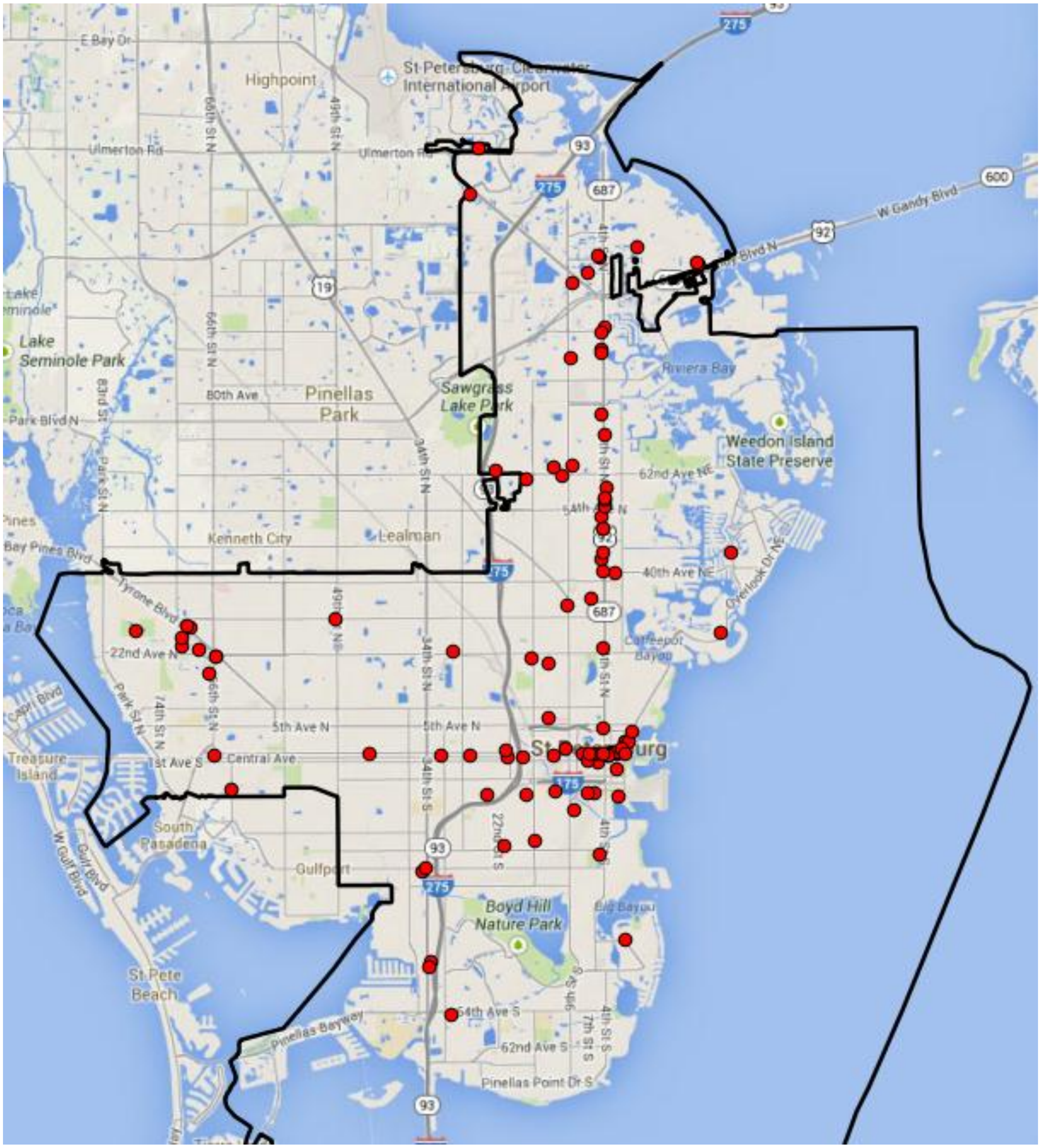


Figure C.12. Destinations in and topography of St. Petersburgh, FL

BIBLIOGRAPHY

Akgün, V., Erkut, E., Batta, R., (2000). On finding dissimilar paths. *European Journal of Operational Research*, 121(2), 232-246.

American College of Sports Medicine. (1986). *Guidelines for graded exercise testing and exercise prescription*. 3rd ed. Philadelphia: Lea & Febiger.

Azevedo, J., Santos Costa, M. E. O., Silvestre Madeira, J. J. E., & Vieira Martins, E. Q. (1993). An algorithm for the ranking of shortest paths. *European Journal of Operational Research*, 69(1), 97-106.

Bassett Jr, D. R., Pucher, J., Buehler, R., Thompson, D. L., & Crouter, S. E. (2008). Walking, cycling, and obesity rates in Europe, North America, and Australia. *J Phys Act Health*, *5*(6), 795-814.

Bekhor, S., Prato, C.G., 2009. Methodological transferability in route choice modeling. *Transportation Research Part B*, 43(4), 422-437.

Ben-Akiva, M., Bergman, M. J., Daly, A. J., & Ramaswamy, R. (1984, July). Modeling inter-urban route choice behaviour. *In Proceedings of the 9th International Symposium on Transportation and Traffic Theory,* VNU Press, Utrecht (pp. 299-330).

Benner, J. G. and Karimi, H. A. Geo-Crowdsourcing. In Advanced Location-Based Technologies and Services (Ed: Karimi, H. A).*Taylor & Francis* (2013).

Besser, L. M., Dannenberg, A. L. (2005). Walking to Public Transit Steps to Help Meet Physical Activity Recommendations. *American Journal of Preventive Medicine*, Vol. 29, No 4. 273-280

Bit, A. K., Biswal, M. P., & Alam, S. S. (1992). Fuzzy programming approach to multicriteria decision making transportation problem. *Fuzzy sets and systems*, 50(2), 135-141.

Bielli, M., Boulmakoul, A., & Mouncif, H. (2006). Object modeling and path computation for multimodal travel systems. *European Journal of Operational Research*, *175*(3), 1705-1730.

Bogo, H., Gomez, D. R., Reich, S. L., Negri, R. M., & San Roman, E. (2001). Traffic pollution in a downtown site of Buenos Aires City. *Atmospheric Environment*, *35*(10), 1717-1727.

Brault, M. W. (2012). Americans with Disabilities: 2010. Current Population Reports, P70–131 Washington: US Census Bureau.

Brown, B. B., Yamada, I., Smith, K. R., Zick, C. D., Kowaleski-Jones, L., & Fan, J. X. (2009). Mixed land use and walkability: Variations in land use measures and relationships with BMI, overweight, and obesity. *Health & place*, *15*(4), 1130-1141.

Buchholz, A. C., McGillivray, C. F., & Pencharz, P. B. (2003). Physical Activity Levels Are Low in Free Living Adults with Chronic Paraplegia. *Obesity research*, 11(4), 563-570.

Carlson, S. A., Fulton, J. E., Schoenborn, C. A., & Loustalot, F. (2010). Trend and Prevalence Estimates Based on the *2008 Physical Activity Guidelines for Americans*. American journal of preventive medicine, 39(4), 305-313.

Carlier, K., Fiorenzo-Catalano, S., Lindveld, C., & Bovy, P. (2003, January). A supernetwork approach towards multimodal travel modeling. In *Proceedings of the 82nd Transportation Research Board Annual Meeting, Washington DC* (pp. 10-2460).

Carr, L. J., Dunsiger, S. I., & Marcus, B. H. (2010). Walk score™ as a global estimate of neighborhood walkability. *American journal of preventive medicine*,*39*(5), 460-463.

Cerin, E., Leslie, E., Owen, N., & Bauman, A. (2008). An Australian version of the neighborhood environment walkability scale: Validity evidence. *Measurement in Physical Education and Exercise Science*, *12*(1), 31-51.

Current, J., Min, H. (1986). Multiobjective design of transportation networks: taxonomy and annotation, *European Journal of Operational Research* 26 187-201.

Das, S. K., Goswami, A., & Alam, S. S. (1999). Multiobjective transportation problem with interval cost, source and destination parameters. *European Journal of Operational Research*, 117(1), 100-112.

De la Barra, T., Perez, B., & Anez, J. (1993). Multidimensional path search and assignment. In PTRC Summer Annual Meeting, 21st, 1993, University of Manchester, United Kingdom.

Derrible, S., & Kennedy, C. (2011). Applications of graph theory and network science to transit network design. *Transport Reviews*, *31*(4), 495-519.

Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische mathematik*, *1*(1), 269-271.

Duncan, D. T., Aldstadt, J., Whalen, J., Melly, S. J., & Gortmaker, S. L. (2011). Validation of Walk Score® for estimating neighborhood walkability: An analysis of four US metropolitan areas. *International journal of environmental research and public health*, *8*(11), 4160-4179.

Edwards, R. D. (2008). Public transit, obesity, and medical costs: assessing the magnitudes. *Preventive Medicine*, 46(1), 14-21.

Ewing, R., Handy, S., Brownson, R. C., Clemente, O., & Winston, E. (2006). Identifying and Measuring Urban Design Qualities Related to Walkability. *Journal of Physical Activity & Health*, *3*.

Ewing, R., & Handy, S. (2009). Measuring the unmeasurable: Urban design qualities related to walkability. *Journal of Urban Design*, *14*(1), 65-84.

Ehrgott, M. (2010). Multicriteria Optimization / Edition 2, Publisher: Springer-Verlag New York, LLC

Eppstein, D. (1998). Finding the k shortest paths. *SIAM Journal on computing*,*28*(2), 652-673.

Finkelstein, M. M., Jerrett, M., & Sears, M. R. (2004). Traffic air pollution and mortality rate advancement periods. *American Journal of Epidemiology*, *160*(2), 173-177.

Forsyth, A., & Southworth, M. (2008). Cities Afoot—Pedestrians, Walkability and Urban Design.

Frank, L. D., Sallis, J. F., Conway, T. L., Chapman, J. E., Saelens, B. E., & Bachman, W. (2006). Many pathways from land use to health: associations between neighborhood walkability and active transportation, body mass index, and air quality. *Journal of the American Planning Association*, *72*(1), 75-87.

Frank, L. D., Sallis, J. F., Saelens, B. E., Leary, L., Cain, K., Conway, T. L., & Hess, P. M. (2010). The development of a walkability index: application to the Neighborhood Quality of Life Study. *British journal of sports medicine*, *44*(13), 924-933.

Friedrich, M., Hofsäß, I., & Wekeck, S. (2001). Timetable-based transit assignment using branch and bound techniques. *Transportation Research Record: Journal of the Transportation Research Board*, 1752(1), 100-107.

Glass, S., & Dwyer, G. B. (Eds.). (2007). *ACSM's Metabolic Calculations Handbook*. Lippincott Williams & Wilkins, 26.

Himann, J. E., Cunningham, D. A., Rechnitzer, P. A., & Paterson, D. H. (1988). Age-related changes in speed of walking. *Med Sci Sports Exerc*, *20*(2), 161-166.

H.S. Mahmassani, T. Hu, and R. Jayakrishnan. (1995). Dynamic traffic assignment and simulation for advanced network informatics (DYNASMART). In N.H. Gartner and G. Improta, editors, *Urban traffic networks: Dynamic flow modeling and control*. Springer, Berlin/New York.

Huang, R., & Peng, Z. R. (2002). Object-oriented geographic information system data model for transit trip-planning systems. Transportation Research Record: *Journal of the Transportation Research Board*, 1804(1), 205-211.

Karimi, H. A., Peachavanish, R. and Peng, J. (2004). Finding Optimal Bus Service Routes: An Internet-Based Methodology to Serve the Transit Patrons. *ASCE Journal of Computing in Civil Engineering*. Vol. 18, No. 2, pp. 83-91.

Karimi, H. A. Zimmerman, B. Ozcelik, A. and Roongpiboonsopit, D. (2009). SoNavNet: A Framework for Social Navigation Networks. *In International Workshop on Location Based Social Networks (LBSN'09)*. Seattle, WA, November 3-6.

Karimi, H. A., Benner, J. G., and Anwar, M. (2011). A Model for Navigation Experience Sharing through Social Navigation Networks (SoNavNets). *International Workshop on Issues and Challenges in Social Computing (WICSOC2011)*. Las Vegas, Nevada, August 2.

Karimi, H. A., Roongpiboonsopit, D., & Wang, H. (2011). Exploring Real-Time Geoprocessing in Cloud Computing: Navigation Services Case Study. *Transactions in GIS*, *15*(5), 613-633.

Karimi, H A. and Socharoentum, M. (2014). Route2Health: A Novel Routing Service to Assist in Increasing Physical Activity. In *Proceedings of the 7th International Conference on health Informatics, Angers, France.*

Kasemsuppakorn, P., & Karimi, H. A. (2009, November). Pedestrian network data collection through location-based social networks. In Collaborative Computing: Networking, Applications and Worksharing, 2009. *CollaborateCom 2009. 5th International Conference on* (pp. 1-9). IEEE.

King, A. C., Sallis, J. F., Frank, L. D., Saelens, B. E., Cain, K., Conway, T. L., ... & Kerr, J. (2011). Aging in neighborhoods differing in walkability and income: associations with physical activity and obesity in older adults. *Social Science & Medicine*, *73*(10), 1525-1533.

Krajzewicz, D., Hertkorn, G., Rössel, C., & Wagner, P. (2002, September). Sumo (simulation of urban mobility). *In Proc. of the 4th Middle East Symposium on Simulation and Modelling* (pp. 183-187).

KuÈnzli, N., Kaiser, R., Medina, S., Studnicka, M., Chanel, O., Filliger, P., ... & Sommer, H. (2000). Public-health impact of outdoor and traffic-related air pollution: a European assessment. *The Lancet*, *356*(9232), 795-801.

Lachapelle, U. (2009). Reconciling the Construct of Walking in Physical Activity and Transportation Research. *American journal of preventive medicine*, 37(4), 372-373.

Leslie, E., Saelens, B., Frank, L., Owen, N., Bauman, A., Coffee, N., & Hugo, G. (2005). Residents' perceptions of walkability attributes in objectively different neighbourhoods: a pilot study. *Health & place, 11*(3), 227-236.

Leslie, E., Coffee, N., Frank, L., Owen, N., Bauman, A., & Hugo, G. (2007). Walkability of local communities: using geographic information systems to objectively assess relevant environmental attributes. *Health & place, 13*(1), 111-122.

Li, Q., & Kurt, C. E. (2000). GIS-based itinerary planning system for multimodal and fixed-route transit network. *In Proceedings of the MID-Continent Transportation Symposium* (pp. 47-50).

Li, J. Q., Zhou, K., Zhang, L., & Zhang, W. B. (2010). A multimodal trip planning system incorporating the park-and-ride mode and real-time traffic/transit information. In *Proceedings of the 17th ITS World Congress*.

MacDonald, J. M., Stokes, R. J., Cohen, D. A., Kofner, A., & Ridgeway, G. K. (2010). The effect of light rail transit on body mass index and physical activity. *American journal of preventive medicine*, 39(2), 105-112.

Malatesta, D., Vismara, L., Menegoni, F., Galli, M., Romei, M., & Capodaglio, P. (2009). Mechanical external work and recovery at preferred walking speed in obese subjects. *Medicine+ Science in Sports+ Exercise*, *41*(2), 426.

Marler, R. T., & Arora, J. S. (2004). Survey of multi-objective optimization methods for engineering. *Structural and multidisciplinary optimization*, 26(6), 369-395.

Marshall, J. D., Brauer, M., & Frank, L. D. (2009). Healthy neighborhoods: walkability and air pollution. *Environmental Health Perspectives*, *117*(11), 1752.

Milkovits, M., Huang, E., Antoniou, C., Ben-Akiva, M., & Lopes, J. A. (2010, August). DynaMIT 2.0: The next generation real-time dynamic traffic assignment system. *In Second International Conference on Advances in System Simulation* (SIMUL), 2010 (pp. 45-51). IEEE.

Modesti, P., & Sciomachen, A. (1998). A utility measure for finding multiobjective shortest paths in urban multimodal transportation networks. *European Journal of Operational Research*, 111(3), 495-508.

Morabia, A., Mirer, F. E., Amstislavski, T. M., Eisl, H. M., Werbe-Fuentes, J., Gorczynski, J., & Markowitz, S. B., 2010. Potential health impact of switching from car to public transportation when commuting to work. *Journal Information*, 100(12).

Nagel, K. (2001). Multi-modal traffic in TRANSIMS. *Pedestrian and evacuation dynamics*, 161-172.

Owen, L. E., Zhang, Y., Rao, L., & McHale, G. (2000, December). Street and traffic simulation: traffic flow simulation using CORSIM. *In Proceedings of the 32nd conference on Winter simulation* (pp. 1143-1147). Society for Computer Simulation International.

Park, D., Rilett, L.R. (1997). Identifying multiple and reasonable paths in transportation networks: a heuristic approach. *Transportation Research Record* 1607, 31-37.

Prato, C. G., & Bekhor, S. (2006). Applying branch-and-bound technique to route choice set generation. *Transportation Research Record: Journal of the Transportation Research Board*, *1985*(1), 19-28.

Prato, C. G. (2009). Route choice modeling: past, present and future research directions. *Journal of Choice Modelling, 2*(1), 65-100.

Pucher, J., Buehler, R., Bassett, D. R., & Dannenberg, A. L. (2010). Walking and cycling to health: a comparative analysis of city, state, and international data. *American Journal of Public Health*, 100(10), 1986-1992.

Rehrl, K., Bruntsch, S., & Mentz, H. J. (2007). Assisting multimodal travelers: Design and prototypical implementation of a personal travel companion. *Intelligent Transportation Systems, IEEE Transactions on*, *8*(1), 31-42.

Ruphail, N.M., Ranjithan, S.R., ElDessouki, W., Smith, T., Brill, E.D. (1995). A decision suort system for dynamic pre-trip route planning. *Applications of advanced technologies. In: Transportation Engineering: Proceedings of The Fourth International Conference*, 325-329.

Sallis, J. F., Frank, L. D., Saelens, B. E., & Kraft, M. K. (2004). Active transportation and physical activity: opportunities for collaboration on transportation and public health research. *Transportation Research Part A: Policy and Practice*, 38(4), 249-268.

Sheffi, Y., & Powell, W. B. (1982). An algorithm for the equilibrium assignment problem with random link times. Networks, 12(2), 191-207.

Skov, H., Hansen, A. B., Lorenzen, G., Andersen, H. V., Løfstrøm, P., & Christensen, C. S. (2001). Benzene exposure and the effect of traffic pollution in Copenhagen, Denmark. *Atmospheric Environment*, *35*(14), 2463-2471.

Smith, L., Beckman, R., & Baggerly, K. (1995). *TRANSIMS: Transportation analysis and simulation system* (No. LA-UR--95-1641). Los Alamos National Lab., NM (United States).

Smith, K. R., Brown, B. B., Yamada, I., Kowaleski-Jones, L., Zick, C. D., & Fan, J. X. (2008). Walkability and body mass index: density, design, and new diversity measures. *American journal of preventive medicine*, *35*(3), 237-244.

Sun, J., Walters, M., Svensson, N., & Lloyd, D. (1996). The influence of surface slope on human gait characteristics: a study of urban pedestrians walking on an inclined surface. *Ergonomics*, *39*(4), 677-692.

Tharrett, S. J., & Peterson, J. A. (Eds.). (2012). *ACSM's health/fitness facility standards and guidelines*. Human Kinetics.

Tsai, W. T., Sun, X., & Balasooriya, J. (2010, April). Service-oriented cloud computing architecture. In *Information Technology: New Generations (ITNG), 2010 Seventh International Conference on* (pp. 684-689). IEEE.

Tsolkas, D., Passas, N., Xenakis, C., Papataxiarhis, V., & Tsetsos, V. (2012, October). Busfinder: a personalized multimodal transportation guide with dynamic routing. *In Informatics (PCI), 2012 16th Panhellenic Conference on (pp. 25-30)*. IEEE.

U.S. Census Bureau: State and County QuickFacts. (2010). Retrieved June 6 from http://www.census.gov/2010census/popmap/.

U.S. Department of Health and Human Services. (1996). Physical Activity and Health: A Report of the Surgeon General. Atlanta, GA: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Chronic Disease Prevention and Health Promotion.

USDHHS. (2008). Physical activity guidelines for Americans. Washington DC: USDHHS, CDC, 2008.

U.S. Department of Health and Human Services. (1996). Physical Activity and Health: A Report of the Surgeon General. Atlanta, GA: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Chronic Disease Prevention and Health Promotion.

Van Dyck, D., Deforche, B., Cardon, G., & De Bourdeaudhuij, I. (2009). Neighbourhood walkability and its particular importance for adults with a preference for passive transport. *Health & place*, *15*(2), 496-504.

Weinstein Agrawal, A., Schlossberg, M., & Irvin, K. (2008). How far, by which route and why? A spatial analysis of pedestrian preference. *Journal of Urban Design*, *13*(1), 81-98.

Ziliaskopoulos, A. K., & Waller, S. T. (2000). An Internet-based geographic information system that integrates data, models and users for transportation applications. *Transportation Research Part C: Emerging Technologies*, *8*(1), 427-444.