Enhanced Transit Ridership Forecasting Using Automatic Passenger Counting Data

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Recent emphasis on sustainable development has carried over into the transportation sector, given the impacts of transportation behavior on environment and equity. Transit is widely recognized as a viable option supporting the sustainability issue providing benefits such as reducing air pollution, alleviating traffic congestion, enhancing mobility, and promoting social well-being (health through walk- and bike-access). An important tool in advancing sustainable transport is to generate more robust transit ridership models to evaluate the benefits of investments in these modes. In particular, this thesis concentrates on two sub-problems of (1) calibration procedures and (2) insufficient data for transit mode choice modules.

The first purpose of this thesis is to improve the calibration procedures through better understanding of calibrated mode constants. First, the magnitude and relative importance of mode constants to measurable components are analyzed using representative data from six cities in North America. The mode constants (representing unmeasured inputs) in study cities account for 41% to 65% of total utilities. The results demonstrate that, in some cases, mode constants are large enough to render models insensitive to changes of important but omitted system factors such as reliability, comfort, convenience, visibility, access environment, and safety. The need to explicitly include mode constant endogenous to the model is verified.

Second, this thesis introduces a framework to improve the utilization of new data sources such as automated vehicle location (AVL) and automated passenger counting (APC) systems in transit ridership forecasting models. The direct application of the AVL/APC data to travel forecasting requires an important intermediary step that links stops activities - boarding and alighting - to the actual location (at the TAZ level) that generated/attracted this trip. The GIS-based transit trip allocation methods are newly developed with focus on considering the case when the access shed spans multiple TAZs. The proposed methods improve practical applicability with easily obtained data in local contexts. The performance of the proposed allocation methods is further evaluated using transit on-board survey data. The results show that the buffer area ratio weighted by employment or population and footprint weighted method perform reasonably well in the study area and can effectively handle various conditions, particularly for major activity generators. The average errors between observed data and the proposed method are about 8% for alighting trips and 18% for boarding trips.

Third, given the outputs from the previous research effort, the application framework of the AVL/APC data to travel forecasting model calibration is demonstrated. In the proposed framework, transit trip allocation methods are employed to identify prediction errors at finer geographic level (at TAZs). In turn, the approach makes it possible to evaluate the zonal characteristics that affect estimation accuracy. Developed multinomial regression models produce equations for the mode choice prediction errors as a function of (1) measurable but omitted market segmentation variables in current mode choice utility function including socio-economic and land use data; and (2) newly quantifiable attributes with new data source or techniques including quality of service variables. The proposed composite index can systematically evaluate and prioritize the major source of prediction errors by quantifying total magnitudes of prediction error and a possible error component.

The outcomes of the research in this thesis can serve as foundation towards more reliable and accurate mode choice models and ultimately enhanced transit travel forecasting.

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Dedication

I dedicate this work to my dear, loving husband Dr. Lee J. K. and devoted parents Jung M. K. and Lee W. Y.

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Chapter 1
Introduction

The performance of transportation networks in accommodating travel demand is a recurring and global area of concern. Poorly performing transportation systems negatively impact the environment, the economy and personal quality of life. The role of the contemporary transportation engineer is to plan, evaluate, design and oversee the implementation of both policies and physical infrastructure that advance the goal of improved transportation systems. A critical part of these responsibilities is the development of robust decision making methods that allow the engineer to assess the relative costs and benefits over the short and long term of various possible interventions. One important tool is the travel forecasting model – a quantitative assessment technique that is developed to represent the current situation, while allowing users to evaluate multiple future scenarios. A thorough review of the structure of travel forecasting models is presented in Chapter 2.

Originally, travel forecasting models were developed for capacity expansion programs in interstate highway systems where automobiles play a key role. At that time, urban planning policies in North America also encouraged people to move to dispersed, lower-density settlements in suburban areas. The resulting urban forms and scattered population distribution influenced the transportation network and the usage of various transport modes – typically increasing automobile transportation while decreasing the use of walking, cycling and public transport. Accordingly, the evolution of travel forecasting models had been oriented toward appropriate representations of system performance for automobile traffic.

More recently, interest has intensified in sustainable urban development, promoting environmental quality and social equity. This emphasis has carried over into the transportation sector, given the impacts of transportation behavior on environment and equity. According to Transport Canada (2010), the transportation sector is the second largest source of greenhouse gas (GHG) emissions in Canada, with a share of 27% of total emissions in 2007. Between 2000 and 2007, transportation emissions grew at a rate of 1.6% per year, while total GHG emissions grew at a rate of 0.6% per year. A study reported that if one person in a household switched his/her commuting trip from driving alone to using existing transit, the energy consumption of the household can be reduced by 30%. This can save an average of two metric tons of carbon dioxide each year (Millar, 2012).

In these contexts, transit is widely recognized as a viable option supporting new paradigms providing benefits such as reducing air pollution, alleviating traffic congestion, and enhancing mobility. Moreover, well-planned and well-implemented transit systems may support social well-being, for instance, by serving people who have fewer transportation choices and by promoting health through walk- and bike-access to transit.

Given the emphasis on public transportation in modern transportation engineering, many transit investments have been evaluated using travel forecasting models, with mixed results. Specific concerns have been identified regarding models' ability to generate realistic mode share results. For example, Pickrell (1992) compared actual and predicted transit ridership for fixed-guideway projects. The actual levels were below 50% of forecasted in six out of seven rail transit systems in the United States. For international projects, actual transit ridership levels were under 80% of the forecasted ridership in about 85% of rail projects (Flyvbjerg et al. 2005). Out of the 18 fixed-guided way transit projects built between 2003 and 2007, eight projects had 80% of the predicted ridership and 10 projects had much lower levels than the forecasted (Federal Transit Administration, 2008). There has been an overall need to improve travel forecasting models, particularly in their estimates of transit ridership.

An important tool in advancing sustainable transport is to generate more robust transit ridership models to evaluate the benefits of investments in these modes. The objective of this dissertation is to improve the performance of regional travel forecasting models, particularly in estimating transit ridership.

1.1 Background – Travel Forecasting Models

Analytical tools such as travel forecasting models are used to support policy decisions by assessing the impact of programs (e.g., pricing, high occupancy lanes, convertible traffic lanes, etc.) as well as facility construction on overall system performance. The models may be used to compare possible interventions in transportation systems. While construction costs are generally estimated in other ways, travel models have the potential to estimate benefits for the general population within a modeled area or, alternatively, for specific population groups (e.g. older people or students). The benefits quantified by models include transportation safety, air quality, as well as congestion concerns (NCHRP, 2012, TMIP 2013).

The success of travel forecasting models and ultimately decision-makers' ability to make sound judgment regarding transportation system changes is predicated upon appropriate models of travel behavior. Understanding traveler behavior is remarkably complex. For a fixed starting point (origin), a traveler has a set of possible destinations at which an activity may take place. To arrive at any destination, the traveler has a set of modes and paths by which the activity may be reached. The traveler may also elect to perform more than one activity in sequence, meaning that the choice of destinations, paths, and modes is influenced by more than one end point. Moreover, the traveler may begin the trip at any point in time. The traveler's behavior is often influenced by household constraints – the availability of a car or the need to travel with others, for example.

A further complicating factor is that not all travelers perceive various trip components in the same way. For example, significant evidence exists that travelers perceive waiting time for transit as more onerous than time spent in-vehicle. It may also be true that some travelers find time spent in a transit vehicle offers positive utility – the ability to read, work or socialize for example – compared to driving an automobile. Linking observable transportation costs to quantitative representations of traveler perceptions of these costs is a fundamental area of research in transportation engineering.

To effectively model travel behavior, models most often use the following approach:

1. The model assumes a trip origin – the location from which the trip will begin. Common origins include home and non-home based trips.
2. The model assumes a trip purpose – the activity that the traveler wishes to complete. Common trip purposes are work, school, shopping and other.
3. Depending on the trip purpose, the destination may be fixed (in the case of work or school trips), or competing destinations may be available (in the case of recreational or shopping trips).
4. In the case of a fixed destination, the model quantifies the cost of traveling from the origin to the destination by multiple paths and modes. For multiple destinations, the model may estimate the cost of accessing each destination by the several paths or modes.
5. The measurable attributes of each candidate trip are then converted to a utility function – typically a sum of the products of actual costs and a representation of the average traveler's perception of that trip component. Mathematically, a common form of a utility function is (Koppelman and Bhat 2006):

$$V_{it} = V(S_t) + V(X_i) + V(S_t, X_i) \quad (1\text{-}1)$$

Where:

V_{it}	is the utility of alternative i for individual t
$V(S_t)$	is the portion of utility associated with characteristics of individual t
$V(X_i)$	is the portion of utility of alternative i associated with the attributes of alternative i
$V(S_t, X_i)$	is the portion of the utility which results from interactions between the attributes of alternative i and the characteristics of individual t

6. The likelihood of a traveler choosing alternative *i* among all alternatives *I*, is calculated stochastically using a discrete choice model. The most commonly used model formulations are logit (or nested logit) and probit models. The differences between these models are explained in chapter 2.
7. The model developed in step 1 through 6 is then used to estimate the behavior of travelers under current conditions. The results of these model predictions are compared to observed data: interzonal and intrazonal travel volumes; volumes on individual facilities; network and corridor-based transit mode shares. If significant errors are identified, the modeller can revisit any of steps 1 through 6.

1.1.1 The need for data

Given this process, the importance of data in generating effective models becomes evident. To complete steps 1 and 2, estimates of the rate at which trips are made for various purposes and from a variety of locations must be known with some certainty. These data are normally gathered through travel surveys or diaries, where respondents record and convey their complete travel activity for a given period of time, normally one day. The data needed for step four – quantifying travel time by various modes along a set of paths (or routes) – are reasonably well estimated by calculations done endogenous to the model. For automobile travel, models estimate travel time using the relationships between trip distance, and travel speed (as dictated by facility, mode, volume and delay). Generally, forecasting the use of the public transportation is more difficult than estimating private auto use. This outcome is a result of two complicating sets of factors. First, transit travel has a more complex cost structure than travel by private auto. Travelers must access the system, wait for the transit vehicle to arrive, experience in-vehicle time (and potentially transfers), and finally travel from the alighting stop to their ultimate destination. Estimates of travelers' perceptions are necessary to convert the travel costs to disutilities for each of these multiple components.

Extensive data are necessary to develop appropriate utility functions – representative measures of how travelers perceive travel costs for a given trip's purpose. The most common way to estimate these representations is through stated preference surveys. Travelers are presented with paired alternatives and asked to choose their preferred option. For example, a traveler may be presented with a situation where a trip can be completed using private auto with 1) a travel time of 30 minutes and an out of pocket expense of $3.00 for tolls or 2) a travel time of 45 minutes, but no toll. The respondent's choice in this situation provides evidence on the relative value of 15 minutes of travel time savings compared to $3.00 cost saving. Utility functions can also be generated from revealed preference or observed behaviors. Although not desirable to do so, when budgets are limited, the relative importance of these cost components may be transferred from previous modeling efforts.

1.1.2 Challenges unique to modeling transit utility and mode choice

Unlike travel by automobile, transit has a number of difficult to quantify attributes. Because the service operates on discrete intervals, departure and arrival times are also discrete (compared to nearly continuous for auto travel), which may create a cost to the traveler (Casello et al., 2009). Transit unreliability also introduces uncertainty into total travel time and the ability for a traveler to arrive on time. Researchers have posited that this is interpreted as a transit disincentive for some travelers (Chorus, 2006). Travel by public transit may also offer very different comfort standards – in terms of temperature, seating / standing, proximity to strangers etc. – all of which may be perceived as a cost, but are very hard to quantify effectively.

Thus, to calibrate transit utility functions, even greater data are necessary, but are not often systematically collected or available for the development of contemporary models. The literature has recognized the poor performance of models in general, and in estimating transit usage. NCHRP special report 288 (2007) summarizes the primary shortcomings as: inherent weakness of the models; errors introduced by modeling practice; lack of reliable data; and biases arising from the institutional climate where models are used. Similarly, Flyvbjerg (2005) diagnosed that inaccuracies of road and rail travel forecasts are related to input assumptions (particularly, land use development) and the model components (especially, trip distribution and trip generation steps and forecasting models in general). Opening delay, design change, and political pressures to achieve a predetermined outcome were evaluated as other factors of forecast errors of rail projects.

The Federal Transit Administration (FTA, 2006) identified major deficiencies in state-of-the-art transit ridership forecasting exist in (1) insufficient data and (2) calibration procedures. Reliable data are equally important for each step of a model's development including estimation, calibration, and validation. However, transit ridership modeling is conducted with limited data, while the models require a more comprehensive dataset both in the system characteristics (e.g., transit travel speed and transit accessibility) and in traveler characteristics (e.g., choice of destination, transit-access mode, and transit-path).

1.2 Mode Constants

One approach to quantify the difficult to measure attributes of travel by a given mode is through the use of so-called mode constants. The mode constants are normally interpreted as a representation of the net influence of all unobserved (or not explicitly included) mode (or individual or trip) characteristics in the variables of utility. The unobserved transit trip attributes and excluded variables include reliability, comfort, convenience, visibility, flexibility, safety, and other factors (Ortuzar and Willumsen, 2001). Increasingly, social norms are beginning to be recognized as influencing travel behavior, but are not included in utility functions.

In practice, without mode constants, utility functions often produce unrealistic results, typically due to the excluded variables. The normal process for incorporating mode constants into travel forecasting models is to identify one mode, normally private automobile, as the reference mode, and to add (or subtract) a cost to all other modes that represents travelers' aversion (or preference) for that mode relative to private auto (Koppelman and Bhat, 2006). Mathematically, Equation (1-2) shows the mode constant - or alternative specific constant - added to the utility function originally presented as equation (1-1).

$$V_{it} = V(S_t) + V(X_i) + V(S_t, X_i) + \beta_{io} \times ASC_i \tag{1-2}$$

Where:

β_{io}	is the change in utility of alternative i relative to the reference mode
ASC_i	is an Alternative Specific Constant, equal to 1 for alternative i and 0 for all other alternatives

In addition to the measurable components shown in Equation (1-1), mode choice models usually include an alternative specific constant, the magnitude of which is represented as $\beta_{io} \times ASC_i$ in equation (1-2).

Naturally, good modeling practice seeks to minimize the magnitude of these mode constants. Modelers should aim to identify all those trip and traveler attributes that influence behavior and, whenever possible, model these components explicitly, such that the impacts of these changes can be evaluated. This is particularly important if a model is to be used over a long time horizon. Assumptions about traveler behavior may not remain constant across time periods and, as such, mode constants developed in the current time period may not apply to future scenarios.

One stream of research has attempted to quantify and incorporate difficult-to-measure attributes in mode choice models. Srinivasan et al. (2007) identified a number of papers that examine the importance of qualitative factors on cost perceptions including comfort and convenience through proxy variables such as seat availability and number of transfers (Algers et al. 1975) and freedom, safety, and anxiety based on ratings of various subjective factors (Forward, 1998). With the inclusion of the qualitative variables such as transit access environment (Evans et al., 1997), transit service reliability (Casello et al., 2009), psychological factors (e.g., attitude, habit and affective appraisal) (Domarchi et al., 2008), the magnitude of mode constants was reduced. Despite these efforts to understand possible components of mode choice constants, and best practice literature that recommends modifying mode constants only as a last resort (Cambridge Systematics, 2010), the use of large, and poorly defined mode constants remains a challenge for many models.

1.3 New Data Sources to Improve Transit Ridership Estimation

The primary purpose of mode choice models is to predict transit ridership – boardings and alightings – at a zonal level. The quality of a model in terms of its accuracy in both the short- and long-term is largely dependent on the data that inform the model development. Models require accurate representation of two primary components: the costs of travel by alternative modes (including time and out of pocket expenses) and travelers' behaviors when presented with these costs. To estimate the first component, models typically rely on conventional data sources that generate highway or arterial speeds to predict transit in-vehicle time, representing impedance and travel time in trip distribution and mode choice, respectively (FTA, 2006). Transit travel times may also be generated endogenously to the model from scheduled headways and run times. Fares represent the primary out of pocket expenses. In general, these data tend to be relatively easy to gather.

The second component, travel behavior, has proven to be more difficult to measure. In the past, estimates of transit ridership have largely been derived from a series of data collection exercises, including: journey to work data from the census; on-board transit ridership surveys; and household travel diaries. More recently, however, new data sources from the transit industry itself have become available that have significant potential to improve modelers' abilities to quantify traveler behavior. Three automated data collection systems have been widely implemented in transit systems: Automatic Vehicle Location (AVL); Automated Passenger Counting (APC); and Automated Fare Collection (AFC) systems.

An AVL system monitors the location of vehicles using Global Position Systems (GPS) or roadside detectors. The most important feature of AVL data for passengers is real-time arrival information at stations; for the transit agency, AVL generates real-time system performance indicators such as vehicle schedule adherence (Furth et al., 2006).

An APC system utilizes pressure-sensitive mats, horizontal beams, or over-head infrared sensors to count the number of passengers boarding and alighting at each stop. If APCs are fully implemented, the independent systems can include both location measurement and stop matching. The benefits of the APC system are automated and low-cost collection of data about station activities; cumulative loading diagrams; maximum load sections; and daily, monthly, or seasonal variations in demand (Furth et al., 2006). Historically, AVL and APC systems were independently developed for real-time and off-line analysis purposes, respectively. Since a combined AVL/APC system reduces the marginal costs for APC installation by relying on the AVL component for location referencing, it has become more popular.

An automatic fare collection (AFC) system refers to an advanced technology of fare media or collection such as magnetic stripe cards/tickets, and smart cards (also known as integrated circuit or chip card). These fare collection devices record a traveler's boarding and sometimes alighting locations; AFC data also include time stamps for when the transaction occurred. Some AFC systems link the travel behavior to a specific traveler, thereby providing a link between demographic data and traveler behavior. AFC systems enable faster boarding and alighting, more opportunities for ridership data collection, greater security, and finally better understanding of customer market segments using transit service (Multi systems, Inc. et al., 2003; Bagchi and White, 2004).

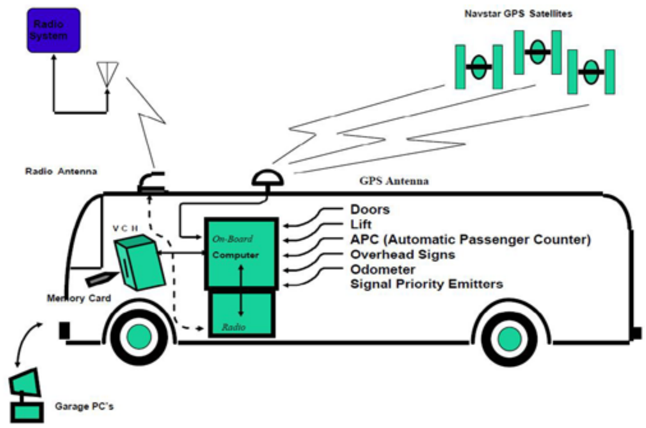


Figure 1-1: Transit boarding and alighting counts using AVL/APC System (Furth et. al. 2006)

The data collected from AVL/APC and AFC systems have great potential to be used as a new or complementary data sources to improve transit ridership forecasting. On the cost side, distributions of transit speed and bus travel times can be directly obtained from AVL data. For passenger demand, AFC systems, especially those linked to demographic information, present the richest data set. However, even in the absence of AFC, APC systems can provide zonally-based, temporally defined ridership counts for individual transit routes. This research considers a method to improve the utilization of new data sources such as AVL/APC systems in transit ridership forecasting models.

1.4 Problem Statement

Travel forecasting models are used to predict the future performance of multimodal transportation systems. There has been a need to improve travel forecasting models, particularly in their estimates of transit ridership. While many challenges exist in developing robust travel forecasting models, particularly mode choice modules, this research concentrates on two sub-problems.

First, as described above, calibrated mode constants are used to generate transit mode shares that reflect the actual modal demands for the time period modeled. These mode constants are then used to forecast mode share over the planning horizon, assuming that all difficult-to-measure cost perceptions remain constant throughout the analysis period. An important question involves the magnitude of the mode constant; if the absolute value is large relative to the measurable cost components, major improvements in system performance (through operational changes or infrastructure investments) may have very small impacts on the likelihood of choosing the improved mode. This research explores several functioning models from various municipalities to understand the magnitude of mode constants.

Next, there is an identified desire amongst modelers to reduce the magnitude of mode share constants by incorporating travel or personal attributes endogenously in the model. Using AVL / APC data, an opportunity exists to explore model prediction errors at a very disaggregate spatial scale – at the TAZ level. This research develops and implements a method to utilize AVL / APC data in the formulation and calibration of more robust utility functions. In order to complete the second objective, innovative methods of converting boarding and alighting data from stop locations to their zonal origins and destinations are necessary. This dissertation presents and evaluates several methods for completing this data structure change.

1.5 Research Objectives

The main objective of this thesis is to enhance the estimation performance of transit ridership through improved calibration procedures of mode choice models in regional travel demand forecasting. Noting an overall need to improve travel forecasting models and their estimates of transit ridership, one concern is around the mode constants used in calibration. To improve calibration procedures, first, we need to understand the mode constants better from state-of-the-art regional travel forecasting models. Accordingly, the first set of research questions is:

1. How big are the mode constants in regional forecasting models? How important are these mode constants relative to the measurable components?

To answer that question, the magnitude and relative importance of mode constants are analyzed using representative data from six cities in North America.

In order to improve the performance of transit ridership forecasting, the issue of insufficient data for both transit system and transit users should be addressed. In recent years, automated data collection systems such as AVL/APC have been implemented in many cities in North America. The direct application of these data to ridership forecasting requires an important intermediary step that links stop activities – boarding and alightings – to the actual location (at the TAZ level) that generated / attracted this trip. This leads to the second research question:

2. How can we link stop boardings (or alightings) to the zones from (or to) which these passengers are actually originated (or destined)?

This research generates four GIS-based methods to complete this linking exercise. Using a very small data set from on an on-board survey, a method is demonstrated on how to select the best performing of these methods.

Having completed the analysis from research question 2, it is then possible to generate transit activity observations – boardings and alightings, as well as mode share – at the zonal level. The observed data can then be compared to the model estimates. Errors in the model's performance are quantified and classified at the zonal level. By classifying the error types – over and under predictions – regression models can be used to identify explanatory variables – both demographic and land use – that may help explain the incorrect predictions. This observation leads to the third set of research questions:

3. By comparing prediction errors at a more disaggregate level, can we effectively identify the source of errors? Can variables which capture these sources of error be explicitly modeled?

To answer these questions, this research proposes a framework which can effectively calculate prediction errors, identify ranges of errors that warrant further investigation, and evaluate the source of errors affecting the accuracy of predicted transit use on a zonal level.

To summarize, the objectives of this dissertation are to:

Obj.1. Examine the magnitude of mode constants using representative data from several cities.

Obj.2. Develop a methodology to assign boardings and alightings at stops to origin and destination zones using APC data.

Obj.3. Develop a framework to effectively assess transit mode share prediction errors and the source of errors affecting the accuracy of predicted transit use on a zonal level.

The successful completion of these three objectives has the potential to improve the understanding of travel forecasting models and to generate more robust estimates of transit ridership.

1.6 Thesis Outline

To achieve the above objectives, the remainder of this thesis is organized as shown in Figure 1-2.

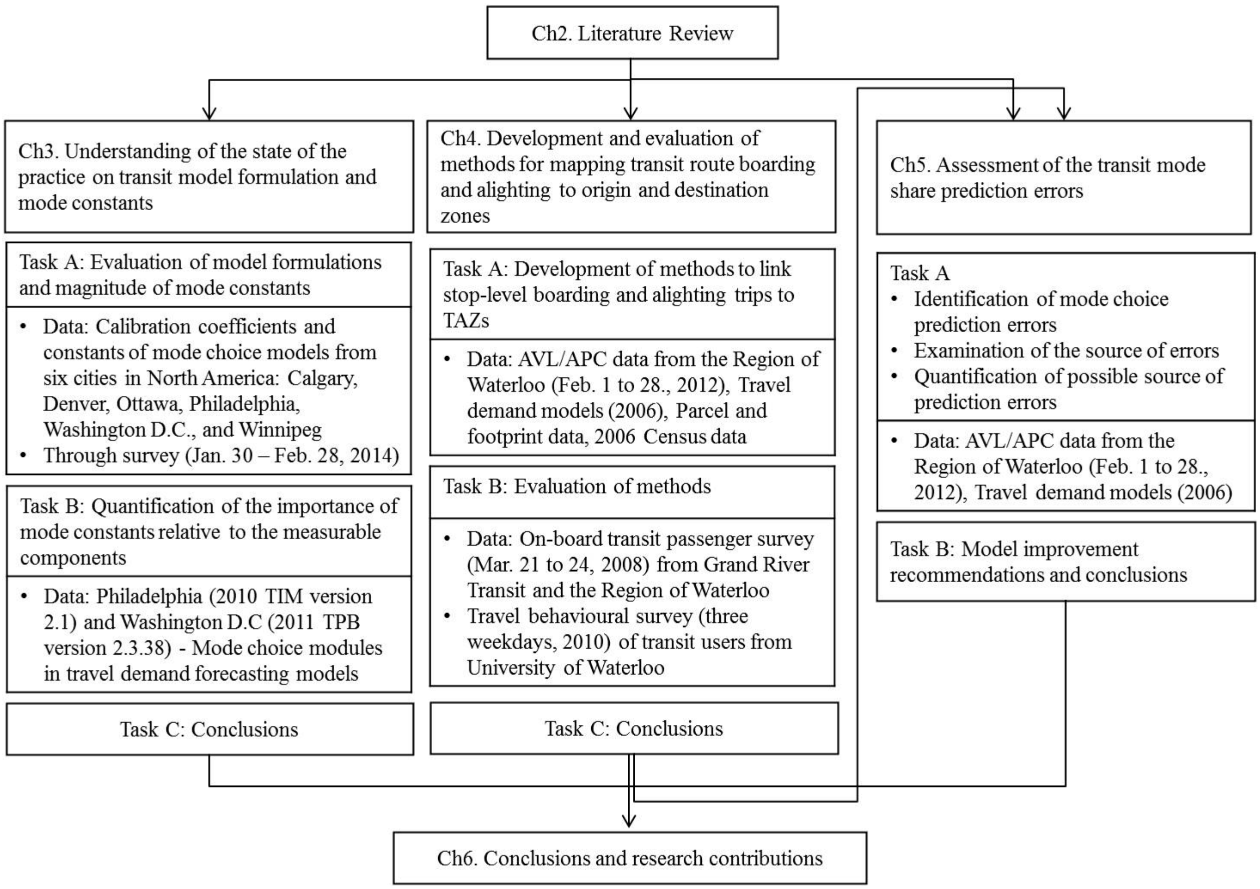


Figure 1-2: Overview flowchart of research

In Chapter 2, conventional travel forecasting models, fundamentals of transit modeling including state-of-the-art mode choice and assignment models are described. Mode constants in these models are presented. Related research linking transit use at stops to their origin/destination zones is identified.

In Chapter 3, the magnitude of mode constants is discussed using representative data from six cities. The magnitude of calibration constants is investigated in terms of in-vehicle time equivalent unit and relative importance of mode constants to the measurable components.

In Chapter 4, methods converting stop-level boarding and alighting trips into TAZ trips are proposed. The accuracy and applicability to regional forecasting models of each proposed method are also tested and discussed.

In Chapter 5, a systematic calibration method to identify and evaluate source of prediction errors of transit use is proposed.

In Chapter 6, conclusions, research contributions and future works are summarized.

Chapter 2

Literature Review

This chapter discusses four issues related to transit ridership forecasting. First, a summary of conventional travel forecasting models, including the four-step model, activity based models, and direct demand models are reviewed. Next, recent advancements in transit travel forecasting models are discussed, focusing on how mode choice models account for taste variation and socio-demographic attributes. A summary of the solution algorithms used for these models is also presented. Third, research on the determinants of transit mode choice - including psychological factors and quality-of-service variables, as well as traditional indicators - is presented. Research associated with mode constants and unobserved attributes in transit modeling is also discussed. The fourth issue identifies and discusses previous studies relevant to assigning stop-level activities to their actual origin and destination zones. The chapter concludes with a summary of the literature reviewed.

2.1 Conventional Travel Forecasting Models

Until recently, the most commonly employed method for travel demand prediction was the traditional four-step model. The basic steps in the model are: to estimate trips generated from and directed to a number of disaggregate spatial areas, or zones; to predict the distribution of these trips between zones; to model the mode by which these trips are completed; and finally assigning these trips to paths or routes they follow (Meyer and Miller, 2001). The four-step model is known to be trip-based; all travel is assumed to contain an origin and a destination. Multiple destination trips, now known as tours, are considered in four step models as multiple decision points.

The main features of a four-step model can be summarized as:

1. A sequential decision process for the traveler, who first chooses a destination, a mode and then a path;
2. An assessment of travel at the trip level, defined as a person or vehicle traveling from an origin to a destination without intermediate stops;
3. An estimate of performance based on the cumulative impact of multiple trips each made for a specific purpose – typically work, school, or shopping;
4. Travel assessments conducted for various times of day, including am/pm peak period, mid-day, etc. (NCHRP, 2012).

In the four-step method, mode choice and traffic assignment are important steps in the estimates of transit demand. The mode choice process involves the computation of demand for each available mode based on the relative cost of completing a given trip by each mode. The traffic assignment step determines the actual highway path (for auto trips) and transit route(s) for public transport trips. A widely recognized weakness of the four step model is in the representation of travel decisions as a sequential problem. For example, the effect of congestion is not reflected in the initial destination choice and mode choice since traffic assignment lies in the last step. To correct this weakness, many four step models now incorporate 'feedback' of travel time (Boyce, 2003) where output travel time is iteratively used to rerun the trip distribution and mode choice steps until a successful convergence (Vuchic, 2005).

2.1.1 Activity based models

While trip-based models had been the dominant modeling approach for several decades, tour- and activity-based models have been developed and increasingly implemented in recent years particularly for large urban areas. The move from the traditional four-step model is motivated by both improved understanding of travel behavior as well as changing public objectives. Contemporary transportation policies in North America have shifted away from addressing congestion through increased infrastructure and capacity for many reasons. The emphasis in transportation planning now tends to focus on strategies to manage demand and incent more sustainable modes. Evidence of these changes includes requirements for mixed land use development, the introduction of economic disincentives for automobiles like congestion or parking pricing, and greater emphasis on accessibility. To evaluate the effectiveness of these policy changes in achieving improved system performance, it becomes necessary to understand travelers' behavior and response to system changes more accurately. The activity- or tour-based models are more suitable for these disaggregated analyses than the conventional trip-based 4-step models.

The U.S. National Cooperative Highway Research Program (NCHRP) report 719 summarizes the five major characteristics of activity-based models as follows:

1. focusing on modeling activity participation (at different points in space and time);
2. using a 'tour' based structure which is defined as a chain of trips beginning and ending at a same location (e.g., home or work place);

3. viewing individuals' activity-travel patterns as a result of their decisions on time use subject to their socio-demographic, spatial, temporal, transportation system constraints;
4. accommodating interactions and joint activity participations among individuals in a household; and
5. simulating the activity-travel patterns of each individual using a microsimulation.

In practice, activity-based travel model systems consist of three major steps: population synthesis, long-term decision-making (e.g., residential location change, auto ownership change, etc.), and activity-based travel models.

Despite the advancement from trip-based to tour-based models, the sophistication of modeling transit components has not yet evolved substantially. The likelihood of a traveler using transit for some part of a tour still depends on a comparison of costs amongst available modes. The use of microsimulation does enhance the representation of measured cost components but does not allow for the quantification of more difficult to measure travel components.

In general, the ability of tour-based models to better represent transit remains an unanswered question. The literature reports that the traditional models are superior in mid- and small sized cities to tour-based models (NCHRP, 2012). In addition, the research on comparison between the four-step and tour-based models (Ferdous et al., 2012) suggests that trip-based models generate superior results to tour-based models at a project-level when additional behavioral and network data are not provided. Both models generate overall the same level of accuracy in a regional-level comparison. An SHRP2 (Strategic Highway Research Program of U.S. Federal Highway Administration) task force further evaluates the capabilities of the two modeling approaches (NCHRP, 2012). While activity-based models are currently implemented partially across Canada and the United States (TMIP, 2011), large-scale activity-based models still lack some system integration of each model component. Moreover, in practical applications, many researchers believe that more studies need to demonstrate their theoretical advantages outweighing their complexities (TMIP, 2013).

2.1.2 Data driven models – STOPS (Simplified Trips-on-Project Software)

As an alternative to regional models, some users of travel forecasting models (e.g., Federal Transit Administration in the U.S. and the UK department for Transport) have recently begun to evaluate and employ data-driven techniques due to cost-effectiveness and some evidence of superior estimates (particularly, in the areas of transit ridership forecasting, pricing policy analysis) when compared to conventional regional travel models.

Data-driven approaches are frequently applied in areas where the existing data on travel demand patterns may be used directly to forecast future behavior. These techniques are also known as incremental forecasting models. The approaches work as follows (Woodford, 2013): (1) conduct a large scale Origin-Destination survey of potential users, (2) construct mode-specific person trip tables, (3) assign person-trip tables to the networks, (4) using demographic information for the base and forecast year, scale OD survey information to represent future conditions, (5) utilize the elasticity or incremental logit models to evaluate alternative future-year mode choice, and (6) assign future trips to report volumes/ridership for individual facilities.

Specifically, FTA (2013) has invested in the development of STOPS (Simplified Trips-on-Project Software) to prepare forecasting of transit passenger trips for proposed transit projects. STOPS is a simplified version of a conventional 4-step travel model. The software considers zone-to-zone travel markets, employs conventional mode-choice models to predict zone-to-zone transit travel, and assigns the transit trips into fixed guideway transit networks including (heavy, light, commuter) rail and bus-rapid transit facilities. On the other hand, STOPS replaces the following standard steps of (FTA 2013, RSG, 2015):

- trip generation and distribution steps with worker-flow tabulations from the Census Transportation Planning Package (CTPP, soon, the American Community Survey) to explain overall travel markets and patterns,
- coded transit network with transit-services data in the General Transit Feed Specification (GTFS) format developed by local transit providers to support mobile and on-line transit trip-planning applications.

To enable forecasts in different years, STOPS scales the trips patterns to population and employment estimates provided by the user, and allows modification and addition of General Transit Feed Specification (GTFS) data. Unlike regional travel models, STOPS does not include any representation of the roadway network and does not assign predicted automobile trips to any network. STOPS relies on zone-to-zone roadway travel times and distances derived from the regional travel model for both the current year and the future year. Therefore, STOPS only computes the change in automobile person-miles of travel resulted from shifts of trips from auto to transit. In addition to its capability, several limitations of the STOPS model should also be recognized (FTA, 2013):

- Since STOPS entirely relies on the regional travel model for information on roadway travel times and distances, it is not suitable for use the model for local-bus planning studies, highway studies, or air-quality conformity analysis.
- STOPS focuses on routine weekday travel by residents of the metro area and does not deal with special market, for example, college students or air passenger, etc.

Overall, for data-driven approaches, significant effort is concentrated on adjusting / correcting the OD matrix and network processing procedures to generate sufficiently accurate results. Although this is not a trivial task, the level of effort is typically much less than that required to calibrate and to validate conventional regional travel models. STOPS can be a useful alternative, particularly to evaluate and rate transit projects for project sponsors when locally maintained methods are unavailable. Further, STOPS can serve a quality-control purpose, providing a second ridership forecast for comparison to a forecast prepared with locally maintained methods.

2.1.3 Direct demand models

When estimates of boardings and alightings are necessary for individual transit routes or stops, practitioners and researchers often employ direct-demand models that estimate these values as a function of measurable station area attributes. For example, Kuby and Upchurch (2014) evaluate actual light rail transit (LRT) ridership versus predicted station boardings using direct-demand regression models in Phoenix. The explanatory variables include station-specific trip generation variables (e.g., employment and population), intermodal connectivity (e.g., airport, park & ride, bus line connecting) and network location (e.g., terminal, transfer, and centrality). Zhao et al. (2014) include CBD dummy variables and bicycle P&R in direct-demand regression models. Although direct-demand models have some advantages over four-step models, specifically greater sensitivity to station-area effects, researchers usually consider these kinds of models as sketch-planning tools for pre-feasibility study (Kuby and Upchurch, 2014).

The common elements for all of these modeling paradigms are a need to accurately represent travel cost, travelers' perception of these costs, and ultimately a choice among travel alternatives. The underlying assumptions of the discrete choice problem are reviewed here.

2.2 Fundamentals of Transit Modeling

Common themes around improving transit travel forecasting in recent studies include disaggregation (or individualization in more recent years), and interactions between demand and supply. The former is the result of research efforts in travel behavior analysis in disaggregate mode choice models and multiclass/multimodal assignment, while the latter stems from the improvement of solution algorithms including feedback mechanisms and combined modeling. This section begins with a comprehensive overview of the evolution of mode choice models.

2.2.1 Mode choice models' frameworks and taste variation

Random utility models attempt to quantify the likelihood of a certain choice amongst alternatives based on both the characteristics of the alternatives and the decision maker. The models are broadly divided into three categories: Multinomial Logit (MNL), Multinomial Probit (MP), and Random Coefficient (or Mixed Logit) models. What differentiates these model formulations are specific assumptions about the distribution of random error terms (Ben-Akiva and Lerman, 1987, Ortuzar and Willumsen, 2001); a second differentiating factor is the ease with which solutions are generated for these models. MNL models have the advantage of generating choice probabilities with a simple closed form solution but the theoretical foundation of the model assumes the so-called "independence of irrelevant alternatives" (IIA) property. Simply stated, the IIA assumption requires that irrelevant alternatives that are excluded from the choice set do not influence the performance of the model. In transportation analysis, this assumption does not always hold true, yet practitioners often overlook this shortcoming due to the simplicity of the solution methods. Further, since MNL models assume that the coefficients of all attributes are the same for all respondents, they are particularly problematic when taste variations exist among individuals.

To overcome the IIA property, Multinomial Probit (MNP) models have been considered as an alternative choice model. Since MNP models have a flexible pattern of error correlation structure which is assumed to be normally distributed, these provide a general framework that allows for the interdependence of alternatives. Min (2007) suggests that there are some issues with MNP models: although MNP models are fundamentally more flexible than multinomial logit models, they are considered more difficult to apply in practice due to their computational complexity. MNPs require computation of multiple integrals without a simple closed-form solution. However, steady improvements both in estimation algorithms and simplification of the covariance matrix have encouraged the application of MNP models.

Some studies have shown that Random Coefficient Models (RCM) - also known as Mixed Logit (ML) models - offer solutions to the problems identified in both MNL and MNP models. RCM models tend to be computationally less complex but are still able to account for taste heterogeneity across individuals in a relatively simple way. In RCM, the weightings of individual utility parameters (e.g., time components and individual preferences) are treated as stochastic by dividing the random error terms into two uncorrelated parts. These parameters are (1) correlated over alternatives and individuals (i.e., flexible components similar to those used in Probit) and (2) independent and identically distributed over alternatives and individuals (Hensher and Greene, 2001, Walker, 2001).

Cherchi and Ortuzar (2003) discuss methods of accounting for taste variation, particularly focusing on random-parameter specification versus the inclusion of socio-economic (SE) characteristics. SE variables are commonly added to utility functions as alternative-specific variables. The authors argue that the conventional method of adding SE variables in a linear-in-the-attributes structure is not theoretically justified. Although this specification certainly influences the total utility associated with its alternative and the difference between options, it does not have any influence on the marginal utility of the level of service variables and value of time. The introduction of SE variables that interact with LOS variables shows better results. Further, in their context, fixed parameter models with interaction terms of socio-economic and LOS variables are notably superior to RCM models in terms of explaining taste variations.

Similarly, Bhat (1997) points out that since RCMs do not systematically consider taste variations, the models cannot be considered as a substitute for the careful identification of systematic variations in the population, nor can they be considered as an alternative approach to account for heterogeneity in choice models.

2.2.2 Market segmentation for systematic taste variation

One approach to more systematically capture taste variation is to estimate mode choice models with market segmentation (MS) techniques. MS in travel forecasting typically refers to the subdivision of a market that is relatively homogenous in terms of traveler characteristics and types. Within each segment, individuals are assumed to have identical preferences and sensitivities to all the variables in the utility function (Bhat, 1997). Two basic approaches to segmenting markets include (1) pre-determined *(a priori)* segmentation, and (2) market-defined (post-hoc) segmentation. Pre-determined segmentation involves selecting certain groups from a population based on past research or common sense. On the other hand, market-defined (post-hoc) segmentation identifies sub-groups based on the analysis of surveys in order to predict market responses (Elmore-Yalch, 1998).

Pre-determined segmentation has often been applied in trip-based regional travel forecasting models using socio-economic variables (e.g., income, car ownership, household structure, age), trip characteristics (e.g., trip purpose, trip distance), and geographical attributes (e.g., CBD ends). The challenges associated with pre-determined market segmentation include: a lack of *a priori* knowledge of the correct segmentation methods; exponential growth in the combinations of market segments; and the cost of collecting sufficient data to calibrate multiple segment utility functions. Moreover, as Elmore-Yalch (1998) suggests, in the dynamic and unstable social environment of recent decades, pre-determined segmentation should be used carefully in transit travel forecasting. There is increasing diversity amongst travelers' behaviors and those segments that are thought to be homogeneous today, may not remain so in the period over which the model is applied.

The market-defined (post-hoc) segmentation method should also be used cautiously. Elmore-Yalch (1998) describes three main challenges of the market-defined segmentation method as follows. First, the cost is often greater than that of using the *a priori* method. Second, it is difficult to understand the specific criteria used to assign a respondent to a certain segment. This is associated with the use of multivariate analysis techniques such as factor or cluster analysis. Third (and most importantly), one cannot know several key factors (e.g., number and size of the segments, stability, and homogeneity) until the data have been gathered and analyzed. Accordingly, the market-defined segmentation begins with the development of a certain hypothesis (e.g., persons who are concerned about the environment are more likely to use transit). Hence, there is always a possibility of poor segmentation resulting from a poorly-defined hypothesis.

To overcome these problems, more quantitatively-rigorous approaches have been formulated to deal more effectively with market segmentation. Structural Equation Modeling (SEM) can help identify the most appropriate segments to monitor. SEM has been applied in some transit ridership estimation research. Ben-Akiva et al. (1999) were amongst the first to apply SEM to study railways in the Netherlands. The authors estimated the importance of comfort and convenience by linking known traveler information (i.e. age) and journey (i.e. travel time, transfers, and class of seating) attributes with stated perception of mode properties (i.e. safety, reliability, flexibility of departures, ease of travel etc.). Significant differences in the relative importance of typical generalized cost variables – for example, travel time and the number of transfers – exist between the model that includes “latent” variables and the model that does not. The former has much better goodness of fit.

Outwater et al. (2003) take a similar approach to estimate ferry ridership. The SEM captures the causal influence of the exogenous variables (socio-economic status) on the endogenous variables (attitudinal statements) through sets of underlying attitudinal factors (e.g., desire to protect the environment, the need to save time, the need for flexibility, sensitivity to travel stress, insensitivity to transport cost, and sensitivity to personal travel experience). The authors define eight market segments by deploying SEM. The results show that the stated preference model, combined with attitude and market segmentation data, improves the accuracy and explanatory power of mode choice and ridership forecasting models.

2.2.3 Evolution of solution algorithms in transit travel forecasting

In large-scale regional travel forecasting models, another common theme to improve transit ridership forecasting is the representation of mutual responses between supply and demand. Here, the supply refers to the provision of facilities (e.g., transport infrastructure and services) for performing activities. The demand refers to requirements for services (e.g., travel demands, travel patterns between locations) at a specific location (Boyce, 1986). In this section, methods of representing feedback mechanisms within travel forecasting procedures are explored.

In the mid-1990s, there was a broad consensus about the need for solutions to the well-known problem of inconsistent travel impedances within travel demand models. Recall that the four-step model sequentially estimates: trip generation and attraction; trip distribution; mode choice; and finally assignment. This approach has the fundamental weakness that the actual costs to complete travel are not known until assignment, therefore approximations are made for the first three steps. These initial approximations are often poor representations of final costs. One approach to solve this inconsistency between initial and final levels of service is to provide a feedback loop that iterates through trip distribution, mode choice, and traffic assignment (with or without a successive averaging step) until some convergence criteria are met (Lan et al., 2003). Accordingly, solving for feedback convergence involves achieving a close match between the origin-to-destination congested travel times used in applying travel model components and those that correspond to the ultimate assigned ink flows (Slavin et al., 2015).

Boyce et al. (2008) compare three alternative feedback conditions: (1) providing direct feedback (i.e., no averaging of trip matrices or link flows); (2) averaging of trip matrices with constant weights, and (3) applying the Method of Successive Averages (MSA) to an existing travel forecasting model from Albany, NY. Averaging the trip matrix using constant weight values produce stable and highly converged solutions.

The other approach is to solve trip distribution, mode choice, and trip assignment simultaneously. This is referred to as a combined model. These models address the effects of congestion by determining transport cost endogenously. The combined models use mathematical programming (i.e., linear or non-linear programs) under the framework of minimizing cost (Chang, 2006). Evans' (1976) partial linearization algorithm became the principle basis for the majority of combined-model research, while a full linearization algorithm was advocated by Florian and Nguyen (1975) and a route-based algorithm was suggested by Lundgren and Patriksson (1998). Florian has contributed to network equilibrium research with variable demand. Many of his methods during 1970s were implemented in EMME/2, and emphasized transit modes (Boyce and Bar-Gera, 2004, De Cea et al., 2008).

An interesting extension of the combined-model research in recent decades involves the incorporation of multiclass and multimodality of origin-destination, mode, departure time period, and route choices (e.g., Florian et al., 2002, Boyce and Bar-Gera, 2004, De Cea et al., 2005). Conversely, conventional combined models assume one homogenous user group. This technique is useful for applying models to large-scale urban areas. For instance, Boyce and Bar-Gera (2003) estimated and validated a multiclass, multimodal combined model at the same level of detail used by transportation planning professionals in the Chicago region. The result was a large-scale combined model in terms of the number of zones (1790) and road network size (12,092 nodes; 39,018 links). De Cea and

Fernandez (2001) developed a performance-demand equilibrium model to forecast passenger and vehicle flows in multimodal urban transportation networks with multiple user classes where demand models have a hierarchical logit structure. This research led to the development of ESTRAUS and related software. In many respects, it was considered to be one of the most detailed multiclass combined models implemented at the time of its creation. The implementation for Santiago had 13 user classes, 3 trip purposes, 7 pure transit modes and 4 combined modes (Boyce and Bar-Gera, 2004).

An overview of relevant research about mode choice models and solution algorithms in large-scale regional travel forecasting models has been provided in the above section. The aforementioned mode choice models and solution algorithms have been widely implemented in contemporary transit travel forecasting practice, including the regional travel forecasting models discussed in the case studies of this thesis.

2.2.4 The transit assignment problem

Transit assignment is also known as transit path choice problem. The ultimate goal is to understand and model how transit travelers choose:

- An appropriate boarding stop near to the actual trip origin;
- A specific route from the set of routes serving the chosen stop;
- A specific vehicle (or departure) amongst all departures from the chosen stop on the chosen route;
- An appropriate destination station (or transfer location) based on the choices made above and the ultimate trip destination.

As with all components of travel forecasting models, the most important premise of transit assignment models is that a traveler chooses a cost-effective path to complete his journey. To this end, the traveler selects amongst a choice set the combination of stops, vehicles and departures that minimizes the disutility. In early models, these costs were estimated using simple, single path representations (Dial et al., 1967, Fearnside and Draper, 1971, Le Clercq, 1972). Yet, in the transit assignment problem, the cost structure – including access time, wait time, in-vehicle time, transfer time and egress time – is very complex and dependent the choice set. Moreover, the solution set is very complex in space – the number of stops and route alignments – and time – the number of possible departures / arrivals. The traveler behavior also depends heavily on several difficult-to-quantify attributes including: the traveler's knowledge of the system (i.e. personal knowledge of choice set); real-time information on system performance (reliability or vehicle loading); and passenger attributes (risk tolerance, trip purpose). Finally, the transit assignment problem may be considered static – once a path is chosen, the traveler does not revisit the choice set – or dynamic – where a traveler may deviate from the original choice and make a subsequent travel decision while in route.

The complexity and quality of models for transit assignment have been evolving over time. A first, important distinction was made by differentiating stops that were served only by a single route and those stops that were served by multiple routes. For the latter case, the so-called common-line situation was defined. For a stop served by multiple routes, only a subset of these routes may be considered "attractive" to the traveler in terms of the destinations served and the total travel time to connect to destination(s). Thus, a traveler departing from a stop with common lines choice set is limited to attractive departures (Spiess and Florian, 1989).

In recent years, the effect of additional information on passengers' path choice behaviors has been discussed. In the presence of reliable, real-time information, for example, remaining waiting time for a certain service, a passenger's behavior can be different; whether to board the coming run of a line, waiting for the next run for the same line or another; or transfer to any of alternative services. Nokel and Wekeck (2009) discussed these issues with several comparative scenarios of information affecting passengers' choice behaviors. They demonstrate that different assumptions result in diverse models of route choice on both boarding and alighting, and produce different splits of passenger volume into different paths.

Contemporary models also consider the issue of vehicle capacity and seat-availability. In highly utilized systems, the concept of failure-to-board (due to capacity limitations) has been paid growing attention in path choice models. As Fu et al. (2012) summarize, methods are utilized to monitor demand relative to capacity and when capacity is reached, additional boardings are prevented (Lam et al., 2002, Teklu, 2008, and Hamdouch and Lawphongpanich, 2008). More sophisticated models also include specifications as to who has the priority of being seated (Hamdouch et al., 2011, Leurent, 2012). In these models, the different travel discomfort experienced by standing and sitting passengers are also quantified producing in-vehicle time costs that are formulated differently and, as a result, produce different behaviors.

Moreover, because transit service reliability also significantly affects passengers' trip decisions as well as their perceptions on transit service, journey time variability (i.e., a reliability measure) is employed in some studies (Szeto et al., 2011, 2013). In these studies, it is observed that the journey time variability is in effect for not only in-vehicle time and wait time, but also walk and other stages of a journey. However, as Szeto (2011) pointed out the effect of variations of generalized journey time is not given much treatment into the decision of route choices in the existing transit assignment models.

The current state-of-the-art practice in transit assignment includes those considerations listed above in one of two overarching approaches. Fu et al. (2012) describe frequency-based (also termed as headway- or line-based) models as those that assume travelers will choose the first arriving (attractive) vehicle from an origin stop. This formulation typically applies to those transit travelers who are less familiar with a network and its performance. The second approach is known as schedule-based (also termed as timetable- or run-based); in this case, travelers select a specific departure vehicle based on its overall properties – total travel time, arrival time, or reliability.

In the frequency-based approach (Cepeda et al., 2006, Nokel and Wekeck, 2007), for single line stops, the wait times for passengers can easily be estimated as a function of the headway. For short headways, the common practice is to assume wait times of one-half the headway. For common line stops, wait times normally vary as a function of the proportion of total departures that are attractive departures.

The schedule-based model structure (Poon and Tong, C.O., 2004, Nuzzolo and Crisalli, 2009) inherently includes specific time stamps for each vehicle in the system. The transit network also represents run-based spatio-temporal graph that shows individually serial runs as scheduled in timetables and competitive lines (Fu et al., 2012). As a result, this approach is computationally more expensive. Wait times in scheduled based models can be developed to reflect system reliability as well as disparate attributes of the traveler.

To conclude, this subsection describes the transit assignment problem. Over time, modeling efforts have evolved from simple, time-based cost estimates to complex models of behavior that reflect a number of system and traveler attributes. Contemporary models attempt to include transit reliability and capacity limitations, sometimes in the presence of real time information.

2.3 Mode Constants and Unaccounted-for Attributes

The concept of mode constants is introduced in the previous chapter. In this section, mode constants identified in the literature will be discussed further.

2.3.1 Mode constants in regional travel forecasting models

De Witte et al. (2013) identified determinants of mode choices from 76 research papers in the US, Europe, and other areas. Among the research studies the authors reviewed, 64 papers included public transport modes, the focus of this study. As shown in Figure 2-1, the authors classified each determinant of mode choice into a number of categories.

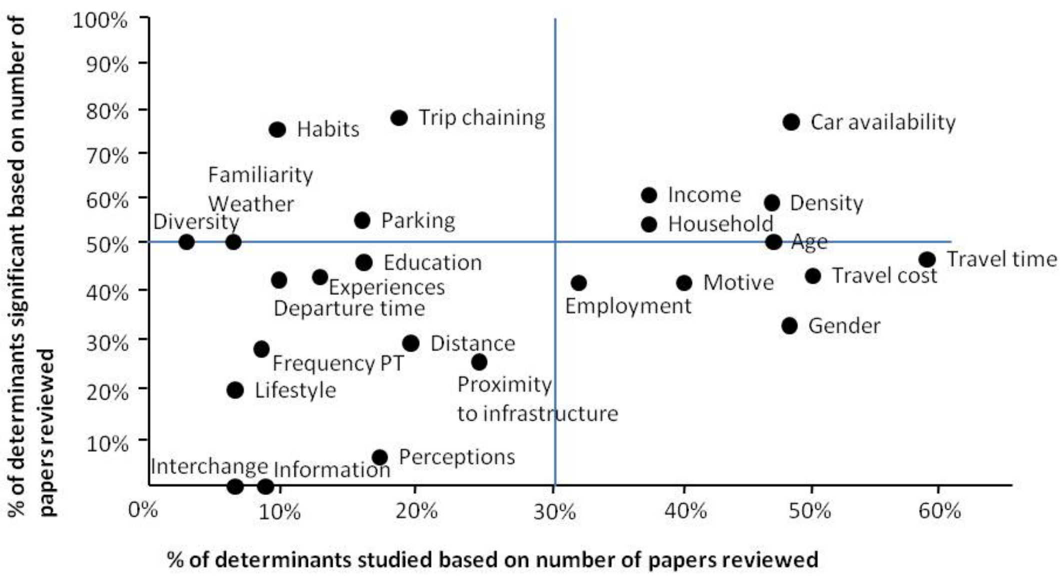


Figure 2-1: Classification of modal choice determinants based on number of papers reviewed (A. De Witte et al., 2013)

The horizontal axis indicates whether a determinant is commonly studied, and the vertical axis shows whether a determinant is frequently recognized as significant. The variables belonging to the right-hand side of the graph (i.e., car availability, income, density, age, gender, employment, travel time and cost) are traditional determinants of socio-economic characteristics and level of service. Overall, these indicators were proven to be significant (i.e., they were identified in over 30% of the studies the authors reviewed). On the other hand, habits, familiarity, and experiences (which appear in the upper left area of the graph) have been understudied, despite their tendency to significantly influence mode choice decision.

Thus, these level-of-service or measurable attributes alone do not adequately account for the variation in mode choice behavior. In functional regional travel demand forecasting models, to deal with these errors, mode constants are added to (or subtracted from) the generalized cost (GC) of a given mode in the model. The justification for these mode constants is to include those immeasurable cost components that a traveler considers but are not explicitly included in traditional GC expressions.

However, the use of mode constants without representing other qualitative or difficult-to-measure attributes creates some problems (FTA, 2006, Outwater et al., 2014). One is that any error introduced in other stages (e.g., person-trip tables, highway and transit networks, observed transit ridership patterns) of the regional travel forecasting procedures can be incorporated in the mode constants. The second problem is associated with project evaluation regarding user benefits. User benefit criteria defined by FTA in the U.S. has been a measure of the difference in the aggregate utility of different alternatives. Heavy reliance on mode constants has been shown to bias to this measure (Outwater et al., 2014). Due to the problems, recently, the project evaluation criteria regarding user benefits of FTA have been adjusted to use the number of trips on the project made by transit dependent persons (FTA, 2013).

One way to improve mode choice models and heavy reliance on mode constants is to account for difficult-to-measure attributes and develop methods to include them exogenously in regional travel forecasting models. These research efforts will be described in the following section.

2.3.2 Accounting for difficult-to-measure attributes

One of the research streams on mode constants focuses on accounting for difficult-to-measure attributes in mode choices. The research has attempted to demonstrate that the influence of unobserved factors (i.e., magnitude of mode constants) may be reduced.

Domarchi et al. (2008) take into account psychological factors - including attitudes, habits, and affective appraisal – on mode choice and attempt to add them into Multinomial Logit (MNL) models. Using revealed preference (RP) survey data, Domarchi et al. (2008) incorporate these factors through dummy variables (i.e. high, medium, and low propensities to use cars and public transport, positive/negative emotions toward each mode, etc.) in utility functions. Results show that when factors were added to the discrete choice model framework, the fitness and statistical significance of these models were improved. With the inclusion of habit variables, mode constants reduce their relative importance. Similarly, Cherchi and Manca (2011) analyze the issue of accounting for inertia effects. Inertia represents the tendency of individuals to be consistent with their past choices when they are faced with new situations. Some indicators of inertia (or habits) include car availability, miles travelled, seasonal public tickets, and number of trips per week.

Evans et al. (1997) present a quantitative approach to incorporating the effects of the transit access environment into a transportation planning model. The authors define a “transit friendliness factor” (TFF) which varies as a function of the characteristics of the station area, including pedestrian-friendly design (e.g., sidewalks, street crossing) and appropriate station amenities (e.g., presence of benches, shelters, bicycle racks, lighting etc.). TFF in the future year is defined as the average change in population and employment density. The authors demonstrate a sizable reduction in the mode constants for transit as a result of the inclusion of the transit friendliness factor in mode choice models.

Outwater et al. (2014) identify and quantify traveler behavior that affects the use of premium transit services (i.e., fixed guideway systems) in different urban contexts, including Salt Lake City, Chicago, and Charlotte. The authors categorize three important attributes that are not traditionally included in mode choice models: Station/stop design features (e.g., real-time information, security, shelter, etc.), on-board features (e.g., seating availability, seating comfort, cleanliness etc.) and other features (e.g., reliability, schedule span, and others). They also demonstrate how premium transit service attributes can be incorporated into travel models. The authors concluded that the combined importance of all premium service characteristics (both for commute and non-commute trips) is between 13 to 29 minutes of in-vehicle time. However, as expected, considerable variation exists in the importance of the premium service attributes among different cities.

Hensher et al. (2003), Litman (2007), Casello et al. (2009) have all quantified the reliability of transit services. Hensher et al. (2003) estimates that an additional minute of delay is equivalent to 2.1 additional minutes of in-vehicle-time, while Litman (2007) suggests an additional minute of unexpected delay is 3.7 times the cost of an additional minute of in-vehicle-time. Casello et al. (2009) evaluated the impact of unreliable service on generalized transit user costs using a simulation model of bus arrivals and passengers’ desired arrival times. The results show that increasing reliability of station arrivals can decrease a transit user's generalized costs significantly, by as much as 15%.

Douglas et al. (2006) quantify station/stop comfort by considering cleanliness, the presence of shelter, availability of seating, and the caliber of the station itself. To quantify the importance of each of these attributes, the authors take the following approach. For each variable, the authors quantify the percent improvement that would produce an equal reduction in generalized cost as a 10% reduction in travel time. In essence, this is an elasticity calculation. The results are that station amenities would need to be improved by 19% in terms of cleanliness, 17% for station structure, 7% for shelter, 5% for seating, and 5% for the platform surface. In this case, cleanliness of the station is nearly twice as important as the in-vehicle time.

Real-time information is known to reduce the costs (specifically perceived time costs) associated with wait time and transfers. Spitz et al. (2007) in a study of New Jersey BRT estimate the value of real-time information as equivalent to a 5-minute reduction of in-vehicle time. In the same study, Spitz et al. (2007) also quantify safety improvements. Adding surveillance cameras and emergency call buttons are the most highly-valued attributes, equivalent to a 7-minute improvement in in-vehicle time in the analysis of 11 New York City train stations.

However, it should be noted that some of these values, particularly for quality-of-service attributes, significantly depend on the context, as implied by Outwater et al. (2014). For example, reliability and real-time information in suburban areas with low-frequency transit services may be more highly valued compared to large urban areas with high-frequency services.

2.3.3 Implementation of difficult-to-measure attributes in regional travel forecasting models

These studies have successfully measured difficult-to-measure attributes such as habits, experiences, perceptions, the transit-access environment, reliability, real-time information, safety, and comfort. However, in most practical implementations, practitioners have attempted to account for the aggregate impact of all unmeasured attributes rather than focus on the particular attributes. Outwater et al. (2014) summarized case studies on application methods of unmeasured inputs into regional travel forecasting models as shown in Table 2-1.

Table 2-2: Model application of difficult-to-measure attributes in regional travel forecasting models (Outwater et al., 2014)

	Case study	Attributes	Model Application	
			Phase	Technique
1	FTA New/Small Starts Modeling Guidance	Reliability, branding, visibility, learn-ability, schedule-free service, hours of frequent service, passenger amenities	Mode Choice	Incremental bias constant
2	TCRP 118-BRT Practitioner's Guide	Running ways, station amenities, vehicle attributes, service patterns, ITS applications and branding	Post-model	Percentage adjustment to ridership
3	Chicago Transit Authority & Metra New Starts Alternatives Analysis	Walk-ability, unmeasured rail preferences	Auto ownership, path-building, mode choice	Utility variable, travel time discount (15%)
4	Discounted travel time coefficient (models for Denver Regional Transportation District and New York Metropolitan Transit Authority)	Sum of all unmeasured LRT attributes	Mode Choice	Discounted travel time coefficient (30% for Denver, 25% for New York)
5	Southeast Florida Regional Planning Model (ver. 6.5)	Sum of all unmeasured premium mode attributes	Mode Choice	Incremental mode-specific bias constant
6	Lower Manhattan-Jamaica/JFK Transportation Project	Seating availability	Mode Choice (suggested)	Utility variable
7	Chicago Transit Authority Smart Card Activity Analysis	Revealed bus vs. rail preference	Mode Choice (suggested)	Discounted travel time (42%) and wait time coefficients (34%)

As presented in Table 2-1, only one case study of Lower Manhattan-Jamaica/JFK Transportation Project includes specific seating availability attribute in travel models directly.

One approach for the regional travel model implementation of these variables involves adopting lump-sum mode constants as FTA New/Small Starts Modeling Guidance (2007) and Southeast Florida Regional Planning Model (ver. 6.5) in Table 2-1. This method uses incremental values according to detailed transit modes (e.g., light rail, arterial BRT, peak commuter rail, heavy rail, and streetcar, etc.). In the FTA modeling guidance for the New/Small Starts programs, they allow for the maximum adjustment of unmeasured attributes for planning for guideway transit. The unmeasured guideway attributes are categorized into three factors: (1) guideway-like character (e.g., reliability, visibility, schedule-free service), (2) span of good service, and (3) passenger amenities at stations. When systems are constructed with high reliability, high frequency, service throughout the day, and well designed-stations, the modeler may credit this system with reductions in generalized costs - i.e. positive utility for these features. The credits can range up to 8, 3, and 4 minutes respectively for each category, or a maximum total of 15 minutes.

Alternatively, instead of adjusting mode constants in regional travel models, the FTA (2007) allows for up to a 20% discount on perceived travel time for well-designed transit. However, applied values from empirical studies are reported to range from 15% to 42% as shown in the case study of Chicago and New York (case study number 3, 4, and 7) in Table 2-1. In the same table, Kittleson & Associates, Inc. et al. (2007) in the TCRP report 118 apply a percentage-based ridership bonus for BRT services of up to 25% considering time, frequency, and cost, to account for the perceived benefits of various BRT amenities.

Chen and Naylor (2011) explicitly include the BRT mode in their regional demand model. While many agencies in North America consider the BRT mode constant to be the same as LRT or local bus in their models, Chen and Naylor (2011) derived new BRT constants from SP survey. The inclusion of the BRT mode constant gives BRT ridership a variation of approximately 15% (higher or lower), compared to the result of applying a local bus or LRT constant to BRT.

Outwater et al. (2014) conducted an implementation test with premium transit service. Instead of revising mode choice models for the non-traditional attributes, the authors revised mode choice by manipulating the costs associated with certain transit path choices. Credits were given for "premium" service and additional costs were added to lower-quality service. The magnitudes of the credits or charges were derived using survey data from Chicago and Charlotte. Although the results showed that the inclusion of premium service attributes could reduce the influence of unobserved variables in mode choice, transit ridership forecasting errors were higher compared to those in existing models. Moreover, the FTA (2007) reported that the usage of the credits (i.e., direct adjustment of mode constants) is more likely to result in an overestimation of the guideway-mode forecast for initial projects than forecasts for system expansion. When the lump-sum credits (of difficult-to-measure attributes) are directly incorporated into the utility functions, the adjustment leads to higher ridership on these guideway modes. Accordingly, the guidelines recommend that credits be applied only in the estimation of user benefits, and not for ridership forecasts.

Although some case studies incorporating difficult-to-measure attributes in regional travel forecasting models have been conducted in recent years, their application results have demonstrated only partial success in terms of transit ridership prediction accuracy. Further study is necessary to quantify and include difficult-to-measure attributes in regional travel forecasting models without compromising transit travel forecasting accuracy. To this end, the goals of the research presented here are to quantify the magnitude of mode constants in several operating travel forecasting models and to explore the use of AVL/APC data as means to reduce these constants.

2.4 Spatial Aggregation of Stop-level Activities

As introduced in Chapter 1, one of the challenges of deploying AVL/APC data for mode choice in regional travel forecasting models is the lack of proper analytical methods to link stop activities to the actual zones in which they occur. Some researchers (Furth et al., 2006, Wilson et al., 2009, Nassir et al., 2011) have noted that it is necessary to convert on-off counts at stops into trips in traffic analysis zones (TAZs) in order to use AVL/APC/AFC data for travel demand modeling. Nassir et al. (2011) suggest that stop-level Origin-Destination estimation should be expanded to a zone- or parcel-level since the activities originate not from a stop but from home or attraction points. Wilson et al. (2009) also indicate that the path choice modeling approach can be extended to the full transit path choice problem (including access and egress links) by using home and work address information that may be available for smart card holders. However, very few research efforts have been made on this subject.

Another challenge in the use of these new data sources involves producing full trip information. Transit systems in North America typically require payment at boarding. Thus, information can be gathered on a user's boarding point. But, without requiring a passenger to "tap out" - indicate the alighting point – it is a difficult task to identify trips – origin-destination pairs for travelers. This problem is known in the literature as the Origin-Destination Matrix Estimation (ODME) problem.

Using surrogate measures from AVL/APC and AFC data has been a significant research focus. To infer destination, Barry et al. (2002), Farzin (2008), Wilson et al. (2009), and Nassir et al. (2011) use a method similar to the trip-chaining approach, which assumes that the destination of each trip can be inferred from the origin of the next AFC (boarding) transaction point. In addition to generating alighting stop alternatives, recent research expands the method from rail-to-rail systems to rail-to-bus systems (e.g., Wilson et al., 2009), and detects transfer trips by considering service headway as well as transfer time thresholds (e.g., Nassir et al., 2011).

To use AVL/APC data in model calibration, it may not actually be necessary to identify the exact stop at which a passenger alighted. Instead, it may be sufficient to know that a passenger left the transit system within a zone. An approach to quantify this kind of activity was presented by Lee et al. (2012) who defined stop aggregation models. The methods solve the problem of AFC data that provide the current location of the transaction instead of the actual boarding stop. For aggregate representation of transit stops, the proposed methods are based on distance between stops, textual similarity of stop names, and catchment. By representing nearby multiple stops as a single node, the methods can be applied in OD estimation process with reduced complexity. The results suggest that depending on the scale of the analysis, error rates were about 18%. In their subsequent study, Lee et al. (2013) extend the aggregation techniques to include temporal considerations and more disaggregate land use data, understanding that times of day are likely to generate direction of travel to or from specific land uses.

Farzin (2008) presents a method of constructing an OD matrix at the zonal-level for bus systems using fare card data and global positioning system (GPS) data in Sao Paulo, Brazil. In this research, each AVL record is affiliated with a particular bus stop, and each stop has an associated zone assignment. Farzin (2008) compares the OD patterns from 2007 to the OD matrix using year 1997 household survey data. The author finds that OD patterns between major zones are reasonably similar but a sizable discrepancy in OD trips exists between the two methods. The author argues that this discrepancy is attributed to (1) no consideration for the change in Sao Paulo's route structure between year 1997 and 2006, (2) limited number of buses with AVL equipment (i.e., only passengers using a bus with AVL equipment are captured in the ODM), and (3) no inclusion of cash-payment passengers. However, it should be noted that the zone definitions may have also been different between the two methods. In Farzin's ODM, a zone is a group of places where passengers are in when they swipe their cards on the bus. In fact, this zone is different from that of travel demand modeling where the activities are generated or attracted. Consequently, the method of aggregating stop-level counting at the zonal-level may not generate results that are compatible with the travel demand model.

Arguably, the best research effort available for the issue of assigning stop counts to TAZs was conducted by Furth et al. (2007). They estimate the impacts of changing stop locations on user costs with assigned transit demand at the parcel level in Boston and Albany. The authors simplify user costs as a function of walking access, and estimate walking distance from each parcel to its closest stop. Their approach of assigning stop counts to its parcels is to solve the many-to-one (i.e., parcels to a stop) trip distribution problem. Parcel level demand is determined by assigning stop on/off counts as a function of strength between two locations represented by (1) a parcel's size attributes in association with its land use type; (2) "propensity", which is an exponential distance decay function type term (i.e., $e^{-calibration\ coeff.*distance}$); and (3) competition factors. The competition factors reflect the fraction of transit demand that is drawn away to other transit lines.

Although the model presented by Furth is conceptually well-designed and considers comprehensive issues in walk-access to transit at a semi-aggregate (i.e., parcel) level, several issues arise in the application process. First, as the authors recognize, the method of determining coefficients, parameters, and factors in their models are crude and arbitrary. In their case study, the first term of the model (i.e., land use and intensity) requires a large amount of trip generation coefficients that need to be calibrated or determined based on expert judgment. The number of coefficients that need to be determined in the case study totals 138. The data needs and approaches make this model difficult to replicate.

If AVL/APC data are to be used as a means to reduce the magnitude of mode constants, a robust method to assign boarding locations to zonal origins (and alighting locations to zonal destinations) is necessary. This research presents and tests the validity of four methods to solve this problem.

2.5 Chapter Summary

To supplement the introduction presented in Chapter 1, the literature related to four issues on the improvement of transit ridership forecasting has been examined in this chapter. The main findings of the review are as follows.

First, the most common structures for travel forecasting models were reviewed. Four-step, activity based, data driven models focusing on STOPS (Simplified Trips-on-Project Software), and direct demand models were presented and assessed. While each model has advantages – simplicity of its solution, ability to account for travel tours, and relatively less effort for model calibration and validation, the accuracy of stop-level predictions – all of these formulations have certain limitations to represent the complexity of traveler behavior.

Second, the advancement of mode choice models, solution algorithms, and transit assignment problems were reviewed. To account for systematic taste variation, socio-economic variables are commonly added to utility function either in a linear-in-the attributes structure or interaction with LOS variables. In a large-scale regional travel forecasting model, market segmentation is commonly applied to capture taste heterogeneity in mode choice. The challenges associated with pre-determined MS include a lack of *a priori* knowledge of the correct segmentation methods, the exponential growth of combinations of market segments, and the cost of collecting sufficient data to calibrate multiple segment utility functions.

On the subject of advancing solution algorithms in regional travel forecasting models, research over the last decade has focused on representing mutual responses between supply and demand, and achieving consistency in model application, namely, feedback mechanisms and combined models. Behavioral motivation for models with feedback loops is to reflect the effects of transportation improvements on land use, trip frequencies, trip distribution, and mode choice. All steps in regional travel forecasting models are related each other through the feedback loops which seek consistency in congested travel time. Therefore, it should be noted that error sources that impede feedback convergence can also affect errors of results generated from other steps including mode choice, trip distribution, or trips generation. The combined models in recent decades have been extended to incorporate multiclass and multimodality of OD, mode, departure time period, and route choices to implement models for large-scale urban areas.

An overview of the transit assignment problem is also presented. Increasing sophisticated research efforts take into account transit reliability, and boarding failure caused by the vehicle capacity or seat-availability when modeling travelers' behaviors.

Third, an overview of mode constants and their impact on regional travel demand forecasting models was presented, with an emphasis on the implementation of unaccounted-for attributes. The significant determinants of transit mode choice were discussed. These include (1) traditionally well-known factors such as car availability, income, density, age, gender, employment, travel time and cost; and (2) significant but yet understudied factors such as habits, familiarity, experiences, transit access environment, reliability, real-time information, stop comfort, and safety.

Traditional measurable attributes alone do not adequately account for the variation in mode choice behavior. To deal with these errors, regional travel demand forecasting models typically include mode constants in the generalized cost (GC) of a given mode. However, the use of mode constants without representing other qualitative or difficult-to-measure attributes creates some problems. One is that any error introduced in other stages (e.g., person-trip tables, highway and transit networks, observed transit ridership patterns) of the regional travel forecasting procedures can be incorporated in the mode constants. The second problem is that heavy reliance on mode constants has been shown to bias to user benefit estimates. One way to improve heavy reliance on mode constants is to account for difficult-to-measure attributes and realistically implement in regional travel forecasting models.

Recent research on mode constants has attempted to account for the aforementioned difficult-to-measure attributes in mode choices, incorporating them in mode choice models, and proving that the influence of unobserved factors (i.e., magnitude of mode constants) has been reduced. In spite of improvements in quantifying difficult-to-measure attributes in mode choice models, a gap remains in practical applications. In recent practice, difficult-to-measure attributes are implemented in mode choice processes either by adopting lump-sum mode constants (which have incremental values with respect to detailed transit modes) or by discounting perceived travel time coefficients (FTA, 2007, Chen and Naylor, 2011). Outwater et al. (2014) have also conducted implementation tests with quantified premium (i.e., fixed guideway) transit services. However, the application efforts have shown partial success. While reducing the influence of unobserved attributes on mode choice, transit ridership forecasting errors have increased compared to existing models. Moreover, since the usage of the credits of mode constants is more likely to result in overestimation of starter project, FTA (2008) recommended that these be applied only when estimating user benefits.

Finally, while automatically collected data (ACD) are increasingly popular, most research focuses maninly on stop-level analysis since the ACD provides direct values of on/off counts at each stop. Little attention has been paid to applying the data to regional travel demand modeling procedures, particularly for mode choice and calibrations. One of the main difficulties of incorporating APC data to the demand modeling process is the lack of appropriate and proven methods to infer trips at the traffic analysis zone (TAZ) level from boardings and alightings at each stop. The need to convert or expand stop-level estimation to full transit trips by connecting origines/destinations of activity is gradually being recognized (Barry et al. 2002, Furth et al. 2006, Chu et.al. 2008, Wilson et al. 2009, and Nassir et al. 2011).

Chapter 3
Mode Constant Magnitudes

3.1 Introduction

A common component of all mode choice models (i.e. conventional four-step, combined, or activity based models) is a need to represent travel cost (or disutility) for available modes between origin-destination pairs. These disutilities are most commonly measured as linear combinations of time and out-of-pocket expenses. The models typically have various utility functions that differ by traveler type and by trip purpose. Despite this disaggregation, mode choice models often systematically over- or underestimate a given mode's utilization when only "measurable" costs are considered.

One difficult-to-measure attribute in utility functions is a traveler's perception of individual modes or technologies. Consider an example where the measurable components of two utility functions – one for private auto and one for bus transit – produced equal disutilities. In most cases, people with access to a private car would choose the car in this case, presumably due to attributes of the car that are "better" than transit – potentially more control over departure time, path choice, return time, etc. But, the probability models would estimate equal likelihood of choosing car or bus.

To deal with these kinds of errors, utility functions usually include "mode constants". These constants are added to (or subtracted from) the generalized cost of a given mode's utility function based on market segmentations in the model. In a practical application, an initial value of the mode constants may be estimated through stated or revealed preference surveys. These estimated mode constants represent travelers' preference for one mode relative to another. The mode constant may also be used to calibrate the mode choice models, such that the error in transit mode share in a specific market segment is minimized throughout the study area.

This chapter describes details about mode constants used in the formulation of regional travel demand models. Using representative data from six cities in Canada and the United States, this chapter focuses on (1) demonstrating an understanding of the state of practice with regards to model formulations; (2) estimating the overall magnitude of various model constants; and (3) quantifying the importance of mode constants relative to the measurable components of utility functions in mode choice models. To accomplish the first goal, a succinct review of several contemporary models from throughout North America and a sample computation for disutility are provided in the first section. In the second section, the size of mode constants is investigated using a well-known technique amongst modelers – converting the magnitude of the mode constant to an implied value of in-vehicle-time (IVT) using data from six regional travel forecasting models used in cities from across North America. For the final investigation, the question I aim to answer is what portion of travel cost between an origin and a destination is comprised of a fixed mode constant. This is important because a very large mode constant relative to measurable attributes can render a model insensitive to changes in systems' unmeasured performance including reliability, comfort, convenience, visibility, access environment, and safety, either through investments in new infrastructure or improved operations. The third analysis is informed using data from the Philadelphia metropolitan region and the Washington D.C. region.

3.2 Data

The review of the magnitude of mode constants is based on mode choice models from recently-developed and implemented regional travel forecasting models. The review covers six cities in North America: Calgary, Denver, Ottawa, Philadelphia, Washington D.C., and Winnipeg. The data were obtained through an informal internet survey as well as individual contact with travel demand modelers responsible for the model development or implementation. While the list of cities surveyed is not exhaustive, the data do reflect a variety of city sizes and governance structures (See Table 3-1) from which generalizable conclusions can be drawn.

Internet survey questionnaires (see Appendix A) were distributed to members of the Travel Model Improvement Program (TMIP) under the U.S. Federal Highway Administration. The TMIP on-line community is an open discussion group related to issues on transportation modeling and analysis. This group has subscribers representing travel forecasting professionals around the globe. The survey dates were January 30 - February 28, 2014; responses were received from three municipalities - Denver, Ottawa, and Cincinnati.[1] Additionally, the same questionnaire was distributed through individual e-mail to the modeling staff of each city in Canada. Calgary and Winnipeg provided data.

From the survey, the following information was collected:

[1] In this study, the data from Cincinnati were excluded due to missing responses.

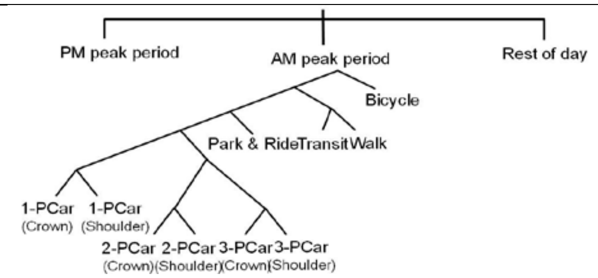
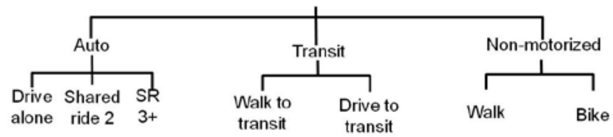
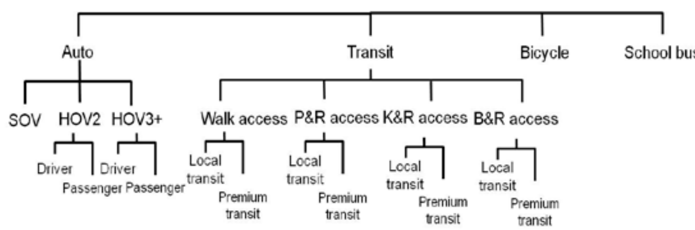
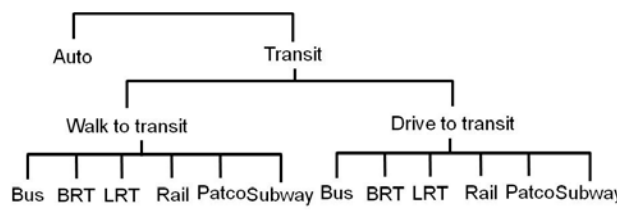
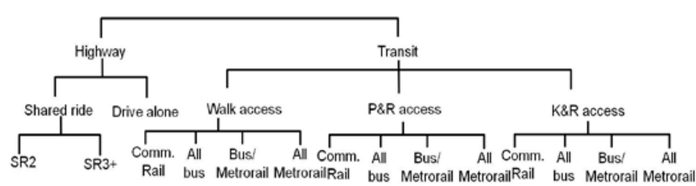
- General information of mode choice models: calibration year, types of models, structure of models etc.;
- Calibration coefficients and constants of mode choice.

For the second analysis (Section 3.5), Philadelphia and Washington D.C. provided data including mode choice inputs corresponding to the year of calibration, application files/data, GIS shape files representing zone area system, output data and relevant documentation from the regional travel forecasting models (2010 TIM version 2.1 and 2011 TPB version 2.3.38, respectively). Given this additional information, the second component of the analysis (understanding the relative impact of mode constants) could be completed for these two models.

Table 3-1 summarizes the general information gathered about the mode choice models of the six cities. The mode choice models were all developed or updated between 2001 and 2014. Denver and Ottawa have adopted tour-based/activity-based travel demand forecasting frameworks while the other cities apply four-step travel demand models (see section Chapter 2 for a description of the differences amongst these models). Philadelphia and Washington D.C. are relatively larger in population size (6 million and 5.9 million, respectively), while the populations of the other cities range from 0.66 million (Winnipeg, year 2011) to 2.7 million (Denver, year 2013). Most of the mode choice models follow a nested logit structure.

As noted in Chapter 1, many models employ a so-called nested structure, where a first choice is made between general categories of modes (i.e. auto versus transit) and a second choice is made from categories within a mode (i.e. rail versus bus transit, or auto driver versus auto passenger). This nested structure requires that several transit sub-modes be defined. In my review of the models (and in Table 3-1), I concentrate on the modal constants associated with these transit modes. Table 3-1 presents a summary of the transit representation including the nesting structure and the sub-modes used in each of the models.

Table 3-1: Overview of mode choice models from six cities' regional travel forecasting models

City	Population	Model Description (Calibration year)	Structure of mode choice models [2] (Home based work trip, AM peak)
Calgary	1.1 mil (2011)	Nested logit (2001)	 1)
Denver	2.7 mil (2013)	Nested logit, Tour-based (2007)	
Ottawa	0.83 mil (2011)	Nested logit Activity-based combined with 4-step (2014)	
Philadel-phia	6.0 mil (2013)	Nested Logit (2010)	
Washington D.C.	5.9 mil (2013)	Nested logit (2012)	
Winnipeg	0.66 mil (2011)	Multinomial logit (2012)	Auto driver, auto passenger, transit, walk/bicycle

1) Nested logit structure for mode and time-of-day,

Peak crown time period: last 1/2 hour, the peak shoulder: 1 and 1/2 hours for a total peak period of 2hours.

2) SOV: Single occupancy vehicle, HOV: High occupancy vehicle, P&R: Park and ride, K&R: Kiss and ride, B&R: Bike and ride, BRT: Bus rapid transit, LRT: Light rail transit

3.3 Understanding Contemporary Travel Forecasting Model Formulations

For this section of the thesis, the primary concern is to provide an explanation of the function of contemporary travel forecasting models' utility functions used in mode choice analyses. As described in chapters 1 and 2, models' utility functions are often disaggregated based on trip purpose (e.g. work, school, shopping) and trip time (e.g. am or pm peak). In this section, I present data for one of these scenarios – typically a work trip made in the am peak.

Recall that the normal form of a utility function involves a linear weighting of trip cost components, including in-vehicle travel time (IVT), out-of-vehicle travel time (OVT) (e.g., transfer time; walking for access, egress, or transferring; waiting time), and fare or out-of-pocket cost. For each of these cost components, a series of coefficients are estimated to represent the perceived relative importance.

Cost perceptions for in-vehicle travel time are known to vary based on mode of travel. The simplest representation of this difference is to generate different cost coefficients for auto and transit in-vehicle times. In some, more complex models, the perception of in-vehicle time can also vary based on disaggregate modal representations. For example, time in an automobile may be perceived differently as a passenger than as a driver. Moreover, the perception of transit IVT may differ if traveling by bus, Light Rail Transit, or Metro.

Different cost representations are often used when a trip is multimodal versus unimodal. For example, auto in-vehicle time may be perceived as less onerous when an entire trip is made by auto versus when auto is being used to access transit. To account for this phenomenon, some models define specific multimodal combinations, such as auto access to transit, and estimate appropriate coefficients for each of the combinations. Commonly considered multimodal trips include drive to transit, resulting in either being dropped off (kiss-and-ride) or parking and transferring to transit (park-and-ride).

Finally, models are often constructed to recognize that travel costs are perceived differently based on:

- the travelers' income level. Generally, lower income travelers tend to represent in the models as perceiving transit less negatively than higher income travelers.

- the area type for which the travel originated or was destined. Travel to and from higher density areas tends to represented in models as less costly by transit than similar trips to lower density areas.

3.3.1 Cost perception in studied models

Normally, travelers perceive different portions of trips as more or less onerous. For example, a traveler may perceive 10 minutes of waiting time (at a transit stop) as significantly longer than 10 minutes of travel time in the transit vehicle. To account for these different perceptions, a convention has been adopted of weighting out-of-vehicle time (e.g., walk and wait time of transit) as two to three times as onerous as in-vehicle time (Bruzelius, 1979; MVA et al., 1987; Steer Davies Gleave, 1997). This convention was widely applied across all six cities.

Quantitatively, the treatment of the perception of travel costs can be measured by the ratio of coefficients for out-of-vehicle-time (OVT) and in-vehicle-time (IVT). For example, from Table 3-2: Philadelphia, this ratio for bus mode is computed to 2.5 (i.e., -0.0625/-0.025). This means that bus transit users perceive OVT as 2.5 times as onerous as IVT.

As shown in Table 3-2, in Philadelphia, this ratio ranges from about 2.5 to 4 depending on modes; in Washington D.C. and Denver the ratio ranges from about 1.5 to 2.5 depending on out-of-vehicle time components. In Ottawa, the values span from 1.4 (drive-access time) to 5.0 (number of boardings). The largest range is in Winnipeg, where the minimum is 1.9 (wait time) and the maximum ratio is 10.6 (number of transfers). In Canadian cities, those maximum values of 3.1 (Calgary), 5.0 (Ottawa), and 10.6 (Winnipeg) indicate ratios of the number of transfers to the in-vehicle time. This means that transit users in these cities perceive number of transfers as significantly more onerous (three times, five times, and ten times, respectively) than travel time in the transit vehicle.

Table 3-2: Perception of travel costs: ratio of OVT/IVT

City	Calgary	Denver	Ottawa	Philadelphia	Washington D.C.	Winnipeg
Out-of-vehicle time / In-vehicle- time ratio	1.5 - 3.1	1.5 - 2.5	1.4 - 5.0	2.5 – 4.0	1.5 - 2.5	1.9 – 10.6

3.3.2 Cost representation in studied models

Table 3-3 presents the components of the overall utility functions for each of the six models studied. In-vehicle times are calculated endogenously to the model and are weighted using coefficients which are typically mode specific. For example, the City of Calgary model has a coefficient for both auto in-vehicle time (-0.088) and transit in-vehicle time (-0.0597). The City of Winnipeg's model differentiates between in-vehicle times for auto drivers, auto passengers and transit users. In Ottawa, the model employs several coefficients for in-vehicle time that represents the quality and location of transit services: a general IVT coefficient; an IVT coefficient specific for travel along the City's higher order transit way; and two additional coefficients that vary based on stop density.

The models for Denver and Philadelphia use multimodal combinations. For example, in Philadelphia, trips that involve driving access to transit are defined as D-trn. Here, the in-vehicle time coefficient depends on the type of transit used. A traveler who drove to a bus stop would have a coefficient (Bus_IVT) of -0.0250 for every minute of in-vehicle time; if the same traveler drove to a subway stop, each minute of travel would be multiplied by Subway_IVT, or -0.0188. In Denver, in conjunction with a general IVT coefficient, the model has two types of coefficients for the proportion of local bus IVT out of total transit IVT (-0.677); and for the proportion of driving access time out of total IVT (-1.433). For example, if the local bus time (that represent low quality-of-service) out of total transit time increases or driving access time out of total IVT increases, the disutility (cost) increases in addition to a general IVT.

Out-of-vehicle times (e.g., access time, waiting time, and number of transfers) vary depending on the disaggregation level of OVT cost components. For example, the model for Philadelphia estimates total OVT for walk-access and drive-access, respectively, and every minute of total OVT is multiplied by -0.0625. On the other hand, the model for City of Ottawa employs four OVT components, and their associated coefficients are -0.0684 for wait time, -0.053 for walk time, -0.114 for number of boardings, and -0.0308 for drive-access time, respectively. In this case, a traveler perceives that transferring (number of boardings) is twice (-0.114/-0.053) as onerous as walking to transit. Again, Table 3-3 summarizes a subset of the data; a full compilation of all model components is contained in Appendix B.

Table 3-3: Summary of mode choice model calibration coefficients in the study cities

Philadelphia (GPR)

	Attributes	Modes Applied	Coeff.
In-vehicle time	Bus_IVT	Auto, W-trn, D-trn	-0.0250
	BRT_IVT	Auto, W-trn, D-trn	-0.0238
	LRT_IVT	Auto, W-trn, D-trn	-0.0213
	Subway_IVT	Auto, W-trn, D-trn	-0.0188
	Rail_IVT	Auto, W-trn, D-trn	-0.0150
Out-of-vehicle time	D-trn_ACC	D-trn	-0.0625
	OVT	Auto, W-trn, D-trn	-0.0625
	# transfer	W-trn, D-trn	0.0000
Constants	**Income constants**		
	Low income	W-trn	0.675
	Low income	D-trn	0.300
	Area-type constants		
	Den12_W-trn	CBD	-0.075
	Den12_D-trn	CBD	-1.125
	Den3_W-trn	Urban	0.000
	Den3_D-trn	Urban	-0.900
	Den4_W-trn	Suburban	-0.475
	Den4_D-trn	Suburban	-0.125
	Den56_W-trn	Rural	-1.125
	Den56_D-trn	Rural	0.000
	Mode constants		
	C_W-trn	W-trn	-1.175
	C_D-trn	D-trn	-1.425

Washington D.C. (MWCOG)

	Attributes	Modes Applied	Coeff.	
In-vehicle time	IVT	DA, SR2, SR2+, WK-Commuter rail, WK-bus, WK-bus/metro, WK-metro, PNR-4 transit modes, KNR-4 transit modes	-0.02128	
Out-of-vehicle time	Initial wait, transfer wait,board time, park time (PNR)	WK-4 transit modes , PNR-4 transit modes, KNR-4 transit modes	-0.05320	
	# transfer		0.00000	
	Access time, other walk time		-0.04256	
	Access time		-0.03192	
Constants	**Income constants**			
	Low income	WK-4 transit modes	2	
	High income	WK-4 transit modes	-2	
	Mode constants (example of Seg.1 and Seg.3)			
			Seg. 1	Seg. 3
	Auto		0.0000	0.0000
	Transit		3.7245	6.6777
	Transit			
	WK-access		0.0000	0.0000
	PNR-access		-3.7643	-8.0902
	KNR-access		-7.3352	-11.2737
	Walk-trn			
	WK-metro		0.0000	0.0000
	WK-commuter rail		-0.8073	-5.6499
	WK-bus		-1.4496	-9.0773
	WK-bus/metro		-1.4604	-8.5955
	PNR-trn			
	PNR-metro		0.0000	0.0000
	PNR-commuter rail		-0.3935	-2.3531
	PNR-bus		-2.4506	-9.5804
	PNR-bus/metro		0.8506	-7.8945
	KNR-trn			
	KNR-metro		0.0000	0.0000
	KNR-commuter rail		3.5730	-0.1115
	KNR-bus		1.2609	-3.9039
	KNR-bus/metro		5.7435	0.8457

City of Calgary

	Attributes	Modes Applied	Coeff.
In-vehicle time	Car IVT	Auto, PNR	-0.0880
	Transit IVT	Transit,PNR	-0.0597
Out-of-vehicle time	Walk time, wait time	Transit, PNR	-0.0910
	# transfer	Transit, PNR	-0.1858
	Park wait time	Auto	-0.2727
Constants	**Mode constants**		
	C_Car 1p	car1p	0
	C_Car 2p	car 2p	-1.3733
	C_Car 3p+	car 3p+	-3.3787
	C_Transit	transit	3.8696
	C_D-trn	PNR	-2.5134

Table 3-3: Summary of mode choice model calibration coefficients in the study cities (cont'd)

	Denver (DRCOG)			City of Winnipeg			City of Ottawa		
	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.
In-vehicle time	IVT	auto, W_trn, D-trn	-0.020	IVT	Auto drive	-0.064	Transit IVTT		-0.0228
	Local bus time/total transit IVT	W_trn, D-trn	-0.677	IVT_Passenger	Auto passenger	-0.078	IVTT transit way	Transit	0.0128
	D-trn_ACC/total IVT	D-trn	-1.433	TIVT	Transit	-0.035	IVTT low stop density		0.0011
							IVTT high stop density		-0.0050
Out-of-vehicle time	Walk mode terminal time	Auto (DA, SR2,SR3+)	-0.050	walk distance (<=3km)	walk/bike	-1.335	Wait time	Transit	-0.0684
	Transit walk, transit first wait time	W_trn, D-trn	-0.050	bike distance (>3km and <=10km)	Walk/bike	-0.466	Walk time	Transit	-0.0530
	Transit other wait	W_trn, D-trn	-0.030	TWALKTOT	Transit	-0.087	# of boarding	Transit	-0.1140
				TWAITTOT	Transit	-0.066	Drive access time	Transit	-0.0308
				# transfer	Transit	-0.371			
Constants	**Mode constants**			**Mode constants**			**Mode constants for AM**		
	C_SR2	SR2	-2.889	C_Auto drive	auto drive	3.976	C_SOV		2.0945
	C_SR3+	SR3+	-3.410	C_Transit	transit	2.902	C_HOV2-dr		0.0121
	C_W-trn	W-trn	-3.956	C_Walk	walk	4.024	C_HOV2-PASS		0.0000
	C_D-trn	D-trn	-4.693	C_Bike	bike	1.619	C_HOV3+-dr		-1.1164
							C_HOV3+-pass		-0.8040
							C_Bus-wak		2.1806
							C_Bus-PNR		-1.9185
							C_Bus-KNR		-3.0607
							C_Bus-BNR		-5.0000
							C_Rail-walk		2.2440
							C_Rail-PNR		-1.1452
							C_Rail-KNR		-2.9609
							C_Rail-BNR		-5.0000

Given the complexity of the model formulations, the meaning of the mode choice coefficients and constants in Table 3-3 may be demonstrated with an example. Here, it is assumed that a commuter in Philadelphia travels from home to work. His home location is an urban area and the workplace is located in the CBD area as shown in Figure 3-1. The commuter uses a bus for his trip and accesses the bus by walking. The full utility expression for the commuter is given by eq. (3-1).

$$\begin{aligned} \text{Utility}_{\text{W-trn}}(\text{t}_{\text{od}}) = \ & \text{Total IVT}_{\text{W-trn, od}} - 0.0625\ \text{OVT}_{\text{W-trn, od}} - 0.00\ \text{no.transfer}_{\text{W-trn, od}} \\ & -0.15\ \text{fare}_{\text{W-trn, od}} + \underbrace{(0.000\text{-}0.075)}_{\substack{\text{Area-type constants} \\ (\text{Den3}_{\text{W-trn}}+\text{Den12}_{\text{W-trn}})}} + \underbrace{0.675\ \text{IC}_{\text{W-trn}}}_{\text{Income constant}} \underbrace{-1.175}_{\text{Mode constant}} \end{aligned} \quad (3\text{-}1)$$

where,

$\text{Utility}_{\text{W}-\text{trn}}\ (\text{t}_{\text{od}})$	Utility for walk-access transit trips from origin to destination
$\text{Total IVT}_{\text{W}-\text{trn,od}}$	Total in-vehicle travel time from origin to destination: $\text{Total IVT}_{\text{W}-\text{trn,od}} = -0.025 busIVT_{W-trn,od} - 0.0238 brtIVT_{W-trn,od} - 0.0213 lrtIVT_{W-trn,od} - 0.0188 subwayIVT_{W-trn,od} - 0.015 railIVT_{W-trn,od}$
$\text{IC}_{\text{W}-\text{trn}}$	1, if low income household 0, otherwise

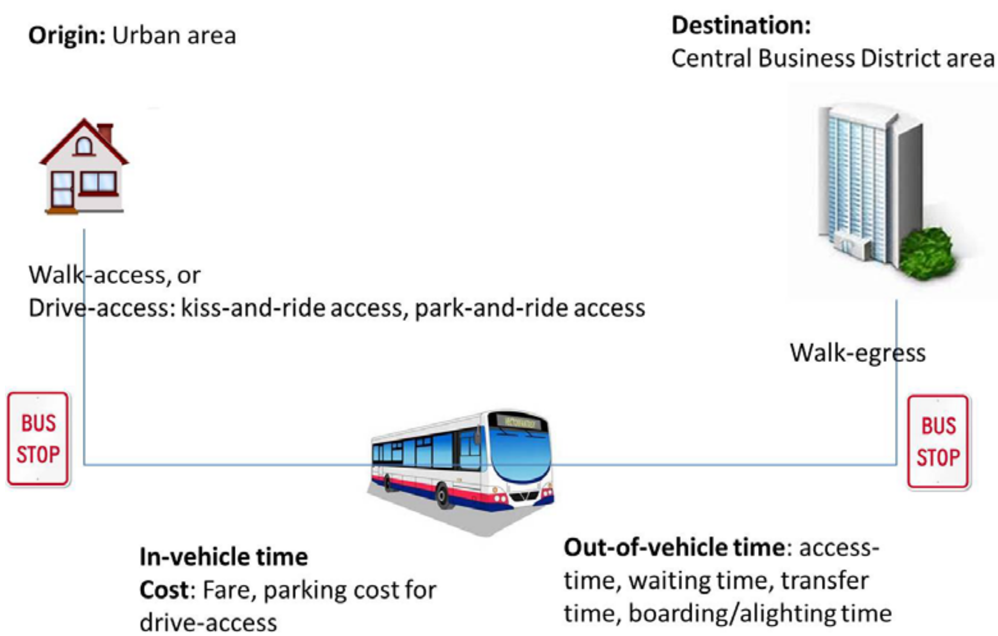


Figure 3-1: An example of a transit trip and travel time/cost components

Since the commuter uses a bus mode in his trip to work, total IVT component would be $-0.025 busIVT_{W-trn,od}$ with no transfer (no. of transfer = 0). In addition to these time and cost components, there are area-specific disutilities in the Philadelphia model. Constants related to these two area types are included in the utility formulation (0.000-0.075).

Table 3-4 illustrates application values to different area-type combinations of ODs in the Philadelphia model. The effect of area-type constants ranges from 0 to 38 min (in IVT value) in walk-access and from 5 min to 64 min in drive-access. In the case of walk-access, suburban production or suburban attraction trips tend to have much larger area-type constants. In drive-access, all CBD origin trips tend to have much larger constants. The models represent higher cost for trips from/to low density areas than similar trips to high density areas. In addition, drive-access trips originated from high density areas are much more costly (due to parking cost etc.) than similar trips from low density areas.

Table 3-4: Values of area-type constants - Philadelphia (Home based work trip, AM peak)

O \ D	walk-access to transit			drive-access to transit		
	CBD	Urban	sub-urban	CBD	Urban	sub-urban
CBD	-0.15 (6)	-0.075 (3)	-0.55 (22)	-1.2 (48)	-1.125 (45)	-1.6 (64)
Urban	-0.075 (3)	0 (0)	-0.475 (19)	-0.975 (39)	-0.9 (36)	-1.375 (55)
sub-urban	-0.55 (22)	-0.475 (19)	-0.95 (38)	-0.2 (8)	-0.125 (5)	-0.6 (24)

( ) equivalent values of IVT - minutes

Winnipeg incorporates the area-type attributes directly to the utility. For example, the model inserts the dummy variable of 'origin zone is suburban high or urban low' for transit utility. Washington D.C. applied 280 nesting constants for HBW trips based on geographic market segmentations and modes. The geographic market is divided into twenty groups (e.g., Seg1: DC core/DC urban to DC core, Seg2: DC core/ DC urban to VA core, etc.) and fourteen modes (15 modes - 1 reference mode).

To consider different cost perceptions based on income level, the Philadelphia and Washington D.C. models add income constants in a utility function. In Philadelphia, from equation (1), if the commuter belongs to a low income household, 0.675 minutes are added to the utility. Since this is a positive value, it increases the utility (positive benefits) of transit. As shown in Table 3-3, in Washington D.C., the income constants are applied for all walk-access modes including walk-access to commuter rail, to bus, to bus and metro, and walk-access to metro. These values are 2 minutes for low income group and -2 minutes for high income group.

In the six models studied, the travel models in Calgary, Denver, Ottawa, and Winnipeg incorporate auto ownership attributes. Philadelphia and Washington D.C. models do not include these types of variables. As shown in Table 3-5, the auto ownership in the model is represented as HH car ownership (Calgary and Denver), or car sufficiency (Winnipeg) or zero car (Ottawa, Winnipeg) dummy variable.

Table 3-5: Auto ownership in the studied models

	Auto ownership attributes	Modes applied	Coeff.	Values of mode constants in minutes	
Calgary	Household(HH) zone car ownership	Auto, PRN	5.628	Transit PNR transit	-65 42
Denver	Number of car in HH	SR2, SR3+ W-trn D-trn	5.045 12.201 9.26	wk-acc to transit dr-acc to transit	198 235
Ottawa	0 car	SOV, bus-PRN, rail-PNR Bus-walk, bus-BNR, rail-walk, rail-BNR Bus-KNR, rail-KNR	-99.0000 0.4075 -0.8517	wk-acc bus wk-acc rail PNR bus PNR rail KNR bus KNR rail BNR bus BNR rail	-96 -98 84 50 134 130 219 219
Philadelphia	n.a.			wk-acc to transit dr-acc to transit	47 57
Washington D.C.	n.a.			refer to Table 3-7	
Winnipeg	0 veh in HH 2+ veh/2+ adults 2 veh/ 3+ adults 1 veh/2 adults 1veh/3 adults 2+ veh/ 2+ adults	Transit Auto drive Auto drive Auto drive Auto drive Auto drive	0.658 0.918 -0.487 -1.294 -1.462 1.934	Transit	-83

PRN: park-and-ride, SR: shared ride, SOV: single occupancy vehicle, BNR: bike-and-ride, KNR: kiss-and-ride

Table 3-5 implies that, in most of the studied models, the auto ownership variables contribute to add positive utility to automobile. For example, in the Calgary model, HH zone car ownership attributes add positive utility for auto and park-and-ride modes with positive coefficient of 5.628. Similarly, in the Winnipeg model, low car sufficiency in a HH contributes to decrease auto drive utility by subtracting -0.487, -1.294, -1.462 depending on the degree of insufficiency. From the following binary logit equation

(3-2), it is possible to interpret that the auto ownership related variables works as impeding transit use by making the utility difference between transit and automobile larger.

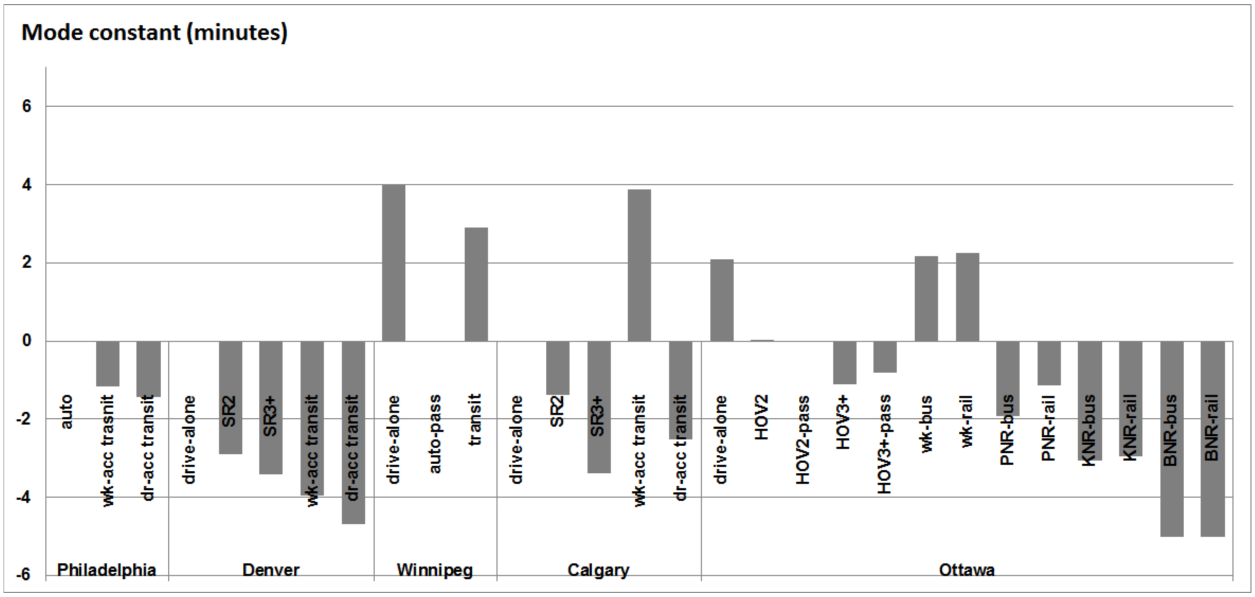
$$P_n(i|C_n) = \frac{\exp(V_{in})}{\sum_{j \in C_n} \exp(V_{jn})} = P_{transit} = \frac{1}{\sum \exp(V_{transit} - V_{auto})} \quad (3\text{-}2)$$

Since the auto ownership is commonly considered as a significant variable of mode choice, omitted these variables may affect the magnitude of mode constants. However, in this study scope, it is difficult to generally state that the large transit mode constants are attributed to the omitted auto ownership variables. Since incorporation of auto ownership variable may also affect the calibration of the other coefficients in automobile utility, further investigations are necessary. Furthermore, as shown in the same Table 3-5, the Philadelphia model which does not include auto ownership variable overall shows the smallest mode constants compared to the other travel models.

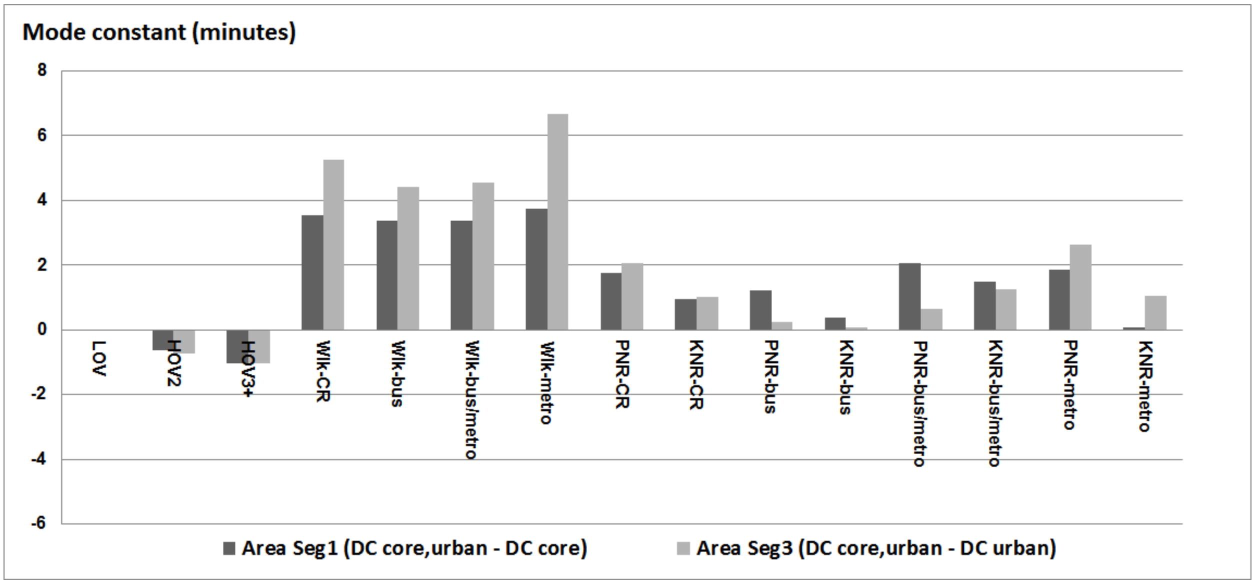
Lastly, in Table 3-3, the reference mode (i.e., mode constant = 0) of most of the cities is auto-drive (or drive-alone), while the reference modes for Winnipeg and Ottawa are auto passenger and HOV2 passenger, respectively. The reference mode affects the interpretation of transit mode constants in next section. In the following section, mode constants of six study cities are examined in more detail.

3.4 The Value of Mode Constants in In-vehicle Time

Figure 3-2 shows the signs and magnitudes of mode constants for each transport mode of the six cities. Figure 3-2(a) shows positive values for transit modes in Winnipeg, Calgary and Ottawa. However, it should be noted that the reference mode (i.e., mode constant=0) for the Winnipeg and Ottawa models is auto-passenger, while that of the other cities is drive-alone. For comparison, the reference mode of auto-passenger can be switched to drive-alone by subtracting (in this case) or adding the same amount of alternative-specific constants from all alternatives without loss of generality. Accordingly, the positive value of the transit mode constant for Winnipeg can be adjusted to -1.074, with auto-drive and auto-passenger changed to 0 and -3.976 respectively. Consequently, the transit mode constant of Winnipeg would also be a negative value.



(a) Philadelphia, Denver, Winnipeg, Calgary, Ottawa



* Top-level equivalent nesting constants

(b) Washington D.C.

Figure 3-2: Summary of mode constants (Home based work trip/tour, AM peak)

In Washington DC (see Figure 3-2 (b)), the modeled area is divided into seven super districts: DC core, VA core, DC urban, MD urban, VA urban, MD suburban, and VA suburban. Travel can occur within or between any of these super-districts, resulting in 49 (7x7) possible origin destination pairs. The DC model collapses these 49 options to only 20, by combining several similar travel pairs. Each of the 20 paired travel options are defined as segments, numbered 1 through 20. To demonstrate the importance of area types on mode constants, the different mode constants for two different segments: Segment 1 (DC core/DC urban to DC core – essentially travel to the CBD) and Segment 3 (DC core, Urban to DC urban – travel within the city, but not to the CBD) are presented. This result suggest that the net influence of the unobserved mode, individual, and trip attributes are greater in CBD to Urban areas than in CBD to CBD areas in this context.

Overall, from Figure 3-2, for a majority of the cities, mode constants for transit modes are negative values (except Calgary and Washington D.C.). The negative values imply that travelers inherently derive negative utility (or experience additional costs) from using transit (relative to the default mode). As a result, the current models without calibrated mode constants would over-predict the actual propensity to use transit sub-modes. On the other hand, it is interesting that the mode constants of all transit sub-modes of Washington D.C. and walk-access to transit modes of Ottawa are positive values. In the Washington DC example, travelers derive a positive utility from using transit compared to the default mode choice. In this case, absent the calibration parameters, the mode choice models would under-predict transit trips; the mode constants have the influence of increasing the transit trips after calibration.

A common practice in evaluating the magnitude of model constants is to convert these values to equivalent minutes of in-vehicle time. Here this approach was taken to estimate conceptually the reduction in in-vehicle time that would be necessary to equivalently eliminate the mode “bias” from the utility function. The values of mode constants in minutes are shown in Table 3-6 to Table 3-7. To estimate the value of calibration constants, each mode constant was divided by the transit in-vehicle time coefficients.

Table 3-6: Values of mode constants in minutes of IVT in regional travel forecasting models - Calgary, Denver, Ottawa, Philadelphia, Winnipeg (Home based work trip, AM peak)

City	In-vehicle time coefficient	Applied modes	Mode coefficient value	Values of mode constants in minutes
Calgary	-0.0597 (Transit, PNR)	Transit	3.8696	-65
		PNR transit	-2.5134	42
Denver	-0.02 (Auto, transit)	wk-acc to transit	-3.9560	198
		dr-acc to transit	-4.6930	235
Ottawa	-0.0228 (Transit)	wk-acc bus	2.1806	-96
		wk-acc rail	2.2440	-98
		PNR bus	-1.9185	84
		PNR rail	-1.1452	50
		KNR bus	-3.0607	134
		KNR rail	-2.9609	130
		BNR bus *	-5.0000	219
		BNR rail *	-5.0000	219
Philadelphia	-0.025 (Bus)	wk-acc to transit	-1.1750	47
		dr-acc to transit	-1.4250	57
Winnipeg	-0.035 (Transit)	Transit	2.9020	-83

* Bike and ride

As shown in Table 3-6, Calgary and Winnipeg tend to have a smaller mode constant value, ranging from 42min to 83min. For combined activity-based and 4-step models, such as those of Denver and Ottawa, the values of mode constants range from 50 min to 235 min. In Philadelphia, the implied impedances of mode constants are 47 min and 57 min for walk-access and drive-access, respectively.

The Table 3-6 implies that mid-sized cities tend to have smaller mode constant values, while metropolitan areas show greater mode constant values. The values of mode constants for IVT are presumably affected by the population size and associated transportation system size of the cities. Furthermore, the magnitudes of mode constants also vary depending on travel distance in the same city. There is a common difference observed in some cities (Denver, Ottawa, Philadelphia) between short distance trips (e.g. walk-access) and long distance trips (e.g. drive-access), since, in drive-access to transit trips, mode constants tend to have larger values than short distance trips of walk-access.

Table 3-7 shows the mode constants for two of the 20 geographic market segments in Washington travel model – Segment 1 and Segment 3 – for 12 of the 14 modal combinations. In addition to the 20 area segments, Washington DC also introduces 14 modal combinations, resulting in 280 market segments per each trip purpose. The range of results is very large. Some notable observations include that for

Segment 1, the implied values of park-and-ride and kiss-and-ride mode constants range from 3 min to 97 min, while the values of walk-access modes are much larger, ranging from 158 min to 175 min.

Table 3-7: Values of mode constants in minutes of IVT in regional travel forecasting models - Washington D.C. (Home based work trip, AM peak, Segment 1 and 3)

City	In-vehicle time coefficient	Applied mode	DC core/urban to DC core (Seg.1)		DC core/urban to Urban (Seg.3)	
			Mode coefficient value*	Values of mode constants in minutes	Mode coefficient value*	Values of mode constants in minutes
Washington D.C.	-0.02128	Wk-CR	3.5226	-166	5.2652	-247
		Wk-bus	3.3621	-158	**4.4084**	**-207**
		Wk-bus/metro	3.3594	-158	4.5288	-213
		Wk-metro	3.7245	-175	**6.6777**	**-314**
		PNR-CR	1.7439	-82	2.0443	-96
		PNR-bus	**1.2296**	**-58**	**0.2375**	**-11**
		PNR-bus/metro	2.0549	-97	0.6590	-31
		PNR-metro	**1.8423**	**-87**	**2.6326**	**-124**
		KNR-CR	0.9501	-45	1.0130	-48
		KNR-bus	0.3721	-17	0.0649	-3
		KNR-bus/metro	1.4927	-70	1.2523	-59
		KNR-metro	0.0568	-3	1.0409	-49

* Top-level equivalent nesting constants (Source: Calibration report for the TPB travel forecasting model, Version 2.3, pp.6-23, 2012)

The value of incremetal mode constants indicates the perceived difference of unmeasured attributes between modes. For example, the Seg.1 of Washington D.C. in Table 3-7 shows a 29 min value (i.e., -58-(-87)) of perceived mode preference for metro over bus in PNR-access. This implies that when measurable attraibues are equal, in order to have the same likelihood of taking bus and metro, a bus mode trip would have to be 29 min faster than a metro mode trip. The value reflects the benefits of metro modes compared to bus resulting from difficult-to measure factors such as reliability, visibility, passenger amenities, and real time infromation. In Seg.3, the percieved values of mode difference between bus and metro are much larger than those in Seg.1. Mode preference of metro over bus are 107 min IVT values for walk-access; and 113 min for PNR-access. This seems to be an unusually large difference between modes that gives motivation to test the relative contributions the mode constants make to overall travel utility estimates. This analysis is presented in the following section.

3.5 Magnitude of Mode Constants Relative to Measurable Utility

The previous section analyzed the magnitude of mode constants in terms of IVT values. This section will examine how big the mode constants are relative to the total values of measurable attributes in a utility function. For the analysis, data from Philadelphia and Washington D.C. are used. These two cities were chosen based primarily on the availability of the full model and sufficient documentation to conduct the analysis. The approach, described in more detail below, was to estimate the total disutility of travel for a subset of origins and destinations in the two metropolitan regions. The total disutility of travel was then disaggregated into two components – measurable travel attributes and costs associated with mode constants. From the previous step, it is a straightforward extension to calculate percentage of total disutility from the mode constant. Because multiple origin destination pairs were analyzed, I was able to generate distributions of results for each metropolitan region. The distributions are presented in this chapter.

3.5.1 Method

The disutility calculations were completed for multiple origins and destinations with various attributes. For the Philadelphia region, 429 zones including CBD, urban, and adjacent suburban areas were selected among 3,399 zones in total. For Washington D.C., 393 zones including DC core and DC urban areas (corresponding to geographic market segments 1 and 3) among 3,722 zones were selected. In order to divide the transit utility into measurable components and mode constants for each OD pair, the measurable component of disutility was estimated using skims – a basic estimate of travel costs between origins and destinations for all modes.

Here, measurable utility includes travel time and out of pocket costs; area-type constants are not included. The inputs into the cost estimations are shown in Table 3-8. Sample computations are shown in Appendix C. One further note of explanation is necessary. The Washington D.C. model use coefficients of 'COST INC $_{G1\text{-}G4}$' to imply the value of time (VOT) and sensitivity to cost for each income group, and are used to convert monetary values of cost to travel time values in generalized cost (utility). In this study, the results using the low income group coefficient, -0.00185, are present. The low income group coefficient is chosen because it is the largest negative value among all income groups. As a result, the generated measurable utilities are maximum (absolute) values relative to mode constants. The results, then, present the lower bounds on the percentage of total disutility that is represented by mode constants.

Table 3-8: The inputs into the cost estimations of measurable utility component

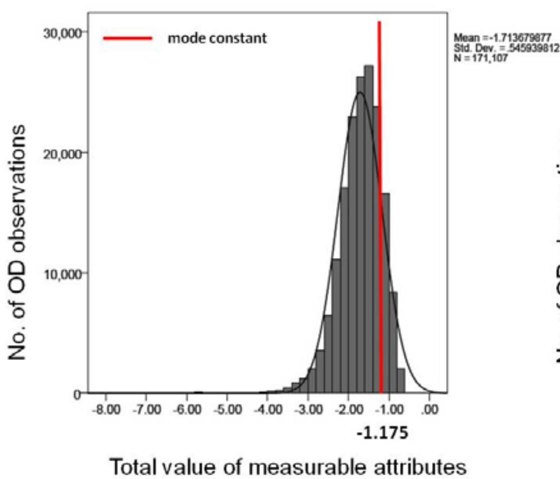
	Applied mode	Input	Unit/Remark	Source
Philade-lphia	Walk-access to transit	IVT_wk acc (RR, subway, PATCO, LRT, BRT, bus, trolley, others) OVT_wk acc No .transfers_wk acc Fare_wk acc	min min - $	Skim values from highway and transit skimming in VISUM
	Dr-access to transit	IVT_dr acc (RR, subway, PATCO, LRT, BRT, bus, trolley, others) OVT_dr acc No .transfers_dr acc Fare_dr acc	min min - $	Output of park-and-ride model which choose the best park-and-ride lots for each OD pair and then compose the transit-drive skims
Washin-gton D.C.	Walk-access	wlk IVT bus ⋮ other walk time	0.01min 2007 cents	AM peak, all bus wk-access skims
	Drive-access (PNR and KNR)	drv IVT bus ⋮ other walk time	0.01min 2007 cents	AM peak, all bus dr-access skims
	All	COST INC $_{G1-G4}$	Cost Inc G1(low income group): -0.00185 Cost Inc G2: -0.00093 Cost Inc G3: -0.00062 Cost Inc G4(high income group): -0.00046	Defined in script ('Hbw nl mc.ctl')
	Walk-access	Income constant	Income group 1: 2 (low income group) Income group 2-3: 0 Income group 4: -2 (high income group)	Defined in script ('Hbw nl mc.ctl')
	Drive-access (PNR and KNR)	Drive-access distance	0.01mile	AM peak, all bus, dr-access skims
	Drive-access (PNR and KNR)	AUOP	Auto operating cost 10cents/mile	Defined in script ('Hbw nl mc.ctl')

* Parking cost data were not available. Only wk-access and KNR-access are analyzed in this study.

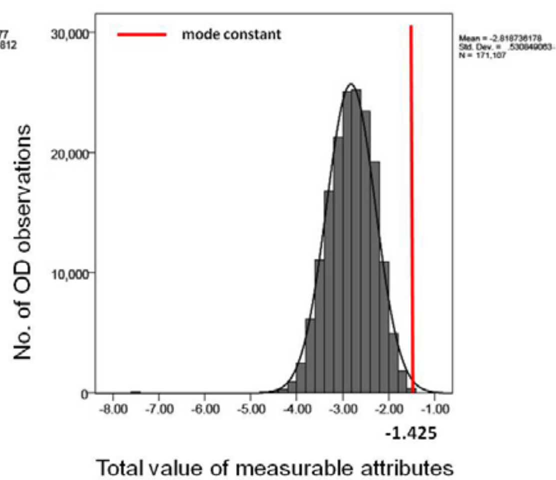
3.5.2 Results for Philadelphia

Recall that the goal of this portion of the research is to understand how much of the total disutility estimated for a given trip is a result of the mode constant and how much of the disutility is from measurable attributes.

The magnitude of mode constants relative to the total value of measurable attributes is shown in Figure 3-3. The vertical axis shows the number of observed OD pairs, and the horizontal axis indicates the total value of measurable attributes in a utility function, including transit travel time and cost components. In the distribution graph, the area to the right side of the mode-constant-value shows OD pairs where the magnitude of immeasurable inputs was greater than measurable inputs. For these cases, the immeasurable inputs "dominate" in the calculation of the total travel costs and, as a result, in the likelihood of choosing transit. In the walk-access to transit case (Figure 3-3 a), 14.3% of OD pairs (see Table 3-9) have mode constants that are greater than the total value of measurable attributes. This reflects a model in which the mode constant may influence future model performance. In the case of drive-access to transit (Figure 3-3 b), mode constants were greater than the quantifiable utility only in 0.04% of the OD pairs (Table 3-10). This mode choice model is much more sensitive to unaccounted attributes change in the future year than for walk access.



(a) Walk-access to transit



(b) drive-access to transit

Figure 3-3: Magnitude of mode constants relative to measurable components: Philadelphia (Home based work trip, AM peak)

In addition to analyzing the number of OD pairs that exhibit properties, the range of contribution of mode constants are quantified for all trips by two modes – transit with walk access and transit with auto access. As shown in Table 3-9 for walk-access to transit mode, mode constants have sizable percentage out of the total utility or generalized cost (GC).

Table 3-9: Magnitude of mode constants relative to measurable components-walk access: Philadelphia (Home based work trip, AM peak)

	Measurable cost component	Area-type constants	Mode constants
% out of total utility (GC)			
AVG.	56.0%	3.3%	40.7%
Max	80.7%	29.6%	71.5%
Min.	28.4%	0.0%	13.4%
% of cases that (mode constants>=total value of measurable components)			14.3%
No. of pairs in which mode constants>=measurable components			24,520
Total no. of OD pairs[1)]			171,107

1) Excluding OD pairs for which transit service is not provided

Table 3-10: Magnitude of mode constants relative to measurable components-drive access: Philadelphia (Home based work trip, AM peak)

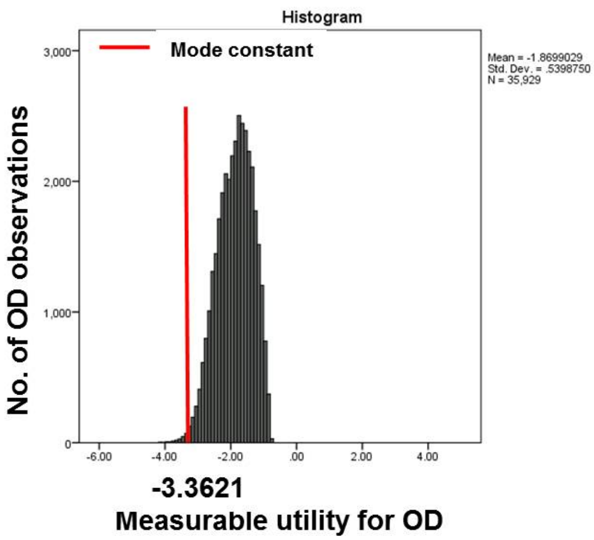
	Measurable cost component	Area-type constants	Mode constants
% out of total utility (GC)			
AVG.	53.9%	18.3%	27.8%
Max	77.1%	33.7%	50.5%
Min.	32.2%	2.1%	12.9%
% of cases that (mode constants>=total value of measurable components)			0.04%
No. of pairs in which mode constants>=measurable components			74
Total no. of OD pairs[1)]			171,107

1) Excluding OD pairs for which transit service is not provided

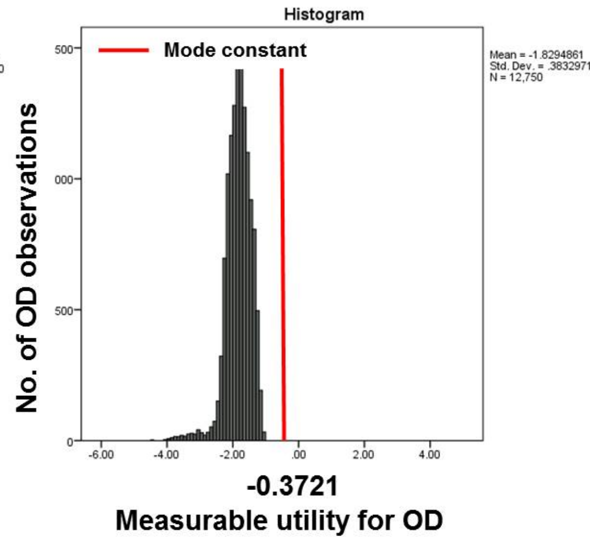
On average, mode constants account for 40.7% of total GC, while the measurable cost component accounts for 56%. Area-type constants cover less than 4%. For drive access modes to transit (see Table 3-9), the impact of mode constants on total GC is less than walk access. The mode constants account for 27.8% of the total utility on average; measurable components account for about 53.9%. The area-type constants cover 18.3%.

3.5.3 Results for Washington D.C.

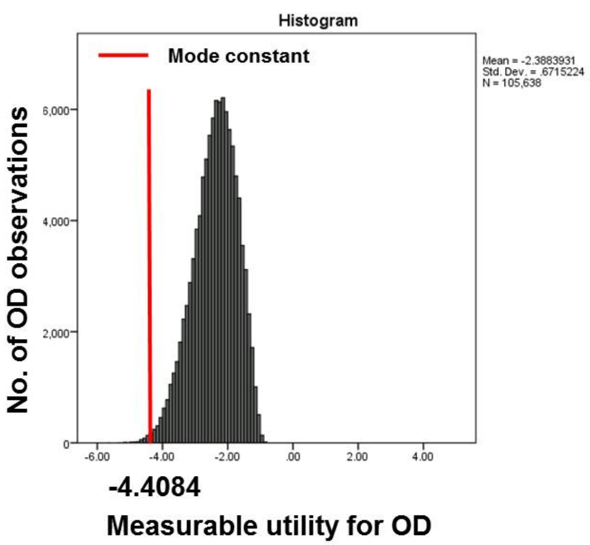
As shown in Figure 3-4, in Washington D.C., signs of mode constants are positive whereas signs of the total values of measurable attributes are all negative. In Figure 3-4, the sign of the mode constants are changed and these are plotted in the same way as Philadelphia. Figure 3-4 a and b show the distribution graphs for Segment 1; c and d present for Segment 3. In the distribution graphs, the area to the right side of the mode-constant indicates OD pairs where the magnitude of unaccounted inputs was greater than measurable inputs. In walk-access to bus modes (Figure 3-4 a, c), mode constants have much larger impact on utility than in KNR-access modes (Figure 3-4 b, d). In walk access to bus transit mode for Seg.1 and Seg.3, 99.6% and 99.7% of OD pairs have mode constants that are greater than the total value of measurable attributes (see Figure 3-4 a and c, respectively). In drive-access to bus transit (Figure 3-4 b, d), both segments have no observed OD pairs in which mode constants are greater than the total value of measurable components. For these cases, the walk access model is much more insensitive to changes in systems' reliability, comfort, convenience, visibility, access environment, and safety attributes than for drive access.



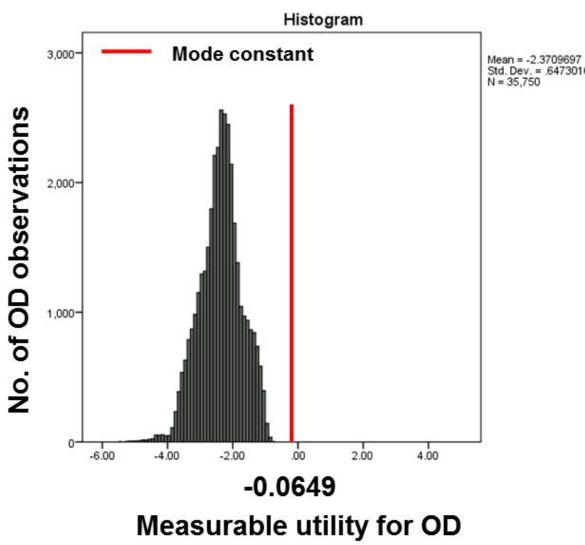
(a) walk-access to bus in Seg.1



(b) KNR-access to bus in Seg.1



(c) walk-access to bus in Seg.3



(d) KNR-access to bus in Seg.3

*mode constants: applied top-level equivalent nesting constants

Figure 3-4: Magnitude of mode constants relative to measurable components: Washington D.C. (Home based work trip, AM peak)

Using the same approach as Table 3-9, in Table 3-11, the range of importance of mode constants for several trip types in Washington D.C. is presented. The percentage of observed OD pairs in which mode constants are greater than the total value of measurable components are 99% for walk-access modes; and 0% for KNR-access modes. In walk-access, on average, mode constants (immeasurable attributes) account for 65% of total disutility while measurable attributes account for only 35%. For KNR-access, the impacts of mode constants on utility are much smaller; these are 17.4% and 2.9% for Seg.1 and Seg.3, respectively.

Table 3-11: Magnitude of mode constants relative to measurable components: Washington D.C. (Home based work trip, AM peak)

	Seg. 1 DC core/urban to DC core		Seg. 3 DC core/urban to DC urban	
	Walk-access to bus	KNR to bus	Walk-access to bus	KNR to bus
No. of pairs in which mode constants>=measurable components	35,783	-	105,305	-
Total no. of OD pairs[1)]	35,929	12,750	105,638	35,750
% of cases that (mode constants>=total value of measurable components)	99.6	0	99.7	0
% of mode constant out of total utility (GC)				
Avg.	64.9%	17.4%	65.5%	2.9%
Max.	81.8%	26.7%	84.1%	7.8%
Min.	45.0%	7.6%	43.8%	1.2%

1) Excluding OD pairs which transit service is not served

Overall, in walk-access to bus, the impact of immeasurable inputs (i.e., mode constants) are much greater than the measurable utility, while mode constants in KNR-access to transit do not have a large influence on the total cost. As calibrated mode constants are used to forecast mode share over the planning horizon assuming that all difficult-to-measure cost components remain constant throughout the analysis period, the walk-access models can become largely insensitive to change of operation or important factors that influence on systems' reliability, comfort, convenience, visibility, access environment, and safety.

- **Impact of mode constant magnitude on model's predictive capacity**

Given the concerns about the large mode constants in specific segments, in this section of the thesis, the impacts of large mode constants on models' functionality are demonstrated through a simple quantitative example. The focus of the demonstration lies on, depending on the size of mode constants, how the probabilities of using transit mode are influenced with respect to the changes of system performance over time.

For this demonstration, the following conditions are assumed. Two utility functions – one for private auto and one for bus transit - are generated. Travel time and cost by each mode for a specific trip from an origin to a destination are assumed as shown in Figure 3-5. For example, in-vehicle-time by bus from the origin to the destination is 20 minutes while the walk time is 10 minutes. Wait time at the stop is 10 minutes and the fare is $2. For the same OD travel by private auto, in-vehicle time is 10 minutes over a distance (to calculate car operating cost) of 5km. Walk time from parking to the destination is 2 minutes and auto ownership (zone average) is 1.5vehicle.

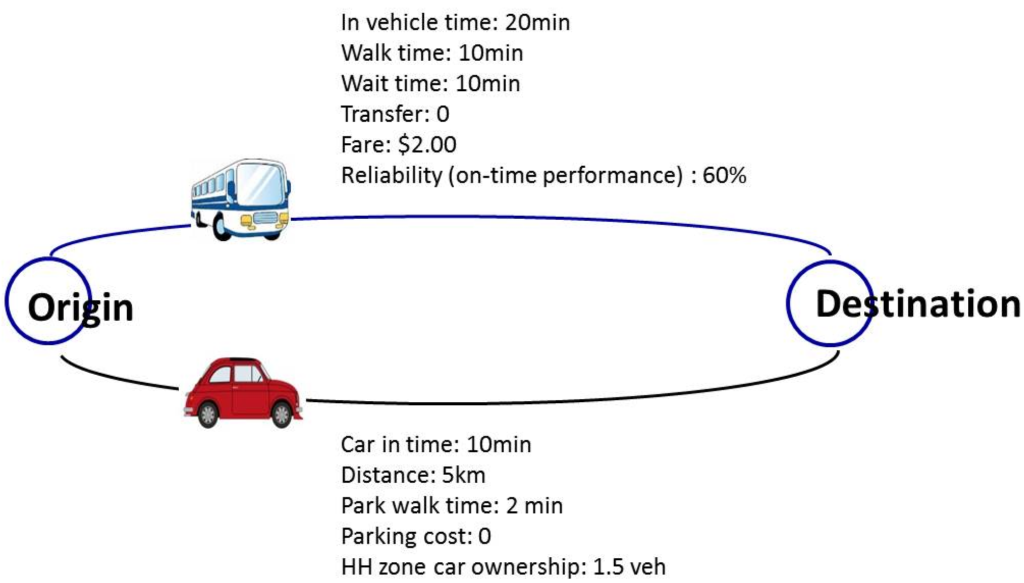


Figure 3-5: Travel characteristic assumptions of transit and automobile to compute influence of mode constant magnitude on model's predictive capacity

The cost representation and the associated coefficients (except mode constant) are broadly derived from the City of Calgary (see Table 3-12, and for original models see Appendix B). The applied coefficients follow a convention that the ratio of OVT/IVT for transit mode ranges from 1.5 (wait time and walk time) to 3.1 (transfer). To estimate probabilities of using transit with respect to system performance change, a simple Multinomial Logit Model (MNL) formulation is applied as described in Table 3-12.

Table 3-12: Applied coefficients and models for mode choice estimation

	Attributes	Modes Applied	Coeff.
In-vehicle time	IVT	Auto Transit	-0.0528 -0.0358
Out-of-vehicle time	Park walk time Transit walk time Transit wait time Number of transfer	Auto Transit Transit Transit	-0.1636 -0.0546 -0.0551 -0.1115
Cost	Operating cost Parking cost Fare	Auto Auto Transit	-0.3167 -0.0317 -0.3167
Others	HH zone car ownership	Auto	3.3768
Applied mode choice model	Multinomial Logit Model (MNL): $\mathrm{P_n}(\mathrm{i}\vert\mathrm{C_n}) = \frac{\exp(\mu V_{in})}{\sum_{\mathrm{j}\in\mathrm{C_n}}\exp(\mu V_{jn})}$ Where, $\mathrm{P_n}(\mathrm{i}\vert\mathrm{C_n})$: probability of choosing *i* alternative among choice set $\mathrm{C_n}$ for individual *n* V_{in}: utility of alternative *i* for individual *n* μ=0.6 *		

*scaled in this study to set the base case.

In this example, two utility functions are developed. The first (Case 1) is a typical utility function that includes traditional cost components. The second function (Case 2) treats reliability explicitly. Using the two different functions, future transit mode share results are compared. To this end, first, transit mode share in base case is set as 6% when the assumed travel time and cost values (in Figure 3-5) are applied. Second, calibration is performed by fixing all coefficients except the mode constant. The calibrated mode constant in Case 1 is 2.334, and the calibrated mode constant accounts for about 49% of total utility while total measurable components account for about 51% (see Table 3-13).

Now, in Case 2, the transit utility function includes the additional variable, reliability. We assume that reliability accounts for about one fourth of the total mode constant. Therefore, new mode constant is 1.734 accounting for 36% of total utility, and reliability accounts for 13% as shown in Table 3-13, under base case column. Consequently, Case 1 has larger mode constant value than Case 2, and Case 2 has new variable of reliability in utility formulation.

Given transit mode share of 6% of two cases in base year, it was examined how the probability of using transit will be influenced by system performance changes in both cases in future years. The following two scenarios are tested:

- Scenario 1: Frequency improvement in bus transit: 20 min headway → 10 minute headway
- Scenario 2: Transit reliability improvement: on-time performance 60% → 80%*

* A review and the definition of transit reliability are presented in 5.2.3 of this thesis.

It should be noted that since the calibration was performed by fixing all coefficients except the mode constants, the final utility formulation may not have addressed all the interactions of the reliability with other variables.

Table 3-13: Impact of mode constant magnitude on model's predictive capacity

	Base case				Scenario1		Scenario2	
	Case 1		Case 2		Case 1	Case 2	Case 1	Case 2
Value of measurable component	-2.447	51.2%	-2.447	51.2%				
Value of Reliability	-	-	0.6	12.5%				
Mode constant	2.334	48.8%	1.734	36.3%				
		100.0%		100.0%				
Mode share of transit	0.061		0.061		0.078	0.078	0.061	0.073
Transit mode share change					+0.017	+0.017	-	+0.012
Increment based on base case (%)					+29.3	+29.3	-	+20.5

In Table 3-13, Scenario 1 tests the case when transit system performance, particularly frequency has increased. The results of mode share indicate that regardless of the magnitude of mode constants (Case 1 or Case 2), the models generate equally increased likelihood of using transit (from 6.1% to 7.8%, 29.3% increase of transit ridership in both cases). This is because frequency improvement can be measured as waiting time in utility functions and does not affect the transit mode share.

Scenario 2 tests the case where transit reliability is increased. On-time vehicle performance is assumed to increase to 80% in the future year from 60% in calibration year. The Case 1 model cannot capture the improved system performance of reliability change as shown in the results under Scenario 2 in the same table. The likelihood of using transit is still 6.1%. On the other hand, in the Case 2 model, transit mode share has increased by 7.3%, and transit ridership forecasting has increased as much as 20.5% compared to the base case. The result implies that larger the mode constants, transit ridership forecasting result errors between future year and base year can be significantly increased.

To sum up, the results indicate that system performance change of 'directly included variables' in the model, frequency in this example, does not influence on overall predictive capacity. However, when reliability is explicitly included in the model (as a result, when mode constants are reduced), the mode choice models generate more sensitive results for the un-accounted system performance (reliability in this example) improvements. The results demonstrate that, the larger the mode constants, the models are insensitive to the changes on the un-accounted for system performance improvement. The errors on transit ridership forecasting will be accumulated over time.

3.6 Chapter Summary

In transit travel forecasting, understanding mode constants is a significant issue, since these constants reflect behavior assumed to be static throughout the analysis period. In this chapter various types of calibration coefficients from the state-of-the-art regional travel forecasting models are introduced and the magnitude of mode constants has been examined using empirical data from six cities in Canada and the US. The magnitude of mode constants has been evaluated by IVT and relative importance to measurable components (i.e., mostly travel time and cost) of mode choice utility. For this, the total disutility of travel was disaggregated into two components – measurable travel attributes and costs associated with mode constants. This chapter has presented three major findings from the case studies as follows.

First, the majority of cities (four cities including Philadelphia, Denver, Winnipeg, and Ottawa) have negative values of mode constants; the other two cities (Calgary and Washington D.C.) have some positive values. A negative mode constant for transit modes means that the mode choice models would over-predict the transit ridership; the mode constants have an influence on decrease of the transit rideship after calibration.

Second, the magnitude of mode constants in IVT values varies, ranging from 42 min to 219 min depending on transportation system size, presumably travel distance, and model types. For example, Calagary and Winnipeg tend to have smaller mode constant values, while Denver and Ottawa have larger values. The magnitude of mode constants can also vary depending on travel distance in the same city. It is observed that there is overall difference between short distance trip (i.e., walk-access) and long distance trip (i.e., drive-access). In drive-access to transit trips, mode constants tend to have larger values than short distance trips of walk-access.

Significant differences exist in the observed magnitude of mode constants across cities. For instance, although Philadelphia is the largest metropolitan area among six cities, the size of mode constants is smaller than those of the other cities. In the case of Washington D.C., the the size of mode constants for PNR and KNR access models are smaller than those of the other six cities, while the mode constants for walk-access are extrememly larger than the others. Those extremely large mode constants suggest a problem with transit travel forecasting.

Third, the importance of mode constants relative to the measurable components is examined. In the study area of Philadelphia, for both access modes (walk access and drive access) to transit, the mode constant itself tends not to have an unusually large influence on the total cost. In about 14% of OD pairs, the mode constants were greater than the total value of measurable components in walk-access; and only 0.04% in drive-access modes. Yet, mode constants still have sizable percentage out of total utilities. On average, total value of unmeasured attributes (i.e., mode constants) account for 41% of total utilities in walk-access, 28% in drive-access.

In Washington D.C., in walk-access to bus modes, the impact of immeasurable inputs (i.e., mode constants) is much greater than that of the measurable utility in almost of all OD pairs. The % of mode constants out of total GC indicates that the average magnitude of mode constants are almost 65% of the total utility in walk-access modes for both study segments. On the other hand, mode constants for KNR-access to transit do not have a large influence on the total cost. As the calibrated mode constants are used to forecast mode share over the planning horizon assuming that all difficult-to-measure cost components remain constant throughout the analysis period, these walk-access models can become largely insensitive to change of operation or important factors that influence on systems' reliability, comfort, convenience, visibility, access environment, and safety.

The objective of the study in this chapter is to demonstrate an understanding of the state of practice with regards to model formulation and mode constants. Moreover, by estimating the overall magnitude of various mode constants and by quantifying the importance of mode constants relative to the measurable components, it provides some evidences on what portion of travel cost between an origin and a destination is comprised of a fixed mode constant. By applying the approach, it is also useful to identify problematic segments that have unusually large mode constants.

Given the concerns about the size of the mode constants and their impacts on models' functionality, an approach to further analyze their impacts on model performance is developed. The approach, presented in Chapter 5 is to identify zones where models under predict or over predict transit ridership. For these zones, I attempt to identify important characteristics of the zone's built form and demographics of its residents that if included explicitly may improve the model's estimate.

The method of identifying over and under predicted zones requires knowledge of where travelers begin and end their trips at the zonal level. The data that are available most frequently are not trip ends, but rather boarding and alighting locations. Thus, it is necessary to develop robust methods to assign transit boardings to origin zones and transit alightings to destination zones. Chapter 4 presents and evaluates four candidate methods to complete this step.

Chapter 4
Allocating Transit Trips to Zones

In this chapter, methods to link the stop-level boarding and alighting trips to the traffic analysis zones from which these passengers actually originated or were destined are formulated. In each case, readily available, local data are used. For each technique proposed here, a method to test the accuracy of predictions using the results of on-board surveys is formulated and applied. The results of the research presented suggest that it is possible to map transit route boardings and alighting to origin and destination zones with sufficient accuracy to allow for the use of these data in calibrating travel forecasting models. More details on the proposed methods and assessment results are described in the following sections.

4.1 Introduction

Technologies such as automated vehicle location (AVL), automated passenger counting (APC), and automated fare collection (AFC) systems have been growing in popularity. In addition to improving transit operations, these automated systems can augment conventional data sources for travel demand modeling and its validation. In contrast to traditional survey methods that sometimes require high costs for limited samples, AVL/APC systems enable modelers to access a rich dataset of transit vehicles' time-at-location as well as spatially and temporally disaggregated information on transit ridership.

With these benefits, usage of automatically collected data (ACD) is increasingly popular, particularly for transit path-choice modeling, transit origin-destination matrix estimation and direct-demand modeling (or sketch planning modeling) research. Most of this research has focused primarily on stop-level analysis since the ACD provides direct values (e.g., on/off counts) at each stop. Stop-level estimates of origins and destinations using AFC data (Barry et al. 2002, Farzin, 2008, Chu and Chapleau, 2008, Wilson et al. 2009, and Nassir et al. 2011) have also been completed. Further, direct-demand models that relate transit ridership at either a station (boarding or alighting) or station-to-station (trip pattern) level to a variety of independent variables have attracted great attention in recent years (Upchurch et al. 2013, Zhao et al. 2013).

In spite of the increasing attention to the APC or AFC data, little attention has been paid to the use of these data more broadly in regional travel demand modeling procedures, especially mode choice. One of the main difficulties of incorporating APC data to the demand modeling process is the lack of appropriate and proven methods to map trips from a stop to the appropriate traffic analysis zone from (or to) which a trip actually begins (or ends). Previous studies that have addressed this problem, and their recognized limitations, are presented in Section 2.3. Additional research results are presented in the following section.

Existing research on spatial aggregation of stop counts at the zonal-level, is not (yet) adequate for implementation in regional travel forecasting models since, in this research, a zone is defined as a group of places where a fare card transaction occurs. This is different from a zone in travel forecasting models, which is defined as an activity generator or attractor.

A general principle used in most of the potential transit demand models is that the boardings at a stop should be allocated to nearby areas based on the density of activity – population or employment for example – and the proximity of this density to the stop itself. To improve previous methods, the definitions of density have been extended by some researchers to the parcel level, by incorporating household data such as number of bedrooms in dewelling unit or household size. One such example is Zhao (2003), who addresses the issues of uneven population distribution in transit access buffer areas by incorporating detailed household variables derived from cadastral data. Kimpel et al. (2007) allocate potential transit demand in overlapping transit service areas to specific stops. They measure the effect of overlapping service areas on passenger boardings by applying scheduled service (i.e., buses per hour) and dwelling units in nearby parcels. Biba et al. (2010) analyze population (i.e., potential transit users) estimates in transit access shed by connecting parcel centroid to cadastral data and to the walking network. They compare the estimates to buffer methods and network-ratio method. Their results show that based on the parcel-network method, network-ratio method overestimates population around stop areas from 11% to 117% depending on transit routes, and buffer method overestimates from 41% to 184%.

Arguably, the best research effort available for the issue of assigning stop counts to TAZs was conducted by Furth et al. (2007). The authors propose a method for assigning stop-level demand at a parcel level in Boston and Albany. Their approach is to solve the many-to-one (i.e., parcels to a stop) trip distribution problem as a function of strength between two locations. However, due to a variety of coefficients and factors that need to be determined based on expert judgments, its application in practice is difficult. On the basis of these previous works, in this chapter, I focus on formulating methods to further improve the allocation of APC data; the methods are introduced in the following section.

4.2 Methods

Four methods are proposed and applied to assign stop boarding/alighting counts to traffic analysis origin and destination zones. The first approach is the buffer area ratio method weighted by population and employment. In this method, I assign trips proportionally to the population / employment and area sizes of competing zones within transit accessible areas. To incorporate more land use information, the second and third approaches consider the number and types of parcels of each competing zone. The fourth method adds weights to these parcels having high-rise buildings. The following sections describes each of the methods in detail.

4.2.1 Defining buffers

In typical transit demand analysis, each stop in a network is assumed to attract passengers from an access shed. The most common way to define these sheds is to create a buffer distance around the stop location. The simplest form of the shed is a circle with the center at the stop location and the radius determined by an acceptable walking distance. To create the boundary, a 400m radius is used as a common guideline for light-rail transit station and bus rapid transit stops; 800m is often considered appropriate for commuter rail stations (O'Sullivan, and Morrall, 1996, Gutierrez and Garcia-Palomares, 2008, Zielstra and Hochmair, 2011). These values tend to be taken from empirical studies. Some studies suggest that transit share diminishes rapidly around this 400m boundary. For example, Crowley et al. (2009) demonstrate that the use of rapid transit significantly dropped in the band between 400m and 800m from a stop location.

Willingness-to-walk distance has also been shown to vary by area type. Table 4-1 shows the summary of empirical studies on willingness-to-walk distance by Lee et al. (2013). Table 4-1 demonstrates different access assumptions for CBDs and suburban areas in Calgary and Toronto. The walking distances in CBD areas tend to be shorter than in suburban areas presumably due to dense land use and better transit service standards (e.g., network coverage). Walking distance to transit also varies by transport mode - train or bus. It is known that people are willing to walk farther to access a higher-order service such as rail modes compared to conventional bus transit. Other research suggests that the access areas should be greater for BRT systems compared to conventional systems.

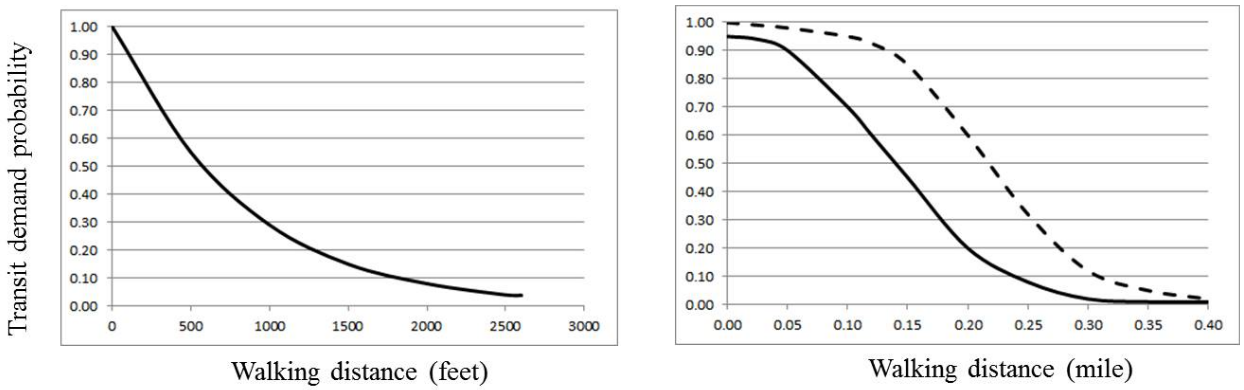
Table 4-1: Summary of willingness-to-walk distance studies (Lee et al., 2013)

Study	Walking distance: distance threshold	Measurement and application	Location	Remark
Lam and Morrall	292m	Median walking distance	Calgary, Canada	Average: 327m; 75th percentile: 450m
O'Sullivan and Morrall	326m: CBD; 649m: suburban	Average walking distance	Calgary, Canada	Distinguish between walking to LRT station in the suburbs and in the CBD
Hsiao et al.	400m	Buffer	Orange County, Calif.	According to the 1990 on-board survey, more than 80% of bus riders would walk up to 400m
Polzin et al.	800m	Buffer	Tampa, Fla.	800m buffers for zonal coverage have been drawn around each route
Zhao et al.	800m	Buffer	Southeast Florida	By applying a decay function, a long walking distance (800-1600m) may be unnecessary
Kittelson and Associates	400m	Aveage walking speed of 5km/h	North American cities	Most passengers (75% to 80% on average) walk 400m or less to a bus stop
Alshalalfah and Shalaby	231m: downtown; 454m: suburban	Median subway access distance	Toronto, Canada	
Utsunomiya et al.	Distribution of minimum daily access distance	Estimated access distance	Chicago, Ill.	In the case of Chicago Card customers, walking access distance vary significantly between rail and bus
Kimpel et al.	536 m (1/3 mi)	Buffer	Portland, Ore.	Initial distance of 1/3 mil and then a distance decay function is applied
Alshalalfah and Shalaby	60% of users live within 300m from their stop	Buffer (an interval of 100m)	Toronto, Canada	Overall, 80% live within a distance of 500m
Hoback et al.	580m	True walking distance	Detroit, Mich.	On average, 1,300m per round trip (e.g., home-transfer-work-transfer-home)

Note: North American cities only. From Lee et al., 2013

Other researchers have been more sophisticated varying the radius based on climate, vertical grades that must be traversed, and the directness of the access paths. Calthorpe (1993) applied slower walking speed of 2.27mph considering walking environment of hills, rivers, and other obstacles in pedestrian movement, and suggested 2000-ft (about 610 m) radius.

Some studies applied distance-decay relationships either taking a negative exponential form derived from an actual walk distribution (Zhao et al., 2003) or a negative logistic function which reflects a more gradual decline in transit demand at short distance, a steeper decline as distance approaches 400m, and a more gradual tail (Kimpel et al., 2007) (see Figure 4-1).



(a) Negative exponential type function (Zhao et al., 2003)

(b) Negative logistic type function: the two different functions reflect different coefficients. From Kimpel et al. (2007)

Figure 4-1: Distance-decay functions to measure willingness-to-walk distance

The idea of distance-decay is that passenger demand decreases with respect to increased walking distance to stops. The function measures the level of accessibility from features (e.g. home, parcel) to stops. In an operationalized model, the use of distance-decay type functions rather than the buffer method may be able to generate more realistic results of transit use.

The maximum willingness-to-walk distance has also been derived from appropriate walking travel time – 5 min and 10 min walk to stops - and walking speed. Gutierrez and Garcia-Palomares (2008) analyzed that buffer radius of 300m and 600m corresponded to these 5 and 10 min walking travel time, respectively.

Choosing the correct boundary of transit access shed is challenging work as the literature demonstrates. In spite of some variance, depending on the study context, the evidence in table 4-1 establishes (from empirical studies) that the walking distance or distance threshold for bus and BRT system ranges from 400 to 450 meters. In this study, the proposed methods are evaluated for BRT routes in the Region of Waterloo. While some research has suggested that larger access sheds may be warranted in analyzing BRT routes, in this research, the traditional 400 meter buffer is used. Operationally, the BRT stop spacing in Waterloo is about 1.2 km. But, in many corridors, the BRT route shares an alignment with conventional services. So while a 400 meter radius leaves gaps between BRT stops, it is likely that those who would begin a trip at the midpoint between stations, would do so using conventional transit.

The next step in the research is to allocate the number of boardings and alighting over a given time period to zones contained in the access shed. In some cases, an access shed may be wholly contained in a single traffic analysis zone (TAZ) at which point the problem becomes trivial – all boardings and alightings are assigned to that zone. The problem becomes more complicated when the access shed spans multiple TAZs. This is the problem I am attempting to solve.

4.2.2 Buffer area ratio weighted by population and employment

The concept of buffer area ratio has been widely used to estimate transit access (O'Neill et al. 1992, Hsiao et al. 1997, Peng and Dueker, 1995, Ayvalik and Khisty, 2002). The first approach employs this concept. The idea of buffer area ratios is that the proportion of trips beginning or ending in a zone should be proportional to the attribute(s) of the candidate zones. Naturally, trip patterns vary as a function of the time of day. On a weekday morning, for example, many transit trips are commuting trips; the expectation in this time period is that transit boardings will be more heavily influenced by the presence of residential land uses near to the boarding location. Similarly, alightings in the morning peak are more likely to be destined to employment locations – commercial or industrial land uses. If the mapping analysis is conducted for a weekday afternoon, the opposite logic may be warranted – boardings are generated by places of work while alightings are destined for residential land uses.

In this research, boarding and alighting data are from the am peak. As such, the presence of residential density is used to allocate origins. Based on the same logic, alighting trips are allocated based on the presence of commercial, business, and institutional areas.

Mathmatically, the method of estimating the transit boardings from zone i (b_i) from the station boarding count, b_{s_k} is represented as equation (4-1).

$$b_{i,S_k} = \frac{(\mathrm{as_i}/\mathrm{AS_i}) \times \mathrm{P_i}}{\sum_{\mathrm{i} \in \mathrm{S_k}} (\mathrm{as_i}/\mathrm{AS_i}) \times \mathrm{P_i}} \times \mathrm{b_{S_k}} \qquad \forall\, \mathrm{S_k} \tag{4-1}$$

Where:

b_{i,S_k}: observed boardings from zone i using Stop k
$\mathrm{as_i}$: area of zone i within the 400m buffer of stop k

$\mathrm{AS_i}$: Total area size of zone i

$\mathrm{b_{S_k}}$: Total boardings at stop k

$\mathrm{P_i}$: Population of zone i

$i \in S_k$: Subset of zones that intersect with stop k within 400m radius

Next, the total number of transit trips originating from zone *i* is computed as the sum of boardings over all stops that have an access shed involving zone i. This summation is shown in equation (4-2).

$$B_i = \sum_{S_k} b_{i,\,S_k} \tag{4-2}$$

Where:

B_i: observed total transit users of origin TAZ i

In the same way, the estimated number of transit alightings to zone j (a_j) from a station's alighting count is computed as equation (4-3) and summed over all the stops in equation (4-4).

$$a_{j,\,S_k} = \frac{(\mathrm{as_j}/\mathrm{AS_j}) \times \mathrm{E_j}}{\sum_{\mathrm{j} \in \mathrm{S_k}} (\mathrm{as_j}/\mathrm{AS_j}) \times \mathrm{E_j}} \times \mathrm{a_{S_k}} \qquad \forall\, \mathrm{S_k} \tag{4-3}$$

Where:

$a_{j,\,S_k}$: observed alightings in zone j using Stop k
$\mathrm{as_j}$: Intersected area of zone j with 400m radius from stop k
$\mathrm{AS_j}$: Total area of zone j
$\mathrm{E_j}$: Employment Population of zone j
$\mathrm{a_{S_k}}$: Alightings at stop k
$\mathrm{j} \in \mathrm{S_k}$: Subset of zones that intersect with stop k within 400m radius

$$A_j = \sum_{S_k} a_{j,\,S_k} \tag{4-4}$$

Where:

A_j: observed total transit users of destination TAZ j

The procedures of the buffer area ratio method are systematically presented in the following steps; Figure 4-2 shows the method graphically.

Step 1	Create a 400 meter (Euclidean distance) buffer around a stop.
Step 2	Intersect zones with the created buffer in step 1 and calculate the ratio of the intersected area and individual zone.
Step 3	Repeat steps 1 to 2 for all stops.
Step 4	Allocate boardings/alightings to individual zones based on area size ratio and population employment.
Step 5	Aggregate the allocated boardings/alightings for each zone.

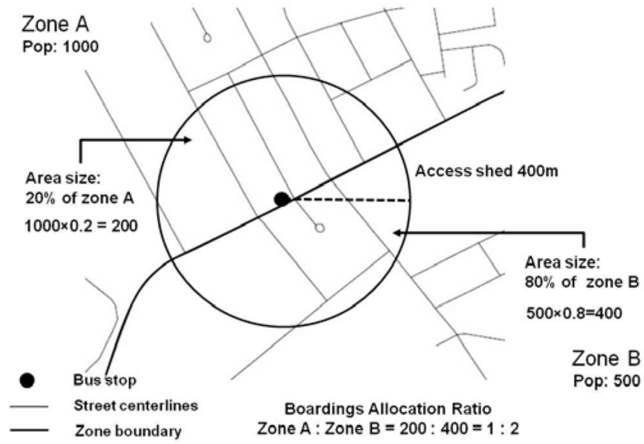


Figure 4-2: Graphical representation of the buffer area ratio weighted by population and employment

4.2.3 Parcel number ratio

To consider the effect of land use density, the second approach allocates trips not as a function of area, but rather as a function of the number of parcels present in the transit access area for each zone. To quantify the approach, the following two calculations are made:

a. **Parcel number ratio method 1:** The trip allocation is completed based on the ratio of the total number of parcel ratios within a zone's transit access shed, relative to all parcels in the access shed.

b. **Parcel number ratio method 2:** The trip allocation is completed based on disaggregate ratios of parcel types. More specifically, boardings are allocated to zones based on the ratio of residential parcels in a given zone to the total number of residential parcels in the full access shed. Similarly, the proportion of alighting trips assigned to a zone is determined based on the proportion of employment parcels – commercial, institutional, or industrial – in a given zone relative to the full access shed.

The procedures are similar to those of the buffer area ratio method.

Step 1 Create a 400 meter buffer around a stop

Step 2 Intersect not only zones but also parcels with the created buffer in step 1

Step 3 Repeat steps 1 and 2 for all stops. As parcel data include land use attributes, the generated GIS outputs from steps 1 to 3 include StopID, TAZ ID, Parcel ID, Land use Code (Residential, Institutional, Commercial, Industrial, Road, Agricultural, and etc.) and shaped parcel areas.

Step 4 With the GIS generated outputs, compute the parcel ratios

Step 5 Based on the estimated numbers of parcel ratios, the transit on/off count data at each stop are multiplied by each ratio and boardings and alightings are aggregated by TAZs.

4.2.4 Footprint weighted parcel ratio method

The fourth method is the weighted parcel method which extends the previous approach to include the relative trip production and attraction of a given parcel based on its overall size or function. This method can improve the accuracy of the parcel number ratio method, particularly where large buildings exist within the catchment areas. The concept motivating this method is that parcels containing large structures, often with multiple dwelling units should be weighted more heavily in assigning trip origins than parcels with smaller buildings and potentially only a single dwelling unit.

To compute the footprint weights, GIS data for building sizes are necessary. In my experience, these data are typically available. To allocate the number of alightings to a zone, the total number of trips is proportioned based on the relative commercial building footprints in each candidate zone.

To allocate the number of boardings to zones, an additional step is taken to quantify the number of dwelling units contained in any building over five stories. In some cases, the number of dwelling units per building is available in a GIS format such that the dwelling unit weights can be directly calculated. If the data are not available, such as in our case, an alternative approach to estimate the number of dwelling units is required. In this study, building height, measured in stories, was available for all parcels. At a larger spatial scale, the dissemination area, the total number of dwelling units and the total building areas were available. From these two data points, it is possible to calculate the average building area per dwelling unit. Thus, the total number of dwelling units on a parcel, dwu_m is estimated as a function of a building's area, its height in stories, and the average area per dwelling unit. The calculations are shown in equation (4-5).

$$dwu_m = \frac{(\mathrm{sa_m}) \times \mathrm{s_l}}{\text{Avg.total area of multi}-\text{dwelling unit}} \tag{4-5}$$

Where:

dwu_m : number of dwelling units in parcel m

$\mathrm{sa_m}$: area of building l with parcel m

$\mathrm{s_l}$: Storey of building l

The summary of procedures of the fourth approach are as follows:

Step 1 Create a 400 meter buffer around a stop

Step 2 Intersect the buffers, zones, parcels, and building footprint

Step 3 Iterate Step 1 and Step 2 for all stops. The produced GIS outputs include StopID, TAZ ID, Parcel ID, Land use code of parcel, Building ID, Building Type, Building Footprint Area, Storey, and Shaped building area with intersected buffer of the stops and TAZs. The outputs are generated only when buildings exist in the intersected areas among buffers and TAZs

Step 4 Merge the GIS outputs (i.e., parcels including buildings) in Step 3 with the GIS outputs (i.e., all parcels information) from the parcel number ratio method in previous section. This is done because we still need to count the number of parcels as well as building weight

Step 5 Delete the duplicate parcel ID records from the merged outputs from Step 4.

Step 6 Estimate weights for parcels including high storey buildings.

Step 7 The transit on/off count data at each stop are multiplied by each ratio, and consequently, boardings and alightings are aggregated by TAZs.

4.3 Application of Methods to a Case Study – The Region of Waterloo

The Regional Municipality of Waterloo is located approximately 100km west of Toronto in southern Ontario. The region is comprised of three cities - Kitchener, Waterloo and Cambridge - and four rural townships. The current population is approximately 550,000. Transit is provided in the three cities by Grand River Transit (GRT), a division of the Regional government. GRT provides 12.2 million vehicle kilometers and 16.6 million passenger trips in the region per year (2008). At the time of the study, the agency had a fleet of 208 vehicles, of which about 90% are equipped with AVL/APC technologies.

For this research, a subset of the Region was identified. The study area, shown in the inset of Figure 4-3, consists of 52 zones. At the boundary of the study area, an additional 35 zones were identified that could be potential origin or destination zones. The land uses observed in the study areas are residential, commercial, industrial and institutional areas, including two universities. This area was chosen because an on-board survey which provides validating data – origin zones and boarding locations, as well as destination zones and alighting locations – was recently conducted.

Transit activity at each stop was provided from the Regional government's AVL/APC database. Data were ascertained for a one month period from February, 2012. The total transit trips may be affected by the seasonal variations caused by weather or academic calendars. However, since this study focuses on transit trip allocation methods that are related with transit access pattern, the influence of those periodical variations on travel access pattern may be minimal. For each stop, the average weekday am peak (7-8am) boarding and alighting counts were calculated for each trip scheduled during the study hour. The sum of the averages for each trip produces an hourly average of boardings and alightings at each stop.

The methods described above were completed using GIS. The input files for the analysis included: the transit network, including all route and stop locations; the boundaries of traffic analysis zones; population, employment, and area for each of the TAZs; parcel information; building footprint and heights in stories; and 2006 census data comprising housing type and number of dwelling units at the dissemination area (DA) level.

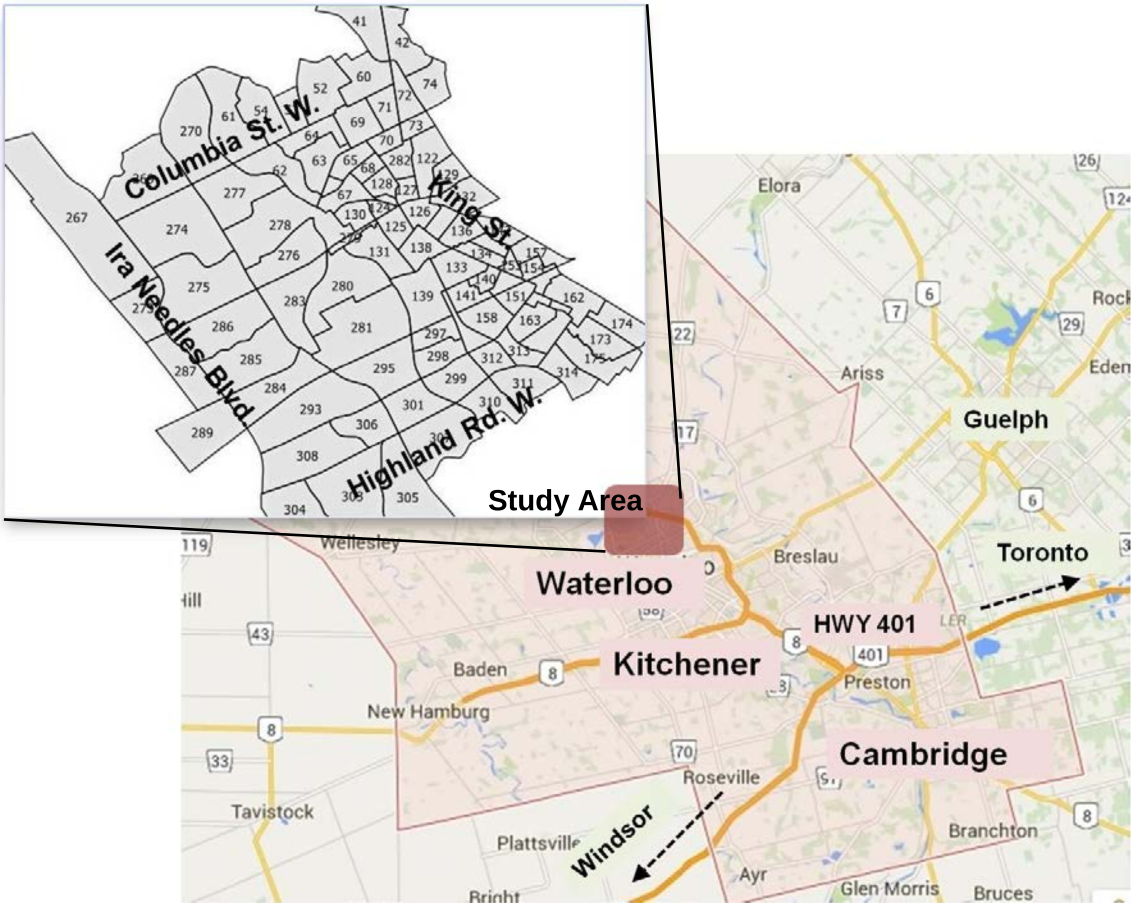


Figure 4-3: The Regional Municipality of Waterloo and study area (Map source: Google maps)

4.3.1 Demonstrating the impacts of the multiple methods

The problem to be solved is the allocation of transit boardings and alightings to a number of candidate TAZs all of which are contained in part by the transit stop's access shed – a 400 meter boundary around the stop itself. Four separate methods have been suggested. To demonstrate the different outcomes that result from the four methods, the following approach was taken. Four representative stops located in King Street (known locally as the Central Transit Corridor (CTC)) from within the study area – Stop IDs 1906, 2540, 3619 and 3719 have been selected. The number of candidate TAZs for these stops range from four (Stop ID 2540) to ten (3719). Each of these stops, the boundaries of their buffers, and the limits of the adjacent TAZs are shown in Figure 4-4.

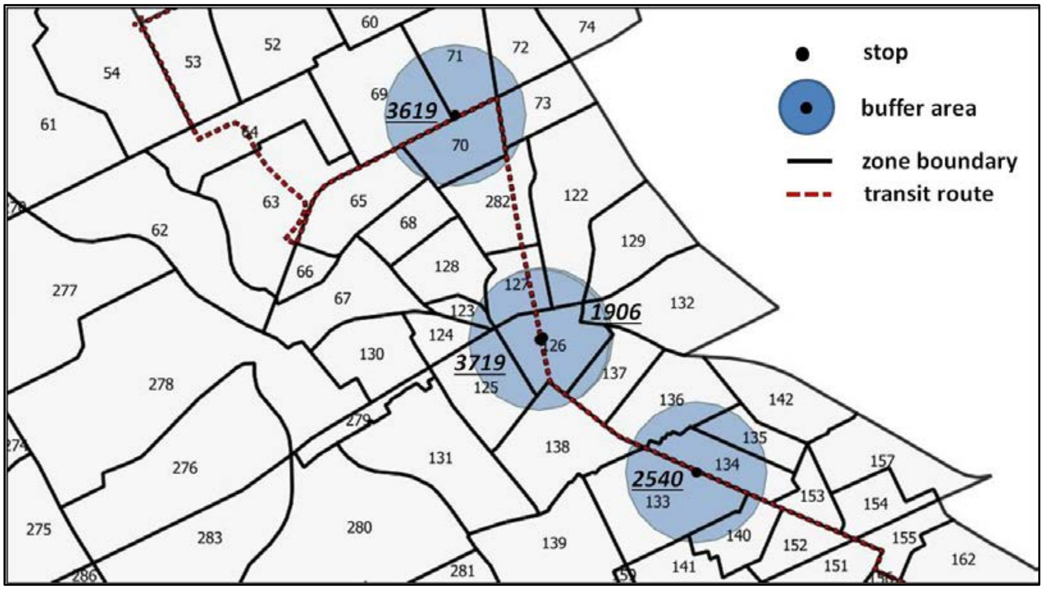


Figure 4-4: Configuration of stops, the buffer areas, and associated zones

For each of these stops, the number of alightings that would be allocated to each TAZ using the four different techniques has been computed. The results are shown in Table 4-2. Note that the table includes only those TAZs with non-zero alighting allocations.

Table 4-2: Allocating results of stop activites to TAZs using four methods

		Buffer area ratio	Parcel number ratio (1)	Parcel number ratio (2)	Footprint weighted parcel ratio
Stop ID	Associated TAZs	% allocation	% allocation	% allocation	% allocation
1906	122	1.6	15.3	10.3	5.4
	123	0.1	0.3	0.7	2.2
	125	2.0	18.7	8.9	2.6
	126	63.5	29.1	40.4	47.1
	127	23.6	18.4	30.8	35.3
	132	0.6	4.3	4.8	3.2
	137	3.6	8.6	2.1	1.8
	138	5.1	5.2	2.1	2.4
	Totals	100.0	100.0	100.0	100.0
2540	133	66.6	38.3	27.5	83.3
	134	25.9	27.1	41.2	5.4
	136	4.1	18.2	15.7	10.7
	140	3.4	16.4	15.7	0.6
	Totals	100.0	100.0	100.0	100.0

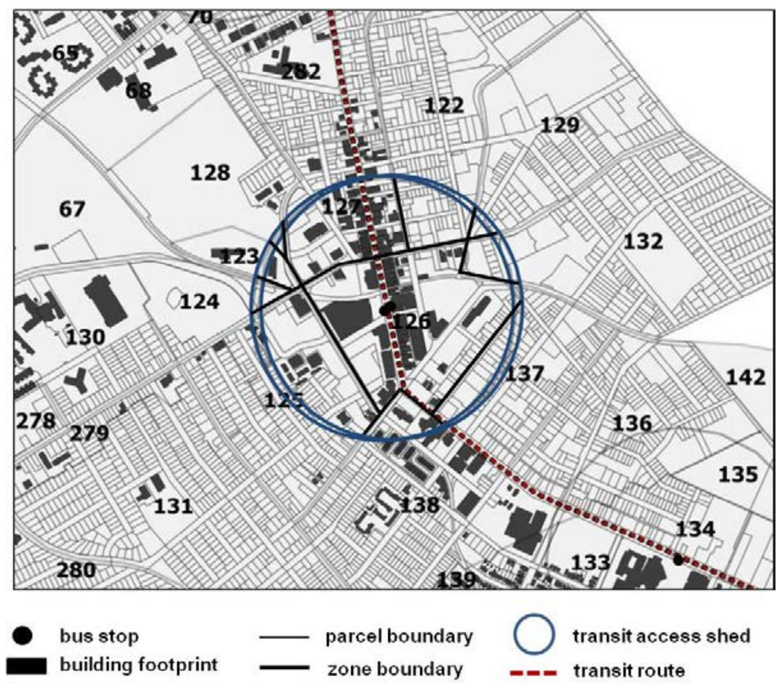
		Buffer area ratio	Parcel number ratio (1)	Parcel number ratio (2)	Footprint weighted parcel ratio
Stop ID	Associated TAZs	% allocation	% allocation	% allocation	% allocation
3619	65	1.7	5.1	0.0	0.0
	69	5.6	35.9	10.0	3.9
	70	41.6	0.7	3.3	80.1
	71	27.3	34.4	13.3	4.3
	72	5.4	4.4	36.7	3.2
	73	16.4	7.0	33.3	8.6
	282	1.9	12.5	3.3	0.0
	Totals	100.0	100.0	100.0	100.0
3719	122	1.4	13.4	9.3	5.3
	123	0.1	0.3	0.7	2.2
	124	0.0	0.6	1.3	0.0
	125	2.2	21.2	9.3	3.0
	126	63.3	28.4	39.3	47.1
	127	23.5	17.9	30.0	34.8
	129	0.3	1.5	1.3	0.0
	132	0.5	4.2	4.7	3.1
	137	3.0	6.9	2.0	1.8
	138	5.5	5.7	2.0	2.5
	Totals	100.0	100.0	100.0	100.0

To explain the data contained in Table 4-2, the characteristics of the areas surrounding several stops are analyzed. Figure 4-5 shows the configuration of parcels and building footprints around the above stop areas.

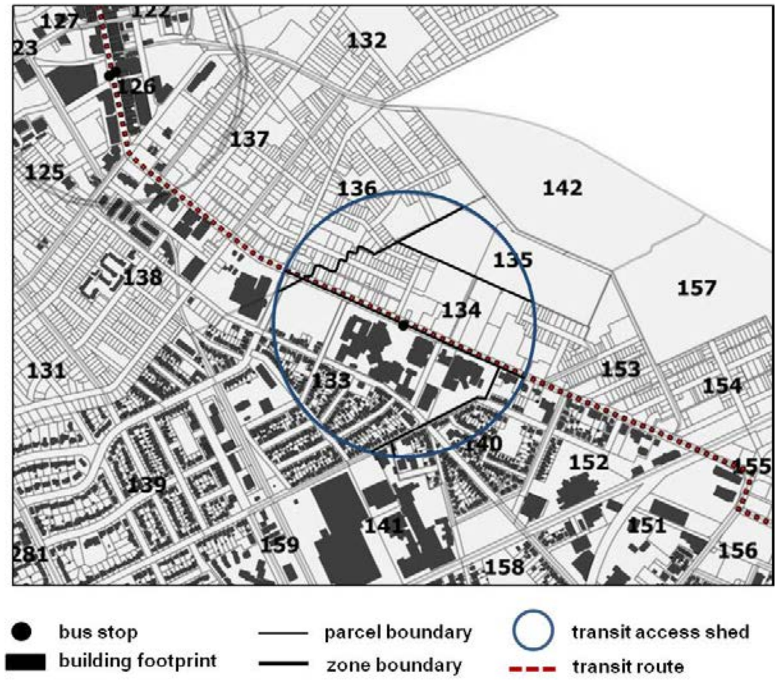
As shown in Figure 4-5 (a), Stops 1906 and 3719 are located in a high density area known as Uptown Waterloo, where low-rise commercial buildings (one to four stories, but mainly one to two stories) are dominant along the transit route. As indicated in Table 4-2, stop 1906 and 3719 generate very similar results since the transit access sheds from these two stops almost completely overlap each other. Accordingly, here, the results for Stop 1906 are shown.

Some differences exist between the four methods, specifically for zones 126 and 127 surrounding Stop 1906. Among these two zones, the buffer area ratio method allocates more alighting trips to zone 126 than 127 (63.5 vs. 23.6% respectively) while the weighted-footprint (47.1% vs. 35.3%) and parcel number ratio (2) (40.4% vs. 30.8%) methods produce more balanced results. As shown in Figure 4-5 (a), in the case of zone 127, commercial buildings are more concentrated in the buffer area surrounding Stop 1906 than in remaining area of the zone 127 outside of the buffer. Since weighted buffer area ratio method assumes even distribution of employment for a zone, the weightings of employment in zone 127 intersected with transit access shed can be underestimated. As a result, the buffer area ratio method allocates more percentage of alighting trips to zone 126 than 127.

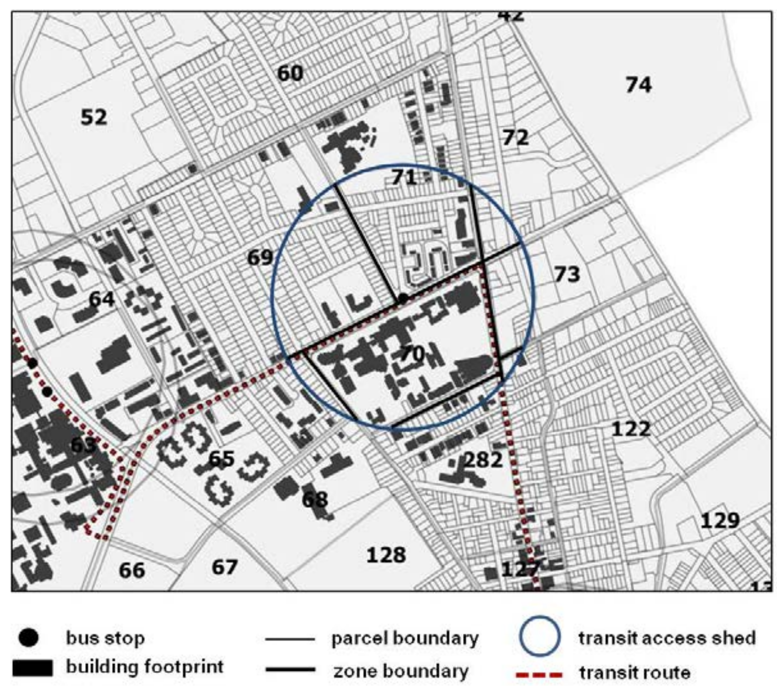
For zones 122 and 125 surrounding Stop 1906, the two parcel number ratio methods allocate over 10% of alighting trips to these zones, while the buffer are ratio and weighted foot-print methods assign much smaller percentages, less than 5%. These zones are comprised of a greater number of residential parcels. Zones 126 and 127 have fewer parcels, but contain some of the highest employment density areas in the region.



(a) Stop ID: 3719 and 1906 (Uptown waterloo - King st. near Town square)



(b) Stop ID: 2540 (Grand River Hospital)



(c) Stop ID: 3619 (Wilfrid Laurier University)

Figure 4-5: Configuration of parcels and building footprints in buffer areas

As shown in Figure 4-5 (b), the buffer area around Stop ID 2540 includes a large parcel (part of zone 133) on which Grand River hospital is located. The buffer area also contains significant residential areas (zone 133 and 134), as well as some commercial zones (part of zone 134). From Table 4-2, the buffer area ratio and footprint-weighted methods generate similar transit trip allocations to TAZs – with a significant proportion of trips destined for Grand River Hospital (zone 133). This is intuitively correct as the hospital is one of the major activity centers in the Region of Waterloo. On the other hand, two parcel number ratio methods more evenly distribute transit trips to surrounding zones. This is mainly because in the buffer area for Stop 2540, zones 133, 134, 136, and 140 have similar total number of parcels as shown in Figure 4-5 (b). Compared to parcel number (1) method, parcel number (2) method (which considers land use type of each parcel) assigns more alighting trips to 134 than 133, since there are more commercial parcels in 134 zones than 133 zones.

An analysis of the trip allocation from Stop 3619 shows that the four methods produce quite different results. As shown in Figure 4-5 (c), zone 70 contains a large parcel where a university (Wilfrid Laurier) is located; other zones consist of commercial areas and residential areas. The buffer area ratio and footprint-weighted parcel methods allocate large portion of trips to the zone 70 followed by 71 due to high employment density and large building footprints. Parcel number ratio (1) method assigns most of the trips to zones 69 and 71 since the number of parcels in these zones is greater than in zone 70. Parcel number ratio method (2) allocates most of the trips to either zone 72 or 73, since the number of parcels where area type is commercial is the greatest in these zones amongst all the candidate zones in the access sheds.

Overall, the buffer area ratio weighted by employment method can effectively handle various conditions, particularly for major activity generators (e.g., hospital, down town or uptown area, university). The data for employment and population are easy to obtain and the application technique is also straightforward. However, as shown in case of Stop 1906 (zone 127), since the buffer area ratio method assumes even distribution of population and employment, careful attention to interpreting the results (e.g., investigating homogeneity of a zone) is still required.

The two parcel number ratio methods and footprint weighted method incorporate land use information (e.g., parcel type, building type, building foot-print area, building story). As shown in the analysis of results for Stops 2540 and 3619, both parcel number ratio methods are limited in their applicability to the whole study area, especially in cases where a large parcel contains high density buildings or major activity centers. In this case, the transit trip allocation results are quite different from our intuition.

The foot-print weighted method generally produces similar results with the buffer area ratio method as demonstrated in the analysis of Stops 2540 and 3619. The one issue is the quality of GIS footprint data. In rare cases, the data include null values on building story or building type. In this case, it may be necessary to edit manually. Furthermore, as described in section 4.2.4, the footprint data are available only for building structure. Therefore, the area size for single dwelling units in residential areas cannot be directly estimated. In such case, the method also requires additional steps as 4.2.4. In the following section, I evaluate the proposed four methods using transit on-board survey data and examine if the benefits from the weighted footprint method can justify the additional effort.

4.3.2 Evaluation setup

In order to assess the performance of the proposed models, actual data on origins and destinations are necessary. These data would typically be gathered through either an on-board transit survey or by other contemporary data collection methods (including AFC data or using GPS travel diaries). In the case study, data from two on-board passenger surveys are used. The first survey was conducted by the Region of Waterloo for the period of March 21 to 24 of 2008; the second data are from a broader travel behavior survey of transit users conducted by the University of Waterloo for three weekdays in 2010. One limitation of the current work is that the data sets for actual origin and destination locations are somewhat sparse. Thus, the assessment methods are presented as to demonstrate how validation can be done; the results on the suitability of each assignment method should be repeated with larger data sets. That work is beyond the scope of this dissertation.

In the study area, GRT- iXpress Routes 200 and 201 are assessed because reliable data are available for nearly all stops (unlike local routes where the data are less reliable). The routes consist of 19 stops in the study area as shown in Figure 4-6 and Table 4-3.

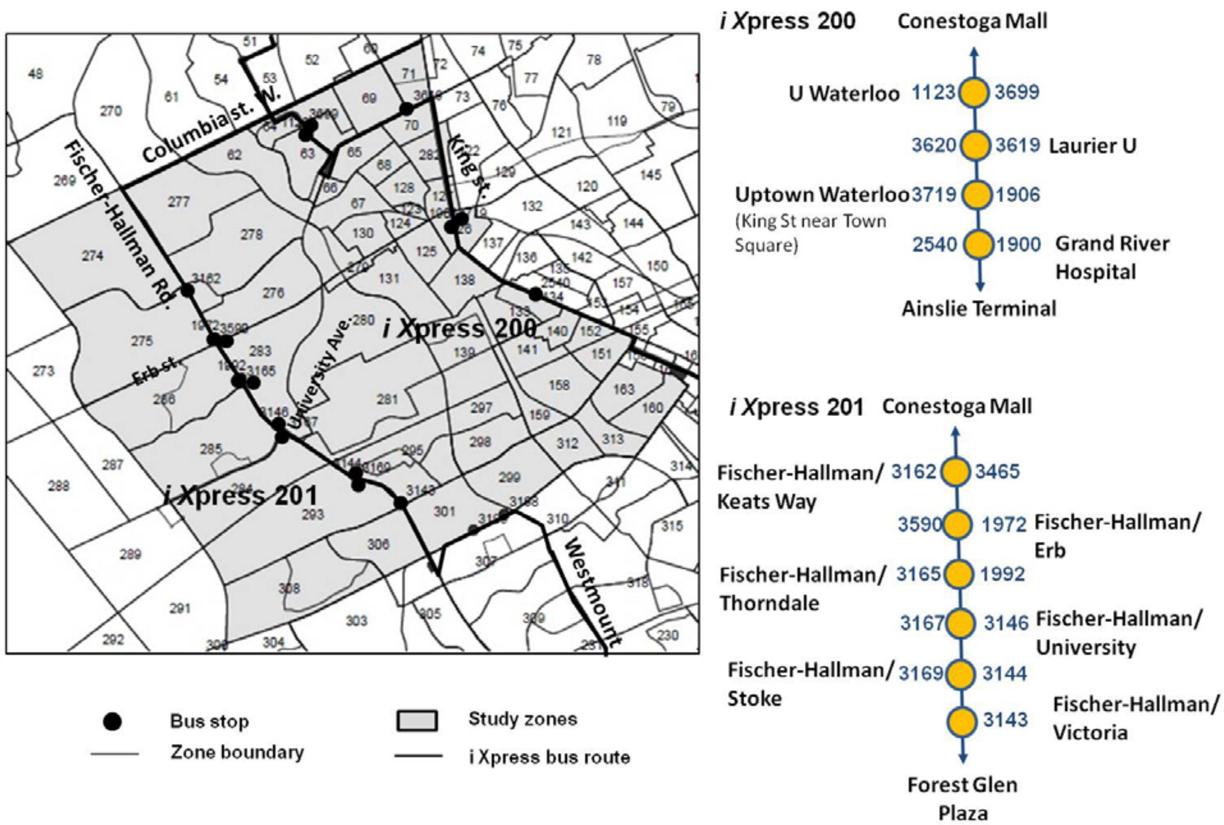


Figure 4-6: Transit routes and stops for evaluation (2012 configuration)

To evaluate the proposed methods, the difference in % allocation for each zone based on the four proposed methods is analyzed and the predicted allocations are compared to the actual results from the on-board survey.

From the data gathered by the on-board surveys, only those trips for which the boarding and / or alighting stops were part of the selected routes, and that occurred during the appropriate study period – the am peak period are of interest. As such, the first step is to filter the full database to include the relevant trips. For these trips, the following information is then recorded:

(1) The actual trip origin, which is geocoded in a GIS and linked spatially to a Traffic Analysis Zone (TAZ)
(2) The boarding location, linked to a stop indexed by the Region of Waterloo's stopID field;
(3) The alighting location indexed in the same way as the boarding location;
(4) The actual trip destination, geocoded in the same way as step 1, to a specific TAZ.

Then, sample trips are expanded to total stop boarding or alighting trips using APC data. Here, the expansion factors for each record (that have stop and its actual origin/destination information) are the number of responses at the stop divided by total transit trips of the route at the stop from APC data.

Table 4-3: The characteristics of the set of stops in study area

Route	Direction		Stop (ID)	Avg. boarding/ alighting (7-8am)
	From	To		
201	**Forest glen plaza**	**Conestoga mall**	**Fischer-Hallman/Erb (1972)**	**13.8**
	Forest glen plaza	**Conestoga mall**	**Fischer-Hallman/Thorndale (1992)**	**5.9**
	Forest glen plaza	**Conestoga mall**	**Fischer-Hallman/Victoria (3143)**	**5.4**
	Forest glen plaza	Conestoga mall	Fischer-Hallman/Stoke (3144)	1.5
	Forest glen plaza	**Conestoga mall**	**Fischer-Hallman/University (3146)**	**7.4**
	Conestoga mall	Forest glen plaza	Fischer-Hallman/Keats way (3162)	0.9
	Conestoga mall	Forest glen plaza	Fischer-Hallman/Thorndale (3165)	2.4
	Conestoga mall	**Forest glen plaza**	**Fischer-Hallman/University (3167)**	**3.4**
	Conestoga mall	Forest glen plaza	Fischer-Hallman/Stoke (3169)	1.6
	Conestoga mall	Forest glen plaza	Fischer-Hallman/Erb (3590)	1.6
200	**Conestoga mall**	**Ainslie terminal**	**Univ. of Waterloo-Davis centre (1123)**	**15.8**
	Ainslie terminal	**Conestoga mall**	**Uptown Waterloo-King St. near Waterloo town square (1906)**	**10.8**
	Conestoga mall	**Ainslie terminal**	**King/Pine-Grand River Hospital (2540)**	**3.4**
	Ainslie terminal	**Conestoga mall**	**University/Hazel-Laurier University (3619)**	**19.9**
	Ainslie terminal	**Conestoga mall**	**Univ. of Waterloo-Davis centre (3699)**	**32.5**
	Conestoga mall	**Ainslie terminal**	**Uptown Waterloo-King St. near Waterloo town square (3719)**	**4.9**

* Omitted stops in the study area have zero boarding and alighting during AM peak (7-8am) hour

4.3.3 Evaluation results

The performances of the four allocation methods of transit boardings and alightings to their origin and destination zones were assessed by investigating (1) the difference in % allocation for each zone based on proposed methods, (2) Root Mean Squared Errors (RMSE) and (3) a probabilistic technique - chi square test. Chi-square is the sum of the squared difference between observed (o) and the expected (e) data, divided by the expected data in all possible categories (N) as shown in equation (4-6).

$$Chi\ x^2 = \sum_{i=1}^{N} \left(\frac{(O_i - e_i)^2}{e_i} \right) \tag{4-6}$$

Where:

o_i = observed
e_i = expected
N = total number of category

The null hypothesis of independence is rejected if x^2 is large, because this means that observed frequencies and expected frequencies are far apart. The chi-square curve is used to judge whether the calculated test statistic is large enough so that the area beyond it (under the chi-square curve with a degrees of freedom) is less than 0.05 of P value (Smith, 2015).

In this study, for observed values for x^2, observed % allocation at each zone was converted into values equivalent to total 100 alighting trips at each zone. For expected values for x^2, estimated % alighting trips at each zone are used. Total number of categories (associated with degree of freedom) corresponds to the number of associated TAZs at each stop.

Among the set of stops of route 200 and 201 in the study area (see Table-4-3), allocation results were evaluated for 11 stops (shown in bold in Table 4-3). In cases where the total number of boarding/alighting trips is very small (less than three trips), those stops are excluded in the evaluation. The allocation results based on four proposed methods, observed data, and the differences in percentage of allocation are shown in Table 4-4.

Table 4-4: Performance evaluation of the trip assignment methods - Alightings

		Obs. Alighting trips		Buffer area ratio			Parcel num ratio (1)			Parcel num ratio (2)			Footprint weighted parcel ratio		
Stop ID	Associated TAZ	Obs.	% allocation (a)	Est.	% allocation (b)	Difference in % allocation (b-a)	Est.	% allocation (c)	Difference in % allocation (c-a)	Est.	% allocation (d)	difference in % allocation (d-a)	Est.	% allocation (e)	Difference in % allocation (e-a)
1123	63, 64	16	100.0	16	98.9	-1.13	14	90.5	-9.52	14	88.2	-11.76	14	88.2	-11.76
	65		0.0	0	1.1	1.13	2	9.5	9.52	2	11.8	11.76	2	11.8	11.76
	Chi-square Probability, P-value					0.284*			0.0012			0.0003			0.0003
1906	118	1	5.9		0.0	-5.88		0.0	-5.88		0.0	-5.88		0.0	-5.88
	122		0.0	0	1.6	1.60	2	15.3	15.34	1	10.3	10.27	1	5.4	5.35
	123		0.0	0	0.1	0.12	0	0.3	0.31	0	0.7	0.68	0	2.2	2.19
	125	1	11.8	0	2.0	-9.78	2	18.7	6.95	1	8.9	-2.86	0	2.6	-9.21
	126	3	23.5	7	63.5	39.93	3	29.1	5.61	4	40.4	16.88	5	47.1	23.60
	127	4	35.3	3	23.6	-11.66	2	18.4	-16.89	3	30.8	-4.47	4	35.3	0.03
	132		0.0	0	0.6	0.57	0	4.3	4.29	1	4.8	4.79	0	3.2	3.20
	137	1	5.9	0	3.6	-2.32	1	8.6	2.71	0	2.1	-3.83	0	1.8	-4.07
	138	1	5.9	1	5.1	-0.82	1	5.2	-0.67	0	2.1	-3.83	0	2.4	-3.45
	276	1	5.9		0.0	-5.88		0.0	-5.88		0.0	-5.88		0.0	-5.88
	282	1	5.9		0.0	-5.88		0.0	-5.88		0.0	-5.88		0.0	-5.88
	Chi-square Probability, P-value					0.0000			0.0000			0.0000			0.0000
2540	133	3	83.3	2	66.6	-16.73	1	38.3	-45.00	1	27.5	-55.88	3	83.3	-0.05
	134		0.0	1	25.9	25.87	1	27.1	27.09	1	41.2	41.18	0	5.4	5.42
	136	1	16.7	0	4.1	-12.53	1	18.2	1.49	0	15.7	-0.98	0	10.7	-5.96
	140		0.0	0	3.4	3.39	1	16.4	16.43	0	15.7	15.69	0	0.6	0.58
	Chi-square Probability, P-value					0.0000			0.0000			0.0000			0.0253

		Obs. Alighting trips		Buffer area ratio			Parcel num ratio (1)			Parcel num ratio (2)			Footprint weighted parcel ratio		
Stop ID	Associated TAZ	Obs.	% allocation (a)	Est.	% allocation (b)	Difference in % allocation (b-a)	Est.	% allocation (c)	Difference in % allocation (c-a)	Est.	% allocation (d)	difference in % allocation (d-a)	Est.	% allocation (e)	Difference in % allocation (e-a)
3619	41	2	12.5		0.0	-12.50		0.0	-12.50		0.0	-12.50		0.0	-12.50
	60	2	12.5		0.0	-12.50		0.0	-12.50		0.0	-12.50		0.0	-12.50
	65		0.0	0	1.7	1.71	1	5.1	5.13	0	0.0	0.00	0	0.0	0.00
	69		0.0	1	5.6	5.59	7	35.9	35.90	2	10.0	10.00	1	3.9	3.87
	70	2	12.5	8	41.6	29.14	0	0.7	-11.77	1	3.3	-9.17	16	80.1	67.56
	71	7	37.5	5	27.3	-10.22	7	34.4	-3.07	3	13.3	-24.17	1	4.3	-33.24
	72	2	12.5	1	5.4	-7.09	1	4.4	-8.10	7	36.7	24.17	1	3.2	-9.31
	73		0.0	3	16.4	16.45	1	7.0	6.96	7	33.3	33.33	2	8.6	8.62
	74	2	12.5	0	0.0	-12.50		0.0	-12.50	0	0.0	-12.50	0	0.0	-12.50
	282		0.0	0	1.9	1.92	2	12.5	12.45	1	3.3	3.33	0	0.0	0.00
	Chi-square Probability, P-value					0.0000			0.0000			0.0000			0.0000
3699	52		0.0	1	3.4	3.41	7	21.7	21.74	9	26.3	26.32	1	2.3	2.32
	53		0.0	0	0.3	0.26	1	4.3	4.35	2	5.3	5.26	1	2.2	2.18
	63, 64	33	100.0	31	96.3	-3.67	24	73.9	-26.09	22	68.4	-31.58	31	95.5	-4.50
	Chi-square Probability, P-value					0.1485*			0.0000			0.0000			0.0946*
3719	122		0.0	0	1.4	1.44	1	13.4	13.43	0	9.3	9.33	0	5.3	5.32
	123		0.0	0	0.1	0.12	0	0.3	0.30	0	0.7	0.67	0	2.2	2.19
	124		0.0	0	0.0	0.02	0	0.6	0.60	0	1.3	1.33	0	0.0	0.00
	125		0.0	0	2.2	2.25	1	21.2	21.19	0	9.3	9.33	0	3.0	3.02
	126	2	47.3	3	63.3	15.99	1	28.4	-18.98	2	39.3	-8.01	2	47.1	-0.21
	127	1	23.7	1	23.5	-0.18	1	17.9	-5.76	1	30.0	6.33	2	34.8	11.17
	129		0.0	0	0.3	0.33	0	1.5	1.49	0	1.3	1.33	0	0.0	0.05
	132		0.0	0	0.5	0.48	0	4.2	4.18	0	4.7	4.67	0	3.1	3.15
	133	1	14.5	0	0.0	-14.49	0	0.0	-14.49	0	0.0	-14.49	0	0.0	-14.49
	136	1	14.5	0	0.0	-14.49	0	0.0	-14.49	0	0.0	-14.49	0	0.0	-14.49

		Obs. Alighting trips		Buffer area ratio			Parcel num ratio (1)			Parcel num ratio (2)			Footprint weighted parcel ratio		
Stop ID	Associated TAZ	Obs.	% allocation (a)	Est.	% allocation (b)	Difference in % allocation (b-a)	Est.	% allocation (c)	Difference in % allocation (c-a)	Est.	% allocation (d)	difference in % allocation (d-a)	Est.	% allocation (e)	Difference in % allocation (e-a)
	137		0.0	0	3.0	2.99	0	6.9	6.87	0	2.0	2.00	0	1.8	1.76
	138		0.0	0	5.5	5.55	0	5.7	5.67	0	2.0	2.00	0	2.5	2.54
	Chi-square Probability, P-value					0.0000			0.0000			0.0000			0.0000
Total alighting trips		86		86			86			86			86		
Min. diff.%						0.02			0.30			0.00			0.00
Max. diff.%						39.9			45.0			55.9			67.6
Avg. diff.%						7.6			11.0			11.5			7.9
RMSE						1.33			2.11			2.69			1.93

From the data in Table 4-4, alighting trips during AM peak tend to concentrate along the activity centers (e.g., University of Waterloo-zone 63, 64; Uptown Waterloo: zone 126, 127; Grand River Hospital: zone 133). A total of 86 trips were observed from the selected stops; 71% of the observed alighting trips are destined for major activity centers in the study area. Table 4-4 indicates that the errors (difference in % allocation) for these major allocation zones, for example, zone 63, 64, and 133 are relatively small for the buffer area ratio and footprint-weighted parcel ratio methods compared to the other two methods.

The results in Table 4-4 show that footprint area ratio method and the buffer area ratio method perform best in the study area. On average, error in allocation is below 10% for both buffer area ratio and footprint weighted parcel ratio approach. The average difference in % allocation between observed data and proposed methods are 8%, 11%, 12%, and 8%, respectively. The maximum allocation error is 40% for buffer area ratio, 45% for parcel number ratio 1, 56% for parcel number ratio 2, and 68% for footprint weighted method. RMSE also indicates that the buffer area ratio approach (RMSE=1.33) and footprint weighted parcel ratio method (RMSE=1.93) are superior to the other two methods.

Similar results are shown for boardings. In Table 4-5, the footprint area weighted method generates the best estimates (RMSE=4.2) followed by the buffer area ratio approach (RMSE=4.4). Average errors (averaged difference in % allocation) are about 18% for all four methods. In Table 4-4 under the section of Chi-square probability, Stop ID 1123 and 3699 show high P values in Buffer area ratio and Footprint weighted methods. This high P value (greater than 0.05) indicates the estimates are similar to observed (i.e., H_0 is not rejected). For many stops, the number of observations are very small, and the expected values are less than one. As a result, Chi square tests are not possible. This reflects the limitation identified above regarding small sample size. That being said, the method remains applicable.

Table 4-5: Performance evaluation of the trip assignment methods - Boardings

		Obs. Boarding trips		Buffer area ratio			Parcel num ratio (1)			Parcel num ratio (2)			Footprint weighted parcel ratio		
Stop ID	Associated TAZ	Obs.	% allocation (a)	Est.	% allocation (b)	Diff. in % allocation (b-a)	Est.	% allocation (c)	Diff. in % allocation (c-a)	Est.	% allocation (d)	Diff. in % allocation (d-a)	Est.	% allocation (e)	Diff. in % allocation (e-a)
1972	275	2	14.2	3	23.9	9.7	1	10.8	-3.4	1	10.6	-3.6	2	12.4	-1.8
	276	4	28.9	5	36.4	7.5	5	33.7	4.9	5	33.3	4.4	4	32.5	3.7
	278	2	14.2	0	3.3	-11.0	1	5.9	-8.3	1	6.0	-8.2	1	5.9	-8.3
	283	2	14.2	2	16.8	2.6	3	18.6	4.4	3	18.7	4.5	3	18.5	4.3
	286	2	14.2	3	19.6	5.4	4	30.9	16.7	4	31.4	17.2	4	30.7	16.5
	275, 276, 283, 286	2	14.2												
3143	295	1	16.1	2	46.3	30.2	2	37.1	21.1	2	37.0	20.9	2	28.6	12.5
	301	1	25.0	1	20.6	-4.4	1	23.1	-1.9	1	22.8	-2.2	2	28.6	3.6
	303	1	8.9	1	11.2	2.3		0.0	-8.9		0.0	-8.9		0.0	-8.9
	306	1	25.0	1	21.9	-3.1	2	39.7	14.7	2	40.3	15.3	2	42.8	17.8
	308	1	8.9		0.0	-8.9		0.0	-8.9		0.0	-8.9		0.0	-8.9
	301,306	1	16.1												
3146	280		0.0	0	1.8	1.8	0	0.5	0.5	0	0.5	0.5	0	0.5	0.5
	281	1	18.0	0	3.6	-14.4	0	3.5	-14.5	0	3.1	-14.9	0	3.0	-15.0
	283		0.0	3	39.9	39.9	2	32.9	32.9	2	32.9	32.9	2	32.1	32.1
	284	2	35.0	1	9.1	-25.9	1	6.9	-28.0	0	5.9	-29.0	1	8.3	-26.6
	285	1	18.0	3	45.7	27.7	4	56.3	38.3	4	57.6	39.6	4	56.1	38.2
	283, 284, 285	2	29.1												
3167	280		0.0	0	1.2	1.2	0	0.3	0.3	0	0.3	0.3	0	0.3	0.3
	281	1	33.3	0	9.1	-24.2	0	5.7	-27.6	0	5.3	-28.0	0	6.1	-27.2
	283		0.0	1	34.2	34.2	1	31.7	31.7	1	31.8	31.8	1	29.2	29.2
	284	1	33.3	1	17.6	-15.8	1	16.0	-17.3	1	15.0	-18.3	1	20.7	-12.6
	285	1	33.3	1	37.9	4.6	2	46.3	13.0	2	47.6	14.3	1	43.7	10.4
1992	275	3	50.0		0.0	-50.0		0.0	-50.0		0.0	-50.0		0.0	-50.0
	283		0.0	3	49.2	49.2	2	37.6	37.6	2	37.5	37.5	2	37.5	37.5
	285		0.0	1	20.4	20.4	2	27.5	27.5	2	27.6	27.6	2	27.6	27.6
	286		0.0	2	30.4	30.4	2	34.9	34.9	2	34.9	34.9	2	34.9	34.9
	283, 285, 286	3	50.0												
Total trips		36		36			36			36			36		
Min. diff. %						1.2			0.3			0.3			0.3
Max. diff. %						50.0			50.0			50.0			50.0
Avg. diff. %						17.7			18.6			18.9			17.8
RMSE						4.4			4.5			4.6			4.2

Following the quantitative analysis, additional evaluation was conducted on the conditions under which each assignment method performed either well or poorly. The observed strengths and weakness of the proposed methods are summarized in Table 4-6.

Table 4-6: Summary of characteristics of proposed transit trip allocation methods

Proposed method	Strength/ Characteristics	Weakness	Comment
Buffer area ratio	Effectively handles major activity generators. Easy acquisition of data. Straightforward technique. Reasonable performance.	Assumption of even distribution of population and employment in buffer areas	Careful attention on the homogeneity of a zone is necessary.
Parcel number ratio	Use of land use information instead of density index (pop or emp)	Limited applicability when parcels contain high density buildings	Use of the ‘number of parcels’ is not appropriate to measure strength (size) of a zone: Combination with density index can be considered.
Footprint weighted	Good performance	The issue of GIS footprint data quality and coverage: it is necessary to edit/correct data cells manually and to construct additional steps	It should be examined if the benefits from the weighted footprint method can outweigh the additional effort.

Comparing Tables 4-4 and 4-6, it appears that the errors are larger for alighting trips than allocating for boarding trips. This is mainly due to a challenge related to the on-board survey where passengers were asked to identify their actual trip origin using an address, an intersection or a postal code. Most respondents chose one of the latter two options. A postal code can contain multiple TAZs. Similarly, an intersection can form the boundary between multiple TAZs. As a result, it is difficult to have certainty when assigning origin TAZs. Future data collection should be designed to eliminate this source of error.

A second challenge arises from the small number of observations at some stops. For example, the largest differences in % allocation (i.e., 50%) are observed surrounding stop ID 1992 where only six boardings were observed. A more extensive on board survey or a trip diary survey method may be necessary to validate the appropriate allocation methods. However, to the author's knowledge, no previous studies have actually tried to validate proposed method compared to observed maps of transit users from homes to stops and stops to destinations.

To conclude, based on an admitted small sample size and analysis area, this study explored transit trip allocation methods. The proposed framework can be useful to lead the choice of an effective method in accordance with user's need. The results of application to this study area provide some evidence that buffer area ratio method weighted by employment and footprint weighted method perform reasonably well compared to the observed data. For boarding trip allocation to their origin zones, footprint weighted parcel ratio method performs the best followed by buffer area ratio approach. Buffer area ratio weighted by population or employment method can effectively handle various conditions including major activity generators with reasonable accuracy, and improve the practical applicability with easy-to-obtain and -use data.

4.4 Chapter Summary

The challenges of using AVL/APC data for travel demand modeling process is the lack of appropriate methods to link stop activity to their actual TAZs. Previous approaches are simple zonal aggregations of boarding and alighting trips based on stop locations (i.e., simple summation of boarding counts of associated stops if coordinates of stops lie in the TAZ). Thus, it has been perceived that stop-level counts are not accurate at zonal level. In addition, it was not clear how to aggregate when stops are located on zone boundaries.

In this chapter, four methods for linking the stop-level boarding (or alighting) to the zone from (or to) which these passengers actually originate (or destined) were proposed. The proposed methods incorporate the concept of transit access area among competing zones. To be practically useful in terms of data acquisition, the proposed methods were developed focused on the availability of data in the local context including socio-economic, parcel, building footprint, and census data, while adequately performing in terms of accuracy and robustness.

The performance of each method was evaluated by comparing the percentage of allocation to candidate zones based on four proposed methods. For observed transit trips from stops to origin/destination zones, transit on-broad survey data were used. To my knowledge, there has not been any research validating proposed method compared to observed maps of transit users from homes to stops and stops to destinations.

For alighting trips and their destination TAZs, the buffer area ratio method weighted by employment (RMSE=1.33) and footprint weighted methods outperform the other models. The average estimation error for allocation to each zone is about 8%. For boarding trips and their origin, the footprint weighted parcel ratio method (RMSE=4.2) performs the best. Similar to the footprint weighted method, buffer area ratio (RMSE=4.4) also can closely approximate the observed trips in origin zones. The average estimation errors of these two methods are about 18%.

The buffer area ratio method provides robust (in terms of both boarding and alighting) and reasonably accurate results using readily available data (i.e., population and employment). However, since the buffer area ratio method assumes even distribution of population and employment, careful attention during interpretation of the data (e.g., investigating homogeneity of a zone, size of zones-if they are small enough for homogeneity) and the application of the method are still required

As expected, the footprint weighted method shows good performance. Yet, in rare cases, GIS foot-print data require manual edits or additional steps to ensure data quality. In the study area, the benefits from the weighted footprint methods do not outweigh the additional effort to the buffer area ratio method.

The results do point to one weakness of this approach. Transfer trips cannot be captured in the proposed methods. However, the issue of transfer trips can be overcome, for example, by using AFC (Automatic Fare Collection) data that allow easy calculation of total transfer trips at each stop.

It should be noted that in most cases, statistical significance of the difference between RMSE results were not attainable due to the limitations of sample size. Additional investigations are necessary with more observations.

Chapter 5 presents the application of these assignment methods with a goal to improve the utilization of AVL / APC data in the calibration of travel forecasting models.

Chapter 5

Assessment of the Transit Mode Share Prediction Errors

5.1 Introduction

The disparity between actual and forecasted transit ridership has been an important area of study and a concern for practitioners for several decades. In order to decrease the discrepancy caused by model property errors, a number of studies focus on better representation of difficult-to-measure cost functions and incorporation of behavioral variables in mode choice models. In spite of the improvement in mode choice models, some gaps still remain in practical applications, particularly for large-scale regional travel forecasting models which are zone-based and aggregated. Given limited resources, planners experience challenges in determining the causes of the prediction errors and, more generally, the overall deficiencies in models. In this chapter, one goal is to propose a method to enhance the processes by which travel forecasting models are calibrated. Further, a better explanation of what components would be the major sources of errors of transit mode choice forecast is pursued.

The proposed method in this chapter effectively calculates prediction errors, identifies ranges of errors that warrant further investigation using statistical techniques, and evaluates the source of errors affecting the accuracy of predicted transit use on a zonal level. Details of the methods are provided in the following sections.

5.2 Methods

5.2.1 Calculating prediction errors

The approach taken to understand the sources of error is as follows. Travel forecasting models predict the number (and percentage) of trips made between all origins and destinations by various modes. When AVL/APC data are available, the actual number of transit boardings occurring in a zone is also known. A comparison of the observed transit boardings to predicted transit boardings in a zone can be used to identify those zones in which the model is performing well and those zones in which significant error exists. For the latter set of zones, a further examination can identify the sources of those errors.

As described in Chapter 4, the first step is to assign the observed boardings to the zone (TAZ) from which the trip actually began. Once this step is complete, there exists a column vector of actual boardings

($B_i^{'}$) for each zone i, in a given time period. The approach to allocate boardings to individual zones is to assign trips proportionally to the population and area size of competing zones within 400 meters of the stop (see Eqs. (4-1) to (4-4), and Fig.4-2). From the travel forecasting model, the predicted number of total trips by all modes between each origin-destination (*i,j*) pair for the same time period are known. By summing the trip matrix over the destinations, it is possible to calculate the total number of trips, T_i, beginning at each origin zone *i*.

From steps 1 and 2, an observed mode share - or the probability of a trip that begins in zone *i* being made by transit can be estimated. Mathematically, this is represented as:

$$Pr^{obs}(t_i) = \frac{B_i^{'}}{T_i} = \frac{B_i^{'}}{\sum_j T_{ij}} \tag{5-1}$$

Where:

$B_i^{'}$: actual boardings for each zone *i*
T_i: total number of trips beginning at each origin zone *i*

Also from the travel forecasting model, the number of predicted transit trips between each *i, j* pair is known. Again, by summing over the destinations, the number of predicted trips by transit beginning from zone *i*, B_i can be estimated. From steps 2 and 4, it is possible to calculate the estimated probability of a trip beginning in zone *i* being made by transit. Mathematically:

$$Pr^{est}(t_i) = \frac{B_i}{T_i} = \frac{B_i}{\sum_j T_{ij}} \tag{5-2}$$

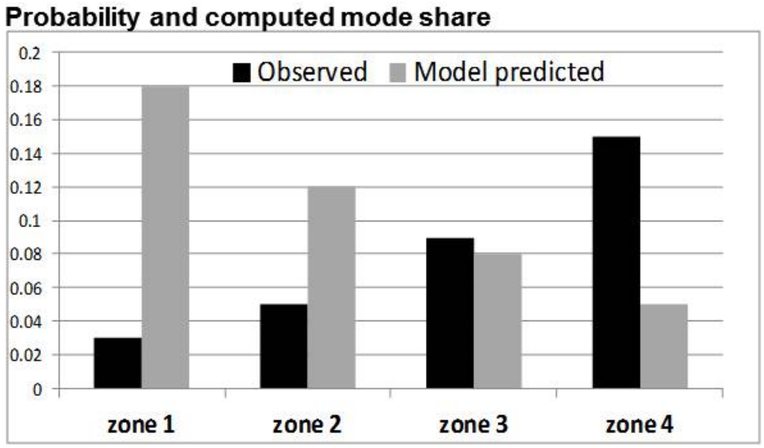
Where:

B_i: predicted boardings from zone *i*
T_i: total number of trips beginning at each origin zone *i*

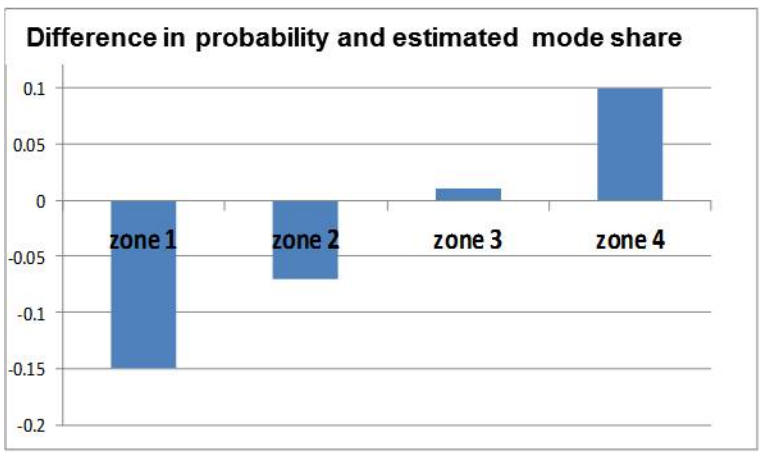
This study defines the mode share error for zone *i*, ε_i as the difference between equations (5-1) and (5-2) as below:

$$\varepsilon_i = Pr^{obs}(t_i) - Pr^{est}(t_i) \tag{5-3}$$

From equation 5-3, mode share errors – the difference between the observed and estimated probabilities of using transit for a trip from zone *i* – can be estimated for each TAZ (see Figure 5-1).



(a) Predicted vs. observed transit uses in each zone



(b) Computed transit mode share errors

Figure 5-1: Illustration of transit mode share error computation

5.2.2 Classifying prediction errors

Having identified the errors at the zonal level, the next step is to identify those zones for which the error represents a (statistically) significant deviation from the overall performance of the model. To this end, the magnitude of prediction errors is categorized based on a well-known outlier labeling technique – the box plot, proposed by Tukey (1977).

Tukey's method constructs a boxplot to display information about symmetry, median, lower quartile (or hinge), upper quartile, lower extreme (or whisker end), and upper extreme of a data set. Since Tukey's method uses a robust statistics of median instead of mean or standard deviation, it is less sensitive to extreme values than other outlier labeling techniques (Seltman 2014, Seo 2002). It is known that the method is not appropriate for a small sample size (Iglewicz and Hoaglin, 1993). An important aspect of Tukey's method is that it makes no assumptions about the distribution of the data and, as a result, is effective in describing data that are not normally distributed.

Figure 5-2 (a) shows an example of box-plot where the data are normally distributed. IQR (Inter Quartile Range) is the distance between the lower (Q1) and upper (Q3) quartiles. Inner fences (or also known as 'whisker end') are located at a distance Q1-1.5IQR and Q3+1.5IQR. Outer fences are located at a distance Q1-3IQR and Q3+3IQR. It is suggested that a value between the inner and outer fences is a possible outlier, and an extreme value beyond the outer fences is a probable outlier (Seltman 2014, Seo 2002).

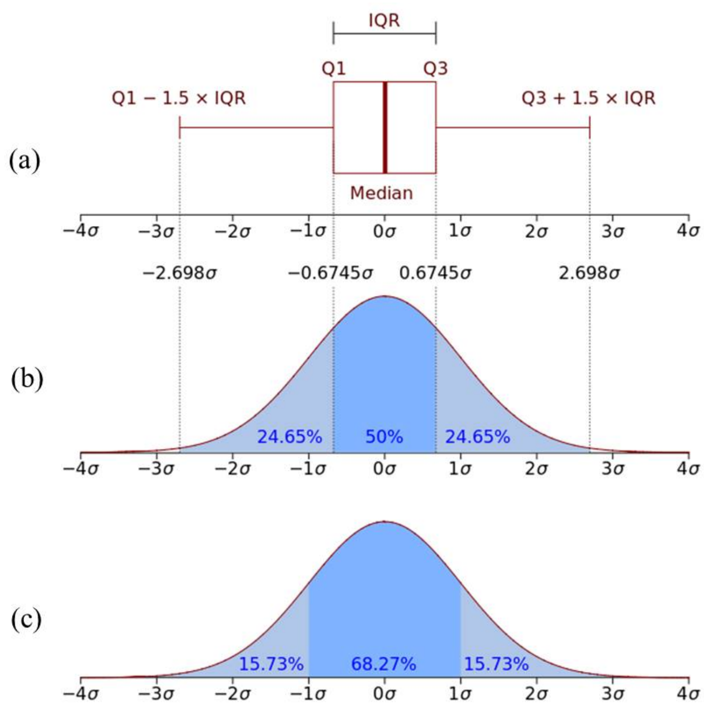


Figure 5-2: **Methods for categorizing zones based on degree of prediction errors and detecting outliers of prediction errors:** (a) Boxplot (modified from "Boxplot vs PDF" by Jhguch at en.wikipedia); (b) (c) Probability density function associated with box plot, (Jhguch at en.wikipedia, Accessed 1 April, 2016)

In this chapter, box plots to visualize and analyze the range of error terms are used. This approach allows for the categorization of zones based on the magnitude and direction of error, and to conduct further analyses across these categories. Zones that are outliers are classified into categories labeled highly under- and highly over-estimated; those that demonstrate significant errors, but are not outliers are labeled as moderately under- and over-estimated. Finally, those zones that are performing within expected boundaries of performance are labeled as reasonably predicted.

5.2.3 Determination of possible source of prediction errors

Next, the factors that could affect these prediction errors on a zone level are examined. Specific attention is paid to those variables that are not directly controlled for via market segmentation (see Table 5-1). For example, the presence of high concentrations of students (percent population of age 18-24) is not assessed since the market segment of post-secondary trips is already included in the model.

Figure 5-3 presents a range of variables that are commonly identified as influencing the propensity to use transit. Additional descriptions of these variables are contained in Chapter 2. The variables are sorted into two categories: those that may be quantified but for which new data sources may be necessary and those that can be readily quantified using existing data sources. Dealing with the latter category first, the approach taken in the analysis is to calculate the summary statistics for each variable for all zones belonging to the five categories which are defined in the previous section. Then, pairwise statistical comparisons of means are completed to identify those variables for which significantly different properties exist. These variables may have the highest explanatory power for reducing the error terms.

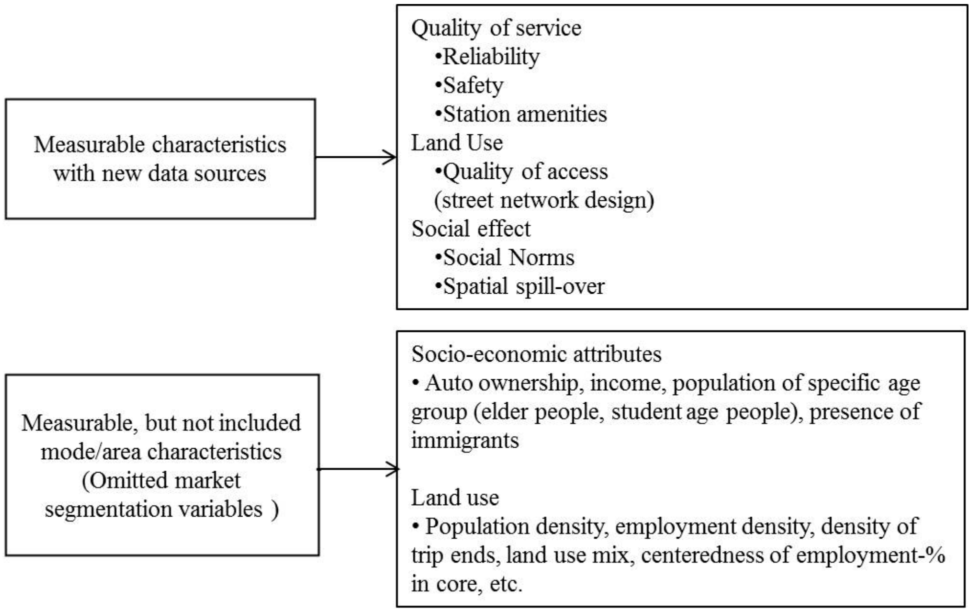


Figure 5-3: Possible elements of mode share errors (sources of variables: Outwater et al., 2011, Lutin et al., 2008, Kittelson et al., 2003, Rosenbloom et al., 1998, Litman, 1995)

Next, two of the three characteristics for which new data sources provide an opportunity to quantify these variables for inclusion in the model are addressed: reliability and accessibility. The following section describes the estimation methods for reliability and accessibility at the zonal level.

Reliability is estimated as the percentage of "on-time vehicles" using AVL/APC data on a zone by zone basis. The literature contains many definitions of "on-time" (Kittelson et al. 2003; Canadian Urban Transit Association 2001; Kimpel et al. 2008). In this case, an on-time vehicle is defined as arriving at a stop no more than 2 minutes late and departing that stop no more than 30 seconds early. These vehicle data are available from the Region's AVL database. The reliability estimation using AVL data takes the following steps:

i. Extracting the required data from AVL dataset. The time stamp on the data must be during the study period 7am-8am. Additionally, the data contain: the route number; operating day; stop number; scheduled arrival time; scheduled departure time; actual arrival time; actual departure time; trip ID, and coordinate.

ii. For each data record, a binary decision is made to label the record as on-time or not on-time. This calculation is done as shown in Equation (5-4).

iii. The data records are merged such that the stop location is linked to the TAZ in which the stop occurred.

iv. Reliability rates are generated for each TAZ. Two assumptions were made for the aggregation: (1) transit users' trips originate within the walking access threshold (400m in this method) from each stop and (2) transit users' perceptions of transit reliability are influenced by on-time performance of all stops associated to a zone (i.e., perceptions of transit reliability in Zone "A" are composed of on-time performance at Stop "a" and Stop "b" in Fig. 5-3.)

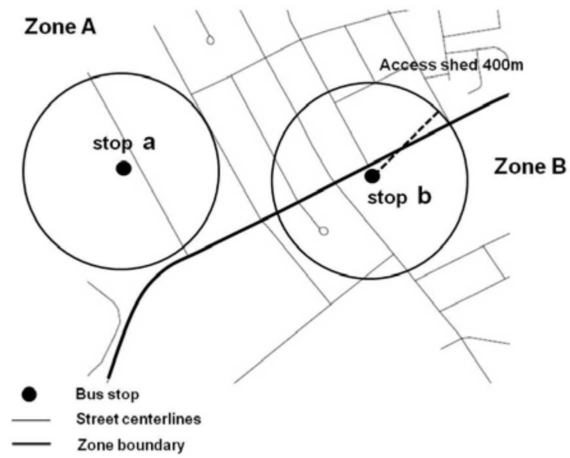


Figure 5-4: A method to estimate reliability at TAZs

$$\mathrm{Pr}_i^{\text{on time}} = 1 - \mathrm{Pr}_i^{\text{not on time}} = 1 - \frac{1}{\mathrm{T}_i} \sum_s \sum_t \mathrm{Max}\,(\mathrm{LA}_{st}, \mathrm{ED}_{st}) \qquad \forall\, s \in i \tag{5-4}$$

If $(\mathrm{AA} - \mathrm{SA}) > l$, then $\mathrm{LA}_{st} = 1$, else 0

If $(\mathrm{AD} - \mathrm{SD}) < -e$, then $\mathrm{ED}_{st} = 1$, else 0

where, i: TAZ s: Bus stop belongs to zone i

t: Bus trip (vehicle in certain period of time in different date)

LA_{st}: Late arrival at stop s and on bus trip t

ED_{st}: Early departure at stop s and on trip t

T_i: Total bus trips in every stop on zone i

AA: Actual arrival time SA: Scheduled arrival time

AD: Actual departure time SD: Scheduled departure time

l: Threshold of late arrival e: Threshold of early departure

The expectation is that zones that experience significant unreliability of service will be correlated with a model's over prediction of transit boardings.

In this study, a robust, network appropriate measure for access distance from origin to transit compared to conventional methods is adopted. Springate (2011) proposed an access tool which can measure walking distance along a pedestrian network from all building footprints to transit. The results generated by the access tool were employed. It is my expectation that significant disparities will exist between the Springate method of analysis and the software employed by the Region. In zones where the Region's software under-estimates transit access, the model will over-predict transit ridership (and vice versa).

5.2.4 Quantifying the sources of error

The previous steps identify those variables that are likely to have the strongest explanatory power in terms of predicting mode share errors. To estimate more formally this explanatory strength, two approaches are taken. First, regression analysis is used to correlate the prediction error as the response variable as a function of the variables presented in Figure 5-3. The second classification method involves z scores. The approach taken is to compute the product of the standardized value of each possible source of error (z_{Xi}) and the reported prediction error (E_i) in zone i. The product of these two variables implies the simplified magnitude of prediction errors and associated possible elements of the errors. If the distance between a prediction error and associated attributes is far from the average, it is interpreted that the composite index as a significant contributor to the error term (See Figure 5-5). When the total score of the composite index is larger, the variable has relatively larger impact on the prediction errors. Absolute values are used to measure magnitude. Finally, the composite scores of possible source of prediction errors are calculated by summing up the magnitude over all i zones or sub-group of zones as shown in equation (5-5).

$$\text{Score of variable x} = \sum_i | z_{Xi} \times E_i | \qquad (5\text{-}5)$$

Where:

z_{Xi}= Z value of variable X of zone i
E_i= transit more share prediction errors of zone i

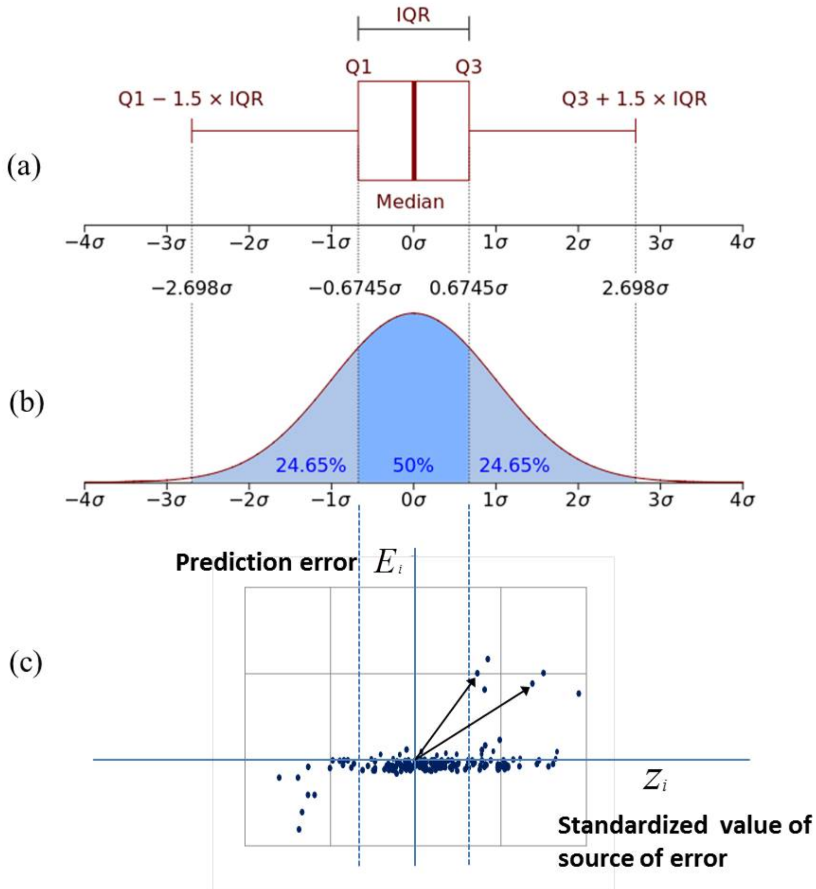


Figure 5-5: Method for assessment of source of the prediction errors related to box plot: (a) (b) from Figure 5-2, (c) Plot for prediction error (Ei) vs. standardized value of source of errors (Zi) for zone $\boldsymbol{i}$.

5.3 Application

5.3.1 Study area

For this section of the thesis, the area of study within the Region is extended to include the urbanized area – the cities of Waterloo, Kitchener, and Cambridge - as shown in Figure 5-6. More background on the Region of Waterloo can be found in Section 4.3.

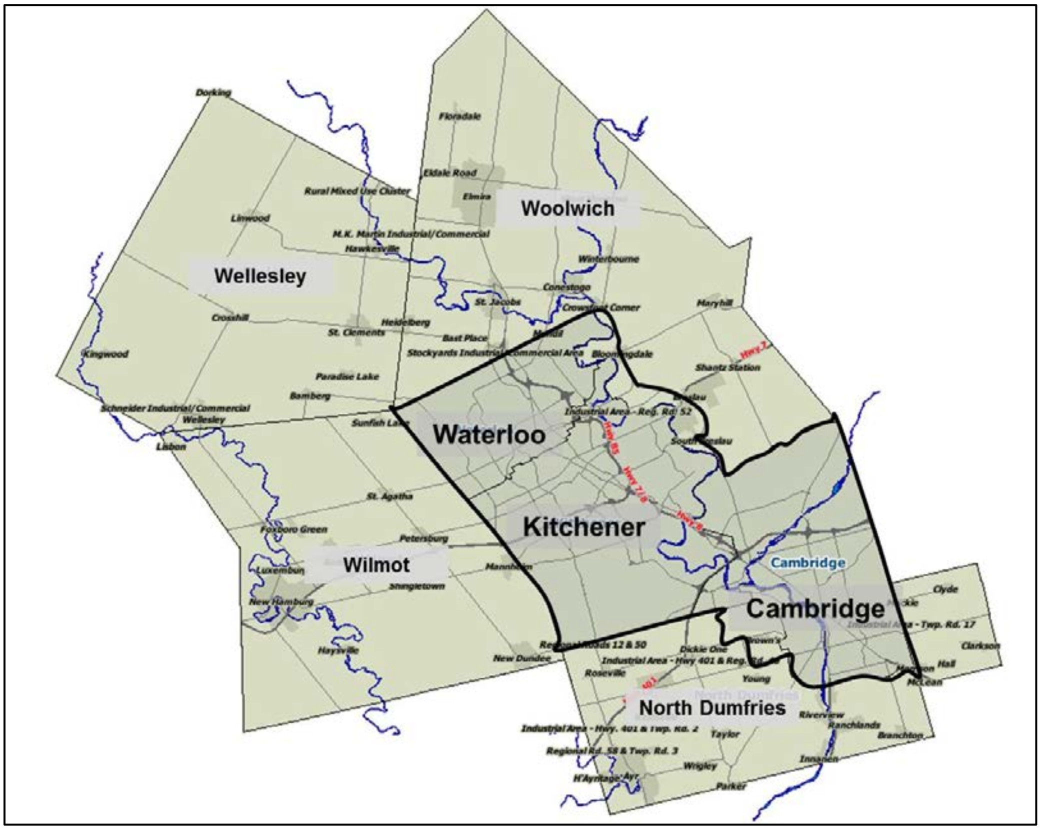


Figure 5-6: Study area

5.3.2 Data

To test the effectiveness of the proposed approach, the methods described in 5.2 are applied in the Region of Waterloo, using the Region's travel forecasting model and its AVL/APC data. Table 5-1 summarizes the structure of the Region's travel forecasting model. Briefly, the model is a standard, four-step model consisting of 386 urban zones and 597 total zones. As is the norm, zones vary in size and density (population and employment), in an effort to balance the consistency of attributes of the zones, while being cognizant of the scale of the model. The model used in the research was calibrated in 2006 on the TransCAD platform. It estimates system performance for the AM peak, from 7am to 8am.

Table 5-1: Parameters of the region's travel forecasting model

No. of zones in urbanized area (total)	386 (597)
Zone size	
Avg. area (km^2)	0.81
Max.	6.45
Min.	0.03
Avg. Population Density	1,900
Max.	14,045
Min.	0.00
Calibration year	2006
Selected time period for this study	7:00–8:00 a.m. (AM peak)
Total trips (Auto+Transit)	83,212
% use of transit (calibration year)	5.89%
Model application code	GISDK (GIS Developer's Kit) in TransCAD : assignment results (Generalized Costs) are fed back to trips distribution
Mode choice model	Multinomial Logit Model[1)]
Headway of transit	Max. 30 min Min. 4 min
Travel modes	bike, walk, auto, transit (bus)
Market Segmentation in mode choice	Trip purposes: Work, High school, Post-secondary, Others

1) Applied two separated Multinomial Logit model for walk trip and transit trips.

$$\mathrm{Bike_{ij}} = \mathrm{Tot_{ij}} \times 0.067 \times e^{-0.221\ \mathrm{Auto\ distance_{ij}}} \tag{5-6}$$

$$\mathrm{Walk_{ij}} = \frac{\mathrm{Tot_{ij}} - \mathrm{Bike_{ij}}}{1 + e^{0.06\,(\mathrm{WlkIp} - \mathrm{AuIp} + \mathrm{AC_{walk}})} + e^{0.06 \times (\mathrm{WlkIp} - \mathrm{TrIp} + \mathrm{TC_{walk}})}} \tag{5-7}$$

$$\mathrm{Transit_{ij}} = \frac{\mathrm{Tot_{ij}} - \mathrm{Bike_{ij}} - \mathrm{Walk_{ij}}}{1 + e^{0.06\,(\mathrm{TrIp} - \mathrm{AuIp} + \mathrm{AC_{transit}})}} \tag{5-8}$$

$$\mathrm{Auto\ p_{ij}} = \mathrm{Tot_{ij}} - \mathrm{Bike_{ij}} - \mathrm{Walk_{ij}} - \mathrm{Trn_{ij}} \tag{5-9}$$

where, i = Origin zone
j = Destination zone
WlkIp = Walk impedance (or walk generalized cost)
AuIp = Auto impedance (auto generalized cost)
TrIp = Transit impedance (transit generalized cost)
ACwalk = Auto mode constant for walk trip
TCwalk = Transit mode constant for walk trip
ACtransit = Auto mode constant for transit trip

The model uses a multinomial logit formulation to compute mode shares amongst bikes, walking, auto and transit (bus only). The mode choice models are shown in the footnote of Table 5-1 as equations (5-6) through (5-9). Bicycle trips are estimated using an exponential decay function of total trips and distance traveled. Two binary logit models are used for walk trips and transit trips, as shown in equation (5-7) to (5-8). Equation (5-8) shows the form of a binary logit model that estimates the likelihood of selecting transit compared to private auto for a trip from *i* zone to *j* zone.

The calibration parameters for the Regional model are shown in Table 5-2.

Table 5-2: Mode choice model calibration coefficients

	Attributes	Modes Applied	Coeff.	Values of **transit** mode constants in minutes
In-vehicle time	IVT	Transit	-0.060	
Out-of-vehicle time	walk time	Transit	-0.096	
	initial wait and transfer wait time	Transit	-0.096	
	Transfer time	Transit	-0.240	
Cost	Fare	Transit	-0.240	
	auto cost ($/km)	Auto	0.1223	
	auto parking cost	Auto	0.5	
	VOT (min/$)	Auto	4.86	
Constants	C_auto_to work	Auto	-0.06	-1
	C_auto_to high-school	Auto	1.56	26
	C_auto_to post-secondary	Auto	0.78	13
	C_auto_others	Auto	-0.84	-14

As shown in Table 5-2, the ratio of out-of-vehicle time and in-vehicle time ranges from 1.6 (walk time/in-vehicle time) to 4 (transfer time/ IVT and fare/IVT). This means that bus transit users in the Region of Waterloo perceive wait time as 1.6 times as onerous as IVT.

Since the reference mode of original mode choice models (see equation 5-8) is set as transit, this affects the interpretation of the performance of the models (i.e., if the model is over-predicting or under-predicting before calibration). For comparison to the other cities in Chapter 3, the reference mode was switched from transit to automobile. Accordingly, from Table 5-2 ‘constants’ column, the mode constant values of transit are adjusted to 0.06, -1.56, -0.78, and 0.84 for work, high-school, post-secondary, and other trip purpose, respectively. The values of mode constants are -1 min (=0.06/-0.06), 26 min (=-1.56/-0.06), 13 min (=-0.78/-0.06) and -14 min (=0.84/-0.06) for each trip purpose.

Based on the computed transit mode constants in Table 5-2, the signs of mode constants for high-school and post-secondary school transit trips imply that the current model before calibration is over-predicting the actual propensity to use transit modes. It is important to note that the area of study in the Region of Waterloo contains two universities. Therefore student ridership constitutes a significant portion of overall transit use.

One additional observation is necessary. The Waterloo Regional Transportation (WRT) model was developed as part of 'Growth management strategy and transit initiative study (2005)'. The model was specifically designed to produce ridership forecasts for a proposed rapid transit system – an LRT system along the central spine of the Region, known locally as the Central Transit Corridor (CTC). Although this model covers the entire Waterloo region, calibration and validation efforts were focused on transit mode and the CTC.

5.4 Results

5.4.1 Identification of the prediction errors

As described in the methodology, both the observed (using APC data from February 15 to March 15, 2012) and predicted mode shares for trips originating in each zone were computed. Next the error term for each zone was calculated. The error terms for the 384 zones in the study area are plotted in Figure 5-7.

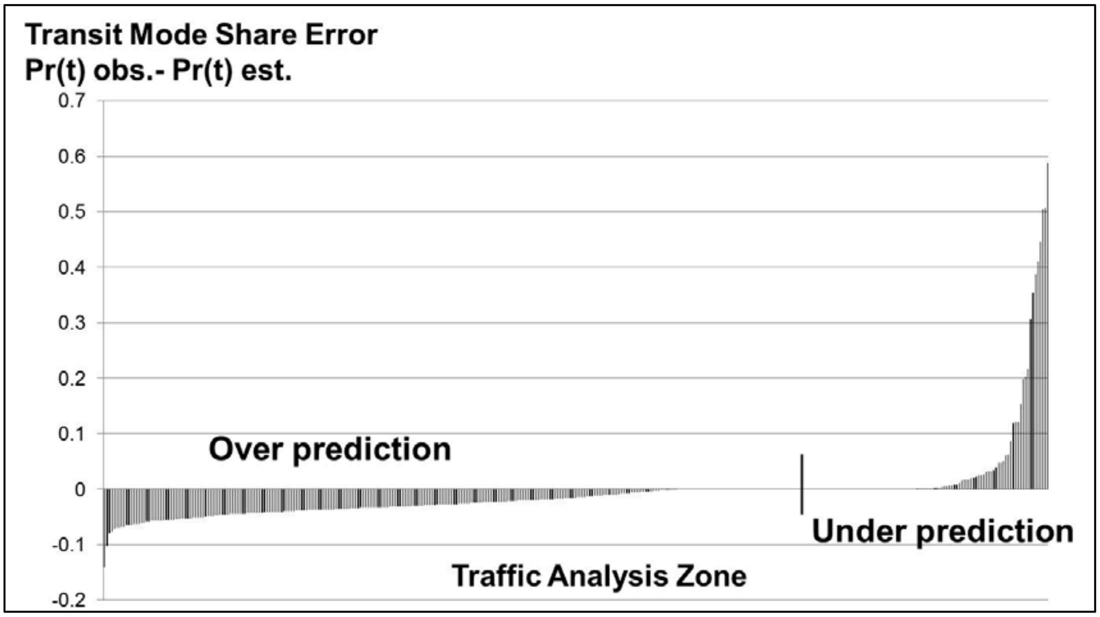


Figure 5-7: Error terms in mode share as computed by original mode constants

In Figure 5-7, the vertical axis shows the sign and magnitude of the error term as calculated in Equation 5-3. Those on the right side of the chart (positive sign) have the observed mode shares that are larger than the model's prediction. The left side of the chart represents the opposite case where the model is over predicting the actual propensity to use transit in a given zone. While the conventional mode constants may minimize the errors in system-wide (e.g., based on market segments in this case), significant over- and under prediction errors exist for individual zones.

In typical mode choice calibration and validation procedures of regional travel forecasting models, it has been difficult to generate error terms in mode share at TAZ level, since observed transit boardings at TAZs are not known. With the use of AVL/APC data and formulated method in Chapter 4, stop counts are able to be converted into TAZ trips, in turn, the errors are identified at the zonal level as shown in Figure 5-7.

It should be noted that the resulting error terms in Figure 5-7 come from an assumption that the travel forecasting model accurately predicts the total travel demand between zones since model predicted total number of trips (T_i) are used as a denominator to obtain observed transit mode share (see eq. 5-1). If functional models have problems in steps affecting estimation of the total number of trips (T_i) including mode choice, trip distribution, or trip generation; or for an activity based models, daily activity pattern generation, tour location choice etc.; or errors in demographic variables, these errors can influence the calculated error terms in Figure 5-7. As noted in Chapter 4, transfers could not be considered in the formulated transit trip allocation methods (see 4.3.3); as a result, an additional source of potential error may be introduced.

5.4.2 Examination of the source of errors

In this section, exploratory data analysis of box plots was performed. Based on the magnitude and direction of mode choice prediction error, it is possible to categorize zones and to conduct further analysis across these categories.

Figure 5-8 shows the upper and lower inner fences, inner quartile range, and points marking outlier zone numbers.

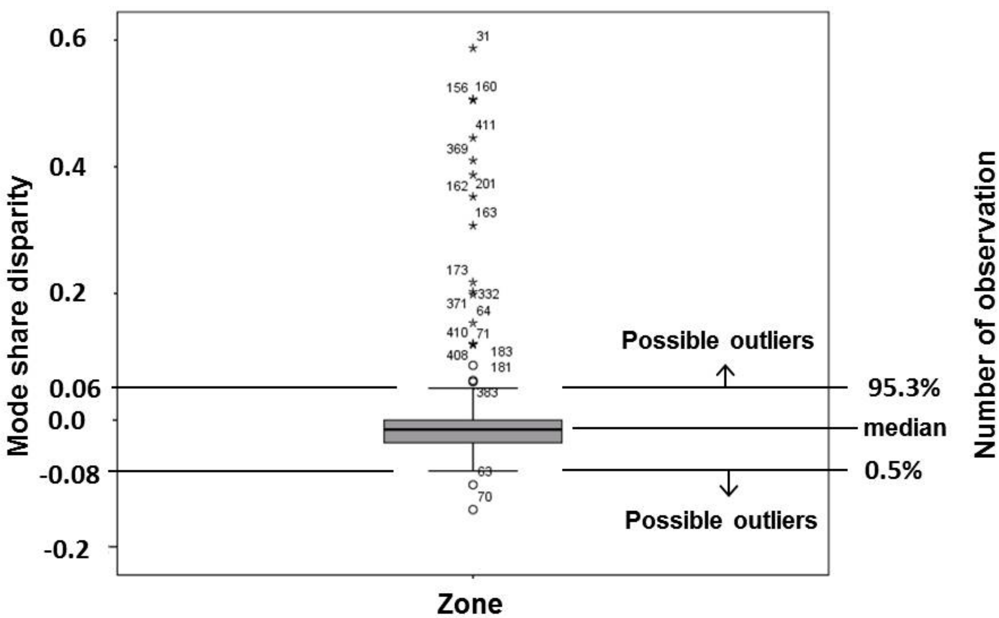


Figure 5-8: Mode share prediction errors in box plots

This analysis suggests the following boundaries and five groups on the degree of the prediction errors:

- $\varepsilon_i < -8\%$: Highly over-estimated: (2 zones)
- $-8\% \leq \varepsilon_i < -0.5\%$: Moderately over-estimated: (218 zones)

- $-0.5\% \leq \varepsilon_i < 0.5\%$: Reasonably estimated: (121 zones)
- $0.5\% \leq \varepsilon_i < 6\%$: Moderately under-estimated: (25 zones)
- $\varepsilon_i \geq 6\%$: Highly under-estimated: (18 zones)

Using these classifications, the characteristics of zones belonging to each category are explored to identify differences among them. In Figure 5-8, mode share disparity values in the zones listed are beyond the upper inner fence (18 zones) or lower inner fence (2 zones). These zones are labeled as highly under- and over-predicted zones. These zones are identified as possible outliers in boxplot analysis as described in section 5.2.2.

Using these classifications, the characteristics of zones belonging to each category are explored to identify differences among them. The summary statistics are shown in Table 5-3. Pairwise statistical comparisons are made between those belonging to moderately over, moderately under and highly under estimated zones. The comparison results highlight which variables should be considered for further analysis.

From Table 5-3, the results of (highly) under-estimated zones generally show transit supportive characteristics such as lower car ownership, lower income, and higher land use density. Transit quality of service, as measured by reliability and accessibility, is also better in these (highly) under-predicted zones. For the means of these variables, t-test results show a statistically significant difference between the two groups (i.e., moderately over-estimated and moderately under-estimated zones; and moderately over-estimated and highly under-estimated zones). In Table 5-3, results in bold indicate statistically significant possible source variables of prediction errors in a category.

Table 5-3: Summary statistics for possible source of errors

The degree of transit ridership estimation error (# of zones)	Highly over-estimate (2)	Moderately over-estimate (218)	Reasonably estimate (121)	Moderately under-estimate (25)	Highly under-estimate (18)	t-Test (two sample assuming unequal variances)	
						Moderately over- vs. Moderately under- P(T<=t) two-tail, (t Stat)	Moderately over- vs. Highly under- P(T<=t) two-tail, (t Stat)
Average Disparity (Mode share)	-0.12	-0.03	0.00	0.02	0.27	-	-
Socio-economic Variables							
Avg. # of cars per household	1.49	**1.52**	1.57	1.33	**1.23**	p >.05 (1.91)	**p < .05*** (2.76)
% of population 65+	13.84	11.36	10.27	10.64	12.47	p >.05 (1.54)	p >.05 (-1.62)
Income ($ CAD)	15,648	**36,403**	37,645	33,674	**31,333**	p >.05 (1.01)	**p < .05*** (2.20)
Land Use Variables							
Pop Density (persons / km2)	3,885	2,560	349	2,916	3,093	p >.05 (-0.89)	p >.05 (-0.96)
Emp Density (jobs / km2)	4,294	**1,125**	1,427	**2,73**2	**3,976**	**p < .05*** (-2.15)	**p < .05*** (-2.24)
Transit Quality of Service Variables							
Reliability (on-time performance)	0.59	**0.51**	0.53	**0.55**	**0.66**	**p < .05*** (-2.27)	**p < .05*** (-5.57)
Avg. access distance[1)] (meters)	242.55	**228.79**	243.70	**143.51**	**173.13**	**p < .05*** (3.33)	**p < .05*** (2.82)

1) Estimation results are available for 110 zones among 386 zones of the study area. Number of observation for access distance in: highly over-estimated zones- 2; moderately over- 77; reasonably- 13; moderately under- 9; highly under- 9.

Interestingly, those zones belonging to the “reasonably estimated” category have properties that are generally considered to be unsupportive of transit use: the group has the highest car ownership, income, and transit access distance and the lowest percentage of seniors. It should be noted that the zones in this group where prediction errors are almost zero include the cases where no people use transit both in model and actual situation.

Table 5-4: Results of regression analysis

	Variable	Coefficient	Std. Error	t-Statistic	Significance
All zones	Constant	-0.099	0.032	-3.117	0.002
	ln (Pop den)	-0.001	0.001	-0.705	0.481
	ln (Emp den)	0.003	0.002	1.530	0.127
	% pop 65+	0.000	0.001	0.527	0.598
	Avg. # of cars per household	-0.020	0.010	**-2.032***	**0.043**
	Income	1.367E-007	0.000	0.434	0.664
	Reliability	0.194	0.035	**5.479***	**0.000**
Over-estimated zones	Constant	-0.042	0.014	-3.109	0.002
	ln (Pop den)	0.001	0.001	1.833	0.068
	ln (Emp den)	0.000	0.001	0.587	0.558
	% pop 65+	-0.001	0.000	**-2.023***	0.044
	Avg. # of cars per household	-0.002	0.004	-0.636	0.525
	Income	7.282E-008	0.000	0.546	0.586
	Reliability (on-time performance)	0.009	0.013	0.694	0.489
Under-estimated zones	Constant	-0.534	0.279	-1.917	0.063
	ln (Pop den)	0.001	0.010	0.091	0.928
	ln (Emp den)	-0.003	0.019	-0.171	0.865
	% pop 65+	0.022	0.011	**2.020***	0.051
	Avg. # of cars per household	0.040	0.062	0.656	0.516
	Income	7.512E-008	0.000	0.035	0.972
	Reliability	0.632	0.247	**2.563***	0.015

Summary

All zones	Adj. R^2 Std. Error of the Estimate Observations	0.11 0.0709 384
Over- estimated zones	Adj. R^2 Std. Error of the Estimate Observations	0.01 0.0182 220
Under-estimated zones	Adj. R^2 Std. Error of the Estimate Observations	0.24 0.1431 43

Next, to identify those zonal characteristics that affect estimation errors, three separate types of zones – all zones, over-estimated zones, and under-estimated zones- were assessed using multinomial regression models. The regression analysis produces equations for the mode choice prediction errors as a function of socio-economic, land use and quality of service variables that are not included in the utility function. The results of this regression are presented in Table 5-4. The results in bold indicate statistically significant variables in the regression results. Based on the t-Statistics, the variables that are shown to be statistically significant for the prediction errors for “all zones” are reliability (on-time performance) and average number of cars per household. In other words, the prediction errors are sensitive to both reliability and the average number of cars per household. For under-estimated zones, the constant is much larger than the over-estimated zones, meaning much greater prediction errors. In these zones, the prediction errors are sensitive to both senior-aged (65+) population and reliability. It seems to be counterintuitive for the signs of some variables, for example, ‘average number of cars per household’ in under-estimated zones. However, it should be noted that the response variable of the regression analysis is prediction errors, not the probability of using transit. In this case, it is interpreted that auto ownership is not significant variable in under-predicted zones.

The goodness-of-fit summary suggests that the model delivers reasonable explanatory power in models for "all zones" and high transit supportive areas (i.e., under-estimated zones). Although the goodness-of-fit for over-estimated zones shows low explanatory power, the primary purpose of the analysis is to understand which predictor variables are related to prediction errors between predicted and actual transit mode choice. Overall, reliability, average car per household and senior-aged (65+) groups are shown to be primary sources of transit mode choice prediction errors.

While three separate types of zones – all zones, over-estimated zones, and under-estimated zones- were evaluated in this section, in future work the regression analysis only for “all zones” may be sufficient to identify major sources of prediction errors because this category represents the largest number of observations.

In this section, possible sources of prediction errors are examined for zones in various categories using various analytical tools. Based on the examination, a composite index to systematically identify the major source of errors is formulated in the following section.

5.4.3 Scoring the source of errors

To effectively identify the major source of the transit mode share prediction errors, a scoring method was formulated. As shown in equation (5-5), the formulation is involves the standardized value of each possible source of error (z_{Xi}) and mode share prediction error (MSE_i) in zone i. The product of these two variables implies the simplified magnitude of prediction errors and associated possible components of the errors. The larger the total score of the composite index, larger the impact the variable has on the prediction errors.

Table 5-5 shows the results of scores for the groups categorized by prediction error degree: two outlier zone groups (highly over-estimated and highly under-estimated) and total zones.

Table 5-5: Score on the source of prediction errors

(no. of zones)	Highly over-estimated (2)	Moderately over-estimated (218)	Reasonably estimated (121)	Moderately under-estimated (25)	Highly under-estimated (18)	Score of highly over- and highly under-	Score of total (384)	Ranking
|Z_ln(pop den) ×MSE[1]|	0.36	4.84	0.03	0.49	3.56	3.92	9.28	4
|Z_ln(emp den)×MSE|	0.27	4.08	0.02	0.37	4.72	4.99	9.45	3
|Z_65+×MSE|	0.18	3.90	0.01	0.23	3.25	3.43	7.58	6
|Z_car×MSE|	0.01	5.24	0.02	0.54	5.73	5.74	11.55	2
|Z_income×MSE|	0.37	4.24	0.03	0.38	2.62	2.99	7.63	5
|Z_reliability×MSE|	0.14	4.59	0.03	0.39	7.34	7.48	12.49	1
|Z_access[2]×MSE|	0.14	2.08	0.00	0.12	0.93	1.07	3.28	-

[1] MSE: mode share error
[2] access: transit accessibility variables are available for 110zones among 384 zones. So I cannot compare the score with the other variables in this study.

In Table 5-5, the highest score among seven possible factors for transit mode share prediction errors is reliability. Car ownership per household is the second most important factor for the forecast errors both in highly over- and under-estimated zones and in overall study areas. These components are also recognized as significant sources of prediction errors in the regression analysis in Table 5-4. Also land use variables including population density and employment density are identified as important variables associated with transit mode share prediction errors.

5.4.4 Model improvement recommendations

Based on the evaluation of factors that affect transit mode share prediction errors, three major components of the errors are determined in the study area: transit reliability (on-time performance), number of cars per household, and employment density as shown in Table 5-6.

Table 5-6: Model improvement recommendation associated to error components

Error component		Score	Recommendation
Quality of service	Transit reliability	12.49	Incorporation of variables in mode choice models
Socio-economic	No. of cars/HH	11.55	Incorporation of the variable in mode choice models
Land use	Employment density	9.45	- Incorporation of the variables (e.g., area-type) in mode choice models - Addition of lump-sum land use mode constants based on area-type (e.g., CBD urban area, sub-urban area, rural area etc.) - Land use feedback loop in travel forecasting models

These variables have the highest scores among the seven possible variables. Further evidence that reinforces their inclusion in models is apparent based on the t-statistics in Table 5-3 and in the regression results for 'all zones' presented in Table 5-4. The variables identified were determined to be statistically significant in explaining mode share prediction errors. The score on the source of prediction errors using developed method further allow prioritization.

From this analysis, to reduce transit mode share prediction errors, the inclusion of transit reliability, number of cars/HH, and employment density directly in the models should be considered. In case of land use variables, to decrease the forecast errors, the following is also suggested: (1) addition of lump-sum land use mode constants (e.g., area-type constants as shown in Table 3-3) in mode choice models, or (2) inclusion of the land use feedback loop in travel forecasting models.

5.5. Chapter Summary

Understanding how a model is different from actual decision making processes (e.g., what is unique to the place and the travelers at the present time or in a calibration year) is among the first steps necessary to refine existing mode choice and, more generally, travel forecasting models. To make this process more systematic, this study proposes a method to efficiently identify and evaluate the sources of prediction errors of transit use on a zonal level.

Model predicted boardings are compared to actual boardings obtained from the transit trip allocation method proposed in Chapter 4. Then errors are calculated and these terms are used to identify zones that should be considered outliers in terms of the model's ability to correctly predict transit boardings. The characteristics of zones and possible sources of the prediction errors are examined. These errors are associated with the omitted market segmentation variables and measurable characteristics with new data sources such as quality of service variables.

This chapter has presented the following major findings from the case studies:

- While the calibrated mode constants may minimize the errors in system-wide (e.g., based on market segments in the case study) boardings, significant over- and under- prediction errors exist for individual zones.
- The under-estimated zones generally show transit supportive characteristics such as lower car ownership, lower income, higher land use density while the over-estimated zones have overall transit un-supportive characteristics.
- Outlier zones of prediction errors commonly have extreme (or larger) standardized z-values in some possible source variables.
- Using the proposed scoring method, major components of the errors in the study area were determined. These variables are: transit reliability as a quality of service variable; number of cars per household as a socio-economic variable; and employment density as a land use variable. This study also suggests methods for model improvement with these variables to reduce the prediction errors.

The explicit inclusion of these additional variables may improve a model's ability to accurately predict transit boardings. The proposed method will be useful in (re)calibrating, updating, or modifying components of travel forecasting models, not only to investigate prediction errors in finer geographic level but also to identify major sources of prediction error of current models.

Chapter 6
Conclusions and Contributions

6.1 Conclusions

To enhance the estimation performance of regional travel forecasting models, particularly with regard to transit ridership, this dissertation concentrated on two sub-problems of (1) understanding the role of mode specific constants and (2) the potential to address insufficient data in mode choice modules.

When a mode choice model is calibrated, the underlying assumption is that all future forecasts (behaviors) will continue to reflect current conditions. Therefore, any misrepresentation of current conditions can generate even larger forecasting errors over the time horizon of the model. Despite the efforts to understand possible components of mode choice constants, and best practice literature, the use of large and poorly defined mode constants remains a challenge for many models and modelers. In the first part of this thesis the magnitude of this problem – the influence of large mode specific constants – was addressed by explicitly quantifying the relative importance of mode constants to measurable components using representative data from six cities in North America.

Second, the quality of a model in terms of its accuracy in both the short- and long-terms is largely dependent on the data that inform the model development. Recently, new data sources from the transit industry including Automatic Vehicle Location (AVL), Automated Passenger Counting (APC), and Automated Fare Collection (AFC) systems, have become available. This availability presents potential to improve modelers' abilities to quantify traveler behavior.

This thesis proposed a framework to improve the utilization of new data sources such as AVL/APC systems in transit ridership forecasting models. The direct application of these data to ridership forecasting requires an important intermediary step that links stop activities – boarding and alightings – to the actual location (at the TAZ level) that generated / attracted this trip. This research proposed GIS-based methods to complete this linking exercise and a framework to select the best performing method.

Lastly, given the research effort above, this thesis demonstrated a method to effectively identify and evaluate the source of transit ridership prediction errors in calibration procedures and to eventually enhance the calibration and model update procedures in the travel forecasting models. The following sections describe each of the above achievements and contributions in more detail.

6.2 Major Contributions

The contributions of this dissertation are summarized as follows.

1. ***Development of a framework to quantify the magnitude and importance of mode constants relative to the measurable components of travel utility functions:*** This research introduced various types of mode constants from state-of-art regional travel forecasting models and investigated the magnitude of these mode constants. Using the proposed framework, the importance of mode constants relative to the measurable components is quantified. The mode constants (representing unmeasured inputs) in walk-access segments of study cities account for 41% to 65% of total utilities. The results demonstrated that, in some cases, mode constants are large enough to render models insensitive to changes in system performance including reliability, convenience and many other factors. As such, the need to explicitly include mode constant endogenous to the model is verified. While it is widely understood in the literature and in practice that large mode constants should be avoided, this thesis presents a novel approach and quantitative evidence that verify the common understanding.

2. ***Development of methods to improve the utilization of AVL/APC data in mode choice calibration:*** This research developed innovative GIS-based methods to link the stop-level boardings and alightings to the traffic analysis zones from/to which these passengers actually originated or were destined. The formulated methods allocate transit trips proportionally to population / employment and area size of competing zones; or land use density (number of parcels, weighted footprint area) of parcels within transit access shed.

   The novel idea behind the four GIS-based methods is to consider the case when the access shed spans multiple TAZs. In some cases, an access shed may be wholly contained in a single traffic analysis zone (TAZ) at which point the problem becomes trivial – all boardings and alightings are assigned to that zone. The problem becomes more complicated when stops are located in zone boundaries.

   The performance of the proposed transit trips allocation methods was evaluated using transit on-board survey data. To the author's knowledge, no previous studies have actually tried to validate a method compared to observed maps of transit users from homes to stops and stops to destinations.

While the sample size of observations precluded conclusive comments on optimal methods, the methods developed reflect an important advance in evaluation methods.

Given the reasonable accuracy of predictions observed, the weighed buffer area ratio or footprint weighted method can improve the utilization of new data source (AVL/APC) to travel forecasting model calibration, particularly in investigating prediction errors at a finer geographic level.

3. ***Development of a method to effectively identify and evaluate the factors affecting the accuracy of predicted transit use on a zonal level:*** This research developed a method which can systematically identify and evaluate the source of mode choice prediction errors. As part of this framework, multinomial regression models were developed to evaluate those zonal characteristics that affect estimation accuracy. The regression analysis produces equations for the mode choice prediction errors as a function of (1) measurable but omitted market segmentation variables in current mode choice utility function including; socio-economic, land use and (2) newly quantifiable attributes with new data source or techniques including; quality of service variables.

   A method to quantify possible source of prediction errors was also developed and applied. The new composite index represents the magnitude of a prediction error and a possible error component as a standardized value at the zone. The total score of the composite index (over all zones, or sub-groups of zones, depending on the necessity) can be utilized to help modelers identify additional variables to be included when calibrating models, or modifying or updating components of travel forecasting models.

6.3 Future Work

In order to enhance transit ridership forecasting, the work presented in this thesis needs to be further improved and complemented. Possible future work is divided into the following four themes.

First, the thesis explored the use of AVL/APC data as means to reduce mode constants. In this thesis, the proposed allocating methods from AVL/APC stop boardings and alightings to zones are configured using 400 meter access shed boundary from a stop. By applying approaches to create more sophisticated transit access sheds – distance decay functions, varying the buffer radius based on climate, directness of the access paths, or creating waking path -, the performance of the transit trip allocation models in this thesis can be further improved.

Second, the proposed transit trip allocation methods currently cannot capture transfer trips since their actual origin or destination zones are located beyond the access sheds and AVL/APC data do not provide transfer information. It is recommended to extend the proposed framework so that it can take into account transfer trips by using AFC (Automatic Fare Collection) data that allow easy calculation of total transfer trips at each stop.

Third, the research presented here dealt with magnitude of mode constant and addressed the need to explicitly include components of mode constants endogenous to the model. Considerable variations existed in magnitudes of difficult-to-measure attributes (i.e., mode constants) among different cities. Future work may include comparative analysis on the importance of quality-of-service variables among different cities including large urban areas and suburban areas. The analysis can improve nationwide transit travel forecasting models considering spatial variations.

Lastly, Chapter 5 addressed a method for systematically identifying and evaluating the source of mode choice prediction errors. The determined variables in regression analysis and in the scoring method using z values have the potential to improve ridership forecasts. An interesting extension of the work presented here would be to reconstruct the mode choice model including the identified variables – reliability, land use density and auto ownership – endogenously in the model. The results could then be evaluated to determine if the mode constants and prediction errors are reduced both in specific zones and region-wide.

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Appendix A

Survey

Questionnaire

on Calibration Coefficients and Constants in Regional Mode Choice Models

This informal survey aims to: (1) take a look at calibration constants in regional mode choice models (Logit, Nested Logit type) in different cities and to (2) relate the estimated transit trips (over- or under-prediction before calibration) to the cities' characteristics.

> Please take a minute to help us by answering the following questions. An **example spread sheet** is provided to help your understanding. Please refer to the attached example sheet or use the sheet to respond.
>
> **OR**
>
> If you can send us the **calibration report** for mode choice travel forecasting models, it would be very valuable for our research.

Please respond to the following questions or input on the attached example spread sheet whichever you are convenient.

1. Municipality (town, city, province/state):
2. Calibration year of mode choice (or travel forecasting) models:
3. Type of mode choice models:
    a. Logit b. Nested Logit
4. Calibration coefficients and constants of mode choice models:
    a. If Logit, conversion factors of Logit:
    a-1. If Nested Logit, nesting coefficients:
    b. Coefficients of time and cost for all transit and auto modes, HBW model
    c. Value of time (with unit), HBW model
    d. Mode/area/segment (specific) constants, HBW model

- Respondent's Name: ________________
- Organization: ________________
- Position: ________________
- TEL: ________________
- E-mail: ________________

Thank You!

Return

After completing the survey, please send it to the indicated below.

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Appendix B

Mode choice model calibration coefficients in the study cities' models

	Philadelphia (GPR)			Washington D.C. (MWCOG)			City of Calgary		
	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.
In-vehicle time	Bus_IVT	Auto, W-trn, D-trn	-0.0250	IVT	DA, SR2, SR2+, WK-Commuter rail, WK-bus, WK-bus/metro, WK-metro, PNR-4 transit modes, KNR-4 transit modes	-0.02128	Car IVT	Auto, PNR	-0.0880
	BRT_IVT	Auto, W-trn, D-trn	-0.0238						
	LRT_IVT	Auto, W-trn, D-trn	-0.0213						
	Subway_IVT	Auto, W-trn, D-trn	-0.0188				Transit IVT	Transit, PNR	-0.0597
	Rail_IVT	Auto, W-trn, D-trn	-0.0150						
Out-of-vehicle time	D-trn_ACC	D-trn	-0.0625	Initial wait, transfer wait,board time, park time (PNR)	WK-4 transit modes , PNR-4 transit modes, KNR-4 transit modes	-0.05320	Walk time, wait time	Transit, PNR	-0.0910
	OVT	Auto, W-trn, D-trn	-0.0625	# transfer		0.00000	# transfer	Transit, PNR	-0.1858
	# transfer	W-trn, D-trn	0.0000	Access time, other walk time		-0.04256	Park wait time	Auto	-0.2727
				Access time		-0.03192			
Cost	Dist(miles)	Auto	0.0000	Fare	WK-4 transit modes , PNR-4 transit modes, KNR-4 transit modes	Cost Inc G1: -0.00185 Cost Inc G2: -0.00093	Car operating cost ($)	Auto, PNR	-0.5278
	OPFARE	Auto, W-trn, D-trn	-0.1500	PCOST	DA, SR2, SR2+, PNR-4 transit modes,	Cost Inc G3: -0.00062	Fare	Ttransit, PNR	-0.5278
	PCOST	Auto, D-trn	-0.3333	OC	DA, SR2, SR2+, PNR-4 transit modes, KNR-4 transit modes	Cost Inc G4: -0.00046	Daily parking cost	Auto	-0.05278

	Philadelphia (GPR)			Washington D.C. (MWCOG)			City of Calgary		
	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.
Others							LRT used auto to transit	PNR	0.4324
							HH zone car ownership	Auto, PNR	5.628
							district to district trips	car 2, car3+	0.000015
Constants	**Income constants**			**Income constants**			**Mode constants**		
	LOWINC	W-trn	0.675	Low income	WK-4 transit modes	2	C_car 1p	car 1p	0
	LOWINC	D-trn	0.300	High income	WK-4 transit modes	-2	C_car 2p	car 2p	-1.3733
	Area-type constatns			**Mode constants** (example of Seg.1 and Seg.3)			C_car 3p+	car 3p+	-3.3787
	DEN12_W-trn	CBD	-0.075		Seg. 1	Seg. 3	C_Transit	transit	3.8696
	DEN12_D-trn	CBD	-1.125	Auto	0.0000	0.0000	C_D-trn	PNR	-2.5134
	Den3_W-trn	Urban	0.000	Transit	3.7245	6.6777			
	Den3_D-trn	Urban	-0.900						
	Den4_W-trn	Suburban	-0.475	Transit					
	Den4_D-trn	Suburban	-0.125	WK-access	0.0000	0.0000			
	Den56_W-trn	Rural	-1.125	PNR-access	-3.7643	-8.0902			
	Den56_D-trn	Rural	0.000	KNR-access	-7.3352	-11.2737			
				Walk-trn					
				WK-metro	0.0000	0.0000			
				WK-commuter rail	-0.8073	-5.6499			
				WK-bus	-1.4496	-9.0773			
				WK-bus/metro	-1.4604	-8.5955			
				PNR-trn					
				PNR-metro	0.0000	0.0000			
				PNR-commuter rail	-0.3935	-2.3531			
				PNR-bus	-2.4506	-9.5804			
				PNR-bus/metro	0.8506	-7.8945			
	Mode constants								
	C_W-trn	W-trn	-1.175	KNR-trn					
	C_DT	D-trn	-1.425	KNR-metro	0.0000	0.0000			
				KNR-commuter rail	3.5730	-0.1115			
				KNR-bus	1.2609	-3.9039			
				KNR-bus/metro	5.7435	0.8457			

Mode choice model calibration coefficients in the study cities' models (cont'd)

	Denver (DRCOG)			City of Winnipeg			City of Ottawa		
	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.
In-vehicle time	IVT	auto, transit	-0.02	IVT	Auto drive	-0.064	Transit IVTT	All transit [2]	-0.0228
	Local bus time/total transit IVT	W_trn, D-trn	-0.677	IVT_Passenger	Auto passenger	-0.078	IVTT transit way	Transit	0.0128
	D-trn_ACC/total IVT	D-trn	-1.433	TIVT	Transit	-0.035	IVTT low stop density	Transit	0.0011
							IVTT high stop density	Transit	-0.005
Out-of-vehicle time	Walk mode terminal time	Auto (DA, SR2,SR3+)	-0.05	walk distance (<=3km)	walk/bike	-1.335	Wait time	Transit	-0.0684
	Transit walk, transit first wait time	W_trn, D-trn	-0.05	bike distance (>3km and <=10km)	Walk/bike	-0.466	Walk time	Transit	-0.053
	Transit other wait	W_trn, D-trn	-0.03	TWALKTOT	Transit	-0.087	# of boarding	Transit	-0.114
				TWAITTOT	Transit	-0.066	Drive access time	Transit	-0.0308
				# transfer	Transit	-0.371	auto free flow time	auto (sov, hov2-dr, hov2-pass, hov3+-dr, hov3+-pass)	-0.0308
							auto delay	auto	-0.0562
Cost	Cost($)-low income Cost($)-medium Cost($)-high income Cost($)-missing	Auto, Transit	-0.246 -0.11 -0.083 -0.103	TOTCOST (OC, PC, FARE)	Auto drive, auto passenger, transit	-0.268	PCOST	Auto	-0.1200

[2] all transit: walk-bus, PNR bus, KNR bus, BNR bus, walk-rail, PNR rail, KNR rail, BNR rail

	Denver (DRCOG)			City of Winnipeg			City of Ottawa		
	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.
Others	arrive at des in AM peak	Auto	-1.003	0 veh in HH	Transit	0.658	Low income	bus-walk, bus-KNR, bus-BRN	1.7428
	leave from des in PM peak	Auto	-0.268	2+ veh/2+ adults	Auto drive	0.918	Low income	bus-PNR	-0.0550
	shopping stops/tours remaining	DA	0.847	2veh/3+ adults	Auto drive	-0.487	Low income	rail-walk, rail-KNR, rail-BNR	1.3425
	escort stops/tours remaining	SR2, SR3+	5.391	1veh/2 adults	Auto drive	-1.294	Low income	rail-PNR	0.8641
	other stops/tours remaining	SR2, SR3+	0.495	1veh/3adults	Auto drive	-1.462	Medium income	bus-walk, bus-KNR, bus-BRN	0.9319
	LOWINC	SR2, SR3+	0.158	2+ veh/2+ adults	Auto passenger	1.943	Medium income	bus-PNR	0.4535
	LOWINC	W-trn	0.308	less than one veh/adults	Auto passenger	1.651	Medium income	rail-walk, rail-KNR, rail-BNR	0.6940
	LOWINC	D-trn	0.043	part time worker with 1+ veh in HH	Auto passenger	0.703	Medium income	rail-PNR	0.2156
	HIGHINC	SR2, SR3+	-0.057	HH with children	Auto drive	0.205	Zero cars	SOV, bus-PNR, rail-PNR	-99.0000
	HIGHINC	W-trn	-1.745	destination University dummy	Transit	0.991	Zero cars	bus-walk, bus-BNR, rail-walk, rail-BNR	0.4075
	HIGHINC	D-trn	-1.215	destination zone is urban low or urban high[3]	Auto drive	-0.353	Zero cars	bus-KNR, rail-KNR	-0.8517
	missing INC	SR2, SR3+	-0.215	destination zone is CBD	Auto drive	-0.417	car sufficiency low	SOV	-0.1110
	missing INC	W-trn	-0.782	origin zone is suburban high or urban low	Transit	0.315	car sufficiency low	bus-PNR	-0.2668
	missing INC	D-trn	-1.156	O and D zones are urban high or CBD	Walk/bike	1.07	car sufficiency low	bus-KNR, rail-KNR	-1.2592

[3] Winnipeg incorporates the area-type attributes directly to the utility. For example, the model inserts the dummy variable of 'origin zone is sub-urban high or unban low' for transit utility.

	Denver (DRCOG)			City of Winnipeg			City of Ottawa		
	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.
Others	No Car in HH	SR2, SR3+	5.045	manufacturing	auto drive	0.351	Emp density	bus	0.0008
	No Car in HH	W-trn	12.201	sales/service	transit	0.456	Emp density	rail	0.0009
	No Car in HH	D-trn	9.26	professional/office constant	auto passenger	-0.275	Pop density	bus-walk, rail-walk	0.0018
	HH cars>0, <workers	SR2, SR3+	1.366	professional/office constant	walk/bike	0.389	Pop density	bus-PNR, bus-KNR, rail-PNR, rail-KNR	-0.0087
	HH cars>0, <workers	W-trn	5.119				% detached HH	SOV, hov2-dr, hov3+-dr	1.0117
	HH cars>0, <workers	D-trn	3.529				% detached HH	bus-walk, rail-walk	-1.3042
	HH cars>=workers, <adults	SR2, SR3+	0.553						
	HH cars>=workers, <adults	W-trn	2.38						
	HH cars>=workers, <adults	D-trn	1.572						
	Female	SR2, SR3+	0.57						
	Female	D-trn	0.656						
	1 person HH	SR2	-1.659						
	1 person HH	SR3+	-2.452						
	2 person HH	SR3+	-1.704						
	Destination intersection density	W_trn, D-trn	11.43						
	Destination retail density	W_trn, D-trn	0.253						
	Origin intersection density	W_trn	6.8						

	Denver (DRCOG)			City of Winnipeg			City of Ottawa		
	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.	Attributes	Modes Applied	Coeff.
Constants	**Mode constants**			**Mode constants**			**Mode constants for AM**		
	C_SR2	SR2	-2.889	C_Auto drive	auto drive	3.976		SOV	2.0945
	C_SR3+	SR3+	-3.41	C_Transit	transit	2.902		HOV2-dr	0.0121
	C_W-trn	W-trn	-3.956	C_Walk	walk	4.024		HOV2-PASS	0
	C_D-trn	D-trn	-4.693	C_Bike	bike	1.619		HOV3+-dr	-1.1164
								HOV3+-pass	-0.8040
								bus-wak	2.1806
								bus-PNR	-1.9185
								bus-KNR	-3.0607
								bus-BNR	-5.0000
								rail-walk	2.2440
								rail-PNR	-1.1452
								rail-KNR	-2.9609
								rail-BNR	-5.0000

Appendix C

Sample computation of measurable utility using skim values for Washington D.C.

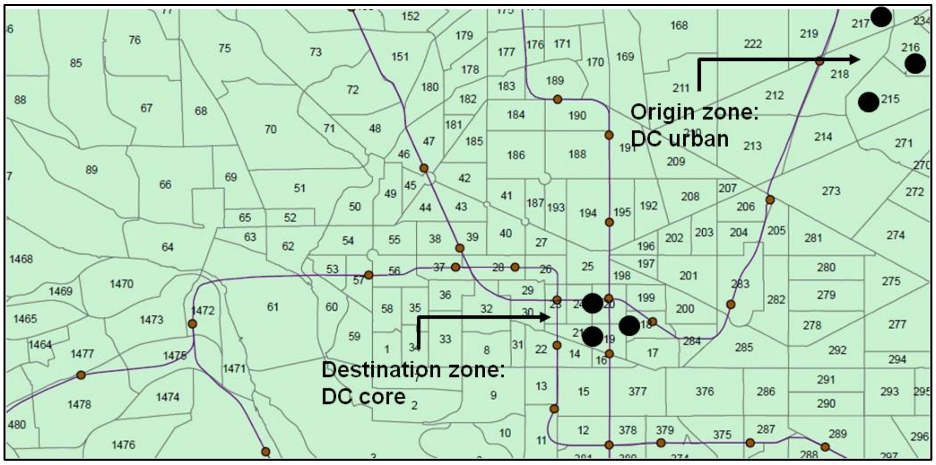

Figure C-1. Sample calculation area (zone 215, 216, 217 → zone 18, 19, 20)

a. Walk-access

Table C-1. Input skim values for walk-access to bus (source: AM_AB_WkAcc_Skims_2007, unit: 0.01min, 0+, cents)

wk ivt local bus				wk ini wait				wk xfer wait				wk transfer			
O\D	18	19	20	O\D	18	19	20	O\D	18	19	20	O\D	18	19	20
215	**1906**	2550	1872	215	**429**	1000	750	215	**0**	0	0	215	**0**	0	0
216	1748	2571	1872	216	750	750	750	216	0	0	0	216	0	0	0
217	1748	2571	1872	217	750	750	750	217	0	0	0	217	0	0	0
wk fare				**wk added board time**				**wk acc time**				**wk other wk time**			
O\D	18	19	20	O\D	18	19	20	O\D	18	19	20	O\D	18	19	20
215	**135**	135	135	215	**500**	500	500	215	**560**	520	740	215	**1300**	460	680
216	135	135	135	216	500	500	500	216	680	600	480	216	840	500	680
217	135	135	135	217	500	500	500	217	460	380	260	217	340	0	180

Example calculation:

zone 215 (DC urban) → zone 18 (DC core) : Area segment 1, HBW trip

$$U_{\text{wk acc}-\text{bus,od}}$$
$$= -0.02128 \times \frac{IVT_{wk\ acc-bus,od}}{100} - 0.0532 \times \frac{wlk\ ini.wait_{wk\ acc-bus,od} + wlk\ xfr\ wait\ time_{wk\ acc-bus,od}}{100}$$
$$- 0.0000 \times wlk\ no.transfers_{wk\ acc-\ bus,od} \ + COST\ INC_{G1} \times wlk\ fare_{wk\ acc-bus,od} \ - 0.05320$$
$$\times \frac{wlk\ added\ board\ time_{wk\ acc-bus,od}}{100} - 0.04256$$
$$\times \frac{wlk\ acc\ time_{wk\ acc-bus,od} + other\ walk\ time_{wk\ acc-bus,od}}{100}$$
$$= -0.02128 \ \times \frac{1906}{100} - 0.0532 \ \times \frac{429 + 0}{100} - 0.000 \times 0 - \ 0.00185 \times 135 - 0.05320 \times \frac{500}{100} - 0.04256$$
$$\times \frac{560 + 1300}{100} = -1.9412$$

Estimated measurable utility for walk access (sample 3×3 zones)

Destination Origin \		DC core **18**	DC core 19	DC core 20
DC urban	**215**	**-1.9412**	-2.0075	-1.9175
DC urban	216	-1.9336	-1.9300	-1.8068
DC urban	217	-1.6272	-1.6236	-1.5004

b. Drive-access

Table C-2. Input skim values for drive access to bus (source: AM_AB_DrAcc_Skims_2007, unit: 0.01min, 0+, 0.01mile, cents)

ivt local bus				dr acc time				dr ini wait time				dr xfr wait time			
O\D	18	19	20	O\D	18	19	20	O\D	18	19	20	O\D	18	19	20
215	**2119**	2473	2473	215	**686**	686	686	215	**450**	450	450	215	**0**	0	0
216	2119	2473	2473	216	600	600	600	216	450	450	450	216	0	0	0
217	2119	2473	2473	217	400	400	400	217	450	450	450	217	0	0	0
dr xfr				dr fare				dr acc distance				dr added board time			
O\D	18	19	20	O\D	18	19	20	O\D	18	19	20	O\D	18	19	20
215	**0**	0	0	215	**135**	135	135	215	**240**	240	240	215	**500**	500	500
216	0	0	0	216	135	135	135	216	210	210	210	216	500	500	500
217	0	0	0	217	135	135	135	217	160	160	160	217	500	500	500
dr wk acc time				dr other wk time				dr park cost				dr park time			
O\D	18	19	20	O\D	18	19	20	O\D	18	19	20	O\D	18	19	20
215	**300**	200	60	215	**360**	500	180	215	**0**	0	0	215	**206**	206	206
216	300	200	60	216	360	500	180	216	0	0	0	216	206	206	206
217	300	200	60	217	360	500	180	217	0	0	0	217	206	206	206

Example calculation:

zone 215 (DC urban) → zone 18 (DC core) : Area segment 1, Income group1, HBW trip

$$
\begin{aligned}
\mathrm{U}_{\mathrm{KNR\ bus,od}} = {} & -0.02128 \times \frac{drv\ IVTbus_{KNR-bus,od}}{100} - 0.03192 \times \frac{drv\ acc\ time_{KNR-bus,od}}{100} - 0.0532 \\
& \times \frac{drv\ ini.wait_{KNR-bus,od} + drv\ xfr\ wait\ time_{KNR-bus,od}}{100} - 0.0000 \\
& \times drv\ no.transfers_{KNR-bus,od} + COST\ INC_{G1} \\
& \times \left[drv\ fare_{KNR-bus,od} + \frac{drv\ acc\ distance_{KNR-bus,od}}{100} \times AUOP_{KNR-bus,od} \right] - 0.05320 \\
& \times \frac{drv\ added\ board\ time_{KNR-bus,od}}{100} - 0.04256 \\
& \times \frac{drv\ acc\ time_{KNR-bus,od} + other\ walk\ time_{KNR-bus,od}}{100} \\
= {} & -0.02128 \times \frac{2119}{100} - 0.03192 \times \frac{686}{100} - 0.0532 \times \frac{450+0}{100} - 0.0000 \times 0 - 0.00185 \\
& \times \left(135 + \frac{240}{100} \times 10\right) - 0.05320 \times \frac{500}{100} - 0.04256 \times \frac{300+360}{100} = -1.7503
\end{aligned}
$$

Estimated measurable utility for drive access (sample 3×3 zones)

Destination Origin \		DC core	DC core	DC core
		18	19	20
DC urban	**215**	**-1.7503**	-1.8427	-1.6469
DC urban	216	-1.7173	-1.8097	-1.6139
DC urban	217	-1.6442	-1.7366	-1.5408