# A TRIP-BASED APPROACH TO MODELLING URBAN TRANSPORTATION GREENHOUSE GAS EMISSIONS FOR MUNICIPALITIES

by

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A Trip-based Approach to Modelling Urban Transportation Greenhouse Gas Emissions for Municipalities

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## Abstract

Transportation has always been a major source of Greenhouse Gas (GHG) emissions all over the world. The fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC) has reported that the transportation sector was responsible for 14% of the total emissions in 2010. In Canada, transportation has been the second largest source of GHG emissions in 2012. Therefore, cutting transportation-related GHG emissions has become a top priority on the international agenda. Many international governments have announced aggressive GHG emissions reduction targets. In response, numerous research efforts have looked at developing tools to model the effect of various transportation and land use policies on GHG emissions reduction. However, most of the developed models are context specific and vary greatly in complexity (e.g. network-wide, corridor-wide, etc.) and level of detail (i.e. macro, meso, and micro). Thus, they cannot be used in other settings. In addition, little has been reported on monitoring progress towards meeting municipal GHG emissions reduction targets.

To contribute to this issue, this research presents a TRIp-Based Urban Transportation Emissions (TRIBUTE) model for municipalities. TRIBUTE integrates two main components: a discrete mode choice/shift model and an emissions forecasting model. Given personal, modal, and land use information, the mode choice/shift model calculates the proportion of trips made by different travel options (e.g. car, bus, walk, etc.). The total Vehicle Kilometres Travelled (VKT) by each mode is then calculated by multiplying the proportion of trips made by each mode by respective average VKT. Finally, total GHG emissions are calculated by multiplying the total VKT by each mode by respective average emissions factors. TRIBUTE is intended to assist municipalities (especially those with no detailed transportation network model) explore the impacts of various transportation and land use planning policies on changing travel behavior, and subsequently GHG emissions from passenger transportation. The City of Kelowna, BC, Canada is selected as a case study. The model validation results show a difference of only 0.3% in GHG emissions between the model prediction and the historical data.

## Preface

Excerpts of this thesis have been presented and submitted for publication in peer reviewed conference proceedings and technical journals. In addition, a technical report, utilizing the developed approach, has been submitted and presented to the City of Kelowna, BC, Canada to investigate the impacts of urban densities on the city's GHG emissions targets.

The author developed the models, analyzed the results, and wrote initial drafts of the manuscripts listed below. The research supervisor provided valuable guidance and helped in the development of the final versions of the publications. The work presented in the thesis has led to the following publications:

Rahman, M. N. and Idris, A. O. (2016). TRIBUTE: A TRIp-Based Urban Transportation Emissions Model for Municipalities. Submitted to the Journal of Sustainable Transportation (Date of submission: April 4th, 2016).

Rahman, M. N., Ruparathna, R., Sekhon, S., Kumar, V., AlHashmi, M., Umer, A., Andrade, M. T. B., Dyck, R., Doberstein, C., Hewage, K., Hicky, R., Idris, A., Li, E., Culver, K., and Sadiq, R. (2016). Investigating the Impacts of Urban Densities on City of Kelowna's GHG Emission Targets. Technical report submitted to the City of Kelowna in January, 2016.

Rahman, M. N. and Idris, A. O. (2016). Modelling On-Road Transportation Greenhouse Gas (GHG) Emissions under Various Land Use Scenarios. Paper presented at the 95th Transportation Research Board (TRB) Annual Meeting, Washington D.C.

Rahman, M. N. and Idris, A. O. (2015). Trip-based Urban Transportation Greenhouse Gas (GHG) Emissions Model. Paper presented at the 2nd Engineering Graduate Symposium, School of Engineering, UBC Okanagan, Kelowna, BC, Canada.

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## List of Abbreviations

| | |
|---|---|
| BAU | Business-As-Usual |
| BC | British Columbia |
| CEEI | Community Energy and Emissions Inventory |
| $CO_2$ eq. | Carbon dioxide equivalent |
| FPM | Forecasting Performance Measure |
| GDP | Gross Domestic Product |
| GHG | Greenhouse Gas |
| GWP | Global Warming Potential |
| HHTS | Household Travel Survey |
| ImPACT | Impact (Im), Population (P), Affluence (A), Intensity of use (C), and Efficiency (T) |
| IPAT | Impact (I), Population (P), Affluence (A), and Technology (T) |
| IPCC | Intergovernmental Panel on Climate Change |
| MASc | Most Aggressive Scenario |
| MNL | Multinomial Logit Model |
| PKT | Passenger Kilometres Travelled |
| SD | School District |
| STIRPAT | STochastic Impacts by Regression on Population, Affluence, and Technology |
| STPCO | Sustainable Transportation Partnership of the Central Okanagan |
| TAZ | Traffic Analysis Zone |
| TRIBUTE | TRIp-Based Urban Transportation Emissions |
| UNFCCC | United Nations Framework Convention on Climate Change |
| USEPA | United States Environmental Protection Agency |
| VKT | Vehicle Kilometres Travelled |
| VMT | Vehicle Miles Travelled |

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Dedicated to my beloved wife
Tasnuva Haque

# Chapter 1: Introduction

## 1.1 Outline

This chapter starts with a discussion of the problem statement and research motivation in Section 1.2, followed by research goal and objectives in Section 1.3. Finally, Section 1.4 demonstrates the structure of the thesis.

## 1.2 Problem Statement and Research Motivation

Transportation has always been a major source of Greenhouse Gas (GHG) emissions all over the world. From 1990 to 2007, GHG emissions from the transportation sector increased substantially, reaching around 15% of the overall GHG emissions in 2010 (International Transportation Forum, 2010). This global trend is further exceeded in North America. In 2008, transportation accounted for 27% of the total GHG emissions in the United States (Mahendra et al., 2012). In Canada, transportation was the second largest source of GHG emissions in 2012, accounting for 24% of the total emissions nationwide (Environment Canada, 2014). At the provincial level, 37.9% of British Columbia's GHG emissions came from the transportation sector (Ministry of Environment, 2012). Such high levels of GHG emissions can be attributed to the large expansion of the urban road network and automobile dependency in many North American cities. For example, GHG emissions from private automobiles in Canada in 2007 were 14% higher than that of 1990 levels (Terefe, 2010).

In light of the above, cutting transportation-related GHG emissions has become a top priority on the international agenda. Many international governments announced aggressive, sometimes optimistic, GHG emissions reduction targets. For example, the United Kingdom government set a target to reduce transportation-related GHG emissions by 60% by 2030 (Hickman and Banister, 2007). The Australian government intended to reduce GHG emissions by 20% below 2000 levels by 2020, and ultimately reach a 50% reduction by 2050 (Stanley et al., 2011). The Government of Canada has also committed to reduce Canada's GHG emissions by 17% below 2005 levels by 2020 under the Copenhagen Accord (Environment Canada, 2013). At the provincial level, British Columbia went further beyond the Canadian threshold and intended to reduce its emissions below 2007 levels by a minimum of 33% by 2020 and 80% by 2050 (Ministry of Environment, 2014c).

In response to these international governments' commitments, GHG emissions have become a major concern within the international scientific community. Numerous research efforts have looked at developing tools to model and forecast GHG emissions from the transportation sector. While useful, the developed tools are context specific and constrained by the availability of data and/or expertise, being of little or no use outside that context. In addition, the available tools for GHG emissions modelling and forecasting vary greatly in complexity (e.g. network-wide, corridor-wide, etc.), level of details (i.e. macro, meso, and micro), and sensitivity to transportation attributes (e.g. travel speed, fuel consumption, etc.) and land use factors (e.g. density, diversity, design, etc.).

It is apparent that there is no universal tool for GHG emissions modelling and forecasting. Unfortunately, most of the developed tools are suitable for estimating GHG emissions in large urban centres where traffic congestion and emissions are major concerns, being of little use in small municipalities where the required data and/or expertise are unavailable. Other tools require a detailed transportation network model to estimate emissions at the link level (i.e. link-based models), being useless in cases where such network model is unavailable. Therefore, more research is still needed to develop GHG emissions modelling and forecasting tools suitable for the context of small and mid-sized municipalities with appropriate complexity, level of details, and sensitivity to transportation attributes and land use factors.

## 1.3 Research Goal and Objectives

This research aims at developing modelling and scenario-comparison tools to explore the impacts of various transportation and land use planning policies on changing travel behavior, and subsequently GHG emissions. The developed tools are intended for estimating GHG emissions from passenger transportation in the absence of a detailed transportation network model. Such goal is achieved through the completion of the following objectives:

- Develop discrete mode choice model to estimate mode shift (i.e. switching modes from cars to public transit and active transportation) in response to changes in density and land use mix

- Develop Passenger Kilometre Travelled (PKT) model to capture the reduction in trip length due to changes in land use attributes

- Develop GHG emissions forecasting model to assist municipalities evaluate alternative policy scenarios and eventually select the scenario(s) that help them to meet their future GHG emissions targets

- Assess the impacts of urban densities and land use policies on the City of Kelowna's GHG emissions targets as a case study

## 1.4 Structure of the Thesis

This thesis consists of six chapters. Chapter 1 introduces the problem statement along with the research goal and objectives, and thesis outline. Chapter 2 reviews the literature on Greenhouse Gas (GHG) emissions and their sources, the controlling factors that affect GHG emissions, and the effects of land use and built environment on travel behavior and GHG emissions reduction. Chapter 3 proposes a TRIp-Based Urban Transportation Emissions (TRIBUTE) model and describes the research methodology and the framework of the developed model. Chapter 4 presents the study area, datasets, and modelling efforts. Chapter 5 applies TRIBUTE to evaluate the impact of alternative land use and transportation policy scenarios on Kelowna's GHG emissions targets. Finally, Chapter 6 concludes the thesis and discusses limitations and future research.

# Chapter 2: Literature Review

## 2.1 Outline

This chapter starts with an overview of Greenhouse Gases (GHGs) in Section 2.2, followed by the sources of GHG emissions in Section 2.3. The factors that affect GHG emissions are presented in Section 2.4. In Section 2.5, the effects of land use and built environment on travel behavior and GHG emissions reduction are discussed. The traditional travel demand modelling approach is presented in Section 2.6.

## 2.2 Greenhouse Gases

Greenhouse gases (GHG) generally act as a global insulator that absorbs surface energy and slows down energy escapes, thus warms the earth's surface and makes it hospitable to life (IPCC, 1996). This phenomenon, warming the earth's surface, is known as the greenhouse effect (Murphy, 2000). The most important natural GHGs associated with the greenhouse effect are water vapor ($H_2O$), carbon dioxide ($CO_2$), nitrous oxide ($N_2O$), methane ($CH_4$), and ozone ($O_3$). However, the increase in concentration of GHGs in the earth's atmosphere has resulted in higher absorption rates of surface energy and subsequently, global temperature rising, leading to a rise in mean sea level (Murphy, 2000).

Human activities such as burning fossil fuels and deforestation can contribute to the increase of GHGs in the earth's atmosphere. Besides the natural GHGs, the Kyoto protocol has dealt with the greenhouse gases sulphur hexafluoride ($SF_6$), hydrofluorocarbons (HFCs) and perfluorocarbons (PFCs) (UNFCCC, 2008). The components of GHGs can be divided into two broad categories: long-lived gases and short-lived gases (IPCC, 2007). The long-lived gases persist a long time in the atmosphere and are chemically more stable. Carbon dioxide, methane, and nitrogen dioxide lies within this category. On the other hand, the short-lived gases are chemically more active and are washed out in the form of precipitation. Short-lived gases include sulphur dioxide and carbon monoxide (IPCC, 2007).

Greenhouse gas emissions for each gas are normally stated and/or measured in terms of their global warming potential (GWP), a measure that allows their impact to be stated in terms of one comparable gas (USEPA, 2016). GWP is an indicator of energy absorption of a particular gas over a given period relative to carbon dioxide over the same period. Usually, the given time is 100 years. The unit of GWP is carbon dioxide equivalent ($CO_2$ eq.), since all GHGs are measured in terms of carbon dioxide. The GWP of major GHGs is given in Table 2-1.

**Table 2-1 Global Warming Potential of GHGs (IPCC, 1995; IPCC, 2007; IPCC, 2014)**

| GHG | 100-Year GWP[1] | 100-Year GWP[2] | 100-Year GWP[3] |
|---|---|---|---|
| **Carbon Dioxide ($CO_2$)** | 1 | 1 | 1 |
| **Methane ($CH_4$)** | 21 | 25 | 28 |
| **Nitrous Oxide ($N_2O$)** | 310 | 298 | 265 |
| **Nitrogen Trifluoride ($NF_3$)** | - | 17,200 | 16,100 |
| **Sulphur Hexafluoride ($SF_6$)** | 23,900 | 22,800 | 23,500 |
| **Hydrofluorocarbon - 23 ($CHF_3$)** | 11,700 | 14,800 | 12,400 |
| **Hydrofluorocarbon - 32 ($CH_2F_2$)** | 650 | 675 | 677 |
| **Perfluorocarbons – 116 ($C_2F_6$)** | 9,200 | 12,200 | 11,100 |

As shown in Table 2-1, the GWP is not the same in all annual reports. The GWP is influenced by many factors, such as the new lifetime of GHGs, change in $CO_2$ impacts, the strength of indirect effects on concentration of GHGs, and change of GHGs over time (Trottier, 2015). Based on the 100-year global warming potential values from the Fifth Assessment Report (5AR), 62% of global emissions come from $CO_2$ fossil fuel and industrial processes (IPCC, 2014). Figure 2-1 illustrates the components of GHGs based on the Fifth Assessment Report (5AR).

[1] IPCC. (1996). Climate change 1995: Economic and social dimensions of climate change. Cambridge University Press.
[2] IPCC. (2007). Climate change 2007: The physical science basis. Intergovernmental Panel on Climate Change.
[3] IPCC. (2014). Climate change 2014: Synthesis report. Contribution of working groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change.

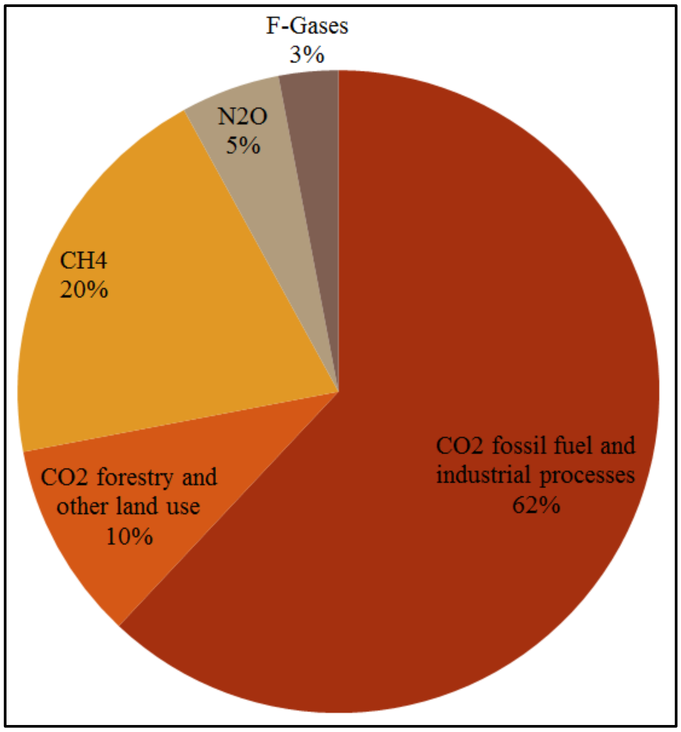


**Figure 2-1 Proportion of Different Components of GHGs (IPCC, 2014)**

## 2.3 Sources of GHG Emissions

According to the IPCC (2014), the sources of GHG emissions can be broadly categorized as direct emissions and indirect emissions from different economic sectors. Direct emissions come from five economic sectors: AFOLU[1], buildings, transport, industry, and other energy sources. Indirect emissions come from electricity and heat production. Indirect emissions are further classified as follows: energy, industry, transport, buildings, and AFOLU (IPCC, 2014). Figure 2-2 illustrates the sources of GHG emissions from different economic sectors in 2010.

[1] Agriculture, forestry, and other land use (AFOLU)

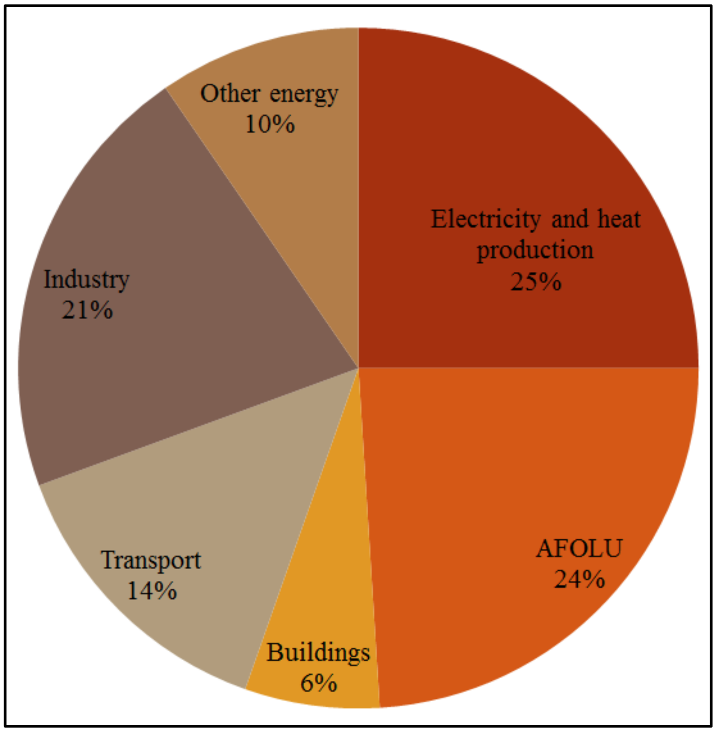


**Figure 2-2 Sources of GHG Emissions[1]**

In Canada, the transportation sector was responsible for 24% of total GHG emissions in 2012, coming second after oil and gas, as shown in Figure 2-3 (Environment Canada, 2014). Within the transportation sector, road transportation came first with 65% of all transportation-related emissions, as shown in Figure 2-4 (Environment Canada, 2014).

According to the Copenhagen Accord, Canada has committed to reduce its GHG emissions by 17% below the 2005 levels by 2020 (Environment Canada, 2013). At the provincial level, British Columbia went further than the Canadian threshold and intended to reduce its emissions below 2007 levels by a minimum of 33% by 2020 and 80% by 2050 (Ministry of Environment, 2014c). In British Columbia, 37.9% of GHG emissions come from the transportation sector (Ministry of Environment, 2012).

[1] Modified from Figure 1.7, page 47 from IPCC, 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, Pachauri, R.K. and Meyer, L. (eds.)]. IPCC, Geneva, Switzerland

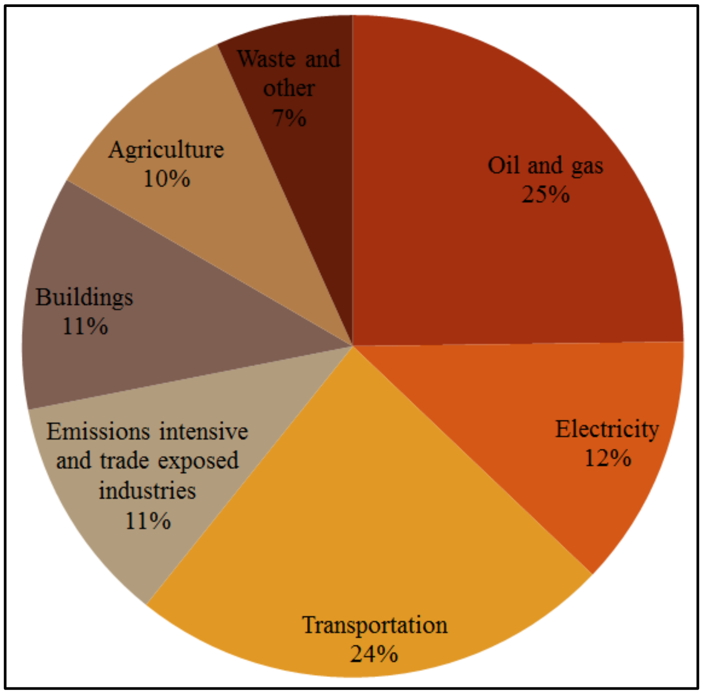


**Figure 2-3 Sources of GHG Emissions in Canada in 2012**[1]

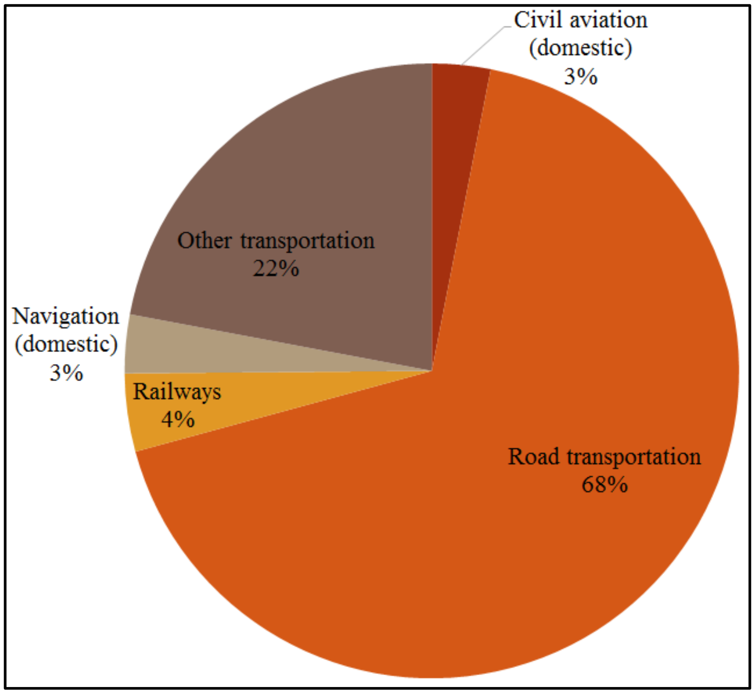


**Figure 2-4 Transportation-related Emissions in Canada (Environment Canada, 2014)**

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[1] © Her Majesty The Queen in Right of Canada, Environment and Climate Change Canada, 2014, by permission

### 2.4 Driving Factors of Transportation GHG Emissions

Understanding the factors influencing global GHG emissions is key to developing appropriate mitigation strategies. Many previous studies have reported on the environmental impact of global GHG emissions and their intensity (Bongaarts, 1992; Bristow et al., 2008; York et al., 2003; Davis and Caldeira, 2010; Jung et al., 2012; Kawase et al., 2006; Kwon, 2005; Myers, 1993; Raskin, 1995; Rosa and Dietz, 1998; Xiangzhao and Ji, 2008). According to the framework for sustainability, introduced by Ehrlich and Holdren (1971), the environmental impact (I) consists of population (P), affluence (A), and technology (T), which is known as IPAT. IPAT establishes a relationship between human activity and its impact on the environment, but it can be used on particular environmental issues (Kwon, 2005). IPAT measures population, affluence, and technology in terms of per capita, per capita consumption, and per unit of consumption, respectively. The first algebraic formulation and the application of IPAT to data analysis was introduced by Commoner et al. (1971):

$$\text{Impact (I)} = \text{Population(P)} \times \text{Affluence (A)} \times \text{Technology (T)}, \quad (2\text{-}1)$$

However, IPAT is unable to use intensity in calculating the impact of environmental issues such as GHG emissions. To resolve this issue, IPAT was further modified by Waggoner and Ausubel (2002) by disaggregating technology (T) into intensity of use (C) and efficiency (T). The modified equation of IPAT is known as ImPACT:

$$\text{Impact (I)} = \text{Population(P)} \times \text{Affluence (A)} \times \text{Intensity (C)} \times \text{Efficiency (T)}, \quad (2\text{-}2)$$

In ImPACT, if the impact (I) is considered as emissions then the other components can be written as population (P), GDP per capita (A), and emissions per GDP (C × T). Many researchers have used IPAT and ImPACT to assess the environmental impact based on different driving factors (Bongaarts, 1992; Holdren, 1991; Myers, 1993; Raskin, 1995; Smil, 1990). The strength of both IPAT and ImPACT is in capturing the factors that have direct impact on the environment.

In addition, Raskin (1995) used quantitative analysis techniques to study the effect of population on environmental changes. In his study, another iteration of IPAT equation was used to find out the explicit role of population in environmental changes. The study concluded that change in population growth is a significant contributing factor to GHG emissions. This finding was further supported by York et al. (2003) who proposed a new stochastic model based on IPAT to study the driving forces of GHG emissions. The new model is known as stochastic impacts by regression on population, affluence, and technology (STIRPAT). The main strength of STIRPAT over IPAT and ImPACT is its ability to test hypotheses without relying on proportionality assumptions. STIRPAT has been used by several researchers in analyzing the effects of driving forces on environmental impacts (Rosa and Dietz, 1998; York et al., 2003). According to York et al. (2003), population has a proportional relationship to emissions, and affluence increases the emissions monotonically. In addition, the authors claimed that urbanization and industrialization have greater impacts on $CO_2$ emissions.

Further, the application of the IPAT with energy and emissions has led to the Kaya framework (Ramanathan, 2006). According to the Kaya framework, global GHG emissions are influenced by the following four driving factors: global population, gross world product, global energy consumption, and carbon intensity of energy (Kaya, 1990), mathematically expressed as follows (Girod et al., 2009):

$$\mathrm{CO_2\ emissions} = \mathrm{Population} \times \frac{\mathrm{GDP}}{\mathrm{Population}} \times \frac{\mathrm{Energy\ use}}{\mathrm{GDP}} \times \frac{\mathrm{CO_2\ emissions}}{\mathrm{Energy\ use}}, \qquad (2\text{-}3)$$

Many researchers relies upon the Kaya equation to estimate global as well as national emissions (Albrecht et al., 2002; Kawase et al., 2006; Mahony, 2013; Ramanathan, 2006; Raupach et al., 2007; Timilsina and Shrestha, 2009; Xiangzhao and Ji, 2008). Raupach et al. (2007) used the Kaya equation to estimate GHG emissions from fossil fuel combustion and industrial processes. The authors claimed that rapidly developing economics have the highest emissions growth rates. This claim was further supported by Xiangzhao and Ji (2008), who found that economic development is the major driving factor of $CO_2$ emissions along with an increase in population. In their study, the authors used a revised version of the Kaya framework to analyze GHG emissions. Improvement in energy efficiency can reduce global $CO_2$ emissions (Xiangzhao and Ji, 2008). In addition, Kawase et al. (2006) studied long-term emissions scenarios in France, Germany, and the UK, as well as medium-term scenarios in Japan by analyzing emissions using an extended form of the Kaya equation to support Japan's long-term emissions scenario development. In their study, the authors claimed that energy intensity and carbon intensity have an enormous effect on reaching emissions reduction targets. In addition, affluence and population growth play important role in global emissions increase. According to Mahony (2013), the extended Kaya equation suggests that energy intensity and fossil fuel also play a role in increasing global emissions. By introducing renewable energy, energy intensity can be significantly reduced and subsequently, emissions can be reduced (Mahony, 2013).

Transportation systems are the lifelines of nations' economies and the preconditions for progress and development. Starting from this interdependent relationship between transportation and economy, Lu et al. (2007) and Wang et al. (2015) studied the driving factors of transportation emissions. The authors claimed that rapid economic growth and development are the most important factors for increasing transportation-related GHG emissions. Further, Timilsina and Shrestha (2009) considered several factors that contribute to transportation-related emissions, such as fuel mix, modal shift, per capita gross domestic product (GDP), population, emissions coefficient, and transportation energy intensity. Based on their study, the per capita GDP, population, and transportation energy intensity are the dominant factors in increasing emission growth rates in the transportation sector.

Furthermore, Mohareb and Kennedy (2012) developed the Pathways to Urban Reductions in Greenhouse Gas Emissions (PURGE) model to estimate emissions considering four sectors, namely, electricity, building, transportation, and waste by utilizing the Kaya framework. According to this PURGE, transportation emissions are a function of fuel consumption and emissions intensity. In a more recent study, Wang et al. (2015)  showed that vehicle stock, fuel consumption, and distance travelled by each vehicle are also considered of the factors controlling GHG emissions from the transportation sector.

Unlike global GHG emissions, which are mainly dependent on Gross Domestic Product (GDP), transportation GHG emissions are dependent on passengers' activities across space and time. Over the years, researchers have used passengers' activities as determinants of GHG emissions from the transportation sector. Yang et al. (2009) examined the GHG emissions target in California from the transportation sector. The authors used an updated form of the Kaya equation to calculate GHG emissions. The updated Kaya equation directly included transportation intensity into the equation instead of GDP. Accordingly, GHG emissions from the transportation sector were estimated by multiplying transportation intensity by the total population.

Scholl et al. (1996) studied passenger transportation emissions in nine different countries from 1973 to 1992. In their study, the authors illustrated the impact of changes in activity, modal composition, and energy intensity on increase in emissions from passenger transportation. Further, the authors concluded that the increase in activity, in terms of passenger kilometres travelled, has a great effect on passenger transportation emissions. In addition, Schipper et al. (2011) analyzed the long-term emissions from the transportation sector in the USA by considering population growth, modal shift, fuel intensity, emissions intensity, and economic growth as the driving factors in increasing emissions. The results suggested that due to changes in transportation activity, emissions have tripled since 1960. The results also showed that transportation activity was a function of economic activity and car ownership.

Lakshmanan and Han (1997) analyzed the factors that affect passenger transportation emissions in the USA. According to their study, the most affecting factors were people's tendency to travel, population growth, and GDP. The results showed that people's tendency to travel can affect more than 50% of total emissions from the passenger transportation sector if other factor remains fixed (Lakshmanan and Han, 1997). Kwon (2005) studied factors affecting car emissions from 1970 to 2000 in Great Britain. The author used the IPAT equation to break down the driving factors associated with car emissions. The results showed that car-driving distance per person (affluence) is the dominant factor in increasing car emissions.

However, mode shift from single occupancy vehicles to high occupancy vehicles (e.g. carpool, public transit, etc.) and non-motorized transportation (e.g. cycle, walk, etc.) results in a reduction in GHG emissions. Schipper and Marie-Lilliu (1999) proposed a different framework to break down emissions from transportation. According to their framework, GHG emissions can be attributed to the total distance travelled by passenger (A), modal share among different transportation modes (S), energy intensity of each transportation mode (I), and fuel used by different modes (F). Energy intensity (I) in turn is a function of three different criteria: efficiency, vehicle characteristics, and inverse of capacity utilization for each mode of transportation. Their framework can be mathematically written as follows (Tiwari et al., 2011):

$$\mathrm{Emissions} = \mathrm{A} \times \mathrm{S} \times \mathrm{I} \times \mathrm{F}, \tag{2-4}$$

On the other hand, ASIF has evolved into a new descriptive framework that elaborately describes the components related to transportation emissions and emissions reduction (Tiwari et al., 2011). The new framework encompasses four descriptive components of $CO_2$ emissions: Avoid, Shift, Improve, and Finance, and the new framework is called the ASIF2 paradigm. According to Tiwari et al. (2011), 'avoid' refers to avoiding emissions by introducing better urban and transportation planning, 'shift' refers to the modal shift to public and non-motorized transportation to reduce emissions, 'improve' refers to operation and efficiency of urban transportation, and finance refers to investment in sustainable transportation to reduce emissions from the transportation sector. The descriptive ASIF2 framework refers to the changes in urban form including the modal shift to public transportation and non-motorized modes.

Furthermore, Yang et al. (2015) studied $CO_2$ emissions from the transportation sector in China. In their study, the authors showed that socio-economic factors, urban form, and transportation development are the three major driving forces of GHG emissions from the transportation sector. The socio-economic development and subsequently, higher residential income causes an increasing trend in total as well as per capita emissions from the transportation sector. Poumanyvong et al. (2012) has categorized different countries into three different types based on their income level to illustrate the impacts of urbanization on on-road emissions. In their analysis, they used the STIRPAT equation to develop a relationship between urbanization and energy use in road transportation. Their study found that the change in urbanization has a greater impact on transportation energy consumption and subsequently, GHG emissions. In addition, Papagiannaki and Diakoulaki (2009) studied emissions from passenger cars in Greece and Denmark form 1990 to 2005. They decomposed $CO_2$ emissions into five categories: vehicle ownership, vehicle kilometres travelled (annual mileage), fuel mix, engine capacity of the passenger cars, and technology of the available cars. The results concluded that for both countries, vehicle ownership is the most influential factor in terms of increasing emissions from passenger cars. Loo and Li (2012) studied emissions from passenger transportation in China that have been measured since 1949. According to their findings, income growth is the dominant factor in increasing emissions from passenger transportation in China, followed by transportation intensity and modal shift.

As summarized above, numerous tools have been developed by researchers to analyze the factors that influence GHG emissions from the transportation sector. Most of the previous studies have looked at global and/or national GHG emissions. However, it is essential to estimate emissions from the transportation sector at the municipal level to suggest planning policies to reduce municipal GHG emissions. To assess the effects of sustainable transportation and land use policies on municipal GHG emissions, it is necessary to integrate those policies into municipal-level GHG emissions models.

Research has shown that various policies that promote public transit and active transportation have substantial effects on urban transportation GHG emissions reduction (Derrible et al., 2010; Ewing and Cervero, 2001; Mahendra et al., 2012; Rodier, 2009; Sugar and Kennedy, 2013; Tiwari et al., 2011; Walsh et al., 2008; Washbrook et al., 2006; Zahabi et al., 2012). Studies have also shown that increasing population density and balancing land use diversity (i.e. mix of activities such as residential and commercial uses) can reduce trip rates and promote non-motorized travel (Cervero and Kockelman, 1997). Further, compact density in urban core areas leads to reduction in the distances between trip origins and destinations, which in turn results in a reduction in GHG emissions (Ewing and Cervero, 2010). Conversely, low residential density increases the distance driven by vehicles, fuel consumption, and emissions (Brownstone and Golob, 2009).

In a more recent study, Derrible et al. (2010) developed a conceptual framework for a model called MUNTAG to help municipalities estimate their GHG emissions. The developed framework was used by Sugar and Kennedy (2013) to calculate GHG emissions from private automobiles, buses, streetcar, light rail transit, and subway. In their model, passenger kilometres travelled were converted into vehicle kilometre travelled (VKT) and then multiplied by GHG emissions factors to get the total GHG emissions for each mode of travel. However, the developed model comprised several empirical equations in capturing the effect of land use on active transportation and travel distance. While insightful, the developed model is not able to capture the impacts on GHG emissions of single land use changes (density or diversity) in the calculation of GHG emissions from the transportation sector.

On a small scale study, Mathez et al. (2013) studied GHG emissions for the trips generated by commuters to McGill University. In their study, the authors used an EMME/3 traffic assignment model to measure the travel distance from an origin-destination (OD) matrix and used emissions factors from the U.S. Environmental Protection Agency's (EPA's) Motor Vehicle Emissions Simulator (MOVES) model to estimate emissions. In addition, by using the Trip Reduction Impacts for Mobility Management Strategies (TRIMMS) planning tool, developed at the University of Florida, and the MOVES model, Mahendra et al. (2012) calculated GHG emissions under various transportation control measures (TCM). However, working with computer related software like MOVES, EMME/3, and/or MOBILE6 requires an explicit amount of information about road networks and vehicle types as well as a substantial amount of data on travel behavior (Derrible et al., 2010).

Household travel surveys (HHTS) are one of the most reliable sources of transportation data (Travel Forecasting Resource, 2016). From such surveys, emissions forecasting models can be developed using various parameters including socio-economic and demographic characteristics of passengers. Ko et al. (2011) used household travel survey data to calculate GHG emissions in the Seoul Metropolitan Area. The household travel survey consisted of socio-demographic information, household data, and transportation service attributes. The authors found that GHG emissions from the transportation sector are dependent on various socioeconomic characteristics of passengers. However, a major drawback of this study was that land use policies were not taken into consideration.

## 2.5 Land Use and Transportation Interactions

Various transportation and land use policies, such as parking management, promoting public transit and active transportation, and increasing land use density and diversity, have shown substantial effect on reducing on-road transportation GHG emissions (Derrible et al., 2010; Ewing and Cervero, 2010; Mahendra et al., 2012; Rodier, 2009; Sugar and Kennedy, 2013; Tiwari et al., 2011; Walsh et al., 2008; Washbrook et al., 2006; Zahabi et al., 2012; Zhang, 2004). Bristow et al. (2008) showed that changes in travel behaviour are more important in reducing emissions than technological development. Cervero and Kockelman (1997) studied the effect of land use and built environment on travel demand in terms of trip rates and mode choices in the San Francisco Bay area. The authors categorized the built environment and land use parameters into three influential categories: density, diversity, and design, also known as the DDD or 3Ds model. In addition, accessibility to transit and distance to destination were also considered among the land use parameters (Cervero and Murakami, 2008). The following subsections discuss the impact of the 3Ds on travel behaviour as well as reducing transportation emissions.

### 2.5.1 Density Indicators

Density can be measured in terms of per unit area of population, employment, dwelling units, etc. The density of the overall activity per unit area can also be measured by adding population and employment (Ewing and Cervero, 2010). Numerous studies have shown that higher densities can reduce trip lengths and promote non-motorized travel (Brownstone and Golob, 2009; Cervero and Kockelman, 1997; Chatman, 2003; Ewing and Cervero, 2010). According to Cervero and Kockelman (1997), high population density reduces trip rates and promotes non-motorized travel. Further, compact density in urban core areas leads to a reduction in the distances between trip origins and destinations, which in turn results in a reduction in GHG emissions (Ewing and Cervero, 2010). Conversely, low residential density increases the distance driven by vehicles, fuel consumption, and emissions (Brownstone and Golob, 2009). Residential density is a function of vehicle ownership, income, and accessibility (Badoe and Miller, 2000).

Holtzclaw et al. (2002) studied the relationship between car ownership and distance travelled by vehicles in response to urban form in the Chicago, Los Angeles, and San Francisco areas. The results concluded that a 33% ~ 40% decrease in car ownership and a 32% ~ 43% decrease in vehicle kilometres travelled can be achieved by doubling residential density.

Furthermore, employment density showed a strong correlation to a modal shift towards active transportation and public transit (Zhang, 2004). Zhang (2004) studied the effects of various land use parameters on travel mode choice in Boston and Hong Kong. In his study, he claims that with an increase in employment density, the active transportation and public transit modal share will increase, further decreasing private vehicle use. In addition, he concludes that a 100% increase in job density will result in an increase of 9% and 0.4% in transit share for work trips and non-work trips respectively.

In addition, Zhang et al. (2012) studied the effects of built environment on distance travelled by vehicles in Seattle, Virginia, Washington DC, and Baltimore. The authors suggested that the population density and employment density are highly correlated with the Vehicle Mile Travelled (VMT) per vehicle. For instance, a 123% increase in residential density in Washington DC resulted in a 19.91% reduction in VMT. Also, a 110% increase in residential density resulted in a 15.80% VMT reduction in Baltimore. Employment density is also responsible for VMT reductions, but to a lesser extent. Population density is much more important in reducing VMT than employment density (Zhang et al., 2012).

Higher population density and employment density have also been associated with higher non-work walk trips (Greenwald and Boarnet, 2001). According to Greenwald and Boarnet (2001), both population and employment densities show a positive influences on walk trips. For example, a 1% increase in population density was found to result in a 0.34% increase in non-work walk trips. The impact of population density on increased walk trips is much higher than employment density.

### 2.5.2 Diversity Indicators

Land use diversity has a strong relationship with the reduction of distance travelled by each vehicle and modal shift towards public transit and active transportation (Cervero and Kockelman, 1997; Chatman, 2003; Ewing and Cervero, 2010; Tiwari et al., 2011; Zhang, 2004). The diversity of land use can be measured in terms of entropy that measures the degree to which different land uses are evenly distributed (Lavoie, 2012). The entropy value ranges from 0 to 1, where the perfect mix use of land is indicated by 1 in a given area. Ewing and Cervero (2010) quantify the effects of land use mix (entropy index) to the walking mode and transit use. According to their study, 1% increase in mixed land use parameters could result in a 0.15% increase in walking trips, and a 0.12% increase in transit use. Moreover, their research concluded that the influence of job-housing balance could be even greater, with an increase of 0.19% in walking trips predicted associated with a 1% increase in mixed land use (Ewing and Cervero, 2010). This finding has been further supported by Zhang (2004) who showed that land use balance at both trip ends is strongly correlated with an increase in transit share as well as a decrease in car modal share.

In addition, mean entropy of mixed land use is highly correlated with the reduction in vehicle miles travelled (VMT) per household (Kockelman, 1996). Kockelman (1996) studied the effect of land use on travel behaviour in the San Francisco Bay area. The author concluded that mean entropy is highly correlated with VMT. Further, mean entropy at both origin and destination has almost the same positive effects on the choice of active transportation, and the parameter values are higher than the other variables. According to Zhang et al. (2012), mixed land use measured in terms of entropy can reduce 7.18%, 0.15%, 3.63%, and 9.29% VMT in response to 44%, 27%, 45%, and 0.54% increase in entropy in Seattle, Virginia, Baltimore, and Washington DC, respectively.

Further, Ewing and Cervero (2010) conducted a meta-analysis of the built environment and land use variables based on the literature until 2009. Based on the analysis, the authors found that the elasticity of mixed land use (measure in terms of entropy index) over VMT is negative 0.09, which means that a 1% increase in mixed land use entropy can reduce VMT by 0.09%. This finding was more pronounced in walk and transit trips that were associated with elasticities of

0.15 and 0.12, respectively. These elasticities imply that a 100% increase in mixed land use entropy can increase walk and transit trips by 15% and 12%, respectively. Since elasticity is less than one, therefore the observed elasticity is considered inelastic.

### 2.5.3 Design Indicators

Design indicators include the built environment and road network characteristics in a given area. Accessibility to bus stops, availability of active transportation facilities, and intersection density are examples of design indicators. Several studies have shown that design indicators are highly correlated with reduced vehicle kilometres travelled and increased transit and walk/bike mode choice (Cervero and Kockelman, 1997; Ewing and Cervero, 2010; Kockelman, 1996). Among all density indicators, the proportion of 4-way intersections – linked to redundancy of walking routes - has a high elasticity with walk trips (Cervero and Kockelman, 1997; Ewing and Cervero, 2010; Zhang, 2004). However, more recent studies have cautioned that it is not road intersection density but walking (and bicycling) route intersection density that is the key factor and that promotes a safer, more sustainable, built environment for all users (Masoud et al., 2015; Sun and Lovegrove, 2013).

Distance to transit stops can play an important role in reducing vehicle kilometre travelled and in increasing walk/bike and transit modal shares (Bento et al., 2005; Ewing and Cervero, 2010; Naess, 2006). Ewing and Cervero (2010) showed that distance to transit stops is a dominant factor in increasing transit share as well as walk trips. The authors claimed that the elasticity[1] between distance to the transit stop and transit ridership is 0.29, which means that a 1% decrease in distance to the transit stop could increase transit ridership by 0.29%. On the other hand, better accessibility to transit could increase walking trips by 0.15%. Design indicators demonstrate an inelastic correspondence to the transit share, walk trips, and VMT.

---

[1] Elasticity estimation formulas (Ewing and Cervero, 2010):
For linear regression: $\mathrm{Elaticity} = \beta \times \frac{\bar{x}}{\bar{y}}$
For logistic regression: $\mathrm{Elaticity} = \beta \times \bar{x}\left[1 - \left(\frac{\bar{y}}{n}\right)\right]$,
$\beta$ is the regression coefficient, $\bar{y}$ is the mean value of the travel parameter, and $\bar{x}$ is the mean value of the built environment variable. $\left(\frac{\bar{y}}{n}\right)$ is the mean estimated probability.

## 2.6 Travel Demand Modelling

Travel demand modelling is at the heart of the urban transportation planning process. For many years, the four-step model has been considered as the building block of travel demand modelling. The four-step model consists of the following four steps: trip generation, trip distribution, mode choice, and trip assignment, as shown in Figure 2-5. Trip generation is concerned with estimating the total number of trips produced in and attracted to a specific zone. Trip distribution deals with the distribution of trips between zones. Mode choice estimates the proportion of trips choosing each mode of travel. Finally, trip assignment focuses on the circulation of trips on the transportation network (McNally, 2007).

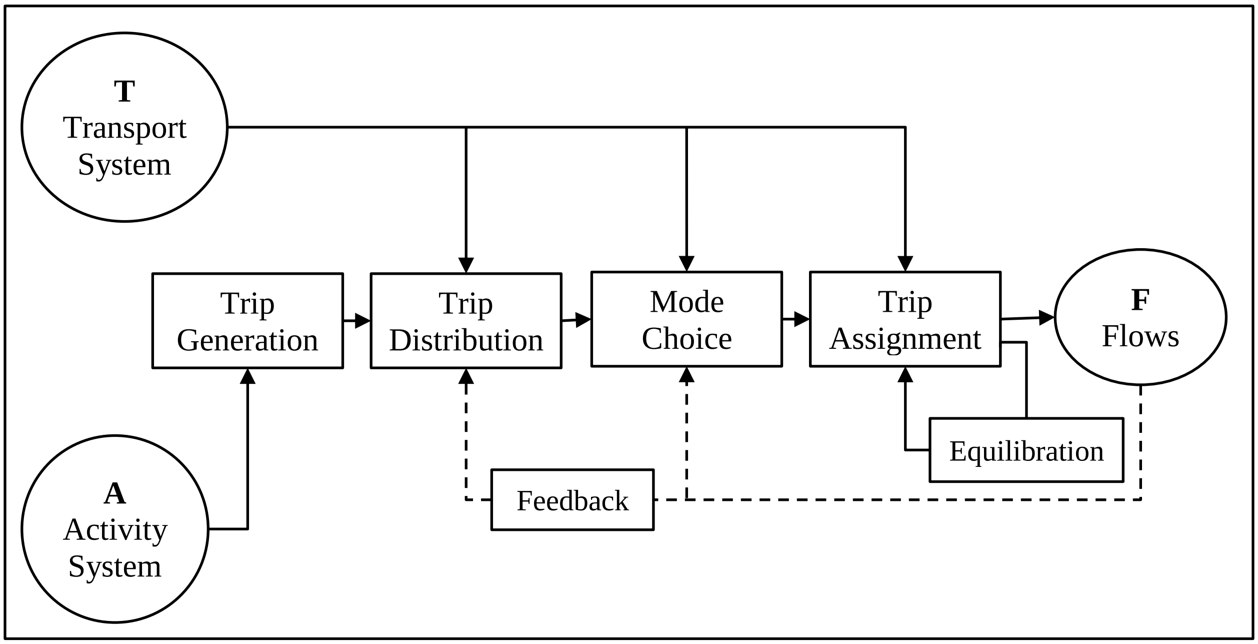



**Figure 2-5 Four-Step Transportation Planning Model[1]**

The main unit of analysis in traditional demand models is the individual trip. Trips are usually classified according to their purposes. Trip purposes refer to the type of activity taking place at trip destination. In general, trips can be classified, according to trip purpose, into commuting

[1] Republished with permission of Emerald Group Publishing Limited from The four step model, McNally, M. G., , Handbook of transport modelling Volume 1, Hensher, D. A. & Button, K. J. (Eds.), (pp. 35-53); permission conveyed through Copyright Clearance Center, Inc.

trips (e.g. work trips, school trips, etc.) and non-commuting or discretionary trips (e.g. shopping, entertainment, etc.), as shown in Figure 2-6. Commuting trips are defined as trips related to work activities (i.e. trips to work or school) (Day et al., 2010; Habib et al., 2009). Therefore, going to work/school from home, and the reverse trips (i.e. coming back to home from work/school), are considered as commuting trips (Habib et al., 2009). In addition, going to work after dropping off children at school is also considered as commuting trips (Acker and Witlox, 2011). However, the first trip of the previous example (i.e. going from home to school) is considered as a non-commuting trip (Acker and Witlox, 2011). On the other hand, non-commuting trips are related to non-work activities such as discretionary trips from home and the reverse trips. Trips can also be categorized into home-based trips and non-home based trips. Home-based trips are defined as trips that start or end at home (National Cooperative Highway Research Program, 2012). Non-home based trips are trips that neither start nor end at home, as shown in Figure 2-7.

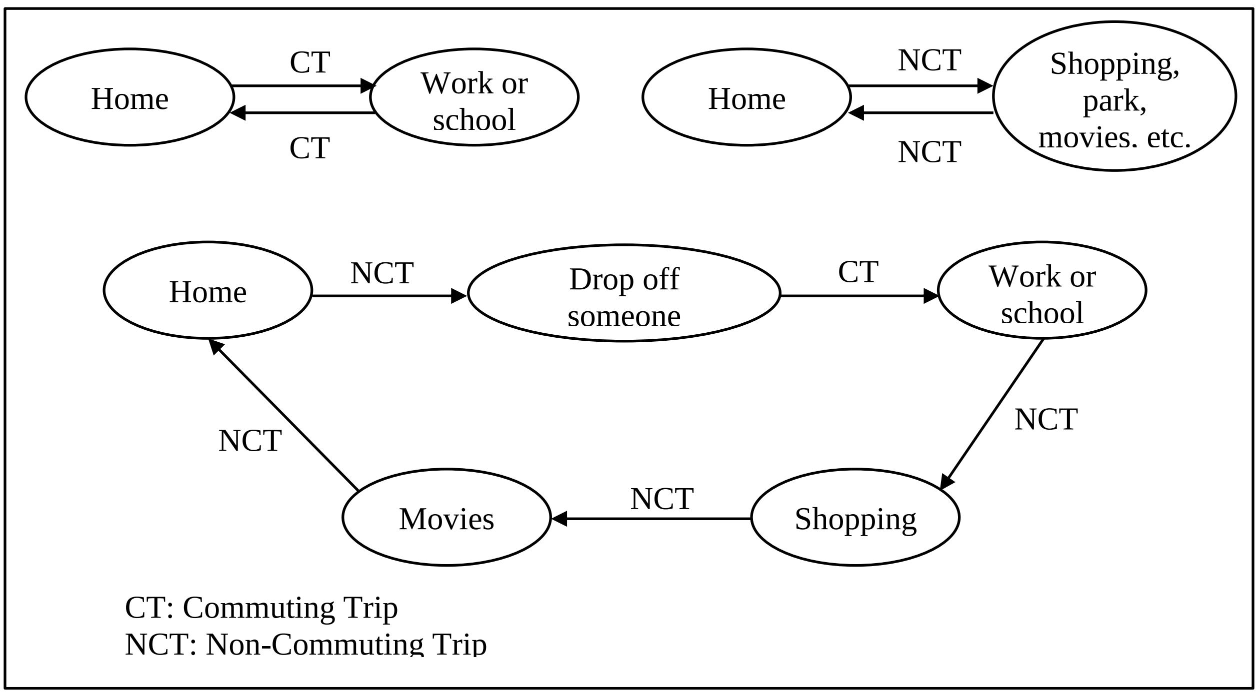



**Figure 2-6 Classification of Trips (Commuting *vs.* Non-Commuting)**

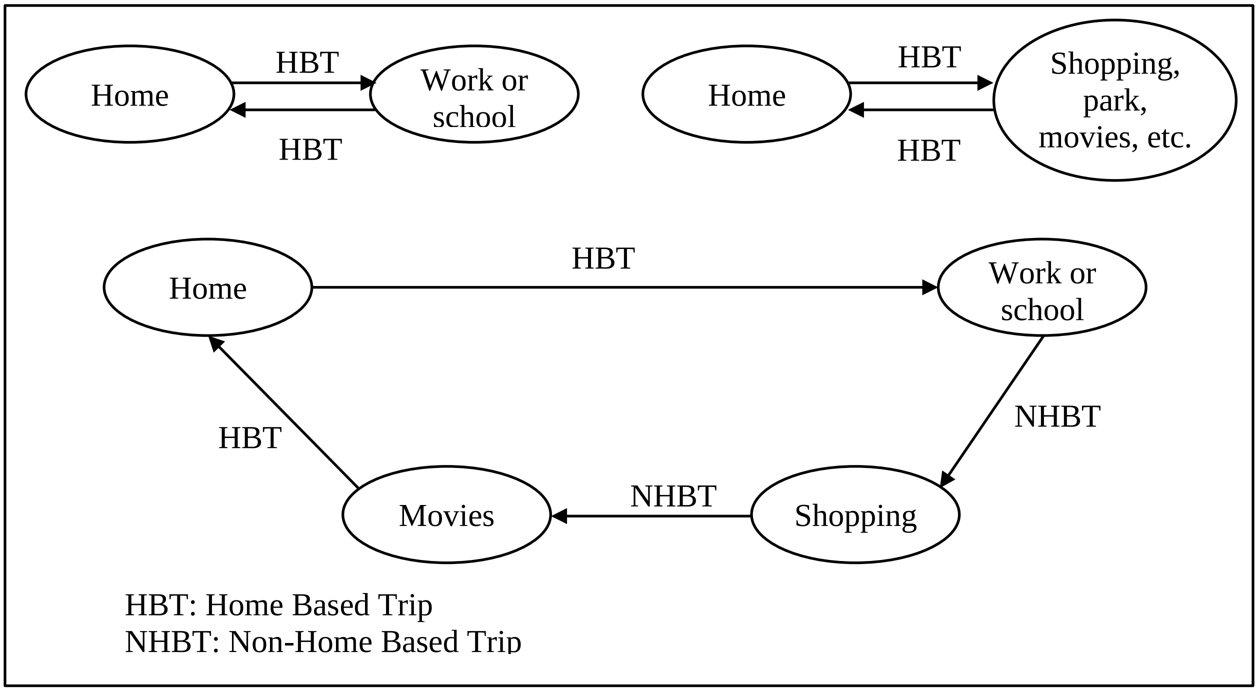



**Figure 2-7 Classification of Trips (Home-Based *vs.* Non-Home Based)**

### 2.6.1 Mode Choice Modelling

Mode choice modelling is the third step in the traditional four-step model. Mode choice can be conceptualized, according to the Random Utility Maximization (RUM) Theory, such that passengers assign weights to the different attributes characterizing each mode of travel and finally select the travel option that maximizes their utilities (Banister, 1978; Ben-Akiva and Boccara, 1995; McFadden, 1974). Under the RUM Theory, random refers to the modeller's lack of knowledge (i.e. individual travellers know their choices but the analyst does not). If analysts thoroughly understood all aspects of the internal decision-making process of individual travellers as well as their perception of alternatives, they would be able to describe that process and predict mode choice using deterministic utility models. Further, utility is a measure of individual travellers' satisfaction. Being rational, individual travellers seek to maximize their utilities by choosing certain modes of travel. According to the RUM framework, utilities are comprised of two parts: a deterministic component that considers observed characteristics of the decision-makers as well as the alternative modes (e.g. socioeconomic and demographic attributes, level of service attributes, etc.) and a stochastic error term (Ben-Akiva and Lerman, 1985; Idris, 2013;

Koppelman and Bhat, 2006). The utility function of a particular mode of travel can be expressed mathematically as follows (Koppelman and Bhat, 2006):

$$U_{it} = V_{it} + \varepsilon_{it}, \tag{2-5}$$

where, $U_{it}$ is the utility of alternative i to individual t, $V_{it}$ is the observable component of utility, and $\varepsilon_{it}$ is the random error term.

The random error term is included in the utility function to account for the fact that the analyst is unable to completely and correctly measure or specify all attributes that determine travelers' mode utility assessment. This includes imperfect information, measurement errors, omission of modal attributes, omission of the characteristics of the individual that influence his/her choice decision, and/or other errors in the utility function. By definition, error terms are unobservable and unmeasurable (Koppelman and Bhat, 2006). Utility is the function of attributes of the alternatives, characteristics of individual, and the interaction between alternatives and individual. This can be represented by the following equation (Koppelman and Bhat, 2006):

$$V_{t,i} = V(S_t) + V(X_i) + V(S_t, X_i), \tag{2-6}$$

where, $V(S_t)$ is the portion of utility of individual t, $V(X_i)$ represents the portion of utility of alternative i, and $V(S_t, X_i)$ is the portion of the utility from interactions between alternative I and individual t (Koppelman and Bhat, 2006).

Different assumptions with regard to the distribution of the error term lead to different types of mode choice models. Normally distributed error terms lead to the Multinomial Probit model (MNP), which can only be calculated using multi-dimensional integration that makes it difficult to use in mode choice analysis (Koppelman and Bhat, 2006). On the other hand, Multinomial Logit (MNL) is the most widely used mathematical model for making probabilistic predictions of mode choices as a function of the systematic portion of the utility of each alternative. Identically and independently distributed (IID) error terms with Type I Extreme Value (Gumbel) distribution lead to the MNL model (Koppelman and Bhat, 2006). However, identically and independently distributed error term fails to capture taste variation (i.e. unexplained variation in travel behaviour; for example, two identical individuals making different choices). Furthermore, MNL models suffer from the Independence from Irrelevant Alternatives (IIA) property. The MNL model can be mathematically expressed as follows (Koppelman and Bhat, 2006):

$$\mathrm{P}(i) = \frac{\exp(V_i)}{\sum_{j=1}^{J} \exp(V_j)}, \tag{2-7}$$

where, P($i$) is the probability of choosing alternative i and $V_{it}$ is the systematic component of alternative j.

#### 2.6.1.1 Model Validation and Forecasting Performance

Ideally, mode choice model validation should be performed using a different dataset that was not involved in the model estimation process. In some cases, where a small sample size is available, the entire dataset is desirable for model estimation (i.e. no independent dataset will be available for model validation). In such cases, the limited disaggregate validation technique can be performed by using market segments of the same dataset used for model estimation (Travel Forecasting Resource, 2016). The market segmentation variables can be categorized as follows:

- Socioeconomic and demographic variables (e.g. income level, vehicle ownership, gender, age, etc.)
- Geographic stratification (i.e. counties, neighborhoods, traffic analysis zones, etc.)
- Level-of-service variables (i.e. trip length, trip time, etc.)

To quantify the forecasting performance of a mode choice model, the developed model can be used to predict known modal shares of an independent subset or the same dataset used for model estimation after market segmentation. The forecasting performance can be quantified using the following formula (Idris et al., 2015):

$$\text{Forecasting Performance Measure (FPM)} = \sum\nolimits_{\mathrm{m}} [(\mathrm{P_m} - \mathrm{O_m})/\mathrm{O_m}, \tag{2-8}$$

where, $P_m$ is predicted trips, $O_m$ is observed trips for each mode (m)

Smaller value of FPM represents lesser forecasting errors with better forecasting performance of the developed model (Habib et al., 2012).

### 2.6.2 Distance Travelled Modelling

The distance travelled by a vehicle is referred to as vehicle kilometres travelled (or vehicle miles traveled), whereas the distance travelled by a person is referred to as passenger kilometres travelled. Researchers have used regression techniques to estimate vehicle kilometres travelled (VKT) and passenger kilometres travelled (PKT) considering various explanatory variables such as socio-economic and demographic attributes, land use and built environment data, etc. (Cervero and Kockelman, 1997; Fan, 2007; Kockelman, 1996; Zegras, 2010; Zhou and Kockelman, 2008).

#### 2.6.2.1 Simple Linear Regression

Relationship between a dependent variable y and a single independent variable x can be estimated by using simple linear regression models. Mathematically, a simple linear regression model can be expressed as follows (Mendenhall and Sincich, 2007):

$$y = \beta_0 + \beta_1 x + \varepsilon, \tag{2-9}$$

where, y is the dependent variable, x is the independent variable, ε is the random error component, $\beta_0$ is the y-intercept of the line and $\beta_1$ is the slope of the line.

Furthermore, the least squares method can be used to estimate unknown parameters ($\beta_0$ and $\beta_1$). The line of means of Equation (2-9) is shown in Equation (2-10) and the fitted line is shown in Equation (2-11), respectively (Mendenhall and Sincich, 2007).

$$E(y) = \beta_0 + \beta_1 x, \tag{2-10}$$

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x, \tag{2-11}$$

where, $\hat{y}$ is an estimator of mean value, and $\hat{\beta}$ and $\hat{\beta}_1$ are estimators of $\beta_0$ and $\beta_1$, respectively.

For a given data point ($x_i$, $y_i$), the observed value of y is $y_i$ and the predicted value of y would be obtained from the prediction equation (Mendenhall and Sincich, 2007).

$$\widehat{y_i} = \hat{\beta}_0 + \hat{\beta}_1 x_i, \qquad (2\text{-}12)$$

The deviation of the *i*th value of y from its predicted value is

$$(y_i - \widehat{y_i}) = [y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_i)], \qquad (2\text{-}13)$$

The sum squares of the deviation of y values with respect to their predicted values is

$$\mathrm{SSE} = \sum_{i=1}^{n} [y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_i)]^2, \qquad (2\text{-}14)$$

Formulas for the least-squares estimates are as follows (Mendenhall and Sincich, 2007):

$$\text{Slope: } \hat{\beta}_1 = \frac{SS_{xy}}{SS_{xx}}, \qquad (2\text{-}15)$$

$$y - \text{intercept: } \hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}, \qquad (2\text{-}16)$$

where,

$$SS_{xy} = \sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}), \qquad (2\text{-}17)$$

$$SS_{xx} = \sum_{i=1}^{n} (x_i - \bar{x})^2, \qquad (2\text{-}18)$$

The goodness of fit of the least square equation, as shown in Equation (2-19), can be measured by estimating coefficient of determination. Coefficient of determination can be mathematically expressed as follows (Mendenhall and Sincich, 2007):

$$R^2 = \frac{SS_{yy} - SSE}{SS_{yy}} = 1 - \frac{SSE}{SS_{yy}}, \tag{2-19}$$

where,

$$SS_{yy} = \sum_{i=1}^{n} (y_i - \bar{y})^2, \tag{2-20}$$

A (1-α)100% prediction interval for y is as follows (Mendenhall and Sincich, 2007):

$$\hat{y} \pm t_{\alpha/2}[\text{Estimated standard deviation of } (y - \hat{y})], \tag{2-21}$$

or,

$$\hat{y} \pm t_{\alpha/2} s \sqrt{1 + \frac{1}{n} + \frac{(x_p - \bar{x})^2}{SS_{xx}}}, \tag{2-22}$$

where, $t_{\alpha/2}$ is based on (n -2) degrees of freedom and n represents the sample size.

#### 2.6.2.2 Multiple Regression Analysis

A general linear regression or multiple regression analysis represents relationship between a dependent variable y and two or more independent variables. Mathematically, the general linear model can be expressed as follows (Mendenhall and Sincich, 2007):

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \varepsilon, \tag{2-23}$$

where, y is the dependent variable, $x_1$, $x_2$, ..., $x_k$ are the independent variables, and ε is the random error term.

Equation (2-23) can be written in a matrix form as follows (Mendenhall and Sincich, 2007):

$$\mathbf{Y} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix} \qquad \mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ 1 & x_{31} & x_{32} & \cdots & x_{3k} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix} \qquad \widehat{\boldsymbol{\beta}} = \begin{bmatrix} \widehat{\beta}_1 \\ \widehat{\beta}_2 \\ \widehat{\beta}_3 \\ \vdots \\ \widehat{\beta}_n \end{bmatrix} \qquad \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

The least-squares matrix equation and solution are shown in Equation (2-24) and Equation (2-25) respectively (Mendenhall and Sincich, 2007).

$$(\boldsymbol{X'}\mathbf{X})\widehat{\boldsymbol{\beta}} = \boldsymbol{X'Y}, \tag{2-24}$$

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X'}\mathbf{X})^{-1}\boldsymbol{X'Y}, \tag{2-25}$$

The multiple coefficient of determination can be defined as (Mendenhall and Sincich, 2007):

$$R^2 = 1 - \frac{SSE}{SS_{yy}}, \tag{2-26}$$

where,

$$\mathrm{SSE} = \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{y_i} - \hat{\mathrm{y}}_i)^2, \tag{2-27}$$

$$\mathrm{SS_{yy}} = \sum_{\mathrm{i}=1}^{\mathrm{n}} (\mathrm{y_i} - \bar{\mathrm{y}})^2, \tag{2-28}$$

A (1-α)100% prediction interval for y is as follows(Mendenhall and Sincich, 2007):

$$\hat{y} \pm t_{\alpha/2} s\sqrt{1 + \mathbf{a}'(\boldsymbol{X}'\mathbf{X})^{-1}\mathbf{a}}, \tag{2-29}$$

where, $\mathbf{a} = \begin{bmatrix} 1 \\ x_1 \\ x_2 \\ \vdots \\ x_k \end{bmatrix}$

### 2.6.2.3 Violation of Assumptions

To use linear regression models, the following assumptions should hold (Corpuz et al., 2005; Montgomery, 2009; Nau, 2016; Neter et al., 1996, Rawlings et al., 2001):

- Linearity – The predicted value of the dependent variable is a straight-line function of each independent variable.
- Normality – The error term is normally distributed with non-negative values
- Statistical independence – No correlation between consecutive errors
- Homoscedasticity – The errors have a constant variance in terms of time, prediction, and other independent variables.

The normality assumption does not affect estimating variances among all linear estimators; however, it does affect the significant test and confidence interval of the parameters. Normality assumptions can be checked by plotting observed residuals, and skewness and kurtosis coefficients (Rawlings et al. 2001). Furthermore, non-normal distributions can be eliminated by introducing transformations of the dependent variables, such as the arcsin, the square root, the logarithmic, and the logistic transformations.

Due to the violation of statistical independence assumption of the linear regression models, the estimates loses precision. As a result, estimates become biased and it nullifies the significant tests (Rawlings et al., 2001). However, residual plotting according to the order may reveal patterns of residuals, which represents correlated errors.

The constant variance (homoscedasticity) plays a significant role in ordinary least squares (Rawlings et al., 2001). The violation of this assumption causes similar effects to the estimator as correlated errors. Due to the heterogeneous variances, least square estimators become inefficient. This issue can be handled by two approaches, such as transformation of the dependent variables and weighted least squares (Rawlings et al., 2001).

Outliers, inconsistent observations with the rest of the observations in the data set, can affect the least square estimators and, subsequently, goodness of fit of the model. Outliers can be detected by plotting observed residuals; however, to have a common variance it is recommended that the residuals first be standardized (Rawlings et al., 2001). If all the assumptions are satisfied then the expected plot of the residuals with respect to the fitted values of the dependent variables should look like the following Figure 2-8 (Rawlings et al., 2001).

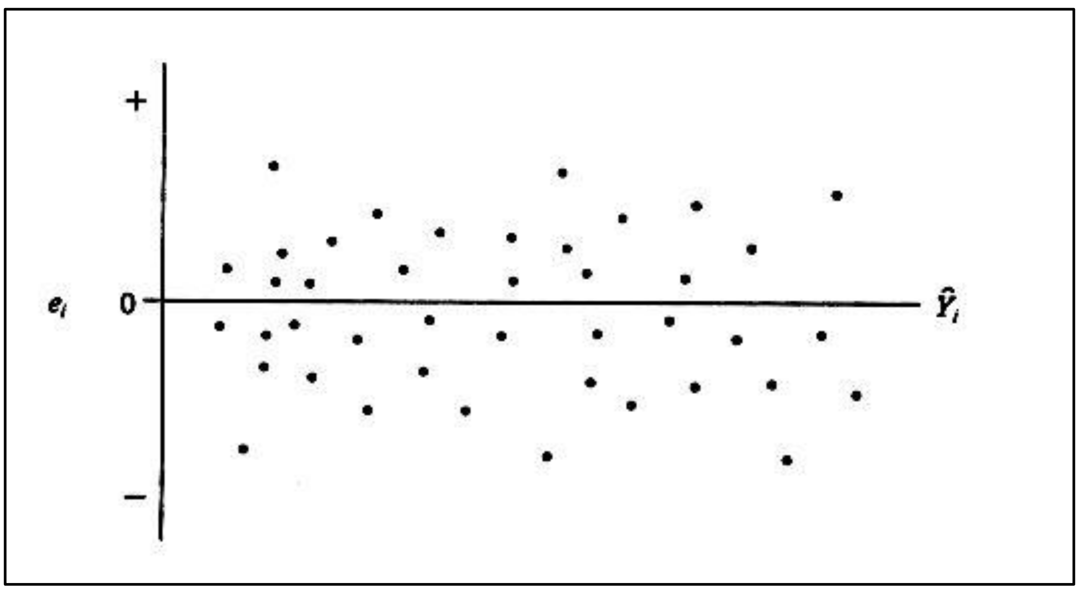



**Figure 2-8 Expected pattern for a plot of residuals versus predicted**[1]

[1] © 1998 Springer-Verlag New York, Inc, from Applied regression analysis: A research tool, Rawlings, J. O., Pantula, S. G., & Dickey, D. A., 2001, with permission of Springer

## 2.7 Summary

GHGs are responsible for warming the earth's surface to make it livable. However, the increase of GHGs beyond the natural absorption capacity of the earth cause climate change. Human activities (e.g. fossil fuels burning) cause an increase of GHGs in the earth's atmosphere. In addition, different economic sectors are responsible for increasing GHG concentrations. Among them, transportation is one of the major sources of GHG emissions. Further, road transportation is the dominant contributing factor in the transportation sector. Different driving forces are associated with on-road GHG emissions. However, proper use of built environment and land use, such as density, diversity, and design factors have a strong correlation with the travel behaviour and subsequently, reduction in GHG emissions from on-road transportation.

# Chapter 3: TRIBUTE: A TRIp-Based Urban Transportation Emissions Model for Municipalities

## 3.1 Outline

This chapter proposes a TRIp-Based Urban Transportation Emissions (TRIBUTE) model. The developed model is trip-based, i.e. it considers the individual trip as the unit of analysis. TRIBUTE is intended to help municipalities estimate road transportation GHG emissions due to changes in various land use and transportation attributes by capturing the relationship between travel behavior and Vehicle Kilometres Travelled (VKT). This chapter presents the methodology of the developed model including model building, linking passenger trips to vehicle trips, and model application.

## 3.2 Methodology

This research introduces a TRIp-Based Urban Transportation Emissions (TRIBUTE) model. TRIBUTE is intended to assist municipalities evaluate the impacts of various transportation and land use planning policies on GHG emissions from passengers transportation at the macroscopic level. The fundamental unit of analysis in TRIBUTE is the individual trip. Data required for model building comes from household travel surveys and emissions inventories. Importantly, TRIBUTE does not need a detailed transportation network model, which is a major advantage for small municipalities where a detailed network model is unavailable.

GHG emissions from on-road transportation are directly proportional to the total Vehicle Kilometres Travelled (VKT). VKT in turn is affected by the built environment. In specific, increasing land use density, balancing diversity (i.e. land use mix), and improving design can significantly decrease VKT, reduce per capita energy use, and lower GHG emissions (Brownstone and Golob, 2009; Cervero, 2010; Cervero and Kockelman, 1997; Chatman, 2003; Ewing and Cervero, 2010; Kockelman, 1996; Taylor, 2001; Tiwari et al., 2011; Zhang, 2004).

In general, VKT reduction can be attributed to two main factors: mode shift (i.e. passengers switching from single occupancy vehicles to high occupancy vehicles or non-motorized options) and trip length reduction (i.e. driving less), as shown in Figure 3-1.

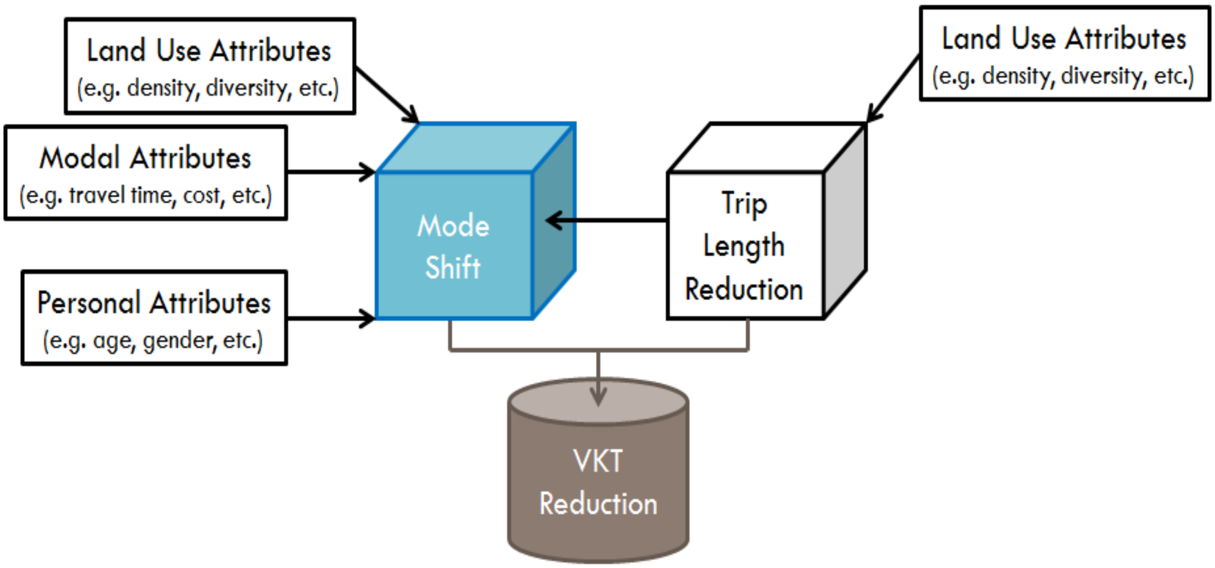



**Figure 3-1 Interaction among Trip Length Reduction, Mode Shift, and VKT Reduction**

Bringing trip ends closer to each other through effective land use policies (e.g. increasing density, diversity, bike paths, sidewalks, etc.) leads to VKT reduction both indirectly (through mode shift) and directly (through driving for shorter distances). For example, if trip origins and destinations get closer to each other after increasing land use diversity, passengers will be more likely to choose active transportation instead of private automobile use. Further, for those passengers who will keep driving, VKT will be less due to driving for shorter distances. While trip length reduction is a function of the built environment, mode shift depends on several variables including personal attributes (e.g. age, income, car ownership, etc.), modal attributes (e.g. travel time, travel cost, travel distance, etc.), and land use attributes (e.g. density, diversity, etc.). As shown in Figure 3-1, trip length has a dual effect on VKT reduction (i.e. an indirect effect being one of the determinants of mode shift and a direct effect through driving less).

Figure 3-2 depicts the conceptual framework of TRIBUTE, with model building (base case scenario) displayed in the upper part, and model application (future scenario) displayed in the lower part. TRIBUTE is composed of two main components: a mode choice/shift model and an emissions forecasting model. The first component accounts for the determinants of VKT reduction (i.e. mode shift and trip length reduction). The second component translates the results in terms of VKT reduction and subsequently GHG emissions. The following subsections describe the components of TRIBUTE in more details.

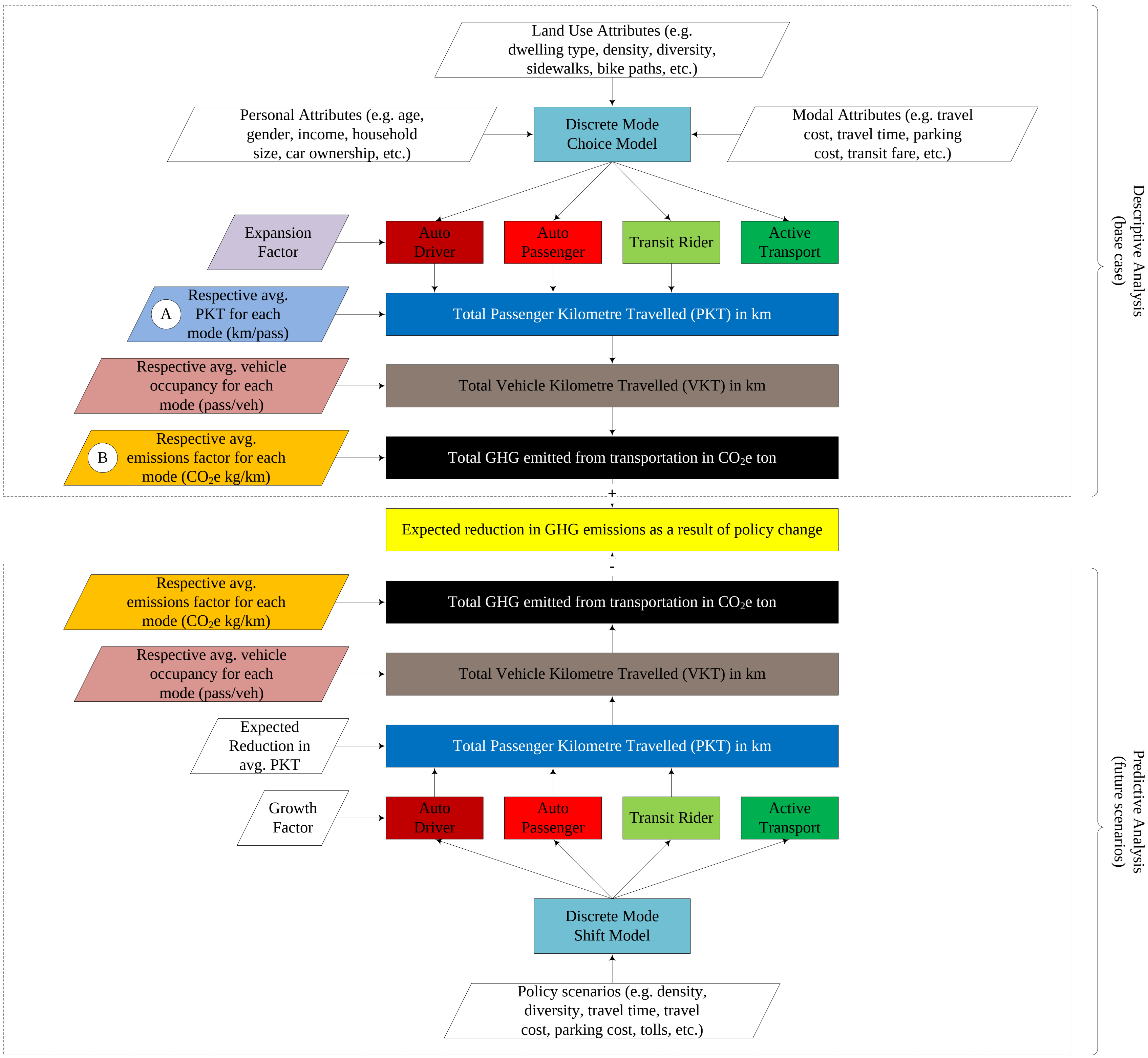



**Figure 3-2 TRIp-Based Urban Transportation Emissions Model**

### 3.2.1 Model Building (Base Case Scenario)

To capture the effect of land use on mode shift, a discrete mode choice model was developed using Biogeme software (Bierlaire, 2003). The developed mode choice model calculates the proportion of trips made by each mode of travel (e.g. car driver, car passenger, transit rider, and active transportation) in response to changes in personal, modal, and land use attributes. Biogeme's user interface, sample code, and sample output results are presented in Appendix A, Appendix B, and Appendix C, respectively. Equations (3-1) through (3-6) show the general structure of the utility functions of the mode choice model.

$$V_{Car} = ASC_{Car} + Beta_{1\_Car} \times x_1 + Beta_{2\_Car} \times x_2 + \cdots + Beta_{n\_Car} \times x_{n,} \tag{3-1}$$

$$\begin{aligned} V_{Car\ pass} = {} & ASC_{Car\ pass} + Beta_{1\_Car\ pass} \times x_1 + Beta_{2\_Car\ pass} \times x_2 + \cdots \\ & + Beta_{n_{Car}pass} \times x_n, \end{aligned} \tag{3-2}$$

$$\begin{aligned} V_{Transit} = {} & ASC_{Transit} + Beta_{1\_Transit} \times x_1 + Beta_{2\_Transit} \times x_2 + \cdots \\ & + Beta_{n_{Transit}} \times x_n, \end{aligned} \tag{3-3}$$

$$\begin{aligned} V_{School\ bus} = {} & ASC_{School\ bus} + Beta_{1\_School\ bus} \times x_1 + Beta_{2\_School\ bus} \times x_2 + \cdots \\ & + Beta_{n_{School}bus} \times x_n, \end{aligned} \tag{3-4}$$

$$V_{Walk} = ASC_{Walk} + Beta_{1\_Walk} \times x_1 + Beta_{2\_Walk} \times x_2 + \cdots + Beta_{n\_Walk} \times x_{n,} \tag{3-5}$$

$$V_{Cycle} = ASC_{Cycle} + Beta_{1\_Cycle} \times x_1 + Beta_{2\_Cycle} \times x_2 + \cdots + Beta_{n\_Cycle} \times x_{n,} \tag{3-6}$$

Where, V is the utility function, ASC is the alternative specific constant, Beta is the parameter value, and x is the explanatory variable.

Further, the proportion of trips made by each mode of travel can be determined using the Multinomial Logit (MNL) model, as shown in Equations (3-7) through (3-12).

$$\mathrm{P_{Car}} = \frac{\exp(V_{Car})}{\sum_{j=1}^{J}\exp(V_j)} \tag{3-7}$$

$$\mathrm{P_{Car\ pass}} = \frac{\exp(V_{Car\ pass})}{\sum_{j=1}^{J}\exp(V_j)}, \tag{3-8}$$

$$\mathrm{P_{Transit}} = \frac{\exp(V_{Transit})}{\sum_{j=1}^{J}\exp(V_j)}, \tag{3-9}$$

$$\mathrm{P_{School\ bus}} = \frac{\exp(V_{School\ bus})}{\sum_{j=1}^{J}\exp(V_j)}, \tag{3-10}$$

$$\mathrm{P_{Walk}} = \frac{\exp(V_{Walk})}{\sum_{j=1}^{J}\exp(V_j)}, \tag{3-11}$$

$$\mathrm{P_{Cycle}} = \frac{\exp(V_{Cycle})}{\sum_{j=1}^{J}\exp(V_j)}, \tag{3-12}$$

After calculating the proportion of trips made by each mode of travel, the total PKT by each mode can be calculated given respective average modal PKT (calculated from emissions inventories). Total PKT can then be converted to VKT using respective average vehicle occupancy for each mode, as shown in Equation (3-13) (the details of linking PKT to VKT are discussed in Section 3.2.2.). Average vehicle occupancies were calculated from the household travel survey by analyzing the survey question: "when travelling by automobile, how many people travelled with you?"

$$\mathrm{VKT} = \frac{\text{Average PKT (km per person)} \times \text{ Modal share(\%)} \times \text{ Population}}{\text{Vehicle occupancy}}, \tag{3-13}$$

Finally, total GHG emissions from passenger transportation for the base case scenario can be calculated through multiplying the total VKT by each mode by respective average emissions factors (calculated from emissions inventories for different vehicle and fuel types).

$$\begin{aligned}&\text{Total GHG Emissions } (CO_2 \text{ eq.}) \\ &\qquad = \text{Total VKT(km)} \times \text{Average emissions factors } (CO_2 \text{ eq. per km}),\end{aligned} \tag{3-14}$$

As previously discussed and presented in Figure 3-1, VKT reduction can be attributed to two main factors: mode shift and trip length reduction. To capture the effect of land use attributes on trip length reduction, a Passenger Kilometres Travelled (PKT) estimation model was developed. Separate PKT estimation models were developed for each mode of travel (car, transit, walk, and cycle) using multiple linear regression analysis. The structure of the developed models is shown in Equations (3-15) through (3-18). Various land use attributes such as density and diversity were considered as explanatory variables in the PKT estimation models.

$$\mathrm{PKT_{Car}} = \mathrm{Intercept_{Car}} + \mathrm{Beta_{1\_Car}} \times \mathrm{x_1} + \mathrm{Beta_{2\_Car}} \times \mathrm{x_2} + \cdots + \mathrm{Beta_{n\_Car}} \times \mathrm{x_{n,}} \tag{3-15}$$

$$\begin{aligned}\mathrm{PKT_{Trasnit}} = {} & \mathrm{Intercept_{Transit}} + \mathrm{Beta_{1\_Transit}} \times \mathrm{x_1} + \mathrm{Beta_{2\_Transit}} \times \mathrm{x_2} + \cdots \\ & + \mathrm{Beta_{n\_Transit}} \times \mathrm{x_n},\end{aligned} \tag{3-16}$$

$$\begin{aligned}\mathrm{PKT_{Walk}} = {} & \mathrm{Intercept_{Walk}} + \mathrm{Beta_{1\_Walk}} \times \mathrm{x_1} + \mathrm{Beta_{2\_Walk}} \times \mathrm{x_2} + \cdots \\ & + \mathrm{Beta_{n\_Walk}} \times \mathrm{x_n},\end{aligned} \tag{3-17}$$

$$\begin{aligned}\mathrm{PKT_{Cycle}} = {} & \mathrm{Intercept_{Cycle}} + \mathrm{Beta_{1\_Cycle}} \times \mathrm{x_1} + \mathrm{Beta_{2\_Cycle}} \times \mathrm{x_2} + \cdots \\ & + \mathrm{Beta_{n_{Cycle}}} \times \mathrm{x_n},\end{aligned} \tag{3-18}$$

### 3.2.2 Linking Passenger Trips to Vehicle Trips

As presented earlier, data required for developing TRIBUTE comes from two main sources: household travel surveys and emissions inventories (described in Section 3.2). Household travel surveys are reliable sources for socioeconomic, demographic, modal share, and average vehicle occupancy data. Data on average VKT, number of registered vehicles, and total GHG emissions were extracted from emissions inventories. Linking household travel survey data to information from emissions inventories was not a straightforward task given that the first reports on passenger trips while the latter reports on vehicle trips. Figure 3-3 depicts the process used for linking passenger trips to vehicle trips and eventually feeding TRIBUTE.

Emissions inventories are considered reliable sources for calculating average PKT and average emissions factors, especially when they utilize the resident-based methodology using vehicle registration data for reporting on emissions (as opposed to other methodologies that rely on fuel sales or modelling). Given that BC's emissions inventories are resident-based (Ministry of Environment, 2014c), they were used to calculate average PKT and average GHG emissions factors for each mode from information on total GHG emissions and total VKT, as shown in Figure 3.3. To differentiate between car drivers' average PKT and car passengers' average PKT, the PKT split was extracted from the household travel survey knowing the origins and destinations of each trip.

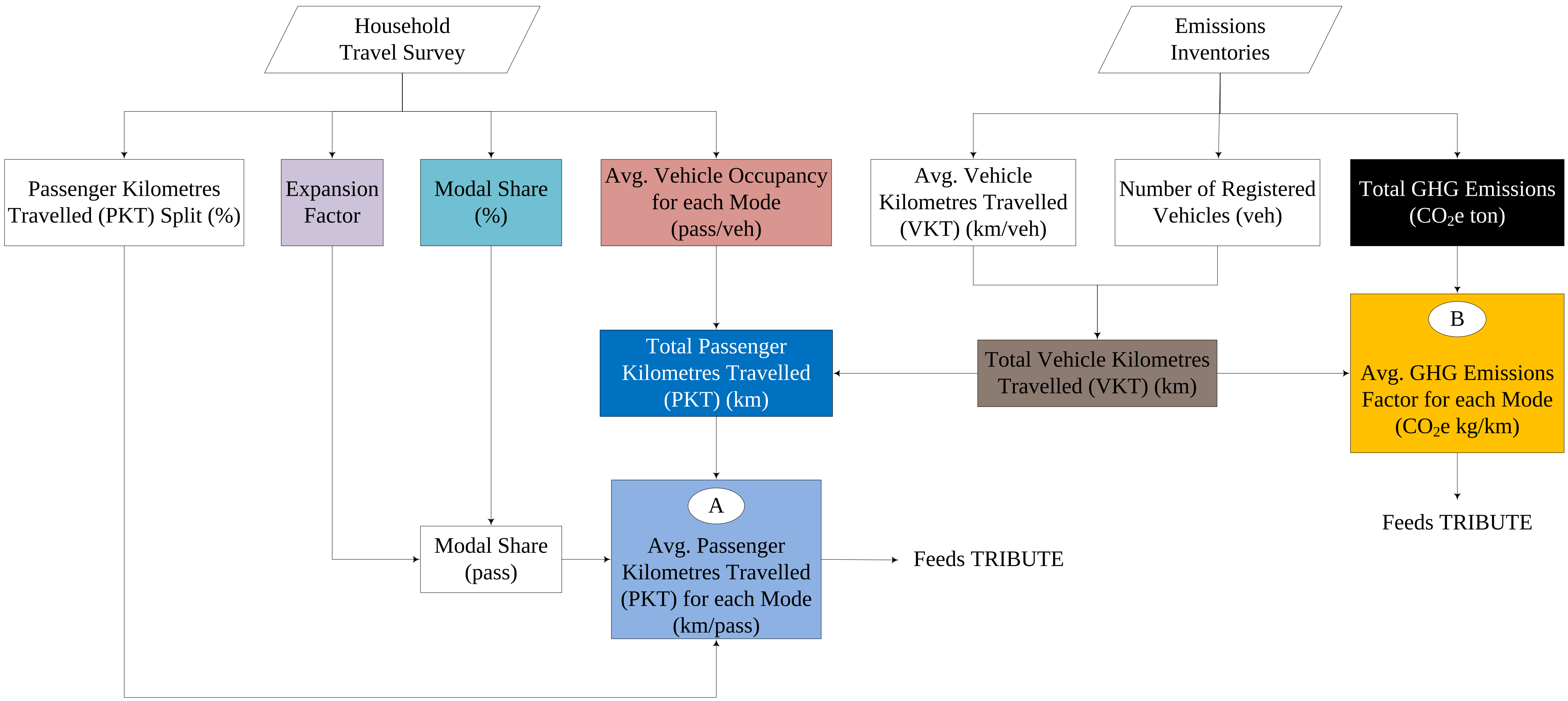



**Figure 3-3 Linking Passenger Trips to Vehicle Trips**

### 3.2.3 Model Application (Future Scenarios)

Upon completion of model building, TRIBUTE can be used to forecast GHG emissions from the transportation sector in response to future transportation and land use policy scenarios by running its joint mode shift and emissions forecasting models. Future estimates are required to account for population growth, new emissions factors for new vehicle technologies, as well as changes in personal, modal, and land use attributes. The following bullets describe the steps required for forecasting future GHG using TRIBUTE:

- Trip length reduction in response to changes in land use attributes (e.g. density, diversity, and design) can be captured by running the PKT estimation model developed in Section 3.2.1.

- Mode shift in response to changes in land use attributes can be captured by running the mode choice model, as shown in Section 3.2.1. Importantly, the trip length reduction model (previous step) is expected to feed in the mode shift model to account for the effect of trip length reduction on mode shift.

- Total VKT by each mode in the future scenario can then be calculated using Equation (3-19) as follows:

$$\text{Future VKT (km)} = \frac{\text{Change in PKT (km)} \times \text{Modal shift (\%)} \times \text{Expected population}}{\text{Vehicle occupancy}}, \tag{3-19}$$

- Next, future GHG emissions can be estimated using Equation (3-20).

$$\text{Emissions in future scenario } (CO_2 \text{ eq.}) = \text{Future VKT (km)} \times \text{Average emissions factors } (CO_2 \text{ eq. per km}), \tag{3-20}$$

- Finally, the change in passenger transportation GHG emissions from base case can be calculated by Equation (3-21). This process can be repeated for different future scenarios and/or land use policies and subsequently, the policy/scenario combination that best meets GHG emissions reduction targets can be selected.

$$\text{Change}(\%) = \frac{\text{Emissions in future scenario} - \text{Emissions in base case}}{\text{Emissions in base case}} \times 100, \qquad (3\text{-}21)$$

## 3.3 Summary

This chapter proposed a TRIp-Based Urban Transportation Emissions (TRIBUTE) model for estimating and forecasting GHG emissions from passenger transportation. TRIBUTE is a trip-based approach given that it uses the individual trip as its fundamental unit of analysis. TRIBUTE can capture the relationship between travel behavior and VKT in estimating as well as in forecasting emissions. As such, it can be used to assist municipalities evaluate alternative transportation and land use policy scenarios and eventually select the one(s) that help them meet their future GHG emissions targets.

# Chapter 4: Case Study

## 4.1 Outline

As described in Chapter 3, the developed emissions forecasting model (TRIBUTE) relies mainly on household travel survey and emissions inventory data. This represents a major advantage of TRIBUTE as it can be used in small municipalities where a detailed transportation network model is unavailable. This chapter presents the application of TRIBUTE to estimate GHG emissions from passenger transportation in the City of Kelowna, British Columbia as a case study. This chapter is comprised of two main parts. In section 4.2, detailed information on the study area is presented including location, demographics, transportation network, and emissions reduction target. In Section 4.3, an overview of the data used and its sources is presented.

## 4.2 Study Area

The City of Kelowna lies in the Okanagan Valley located in the Southern Interior of British Columbia, Canada. With a total area of 211.8 square kilometres and population of 117,312 in 2011, Kelowna is considered the largest city in British Columbia's Okanagan Valley (Statistics Canada, 2016). Similar to many North American cities, the City of Kelowna faces severe suburbanization and urban sprawl promoted by the popularity of low-density car-oriented developments. As comparison, Kelowna's average population density (117,312 residents/211.8 $km^2$ = 554 residents/$km^2$) is approximately one tenth (1/10) of Vancouver's, which has a much higher active transportation modal share. The City of Kelowna is comprised of 10 sectors with 191 traffic analysis zones. Figure 4-1 shows the distribution of population density among the city's 10 sectors and 191 traffic analysis zones (TAZs).

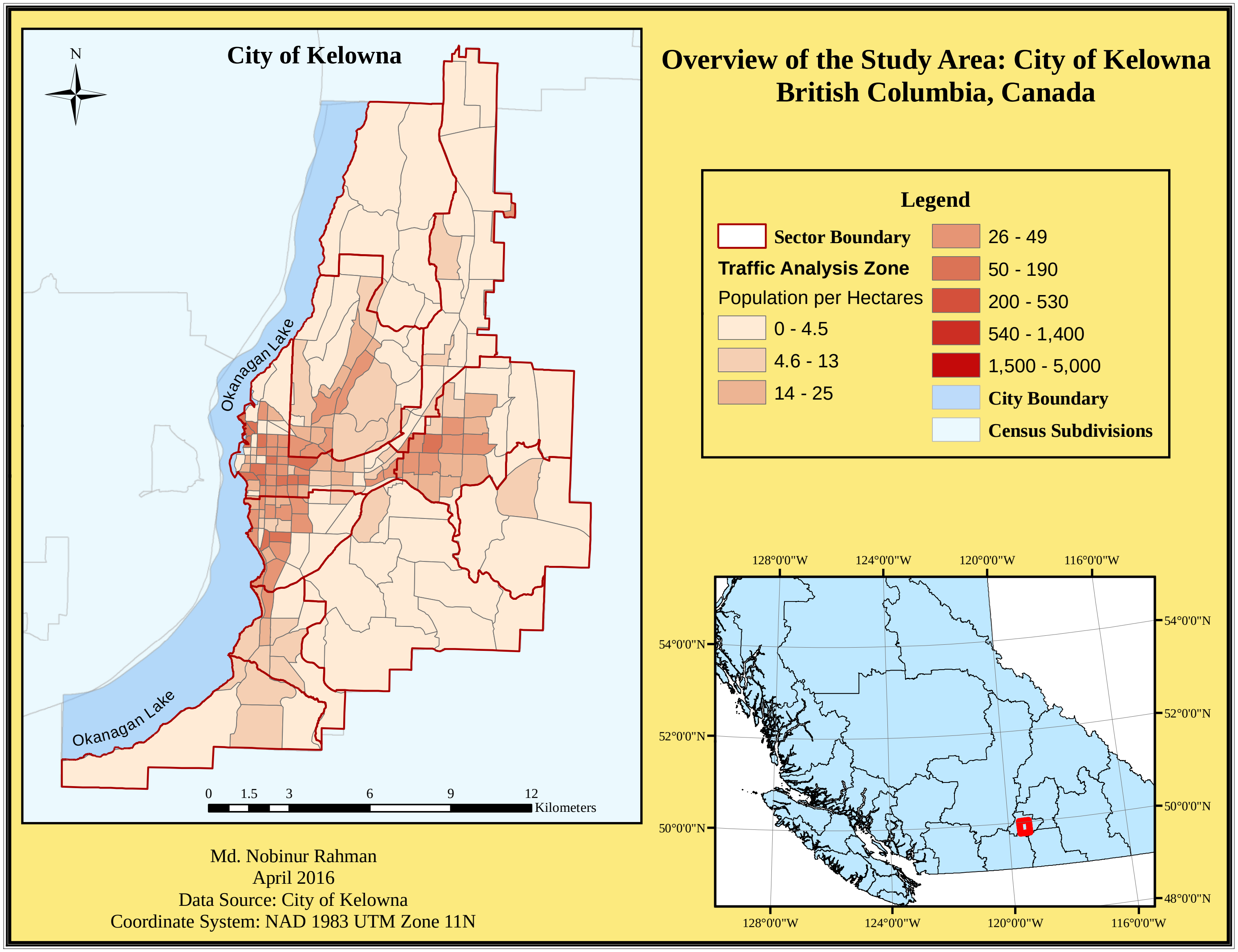



**Figure 4-1 Distribution of Population Density in the City of Kelowna**

### 4.2.1 Kelowna’s Growth Projections

The City of Kelowna is expected to accommodate additional 63,070 people by the end of 2040, on top of its 117,312 people, which will result in a total population of 180,382. Among all age groups, the senior population is expected to increase substantially. The average household size is expected to be 2.11 persons per unit by 2030 (City of Kelowna, 2013). Table 4-1 outlines Kelowna’s population growth projections (Rahman et al., 2016). In 2013, the City of Kelowna’s total population was 119,801, which was calculated by taking the same growth rates between 2011 and 2014.

**Table 4-1 Kelowna’s Projected Growth Rates (Rahman et al., 2016)**

| Time Period | Average Annual Growth Rate | Population at End of Period |
|---|---|---|
| 2014 | - | 121,045 |
| 2015 - 2019 | 1.7% | 131,690 |
| 2020 - 2024 | 1.6% | 142,708 |
| 2025 - 2029 | 1.5% | 153,889 |
| 2030 - 2034 | 1.5% | 165,782 |
| 2035 - 2039 | 1.4% | 177,891 |
| 2040 | 1.3% | 180,382 |

### 4.2.2 Kelowna’s Transportation Network

Over the past few years, the City of Kelowna has pursued several measures in constructing infrastructure for active transportation and public transit. For example, to promote walking in the City of Kelowna, different walking facilities such as sidewalks, crosswalks, and shared pathways have been developed (City of Kelowna, 2016). To promote bicycling, the City of Kelowna has installed one of the most widespread bicycle networks in Canada (City of Kelowna, 2016). The city has nearly 300 km on-street bicycle lanes. Moreover, during 2012-2014, the City of Kelowna has also carried out various transit infrastructure and service projects (e.g. improving transit facilities, increasing frequency of the transit service, and improving transit route coverage) (City of Kelowna, 2016). The road network, active transportation network, and public transit network of the City of Kelowna are illustrated in Figure 4-2, Figure 4-3, and Figure 4-4, respectively.

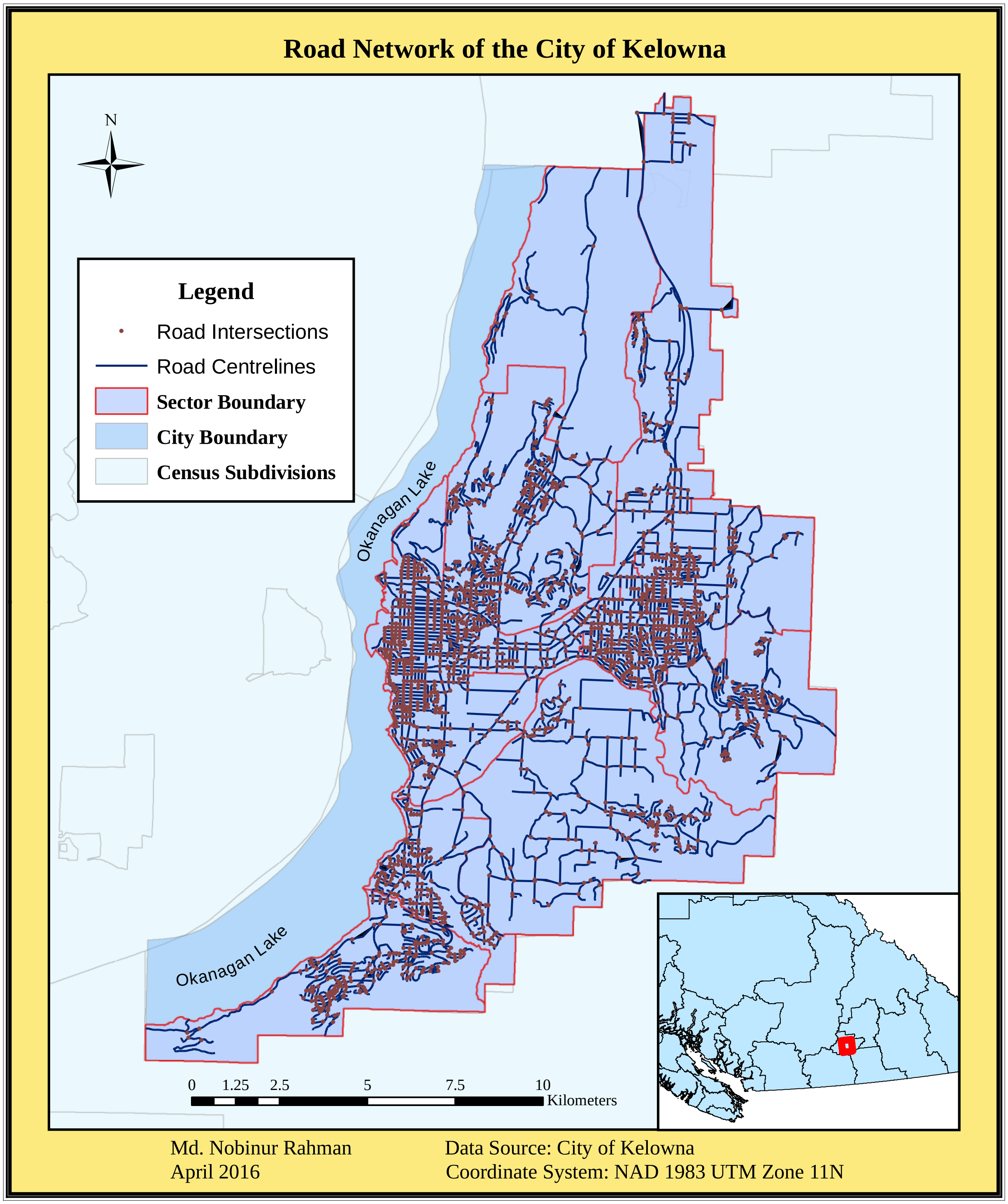



**Figure 4-2 Road Network in the City of Kelowna**

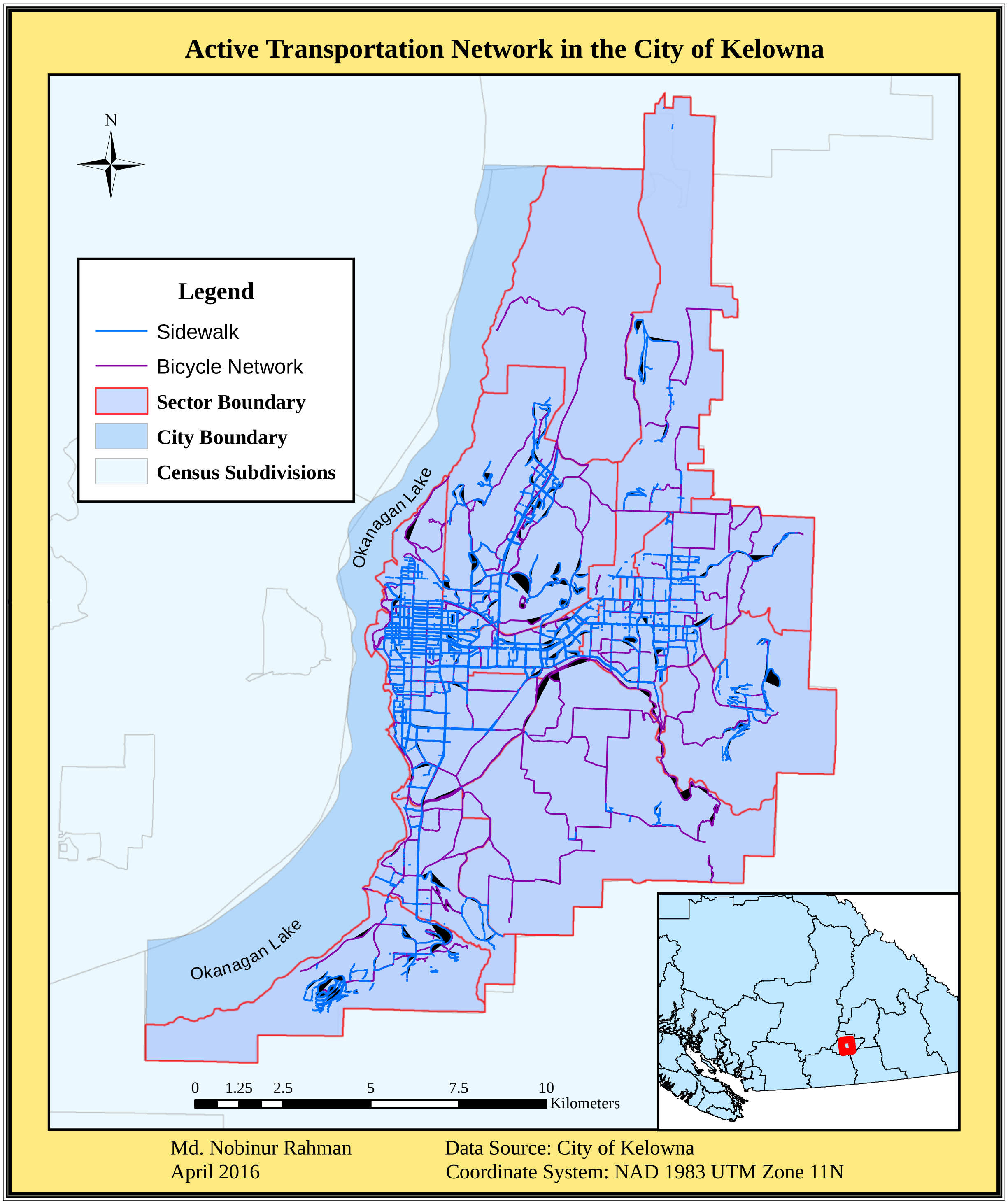



**Figure 4-3 Active Transportation Network in the City of Kelowna**

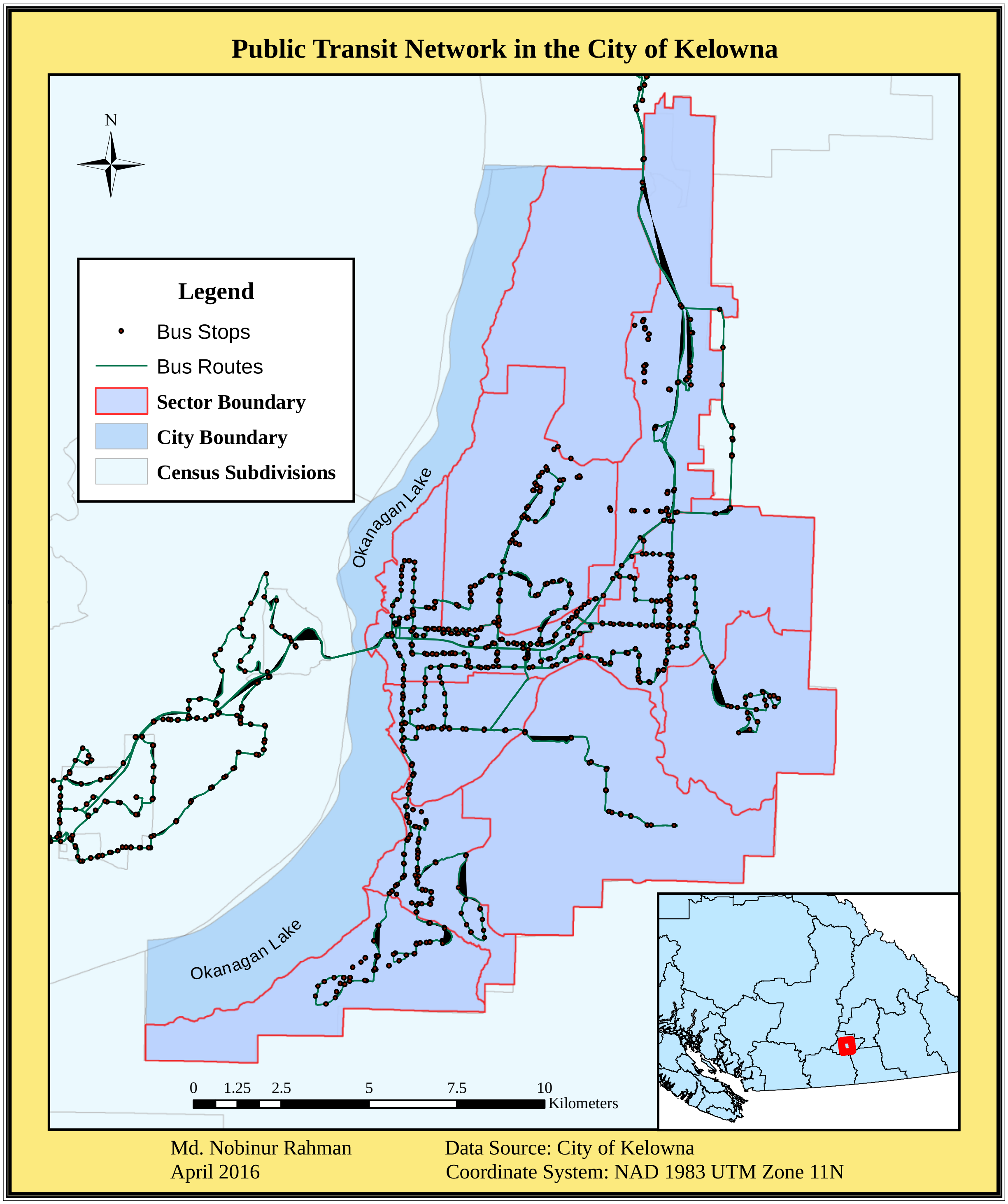



**Figure 4-4 Public Transit Network in the City of Kelowna**

#### 4.2.3 Kelowna's GHG Emissions

Much of the motivation for active transportation improvements in the city has arisen from Kelowna's traditionally high car dependency. The high car dependency in Kelowna has produced the second highest per-capita road transportation carbon footprint in British Columbia, coming after Prince George (City of Kelowna, 2009). According to the 2007 Community Energy and Emissions Inventory (CEEI), on-road transportation contributed 506,640 $CO_2$ eq. ton, representing about 65% of Kelowna's community GHG emissions in 2007 (City of Kelowna, 2012). Figure 4-5 depicts the three major sources of GHG emissions in the City of Kelowna.

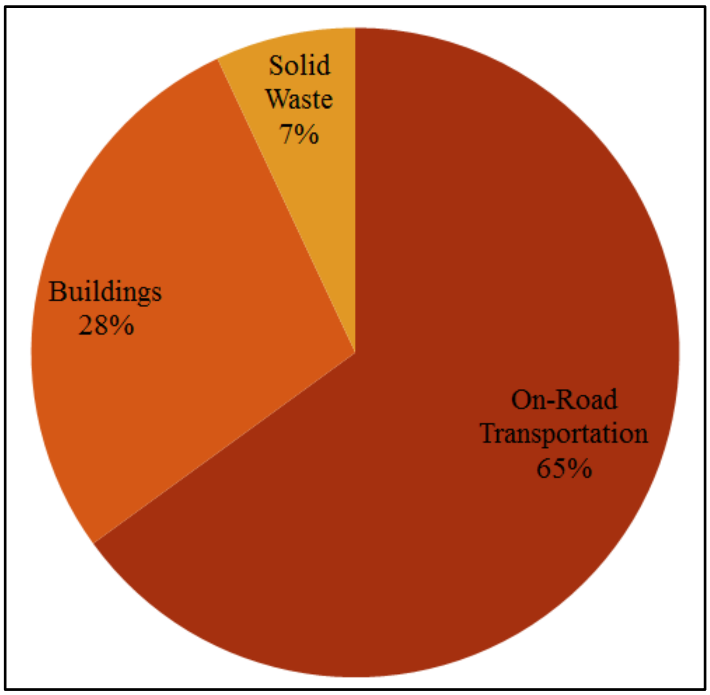



**Figure 4-5 Sources of GHG Emissions in the City of Kelowna (City of Kelowna, 2012)**

Kelowna residents depend highly on personal vehicles (mainly light trucks, vans, and SUVs) as a mode of travel. As a result, personal vehicles were responsible for almost two thirds of the on-road emissions produced in 2007 (Figure 4-6). If the city continues business-as-usual, on-road transportation GHG emissions are expected to escalate to unprecedented levels by 2040, putting citizens' health and quality of life in question. In response, the City of Kelowna has committed to finding ways to tackle the challenges posed by climate change and pledged to reducing its GHG emissions by 33% from 2007 levels by 2040 (City of Kelowna, 2012).

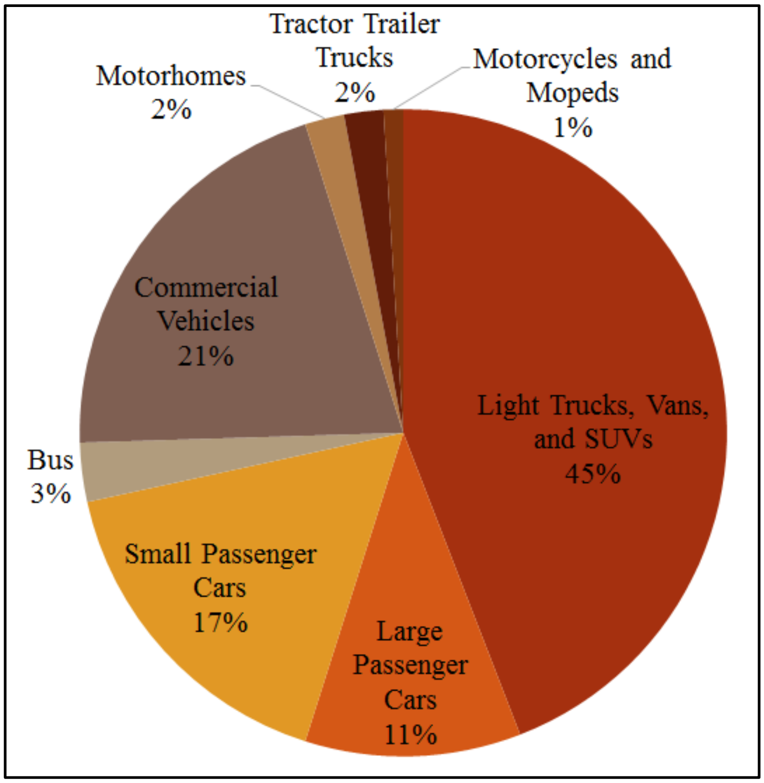



**Figure 4-6 On-Road Emissions from Different Vehicle Types (City of Kelowna, 2009)**

## 4.3 Dataset Description

The data used in this analysis came from two main sources: a household travel survey and emissions inventories. Socioeconomic, demographic, modal shares, and average vehicle occupancy data was acquired from the 2013 Okanagan Household Travel Survey (HHTS). The Okanagan HHTS is a household-based survey conducted in fall 2013 and includes detailed socioeconomic and demographic information about residents of the Central Okanagan and the City of Vernon along with their travel choices.

A sample of 13,633 trips, which represents a total of 429,559 trips that originate in the City of Kelowna on a typical week day, is recorded in the Okanagan HHTS. Among these trips, 89.64% stayed in Kelowna and 10.36% crossed the city boundaries to different destinations in the Okanagan Valley including Vernon, Lake Country, West Kelowna, West Bank First Nation (WFN), Peachland, Central Okanagan East, Central Okanagan West, North Okanagan, and South Okanagan. For each trip, the trip purpose and mode of travel are reported. The descriptive statistics of the 2013 Okanagan HHTS are shown in Table 4-2. Among the cross boundary trips, the highest number of trips (4.28%) ends in West Kelowna, and the second and third highest end in Lake Country (1.80%) and Westbank (1.36%), respectively, as shown in Figure 4-7.

**Table 4-2 Descriptive Statistics of 2013 Okanagan HHTS**

| Variable | Value | Sample Size | Percentage |
|---|---|---|---|
| **Destinations** | Vernon | 146<br>(4,145)* | 1.07%<br>(0.97%)* |
| | Lake Country | 292<br>(7,715)* | 2.14%<br>(1.80%)* |
| | Kelowna | 12,057<br>(385,055)* | 88.44%<br>(89.64%)* |
| | West Kelowna | 613<br>(18,400)* | 4.50%<br>(4.28%)* |
| | WFN | 207<br>(5,851)* | 1.52%<br>(1.36%)* |
| | Peachland | 71<br>(1,564)* | 0.52%<br>(0.36%)* |
| | Central Okanagan East | 141<br>(3,987)* | 1.03%<br>(0.93%)* |
| | Central Okanagan West | 23<br>(648)* | 0.17%<br>(0.15%)* |
| | North Okanagan CMA (minus Vernon) | 18<br>(538)* | 0.13%<br>(0.13%)* |
| | South Okanagan CMA | 7<br>(161)* | 0.05%<br>(0.04%)* |
| | External | 57<br>(1,494)* | 0.42%<br>(0.35%)* |
| **Trip Purposes** | To Work | 2,127<br>(64,987)* | 15.66%<br>(15.17%)* |
| | To grade school | 484<br>(17,828)* | 3.56%<br>(4.16%)* |
| | To post-secondary school | 382<br>(12,225)* | 2.81%<br>(2.85%)* |
| | To Restaurant | 397<br>(11,944)* | 2.92%<br>(2.79%)* |
| | For Recreation | 627<br>(19,811)* | 4.62%<br>(4.62%)* |

*Values between parentheses represent the expanded sample size

**Table 4-2 Descriptive Statistics of 2013 Okanagan HHTS (Continued)**

| Variable | Value | Sample Size | Percentage |
|---|---|---|---|
| **Trip Purposes** | For a Social outing | 496 (15,193)* | 3.65% (3.55%)* |
| | For Shopping | 1,496 (45,499)* | 11.01% (10.62%)* |
| | For Personal business | 897 (27,199)* | 6.60% (6.35%)* |
| | To Home | 4,980 (158,023)* | 36.66% (36.89%)* |
| | To drive or pick-up someone | 1,062 (35,277)* | 7.82% (8.24%)* |
| | Other | 638 (20,383)* | 4.70% (4.76%)* |
| **Mode of Transportation** | Car Driver | 9,194 (284,122)* | 67.57% (66.35%)* |
| | Car Passenger | 2,041 (66,691)* | 15.00% (15.57%)* |
| | Transit | 600 (20,577)* | 4.41% (4.81%)* |
| | Walk | 1,087 (33,530)* | 7.99% (7.83%)* |
| | Cycle | 166 (6,122)* | 1.22% (1.43%)* |
| | School Bus | 426 (14,156)* | 3.13% (3.31%)* |
| | Other | 93 (3,015)* | 0.68% (0.70%)* |

*Values between parentheses represent the expanded sample size

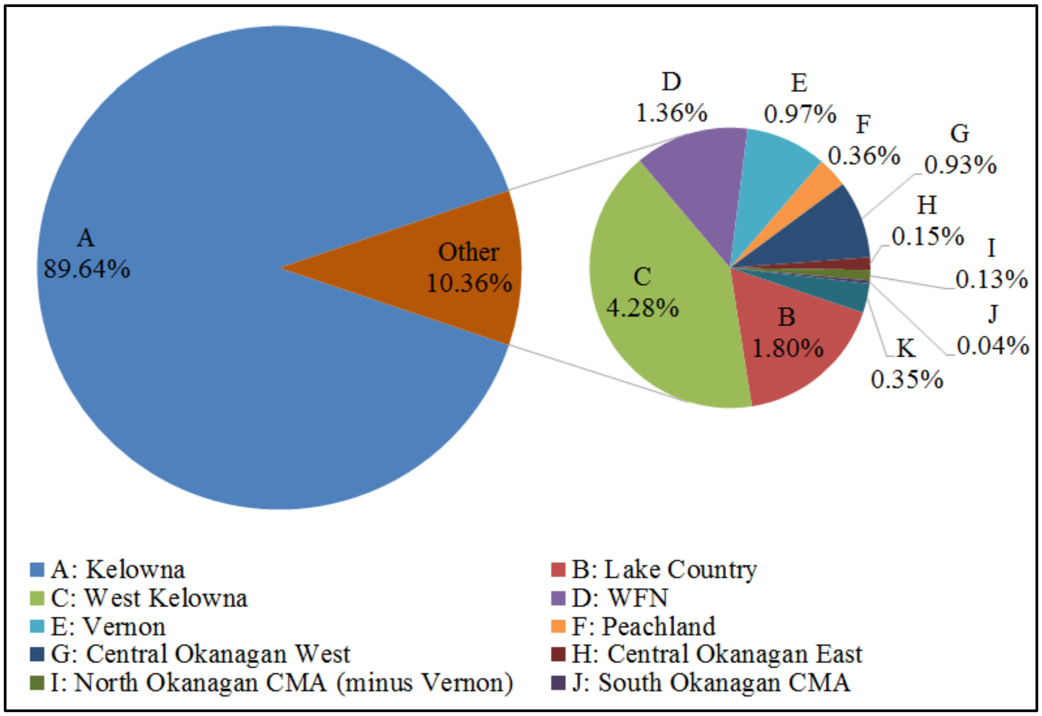



**Figure 4-7 Distribution of Trips Originated in Kelowna**

The most frequent trip purpose recorded in the Okanagan HHTS is “to home”. The trip purpose “to home” indicates that going back home may either come from work/school or other locations. The work trips, going to work regardless of origin locations, are the second highest trips at 15.17% of total trips, which is followed by shopping trips (10.62%), as illustrated in Figure 4-8.

According to the HHTS, there is a very high percentage (81.92%) of car users in the study area (66.35% car drivers and 15.57% car passengers), as shown in Figure 4-9. On the other hand, active transportation accounts for 9.26% (7.83% walk and 1.43% cycle), public transit represents 4.81%, and only 3.31% of all trips are made by school bus.

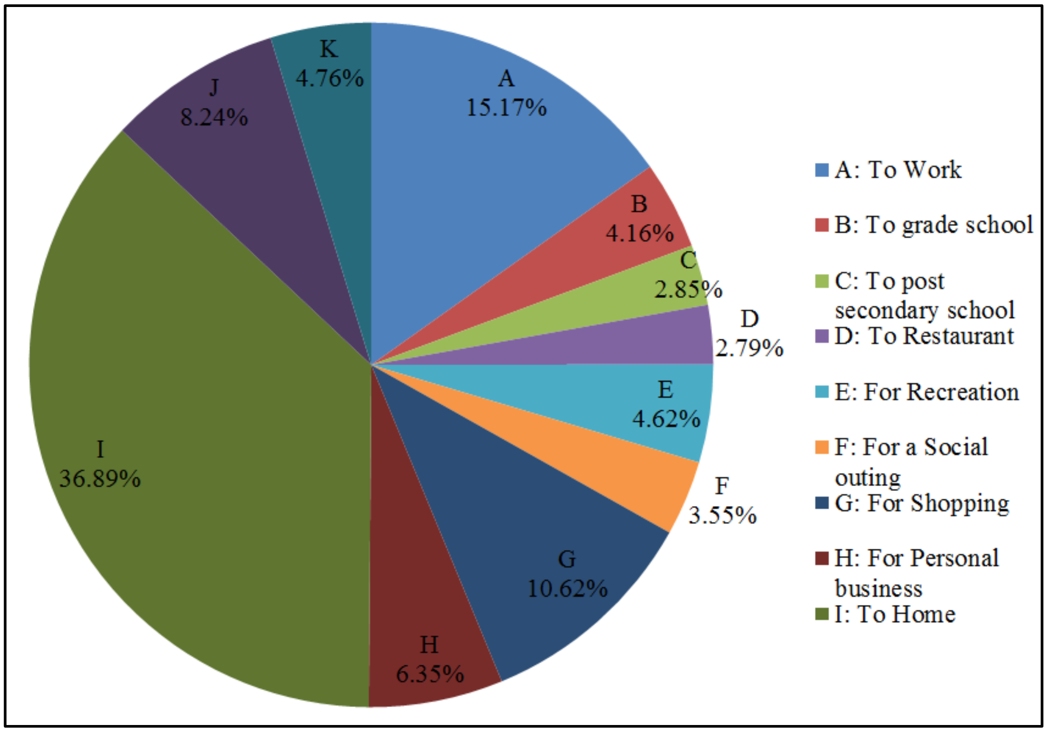



**Figure 4-8 Trips Purposes**

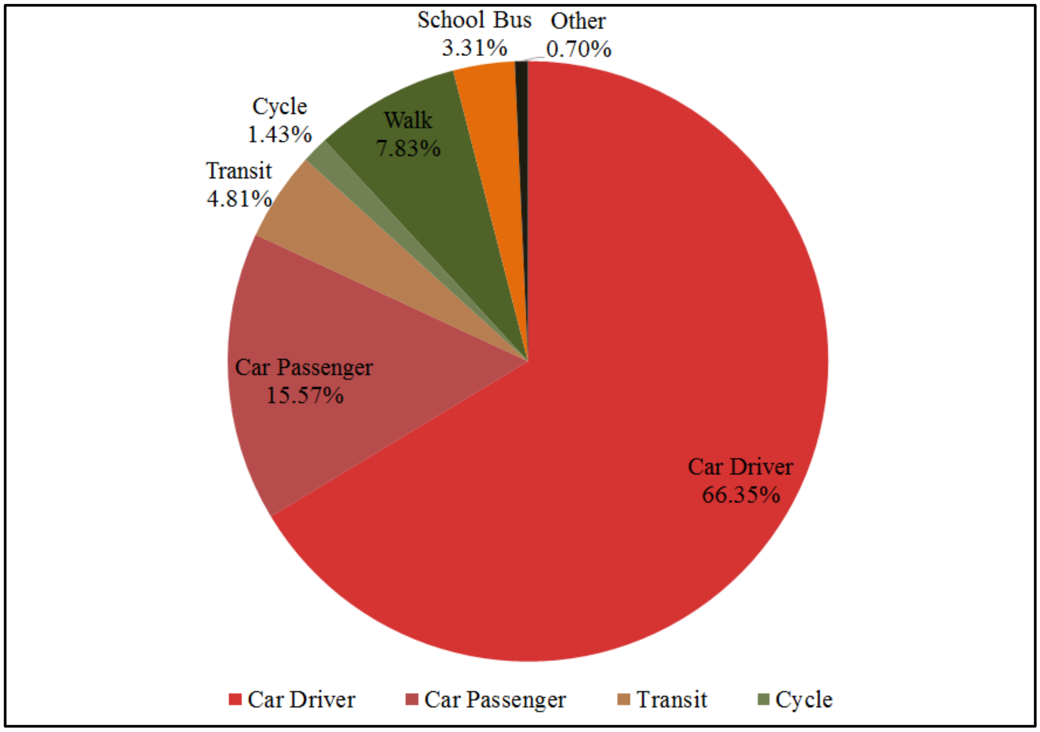



**Figure 4-9 Modal Share**

This research focused on trips that originated and ended within Kelowna (i.e. cross-boundary trips were outside the scope of this study). A subset of the trips originated in Kelowna (described in the Table 4-2) was extracted to include only trips that both originated and ended in Kelowna. The extracted subset included a sample of 12,057 trips which represents a total of 385,055 trips that stay within the boundaries of the City of Kelowna on a typical week day. Further, the trips within Kelowna (a sample of 12,057 trips) were divided into two broad categories based on the trip purposes, namely, commuting trips, and non-commuting trips. The following section describes the descriptive statistics of the commuting and non-commuting trips separately.

### 4.3.1 Commuting Trips

Commuting trips refer to trips associated with work-related activities. The HHTS includes a total number of 4,299 commuting trips (i.e. home to work/school, work/school to home, and other than home locations to work/school). There are 3,533 home-based commuting trips, i.e. home to work/school and the reverse trips, in the 2013 HHTS. In addition, there are various complex tours that consist of a numbers of linked trips in the HHTS. For example, the tour "dropping children off at school from home before going to work" consists of two trips: going from home to school and from school to work. In such tour, only the second trip (i.e. school to work) is considered as a commuting trip (Acker and Witlox, 2011). There are 766 commuting trips starting at locations other than home and ending at the work place. The descriptive statistics of commuting trips are shown in Table 4-3.

**Table 4-3 Descriptive Statistics of Commuting Trips**

| Variable | Value | Sample Size | Percentage |
|---|---|---|---|
| **Gender** | Male | 2,055 (66,765)* | 47.80% (47.95%)* |
| | Female | 2,244 (72,482)* | 52.20% (52.05%)* |
| **Age** (In years) | 05-14 | 616 (23,261)* | 14.33% (16.70%)* |
| | 15-24 | 719 (24,428)* | 16.72% (17.54%)* |
| | 25-34 | 753 (22,375)* | 17.52% (16.07%)* |

*Values between parentheses represent the expanded sample size

**Table 4-3 Descriptive Statistics of Commuting Trips (Continued)**

| Variable | Value | Sample Size | Percentage |
|---|---|---|---|
| **Age** (In years) | 35-44 | 729 (23,815)* | 16.96% (17.10%)* |
| | 45-54 | 779 (25,393)* | 18.12% (18.24%)* |
| | 55-64 | 612 (17,361)* | 14.24% (12.47%)* |
| | 65 and over | 91 (2,616)* | 2.12% (1.88%)* |
| **Household Size** | 1 | 353 (14,804)* | 8.21% (10.63%)* |
| | 2 | 1,642 (39,429)* | 38.19% (28.32%)* |
| | 3 | 802 (27,459)* | 18.66% (19.72%)* |
| | 4+ | 1,502 (57,557)* | 34.94% (41.33%)* |
| **Number of Vehicles** | 0 | 121 (4,134)* | 2.81% (2.97%)* |
| | 1 | 1,169 (36,991)* | 27.19% (26.56%)* |
| | 2 | 1,851 (58,036)* | 43.06% (41.68%)* |
| | 3+ | 1,158 (40,087)* | 26.94% (28.79%)* |
| **Transit Pass Holding** | Yes | 534 (18,019)* | 12.42% (12.94%)* |
| | No | 3,765 (121,229)* | 87.58% (87.06%)* |
| **Driver's License Holding** | Yes | 3,405 (106,732)* | 79.20% (76.65%)* |
| | No | 894 (32,516)* | 20.80% (23.35%)* |
| **Dwelling Type** | Single Detached House | 2,922 (96,691)* | 67.97% (69.44%)* |
| | Apartment or Condo | 676 (20,451)* | 15.72% (14.69%)* |
| | Townhouse or Row House | 477 (14,422)* | 11.10% (10.36%)* |
| | Duplex | 187 (6,338)* | 4.35% (4.55%)* |

*Values between parentheses represent the expanded sample size

**Table 4-3 Descriptive Statistics of Commuting Trips (Continued)**

| Variable | Value | Sample Size | Percentage |
|---|---|---|---|
| **Occupation** | Professional | 1,291 (40,736)* | 43.67% (44.32%)* |
| | Business | 292 (8,642)* | 9.88% (9.40%)* |
| | Skilled Technical Worker | 208 (6,493)* | 7.04% (7.06%)* |
| | Sales | 148 (4,678)* | 5.01% (5.09%)* |
| | Clerical | 226 (6,835)* | 7.65% (7.44%)* |
| | Trades | 215 (6,407)* | 7.27% (6.97%)* |
| | Commercial Driver | 22 (711)* | 0.74% (0.77%)* |
| | Other | 554 (17,412)* | 18.74% (18.94%)* |
| **Household Income** | Less than $25,000 | 300 (9,936)* | 6.98% (7.14%)* |
| | $25,000 to Less than $45,000 | 514 (17,119)* | 11.96% (12.29%)* |
| | $45,000 to Less than $65,000 | 675 (21,187)* | 15.70% (15.22%)* |
| | $65,000 to Less than $100,000 | 1,252 (39,766)* | 29.12% (28.56%)* |
| | $100,000 or more | 1,558 (51,241)* | 36.24% (36.80%)* |
| **Modes of Transportation** | Car Driver | 2,547 (79,418)* | 59.25% (57.03%)* |
| | Car Passenger | 562 (19,629)* | 13.07% (14.10%)* |
| | Transit | 348 (11,701)* | 8.09% (8.40%)* |
| | Walk | 443 (14,499)* | 10.30% (10.41%)* |
| | Cycle | 235 (7,853)* | 5.47% (5.64%)* |
| | School Bus | 142 (5,425)* | 3.30% (3.90%)* |
| | Other | 22 (724)* | 0.51% (0.52%)* |

*Values between parentheses represent the expanded sample size

In the HHTS, it is reported that females make slightly more commuting trips (52.05%) than males in the City of Kelowna, as shown in Figure 4-10. The highest percentage of commuting trips is made by people in the 45 to 54 years age category, followed by 15 to 24 years, and then 35 to 44 years, as shown in Figure 4-11.

It is also seen from the HHTS that four or more people living in a single household are responsible for more commuting trips (41.33%) than the lower number of people in a household, as illustrated in Figure 4-12. The second highest trip making percentage (28.32%) is made by households having two people, followed by households having three people, and then single occupant households. On the other hand, two vehicles households are recorded as making the highest percentage of commuting trips in the 2013 Okanagan HHTS, as shown in Figure 4-13.

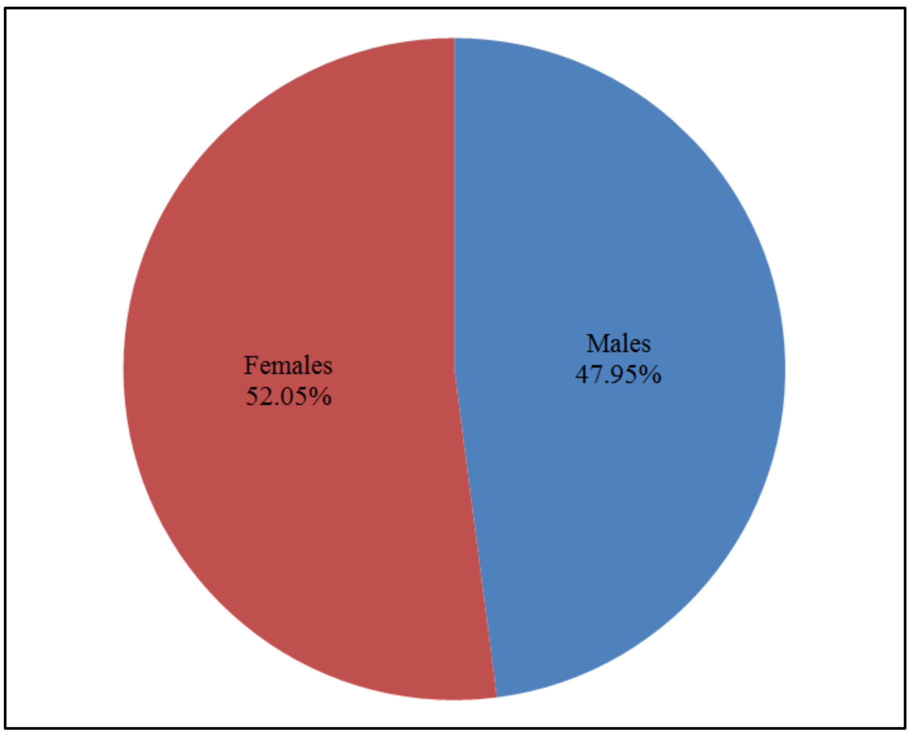



**Figure 4-10 Gender Distribution (Commuting Trips)**

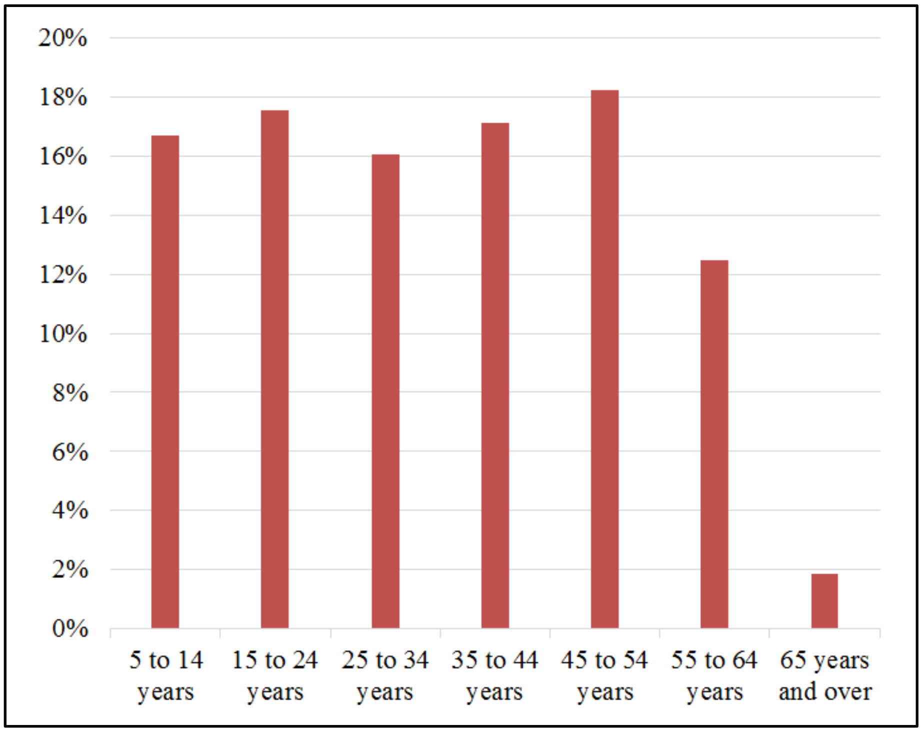



**Figure 4-11 Age Distribution (Commuting Trips)**

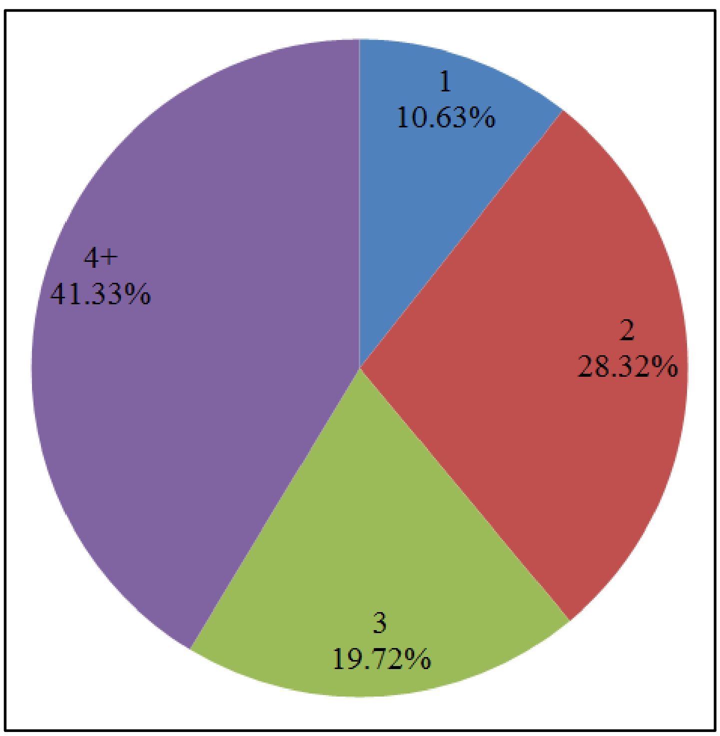



**Figure 4-12 Household Size (Commuting Trips)**

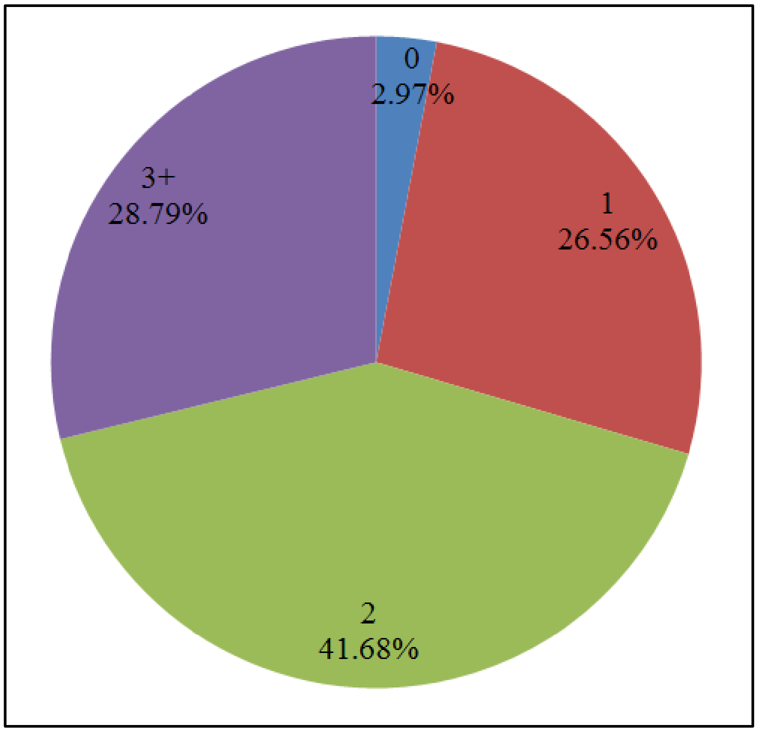



**Figure 4-13 Vehicle Ownership (Commuting Trips)**

In addition, 76.65% of people are recorded in the HHTS as having their driver's license, while 12.94% have a transit pass, as shown in Figure 4-14 and Figure 4-15, respectively. Higher numbers of people having a driver's licence and a lower percentage of people without a transit pass indicates higher auto dependency and lower transit ridership for commuting trips.

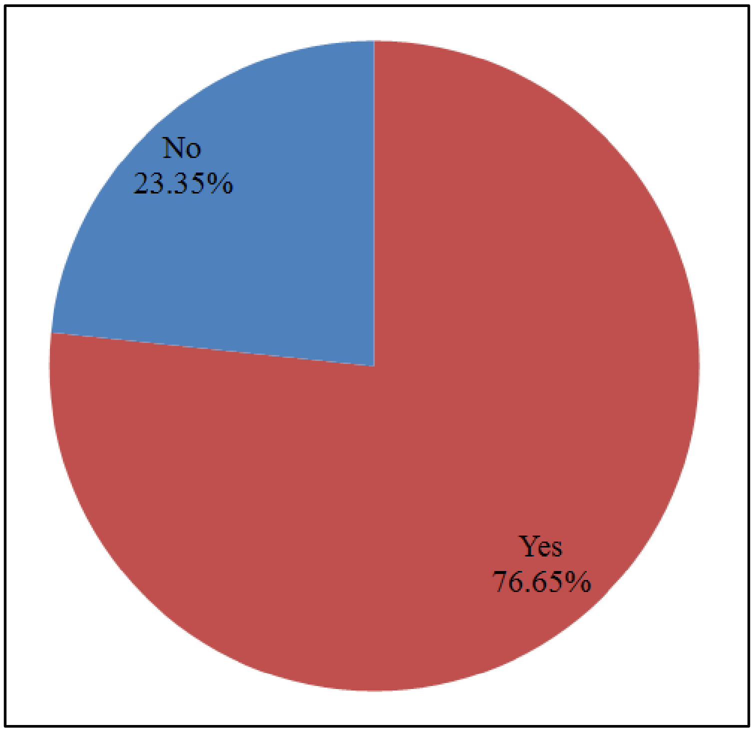



**Figure 4-14 Driver License (Commuting Trips)**

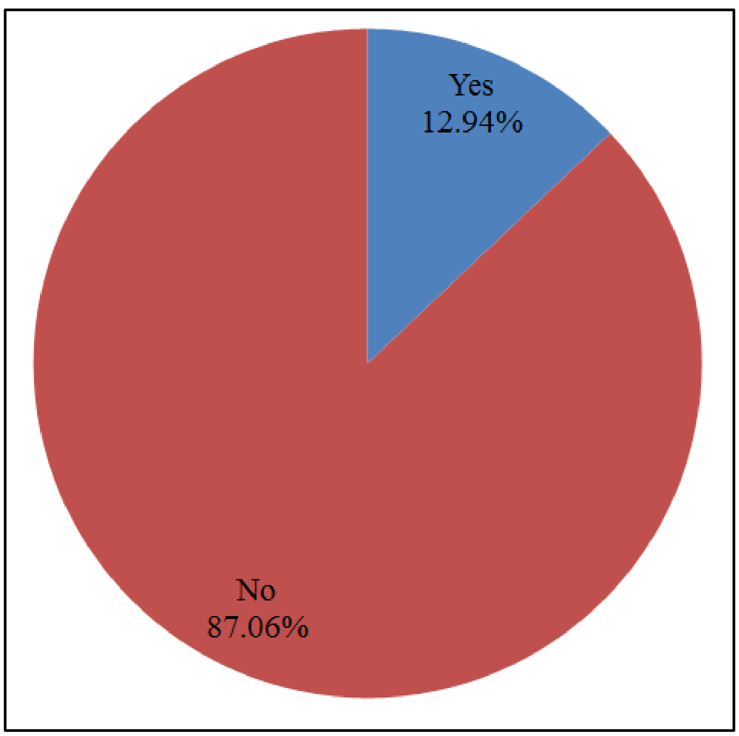



**Figure 4-15 Transit Pass (Commuting Trips)**

Different types of dwellings and occupancies give an idea about the standard of living. The HHTS shows that the dominant dwelling type is a single detached house, and that includes 69.44% of the total different dwelling types, as shown in Figure 4-16. This is followed by apartments then townhouses. On the other hand, the dominant occupation in the HHTS is professional, consisting of 44.32% of all commuting trips, as illustrated in Figure 4-17. In addition, more than 35% of people have an income level more than $100,000, which is almost equal to the people having salaries less than $65,000, as depicted in Figure 4-18. A person with a professional occupation, living in a single detached house, and having a higher income exhibits higher tendency to auto dependency.

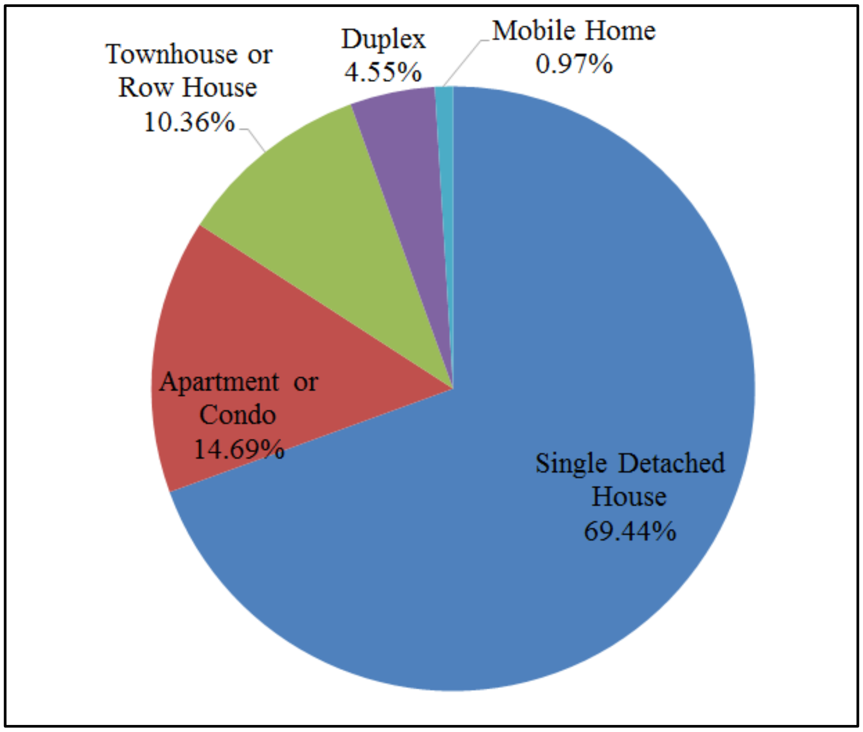



**Figure 4-16 Dwelling Types (Commuting Trips)**

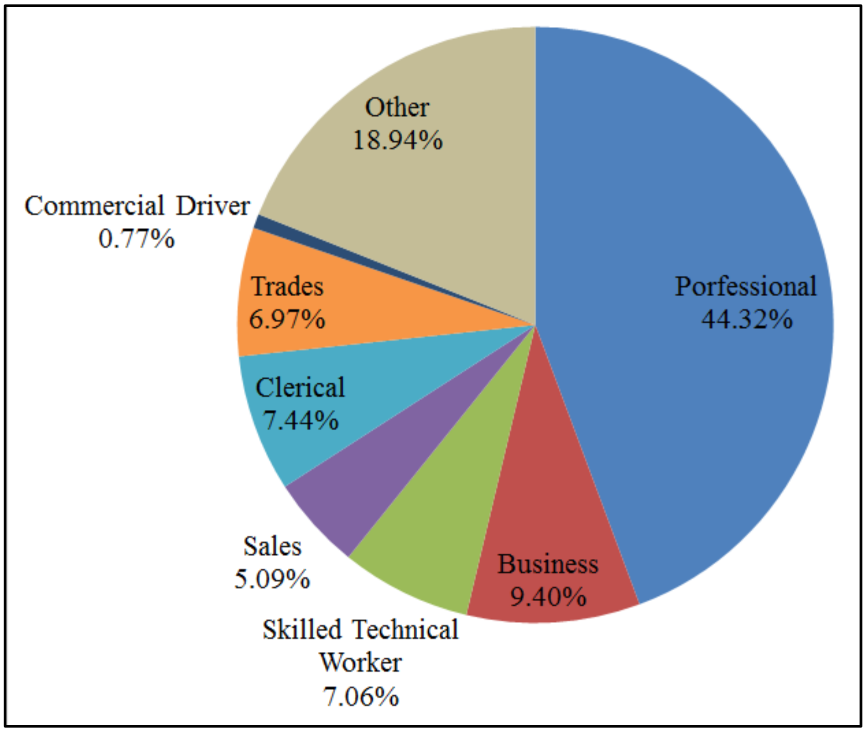



**Figure 4-17 Occupation Distribution (Commuting Trips)**

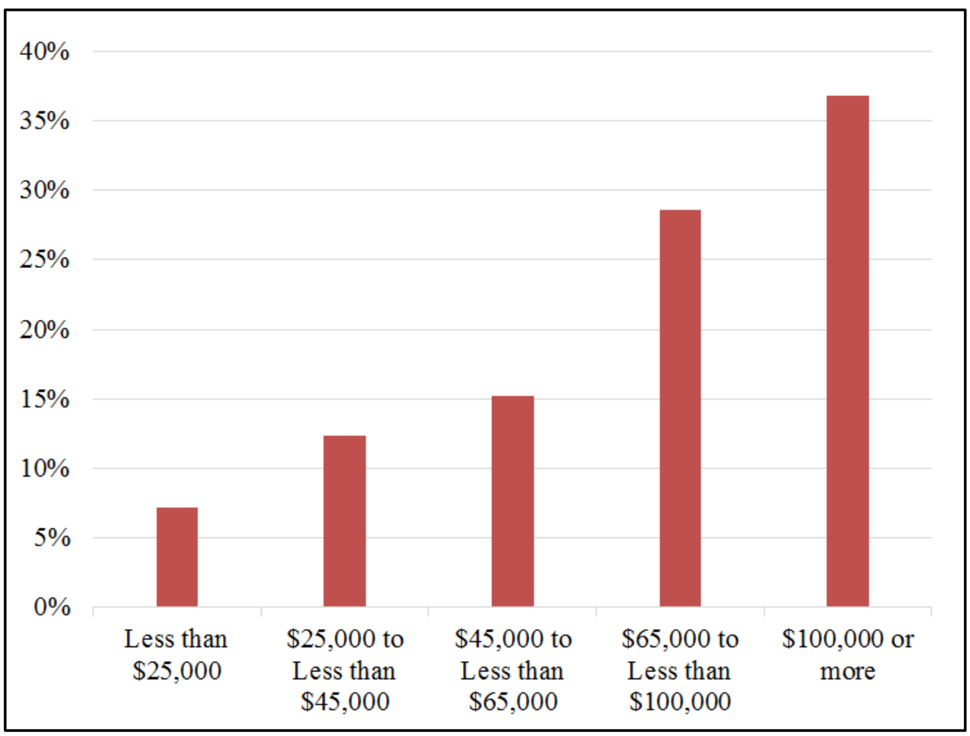



**Figure 4-18 Income Distribution (Commuting Trips)**

The City of Kelowna consists of over 71% of commuting trips using cars, including 57.03% car drivers and 14.10% car passengers, as shown in Figure 4-19. On the other hand, over 16% of commuting trips are made by active transportation that includes 10.41% of walking. In addition, transit ridership is 8.40% in 2013 for commuting trips.

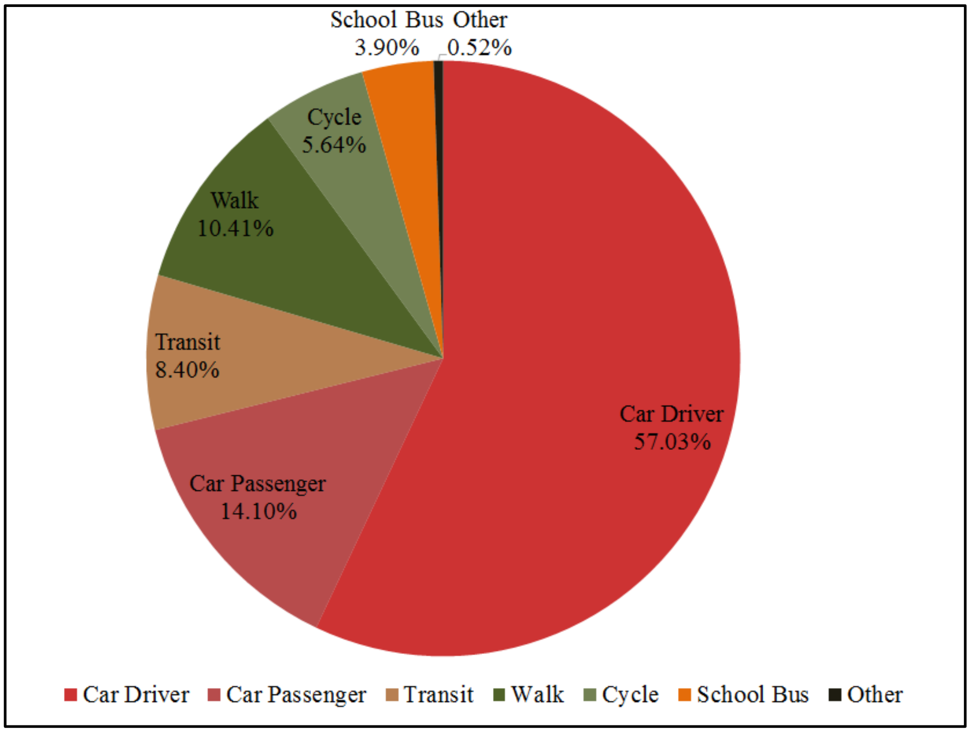



**Figure 4-19 Modal Share (Commuting Trips)**

### 4.3.2 Non-commuting Trips

Non-work-related activities were considered as non-commuting trips in this research. Non-commuting trips are comprised of home-based discretionary trips (e.g. shopping, entertainment, etc.), non-home-based discretionary trips, and work to discretionary trips. Home-based discretionary trips are those trips that either start or end at home (National Cooperative Highway Research Program, 2012). The total number of home-based discretionary trips are 5,046, as recorded in the HHTS. In addition, there are 1,933 trips categorized as non-commuting trips as their origins and destinations are neither home nor work or school. Furthermore, there are 779 trips originating at work or school and with destination at discretionary locations. By combining different types of non-commuting trips, there are a total of 7,758 non-commuting trips recorded in the HHTS. The descriptive statistics of non-commuting trips are shown in Table 4-4.

**Table 4-4 Descriptive Statistics of Non-Commuting Trips**

| Variable | Value | Sample Size | Percentage |
|---|---|---|---|
| **Gender** | Male | 3,054 (95,284)* | 39.37% (38.76%)* |
| | Female | 4,704 (150,559)* | 60.63% (61.24%)* |
| **Age** (In years) | 05-14 | 547 (19,835)* | 7.05% (8.07%)* |
| | 15-24 | 589 (20,473)* | 7.59% (8.33%)* |
| | 25-34 | 1,015 (29,826)* | 13.08% (12.13%)* |
| | 35-44 | 1,338 (45,564)* | 17.25% (18.53%)* |
| | 45-54 | 1,309 (44,561)* | 16.87% (18.13%)* |
| | 55-64 | 1,474 (42,569)* | 19.00% (17.32%)* |
| | 65 and over | 1,486 (43,017)* | 19.15% (17.50%)* |
| **Household Size** | 1 | 900 (38,133)* | 11.60% (15.51%)* |
| | 2 | 3,554 (85,363)* | 45.81% (34.72%)* |
| | 3 | 1,270 (43,455)* | 16.37% (17.68%)* |
| | 4+ | 2,034 (78,893)* | 26.22% (32.09%)* |
| **Number of Vehicles** | 0 | 294 (10,014)* | 3.79% (4.07%)* |
| | 1 | 2,430 (77,073)* | 31.32% (31.35%)* |
| | 2 | 3,312 (100,019)* | 42.69% (40.68%)* |
| | 3+ | 1,722 (58,736)* | 22.20% (23.89%)* |
| **Transit Pass Holding** | Yes | 526 (17,222)* | 6.78% (7.01%)* |
| | No | 7,232 (228,621)* | 93.22% (92.99%)* |

*Values between parentheses represent the expanded sample size

**Table 4-4 Descriptive Statistics of Non-Commuting Trips (Continued)**

| Variable | Value | Sample Size | Percentage |
|---|---|---|---|
| **Driver's License Holding** | Yes | 6,842 (214,025)* | 88.19% (87.06%)* |
| | No | 916 (31,818)* | 11.81% (12.94%)* |
| **Dwelling Type** | Single Detached House | 5,367 (172,602)* | 69.18% (70.21%)* |
| | Apartment or Condo | 1,195 (37,277)* | 15.40% (15.16%)* |
| | Townhouse or Row House | 882 (26,542)* | 11.37% (10.80%)* |
| | Duplex | 234 (6,993)* | 3.02% (2.84%)* |
| | Mobile Home | 80 (2,431)* | 1.03% (0.99%)* |
| **Occupation** | Professional | 1,703 (55,040)* | 52.50% (53.20%)* |
| | Business | 385 (11,608)* | 11.87% (11.22%)* |
| | Skilled Technical Worker | 232 (7,145)* | 7.15% (6.91%)* |
| | Sales | 171 (5,229)* | 5.27% (5.05%)* |
| | Clerical | 331 (10,204)* | 10.20% (9.86%)* |
| | Trades | 229 (7,082)* | 7.06% (6.85%)* |
| | Commercial Driver | 25 (812)* | 0.77% (0.78%)* |
| | Other | 168 (6,340)* | 5.18% (6.13%)* |
| **Household Income** | Less than $25,000 | 1,060 (35,462)* | 13.66% (14.42%)* |
| | $25,000 to Less than $45,000 | 1,139 (37,162)* | 14.68% (15.12%)* |
| | $45,000 to Less than $65,000 | 1,316 (39,151)* | 16.96% (15.93%)* |
| | $65,000 to Less than $100,000 | 2,180 (66,079)* | 28.10% (26.88%)* |
| | $100,000 or more | 2,063 (67,990)* | 26.59% (27.66%)* |

*Values between parentheses represent the expanded sample size

Table 4-4 Descriptive Statistics of Non-Commuting Trips (Continued)

| Variable | Value | Sample Size | Percentage |
|---|---|---|---|
| **Mode of Transportation** | Car Driver | 5,439<br>(170,971)* | 70.11%<br>(69.54%)* |
| | Car Passenger | 1,258<br>(40,791)* | 16.22%<br>(16.59%)* |
| | Transit | 192<br>(6,780)* | 2.47%<br>(2.76%)* |
| | Walk | 651<br>(19,773)* | 8.39%<br>(8.04%)* |
| | Cycle | 180<br>(6,170)* | 2.32%<br>(2.51%)* |
| | Other | 38<br>(1,360)* | 0.49%<br>(0.55%)* |

*Values between parentheses represent the expanded sample size

Females are responsible for more non-commuting trips than males, as shown in Figure 4-20. In particular, females are responsible for 61.24% of non-commuting trips, which is even higher than their share of commuting trips. Males generated 38.76% of non-commuting trips as recorded in the HHTS. On the other hand, those aged 35 years and over generates over than 70% of non-commuting trips, as illustrated in Figure 4-21.

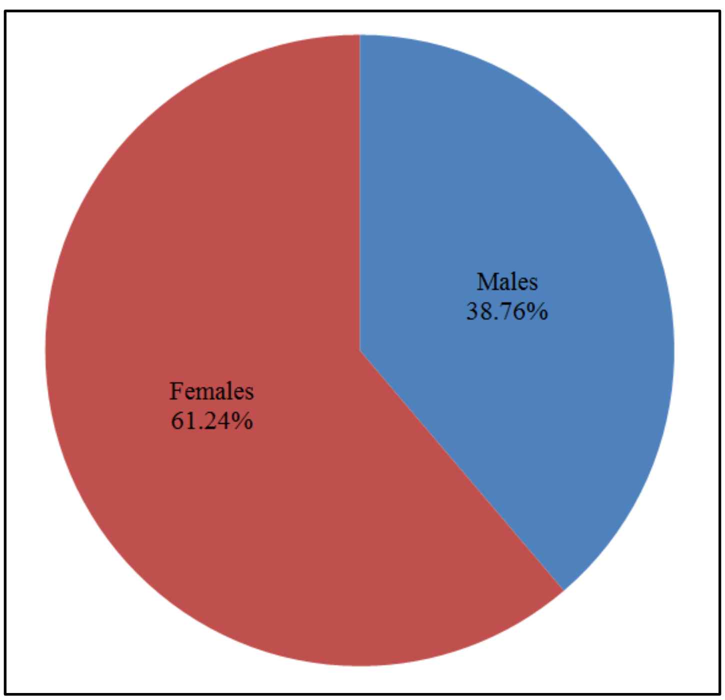



**Figure 4-20 Gender Distribution (Non-Commuting Trips)**

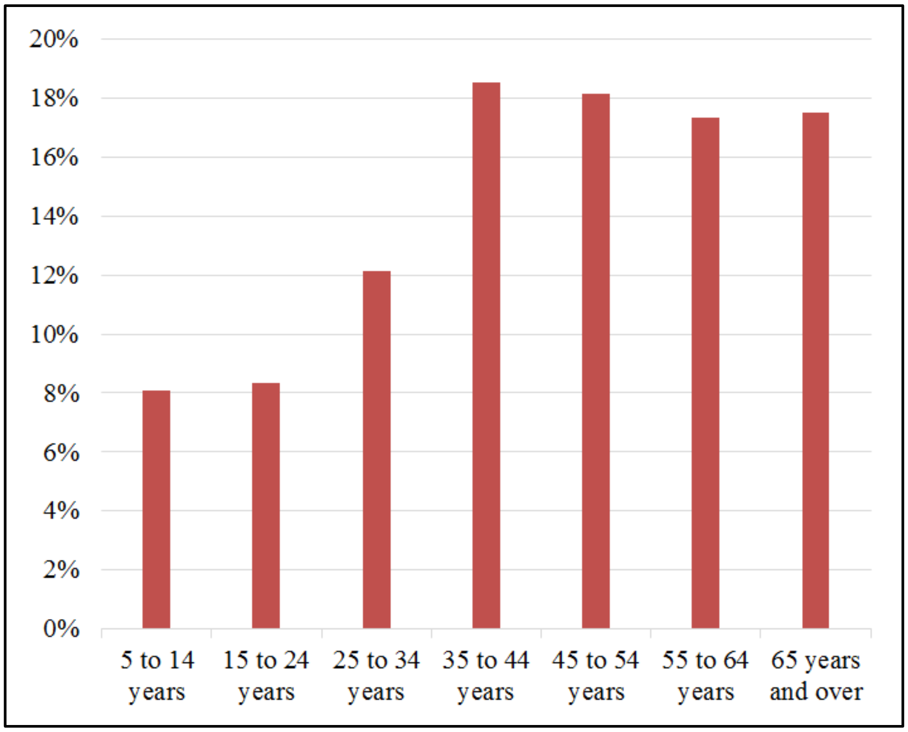



**Figure 4-21 Age Distribution (Non-Commuting Trips)**

From the HHTS, it is seen that the majority (34.72%) of non-commuting trips are coming from households having two persons living together, as shown in Figure 4-22, followed by those having four or more persons in a single household, and then three people in a single household. However, 40.68% of non-commuting trip makers have two vehicles in their household, while only 4.07% have no vehicles, as shown in Figure 4-23. In addition, 31.35% household have one vehicle, while 23.89% have three or more vehicles in their household.

A very high percentage of people (92.99%) does not have a transit pass of their own and 87.06% of people does have a driver's license, as depicted in Figure 4-24 and Figure 4-25, respectively, which indicates a higher auto dependency for non-commuting trips in the City of Kelowna.

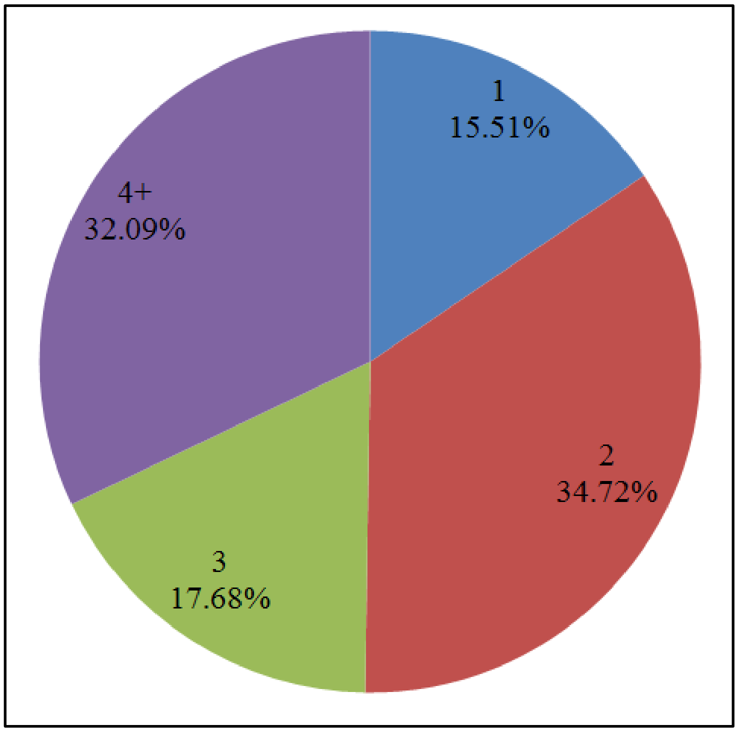



**Figure 4-22 Household Size (Non-Commuting Trips)**

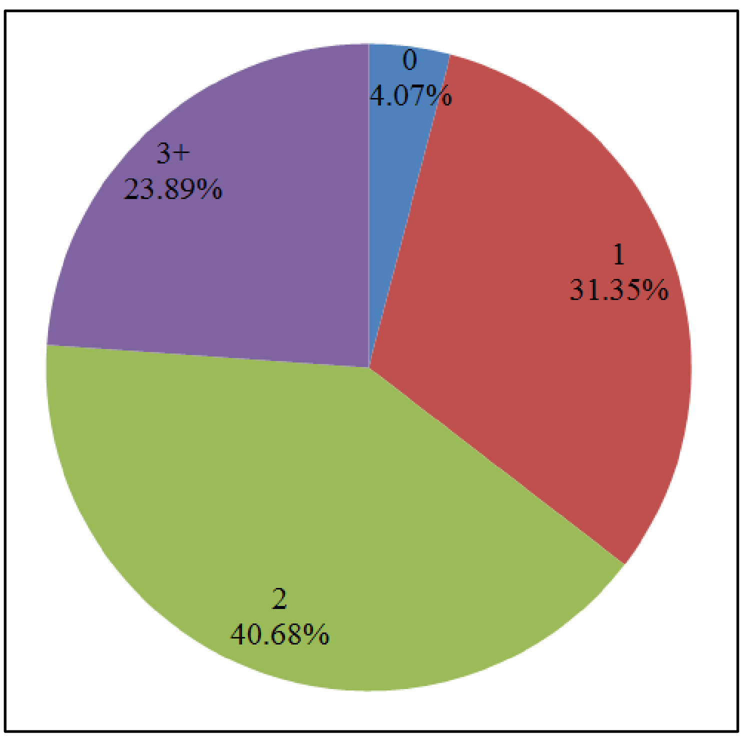



**Figure 4-23 Vehicle Ownership (Non-Commuting Trips)**

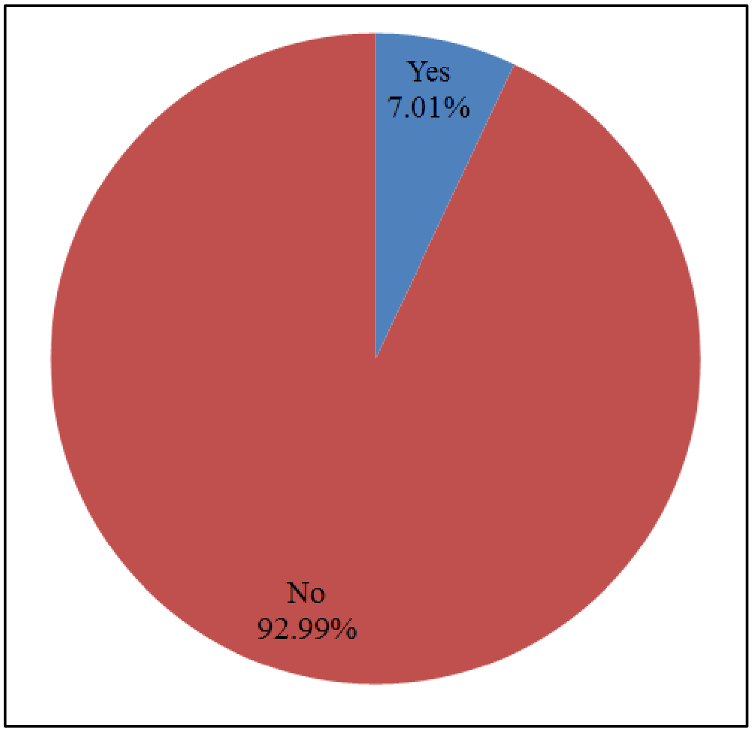



**Figure 4-24 Transit Pass (Non-Commuting Trips)**

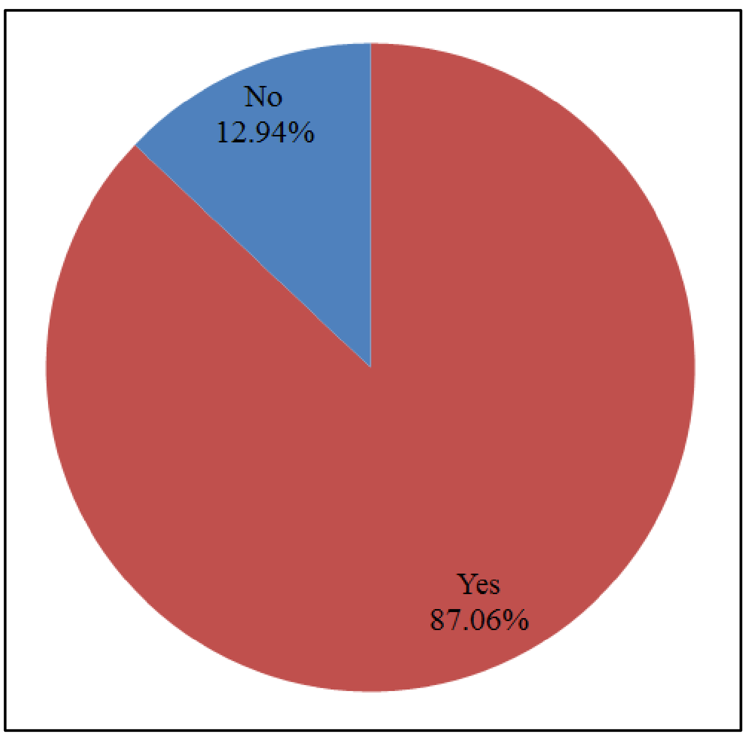



**Figure 4-25 Driver License (Non-Commuting Trips)**

The majority of non-commuting trip makers are living in a single detached house (70.21%), as shown in Figure 4-26, followed by those living in an apartment (15.16%), and then those living in a townhouse (10.80%). In terms of occupation, the majority of non-commuting trips are made by professionals (53.20%), as illustrated in Figure 4-27, while 11.22% of non-commuting trips were made by businesspersons. In addition, over 50% of people are involved in generating non-commuting trips have salaries over $65,000, as depicted in Figure 4-28. This indicates that professional people living in single detached houses and having comparatively higher salaries are making a higher percentage of non-commuting trips.

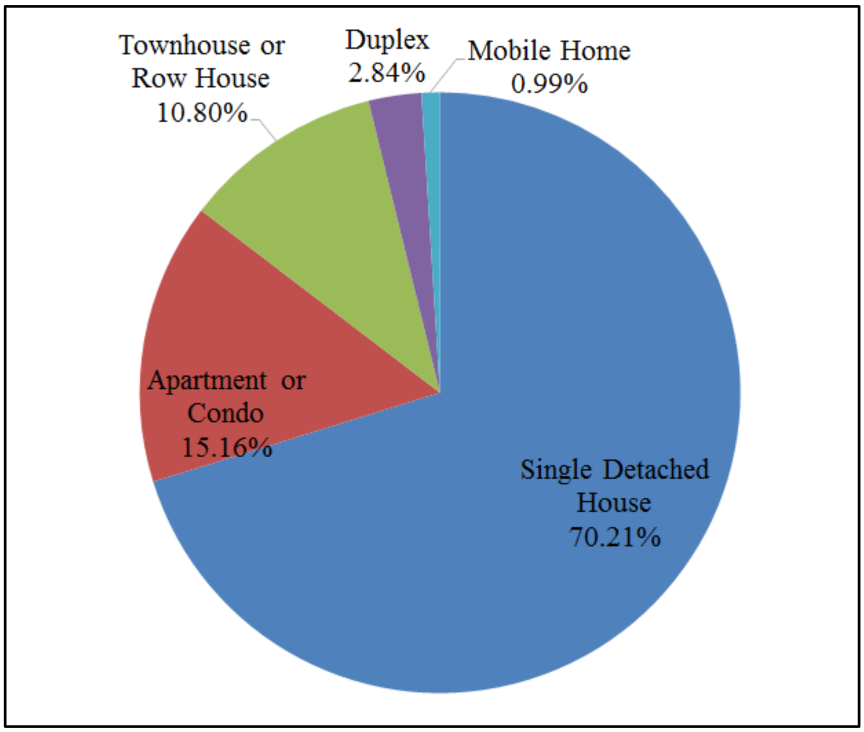



**Figure 4-26 Dwelling Type Distribution (Non-Commuting Trips)**

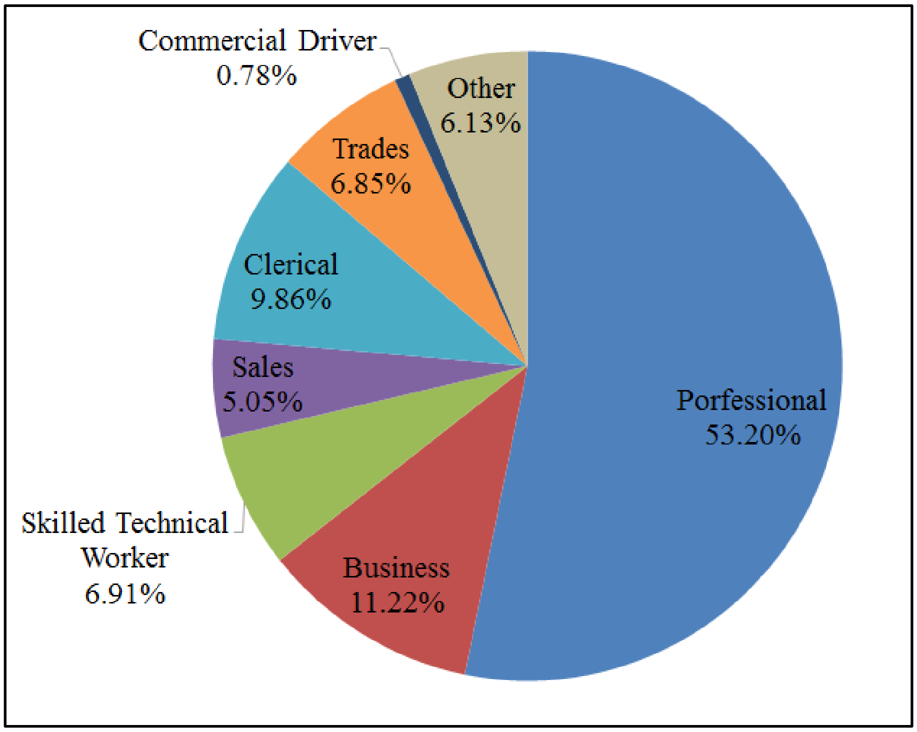



**Figure 4-27 Occupation Distribution (Non-Commuting Trips)**

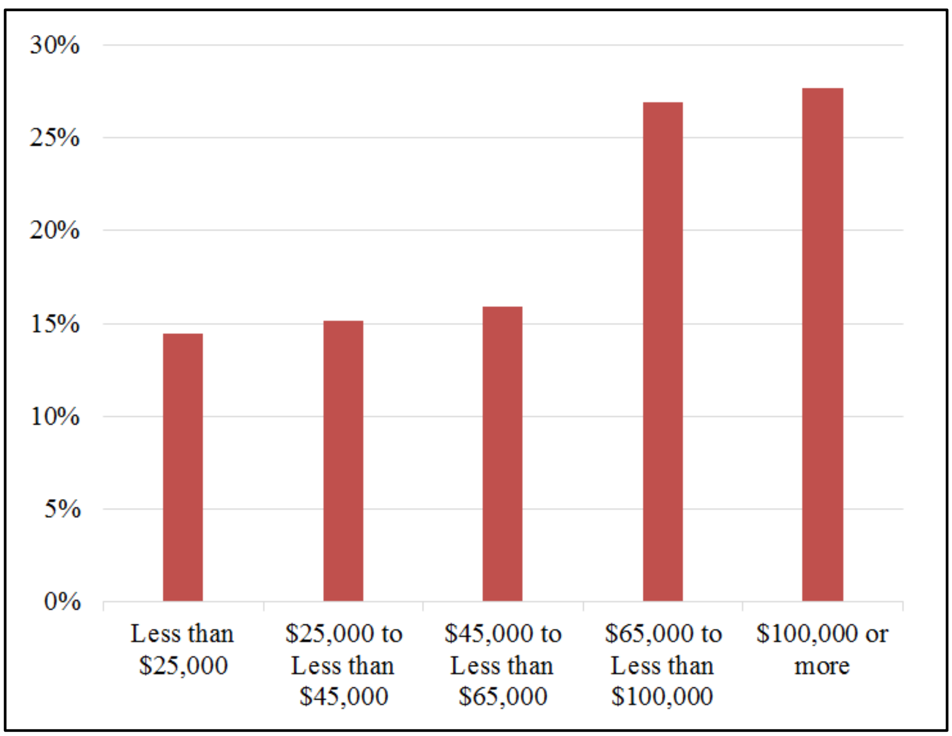



**Figure 4-28 Income Distribution (Non-Commuting Trips)**

The majority of non-commuting trips (86.13%) are made by using cars where car drivers are responsible for 69.54% of non-commuting trips, as shown in Figure 4-29. However, slightly more than 10% of people take active transportation in making non-commuting trips. Furthermore, transit ridership is very low (2.76%) in non-commuting trips. The school bus option is absent in non-commuting trips.

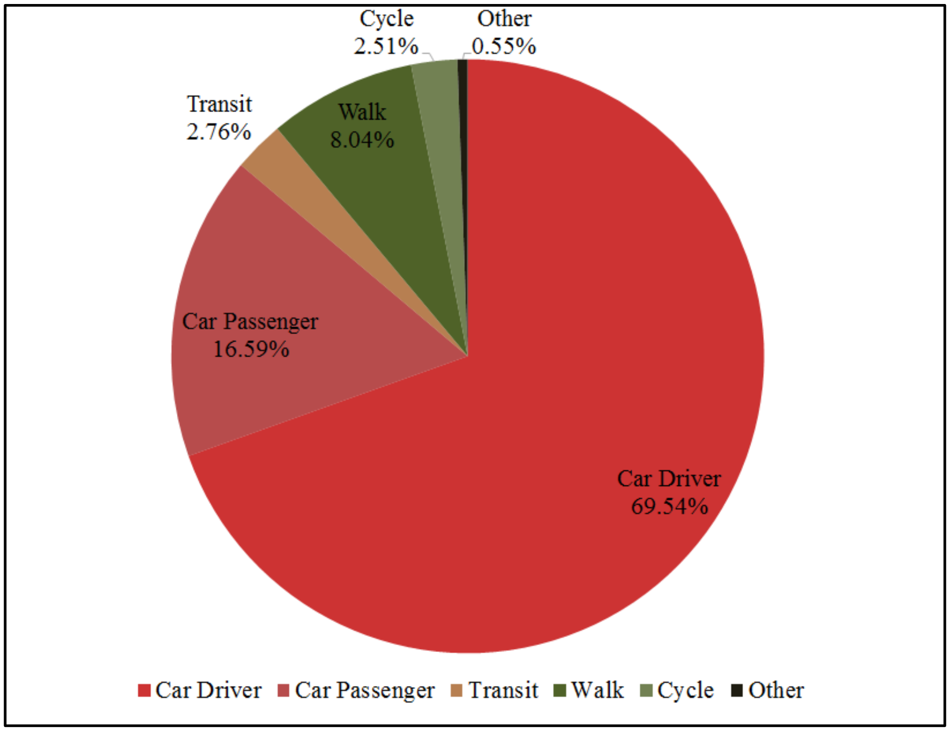



**Figure 4-29 Modal Share (Non-Commuting Trips)**

### 4.3.3 Vehicle Occupancy

Average car occupancies were estimated from the 2013 HHTS by analyzing the answer of the survey question: "When travelling by automobile, how many people travelled with you?" By summing up the number of passengers (i.e. people who rode with the driver) in a specific vehicle, average vehicle occupancies were calculated. If the driver drove alone then the occupancy of the vehicle was taken as 1. Average transit bus and school bus occupancies were acquired from the Sustainable Transportation Partnership of the Central Okanagan (STPCO) and School District (SD) No. 23 respectively. STPCO is a partnership of four local governments, a first nation, and the regional district of Central Okanagan. The average vehicle occupancies for different travel modes are shown in Table 4-5.

**Table 4-5 Average Vehicle Occupancy**

| Travel Mode | Car Driver | Car Passenger | Transit Bus | School Bus |
|---|---|---|---|---|
| **Vehicle Occupancy** | 1.39 | 2.69 | 10 | 50 |

### 4.3.4 GHG Emissions Factors

Data on average vehicle kilometres travelled (VKT), number of registered vehicles, and total GHG emissions was extracted from the Community Energy and Emissions Inventory (CEEI) (Ministry of Environment, 2014b). Different vehicle types, fuel types, fuel consumption, and corresponding emissions were recorded in the CEEI report. The previous data was used to calculate weighted average emissions factors for the car and transit options. Emissions factors, however, have changed between 2007 and 2010 due to the changes in fuel content as well as the imposed legislation to use renewable fuel (Ministry of Environment, 2014a). The most updated emissions factors obtained from the CEEI report are shown in Table 4-6.

**Table 4-6 GHG Emission Factors (Ministry of Environment, 2014b)**

| | | Total Consumptions (Litres) | No. of Vehicles | Average VKT (km/veh) | GHG ($CO_2$ eq. ton) | EF[1] (kg/km) | Ave. EF[2] (kg/km) |
|---|---|---|---|---|---|---|---|
| **Small Passenger Cars** | Hybrid | 64,366 | 58 | 21,100 | 144 | 0.118 | 0.278 |
| | Gasoline | 40,006,983 | 25,125 | 16,600 | 89,728 | 0.215 | |
| | Diesel | 1,098,410 | 682 | 23,900 | 2,913 | 0.179 | |
| **Large Passenger Cars** | Hybrid | 348,611 | 243 | 25,300 | 776 | 0.126 | |
| | Gasoline | 23,244,105 | 12,350 | 16,500 | 52,202 | 0.256 | |
| | Diesel | 166,165 | 123 | 14,500 | 440 | 0.247 | |
| **Light trucks, Vans, SUVs** | Hybrid | 271,452 | 118 | 26,400 | 612 | 0.196 | |
| | Gasoline | 93,983,001 | 32,497 | 20,100 | 212,846 | 0.326 | |
| | Diesel | 3,096,191 | 970 | 19,800 | 8,190 | 0.426 | |
| | Other | 238,570 | 120 | 11,700 | 365 | 0.260 | |
| **Buses** | Gasoline | 302,518 | 113 | 17,500 | 677 | 0.342 | 0.543 |
| | Diesel | 604,612 | 115 | 18,900 | 1,579 | 0.726 | |

[1] Emission Factors
[2] Weighted Average Emission Factors

### 4.3.5 Land Use Data

Land use data was quantified at the Traffic Analysis Zone (TAZ)'s level by combining information from census, BC Assessment, Canada Business Points, and enrolment counts from Central Okanagan School District (SD23), among other sources. Density, diversity, and design indicators (also known as Cervero's 3D) were considered as the land use variables in this research. The variables corresponding to each indicator are as follows:

- Density indicators included activity density and school job density in each neighborhood of the City of Kelowna. Activity density was measured by combining the density of population and jobs within a specific neighborhood. The descriptive statistics of density indicators are shown in Table 4-7.

- Diversity indicators indicate the mixed use of land within a specific area. Mixed land use was measured in terms of entropy (a measure of the homogeneity of an area). Entropy for diversity indicators was calculated according to Equation (4-1) (Zhang et al., 2012; Zhang, 2004). The value of entropy lies between zero and one, with higher values indicating a better balance of mixed land use. Different entropies were calculated to capture the effect of mixed land use (residential/non-residential) and mixed employment (retail/non-retail) at both trip origins and destinations. The descriptive statistics of diversity parameters are shown in Table 4-7.

$$\text{Entropy} = -\frac{\sum_j [\, P_j \times \ln P_j \,]}{\ln J} \tag{4-1}$$

  Where, $P_j$ is the proportion of land development of the $j^{th}$ type and J is the number of different land use types.

- Design indicators included availability of bus stops, sidewalks, and bike paths within suitable proximity (400 m) from trip origins and destinations. These indicators provide an idea about the transit bus availability and the infrastructure availability for active transportation.

**Table 4-7 Characteristics of Built Environment and Land Use Variables**

| Variables | Commuting Trips | | | Non-commuting Trips | | |
|---|---|---|---|---|---|---|
| | Mean | Median | Standard Deviation | Mean | Median | Standard Deviation |
| Population density at origin (person/hectare) | 10.26 | 9.37 | 4.71 | 11.31 | 14.12 | 4.65 |
| Population density at destination (person/hectare) | 10.42 | 9.37 | 4.70 | 11.23 | 14.11 | 4.67 |
| Employment density at origin (person/hectare) | 12.06 | 6.87 | 11.29 | 14.66 | 6.86 | 11.86 |
| Employment density at destination (person/hectare) | 12.60 | 6.87 | 11.28 | 14.38 | 6.87 | 11.90 |
| Activity density at origin (person/hectare) | 25.97 | 20.99 | 15.93 | 25.97 | 20.99 | 15.93 |
| Activity density at destination (person/hectare) | 25.61 | 20.99 | 16.00 | 25.61 | 20.99 | 16.00 |
| School job density at origin (person/hectare) | 0.18 | 0.13 | 0.10 | 0.18 | 0.13 | 0.10 |
| School job density at destination (person/hectare) | 0.18 | 0.13 | 0.10 | 0.18 | 0.13 | 0.10 |
| Mixed land use at origin (entropy: residential, and jobs) | 0.90 | 0.94 | 0.11 | 0.90 | 0.94 | 0.11 |
| Mixed land use at destination (entropy: residential, and jobs) | 0.90 | 0.94 | 0.11 | 0.90 | 0.94 | 0.11 |
| Mixed employment at origin (entropy: retail, non-retail, and school jobs) | 0.57 | 0.52 | 0.10 | 0.57 | 0.52 | 0.09 |
| Mixed employment at destination (entropy: retail, non-retail, and school jobs) | 0.57 | 0.52 | 0.1 | 0.57 | 0.52 | 0.09 |

## 4.4 Summary

This chapter described the study area and the different sources of data used in this research. The City of Kelowna was selected as the study area for this investigation. This chapter also described population growth projection of the city and its transportation networks including road, active transportation, and public transportation networks. Further, this chapter thoroughly described the data from household travel survey and emissions inventories. In addition, land use data was quantified at the Traffic Analysis Zone (TAZ)'s level by combining different sources, such as census, BC Assessment, Canada Business Points, and enrolment counts from Central Okanagan School District (SD23).

# Chapter 5: Modelling Results

## 5.1 Outline

This chapter presents the methodology to apply, and results of applying, TRIBUTE to explore the impacts of land use on passenger transportation GHG emissions in the City of Kelowna as a case study. The following sections of this chapter are arranged as follows: generating level-of-service attributes for the individual trips recorded in the HHTS is presented in Section 5.2. The relationship between travel time and travel distance is modelled in Section 5.3. Modelling the base case scenario using existing land use and built environment attributes is presented in Section 5.4. Different future scenarios are modelled in Section 5.5. After applying TRIBUTE, expected GHG emissions from future scenarios are presented in Section 5.6.

## 5.2 Generating Level-of-Service Attributes

To develop the mode choice component of TRIBUTE, it was necessary to generate the Level-of-Service (LOS) attributes (i.e. travel time and travel distance) for each mode of travel for each trip, regardless of the actual chosen mode. In this study, LOS attributes were generated for car, transit, walk, and cycle options using the Google Directions API with the help of origin and destination postal codes collected from HHTS (Idris, 2013).

## 5.3 Relationship between Travel Distance and Travel Time

Link travel time is a function of traffic volume on that link (Spiess, 1990). Mathematically, link travel time can be estimated using a volume-delay function. A volume-delay function reflects the congested link travel time by taking into account the ratio of the total traffic volume to the maximum capacity of that link. The most commonly used volume-delay function is the Bureau of Public Roads (BPR) function, as shown in Equation (5-1) (Spiess, 1990):

$$t^{BPR}(v) = t_o[1 + \left(\frac{v}{c}\right)^{\alpha}], \tag{5-1}$$

where, $t_o$ is free flow travel time, v is traffic volume, c is the capacity of the road. The higher value of α represents congestion effects.

A volume-delay function is applicable where a detailed network data is available. The developed emissions model (TRIBUTE, as described in Chapter 3) does not deal with link volumes and does not require a transportation network model as it mainly relies on HHTS data. As such, it was necessary to translate the reduction in VKT (i.e. travel distance), in response to land use policies, in terms of travel time to feed in the mode choice model.

Modelling the relationship between travel distance and travel time using linear regression is not uncommon in the literature. Harmel and Janda (2015) studied the correlation between straight-line travel distance and travel time in upstate New York. The developed models showed a linear relationship between straight-line travel distance and travel time with a goodness of fit (R-squared) range of 0.685 to 0.973.

In this research, the relationship between travel distance and travel time was modelled using linear regression, described in Section 2.6.2.1. Different functional forms (linear and non-linear) for the relationship between travel distance and travel time were examined before selecting the linear functional form as the best fit. Figure 5-1 and Figure 5-2 show the scatter plot of the relationship between travel distance and travel time along with the developed models for car and transit, respectively. The detailed models are shown in Table 5-1. To check the constant variance, residual plots of the developed regression models are shown in Appendix D.

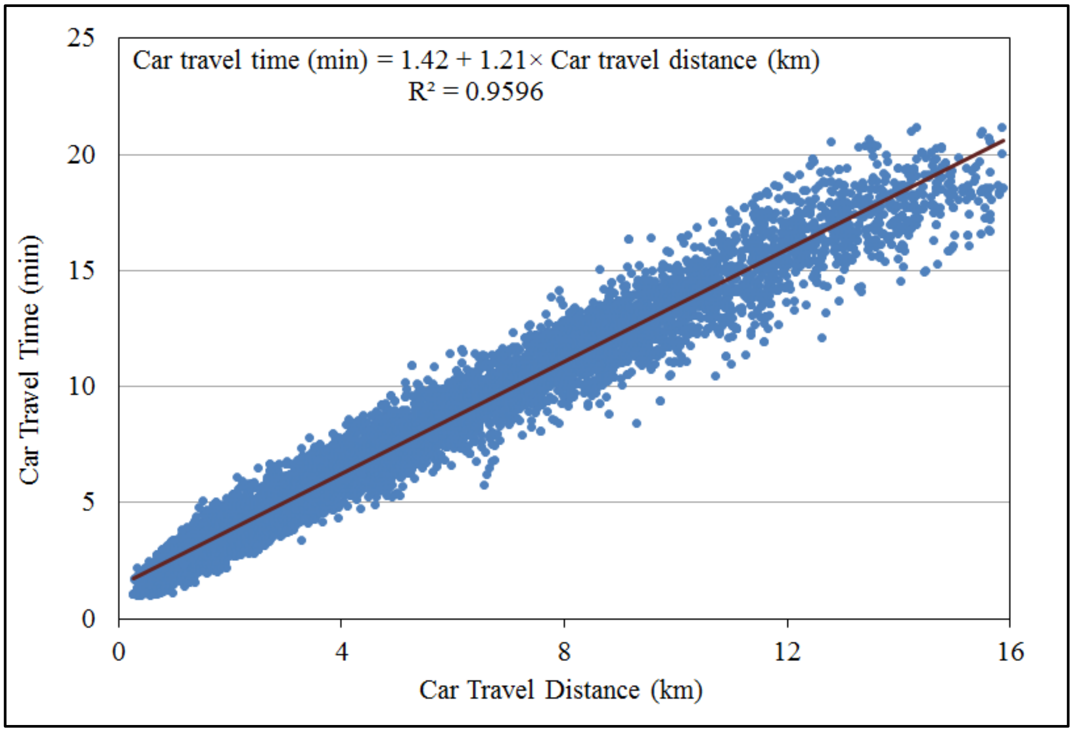



**Figure 5-1 Relationships between Travel Distance and Travel Time for Car**

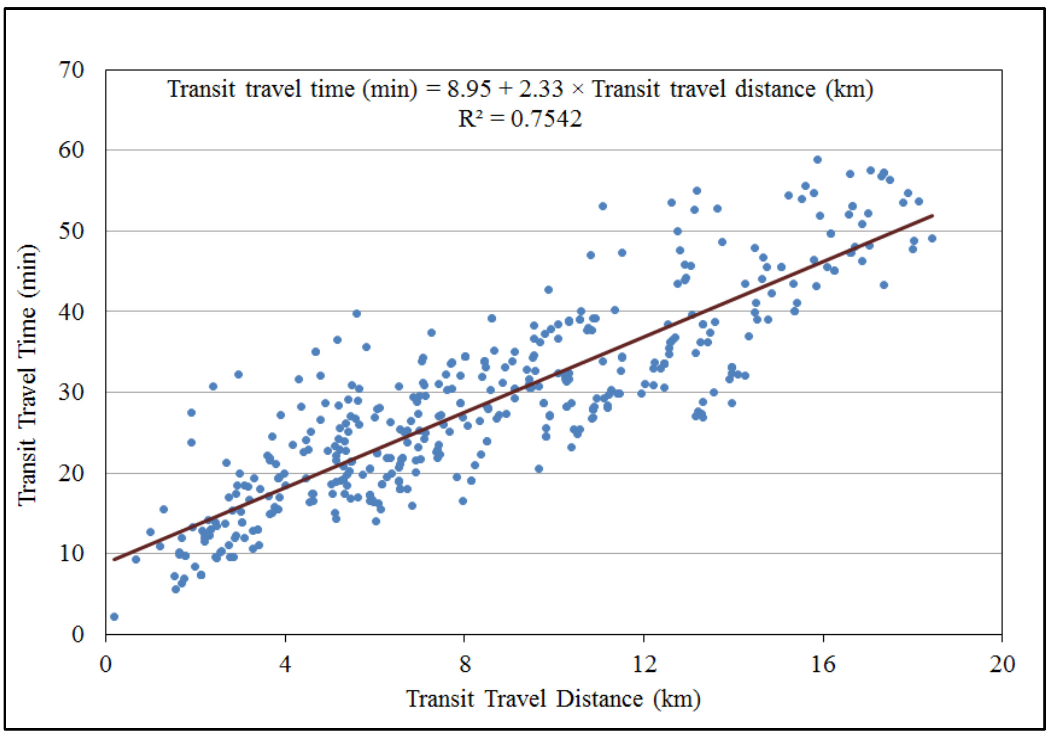



**Figure 5-2 Relationships between Travel Distance and Travel Time for Transit**

**Table 5-1 Relationships between Travel Distance and Travel Time**

| | Travel Time (Minutes) | |
|---|---|---|
| | **Car** | **Transit** |
| $R^2$ | 0.96 | 0.75 |
| Standard Error | 0.87 | 5.81 |
| **Variable** | **Parameter** | **Parameter** |
| Intercept | 1.42<br>(84.37)* | 8.95<br>(17.40)* |
| Travel Distance (Km) | 1.21<br>(472.01)* | 2.33<br>(36.58)* |

*Values between parentheses shows the t-statistics value

### 5.3.1 Error Analysis

To assess the predictability of the developed models, the standard error of the regression analysis was used to generate a prediction interval (PI) based on 95% confidence level. This indicates that the predicted value (travel time) of 95% of the sample (travel distance) falls within the interval around the linear regression (shown in Table 5-1). The prediction interval for the developed model was calculated by using Equation (2-21). The ranges of the prediction intervals were ±25% and ±45% for the developed linear regression models for car and transit, respectively. The estimated error envelope for the developed models for car and transit (shown in Table 5-1) are shown in Figure 5-3 and Figure 5-4, respectively.

$$(\widehat{TT}_{\text{Car}} - \widehat{TT}_{\text{Car}} \times 25\%) \leq \text{PI of } \widehat{TT}_{\text{Car}} \leq (\widehat{TT}_{\text{Car}} + \widehat{TT}_{\text{Car}} \times 25\%), \quad (5\text{-}2)$$

$$(\widehat{TT}_{\text{Transit}} - \widehat{TT}_{\text{Transit}} \times 45\%) \leq \text{PI of } \widehat{PKT}_{\text{Transit}} \leq (\widehat{TT}_{\text{Transit}} + \widehat{TT}_{\text{Transit}} \times 45\%), \quad (5\text{-}3)$$

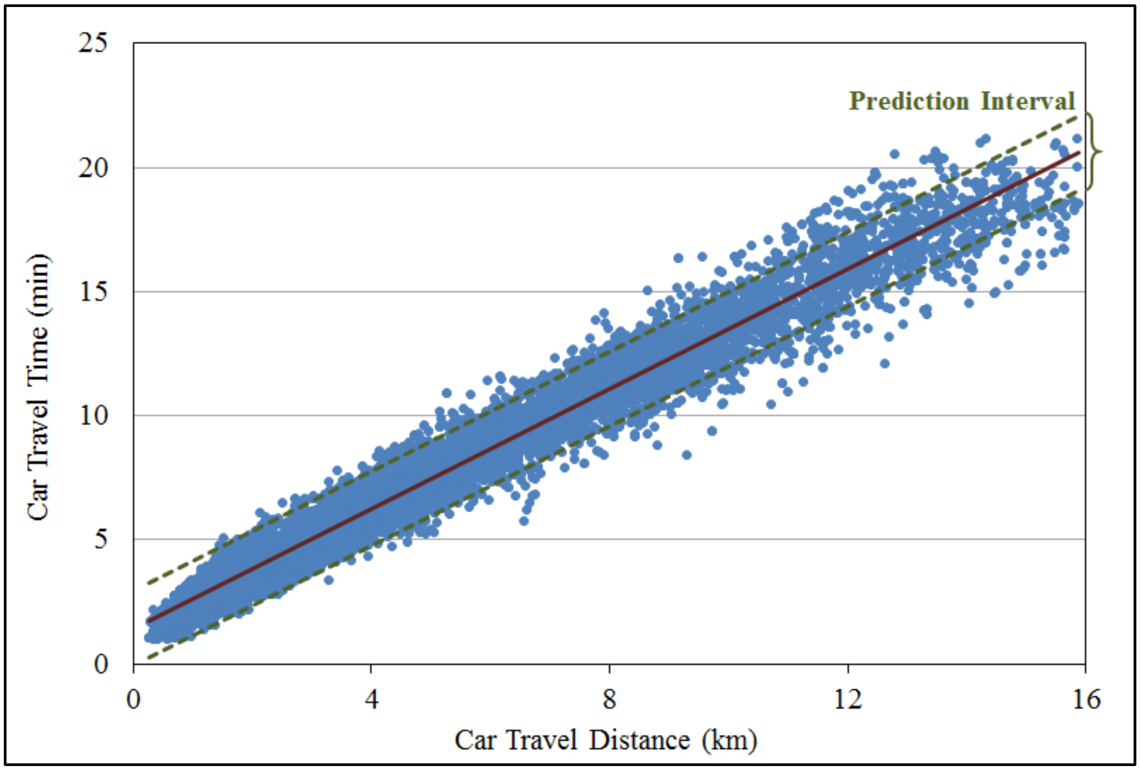



**Figure 5-3 Error Envelope of Travel Time and Travel Distance Estimation for Car**

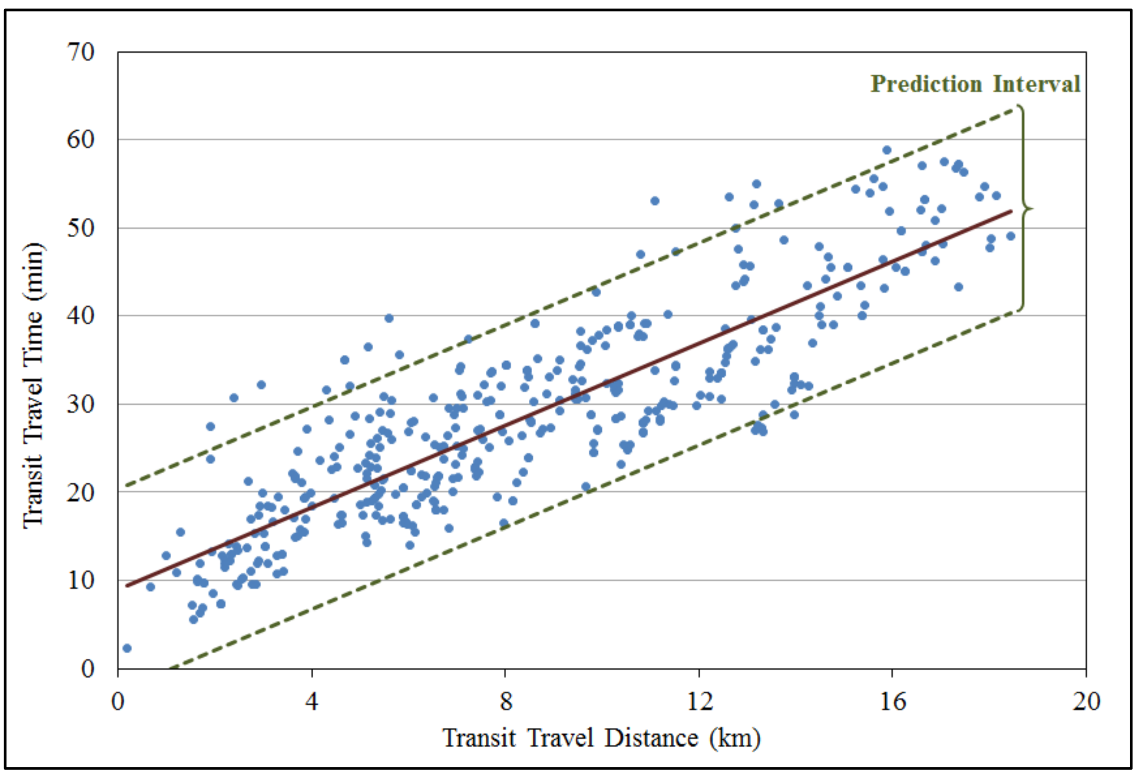



**Figure 5-4 Error Envelope of Travel Time and Travel Distance Estimation for Transit**

### 5.4 Passenger Kilometre Travelled (PKT) Estimation Model

As discussed earlier, VKT reduction can be attributed to two main factors: mode shift and trip length reduction (as shown in Figure 3-1). As such, PKT estimation models were developed for four travel options: car, transit, walk, and cycle to capture trip length reduction in response to policy changes. Existing land use and built environment attributes were used to develop PKT models to demonstrate their effect on distance travelled by each passenger. SPSS computer software was used in developing PKT estimation models.

#### 5.4.1 Dependent Variables

PKT was the only dependent variable of the developed models to estimate distance travelled by different travel options. Actual PKT values were used in model development. However, the actual values did not satisfy homoscedasticity, i.e. the constant variance assumption. Therefore, to fix this problem, different transformations were tried and finally, the square root transformation satisfied homoscedasticity. Furthermore, it was kept in mind that the PKT output of the model needed to be squared to get actual predicted PKT values.

#### 5.4.2 Explanatory Variables

Different land use and built environment attributes such as, density and diversity were considered as explanatory variables in the models. Activity density, sum of population density and employment density, was included in the model as the density indicators. On the other hand, mixed use of land and balanced employment types (as described in Section 4.3.5) were considered as the diversity indicators.

The explanatory variables were chosen in such a way to minimize the effect of multicollinearity. Multicollinearity assumption was verified by using Pearson's correlation coefficient on SPSS software. According to Gerstman (2016), the correlation coefficient can be classified as weak, moderate, and strong based on the range of less than 0.3, 0.3 to 0.7, and greater than 0.7, respectively. In this research, the threshold for the Pearson's correlation coefficient was taken as less than 0.3.

### 5.4.3 Empirical Analysis

Using ordinary least square analysis, PKT estimation models were developed by incorporating existing built environment and land use variables, as shown in Table 5-2. Although the models showed low goodness of fit, it is not uncommon to attain such $R^2$ value given the inherently high amount of unexplainable variability in the dataset (Cervero and Kockelman, 1997; Kockelman, 1995; Kockelman, 1996). For example, Kockelman (1997) studied the influence of various land use parameters, namely, accessibility, mixed land use, and land use balance on household VKT in the San Francisco Bay area. The author developed a household-based VKT model using multiple regressions analysis. The goodness of fit of the developed regression models were very low ($R^2$= 0.04 ~ 0.15) because of the large number of unexplained variability in the data.

**Table 5-2 PKT Estimation Models (Square Root of PKT)**

| | **Car** | **Transit** | **Walk** | **Cycle** |
|---|---|---|---|---|
| $R^2$ | 0.137 | 0.178 | 0.119 | 0.104 |
| Standard Error | 0.79 | 0.80 | 0.83 | 0.87 |
| **Variable** | **Parameter** | **Parameter** | **Parameter** | **Parameter** |
| Intercept | 6.13 (42.35)* | 7.99 (9.90)* | 5.79 (42.34)* | 5.77 (40.27)* |
| **Density Indicators** | | | | |
| Activity density at origin (Sum of population and job density) | -0.012 (-20.34)* | -0.014 (-5.46)* | -0.011 (-20.75)* | -0.011 (-19.51)* |
| Activity density at destination (Sum of population and job density) | -0.011 (-18.55)* | -0.018 (-7.23)* | -0.011 (-19.11)* | -0.011 (-17.82)* |

*Values within parentheses shows the t-statistics value

**Table 5-2 PKT Estimation Models (Square Root of PKT) (Continued)**

| | Car | Transit | Walk | Cycle |
|---|---|---|---|---|
| $R^2$ | 0.137 | 0.178 | 0.119 | 0.104 |
| Standard Error | 0.79 | 0.80 | 0.83 | 0.87 |
| **Variable** | **Parameter** | **Parameter** | **Parameter** | **Parameter** |
| Intercept | 6.13 (42.35)* | 7.99 (9.90)* | 5.79 (42.34)* | 5.77 (40.27)* |
| **Diversity Indicators** | | | | |
| Mixed land use at origin (Entropy: residential, and jobs) | -0.879 (-10.03)* | -1.547 (-3.59)* | -0.791 (-9.28)* | -0.71 (-7.94)* |
| Mixed land use at destination (Entropy: residential, and jobs) | -1.060 (-12.09)* | -0.553 (-13.33)* | -0.898 (-10.53)* | -0.836 (-9.35)* |
| Mixed employment at origin (Entropy: retail, non-retail, and school jobs) | -1.430 (-14.62)* | -2.073 (-4.76)* | -1.507 (-15.85)* | -1.577 (-15.84)* |
| Mixed employment at destination (Entropy: retail, non-retail, and school jobs) | -1.386 (-14.19)* | -2.220 (-5.08)* | -1.440 (-15.15)* | -1.431 (-14.37)* |

*Values within parentheses shows the t-statistics value

The modeling results, as shown in Table 5-2, indicated that the PKT has an inverse relationship with the built environment and land use indicators. The bullets below presents a detailed discussion on the developed models.

- Activity density demonstrated negative influence on PKT for all travel options. In particular, the parameter value of activity density at trip origin (-0.012) was higher than that at the destination (-0.011) for the car option. Although the effect was very small, density at the origin was more important than at the destination. However, the transit option showed the opposite result of the car. For the transit option, density at the destination was more dominant than that at the origin. On the other hand, density showed the same effect for active transportation (i.e. walk/cycle) users at both origin and destination.

- From the Table 5-2, it can also be said that the diversity indicators have a dominant effect on the PKT over density. The parameter values of the model for all travel modes were much higher than density. In particular, mixed use of land has a negative parameter value both at origin (-0.879) and destination (-1.060) for car travel modes. In addition, mixed use of land was more influential for transit, which has a parameter value -1.547 at origin. Furthermore, the PKT was greatly influenced by the balanced use of employment among different job categories. In general, diversity indicators showed higher PKT reduction for transit than that of other modes of travel.

The summary of the impacts of land use and built environment indicators on PKT is showing in Table 5-3. In general, land use indicators showed a negative impact on PKT. This also indicated that the increase in activity density, mixed use of land, and balanced use of different job categories would reduce the distance travelled by each passenger, and subsequently reduce VKT.

**Table 5-3 Resultant Impacts of Land Use and Built Environment on PKT**

| **Variables** | **Resultant Impacts on PKT for All Modes of Transportation (e.g. car, transit, walk, cycle)** |
|---|---|
| Activity density (person/acre) | Negative |
| Mixed land use (Entropy: residential, and jobs) | Negative |
| Mixed employment (Entropy: retail, non-retail, and school jobs) | Negative |

### 5.4.4 Model Prediction Error

To generate the prediction error envelope for the developed PKT estimation models, the same procedure was followed as described in Section 5.3.1. The range of the prediction error was 18% to 38% based on the different PKT estimation models for different travel modes. In particular, the PKT model for the transit travel option showed a smaller interval (±18%), while the PKT model for walk and cycle demonstrated larger prediction intervals (±38% and ±37%, respectively). Due to the disperse PKT values of walk and cycle options, the prediction interval was larger for walk and cycle. However, the prediction interval for the car fell between -24% and

+24%. The error envelopes for the developed PKT models are shown in equations (5-5) through (5-8):

$$(\widehat{PKT}_{\text{Car}} - \widehat{PKT}_{\text{Car}} \times 24\%) \leq \text{PI of } \widehat{PKT}_{\text{Car}} \leq (\widehat{PKT}_{\text{Car}} + \widehat{PKT}_{\text{Car}} \times 24\%), \tag{5-4}$$

$$\begin{aligned}(\widehat{PKT}_{\text{Transit}} - \widehat{PKT}_{\text{Transit}} \times 18\%) &\leq \text{PI of } \widehat{PKT}_{\text{Transit}} \\ &\leq (\widehat{PKT}_{\text{Transit}} + \widehat{PKT}_{\text{Transit}} \times 18\%),\end{aligned} \tag{5-5}$$

$$(\widehat{PKT}_{\text{Walk}} - \widehat{PKT}_{\text{Walk}} \times 38\%) \leq \text{PI of } \widehat{PKT}_{\text{walk}} \leq (\widehat{PKT}_{\text{Walk}} + \widehat{PKT}_{\text{Walk}} \times 38\%), \tag{5-6}$$

$$(\widehat{PKT}_{\text{Cycle}} - \widehat{PKT}_{\text{Cycle}} \times 37\%) \leq \text{PI of } \widehat{PKT}_{\text{Cycle}} \leq (\widehat{PKT}_{\text{Cycle}} + \widehat{PKT}_{\text{Cycle}} \times 37\%), \tag{5-7}$$

where, $\widehat{PKT}$ indicates the predicted PKT value of the model.

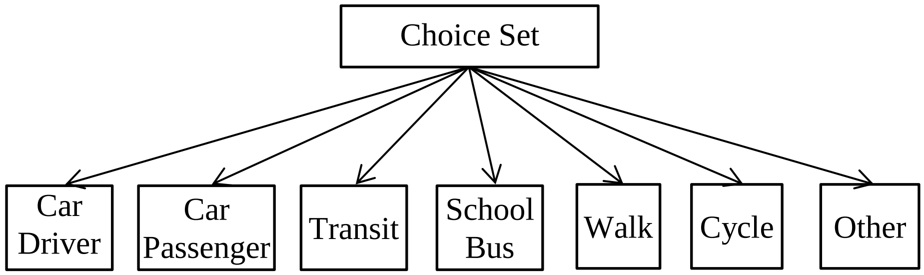
## 5.5 Base Case Estimates

### 5.5.1 Mode Choice Modelling

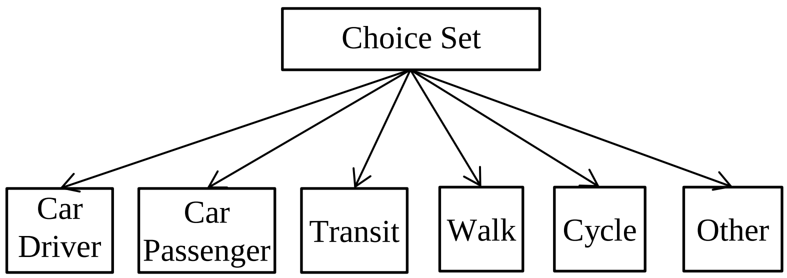
To calculate the base case estimates, the development of the mode choice model (as described in Section 3.2.1) was imperative. Separate mode choice models were developed for both commuting and non-commuting trips given the different choice behaviour associated with each of these trip purposes. The models were developed using land use and built environment indicators and transportation level-of-service attributes (e.g. travel time, travel distance, etc.), as discussed below.

#### 5.5.1.1 Modes of Travel

As mentioned earlier, two types of trip purposes were considered in this investigation, commuting and non-commuting trips. For commuting trips, a choice set of seven modes was used, including (1) car driver, (2) car passenger, (3) transit bus, (4) school bus, (5) walking, (6) cycling, and (7) others. For non-commuting trips, the school bus was excluded from the choice set given its irrelevance. The choice sets for the developed mode choice models are shown in Figure 5-5.




(a) Choice Set for Commuting Trips




(b) Choice Set for Non-commuting Trips

**Figure 5-5 Choice Set for Mode Choice Models**

The availability of the car driver option in the choice set was assumed based on driver's license holding and car ownership. If a person has a car as well as a driver's licence, then car was added to the model as an available option. However, missing either a car or a licence removed the car as an option from the choice set. On the other hand, car passenger and public transit were assumed available to all travelers.

The mode choice models also dealt with active transportation. From the HHTS and generated LOS attributes (as described in Section 5.2), the cumulative percentage of commuting and non-commuting trips were plotted with respect to the walk distance and cycle distance, as shown in Figure 5-6 and Figure 5-7, respectively. To get the available active transportation options, trip distance for 95% of trips was taken as a threshold. From Figure 5-6, it is seen that 95% of commuting walk trips were within 3 km, while 95% of commuting cycle trips were within 7 km. In the development of the mode choice model for commuting trips, trip distances of up to 3 km and 7 km were considered as having potential to attract walk and cycle trips, respectively.

In addition, the same threshold was applied for non-commuting trips to identify the travel distance for walk and cycle. For non-commuting trips, 95% of the walking trips were less than 3 km, while 95% of cycle trips were within 9 km. Therefore, the availability of walk and cycle as travel options in the mode choice model for non-commuting trips was determined based on 3 km and 9 km thresholds, respectively.

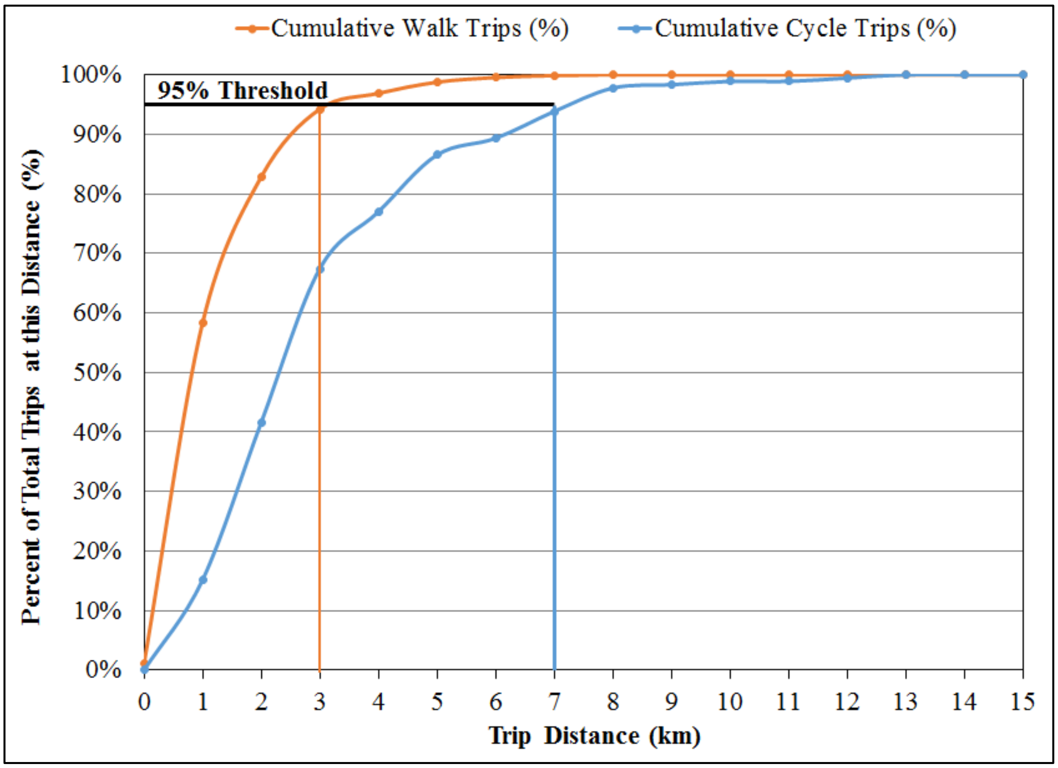



**Figure 5-6 Non-Motorized Trip Distance in Commuting Trips**

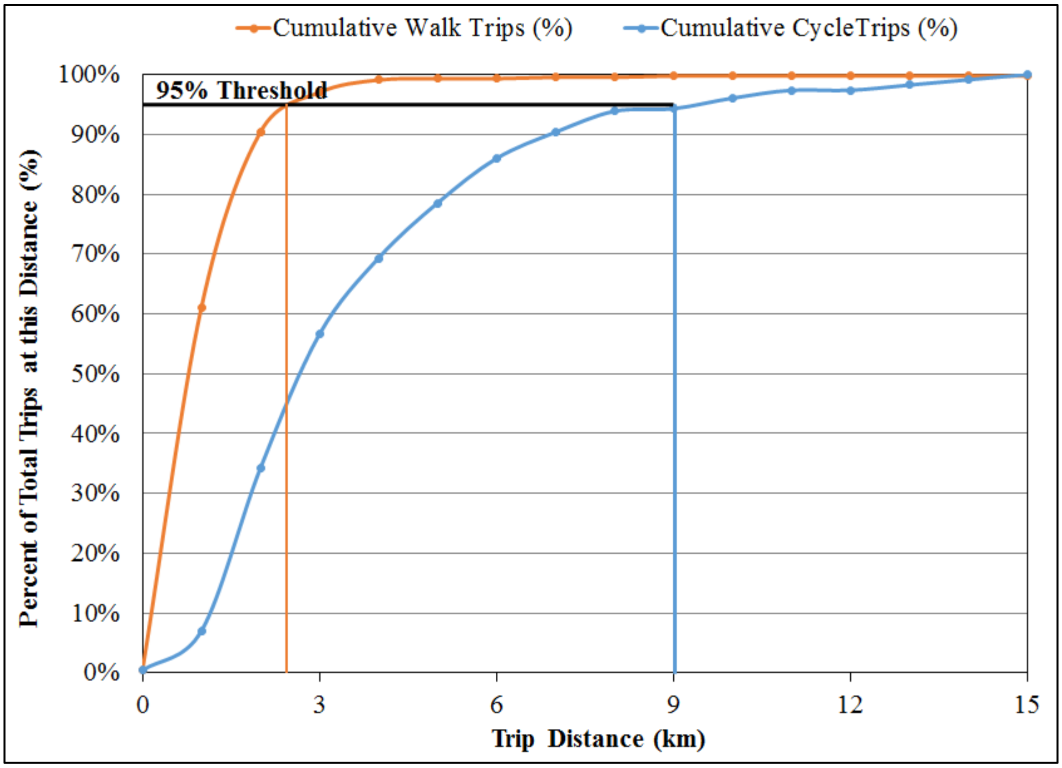



**Figure 5-7 Non-Motorized Trip Distance in Non-Commuting Trips**

#### 5.5.1.2 Empirical Analysis

The inclusion of parameters in the developed MNL models was determined based on the following three criteria (Koppelman and Bhat, 2006): a) informal tests, b) goodness of fit measures, and c) statistical tests. The informal tests consist of the sign of the parameters to evaluate reasonableness of the implications. The overall goodness of the fit measures were calculated based on the following equation (Ben-Akiva and Lerman, 1985):

$$\text{Goodness of fit} = 1 - \frac{\text{Final loglikelihood}}{\text{Null loglikelihood}} \tag{5-8}$$

where, the null likelihood of the model shows a model with no parameter value considering all alternatives as being equally likely to be chosen. The range of the goodness of the fit varies between 0 to 1, and the closer to the value of 1, the better the fit of the model (Day et al., 2010).

An open source software (BIOGEME), which was developed by Bierlaire (2003), was used to developed the MNL models. In terms of statistical significant, the critical value (1.96) of the t-statistic with a 95% confidence limit was considered as the threshold value of considering variables in the model. A series of specifications was tested and final specifications were reached based on the accommodation of variables with proper signs, overall goodness of fit, and statistical significance, at a 95% level of confidence test. However, some parameters with t-stat values lower than 1.96 were retained in the model because the corresponding variables provide considerable insight into the behavioural process, shown in Table 5-4. According to (Koppelman and Bhat, 2006), a low t-statistic value does not require removing a variable from the model if the variable has a strong reason to be included and the sign of its parameter is correct. Moreover, the inclusion of the insignificant parameters may improve the overall predictability of the model (Cervero, 2002). According to McFadden, Rho-squared values between 0.2 and 0.4 indicate excellent fit for discrete mode choice models (McFadden, 1977). Given the Rho-squared values of 0.443 and 0.524 for commuting and non-commuting trips, respectively, shown in Table 5-4, the developed models have acceptable goodness of fit and explanatory power. In addition, significance test of the model was tested by calculating confidence interval for parameters (Hosmer and Lemeshow, 2000), shown in Equation (5-9) and Equation (5-10).

A 100(1-α)% confidence interval for the slope coefficients:

$$\widehat{\beta_1} \pm z_{1-\alpha/2}\, \widehat{\mathrm{SE}}(\widehat{\beta_1}), \tag{5-9}$$

And for the intercept:

$$\widehat{\beta_0} \pm z_{1-\alpha/2}\, \widehat{\mathrm{SE}}(\widehat{\beta_0}), \tag{5-10}$$

where is the upper 100(1- α/2)% point from the standard normal distribution and $\widehat{\mathrm{SE}}(\cdot)$ denotes standard error of the respective parameter estimator.

**Table 5-4 Mode Choice Models**

| Variable | Mode | Commuting Trips | | | Non-Commuting Trips | | |
|---|---|---|---|---|---|---|---|
| Null Log-Likelihood | | -8,299.307 | | | -13,785.797 | | |
| Final Log-Likelihood | | -4,624.26 | | | -6,565.491 | | |
| Rho-Squared | | 0.443 | | | 0.524 | | |
| **Variable** | **Mode** | **Parameter** | **Std. Error** | **t-Stat** | **Parameter** | **Std. Error** | **t-Stat** |
| Alternative Specific Constant | Auto | **5.910** | 0.392 | 15.31 | **7.000** | 0.471 | 14.87 |
| | Auto Passenger | **7.710** | 0.560 | 14.72 | **5.170** | 0.512 | 10.04 |
| | Transit Bus | **-4.660** | 1.240 | -4.48 | **-0.303** | 1.180 | -0.26 |
| | School Bus | **1.860** | 0.229 | 8.14 | No school bus | | |
| | Walk | **5.890** | 0.749 | 7.91 | **5.680** | 0.502 | 11.30 |
| | Bike | **3.040** | 0.854 | 4.98 | **3.110** | 0.326 | 9.53 |
| | Other | Fixed | | | Fixed | | |
| **Density Indicators** | | | | | | | |
| Activity density at origin (Person/Acre) | Auto Passenger | **-0.0115** | 0.00395 | -2.39 | -0.004 | 0.002 | -1.75 |
| Activity density at destination (Person/Acre) | Auto Passenger | **-0.0236** | 0.00386 | -6.05 | -0.00316 | 0.0022 | -1.44 |
| | Transit Bus | - | | - | 0.00865 | 0.00564 | 1.53 |
| School job density at origin (Job/Acre) | Auto | **-0.926** | 0.365 | -2.53 | - | | - |
| | Auto Passenger | - | | - | **-0.894** | 0.401 | -2.23 |
| | Walk | 0.019 | 1.000 | 0.02 | 0.110 | 0.685 | 0.16 |
| | Bike | 0.167 | 0.690 | 0.24 | 0.371 | 0.807 | 0.46 |
| School job density at destination (Job/Acre) | Auto | -0.470 | 0.559 | -0.86 | - | | - |
| | Auto Passenger | - | | - | -0.374 | 0.428 | -0.87 |
| | Walk | - | | - | 0.256 | 0.722 | 0.35 |
| | Bike | - | | - | 0.652 | 0.833 | 0.78 |

Bold text indicates statistically significant values at the 95% confidence level ($p<0.05$)

**Table 5-4 Mode Choice Models (Continued)**

| Variable | Mode | Commuting Trips | | | Non-Commuting Trips | | |
|---|---|---|---|---|---|---|---|
| Null Log-Likelihood | | -8,299.307 | | | -13,785.797 | | |
| Final Log-Likelihood | | -4,624.26 | | | -6,565.491 | | |
| Rho-Squared | | 0.443 | | | 0.524 | | |
| **Variable** | **Mode** | **Parameter** | **Std. Error** | **t-Stat** | **Parameter** | **Std. Error** | **t-Stat** |
| **Diversity Indicators** | | | | | | | |
| Mixed land use at origin (Entropy: residential, and jobs) | Auto Passenger | **-1.100** | 0.454 | -2.08 | - | | - |
| | Transit Bus | **4.360** | 0.888 | 4.98 | 1.210 | 0.941 | 1.28 |
| Mixed land use at destination (Entropy: residential, and jobs) | Auto Passenger | **-1.530** | 0.536 | -2.67 | - | | - |
| | Transit Bus | **3.320** | 0.881 | 5.00 | 0.186 | 0.904 | 0.21 |
| | Bike | **1.810** | 0.867 | 2.39 | - | | - |
| Mixed employment at origin (Entropy: retail, non-retail, and school jobs) | Auto | - | | - | -0.764 | 0.400 | -1.91 |
| | Walk | 0.270 | 1.600 | 0.17 | - | | - |
| Mixed employment at destination (Entropy: retail, non-retail, and school jobs) | Auto | -0.482 | 0.658 | -0.75 | -0.828 | 0.611 | -1.36 |
| | Auto Passenger | - | | - | -0.651 | 0.717 | -0.91 |
| | Walk | 0.848 | 1.250 | 0.68 | - | | - |

Bold text indicates statistically significant values at the 95% confidence level (p<0.05)

**Table 5-4 Mode Choice Models (Continued)**

| | | Commuting Trips | | | Non-Commuting Trips | | |
|---|---|---|---|---|---|---|---|
| Null Log-Likelihood | | -8,299.307 | | | -13,785.797 | | |
| Final Log-Likelihood | | -4,624.26 | | | -6,565.491 | | |
| Rho-Squared | | 0.443 | | | 0.524 | | |
| **Variable** | **Mode** | **Parameter** | **Std. Error** | **t-Stat** | **Parameter** | **Std. Error** | **t-Stat** |
| **Design Indicators** | | | | | | | |
| Bus stop availability at origin (Yes) | Auto | - | | - | **-0.297** | 0.129 | -2.30 |
| | Auto Passenger | -0.116 | 0.120 | -0.97 | -0.178 | 0.147 | -1.21 |
| | Transit Bus | **0.668** | 0.194 | 3.42 | 0.415 | 0.291 | 1.43 |
| Bus stop availability at destination (Yes) | Auto | - | | - | -0.075 | 0.073 | -1.03 |
| | Transit Bus | **1.010** | 0.215 | 4.67 | **0.862** | 0.304 | 2.84 |
| Sidewalk availability at origin (Yes) | Walk | 0.607 | 0.427 | 1.42 | 0.120 | 0.373 | 0.32 |
| Sidewalk availability at destination (Yes) | Walk | - | | - | 0.006 | 0.360 | 0.02 |
| **Level-of-Service Attributes** | | | | | | | |
| Travel Time (min) | Auto | **-0.063** | 0.012 | -5.20 | **-0.091** | 0.020 | -4.56 |
| | Auto Passenger | **-0.194** | 0.016 | -12.32 | **-0.078** | 0.021 | -3.78 |
| | Transit Bus | -0.005 | 0.004 | -1.24 | **-0.022** | 0.006 | -3.53 |
| Travel Distance (km) | Walk | **-1.640** | 0.079 | -20.71 | **-1.170** | 0.056 | -21.02 |
| | Bike | **-0.351** | 0.031 | -11.51 | **-0.385** | 0.042 | -9.08 |

Bold text indicates statistically significant values at the 95% confidence level ($p<0.05$)

The developed mode choice models are sensitive to land use variables such as, density, diversity, and design indicators in addition to LOS attributes. The effects of land use variables are discussed in the following bullets.

- Activity density, sum of population density and job density, was considered as one of the density indicators in the mode choice models. Overall, activity density showed a positive impact on transit, but a negative impact on car users. In particular, activity density has a stronger reciprocal relationship with car use for commuting trips than non-commuting trips. In addition, lower parameter values for activity density in non-commuting trips indicates lower effects of density on choosing travel modes. On the other hand, school jobs density showed strong negative impacts on car use for both commuting and non-commuting trips. In addition, school jobs density has a positive sign for active transportation, which indicates that an increase in school jobs density leads to an increase in active transportation modal shares. Furthermore, activity at trip destination was more important than that at its origin, whereas school job density showed more influence on promoting active transportation at trip origin than at trip destination.

- Diversity indicators were measured in terms of mix use of land (entropy) calculation. The developed mode choice model was sensitive to two types of diversity indicators: mixed use of land in terms of population and employment, and mixed use of jobs in terms of retail, non-retail, and school jobs. The parameter values associated with the diversity indicators were very high for the transit options. On the other hand, diversity indicators showed a negative sign for car users and the parameter values were higher than the density indicators. From
- Table 5-4 5-4 it can be seen that the mixed use of land was more important in terms of increasing public transit and active transportation than that of density indicators. Furthermore, diverse use of land at origin was more important than at destination for commuting trips. However, non-commuting trips showed mixed use of land at destination was more important than at origin.

- In this investigation, the availability of bus stops and sidewalks at both origin and destination were considered as design indicators. The availability of bus stops demonstrated positive parameter value for transit and negative parameter value for car use indicating that the availability of bus stops is important to promote public transit. However, the lower parameter value for availability of bus stops at origin indicated the bus stop at destination was more important than bus stop at origin. On the other hand, availability of sidewalks was associated with the positive parameter value for the walk option, and has higher parameter value at origin than destination.

- The fourth explanatory variable of the mode choice model was modal attributes that include travel time for motorized travel modes and travel distances for non-motorized travel modes. The developed mode choice models showed a negative parameter value for modal attributes. In addition, the walking option was affected more by the increase in travel distance between origins and destinations.

The summary of the impacts of land use and built environment indicators on choosing travel modes is shown in Table 5-5. In general, there was a negative influence of land use indicators on using the car option. Conversely, a positive relationship was observed for transit and active transportation. This indicates that the increase in density and better mix of land use would promote transit and active transportation at the expense of car use.

**Table 5-5 Resultant Impacts of Land Use and Built Environment on Mode Choice**

| **Variables** | **Resultant Impact on Different Modes** | | |
|---|---|---|---|
| | **Cars** | **Transit** | **Active Transportation** |
| Activity density (person/acre) | Negative | Positive | Positive |
| School job density (job/acre) | Negative | Positive | Positive |
| Mixed land use (Entropy: residential, and jobs) | Negative | Positive | Positive |
| Mixed employment (Entropy: retail, non-retail, and school jobs) | Negative | Positive | Positive |
| Bus stop availability (yes/no) | Negative | Positive | Positive |
| Sidewalk availability (yes/no) | Negative | Positive | Positive |

#### 5.5.1.3 Forecasting Performance

In this study, the entire dataset was used for model estimation. As such, market segmented subsets were used to validate the developed mode choice models and measure their forecasting performance. In particular, two subsets were created based on vehicle ownership (including 0 vehicle, 1 vehicle, 2 vehicles, and 3+ vehicles) and geographic location (including trips originated in central city and trips originated outside central city), as shown in Table 5-6 and Table 5-7, respectively.

The Forecasting Performance Measure (FPM) was quantified for both subsets. For vehicle ownership segmentation, FPM values were between 0.566 and 1.617 (Shown in Table 5-6). The aggregate forecasting error of the developed models was smaller (0.566) for single vehicle availability than multi vehicles availability (1.617 and 1.314). On the other hand, the geographic location segmentation showed even smaller (0.029 and 0.186) FPM value than the market segment subset of vehicle ownership. Idris et al. (2015) studied the mode shift model forecasting performance of five different developed mode choice models, where the FPM values were between 0.003 and 1.974. Given the FPM values between 0.566 and 1.617 for vehicle ownership segment, and between 0.029 and 0.186 for geographic location segment, it can be concluded that the developed models have acceptable forecasting power.

**Table 5-6 FPM of the Developed Mode Choice Models based on Vehicle Ownership Segmentation**

| Mode Alternative | Observed Mode Choice | Predicted Mode Choice | Mode choice difference (Predicted - Observed) | FPM |
|---|---|---|---|---|
| **0 Vehicle** | | | | |
| Car Driver | 6.99% | 12.62% | 5.63% | 1.346 |
| Car Passenger | 12.05% | 10.37% | -1.68% | |
| Transit Bus | 38.80% | 35.78% | -3.02% | |
| School Bus | 0.00% | 0.00% | 0.00% | |
| Walk | 35.18% | 36.33% | 1.15% | |
| Cycle | 4.82% | 4.50% | -0.32% | |
| Other | 2.17% | 0.40% | -1.77% | |
| **1 Vehicle** | | | | |
| Car Driver | 59.56% | 65.21% | 5.65% | 0.566 |
| Car Passenger | 17.14% | 14.56% | -2.58% | |
| Transit Bus | 5.01% | 4.45% | -0.56% | |
| School Bus | 0.76% | 0.96% | 0.20% | |
| Walk | 12.21% | 10.73% | -1.48% | |
| Cycle | 5.04% | 3.64% | -1.40% | |
| Other | 0.28% | 0.45% | 0.17% | |
| **2 Vehicles** | | | | |
| Car Driver | 71.30% | 66.70% | -4.60% | 1.617 |
| Car Passenger | 15.12% | 15.49% | 0.37% | |
| Transit Bus | 2.32% | 4.26% | 1.93% | |
| School Bus | 1.56% | 1.23% | -0.33% | |
| Walk | 6.75% | 8.49% | 1.74% | |
| Cycle | 2.67% | 3.33% | 0.66% | |
| Other | 0.27% | 0.51% | 0.24% | |
| **3+ Vehicles** | | | | |
| Car Driver | 74.95% | 68.03% | -6.92% | 1.314 |
| Car Passenger | 12.84% | 15.22% | 2.38% | |
| Transit Bus | 2.35% | 4.53% | 2.18% | |
| School Bus | 1.26% | 1.50% | 0.23% | |
| Walk | 5.26% | 7.03% | 1.77% | |
| Cycle | 2.42% | 3.17% | 0.74% | |
| Other | 0.91% | 0.53% | -0.38% | |

**Table 5-7 FPM of the Developed Models based on Geographic Location Segmentation**

| Mode Alternative | Observed Mode Choice | Predicted Mode Choice | Mode choice difference (Predicted - Observed) | FPM |
|---|---|---|---|---|
| **Trips Originated in Central City (Sector 3)** | | | | |
| Car Driver | 66.36% | 65.72% | -0.64% | 0.029 |
| Car Passenger | 13.91% | 13.80% | -0.11% | |
| Transit Bus | 4.06% | 4.65% | 0.59% | |
| School Bus | 0.52% | 0.95% | 0.43% | |
| Walk | 10.82% | 10.72% | -0.10% | |
| Cycle | 3.85% | 3.72% | -0.13% | |
| Other | 0.49% | 0.45% | -0.04% | |
| **Trips Originated Outside Central City** | | | | |
| Car Driver | 66.58% | 67.76% | 1.18% | 0.186 |
| Car Passenger | 17.22% | 17.42% | 0.20% | |
| Transit Bus | 5.02% | 3.94% | -1.08% | |
| School Bus | 2.42% | 1.62% | -0.79% | |
| Walk | 5.71% | 5.89% | 0.18% | |
| Cycle | 2.56% | 2.80% | 0.24% | |
| Other | 0.50% | 0.57% | 0.07% | |

### 5.5.2 Estimation and Validation

TRIBUTE was utilized by jointly running its mode choice and emissions forecasting models. Community Energy and Emissions Inventory (CEEI) reports were used for estimating and validating the TRIBUTE model. In the CEEI report, the total GHG emissions in 2007 and 2010 were calculated based on fuel consumption and number of vehicles in Kelowna, BC (Ministry of Environment, 2014b).

The mode choice component of TRIBUTE was first used to estimate the proportion of trips made by each mode. Next, the emissions forecasting component of TRIBUTE was used to calculate the total PKT by each mode given respective average modal PKT (calculated from CEEI reports). The total PKT was converted to total VKT. For this task, respective average vehicle occupancy was used (described in Section 4.3.3). Finally, the total GHG emissions from the transportation sector were calculated by multiplying the total VKT by each mode by respective average emissions factors. For model estimation, respective emissions factors were calculated from the CEEI report (described in Section 4.3.4).

For model validation, TRIBUTE was utilized to forecast the 2010 GHG emissions. The forecasted results were then compared to the total emissions reported in the 2010 CEEI report. Table 5-8 shows a comparison between the GHG emissions calculated using TRIBUTE and those reported in the CEEI reports. The validation results showed a very small difference (-0.3%) between the forecasted emissions using TRIBUTE and the reported emissions in 2010 CEEI report.

**Table 5-8 TRIBUTE Validation Results**

| | **TRIBUTE** | | **CEEI Report (Ministry of Environment, 2014b)** | |
|---|---|---|---|---|
| **Year** | **2007** | **2010** | **2007** | **2010** |
| Car Emissions ($CO_2$e ton) | 370,229 | 362,307 | 370,229 | 368,250 |
| Buses Emissions ($CO_2$e ton) | 3,224 | 7,588 | 3,224 | 2,280 |
| Other Emissions ($CO_2$e ton) | 891 | 644 | 891 | 1,185 |
| Total Emissions ($CO_2$e ton) | 374,344 | 370,539 | 374,344 | 371,715 |
| Difference | -0.3% | | | |

From Table 5-8, it is seen that the difference in total emissions calculation between TRIBUTE and CEEI report was very small (0.3%); emissions from individual modes (car, bus, and other), however, showed higher differences. In particular, TRIBUTE over-predicted bus emissions and under-predicted emissions from cars. This discrepancy was because of changes in the emissions factor in 2010. The emissions factor for buses became higher in 2010 than that of 2007. On the other hand, the car emissions factor went down in 2010 due to the introduction of hybrid cars as well as higher fuel efficiency. In addition to the emissions factor, modal share played an associating role for the discrepancy. Since TRIBUTE considered individual trips in estimating emissions, and transit share was higher in 2010 than 2007, TRIBUTE estimated higher emissions from buses in 2010. In general, TRIBUTE looks promising at estimating total emissions. However, estimated emissions from individual modes involved a higher degree of error.

## 5.6 Future Scenario Development

It is worth mentioning that TRIBUTE was used to help the City of Kelowna evaluate and select the best future density scenario to reduce GHG emissions in 2040 (Rahman et al., 2016). However, such real-world exercise is not included in this thesis due to the confidential nature of the project. For illustration, a hypothetical scenario was developed and tested using TRIBUTE considering a better land use mix in comparison to the business-as-usual (BAU) scenario. The assumptions behind the developed scenarios are described below.

- Existing Scenario (2013) – The existing scenario was developed based on the existing land use and built environment in the City of Kelowna in 2013. In this scenario, population density, job density, and mixed land use were calculated based on the present conditions.

- Business-as-Usual (BAU) Scenario – In the BAU case, population was altered to account for the expected total growth in population from 2013 to 2040. It was also assumed that the total number of jobs will follow the same growth rate as population. All other factors (e.g. distribution of population, land use types, locations, design indicators, etc.) were fixed across the city. This change has resulted in the same land use diversity in the BAU scenario as in the existing scenario.

- Hypothetical scenario – Similar to the BAU scenario, population and jobs were altered to account for the expected total growth in population and jobs from 2013 to 2040 in the hypothetical scenario, but with different distribution. In particular, population density was doubled in the urban core of the city and the remaining growth was distributed to the remaining sectors in a similar manner to the BAU. Moreover, employment density was re-allocated to balance the increase in population and maintain higher entropy (i.e. higher mix of land use) in all ten sectors. In addition, different types of jobs (retail, non-retail, and school jobs) were also re-allocated to attain the maximum mix of employment among different sectors in Kelowna. This hypothetical scenario can also be referred to as the Most Aggressive Scenario (MASc).

The developed scenarios were designed based on altering land use attributes (i.e. density and diversity). However, the developed emissions forecasting model, TRIBUTE, is also sensitive to changes in the transportation network, such as inclusion of high-bike-infrastructure, new transit route, etc. For simplicity, it was assumed that the public transit and active transportation infrastructure would be the same as the existing scenario in all future scenarios. This means that the number of bus stops, sidewalk coverage, bike paths coverage, road network, and transit route coverage of the City of Kelowna will be the same in 2040 as in 2013. This would control for confounding factors, and allow the developed MASc models to be focused on land use planning policies. Mixed land use and mixed employment in the BAU and hypothetical scenarios are shown in Figure 5-8 and Figure 5-9, respectively.

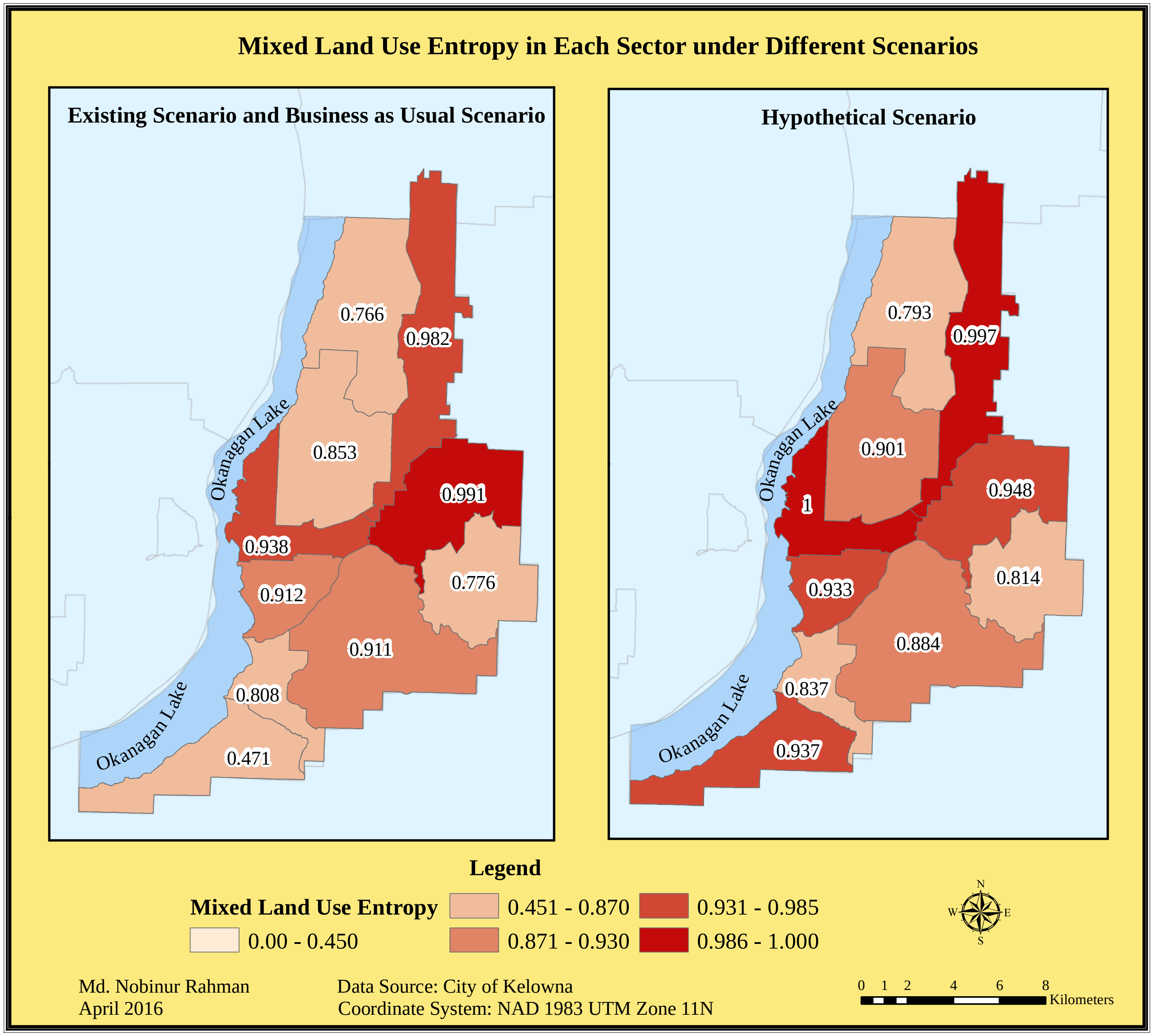



**Figure 5-8 Mixed Land Use Entropy in BAU and Hypothetical Scenario**

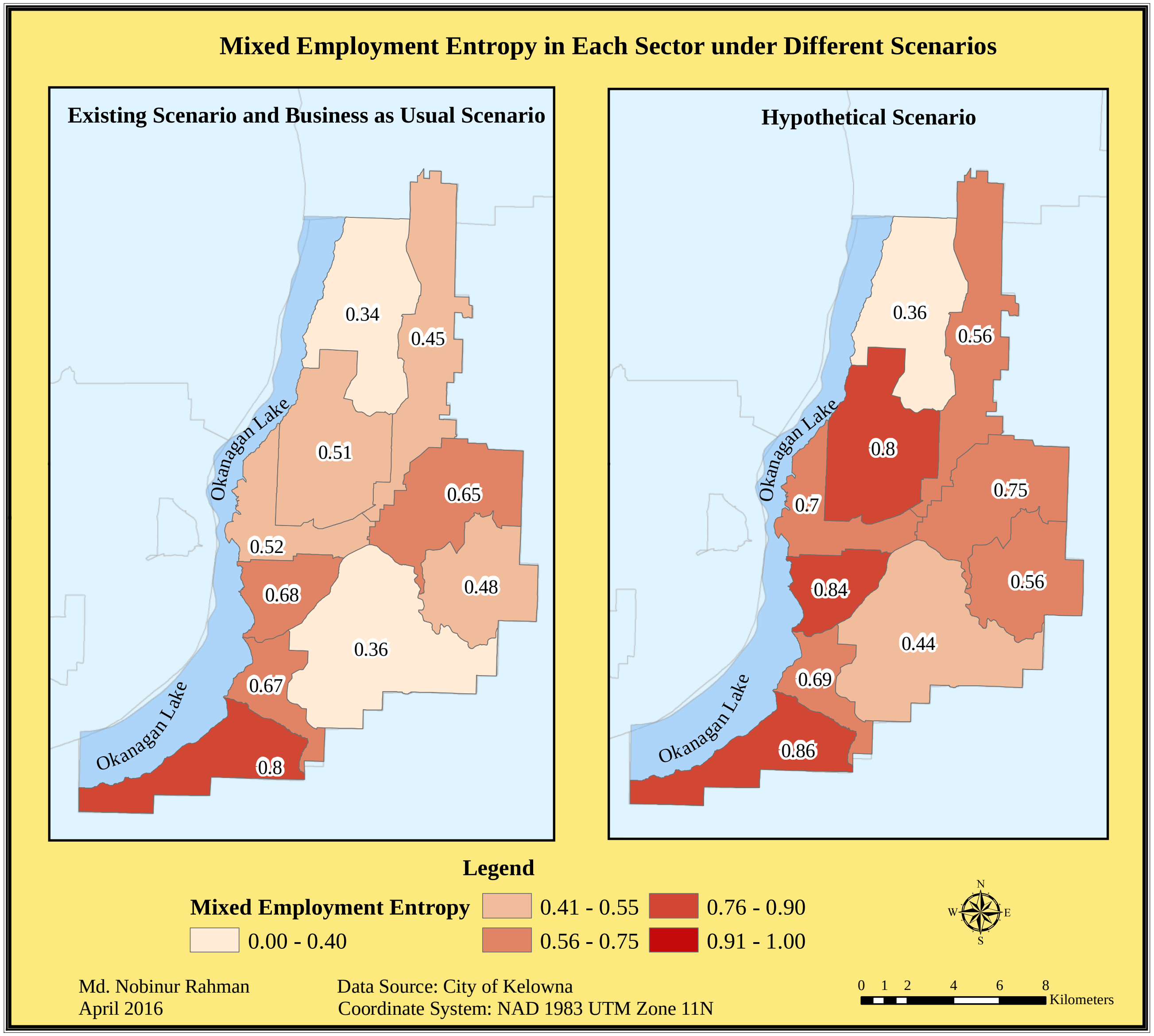



**Figure 5-9 Mixed Employment Entropy in BAU and Hypothetical Scenario**

## 5.7 Scenario Estimates

After validating the model (as described in Section 5.5.2), TRIBUTE was then used to forecast GHG emissions from the transportation sector in 2040 for three scenarios: the existing scenario, the business-as-usual (BAU), and a hypothetical future scenario (described in 5.6). The emissions forecasting steps for the future scenarios are discussed below.

### 5.7.1 Reduction in PKT

To calculate the reduction in PKT, the developed PKT estimation models were used for each scenario (as described in Section 5.4). From Figure 5-10, it is seen that the hypothetical scenario was responsible for a higher reduction in PKT for all modes of travel. The hypothetical scenario has been developed based on the higher density and higher mix of land use, and the effect of them on PKT reduction was higher (Figure 5-10). On the other hand, the unbalanced distribution of population and employment densities in the BAU scenario led to a lower reduction in PKT (Figure 5-10). The only contributing factor to PKT reduction in the latter case was diversity in terms of both population and job mix as well as a proper mix of different types of jobs. The calculated reduction in PKT was applied to the level-of-service attributes (i.e. travel time for motorized modes and travel distance for non-motorized modes) before running TRIBUTE's mode shift component. Based on the error analysis discussed in Section 5.5.1.3, the prediction range of PKT is given in Table 5-9.

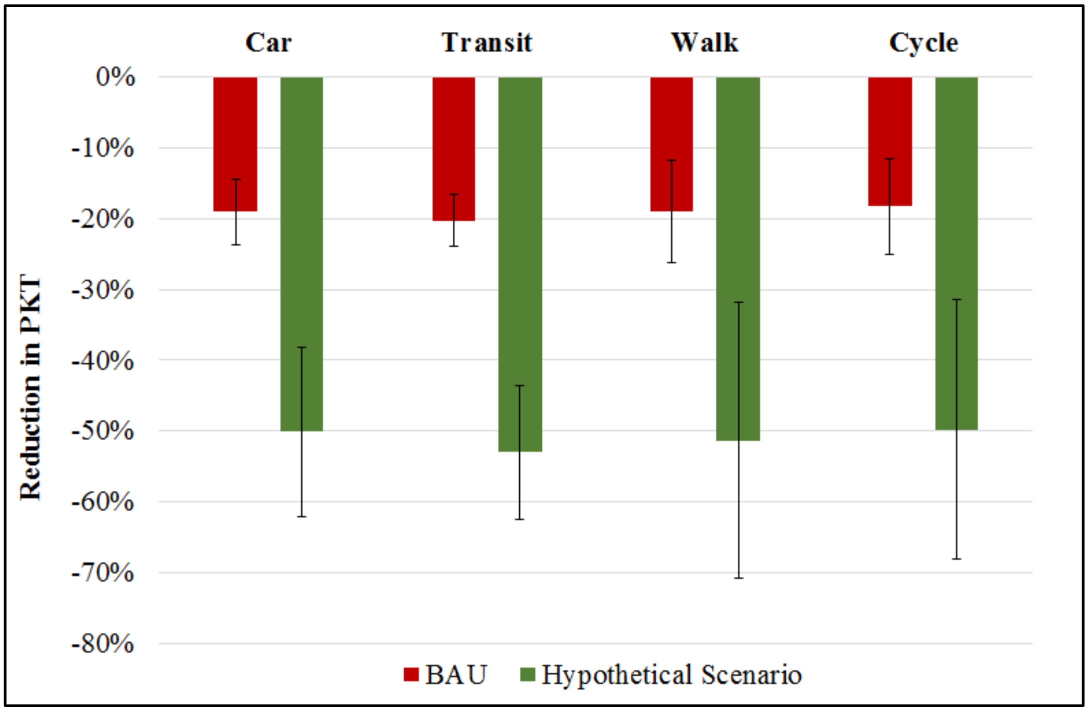



**Figure 5-10 Estimated PKT Reduction**

**Table 5-9 Reduction Interval in PKT**

| | | Car | Transit | Walk | Cycle |
|---|---|---|---|---|---|
| **Business as Usual** | Highest Reduction | -23.64% | -23.97% | -26.49% | -25.38% |
| | Estimated Reduction | -19.04% | -20.28% | -19.23% | -18.54% |
| | Lowest Reduction | -14.44% | -16.59% | -11.97% | -11.70% |
| **Hypothetical Scenario** | Highest Reduction | -62.22% | -62.69% | -71.28% | -68.63% |
| | Estimated Reduction | -50.11% | -53.04% | -51.75% | -50.14% |
| | Lowest Reduction | -38.00% | -43.39% | -32.21% | -31.65% |

### 5.7.2 Modal Shift

The mode shift component of TRIBUTE was used to calculate modal shift in the BAU and hypothetical scenarios, as shown in Figure 5-11 and Table 5-10, respectively. The results showed that the modal share of car in the BAU scenario was lower and walk share was higher than that of the existing scenario, given the increase in population density and job density in the BAU scenario. In addition, car share was further reduced in the hypothetical scenario because of the proper distribution of population and job densities. Walking, in the hypothetical scenario, was also increased by almost three times compared to the existing scenario due to the shorter distances between trip origins and destinations, because of better density and diversity. In addition, transit share was slightly increased in the BAU scenario as the population and job density increase regardless of their proper distribution. Furthermore, due to the balanced distribution of population and jobs in the hypothetical scenario, the transit share was also increased by almost one and half times compared to that of the existing scenario. Since the design indicators were unaltered in both future scenarios, the transit share was only affected by density and diversity. The modal shares in 2007 and 2013 were extracted from the 2007 and 2013 Okanagan HHTS, respectively.

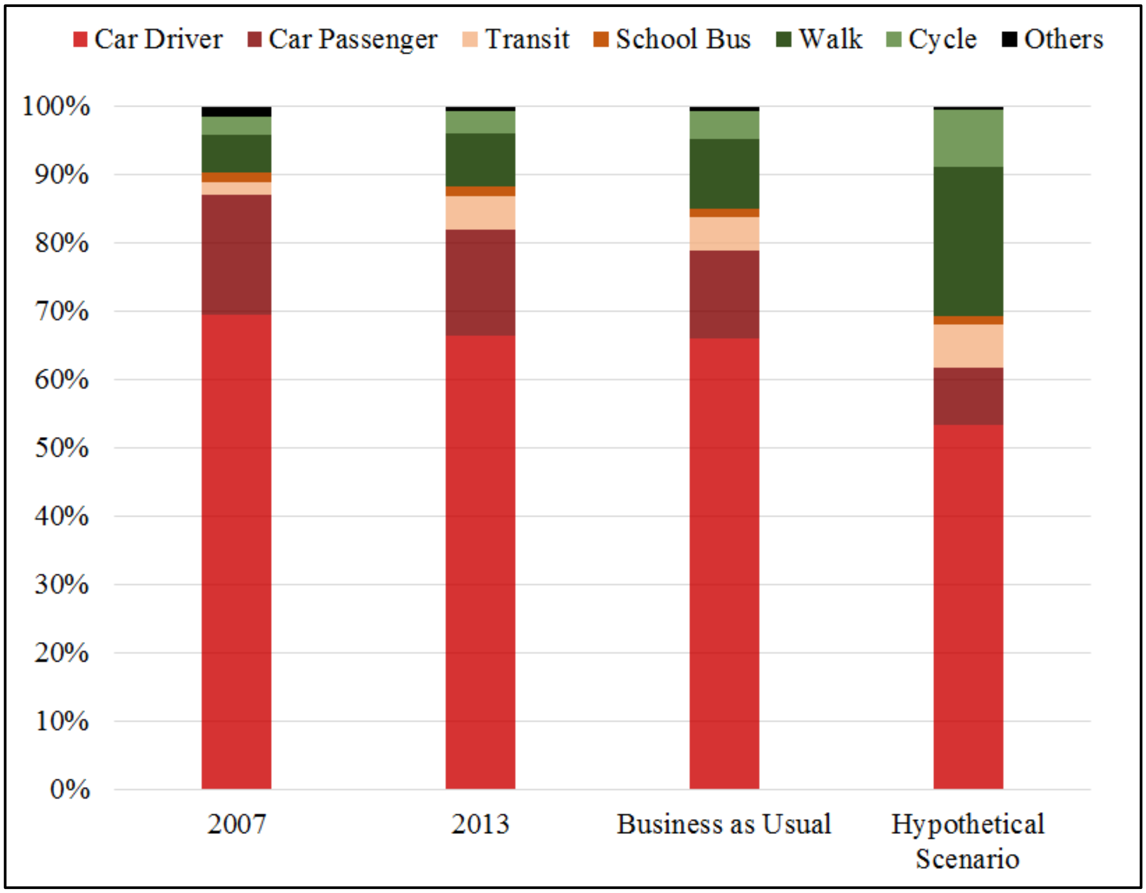



**Figure 5-11 Modal Shift (Estimated)**

**Table 5-10 Modal share Interval in Different Scenarios**

| | | **Car Driver** | **Car Passenger** | **Transit** | **School Bus** | **Walk** | **Cycle** | **Others** |
|---|---|---|---|---|---|---|---|---|
| **Business as Usual** | Highest Shift | 64.5% | 10.0% | 7.4% | 1.1% | 11.4% | 5.1% | 0.4% |
| | Estimated Shift | 66.1% | 12.8% | 4.9% | 1.3% | 10.2% | 4.1% | 0.6% |
| | Lowest Shift | 67.7% | 15.5% | 2.4% | 1.5% | 8.9% | 3.1% | 0.8% |
| **Hypothetical Scenario** | Highest Shift | 51.8% | 5.5% | 8.8% | 1.0% | 23.1% | 9.4% | 0.3% |
| | Estimated Shift | 53.4% | 8.3% | 6.3% | 1.2% | 21.8% | 8.3% | 0.6% |
| | Lowest Shift | 55.1% | 11.0% | 3.9% | 1.4% | 20.6% | 7.3% | 0.8% |

### 5.7.3 Forecasting GHG Emissions

With the observed reduction in PKT and modal shift, the GHG emissions were forecast for all future density scenarios based on the methodology described in Section 3.2. Figure 5-12 shows the forecast GHG emissions from urban transportation in the City of Kelowna in the existing scenario (2013), as well as the two future scenarios for 2040; one for the BAU case and the other for the hypothetical scenario. Figure 5-12 also shows 2007 and 2010 GHG emissions that were used for model estimation and validation, respectively. By using the existing PKT values (generated in Section 5.4) and the observed mode share (from HHTS), the emissions from road transportation were calculated in 2013 (existing scenario). The difference between the estimated emissions by TRIBUTE and from inventories (shown in Table 5-8) was used to calculate the emissions estimation envelope for 2013. After 2010, there was an increasing trend in total GHG emissions because of population growth. Although population growth and car share were higher in 2013 than in 2010, total car users were higher in 2013 than in 2010. Since cars were primarily responsible for the majority of emissions, the total emissions in 2013 increased again from 2010. However, it is worth mentioning that the emissions factors were kept constant for forecasting emissions in 2040, but it can be changed to respond to new fuel technology, new travel modes (electric vehicle, telecommunication, etc.). Most importantly, TRIBUTE can capture those changes in forecasting emissions by looking new emission factors and proportion of switched trips towards new travel options. By combining error envelopes in PKT reduction (described in Section 5.4.4) and modal shift (described in Section 5.7.2), the prediction error was calculated in estimating GHG emissions in future scenarios, as shown in Table 5-11. The BAU scenario resulted in 11.1% to 30.8% increase in emissions above the 2007 levels. However, the hypothetical scenario showed a 22.8% to 55.6% reduction in emissions below the 2007 levels.

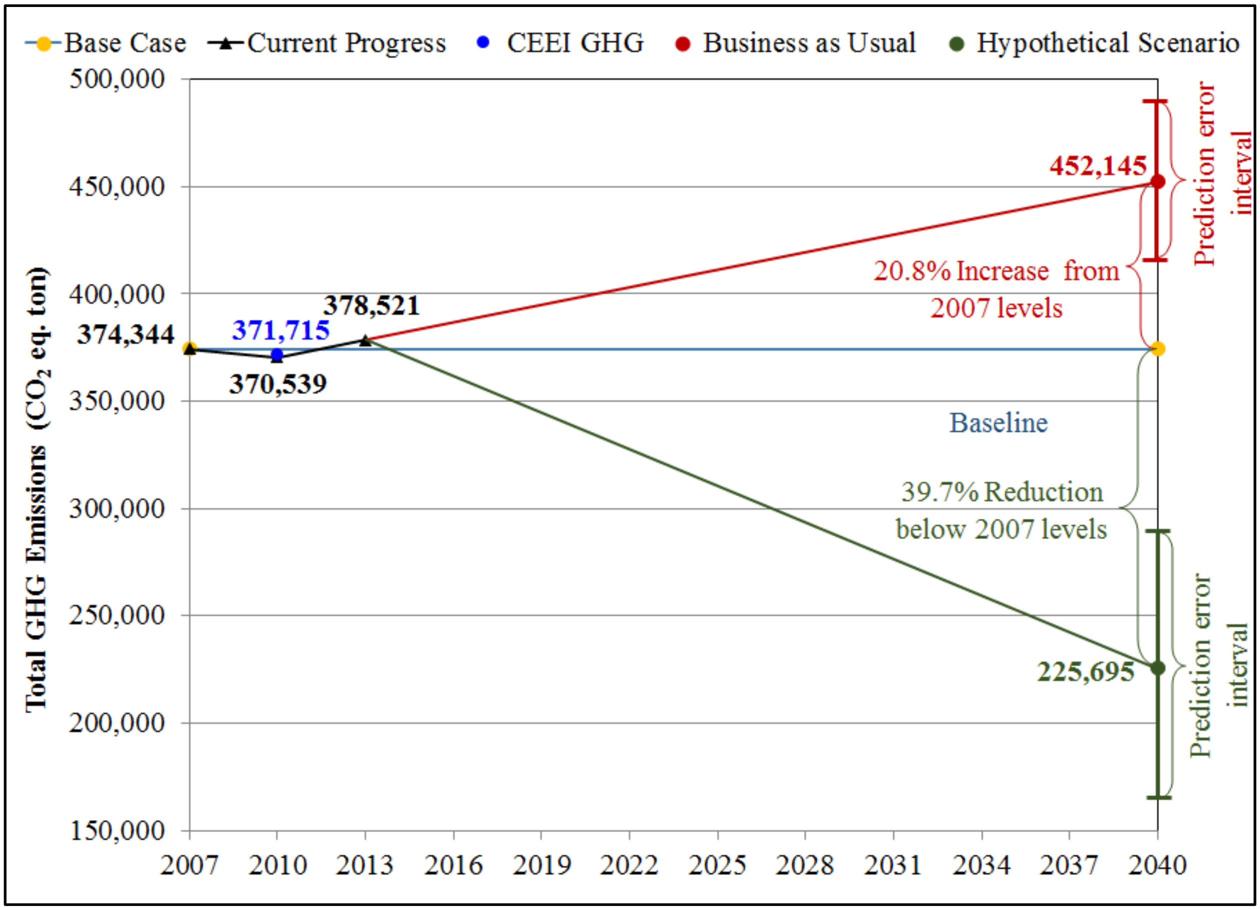



**Figure 5-12 Forecasted GHG Emissions in the City of Kelowna**

**Table 5-11 Emissions Estimation Window in Different Scenarios**

| | | **Emissions ($CO_2$ eq. ton)** | **Difference from Base Level (%)** | **Emissions Per Capita** |
|---|---|---|---|---|
| **2013 (Existing Scenario)** | Upper Limit | 379,715 | 1.4% | 3.17 |
| | Estimated | 378,521 | 1.1% | 3.16 |
| | Lower Limit | 377,327 | 0.8% | 3.15 |
| **Business as Usual** | Upper Limit | 489,460 | 30.8% | 2.71 |
| | Estimated | 452,145 | 20.8% | 2.51 |
| | Lower Limit | 415,914 | 11.1% | 2.31 |
| **Hypothetical Scenario** | Upper Limit | 288,836 | -22.8% | 1.60 |
| | Estimated | 225,695 | -39.7% | 1.25 |
| | Lower Limit | 166,191 | -55.6% | 0.92 |

In particular, there was a 39.7% reduction in emissions below 2007 levels in the hypothetical scenario, while there was a 20.8% increase in emissions above 2007 levels in the BAU scenario (Figure 5-132). Although the BAU scenario was projected to achieve a 20.8% increase in total GHG emissions by 2040, the per capita emissions were expected to be lower than the 2007 levels. Figure 5-13 shows the per capita GHG emissions for all scenarios. The hypothetical scenario showed the lower per capita emissions in 2040 and the ranges of per capita emissions were between 1.60 and 0.92 $CO_2$ eq. ton per person. On the other hand, per capita emissions in BAU were between 2.71 and 2.31 $CO_2$ eq. ton per person.

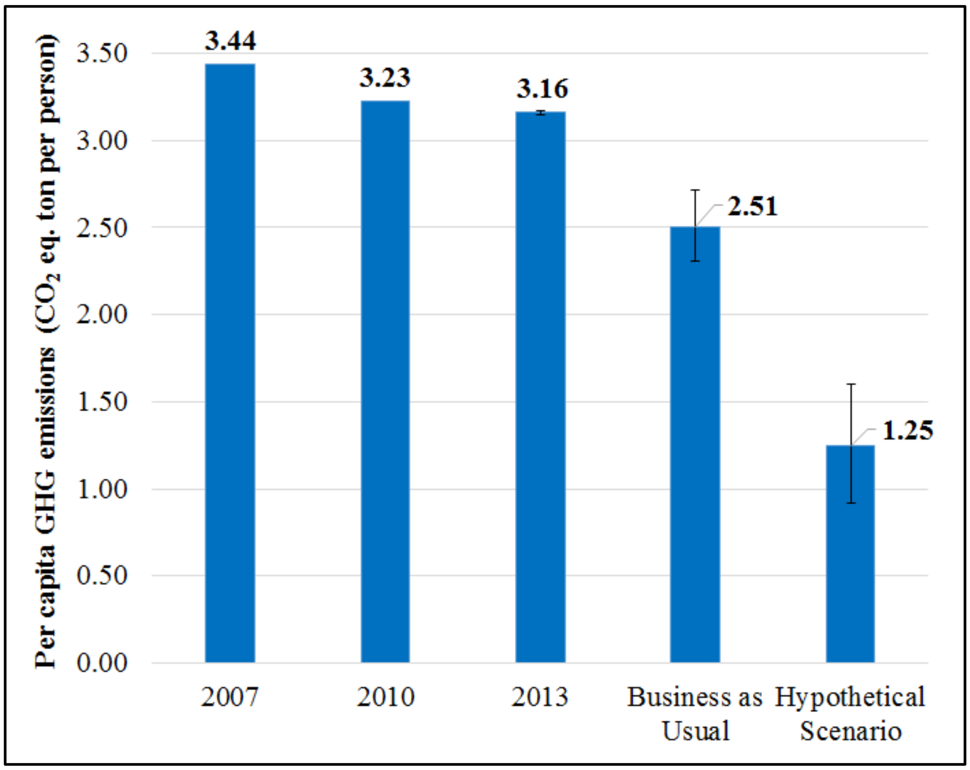



**Figure 5-13 Per Capita GHG Emissions**

## 5.8 Summary

This chapter demonstrated the applicability of TRIBUTE in estimating and forecasting GHG emissions under different land use policy scenarios. The validation results showed a very small difference between TRIBUTE forecasts and the emissions inventories which gave more confidence in using TRIBUTE for estimating emissions for future scenarios. The business-as-usual, do-nothing scenario, shows higher emissions from on-road transportation than the hypothetical scenario. Since the hypothetical scenario is developed considering proper mix of land use and high density, it shows a higher modal shift to public transportation and active transportation at the expense of car than BAU. In addition, there is a higher reduction in trip length, due to the shorter trip distance between origin and destination, than BAU. Therefore, the combined effect of trip length reduction and modal shift further reduced the emissions in the hypothetical scenario. In light of the above, TRIBUTE can help transportation planners make decisions regarding the implementation of land use and transportation policies that aim to reduce GHG emissions from passenger transportation.

# Chapter 6: Conclusions and Future Research

## 6.1 Outline

This chapter is organized as follows: summary of the presented research is demonstrated in Section 6.2, followed by the recommendations to the City of Kelowna to reduce emissions from passenger transportation in Section 6.3. Finally, limitation of the presented research and ideas for future continuation of this research are discussed in Section 6.4.

## 6.2 Conclusions

This research introduced a novel TRIp-Based Urban Transportation Emissions (TRIBUTE) model for municipalities. The developed model is comprised of two main components: a discrete mode choice model and an emissions forecasting model. The mode choice model considers personal, modal, and land use information as its input, and the output of this model is the proportion of trips made by each mode. The emissions forecasting model, on the other hand, estimates and predicts emissions under various land use policies. TRIBUTE can be applied to those areas where extensive transportation network data is not available. TRIBUTE relies mainly on household travel survey and emissions inventories to estimate and validate passenger transportation emissions.

TRIBUTE was applied to the City of Kelowna to find the best alternative scenario among four different future density scenarios to reduce GHG emissions from the transportation sector, and to assist the city in meeting its emissions reduction target. The City's actual future density scenarios, however, could not be included in this thesis for confidentiality reasons. Therefore, a hypothetical and a business-as-usual scenario (BAU) were developed to show the applicability of TRIBUTE in estimating and predicting GHG emissions. The different scenarios were designed considering different land use policies, such as density and diversity along with population growth rates. The hypothetical scenario was developed by relocating people and jobs to achieve higher density and a better mix of land uses within a neighborhood. The BAU scenario represented the "do-nothing" scenario, in which the growth of population and job, and their locations will be the same as exists in Kelowna today.

TRIBUTE was then validated by using available emissions inventories for the City of Kelowna. The validation results showed that there was a very little difference (0.3%) between the estimated emissions using TRIBUTE and emissions inventories. This result suggests that TRIBUTE is a reliable tool for predicting emissions in future scenarios.

Trip length reduction is directly related to reducing GHG emissions. Therefore, a series of passenger kilometres travelled (PKT) estimation models were developed for car, transit, walk, and cycle options to capture trip length reduction by implementing transportation and land use policies. The results suggested that the distance travelled by each passenger would reduce due to increased density and balanced mixed use of land. Density parameters showed negative influence in all PKT models for different travel options. Moreover, diversity and mixed use of land were the dominating factors in reducing PKT for transit mode as it has higher parameter values. The goodness of fit of the models, however, were between 0.10 and 0.17 indicating high unexplained variability within the dataset. Therefore, the prediction interval was measured for the developed models and the interval was comprised of 95% of predicted values for given observations. Using the developed PKT models, the reduction in length was measured for both hypothetical MASc and BAU scenarios. Due to the higher density and proper mix of land, the hypothetical scenario showed higher reduction (~50%) in PKT for all travel options (with ±24% to ±37% forecast error). The organic growth of the population reduced the trip length in the BAU scenario as well, which was smaller than in the hypothetical scenario.

Mode shift, switching modes from motorized vehicle to non-motorized vehicles, can also reduce GHG emissions from passenger transportation. Therefore, a discrete mode choice model was developed to estimate modal shift by introducing land use policies. The developed mode choice models showed that density, diversity, and design indicators have negative parameter values for transit and active transportation options. However, the car option was associated with positive parameter values in the utility functions. This indicates that the increase in density and proper mixed use of land will increase transit rider, and walk and cycle trips at the expense of the car option. In addition, improved design indicators, such as availability of bus stops within proximity of a trip maker, will increase transit riders. Further, availability of sidewalks will increase walk trips. The estimated modal share from the developed mode choice model was then compared with the actual modal share from HHTS to calibrate the developed mode choice models. After calibrating and validating, the developed models were further applied to the future scenarios (hypothetical scenario and BAU) to capture the changes in land use parameters on modal share. The results showed that the hypothetical scenario had higher shift towards transit and active transportation than BAU.

By running the PKT estimation model and the mode shift model, TRIBUTE was used to forecast emissions from passenger transportation for both hypothetical and BAU scenarios. The results showed that the hypothetical scenario would be associated with a 22.8% ~ 55.6% reduction in GHG emissions below 2007 levels. On the other hand, the BAU scenario would realize a 11.1% ~ 30.8% increase in GHG emissions from 2007 levels.

Therefore, TRIBUTE was able to test different scenarios and estimate emissions from passenger transport. TRIBUTE can capture the influence of different built environment and land use indicators on reducing emissions. The main advantage of TRIBUTE is the relatively moderate data requirement and ease with which it can be applied. It can be effectively used where extensive data/expertise/transportation models are not available. TRIBUTE can assist municipalities in evaluating alternative policy scenarios and eventually selecting the one(s) that will help them meet future GHG emission targets.

## 6.3 Recommendations to the City of Kelowna

TRIBUTE was applied to the future density scenarios of the City of Kelowna and the best alternative scenario was chosen to meet future GHG emissions targets. Based on the result of the investigation, the following recommendations are made for the City of Kelowna to reduce GHG emissions from passenger transportation.

### 6.3.1 Increase Mixed Land Use Diversity

Mixed land use diversity refers to the proper balance among residential, commercial, and industrial activities within a neighbourhood. The mode choice model component of the developed TRIBUTE model has demonstrated that the proper mix of residential population and employment has a strong effect on transit and non-motorized transportation modal shares. In addition, increasing land use diversity reduces the trip length between origins and destinations and subsequently, reduces the need to travel long distances. Furthermore, it would cause a modal shift towards public transit and active transportation as well as a reduction in trip length, both of which results in reducing GHG emissions from passenger road transportation. Due to these findings, it is recommended that the City of Kelowna should pay proper attention to mixed uses of land in developing future scenarios. The mixed use of land can be achieved by relocating residential locations and employment locations among ten sectors in the City of Kelowna, as well as compacting the urban cores (downtown area) considering both population and employment.

### 6.3.2 Improve Public Transit

Mode shift from single occupancy vehicles to public transit is another way to lower GHG emissions. Public transit can compete with the automobile for intermediate and long trips if appropriate funding and service planning are provided. It is evident in the developed mode choice models that several transit design indicators, such as bus stop availability and travel time, have a strong influence on increasing mode shift to transit at the expense of automobile use. Accordingly, the City of Kelowna should explore opportunities to improve its transit service by providing better infrastructure, increasing frequency, improving access, etc. as part of all future scenarios. This should be complemented by adopting different Transportation Demand Management (TDM) policies to incentivize (disincentivize) transit (car) use.

### 6.3.3 Promote Active Transportation

As per the developed mode choice models, the availability of sidewalks is the most important factor that influences walking modal shares. Walk and cycle can compete with the automobile for short and intermediate trips if better active transportation infrastructure and end-of-trip facilities are provided. In addition, public education about the benefits of switching to transit and active transportation is imperative.

## 6.4 Limitations and Future Research

This section describes limitations and the possible future research that have been identified during this research as follows:

- Since community energy and emissions inventory 2010 is the most updated inventory in BC until now, it was applied to the validation of TRIBUTE. In addition, the 2013 household travel survey was used in developing TRIBUTE. Therefore, it is necessary to validate TRIBUTE again by integrating BC's next updated emissions inventories with the most recent HHTS in future research.

- This research considered individual trips as a fundamental unit of analysis. However, activity based analysis can be taken into consideration in developing mode choice model in future studies.

- The mode choice component of TRIBUTE consists of commuting and non-commuting trips separately. However, a series of mode choice model can be developed by considering other trip purposes such as home-based trips, non-home based trips etc. in future research.

- This research mainly focused on the effect of land use parameters, such as density, diversity, and design indicators in reducing emissions. However, socio-economic and demographic variables were not included in the mode choice model and PKT estimation model. Therefore, socio-economic and demographic variables can be added to increase the predictability of the models in future studies.

- This research considered various transportation and land use policies in the development of future scenarios. However, safety issues were not included to the scenario development. Therefore, in future research, various safety issues can be analyzed for the developed future scenarios.

- TRIBUTE does not (yet) incorporate economic metrics in its scenario development and output measures; adding in economic metrics would provide a tangible means for the City of Kelowna to reflect on and make decisions related to its infrastructure investments and supporting policies in addition to more detailed scenario impact costs and benefits.

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# Appendices

## Appendix A : Biogeme Software User Interface

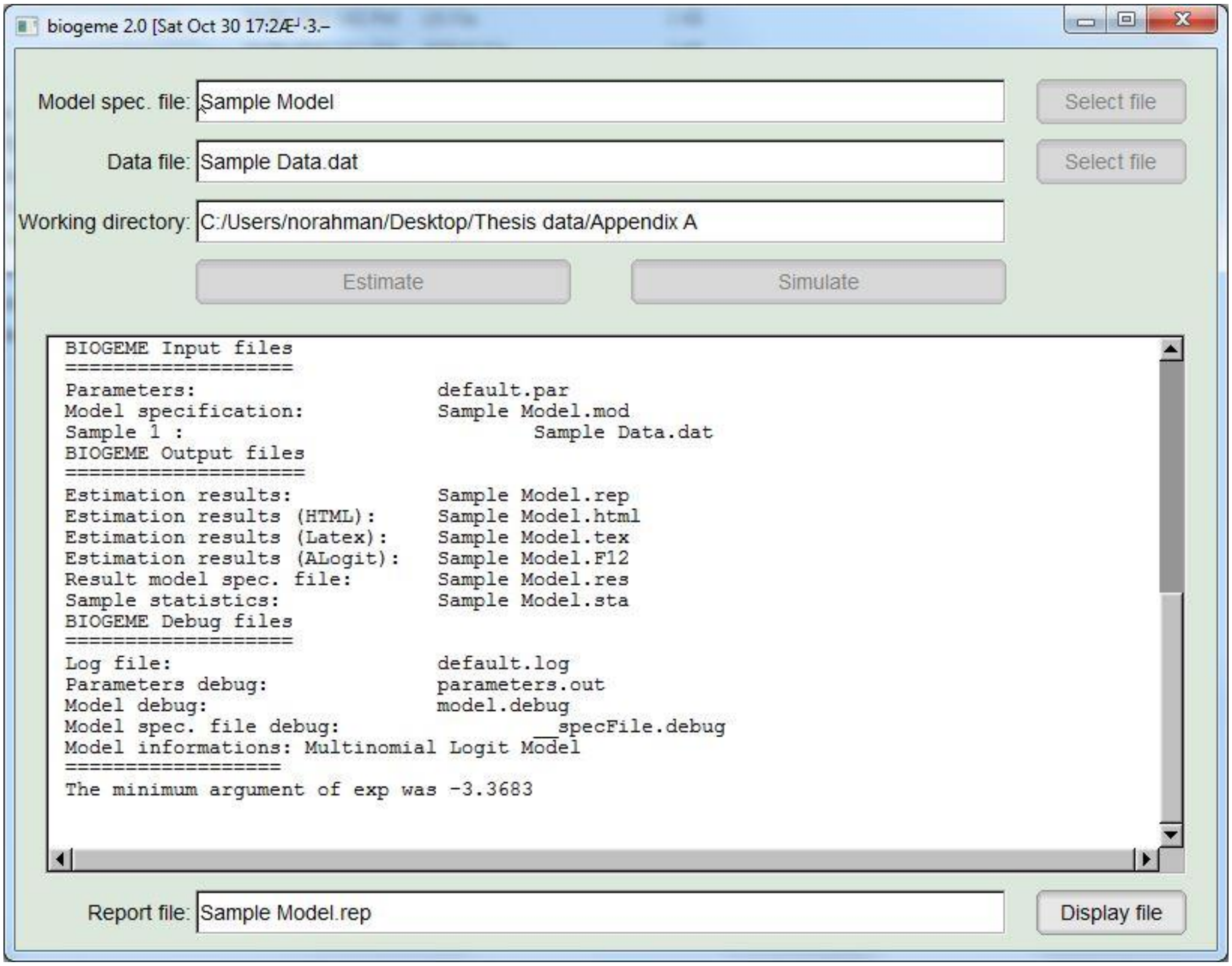


**Figure A-1 User Interface of Biogeme Software**

**Appendix B : Sample Model on Biogeme Software**

```
[Choice]
// Column representing mode choice
choice

[Beta]
// Model parameters (Betas)
// Name          Value   LowerBound  UpperBound   status (0=variable, 1=fixed)
ASC_CAR          0.0     -100.0      100.0        0
ASC_RAIL         0.0     -100.0      100.0        1
BETA_COST        0.0     -100.0      100.0        0
BETA_TIME        0.0     -100.0      100.0        0

[Utilities]
// Systematic utility specifications
// Id    Name  Avail   linear-in-parameter expression (beta1*x1 + beta2*x2 + ... )
0       Car    one     ASC_CAR * one + BETA_COST * car_cost + BETA_TIME * car_ivtt
1       Rail   one     ASC_RAIL * one + BETA_COST * rail_cost + BETA_TIME * rail_ivtt

[Expressions]
// Define here arithmetic expressions for name that are not directly
// available from the data
one =1

[Model]
// Currently, only $MNL (multinomial logit), $NL (nested logit), $CNL
// (cross-nested logit) and $NGEV (Network GEV model) are valid keywords
//
$MNL
```

**Appendix C : Sample Output Results from Biogeme**

# biogeme 2.0 [Sat Oct 30 17:26:53 CEDT 2010]

## Michel Bierlaire, EPFL

This file has automatically been generated.

Tip: click on the columns headers to sort a table [Credits]

```
                       Model: Multinomial Logit
Number of estimated parameters: 3
       Number of observations: 228
        Number of individuals: 228
          Null log-likelihood: -158.038
           Cte log-likelihood: -148.347
          Init log-likelihood: -158.038
         Final log-likelihood: -129.572
        Likelihood ratio test: 56.932
                   Rho-square: 0.180
          Adjusted rho-square: 0.161
          Final gradient norm: +2.385e-004
                   Diagnostic: Convergence reached...
                   Iterations: 9
                     Run time: 00:00
          Variance-covariance: from analytical hessian
                  Sample file: Sample Data.dat
```

## Utility parameters

| Name | Value | Std err | t-test | p-value | | Robust Std err | Robust t-test | p-value | |
|---|---|---|---|---|---|---|---|---|---|
| ASC_CAR | -0.252 | 0.231 | -1.09 | 0.28 | * | 0.238 | -1.06 | 0.29 | * |
| ASC_RAIL | 0.00 | fixed | | | | | | | |
| BETA_COST | -0.0497 | 0.00996 | -4.99 | 0.00 | | 0.0103 | -4.81 | 0.00 | |
| BETA_TIME | -0.743 | 0.370 | -2.01 | 0.04 | | 0.377 | -1.97 | 0.05 | |

## Utility functions

| Id | Name | Availability | Specification |
|---|---|---|---|
| 0 | Car | one | ASC_CAR * one + BETA_COST * car_cost + BETA_TIME * car_ivtt |
| 1 | Rail | one | ASC_RAIL * one + BETA_COST * rail_cost + BETA_TIME * rail_ivtt |

## Correlation of coefficients

| Coefficient1 | Coefficient2 | Covariance | Correlation | t-test | p-value | | Rob. cov. | Rob. corr. | Rob. t-test | p-value | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ASC_CAR | BETA_COST | 0.00173 | 0.751 | -0.91 | 0.37 | * | 0.00188 | 0.765 | -0.88 | 0.38 | * |
| ASC_CAR | BETA_TIME | -0.00864 | -0.101 | 1.08 | 0.28 | * | -0.0126 | -0.140 | 1.04 | 0.30 | * |
| BETA_COST | BETA_TIME | -6.19e-006 | -0.00168 | 1.87 | 0.06 | * | -9.34e-005 | -0.0240 | 1.84 | 0.07 | * |

Smallest singular value of the hessian: 7.20438

**Figure C-1 Output Results from Biogeme**

## Appendix D : Residual Plots of the Developed Regression Models

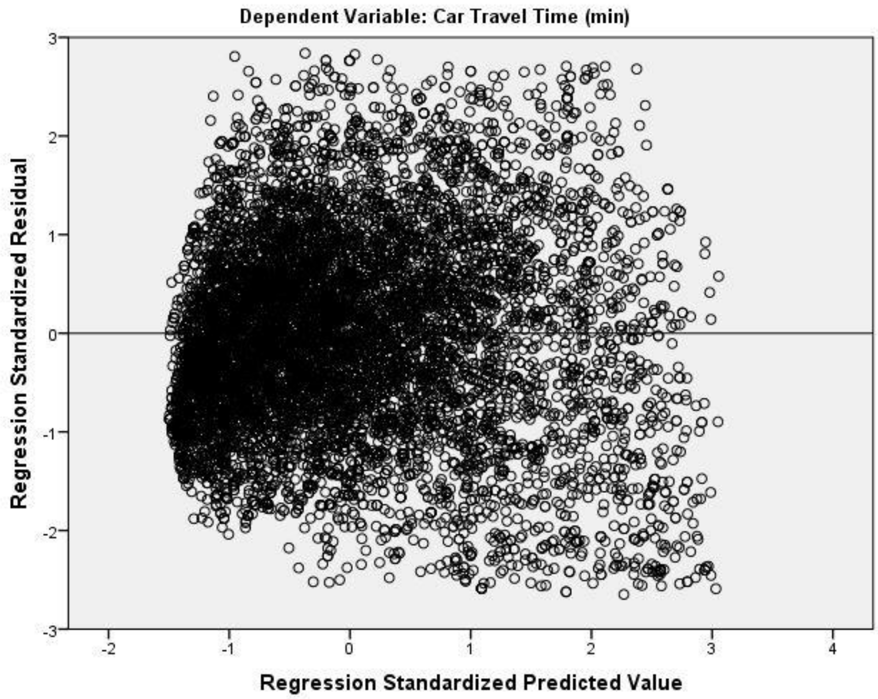


**Figure D-1 Residual Plot of the Travel Distance and Travel Time for Car**

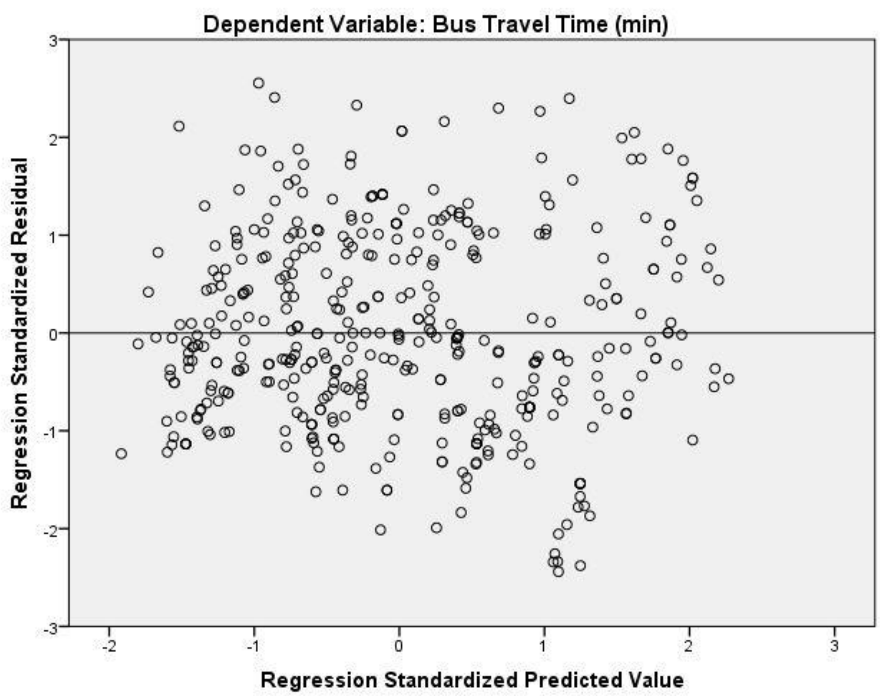


**Figure D-2 Residual Plot of the Travel Distance and Travel Time for Transit**