Upgrading a Commercial Vehicle Model Using a Roadside Truck Survey: Application for the City of Edmonton

by

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A thesis submitted in conformity with the requirements for the degree of Master of Applied Science

Civil Engineering

University of Toronto

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Abstract

The movement of goods and services are central to the economy of the City of Edmonton. The City understood the importance of incorporating commercial vehicle movements as part of their overall planning process and developed a commercial vehicle model in 2006. Since the development of the original model, no further analysis has been conducted to ensure that the model is estimating commercial vehicle movements accurately. Preferably, an updated establishment-based survey would be collected and a complete re-estimation of the tour-based microsimulation model would be performed. However, this research aims to provide a cost effective approach to upgrade the City of Edmonton’s commercial vehicle model to reflect current conditions using the truck counts collected in a roadside truck survey. This research has provided the City with an effective iterative adjustment procedure which has resulted in a model which outperforms the original model and is re-calibrated to the new road count data.
Acknowledgments

When I began my academic career at the University of Toronto as a first year Civil Engineering student, I had no idea I was embarking on a six and a half year journey culminating in a master’s degree. I must admit it has been the most challenging and rewarding experience of my life thus far.

Foremost, I want to thank my supervisor Professor M. J. Roorda who realized my potential even before I did and encouraged me to pursue a master’s degree. He has been a guiding voice throughout my research and has provided me with the tools and support to succeed. I want to especially thank him for believing in me and steering me in the right direction during the difficult and challenging moments over the past few years. Matt: I look forward to working with you in the future and I thank you for all that you’ve done for me.

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Chapter 1

1 Introduction

Chapter 1 will outline the background and motivation, purpose and scope, significance and potential and general structure for this thesis.

1.1 Background and Motivation

Commercial vehicle movements are a considerable portion of all vehicle movements in urban areas, yet have rarely been incorporated as part of policy analysis and urban planning. The City of Edmonton understood the importance of incorporating commercial vehicle movements as part of their overall planning process and developed a commercial vehicle model (CVM) in 2006. The original CVM was estimated using the results of a 2001 commodity flow survey (CFS) and was calibrated using the same data. A full description of the original CVM will be given in Chapter 3. Since the development and calibration of the original CVM, no further analysis has been conducted to ensure that the model is estimating commercial vehicle movements correctly. Preferably, an updated establishment-based survey would be collected and a complete re-estimation of the tour-based microsimulation model would be performed. However, the City of Edmonton does not have the resources to undertake this kind of data collection at the moment. The only new sources of data available to the City of Edmonton are a roadside commercial vehicle survey conducted in 2012 and updated land use, road network information, and other truck counts for 2014. The aim of this research is to provide a cost effective approach to upgrade the original commercial vehicle model to reflect current conditions using the most recent available data.

1.2 Purpose and Scope

The proposed methodology to upgrade the original commercial vehicle model to reflect current conditions involves adjusting selected model parameters. In addition to adjusting model parameters, the City of Edmonton will update model inputs such as land use and road network characteristics. The objective of this research is to develop, test and confirm that the proposed method results in commercial vehicle patterns that better reflect the most recent road counts.
The scope of this research includes:

1) A literature review of freight demand modelling and calibration methods

2) A full inventory of the original Edmonton CVM, including data sources, and operating processes

3) A methodology for updating the City of Edmonton’s original CVM to reflect the latest available data from the 2012 Edmonton Roadside Truck Survey and other counts

4) Preliminary testing of the proposed methodology for adjusting the City of Edmonton’s original CVM

5) Demonstrate proof of the proposed method by comparing the outcomes of the City of Edmonton’s original CVM with the adjusted model and the observed counts

Figure 1: Study Area
The proposed methodology is applied to the City of Edmonton’s commercial vehicle model for the study year of 2012. The study year has been chosen to coincide with the City of Edmonton’s Roadside Truck Survey which was completed in 2012. Furthermore, the most recent land use and road network information is available for 2012. The study area is defined in Figure 1 and includes the Edmonton Census Metropolitan Area (CMA), which comprises the City of Edmonton, St. Albert, Sherwood Park, and the Counties of Leduc, Strathcona, Sturgeon and Parkland.

1.3 Significance and Potential

Estimating a commercial vehicle tour-based microsimulation model for a metropolitan area requires extensive data. Hunt and Stefan (2007) developed the underlying framework for the tour-based microsimulation of urban commercial movements for the City of Calgary in 2001 based on data obtained in a set of surveys which collected information on approximately 37,000 tours and 185,000 trips. Unlike Hunt and Stefan (2007), this research is novel in its approach since it bypasses the need for new and expensive data collection. Using original model parameters with updated information about land use, road network characteristics, and recent road counts, an out-of-date model can be re-calibrated to better reflect current conditions. This approach has great significance and potential for municipal planning organizations that are unable to fund large data collection efforts for full model re-estimations.

This research contributes to the literature on tour-based microsimulation of urban commercial vehicle movements by re-calibrating a commercial vehicle model in a more robust manner (i.e. using truck counts) rather than simply matching high-level target values from a commodity flow survey (i.e. trip length, trips per tour). The adjusted model gives more reliable results for the study year. Furthermore, the method provides the user with an effective process for updating model parameters in future years when new road count data becomes available. The Edmonton Goods Movement Strategy, released in June 2014 (Edmonton, 2014), identified seven objectives and 35 actions to benefit goods movement within the region. The adjustment to the CVM would fall within the fourth objective: “improving network planning and forecasting”. The re-calibrated model has the potential to answer policy and planning questions for the City of Edmonton in regards to truck route restrictions, large capital spending projects, and transportation impact studies.
1.4 Structure of Thesis

This thesis is organized into seven chapters. The first chapter gives an introduction to the research question, the motivation for the work and its significance. Chapter 2 presents relevant literature pertaining to freight demand modelling and various approaches taken to model this complex subset of transportation as well as available literature on calibration methods. Chapter 3 discusses the original Edmonton CVM, the data sources that it was built with, and the shortcomings of the original model. Chapter 4 provides a comparison of the original model to observed data and identifies an approach for improving correspondence between the original model and observed data. Chapter 5 outlines the proposed methodology for upgrading the original CVM using the most recent truck counts. Chapter 6 describes how the proposed methodology was applied to the original model to update model parameters. Chapter 7 presents the results of the adjusted model, including how the re-calibrated model performed in terms of reflecting current conditions over the original model. Chapter 8 summarizes the thesis project and states the findings of the work and potential future extensions to the research.
Chapter 2

2 Literature Review

Chapter 2 presents a review of available literature pertaining to freight demand modelling and calibration techniques for traffic simulation models. These two concepts are at the fundamental purpose of this research. Firstly, it is important to have a basic understanding of tour-based urban commercial vehicle modelling and its advantages. Secondly, the scope of this research involves upgrading a commercial vehicle model through re-calibration of its parameters. Therefore, an in-depth knowledge of available calibration techniques is essential.

2.1 Freight Demand Modelling

Freight demand modelling can be thought of in terms of two approaches: conventional and state-of-the-art methods. Conventional methods can be summarized as either growth factor methods or four-step models. Chow et al (2010) identifies state-of-the art methods as urban logistic models, tour-based models and hybrid approaches. The following sections will outline both conventional and state-of-the art approaches and discuss the limitations of conventional approaches and why state-of-the art approaches have been proposed to address these limitations.

2.1.1 Conventional Methods

Conventional approaches can be classified into two categories: growth factor methods and four-step models. These models were originally developed for passenger transport and have been applied to urban freight transport despite their inability to accurately capture the behaviour of freight transport.

2.1.2 Growth Factor Methods

Growth factor methods involve applying growth factors to base freight traffic data or economic variables in order to project the future freight travel demands (FHWA, 2007). Growth factor methods have been classified into two types: forecasting activity based on historical traffic trends and forecasts based on future economic activity. The first is the most commonly used application whereas the latter is less common. The application of growth factors is both simple and inexpensive however the underlying assumption that freight demand will continue to follow
historical trends or future economic activity is inflexible. These methods do not allow for policy analysis or assessing the impacts of changes to freight activity, therefore their predictive power is limited to analyzing incremental changes and should not be used for long range planning (FHWA, 2007).

2.1.2.1 Four Step Models

The traditional four-step model is the second conventional way to forecast freight travel. Most prominent in passenger vehicle travel, this method includes four steps: trip generation, trip distribution, mode split and trip assignment. The difference between the passenger vehicle four-step model and that of freight is that trip generation and trip distribution can be expressed either in the form of commodities or trucks (FHWA, 2007). To determine which form a model would take would depend on the input data provided (i.e. volume, weight, or trucks). However, for the purpose of trip assignment all forms of freight are converted to vehicles in order to be assigned to the network (FHWA, 2007). Figure 2 depicts the four-step process of freight forecasting as illustrated by the Quick Response Freight Manual II. According to de Jong et al, the four-step model is an attractive means of estimating commercial vehicle movements because it is analogous to the four step model used for passenger travel. However, due to the complexity of freight transport and the diversity of decision-makers and items being transported, it is reasonable to suggest that the four-step model is limited in its ability to forecast freight travel. Stephan and Hunt (2004) emphasize the point that the four-step approach is more of a three-step model because it does not consider mode choice explicitly and instead includes it in the trip generation portion of the model. Furthermore, the four-step model frequently considers only larger vehicles, and emphasizes trips rather than tours (Hunt and Stephan, 2007). In an urban context, where commercial vehicle movements are characterized by a tour-based nature, the four-step model neglects this behaviour (Hunt and Stephan, 2007). In urban settings, service trips make up 45% of all commercial vehicle movements and the four-step model focuses on goods movement alone thereby neglecting these trips altogether (Hunt and Stephan, 2007). Holguin-Veras and Patil (2005) found that commercial vehicles make tours composed of approximately 5.6 trips per tour which are interrelated by underlying logistical decisions. Therefore, the assumptions that trips are independent and trips between origin-
destination (OD) pairs are a function of zonal attributes and travel impedance between zones does not hold (Wang and Holguin-Veras, 2009).

<table>
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<th>Total Tons</th>
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<td>Tons by O-D</td>
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<td>O-D Tons by Mode</td>
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<tr>
<td>O-D Tons by Mode and Route</td>
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**Figure 2: Four-Step Process of Freight Forecasting (FHWA, 2007)**

### 2.1.3 State-of-the-art Methods

Limitations in conventional approaches to freight modelling have been emphasized by several authors including Fischer et al. (2005), and Friesz and Holguin-Veras (2005). Hensher and Figliozi (2007) concluded that the four-step model is unable to account for supply chain behaviour of freight transport and thus are inadequate in dealing with a “21st century global customer-driven economy”. As a result, a shift from aggregate approaches which are insensitive to policy analysis and economic behaviour has been made to a more disaggregate approach (Chow et al, 2010). Developments in disaggregate approaches have been focused on addressing two areas: supply chain behavior/logistics and truck touring. The following section will discuss supply chain logistic models, tour-based urban commercial vehicles models, and a hybrid approach of the two.

#### 2.1.3.1 Supply Chain Models

Supply chain/logistic models attempt to explain the relationship between the different players in a supply chain – suppliers, warehouses, and consumers (Boerkamps et al, 2000) (Hunt and
Stephan, 2007). Supply chains involve the movement of goods from their raw state to finished products, therefore these models focus on the flow of commodities rather than vehicles (Chow et al, 2010). Chow et al. (2010) identified four types of supply chain models: regional logistics models, agent-based freight transport models, joint shipment size and transport chain choice models, and urban logistics models. Although each of these models differ in terms of the use of aggregate or disaggregate data, they share the common goal of incorporating more than a single origin and destination, having multiple intermediate stops to represent distribution channels (Chow et al, 2010). In an urban context, the use of an urban logistics model such as the Goodtrip model developed by Boerkamps et al. (2000) would be advantageous. The Goodtrip model is able to analyze changes in supply chain organizational behaviour in addition to assessing the impacts of environmental improvements (Chow et al, 2010). Roorda et al. (2010) developed a conceptual framework for agent-based modelling of logistical services which explicitly represents the behaviour of the various actors in a supply chain (i.e. consumers, producers, and transporters of goods and services). It is advantageous over other logistics models since it is able to represent contracts as well as commodity and service prices within markets more realistically. However, this approach is conceptual in nature and has not been put into application as an operational model. Logistics models in general are able to address many of the needs that conventional models neglect such as modal diversion analysis, commodity flow analysis and policy studies to name a few.

2.1.3.2 Tour-based Models

Tour-based models have been formulated to address the limiting assumptions of conventional approaches such as the four-step model. Since it has been shown that commercial vehicles make tours composed of many trips, and these trips are interrelated according to the underlying logistic decisions (Wang and Holguin-Veras, 2009), new methods of forecasting commercial vehicle movements are needed. The literature shows that two approaches have emerged: disaggregate models and aggregate models. Disaggregate models are the most widely used approach and involve one of two methods: (1) the solving of a vehicle routing problem (Donnelly 2007) or (2) microsimulating tour-based movements by using selection probabilities estimated from discrete choice models (Hunt and Stephan 2007). A less common approach is the aggregate tour-based approach. A review of the literature shows two cases in which the aggregate approach has been
employed. Maruyama and Harata (2005) developed three types of combined network equilibrium models which account for trip chaining behaviour. However, these models were developed for overall vehicle travel demand and freight demand was not included explicitly. Wang and Holguin-Veras (2009) developed an aggregate approach in which a tour-based entropy maximization formulation was used to estimate tour flows of commercial vehicles. The following sections will present the disaggregate approach using Hunt and Stephan (2007) as an example and the aggregate approach using Wang and Holguin-Veras (2009) to highlight the benefits and limitations of each method.

2.1.3.2.1 Disaggregate Tour-based Models

Vehicle touring models or tour-based commercial vehicle models have been proposed to incorporate the movements of vehicles and decisions of carriers realistically (Chow et al, 2010). This section will examine a vehicle touring model developed by Hunt and Stephan (2007) for Calgary, Alberta. The Calgary commercial vehicle movement model employed a combined approach with three groups modelled separately. The first group – external and internal movements – was modelled using singly-constrained gravity models and captured the trips being made outside of the study area. The second group – fleet allocator movements – was modelled using an aggregate generation and gravity-style distribution framework, however a tour based approach is said to be in development. This group is characterized by vehicles performing services such as newspaper delivery, garbage pick-up, and road maintenance. The third group – tour based movements – was modelled using a tour-based microsimulation and was used to model vehicles carrying small sets of individual shipments. The overall tour-based microsimulation framework is depicted in Figure 3. The first step in the microsimulation is tour generation. This step involves using an aggregate trip generation model to determine the number of tours based in each zone. Vehicle type and tour purpose are identified one at a time for each tour in the list for each zone. This process is completed using Monte Carlo processes. Once a vehicle type and tour purpose has been identified a tour start time can also be identified. At this point in the microsimulation, the characteristics of each stop in the tour can be identified. In an iterative manner, tours progressively ‘grow’ by having a ‘return-to-establishment’ alternative as one of the next stop purposes. Therefore, the next stop purpose dictates whether the tour continues or if it ends back at the establishment. The microsimulation uses logit models to
determine the selection probabilities at each step. According to Chow et al. (2010), a disadvantage to this framework is the extensive data (i.e. interviews) required to undertake such a study. However, it is also stated that this framework is able to address many of the issues that conventional models lack; such as policy studies and needs analysis. Similarly, Gliebe et al. (2007), utilized ‘travelling workers’ as agents of the tour-based model which was prepared for the Ohio State Department of Transportation.

![Diagram of Tour-based microsimulation framework](image)

**Figure 3: Tour-based microsimulation framework (Hunt and Stephan, 2007)**

### 2.1.3.2.2 Aggregate Tour-based Models

Aggregate tour-based models have been developed to address the limitations of disaggregate tour-based models, however are limited in their application as well. Although disaggregate models are able to capture the decision making behaviour underlying the movement of commercial goods, these models have extensive data requirements which are often costly. Furthermore, Wang and Holguin-Veras (2009), indicate that disaggregate tour-based models are based on strong assumptions about logistical decisions and are burdened by long computation times. The following section will describe a method developed by Wang and Holguin-Veras (2009) that aims to estimate the tour flows of commercial vehicles using two variations of an entropy maximization formulation.

The method involves using known aggregate information about the total number of trip productions and trip attractions to each zone and the total impedance of the network as
constraints to determine the most likely set of tour flows which satisfy these constraints. Impedance is considered in two ways: (1) total impedance is equal to the summation of the tour travel impedance (i.e. impedance along a tour) and tour handling impedance (i.e. impedance at each stop along the tour) and (2) travel tour impedance and tour handling impedance are considered separately to assess their individual effects. The authors make a clear distinction as to the difference between trips, tours, and tour flows. Trips are defined as vehicle movements between two stops whereas tours are the sequence of stops followed by a vehicle which starts and ends at its home base. The aggregate model is interested in estimating tour flows, which are defined as the number of vehicle journeys following a specific tour during a specific time period. However, tour flows can only be estimated once a set of tours for the entire network have been specified. Therefore, the proposed approach takes the form of a sequential modelling framework composed of a tour choice model and a tour flow model. The basis of these two models can be further investigated in Wang and Holguin-Veras (2008) and Wang (2008). Once the tour choice model estimates a set of tours, the tour flow model essentially enumerates all the different possible ways to distribute these tour flows within the network. The problem lies in the large number of ways to distribute these flows and therefore entropy maximization has been proposed to address this issue. The paper focuses on using entropy maximization to find the most likely set of tour flows to satisfy the input information as explained above. Two assumptions that should be considered when employing this model is that nodes in the network are aggregated to the traffic analysis zone (TAZ) level and the tour set and impedance of each tour must be known from the tour choice model.

In using this method to solve the distribution of flows, it was found that the trip-based formulations were convex and thus a convex optimization algorithm was used to solve the problem. The authors used a method for optimization programs with convex objectives (PDCO) which is a primal-dual interior method for solving convex programs with linear constraints (Wang and Holguin-Veras, 2009). This method is attractive because of its ability to solve large-scale entropy maximization formulations and it allows for lower and upper bounds of decision variables to be set to define realistic ranges for the decision variables.

The formulation is set up in two ways: (1) considering total tour impedance and (2) considering travel tour impedance and handling tour impedance separately, as described previously. For each
formulation, an objective function and five constraints are specified. Specifically, one constraint each for the trip productions, trip attractions, total impedance, and non-negativity are specified. Refer to Wang and Holguin-Veras (2009) for detailed mathematical descriptions of each formulation and their associated first order and second order conditions.

The method was applied to a case study in the Denver metropolitan area. Results of the case study showed that the tour flow problem was solved in two seconds using the PDCO algorithm and an excellent match between observed and estimated tour flows was evident. The mean absolute percentage errors (MAPE) of the estimated tour flows were 6.71% and 6.61% for formulations 1 and 2 respectively. An interesting outcome of the model showed that tour handling time (i.e. time spent at stops) was found to have a positive sign indicating that the time spent at a stop does not discourage travel. The authors hypothesized that longer wait times may be a proxy for the amount of commodities available in a tour or effort needed to serve a customer and thus may encourage more travel on the tour. A sensitivity analysis indicated that total tour time has an impact on the performance of the model. If the difference between input tour times and actual times are significantly different, estimated tour flows deviate from observed ones drastically.

The paper concludes by presenting two ways in which the method can be used to forecast urban freight demand. The first case involves knowing the base-year tours and impedance, aggregating to obtain trip productions and attractions then estimating parameters using the entropy maximization formulations to estimate future-year flows. The second case involves using observed tour data in the base year to develop tour choice models that estimate future-year tours and impedances. These future-year tours and impedances are used as inputs to the entropy maximization to estimate future-year tour flows.

2.1.3.3 Urban Logistic – Tour-based Hybrid Approach

In an attempt to combine the benefits of a supply-chain model and tour-based model, Fischer et al. (2005) created a hybrid approach for the Los Angeles County Metropolitan Transportation Authority (MTA). The MTA was in need of a modelling approach which was comprehensive, multimodal, and multidimensional (Fischer et al, 2005). Although efforts to capture travel associated with international trade have been developed, the goal of the project was to focus on
domestic freight movements. The framework considered four types of freight movements: domestic, warehousing/distribution, local delivery and service trips. Considering the wide variety of freight modelling frameworks currently used in practice and the state-of-the-art models developed, the authors concluded that in order to meet all of the MTA’s needs a new integrated modelling framework which combined features of both supply chain and tour-based models was needed. An overview of the integrated modelling approach is depicted in Figure 4. By incorporating both logistics and tour-based models this approach is able to capture the behaviour related to the decision-makers of the logistics planners when considering activities that occur within the supply chain (Fischer et al, 2005). Furthermore, this approach will also be able to accurately estimate the number of vehicle trips in a tour and consider the choices made at each stop in a tour (Fischer et al, 2005). It should also be noted that the authors indicated that the supply chain model will be most suited to domestic freight and warehouse/distribution truck trip types associated with commodities that move in large shipment sizes such as: primary metals, and bulk raw materials. In contrast to this, the tour-based approach is more suited to all other commodities.

![Figure 4: Overview of integrated modelling approach (Fischer et al, 2005)](image)

2.2 Microsimulation Model Calibration Techniques

Calibration is the adjustment of model parameters to ensure that a traffic model reproduces real-world traffic conditions accurately (FHWA, 2004). Since traffic simulation models are complex
and include several parameters which work in combination to affect the ability of the model to produce accurate results; closed-form equations are rarely formulated and solved to find an optimal solution (FHWA, 2004). To deal with the complexity of the model, search algorithms are used to iteratively search a large number of possible solutions and find the optimum value (FHWA, 2004). A review of relevant literature has indicated that manual search (i.e. trial-and-error), artificial intelligence (i.e. genetic algorithms), and other approaches such as the simplex-based, and the gradient approach are common calibration techniques used in traffic simulation models (Zhang & Ma, 2008) (Kim, Kim, & Rilett, 2005). The particular search algorithm employed will depend on the degree of complexity of the model and the specific parameters being calibrated. Section 2.2.1 will describe the manual search method and Section 2.2.2 will describe the artificial intelligence approach. Section 2.2.3 will outline additional calibration techniques that are less common but have been used in past literature such as the simplex-based approach, gradient approach and simulated annealing method.

2.2.1 Manual Search Method

The manual search or trial-and-error heuristic approach involves iteratively adjusting parameters in a manual process (Zhang & Ma, 2008). The trial-and-error approach is commonly used because it is less complex, intuitive, and gives the user control over stopping criteria (Kim, Kim, & Rilett, 2005). The typical process for using a manual search method involves running the simulation based on combinations of selected parameters by changing the value of a parameter one at a time (Zhang & Ma, 2008). The process continues until convergence criteria (i.e. precision and performance requirements) are met. Manual search methods are commonly carried out in spreadsheet formats. Methods that are employed in manual spreadsheet search applications include: Newton’s Method, Secant Method, Quadratic Approximation Methods, and the Golden Section Method (FHWA, 2004). These techniques are used for finding the value of a single parameter or multiple parameters that minimize the squared error between observed and modelled results (FHWA, 2004).

Since the choice of feasible parameter values is large, and the process to change parameters is usually based on engineering judgement or ad hoc process, the process takes a considerable amount of time and effort. This trial-and-error method is usually not a feasible approach when the number of parameters to be calibrated is too large (Zhang & Ma, 2008).
2.2.2 Genetic Algorithm Approach

Genetic algorithms (GA) are appropriate for cases where the objective function is non-linear and non-differentiable, or where local minima and maxima cannot be ruled out. A genetic algorithm simulates Darwinian evolution and has been used in the literature as a method for searching multi-dimensional space according to some criteria (Back, 1996). A genetic algorithm is analogous to the notion of natural selection and the idea that the “fittest” survive. According to Back (1996), there are three operators that comprise a genetic algorithm: reproduction, mutation, and crossover. Those organisms with the genetic makeup that is most well adapted to the environment are most likely to survive and reproduce, resulting in a population that is increasingly ‘fit’. A genetic algorithm can be applied to the problem of model parameter estimation as follows:

- Chromosome: a vector of parameters
- Gene: individual parameter within a vector

The genetic algorithm begins by initializing a population of chromosomes – a group of feasible parameter sets. This initial population forms the first generation of the evolutionary process. The fitness of each of those chromosomes is the evaluated. Based on the fitness of each of the chromosomes in the population, a process of selection takes place in which chromosomes with higher fitness survive and unfit chromosomes are discarded. Reproduction involves the selection and the mixing of genes of two parent chromosomes (that have survived the selection process) to result in child chromosomes. The process of reproduction involves recombination, the mixing of genetic information from the two parents, and mutation – the introduction of slight modifications to individual genes in the chromosome. The next generation is then built using an assembly step, in which a subset of the parent and child populations is chosen through the process of selection. This evolutionary process repeats itself over many generations, and the overall fitness of the population improves in each generation. The chromosome with the highest fitness can be considered the calibrated parameter set.

Several studies have used genetic algorithms to address the calibration of microscopic traffic simulation models in the past. Ma and Abdulhai (2001) calibrated the mean headway, mean
reaction time, feedback, perturbation, and familiarity parameters of their PARAMICS simulation model using a GA with traffic counts as the objective function. Roorda et al. (2006) employed a genetic algorithm to search for a parameter set which maximized the log-likelihood function for a within-household level mode choice model. The mode choice model developed by Roorda et al. (2006) is a good example of how a genetic algorithm can be utilized to efficiently determine parameter estimates within acceptable model run times and with reasonable results. Other authors who have conducted studies using a GA for calibration and estimation of model parameters include: Gardes et al. (2002), and Lee et al. (2001).

2.2.3 Additional Calibration Techniques

Other techniques for calibration of microsimulation traffic models (Lee, D-H. et al., 2001) are the simplex-based approach, gradient approach and simulated annealing method.

The simplex-based approach is a type of pattern search technique that assumes a successful shift in a given direction is worth repeating if the resulting outcome is favourable (Kim, Kim, & Rilett, 2005). When a series of simple moves are continuously repeated, the resulting simplex either grows or shrinks (Kim, Kim, & Rilett, 2005). The process continues until the resulting simplex cannot be improved anymore (Kim, Kim, & Rilett, 2005).

The gradient approach adjusts parameters in a given direction based on the perceived benefit to the objective function as a result of a move in that direction (Kim, Kim, & Rilett, 2005). The goal is to achieve the most optimal value of the objective function (Kim, Kim, & Rilett, 2005). The parameters are adjusted based on the magnitude of its slope (Kim, Kim, & Rilett, 2005). Roorda et al. (2010) employed the gradient method for estimating truck origin-destination (O-D) matrices. The gradient method was used to make small adjustments to initial O-D matrices such that the trip assignment models resulted in modelled volumes that matched freeway classification counts (Roorda et al., 2010).

The simulated annealing (SA) approach is similar to a GA since it employs a stochastic approach to search for global optima (Zhang & Ma, 2008). However, it is different than a GA because it has the ability to search beyond local maxima by allowing for larger temporary increases in the error term (i.e. difference between simulated and observed results) to search a broader space...
(Zhang & Ma, 2008). Aarts and Korst (1989) were able to show that the SA process asymptotically converges to the global optima.
Chapter 3

3 Original Edmonton Commercial Vehicle Model

Chapter 3 describes the original City of Edmonton Commercial Vehicle Model. Section 3.1 will outline the current state of the City of Edmonton’s commercial vehicle model and Section 3.2 will describe the original calibration process for the Edmonton CVM. Section 3.3 lists the shortcomings of the original CVM. Section 3.4 will outline all available data that has been utilized to generate the original CVM and Section 3.5 will discuss the new data available to update the CVM. Finally, Section 3.6 will present the chosen count locations and the method for choosing them.

3.1 Original CVM Structure

The City of Edmonton currently employs a tour-based microsimulation approach to estimate commercial vehicle movements based on a commodity flow study conducted in 2001. The microsimulation is executed using Java applications and two main sets of inputs: an EMME databank which provides information about the area being modelled and 30 coefficient files containing model specifications and parameter estimates. Hunt and Stephan (2007) developed a tour-based microsimulation for the City of Calgary and many of the specifications and estimates for the City of Edmonton model were borrowed directly from the City of Calgary.

Figure 5 shows the framework developed by Hunt and Stephan (2007) that was used in the development of the Edmonton CVM. First, aggregate tours are generated within EMME to create a list of tours using both logit and regression techniques. The aggregate tour generation consists of three parts: tour generation, vehicle type/ tour purpose, and tour start time. Second, individual tours generated from each zone in EMME are assigned a next stop purpose, next stop location and next stop duration using a microsimulation process. In this process, Monte Carlo techniques are used to incrementally ‘grow’ a tour by having a ‘return-to-establishment’ alternative within the next stop purpose allocation. If the next stop purpose is not ‘return-to-establishment’, then the tour extends by one more stop. The selection probabilities used in the microsimulation processes are established using logit models which were estimated from the choice data collected in the surveys. The model considers four vehicle types: light, intermediate,
medium, and heavy trucks. Six establishment categories are used to classify business establishments: industrial (IN), wholesale (WH), service (SE), retail (RE), transport and handling (TH) and fleet allocator (FA). Five time periods are considered in the model: early off-peak (midnight – 7 AM), AM peak (7 – 9 AM), midday off-peak (9 AM – 4 PM), PM peak (4 – 6 PM), and late off-peak (6PM – midnight). The model also considers five land use types: industrial, residential, commercial, employment node, low density, and power centre.

Calibration of the model occurs once all initial values of the coefficients are determined. The calibration process matches estimated values to target values derived from the 2001 CFS. Since the elements of the microsimulation are interdependent, adjustments to one element’s coefficients can affect the output of another element. As a result, aggregate targets were considered and will be discussed further in Section 3.2. Both EMME and Java work together to output adjusted coefficients to better match the target values.

The Edmonton CVM can provide decision makers with a representation of commercial vehicle movements within the region for use in forecasting and policy analysis since the model is sensitive to changes in population, employment, transport supply conditions, and vehicle specific characteristics. As a result, impacts to model outputs such as traffic flow and vehicle travel times can be assessed. These outputs are analyzed to determine if policies such as truck route restrictions are effective or require revision.
3.1.1 Tour Generation

The number of tours originating in each zone is established using an aggregate tour generation model and are microsimulated with specific attributes. Tour generation is determined for the entire day for each category of establishment for each zone using an exponential regression equation with zonal level attributes as the independent variables. This rate is multiplied by the number of employees in the relevant category of establishment in the zone to produce a total number of tours generated in the zone by that industry for the entire day.

3.1.2 Vehicle and Tour Purpose

Prior to determining the vehicle and tour purpose, the tour start time model determines the time of day in which the tour will start. The list of tours is split among time periods of the day to establish the number of tours in each time period by establishment type in each zone. For example, one of the five time periods will be assigned to each tour. The split is estimated using a multinomial logit model.

Once the time of day is assigned, each tour for each zone listed from the tour generation model is assigned a primary purpose and vehicle type. This is achieved using a Monte Carlo process simultaneously. Selection probabilities are determined for each establishment category using multinomial logit models with utility functions that include zonal level land use, establishment location and accessibility attributes.

The model was estimated using three alternatives for the primary purpose of the tour: goods, service or other. A goods tour involves delivering some type of parcel, whereas a service tour would be comprised of mostly stops in which services are provided (i.e. cable repair). An ‘other’ tour is comprised mainly of stops made to fuel or repair a vehicle, stops at home, stops for a meal or a personal stop. Once the primary tour purpose is established, a vehicle type is assigned from the four possible alternatives.

3.1.3 Tour Start Time

Once the tour generation model populates the list of tours and each tour is allocated to one of the five time periods during the day the tour start time model assigns a precise start time for each tour in the list. This is achieved using a Monte Carlo process with sampling distributions based
on the weighted sample of observed start times by different establishment categories and time periods. The sampling distribution is a cumulative percentage distribution function calculated by curve fitting observed data.

### 3.1.4 Next Stop Purpose

The next stop purpose model is the first step in the tour-based microsimulation process. A Monte Carlo process is used to assign the next stop purpose with selection probabilities determined for each commercial movement segment using a multinomial logit model. Fourteen (14) different segments of commercial movements were estimated based on combinations of: industry category, vehicle type and primary tour purpose. These 14 segments are defined in Table 1.

#### Table 1: Segment categories for next stop purpose

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>S-S-L</td>
<td><em>service</em> tours by <em>service</em> establishments using <em>light</em> vehicles;</td>
</tr>
<tr>
<td>S-S-MH</td>
<td><em>service</em> tours by <em>service</em> establishments using <em>medium or heavy</em> vehicles;</td>
</tr>
<tr>
<td>G-S-LMH</td>
<td><em>goods</em> tours by <em>service</em> establishments using <em>any</em> vehicle type;</td>
</tr>
<tr>
<td>S-R-LMH</td>
<td><em>service</em> tours by <em>retail</em> establishments using <em>any</em> vehicle type;</td>
</tr>
<tr>
<td>G-R-LMH</td>
<td><em>goods</em> tours by <em>retail</em> establishments using <em>any</em> vehicle type;</td>
</tr>
<tr>
<td>S-I-L</td>
<td><em>service</em> tours by <em>industrial</em> establishments using <em>light</em> vehicles;</td>
</tr>
<tr>
<td>S-I-MH</td>
<td><em>service</em> tours by <em>industrial</em> establishments using <em>medium or heavy</em> vehicles;</td>
</tr>
<tr>
<td>G-I-LMH</td>
<td><em>goods</em> tours by <em>industrial</em> establishments using <em>any</em> vehicle type;</td>
</tr>
<tr>
<td>S-W-LMH</td>
<td><em>service</em> tours by <em>wholesale</em> establishments using <em>any</em> vehicle type;</td>
</tr>
<tr>
<td>G-W-L</td>
<td><em>goods</em> tours by <em>wholesale</em> establishments using <em>light</em> vehicles;</td>
</tr>
<tr>
<td>G-W-MH</td>
<td><em>goods</em> tours by <em>wholesale</em> establishments using <em>medium or heavy</em> vehicles;</td>
</tr>
<tr>
<td>B-T-LMH</td>
<td><em>business</em> tours by <em>transport</em> establishments using <em>any</em> vehicle type;</td>
</tr>
<tr>
<td>O-X-LMH</td>
<td><em>other</em> tours by <em>any</em> establishments using <em>any</em> vehicle type;</td>
</tr>
<tr>
<td>S-S-L</td>
<td><em>service</em> tours by <em>service</em> establishments using <em>light</em> vehicles;</td>
</tr>
<tr>
<td>S-F-LMH</td>
<td><em>service</em> tours by <em>fleet</em> establishments using <em>any</em> vehicle type;</td>
</tr>
</tbody>
</table>

The possible alternatives for the next stop purpose are: goods (if primary purpose was goods), service (if primary purpose was service), other (if primary purpose of tour was goods, service or other), and return-to-establishment (if next stop is not the first stop on the tour). It should be noted that a business stop refers to stops made by transport and handling vehicles because they provide the service of moving goods. Furthermore, it should be noted that selection probabilities for service tours by fleet establishments (S-F-LMH) are borrowed from the nesting structure of service tours.
3.1.5 Next Stop Location

The next stop location model is the second step in the tour-based microsimulation. The next stop location model is similar to the next stop purpose model. However, instead of using the primary tour purpose as the independent variable, the next stop purpose is used. Assuming the next stop purpose is not “return-to-establishment”, the available alternatives for the next stop location are the remaining model zones. A Monte Carlo process is used in the selection of the next stop location with the selection probabilities determined by multinomial logit models. The logit models are developed for 14 ‘segment’ categories similar to the categories outlined in Section 3.1.4. In the case of the next stop location model, the 14 segments are based on combinations of industry category, vehicle type, and next stop purpose.

The generalized utility function for each zone in the next stop location model includes a term for the enclosed angle for zone j. This measure is the angle enclosed by the straight line from the current zone to the zone containing the establishment and the straight line from the current zone to zone j. The enclosed angle term is depicted in Figure 6. A value of zero degrees would indicate that zone j is in the direction of the establishment and 180 degrees would indicate that the establishment is in the opposite direction of zone j. This is an interesting feature of the existing model since it affects the geometry and length of tours.

![Figure 6: Example of enclosed angle for zone ‘j’](image-url)
3.1.6 Stop Duration Model

The stop duration model is the third and final step in the microsimulation process. In this step, a precise duration is assigned to each stop. This is done using a Monte Carlo process with sampling distributions based on the weighted sample of observed durations differentiated by the 14 segmented categories. The stop duration model is important because it allows vehicles to be delayed at stops thus spreading trips throughout the day and into different time periods. The microsimulation uses these durations to advance the clock that keeps track of the exact start and end times for each stop.

3.2 Original CVM Calibration Process

After the model parameters for the six models in Section 3.1 have been estimated, the CVM can be calibrated. Since the elements of the microsimulation are interdependent, adjustments to one element’s coefficients can affect the output of another element. As a result, the calibration process uses a series of aggregate targets for fine tuning of the model.

In the calibration process, EMME is used to generate aggregate tours which are then converted to trips and passed to the JAVA program which microsimulates the next stop purpose, next stop location and stop duration model. The JAVA program keeps track of which zones trips originate from and which zones trips are destined to. The JAVA program then passes the trips back to EMME where they are converted and stored in origin-destination matrices. The results of the microsimulation are saved in output files from EMME which are read into an excel worksheet that is used to determine if the model is calibrated. If the model is not calibrated, adjustments are made to model parameters based on the deviation from target values. The adjusted coefficients are updated in EMME and JAVA input files and the calibration process is redone. Many iterations are performed to bring the model within an acceptable tolerance of the target values. The sets of aggregate targets considered and the coefficients adjusted to improve the match to these targets are listed in Table 2.

The original Edmonton CVM uses the aggregate target values to calibrate the model and uses differences between modelled and observed results to update parameters. Once the modelled values match the observed target values within an acceptable level of tolerance, it can be said that the model has converged and is calibrated. The disadvantage to this approach is that the
observed target values are based on data collected in 2001 and is expected to have changed over time. Therefore, the model is continuously being calibrated to out-of-date information and is not flexible to changes in network conditions. In particular, average trip lengths, trips to particular sectors, and intra-sector trips are likely to have changed over time as trip generating activities and the road network have evolved since 2001.

Table 2: Original Edmonton CVM Calibration Targets

<table>
<thead>
<tr>
<th>Target</th>
<th>Coefficients Adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio of Employees that ship/Total Employees by Industry Type and Area</td>
<td>Adjust tour generation constants</td>
</tr>
<tr>
<td>Daily Tour Generation (scaled) by Industry Type and Area</td>
<td>Adjust tour generation constants</td>
</tr>
<tr>
<td>Tour Generation (scaled) by Industry Type and Time of Day</td>
<td>Adjust time of day alternative specific constant</td>
</tr>
<tr>
<td>Daily Tour Generation (scaled) by Industry Type and Tour Purpose</td>
<td>Adjust tour purpose alternative specific constant</td>
</tr>
<tr>
<td>Daily Tour Generation (scaled) by Industry Type and Vehicle Type</td>
<td>Adjust vehicle type alternative specific constant</td>
</tr>
<tr>
<td>Trips/Tour (scaled) by Industry Type and Tour Purpose</td>
<td>Adjust return to establishment next stop purpose alternative specific constant</td>
</tr>
<tr>
<td>Average Trip Length (km) by Industry Type and Vehicle Type</td>
<td>Adjust next stop location alternative specific constant</td>
</tr>
<tr>
<td>Destination Sector Factors by Industry Type and Vehicle Type</td>
<td>Adjust zonal k-factor for destination zones</td>
</tr>
<tr>
<td>Intra-sector Factors by Industry Type and Vehicle Type</td>
<td>Adjust intra-zonal k-factor for destination zones</td>
</tr>
</tbody>
</table>

3.3 Shortcomings of Original CVM

The original calibration process uses the aggregate targets listed in Table 2 to update model parameters. The aggregate targets are derived from information collected in the establishment based survey conducted in 2001. The City of Edmonton has seen substantial growth since 2001 and it is reasonable to expect that the information collected in 2001 is now outdated. However, certain general travel patterns have not changed and so there is some benefit to retaining selected target values from the 2001 survey. The most significant shortcoming of the original CVM is that it was never validated using truck counts. Therefore, the model is continuously being calibrated to out-of-date aggregate target values and is not flexible to changes in network
conditions. In particular, vehicle type shares and truck trip patterns are likely to have changed over time as trip generating activities and the road network have evolved since 2001.

3.4 Existing Data Sources

Section 3.4 is a comprehensive overview of the sources of data that were available to the City of Edmonton in developing the commercial vehicle model.

3.4.1 2001 Commodity Flow Survey

In October 2001, the City of Edmonton and Alberta Transportation conducted a major survey of business establishments to better understand the characteristics of goods and service movements in the Edmonton Region. A total of 27,478 business establishments were contacted, of these establishments 50% were eligible to participate in the survey, and of the eligible establishments, 31% agreed to participate. The study area for the survey consisted of the Edmonton Census Metropolitan Area (CMA) which is comprised of the City of Edmonton and its six surrounding counties as depicted in Figure 1. The CFS provided information on goods shipments, service visits, vehicle types, gross vehicular weight, fuel type, vehicle ownership, vehicle trip origins and destinations and commercial vehicle traffic volumes.

The major findings of the CFS (City of Edmonton & Alberta Transportation, 2003) include:

- 37% of surveyed establishments ship goods
- 45% of surveyed establishments make service ‘visits’
- Three general vehicle categories are used to deliver goods or services; passenger vehicles, single-unit trucks, and multi-unit trucks
- Gross-vehicular weight of single unit and multi-unit trucks range between 12,000 kg and 60,000 kg
- 90% of passenger vehicles use gas, while 98% of multi-unit trucks use diesel and less than 2% of all vehicles use propane
- Majority of vehicles used to deliver goods or services are owned by the company
- 165,000 vehicle trips are generated daily within the Edmonton CMA for commercial purposes
The northwest and the southeast suburbs of the City of Edmonton generate nearly four out of every ten daily commercial vehicle trips, while Leduc/Nisku/Airport and Highway 16 Corridor generate the most commercial vehicle trips of the regional sectors.

1 out of every 3 trips was made for the purpose of delivering a good or product.

Just over half of all commercial vehicle trips were made for service purposes.

The northwest and southeast suburbs generate the most goods trips across most goods categories; printed matter is the most common product shipped from the central area of Edmonton.

Most service trips originate in the northwest and southeast suburbs, with 10% of all transportation service trips (e.g. trips by courier companies) originating in the central area of Edmonton.

The peak hour for all commodity movement vehicle trips is 9:00AM to 10:00AM and 15% of daily commodity vehicle trips take place during the 7:00AM to 10:00AM peak period.

The major daily truck volumes are observed on the Yellowhead Trail and on Whitemud Drive, with daily truck volumes ranging between 3,000 and 4,000 trucks per day on both roadways. Truck volumes on Highway 2 south and Highway 16 west range between 1,000 and 3,000 vehicles per day.

### 3.4.2 2001 Regional External Truck/Commodity Survey

In 2001, the City of Edmonton and Alberta Transportation conducted an External Truck/Commodity Survey to study commercial movements made by trucks into and out of the Edmonton Region. Over 6,500 roadside interviews were conducted between the period of September and November 2001 at 24 sites on provincial highways entering the study area.

The following is a summary of the findings of the survey (City of Edmonton & Alberta Transportation, 2003):

- Almost 16,000 trucks enter or exit the region on a typical weekday on a 24-hour basis.
- Approximately 16,200 Commodity trips are made on a typical weekday on a 24-hour basis;
• The highways that carry the majority of the trips into and out of the region include Highway 2 South (20%), Highway 16W (13%), Highway 43 (10%), Highway 16E (9%) and Highway 21 (7%);
• For highways where 24-hour truck counts were conducted it was observed that:
  • 40 percent of all truck travel occurs between 8:00AM and 4:00PM;
  • Truck traffic peaks between 5:30PM and 6:00PM
  • Highway 43 carries the highest proportion of trucks, followed closely by Highway 2 South, Highway 16 West and Highway 16 East
• 72% of the trucks were owned by the company producing goods being shipped
• Total tonnage or Gross Vehicle Weight amounted to 660,000 metric tons on the highways
• 77% of all trucks were Multi Unit trucks and 23% were Single Unit trucks
• 36% of all trucks were empty, 19% carried manufactured goods, machinery, equipment and transportation related items
• 62% of the trucks carried a single commodity and only 2% carried more than one commodity
• 42% of the trips originated or were destined to the City of Edmonton, 37%
• originated or were destined to rest of the Edmonton Region and 21% were external to external trips

### 3.5 New Data Sources

Section 3.5 is an overview of the new sources of data that have been collected by the City of Edmonton for use in updating the original CVM.

#### 3.5.1 2012 Roadside Truck Survey

The City of Edmonton conducted a roadside truck survey in September and October of 2012 to provide input to the development of the Edmonton Goods Movement Strategy. Only trucks with a gross weight exceeding 4,500 kg were interviewed in regards to: trip origins and destinations, route choice on local roads and highways, commodities carried, and experiences with the Edmonton transportation network. In total, 2,294 surveys were completed in a 14 day period. The survey was conducted between Tuesday and Friday and between 9 a.m. and 3 p.m. to coincide with the peak period of truck traffic in Edmonton. The days selected for the survey were
chosen to coincide with the Edmonton Police Service and Provincial fall check program, and since truck volumes are typically higher Tuesday through Friday and during the off-peak periods.

The results of the survey are summarized as follows (Edmonton, 2013):

- Within the city, the largest movement of trucks is between the Northwest and Southeast quadrants – consistent with results of the 1996 Truck Study and the 2001 Commodity Flow Survey
- 74% of trucks began and ended their day at the same location, their ‘home-base’ - a trip pattern that is consistent with the results from the 2001 Commodity Flow Survey
- Between the region and the city, the highest volume of movement occurred between the East, West and South Regions; previous studies have found similar trends although the West and East Regions have become more important as generators of trips to and from the city
- Yellowhead Trail is the most used facility with 67% of truck drivers indicating using the roadway and 60% using Anthony Henday Drive
- 60% of trucks using Yellowhead Trail and Anthony Henday Drive had as part of their trip an origin or a destination in the City of Edmonton while nearly a quarter of all trucks using of Yellowhead Trail and Anthony Henday Drive had an origin or destination in the region
- 81% of truck drivers surveyed indicated they chose their routes because they were the most direct
- Edmonton’s roads are important to the oil, gas and construction industries – 54% of trucks carry materials such as chemicals, fuel petroleum and construction materials
- Truck drivers reported a high level of overall satisfaction (62%) with Edmonton’s truck routes and roadways - much higher than other jurisdictions in Canada and the United States
- Most frequent suggestions from truck drivers about the roadway network included improvements to pavement condition, opening 75 Street to trucks and improvements to signage and truck route information
3.5.2 Additional Truck Count Data

In addition to the 2012 Roadside Truck Survey, truck counts were collected in 2014 to supplement the original counts from 2012. These counts were collected using video camera technology which identifies vehicle types and classifies them based on size. The 2014 truck counts were used to determine the distribution of truck types for certain count locations and applied to the total truck volume at a count location observed in 2012. This method was used to approximate the truck counts in 2012 at count locations for which vehicle type distributions were missing. This method is reliable since the difference between total truck volumes observed in 2012 and 2014 at count locations was negligible.

3.6 Chosen Count Locations

Given the count location information collected in the 2012 Roadside truck survey and the additional truck count data collected in 2014, a set of these locations were chosen for use in updating the original Edmonton CVM. Twenty-two (22) count locations were ultimately chosen to validate the model outcomes to current road conditions. The locations were selected based on the following criteria:

- quality of the count location data (i.e. roadside truck survey versus video camera count),
- high volume truck route,
- time of year counts were conducted,
- distribution of count locations across different traffic districts,
- significance to policy questions, control locations (i.e. bridges, gateways),
- limiting redundant locations,
- 24-hour versus 11-hour count locations

Based on the criteria for selecting a count location, all of the 2012 Roadside Truck Survey count locations were included for validation purposes. The roadside survey highlighted fourteen (14) count locations. In addition to the 14 locations from the Roadside Truck Survey, eight (8) count locations with 11-hour traffic count data from 2014 which were collected using traffic camera technology were also included.

In order to choose which of the 11-hour count locations to select, each location was ranked in descending order based on its two-way truck volume totals. After ranking all locations, each was screened based on the following criteria:
- two-way truck volume must be greater than 800 vehicles,
- the location cannot be located directly before or after a 2012 Roadside Truck Survey locations on a given roadway (to reduce redundancy)

Using the criterion discussed above, the twenty-two (22) locations that were chosen have been listed in Table 3 and are displayed on a map of the City of Edmonton in Figure 7.

**Table 3: Selected Count Locations**

<table>
<thead>
<tr>
<th>Site</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Yellowhead Trail West of 121 Street</td>
</tr>
<tr>
<td>2</td>
<td>Whitemud Drive at 75 Street</td>
</tr>
<tr>
<td>3</td>
<td>Anthony Henday Drive North of Lessard Road</td>
</tr>
<tr>
<td>4</td>
<td>170 Street North of Yellowhead Trail</td>
</tr>
<tr>
<td>5</td>
<td>50 Street North of Eleniak Road</td>
</tr>
<tr>
<td>6</td>
<td>Yellowhead Trail West of 50 Street</td>
</tr>
<tr>
<td>7</td>
<td>Wayne Gretzky Drive at 101 Avenue (northbound) and 116 Avenue (southbound)</td>
</tr>
<tr>
<td>8</td>
<td>99 Street South of 39 Avenue</td>
</tr>
<tr>
<td>9</td>
<td>Sherwood Park Freeway West of 34 Street</td>
</tr>
<tr>
<td>10</td>
<td>Anthony Henday Drive near St. Albert Trail</td>
</tr>
<tr>
<td>11</td>
<td>75 Street South of Wagner Road</td>
</tr>
<tr>
<td>12</td>
<td>Manning Drive North of 153 Avenue</td>
</tr>
<tr>
<td>13</td>
<td>Highway 16A at Winterburn Road</td>
</tr>
<tr>
<td>14</td>
<td>Gateway Boulevard North of 23 Avenue (northbound) and Calgary Trail South of 42 Avenue (southbound)</td>
</tr>
<tr>
<td>15*</td>
<td>Yellowhead Trail West of 231 Street</td>
</tr>
<tr>
<td>16*</td>
<td>Calgary Trail South of Ellerslie Road</td>
</tr>
<tr>
<td>17*</td>
<td>Whitemud Drive at Quesnell Bridge</td>
</tr>
<tr>
<td>18*</td>
<td>170 Street South of 87 Avenue</td>
</tr>
<tr>
<td>19*</td>
<td>Baseline Road West of 17 Street</td>
</tr>
<tr>
<td>20*</td>
<td>184 Street North of Yellowhead Trail</td>
</tr>
<tr>
<td>21*</td>
<td>97 Street North of 137 Avenue</td>
</tr>
<tr>
<td>22*</td>
<td>Terwillegar Drive North of Anthony Henday Drive</td>
</tr>
</tbody>
</table>

* Video camera count location
Figure 7: Selected Count Locations
Chapter 4

4 Comparison of Original Model to Observed Counts

Chapter 4 compares the original modelled volumes to the observed counts from the 22 count locations. To illustrate the discrepancies between the original model and observed counts a comparison of overall total truck counts is presented as well as a detailed analysis at each count location.

4.1 Overall Comparison

Figure 8 presents the observed and original modelled daily truck totals categorized by vehicle type. The original model under-simulates the intermediate truck type by 77% and over-simulates the medium truck type by 85%. The original model has better correspondence for the heavy truck type compared to the other two types; over-simulating by 17%.

Figure 8 highlights that the original model is resulting in incorrect vehicle type shares when compared with the observed counts. However, the original model is only over-simulating the total number of trucks in total for all vehicle types by 5%, which suggests that the discrepancy between observed and modelled volumes is attributed to the vehicle type shares and not the overall generation of trucks.

Figure 9 presents the observed and original modelled total truck volumes categorized by time period. The original model considers five time periods: early morning off-peak, AM peak, midday off-peak, PM peak and late evening off-peak. For this analysis, the three off-peak periods have been combined. The original model reproduces the distribution of trips by time period relatively well according to Figure 9. The original model under-simulates by 14% in the AM period, over-simulates by 8% in the PM and OFF peak periods and over-simulates in the 24-hour period by 5%.
Figure 8: Observed vs. Modelled Counts by Vehicle Type

Figure 9: Observed vs. Modelled Count by Time Period
Figure 10 presents the daily truck totals for each count location. The original model predicts 68% of count location to within an error of 40%. The largest discrepancies are seen at count locations 14 and 21.

Figure 11: Truck Totals by Count Location – AM Peak
Figure 11, Figure 12, and Figure 13 present the truck totals for the three time periods by count location. 68% of count locations are within an error of 40% in the AM peak where the largest differences are seen at count locations 7 and 14. 55% of count locations are within an error of 40% in the PM peak where the largest differences are seen at count locations 21 and 22. 64% of count locations are within an error of 40% in the OFF peak period where the largest differences are seen at count locations, 14 and 21.
Comparing the observed to original model results at the aggregate level of Figures 8 – 13 is useful for understanding the deficiencies in the model. However, a more detailed investigation of each count location for each vehicle type and time period is needed to fully realize the differences between the original model and the observed counts.

4.2 Detailed Comparison

Figures 14 -25 present the correspondence between observed and original model truck totals for each count location by time period and truck type.

Figure 14: Count Location Correspondence (AM Peak – Intermediate Trucks)
Figure 15: Count Location Correspondence (AM Peak – Medium Trucks)

Figure 16: Count Location Correspondence (AM Peak – Heavy Trucks)
Figure 17: Count Location Correspondence (PM Peak – Intermediate Trucks)

Figure 18: Count Location Correspondence (PM Peak – Medium Trucks)
Figure 19: Count Location Correspondence (PM Peak – Heavy Trucks)

Figure 20: Count Location Correspondence (OFF Peak – Intermediate Trucks)
Figure 21: Count Location Correspondence (OFF Peak – Medium Trucks)

Figure 22: Count Location Correspondence (OFF Peak – Heavy Trucks)
Figure 23: Count Location Correspondence (24 Hour – Intermediate Trucks)

Figure 24: Count Location Correspondence (24 Hour – Medium Trucks)
Although Figures 11 – 13 indicate that the correspondence between the original model and observed counts is adequate when combining all vehicle types, the more detailed analysis shown in Figures 14 – 25 indicates that there are serious differences between the observed counts and the original model. Specifically, the original model under-simulates intermediate trucks for all time periods and most count locations and over-simulates medium trucks for all time periods and most count locations.

Table 4 is a summary of the original model performance for each time period and vehicle type. Table 4 presents the percentage of count locations where the original model predicted the observed truck counts within an error of 40%. For eight of twelve categories the model reproduces less than half of the observed counts within an error of 40%.

Table 4 demonstrates that the model is performing poorly for the intermediate vehicle type in all time periods. Of the twelve vehicle type – time period categories, the model simulates the AM period with the least error compared to the other categories. Considering the 24 hour daily truck totals, the original model can only reproduce half of the heavy vehicles within an error of 40% and less than half for the intermediate and medium vehicles.

**Figure 25: Count Location Correspondence (24 Hour – Heavy Trucks)**
Table 4: Percent of Count Locations where Model Volumes are within 40% of Observed

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Vehicle Type</th>
<th>Percent of Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>AM</td>
<td>Intermediate</td>
<td>5%</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>55%</td>
</tr>
<tr>
<td></td>
<td>Heavy</td>
<td>50%</td>
</tr>
<tr>
<td>PM</td>
<td>Intermediate</td>
<td>5%</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>32%</td>
</tr>
<tr>
<td></td>
<td>Heavy</td>
<td>41%</td>
</tr>
<tr>
<td>OF</td>
<td>Intermediate</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>27%</td>
</tr>
<tr>
<td></td>
<td>Heavy</td>
<td>55%</td>
</tr>
<tr>
<td>24 Hour</td>
<td>Intermediate</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>Medium</td>
<td>27%</td>
</tr>
<tr>
<td></td>
<td>Heavy</td>
<td>55%</td>
</tr>
</tbody>
</table>

4.3 Approach for Improving Correspondence

Section 4.1 and 4.2 provide a summary of the issues inherent in the original Edmonton CVM. To summarize, the model does not simulate the shares of the vehicle types correctly according to the count data. Furthermore, a detailed investigation of each count location shows large differences between observed and modelled volumes for all vehicle types and time periods. To improve model correspondence to the observed count data, the following approach was used to guide the iterative procedure in adjusting model parameters to receive maximum improvement to model outcomes:

i. The total truck volumes are within a reasonable degree of tolerance from the total observed counts. Therefore, changes to tour generation coefficients are not warranted.

ii. Re-calibrate the vehicle type alternative specific constants in the tour purpose and vehicle type model to adjust the shares of the truck types in accordance with the shares exhibited in the count data.

iii. The total truck volumes for each time period are also within a reasonable degree of tolerance from the counts. Therefore, adjustments to these coefficients are not warranted.

iv. If adjustments to the vehicle type alternative specific constants in the tour purpose and vehicle type model (ii) do not produce a sufficient improvement to the model; adjustments to the alternative specific constants in the next stop location model should be made.
Chapter 5

5 Method

The purpose of this research is to provide the City of Edmonton with a cost effective approach to upgrade the original Edmonton CVM without having to collect an updated establishment-based survey and completely re-estimate each of the tour-based microsimulation models. A full model upgrade would be very costly and time consuming; the scope of this research is to make minimal changes to the original model while achieving the greatest possible benefit in terms of model outcomes.

To achieve this benefit, selected model parameters are adjusted such that the resulting commercial vehicle patterns better reflect the most recent road counts. Furthermore, the method incorporates original measures of model performance such as the number of trips per tour and average trip length to ensure the model does not deviate grossly from original model targets at the expense of calibrating to new truck counts. Secondly, updates to model inputs such as land use and road network characteristics have been performed. Updates to model inputs are straightforward and do not require methodological developments. Population and employment estimates for the 2012 base year have already been developed by the City of Edmonton, and a 2012 road transportation network is also available.

Chapter 5 will outline the parameters to be re-calibrated, the method to re-calibrate these parameters, and measures of model performance used to assess the goodness-of-fit between the observed and modelled truck counts. Several methods for re-calibrating model parameters for better count correspondence were discussed in Section 2.2. Of the available methods reviewed, a manual search method or iterative procedure was chosen to adjust model parameters. The manual search method was chosen because it was able to converge on a solution quickly and was flexible enough to be incorporated into the complex original model structure and calibration process. Although other methods such as genetic algorithms and gradient search approaches mentioned in Section 2.2.2 and 2.2.3 had the potential to converge to optimal solutions, computation time constraints prevented the use of these methods.
5.1 Parameters to be Re-Calibrated

The Edmonton CVM includes two types of parameters: (1) behavioural parameters estimated from survey data, and (2) calibration coefficients estimated using a spreadsheet tool which adjusts the coefficients until aggregate target values are within a reasonable degree of tolerance. The model specifications and parameters are stored in thirty (30) comma-separated values (CSV) format coefficient files. Each of the 30 files represents an industry and time period in the model. Each line in the coefficient file refers to a parameter to be used in the simulation of the commercial vehicle model. Table 5 describes the contents of each row of the coefficient file.

Many parameters that describe the decision-making behavior of the business establishments cannot be re-estimated reliably using road count data alone. Therefore, there is benefit to retaining the behavioural parameters for which there is greater confidence, while adjusting calibration parameters for which there is less confidence.

Table 5: Description of coefficient file contents

<table>
<thead>
<tr>
<th>Row</th>
<th>Contents</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Heading</td>
</tr>
<tr>
<td>2</td>
<td>Location of input tour generation matrix</td>
</tr>
<tr>
<td>3-10</td>
<td>Tour start time model</td>
</tr>
<tr>
<td>11-25</td>
<td>Location of output trip matrices</td>
</tr>
<tr>
<td>26-34</td>
<td>Location of input travel time matrices</td>
</tr>
<tr>
<td>35-43</td>
<td>Location of input travel disutility (generalized cost) matrices</td>
</tr>
<tr>
<td>44</td>
<td>Land use type code</td>
</tr>
<tr>
<td>45-194</td>
<td>Tour purpose and vehicle type model</td>
</tr>
<tr>
<td>195-269</td>
<td>Next stop purpose model</td>
</tr>
<tr>
<td>270-818</td>
<td>Next stop location model</td>
</tr>
</tbody>
</table>

In the Edmonton CVM, the parameters that are considered to be most suitable for adjustment are the parameters used for model calibration in the preliminary development of the Edmonton CVM in 2001 that have the most impact on road counts. Since the original model is not simulating the shares of vehicle types correctly, the vehicle type constants in the tour purpose and vehicle type model have been selected for adjustment to correct this discrepancy. The correspondence between modelled and observed truck volumes at specific truck count locations is also poor. It was hypothesized that adjustments to the zonal k-factors for the next stop location model would improve the correspondence at site specific locations.
5.1.1 Vehicle Type Constants

The vehicle constants in the vehicle type and tour purpose model are suitable candidates for parameter re-calibration because they affect the generation of tours by different vehicle types for different industry categories. Twenty-four (24) vehicle constants exist (i.e. 4 vehicle types and 6 industry categories) and represent the alternative specific constant for a given combination of tour purpose and vehicle choice in the tour purpose and vehicle type model. It is expected that by adjusting these vehicle constants, the number of tours and therefore the number of trips by different vehicle types are impacted. By adjusting these parameters to increase or decrease the tour generation for different vehicle types, changes at selected truck count locations should be noticeable.

5.1.2 K-factors in the Next Stop Location Model

Two types of k-factors are used to calibrate the next stop location model. The first is a zonal k-factor and the second is an intra-zonal k-factor.

Zonal k-factors in the next stop location model adjust the propensity of a stop to occur within a given superzone. Each combination of industry category and time period (i.e. six establishment types and five time periods) has its own next stop location model. Every next stop location model is adjusted by the same amount for calibration purposes, so every next stop location model has a “slave control” that refers to this master control. For example, k-factors for ‘service’ establishments in the ‘early’ time period act as master control coefficients for all ‘service’ establishments in the other four time periods. By updating these coefficients, all of the coefficients are updated. The constants are adjusted in the calibration process to match target proportions for trips to twenty (20) destination zones. There are 480 unique zonal k-factors for the next stop location model (20 sectors x 4 vehicle types x 6 industry types).

Intra-zonal k-factors are very similar to the zonal k-factors (calibration factors) for the next stop location model mentioned previously. Intra-zonal k-factors affect the propensity of a stop to occur within a superzone, given that the vehicle is currently in that superzone. These factors are used in the calibration process to adjust the constants to match target proportions for intra-sector trips in the 20 destination zones. There are 480 intra-zonal k-factors (calibration factors) for the next stop location model (20 sectors x 4 vehicle types x 6 industry types).
According to the City of Edmonton Roadside Truck Survey, the largest movements of trucks occur between the northwest and southeast industrial areas (Edmonton, 2013), see Figure 26. Furthermore, the study also states that the highest volume of movements occur between the east, west and south regions (Edmonton, 2013). The northwest and southeast industrial areas have become important generators for trips to and from the City of Edmonton according to the study (Edmonton, 2013). The movement of trucks between traffic zones is simulated through the next stop location model in the Edmonton CVM structure, see Section 3.1.5. Each of the smaller traffic analysis zones are aggregated into 20 larger superzones for calibration purposes. The zonal k-factors mentioned above are used in the calibration of the next stop location model to adjust the propensity of a trip to occur within a given superzone. Of the two types of calibration parameters available in the model that are suitable candidates for recalibration (i.e. zonal and intra-zonal k-factors), only the zonal k-factors are considered. Although intra-zonal k-factors would also affect road counts, they only affect the propensity of trips to occur within a given superzone and not between superzones, and given the prominent pattern of truck traffic between the northwest and southeast superzones, these factors are not expected to have a noticeable impact on truck counts.
5.2 Method for Parameter Estimation

Part of the approach to upgrade the commercial vehicle model to reflect current conditions is to adjust selected model parameters such that the resulting commercial vehicle patterns better reflect the most recent road counts. Section 2.2 presented various methods for the estimation and calibration of microsimulation models.

Of the available methods discussed in Section 2.2, two options were investigated further for application to the Edmonton CVM: the genetic algorithm approach, and a manual search algorithm approach. The Edmonton CVM is a complex model that uses hundreds of parameters to describe many different sets of behavioural models used to facilitate the microsimulation of commercial vehicles. The optimization of such a complex model is well suited to the strengths of the genetic algorithm approach. However, a genetic algorithm also requires a large population of chromosomes to be initialized to effectively search for the optimal solution. The optimum population size is a function of the complexity of the problem (Alander, 1992). In the case of the Edmonton CVM, the problem is very complex due to the interdependence of model parameters on model outcomes and the sheer number of parameters in the model. For example, 480 unique
calibration coefficients exist for the zonal k-factors used in the next stop location model. Since the Edmonton CVM takes hours per model run – evaluating such a large number of generations would take an unreasonable amount of computation time. Therefore, it was evident that the genetic algorithm approach would not be practical for this application due to computation time constraints.

Manual search methods are another common approach taken to calibrate microsimulation models. Although manual search methods can be time consuming and ad hoc, after many iterations they can achieve similar results as other methods (Zhang & Ma, 2008). Manual search methods are specific to each model they are applied to but often take the form of a spreadsheet algorithm (FHWA, 2004). As described in Section 3.2 the original Edmonton CVM currently uses a manual spreadsheet algorithm for calibration purposes. The proposed method for parameter re-calibration builds on the existing manual spreadsheet algorithm with the added functionality of calibrating to truck counts.

Section 5.2.1 will describe the vehicle constant re-calibration procedure and Section 5.2.2 will present the zonal k-factor re-calibration procedure for the next stop location model.

### 5.2.1 Vehicle Constant Re-Calibration Procedure

The vehicle type and tour purpose model assigns each tour both a purpose and a vehicle type. This is achieved using selection probabilities estimated for each establishment category using multinomial logit models with utility functions that include zonal-level land use, establishment location and accessibility attributes. The utility function for vehicle choice is presented in equation 1.

\[
V_k = \beta_{0k} + \beta X \tag{1}
\]

Where,

- \(V_k\) = utility function for vehicle choice (k)
- \(\beta_{0k}\) = alternative specific constant for vehicle type (k)
- \(X\) = vector of other explanatory variables. These explanatory variables do not vary between alternative vehicle types.
- \(\beta\) = vector of parameters for the other explanatory variables
By adjusting the vehicle type alternative specific constant, the propensity of a tour to be made by a given vehicle type can be influenced. Therefore, the number of trucks for a given vehicle type at truck count locations can also be impacted. A simplifying assumption made is that a change in the number of tours simulated by a given truck type will result in the same change in the number of truck trips modelled. Under this assumption, the adjustment process for vehicle type constants is as follows.

The logit model probability for each truck type is given by:

$$P_k = \frac{e^{V_k}}{\sum_{k'} e^{V_{k'}}} \quad (2)$$

We can influence the number of trips made by each vehicle type by modifying the logit model probabilities. For any pair of truck types, the logit model predicts relative choice probabilities as follows.

$$\frac{P_{k_1}}{P_{k_2}} = \frac{e^{V_{k_1}}}{e^{V_{k_2}}} \quad (3)$$

Where,

- $P_{k_1}$ = Probability of choosing vehicle type $k_1$
- $P_{k_2}$ = Probability of choosing vehicle type $k_2$

The application of the CVM model leads to model traffic volumes by vehicle type $k$ at each count location $l$. From these model outcomes we can compute the ratio of total modelled trips (at the count stations ‘l’) by vehicle types ‘$k_1$’ and type ‘$k_2$’, as shown in equation 4.

$$\gamma = \frac{\sum_l T_{k_1l}}{\sum_l T_{k_2l}} \quad (4)$$

Where

- $\gamma$ = ratio of total modelled trips by vehicle type ‘$k_1’ to type ‘$k_2’$
- $T_{kl}$ = modelled truck trips at count location ‘l’ by vehicle type ‘k’

We would like this ratio, $\gamma$, of modelled trips to reflect the ratio $\alpha$ of total observed truck counts (at the count stations) by vehicle type $k_1$ and $k_2$ as shown in equation 5.
\[ \alpha = \frac{\sum_l C_{k1l}}{\sum_l C_{k2l}} \quad (5) \]

Where,

\[ \alpha = \text{ratio of total observed trips by vehicle type 'k' to type 'k'} \]
\[ \sum_l C_{kl} = \text{observed truck trips at count location 'l' by vehicle type 'k'} \]

Equation 6 presents the adjustment factor \( F_{k1, k2} \) to be used to re-calibrate the vehicle type constants. It is formulated as the relative ratios of total observed trips by vehicle type ‘k’ to type ‘k’ (\( \alpha \)) to the total modelled trips by vehicle type ‘k’ to type ‘k’ (\( \gamma \)). If the model perfectly simulated the proportion of trips by vehicle type in the observed count data then the adjustment factor (\( F_{k1, k2} \)) would equal 1.

\[ F_{k1, k2} = \frac{\alpha}{\gamma} \quad (6) \]

\( F_{k1, k2} \) = adjustment factor for the ratio of the proportion of observed to modelled trips

We then use the adjustment factor in an iterative process to modify vehicle type choice probabilities.

\[ \frac{(P_{k1})_{new}}{(P_{k1})_{old}} = \frac{(e^{V_{k1}})_{new}}{(e^{V_{k1}})_{old}} = F_{k1, k2} \quad (7) \]

If we choose vehicle type k=2 to be the reference alternative, then it’s utility function remains the same and:

\[ (e^{V_{k2}})_{new} = (e^{V_{k2}})_{old} \quad (8) \]

Therefore,

\[ \frac{(e^{V_{k1}})_{new}}{(e^{V_{k1}})_{old}} = F_{k1, k2} \quad (9) \]

Substituting (1) into (9) and taking the natural logarithm,
\[(\beta_{0k1} + \beta X)_{new} - (\beta_{0k1} + \beta X)_{old} = \ln(F_{k1,k2}) \quad (10)\]

Solving for \(\beta_{0k1}^{new}\),
\[
\beta_{0k1}^{new} = \ln(F_{k1,k2}) + \beta_{0k1}^{old} \quad (11)
\]

The re-calibrated vehicle type constant (\(\beta_{0k1}^{new}\)) is calculated using equation 11. The new constant replaces the old constant in the utility function. If the adjustment factor (\(F_{k1,k2}\)) is less than 1, the new constant will be smaller than the old constant to ensure that fewer tours/trips by this truck type are made. Conversely, if the adjustment factor is (\(F_{k1,k2}\)) is greater than 1, the new constant will be larger than the old constant to ensure that more tours/trips by this truck type are made. After several iterations using this method, the adjustment factor (\(F_{k1,k2}\)) should converge to 1.

### 5.2.2 Zonal k-Factor Re-Calibration Procedure

The proposed method for re-calibrating zonal k-factors involves applying an adjustment factor for each destination zone and vehicle type pair to the original model parameter. The Edmonton CVM uses the zonal k-factors to adjust the propensity of a stop to occur within a given superzone. There are no coefficients in the model that directly impact link volumes at specific locations. However, adjustments to the zonal k-factors can influence road counts by varying the number of trips that travel to different destination zones. The k-factors would directly impact how trips would be made and to which destination sectors, thus changing which routes and which links are used.

It was hypothesized that adjusting the zonal k-factors using a similar method as the vehicle choice model would result in better correspondence at select count locations. The method is presented in Appendix A. Although this method is theoretically appealing, it did not result in a better fit to the observed counts when applied practically. The large number of k-factors used in the original model complicates the adjustment procedure. Only one adjustment factor is calculated based on the counts for each destination zone and vehicle type. This factor is then applied to all combinations of industry category, vehicle type and destination zone. Using a common adjustment factor may be the reason a substantial difference in correspondence was not
observed. Therefore, the zonal k-factors were excluded from the adjustment procedure and the original CVM was re-calibrated by making adjustments to the vehicle type constants alone.

5.3 Measures of Model Performance

Section 3.2 outlined the nine aggregate targets used to assess the performance of the model in the original Edmonton CVM. Since an updated commodity flow survey is not available, the aggregate targets in section 3.2 cannot be used to re-calibrate the original model reliably. Truck counts for 22 locations in the Edmonton CMA are the only new sources of information available to re-calibrate model parameters. The method for updating calibration parameters has been presented in Sections 5.2.1 and 5.2.2.

In order to determine if the vehicle constant re-calibration method presented in Section 5.2.1 and the zonal k-factor re-calibration method in Section 5.2.2 are providing improved results over the original model, the model’s outcomes must be tested using standard measures of model performance. The quality of the model outcomes can be measured as the deviation between modelled and observed volumes at count locations. Model volumes should ideally reflect road counts for all truck types, all time periods, and for a selection of road count locations.

To assess the model’s performance five acceptance targets have been evaluated.

i. Sum of modelled link volumes within 15% of sum of observed link counts by vehicle type ‘k’.

\[
\text{Percent Error (\%)} = \frac{\sum_p \sum_l C_{kpl} - \sum_p \sum_l T_{kpl}}{\sum_p \sum_l C_{kpl}} \times 100 \quad (12)
\]

Where,

\[
\sum_p \sum_l T_{kpl} = \text{Sum of modelled link volumes for truck type ‘k’}
\]

\[
\sum_p \sum_l C_{kpl} = \text{Sum of observed link counts for truck type ‘k’}
\]

ii. Sum of modelled link volumes within 10% of sum of observed link counts

\[
\text{Percent Error (\%)} = \frac{\sum_k \sum_p \sum_l C_{kpl} - \sum_k \sum_p \sum_l T_{kpl}}{\sum_k \sum_p \sum_l C_{kpl}} \times 100 \quad (13)
\]

Where,
\[ \sum_k \sum_p \sum_l T_{kpl} \] = Sum of modelled link volumes by truck type ‘k’ in period ‘p’ through count location ‘l’

\[ \sum_k \sum_p \sum_l C_{kpl} \] = Sum of observed link counts by truck type ‘k’ in period ‘p’ through count location ‘l’

iii. Adjustment factor for the ratio of the proportion of observed to modelled trips.

\[ F_{k1,k2} = \frac{\alpha}{\gamma} \]

iv. Percent of modelled volumes, by truck type and time period, at individual count locations within 40% of the observed counts.

\[ \delta = \frac{c_{40}}{n} \times 100 \quad (14) \]

Where,

\[ \delta \] = Percent of modelled volumes within 40% of observed counts
\[ c_{40} \] = Number of count locations where percent error between modelled and observed counts is less than 40%
\[ n \] = Total number of count locations (n = 22 count locations * 3 vehicle types * 3 time periods = 198)

v. GEH statistic less than 5 for individual modelled volumes in at least 60% of cases

\[ GEH = \sqrt{\frac{(T_l - C_l)^2}{(T_l + C_l)/2}} \quad (15) \]

Where,

\[ T_l \] = Individual modelled volume for count location ‘l’
\[ C_l \] = Individual observed truck count for count location ‘l’

The model can be considered calibrated when all calibration acceptance targets are met. The calibration acceptance targets are shown in Table 7. The calibration acceptance targets were adapted from the Wisconsin Department of Transportation (DOT) freeway model calibration criteria and FHWA guidelines (Wisconsin DOT, 2002) which were originally developed in the
United Kingdom. The FHWA targets were chosen because they provide guidelines that are commonly applied in practice and would be useful to practitioners at the City of Edmonton in assessing model performance.

Table 6: Percent of Count Locations within Percent Error of Observed (Original Model)

<table>
<thead>
<tr>
<th>Percent Error (%)</th>
<th>Intermediate</th>
<th>Medium</th>
<th>Heavy</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>0%</td>
<td>41%</td>
<td>68%</td>
<td>73%</td>
</tr>
<tr>
<td>40</td>
<td>0%</td>
<td>27%</td>
<td>55%</td>
<td>68%</td>
</tr>
<tr>
<td>30</td>
<td>0%</td>
<td>14%</td>
<td>50%</td>
<td>59%</td>
</tr>
<tr>
<td>20</td>
<td>0%</td>
<td>14%</td>
<td>45%</td>
<td>41%</td>
</tr>
<tr>
<td>10</td>
<td>0%</td>
<td>9%</td>
<td>23%</td>
<td>18%</td>
</tr>
<tr>
<td>5</td>
<td>0%</td>
<td>9%</td>
<td>9%</td>
<td>5%</td>
</tr>
</tbody>
</table>

In addition to the FHWA measures, two extra measures were included. The adjustment factor check was included to indicate when the adjustment procedure had converged on a solution. The values of 0.95 and 1.05 were chosen arbitrarily but represent that a 5% difference in shares provides a better solution over the original model. The percent of modelled volumes within 40% of observed counts metric was included to compare the original and adjusted modelled results and emphasize the degree to which the adjustment model is outperforming the original model. The value of 40% was chosen to provide an adequate means for comparing the original and adjusted model results. To determine if an error of 40% would provide a good comparison, a sensitivity analysis was conducted by varying this criterion from 5% to 50% and observing the percentage of count locations at each level. Table 6 presents the sensitivity analysis for the original model. It is clear that the model performs very poorly when considering a percent error of 5 – 20%. Furthermore, the percentage of count locations does not exceed 50% (i.e. half of the locations) for more than one vehicle type below 40% error. To gain a true understanding of the deficiencies of the original model and determine to what degree the adjusted model outperforms the original, 40% was chosen.

Table 7: Calibration Acceptance Targets

<table>
<thead>
<tr>
<th>Measure</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum of link volumes by vehicle type</td>
<td>Less than or equal to 15%</td>
</tr>
<tr>
<td>Sum of link volumes</td>
<td>Less than or equal to 10%</td>
</tr>
<tr>
<td>Adjustment Factors (F_{k1,k2}) and (F_{j1,j2})</td>
<td>(0.95 \leq F_{k1,k2} \leq 1.05)</td>
</tr>
<tr>
<td>Percent of count locations with model volumes within 40% of observed counts</td>
<td>Greater than or equal to 50%</td>
</tr>
<tr>
<td>--------------------------------------------------------------------------</td>
<td>-------------------------------</td>
</tr>
<tr>
<td>GEH statistic less than 5 for individual link volumes</td>
<td>Greater than or equal to 50%</td>
</tr>
</tbody>
</table>
Chapter 6

6 Application of Methodology to the Edmonton CVM

Chapter 6 will describe the re-calibration process, how the methods described in Chapter 5 were applied to the original Edmonton CVM, and how it overcomes the original model calibration shortcomings.

6.1 Model Re-Calibration Process

The model re-calibration process is presented in Figure 27. The re-calibration is a seven step iterative and cyclical process.

The first step of the re-calibration requires that a calibration run is performed by executing the JAVA-EMME program (i.e. calibration run) using the most recent set of model parameters. A calibration run only considers commercial vehicles and the microsimulation of these movements.

The second step involves transferring the commercial vehicle tours microsimulated by the calibration run into three separate EMME databanks (i.e. one for each model time period – AM, PM, OF). Once the tours are transferred, a standard traffic assignment is done in each of the databanks for the three time periods. The traffic assignment is a generalized cost multiclass user-equilibrium traffic assignment with stopping criteria of 999 iterations and a best relative gap (bgap) of 0.01. A bgap of 0.01 is used to ensure that the maximum difference of the current solution from the equilibrium solution is at least 0.01.

Following the traffic assignment, modelled truck volumes for each of the three vehicle types (intermediate, medium and heavy) at each of the 22 count locations are exported to text files.

The fourth step involves importing the exported modelled truck volumes into a spreadsheet and comparing them to the observed counts. The fifth step uses the measures of model performance listed in Table 7 to assess the results of the current model outcomes. If the acceptance targets are not satisfied, a new iteration is required. If a new iteration is required, the model parameters are updated in the calibration spreadsheet using the method presented in Section 5. Once the model
parameters are updated they are saved in new input files and the next calibration run is executed. This circular process continues until the calibration acceptance targets are met.

![Diagram of Model Re-Calibration Process](image)

**Figure 27: Model Re-Calibration Process**

### 6.2 Benefits of the Re-Calibration Process

Section 3.3 described the shortcomings of the original calibration process. The most significant shortcomings were that the original calibration process only used aggregate targets listed in Table 2 to update model parameters and that the original CVM was never validated using truck counts. The results of the original model comparison to the observed counts showed that using aggregate targets alone to calibrate the model produced incorrect vehicle type shares and large differences between modelled and observed counts at selected count locations. The re-calibration process is an upgrade from the original calibration process because it incorporates observed count data while maintaining a level of accuracy at the aggregate level. The re-calibration process is also very similar to the original calibration process with acceptable model run times which makes it a viable and practical approach to be used by the City of Edmonton in the future. Model parameters are reliably adjusted according to differences between modelled and observed counts with certain simplifying assumptions that produce results which are an improvement over the original model.
Chapter 7

7 Results

Section 7 compares the original model volumes to the adjusted model volumes and the observed counts from the 22 count locations. To illustrate the improvement between the original model and the adjusted model a comparison of overall total truck volumes is presented as well as a detailed analysis of each count location. Five iterations of the model re-calibration process presented in Section 6 were required to meet the calibration acceptance targets.

7.1 Overall Comparison

Figure 28 presents the observed and modelled daily truck totals categorized by vehicle type for the original and adjusted model as well as the observed counts. The adjusted model now over-simulates the intermediate truck type by 4% compared to under-simulating by 77% for the original model. The adjusted model now over-simulates the medium truck type by 7% compared to over-simulating by 85% for the original model. Lastly, the adjusted model over-simulates the heavy truck type by 7% compared to over-simulating by 17% in the original model. The overall number of trucks being over-simulated in the adjusted model is 6% compared to 5% in the original model. This increase in total number of trucks is negligible and within an error of 10% from the observed counts.

The method outlined in Section 5 was successful in correcting the vehicle shares simulated by the model. Furthermore, the method was able to converge on a reasonable answer relatively quickly, needing only five model runs to achieve the desired results.
Figure 28: Observed vs. Modelled Counts by Vehicle Type

Figure 29 presents the observed and modelled truck totals categorized by time period. Figure 29 shows that the original model reproduced the shares of overall trucks in the model by time period relatively well and the adjusted model has not affected the time period shares negatively despite correcting the vehicle type shares. The percent error for the AM period is now only 13% compared to 14% and the PM and Off-peak periods are still within 10% of the observed values.
Figure 30: Daily Truck Totals by Count Location

Figure 30 presents the original, adjusted, and observed daily truck totals for each count location. 55% of count locations show an improvement over the original model. Six locations were within an error of 40% from the observed counts for the original model. The adjusted model has shown a small improvement with eight count locations now within an error of 40%.

Figure 31: Truck Totals by Count Location – AM Peak
Figure 32: Truck Totals by Count Location – PM Peak

Figure 33: Truck Totals by Count Location – OFF Peak

Figure 31 – Figure 33 present the original, adjusted, and observed truck totals for each count location in the AM, PM, and OFF peak periods respectively. In the AM peak period, the adjusted model only made an improvement over the original model in 8 of 22 locations. The adjusted model predicted 32% of the count locations within an error of 40% compared to 36% for the original model. In the PM peak period, the adjusted model made an improvement over the original model in 13 of 22 locations. The adjusted model predicted 32% of the count locations...
within an error of 40% compared to 27% in the original model. In the OFF peak period, the adjusted model made an improvement over the original model in 11 of 22 locations. The adjusted model predicted 73% of the count locations within an error of 40% compared to 50% for the original model. A significant improvement was not observed for truck totals in the AM, PM and OFF peak periods. This was expected since the method only adjusted vehicle type shares to match the distribution of vehicles observed in the counts. To truly understand the improvements made by the adjustment procedure, a detailed analysis of the correspondence between observed, original, and adjusted model truck totals for each count location by time period and truck type is required.

### 7.2 Detailed Comparison

Figures 34 – 45 present the correspondence between observed counts, original modelled volumes and the adjusted model volumes for each count location, time period, and truck type.

![Figure 34: Count Location Correspondence (AM Peak – Intermediate Trucks)](image)

Figure 34 presents the count location correspondence for intermediate trucks in the AM peak period. The adjusted model made an improvement over the original model in 21 of 22 count locations and predicted 55% of the count locations within an error of 40% compared to 5% for the original model.
Figure 35: Count Location Correspondence (AM Peak – Medium Trucks)

Figure 35 presents the count location correspondence for medium trucks in the AM peak period. The adjusted model made an improvement over the original model in only 10 of 22 count locations and predicted 36% of the count locations within an error of 40% compared to 55% for the original model. The adjustment procedure diminished the performance of the model for this time period and truck type.

Figure 36: Count Location Correspondence (AM Peak – Heavy Trucks)

Figure 36 presents the count location correspondence for heavy trucks in the AM peak period. The adjusted model made an improvement over the original model in 15 of 22 count locations and predicted 59% of the count locations within an error of 40% compared to 50% for the original model.
The adjustment procedure was able to improve the performance of the model in the AM period for the intermediate and heavy truck types. However, the performance was diminished for the medium truck type. Although this result is not favourable, it was expected that the medium truck type would lose trips at the expense of generating more intermediate truck since the total number of trucks being generated stays constant.

Figure 37: Count Location Correspondence (PM Peak – Intermediate Trucks)

Figure 37 presents the count location correspondence for intermediate trucks in the PM peak period. The adjusted model made an improvement over the original model in 20 of 22 count locations and predicted 86% of the count locations within an error of 40% compared to 5% for the original model.
Figure 38: Count Location Correspondence (PM Peak – Medium Trucks)

Figure 38 presents the count location correspondence for medium trucks in the PM peak period. The adjusted model made an improvement over the original model in 14 of 22 count locations and predicted 36% of the count locations within an error of 40% compared to 32% for the original model. The adjustment procedure was able to bring 64% of the count locations to within 40% of the observed counts. However, count locations 4, 7, 9, 12, 14 – 18, 20 – 22 were already over-simulating by more than 100% and minimal improvement was observed at these locations.

Figure 39: Count Location Correspondence (PM Peak – Heavy Trucks)
Figure 39 presents the count location correspondence for heavy trucks in the PM peak period. The adjusted model made an improvement over the original model in 13 of 22 count locations and predicted 45% of the count locations within an error of 40% compared to 41% for the original model.

The adjustment procedure was able to improve the performance of the model in the PM period for the intermediate and heavy truck types. The performance was minimally improved for the medium truck type but major discrepancies still persist in the adjustment model. Since the adjustment procedure is constrained to adjusting the vehicle type shares, there is no mechanism to improve individual count locations.

Figure 40 presents the count location correspondence for intermediate trucks in the OFF peak period. The adjusted model made an improvement over the original model in 19 of 22 count locations and predicted 82% of the count locations within an error of 40% compared to 0% for the original model.
Figure 41: Count Location Correspondence (OFF Peak – Medium Trucks)

Figure 41 presents the count location correspondence for medium trucks in the OFF peak period. The adjusted model made an improvement over the original model in 16 of 22 count locations and predicted 59% of the count locations within an error of 40% compared to 27% for the original model.

Figure 42: Count Location Correspondence (OFF Peak – Heavy Trucks)

Figure 42 presents the count location correspondence for heavy trucks in the OFF peak period. The adjusted model made an improvement over the original model in 15 of 22 count locations.
and predicted 64% of the count locations within an error of 40% compared to 55% for the original model.

The adjustment procedure was able to improve the performance of the model in the OFF period for the intermediate, medium, and heavy truck types. The greatest improvements were made in the intermediate and medium truck types, while the heavy truck type improved minimally.

Figures 43 – 45 present the count location correspondence for the 24 hour period for each count location and vehicle type. The 24 hour period is simply the summation of the AM, PM, and OFF peak periods. The 24 hour period analysis has been included for completeness and to give an overall understanding of the number of trucks simulated throughout the entire day.

Figure 43: Count Location Correspondence (24 hour – Intermediate Trucks)

Figure 43 presents the count location correspondence for intermediate trucks in the 24 hour period. The adjusted model made an improvement over the original model in 19 of 22 count locations and predicted 82% of the count locations within an error of 40% compared to 0% for the original model.
Figure 44: Count Location Correspondence (24 hour – Medium Trucks)

Figure 44 presents the count location correspondence for medium trucks in the 24 hour period. The adjusted model made an improvement over the original model in 16 of 22 count locations and predicted 55% of the count locations within an error of 40% compared to 27% for the original model.

Figure 45: Count Location Correspondence (24 hour – Heavy Trucks)
Figure 45 presents the count location correspondence for heavy trucks in the 24 hour period. The adjusted model made an improvement over the original model in 14 of 22 count locations and predicted 68% of the count locations within an error of 40% compared to 55% for the original model.

Figures 43 – 45 demonstrate that the adjusted model outperforms the original model for the majority of count locations in each time period. Table 8 is a summary of the comparison between the original and adjusted model performance for each time period and vehicle type. Table 8 presents the percentage of count locations where the original and adjusted models predicted the observed truck counts within an error of 40%. The adjusted model outperforms the original model in each category except in the AM period for medium trucks. Furthermore, the adjusted model makes the largest improvement in the intermediate truck type in each time period.

Table 8 demonstrates that the method was successful in correcting the vehicles shares and generating more intermediate truck trips. Furthermore, the method was able to bring the medium and heavy truck types into better correspondence with observed counts compared to the original model.

Table 8: Percent of Count Locations where Model Volumes are within 40% of Observed

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Vehicle Type</th>
<th>Original</th>
<th>Adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>AM Intermediate</td>
<td>5%</td>
<td>55%</td>
<td></td>
</tr>
<tr>
<td>AM Medium</td>
<td>55%</td>
<td>36%</td>
<td></td>
</tr>
<tr>
<td>AM Heavy</td>
<td>50%</td>
<td>59%</td>
<td></td>
</tr>
<tr>
<td>PM Intermediate</td>
<td>5%</td>
<td>86%</td>
<td></td>
</tr>
<tr>
<td>PM Medium</td>
<td>32%</td>
<td>36%</td>
<td></td>
</tr>
<tr>
<td>PM Heavy</td>
<td>41%</td>
<td>45%</td>
<td></td>
</tr>
<tr>
<td>OF Intermediate</td>
<td>0%</td>
<td>82%</td>
<td></td>
</tr>
<tr>
<td>OF Medium</td>
<td>27%</td>
<td>59%</td>
<td></td>
</tr>
<tr>
<td>OF Heavy</td>
<td>55%</td>
<td>64%</td>
<td></td>
</tr>
<tr>
<td>24 Hour Intermediate</td>
<td>0%</td>
<td>82%</td>
<td></td>
</tr>
<tr>
<td>24 Hour Medium</td>
<td>27%</td>
<td>55%</td>
<td></td>
</tr>
<tr>
<td>24 Hour Heavy</td>
<td>55%</td>
<td>68%</td>
<td></td>
</tr>
</tbody>
</table>
The calibration acceptance targets listed in Table 7 were used to determine when to end the iterative re-calibration procedure outlined in Figure 27. Table 9 presents the results of the final iteration of the re-calibration procedure.

**Table 9: Re-Calibration Acceptance Criteria Results**

<table>
<thead>
<tr>
<th>Measure</th>
<th>Target</th>
<th>Original</th>
<th>Adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sum of link volumes by vehicle type</td>
<td>Less than or equal to 15%</td>
<td>Intermediate 77%</td>
<td>4%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium 85%</td>
<td>7%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Heavy 17%</td>
<td>7%</td>
</tr>
<tr>
<td>Sum of link volumes</td>
<td>Less than or equal to 10%</td>
<td>Intermediate 5%</td>
<td>6%</td>
</tr>
<tr>
<td>Adjustment Factor ((F_{k1, k2}))</td>
<td>0.95 ≤ (F_{k1, k2}) ≤ 1.05</td>
<td>Intermediate -</td>
<td>1.007</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium -</td>
<td>0.967</td>
</tr>
<tr>
<td>Percent of count locations where daily total model volumes within 40% of observed counts by vehicle type</td>
<td>Greater than or equal to 50% of locations</td>
<td>Intermediate 0%</td>
<td>82%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium 25%</td>
<td>55%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Heavy 55%</td>
<td>68%</td>
</tr>
<tr>
<td>GEH statistic less than 5 for individual link volumes</td>
<td>Greater than or equal to 50% of locations</td>
<td>Intermediate 0%</td>
<td>55%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Medium 16%</td>
<td>30%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Heavy 27%</td>
<td>34%</td>
</tr>
</tbody>
</table>

The final iteration resulted in adjusted modelled volumes which showed an improvement over the original modelled volumes. The sum of link volumes by vehicle type is below the target value of 15% for all truck types and the sum of link volumes is also below the target value of 10%.

The adjustment factor \(F_{k1, k2}\) is between 0.95 and 1.05 indicating that the ratio of total observed trips by vehicle type ‘\(k_1\)’ to type ‘\(k_2\)’ is nearly equal to the ratio of total modelled trips by vehicle type ‘\(k_1\)’ to type ‘\(k_2\)’.

The percent of count locations within an error of 40% is greater than 50% for all vehicle types. This indicates that the adjusted model is able to predict more than half of count locations to within 40% of the observed counts. The largest improvement was observed for the intermediate and medium truck types. This was expected since the method was targeted to improve the shares of vehicle types according to the counts.
The GEH statistic is recommended by the US Department of Transportation (USDOT) Federal Highway Administration (FHWA) as an appropriate measure to evaluate modelled and observed count data. The GEH (Geoffery E. Havers) statistic is an empirical formula which tests the goodness-of-fit of modelled volumes and has a functional form which penalizes large differences more heavily than small differences by squaring the difference between modelled and observed values. The GEH statistic was less than 5 for 55% of count locations for the intermediate truck type for the adjusted model compared to 0% for the original model. However, the adjusted model did not meet the target criteria for the medium and heavy truck but made an improvement over the original model in terms of percent of locations with a GEH statistic less than 5.

Table 10 shows the re-calibrated vehicle type constants used in the vehicle type and tour purpose model in both the original model and the adjusted model. The goal of the re-calibration procedure was to increase the overall number of intermediate trucks generated and decrease the number of medium trucks generated to better match the distribution observed in the counts. The re-calibration procedure was successful in making the alternative specific constants (ASCs) more positive for the intermediate truck type to facilitate more tours generated by this truck type and making the ASCs for the medium truck type less positive to decrease the number of tours generated. Since the heavy truck type was used as the reference vehicle type, its ASC remains unchanged.

**Table 10: Vehicle Type Alternative Specific Constants**

<table>
<thead>
<tr>
<th>Vehicle Type ASC</th>
<th>IG</th>
<th>IS</th>
<th>IO</th>
<th>MG</th>
<th>MS</th>
<th>MO</th>
<th>HG</th>
<th>HS</th>
<th>HO</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Original</strong></td>
<td>-2.4640</td>
<td>-2.4640</td>
<td>-2.4640</td>
<td>-0.5749</td>
<td>-0.5749</td>
<td>-0.5749</td>
<td>-1.5427</td>
<td>-1.5427</td>
<td>-1.5427</td>
</tr>
<tr>
<td><strong>Adjusted</strong></td>
<td>-0.5917</td>
<td>-0.5917</td>
<td>-0.5917</td>
<td>-1.6330</td>
<td>-1.6330</td>
<td>-1.6330</td>
<td>-1.5427</td>
<td>-1.5427</td>
<td>-1.5427</td>
</tr>
</tbody>
</table>

Chapter 8

8 Conclusion

The objective of this thesis was to improve the City of Edmonton’s original model developed in 2006 and calibrated to 2001 data with a cost effective approach by using new truck count data. The method presented in Section 5.2.1 has provided the City with an effective iterative adjustment procedure which has resulted in a model which outperforms the original model and is re-calibrated to the new road count data.

The Edmonton CVM has a complex model structure which was estimated using a large establishment-based survey collected in 2001. Since the original models which form the basis for the microsimulation of commercial vehicles are now outdated, the outcomes of the model do not reflect the current conditions on Edmonton roadways. Since 2001, the City’s land use, population and employment have changed and grown. Due to these changes, the original model has shown poor correspondence to road counts conducted in 2012. The original model under-simulated intermediate trucks, over-simulated medium and heavy trucks and was not able to predict most count locations within an error of 40% of the observed counts.

Since the original model was unable to reproduce the shares of vehicle types correctly, the method was focused on making improvements to the vehicle choice model. A novel approach was taken to adjust the vehicle type alternative specific constants in the vehicle choice model. The method utilized new road counts at 22 locations and the deviation between observed and modelled total daily truck volumes by vehicle type to adjust the alternative specific constants using the independence of irrelevant alternatives property inherent in the logit model. The method improved model outcomes compared to the original model and showed close correspondence to observed values.

This research contributes to the literature on tour-based microsimulation of urban commercial vehicle movements by re-calibrating a commercial vehicle model using truck counts rather than simply matching high-level target values from a commodity flow survey (i.e. trip length, trips per tour). The adjusted model gives more reliable results for the study year. Furthermore, the method provides the user with an effective process for updating model parameters in future years.
when new road counts becomes available. This method also provides the City with a means to produce reliable truck volumes in the short term until a full commodity flow survey and full model re-estimation can be performed.

Although the method was able to make an improvement over the original model, the adjusted model continues to have shortcomings which are a result of the methods limitations. The method is limited to adjusting the alternative specific constants in the vehicle choice model. There is no mechanism to improve site specific count locations based on the deviation between observed and modelled volumes at the location. Furthermore, the method is highly dependent on the quality of the counts provided. In this research twenty-two locations were selected and the adjusted model has been calibrated based on the data provided for these select locations.

As an extension to this research, the method presented in Appendix A can be further refined to address site specific issues. If access to the JAVA program is provided, a more comprehensive approach to adjusting that model could also be formulated. Furthermore, if an origin-destination survey can be collected the tour generation models can be re-calibrated to better match the patterns of commercial vehicles on Edmonton roadways in the study year. This research is a short term solution – that utilizes available data that is relatively cost effective to collect – to improve the reliability of a model that is estimated and calibrated to outdated information. The larger solution to this problem would be to collect an updated establishment-based survey and re-estimate each component of the model structure. Furthermore, the newly estimated model should be validated using road counts unlike in the original development of the CVM.
Bibliography


Gardes, Y. et al. (2002). Bay Area Simulation and Ramp Metering Study- Year 2 Report. PATH Research Report, University of California, Berkeley, Institute of Transportation Studies, Berkeley, California.


Appendix A

Appendix A presents the method used to adjust the zonal k-factors in the next stop location model. The next stop location model is formulated in equation 16.

\[ V_j = \beta X + k_j \]  

(16)

Where,

- \( V_j \) = utility function for next stop location or destination zone (j) choice
- \( k_j \) = zonal k-factor for destination zone (j)
- \( X \) = vector of other explanatory variables. These explanatory variables do not vary between alternative destination zones.
- \( \beta \) = vector of parameters for the other explanatory variables

A simplifying assumption made is that a change in the number of trips made to a destination zone will result in a proportional change in the number of truck trips observed at count locations. Under this assumption, the adjustment process for zonal k-factors is as follows.

The logit model probability for each destination zone is given by:

\[ P_j = \frac{e^{V_j}}{\sum_{i} e^{V_i}} \]  

(17)

We can influence the number of trips to each destination zone by modifying the logit model probabilities. For any pair of destination zones, the logit model predicts relative choice probabilities as follows.

\[ \frac{P_{j_1}}{P_{j_2}} = \frac{e^{V_{j_1}}}{e^{V_{j_2}}} \]  

(18)

Where,

- \( P_{j_1} \) = Probability of choosing destination zone \( j_1 \)
- \( P_{j_2} \) = Probability of choosing destination zone \( j_2 \)

The application of the CVM model leads to the total modelled trips to different destination zones ‘\( j \)’ through count locations ‘\( l \)’. From these model outcomes we can compute the ratio of total modelled trips to destination zone ‘\( j_1 \)’ and ‘\( j_2 \)’, as shown in equation 19.
\[ \varphi = \frac{\sum_l \sum_i (T_{ij1} \cdot p_{j1l})}{\sum_l \sum_i (T_{ij2} \cdot p_{j2l})} \]  

(19)

Where,

- \( T_{ij1} \) = Total modelled trips from zone ‘i’ to destination zone ‘j_1’
- \( T_{ij2} \) = Total modelled trips from zone ‘i’ to destination zone ‘j_2’
- \( p_{j1l} \) = Proportion of trips to destination zone ‘j_1’ through count location ‘l’
- \( p_{j2l} \) = Proportion of trips to destination zone ‘j_2’ through count location ‘l’

We would like this ratio, \( \varphi \), of modelled trips to reflect the ratio \( \tau \) of total observed truck counts (through all count locations) to destination zone ‘j_1’ and ‘j_2’, as shown in equation 20.

\[ \tau = \frac{\sum_l (C_l \cdot p_{j1l})}{\sum_l (C_l \cdot p_{j2l})} \]  

(20)

Where,

- \( \tau \) = Ratio of total observed truck counts (through all count locations) to destination zone ‘j_1’ and ‘j_2’
- \( C_l \) = Observed truck trips at count location ‘l’
- \( p_{j1l} \) = Proportion of trips to destination zone ‘j_1’ through count location ‘l’
- \( p_{j2l} \) = Proportion of trips to destination zone ‘j_2’ through count location ‘l’

The proportion of trips that travelled through count location ‘l’ to destination zone ‘j’ is calculated in equation 21.

\[ p_{jl} = \frac{\sum_i T_{ijl}}{\sum_l (\sum_i T_{ijl})} = \frac{T_{jl}}{\sum_l T_{jl}} \]  

(21)

Where,

- \( T_{ijl} \) = Modelled trips from zone ‘i’ to zone ‘j’ through count location ‘l’
- \( T_{jl} \) = Total number of modelled trips to zone ‘j’ through count location ‘l’
- \( p_{jl} \) = Proportion of trips to destination zone ‘j’ through count location ‘l’

Equation 22 presents the adjustment factor \( F_{j1,j2} \) to be used to re-calibrate the zonal k-factors. It is formulated as the relative ratios of total observed trips to destination zones ‘j_1’ to zone ‘j_2’ (\( \tau \)) to the total modelled trips to destination zones ‘j_1’ to zone ‘j_2’ (\( \varphi \)). If the model perfectly
simulated the proportion of trips to each destination zone in the observed count data then the adjustment factor \((F_{j1, j2})\) would equal 1.

\[
F_{j1, j2} = \frac{r}{q} \quad (22)
\]

\(F_{j1, j2}\) = adjustment factor for the ratio of the proportion of observed to modelled trips

We then use the adjustment factor in an iterative process to modify next stop location probabilities.

\[
\frac{(P_{j1})_{new}}{(P_{j2})_{old}} = \frac{(e^{V_{j1}})}{(e^{V_{j2}})}_{new} = F_{j1, j2} \quad (23)
\]

If we choose destination zone \(j=2\) to be the reference alternative, then it’s utility function remains the same and:

\[
(e^{V_{j2}})_{new} = (e^{V_{j2}})_{old} \quad (24)
\]

Therefore,

\[
\frac{(e^{V_{j1}})_{new}}{(e^{V_{j1}})_{old}} = F_{j1, j2} \quad (25)
\]

Substituting (16) into (25) and taking the natural logarithm,

\[
(k_{j1} + \beta X)_{new} - (k_{j1} + \beta X)_{old} = \ln(F_{j1, j2}) \quad (26)
\]

Solving for \(k_{j1}^{new}\),

\[
k_{j1}^{new} = \ln(F_{j1, j2}) + k_{j1}^{old} \quad (27)
\]

The re-calibrated zonal k-factor \((k_{j1}^{new})\) is calculated using equation 27. The new k-factor replaces the old k-factor in the utility function. If the adjustment factor \((F_{j1, j2})\) is less than 1, the new k-factor will be smaller than the old k-factor to ensure that fewer trips to this destination zone are made. Conversely, if the adjustment factor is \((F_{j1, j2})\) is greater than 1, the new k-factor
will be larger than the old k-factor to ensure that more trips to this destination zone are made. After several iterations using this method, the adjustment factor ($F_{j1,j2}$) should converge to 1.