Assessment of Commercial Vehicle Emissions and Vehicle Routing of Fleets using Simulated Driving Cycles

by

Glareh Amirjamshidi

A thesis submitted in conformity with the requirements for the degree of Doctor of Philosophy

Department of Civil Engineering
University of Toronto

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Abstract

Growing concern over greenhouse gas emissions and their adverse effect on the environment has prompted research on identifying means to control and reduce these emissions across various sectors. In transportation, vehicle emissions are strongly correlated with driver behaviour. Currently, in research on relating driving behaviour with emissions, driving cycles that are assumed to be constant regardless of vehicle type for a specific area are used to analyse emissions. However, a more realistic model of driving behaviour would enable better estimation of such emissions which can consequently be used to support decision making and policy design.

Currently, in the field of transportation management, driving behaviour is generally modelled using driving cycles. Using a single driving cycle, however, is simplistic for emission estimation purposes as there is significant variance in the driving behaviour of different vehicle types on various road types.

In this research, microsimulation models are used to generate road and vehicle specific driving cycles to improve emission estimation. Typically, the calibration of microsimulation models are carried out using vehicle counts and, in some cases, average speed of vehicles on roads. This research uses a genetic algorithm to show that by calibrating a microsimulation model against
acceleration data in addition to average speed and vehicle count, the model would provide a more accurate representation of driver behaviour. This claim is validated by comparing simulation results with observed values of 13 different parameters related to driving behaviour that were highlighted as influencing factors on emissions and the acceleration-calibrated microsimulation model is shown to be an efficient tool for determining a rich array of driving cycles. The model is then used to create improved driving cycles for various types of vehicles on different types of roads. Use of simulation allows data to be collected under consistent traffic conditions for all vehicle and road types. It is also shown that using simulated driving cycles produces emission factors that are closer to the observed compared to using the average speed model.

Finally, in order to provide a demonstration of the application of these driving cycles, a green routing problem has been used as a test case. In this test case, the driving cycles generated from the acceleration-calibrated model have been used to optimize the routes of a hypothetical delivery company to minimize their emissions and costs under various circumstances incorporating the effect of vehicle load in estimating emissions. Results show statistically significant differences in total distance travelled, driving time, and CO₂-emitted as the result of different minimization criteria of distance-, time-, and emissions optimal. As a result of the test case optimization, it is shown that by using the proposed approach, intricate and insightful analysis of emissions under various policies of cap-and-trade vs. carbon taxing can be conducted with good accuracy without requiring technology changes or other investments which may be expensive.

Keywords: Emission modelling, microsimulation calibration, driving cycles, vehicle routing, carbon pricing
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This thesis is dedicated to my parents who have given me the opportunity of an education from the best institutions and have supported me throughout my life.

Mom, Dad; You have been the inspiration throughout my life.

This is for YOU!
In this thesis, portions of two chapters (chapters 3 and 4) have been based on published/under review material.

These chapters are:

Chapter 3:


Chapter 4:

Amirjamshidi G., Roorda M., Development of Simulated Driving Cycles: Case Study of Waterfront Area in Toronto, Canada, poster and publication at the 92nd Annual Meeting of the Transportation Research Board, Washington, DC 2013.

Amirjamshidi G., Roorda M., Development and Analysis of Simulated Driving Cycles for the City of Toronto. Submitted to Transportation Research Part D: Transport and Environment (Accepted).
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<th>Description</th>
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<tbody>
<tr>
<td>CH4</td>
<td>Methane</td>
</tr>
<tr>
<td>CMEM</td>
<td>Comprehensive model emission model</td>
</tr>
<tr>
<td>CO</td>
<td>Carbon monoxide</td>
</tr>
<tr>
<td>CO₂</td>
<td>Carbon Dioxide</td>
</tr>
<tr>
<td>CO₂-eq</td>
<td>Carbon dioxide equivalent</td>
</tr>
<tr>
<td>CVRP</td>
<td>Capacitated vehicle routing problem</td>
</tr>
<tr>
<td>EF</td>
<td>Emission factor</td>
</tr>
<tr>
<td>EPA</td>
<td>Environmental protection agency</td>
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<tr>
<td>EU ETS</td>
<td>European Union emission trading system</td>
</tr>
<tr>
<td>FCR</td>
<td>Fuel consumption rate</td>
</tr>
<tr>
<td>GA</td>
<td>Genetic algorithm</td>
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<tr>
<td>GEH</td>
<td>Geoffrey E. Havers measure</td>
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<tr>
<td>GHG</td>
<td>Greenhouse gas</td>
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<tr>
<td>GTA</td>
<td>Greater Toronto Area</td>
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<td>GTHA</td>
<td>Greater Toronto and Hamilton Area</td>
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<tr>
<td>GVRP</td>
<td>Green vehicle routing problem</td>
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<tr>
<td>GWP</td>
<td>Global warming potential</td>
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<tr>
<td>HC</td>
<td>Hydrocarbons</td>
</tr>
<tr>
<td>HD-</td>
<td>Heavy duty urban dynamometer driving schedule</td>
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<tr>
<td>UDDS</td>
<td>Highway fuel economy driving schedule</td>
</tr>
<tr>
<td>HDV</td>
<td>Heavy duty vehicle</td>
</tr>
<tr>
<td>HWFET</td>
<td>Intergovernmental panel on climate change</td>
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<td>LA92</td>
<td>California unified cycle</td>
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<td>LDV</td>
<td>Light Duty Vehicle</td>
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<tr>
<td>MDV</td>
<td>Medium duty vehicle</td>
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<tr>
<td>MOVES</td>
<td>Motor vehicle emission simulator</td>
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<tr>
<td>MSE</td>
<td>Mean square of errors</td>
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<tr>
<td>MTO</td>
<td>Ministry of Transportation of Ontario</td>
</tr>
<tr>
<td>N₂O</td>
<td>Nitrous oxide</td>
</tr>
<tr>
<td>NOₓ</td>
<td>Nitrogen oxide</td>
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<tr>
<td>NYCC</td>
<td>New York city cycle</td>
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<tr>
<td>RMSA</td>
<td>Root mean square of acceleration</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean square of errors</td>
</tr>
<tr>
<td>RMSPE</td>
<td>Root mean square of positive kinetic energy over weight</td>
</tr>
<tr>
<td>TDVRP</td>
<td>Time dependant vehicle routing problem</td>
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<tr>
<td>UDDS</td>
<td>Urban dynamometer driving schedule</td>
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<tr>
<td>US06</td>
<td>Supplemental Federal Test Procedure (FTP)</td>
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<tr>
<td>VRP</td>
<td>Vehicle Routing Problem</td>
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<tr>
<td>VRPTW</td>
<td>Vehicle routing problem with time windows</td>
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<td>VSP</td>
<td>Vehicle specific power</td>
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<tr>
<td>VT-Micro</td>
<td>Virginia Tech Microscopic Energy and Emission Model</td>
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<td>WCI</td>
<td>Western climate initiative</td>
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1 Introduction

Global warming, an almost certain result of pollution and greenhouse gas (GHG) emissions, has become a major concern over the last decade. Globally, transportation is responsible for about 25% of energy-related carbon dioxide (CO$_2$) (Timilsina and Dulal, 2011). In Canada, emissions from the transportation sector increased by 31% between 1990 and 2005 (Environment Canada, 2013). In 2011, transportation was the largest contributor to Canada’s GHGs, responsible for 24% of the total GHGs (ibid.). In Ontario, transportation is responsible for approximately one third of GHG emissions (Miller, 2013).

In this chapter, an overview of GHG emissions, the role of the transportation sector in emitting the harmful substances and existing policies that have been designed to control such emissions are introduced. The aims and objectives of this research for supporting the efforts to reduce these emissions are then presented together with the overall approach and research methodology. The chapter is concluded with the overall structure of the thesis.

1.1 Background

The major natural GHGs in the atmosphere are water vapour, carbon dioxide, methane, ozone, and nitrous oxide (Ministry of Transportation, 2009). The Intergovernmental Panel on Climate Change (IPCC)$^1$ (2006) provides a list of other GHGs, some of which are sulfur hexafluoride, hydrofluorocarbons and perfluorocarbons. The effect of GHGs on climate change is known as the greenhouse effect. Important transportation-related GHGs are carbon dioxide (CO$_2$), methane (CH$_4$), and nitrous oxide (N$_2$O), which are mostly the result of engine combustion, unburned fuel, and use of air conditioning.

Not all GHGs have the same effect; each has a distinct average atmospheric lifetime and heat-trapping potential. GHG emissions are often calculated and reported in terms of carbon dioxide equivalent (CO$_2$-eq), which represents how much CO$_2$ would be needed to produce the same warming effect. This is done by using the Global Warming Potential (GWP) weight equivalence for each gas. For example, the GWP for methane and nitrous oxide are 21 and 310 CO$_2$-Eq,

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$^1$ A scientific intergovernmental body tasked to evaluate the risk of climate change caused by human activity.
respectively. This means that each tonne of CH$_4$ and N$_2$O emitted has the same global warming effect as 21 and 310 tonnes of CO$_2$, respectively (Environment Canada, 2009).

Emissions are considered to be one of the major external costs of vehicles (considered as mobile sources of emissions) and pose an inherent problem in populated urban areas. Reducing this cost cannot be addressed in an isolated manner and urban policies have to be based on integrated approaches, meaning that they should combine solutions from various fields like technology (e.g. new vehicles), economics (e.g. operating costs) and methodology (e.g. green routing). In other words, to reduce the problem, there should be both an improvement in technology to achieve safer and less polluting vehicles, and also an implementation of policies that will result in less emissions while optimizing the operating and user costs.

Prior to 2004, modelling emissions mostly concentrated on light duty vehicles (LDVs). Although LDVs still make up most of the traffic on roads, trucks play an important role in today’s freight transportation system. Additionally, with regards to emissions, heavy-duty trucks and buses are responsible for a large proportion of all transportation sector GHG emissions (Barth et al., 2004). In Ontario, GHG emissions from trucks increased by 90% from 1990 to 2007 and account for one-third of the transport sector’s total GHGs (Miller, 2010).

### 1.2 Reducing GHG Emissions

In general, GHG emissions are a function of four factors: 1. vehicle engine and fuel efficiency; 2. the carbon content of the fuel; 3. the total distance travelled and the traffic environment; and, 4. the operational efficiency experienced during travel, also referred to as the driver behaviour (Boriboonsomsin et al., 2012; Cambridge Systematics, 2009; Ericsson, 2001; Faccio et al., 2013; Freij and Ericsson, 2005). Therefore, GHG emissions can be reduced through improvements in any of the aforementioned categories as follows:

*Vehicle technology/engine:* by using more advanced engine technology, such as hybrid technology or anti-idling technologies, the energy efficiency of the fleet can be improved.
**Fuel technology:** the carbon content of the fuel can also be reduced, or alternative fuels, like natural gas\(^2\) or hydrogen, can be used instead. See Lumbreras et al. (2008) as an example.

**Travel activity:** travel activity can be improved in different ways, such as using other modes of transportation or reducing the total miles travelled by better routing of the fleet. Most policies that are discussed in the next section focus on this approach to reducing emissions.

**Vehicle and system operations:** this happens either when the transportation network is used in a more efficient way, for instance, assigning travel in a way to ensure smoother traffic flow and higher speed in the network, or when drivers are educated to change driving behaviour so as to reduce emissions.

Various policies and programmes have been proposed to encourage the reduction of emissions. A review of those that focus on system operations – the relevant apparatus for this research – is presented in the next section.

### 1.3 GHG Reduction Targets and Policies

Between the years 1990 and 2007, Ontario's GHG emissions rose by 13%; Canada's rose by 26% (Ministry of the Environment of Ontario, 2009). Therefore, Ontario, along with other provinces, started setting GHG reduction targets to help fight climate change. Ontario, B.C., Quebec, and Manitoba are also members of the Western Climate Initiative (WCI)\(^3\), a collaboration that has the objective of tackling climate change at a regional level (WCI, 2014). Ontario’s targets for GHG reduction are: reduce the province’s emissions to 6% below 1990 levels by 2014\(^4\) – a reduction of 61 megatonnes relative to business as usual; to 15% below 1990 levels by 2020 – a reduction of 99 megatonnes; and to 80% below 1990 levels by 2050 (Ministry of the Environment of Ontario, 2009). The government plans to achieve these goals through a set of programs affecting households and industries. One of the smaller programs included was the Ontario Home Energy Savings  

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\(^2\) Natural gas is a clean-burning fuel that produces fewer toxic pollutants and GHG emissions and if handled properly, it is as safe as gasoline. Canada is one of the largest producers of natural gas in the world. Therefore using natural gas will lessen its reliance on other countries and create jobs and investment opportunities (Natural Resources Canada, 2008).

\(^3\) “The WCI is a collaboration of independent jurisdictions working together to identify, evaluate, and implement emissions trading policies to tackle climate change at a regional level”. (WCI, 2014)

\(^4\) However current strategies were only able to reduce GHGs to within 91% of the 2014 targets (Environment Canada, 2013), which is discussed later in this section.
Program (OHESP), offering up to $5,000 in tax-free grants per household for home energy improvements and rebates on retail sales taxes paid on some eligible solar, wind and other equipment (Brady, 2011; Tapper, 2012). This program was later cancelled in 2011 by the conservative government (ibid.).

Among the land use and transportation related plans were the Green Commercial Vehicle Program (GCVP), Metrolinx’s The Big Move, and MoveOntario2020, for the Greater Toronto and Hamilton Area (GTHA) that are discussed further below.

1.3.1 Green Commercial Vehicle Program (GCVP)

The GCVP began on November 18, 2008 and was designed as a four-year, $15 million project in Ontario. With this program, the province of Ontario encouraged businesses to become green and help fight climate change. This program offered grants to companies that either bought fuel-efficient, low GHG-emitting, medium duty alternative fuel commercial vehicles (such as hybrid electric, propane or natural gas), or added anti-idling technologies like auxiliary power units (APU), cab heaters and cab coolers to their heavy duty vehicles.

According to the Ministry of Transportation (MTO), the expected benefits of this project were to:


However, this program was cancelled in late 2010, due to the lack of participation from companies and limited number of alternative fuel vehicles (Miller, 2013).

1.3.2 The Metrolinx RTP (The Big Move)

Proposed by Metrolinx in November 2008, the Metrolinx regional transportation plan (RTP) is a 25-year plan for the Greater Toronto and Hamilton Area (GTHA) that concentrates on expanding public transit, and reducing travel times, thereby reducing GHG emissions per resident. Among many goals of The Big Move is to lower GHG emissions from the transportation system. This plan intends to reduce the transportation emissions per passenger to half of what was the case in 2008.
It consists of many strategies and projects around the GTHA. More detailed description of the projects is available at Metrolinx’s website (Metrolinx, 2008).

1.3.3 MoveOntario 2020

MoveOntario 2020 is another major plan by the Government of Ontario for the GTHA and, in many ways, is part of the Metrolinx RTP (referred to as phase two). It involves a $17.5 billion commitment from the Government of Ontario to 52 rapid transit improvements and expansions. 66% of the projects are expected to be completed by 2015, and 95% by 2020. It is projected that this would increase the number of transit trips by 800 million per year, and reduce 300 million car trips in the Greater Toronto Area (GTA). By 2020, it is expected to reduce carbon dioxide emissions in the region by 10 megatonnes (Metrolinx, 2008).

1.3.4 Other Policies Inside and Outside Canada

There are some smaller projects aimed at reducing GHG emissions in Ontario. The Next Generation of Jobs Fund (NGOJF) is a $1.15 billion program that supports research, development, and the use and sale of clean and green technologies for businesses in Ontario. Another program was the Eco Challenge Fund, which was a $20 million fund to help municipalities improve their infrastructure. The fund was initiated in 2007 and cancelled in 2009. A voluntary agreement was also signed in Canada between the automobile industry and the government to reduce the GHG emissions of LDVs by 5.3 metric tonnes of CO2eq (MtCO2-eq) by 2010. Lutsey and Sperling (2007) studied this agreement and concluded that it was mostly irrelevant. They surmised that, irrespective of this agreement, through the implementation of the new technologies that were being utilised at the time, or were scheduled to come into use by 2010 in vehicles, the targets would have been met. It was noted, however, that as this was a voluntary based policy rather than an enforced one, it served as a guideline for good practice.

There are policies like the Alternative Motor Fuels Act (AMFA) and Corporate Average Fuel Economy (CAFÉ) being implemented in the US. CAFÉ is a policy to improve the fleet average kilometres per litre of automobile manufactured in the US and, hence, reduce the diesel use of a fleet. Introduced in 1988, AMFA allows auto producers to receive incentives if they use natural gas or other alternative fuels (Liu and Helfand, 2009).
In January 2013, the Ontario Ministry of Environment released several reports stating that current strategies can reduce GHGs to within 91% and 66% of the 2014 and 2020 targets, respectively. Therefore, Ontario should start looking at regulating GHGs in the transportation sector through policies such as the carbon tax and the cap-and-trade policy that are currently in place in other sectors in select provinces and states in North America (Miller, 2013; Ministry of the Environment of Ontario, 2013). These are discussed in the next section.

1.4 Carbon Pricing

Carbon pricing is a policy initiated by the government with the purpose of reducing pollution, both by companies and private households, by putting a meaningful price on emissions. This research focuses on emission taxes and cap-and-trade, the most widely used policies in this category.

1.4.1 Emission Taxes

A report by the World Bank identifies three types of emission taxes which are used to reduce transportation emissions. These are taxes on local air pollutants (such as VOCs), local as well as regional air pollutants (such as NO₃), and GHG emissions also referred to as carbon tax (Timilsina and Dulal, 2011). Carbon tax is different from motor fuel tax in the sense that motor fuel tax applies only to fuel purchased to power internal combustion engines, while carbon tax applies to the purchase or use of any type of fuel (gasoline, natural gas, heating fuel, propane, etc.) to produce energy or heat. The carbon tax applies to individuals, businesses, industry, etc., encouraging them to emit less GHG by requiring them to pay for the amount of emissions they create (Government of British Columbia, 2014).

The British Columbia carbon tax is a clear example of carbon tax in action, as it is estimated that it can reduce GHG emissions in 2020 by up to three million tonnes of CO₂-eq annually. This tax was introduced by the Government of B.C. in 2008 as a revenue-neutral tax, meaning that the revenue is returned to British Columbians through reduction in other taxes such as income tax. As a result, B.C. has the lowest income tax rate for individuals earning up to $122,000 CAD and one of the lowest corporate income taxes in North America or among G7 nations (Ministry of Finance of British Columbia, 2014). The tax rate started low and increased gradually to the point where the

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5 Equal to taking almost 787,000 cars off the road each year (Ministry of Finance of British Columbia, 2014).
rate in 2012 was $30 per tonne of CO$_2$-eq (an increase of $5 per tonne when compared to rates in 2011). Moreover, the policy has a low income climate action tax credit designed to offset the carbon tax paid by low income families.

According to Bramley et al. (2009), implementing the carbon tax to meet the Canadian Government’s emission targets can produce over $45 billion per year by 2020; some of this can be revenue-neutral and the rest can fund GHG emission reduction investments.

1.4.2 Cap-and-Trade

The cap-and-trade policy allows the government to control the amount of GHG emissions by a company. In this policy, each company is given an “allowance” or “cap” by the government as to how much GHG they may emit, based on emission data reported in previous years and on future reduction targets. If a company produces less than its limit, the resulting “surplus” can be sold to make profit or “banked” for future use. However, if a company produces more than its allowance, it must either buy the surplus from another company or pay a fine to the government for non-compliance (Ministry of the Environment of Ontario, 2009; WCI, 2008). The allowance$^6$ can also be bought through auctions, traded between companies, or created through offset projects$^7$. The government would reduce the cap each year, in order to reach the desired GHG targets. The cap-and-trade system results in a new expense for private companies, to be included in their logistics plan.

The cap-and-trade program and the carbon tax are both market-based schemes. While cap-and-trade provides little certainty about the price of emissions set by the emissions trading market, it has the key environmental advantage of providing more certainty about the amount of emissions reduction that will result. A carbon tax, on the other hand, provides certainty about the price of emissions with little certainty about the consequent amount of emissions reduction. In comparison the carbon tax policy has the key advantage of being easier and quicker for governments to implement. Examples of current implementations of cap-and-trade include:

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$^6$ Under the current policies, each allowance caters for one tonne of CO$_2$-eq.

$^7$ The inclusion of carbon offset, referred to as “additional”, has been introduced in some programs such as the California cap-and-trade program in which companies can increase their allowance by funding activities they would not otherwise do to help reduce the effect of GHG emissions. An example would be paying for the long-term preservation of a forest, arguing that since the effect of greenhouse gases is global, a reduced ton of carbon dioxide emissions anywhere in the world has the same effect as the same ton reduced in California.
The European Union Emissions Trading System® (EU ETS)

Currently in its third phase, the cap-and-trade program originated from the European Union in 2005 with the goal of reducing GHG emissions by 21% in 2020. Between 2005 and 2008, the first phase—named “learning by doing”—only covered emissions from power generators and energy-intensive industrial sectors with almost all allowances given free of charge, and a penalty of €40 per tonne for non-compliance. During this phase, participating businesses reported verified emission data annually.

During the second phase (2008-2012), a few more EU members joined the program, the price of non-compliance was raised to €100 per tonne, and the total volume of allowances was reduced by 6.5% compared to 2005 levels. As of 2013, the fine was €100 per tonne of CO2-eq; and increases annually with the annual rate of inflation in the EU.

Currently, the EU ETS covers more than 11,000 power stations and industrial plants in 31 countries. It is also the largest international system for trading GHG emission allowances. According to the European Commission, “daily trading volumes exceeded 40 million allowances in early 2009, touched 60 million in early 2011 and exceeded 70 million in mid-2011”.

EU ETS began regulating aviation in January, 2012, including operators of flights to and from the EU, Iceland, Liechtenstein, and Norway and with a 97% cap on its emissions compared to the 2004-2006 reference period.

Western Climate Initiative’s (WCI) Cap-and-Trade Program

The cap-and-trade policy is a key element of the WCI’s goal to reduce GHG emissions by 15% below 2005 levels by 2020, encouraging investment in the development of clean-energy technologies, and creating green jobs. The program has two phases. Phase one began in January 2013, and covers emissions from “electricity imports, industrial combustion at large sources, and industrial process emissions”. The second phase, set to begin in 2015, will expand to include “transportation fuels and residential, commercial and industrial fuels not otherwise covered in the first phase”. The program also allows for expansions to include additional sectors, facilities, or new partners in the cap-and-trade program. In this program, if an entity emits more than its

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8 This section is mostly based on (European Commission, 2011).
9 85% of the allowances were free of charge.
allowance, it will not only have to pay a fine, but also surrender some of its allowances for the next period (WCI, 2014).

Out of the current 13 WCI members, only Quebec and California have decided to formally establish a cap-and-trade system to regulate reductions of GHG emissions. Their cap-and-trade system is intended for businesses that emit 25,000 MtCO₂-eq\textsuperscript{10} or more annually. While California’s first phase started prior to that of Quebec, both programs will start phase two in 2015. Both programs also allow for non-covered entities- participants who do not emit more than 25,000 MtCO₂-eq but could voluntarily join the program for various reasons.

Some of the considerations included by the California Air Resources Board (CARB) in California’s cap-and-trade program are: allowing the government to stay involved to make sure the auction price does not become too low or too high (in 2012 the price floor was set at $10 with a 5% increase per year plus inflation), and reserving the government’s right to release allowances from the Allowance Price Containment Reserve starting at $40 per allowance (Hoover, 2013).

In January 2013, Quebec became the first province in Canada to implement the cap-and-trade system, linking its program with that of California’s in January, 2014. As a result, offsets and allowances can now be traded across the two jurisdictions. The minimum price per allowance in Quebec was $10.75 CAD in 2013, and is scheduled to rise at a rate of 5% plus inflation every year until 2020. To participate in the cap-and-trade system, entities and other participants must register in the system and disclose full information on corporate and business relationships to ensure the reliability and the transparency of the system and the operation of a free market. This is an indication of the potential complexities in the implementation of this policy.

Also if an entity fails to account for its real emissions, it will be committing an offence based on the Environment Quality Act and will be liable for a minimum fine of $15,000 and a maximum fine of $3,000,000 (Gouvernement du Quebec, 2013).

Ontario joined the International Carbon Action Partnership (ICAP) in 2009. Initiated in October 2007, the ICAP is a cap-and-trade international system with more than 30 countries from the EU,

\textsuperscript{10}Roughly equivalent to the emissions generated by about 5,000 passenger vehicles or electricity for 3,000 homes based on EPA’s averages (source: http://www.epa.gov/cleanenergy/energy-resources/refs.html#gasoline).
the Regional Greenhouse Gas Initiative members (RGGI), the Western Climate Initiative members (WCI) and other members (ICAP, 2010).

It should be noted that the success of the cap-and-trade system relies on having a meticulous emission reporting system (WCI, 2014). That is why Ontario, like California and Quebec, has required entities emitting more than 25,000 MtCO$_2$-eq GHGs each year from a list of 26 sources (e.g. cement manufacturing, glass production, electricity generation) to submit an annual GHG emissions report since 2009 (Government on Ontario, 2011). Although road traffic is a major contributor to GHG emissions in EU and WCI member regions, the cap-and-trade policy has not been directly implemented in this sector.

In this research, these policies and their potential impacts on fleet management will be studied. This is timely as deeper insight into the mechanisms with which cap-and-trade affects the freight transportation sector and the extent of these effects could provide the necessary data for selecting appropriate emerging policies to control emissions without incurring unnecessary costs.

1.5 Research Aims and Objectives

Until recently, most firms used vehicle routing solvers to produce routes that would generally minimize distance, or time. However, increasing concern about the external costs of transportation (such as emissions) from governments and customers are forcing companies to consider “greening” their operations by considering their fleet’s GHG emissions, noise pollution and other externalities. The aim of this research is to reduce the GHG emissions of the fleet, by providing a platform for estimating fleet emissions more accurately, and assessing the effect of carbon pricing on emissions and costs.

A good estimate of a vehicle’s emission is a function of many parameters, including its speed and acceleration profiles throughout its trip. Speed and acceleration are also functions of many parameters, such as traffic conditions and signals. Given that each vehicle’s driving is unique, the research presented in this thesis develops a vehicle and road type specific average driving pattern (referred to as the driving cycle) to estimate the average emission factor of the vehicle more accurately compared to models that are based on only the average speed of the vehicle.
Currently, driving cycles used for emissions estimation are developed based on the driving behaviour of a small sample of vehicles, which might not be able to adequately represent the driving behaviour of all vehicles. Also it is costly to collect data for all types of vehicles on all types of roads using probe vehicles. Therefore, this research aims to build the platform for developing representative simulated driving cycles using simulated speed and acceleration data for the entire range of vehicles traversing a network that can be generated at a much lower cost.

The simulated speed and acceleration data can be generated using a microscopic traffic simulation, such as Vissim, Paramics, or Aimsun. However, the use of such models is justified only when they can adequately represent the real driving behaviour of vehicles on the road. Another aim of this research is to look at the level of calibration required in a microscopic traffic simulation model so that it can be used to produce the driving behaviour of the multiple types of vehicles and on every type of road.

To realise these aims, the following objectives have been identified:

1. **Extend calibration methods for the microsimulation model to incorporate observed road counts as well as speed and acceleration data collected by GPS; and analyze how well the driving behaviour is represented in the microsimulation model.**

2. **Develop and demonstrate a method for efficiently developing driving cycles that represent specific combinations of roadway class, time of day and vehicle attributes using simulated data from the calibrated microscopic traffic simulation model in the Toronto Waterfront Area. The simulation method addresses some of the limitations with standard driving cycles; and could reflect varying conditions by time of day, by vehicle type and reflect or forecast changes in traffic conditions.**

3. **Propose and verify a mathematical and computational model for the drop-off capacitated vehicle routing problem (CVRP) with a homogeneous fleet capable of minimizing distance, time, or emissions incorporating the developed driving cycles and the effect of the load of the vehicle.**

4. **Develop a suitable test case using the proposed model with exact solutions to demonstrate optimization of a) distance, time and emissions, individually; b) generalized total cost including distance, time, and emissions (with the carbon tax policy); c) generalized total cost including distance, time, and the cap-and-trade policy.**
Conduct sensitivity analysis on key inputs, such as the effect of the cost of carbon on results and assess and compare the effect of the two policies on costs incurred by companies and potential costs to the government.

1.6 Method and Scope

This dissertation brings together elements of policy making, traffic microsimulation, emission modelling, and operations research; and is divided into three phases (Figure 1-1) which are summarized in this section. As mentioned in the previous section, one aim of this research is to reduce the GHG emissions of the fleet, using a more accurate estimate of vehicle emissions compared to current models that are based on a vehicle’s average speed. To do so, this research introduces the use of simulated driving cycles that can be developed for any vehicle/road combination using data from a traffic simulation model. Use of a microscopic traffic simulation allows the researcher to follow all vehicles in a network, as opposed to only a small sample of probe vehicles which can realistically be deployed to develop real world driving cycles. It also allows for analysis of the changes to the driving cycle as a result of future traffic conditions, infrastructure or technology changes. The platform designed in this research (phase one) is implemented on the Toronto Waterfront Network, but can be implemented on other networks as well. The reason for choosing this network was twofold. First, this area consists of the central business district of Toronto and inner urban areas to the east and west. The network includes arterial, collector and local roads and two freeways that play an important role in transporting goods and people to and from the downtown area. Second, the microsimulation model for this network was available as a result of a previous project where efforts were invested into building the correct geometry, defining the roadway attributes (speeds, and land configurations) and coding signal timing\(^\text{11}\) (Abdulhai et al., 2002).

When using simulated data, the quality of the outcome of the emissions model is directly tied to the quality of the microsimulation, requiring a robust and well-calibrated model. To illustrate the point, consider the example of aggressive driving. Studies have shown that aggressive driving consumes more fuel and causes more emissions (Ericsson, 2001; Faccio et al., 2013). Ericsson

\(^{11}\) It should be noted that the available 2002 microsimulation model was not calibrated to the extent required for emission analysis.
argued that there are many factors that affect the fuel consumption and emissions of a vehicle (he found 62). Since most of them are correlated, he used factorial analyses to come up with 16 independent factors representing different driving dimensions. He built a regression model relating emissions and fuel consumption to these factors and found that nine of these (related to acceleration and power demand, gear-changing behaviour, and speed level) being related to driving behaviour have the strongest effect. A simulation thus has to be representative of the domain in these factors.

Shawarby et al. (2005) used an on-road emission measurement (OEM) device to conduct measurements for a freeway and a road segment of 1-1.4 km, with a 3-6% grade at different constant speeds and different speed profiles, for a light duty test vehicle. They measured second-by-second emissions, fuel consumption, vehicle speed, engine speed, temperature and some more engine characteristics. Their results showed that the best fuel consumption and emission rates are at constant speeds of 60-90 kph, with the optimal being 72 kph. Their results also showed that mild acceleration results in higher fuel consumption and emission rates for most emissions, except CO and HC which are highest for aggressive driving.

For the simulation to be considered suitable for driving cycle construction, calibration must be undertaken for the elements of the cycle that are important, including traffic counts, vehicle speeds and variation in acceleration. Therefore, three objective functions including goodness-of-fit measures of counts, speed, and acceleration are defined and optimized in phase one of this research.

Due to the stochastic nature of the microsimulation, and the complex relationship between model parameters and the objective function, heuristic methods are used for model calibration (Fellendorf and Hirschmann, 2010; Liu et al., 2006; Ma et al., 2007; Park and Won, 2006; Zhang and Ma, 2008). Compared to the trial-and-error technique, the heuristic methods are robust, and the computation is automated to avoid exhaustive computation in search of the global optimum. Among the heuristic models, according to Ma et al. (2007), “One cannot safely say that one particular method outperforms all others”. In this research, a genetic algorithm was used because, compared to the other used optimization algorithms, it has the advantage of not requiring gradient information without obvious disadvantages. The technique has been widely used in similar research and the results have been shown to be stable in similarly formulated problems (Henclewood et al., 2012; Kim et al., 2005; Ma et al., 2007; Manjunatha et al., 2013).
After the model is calibrated to the required level of accuracy, information for all the vehicles in the network is collected and simulated driving cycles are developed (phase two). General guidelines available in the literature have then been used to develop driving cycles. However, given the large amount of data available from the microsimulation, and to make the application transferrable to other networks, a platform is designed so that outputs of the microsimulation can easily be imported into SQL data management\textsuperscript{12} and driving cycles can be developed for any road category, time of day, and vehicle class set by the user. EPA’s state of the art emission model, MOVES, is then used to estimate emission factors for the developed driving cycles of the Toronto Waterfront Area.

In phase three, the estimated emission factors are used in a vehicle routing problem (VRP) for a simplified version of the Toronto Waterfront Area. Data for a real case were not available in downtown Toronto. Therefore, customer information (their locations and demands) were generated using Monte Carlo simulation for a hypothetical case of a beverage delivery company using trucks, assuming one depot and random customers with random demands. Results for scenarios of minimizing distance, time, emission, or the generalized cost function are then compared.

The focus of this research is to use the new information about how CO\textsubscript{2} emissions vary across different roads as a basis for innovative routing. Therefore, only exact solutions of the vehicle routing problem were considered in this research. The exact solution allows the study of the effect of various emission reduction policies without concerns about errors that could be introduced by non-exact (e.g. metaheuristic) methods.

1.7 Thesis Structure

This thesis is structured into 6 chapters as shown in Figure 1-2. The current chapter summarizes the background and motivation behind the research and introduces the remainder of the thesis. In Chapter 2, some of the most relevant literature is reviewed to inform the methodology, provide appropriate context and identify existing research gaps. The main areas of literature that have been investigated are traffic microsimulation calibration for the purpose of emission modelling, driving

\textsuperscript{12} Structured Query Language (SQL) is a data management programming language that can interact with other applications and handle large amount of data.
cycle development, and different vehicle routing models and solution algorithms. Specific attention has been paid to green vehicle routing.

Chapter 3 describes the calibration of the Toronto Waterfront Area microsimulation network using a genetic algorithm. Simulated road type, time period, and vehicle specific driving cycles are developed and analyzed in chapter 4. The developed driving cycles are used in chapter 5 in the vehicle routing problem for a hypothetical case study of the waterfront minimizing distance, times, or emissions. The information is also used to analyze the effect of carbon policies such as carbon tax and cap-and-trade. Finally, chapter 6 summarizes the results, presents the conclusions and outlines the future steps that could be taken to extend the research.
Figure 1-2: Thesis Road Map
2 Literature Review

The microsimulation literature has been used to establish the context of the first phase of the research and identify the existing gaps in calibration methods. The emission modelling literature review afterwards has inspired the emission modelling methodology in phases two and three. Finally, the vehicle routing literature has been utilised in developing the test platform in phase 3.

2.1 GPS Data and Calibration of Microscopic Traffic Simulation Models

Microscopic traffic simulation is widely used in research for policy analysis and network performance evaluation. There are several microsimulation packages available including Paramics, Vissim, Aimsun, TRANSIM\(^\text{13}\), and CORSIM\(^\text{14}\). Two data sets are required for model preparation: one to calibrate the model, and one to validate. Calibration refers to the process of adjusting the model parameters used in the various mathematical relationships within the model to reflect reality. In other words, it is the process by which various parameters of the microscopic traffic simulation model are optimized to achieve the best possible representation of traffic conditions on the real network. Calibration of those parameters requires the definition of goodness-of-fit measures to compare model outcomes to observations of the system being modelled. Validation is done by using external data not used in calibration to test the model’s ability to forecast key system characteristics.

Each of these microsimulation packages provides outputs as a function of a set of parameters that affect the results of the simulation. Inappropriate choice of model parameters that describe driving behaviour, traffic system operations and traffic flow characteristics will lead to erroneous model results. Therefore collecting sufficient data is essential to calibrate and validate the network. Current studies in the literature using microsimulation differ from each other in one or more of the

\(^{13}\) TRANSIM has some limitations compared to Paramics, Vissim, and Aimsun. As an example, TRANSIM, does not model actuated traffic signals (Kwak et al., 2012)

\(^{14}\) CORSIM is not as complete as Paramics, Vissim, or Aimsun. CORSIM was developed mostly to generate the correct overall flow on the links, and individual vehicle interactions and driver behaviour was not as critical as link flows in this model. It also has some modelling limitations such as not being capable of modelling roundabouts, timesteps less than 1 second, and U-turns (Holm et al., 2007).
following ways: the size of the network, the objective of the study, the scope of the calibration (whether or not the model was only calibrated, or was sufficient effort also put into validating the model), formulation of the calibration objective function (how the model’s goodness-of-fit is measured), and whether or not the solution algorithm used for calibration was automated.

Zhang and Ma (2008) categorize the solution algorithms into trial-and-error heuristics, genetic algorithms, and simulated annealing. Most of the papers in the literature follow the trial-and-error method. The most commonly used goodness-of-fit measure is a function of the difference between observed and simulated road counts (Abdelgawad et al., 2010; Amirjamshidi and Roorda, 2011; Smith et al., 2008). Some studies have used other goodness-of-fit measures such as travel time, travel speed, and density depending on the purpose of the research (Bham, 2011; Liu et al., 2006; Panis et al., 2006). Measures mostly used for microsimulating intersections include: total queue time, percentage stopped, delay time in seconds per vehicle, and maximum queue length in vehicles (Manjunatha et al., 2013; Merritt, 2004). A more in depth summary of different objective functions can be found in (Hollander and Liu, 2008). The remainder of this section and the next section look at how GPS data has been used as a source for model calibration as well as how microsimulation has been used to estimate emissions.

GPS technology has many applications like real-time monitoring, calibration of the 4-step based models, speed management, etc. In 2005, a meeting was organized by the US Federal Highway Administration (FHWA) with more than 20 academics in order to try and come up with new ways to use the data collected by GPS. One topic under consideration was to analyze the use of GPS data in developing driver behaviour profiles to validate a microsimulation network (Goulias and Janelle, 2006). Relatively few studies have used GPS data for this purpose, as follows.

Yu et al. (2006) calibrated a network in Vissim using GPS and traffic data to evaluate the Beijing BRT system before the 2008 Olympics. Using the GPS data, they calculated speed at selected cross sections spaced at 20-meter intervals. They used the sum of square of errors between the observed and estimated speed at those points as the goodness-of-fit function and used a genetic algorithm for model calibration. Calibrated parameters included waiting time before diffusion, minimum headway, maximum deceleration, accepted deceleration, maximum look ahead distance, and average stand still distance.
Wong and Nikolic (2007) simulated HOV lanes for Hwy 404 between Hwy 401 and Hwy 7 in Toronto using Vissim. They used both travel time and speed data collected by iTREC\textsuperscript{15} along with traffic counts to calibrate and validate the network.

In a more recent study, Fellendorf and Hirschmann (2010) used high-precision GPS data\textsuperscript{16}, collected using two vehicles, to calibrate a Vissim network for an urban arterial with 12 signalized intersections for the city of Graz, Austria by also calibrating the maximum acceleration and deceleration for vehicles in the simulation. They used a manual calibration method, calibrating simulation parameters such as desired speed and maximum acceleration rates, and comparing simulated dwell times, mean and journey speeds, cruising rate and positive acceleration.

## 2.2 Emissions Modelling and Microsimulation

Concern for on-road vehicle emissions, responsible for the largest proportion of emissions of the transportation sector, has increased over the last decade (Barth et al., 2004; Miller, 2013). Studies that focus on modelling emissions vary in size of the network and the scale of the study. Originally, models were built on a case-by-case basis to estimate emissions. Noland et al. (2006) used multivariate linear regression models to model and validate the second by second PM emission rate for light duty diesel vehicles based on acceleration, vehicle specific power, and the CO, CO\textsubscript{2} and NO emission rates. Wu et al. (2008) used a three layer dynamic particle swarm optimization (PSO)-neural network to model emissions. The inputs to the model were speed, acceleration and altitude, and the outputs were the emission rate of NO\textsubscript{x}, HC and CO.

Over the last decade, research on modelling on-road vehicle emissions has increased substantially. Most of the emissions studies have used a three step approach: 1) calculate the average speed on each link or roadway segment, 2) estimate the emission rate for each link for each vehicle type and model year, and 3) calculate the total emissions for each time interval and pollutant by multiplying the emission rate by the vehicle kilometers travelled (VKT). Models following this approach include Mobile6 (US Environmental Protection Agency, 2003), COPERT-4 (European Environment Agency, 2011), and EMFAC (California Environment Protection Agency, 2009).

\textsuperscript{15} iTREC is a GPS/GIS based traffic counting software developed by iTRANS.

\textsuperscript{16} Recorded at a rate of up to 20 Hz.
Examples of applications of such models can be found in Gokhale (2012), Hatzopoulou (2011), and Potoglou and Kanaroglou (2005).

However, the accuracy of emissions models that rely on average speed is limited, since a wide variety of drive cycles (vehicle speed trajectories) can result in the same average speed. The accuracy of an emissions model highly depends on its ability to capture fluctuations in the speed (Ahn and Rakha, 2008; Palmer, 2007; Pandian et al., 2009; Panis et al., 2006). Over the last decade, methods for emissions estimation incorporating fluctuations in speed have been developed. Software packages that have been developed, and are widely used in the literature include Comprehensive Modal Emission Model (CMEM) (Barth et al., 2004; Barth et al., 2000), The Virginia Tech Microscopic Energy and Emission Model (VT-Micro) (Ahn et al., 2002; Rakha et al., 2004), and MOtor Vehicle Emission Simulator (MOVES) (US Environmental Protection Agency, 2009).

2.2.1 Comprehensive Modal Emission Model (CMEM)
CMEM was first developed in the late 1990s with sponsorship from the National Cooperative Highway Research Program (NCHRP) and the U.S. Environmental Protection Agency (EPA) for the purpose of microscopic emissions modelling (Barth et al., 2004). The main objective was to verify and develop a model that could accurately estimate the mobile-source emissions resulting from a vehicle’s operating mode.

CMEM is microscopic in the sense that it predicts second-by-second tailpipe emissions and fuel consumption based on different modal operations of the vehicles in the fleet. In CMEM, the fuel consumption and emissions process is broken down into different components based on the physical phenomena associated with vehicle operation and emissions production. Each of these components is modelled separately with an analytical representation involving parameters that vary according to the vehicle type, engine, emission technology, and level of deterioration.

The required inputs for CMEM include vehicle activity (second-by-second speed profile) and fleet composition of the traffic being modelled. The initial version of CMEM contained 23 light-duty gasoline vehicle/technology categories characterized by emission control technology, emission certification standard, mileage, power-to-weight ratio, and high emitting characteristics. With the support of the U.S. EPA, CMEM has been maintained and updated by adding new
vehicle/technology categories as they become available such as ultra-low emission vehicles, super ultra-low emission vehicles, and partial zero emission vehicles. In addition, CMEM has been expanded to include heavy-duty diesel vehicles. To do this, the University of California, Riverside developed the first mobile laboratory. This Mobile Emission Research Laboratory (MERL) has a 53-ft (17 meter) trailer loaded with a full dilution tunnel and an instrument capable of measuring the total emission from any truck pulling the MERL. By doing so, a number of trucks were tested under different operating situations and the study was used to develop emissions models for heavy duty diesel vehicles that were later added to CMEM (Barth et al., 2004). The current version of CMEM (version 3.1, 2005) has 28 light-duty vehicle/technology categories and 3 heavy-duty vehicle/technology categories. An advantage of using this model is that a plug-in is already available that allows for integration with microsimulation software such as Paramics and Vissim. Another advantage of using CMEM is that it is possible to adjust many of its physical parameters to predict energy consumption and emissions of future vehicle models and applications of new technology (University of California, 2009); however to do so, detailed vehicle and engine specifications are required for the estimation of vehicle emissions.

2.2.2 The Virginia Tech Microscopic Energy and Emission Model (VT-Micro)
This model was first developed in 2002 using chassis dynamometer data on nine light duty vehicles. The model was later expanded to include data from 60 vehicles covering 5 categories of light duty vehicles and 2 categories of light duty trucks. In 2010, the model was again expanded to include emission models for heavy duty trucks as categorized in the CMEM model. In general, the model uses polynomial regression equations based on instantaneous speed, acceleration, and available coefficients for CO, HC, NOx (includes NO, NO2), and CO2. This emission model is incorporated into the INTEGRATION microsimulation model as is widely used in studies done for the state of Virginia, US. More details about how the model was developed can be found in (Ahn et al., 2002; Park et al., 2010; Rakha et al., 2004).

2.2.3 MOtor Vehicle Emission Simulator (MOVES)
MOVES is developed by the EPA’s office of transportation and air quality (OTAQ) with the intent of replacing MOBILE6, providing a graphical user interface and updated mobile source emissions modelling. Some of the inputs into this software are vehicle type, time periods, geographical data, vehicle operating characteristics that are a direct output of the microsimulation, and road types.
MOVES2010b, released in June 2012, is the open-source version of this software, currently available through the EPA’s website.

MOVES can be used to estimate emissions on a national, county, or project scale. The project level modelling is the finest level of modelling in MOVES, used for analysis of link level projects, and requires the user to define a set of files (such as the driving cycle, meteorology, fuel/vehicle combination, etc.) for each MOVES run. MOVES emission rates are averages for specific operating modes, which are combinations of instantaneous speed and vehicle specific power.

Vehicle Specific Power (VSP), shown below, was introduced by Jimenez-Palacios in 1999 to better relate emissions to a vehicle’s operating conditions; and is defined as the instantaneous load per unit of mass (kW/ton). A vehicle’s VSP distribution significantly affects the vehicle’s emissions.

\[ VSP = v \cdot [1.1 \cdot a + 9.81 \cdot grade + 0.132] + 0.000302 \cdot v^3 \]

Where:

- VSP: is the vehicle specific power (kW/ton)
- v: is the vehicle speed (m/s)
- a: is the vehicle acceleration (m/s^2)
- grade: is grade (%)  

To estimate the emissions from a trip, MOVES calculates the VSP for each second of travel of a driving schedule and adds the operating mode emission rates which results in total emissions for the trip (US Environmental Protection Agency, 2009). The current version of MOVES models 13 vehicle classes, 5 road categories, and 6 fuel types.

For the purposes of this research the project scale of MOVES was selected due to the following reasons.

1. MOVES is the state-of-the-art EPA recommended model for emission analysis;
2. Study area is considered flat (research has shown that compared to MOVES, CMEM model is more sensitive to road grade (Cadle et al., 2008));
3. Integrating the emission model with the traffic microsimulation model was not among the objectives of the research (CMEM and VT-Micro are easily integrated with Paramics and INTEGRATION, respectively);
4. MOVES model is based on a larger data compared to CMEM, and VT-Micro; and can model more vehicle/fuel combination categories, is more up-to-date, and can be used to model emissions for years 1999-2050.

2.2.4 Emissions Modelling Applications
Over the last decade, microemission models have been used with traffic microsimulation models for emissions analysis. Boriboonsomsin and Barth (2007) assessed air quality impacts of allowing hybrid vehicles to use HOV lanes by integrating Paramics with CMEM. Noland and Quddus (2006) integrated Vissim with CMEM to analyze the effect of increasing motorway capacity on the number of accelerations and decelerations leading to decreased emissions. Panis et al. (2006) analyzed how intelligent speed adaptation (ISA\textsuperscript{17}) system can be used to reduce pollutant emissions. The integrated microsimulation and emission models have also been used to analyze the effect of signal optimization on emissions in networks with few intersection (Kwak et al., 2012; Lv and Zhang, 2012).

In a more recent application, Guo et al. (2012) integrated TRANSIM and MOVES to approximate “Green User Equilibrium” for the greater Buffalo-Niagara region and compare its results with the traditional user equilibrium. Their study showed that green routing would result in lower emissions, with an increase of total travel time. The study looked at the case where drivers were selected randomly to choose the greenest route vs. the scenario where drivers with the highest likely reduction in emissions were selected. For their case study, their results showed an almost linear trend in emissions reduction for random market penetration. However, for the case of targeted market penetration, a market penetration of only 40% would provide the most environmental benefits\textsuperscript{18}.

In another study, Amirjamshidi et al. (2013) built an integrated tool that models traffic at the individual vehicle level, estimates emissions from on-road vehicle sources, estimates how those

\textsuperscript{17} This system changes the maximum allowable speed of the vehicle and informs the driver of this change.

\textsuperscript{18} For CO emission, the random market penetration showed a linear reduction up to approximately 13%, while a targeted penetration of only 40% would provide 12% reduction in CO emission.
emissions are dispersed through the atmosphere; and finally estimates the exposed population at times of peak emissions for the Toronto Waterfront Area. The modelling system was used to evaluate scenarios when medium duty diesel trucks are converted to ultra-low emission vehicles.

Other emission studies using similar methods are (Beydoun and Guldmann, 2006; Brownstone et al., 2008; Silva et al., 2006; Smit et al., 2007; Xie et al., 2012; Fellendorf and Hirschmann, 2010). Most of the studies described have either used default parameters for the microsimulation model, or have calibrated the model to reflect road counts and/or average speeds. However, using default parameters for microsimulation models tends to produce unrealistic driving behaviour that is too aggressive, with higher acceleration and deceleration rates than are observed in reality (Dowling et al., 2004; Hallmark and Guensler, 1999; Manjunatha et al., 2013; Zhang et al., 2012). Therefore, the accuracy of the emissions outcomes may be limited, because the microsimulation parameter calibration did not attempt to replicate the speed acceleration profile, which is crucial for models such as CMEM, MOVES, and VT-Micro.

Some progress has been made to improve the component models of microsimulation by software developers. However, default parameters for microsimulation models still tend to produce unrealistic driving behaviour that is too aggressive, with higher acceleration and deceleration rates than are observed in reality (Dowling et al., 2004; Hallmark and Guensler, 1999; Manjunatha et al., 2013; Zhang et al., 2012). To address this shortcoming, default parameters for microsimulation models should be calibrated to not only counts and speed (Menneni et al., 2008; Merritt, 2004), but also to accurately reproduce vehicle acceleration and deceleration profiles (Song et al., 2011; Younglove et al., 2005).

Song et al. (2013) compared the ability of five car-following models to estimate emissions, two of which were the psychophysical models used in Vissim and Paramics. Models were compared

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19 The work done in Amirjamshidi et al. (2013) was a precursor to the research in this thesis. The author was responsible for traffic microsimulation and emission modelling in that paper. A copy is provided in Appendix H for review.

20 As mentioned in section 2.1, these are the model parameters used in various mathematical relationships within the model to reflect reality, and need to be calibrated for each study.

21 The car-following model used in Vissim is based on Wiedemann’s model first presented in 1974 and continuously updated since. The car-following model in Paramics was developed over a period of 5 years (1992-1997). This car-following model was partly based on the model developed by Fritzsche in 1994; but in most respects it was built from scratch and calibrated to the driving conditions in the UK (Olstam and Tapani, 2004).
against field data collected with a GPS-equipped light duty vehicle (a total of 962 trajectories and 875,916 seconds of data). Field and simulated VSP distributions, vehicle emissions, and acceleration distributions were compared for each car-following model. Their results demonstrated that the VSP distribution is highly correlated with the acceleration distribution. Also their comparisons of observed vs. simulated histograms of VSP distributions showed that the Wiedemann car-following model overestimates VSP fractions around the peak and underestimates the right-side fractions; however the Fritzsche car-following model has the potential to produce realistic VSP distributions.

Literature has shown that for the purpose of emissions analysis, calibration methods for traffic microsimulation should also produce accurate vehicle dynamics including speed, acceleration and deceleration profiles (Ahn and Rakha, 2008; 2009; Della Ragione and Meccariello, 2010; Nam et al., 2003; Panis et al., 2006; Shawarby et al., 2005), and VSP distribution (Song et al., 2011; 2012; 2013). The detailed calibration and validation in chapter 3 was motivated by the fact that, at the moment, such a method does not exist, presenting a significant gap in research. A multicriteria objective function is thus introduced for traffic microsimulation calibration that includes goodness-of-fit measures for traffic counts, speeds and acceleration/deceleration patterns. This objective function is used to calibrate a relatively large and complex study area network (the Toronto Waterfront Area) using a genetic algorithm. The model is then validated by comparing attributes of simulated and observed vehicle specific power distribution, driving cycles (as the input into the emissions model), and most importantly in the context of this research, their corresponding emissions.

2.3 Driving Cycles

New research in the field of emissions modelling has focused on developing better methodologies for emissions estimation incorporating fluctuations in speed. A common method to achieve this is to determine the driving cycle for a city or a region and different vehicle types. In general, a driving cycle is a representative speed-time profile for a study area within which a vehicle can be idling, accelerating, decelerating, or cruising. However, speed-time profiles vary across cities due to each city’s unique topography and road driving behaviour and they have been shown to vary by vehicle type, time of day and type of road (Ericsson, 2001; Kamble et al., 2009; Montazeri-Gh and Naghizadeh, 2007; Saleh et al., 2009; Wang et al., 2008; Yu et al., 2010a).
Two categories of driving cycles can be found in the literature: synthesized (or model\textsuperscript{22}), and real world (or transient) driving cycles. Synthesized driving cycles are built from combining different phases of idling, constant acceleration/deceleration and steady speed. Examples include the European cycle, and the Japanese cycle (ECOpoin! Inc., 2011). However in such driving cycles the transition between the different phases is unrealistic\textsuperscript{23} (Chugh et al., 2012; Kamble et al., 2009; Tong and Hung, 2010), which could result in erroneous emission estimates (Knez et al., 2013; Pandian et al., 2009; Pelkmans and Debal, 2006; Weiss et al., 2011).

Real world driving cycles (or transient driving cycles) are developed by recording speed-acceleration profiles while driving on the real world roadway network (often chasing a randomly selected vehicle). In other words, these cycles are synthesized from real-world speed data. Examples include FTP-75 in the US, and driving cycles for Pune (Kamble et al., 2009), and Hong Kong (Hung et al., 2007).

A driving cycle is made up of micro-trips where a micro-trip is defined as the trip between two idling periods. A driving cycle is usually for a 10-30 min interval, which is long enough to contain enough micro-trips to reflect the diversity of real world driving behaviour, but short enough to be practical and cost effective in terms of data collection (Hung et al., 2007; Lai et al., 2013; Yu et al., 2010b).

This research introduces a new method to develop representative driving cycles using simulated data from the calibrated microscopic traffic simulation model. This concept has been studied by Della Ragione and Meccariello (2010). They evaluated the ability of four car-following models\textsuperscript{24} to produce simulated driving cycles using data from four vehicles equipped with GPS in the Naples Metropolitan Area. Their results showed that all but one of the models (the linear Helly model) produce driving cycles and emission values close to the observed; however they concluded that further calibration and investigation is required.

Simulated driving cycles use simulated data from a calibrated microscopic traffic simulation for cycle development. Use of a microscopic traffic simulation allows the researcher to follow all

\textsuperscript{22} A few studies have used the term “polygonal” cycles.

\textsuperscript{23} Since a synthesized driving cycle “statistically smoothes” the effect of acceleration and deceleration.

\textsuperscript{24} The car-following models analyzed were the Newell, Gipps (used in Aimsun and is a safety-distance car-following model), Wiedemann (used in Vissim), and the linear Helly model (Della Ragione and Meccariello, 2010).
vehicles in a network, as opposed to only a small sample of probe vehicles which can realistically be deployed to develop real world driving cycles. It also allows for analysis of the changes to the driving cycle as a result of future traffic conditions, infrastructure or technology changes. However, the quality of the outcomes of the emissions model are directly tied to the quality of the microsimulation, requiring a robust and well-calibrated model. For the simulation to be considered suitable for driving cycle construction, calibration must be undertaken for the elements of the cycle that are important, including traffic counts, vehicle speeds and variation in acceleration; which is the focus of chapter 3.

Development of a driving cycle generally involves three steps: test route selection, data collection, and cycle construction. Test route selection involves selecting the route on which data are to be collected. The intention is to select routes that exhibit vehicle motion that is representative of typical driving conditions of the full population of vehicles. The ability of a test route to be fully representative is, of course, limited. Test route selection is not necessary for simulated driving cycles, since data can be collected on all routes within a desired roadway classification.

The data collection step generally involves the collection of the speed of a sample of vehicles at frequent time intervals (usually on a second-by-second basis). The data collection step most commonly reported in the literature uses car chasing\textsuperscript{25} or onboard measurements on probe vehicles using GPS devices (Table 2-1). Collection of real world data to develop driving cycles for different vehicles and road types, for a large enough representative sample of vehicles would either be too costly or biased (if data were collected on a day with unusual congestion patterns). In one case, for example, Chugh et al. (2012) developed passenger driving cycles for emission analysis using only 2 gasoline, and 2 diesel passenger cars resulting in data for a total of 224 trips over 120 days using the on-board measurement method. For this reason, this research proposes the use of sufficiently calibrated simulated traffic data, which can be collected for all vehicles under consistent and calibrated traffic conditions. Using data from multiple simulation replications also accounts for stochastic variations in traffic conditions, allowing a driving cycle to be more representative.

The third step, cycle construction, consists of the following (Hung et al., 2007):

\textsuperscript{25} This technique is a random selection of a vehicle in the traffic and having the survey vehicle simply follow that vehicle keeping approximately a constant distance during different modes of operation (Kamble et al., 2009).
1. Define the set of assessment measures used to describe a driving cycle;
2. Calculate the assessment measures for the collected data (called target statistics);
3. Develop a candidate driving cycle from the pool of micro-trips available (called candidate cycle);
4. Calculate the same assessment measures for the candidate cycle (called test statistics);
5. Identify the candidate cycle whose test statistics are closest to the target statistics and below an acceptable threshold.

The studies in the literature are distinguished based on how the candidate driving cycles are developed, and the set of assessment measures used for comparison. Table 2-1 presents a summary of studies that develop real world driving cycles in the literature, including the study objective, the data collection method, and the assessment measures that were used to evaluate the representativeness of the selected driving cycle.

Hung et al. (2007) introduced a method following the above three steps that has been widely used in other research. Their method uses 13 statistical parameters (driving activity measures) to develop a driving cycle. They applied their method for Hong Kong, for normal weekday trips in the morning and evening peak. They also compared their results with some other driving cycles such as FTP72, FTP75, NYCC, LA92, SFTP-SC03, ECE15, 10 mode, 10-15 mode and IM240 confirming that each city has a unique driving cycle.

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26 A driving cycle for cars and light duty trucks performed on a chassis dynamometer in the US, which simulates an urban route with frequent stops.
27 Derived from the FTP-72, is used for emission certification testing of cars and light duty trucks in the USA.
28 The driving cycle for low-speed city driving in NY.
29 The California UC dynamometer driving schedule.
30 A supplemental FTP procedure to simulate emissions associated with the use of air conditioning units.
31 A combined chassis dynamometer test used for emission testing and certification in Europe. It is composed of four ECE Urban Driving Cycles, simulating city driving, and one Extra Urban Driving Cycle (EUDC), simulating highway-driving conditions. The cold-start version of the test, introduced in 2000, is also referred to as the New European Driving Cycle (NEDC).
32 Urban driving cycle used for emission testing from light-duty vehicles, later replaced by the 10-15 mode cycle in Japan.
33 Urban driving cycle for emission certification and fuel economy determination of light-duty vehicles in Japan.
34 Inspection & Maintenance driving cycle used for emission measurements from in-use vehicles.
Other similar studies include Wang et al. (2008), who developed driving cycles for 11 cities in China disaggregating by road type and time of day, Saleh et al. (2009) in Edinburgh, Kamble et al. (2009) in Pune, India, and Coelho et al. (2009) who found significant correlation between vehicle specific power and second-by-second emissions. Manzie et al. (2007) used driving cycles to compare the fuel consumption of a conventional vehicle and a hybrid electric vehicle showing about 20% improvement in fuel economy.

Most of the studies in the literature have used random selection of microtrips as the method for producing a candidate cycle (Hung et al., 2007; Kamble et al., 2009; Wang et al., 2008; Xiao et al., 2012b). A few studies have used the driving data clustering method (Fotouhi and Montazeri-Gh, 2013; Ou et al., 2011), where assessment measures are calculated for each microtrip individually; and microtrips are clustered (categorized) into several “traffic conditions”. A sub-cycle is developed for each cluster (either based on random selection or selecting the one closest to the center of cluster); and the final result can either be a separate cycle for each cluster (e.g. Ou et al., 2011) where different cycles were developed for the low, medium, and high speed clusters), or a combination of the sub-cycles (e.g. Fotouhi and Montazeri (2013) where the duration of each sub-cycle is proportionate to the length of microtrips in that cluster to all the data). This method should not be considered a different method than the random selection method, since clustering only results in developing unique driving cycles for each road type or traffic condition. For example, the method for the Tehran driving cycle resulted in four clusters of congested, urban, extra-urban, and highway traffic conditions (Fotouhi and Montazeri-Gh, 2013). Using a microsimulation allows the researcher to do the clustering at the first stage by filtering data based on road type, vehicle type, time of day, etc.
<table>
<thead>
<tr>
<th>Study</th>
<th>Location</th>
<th>Main Study Objective</th>
<th>Data Collection Method</th>
<th>Assessment Measures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Montazeri and Naghizadeh</td>
<td>Tehran (Iran)</td>
<td>Comparing driving in Tehran vs. the FTP driving cycle</td>
<td>Auxiliary Wheel, and photo electronic sensor</td>
<td>Average Speed; %Time Idling</td>
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<tr>
<td>Kamble et al. (2009)</td>
<td>Pune (India)</td>
<td>Cycle Construction and comparison to IDC and ECE-15 + EUDC</td>
<td>Car chasing</td>
<td>Average Speed; %Time Accelerating, Decelerating, Cruising, Idling</td>
</tr>
<tr>
<td>Coelho et al. (2009)</td>
<td>Mol (Belgium)</td>
<td>Comparing driving cycles and emission of light duty gasoline vs. diesel vehicles</td>
<td>Portable Emission Measurement System (PEMS) and GPS device</td>
<td>14 modes of Vehicle Specific Power (VSP)</td>
</tr>
<tr>
<td>Tzirakis et al. (2006)</td>
<td>Athens (Greece)</td>
<td>Development and comparison of Athens’ urban driving vs. the European driving cycle</td>
<td>Car chasing</td>
<td>Previously developed software accounting for topographical and other characteristics</td>
</tr>
<tr>
<td>Hung et al. (2007)</td>
<td>Hong Kong</td>
<td>Introducing a practical method for developing real world driving cycles</td>
<td>On-board measurement, and car chasing</td>
<td>Same as Hung et al. excluding % Time creeping</td>
</tr>
<tr>
<td>Wang et al. (2008)</td>
<td>11 cities in China</td>
<td>Development and comparison of driving cycles for 11 cities</td>
<td>Car chasing</td>
<td>Same as Hung et al. excluding % Time creeping</td>
</tr>
<tr>
<td>Saleh et al. (2009)</td>
<td>Edinburgh (UK)</td>
<td>Development and comparison of rural vs. urban driving cycles</td>
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<td>Green and Barlow (2004)</td>
<td>UK</td>
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<td>On-board measurement, and GPS; along with video camera for</td>
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<td></td>
<td></td>
<td>categories, and three control cycles</td>
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</tr>
<tr>
<td>Yu et al. (2010a)</td>
<td>Houston (Texas)</td>
<td>Use of a genetic algorithm-based approach for developing driving cycles</td>
<td>PEMS and GPS device</td>
<td>• Average speed, Running speed, Acc, Dec; Maximum speed; %Time Accelerating, Decelerating, Idling, Constant speed;</td>
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<tr>
<td></td>
<td></td>
<td>comparing four assessment measures</td>
<td></td>
<td>• 17 bins of Vehicle Specific Power (VSP)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>• Average fuel consumption rate for each VSP bin based on MOVES</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>• Product of VSP and fuel consumption</td>
</tr>
<tr>
<td>Study</td>
<td>Location</td>
<td>Main Study Objective</td>
<td>Data Collection Method</td>
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<tr>
<td>Chugh et al. (2012)</td>
<td>Delhi (India)</td>
<td>Developing a realistic passenger driving cycle for in emission assessment</td>
<td>On-board measurement, and GPS</td>
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<td></td>
<td></td>
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<td></td>
<td>• Verification: average speed, Average running speed, Average acceleration and deceleration, % time idling, cruising, accelerating and decelerating, fuel consumption</td>
</tr>
<tr>
<td>Srinivas et al. (2011)</td>
<td>India</td>
<td>Development of highway, urban, and Ghats passenger driving cycles for India</td>
<td>On-board measurement, and GPS</td>
<td>%Time accelerating, decelerating, idling, cruising; average and maximum speed; maximum acceleration and deceleration; and the number of stops per km</td>
</tr>
<tr>
<td>Ou et al. (2011)</td>
<td>Dalian (China)</td>
<td>Development of hybrid city bus’s driving cycle</td>
<td>Onboard sensors that transmitted data through 3G wireless communication</td>
<td>Running length; max, mean, running, and std. of speed; %time accelerating, decelerating, idling, cruising; max, min, mean, std. of acceleration.</td>
</tr>
<tr>
<td>Risam et al. (2012)</td>
<td>India</td>
<td>Development of the Indian driving cycle for durability evaluation for different business purposes</td>
<td>Wheel speed sensor</td>
<td>Average speed, Running speed, the number of stops per km, %Time idling</td>
</tr>
<tr>
<td>Shahidinejad et al. (2010)</td>
<td>Winnipeg (Canada)</td>
<td>Development of hourly driving cycles; and daily duty cycles that could be used for designing electrical vehicles</td>
<td>GPS and on-board diagnostics on 76 passenger cars over the period of 1 year</td>
<td>Use of the parameters in Hung et al (2007), plus 12 more measurements about the energy usage, trip distance, and time percentage in more speed brackets</td>
</tr>
<tr>
<td>Han et al. (2012)</td>
<td>Korea</td>
<td>Development of a gradient-sensitive driving cycle for diesel military vehicles(^{35})</td>
<td>GPS data recording</td>
<td>Mean and Std. of speed; average and Std. of gradient</td>
</tr>
<tr>
<td>Prasad et al. (2012)</td>
<td>India</td>
<td>Compare different set of statistics to find which set better represents real engine operations</td>
<td>On-board measurement, and GPS</td>
<td>A subgroup of: Average and maximum speed; number of stops per km; maximum and average acceleration and deceleration; drive closeness(^{36})</td>
</tr>
</tbody>
</table>

\(^{35}\) The military vehicle was a K311A1; which is a 1.25 ton cargo truck.

\(^{36}\) Represents the matrix of percent time in a particular range of speeds and levels of acceleration/deceleration.
Yu et al. (2010) used a genetic algorithm for part of the cycle development. In that paper, the assessment measure for each micro-trip is calculated, and micro-trips are sorted accordingly. The top 20% from the sorted list are selected and a lower and upper limit for the number of required micro-trips in a driving cycle is estimated. A genetic algorithm is then used to develop candidate driving cycles for each number of micro-trips in the cycle (between the upper and lower level). Finally, the cycle with the best performance according to an assessment measure is selected as the final driving cycle (Yu et al., 2010a). Although this method improves slightly upon the random selection method, the large computational time for a 20% sample of the micro-trips is prohibitive. Consequently, in this research, the random selection method was chosen.

The other difference between studies is the type and number of assessment measures used (as can be seen in Table 2-1). Driving activity measures and the VSP method have both been widely used in the literature. Activity measures refer to the use of statistics like speed and acceleration (Hung et al., 2007; Montazeri-Gh and Naghizadeh, 2007; U.S. Environmental Protection Agency, 2010; Wang et al., 2008). The VSP method, which is a bin based method, focuses on instantaneous power per unit of a vehicle and is a nonlinear function of instantaneous speed, instantaneous acceleration and road grade (Coelho et al., 2009; Yu et al., 2010a). In Yu et al. (2010a) the VSP method produced 2% less CO₂ prediction error compared to the driving activity method. However, that research only used nine of the widely used driving activity measures, where most studies using driving activity measures use more measurements (Hung et al., 2007; Saleh et al., 2009; Wang et al., 2008). Using more driving activity measures would likely reduce the difference in CO₂ prediction error between the VSP and the driving activity method. Also, Yu et al. (2010a) used data points for all road types in their comparison, which would affect their results and comparison.

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37 AVL is an advance device for tracking and monitoring based on GPS technology.
in selecting the best method for cycle development. Hence, in this research the driving activity measures presented by Hung et al. (2007) are used and are discussed in detail in chapter 4.

2.4 Vehicle Routing Problem

The basic vehicle routing problem (VRP) consists of optimal selection of routes for a set of vehicles where there is one depot, with multiple vehicles of the same type with the same capacity that service several customers with known demands, with the objective of minimizing the total cost. Dentzig and Ramsar (1959) first formulated this problem as a generalization of the Traveling Salesman Problem (TSP) with or without capacity constraints.

Since the vehicles always have a capacity assigned to them, this problem is also known as the Capacitated VRP (CVRP). Based on the current literature, a more general definition for the VRP is defined as selecting the routes in a network in order to minimize a generalized cost function, while satisfying certain constraints. The cost function can be a combination of distance, travel time for each vehicle type, fuel cost, emission cost, etc. The VRP constraints are mostly fleet capacity, driver related constraints, depot constraints, and customer time windows.

Different constraint combinations give rise to different categories of VRP and there is no single universally accepted definition or solution for VRP (Laporte, 2007). What is agreed upon is that, in almost every form, VRP is an NP-Hard problem (ibid). This research mainly focuses on the CVRP with focus of reducing GHG emission. However, as part of reviewing the literature, a brief introduction to each of the different categories of VRP and different solution methods is presented in the following section.

2.4.1 Main Extensions to the VRP

*Stochastic Vs Deterministic*

When one or more variables in the problem, e.g. demand or travel time, are not deterministic (fixed), they would be stochastic (random) and the problem would become the Stochastic VRP (SVRP). This problem was first introduced in 1982 by Stewart and Golden. With the introduction of stochastic variables the computational difficulty of solving the problem increases enormously regardless of the specific entities that are assumed to be random (Larson and Odoni, 2007).
If only one variable is random, a simplified method is to optimize the expected value of the cost by using the expected value of the random variable. Although substituting the average does result in some errors the method is widely used in practice. However, if there is more than one random this method cannot be employed and more sophisticated SVRP approaches must be used (Larson and Odoni, 2007; Stewart, 1983).

**Dynamic Vs Static**
The term dynamic refers to cases where a company usually has some known offline demands (demand that is known before the day in question), plus some online demands that are unknown before the day. In this case, the planning is usually done for one day and the decision variable for the company is to decide on whether to accept or reject the online request as it becomes available on the day of delivery (Angelelli et al., 2009).

In most scheduling studies, dynamic refers to when the main problem is a multi-stage problem, meaning that the decision at each stage is dependent on the decision made in the previous stage. In the Dynamic VRP (DVRP), a stage is defined as the point when a decision has to be made; and each state is defined as the position of the system at that moment (Figliozzi et al., 2007; Powell et al., 2000).

**Periodic VRP (PVRP)**
In some situations it is not possible to optimize the objective function for only one day, due to the type of demand (e.g. the demand is 2 times a week). In these cases where there is a known demand with a known frequency over a planning period that must be at least K days apart and at most U days apart, the problem is referred to as the Periodic VRP. An extension of PVRP is when the frequency of the visit is also a decision variable and is called the PVRP with Service Choice (PVRP-SC) (Francis and Smilowitz, 2006; Francis et al., 2006; Gaudioso and Paletta, 1992).

**Time Window VRP (VRPTW)**
This problem deals mostly with situations where there is a sensitive product in question, or cases where the customer has specific timelines, meaning that the vehicle cannot arrive at the customer location before a certain time, or later than a specific time (Repoussis and Tarantilis, 2009).
**Time Dependant VRP (TDVRP)**

Introduced by Malandraki and Daskin (1992), the TDVRP assumes that the travel time in the network varies by time of day, which is mostly the case in urban areas. The problem is a Mixed Integer Linear Problem (MILP); and a common way to solve these models is to divide the time into M time steps and solve for each time step. A review of the literature on the TDVRP is presented by Figliozzi (2009).

**Long-Haul Distances**

If the trips are for long-haul distances, then the travel time would be known. This is the case for most intercity trips. In this case, the main objective would be to reduce the total cost by optimizing the rest time. These problems usually look at driver scheduling and their hours of service (Archetti and Savelsbergh, 2009).

**Open VRP**

In this model, vehicles are not required to return to the depot. This model is mostly used in cases with for-hire fleets.

**Arc Routing Problems**

This method is used when there is a service that has to be carried out over a link, as opposed to at the node like other VRPs (e.g. snow clearing, or garbage collection).

2.4.2 Minor Add-ons to the VRP

This section introduces the minor assumptions that can be used with different VRPs defined in the previous section.

**Homogeneous vs. Heterogeneous (Mixed) Fleet**

In some cases, the fleet has more than one vehicle type, with its own specific capacity, cost, or other characteristics. In these cases a notation is added for vehicle type when formulating the VRP. In these models, the objective function usually accounts for the trade-off between the fixed cost and operation cost of each type of vehicle (Repoussis and Tarantilis, 2009).

**Single Depot vs. Multi Depot (VRP vs. MDVRP)**

The general VRP assumes only one depot. However, in many cases a firm would have more than one depot and different costs would be associated with a vehicle departing from each one of the depots. This problem is known as the multi depot VRP (MDVRP).
**VRP with Pickup and Delivery**

This type of modelling is used when an item has to be picked up from one customer and delivered to another customer. A simpler model is when some of the customers have pickup requests (that have to be transported back to the depot), while some other customers have delivery orders (also referred to as the VRP with backhauls).

This model is also used a lot in transit planning problems such as Dial-A-Ride. In these cases the problem usually also has time windows and is mostly solved by heuristic methods (Luo and Schonfeld, 2007).

**Split Delivery VRP (SDVRP) vs. Single Source VRP**

In some VRP cases, it is possible to allow a customer to be serviced by more than one vehicle, by splitting the demand for that customer between several vehicles. This problem has been solved mostly using branch-and-bound, Dynamic Programming (DP), and heuristic algorithms (Ceselli et al., 2009; Lee et al., 2006).

**Green VRP**

In all other VRPs, the generalized cost function optimized is mostly a function of travel distance, or time. In the green VRP, the main objective would be to make the network more sustainable, by implementing strategies to reduce the environmental effects of the system (mainly emissions) either directly or indirectly (by reducing fuel usage or total energy) (Bektaş and Laporte, 2011; Erdoğan and Miller-Hooks, 2011; Kara et al., 2007; Lin et al., 2014). The green VRP is the extension that is highly interdisciplinary, requiring knowledge in the fields of fleet management and operation research, environmental analysis and energy use, and transportation system engineering and urban planning (Lin et al., 2014; Salimifard et al., 2012). Since the green VRP is the focus of this research, a more thorough literature review is presented on the topic later in section 2.5; and the next section summarizes the methods for solving various types of the vehicle routing problems.

**2.4.3 Methods for Solving the VRPs in General**

VRP algorithms can be categorized into three main categories: exact algorithms, classical heuristics, and metaheuristics.
**Exact Algorithms**

These algorithms focus on the classical VRP which include an undirected graph, a symmetric cost matrix, a number of identical vehicles, and one or in some cases multiple depots.

General methods used are: Dynamic Programming (DP)\(^{38}\), branch-and-bound\(^{39}\), and Integer Linear Programming (ILP). There are three formulation techniques mostly used when using exact algorithms: Two-index Vehicle Flow Formulation (VF), Two-index Two-commodity Flow Formulation (CF) and the Set Partitioning Formulation (SP) (also known as the Set Covering Problem, SCP) (Laporte, 2007; 2009). In the SCP, the goal is to service a set of demand points with minimum number of facilities. There are different algorithms for solving the SCP. For cases with no resource constraint, the matrix reduction is more reliable (Larson and Odoni, 2007); however for cases with resource constraint (RSCP), the column generation is used (Laporte, 2007). Since the SCP would be an integer problem, the column generation splits the original problem into a Restricted Master Problem (RMP) and a pricing sub-problem of finding which path to bring in the problem (like simplex) with the most negative reduced cost (Desaulniers et al., 2005). It should be noted that the answer from this method is not integer and will be used as a valid lower bound for the problem, after which a branch-and-bound algorithm could be used to find the optimal integer solution (Desaulniers et al., 2005). It is also possible to use dynamic programming to solve the pricing problem (Ceselli et al., 2009).

Exact algorithms are computationally challenging and limited in solving large problems. Most sophisticated algorithms can face difficulty solving problems with more than 100 customers, which is why a specific field of research is dedicated to developing and improving exact and heuristic algorithms that can reduce the computation time without compromising the quality of the result for large realistic cases (Laporte, 2009).

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\(^{38}\) A method that has not been used a lot in research (Laporte, 2009).

\(^{39}\) The main idea of this method is dividing the feasible area into subsections as to find the optimal solution which would be between an upper and lower bound. The upper bound is found by solving the linear programming problem, and the lower bound is the maximum of the values found in the current tree.
Classical Heuristics

Classical heuristics are more flexible, and have two parts. The first part tries to calculate a fast feasible solution (also known as constructive heuristics). The second part tries to improve the solution, which is also called the improvement heuristic (Laporte, 2007).

Constructive Heuristics

These methods were mostly developed between 1960 and 1990. They can be categorized into the following groups:

Saving Algorithms: within this class, the Clark-Wright is the best known method (Cordeau et al., 2002). This algorithm is not the most accurate algorithm, but it is popular because it is fast and simple to implement.

Petal Heuristics or Set Partitioning Heuristics: these algorithms first partition the set of customers into several subsets of customers and then solves the VRP for each subset. One example is the sweep algorithm which starts from one point and adds customers to the same route until it becomes infeasible. The results of this algorithm will never have intersecting routes, and are rather rudimentary. More information and review of improvements to the basic petal heuristics can be found in Laporte (2007).

Cluster-first, Route-second Algorithms: These methods concentrate on locating a seed at regions where it is likely that we would have a route, and defining a cluster of customers around that seed. The best known algorithm belongs to Fisher and Jaikumar (1981). The procedure solves a Generalized Assignment Problem (GAP) which itself is NP-hard, taking into account that the demand for each cluster should not exceed the capacity of the vehicle. The GAP method tries to minimize the distance between the customers and the seed. After defining the clusters, a TSP is solved for each cluster.

Improvement Heuristics

This procedure is done after the constructive heuristic, and tries to improve the basic solution obtained in the previous part. There are many methods suggested for improving the solution, some

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40 They are called heuristic because unlike the metaheuristic methods, the objective function does not change from one iteration to the next (Laporte, 2009).
of which are intraroute and some are interroute. A brief review of some of the methods can be found in Laporte (2007; 2009).

**Metaheuristic**

These methods have been used in the past 15 years. Some of the best metaheuristic methods can solve networks with more than 100 vertices in a reasonable time and arrive to a solution within 0.1% of the best known solution (Laporte, 2009). Metaheuristic methods can be divided into: local search, population search, and learning methods.

Local search methods start with an initial solution and then search the neighbourhood to improve the answer. The search ends after a certain number of iterations or if there is no significant improvement in the answer. Examples of the local search method are: tabu search\(^{41}\), variable neighbourhood search (VNS)\(^{42}\), very large neighbourhood search\(^{43}\), and adaptive large neighbourhood search\(^{44}\) (Laporte, 2007; Laporte, 2009).

Population search methods rely on a set of solutions, entitled populations, as opposed to a single solution in each iteration. The three methods used are: Genetic algorithm (GA), Memetic algorithm, and Adaptive memory procedure (AMP) (Laporte, 2007).

The two most popular learning methods are: Neural Networks (NN), and Ant colony optimization. However, literature suggests that the learning methods have not proven to be as good as the others, hence there is less research available on them (Laporte, 2007).

\(^{41}\) The tabu search starts from one current solution and searches the neighborhood \(N(s)\) of that solution. The initial solution does not necessarily have to be a feasible solution; for example, if we satisfy the conditions of each customer belonging to one route and each route starting and ending at depot (for the VRPTW), then we will calculate a penalty (cost) for the excessive violation of load, time window and duration of trip. This function would be a linear combination of these and when we remove one customer from one route, we assign a tabu (forbidden sign) on that customer that for a certain number of iterations that customer will not enter that route. Other factors can also be taken into account when penalizing a solution.

\(^{42}\) This method, first proposed by Mladenovic and Hanson (1997), starts by searching the neighbourhood with a known radius of the last known best solution. If there cannot be any improvements to the answer the radius is increased to search a bigger area.

\(^{43}\) This method is for cases where the neighbourhood size is very large, that might require solving a separate optimization problem to determine the best solution.

\(^{44}\) Presented by Ropke and Pisinger (2006), this method extends the neighbourhood search by allowing the use of several heuristics in the same search process.
Table 2-2 summarizes some of the VRP papers reviewed in the form of their assumption and solution method used. A thorough review of classical and evolved VRPs, and methods used for solving different VRPs can be found in (Cordeau et al., 2002; Laporte, 2007; 2009; Lin et al., 2014; Potvin, 2009; Toth and Viego, 2002).

This research focuses on the basic CVRP with the extension of minimizing total GHG emissions (Green VRP), with the purpose of implementing the cap-and-trade policy in the formulation; and analyzing the results for a simplified network using simulated driving cycles (Chapter 5). As mentioned before, this research does not aim to identify new solution algorithms for the VRP, but to enrich the model with more accurate information about CO$_2$ emissions and their variation based on various types of vehicles on different roads. Thus, existing methods will be used to solve the generated model with the main focus on exact solution methods to eliminate the inaccuracies that could result from using the non-exact methods.
<table>
<thead>
<tr>
<th>Study</th>
<th>Stochastic</th>
<th>Dynamic</th>
<th>Periodic</th>
<th>Time Window</th>
<th>Time dependent</th>
<th>Other</th>
<th>Minor considerations</th>
<th>Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Stewart, 1983)</td>
<td>×</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Chance-constrained; Penalty function</td>
</tr>
<tr>
<td>(Figliozzi et al., 2007)</td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Competitive environment Backward induction</td>
</tr>
<tr>
<td>(Powell et al., 2000)</td>
<td>×</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Column generation</td>
</tr>
<tr>
<td>(Ceselli et al., 2009)</td>
<td>×</td>
<td>×</td>
<td></td>
<td>Open route</td>
<td></td>
<td></td>
<td></td>
<td>Heterogeneous fleet; MD; For hire &amp; private Column generation; the pricing problem: DP</td>
</tr>
<tr>
<td>(Gaudioso &amp; Paletta, 1992)</td>
<td>×</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>one depot; homogeneous fleet Heuristic</td>
</tr>
<tr>
<td>(Cordeau et al., 2001)</td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
<td></td>
<td>MD</td>
<td></td>
<td>Tabu search</td>
</tr>
<tr>
<td>(Figliozzi, 2010)</td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
<td></td>
<td>EE</td>
<td></td>
<td>GNNH</td>
</tr>
<tr>
<td>(Malandraki &amp; Daskin, 1992)</td>
<td>×</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Heuristics (NN) &amp; cutting plane</td>
</tr>
<tr>
<td>(Kara et al., 2007)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>EMVRP</td>
<td></td>
<td>CPLEX 8.0 (exact Alg)</td>
</tr>
<tr>
<td>(Lee et al., 2006)</td>
<td>×</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Forward search (A heuristic Algorithm45) Split pick-ups (can have more than truckload)</td>
</tr>
<tr>
<td>(Ouyang, 2007)</td>
<td>×</td>
<td></td>
<td>(customer location)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>VRZ, Special partitioning+ TSP</td>
</tr>
<tr>
<td>(Angelelli et al., 2009)</td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>DynaSeach (VNS) No capacity constraint</td>
</tr>
<tr>
<td>(Potvin et al., 2006)</td>
<td>×</td>
<td>×</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Tabu Search (decomposition and Adaptive) No capacity constraint</td>
</tr>
<tr>
<td>(Repoussis &amp; Tarantilis, 2009)</td>
<td>×</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Adaptive Memory Programming (AMP) Heterogeneous fleet; fleet size</td>
</tr>
</tbody>
</table>

45 It is a heuristic search method that finds the least-cost path from a given initial node to the one goal node. It is a good method because it also keeps track of the distance travelled from the origin and it guarantees to find the optimal path (Lee et al., 2006).
2.5 Green VRP

The concept of expanding the traditional VRPs to minimize energy or emissions is a relatively recent field, and is referred to as Green VRP (GVRP), or green logistics. The concept is motivated by the need to make supply chains sustainable and decrease their environmental externalities. Kara et al. (2007) looked at the costs that cannot be introduced as a function of distance travelled like vehicle weight, fuel price or time spent on a node. They minimized the load weight carried by a vehicle stating that for cases where fuel prices are relatively more important than costs such as driver’s wages, this function can better optimize the costs and named this the emission minimization VRP (EMVRP). Their study was limited by assuming a fixed travel speed in the network, and using a very simple relationship between the vehicle’s weight and fuel usage. In other words, that study minimized the total weight travelled in the network.

Since then, benefits achieved from reducing emissions by improving the routing model has been studied. The studies differ from one another mainly in the following ways: the VRP category (CVRP, VRPTW, etc.), solution algorithm, and the method for estimating emission. The latter is the focus of this review. Based on the emission estimation method, current GVRP studies can be divided into speed-based models, and rate-based models.

Speed-based models mostly build on the study by Kara et al. (2007) by using analytical emission models that estimate emissions as a polynomial function of the vehicle’s average speed (mostly by simplifying formulations used in emission models such as MEET, MOBILE, CMEM [macro version]).

A few recent studies have focused on finding the optimal path for drivers aiming to reduce their fuel consumption or emissions (referred to as eco-drivers). These studies have used an integrated traffic simulation model and an emission model to calibrate the fuel consumption model as a polynomial function of average speed that are used in some GVRP studies (Boriboonsomsin et al., 2012; Li et al., 2013; Nie and Li, 2013). These models are limited since only a small sample of real driving cycles were used to calibrate the emission model. Also, collection of real time data for a large enough representative sample of vehicles would either be too costly or biased (as mentioned in Section 2.3). A review of the literature on eco-driving is outside the scope of this research, since these studies all focus on one eco-driver optimizing their path using the shortest path algorithm,
and not a fleet manager constrained by vehicle capacity, customer time windows, etc. However, an overview of their models was necessary since some of the speed-based GVRP models have used the same polynomial functions for estimating emissions.

The main limitation of the speed-based models are: (a) ignoring the effect of the load of the truck in most cases, (b) ignoring the effect of acceleration on emissions, (c) assuming a fixed average speed for the vehicle, and in some cases not applicable at low speeds (Bektaş and Laporte, 2011; Figliozzi, 2010; 2011), and (d) not incorporating real road traffic conditions due to the lack of real traffic data. Table 2-3 summarizes the literature on GVRP speed-based models.

Rate-based models include studies in which the emissions or fuel consumption is calculated using either a fuel consumption rate (calculated as a function of speed or using fixed values), or an emission model (such as MOVES and CMEM) that estimates the emission factor based on a given average speed. Erdoğan and Miller-Hooks (2012) formulated a GVRP to find the set of tours for vehicles starting at the depot and visiting a set of customers. Their model allowed the vehicles to visit an alternative fuel station for refuelling (if necessary) using a fixed fuel consumption rate (FCR) that when multiplied by the distance travelled would result in the total fuel consumption.

Xiao et al. (2012a) minimized the fixed vehicle cost, and the fuel cost, using the FCR. The FCR associated with each link was calculated using a linear function of the vehicle load, FCR at full-load and no-load. Results for a CVRP problem for vehicles less than 3,000 Kg showed that fuel consumption can be reduced by an average of 4.14% with 2.63% increase in total distance travelled. However, one of the main limitations of their study was assuming arbitrary values of 1 and 2 for the full-load and no-load FCR.
<table>
<thead>
<tr>
<th>Study</th>
<th>VRP extension</th>
<th>Solution algorithm</th>
<th>Emission/Energy formulation</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figliozzi</td>
<td>TDVRP</td>
<td>Heuristic method</td>
<td>Kara et al (2007) + a function of speed squared and speed inversed</td>
<td>Potential for reducing emissions between 8-25%; Speed is a decision variable which is not always possible in real traffic conditions.</td>
</tr>
<tr>
<td>(2010)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urquhart et al.</td>
<td>Travelling salesman problem (TSP)</td>
<td>Evolutionary algorithm (metaheuristic)</td>
<td>A polynomial emission factor (EF) model introduced by the UK national atmospheric inventory</td>
<td>Only a small improvement was possible using this model; but authors acknowledge that the model does not account for all factors, including waiting time at junctions.</td>
</tr>
<tr>
<td>(2010b)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urquhart et al.</td>
<td>VRPTW</td>
<td>Evolutionary algorithm (metaheuristic)</td>
<td>A power-based instantaneous fuel consumption model by Bowyer, Biggs, and Akçelik (1985)</td>
<td>An average speed is converted to a driving cycle using cycles developed by Green and Barlow (2004); Results (depending on the problem instance and ranking criterion) showed emission reductions between 5-10%, with an increase of 5.9% in distance.</td>
</tr>
<tr>
<td>(2010a)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Figliozzi</td>
<td>VRPTW</td>
<td>Heuristic developed by Figliozzi (2009)</td>
<td>Polynomial function of speed</td>
<td>Tight time windows increases the total fleet emissions.</td>
</tr>
<tr>
<td>(2011)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bektaş and</td>
<td>VRP with and</td>
<td>CPLEX (exact solution)</td>
<td>Simplified version of the energy estimation model used in CMEM (Section 2.2.1); includes the effect of weight</td>
<td>Driver’s cost is the dominating factors in route selection (when optimizing the general cost); Potential for reducing energy by 2-12%. The problem is referred to as the pollution routing problem, PRP.</td>
</tr>
<tr>
<td>Laporte (2011)</td>
<td>without TW (PRP)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Saberi and</td>
<td>Continues approximation method</td>
<td>Figliozzi (2011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Verbas (2012)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Study</td>
<td>VRP extension</td>
<td>Solution algorithm</td>
<td>Emission/Energy formulation</td>
<td>Notes</td>
</tr>
<tr>
<td>------------------------------</td>
<td>-------------------------------</td>
<td>----------------------------</td>
<td>-------------------------------------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Omidvar and Tavakkoli-Moghaddam (2012)</td>
<td>TDVRP with TW</td>
<td>Compared the solutions of two metaheuristics (SA, and GA); and an exact solution</td>
<td>a function of speed squared and speed presented by the Transportation Research Laboratory in 1999</td>
<td>During congestion, alternative fuel vehicles (AFV) emit less than half of the conventional vehicles; The SA algorithm performs better than the GA, but takes much longer.</td>
</tr>
<tr>
<td>Lin and Ng (2012)</td>
<td>VRP with backhauls and allowing for collaboration</td>
<td>Tabu search</td>
<td>A linear function of a base EF and speed (using separate coefficients for speeds higher and lower than the base speed)</td>
<td>Their results showed a 3-20% reduction of emissions in a freight network compared to the case that collaboration is not possible; Also the backhaul company signs fewer contracts as the carbon credit increases.</td>
</tr>
<tr>
<td>Pradenas et al. (2012)</td>
<td>VRPTW and backhauls</td>
<td>Scatter search (SS) metaheuristic</td>
<td>Bektaş and Laporte (2011)</td>
<td>Authors concluded that more vehicles are needed to decrease the vehicle’s load which affects the vehicles’ energy consumption</td>
</tr>
<tr>
<td>Jabali et al. (2012)</td>
<td>TDVRP, CO₂ and time optimal</td>
<td>Tabu search</td>
<td>Polynomial function similar to Figliozzi (2011)</td>
<td>Minimizing carbon emissions for an airport shuttle service (treating passengers as loads)</td>
</tr>
<tr>
<td>Yang et al. (2013)</td>
<td>VRPTW</td>
<td>Nearest point first double-sided sweep algorithm (heuristic)</td>
<td>Bektaş and Laporte (2011)</td>
<td>The authors introduces their formulation as the sustainable routing problem (SRP) by introducing the effect congestion on the average speed; They also consider three type of driving (calm, normal, and aggressive), by using different average accelerations</td>
</tr>
<tr>
<td>Faccio et al. (2013)</td>
<td>Classical VRP, but minimizing only CO₂.</td>
<td>A constructive heuristics algorithm</td>
<td>A linear function of average speed and average acceleration.</td>
<td></td>
</tr>
<tr>
<td>Study</td>
<td>VRP extension</td>
<td>Solution algorithm</td>
<td>Emission/Energy formulation</td>
<td>Notes</td>
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</tr>
<tr>
<td>Franceschetti et al. (2013)</td>
<td>TD-PRP</td>
<td>Metaheuristic method described in (Demir et al., 2012) while optimizing departure time and speed optimization</td>
<td>Time dependant formulation of Bektaş and Laporte (2011)</td>
<td></td>
</tr>
<tr>
<td>Demir et al. (2014)</td>
<td>Bi-objective</td>
<td>Multi-objective optimization using the adaptive large neighborhood search (ALNS)</td>
<td>Bektaş and Laporte (2011)</td>
<td>Using different multi-objective optimization methods (weighting, normalized weighting, etc.) showed that significant reduction in fuel consumption or driving time can be achieved with only a slight increase in travel time or fuel cost, respectively.</td>
</tr>
</tbody>
</table>
Huang et al. (2012) used the FCR formulation by Xiao et al. (2012a) to formulate a VRP with split pickup and delivery (VRPSPD). The generalized cost for that study included minimizing the distance travelled, fuel consumption and carbon emissions, along with the total number of vehicles. Their results showed that the emission-optimal, and the general-cost-optimal models produce similar results and can reduce total emissions by 4.2-6.5% compared to the distance-optimal model; with an increase of 1.8% in total distance. Their analysis also revealed that a smaller fuel consumption rate increases the total emission that can be reduced by the emission-optimal model. This shows the importance of requiring the best estimate of the parameter when analysing policies. Although their study improves on Xiao et al. (2012a) in that FCRs are based on numbers produced by truck manufacturers, it is still limited by using fixed FCRs on all routes as only a function of the vehicle’s weight and not the vehicle’s driving cycle (which accounts for fluctuations in speed and acceleration).

A recent study by Kwon et al. (2013) introduced the cap-and-trade policy for a VRP with a heterogeneous fleet, using emission factors of Xiao et al. (2012a), with the objective of minimizing the fuel and carbon cost. The study implemented the policy on several benchmark networks using the Tabu search. Also the emission allowance for each instance was set equal to the emissions from the initial solution. Similar studies to Xiao et al. (2012a) and Huang et al. (2012) are (Eguia et al., 2012; Kopfer et al., 2014; Kuo, 2010; Lewczuk et al., 2013; Suzuki, 2011; Suzuki and Dai, 2013; Ubeda et al., 2011; Van Duin et al., 2013).

A detailed scrutiny of the paper by Kwon et al. (2013) provides further justification for focusing on exact solution methods in this research. In this paper, the objective function for the optimization is defined as:

\[
\text{Minimize } \sum_{k \in K} \sum_{(i,j) \in A} v_k \cdot d_{ij} \cdot x_{ijk} + c \cdot PC
\]

Where \(v_k\) is the variable operation cost of a vehicle of type \(k\) (of the set of the possible vehicles \(K\)) per unit distance, \(i\) and \(j\) customer nodes, \(x_{ijk}\) is one if a type \(k\) vehicle travels from node \(i\) to \(j\) and otherwise zero, \(d_{ij}\) the distance between the nodes, \(c\) the cost of carbon and \(PC\) the difference between the carbon emissions of the company and the allowance. \(PC\) is defined as:
\[ PC = \sum_{k \in K} \sum_{(i,j) \in A} e_k \cdot d_{ij} \cdot x_{ijk} - AE \]

Where \( e_k \) is the emissions of vehicle type \( k \) per unit of distance and \( AE \) the carbon allowance for the company.

Replacing PC in the objective function with the equivalent from the second equation gives:

\[
\text{Minimize } \sum_{k \in K} \sum_{(i,j) \in A} v_k \cdot d_{ij} \cdot x_{ijk} + c \cdot \left( \sum_{k \in K} \sum_{(i,j) \in A} e_k \cdot d_{ij} \cdot x_{ijk} - AE \right)
\]

Or

\[
\text{Minimize } \sum_{k \in K} \sum_{(i,j) \in A} (v_k + c \cdot e_k) \cdot d_{ij} \cdot x_{ijk} - c \cdot AE
\]

From this formulation of the objective function it is clear that the emission limit is a constant in the objective function and thus modifying this value, ceteris paribus, should not affect the selection of routes, and consequently the total amount of emissions, despite changes in the overall cost. However, the authors consistently report variations in the emissions where only the emission limit was changed. These variations can only be attributed to the effects of using non-exact solution methods for optimization and could influence the interpretation of the results where policies are being compared for emission reduction.

A few studies improved the rate-based models by using an emission model, such as MOVES or CMEM when estimating the emission factor. Pitera et al. (2011) used MOVES average speed model to improve the University of Washington mailing services using a TDVRP with heterogeneous fleet on freeway or urban roads. Their analysis showed that the current mail delivery system can be improved through different scenarios such as demand consolidation, simple rerouting, fleet size reduction, and changing driver break policies. Using the same method, Wygonik and Goodchild (2011) developed an ArcGIS model to analyse multiple scenarios for a real case of VRPTW. They also used MOVES average speed model for uncongested road conditions. Their study concluded that the fact that customers prefer shorter time windows results in an increase in service and emission costs (same as Figliozzi (2011)). Results also showed that
increasing the cost of fuel or CO$_2$ for fleet operators would be the most effective way to impact their operations. Similar studies are presented in (Maden et al., 2010; Scott et al., 2010).

The above rate-based models are limited by the fact that they do not include a link between the transportation model and the routing model. In other words, traffic congestion and road type is only reflected by using the free flow travel speed or a factor of it (to show congestion) as the input into the emission model.

Palmer (2007) improved on these models by making the connection between a transportation model and the routing model. The transportation model used in that study produces average speeds for four different road categories of urban, suburban, rural, and motorway. Average speeds on urban and suburban roads are then transformed into second-by-second driving cycles using generic driving cycles developed by Green and Barlow (2004) for six towns in the UK (shown in Table 2-1). The fuel consumption is estimated as a function of the each second’s tractive force (from Bowyer et al, 1985). However since Green and Barlow (2004) do not have generic driving cycles for motorways and rural roads, an average speed model is used to estimate fuel consumption on these roads. Palmer (2007), used a heuristic algorithm to solve the VRPTW for a home grocery delivery network in the UK. Results showed that CO$_2$ reductions of 4.8% and 1.2% can be seen between the CO$_2$-optimal routes and time-optimal and distance-optimal routes, respectively; while increasing the time and distance by 3.8% and 2.4% respectively.

Although Palmer (2007) improved on the previous rate-based models by introducing the link between the transportation model and the routing model, the study is still limited by not using site-specific driving cycles and ignoring the effect of intersections and signals on traffic congestion. The study also uses the average speed model for motorways, and rural roads where no generic driving cycles were available. The study also does not allow for multiple performance measures to be optimized simultaneously, nor does it consider any policy implications.

2.6 Critique

The aim of this research is to develop a method that would enable freight routing to minimize GHG emissions using simulated driving cycles, by bringing together elements of policy making, traffic microsimulation, emission modelling, and operations research.
There are microsimulation models built for larger areas than the Toronto Waterfront Area (Smith et al., 2008) which have been calibrated to vehicle counts using the genetic algorithm. There are also studies that have focused on calibrating a relatively smaller network to a combination of counts, speeds and maximum acceleration and deceleration using GPS data (Fellendorf and Hirschmann, 2010). One objective of this research is to show how available GPS and count data (collected by governmental agencies not specifically collected for calibration purposes) can be used to calibrate a relatively large and complex microsimulation network using a multi-objective calibration function, and validate the network against observed driving cycles and cycle emissions, resulting in a network that can be used for various emission analyses with a good level of confidence.

The second objective of this research is to develop and demonstrate a method for efficiently developing driving cycles that represent specific combinations of roadway class, time of day, and vehicle attributes. There are several applications for a disaggregate set of driving cycles. Emissions and fuel consumption impacts of changing congestion patterns, new infrastructure, and vehicle specific driving behaviour could be better addressed. The emissions benefits of new vehicle technology could be assessed more specifically for different roadway types (e.g. when and where would the greatest benefits of plug-in hybrid electric vehicles be attained?). Vehicle routing algorithms could be developed that include congestion-sensitive fuel consumption and emissions in the objective function, for example, to service congested areas with lower emitting vehicles during off-peak hours.

The third objective uses the developed simulated driving cycles, representing traffic conditions, in a vehicle routing problem of the study area to analyse the trade-offs between a distance-optimal, time-optimal, and emission-optimal solutions. Finally, the research improves on current studies by analysing how implementing the cap-and-trade policy will affect the formulation and results of the vehicle routing.

In short, this research builds on existing literature by: a) using a traffic microsimulation model to represent the effect of congestion and signals on traffic movement and queue formation, b) developing road-specific driving cycles that can be used to produce a more accurate estimate of emissions, c) proposing a VRP formulation that allows for minimizing a combination of time, distance, and emissions, and d) analysing the effect of introducing the cap-and-trade policy.
3 Development and Calibration of the Traffic Simulation Model

3.1 Introduction

Use of traffic microsimulation for emission estimation and traffic analysis has increased over the last decade. As mentioned in section 2.3, the quality of the emissions model outcomes are directly tied to the quality of the microsimulation, requiring a robust and well-calibrated model. The software selected for this modelling step is Paramics (Quadstone, 2008). This software is designed to explicitly represent individual vehicle movements in a congested network, with explicit representation of:

- Detailed geometric configuration of the roadway system,
- Traffic signal timing,
- Vehicle routing decisions that reflect time-varying congestion patterns in the network,
- Detailed driver behaviour such as lane changing and car following,
- Queuing of vehicles at intersections and on freeway segments that can sometimes result in queues that propagate backward, causing gridlock.

The calibration of this model is important since the ability to produce accurate simulated driving cycles relies on the traffic simulation model accurately representing reality. This chapter describes the calibration of the Toronto Waterfront Area microsimulation network based on three different objective functions. A genetic algorithm with a multi-criteria objective function is used, that includes goodness-of-fit measures for traffic counts, speeds and acceleration/deceleration patterns.

The calibration is summarized in seven sections. Section 3.2 introduces the Toronto Waterfront Network as the study area selected, followed by a brief overview of the different data sources used for the purpose of the calibration and validation in section 3.3. Sections 3.4 and 3.5 introduce the calibration parameters and the objective function used for calibration. Section 3.6 explains the assumptions of the genetic algorithm used for calibrating the microsimulation. Lastly, section 3.7 presents the results of the calibration, and validation of driving cycles, vehicle specific power, and emissions.
3.2 Study Area

The traffic simulation is developed for the Toronto Waterfront Area (Figure 3-1) which is located south of Dundas Street, west of Woodbine Avenue, and east of Parkside Drive. This area consists of the central business district of Toronto and inner urban areas to the east and west. The network includes arterial, collector and local roads and two freeways, the Don Valley Parkway (DVP) and the Gardiner Expressway, that play an important role in transporting goods and people to and from the downtown. The network was originally coded in Paramics V5 in a project conducted for the Toronto Waterfront Revitalization Corporation (Abdulhai et al., 2002). Within that project, efforts were invested into building the correct geometry, defining the roadway attributes (speeds, and land configurations) and coding signal timing. For signalized intersections, actuation algorithms were developed to best represent the SCOOT traffic signal control system in the Waterfront area. Detailed information about the steps taken is available in (Abdulhai et al., 2002). The model had been calibrated for 2001 traffic conditions and vehicle demand; therefore, significant additional calibration was required for this research to update the model for 2009 traffic conditions. The final network in Paramics V6.9.1 consists of 4012 roadway links, 1841 nodes, 44 internal zones, 35 external gateways, and 227 signals and 1092 intersections, approximately 26 km of freeway, and about 471 km of total road. The network presents an area of about 27 km².

Figure 3-1- The Toronto Waterfront Area

46 2009 was selected as the study year, as observed road counts and speed data were available for year 2009.
Demand inputs for this study were generated by Roorda et al. (2010), using a multiclass generalized cost static user equilibrium assignment (in the EMME modelling software) for the Greater Toronto and Hamilton Area for light, medium and heavy trucks and passenger cars. Passenger vehicle demand was derived from the household travel survey in Toronto, and truck demand was developed using a three stage truck trip model based on data from a shipper based survey of truck demand and truck roadside interview data. The demand was calibrated at the regional level to reflect traffic counts at cordons across the region, and was further calibrated for the Toronto Waterfront Area using OD matrix updating. The estimation of the demand is beyond the scope of this research and details about the steps for this stage and the data sources used are described in detail in Roorda et al. (2010; 2011). The results of the demand estimation showed that a total of 54,916 passenger cars, 4129 LDTs, 1518 MDTs, and 666 HDTs traverse the network between the hours of 8:00 and 9:00 AM.

3.3 Observed Data

This section summarizes all the available data between September 2008 and 2009 that was used for calibrating and validating the microsimulation model (as mentioned in section 2.1) see Appendix A for further details.

3.3.1 Road Counts

The traffic counts were obtained from the 2009 cordon count program for Toronto and from the City of Toronto traffic counting program. 45 count locations were selected at roads crossing Bathurst Street (west of the CBD), the Don River (east of the CBD) and along Richmond Street (north of the CBD), as well as on the Gardiner Expressway, and Don Valley Parkway mainline sections and ramps (see Appendix A for a list of all count locations).

3.3.2 MTO Travel Time Survey

Average speed and standard deviation of acceleration on major road segments (major north/south and east/west arterials in the downtown and the two freeways) were calculated using data provided by the Ministry of Transportation of Ontario. The data were collected using passenger GPS-equipped probe vehicles using the car following approach. A fleet of 11 probe vehicles made 29 trips in the study network between 8:00-9:00 am from September to October of 2008, recording speed and location data every 2 to 10 seconds. In total, speed and acceleration values calculated
for each link were based on data from a maximum of 4 vehicles (Ministry of Transportation, 2009). The MTO travel time survey was used to calculate speed and acceleration data for 71 links in the network along Adelaide St., Spadina Ave., Bathurst St., Yonge St., and Gardiner Expressway (see Appendix A for a list of all count locations).

### 3.4 Calibration Parameters

Traffic microsimulation software packages, such as Paramics, Vissim, and Corsim, rely on a set of parameters that require calibration. Paramics uses two sets of parameters: parameters that the analyst is certain about and does not wish to adjust (e.g. the size of the vehicles) and the parameters that the analyst is less certain about and willing to adjust. The set of adjustable parameters is then further subdivided into those that impact capacity (e.g. mean headway and reaction time) and those that directly impact route choices made by drivers (e.g. driver familiarity with the network). The adjustable parameters used for network calibration are introduced in Table 3-1. Calibrating the acceleration and deceleration profiles of all vehicle types is done by changing the maximum acceleration and deceleration value for passenger cars. Maximum acceleration and deceleration for each truck type were set proportionally to the respective maximum values for passenger cars. By changing the maximum acceleration and deceleration for passenger vehicles, the acceleration and deceleration profiles for the 3 truck types would thus be adjusted accordingly.

### 3.5 Multi-criteria Objective Function

Calibration of the parameters presented in section 3.4 requires the definition of goodness-of-fit measures to compare model outcomes to observations of the system being modelled. Three models are calibrated for the AM peak hour (8:00-9:00 am) using a simple genetic algorithm (GA) (described in section 3.6). Each model uses a different objective function:

1) C Model - calibrates to road counts only
2) CS Model - calibrates to road counts and link average speeds
3) CSA Model - calibrates to road counts, link average speeds, and link standard deviation of acceleration
<table>
<thead>
<tr>
<th>Parameter Category</th>
<th>Parameter</th>
<th>Description</th>
<th>Default Values and Acceptable Range *</th>
</tr>
</thead>
<tbody>
<tr>
<td>Core Paramics</td>
<td>Headway (sec)</td>
<td>The global mean target headway between a vehicle and a following vehicle.</td>
<td>0.6-2.2 (default = 1.0)</td>
</tr>
<tr>
<td></td>
<td>Reaction Time (sec)</td>
<td>The mean reaction time of each driver. This value is associated with the lag in time between a change in speed of the preceding vehicle and the following vehicle reaction to that change.</td>
<td>0.3-1.9 (default = 1.0)</td>
</tr>
<tr>
<td></td>
<td>Timesteps</td>
<td>Number of discrete simulation intervals that are simulated per second.</td>
<td>2-9 (default = 3)</td>
</tr>
<tr>
<td></td>
<td>Maximum Acceleration and Deceleration of a Passenger Vehicle (m/s²)</td>
<td>The maximum acceleration and deceleration value assigned to a vehicle type will be used in the car following calculations.</td>
<td>Maximum and minimum values were set based on observed data</td>
</tr>
<tr>
<td>Traffic Assignment Parameters</td>
<td>Feedback Interval (min)</td>
<td>Sets the period at which link times are updated (fed back) into the routing calculation. Route cost tables are updated at the beginning of each feedback interval for each network node to each destination zone for each routing table.</td>
<td>2-10 (default = 5)</td>
</tr>
<tr>
<td></td>
<td>Familiarity (%)</td>
<td>Percentage of drivers aware of dynamically updated cost to destination each feedback interval.</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>Perturbation (%)</td>
<td>Models perception error or variation in perceiving true travel costs by adding random perturbation (noise) to the true cost, distributed across the driver population, which affects stochastic assignment of traffic.</td>
<td>--</td>
</tr>
</tbody>
</table>

* Source: (Park and Qi, 2004; Quadstone Paramics, 2009)
For the CS and CSA models, which have more than one goodness-of-fit measure, the problem is referred to as multicriteria optimization. There are two multiobjective optimization methods: the Scalar method, and the Pareto method (Coello, 2011; Jozefowiez et al., 2008). The scalar method combines goodness-of-fit measures into a single objective function using linear or non-linear combinations. In the Pareto method, the optimal solution is the solution that cannot be improved with respect to any of the objective functions without jeopardizing at least one of the other objective functions. The scalar method is used for this research because it is relatively easy to implement and computationally efficient.

Equation 1 is the objective function in the CSA network, where the model is calibrated to counts, speeds, and accelerations. The formulas under the square roots are the Mean Square of Errors (MSE) between model estimates and field measurements for counts, speeds, and standard deviation of acceleration. The reason for selecting the standard deviation of acceleration is that given that the speed of a vehicle at the start and end of its trip is zero, the accelerations will cancel out the decelerations; and the mean acceleration of a vehicle during its trip would be zero. The standard deviation of acceleration better represents the deviation from mean acceleration either positive (for acceleration) or negative (for deceleration).

The reasons for squaring the difference between the observed and simulated are twofold: so that higher penalty is placed on larger errors; and also so that errors of different signs do not balance each other out. The Root Mean Square of Errors (RMSEs) are normalized by dividing their square root by their average value. \((\alpha, \beta, \gamma)\) are weights representing the relative importance of each term in the objective function. Since no information was available about which term was more important, it was assumed that all terms have equal importance and hence a relative weight of 1 was assigned to each term in the objective function. Therefore, the vector of weights is (1,0,0), (1,1,0), and (1,1,1) for the C, CS, and the CSA models respectively. The objective functions for the C and the CS models are the same as Equation 1 but with terms removed.
Objective function =

\[ \alpha \times \frac{1}{n_1} \sum_{i=1}^{n_1} (\text{SimCount}_i - \text{ObsCount}_i)^2 \text{ AvgCount} + \beta \times \frac{1}{n_2} \sum_{j=1}^{n_2} (\text{SimSpeed}_j - \text{ObsSpeed}_j)^2 \text{ AvgSpeed} + \gamma \times \frac{1}{n_2} \sum_{j=1}^{n_2} (\text{SimStd}(acc)_j - \text{ObsStd}(acc)_j)^2 \text{ AvgStd(acc)} \]

Equation 1

Where:

- \( n_1 \) is the number of count locations;
- \( n_2 \) is the number of links for which speed information was provided by the Ministry of Transportation of Ontario;
- \( \text{ObsCount} \) and \( \text{SimCount} \) are observed and simulated traffic volume on a link, respectively;
- \( \text{ObsSpeed} \) and \( \text{SimSpeed} \) are observed and simulated average speeds on a link, respectively;
- \( \text{ObsStd}(acc) \) and \( \text{SimStd}(acc) \) are observed and simulated standard deviation of acceleration values on a link, respectively;
- \( \text{AvgCount} \), \( \text{AvgSpeed} \), and \( \text{AvgStd}(acc) \) are the average of observed road counts, link speeds, and link acceleration standard deviation, respectively.

3.6 Genetic Algorithm for Model Calibration

Traffic simulation parameters, which impact capacity, route choice, and speed and acceleration profiles, were calibrated using a simple genetic algorithm\(^{48} \) (GA) to reflect observed local conditions (Figure 3-2). The GA is a heuristic method used in solving optimization problems with large search areas based on the Darwinian concept of “survival of the fittest” through selection and evolution. This section outlines the GA representation (chromosomes), selection scheme, operators (encoding of the chromosomes, crossover, and mutation), their parameters (population size, crossover and mutation probability), and stopping criteria.

\(^{47}\) The simulated average speed and std. of acceleration was calculated using 50% of the vehicles in the simulation; since averaging over all the vehicles would increase the post-processing time significantly without significantly impacting the results (See Appendix B).

\(^{48}\) Compared to other GA types which are steady GA, crowding GA, and the incremental GA, the simple GA is the most common method used. In the steady GA, a portion of the population is replaced by new individuals. One extreme is where all the population is replaced which would be the simple GA; and the other extreme where only one or two individuals are replaced would be the incremental GA. In the crowding GA, multiple populations are created with the steady GA, but the new individuals will replace the parents most similar to themselves.
Each of the model parameters being adjusted with the GA - such as headway, and reaction time - represent one gene within a chromosome. Real-value coding of the genes was selected (compared to binary coding), since real-valued genes offer: increased efficiency, require less memory, no precision is lost, and have the advantage of allowing for higher mutation rates (Wright, 1990).

The population size was constrained by the amount of time to complete each Paramics run (which could be between 15 to 45 minutes). A fundamental assumption was made here that the genetic algorithm would converge in a reasonable time. However, a small population size could lead to quick convergence to the local minimum. Conversely, a large population size would act the same as a random search and increase the time of convergence to infeasible limits (Ma and Abdulhai, 2001). A common rule of thumb is to select a population size that is more than 2 times the number of calibration parameters (set to 20, since there are 8 calibration parameters). This led to a computation time in the range of 10 hours per generation which was reasonable, and results showed that this led to stable outcomes.

The initial population (with a population size of 20) was defined using random values for each parameter (gene). The fitness of each chromosome is the value of the objective function from one run of the simulation. In each GA iteration, a set of parents that have lower fitness values (since the problem is a minimization problem) are selected to breed the new offspring using the elitism and roulette wheel as follows.

First the best individual according to the elitist strategy is directly copied to the next generation. The roulette wheel selection mechanism is used to select the individuals to mate and generate new offspring (using the weighted average cross-over operator). The crossover operator underpins the process of producing offspring from selected parents. Some of the common operators used are simple and two-point crossover, uniform\(^{49}\), arithmetic (or averaging), and heuristic. In the heuristic crossover method, the better of the two parents is passed over as one of the offspring. The heuristic method might also produce unfeasible offspring (if one or more genes are outside their allowable upper and lower bounds). For this research, it was decided that the fittest parent from the population is passed over to the next generation to provide a “search memory”. This and the

\(^{49}\) The simple, two-point, and uniform crossover result in new chromosomes, but not new genes. Compared to these methods, the arithmetic method is more beneficial since it will allow for new values for each gene.
complexity of the objective function, led to the decision of using the arithmetic method for producing offspring. Therefore, for each set of parents selected for crossover, a random number is generated. The two offspring are then calculated as linear combinations of the two parents, and passed over to the next generation.

Finally, the two best unselected parents not used in the cross-over operator are mutated to avoid premature convergence. The mutation operator reduces the chances of the objective function converging to a local minimum by making a random change to some of the parental genes. Hence, in designing the mutation operator (increase or decrease the value), there is the question of whether or not a gene will be mutated (probability of mutation), how to select the direction of the mutation, and the change that will be made to the gene (mutation size). A coin toss mechanism is used to select the genes for mutation. The direction of mutation is also selected randomly with a probability of 0.5, and the gene is mutated with a range of ±10% (or replaced by the upper or lower boundaries).

This process (shown in the dotted rectangle of Figure 3-2) is repeated until a termination criterion is reached. The most common stopping conditions are (Kumar et al., 2010):

- “A solution is found that satisfies minimum criteria;
- Fixed number of generations reached;
- Allocated budget (computation time/money) reached;
- The highest ranking solution’s fitness is reaching or has reached a plateau such that successive iterations no longer produce better results;
- Manual inspection;
- Combinations of the above.”
For calibrating the microsimulation, the desired value of the objective function is zero (simulation matches all the observed counts, speeds, and accelerations). But 100% calibration is never achievable, so some realistic criterion would need to be set. The plateau reaching termination clause, offers a good balance between computational effort and controlling the uncertainty of the quality of results as the number of iterations without observing improvements can be controlled. Thus, the GA is allowed to run until no further improvements could be made for ten consecutive generations within reasonable computational effort (a maximum of 30 generations which has also been used in similar studies (Smith et al., 2008) was also tried with no significant improvements).
3.7 Results

The network was calibrated for the AM peak hour of 8:00-9:00 am. A warm-up period of 30 minutes (7:30-8:00 am) was used in this study, during which demand is gradually increased. Results from these 30 minutes were not included in the analysis. The following figures - showing the convergence of the best and average solution, for the CSA model as an example - show that there is little improvement likely after 28 iterations.

To show the importance of calibrating the model to more than just counts, or even counts and speed, this section presents results of the calibration by comparing the calibrated parameters. Detailed comparison of counts, average speeds and the standard deviation of accelerations between the three models and the observed values are presented in Appendix C showing improvements in acceleration calibration in the CSA model without substantial sacrifices in counts or speeds. The following section also compares the driving cycles for each model against the observed by comparing their assessment measure, their vehicle specific power distribution, and their emission factors.

![Figure 3-3](image_url)

**Figure 3-3** Improvement of the Value of the (a) Average Objective Function, and (b) Best Solution's Objective Function for the CSA Model
3.7.1 Comparison of Calibrated Parameters

Table 3-2 shows the results of the calibration. The following observations can be made.

1. As speed and acceleration terms are added to the objective function, the average headway increases and the mean reaction time decreases. This is consistent with less aggressive driving behaviour and the values are well within the ranges that are accepted as being realistic in the literature (Park and Won, 2006).

2. As speed and acceleration terms are added to the objective function, the maximum acceleration and deceleration rates decrease.

These two observations show that more unrealistically aggressive driving is permitted when terms for acceleration and speed are not included in the objective function.

Table 3-3 shows the terms in the objective function (RMSE for counts, speed, acceleration), and other goodness-of-fit measures used for comparison for each model. The GEH\(^{50}\) is a parameter that represents the model fit, and is a measure of individual road segment performance that is recommended for freeway calibration (Balakrishna et al., 2007; Dowling et al., 2004). The GEH measures the percent error with respect to the mean value of the observed and simulated counts.

The GEH is calculated by Equation 2.

\[
GEH = \sqrt{\frac{(Obs - Sim)^2}{(Obs + Sim)/2}}
\]

Equation 2

Where:

Obs is the observed road count at a specific location,

Sim is the simulated traffic volume at a specific location

GEH values below 5 are considered to be a good match between model volumes and observed counts. According to Wisconsin DOT freeway model calibration, at least 85% of the observed links in a traffic model should have a GEH less than 5 (Dowling et al., 2004). However, it should be noted that the threshold defined is purely empirical (Barceló, 2010). While these criteria provide a useful benchmark for freeway microsimulation models, it was not possible to achieve this level

\(^{50}\) The GEH measure gets its name from Geoffrey E. Havers, who invented it in the 1970s.
of fit for the Toronto Waterfront Area as a whole, since the network consists of a complicated system of freeways, arterials, collectors and some local road segments. Furthermore, the road counts available for network calibration are largely obtained from single day counts that exhibit significant day to day variability. Thus the GEH criterion is used in this research as another means of comparing each model’s ability in replicating road counts.

Theil’s inequality index, used widely in the literature for testing goodness of simulations (Hourdakis et al., 2003), is also calculated for the three models. Theil’s index is defined as:

\[ U = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - x_i)^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^{n} y_i^2} + \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}} \]

Where \( x_i \) and \( y_i \) denote the observed and simulated values, respectively. A value of 0.2 or less for this index shows a good fit. In addition, the index can be decomposed into three components: bias, variance and covariance (Hourdakis et al., 2003; Polasek, 2013):

\[ U_m = \frac{n(\bar{y} - \bar{x})^2}{\sum_{i=1}^{n} (y_i - x_i)^2} \]  \hspace{1cm} \text{Equation 4}

\[ U_s = \frac{n(\sigma_y - \sigma_x)^2}{\sum_{i=1}^{n} (y_i - x_i)^2} \]  \hspace{1cm} \text{Equation 5}

\[ U_c = \frac{2(1 - r)n\sigma_y \sigma_x}{\sum_{i=1}^{n} (y_i - x_i)^2} \]  \hspace{1cm} \text{Equation 6}

Where \( U_m \) is the bias proportion, measuring the systematic error (estimating consistent over or underestimating of the measurement); \( U_s \) is the variance proportion, measuring the model’s ability to reproduce the variability of the actual measurement; and \( U_c \) is the covariance proportion, which measures the unsystematic error.
In the above equations, $\bar{x}$ and $\bar{y}$ are the mean of the observed and simulated values, respectively; $\sigma_x$ and $\sigma_y$ the standard deviations of the observed and simulated; $n$ is the number of locations; and $r$ is the correlation coefficient defined in Equation 7.

$$r = \frac{1}{n-1} \sum_{i=1}^{n} \frac{(x_i - \bar{x})(y_i - \bar{y})}{\sigma_x \sigma_y}$$

Equation 7

A high covariance together with low values for bias and variance indicates that discrepancies between the observations and the model are unsystematic and therefore indicates a good fit. The sum of the three components is 1.

It can be seen from Table 3-3 that:

1. The RMSE_Count increases when speed and acceleration terms are added to the objective function, since calibrating to multiple criteria results in greater error for each of the individual criteria.

2. The RMSE_Speed is lower in the CS model compared to the C model, as expected. However the RMSE_Speed increases in the CSA model. This, like the previous observation, is a result of adding the acceleration term to the objective function. The CSA calibration is sacrificing the goodness-of-fit for counts and speeds to better simulate acceleration.

3. The percentage of links with GEH greater than 10 is less in the C and CS models compared to the CSA model. This again is the direct result of sacrificing the goodness-of-fit for counts and speeds to better reproduce acceleration.

4. Theil’s index (U) is below 0.2 for the three models; and the majority of the inequality is coming from unsystematic sources as shown by the high value of Uc compared to Um and Us. In the CSA model, despite losing some of the goodness due to focusing on acceleration, the counts still show a good fit.
### Table 3-2: Calibrated Parameters

<table>
<thead>
<tr>
<th>Parameter [range]</th>
<th>C Model</th>
<th>CS Model</th>
<th>CSA Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reaction time (sec) [0.3-1.9]</td>
<td>0.85</td>
<td>0.86</td>
<td>0.63</td>
</tr>
<tr>
<td>Headway (sec) [0.6-2.2]</td>
<td>0.83</td>
<td>0.8</td>
<td>1.94&lt;sup&gt;51&lt;/sup&gt;</td>
</tr>
<tr>
<td>Timestep per second [2-6]</td>
<td>3</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>Feedback interval (min) [2-5]</td>
<td>3</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Familiarity (%) [80-95]</td>
<td>86%</td>
<td>86%</td>
<td>89%</td>
</tr>
<tr>
<td>Perturbation (%) [0-20]</td>
<td>8%</td>
<td>8%</td>
<td>14%</td>
</tr>
<tr>
<td>Maximum passenger car acc (m/s&lt;sup&gt;2&lt;/sup&gt;) [1.5-4]</td>
<td>2.71</td>
<td>2.53</td>
<td>1.88</td>
</tr>
<tr>
<td>Maximum passenger car dec (m/s&lt;sup&gt;2&lt;/sup&gt;) [(-1)-(-6)]</td>
<td>-3.68</td>
<td>-3.73</td>
<td>-2.61</td>
</tr>
</tbody>
</table>

### Table 3-3: Goodness-of-Fit Measures

<table>
<thead>
<tr>
<th>Goodness-of-fit measures</th>
<th>C Model</th>
<th>CS Model</th>
<th>CSA Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE_Count (veh/h)</td>
<td>250.7</td>
<td>257.1</td>
<td>349.5</td>
</tr>
<tr>
<td>RMSE_Speed (km/h)</td>
<td>10.7</td>
<td>10.0</td>
<td>11.3</td>
</tr>
<tr>
<td>RMSE_Acc (m/s&lt;sup&gt;2&lt;/sup&gt;)</td>
<td>0.821</td>
<td>0.7794</td>
<td>0.454</td>
</tr>
<tr>
<td>GEH=5&lt;5</td>
<td>48.9%</td>
<td>53.3%</td>
<td>48.9%</td>
</tr>
<tr>
<td>5&lt;GEH=10</td>
<td>37.8%</td>
<td>33.3%</td>
<td>24.4%</td>
</tr>
<tr>
<td>GEH&gt;10</td>
<td>13.3%</td>
<td>13.3%</td>
<td>26.7%</td>
</tr>
<tr>
<td>U</td>
<td>0.13</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>U&lt;sub&gt;m&lt;/sub&gt;</td>
<td>0.006</td>
<td>0.008</td>
<td>0.062</td>
</tr>
<tr>
<td>U&lt;sub&gt;s&lt;/sub&gt;</td>
<td>0.000</td>
<td>0.016</td>
<td>0.170</td>
</tr>
<tr>
<td>U&lt;sub&gt;c&lt;/sub&gt;</td>
<td>0.994</td>
<td>0.976</td>
<td>0.786</td>
</tr>
</tbody>
</table>

<sup>51</sup> This number is consistent with the ranges that Michael et al. (2000) observed in their studies.
3.7.2 Comparison of Driving Cycles

In addition to the goodness-of-fit measures for counts, average speeds and standard deviation of acceleration, it is informative to compare the speed-acceleration profiles of vehicles in the model versus those of the probe vehicles. Because each individual vehicle’s speed-acceleration profile is unique, representative driving cycles for comparison were developed (based on section 4.2).

To compare the driving cycles of each model against the observed cycles, Table 3-4 compares the 13 statistics that represent a cycle’s attributes. For each of the 13 driving cycle attributes, the CSA attribute is the closest to the observed statistic. There is, however, a large difference between the observed vs. simulated average microtrip duration and percent of time spent in idling mode. The reason for this difference is that probe vehicles, when they reduce their speed due to congestion, do not come to a full stop on the freeway. The simulation however, allows vehicles to reach zero speed on the freeway.

<table>
<thead>
<tr>
<th>Driving Cycle Statistic</th>
<th>C Model</th>
<th>CS Model</th>
<th>CSA Model</th>
<th>Observed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Speed (m/s)</td>
<td>18.1</td>
<td>18.1</td>
<td>15.2</td>
<td>14.5</td>
</tr>
<tr>
<td>Average Running Speed (m/s)</td>
<td>19.0</td>
<td>19.3</td>
<td>15.6</td>
<td>14.5</td>
</tr>
<tr>
<td>Average Acceleration (m/s²)</td>
<td>0.604</td>
<td>0.581</td>
<td>0.358</td>
<td>0.283</td>
</tr>
<tr>
<td>Average Deceleration (m/s²)</td>
<td>-0.719</td>
<td>-0.678</td>
<td>-0.523</td>
<td>-0.326</td>
</tr>
<tr>
<td>Average Micro-trip Duration (sec)</td>
<td>121</td>
<td>110</td>
<td>123</td>
<td>612</td>
</tr>
<tr>
<td>Average number of acceleration-deceleration changes</td>
<td>0.266</td>
<td>0.278</td>
<td>0.211</td>
<td>0.118</td>
</tr>
<tr>
<td>Proportion of time accelerating</td>
<td>45%</td>
<td>43%</td>
<td>57%</td>
<td>53%</td>
</tr>
<tr>
<td>Proportion of time decelerating</td>
<td>38%</td>
<td>37%</td>
<td>37%</td>
<td>45%</td>
</tr>
<tr>
<td>Proportion of time idling (speed=0)</td>
<td>4%</td>
<td>6%</td>
<td>2%</td>
<td>0%</td>
</tr>
<tr>
<td>Proportion of time cruising</td>
<td>13%</td>
<td>13%</td>
<td>4%</td>
<td>2%</td>
</tr>
<tr>
<td>Proportion of time creeping (speed&lt;4 kph)</td>
<td>5%</td>
<td>7%</td>
<td>3%</td>
<td>2%</td>
</tr>
<tr>
<td>Root Mean Square Acceleration (m/s²)</td>
<td>0.926</td>
<td>0.856</td>
<td>0.687</td>
<td>0.436</td>
</tr>
<tr>
<td>Root Mean Square of Positive Kinetic Energy Over Weight (m/s)</td>
<td>14.2</td>
<td>14.3</td>
<td>12.1</td>
<td>11.6</td>
</tr>
</tbody>
</table>
3.7.3 Comparison of Vehicle Specific Power

In this section, the Vehicle Specific Power (VSP) distribution of the simulated driving cycles for each model is compared against that of the observed. As mentioned in section 2.2, the VSP was introduced by Jimenez-Palacios in 1999 to better relate emissions to a vehicle’s operating conditions (Equation 8); and is defined as the instantaneous load per unit of mass (kW/ton). A vehicle’s VSP distribution significantly affects the vehicle’s emissions. Some studies have used VSP as the means to compare the results of a simulation to the observed data (Song et al., 2011; 2012).

\[
VSP = v \times [1.1 \times a + 9.81 \times \text{grade} + 0.132] + 0.000302 \times v^3
\]

Equation 8

Where VSP is the vehicle specific power (kW/ton), \(v\) is the vehicle speed (m/s), \(a\) is the vehicle acceleration (m/s\(^2\)), and grade is the road grade (%).

To compare the VSP distributions, the observed and simulated driving cycles were divided into speed bins with 2 m/s interval (a total of 15 bins). Figure 3-4 shows the VSP cumulative distribution for a sample of the speed bins. In each figure the cumulative distribution of the observed, CSA, CS, and the C model are shown with solid, dash-dash, dash-dot, and dotted lines respectively. Visual inspection of the VSP cumulative distribution shows that the CSA model is closest to the observed for most of the speed bins. The minimum and maximum VSP in each speed bin for each of the models were compared against that of the observed. The maximum VSPs for the CSA model is closest to the observed in all speed bins. In other words, the C and CS models allow driving with higher VSPs compared to the observed, which in turn result in different emission values. Comparing the lowest VSPs, the CSA model is not the closest for all the speed bins. Still, compared to the other models, the CSA model is closest to the observed in more speed bins.

The two-sample Kolmogorov-Smirnov test was also used to evaluate the difference between the cumulative distribution functions (CDFs) of each of the models against that of the observed. In this test the null hypothesis is that the two samples are from the same continuous distribution; against the alternative hypothesis that the two samples are from different continuous distributions.
At a 5% significance level, the null hypothesis that the VSP distributions are from the same distribution could not be rejected for 46.7% of the bins when comparing the CSA and the observed. However, comparing the C and the CS models against the observed, the null hypothesis that the VSP distributions are from the same distribution could not be rejected for 33.3% of the bins.

The above analyses show that although the CSA model is not a perfect replica of the observed; the acceleration-calibrated model has shown significant improvement is simulating the VSP distribution of the driving cycles (which directly affect emissions).

3.7.4 Cycle Emission Comparison

Lastly, emissions from the three simulated and the observed driving cycles are estimated using MOVES2010b. A 2001 gasoline passenger car was selected as the test vehicle, since the average vehicle age in 2009 was 8 years (Statistics Canada, 2009). A summary of the input files required for each MOVES run is presented in Appendix F.

As can be seen from Table 3-5, as speed and acceleration goodness-of-fit terms are added to the calibration objective function, the emission factors from the simulated driving cycles become closer to the observed emission factors. The ratio of modelled to observed emission factors reduces as we move from the C model to the CSA model.

<table>
<thead>
<tr>
<th></th>
<th>C Model</th>
<th>CS Model</th>
<th>CSA Model</th>
<th>Observed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>gr/km</td>
<td>%Diff</td>
<td>gr/km</td>
<td>%Diff</td>
</tr>
<tr>
<td>CO₂</td>
<td>250</td>
<td>+18%</td>
<td>235</td>
<td>+11%</td>
</tr>
<tr>
<td>CO</td>
<td>2.53</td>
<td>+109%</td>
<td>1.97</td>
<td>+63%</td>
</tr>
<tr>
<td>NOₓ</td>
<td>0.313</td>
<td>+87%</td>
<td>0.281</td>
<td>+69%</td>
</tr>
</tbody>
</table>
Figure 3-4- Simulated vs. Observed VSP Cumulative Distribution for (a) 6-8 m/s, (b) 16-18 m/s, and (c) Greater than 28 m/s
3.8 Summary

This chapter addressed the concern that poorly calibrated traffic microsimulation models, relying on incorrect speed acceleration profiles, can result in inaccurate emissions estimates. This chapter builds upon previous research efforts on calibration with the following objectives:

- Introducing a multicriteria objective function for traffic microsimulation calibration that includes goodness-of-fit measures for traffic counts, speeds and acceleration/deceleration patterns.
- Demonstrating the solution of this objective function using a genetic algorithm, on a complex study area network in the Toronto Waterfront Area.
- Validating the outcome of the calibration effort by comparing attributes of simulated and observed driving cycles, vehicle specific power, and emissions.
- Showing the improvements that result from adding speed and acceleration / deceleration terms in the objective function.

A number of assumptions and limitations should be noted in respect to the calibration: signalised intersections were simplified in the utilised model, this was left unchanged; scalar method for multi-objective optimization was used instead of the more complicated Pareto optimal method; acceleration and deceleration were considered together; the same weight was assigned to the importance of counts, speeds and acceleration goodness of fit; and, a simple genetic algorithm was used as seeking the fastest algorithm was not the goal of this study.

Results show that the model calibrated to counts, speed and acceleration is closest to the observed data on most measures, and results in less aggressive driving compared to the other two models. The disadvantage is that counts and speeds are not as accurately replicated when the acceleration criterion is included in the calibration objective function. For applications in emissions modelling, this is considered to be a worthwhile sacrifice to attain more accurate emissions factors.
4 Driving Cycles

4.1 Introduction

State-of-the-art vehicle emission models use driving cycles as an important input. Development of a driving cycle requires access to second-by-second vehicle speed for a representative set of vehicles. So far, no real-world driving cycle has been developed for the Toronto area. The only recent driving cycles developed for the Toronto area were synthesized using CALMOB6 (Busawon and Checkel, 2006) reflecting average speeds from a travel demand model using the Transportation Tomorrow Survey (TTS) (Raykin et al., 2012). For this reason this chapter presents the methodology of using simulated data from a calibrated microsimulation model to develop road, time, and vehicle specific driving cycles using the Toronto Waterfront Area as a case study. This chapter focuses on the second phase of the research (Figure 1-1) with the objective of developing representative simulated driving cycles, using simulated data, for different combinations of roadway class, and vehicle attributes. The methodology and results are presented in six sections. Section 4.2 describes the method for developing driving cycles using simulated data from the traffic simulation model calibrated to reflect road counts, link speeds, and accelerations (presented in chapter 3). Section 4.3 introduces the different road categories observed in the Toronto Waterfront Network; and the results for the AM peak hour driving cycles for light, medium and heavy duty trucks are presented and analyzed in section 4.4. These driving cycles are also compared against a range of available driving cycles, showing different traffic conditions and driving behaviours, confirming the need for city-specific driving cycles. Lastly, in section 4.5., the CO2-eq emission factors for each driving cycle are estimated using EPA’s MOVES microemission model and are shown to be more representative of observations compared to average speed models.

4.2 Method

Development of a driving cycle generally involves three steps: test route selection, data collection, and cycle construction; however as discussed in section 2.3, test route selection is not necessary for simulated driving cycles, since data can be collected on all routes within a desired roadway classification.
4.2.1 Data Collection

Data collection was done by writing a plug-in in Paramics that would record the speed of each vehicle at every second of its trip from origin to destination. Due to the stochastic nature of microsimulation models; each run with a random seed is regarded as a random experiment and it cannot be regarded as the average condition for the basis of any comparison. Some runs can represent typical days while others would represent extreme light or heavy traffic conditions. Therefore, numerous runs are required for each scenario. Statistical analysis was performed to determine a sufficient number of replications. In this analysis, mean roadway link volumes were computed for batches of 5, 10, 20, 25 and 30 replications and these mean volumes were compared against those computed over 15 replications. The results showed that less than 5% of links had statistically different mean link volumes (at the 95% confidence level) when the number of simulations exceeded 15. Hence, 15 replications were considered to be sufficient (details presented in Appendix D).

The plug-in produces text files that include the vehicle ID, vehicle type ID, link ID, simulation time (sec), and the vehicle speed (m/s) for each vehicle in the network for each simulation run. Table 4-1 shows parts of the output for a heavy duty truck (vehicle type id=15) entering the network at 8:00 a.m., and reaching its destination approximately 28 minutes later. Second-by-second speed of each vehicle on each road was recorded using this plug-in so that driving cycles for different road categories could later be developed.

<table>
<thead>
<tr>
<th>Vehicle ID</th>
<th>Vehicle Type ID</th>
<th>Link ID</th>
<th>Time (sec)</th>
<th>Speed (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>7173</td>
<td>15</td>
<td>220z:219z</td>
<td>28801</td>
<td>0</td>
</tr>
<tr>
<td>7173</td>
<td>15</td>
<td>220z:219z</td>
<td>28802</td>
<td>0</td>
</tr>
<tr>
<td>7173</td>
<td>15</td>
<td>220z:219z</td>
<td>28803</td>
<td>0</td>
</tr>
<tr>
<td>7173</td>
<td>15</td>
<td>220z:219z</td>
<td>28804</td>
<td>0</td>
</tr>
<tr>
<td>7173</td>
<td>15</td>
<td>220z:219z</td>
<td>28805</td>
<td>0</td>
</tr>
<tr>
<td>7173</td>
<td>15</td>
<td>220z:219z</td>
<td>28806</td>
<td>0.067</td>
</tr>
<tr>
<td>7173</td>
<td>15</td>
<td>220z:219z</td>
<td>28807</td>
<td>0.125</td>
</tr>
<tr>
<td>7173</td>
<td>15</td>
<td>220z:219z</td>
<td>28808</td>
<td>0.036</td>
</tr>
<tr>
<td>7173</td>
<td>15</td>
<td>220z:219z</td>
<td>28809</td>
<td>0.106</td>
</tr>
<tr>
<td>7173</td>
<td>15</td>
<td>220z:219z</td>
<td>28810</td>
<td>0</td>
</tr>
<tr>
<td>7173</td>
<td>15</td>
<td>220z:219z</td>
<td>28811</td>
<td>0.075</td>
</tr>
<tr>
<td>7173</td>
<td>15</td>
<td>220z:219z</td>
<td>28812</td>
<td>0.139</td>
</tr>
</tbody>
</table>
4.2.2 Cycle Construction

The method used for developing simulated vehicle and/or road-specific driving cycles is shown in Figure 4-1. The inputs are the second-by-second speed, location, and vehicle type information of all vehicles from the simulation. The data are first categorized based on road (section 4.3) and vehicle type (LDTs, MDTs, and HDTs), and micro-trips (defined as the trip between two idling periods) are generated. Cycle construction, consists of the following steps:

1. Define the set of assessment measures used to describe a driving cycle;
2. Calculate the assessment measures for the collected data (called target statistics);
3. Develop a candidate driving cycle from the pool of micro-trips available (called candidate cycle);
4. Calculate the same assessment measures for the candidate cycle (called test statistics);
5. Identify the candidate cycle whose test statistics are closest to the target statistics.

Target statistics are calculated using micro-trips for each vehicle-road type combination. Then a test cycle is generated by appending randomly selected micro-trips until the total test cycle duration is between 10 to 30 minutes. Then the test cycle is evaluated (as shown in the dotted rectangle in Figure 4-1) and if it passes all criteria with an acceptable threshold of 15%, it is accepted as a candidate driving cycle. The reasons for selecting a 15% threshold were twofold.
First, to ensure that each assessment measure of the candidate driving cycles is within 15% of the target measure. Second, to allow for having multiple candidate driving cycles for each vehicle type. The objective is to find the best driving cycle that minimizes the difference between the drive cycle statistics and the target statistics.

The set of assessment measures selected for this study are adapted from those used in the literature (Hung et al., 2007; Saleh et al., 2009; Wang et al., 2008). Table 4-2 shows the 13 assessment measures used to compare attributes of a candidate driving cycle to the mean attributes of all micro-trips. The stopping criteria are satisfied when either 20 candidate cycles are identified, or a maximum of 10,000 test cycles are tested. Under these criteria, there will generally be more than one candidate driving cycle and hence another goodness-of-fit measure is required to select the best candidate as the final driving cycle. The performance value (PV) (Equation 9), also adapted from Hung et al. (2007) and Saleh et al. (2009), represents the sum of the normalized absolute difference between the test statistics and the target statistics.

\[
PV = \sum_{k} w_k \left| \frac{\text{test stat}_k - \text{tar stat}_k}{\text{tar stat}_k} \right| \quad \text{for } k = 1, \ldots, 13 \tag{Equation 9}
\]

In this equation test stat\(_k\) is the \(k^{th}\) assessment measure for the candidate driving cycle, tar stat\(_k\) is the \(k^{th}\) target assessment measure, and \(w_k\) shows the importance of the \(k^{th}\) measure relative to the other 12. Current literature on driving cycles considers all measures equally important (\(w_k=1\)) (Hung et al., 2007; Kamble et al., 2009; Saleh et al., 2009; Yu et al., 2010a). The PV is calculated for all candidate driving cycles, and the candidate with the lowest PV is selected as the final driving cycle for the particular vehicle/road type.
Figure 4-1- Method for the Development of a Simulated Driving Cycle

Table 4-2- Assessment Measures Used for Cycle Construction

<table>
<thead>
<tr>
<th>Assessment Measure</th>
<th>Abbreviation</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average speed</td>
<td>V</td>
<td>m/s</td>
</tr>
<tr>
<td>Average running speed (exclude points where speed is equal to zero)</td>
<td>V_r</td>
<td>m/s</td>
</tr>
<tr>
<td>Average acceleration</td>
<td>Acc</td>
<td>m/s^2</td>
</tr>
<tr>
<td>Average deceleration</td>
<td>Dec</td>
<td>m/s^2</td>
</tr>
<tr>
<td>Time proportion of driving modes in idling</td>
<td>P_i</td>
<td>%</td>
</tr>
<tr>
<td>Time proportion of driving modes in accelerating</td>
<td>P_a</td>
<td>%</td>
</tr>
<tr>
<td>Time proportion of driving modes in decelerating</td>
<td>P_d</td>
<td>%</td>
</tr>
<tr>
<td>Time proportion of driving modes in cruising (speed&lt;4 kph)</td>
<td>P_crs</td>
<td>%</td>
</tr>
<tr>
<td>Time proportion of driving modes in creeping (speed&lt;4 kph)</td>
<td>P_crp</td>
<td>%</td>
</tr>
<tr>
<td>Average micro-trip duration</td>
<td>D</td>
<td>Sec</td>
</tr>
<tr>
<td>Average percentage of acceleration-deceleration changes</td>
<td>Acc-dec</td>
<td>%</td>
</tr>
<tr>
<td>Root mean square acceleration (RMSA)</td>
<td>RMSA</td>
<td>m/s^2</td>
</tr>
<tr>
<td>Root mean square of positive kinetic energy over weight (RMSPKE)</td>
<td>RMSPKE</td>
<td>m/s</td>
</tr>
</tbody>
</table>
4.3 Road Categories

There are several applications for a disaggregate set of driving cycles. Emissions and fuel consumption impacts of changing congestion patterns, peak spreading, new infrastructure, and vehicle specific driving behaviour could be better addressed. The emissions benefits of new vehicle technology could be assessed more specifically for different roadway types, e.g. when and where would the greatest benefits of plug-in hybrid electric vehicles be attained?.

For this reason, the links in the Toronto Waterfront were categorized into the following five groups based on their speed limits and driving behaviours: Freeway, Lake Shore Blvd., University Avenue, major arterial, and major arterial with transit (this category consists of arterials with streetcars). University Avenue was categorized separately for two reasons: 1) it has a different speed limit compared to other major arterials or Lake Shore Blvd., 2) the simulation also shows (as will be presented in section 4.4) more aggressive driving on University Avenue compared to Lake Shore Blvd., and more traffic compared to other major arterials.

4.4 Results

4.4.1 Toronto Simulated Driving Cycles

Based on the method described in section 4.2.2, simulated driving cycles were developed using second-by-second speed data from 15 simulation runs for LDTs, MDTs, and HDTs on each road category. As an example, Figure 4-2 shows the simulated driving cycles on freeways and major arterials for each vehicle category (all the driving cycles are presented in Appendix E). The assessment parameters for all the simulated driving cycles are presented in Table 4-3. The following observations can be made from comparing the effect of road type on a vehicle’s driving cycle.

1. Compared to arterials, as expected, the average speed is higher on the freeway, then on Lake Shore Blvd;
2. Arterials have higher accelerations compared to the freeway and Lake Shore Blvd.;
3. Lake Shore Blvd. and all the arterials have higher decelerations, which reflects more aggressive driving and more interactions with other vehicles;
4. Average microtrip duration for the freeway cycle is much longer than the other driving cycles, mainly because there are no signals; and because stops only occur as a result of congestion;

5. As expected, the percentage of time in idling mode is much lower on freeways, followed by Lake Shore Blvd., compared to other road categories;

6. Longer time spent idling, lower speeds, and significantly less cruising time on University Ave suggests a higher level of traffic on this street;

7. The freeway cycle is smoother than other cycles (higher speeds, longer microtrip duration, less time spent creeping and idling, and lower acceleration and deceleration values). However all freeway cycles show bottlenecks during the morning peak as part of the cycle that is more congested than the rest of the cycle (e.g. the bottleneck in the area of Gardiner Expressway and Spadina Ave.);

8. The effect of signals can also be seen visually in the cycles (more stops on University Avenue and other arterials);

9. For all vehicle classes, the cycle on University Avenue is more aggressive. This could be because University Avenue has twice the number of lanes of other arterials, so drivers would want to drive at higher speeds. However, there are lights and traffic, requiring drivers to slow down that might result in more aggressive driving. It also has higher acceleration and deceleration values, and the lowest cruising time;

10. Driving cycles for arterials with and without transit are similar in the majority of assessment measures. The only major difference between the two cycles is in the percentage of time spent cruising, which is higher on arterials with transit. This can be a reflection of how vehicles adjust their speeds and behaviour towards the street cars, thereby reducing the vehicles’ aggressiveness. It should be noted that in the morning peak hour both road categories are at capacity and this could be the main reason for the observed similarity.

Although cycles for arterials with and without transit are similar in most assessment measures, it was nonetheless decided not to combine the two road categories for the following reasons: 1) for those assessment measures where there is a difference, the difference is not small; 2) emission analysis showed that they produce different CO₂ emission factors; and, 3) it would be expected that the two road categories show even more substantial difference for off-peak hours.
Figure 4-2- Simulated Driving Cycles Developed for a) HDT Freeways; b) MDT Freeways; c) LDT Freeways; d) HDT Major Arterials; e) MDT Major Arterials, and f) LDT Major Arterials
The following results are noted from comparing the driving cycles for different vehicle classes:

1. In all cases speed and running speed for LDTs is the highest of the three, with a very small difference between the average speeds of HDTs and MDTs. Also comparing the cycles’ average speeds against each road’s speed limit shows that cycles clearly reflect the congestion in the morning;

2. LDTs have much higher average deceleration compared to MDTs and HDTs on freeways. This difference is less pronounced on Lake Shore Blvd., University Avenue and major arterials, and is small on arterials with transit;

3. A similar relationship is noted for average acceleration, except that differences in average acceleration are greater than differences in average deceleration;

4. In most cases, average microtrip duration is longest for HDTs, followed by MDTs and LDTs suggesting that LDTs drive more aggressively compared to other truck classes;

5. For all cases, the percentage of time in cruising mode is highest for LDTs, followed by HDTs. This likely occurs because LDTs accelerate more quickly, leaving more time for vehicle cruising.

### Table 4-3: Assessment Measures for the Developed Driving Cycles

<table>
<thead>
<tr>
<th>Assessment Measure</th>
<th>Freeway</th>
<th>Lake Shore Blvd.</th>
<th>University Ave.</th>
<th>Major Arterials</th>
<th>Arterials With Transit</th>
</tr>
</thead>
<tbody>
<tr>
<td>HDT</td>
<td>MDT</td>
<td>LDT</td>
<td>HDT</td>
<td>MDT</td>
<td>LDT</td>
</tr>
<tr>
<td>V (kph)</td>
<td>40.9</td>
<td>39.7</td>
<td>52.7</td>
<td>28.4</td>
<td>25.7</td>
</tr>
<tr>
<td>Vr (kph)</td>
<td>41.9</td>
<td>40.6</td>
<td>54.0</td>
<td>33.3</td>
<td>29.4</td>
</tr>
<tr>
<td>Acc (m/s²)</td>
<td>0.147</td>
<td>0.135</td>
<td>0.293</td>
<td>0.280</td>
<td>0.265</td>
</tr>
<tr>
<td>Dec (m/s²)</td>
<td>-0.282</td>
<td>-0.336</td>
<td>-0.544</td>
<td>-0.605</td>
<td>-0.647</td>
</tr>
<tr>
<td>D (sec)</td>
<td>159</td>
<td>132</td>
<td>112</td>
<td>33</td>
<td>38</td>
</tr>
<tr>
<td>Acc-dec (%)</td>
<td>15</td>
<td>16</td>
<td>17</td>
<td>20</td>
<td>19</td>
</tr>
<tr>
<td>Pₐ (%)</td>
<td>62.8</td>
<td>69.4</td>
<td>61.2</td>
<td>59.3</td>
<td>62.8</td>
</tr>
<tr>
<td>P₃ (%)</td>
<td>32.8</td>
<td>27.8</td>
<td>33.0</td>
<td>27.5</td>
<td>25.7</td>
</tr>
<tr>
<td>P₅ (%)</td>
<td>1.9</td>
<td>1.6</td>
<td>2.1</td>
<td>11.7</td>
<td>10.4</td>
</tr>
<tr>
<td>P₈ (%)</td>
<td>2.5</td>
<td>1.2</td>
<td>3.8</td>
<td>1.4</td>
<td>1.2</td>
</tr>
<tr>
<td>P₉ (%)</td>
<td>2.9</td>
<td>3.5</td>
<td>3.5</td>
<td>23.7</td>
<td>23.5</td>
</tr>
<tr>
<td>RMSA (m/s²)</td>
<td>0.324</td>
<td>0.344</td>
<td>0.597</td>
<td>0.571</td>
<td>0.521</td>
</tr>
<tr>
<td>RMSPKE (m/s)</td>
<td>9.17</td>
<td>8.82</td>
<td>11.34</td>
<td>7.04</td>
<td>6.44</td>
</tr>
</tbody>
</table>
4.4.2 Comparison of the LDT Toronto Driving Cycles with International Cycles

To analyze the differences between the Toronto cycles and other available cycles, the developed LDT freeway simulated driving cycles are compared against two categories of driving cycles. One category includes other real world driving cycles representing peak hour driving of light duty vehicles in other cities, for which most of the assessment measures are reported in the literature (Hung et al., 2007; Wang et al., 2008). Freeway cycles are also compared to the Highway Fuel Economy Driving Schedule (HWFET) developed by the EPA (Figure 4-3) to measure the fuel consumption of light duty vehicles for a highway cycle of 765 seconds, 10.2 miles, and average running speed of 77.3 kph (U.S. Environmental Protection Agency, 2010).

![Figure 4-3- HWFET Driving Cycle](image)

Table 4-4- LDT Freeway Cycles vs. Available International Light Duty Freeway Driving Cycles

<table>
<thead>
<tr>
<th>Assessment Measure</th>
<th>Simulated Toronto LDT Driving Cycles</th>
<th>Driving Cycles for Chinese Cities</th>
<th>Hong Kong&lt;sup&gt;1&lt;/sup&gt; Driving Cycle</th>
<th>US HWFET</th>
</tr>
</thead>
<tbody>
<tr>
<td>V (kph)</td>
<td>52.7</td>
<td>Beijing</td>
<td>38.3</td>
<td>77.1</td>
</tr>
<tr>
<td>V&lt;sub&gt;r&lt;/sub&gt; (kph)</td>
<td>54.0</td>
<td>Shanghai</td>
<td>41.8</td>
<td>77.7</td>
</tr>
<tr>
<td>Acc (m/s²)</td>
<td>0.293</td>
<td>Chongqing</td>
<td>0.398</td>
<td>0.288</td>
</tr>
<tr>
<td>Dec (m/s²)</td>
<td>-0.544</td>
<td>Tianjin</td>
<td>0.39</td>
<td>0.07</td>
</tr>
<tr>
<td>D (sec)</td>
<td>112</td>
<td>Chengdu</td>
<td>-0.414</td>
<td>-0.383</td>
</tr>
<tr>
<td>P&lt;sub&gt;s&lt;/sub&gt; (%)</td>
<td>61.2</td>
<td></td>
<td>37.5</td>
<td>26.1</td>
</tr>
<tr>
<td>P&lt;sub&gt;d&lt;/sub&gt; (%)</td>
<td>33.0</td>
<td></td>
<td>36.2</td>
<td>19.5</td>
</tr>
<tr>
<td>P&lt;sub&gt;i&lt;/sub&gt; (%)</td>
<td>2.1</td>
<td></td>
<td>8.4</td>
<td>0.7</td>
</tr>
<tr>
<td>P&lt;sub&gt;crs&lt;/sub&gt; (%)</td>
<td>3.8</td>
<td></td>
<td>17.2</td>
<td>53.8</td>
</tr>
<tr>
<td>P&lt;sub&gt;crp&lt;/sub&gt; (%)</td>
<td>3.5</td>
<td></td>
<td>0.7</td>
<td>0.0</td>
</tr>
<tr>
<td>RMSA (m/s²)</td>
<td>0.597</td>
<td></td>
<td>0.494</td>
<td>0.379</td>
</tr>
</tbody>
</table>

<sup>1</sup>- Not all 13 statistics were used in Wang et al. (2008), or defined the same way in Hung et al. (2007). Therefore, only some parameters are used for comparison.
The following observations can be made from Table 4-4. First, compared to the HWFET cycle, Toronto freeways experience lower speeds, shorter microtrips, and longer idling and creeping periods, representing more congestion on the Toronto freeways which would be expected since the HWFET was not prepared specifically for peak traffic conditions. Second, higher values for average deceleration and RMSA, time proportions spent accelerating, decelerating, and the shorter cruising period suggests more aggressive driving for the Toronto freeway cycle compared to the HWFET cycle. Third, compared to other real world cycles developed specifically for the peak traffic conditions in China and Hong Kong, higher speeds and less time spent idling suggest less congestion in the Toronto freeway cycle. Lastly, lower average acceleration and longer time spent accelerating, along with an average deceleration and time proportion spent decelerating that are in the same range of the other cities, suggests that the Toronto freeway cycle is less aggressive than other real world cycles shown in Table 4-4.

Simulated LDT cycles for the other road categories are also compared against real world driving cycles representing peak hour driving for arterial cycles and test cycles used in the US for vehicle emission testing (Table 4-5). Shanghai has the most aggressive cycle among the Asian cycles, possessing the highest average acceleration and deceleration, highest percentage of time spent idling, while also having high speed and running speed. Comparing the Asian cycles with LDT urban cycles shows that, in general, the simulated LDT cycles have higher average deceleration (except compared to Shanghai); lower speed, and higher average acceleration compared to Beijing, Chongqing, and Tianjin; and smaller acceleration than Shanghai, Chengdu and Hong Kong. These along with the fact that the Toronto cycles spent a longer percentage of time in the accelerating, decelerating and creeping modes, and less time in the idling mode suggests that the Toronto cycles are more aggressive and experience more stop-and-go traffic. This could be explained by the fact that downtown Toronto consists of many signalized intersections that are very close to one another.

The Lake Shore Blvd. cycle is compared against the Hong Kong cycle since they have very similar speeds. The comparison shows that other than the smaller average deceleration, the Hong Kong cycle has a longer average microtrip duration, much smaller percentage of time spent in the creeping mode, and a smaller root mean of square acceleration. These results suggest that the Hong Kong cycle is less aggressive and that the Lake Shore Blvd. cycle is probably more affected by
traffic signals and its resulting bottlenecks, resulting in a more stop and go traffic in parts of the cycle, and less congested traffic after the signal (hence similar values of speeds).

The simulated LDT urban cycles are also compared against the following test cycles used in the US for vehicle emission testing: the Urban Dynamometer Driving Schedule (UDDS) representing city driving, the New York City Cycle (NYCC) representing city driving under low speed and stop-and-go traffic condition, the US06 cycle (also referred to as the “supplemental FTP”) for high acceleration aggressive driving, and the LA92 cycle (also referred to as the “Unified driving schedule”) for driving under less aggressive speeds and acceleration compared to the US06 cycle (Figure 4-4).

Table 4-5- LDT Urban Cycles vs. Available International Urban Cycles for Light Duty Vehicles and Light Duty Driving Cycles used for Emission Testing

<table>
<thead>
<tr>
<th>Assessment Measure</th>
<th>Simulated Toronto LDT Driving Cycles</th>
<th>US Driving Cycles used for Emission Testing</th>
<th>Driving Cycles for Chinese Cities</th>
<th>Hong Kong Driving Cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lake Shore Blvd.</td>
<td>University Ave.</td>
<td>Major Arterials with Transit</td>
<td>UDDS</td>
</tr>
<tr>
<td>V (kph)</td>
<td>34.8</td>
<td>13.9</td>
<td>18.4</td>
<td>19.4</td>
</tr>
<tr>
<td>V_t (kph)</td>
<td>40.6</td>
<td>18.5</td>
<td>23.5</td>
<td>23.6</td>
</tr>
<tr>
<td>Acc (m/s^2)</td>
<td>0.569</td>
<td>0.598</td>
<td>0.580</td>
<td>0.572</td>
</tr>
<tr>
<td>Dec (m/s^2)</td>
<td>-0.752</td>
<td>-0.747</td>
<td>-0.705</td>
<td>-0.572</td>
</tr>
<tr>
<td>D (s)</td>
<td>30</td>
<td>18</td>
<td>20</td>
<td>22</td>
</tr>
<tr>
<td>P_a (%)</td>
<td>45.7</td>
<td>44.3</td>
<td>43.8</td>
<td>36.8</td>
</tr>
<tr>
<td>P_d (%)</td>
<td>34.6</td>
<td>35.5</td>
<td>36.1</td>
<td>36.8</td>
</tr>
<tr>
<td>P_i (%)</td>
<td>11.5</td>
<td>19.5</td>
<td>17.1</td>
<td>14.1</td>
</tr>
<tr>
<td>P_{crs} (%)</td>
<td>8.2</td>
<td>0.7</td>
<td>3.0</td>
<td>12.3</td>
</tr>
<tr>
<td>P_{crp} (%)</td>
<td>24.1</td>
<td>41.6</td>
<td>40.4</td>
<td>28.4</td>
</tr>
<tr>
<td>RMSA (m/s^2)</td>
<td>0.940</td>
<td>0.815</td>
<td>0.824</td>
<td>0.704</td>
</tr>
</tbody>
</table>
Table 4-5 shows observable differences between the simulated Toronto cycles and US cycles used for emission testing shown in Figure 4-4. Given that the NYCC cycle has lower average speeds, higher accelerations, and in most cases lower decelerations and higher average microtrip duration, longer time spent idling, relatively shorter time spent cruising or accelerating, and a longer time
spent creeping suggests that the NYCC cycle represents similar behaviour but more congested traffic conditions than the Toronto simulated cycles.

Compared to the simulated driving cycles, the UDDS cycle has higher speed values, longer average microtrip duration, smaller average acceleration and deceleration values, smaller RMSA value, and shorter percentage of time spent in the creeping mode. This suggests that the UDDS cycle in less aggressive and less congested than the peak Toronto cycles.

Similar to the UDDS cycle, the US06 cycle is less congested allowing for higher average speeds and average microtrip duration. However higher average acceleration and deceleration values, longer amount of time spent accelerating and decelerating, along with a higher RMSA values suggests that the US06 cycle is more aggressive than the Toronto LDT cycles. Lastly, the LA92 cycle shows higher values of speed, acceleration, much longer average microtrip duration, and time spent cruising. These along with a smaller value of RMSA and a similar deceleration value suggests that the LA92 cycle represents less congested, but not necessarily less aggressive driving than the Toronto cycles.

4.4.3 MDT and HDT vs. the Heavy Duty Urban Dynamometer Driving Schedule
In this section, the simulated HDT and MDT driving cycles are compared against the Heavy Duty Urban Dynamometer Driving Schedule (HD-UDDS) (Figure 4-5), developed by the EPA, and used for estimating tailpipe emissions for urban heavy duty driving (U.S. Environmental Protection Agency, 2010). As can be seen from the figure, parts of this cycle reflect highway driving (approximately from time 550 to 800). However, most of the cycle still represents arterial driving. Therefore the comparison focuses on the differences between the HD-UDDS cycle and simulated arterial driving cycles with more focus on Lake Shore Blvd. as the arterial that, if not congested, allows for higher speed driving (Table 4-6).

The table shows that the HD-UDDS cycle has higher average speeds, longer average microtrip durations, shorter amount of time spent accelerating or decelerating, and longer time in the cruising mode; suggesting that the HD-UDDS cycle is less congested than the simulated cycles. Also the HD-UDDS cycle shows congestion with the high percentages of time spent idling and creeping without taking into account the effect it would have on the microtrip durations, which is better represented in the simulated driving cycles by showing more stop-and-go traffic. This confirms
that real-world road and vehicle-specific driving cycles are a better representation of actual driving than the current dynamometer test recommended by the EPA. Considering that good representation of driving behaviour is pertinent for creating good estimates of emissions, these driving cycles which capture a variety of behaviours depending on the road type and vehicle, provide a useful foundation for emission estimation. In turn, such estimates can be used for micro level optimization through green vehicle routing as well as the macro level for policy making decisions by providing a better understanding of how road types and vehicle types affect driver behaviour.

![Figure 4-5: The HD-UDDS driving cycle](image)

<table>
<thead>
<tr>
<th>Assessment Measure</th>
<th>Simulated HDT Toronto Driving Cycles</th>
<th>Simulated MDT Toronto Driving Cycles</th>
<th>EPA HD-UDDS cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lake Shore Blvd.</td>
<td>University Avenue</td>
<td>Arterials</td>
</tr>
<tr>
<td>V (kph)</td>
<td>28.45</td>
<td>12.40</td>
<td>16.57</td>
</tr>
<tr>
<td>V_r (kph)</td>
<td>33.28</td>
<td>16.74</td>
<td>20.53</td>
</tr>
<tr>
<td>Acc (m/s^2)</td>
<td>0.280</td>
<td>0.403</td>
<td>0.398</td>
</tr>
<tr>
<td>Dec (m/s^2)</td>
<td>-0.605</td>
<td>-0.598</td>
<td>-0.585</td>
</tr>
<tr>
<td>D (s)</td>
<td>33</td>
<td>21</td>
<td>22</td>
</tr>
<tr>
<td>P_a (%)</td>
<td>59.3</td>
<td>46.0</td>
<td>49.3</td>
</tr>
<tr>
<td>P_d (%)</td>
<td>27.5</td>
<td>31.1</td>
<td>33.5</td>
</tr>
<tr>
<td>P_t (%)</td>
<td>11.7</td>
<td>22.3</td>
<td>15.6</td>
</tr>
<tr>
<td>P_{crs} (%)</td>
<td>1.4</td>
<td>0.6</td>
<td>1.6</td>
</tr>
<tr>
<td>P_{crp} (%)</td>
<td>23.7</td>
<td>39.2</td>
<td>31.8</td>
</tr>
<tr>
<td>RMSA (m/s^2)</td>
<td>0.571</td>
<td>0.583</td>
<td>0.603</td>
</tr>
</tbody>
</table>
4.5 Emission Estimation and Comparison

As mentioned in section 4.3, there are several applications for a disaggregate set of driving cycles. One application that is the focus of this research is to see how the time-optimal, distance-optimal, and emission-optimal vehicle routing problems will produce different results. As such this section uses MOVES2010b EPA emission model to estimate running CO$_2$-eq emission factors$^{52}$ that will be used in the routing problems in chapter 5.

4.5.1 Use of Average Speed Model vs. Driving Cycles for Emission Estimation

As stated in the literature review (section 2.3), using average speed or driving cycles produces different estimates of emissions. This is also shown in Table 4-7 for the case of the Waterfront Toronto Network, where MOVES2010b is used to estimate link emission factors (in CO$_2$-eq grams per km) using both observed (probe data) and simulated (the CSA model) link average speeds and driving cycles.

As previously described in section 3.3.2, probe data were collected on Gardiner Expressway, Yonge St., Bathurst St., Spadina Ave., and Adelaide St. Given that the Gardiner Expressway is the major freeway in the network and the only other freeway in the network is a small section of DVP, the available observed data on Gardiner is assumed to represent driving on freeways in the network. For major arterials in the network, there are observed data on Yonge St., Spadina Ave., and Adelaide St., representing different major arterials in all directions. However, Bathurst St. is the only representative of major arterials with transit (which would also include streets like King, Dundas, Queen, etc.). Due to data limitations, the available data on Bathurst St. was used for calibrating the microsimulation (chapter 3), but should be considered less reliable when validating the driving cycle for all major arterials with transit.

The following observations can be made from Table 4-7: First, simulated driving cycles produce emission factors that are closer to the observed compared to simulated average speeds on freeways and major arterials. Also the simulated driving cycles are closer to the observed when compared against the estimated emission factors using observed average speeds for freeways and major arterials. This suggests that the additional effort to collect observed data in order to build a good

$^{52}$ In running emission factors, it is assumed that the vehicle is warmed up to their operating temperature.
quality CSA model produces a more reliable source for scenario analysis compared to using the average speed model. Second, the table suggests that the average speed model produces better results for arterials with transit. However, the results for arterials with transit are less reliable than results for freeways and major arterials since observed data was only available on Bathurst St.

Table 4-7- Comparison of CO$_2$-eq Emission Factor (gr/km) for Roads with Available Probe Data using the Average Speed and Driving Cycles Model

<table>
<thead>
<tr>
<th>Road type</th>
<th>Method for emission estimation</th>
<th>Observed DC (1)</th>
<th>Simulated DC (2)</th>
<th>Observed average speed (3)</th>
<th>Simulated average speed (4)</th>
<th>%Diff (2) vs. (1)</th>
<th>%Diff (3) vs. (1)</th>
<th>%Diff (4) vs. (1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Freeways</td>
<td></td>
<td>211</td>
<td>218</td>
<td>181</td>
<td>187</td>
<td>+3.3%</td>
<td>-14.2%</td>
<td>-11.4%</td>
</tr>
<tr>
<td>Arterials</td>
<td></td>
<td>408</td>
<td>446</td>
<td>305</td>
<td>282</td>
<td>+9.1%</td>
<td>-25.2%</td>
<td>-30.8%</td>
</tr>
<tr>
<td>Arterials with transit</td>
<td></td>
<td>349</td>
<td>484</td>
<td>291</td>
<td>316</td>
<td>+38.6%</td>
<td>-16.7%</td>
<td>-9.5%</td>
</tr>
</tbody>
</table>

The above table supports the argument that the additional effort in collecting data for calibrating the microsimulation would result in a more realistic estimate of emissions for different scenario analysis focusing on GHG emissions or as inputs for the vehicle routing problem. The next section presents GHG emissions using the developed driving cycles for medium and heavy duty trucks that will be used in the next chapter.

4.5.2 Driving Cycle Emission Estimation

This section estimates emissions for medium$^{53}$ and heavy$^{54}$ duty trucks; and compares the results to that of the HD-UDDS cycles (since this cycle is the EPA dynamometer cycle used for estimating tailpipe emissions for urban heavy duty driving). The following are some of the key model assumptions.

---

$^{53}$ MOVES source type ID= 52 (single unit short-haul truck), and the fuel type ID is 1 for gasoline and 2 for diesel. Descriptions available in Appendix F.

$^{54}$ MOVES source type ID= 61 (combination short-haul truck). Descriptions available in Appendix F.
• The modelled pollutants are carbon dioxide, methane, and nitrous oxide, and CO\textsubscript{2}-eq (contains all three pollutants using their global warming potential) since these are the major transportation related greenhouse gasses.

• Emission factors used in the vehicle routing problem are estimated using a 2001 medium or heavy duty vehicle due to the following reasons:
  o Average fleet age for medium and heavy duty trucks for the year 2009 in Ontario was 8 years (Statistics Canada, 2009).
  o No data on the fleet composition for a real case study were available for downtown Toronto.

Using MOVES\textsuperscript{55}, the three major GHGs were estimated for gasoline and diesel medium duty trucks and heavy duty diesel trucks on different road categories in the network. The CO\textsubscript{2}-eq of the three is also calculated using global warming potentials of 21 and 310 (CO\textsubscript{2}-Eq) for methane and nitrous oxide respectively (Table 4-8). The same calculations were done for the HD-UDDS cycle on an urban unrestricted road, representing all but the freeway road category in the Toronto Waterfront Network (Table 4-9).

As can be seen from Table 4-8, diesel medium duty trucks produce higher CO\textsubscript{2}-eq emission factors compared to gasoline vehicles by an average of 35%. Heavy duty trucks result in about 60% higher CO\textsubscript{2}-eq emission levels compared to medium duty trucks. Also comparing the emission factors of simulated cycles with the HD-UDDS cycle (Table 4-9) shows that the HD-UDDS cycle produces emission factors higher than freeway driving, lower than Lake Shore Blvd., and much lower than University Ave. and arterials with and without transit.

<table>
<thead>
<tr>
<th>Road category</th>
<th>Vehicle category</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MDT Gasoline</td>
<td>MDT Diesel</td>
<td>HDT Diesel</td>
<td></td>
</tr>
<tr>
<td>Freeway</td>
<td>539.12</td>
<td>761.07</td>
<td>1189.70</td>
<td></td>
</tr>
<tr>
<td>Lake Shore Blvd.</td>
<td>705.52</td>
<td>977.06</td>
<td>1676.03</td>
<td></td>
</tr>
<tr>
<td>University Ave.</td>
<td>1139.20</td>
<td>1504.92</td>
<td>2404.95</td>
<td></td>
</tr>
<tr>
<td>Major Arterials</td>
<td>995.84</td>
<td>1328.69</td>
<td>2112.23</td>
<td></td>
</tr>
<tr>
<td>Major Arterials with Transit</td>
<td>963.62</td>
<td>1286.71</td>
<td>1972.07</td>
<td></td>
</tr>
</tbody>
</table>

\textsuperscript{55} An overview of the basic input files required for running MOVES2010b is presented in Appendix F.
### Table 4.9: HD-UDDS CO₂-eq Emission Factor (gr/km) for Diesel HDT/MDT and Gasoline MDTs on Urban Unrestricted Roads

<table>
<thead>
<tr>
<th>Vehicle category</th>
<th>MDT Gasoline</th>
<th>MDT Diesel</th>
<th>HDT Diesel</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO₂-eq Emission Factor (gr/km)</td>
<td>729.189</td>
<td>801.237</td>
<td>1540.62</td>
</tr>
</tbody>
</table>

### 4.6 Summary

This chapter developed and demonstrated a method for efficiently developing driving cycles that represent specific combinations of roadway class, time of day and vehicle attributes using simulated data. Important features of this method are:

- Use of simulation allows data to be collected under consistent traffic conditions (representing the same day) for all vehicle and road types.
- Use of 13 statistics represented in Table 4-2 ensures the development of a good quality driving cycle.
- Using simulated driving cycles produces emission factors that are closer to the observed compared to using the average speed model (using simulated or observed average speeds); suggesting that the additional effort to collect observed data in order to build a good quality CSA model produces a more reliable source for scenario analysis compared to using the average speed model.
- The method is computationally efficient.
- Analyzing the impact of road type on driving cycles showed that freeway cycles are generally smoother and less aggressive, and have higher average speeds, lower accelerations and decelerations, longer microtrips, and less time spent creeping and idling. Also for the AM peak simulated cycles, arterials with and without transit showed similar characteristics, since both road categories are at capacity. Results also showed that on all roads, simulated LDT cycles have higher average speeds, acceleration and deceleration, and the shortest average microtrip duration; suggesting that LDT cycles are more aggressive and spent less time cruising.
- Emission results show that diesel vehicles produce an average of 35% higher CO₂-eq emission factors compared to gasoline vehicles. Similarly, heavy duty trucks result in about 60% higher emission levels compared to medium duty trucks.
Clearly, driving patterns differ for different cities and different vehicle types, indicating that the development of city-, time-, road type- and vehicle-specific cycles are justified. Differences between the assessment measures of the simulated cycles and available international driving cycles show the uniqueness of Toronto’s driving conditions. Currently, US cycles are used by car manufacturers in Canada for emission testing, however these results show the need for more specific driving cycles for specific emissions analysis scenarios.
5 Vehicle Routing Problem Incorporating Site Specific Driving Cycles and Emission Outputs

5.1 Introduction

Until recently, most vehicle routing problems were solved to find routes that would generally minimize distance, or time. However, increasing concerns about the external costs of transportation (such as emissions) from governments and customers are forcing companies to consider “greening” their operations by considering their fleet GHG emissions and thus attempting to solve the routing problem with more complex objectives. As stated in Chapter 1, the aim of this research is to reduce GHG emissions of a fleet with heavy duty trucks operating in the study area, by providing the platform for estimating fleet emissions more accurately. The analysis is based on results from chapters 3 and 4 which described how microscopic traffic simulation models can be used to develop simulated driving cycles that would provide better emission estimates.

This chapter focuses on the third phase of the research (as presented in Figure 1-1), demonstrating how outputs from the previous steps can be used to reduce GHG emissions. In this chapter, the green vehicle routing problem (GVRP), a relatively new extension of the VRP, will be utilized for this purpose. The problem will be formulated for a firm that is assumed to have rich information about the emissions costs through the simulated driving cycles obtained from the microsimulation model. The objective for this chapter is to investigate the differences and assert their statistical meaningfulness when routing vehicles to optimize total distance, time and emissions. The effect of introduction of a cap-and-trade policy on the routing is also investigated. This chapter builds on current literature by solving a GVRP under the following considerations:

- The model is constructed to link the transportation network and the routing model, incorporating traffic conditions accounting for the effect of signals, accelerations, and congestion;
- The effect of vehicle load is incorporated in the emissions estimates;
- The model allows for multiple performance measures to be optimized simultaneously, and policy implications of using these performance measures are considered;
The effect of different potential costs of emissions on the results are explored.

Chapter 5 is structured as follows. First the VRP formulation, incorporating the effect of vehicle load, is presented in section 5.2. Section 5.3 briefly explains the branch-and-cut solution algorithm used for solving the GVRP. Section 5.4 presents the hypothetical case study of beverage delivery in the study network. Selection of monetary costs for distance, time, and CO₂-eq is summarized in section 5.5. The details of the method are further presented in 5.6 followed by results in 5.7 and a discussion of differences in 5.8. Finally, the formulation of the cap and trade policy is presented in 5.9 followed by an analysis of the effects of introducing such a policy in 5.10. The chapter is concluded by summary in 5.11.

5.2 VRP Formulation Incorporating Time, Distance, and Emissions

This research focuses on the basic capacitated vehicle routing problem (CVRP) - first formulated by Dantzig and Ramsar (1959). The formulation is extensible and may be modified to incorporate other extensions of the VRP. However, as the proof of concept and for the purposes of using an exact algorithm to find the optimal solution, this research only focuses on the CVRP. The formulation assumes one depot, multiple vehicles of the same class, and a set of customers with known demands.

Let G= (V, A) be a graph where V={V₀ ,V₁ ,..., Vᵢ₋₁ ,Vₙ} is the vertex set and the set of arcs A={(i,j)|Vᵢ ,Vⱼ ∈ V , i≠j}. Vertex V₀ is the depot, and V₁ to Vₙ are customer nodes. qᵢ is the demand for customer (i); and dᵢⱼ, tᵢⱼ, and eᵢⱼ represent the distance, time, and emission of travelling from customer i to j, respectively. The formulation assumes that there are K identical vehicles available at the depot that can be used to deliver goods to customers, each with capacity Q (Q and qᵢ are of the same unit). The basic VRP formulation for a drop-off CVRP is shown below.

Min Σᵢ Σⱼ (Cdᵢⱼxᵢⱼ + Ctᵢⱼxᵢⱼ + Ceᵢⱼxᵢⱼ)  

s.t. 

Σⱼ xᵢⱼ = 1 ∀Vⱼ ∈ V\{V₀}  

Σᵢ xᵢⱼ = 1 ∀Vᵢ ∈ V\{V₀}
\[ q_j x_{ij} \leq f_{ij} \leq (Q - q_i) x_{ij} \quad \forall (i, j) \in A \]  \hfill (13)

\[ \sum_{V \in V} f_{ji} - \sum_{V \in V} f_{ij} = q_i \quad \forall V \in V \setminus \{V_0\} \]  \hfill (14)

\[ \sum_{V \in V} x_{0j} = \sum_{V \in V} x_{i0} \leq K \]  \hfill (15)

\[ \sum_{V \in S} \sum_{V \in S} f_{ij} \leq |S| - 1 \quad \forall S \subseteq V \setminus \{V_0\}, |S| \geq 2 \]  \hfill (16)

\[ x_{ij} = 0, 1 \quad f_{ij} \geq 0 \quad \forall i, j \]  \hfill (17)

Where:

\[ x_{ij} \] = binary variable equal to 1 if vehicle leaving node i, will visit node j next and 0 otherwise

\[ f_{ij} \] = load of the vehicle travelling from customer i to customer j

S = any subset of customers not including the depot

The objective function (10) represents the generalized cost of the fleet, which is the sum of the total distance, time, and emissions multiplied by their unit costs \((C_d, C_t \text{ and } C_e)\). Constraints (11) and (12) assure that each customer is visited only once, and that a vehicle arriving at a node leaves that node, unless it is the depot. Constraint (13) guarantees that customers i and j can only be serviced by the same vehicle if the required load for the vehicle does not exceed its capacity. Constraint (13) also guarantees that if customers i and j are not visited by the same vehicle \((x_{ij} = 0)\), then \(f_{ij} = 0\). Constraint (14) enforces the conservation of flow on each node. Constraint (15) assures that any vehicle leaving the depot will return to the depot, and that the total number of vehicles should be equal to or less than the maximum number of available vehicles, K. The basic formulation does not include a fleet optimization component. Therefore, K is assumed to be the sum of the number of customers which will be the maximum number of trucks required to respond to all the deliveries.

Finally, constraint (16) is the sub-tour elimination constraint. This constraint requires that, for any subset of customers S, the number of links travelled between the nodes in S (represented by
be less than or equal to the number of customers in S minus 1. This guarantees that no tours will be generated that do not include the depot.

5.2.1 The Effect of Load on Emission

As stated in section 2.2, MOVES and similar emission models were developed using emission measurements from on-board measuring or chassis dynamometer testing. Since these data included vehicles with different payloads, the emission factor calculated by MOVES is assumed to represent a vehicle with an average payload. However the load carried by a vehicle highly impacts its emissions (Boriboonsomsin et al., 2011; Brodrick et al., 2004; Gajendran and Clark, 2003; Huang et al., 2012; Merrick, 2010; Strimer et al., 2005; Xiao et al., 2012a). Most of the available research looks at the effect of load on NOx, since NOx is of more concern when considering health impacts of transportation (Brodrick et al., 2004; Gajendran and Clark, 2003). However, NOx (which includes NO and NO2) is not a GHG and modelling it is outside the scope of this research. This section summarizes the findings of existing studies on the relationship between vehicle weight and CO2 emissions. The objective function of the GVRP is then modified to include the effect of load.

In general, data showing the relationship between vehicle weight and emissions is scarce. Merrick (2010) argued that the relationship between a HDT’s weight and its emission is a concave relationship shown by equation (18). In this equation, \( w_d \) is the total weight of the truck, and \( e \) is the emission factor (EF) based on MOBILE6 and assumed to represent the EF of the empty vehicle. However, based on this equation, EF would decrease above a certain weight, which is counterintuitive and not in accordance with other studies in the literature.

\[
CO_2 \ EF = (-0.000000814w_d^2 + 0.0407w_d + 210.45)e
\]  

(18)

Gajendran and Clark (2004) showed that CO2 emission factor increases linearly with weight, but did not formulate the exact relationship. Xiao et al. (2012a) used a fuel consumption rate (FCR) that is dependent on the load of the vehicle presented by equation (19) in a CVRP problem for vehicles less than 3,000 kg. In this equation \( Q \) is the maximum capacity of the vehicle, \( Q_1 \) is the carried load, \( \rho_0 \) is the no-load fuel consumption rate (FCR), \( \rho^* \) is the full-load FCR, and \( \rho(Q_1) \) is the FCR when carrying load \( Q_1 \).
\[ \rho(Q_1) = \rho_0 + \frac{\rho^* - \rho_0}{Q} Q_1 \]  

Huang et al. (2012) used the same formulation presented by Xiao et al. (2012) to solve a VRP with simultaneous pickup and deliveries for heavy diesel vehicles of 24 ton capacity. Using FCRs of 36.08, 28.84, and 21.18 litres for full-load, half-load, and no-load, Huang et al. (2012) calculated FCR and EF at any given load using equations (20) and (21). In these equations load is presented in ton, and \( \mu \) (gr/L) is the mass of emission per litre of fuel consumed.

\[
\text{FCR} = (6.208 \times 10^{-3} \times \text{load} + 0.2125) \\
\text{EF} = \text{FCR} \times \mu
\]

\[ (20) \]

\[ (21) \]

5.2.2 Updated Objective Function for the GVRP

Based on the above literature, the formulation presented by Huang et al. (2012) is used to calculate the effect of the truck’s load on the emission factor as estimated by MOVES. With the density of diesel fuel being approximately 0.85 kg/l, and the assumption that MOVES provides EFs for the truck with average payload of \( Q_{avg} \), the EF given by MOVES can be represented by (22). In this equation \( Q_{avg} \) is equal to the sum of the weight of the empty truck \( Q_0 \) and the average payload, \( P_{avg} \).

\[
EF(Q_{avg}) \left( \frac{gr}{km} \right) = 0.85 \times 10^3 (6.208 \times 10^{-3} Q_{avg} + 0.2125) \mu \\
Q_{avg} = Q_0 + P_{avg}
\]

\[ (22) \]

\[ (23) \]

To update the emission component of the objective function in (10), the truck’s \( EF \) at any given weight \( (EF(Q_{ij} = Q_0 + f_{ij}) \) shown by equation (24)) must be presented as a ratio of \( EF(Q_{avg}) \). Using the same calculation, the final relationship between a truck’s \( EF \) carrying load \( f_{ij} \) and the \( EF \) estimated by MOVES is shown by (25). Lastly, the average payload for class 8 trucks \( (P_{avg}) \) was estimated at approximately 9 tons based on data reported by the USEPA SmartWay program.

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56 The unit for the formula in the brackets is l/km; but the EF is in gr/km. To convert litre to gram, it has to be multiplied by 0.85 kg/l*1000 gr/kg

57 SmartWay was launched in 2004 and is an EPA program that “reduces transportation-related emissions by creating incentives to improve supply chain fuel efficiency”. This program provides Trends, Indicators, and Partner...
and the 2002 US Census bureau Vehicle Inventory Use Survey (VIUS). Figure 5-1 shows the EF changes according to loads for HDTs driving on freeways. The average EF for these trucks is assumed to be 1189.7 gr/km based on MOVES, as an example. Using equation (25) shows that the EF for a truck would be in the range of 84.5% to 120.1% of the EF estimated by MOVES for a truck with average payload of 9 tons for each road category (Figure 5-2).

\[
EF(Q_{ij}) = 0.85 \times 10^3 (6.208 \times 10^{-3} (Q_0 + f_{ij}) + 0.2125) \mu
\]  

\[
\rightarrow \frac{EF(Q_{ij})}{EF(Q_{avg})} = \frac{6.208 \times 10^{-3} (Q_0 + f_{ij}) + 0.2125}{6.208 \times 10^{-3} (Q_0 + P_{avg}) + 0.2125} = 1 + \frac{6.208 \times 10^{-3} (f_{ij} - P_{avg})}{EF(Q_{avg})}
\]

\[
\rightarrow EF(Q_{ij}) = \left(1 + 0.017173 (f_{ij} - P_{avg})\right) EF(Q_{avg})
\]  

Using (25), the objective function in (10) is updated as follows.

\[
\text{Min} \sum_i \sum_j [C_d d_{ij} x_{ij} + C_t t_{ij} x_{ij} + (1 + 0.017173 (f_{ij} - P_{avg})) C_e e_{ij} x_{ij}]
\]  

(26)

At first glance the new objective function in (26) is non-linear. However, given constraint (13), \(f_{ij}\) is zero if \(x_{ij}\) is zero, so \(f_{ij} x_{ij} = f_{ij}\). Therefore the objective function can be converted to the linear function in (27).

\[
\text{Min} \sum_i \sum_j [C_d d_{ij} x_{ij} + C_t t_{ij} x_{ij} + C_e e_{ij} x_{ij} + 0.017173 C_e e_{ij} (f_{ij} - P_{avg} x_{ij})]
\]  

(27)

Statistics (TIPS) about leading freight movement industries in the US and the world. Their information is intended to be used by anyone with an interest in goods movement sustainability (academia, industry, etc.).
5.3 Solution Algorithm

As stated in section 1.6, it has not been the intention of this research to identify new solution algorithms for the VRP, but to see how new information about CO₂ emissions across different roads impact routing. IBM ILOG CPLEX Optimization Studio was therefore selected for solving the GVRP since it provides exact solution methods and is considered to be among the state-of-the-art efficient optimization toolkits widely used in the literature. Furthermore, CPLEX can also be
integrated with different programming languages such as C++, Java, C#, Python, and MATLAB allowing flexible frameworks to be considered around the optimization for sensitivity analysis or scenario assessment. When looking for an exact solution to a mixed integer linear problem, CPLEX uses the branch-and-cut method. The algorithm is a combination of the branch-and-bound method and the cutting plane method.

In this method, the problem is first solved by relaxing the integrality constraints to find a root node. A branch is the creation of two nodes from a parent node, by setting bounds on a single variable. In the case of the current GVRP where branching occurs on binary variables, the variable will take the value of 0 in one node and 1 in the other. A cut is when a constraint is added to the model for the purpose of limiting the solution domain without eliminating any integer solutions. An active node is a node that has not been processed yet. With these definitions, the branch-and-cut procedure continues to create branches, apply cuts, and solve the problem in active nodes until either a previously defined limit has been reached, or that there are no more active nodes available in the tree.

Further detail about the algorithm is outside the scope of this research, since the focus of this research is not on the solution algorithm but rather its results. A simple example of the branch-and-bound and the cutting plane method is presented in Appendix G. More detail about the algorithm can be found in the CPLEX manual, or relevant references cited in section 2.4.3.

5.4 Case Study

This section describes the network used as the case study for the formulated GVRP problem, together with the selection process for the customer nodes and their demands, and the formulation of the monetary costs of distance, time and emissions.

5.4.1 Simplified Toronto Waterfront Network

Given that the driving cycles were developed using the Toronto Waterfront network, a simplified version of the same network (Figure 5-3), focusing on a smaller part of the downtown is used in this chapter. Since no data for a real case were available in downtown Toronto, the routing was solved for a hypothetical case of beverage trucks, assuming one depot and random customers with random demands. Initial assumptions of the problem are: 1. Node 0 is the depot for all cases
(shown with a star in Figure 5-3); and 2. Ten nodes are randomly selected as customer nodes in each run (representing 20% of all nodes).

Using the same road categories defined in section 4.3, Table 5-1 shows the estimated value for the three major GHGs for heavy duty diesel trucks on each road category in the network using MOVES2010b based on the data from previous chapters. The CO₂-eq of the three is also calculated using global warming potentials of 21 and 310 (CO₂-Eq) for methane and nitrous oxide, respectively. Average speed reported in this table is calculated from the microsimulation to reflect road conditions in the morning peak.

| Table 5-1: Average Speed, and Emission Factor for Different Road Types in the Network |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                                 | N₂O EF (gr/km) | CH₄ EF (gr/km) | Atmospheric CO₂ EF (gr/km) | CO₂-eq EF (gr/km) | Average speed (kph) |
| Freeway                         | 0.002010       | 0.001931       | 1189.04                      | 1189.70          | 41.0             |
| Lake Shore Blvd.                | 0.002893       | 0.002451       | 1675.09                      | 1676.03          | 28.5             |
| University Ave.                 | 0.006636       | 0.004983       | 2402.79                      | 2404.95          | 12.4             |
| Major arterial                  | 0.004968       | 0.003969       | 2110.60                      | 2112.23          | 16.6             |
| Major arterial with transit     | 0.004878       | 0.003881       | 1970.48                      | 1972.07          | 16.9             |
Figure 5-3- Simplified Waterfront Network used for the Vehicle Routing Problem
5.4.2 Customers’ Demands
Customer demands are generated randomly using a discrete uniform distribution\(^{58}\). To gather information, a Metro store, a Loblaws store and a Mac’s Milk store were visited to determine reasonable values for minimum and maximum demands for a customers. Based on the collected data, it is assumed that the delivery truck delivers drinks such as Coca-Cola or Pepsi, in packs of 12 soda cans (Figure 5-4), with dimensions of 13×13×40 cm and a weight of 4.7 kg. A standard size container (also referred to as a 20 ft. container) is 8×8×20 ft. (243×243×609 cm), and has a maximum payload of 48,000 lbs. (approximately 21.7 ton). With these dimensions a fully loaded truck could carry 4335 packs (17×17×15)\(^{59}\), weighting 20.4 tons (close to the maximum payload of the truck). Further details for each store were determined as follows:

**Figure 5-4- 12 Pack of Soda Cans being Delivered to Customers**

*Source: google image*

**Metro**
Pepsi and Coca-Cola each visit this particular Metro store twice a week. Coca-Cola delivers 3-4 pallets/week (an average of 1.5-2 pallets\(^{60}\) per order), resulting in a total of 390-520 boxes per order. Pepsi delivers 1 pallet per order of boxed cans to this store.

---

\(^{58}\) A discrete uniform distribution was assumed so that demand values (between the minimum and maximum values) will have equal probabilities of being assigned to customers.

\(^{59}\) 243 divided by 13 is 18 boxes that would fit from bottom to the top of the container (or from left to right) leaving only 9 cm of space; which might not be realistic and might make it difficult to load and unload. Hence, it is assumed that that 1 less row of boxes (17 boxes) is put into the container.

\(^{60}\) Each pallet includes around 260 boxes.
**Loblaws**
This store gets deliveries of 1.5 pallet 3 times a week from Coca-Cola, 0.5 pallet once a week by Pepsi, and 0.5 pallet 5 times a week by PC.

**Mac’s Milk**
Since this store is much smaller than Metro and Loblaws, it is visited by Pepsi and Coca-Cola once every 2 weeks, and requires a total of 12-14 boxes of each.

**Demand Adjustments to the Formulation**
Based on the gathered information, the following assumptions are made in the GVRP problem in this research.

- Weight of 1 unit of demand is set to 4.7 Kg (weight of a box);
- Capacity of the truck is set to 4335 units (maximum number of boxes that can fit in a 20 ft. container);
- The minimum and maximum values of demand per customer was set to\(^ {61}\):
  - Minimum demand = 1 box
  - Maximum demand = 1000 boxes (double the maximum demand reported by the 2 stores)

5.4.3 Test Case Limitations
The test case has been designed to be exactly soluble. This would avoid additional errors resulting from inexact methods and would provide a suitable demonstration for the use of simulated driving cycle in optimization of emissions without detracting from the main focus of the work. Meeting this requirement resulted in a number of limitations:

- The network had to be simplified as the number of nodes would increase the solution time exponentially. Care was taken to keep the network realistic by including various types of roads and allowing various feasible routes between nodes and thus not reducing the network to a trivial set of links.

\(^ {61}\) These values were selected because information was only gathered from 3 sample stores, and there are probably more local stores that require less boxes per delivery or bigger Metro and Loblaws stores that might require more boxes per delivery.
A single product was used in designing the test case. It is conceivable that in reality the trucks would be used to deliver more products in parallel. The effects of multiple products and the resulting complexities are thus ignored in the test case.

In compiling the simplified test case, the following limitations resulted from limited availability of data:

- The ranges for demands, truck capacities and the product dimensions are selected according to approximations based on limited data. In a real delivery scenario these figures could deviate from the assumed numbers.
- The location of the depot was selected based on the observed location of a Fedex depot and assumed to be on a corner of the network. Selecting an alternative location could affect the output of the optimization.

5.5 Monetary Costs for Time, Distance, and Emissions

Equation (27) minimizes the total cost of operating a fleet, where the general cost (in dollar values) is estimated by multiplying total distance, time, and emissions by their unit costs \( (C_d, C_t, C_e) \) as described in Table 5-2. Values for these coefficients used in this research are based on available literature since finding exact values requires a detailed survey which is outside the scope of this thesis. Available values for \( C_d \), and \( C_t \) are summarized in Table 5-3. Values presented by Trego and Murray (2010) is used for \( C_d \) in this research since the study is more recent and based on a larger sample size compared to other values\(^{62}\). For \( C_t \), average truck driver’s salary in Toronto was available online based on data from Statistics Canada.

<table>
<thead>
<tr>
<th>Monetary Cost</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C_d )</td>
<td>Cost per km for operating the vehicle. This would typically include insurance, licensing, fuel, oil, maintenance, ownership or lease, and tires.</td>
</tr>
<tr>
<td>( C_t )</td>
<td>Cost per minute for operating the vehicle. This would typically include the cost of the driver pay, bonuses, and benefits.</td>
</tr>
<tr>
<td>( C_e )</td>
<td>Cost of CO(_2)-eq per tonne emitted. This would include the cost to offset the current and future damage by one unit of carbon dioxide equivalent emissions.</td>
</tr>
</tbody>
</table>

\(^{62}\) Trego and Murray (2010) calculated their number based on a survey of over 55,700 trucks in the US.
### Table 5.3: Summary of Relevant Values for $C_d$ and $C_t$

<table>
<thead>
<tr>
<th>Study</th>
<th>$C_d$ (price/distance)</th>
<th>$C_t$ (price/hr.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Huang et al. (2012)</td>
<td>€0.175/km (Only ownership cost)</td>
<td></td>
</tr>
<tr>
<td>Trego and Murray (2010)</td>
<td>US$1.13/mile = US$0.71/km (for 2008)</td>
<td>US$25.02</td>
</tr>
<tr>
<td>Bektas and Laporte (2011)</td>
<td></td>
<td>£8</td>
</tr>
<tr>
<td>Barton &amp; Associates (2006)</td>
<td>$1.65/km in congested conditions</td>
<td>$22.8</td>
</tr>
<tr>
<td></td>
<td>$1.41/km in uncongested conditions (for 2000)</td>
<td></td>
</tr>
<tr>
<td>Living in Canada (2014)</td>
<td></td>
<td>$20.01 (range: $15-26.29)</td>
</tr>
</tbody>
</table>

### Table 5.4: Summary of Relevant Values for $C_e$

<table>
<thead>
<tr>
<th>Study</th>
<th>$C_e$ (price/tonne CO$_2$-eq)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DEFRA (2007)</td>
<td>1- £26.5 for 2009 (£18.6 for 2000 and 2% increase each year after that)</td>
</tr>
<tr>
<td></td>
<td>2- US$25-85 based on Stern’s review on Economics of climate change</td>
</tr>
<tr>
<td>Huang et al. (2012)</td>
<td>€31 (£27 for year 2010, based on DEFRA (2007))</td>
</tr>
<tr>
<td>Eguia et al. (2012)</td>
<td>€25 (for 2010)</td>
</tr>
<tr>
<td>Stastna (2013)</td>
<td>US$36 (for 2013)</td>
</tr>
<tr>
<td>Government of Canada (2013)</td>
<td>1- CAD $28.44 (for 2012)</td>
</tr>
<tr>
<td></td>
<td>2- CAD $112.37 (to avoid a climate catastrophe$^{63}$)</td>
</tr>
<tr>
<td>IPCC (2007)</td>
<td>Average of US$11.73 with Std. of US$22.64 (for 2007) with 2.4% increase each year based on the several available studies.</td>
</tr>
<tr>
<td>Rabl and Spadaro (2000)</td>
<td>€29 (damage cost by power plants)</td>
</tr>
<tr>
<td>Tol (2005)</td>
<td>$US93 and can be as high as $US350 (based on data from 28 published studies)</td>
</tr>
<tr>
<td></td>
<td>2- Extreme costs of US$93 and US$350 (based on Tol, 2005)</td>
</tr>
<tr>
<td>Waldhoff et al. (2011)</td>
<td>US$8; but different assumptions could lead to higher values of US$18, US$51, and US$154.</td>
</tr>
<tr>
<td>Pitera et al. (2011)</td>
<td>$US 15 (for year 2005)</td>
</tr>
<tr>
<td>Gouvernement du Québec (2013)</td>
<td>Québec’s cap-and-trade program:</td>
</tr>
<tr>
<td></td>
<td>Price for allowance sold from reserve: CAD $40-$45-$50</td>
</tr>
</tbody>
</table>

$^{63}$ This value was estimated based on arguments by Weitzman (2011) and Pindyck (2011). These studies have argued that climate change policies should be based on the willingness-to-pay to avoid low-probability, extreme-impact outcomes (using a fat-tailed distribution) given the following unknowns: “1) having uncertain climate change response to the kind of unprecedented increase in GHGs; 2) big uncertainties about how GHG flow emissions accumulate via the carbon cycle into GHG stock concentrations; 3) big uncertainties about how and when GHG...
Values considered for $C_e$ in the literature are presented in Table 5-4. According to this table, $C_e$ can be as low as $10 per tonne of CO₂-eq (minimum auction price for Quebec’s cap-and-trade policy). However, according to Tol (2005), to avoid climate catastrophe, this value can be as high as $350. For this reason, a range of $10-350 per ton of CO₂-eq for $C_e$ is considered in this research. In conclusion, Table 5-5 summarizes the monetary costs for distance, time, and emissions used in this research.

<table>
<thead>
<tr>
<th>Table 5-5- Selected Monetary Costs for Distance, Time, and Emissions in this Research</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_d$</td>
</tr>
<tr>
<td>$C_t$</td>
</tr>
<tr>
<td>$C_e$</td>
</tr>
</tbody>
</table>

5.6 Method

Figure 5-5 outlines the method used for estimating the inputs required, solving, and post-processing the optimization problem in (27) subject to (11)-(17). As stated in section 5.4.1, the study area has one depot (node 0), and 50 regular nodes. Since no data for a real case were available in downtown Toronto, the routing is solved using Monte Carlo simulation for a hypothetical case of beverage trucks, assuming random customers with random demands. Demand preparation for all runs involves generating the demand matrix for each simulation (each optimization criteria is simulated 1000 times). For each run 20% of the nodes are selected randomly as customers. Each customer is then assigned a random demand value using a discrete uniform distribution on the interval [1, 1000].

The optimization problem with the objective function presented in (27) was initially solved for the following 3 optimization criteria:

1. Distance-optimal: where the values for $C_d$, $C_t$, and $C_e$ are (1,0,0) respectively, and results are presented as total kilometres travelled;
2. Time-optimal: where the coefficient vector is (0,1,0), with results being the total time spent in the network (in minutes);

stock concentrations translate into global average temperature changes; 4) big uncertainties about how global average temperature changes decompose into specific changes in regional weather patterns; 5) big uncertainties about how adaptations to, and mitigations of, climate change damages at a regional level”.
3. Emission-optimal: where the coefficient vector is (0,0,1), with results being the total fleet emissions (in grams of CO$_2$-Eq).

It should be noted that the values for $d_{ij}$, $t_{ij}$, and $e_{ij}$ in function (10) refer to the values of distance, time, and emission between any pair of customer nodes $(i,j)$, so that the optimization problem can find the sequence of deliveries in the most efficient manner. Therefore in each run, the study area (with 50 nodes) must first be converted to a complete graph with one depot and 10 customer nodes. In this case, link $(i,j)$ represents the path with the shortest distance, fastest time, or lowest emission between the two customer nodes. This conversion is done by running a Dijkstra shortest path algorithm for each demand matrix and optimization criterion.

---

**Figure 5-5:** Method for Estimating Inputs, Solving, and Post-processing the Optimization Problem
An example of this is shown in Figure 5-6. In this diagram point A and B (shown by blue circles) represent two customer locations. As can be seen from this figure, there are many routes available between the two nodes (three of which are shown in this figure). The key parameters for each link are distance, time, and CO2-eq emissions. The Dijkstra shortest path algorithm finds the route that minimizes one of these parameters for every depot and delivery location combination. The resulting matrices are required to run the CVRP model. For instance in the time-optimal problem, the quickest route between any two locations will be calculated by the Dijkstra algorithm and used as $t_{ij}$ values when solving the CVRP (the distance and emissions for this route are also required but are calculated in the post-processing phase).

The problem becomes more complicated for the emission-optimal problem, where $e_{ij}$ is also a function of $f_{ij}$. However since $e_{ij}$ has a linear relationship with $f_{ij}$, it is sufficient to determine the minimum emission routes using the Dijkstra algorithm based on the average emission values estimated by MOVES.

Once the values for $d_{ij}$, $t_{ij}$, and $e_{ij}$ are estimated, CPLEX finds the exact solution for the optimization problem in (27) subject to (11)-(17) using the branch-and-cut algorithm. The results for all the runs are then post-processed and compared in MATLAB. These results are presented in the next section.

Figure 5-6- Example of Possible Routes Between Nodes A, and B

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5.7 Distance vs. Time vs. Emission Optimal Solutions

Table 5-6 shows the average and standard deviation of total distance travelled, driving time, and CO₂-eq emitted for the 1000 simulations for each of the optimization criteria. As expected, the table shows that the time-optimal problem produces the least time taken than the other problems. Similarly, the distance-optimal produces the least number of kilometres, and the emission-optimal produces the least emissions. The differences between the results of the three optimization problems are caused by the different roads used between the customers and the sequence in which they are visited.

Table 5-6- Average Total and Standard Deviation of Network Distance Travelled, Driving Time, and Emissions for 1000 Simulation Runs for the Beverage Delivery Problem

<table>
<thead>
<tr>
<th>Optimization Criteria</th>
<th>[Total Distance, Std.] (km)</th>
<th>[Total time, Std.] (min)</th>
<th>[Total CO₂-Eq, Std.] (grams)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance-optimal</td>
<td>[16.633, 2.840]</td>
<td>[41.91, 6.43]</td>
<td>[29028, 4393]</td>
</tr>
<tr>
<td>Time-optimal</td>
<td>[17.054, 2.969]</td>
<td>[39.79, 5.83]</td>
<td>[26182, 3825]</td>
</tr>
<tr>
<td>Emission-optimal</td>
<td>[16.987, 2.948]</td>
<td>[40.14, 5.93]</td>
<td>[25720, 3712]</td>
</tr>
</tbody>
</table>

To calculate the average variability in distance, driving time, and emissions that can be expected for each of the three minimization criteria, each of the 1000 runs is analyzed individually (Table 5-7 shows the calculation for emissions differences). Table 5-7 suggests that the emission-optimal solution reduces total CO₂-eq emissions by an average of 12.81% and 1.79% compared to the distance-, and time-optimal problems, respectively. To test the significance of these results, hypothesis tests on the significance of the average improvements were conducted (Table 5-8). The analysis confirms that the percent differences in total distance travelled, driving time, and CO₂-eq emitted as the result of different minimization criteria are statistically significant with 95% confidence. In other words, these values are not just the result of random simulations.
Table 5-7: Calculating the Percent CO₂ Reduction in the Emission-optimal Problem Compared to Distance-, and Time-optimal (Sample of 5 Runs)

<table>
<thead>
<tr>
<th>Run number</th>
<th>Total demand</th>
<th>Total CO₂-eq Emission (gr)</th>
<th>%Diff ((3) vs. (1))</th>
<th>%Diff ((3) vs. (2))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Distance-optimal (1)</td>
<td>Time-optimal (2)</td>
<td>Emission-optimal (3)</td>
</tr>
<tr>
<td>0</td>
<td>4542</td>
<td>30528</td>
<td>27024</td>
<td>26495</td>
</tr>
<tr>
<td>1</td>
<td>3869</td>
<td>22811</td>
<td>21050</td>
<td>21050</td>
</tr>
<tr>
<td>2</td>
<td>4469</td>
<td>31334</td>
<td>29489</td>
<td>27407</td>
</tr>
<tr>
<td>3</td>
<td>4634</td>
<td>32602</td>
<td>30141</td>
<td>29522</td>
</tr>
<tr>
<td>4</td>
<td>4494</td>
<td>24378</td>
<td>21347</td>
<td>20165</td>
</tr>
</tbody>
</table>

...  

Average  | 4249        | 26495                     | 27024               | 26495               | 12.81% | 1.79%  
Std.      |             |                          |                     |                     | 4.01%  | 1.94%  

Table 5-9 summarizes the results of Table 5-8. It can be seen that compared to the distance-optimal solution, the emission-optimal solution produced an average emissions reduction of 12.81%, at a 95% confidence interval of +/-0.25%. This means that the average reduction value would fall within the range of 12.56% to 13.06%, with an average increase of 2.10% in total distance. A similar analysis between the emission-optimal and time-optimal problem shows an average emission reduction of 1.79% at a 95% confidence interval of +/-0.12%, giving a smaller range of 1.67% to 1.91% with an increase of 0.88% in total driving time.

Table 5-8: Percentage Difference between Minimization Criteria, Their Statistics, and Results for the Hypothesis Testing

<table>
<thead>
<tr>
<th>Problems compared</th>
<th>Average improvement measure (Φ)</th>
<th>Calculated value for Φ</th>
<th>Std.</th>
<th>Min</th>
<th>Max</th>
<th>p-value</th>
<th>t-stat</th>
<th>Confidence Interval for Φ (α=5%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance vs. Time optimal</td>
<td>Total Distance</td>
<td>2.50%</td>
<td>2.73%</td>
<td>0</td>
<td>13.93%</td>
<td>1.3E-134</td>
<td>28.9</td>
<td>2.33%</td>
</tr>
<tr>
<td>Distance vs. Emission optimal</td>
<td>Total Distance</td>
<td>2.10%</td>
<td>2.37%</td>
<td>0</td>
<td>11.45%</td>
<td>4.1E-128</td>
<td>28.0</td>
<td>1.95%</td>
</tr>
<tr>
<td>Time vs. Distance optimal</td>
<td>Total Time</td>
<td>5.32%</td>
<td>4.58%</td>
<td>0</td>
<td>29.65%</td>
<td>5.9E-188</td>
<td>36.7</td>
<td>5.03%</td>
</tr>
<tr>
<td>Time vs. Emission optimal</td>
<td>Total Time</td>
<td>0.88%</td>
<td>1.17%</td>
<td>0</td>
<td>7.70%</td>
<td>2.4E-98</td>
<td>23.6</td>
<td>0.80%</td>
</tr>
<tr>
<td>Emission vs. Distance optimal</td>
<td>Total Emissions</td>
<td>12.81%</td>
<td>4.01%</td>
<td>0</td>
<td>30.79%</td>
<td>0</td>
<td>101.1</td>
<td>12.56%</td>
</tr>
<tr>
<td>Emission vs. Time optimal</td>
<td>Total Emissions</td>
<td>1.79%</td>
<td>1.94%</td>
<td>0</td>
<td>12.93%</td>
<td>8.0E-136</td>
<td>29.1</td>
<td>1.67%</td>
</tr>
</tbody>
</table>
### Table 5-9: Percentage Difference in the Total Distance, Time, and Emissions Compared to the Optimal Case

<table>
<thead>
<tr>
<th>Optimization Criteria</th>
<th>Total Distance</th>
<th>Total time</th>
<th>Total CO₂-Eq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance-optimal</td>
<td>5.32%</td>
<td></td>
<td>12.81%</td>
</tr>
<tr>
<td>Time-optimal</td>
<td>2.50%</td>
<td></td>
<td>1.79%</td>
</tr>
<tr>
<td>Emission-optimal</td>
<td>2.10%</td>
<td>0.88%</td>
<td></td>
</tr>
</tbody>
</table>

#### 5.8 Generalized Cost Function Solution Compared to Individual Solutions

This section summarizes the results of the objective function incorporating the monetary costs of distance, time, and emissions presented in Table 5-5, henceforth referred to as the cost-optimal problem. In other words, the cost-optimal problem analyzes the case where the objective is to reduce the total cost of operating a fleet under the carbon taxing policy (as explained in section 1.4.1). Figure 5-7 shows how the total distance, time, and emissions change as the cost of CO₂-eq changes from 0-350 ($/tonne CO₂-eq).

The following observations can be made:

- The maximum emission reduction possible is 1.22% which occurs at the maximum value for Cₑ;
- With the maximum emissions reduction, total travel distance and time increase by only 0.14% and 0.09%, respectively;
- If Cₑ is set to $30 (which is approximately what the Government of Canada and most of the studies in Table 5-4 have recommended), emissions would decrease by 0.53% with almost no change in total distance and time;
- If Cₑ is set to $150 (which is used by the European Union Emissions Trading System), emissions would decrease by 0.90% with an increase of 0.06% and 0.01% in total travel distance and time, respectively.
As mentioned in section 1.3, in Ontario, current strategies can reduce GHGs to within 91% and 66% of the 2014 and 2020 targets, respectively (Miller, 2013; Ministry of the Environment of Ontario, 2013). The results of this section for implementing a carbon tax on GHG emissions show that this policy, alone, has potential to slightly help provinces reach their targets on the assumption that commercial vehicle operators will act to reduce total costs. To better analyze the impact of value of \( C_e \) and the importance of accurately estimating emissions in the optimization problem function, Figure 5-8 shows the difference between the total operating costs of the fleet the following cases. Case 1: total cost if routing is done only based on distance and time, but the fleet later has to pay for its CO2-eq emissions. Case 2: the current case where the cost of emissions is considered before the routing.
Figure 5-7 together with Figure 5-8 show that under the carbon tax policy, a company using the methods described in this research can reduce their emissions by 1.22% while reducing their costs by 0.22%. It is noteworthy that these savings can be produced without requiring costly technology changes or other expensive investments. It can be further concluded from these results, that under the carbon pricing policy:

1- Using low values for \( C_e \) do not have the potential of making a fleet change its operating as a whole;

2- At a relatively high price of $350/ ton CO\(_2\)-eq, this scenario has the potential to reduce total GHG emissions by up to 1.22% while only reducing the operating cost by 0.22%;

![Figure 5-8- Difference Between the Total Operating Costs of the Fleet](image)

### 5.9 Formulation of the VRP with Cap-and-Trade

Cap and trade policies are those that seek to impose limits on the total emission that is generated within a sector (Ministry of the Environment of Ontario, 2009; WCI, 2008). The legislative entity – usually the government – defines a limit for emissions.

The licence to emit greenhouse gases is then auctioned or otherwise allocated to the companies within a sector. The companies can then trade their unused emission capacity with each other. The
fundamental ideology driving this policy is that it encourages research towards better technologies as a result of competition (WCI, 2014). The companies emitting larger amounts of greenhouse gasses as a result of older technologies would have to pay more to buy the unused capacity of those with better technologies, making their products less competitive (ibid).

From the policymakers’ perspective, the advantage is that the limit of emissions can be directly controlled. In taxing emissions, the control is indirect and it may be difficult to ascertain what the total amount of emissions will be.

In this section, the GVRP model presented in 5.2 will be augmented to incorporate the effects of a cap and trade policy. As mentioned above, the cap and trade policy would result in a market (that may or may not be regulated by the policymaker) resulting in variable pricing for emission capacity over time. The main focus of this research is on better analysis and optimization of emissions. Analysis of the cap and trade market dynamics is beyond the scope of this work and would require additional business insight. As a result, several simplifying assumptions have been made in constructing the model:

1. The initial selling price of the emission capacity is assumed to be somewhere within the range of values used for carbon taxing in section 5.4. This assumption is justifiable as values outside this range would affect the entire transportation market to the point that existing business models would no longer be viable. For values outside this range, a more elaborate model of the underlying business (including profits, uncertainties and risks) would be necessary to make reliable forecasts.

2. It is assumed that a company can predict its emissions with a 20% accuracy. An established transportation company would be able to use data from previous years to project their level of business and based on that roughly calculate their emissions. The assumption in the previous section would enable the company to pay for purchasing the required cap without changing its business model.

3. The price of the licence for emitting a tonne equivalent of CO\textsubscript{2} of greenhouses is assumed to be in the range of 0.1 to 10 times the initial purchase price. Changes in price beyond this range would signify an unstable market and it has been suggested that in such cases the policymaker would introduce spare capacity to regulate the market (WCI, 2014). Similar to Kown et al (2013), it is
further assumed that the trading price of carbon remains constant and is known in advance during the modelling horizon as dynamic price models would require intimate knowledge of the market.

The actions of a company in the cap and trade scenario can be considered under two circumstances: when the company has initially bought excess allowance and will sell this excess in the market – henceforth called the selling scenario – and when the company has not bought sufficient allowance and would require to top-up by buying excess allowance from another company – henceforth called the buying scenario.

The goal of the optimization model would be to minimise the total cost. The cost in the selling scenario can be modelled as

\[ C_t = C_{\text{distance}} + C_{\text{time}} + C_{\text{allowance}} - R_{\text{selling}} \]

(28)

Where \( C_{\text{distance}} \) is the total cost associated with the distance that the vehicles travel, \( C_{\text{time}} \) the total cost that is associated with the time that the vehicles travel, \( C_{\text{allowance}} \) the money that the company spends initially on buying the allowance and \( R_{\text{selling}} \) the revenue that the company generates by selling excess allowance. If the unit cost of carbon in the trading market is \( C_e \), then the revenue would be:

\[ R_{\text{selling}} = C_e (EL - TE) \]

(29)

Where TE is the total emissions and EL the emission allowance that the company initially purchases. For the buying scenario the total cost is

\[ C_t = C_{\text{distance}} + C_{\text{time}} + C_{\text{allowance}} + C_{\text{buying}} \]

(30)

where \( C_{\text{buying}} \) is the cost of buying the necessary top up carbon emission allowance. This cost is

\[ C_{\text{buying}} = C_e (TE - EL) \]

(31)

As \( C_{\text{buying}} = -R_{\text{selling}} \) the overall objective of the optimization would be

\[ C_t = C_{\text{distance}} + C_{\text{time}} + C_{\text{allowance}} + C_e (TE - EL) \]

(32)

The cost associated with distance and time is the same as previous models and the cost of initial allowance is

\[ C_{\text{allowance}} = kEL \]

(33)
where \( k \) is the initial cost of unit of carbon. The total cost can thus be written as

\[
C_t = C_{distance} + C_{time} + C_e TE + (k - C_e) EL
\]

(34)

Assuming that there is a limit to the allowance that the company can initially purchase (L), the following constraint should be added to the model:

\[
0 \leq EL \leq L
\]

(35)

The first three elements of the objective function are identical to carbon taxing, albeit with a different \( C_e \). The behaviour of the final element of the objective function in relation with constraint (35) is trivial: if \( (k > C_e) \) then 0 will be chosen for EL as the minimum value and if \( (k < C_e) \) then the maximum allowable value for EL will be chosen (L).

From this formulation it is evident that from an optimization point of view, the route selection will be identical to the case of carbon taxing. The important difference is that due to the fact that the price of carbon is determined in the trading market and does not have to be explicitly set by the legislators, there would be a potential for much wider range of prices.

5.10 Results with the Cap-and-Trade Policy

In order to assess the effect of the market price on the total emissions, the model presented in section 5.6 is optimized with the wider cost range from 10$ to 3500$ per tonne. The results are shown in Figure 5-9.

As observed in the graph, beyond the initial low prices, the sensitivity of the value of emissions to the unit cost of carbon in the market is very low when the total cost is optimized. This shows that the initial assumption of the known price of carbon is valid as changes in the price beyond 350$ decrease emissions by less than 0.6% signifying that the majority of the routes remain consistent.

The low sensitivity shows that the higher emission costs that would be inflicted upon companies in the cap and trade scenario would not affect their route choices. As a result, whilst the costs increase, the emissions do not decrease substantially and as such, cap-and-trade, with its difficulty of implementation is not a particularly good choice for controlling transportation carbon emissions when compared to direct taxation for transportation.
In this chapter a vehicle routing problem was formulated and solved to demonstrate the use of the vehicle and road type specific driving cycles that were developed in chapter 4. The formulation allowed a hypothetical beverage delivery company to optimize their costs under various carbon emission reduction policies to assess the effects of these policies on emissions and costs incurred by the companies.

In modelling and solving the VRP the following limitation was observed. The formulation used by Huang et al. (2012) was the best available in the literature; however it was based on data available from truck manufacturers. This formulation can be updated if better estimates becomes available.

So far only a few studies have looked at the effect of emissions in the VRP (Figlioizzi, 2010, Kara et al., 2007). But those studies did not include emissions as a function of driving behaviour. In Figlioizzi (2010) a simple emission formulation based on average speed of the link was used.

Having fuel cost and link emission in more detail and for both regular trucks and hybrid trucks (like the travel distance or travel time), will help improve the results from the VRP. This step is beneficial because firms will not need to run the simulation, but once provided by the simulated
driving cycles they will be able to use a better cost function in their VRP and hence obtain better results compared to the studies that use average speed as a way to model emission and fuel costs.

In this chapter, the effect of implementing a cap-and-trade policy for reducing carbon emissions in transportation was also discussed. The assumptions that would apply to most realistic scenarios, are such that this policy would have no advantages over direct carbon taxing in reducing emissions. The complications that could arise in applying this policy, however, mean that it would be unlikely for this policy to be the most efficient in reducing emissions in transportation.
6 Conclusions

6.1 Summary

The accuracy of representation of driving behaviour for emission modelling purposes can be improved by calibrating microsimulation models against observed acceleration profiles of vehicles. Currently, models calibrated to count and average speed fail to match the performance of the acceleration-calibrated model for determining the parameters that have been shown to influence vehicle emissions.

Vehicle and road specific driving cycles provide a better representation of the emission affecting factors compared to generalised driving cycles that are currently used.

The acceleration-calibrated microsimulation model allows such driving cycles to be generated without the necessity of expensive vehicle chasing projects. The driving cycles are shown to be representative of driving behaviour through comparison of multiple parameters against observed data.

The specific driving cycles provide a wealth of information for emission modelling and optimization purposes as shown in the test case. A wide range of emission and cost optimization analysis is possible as different emission profiles can be associated with different types of roads resulting in a rich model.

The applicability of the proposed calibration and driving cycle generation methods in the thesis are demonstrated in the test case. The outcomes of the model are shown to be useful in assessing the effectiveness of various environmental policies.

The results from the test case show that the effect of cap-and-trade policies in reducing carbon emissions for transportation is similar to carbon taxing; and considering the extra costs involved in implementing such policies, direct taxation is a marginally better solution. However, significant decreases in emissions are not achievable solely through green routing of vehicles.
6.2 Research Contributions

This work of research focused on the increasingly important topic of reducing greenhouse gas emissions. Contributions were made to the calibration methodology of microsimulation models used in transportation for the specific purpose of simulating carbon emissions and in the process a robust genetic algorithm was developed for this purpose. The calibrated model was then used to simulate driving cycles with the novelty that a specific cycle was generated based on vehicle type and road type; a step forward from the existing universal driving cycles for each city. A method for incorporating the simulated driving cycles in a green vehicle routing problem was then presented. Finally, it was shown that, within the scope of this research, the cap-and-trade approach would have no advantages over direct carbon taxing in reducing emissions.

6.2.1 Calibrating a Microsimulation Model Based on Acceleration Profiles

In chapter 3 of this thesis, the methods found in the literature for calibrating microsimulation traffic models were enhanced to incorporate observed data about the acceleration profiles of vehicles. It was shown that for model applications where acceleration of vehicles has a significant effect on the value of the objective function the acceleration calibrated model is more accurate than a count, or count and speed calibrated model. Estimating carbon emissions is one application where these circumstances hold. Other researchers focusing on an acceleration centric entity (e.g. design of turbochargers and their potential effects) could use the outcome of the calibration from this research to inform their studies.

6.2.2 Proposing a Genetic Algorithm for Acceleration Profile based Calibration

A genetic algorithm was developed to carry out the calibration of the microsimulation model. This algorithm was shown to be robust and successful for calibrating a large network. The algorithm can thus be utilised by other researchers trying to calibrate other road networks on the basis of acceleration profiles.

6.2.3 Simulated Driving Cycles

In chapter 4, it was shown that representing the driving behaviour in each city using a single driving cycle is not sufficiently accurate for studying attributes that are related to functions of a higher order than speed of driving. Again, emissions are but one of such attributes and other works of
research focusing on driving characteristics could benefit from the vehicle type, road specific driving cycles that have been developed in this research.

6.2.4 Commentary on Implementation of the Cap-and-Trade Policy in Transportation

In chapter 5, it was shown that, within the scope of this research, the behaviour of transportation fleets would be the same under carbon taxing and cap-and-trade with respect to route selection. The difference would be in the effective cost of carbon where in one scenario it is directly controlled by the government and in the other results from the economic equilibrium in the carbon trading market. Considering the challenges in implementing this policy in the transportation sector, i.e. specifying robust reporting standards, incorporating sufficient market control, implementing legal devices for dealing with excess emissions, etc. it is less likely to be a preferable option for reducing carbon emissions in this sector.

6.3 Recommendations for Future Research

The research presented in this thesis can be extended to cover a larger domain. The specific recommendations have been provided in two categories: long term and short term.

6.3.1 Long-term Recommendations

Calibrating microsimulation traffic models based on higher order functions of vehicle movement can be used to provide more realistic representations of driving behaviour in a traffic domain. Here the focus was on acceleration due to the established links between acceleration and vehicle emissions. In future research, more intricate calibration can be attempted by separating acceleration and deceleration or including higher order functions of position (e.g. jerk) in the objective function.

The work in this research was limited in the amount of computational power that was available in the calibration phase. In future research, through the use of more powerful parallel computers, the calibration can be carried out with more accuracy and tougher criteria for acceptance. Impact of relative weights on the calibration results can also be investigated. Together with the higher order calibration functions, this can be used, in the future, to develop traffic microsimulation models that are more precise and accurate than existing ones for modelling driving in cities to provide
researchers with a cheaper and more accessible platform for various experiments and scenario tests.

In order to get a more thorough understanding of the cap-and-trade policy, it is recommended that a dynamic model of the carbon trading market be established. Such a model would allow assessment of the effect of the policy without assuming that each has prior knowledge of prices.

Another potential extension to the test case VRP model in this research would be to add the business dynamics for an actual delivery business to assess scenarios where particular deliveries will be cancelled or not accepted due to high emissions associated with that specific delivery (or additional charges will be levied against the customer). This would require a thorough understanding of the business in question and would be specific to each company.

6.3.2 Short-term Recommendations

The research presented in this thesis can be extended in the short term by considering the road categories in forming the driving cycles in more detail. Establishing an appropriate hierarchy of road types according to the purpose of the model could have the benefit of providing city planners with additional data when the road network is extended or refurbished. More granular consideration of road types could also provide interesting insight: looking at different directions of traffic separately or categorizing roads based on their direction towards the CBD could highlight significant differences in driving behaviours based on details hitherto ignored.

In this research, emissions estimations were based on data from a county closest to Toronto in terms of their meteorological characteristics. Another recommendation would be developing a “Custom Domain” for Toronto in MOVES and comparing the emissions results to assess the sensitivity of the estimates to geographic parameters. This would be useful for future works of research where this methodology for emission estimation is likely to be utilized.

In terms of enhancing the VRP model, idle emissions can be estimated and added to the vehicle routing problem formulation. This would allow the optimization to be carried out with time window constraints, potentially increasing the accuracy of the model.

Furthermore, studying a heterogeneous fleet, which is still not fully explored in the current GVRP literature, would allow fleet operators to better evaluate the use of hybrid vehicles in their fleet.
Finally, calibrating afternoon and off-peak microsimulation models using the approach presented in this thesis would allow modelling of off-peak deliveries to assess resulting costs and emissions and comparing these to their peak counterparts. Consequently, with reformulation of the vehicle routing problem, more complex optimizations including variables such as departure time choice would be achievable.
7 References


Boriboonsomsin, K., Scora, G., Wu, G., and Barth, M., 2011. Improving Vehicle Fleet, Activity, and Emissions Data for on-Road Mobile Sources Emissions Inventories. Sponsoring Entity: Center for Environmental Research and Technology University of California at Riverside.


IPCC, 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. , IGES, Japan Sponsoring Entity: The Institute for Global Environmental Strategies (IGES) on behalf of the IPCC.


U.S. Environmental Protection Agency. U.S. Environmental Protection Agency, Dynamometer Driver's Aid [last Updated June 16, 2010].


Riverside University of California. CMEM: Comprehensive Model Emission Model [last Updated Dec/17].


US Environmental Protection Agency. MOVES [last Updated Dec/23].


Sponsoring Entity: Oregon Office of the Governor.


Sponsoring Entity: iTrans.


Younglove, T., Scora, G., Barth, M., 2005. Designing on-road vehicle test programs for the development of effective vehicle emission models. Transportation Research Record: Journal of the Transportation Research Board (1941), 51-59.


Appendices

Appendix A. Observed Count, Speed, and Acceleration Data

2009 cordon count program for Toronto, and the travel time survey by the MTO was used to calculate observed counts (Table A-1), speed, and acceleration (Table A-2) that were used for calibration.

Table A-1- Observed Road Counts and Count Locations for the AM Network

<table>
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<tr>
<th>Count Location</th>
<th>Link ID in Paramics</th>
<th>Road Counts</th>
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<tr>
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<td>773</td>
</tr>
<tr>
<td>Richmond at Spadina-SB</td>
<td>'43:278'</td>
<td>623</td>
</tr>
<tr>
<td>Richmond at John-SB</td>
<td>'597z:579'</td>
<td>223</td>
</tr>
<tr>
<td>Richmond at University-SB</td>
<td>'6z:12z'</td>
<td>1663</td>
</tr>
<tr>
<td>Richmond at Bay-SB</td>
<td>'163z:68z'</td>
<td>505</td>
</tr>
<tr>
<td>Richmond at Yonge-SB</td>
<td>'86z:85z'</td>
<td>473</td>
</tr>
<tr>
<td>Richmond at Church-SB</td>
<td>'98z:100z'</td>
<td>651</td>
</tr>
<tr>
<td>Richmond at Jarvis-SB</td>
<td>'146z:147z'</td>
<td>1140</td>
</tr>
<tr>
<td>Richmond at Sherbourne-SB</td>
<td>'167z:169z'</td>
<td>387</td>
</tr>
<tr>
<td>Richmond at Parlaiment-SB</td>
<td>'183z:184z'</td>
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<tr>
<td>Richmond at John-NB</td>
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<td>Richmond at Sherbourne-NB</td>
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<td>QQ &amp; Bathurst-EB</td>
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<td>Gardiner west of Spadina-EB</td>
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<td>Road Counts</td>
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<td>--------------------</td>
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<td>1999:262</td>
<td>3007</td>
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<tr>
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<td>Queen &amp; Bathurst-WB</td>
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<td>Richmond &amp; Bathurst-WB</td>
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<td>QQ &amp; Bathurst-WB</td>
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<td>Lake Shore Blvd. east of stadium Rd-WB</td>
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<tr>
<td>Dundas at Don River Bridge-WB</td>
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<td>Queen St at Don River Bridge-WB</td>
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Table A-2-Observed Speed and Acceleration Data from the MTO Travel Time Survey

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<th>std_Acc</th>
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<td>'Adelaide EB-Spadina-TO-Peter St'</td>
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<td>'Adelaide EB-John St-TO-Duncan St'</td>
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<td>'Adelaide EB-Duncan St-TO-Simcoe St'</td>
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Appendix B. Simulated Data

At each run of Paramics, road counts, link average speeds, and standard deviation of acceleration were calculated and compared against the observed to measure the goodness of that run. This section briefly outlines the output files used to do the calculation (described in section 3.5). Simulated traffic volumes were calculated using the “link-counts” output files for the intervals of 8:00 to 8:30, and 8:30 to 9:00 AM.

To measure the simulated link average speed and standard deviation of acceleration, second-by-second speed information for passenger vehicles traversing 206 links in Paramics (representing the 71 road segments) was recorded using the vehicle trajectory recording option in Paramics. Analysis showed that measuring second-by-second information of 50% of the passenger vehicles (instead of every vehicle) reduces the post-processing time by approximately 80% (Figure B-1) without jeopardizing the results (Figure B-2). Therefore second-by-second speed information of 50% of the vehicles were used for calibration purposes.

![Figure B-1- The Effect of Sample Size on Run Time, and Post-processing Time for a Sample Run](image)
Figure B-2-RMSE Value for a) Acceleration, and b) Speed for Different Percentage of Passenger Vehicles Recorded
Appendix C. Additional Comparison of the C, CS, and CSA Models

Tables C-1 to C-5 compare the vehicle counts between the three models and the observations. The tables have been divided to separate Gardiner Expressway ramps, the screenlines and Gardiner Expressway and Lake Shore Blvd.

![Gardiner Expressway Ramps](image)

**Figure C-1** - Comparison of Road Counts vs. Simulated C, CS, and CSA Volumes for Gardiner Expressway Ramps
Figure C-2- Comparison of Road Counts vs. Simulated C, CS, and CSA Volumes for the North Screenline at Richmond Street

Figure C-3- Comparison of Road Counts vs. Simulated C, CS, and CSA Volumes for the West Screenline at Bathurst Street
Figure C-4- Comparison of Road Counts vs. Simulated C, CS, and CSA Volumes for the East Screenline at Don River

Figure C-5- Comparison of Road Counts vs. Simulated C, CS, and CSA Volumes for Gardiner Expressway and Lake Shore Blvd
Tables C-6 to C-10 compare the average speed between the observations and the three models. The tables are divided based on category-ID presented in Table A-2.

**Adelaide St.**

![Graph](Image1)

**Bathurst St.**

![Graph](Image2)

**Spadina Ave.**

![Graph](Image3)

**Figure C-6-** Comparison of Observed Average Speed vs. Simulated C, CS, and CSA Speeds along Adelaide Street

**Figure C-7-** Comparison of Observed Average Speed vs. Simulated C, CS, and CSA Speeds along Bathurst Street

**Figure C-8-** Comparison of Observed Average Speed vs. Simulated C, CS, and CSA Speeds along Spadina Avenue
Figure C-9- Comparison of Observed Average Speed vs. Simulated C, CS, and CSA Speeds along Yonge Street

![Yonge St. Comparison Chart](chart.png)

Figure C-10- Comparison of Observed Average Speed vs. Simulated C, CS, and CSA Speeds along Gardiner Expressway and Lake Shore Blvd.

![Gardiner Expressway+ Lake Shore Blvd. Comparison Chart](chart2.png)
Tables C-11 to C-15 compare the standard deviation of accelerations between the observations and the three models. The tables are divided based on road categories.

**Adelaide St.**

*Figure C-11- Comparison of Observed Standard Deviation of Acceleration vs. Simulated C, CS, and CSA Deviations of Acceleration along Adelaide Street*

**Bathurst St.**

*Figure C-12- Comparison of Observed Standard Deviation of Acceleration vs. Simulated C, CS, and CSA Deviations of Acceleration along Bathurst Street*
Figure C-13- Comparison of Observed Standard Deviation of Acceleration vs. Simulated C, CS, and CSA Deviations of Acceleration along Spadina Avenue

Figure C-14- Comparison of Observed Standard Deviation of Acceleration vs. Simulated C, CS, and CSA Deviations of Acceleration along Yonge Street

Figure C-15- Comparison of Observed Standard Deviation of Acceleration vs. Simulated C, CS, and CSA Deviations of Acceleration along Gardiner Expressway and Lake Shore Blvd.
Appendix D. Required Number of Model Runs

Microscopic traffic simulation models are widely used in most areas of transportation engineering. However due to their stochastic nature, each run with a random seed is regarded as a random experiment and it cannot be regarded as the average condition for the basis of any comparison. Some runs can represent typical days while others would represent extreme light or heavy traffic conditions. Therefore, numerous runs are required for each scenario. The appropriate number of runs depends on the nature and size of the network. Some studies have used theories of probability and statistics (Equation 36) to calculate the required number of runs (Hollander and Liu, 2008; Lindgren and Tantiyanugulchai, 2003; Merritt, 2004).

$$n_r \geq \left( \frac{s t_{a/2}}{\bar{x} \epsilon} \right)^2$$  \hspace{1cm} \text{Equation 36}

Were: \( \bar{x}, s \) = mean and variance of the examined traffic measure

\( t_{a/2} \) = threshold value for a 100(1-\( \alpha \)) percent confidence interval

\( n_r \) = required number of runs

\( \epsilon \) = maximum acceptable error of the estimate

This equation worked well for those cases because the authors were investigating a small interchange.

For the waterfront network, the same approach could have been used. However since there are approximately 4000 links coded in the model, using this approach would have provided one “\( n_r \)” for each link and the maximum \( n \) would have been the required number of runs. Hence another statistical analysis method was used in this research as discussed below.

In previous research done on the waterfront network and the 400-series network, the optimal number of runs was 15 (Abdulhai et al., 2002; Abdelgawad et al., 2010). To see if 15 runs would be sufficient for this network, the model was run 30 times. The process of updating the configuration file and running Paramics was automated using MATLAB. As a result, average link flows on each link were calculated through an excel macro. Then a series of statistical inference for two samples on the difference in their population means were tested comparing the results of
flow counts for 15 runs vs. 5, 10, 20, 25, and 30 runs. The following example for the case of 30 runs explains the procedure in more detail.

In this case, one sample includes 15 values for the link flow on each link, and another sample has 30 values for the same link (an example is shown in Table D-1 for link 5:96). It should be noted that half of the numbers between the two samples are the same, meaning that we are testing to see if running the model 15 more times would significantly change the average road counts.

Table D-1- Simulated Link Flows used as Data Input for Statistical Inference for Link 5:96 on the Difference in Population Means

<table>
<thead>
<tr>
<th>30 runs</th>
<th>15 runs</th>
</tr>
</thead>
<tbody>
<tr>
<td>453</td>
<td>453</td>
</tr>
<tr>
<td>646</td>
<td>646</td>
</tr>
<tr>
<td>616</td>
<td>616</td>
</tr>
<tr>
<td>558</td>
<td>558</td>
</tr>
<tr>
<td>530</td>
<td>530</td>
</tr>
<tr>
<td>618</td>
<td>618</td>
</tr>
<tr>
<td>586</td>
<td>586</td>
</tr>
<tr>
<td>622</td>
<td>622</td>
</tr>
<tr>
<td>533</td>
<td>533</td>
</tr>
<tr>
<td>525</td>
<td>525</td>
</tr>
<tr>
<td>580</td>
<td>580</td>
</tr>
<tr>
<td>543</td>
<td>543</td>
</tr>
<tr>
<td>616</td>
<td>616</td>
</tr>
<tr>
<td>548</td>
<td>548</td>
</tr>
<tr>
<td>570</td>
<td>570</td>
</tr>
<tr>
<td>545</td>
<td></td>
</tr>
<tr>
<td>514</td>
<td></td>
</tr>
<tr>
<td>597</td>
<td></td>
</tr>
<tr>
<td>506</td>
<td></td>
</tr>
<tr>
<td>598</td>
<td></td>
</tr>
<tr>
<td>626</td>
<td></td>
</tr>
<tr>
<td>511</td>
<td></td>
</tr>
<tr>
<td>512</td>
<td></td>
</tr>
<tr>
<td>527</td>
<td></td>
</tr>
<tr>
<td>529</td>
<td></td>
</tr>
<tr>
<td>562</td>
<td></td>
</tr>
<tr>
<td>593</td>
<td></td>
</tr>
<tr>
<td>546</td>
<td></td>
</tr>
<tr>
<td>617</td>
<td></td>
</tr>
<tr>
<td>455</td>
<td></td>
</tr>
</tbody>
</table>
The same procedure was done for all links, comparing the results of 15 and 30 runs. Out of the 4013 links, the null hypothesis that the estimated means are the same was rejected in only 4.57% of cases. This concludes that the average flow on a link does not significantly vary when the simulation is run for an extra 15 seeds.

The same comparison was done for 5, 10, 20, and 25 runs. As can be seen from Table D-2, the differences between the link flows are significant in less than 5% of cases for 15 runs or higher. Hence 15 runs are sufficient to capture the stochastic nature of the microsimulation assignment.

<table>
<thead>
<tr>
<th>Number of runs compared to 15 runs</th>
<th>% of links with average means significantly different than 15 runs</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 runs</td>
<td>26.2%</td>
</tr>
<tr>
<td>10 runs</td>
<td>6.2%</td>
</tr>
<tr>
<td>20 runs</td>
<td>3.57%</td>
</tr>
<tr>
<td>25 runs</td>
<td>4.57%</td>
</tr>
<tr>
<td>30 runs</td>
<td>4%</td>
</tr>
</tbody>
</table>

Table D-2- Two Sample Hypothesis Testing of Population Means
Appendix E.  Toronto Simulated Driving Cycles

Based on the method described in section 4.2.2, this section presents the final simulated driving cycles developed using second-by-second speed data from 15 simulation runs for LDTs, MDTs, and HDTs on each road category.

Simulated driving cycles for HDTs are shown in Figure E-1. The value of the 13 assessment measures used as target statistics and final cycle statistics are also presented in Table E-1. Same results for the MDT, and LDT simulated driving cycles are shown in Figure E-2 and Table E-2; and Figure E-3 and Table E-3, respectively.

<table>
<thead>
<tr>
<th>Assessment</th>
<th>Freeway</th>
<th>Lake Shore Blvd.</th>
<th>University</th>
<th>Major Arterials</th>
<th>Arterials With Transit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measure</td>
<td>Target</td>
<td>Final</td>
<td>Target</td>
<td>Final</td>
<td>Target</td>
</tr>
<tr>
<td>V (kph)</td>
<td>44.7</td>
<td>40.9</td>
<td>28.5</td>
<td>28.4</td>
<td>12.6</td>
</tr>
<tr>
<td>Vr (kph)</td>
<td>45.8</td>
<td>41.9</td>
<td>33.3</td>
<td>33.3</td>
<td>17.3</td>
</tr>
<tr>
<td>Acc (m/s²)</td>
<td>0.142</td>
<td>0.147</td>
<td>0.280</td>
<td>0.280</td>
<td>0.399</td>
</tr>
<tr>
<td>Dcc (m/s²)</td>
<td>-0.304</td>
<td>-0.282</td>
<td>-0.614</td>
<td>-0.605</td>
<td>-0.574</td>
</tr>
<tr>
<td>D (sec)</td>
<td>159.3</td>
<td>158.8</td>
<td>34.6</td>
<td>33.1</td>
<td>20.5</td>
</tr>
<tr>
<td>Acc-dcc (%)</td>
<td>14.5</td>
<td>14.8</td>
<td>18.7</td>
<td>20.0</td>
<td>26.0</td>
</tr>
<tr>
<td>Pa (%)</td>
<td>66.4</td>
<td>62.8</td>
<td>60.1</td>
<td>59.3</td>
<td>46.2</td>
</tr>
<tr>
<td>Pτ (%)</td>
<td>29.1</td>
<td>32.8</td>
<td>26.5</td>
<td>27.5</td>
<td>30.0</td>
</tr>
<tr>
<td>Pcr (%)</td>
<td>1.9</td>
<td>1.9</td>
<td>12.0</td>
<td>11.7</td>
<td>23.2</td>
</tr>
<tr>
<td>Pcr (%)</td>
<td>2.6</td>
<td>2.5</td>
<td>1.4</td>
<td>1.4</td>
<td>0.60</td>
</tr>
<tr>
<td>RMSA (m/s²)</td>
<td>0.352</td>
<td>0.324</td>
<td>0.636</td>
<td>0.571</td>
<td>0.582</td>
</tr>
<tr>
<td>RMSPKE (m/s)</td>
<td>9.63</td>
<td>9.17</td>
<td>7.04</td>
<td>7.04</td>
<td>3.58</td>
</tr>
</tbody>
</table>
Figure E-1- Simulated HDT Driving Cycles Developed for a) Freeways, b) Lake Shore Blvd., c) University Avenue, d) Major Arterials, and e) Major Arterials with Transit
### Table E-2- MDT Target and Final Statistics

<table>
<thead>
<tr>
<th>Assessment</th>
<th>Freeway</th>
<th>Lake Shore Blvd.</th>
<th>University</th>
<th>Major Arterials</th>
<th>Arterials With Transit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measure</td>
<td>Target</td>
<td>Final</td>
<td>Target</td>
<td>Final</td>
<td>Target</td>
</tr>
<tr>
<td>V (kph)</td>
<td>43.7</td>
<td>39.7</td>
<td>29.3</td>
<td>25.7</td>
<td>13.2</td>
</tr>
<tr>
<td>Vr (kph)</td>
<td>44.7</td>
<td>40.6</td>
<td>33.3</td>
<td>29.4</td>
<td>17.1</td>
</tr>
<tr>
<td>Acc (m/s²)</td>
<td>0.127</td>
<td>0.135</td>
<td>0.241</td>
<td>0.265</td>
<td>0.370</td>
</tr>
<tr>
<td>Dcc (m/s²)</td>
<td>-0.342</td>
<td>-0.336</td>
<td>-0.648</td>
<td>-0.647</td>
<td>-0.572</td>
</tr>
<tr>
<td>D (sec)</td>
<td>145.4</td>
<td>132.3</td>
<td>36.5</td>
<td>37.6</td>
<td>21.2</td>
</tr>
<tr>
<td>Acc-dcc (%)</td>
<td>14.0</td>
<td>15.7</td>
<td>17.5</td>
<td>18.8</td>
<td>24.8</td>
</tr>
<tr>
<td>Pₐ (%)</td>
<td>71.1</td>
<td>69.4</td>
<td>65.3</td>
<td>62.8</td>
<td>50.5</td>
</tr>
<tr>
<td>P₃ (%)</td>
<td>25.9</td>
<td>27.8</td>
<td>23.7</td>
<td>25.7</td>
<td>30.4</td>
</tr>
<tr>
<td>P₁ (%)</td>
<td>1.8</td>
<td>1.6</td>
<td>9.8</td>
<td>10.4</td>
<td>18.6</td>
</tr>
<tr>
<td>Pₐₚ (%)</td>
<td>1.2</td>
<td>1.2</td>
<td>1.1</td>
<td>1.2</td>
<td>0.4</td>
</tr>
<tr>
<td>P₃ₚ (%)</td>
<td>3.2</td>
<td>3.5</td>
<td>20.7</td>
<td>23.5</td>
<td>37.2</td>
</tr>
<tr>
<td>RMSA (m/s²)</td>
<td>0.348</td>
<td>0.344</td>
<td>0.593</td>
<td>0.521</td>
<td>0.563</td>
</tr>
<tr>
<td>RMSPE (m/s)</td>
<td>9.48</td>
<td>8.82</td>
<td>7.16</td>
<td>6.44</td>
<td>3.63</td>
</tr>
</tbody>
</table>

### Table E-3- LDT Target and Final Statistics

<table>
<thead>
<tr>
<th>Assessment</th>
<th>Freeway</th>
<th>Lake Shore Blvd.</th>
<th>University</th>
<th>Major Arterials</th>
<th>Arterials With Transit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measure</td>
<td>Target</td>
<td>Final</td>
<td>Target</td>
<td>Final</td>
<td>Target</td>
</tr>
<tr>
<td>V (kph)</td>
<td>51.7</td>
<td>52.7</td>
<td>34.8</td>
<td>34.8</td>
<td>14.4</td>
</tr>
<tr>
<td>Vr (kph)</td>
<td>54.0</td>
<td>54.0</td>
<td>40.4</td>
<td>40.6</td>
<td>18.7</td>
</tr>
<tr>
<td>Acc (m/s²)</td>
<td>0.313</td>
<td>0.293</td>
<td>0.560</td>
<td>0.569</td>
<td>0.566</td>
</tr>
<tr>
<td>Dcc (m/s²)</td>
<td>-0.503</td>
<td>-0.544</td>
<td>-0.739</td>
<td>-0.752</td>
<td>-0.688</td>
</tr>
<tr>
<td>D (sec)</td>
<td>117.7</td>
<td>112.1</td>
<td>32.4</td>
<td>30.5</td>
<td>30.8</td>
</tr>
<tr>
<td>Acc-dcc (%)</td>
<td>18.9</td>
<td>17.3</td>
<td>26.5</td>
<td>28.1</td>
<td>30.8</td>
</tr>
<tr>
<td>Pₐ (%)</td>
<td>59.7</td>
<td>61.2</td>
<td>47.1</td>
<td>45.7</td>
<td>45.9</td>
</tr>
<tr>
<td>P₃ (%)</td>
<td>34.9</td>
<td>33.0</td>
<td>34.1</td>
<td>34.6</td>
<td>35.0</td>
</tr>
<tr>
<td>P₁ (%)</td>
<td>2.0</td>
<td>2.1</td>
<td>11.3</td>
<td>11.5</td>
<td>18.4</td>
</tr>
<tr>
<td>Pₐₚ (%)</td>
<td>3.4</td>
<td>3.8</td>
<td>7.5</td>
<td>8.2</td>
<td>0.7</td>
</tr>
<tr>
<td>P₃ₚ (%)</td>
<td>3.2</td>
<td>3.5</td>
<td>23.1</td>
<td>24.1</td>
<td>40.6</td>
</tr>
<tr>
<td>RMSA (m/s²)</td>
<td>0.646</td>
<td>0.597</td>
<td>0.926</td>
<td>0.940</td>
<td>0.791</td>
</tr>
<tr>
<td>RMSPE (m/s)</td>
<td>11.44</td>
<td>11.34</td>
<td>8.75</td>
<td>8.87</td>
<td>4.23</td>
</tr>
</tbody>
</table>
Figure E-2- Simulated MDT Driving Cycles Developed for a) Freeways, b) Lake Shore Blvd., c) University Avenue, d) Major Arterials, and e) Major Arterials with Transit
Figure E-3- Simulated LDT Driving Cycles Developed for a) Freeways, b) Lake Shore Blvd., c) University Avenue, d) Major Arterials, and e) Major Arterials with Transit
Appendix F. Running MOVES

MOVES can be used to estimate emissions on a national, county, or project scale. Since this research is focusing on estimating emissions for different driving cycles, the project scale of MOVES is selected. The project level modelling is the finest level of modelling in MOVES, used for analysis of link level projects, and requires the user to define the following 6 input files for each MOVES run.

- Meteorology

This file defines the temperature and humidity data for the geographic location of the model. MOVES model includes detailed information about the counties in the US but not Canada. One way to modelling emissions for Canadian cities is by defining a new “Custom County” within MOVES and defining the barometric pressure and the vapor and spill adjustment factors. However, in this research for simplicity, it was decided to use available temperature data for Toronto to select a substitute county in the US that is closest to Toronto in terms of weather conditions.

To see which county in the US is closest to Toronto in terms of weather conditions, 4 counties were considered (considering the counties that are either in close proximity of Toronto or have the same latitude as Toronto as shown in Figure F-1). Comparing the average temperature and relative humidity of these four counties against data available for the city of Toronto\(^\text{64}\) showed that data from the Niagara County in NY (zone ID= 36063) can be used when modelling Toronto.

\(^{64}\) Unfortunately temperature and relative humidity data for the Toronto area was not available for the year 2009. Available data included average monthly temperature for years 1996-2000, and relative humidity for years 2011-2013 for Toronto.
Figure F-1- Map Showing the US Counties in Close Proximity or Having the Same Latitude as Toronto
[source: http://www.newyorkstatesearch.com/maps/New_York_State_county_map.html]

- Links

Links file defines the link ID, county ID, zone ID, road type ID, link length (in miles), link volume (units of vehicle per hour), link average speed (in mph), link description, and the link average grade (%) for each link that is being modelled. Different road categories defined in MOVES are presented in Table F-1. Urban restricted access represents freeways driving, and roads with unrestricted access are used to model emissions on Lake Shore Blvd., University Ave., major arterials, and major arterials with transit.
### Table F-1- Road Categories used in MOVES

<table>
<thead>
<tr>
<th>Road Type ID</th>
<th>Road Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Off-network</td>
<td>Locations where the predominant activity is vehicle starts, parking and idling (such as parking lots, truck stops, rest areas, freight or bus terminals)</td>
</tr>
<tr>
<td>2</td>
<td>Rural restricted access</td>
<td>Rural highways that can be accessed only by an on-ramp</td>
</tr>
<tr>
<td>3</td>
<td>Rural unrestricted access</td>
<td>All other rural roads (arterials, connectors, and local streets)</td>
</tr>
<tr>
<td>4</td>
<td>Urban restricted access</td>
<td>Urban highways that can be accessed only by an on-ramp</td>
</tr>
<tr>
<td>5</td>
<td>Urban unrestricted access</td>
<td>All other rural roads (arterials, connectors, and local streets)</td>
</tr>
</tbody>
</table>

- **Link Source Type**

  This file is only required when modelling project-specific emissions. This importer includes the link ID, source type ID (showing the vehicle type), and the source type hour fraction. Different vehicle categories defined in MOVES are presented in Table F-2. The source type hour fraction shows the fraction of each link’s traffic volume driven by each vehicle type.

- **Age Distribution**

  The age distribution importer allows the user to provide information about the age of the fleet. This importer includes the following fields: source type ID (showing the vehicle type), year ID (showing the model year), age ID (the age of the vehicle relevant to the modelled year), and age fraction (percentage of each vehicle class with that particular age ID). This can be used for cases when detailed information about the age distribution of the fleet is available. Since no real information about the age distribution of a fleet (for solving the VRP) was available, the average age of the fleet according to Statistics Canada was used in this research.
<table>
<thead>
<tr>
<th>Source Type ID</th>
<th>Source Use Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>Motorcycle</td>
<td>Vehicles with less than four wheels</td>
</tr>
<tr>
<td>21</td>
<td>Passenger Car</td>
<td>Four wheel, two axle vehicles whose primary function is passenger transport</td>
</tr>
<tr>
<td>31</td>
<td>Passenger Truck</td>
<td>Four wheel, two axle trucks whose primary functional design is for cargo, but are used primarily for passenger transport</td>
</tr>
<tr>
<td>32</td>
<td>Light Commercial Truck</td>
<td>Four wheel, two axle trucks used primarily for cargo transport</td>
</tr>
<tr>
<td>41</td>
<td>Intercity Bus</td>
<td>Passenger vehicles with a capacity of 15 or more persons primarily used for transport between cities</td>
</tr>
<tr>
<td>42</td>
<td>Transit Bus</td>
<td>Passenger vehicles with a capacity of 15 or more persons primarily used for transport within cities</td>
</tr>
<tr>
<td>43</td>
<td>School Bus</td>
<td>Passenger vehicles with a capacity of 15 or more persons used primarily for transport of students for school</td>
</tr>
<tr>
<td>51</td>
<td>Refuse Truck</td>
<td>Trucks primarily used to haul refuse to a central location</td>
</tr>
<tr>
<td>52</td>
<td>Single Unit Short-haul Truck</td>
<td>Single unit trucks with more than four tires with a range of operation of up to 200 miles</td>
</tr>
<tr>
<td>53</td>
<td>Single Unit Long-haul Truck</td>
<td>Single unit trucks with more than four tires with a range of operation of over 200 miles</td>
</tr>
<tr>
<td>54</td>
<td>Motor Home</td>
<td>Trucks whose primary functional design is to provide sleeping quarters</td>
</tr>
<tr>
<td>61</td>
<td>Combination Short-haul Truck</td>
<td>Combination tractor/trailer trucks with more than four tires with a range of operation of up to 200 miles</td>
</tr>
<tr>
<td>62</td>
<td>Combination Long-haul Truck</td>
<td>Combination tractor/trailer trucks with more than four tires with a range of operation of over 200 miles</td>
</tr>
</tbody>
</table>
• Fuel

To provide information about the fuel used by each vehicle class, two importers are used together: fuel formulation, and fuel supply. The fuel formulation shows all the specifications of the fuel (e.g., sulfur level (ppm), T50 and T90\(^{65}\)). In this research, the default fuel formulation table available in MOVES is used. Table F-3 shows the fuels types that can be modelled using MOVES.

<table>
<thead>
<tr>
<th>Fuel Type ID</th>
<th>Fuel Type description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Gasoline</td>
</tr>
<tr>
<td>2</td>
<td>Diesel Fuel</td>
</tr>
<tr>
<td>3</td>
<td>Compressed Natural Gas (CNG)</td>
</tr>
<tr>
<td>4</td>
<td>Liquefied Petroleum Gas (LPG)</td>
</tr>
<tr>
<td>5</td>
<td>Ethanol</td>
</tr>
<tr>
<td>9</td>
<td>Electricity</td>
</tr>
</tbody>
</table>

• Operating Mode or Drive Schedule or Average Speed

MOVES can estimate emission using only the average speed (provided in the links file), the detailed driving cycle provided in the drive schedule importer, or the operating mode distribution of the cycle showing the amount of time the vehicle drives in each operating mode (the operating mode is based on the VSP and the vehicle’s instantaneous speed (in mph)). If the driving cycle is provided, MOVES will calculate the average speed and the operating mode distribution.

Given the above 6 files, MOVES estimates emission factors for any number of pollutants selected from the list of pollutants available in MOVES. Since the goal of this research is to use emission factors from the driving cycles in the VRP problem, and it is assumed that the vehicles are driving between two customers or a customer and the depot without stopping, only running exhaust emissions are estimated with MOVES (as opposed to start emissions, evaporative emissions, etc.). For the purposes of this research, only greenhouse gasses are estimated with MOVES, which are:

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\(^{65}\) Temperature (F) where 50% and 90% of the fuel is vapor.
Nitrous oxide (N\textsubscript{2}O)	extsuperscript{66}, Methane (CH\textsubscript{4})\textsuperscript{67}, Carbon dioxide (CO\textsubscript{2})\textsuperscript{68}, and CO\textsubscript{2} equivalent\textsuperscript{69} (contains all three pollutants using their global warming potential) of the GHGs.

\textsuperscript{66} Pollutant ID=6.
\textsuperscript{67} Pollutant ID=5.
\textsuperscript{68} Pollutant ID=90.
\textsuperscript{69} Pollutant ID=98.
Appendix G. CPLEX Branch-and-Cut Algorithm

As stated in section 5.3, CPLEX uses a combination of the branch-and-bound and the cutting plane method to solve mixed integer problems (MIP). This appendix provides a more detailed overview of the branch-and-bound and the cutting plane with examples.

Branch-and-Bound Algorithm

The branch-and-bound method is based on “divide and conquer” algorithm. The main idea is to continue dividing the problem into smaller sub-problems that are easier to solve. The algorithm uses an enumeration tree to show results for each sub-problem. Assume the following maximization problem.

\[ z^* = \max Z = 5x_1 + 8x_2 \]
\[ s.t. \]
\[ x_1 + x_2 \leq 6 \]
\[ 5x_1 + 9x_2 \leq 45 \]
\[ x_1, x_2 \geq 0 \text{ and integer} \]

The integrality constraint is relaxed in the above problem to define the root node in the tree. The branch-and-bound algorithm starts by finding the solution to the root node (graphical solution shown in Figure G-1). As can be seen from this figure, the solution to the linear problem is \((2.25, 3.75)\) with \(z^0=41.25\). It is clear that simply rounding these numbers will not produce the optimal results. In other words, rounding these numbers to \((2, 4)\) produces an infeasible solution to the problem. Also the nearest integer values \((2, 3)\) result in \(z=34\), which (results will show) is far from the optimal solution.

A MIP is a linear problem with added integrality conditions. Therefore, in a maximization problem, the optimal solution for the linear problem serves as an upper limit for the MIP\(^71\). In other

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\(^{70}\) Material used in this appendix is based on lecture notes from Operations Research (Zokaei Ashtiani, 2006).

\(^{71}\) It will be a lower bound in a minimization problem.
words, \( z^* < 41.25 \). Given that the coefficients in the objective function are integer, \( z^* \leq 41 \). Also, each feasible point will serve as a lower bound for the optimal solution.

The solution tree for the branch-and-bound in this example is shown in Figure G-2, where one of the variables is converted to an integer solution, producing problems \( L_1 \) and \( L_2 \). Solving \( L_1 \) results in \( x_1 = 1.8 \), and \( x_2 = 4 \). Given that \( x_1 \) is still non-integer, \( L_1 \) is divided into \( L_3 \) with \( x_1 \geq 2 \) and \( L_4 \) with \( x_1 \leq 1 \). At this stage, problem \( L_3 \) becomes unfeasible and this node becomes inactive (the “*” under this node means that \( L_3 \) cannot be divided into any more sub-problems. Either \( L_2 \) or \( L_4 \) must be analyzed at this point. Following the same procedure on \( L_4 \) results in problems \( L_5 \) and \( L_6 \). At this stage, problem \( L_5 \) produces integer solutions (\( x_1 = 1 \), and \( x_2 = 4 \)). The algorithm continues since problems \( L_2 \) and \( L_6 \) have not yet been analyzed. However, the solution for \( L_5 \) (\( z = 37 \)) is set as the lower bound for the MIP.

The only feasible solution for \( L_6 \) is \( x_1 = 0 \), and \( x_2 = 6 \), with \( z = 40 \). The values of \( z \) in \( L_6 \) is higher than the value of \( z \) in \( L_5 \). In other words, the lower bound for the problem has increased, and \( 40 \leq z^* \leq 41 \). It is possible to stop at this point, given that the difference between the upper and lower bounds for the MIP is 2.5%. However based on the precision required, it is still possible to continue to node \( L_2 \).
As can be seen from the solution tree, node L₂ results in \( x_1 = 3 \), and \( x_2 = 3 \), with \( z = 39 \). Given that this value is lower than the objective function in \( L_6 \), point \( x_1 = 0 \), and \( x_2 = 5 \) would be the optimal solutions to the MIP. Even if \( L_2 \) resulted in a non-integer solution (but with \( z < 40 \)), the algorithm would stop given that no branch from \( L_2 \) would be able to produce better results than \( L_6 \).

To summarize, the branch-and-cut algorithm divides the solution domain in order to find \( \underline{z} \leq z^* \leq \overline{z} \). \( z^* \) is the optimal solution, \( \underline{z} \) is the lower bound (maximum of the solutions found up to the current stage), and \( \overline{z} \) is the upper bound (solution to the linear problem). The process is repeated until there are no active nodes left. A node, \( L_j \) becomes inactive if:

a) \( L_j \) is unfeasible;

b) Solution for node \( L_j \) is integer;

c) Solution for node \( L_j \) is less than the lower bound \( z^j \leq \underline{z} \).
Cutting plane method

The cutting plane method changes the solutions of a linear programming (LP) model, by adding constraints. Unlike the branch-and-bound method, the cutting plane method does not divide the solution domain. The algorithm operates by adding constraints (cuts) that would reduce the solution domain, until the optimal solution is found. As an example of a cut, the following constraint with three binary variables is considered.

\[ 20x + 25y + 30z \leq 40 \]

A sample cut that can be added to the problem without eliminating any feasible integer solutions is as follows.

\[ x + y + z \leq 1 \]

The branch-and-cut algorithm in CPLEX continues to create branches, apply cuts, and solve the problem in active nodes until either a previously defined limit has been reached, or that there are no more active nodes available in the tree.
Appendix H. Paper\textsuperscript{72}: Integrated Model for Microsimulating Vehicle Emissions, Pollutant Dispersion, and Population Exposure

Glareh Amirjamshidi, Toka S. Mostafa, Aarshabh Misra, Matthew J. Roorda

Department of Civil Engineering, University of Toronto, M5S 1A4, Canada

Abstract

This paper models traffic at the individual vehicle level, estimates emissions from on-road vehicle sources accounting for drive cycles, estimates how those emissions are dispersed through the atmosphere; and finally estimates the exposed population at times of peak emissions. In the study area, the Toronto Waterfront Area, emissions are highest on the high capacity roadways, and higher in the peak direction of traffic. Pollutant concentrations are higher along the freeways. However, population exposure to these pollutants is highest in the central business district due to the higher population density. Evaluation of scenarios shows significant NOx and HC reduction of 12\% and 4\% when medium duty diesel trucks are converted to ultra-low emission vehicles.

Keywords: Microsimulation modeling; Emissions dispersion models; Pollution exposure

1. Introduction

Until recently, most efforts to model on-road vehicle emissions have used a three step approach calculating the average speed on each link, the emission rate for each link for each vehicle type and model year, and the emissions for each time interval and pollutant by multiplying the emission rate by the vehicle kilometers traveled. Such average speed models are limited because the accuracy of an emissions model highly depends on its ability to capture fluctuations in the speed. Thus, methods for emissions estimation incorporating fluctuations in speed have been developed.

Assessment of the ultimate impact of vehicle emissions on population health requires analysis of pollutant dispersion and population exposure. Dispersion modeling is the application of mathematical formulations that assess atmospheric conditions and describe processes that explain plume movement to estimate pollutant concentrations at receptor locations. This paper uses an integrated modeling system for the analysis of microscopic vehicle movements, emissions, emission dispersion, population location, and population exposure for the Toronto Waterfront Area and applies the system to a set of scenarios related to the conversion of medium duty trucks to low emission vehicles.

2. Integrated modeling system

Figure 1 summarizes the integrated modeling system including regional travel demand models for the Greater Toronto and Hamilton Area (GTHA), a microscopic traffic simulation model of the

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Toronto Waterfront Area, a model of vehicle emissions that is sensitive to vehicle driving cycles, a model of pollutant dispersion, and an assessment of population location by time of day for estimating personal exposure to vehicle generated emissions.

Figure 1 Integrated modeling system for estimating population exposure to emissions

Travel demand was estimated using a multi-step process, shown in Figure 2, and was used as input for the microscopic traffic simulation model. Preliminary demand inputs were generated using a multiclass generalized cost static user equilibrium assignment (in the EMME modeling software) for the GTHA for light, medium and heavy trucks and passenger cars (Roorda et al., 2010).

The methodological steps outside the dotted line are those that were specifically applied for the Toronto Waterfront Area (Figure 2). In summary, a set of traversal matrices (the “seed” OD matrices) were extracted from the GTHA EMME model, these traversal matrices were assigned on a subarea network for the Toronto Waterfront, and were subsequently updated using the gradient method (Spiess, 1990) to better reflect road counts (classified by vehicle type) at a set of screenlines within the Toronto Waterfront Area. The results of this step are four O-D matrices representing travel demand in the Toronto Waterfront Area for passenger cars, light, medium and heavy-duty trucks for the year 2009.

The second component is a microscopic traffic simulation model that explicitly represents the acceleration and deceleration patterns of vehicles in congestion, which are essential for the estimation of vehicle emissions. The software selected for this modeling step is Paramics (Quadstone Paramics Ltd., ). The Toronto Waterfront network was available from a previous project conducted for the Toronto Waterfront Revitalization Corporation (Abdulhai et al., 2002). This model had been calibrated for 2001 traffic conditions and vehicle demand, therefore, significant additional calibration was required to update the model for 2009 traffic conditions.

Details of the development of O-D matrices can be found in Roorda et al. (2011).
A two-step calibration/validation procedure was used for the morning peak hour. First, adjustments were made to the model parameters, demand matrices and the road network so that model results reflected available intersection and highway vehicle counts. Second, speed information from loop detectors and global positioning system probe vehicles were used to validate the calibrated network. The calibrated parameters for the am peak (8:00 to 9:00 am) were: a headway of 1.85 seconds, reaction time of 0.65 seconds, two time-steps per second, a feedback period of two minutes, 90% familiarity in the drivers in the network, 5% perturbation and a distance cost coefficient of zero.

For model validation, global positioning system data for medium and heavy-duty trucks were made available by Turnpike Global Technologies (TGT) for three months in 2009. Ontario’s Ministry of Transportation (MTO) (2009) provided probe vehicle speed data from their travel time survey which were used as an additional source of data for model validation. For 70% of the roadway segments, the null hypothesis that the observed and simulated mean travel speeds are equal could not be rejected at a 95% confidence level. This provides a reasonable calibration result for traffic volumes and for vehicle speeds.

CMEM was selected as the emissions simulation model for this project. CMEM is microscopic in that it predicts second-by-second tailpipe emissions and fuel consumption based on modal operations of the vehicles in the fleet. In CMEM, the fuel consumption and emissions process is broken down into components based on the physical phenomena associated with vehicle operation.

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74 Details of this calibration can be found in Amirjamshidi and Roorda (2011).
and emissions production. Each of these components is modeled separately with an analytical representation involving parameters that vary according to the vehicle type, engine, emission technology, and level of deterioration (University of California, 2009).

The required inputs for CMEM include vehicle activity (second-by-second speed profile) and fleet composition of traffic. The most recent version of CMEM, used in this project, has 28 light duty vehicle/technology categories and three heavy-duty vehicle/technology categories. These vehicle classifications are more detailed than the passenger car, light-duty truck, medium-duty truck and heavy-duty truck classifications that are the features of the travel demand models. Passenger vehicles are classified into CMEM categories based on model year, odometer mileage, power-to-weight ratio, technology (e.g. carbureted engine, low emission vehicle), and presence of engine problems that result in high emission. Light duty trucks are distinguished based on model year, vehicle weight, power-to-weight ratio, and presence of engine problems that result in high emission. Medium duty trucks are distinguished according to the fuel used (gasoline versus diesel). Finally, heavy-duty diesel trucks are distinguished according to vehicle age.

Average annual odometer mileage (16,000 km) and the vehicle age distribution were obtained from the 2009 Canadian Vehicle Survey (Statistics Canada, 2010). The distribution of vehicle power-to-weight ratio was determined based on the sales information of the most popular passenger cars sold in Canada for 2009, leading to an average distribution of 20% low and 80% high power to weight ratio. 0% carbureted engines and 0.29% ultra-low emission vehicles were assumed based on personal communication with experts from the DesRosiers Automotive Consultants Inc. The proportion of vehicles with engine problems was based on CMEM default values, since no Canada-specific information was found. Based on information available from the Canadian Vehicle Survey (Statistics Canada, 2010), 13% of medium duty trucks were assigned to be gasoline powered and 87% to be diesel powered. Heavy-duty trucks were divided into three CMEM vehicle categories based on the vehicle’s age. A Monte Carlo simulation was used to assign a vehicle type to individual vehicles in the network.

The fourth component of the integrated modeling suite assesses how vehicle emissions are dispersed in the air to result in human exposure to these emissions. Most air dispersion models used for regulatory purposes are based on the Gaussian model (Holmes and Morawska, 2006), including the US Environmental Protection Agency (2011) preferred regulatory models for both near-field and long-range applications. Based on the level of complexity and size of the study network, a Gaussian plume model was selected for this project because of its simplicity, reasonable data requirements and computational performance.

Pollutant concentrations are described using a Gaussian distribution curve in both the vertical and the cross-wind directions. Plume rise (the height of the plume above the point of emission) was assumed to be zero and the receptor height was fixed at the breathing height of an average individual. The net pollutant concentration at any given receptor location due to a point source is a function of the downwind movement of the plume as well as the cross-wind and vertical plume distributions.

The AERMET meteorological model (Lakes Environmental, 2011) was used to obtain wind rose patterns for a period from September 2009 to December 2009 for the morning peak period. The
The predominant wind direction was estimated to be from west to east with an average speed of 3.25 m/s. The dispersion model was coded in a geographic information system incorporating the pollution emissions resulting from the CMEM model.

The final component of the system estimates population location by time of day for assessing personal exposure to vehicle generated emissions. By comparing pollutant concentrations and population density in a zone, potential population exposure can be estimated. A zone-based time-varying population density distribution is developed for this purpose.

Data from the 2006 Transportation Tomorrow Survey (TTS) (DMG, 2008) and EMME3 modeled travel times were used for the analysis. The TTS is a household travel survey that collects trip origins, destinations and start times over 24 hours for a sample of approximately 5% of the population in the Greater Toronto and Hamilton Area (GTHA).

Initially, travel times were estimated for modes (automobile, transit, walking and bicycling) for all possible origin to destination (O-D) pairs. Auto travel times (including motorcycles, taxis, school buses) were computed using the EMME3 transportation planning software, in which the GTHA road network was loaded with hourly trip matrices developed from the 2006 TTS. Transit travel times were available from previous projects. Bicycle and walk travel times were assumed, based on a Manhattan grid distance and an average walking/cycling speed. Auto travel times were assumed to represent travel times experienced by motorcycles, taxis, school buses, and all ‘other’ miscellaneous modes.

Secondly, trip arrival times are also required to determine a person’s location by time of day. The travel time matrices generated for the modes in the first step were integrated with the TTS observed start times to obtain trip arrival times for all surveyed trips.

Population distribution by time of day was then determined. Figure 3 shows the population density distribution for the 8:30 am analysis period. At this time, many people are either en route to or have arrived at their workplace. As expected, this results in a high population density in the Central Business Districts of Toronto, Mississauga, Hamilton, and the downtown Whitby-Oshawa area.
3. **Base case results**

The CMEM emissions model is used to calculate CO$_2$, CO, HC and NOx emissions, and fuel consumption for each roadway link. As an example, Figure 4 shows the NOx emissions (grams per kilometer) for the am peak hour. Several observations can be made. First, emissions are highest on the high capacity roadways, including the Gardiner Expressway, Don Valley Parkway, Lakeshore Blvd, and University Avenue. Second, vehicle emissions tend to be higher in the inbound direction in the am peak hour. This is because there are a greater number of vehicles traveling inbound at that time of day.

Microscopic traffic simulation provides a more detailed representation of emissions output compared to standard emission factor models that use the average speed. In the emissions factor models; emission factors do not vary from link to link. However, the use of the microscopic traffic/emission model showed significant differences in NOx and other pollutant emissions factors in parts of the network.

Emission outputs for other pollutants were also calculated (Roorda et al. 2011). Notable patterns are:

- NOx emission factors are higher in the Portlands Area, an industrial district on the waterfront to the east of Downtown, where truck traffic is a greater proportion of traffic flow. Since diesel fuelled vehicles contribute a disproportionate share of NOx emissions, this result is intuitive.
- For emission factors, fuel rate is most highly correlated with CO$_2$ and HC emission factors. This makes sense because CO$_2$ is a normal by product of fuel consumption, and HC is simply unburned fuel.
- CO emission factors follow a somewhat different pattern than other pollutants and tend to be higher on a smaller number of heavily traveled routes.
A Gaussian plume model was coded in a geographic information system incorporating the pollution emission rates resulting from the CMEM model. The results of this model are am peak hour CO, NOx, and HC pollution concentrations (gm/m³) for the waterfront area calculated at zone centroids. CO₂ concentrations are neglected in the analysis because CO₂ is not considered a criteria pollutant, even though the emitted CO₂ is obviously important because of its role as a greenhouse gas. The top element of Figure 5 shows the model results of NOx pollution concentration, as an example. Similar graphs were developed for CO, and HC. The top element of Figure 5 shows that:

- In the am peak hour, NOx pollutant concentrations (from vehicle sources) at all zone centroids are less than 0.03 mg/m³. By comparison, Environment Canada (n.d.) mandates the standard for NO₂ pollution concentration to be less than 0.4 mg/m³.
- Zones along the Gardiner Expressway/Lakeshore Blvd/Don Valley Parkway corridor are experiencing relatively high pollution concentrations, mainly because these roadways are the largest sources of vehicle emissions.
- Zones in residential areas tend to experience lower NOx concentration, whereas zones in the central core of the city (between Bathurst Street and Parliament Street) experience higher concentration.
The wind direction is west to east, which leads NOx emissions generated in downtown Toronto and on the Don Valley Parkway/Gardiner Expressway to disperse in an eastward
direction. In addition, the high pollutant concentration just east of the downtown core confirms this dispersion pattern.

- Boundary zones exhibit low pollutant concentration, but it is important to view boundary zone concentrations with caution, since pollutants from roads outside the study area are not included in these estimates.

A caveat to this analysis is that pollutant concentration at zone centroids is generally lower than what would be expected at the roadside. Pollutant concentrations dilute rapidly at distances of five to ten meters from the source. Thus, it is expected that people walking on sidewalks, waiting for a bus, cycling or using the street in other ways would experience higher levels of pollutant concentration.

Population exposure to emissions was estimated simply as a multiplication of the population located in each zone and the pollutant concentration at the zone centroid. The lower element of Figure 5 shows the outcome of this multiplication for the am peak hour for NOx emissions. The figure shows a rather different pattern from the distribution of pollutant concentrations shown in the upper element. That is because the zones in the central business district, which have moderate/high relative NOx pollutant concentrations (as shown in the top element of Figure 5), have also very high population during the am peak hour (shown in Figure 3). Notable levels of exposure are also found in the Parkdale neighborhood (located in the vicinity of the Dufferin Street and King Street intersection) and the Central Waterfront Area, as population density is relatively high and greater pollution concentrations are generated from the Gardiner Expressway/Lakeshore Blvd corridor. Other locations along the Gardiner Expressway/DVP do not result in the same high levels of population exposure to NOx because of the lower adjacent population densities.

4. Sensitivity analysis

Sensitivity of the integrated modeling system was tested by evaluating scenarios that reflect investment toward the conversion of medium duty trucks to ultra-low emission vehicles (ULEV). The following three scenarios were tested:

- Scenario A: Convert 100% of gasoline medium duty trucks to ultra-low emission vehicles
- Scenario B: Convert 100% of diesel medium duty trucks to ultra-low emission vehicles
- Scenario C: Convert 100% of gasoline and diesel medium duty trucks to ultra-low emission vehicles.

This set of scenarios reflects the maximum achievable reduction given readily available engine technologies, and assuming full participation of all companies whose medium duty trucks access the Toronto Waterfront Area. In the am peak hour, medium duty trucks comprise approximately 2.5% of all vehicles traveling in the Toronto Waterfront Area. Nearly 6% of these medium duty trucks are diesel fuelled, and 13% are gasoline powered (Statistics Canada, 2010).

The network emission reductions that result from these vehicle technology conversions are shown in Figure 6. The following can be seen:
• Fuel consumption and CO$_2$ emissions are reduced by approximately 1% for Scenario C. Given that approximately 2.5% of vehicles are medium duty trucks; this reflects a reduction of approximately 40% in fuel consumption and CO$_2$ emissions for medium duty trucks.

• A slight increase in CO emissions is observed for Scenarios B and C. This occurs because gasoline powered vehicles emit the majority of CO. Thus, the conversion of diesel powered medium duty trucks to ultra-low emission vehicles, which are gasoline powered, results in a slight increase in CO.

• HC emissions are reduced by over 4%, and all of this reduction is a result of the conversion of diesel powered trucks. Notably, HC emissions are over-represented in diesel powered vehicles.

• NOx emissions are reduced by 12% and almost all of this reduction is due to the conversion of diesel powered trucks. This major reduction is expected because NOx is a by-product of diesel fuel combustion.

Figure 6 Network emissions reductions

Emission reductions at the source lead to reduced pollution concentrations at receptor points, after pollutant dispersion is accounted for. Figure 7 shows the reduction in NOx pollution concentration in each zone for each of the three scenarios. Clearly, the reductions are small overall for all zones for Scenario A, which is consistent with the small NOx reduction shown in Figure 6. NOx concentration reductions are larger for Scenarios B and C across most zones, because both of these scenarios reflect a conversion of diesel vehicles, which are the primary emitters of NOx. The largest concentration reduction is predicted to occur in the zones along the Gardiner Expressway, the Don Valley Parkway and in the downtown core of the city.
5. Conclusions

Within the Toronto Waterfront Area, emissions of HC, CO, CO$_2$ and NOx are highest on the high capacity roadways, including the Gardiner Expressway, Lakeshore Blvd, and University Avenue, and are higher in the peak directions. Emission factors (emissions/vehicle kilometer traveled) were found to vary over each roadway segment in the network because of the unique speed acceleration profile and traffic composition on each roadway. This justifies the use of a microscopic simulation of emissions rather than an emission factor model, if localized air pollution is of interest.

The outcome of the dispersion model is that CO, NOx and HC vehicle emissions lead to pollutant concentrations at zone centroids that are within recommended levels on a day with typical wind direction and average wind speed. Zones along the Gardiner Expressway, Lakeshore Blvd, and the Don Valley Parkway experience higher pollutant concentrations than other zones, because these roadways are the largest sources of vehicle emissions.

Analysis of population location determined that the greatest daytime populations in the GTHA are within the central core of Toronto. It is assumed that people within a zone are potentially experiencing pollution that is measured at zone centroids. Under this assumption, the areas of greatest concern are those very densely populated zones in the Central Business District of Toronto and the Central Waterfront, and densely populated areas near the major highways (such as the Parkdale neighborhood). In these zones, both emissions and population are high during peak hours of travel, resulting in higher potential exposure to vehicle emissions.
Finally, a sensitivity analysis indicates that NOx and HC emissions are reduced significantly when diesel powered medium duty trucks are converted to ultra-low emission vehicles. In the am peak hour, for example, a 100% conversion of diesel powered medium duty trucks (which represents 2.2% of vehicles in the am peak hour) is estimated to reduce HC and NOx emissions by 4% and almost 12%.

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References


