MODELING THE TRAFFIC RELATED POLLUTION REDUCTION THROUGH INCREASED USE OF HYBRID-ELECTRIC VEHICLES (HEVs) IN HAMILTON, ONTARIO, CANADA

MODELING OF REDUCTION IN THE TRAFFIC RELATED POLLUTION EMISSION THROUGH INCREASED USE OF HYBRID-ELECTRIC VEHICLES (HEVs) IN HAMILTON, ONTARIO, CANADA

By

NAOYA KANEDA, B.Sc. B.A

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AUTHOR: Naoya Kaneda

SUPERVISOR: Pavlos S. Kanaroglou

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ABSTRACT

In this study, the effect of HEVs on traffic related pollution was assessed in the Hamilton CMA. This thesis aimed to combine findings from these two fields in a traffic simulation procedure. By introducing the HEVs in incremental levels to the vehicle travel pattern of more than 700,000 people in the study area, changes occurring in traffic related pollution at different levels were modeled.

The hypothetical HEV spatial distribution patterns models were derived through negative binomial regression modeling based on 2006 census data and 2008 vehicle registration data. The distribution of predetermined number of HEVs throughout the Hamilton CMA was completed through these models and results were used to modify input OD matrices for the TRAFFIC program. The link-based emissions were calculated in combination with traffic emission factors for HEV.

The results indicated that converting 10% of the total fleet into HEVs was needed to make significant reductions to the HC and CO aggregate emissions in all five models. An important finding with the incremental HEV penetration levels was the approximately linear trend between the percent reduction in the traffic emissions and the percent of HEVs in the total fleet. This trend allows calculations of approximate traffic emission reduction expected with any HEV level. The results illustrating links with more than 10% reduction in traffic emissions indicated that HEV technology as an effective method in dealing with environmental concerns.

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1 Introduction

Motorized transportation (cars, SUVs, vans, trucks, and airplanes) use approximately 19% of the world's total energy supplies, of which over 95% is from petroleum (Romm, 2005; Carpenter et al., 2008). In 2005, there were over 865 million motorized land transportation vehicles registered in the world. Most of these vehicles were in developed countries and some parts of Asia, the Middle East, Central and South America; areas with a collective population of approximately two billion people (Romm, 2005; Carpenter et al., 2008). In the United States, 570 billion litres of petroleum were used for transportation in 2005 and is projected to reach 1 trillion litres by 2050. With 5% of the world's population, the massive consumption of petroleum in the United States accounts for 25% of the world's total greenhouse gas emissions. (Kromer and Heywood, 2007)

There are many different ways of reducing greenhouse gas (GHG) emissions and/or consumption of fuel. The three general approaches in transportation are: to adopt advanced vehicle technologies, to reduce vehicle kilometres traveled, and to switch to low GHG fuels (Chiumiento et al., 2008). Some of these require changes in manufacturing such as reducing the weight of cars, improving the thermal efficiency of the engines with new materials, reduction of tire rolling resistance, and hybridization; while others require changes in travel behaviour such as carpooling, using public transit, and biking or walking (Carpenter et al. 2008).

With the increase of oil prices in the mid-2000's, the production of more fuel efficient vehicles to reduce CO_2 emissions, thereby improving air quality, has become one of the top priorities for auto manufacturers and policy makers (Fontaras et al., 2008). It is no longer news to hear about the environmental concerns in the policies of major automobile companies. Development of Alternative Fuel Vehicles (AFVs) has been one of the most debated topics in this sector. While there are a few available options in terms of fuel types, gasoline and diesel powered vehicles have dominated the market and alternative fuels consumed in AFVs substitute a small fraction of total gasoline consumption (Romm, 2006). An announcement made by the Ontario Premier in July of 2009, included $4,000 to $10,000 subsidy incentives for plug-in hybrid and battery electric vehicles purchased after July 1, 2010 aimed to show support towards the transition to cleaner vehicle technologies (OPO, 2009).

While research and development for AFVs and to improve the performance of conventional vehicles is ongoing, there have been some concerns noted relating to its effects. One of these concerns is the "rebound" or "take-back" effect. The rebound effect has its root in neoclassical economic theory and refers to the phenomenon where the cost of the processing decreases as the energy service supply improves, thereby the incentive for use increases (Greening et al., 2000; Small and Van Dender, 2007). In terms of transportation, increased fuel efficiency and decreased cost per unit distance of travel, may lead to an increase in total distance travelled possibly resulting in higher congestion and traffic emissions. To add to the rebound effect, there are studies suggesting that humans have an intrinsic drive for mobility, where one will choose to travel even when the opportunity to engage in the same activity is available at shorter distances (Salomon and Mokhtarian, 1998). If travel is desired by drivers, then the effort to produce more fuel efficient vehicles can be offset by both the rebound effect and the "drive to drive". It has been hypothesized that with newer vehicles becoming more and more fuel efficient with gasoline, diesel, or HEV technologies, those who purchase these new vehicles are also likely to travel more frequently and for longer distances (Roorda et al., 2000). While the short distance travel capacity in some AFVs may help cut-back on these rebound effects, the appeals for these new technologies are the fusion of the environmental friendliness and the availability of the current travel behaviour.

While there are a few different types of AFVs available, both from the major manufacturers and the smaller privately owned companies, the focus in this study will be on the Hybrid-Electric Vehicles (HEVs). Since their introduction, HEVs have reached technological maturity in the last 10 years and have successfully penetrated the market. There were over 30 models from different manufacturers available in the market at the end of 2008; more than 350,000 and 300,000 HEVs have been sold in 2007 and 2008, respectively, in the United States alone (Alessandrini et al., 2009; Walsh, 2009). HEVs can be divided into three types depending on the level of hybridization, each producing different level of fuel efficiency and power output: full hybrids (e.g. Toyota Prius), power assist or mild hybrids (e.g. Honda Civic Hybrid), and plug-in hybrids (e.g. Prius+) (Chiumiento et al., 2008). HEVs combine a conventional gasoline combustion engine with an electric motor powered by battery, each being utilized to create the most efficient operational modes: engine for high-speed and motor for low-speed. This has increased the fuel efficiency of vehicles considerably compared to gasoline vehicles of equivalent size, despite a weight increase incurred by the addition of an electric motor and battery

(Diamond, 2009). Since a HEV utilizes its gasoline engine at high-speed driving, it was suggested that clean diesel vehicles are more suitable in less-urbanized environments with higher travel speeds since diesel vehicles are more fuel efficient than gasoline vehicles (ACEA, 2007).

The objective of this study was to investigate the contribution on reduction of traffic related pollution with increased used of HEVs in the Hamilton Census Metropolitan Area (CMA). While there are many studies published in the topic of HEVs and other AFVs, many of these have focused on either the market penetration or the performance improvement. This thesis attempted to fill the gap left from separating the two areas by combining the estimated market penetration and performance data of HEVs with components of Integrated Urban Models (IUMs) in the Hamilton CMA. This study has its root in one of the projects completed for Environment Canada by the Centre for Spatial Analysis (CSpA) at McMaster University, Hamilton, Ontario. The original projects were designed to apply IUM to a number of major cities throughout Canada, designated by Environment Canada, to assess the effect of projected population and employment growth in each city has on its traffic emissions. By introducing the HEVs in incremental levels to the vehicle travel pattern of more than 700,000 people in the study area, the effectiveness of HEVs in reduction of overall traffic related pollution was modeled as well as the spatial variations of the emissions. This study also includes a possible scenario with Electric Vehicles (EVs) in place of HEVs. In the following chapters, the report is presented in order of literature review, data and methodology, results, discussion, and conclusion.

2 Literature Review

Research in traffic involving alternative fuel vehicles can be divided into market penetration and vehicle performance. Market penetration includes survey studies and mathematical modeling of consumer choices, whereas vehicle performance includes the analysis on the level of emission produced by each type of vehicle in different driving cycles involving varying degree of modes (acceleration, deceleration, cruise, and idle). It extends from the series of research conducted to verify the driving cycles used to estimate the emission levels of vehicles. In the following two sections, an evaluation of the research found in these two categories are reviewed, followed by a discussion of the traffic modeling which thus far have not included alternative vehicles.

2.1 Analysis of the Market Penetration of AFVs

So far, AFVs have struggled in the market for several reasons including higher price, higher fueling cost, safety and liability concerns, limited availability of fueling stations, limited range, and improvements in gasoline and diesel vehicles (Romm, 2006). To help aid the infiltration of AFVs into the market, many government bodies in North America are now promoting the purchase of AFVs through tax-rebate or monetary incentives, and this is having a positive effect in the purchase rates of HEVs (Diamond, 2009; OPO, 2009). While there are some drawbacks, it is a positive movement that governments at all levels are leading the shift towards new and more environmentally friendly vehicle choices. The city of Hamilton has produced the Green Fleet Implementation Plan and has been pursuing a path to be the leader in “Green Fleet” implementation. By the end of 2008, the city of Hamilton owned 174 vehicles considered to be “green” and by April 2009, this number has grown to 364, or 23%, out of the 1569 vehicles used by the central fleet, the transit, the police, the fire and the emergency services. These “green” vehicles included HEVs, natural gas vans/pickups, natural gas buses, diesel-electric hybrid buses, biodiesel vehicles, vehicles with added modifications, and non-road vehicles. (Hamilton Central Fleet, 2009)

While the initiatives by the policy makers to introduce the monetary incentives for AFV purchases are good, there are some drawbacks. First, the incentives to purchase new AFVs can cause buyers to sell their current vehicles and reintroduce them back into the used-car market at a lower price. This causes an increase in the total vehicle count while increasing AFV sales and keeps the share of AFVs low (Struben and Sterman, 2008). Second, the incentive program has to be installed long enough for AFV diffusion to become self-sustaining since the failure could lead to repulsion of new technologies by the consumers (Struben and Sterman, 2008; Flynn, 2002; Moore et al, 1998).

To understand what factors influence the sales share changes of AFVs from the buyers’ point of view involves an analysis of market penetration. The analysis of a market penetration involves determining who buys what and why people choose to buy. Most study on market penetration involves survey method to find the characteristics of people and/or an item of interest, which in the case related to this study, is the AFVs or more specifically the HEVs. The choice to purchase any of AFVs available comes as a part of the vehicle purchase process. A consumer must decide to purchase a vehicle before considering the option of an AFV. Studies dealing with car ownership in terms of number of vehicles as well as studies involving AFV's potentials market penetration were reviewed.

There are many automobile ownership models developed in the past to investigate the number of vehicles owned by household members. These automobile ownership models were often developed as part of the trip production models, mode-choice models, and travel demand models (Chu 2002). Of the two methods of auto ownership forecasts, aggregate and disaggregate models, the disaggregate models have become the preferred approach due to its more behavioural nature compared to aggregate models (Bhat and Pulugurta, 1998; Chu, 2002). This is partly due to the aggregate models using zonal, regional, or national level data while the disaggregate models use the household as the Decision Making Unit (DMU), which can capture the casual relationship between auto ownership determinants and automobile ownership levels (Bhat and Pulugurta, 1998).

In order to collect data at disaggregate level, many studies use household surveys. Households are used as the DMU over individuals because allocation of daily activities and its supporting resources are allocated at the household level (Chu, 2002). The previous studies show the household income or variables that were related to income levels such as housing type or tenure as significant factors in estimating the number of vehicles owned by a household (Bhat and Pulugurta, 1998; Chu 2002; Hess and Ong 2002; Potoglou and Kanaroglou 2008). Increased income was also found to be an indicator of increased probability of replacement or purchase of vehicles while an increase in the number of vehicles owned suggested greater probability of disposing or replacement (Roorda et al., 2000). Exposure to alternative technologies has been shown to increase the probability of considering AFV as an option for the next vehicle to purchase (Struben and Sterman, 2008). On the other hand, a factor that was found to reduce the number of vehicles owned was the mixed land use type around the locations of surveyed households. This was likely due to greater attractiveness of alternative travel methods compared to the cost of owning vehicles (Chu 2002; Hess and Ong 2002; Potoglou and Kanaroglou 2008).

The modern economics and settlement pattern have evolved around the automobile, internal combustion, and petroleum. This makes the successful introduction of AFVs being more difficult and complex than other products. With the current large installation of vehicles with the internal combustion engine (ICE) and the long life of vehicles, the share of AFVs in the installed base will increase slowly even if AFVs have a large share of new vehicle sales (Struben and Sterman, 2008). It has been showed that the improvement in performance and suitable infrastructure for refueling and maintenance equivalent to that of ICE is required for AFVs to be competitive in the market (Ewing and Sarigollu, 1998; Ewing and Sarigollu, 2000; Dagsvik et al., 2002; Potoglou and Kanaroglou, 2007; Diamond, 2009). The research and development by the manufacturers have also refined conventional ICE vehicles to create a powerful, highly reliable, low emission, and high fuel economy vehicle such as Toyota Corolla (Lave and MacLean, 2002). It has been predicted that for Toyota Prius (HEV) to be more attractive to consumers than Toyota Corolla (ICE), the gasoline price must be above $2.50/gal in 2002 dollar value (Lave and MacLean, 2002). Other than HEV, most AFV do not have the performance seen in ICE such as range, acceleration, and recharging or refueling time.

The importance of reducing traffic related pollution and positive attitudes do exist, however, the required change in behaviour required in using AFVs is another story. A consumer analysis on those who have purchased and currently own HEV revealed that the gasoline price fluctuations have significant impacts on HEV sales. It is evident that the higher percent of owners having household income higher than $100,000, as well as consumers have strong tendency to buy a HEV in the same vehicle class as previously owned (Gallon, 2009). This consumer survey result can provide insights for studies mentioned previously. First, despite policies such as increasing gasoline price, shortening travel time, free parking was shown to have very little effect on attractiveness of AFVs, the market reaction told a completely different story where increased gasoline price led to increased HEV sales (Ewing and Sarigollu, 1998; Ewing and Sarigollu, 2000; Dagsvik et al., 2002; Potoglou and Kanaroglou, 2007; Diamond, 2009; Gallon, 2009). Secondly, disposable income of the household must be able to afford the higher price tag placed on most AFVs. Lastly, the preference for the same vehicle size as previously owned supports the theory that AFVs must match or out-perform ICE to provide least amount of behavioural alterations.

2.2 Analysis of the Performances of AFVs

The major selling point for all AFVs is the environmental friendliness. This can be seen as it is often used as one of the vehicle attributes in survey studies. Being an environmentally friendly vehicle can be accomplished with reductions in input and output of a vehicle compared to conventional ICE vehicles. These reductions of input and output are accomplished by: improving fuel efficiency to decrease petroleum consumption and lowers the tailpipe emissions. Although the fuel efficiency is the most readily available measure of clean vehicles to consumers, the measurements of tailpipe emissions are the focus in many studies related to AFV performance to compare the effectiveness of different AFVs.

The measurements of tailpipe emissions take place with the test vehicles either on a chassis dynamometer or on actual roads. Studies with the chassis dynamometer intends to measure emissions with predetermined driving cycles and therefore standardizing vehicle operation. With vehicles on the road, studies aim to determine the emission levels during the daily driving conditions. Measurements taken by portable emission measurement system (PEMS) are becoming more popular in collection of second-to-second tailpipe emissions (Yu et al., 2008; Frey et al., 2008). These microscopic measurements of emission were taken to create new driving cycle models, investigate different road conditions that effects emission, and variation in emission patterns from multiple drivers (Yu et al., 2008; Frey et al., 2008; Alessandrini et al., 2009).

Some studies revealed results that may not favour AFVs. Durbin et al, (1998) tested Compressed Natural Gas (CNG) vehicles and 85% methanol/15% gasoline (M85) fueled vehicles against conventional gasoline. CNG vehicles produced lower non-methane hydrocarbon (NMHC) and carbon monoxide (CO) with oxides of nitrogen (NO_x) emission comparable to gasoline. M85 produced lower NO_x and higher CO in one driving cycle but lower NO_x, CO, NMHC and total hydrocarbons (THC) in another driving cycle compared to gasoline (Durbin et al., 1998). Graham et al. (2008) tested the different levels of gasoline-ethanol blends available today, to find that use of E10 (10% ethanol content) fuel was effective in reducing CO emissions while showing no change in NO_x, CO_2, CH_4, N2O, or formaldehyde emissions compared to 100% gasoline fuel. The use of E85 showed reduction in NOx, NMHC, 1,3-butadiene, and benzene while showing no change for CO, CO_2, and NMOG emissions. For both fuel types, significant increases in some pollutants were observed. These results show that alternative fuels have some benefits over gasoline and where it falls short. This duality could be traced back to the fundamental design of ICE. The amount of fuel used to propel the vehicle may not differ significantly between gasoline, M85, E10, and E85 fuels. In other words, reducing the time ICE is used to propel the vehicle can reduce the amount of tailpipe emissions.

HEV drive train combines benefits of two propulsion sources: quick acceleration from electric motors and supreme performance of ICE at constant speeds (Emadi et al., 2005). In conventional ICE, only 10-15% of energy contained in gasoline is converted to traction to propel the vehicle, while rest is lost as heat. In an HEV, the drive train efficiency could be improved to 30-40%, which reduces the emissions and increases fuel economy (Emadi et al., 2005). Frontaras et al. (2008) concluded that fuel consumption by HEVs is 40-60% lower than the average conventional gasoline vehicle in urban situations. Although HEVs may be more fuel efficient, that does not mean their engines are cleaner than conventional engines. There are reports indicating that emission levels from HEVs are comparable to those in the same class at higher vehicle speeds (Alessandrini et al., 2009; Frontaras et al., 2008; An and Sauer, 2004).

In the test to compare gasoline ICE vehicle to HEV driven by multiple drivers, Alessandrini et al. (2009) found that HEV always performs better, up to 90% reduction in

CO and up to 30% reduction in CO_2, with wide variations in measurements from driving behaviours. They concluded that women are less aggressive and steadier on the accelerator pedal than men, leading to reduced consumption and emission. The relationship between acceleration, vehicle speed, and emission has been found in previous studies where high emissions events coinciding with periods of high acceleration and speed (Frey et al., 2006; Yu et al., 2008). During acceleration, the emissions of HC and CO_2 are five times greater than during idle and 10 times greater for NO_x and CO (Frey et al., 2003). These are indication that reducing the incidents of sudden acceleration and idle length is an effective way to use ICE. Manzie et al. (2007) achieved fuel efficiency that was equivalent to HEVs through used of the intelligent vehicles with ICE and capacity to process traffic flow information ahead to aid or to replace the driver.

In a study comparing different type of urban growth, change in vehicle miles travelled (VMT), and vehicle fleet hybridization in 11 different metropolitan regions, Stone et al. (2009) found that full dissemination of HEVs in business-as-usual (BAU) development can offset the projected CO_2 growth. The implementation of smart growth scenarios, the total population is the same as BAU but growth occurs more in urban and suburban areas than rural areas, can reduce the CO2 emission by reducing VMT. The smart growth scenarios coupled with HEV fleet can counteract the CO2 emission growth due to BAU development from 2000 to 2050 and reduce it to below the level of 2000 (Stone et al., 2009). Frey et al. (2009) also estimated the regional emission change through use of AFVs. In this case, they have developed correction factors with data collected through PEMS to adjust the emissions of conventional vehicles to different types of AFVs. The simulated market penetration of AFVs and VMT growth from 2005 to 2030 contrasted how the magnitude of AFV use can influence the regional emission. The NOx and CO2 emissions were not significantly different between conventional ICE only to 27% AFV scenario in the baseline year of 2005. Comparing the two years of 2005 and 2030, the reductions in all estimated emissions were significantly (58% or more) lower for 2030 with or without AFV. Frey et al. (2009) explains this to be due to the turnover of fleet to more fuel efficient vehicles. The concept of estimating regional change in tailpipe emission through vehicle fleet hybridization seen in both of these studies was the hints for this study.

3 Data and Methodology

In this section, three major parts of the research are explained: study area, data used, and the methodology in estimating the current and future traffic emissions. The major backbone of this thesis project was created for a series of previous projects aimed to estimate traffic emissions in several major Canadian cities at the Centre for Spatial Analysis (CSpA), McMaster University, carried out between spring of 2009 and fall of 2010. The detailed explanations of data used and the software components created are available in the Environment Canada project report (CSpA, 2009) and will not be discussed here. This section gives an overview of the study area followed by new data used and methods specifically designed for this thesis project.

3.1 Study Area

The study area for this thesis was the Hamilton CMA, Ontario. The Hamilton CMA includes the cities of Hamilton and Burlington and the town of Grimsby (Figure 3.1). However, the traffic simulation model produced prior to this study and used here only included the cities of Hamilton and Burlington. The “Hamilton CMA” points to the area including only the two cities of Hamilton and Burlington from here on in this thesis report unless noted otherwise.

The Hamilton CMA, located at the southwestern tip of Lake Ontario, has a population of approximately 700,000 including the town of Grimsby (505,000 in Hamilton and 165,000 in Burlington) as of 2006 (Statistics Canada, 2010). Each city of Hamilton and Burlington belongs to different Regional Municipalities and therefore has separate growth projections. The population of the city of Hamilton is projected to grow to 540,000 by 2011 and 590,000 by 2021 while the city of Burlington is estimated to grow to 184,500 by 2021 (MPIR, 2006; Halton Region, 2006). Hamilton is an industrial city with two major steel companies located on the harbor along with other heavy and light industries located throughout the city. The street network in the Hamilton CMA includes the provincial highways (Queen Elizabeth Way (QEW), Hwy 401, Hwy 403, and Hwy 407), the municipal highways (Lincoln M. Alexander Parkway, and Red Hill Valley Parkway), and the local arterial network. These major highways link together Toronto, Hamilton, London, the United States, and other local communities.

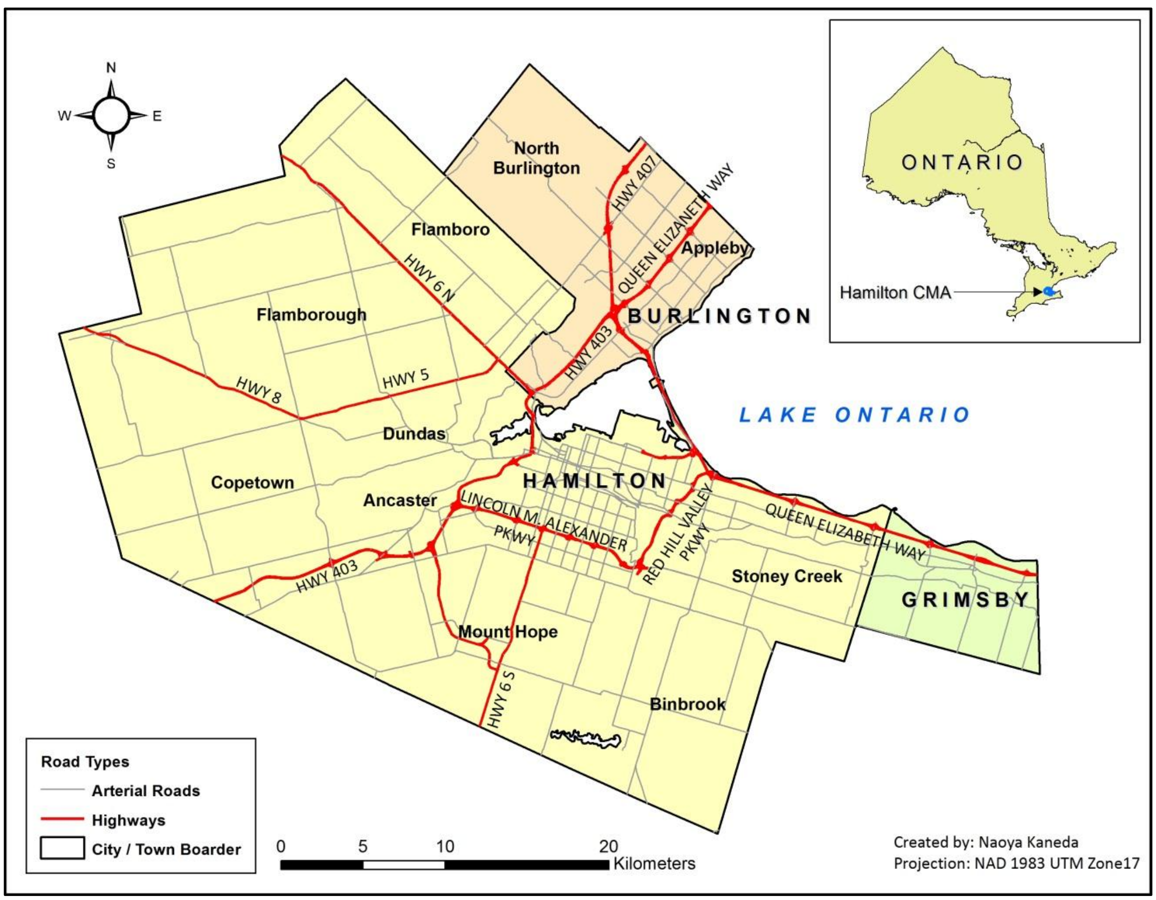


Figure 3.1: The Hamilton CMA including Hamilton, Burlington, and Grimsby

Despite the availability of public transportation, residents of the Hamilton CMA are heavily dependent on personal transportation, as with many Canadians. The 2001 Transportation Tomorrow Survey indicated that 68% of Hamilton residents use personal transportation (TTS, 2001). The census of 2006 also showed 76% of the employed population in Hamilton commutes using personal transportation on a daily basis (Statistics Canada, 2008). These figures show the intensity with which the road network in the Hamilton CMA is being used and the potential for improvement in terms of traffic emissions through the introduction of environmentally friendly vehicles.

3.2 Data

This section provides the description of two sets of data introduced for this study: the vehicle registration data and the census data. These two data sets were used for the development of the future market penetration estimates. This section outlines and provides a descriptive analysis of these data.

3.2.1 Vehicle Registration Data

The vehicle registration data for the study area for the year 2008 was obtained from DesRosiers Automotive Consultants Inc. The data contained information on the vehicle types, fuel types, model years, and Gross Vehicle Weight Rating (GVWR) classifications for every light duty vehicle registered and operating within the Hamilton CMA. Each vehicle was geocoded and aggregated using the census tracts (CTs) of 2006, totalling 393,079 vehicles with 240,085 passenger cars and 152,994 light trucks. The distribution of all vehicles registered in the Hamilton CMA at the CT level is displayed in Figure 3.2.

The areas with most registered number of vehicles were at the outskirts of the city such as Mount Hope, Binbrook, Flamborough, Flamboro, Appleby, and parts of Ancaster. These areas are new suburban developments currently going through rapid expansion as Hamilton continues to grow larger in population and size.

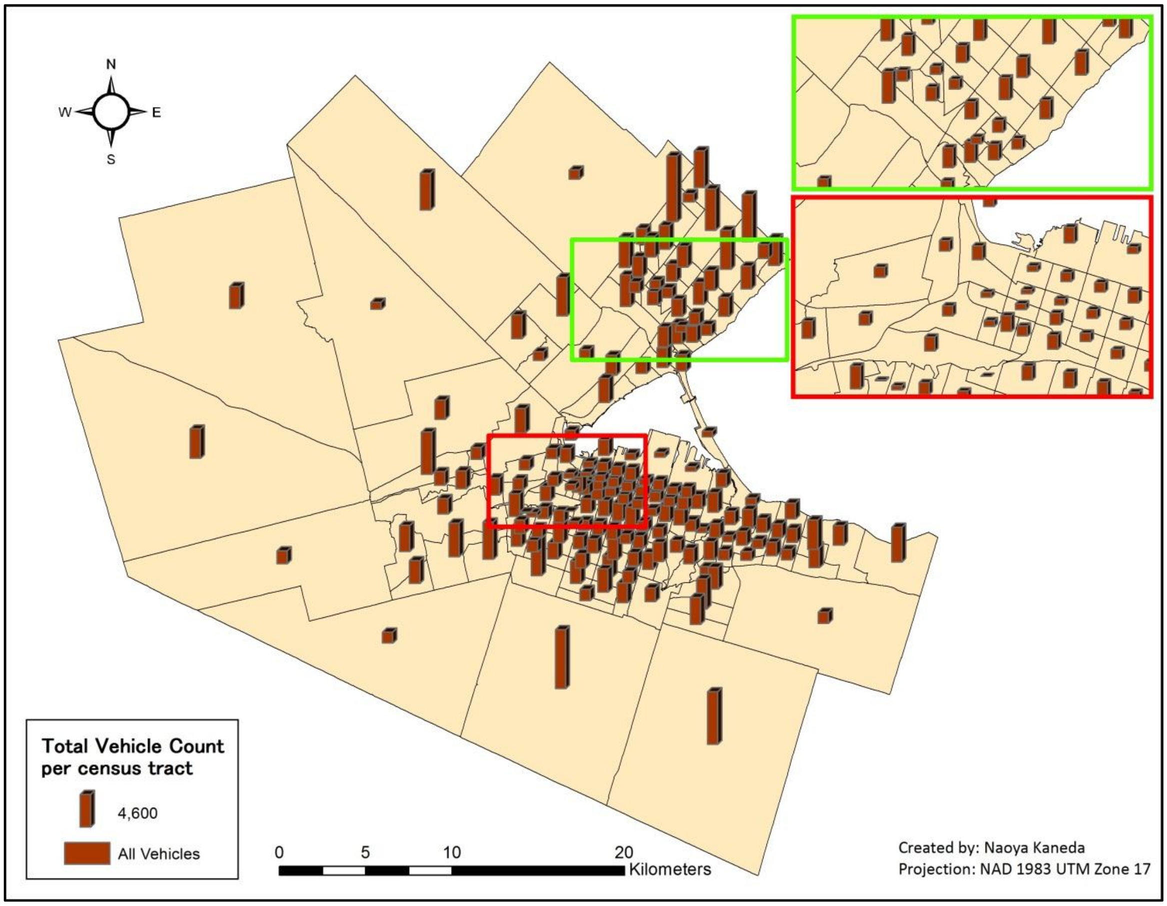


Figure 3.2: Distribution of all vehicles in the Hamilton CMA in 2008

The vehicles fuel types were divided into six categories of gasoline, diesel, gasoline-electric hybrid or hybrid electric vehicle (HEV), propane, flex fuel (gasoline-methanol/ethanol), and unknown. The flex fuel vehicles can run on either gasoline or E85 fuel and are considered to be a type of alternative-fuel vehicles (AFVs). Currently there are no propane or E85 fueling stations available for use by the public in the Hamilton

CMA. The flex fuel vehicles were considered as running on gasoline in scenarios of present emission estimates. In view of the future potential market penetration, these vehicles were regarded as AFVs. The distribution of the fuel types were 88.37% Gasoline, 1.86% Diesel, 0.54% Flex Fuel, 0.21% HEV, 0.005% Propane, and 9.02% unknown.

There were two CTs with high counts of HEVs. One was located in CT 5370061 in Hamilton and another in CT 5370206 in Burlington. Figure 3.3 shows the locations of these CTs within the study area. The vehicles owned by each of the municipal government had been registered in each of these CTs. As a part of the Green Fleet Implementation Plan the city of Hamilton has produced, the city owned 174 vehicles considered to be "green" including 92 HEVs by the end of 2008 (Hamilton Central Fleet, 2009). Of the vehicles owned by the city, many of them are registered in central fleet at the Wentworth Garage located in CT 5370061. A similar case was also true for CT 5370206 in Burlington. For the purpose of this study, with its focus on potential market penetration of HEVs to the general public, these extreme values were adjusted to reflect the counts owned by the public. In Hamilton, the HEV count in CT 5370061 was reduced from 65 to 1. This was done by taking the average of the counts in CTs surrounding 5370061 since the accurate count owned by the city in 2008 was not available. The HEV count in CT 5370206 in Burlington was reduced from 42 to 28 with an accurate count on city owned HEVs was in Greening the Corporate Fleet Transition Strategy (City of Burlington, 2008). In the following descriptive analysis of HEV data, these two census tracts were ignored when the model year and vehicle types were involved in groupings since these were unknown for the adjusted HEV counts.

At the end of 2008, there were 818 HEVs in the Hamilton CMA, 633 in passenger cars and 185 in light trucks, comprising only 0.21% of the total vehicle counts (0.26% in passenger cars and 0.12% in light trucks). Of the 173 CTs in the study area, 142 had registered HEVs ranging from one to 32 (Figure 3.3). The HEV distribution in the Hamilton CMA had the mean at 4.90 with the median of 3, the variance of 36.59, and the standard deviation of 6.05. With the kurtosis of 4.38 and the skewness of 2.03, the distribution had a narrow peak and a skew to the right (Figure 3.4). This skewness posed problems during the process of regression analysis, which is discussed in section 3.3.2.1.

The spatial distribution of HEVs in the Hamilton CMA by raw count and percent proportion to total vehicle count, both without the government owned HEVs, are shown in Figure 3.5 and Figure 3.6. These two maps of HEV spatial distribution show slightly different patterns. The HEV count, shown in Figure 3.5, follows the similar trend as that of Figure 3.2 with CTs in west Hamilton, Mount Hope, and east Burlington having higher counts. The relationship between HEVs counts and total vehicle counts is shown in Figure 3.6. In contrast to Figure 3.5, those CTs with high HEVs counts and high total vehicle counts have moved down the scale. On the other hand, CTs with high HEV counts and lower total vehicle counts have moved up. Such CTs include Ancaster, Flamborough, and North Burlington. The CTs with low HEV counts, such as those in lower Hamilton remained in the lower end of the scale for both distribution maps.

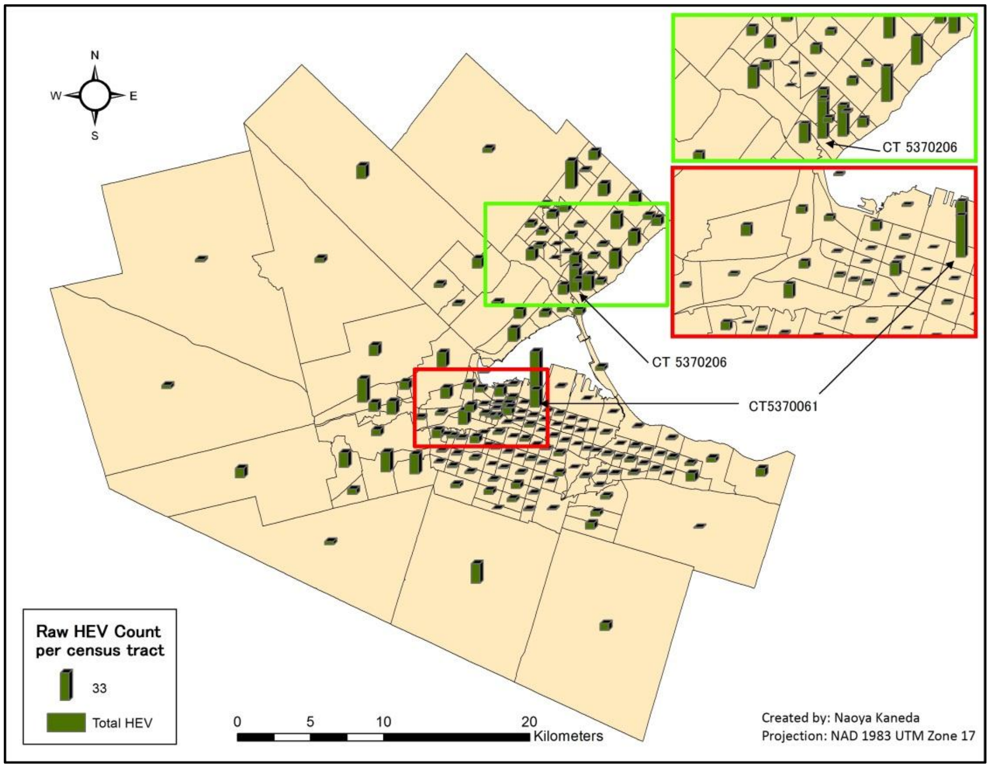


Figure 3.3: Spatial distribution of HEV raw counts in the Hamilton CMA in 2008

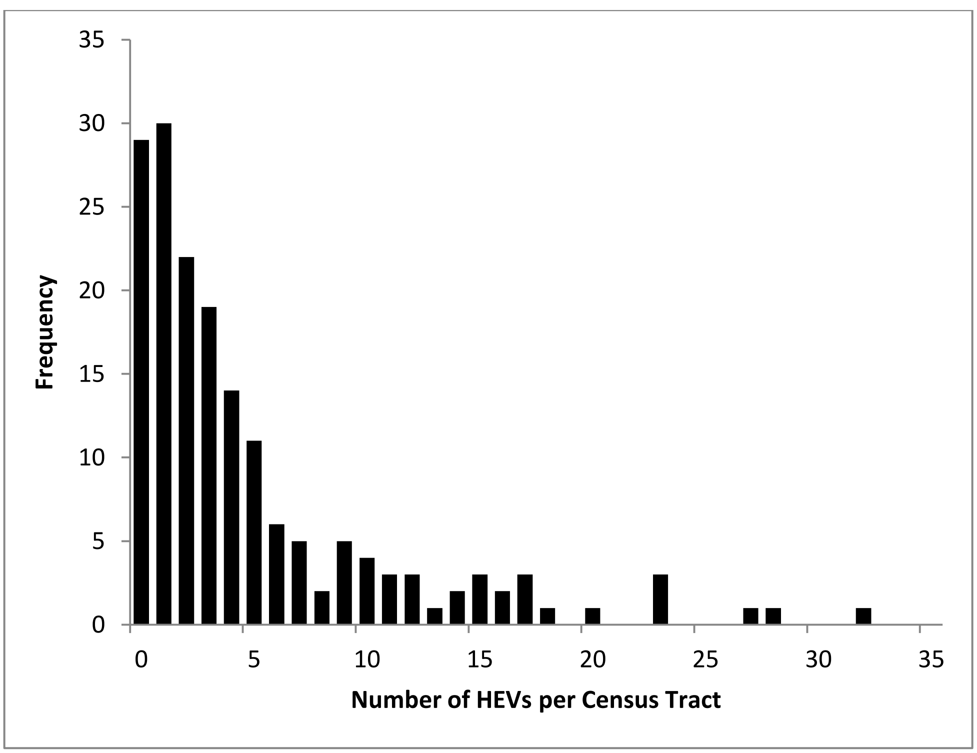


Figure 3.4: Distribution of HEVs per census tract

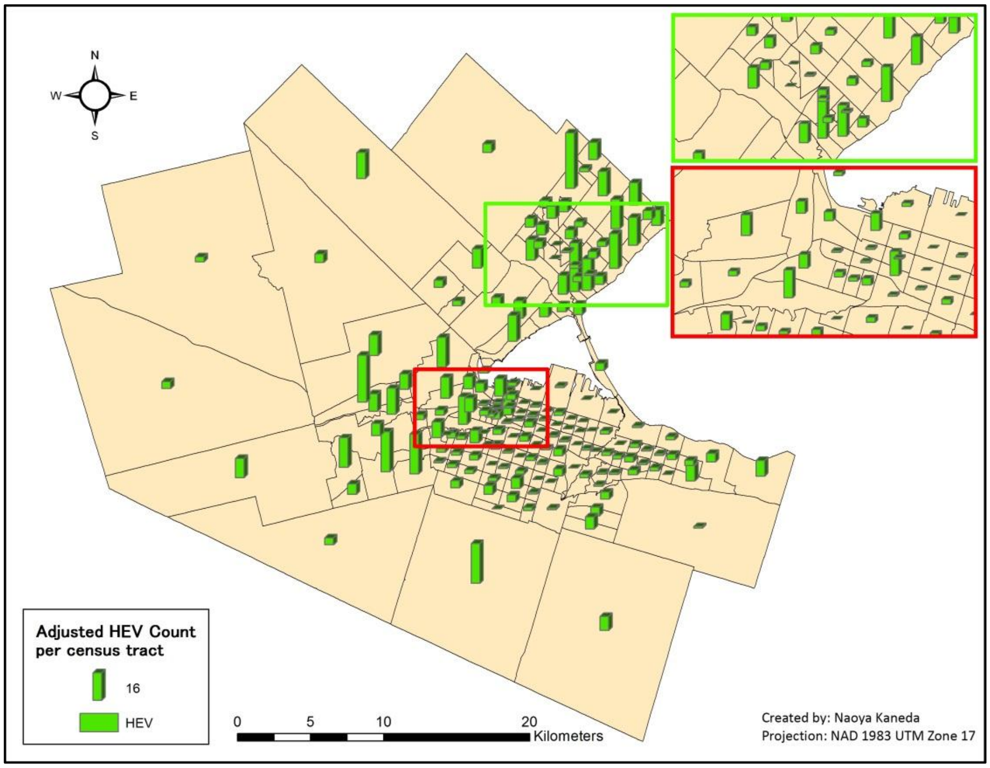


Figure 3.5: Spatial distribution without the government owned HEVs

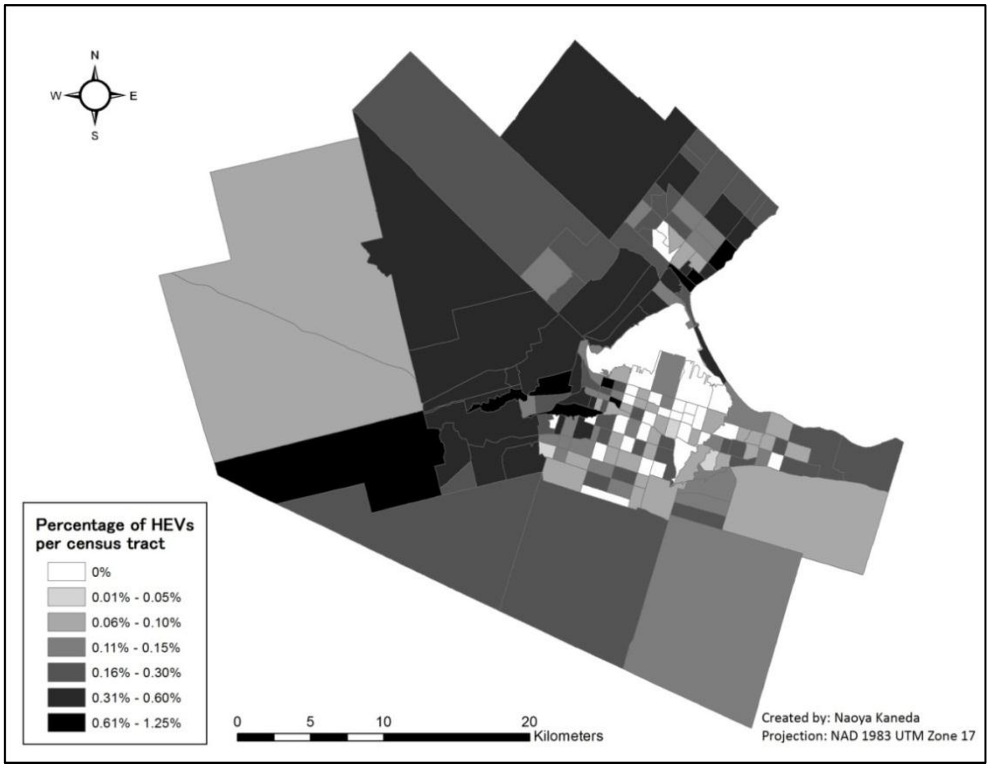


Figure 3.6: Spatial distribution of HEVs in percentage in the Hamilton CMA, 2008

The distribution of total vehicles and HEVs by vehicle model year is shown in Figure 3.7 and Figure 3.8. For total vehicle counts, it is easily noticed that the vehicles from the last 10 years dominates the vehicle fleet with the most abundant vehicles from 2002 and 2003 model years followed by vehicles from year 2000 and years 2005-2007. For HEVs, the model years 2007 and 2008 had the highest counts adding up to over 60% of all HEVs. Since these data were cross-sectional data capturing a snapshot of time trend, it cannot be concluded that these peaks or larger proportions to be the same as the market trend in those years. It is likely that they are closely related, especially for the most recent four to five years. The larger proportions of HEVs of recent model years may suggest the increased awareness of HEV as an option in new vehicle purchase and the shift towards more fuel efficient vehicles with increased gasoline prices.

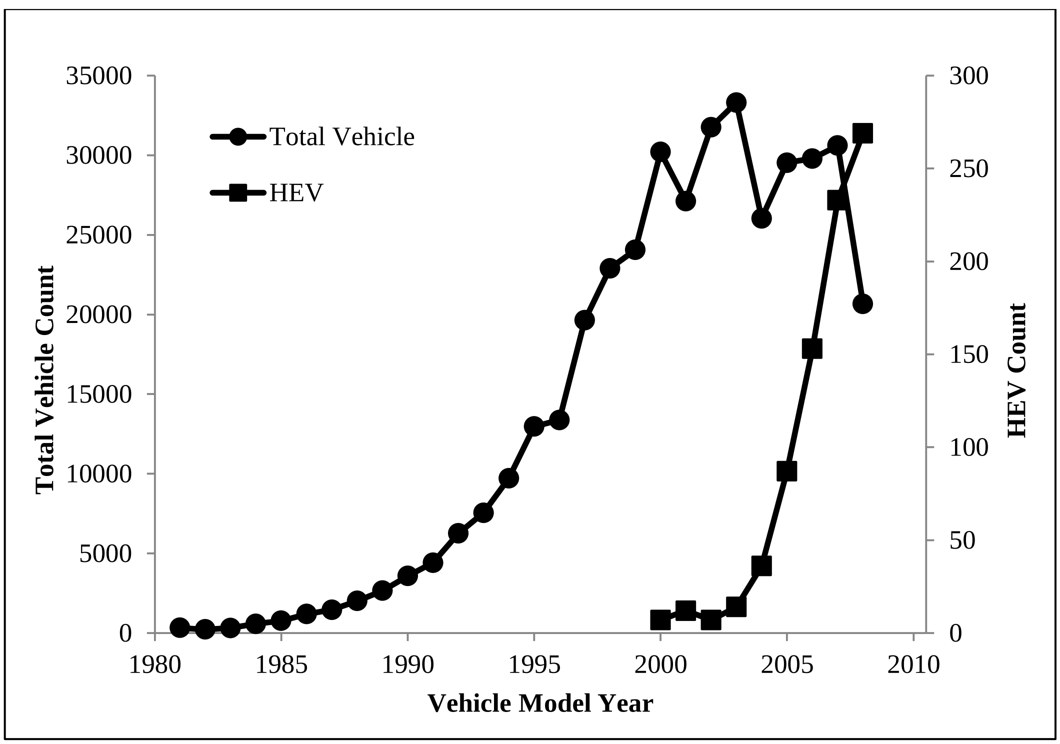


Figure 3.7: Total vehicle count and HEV count by vehicle model year

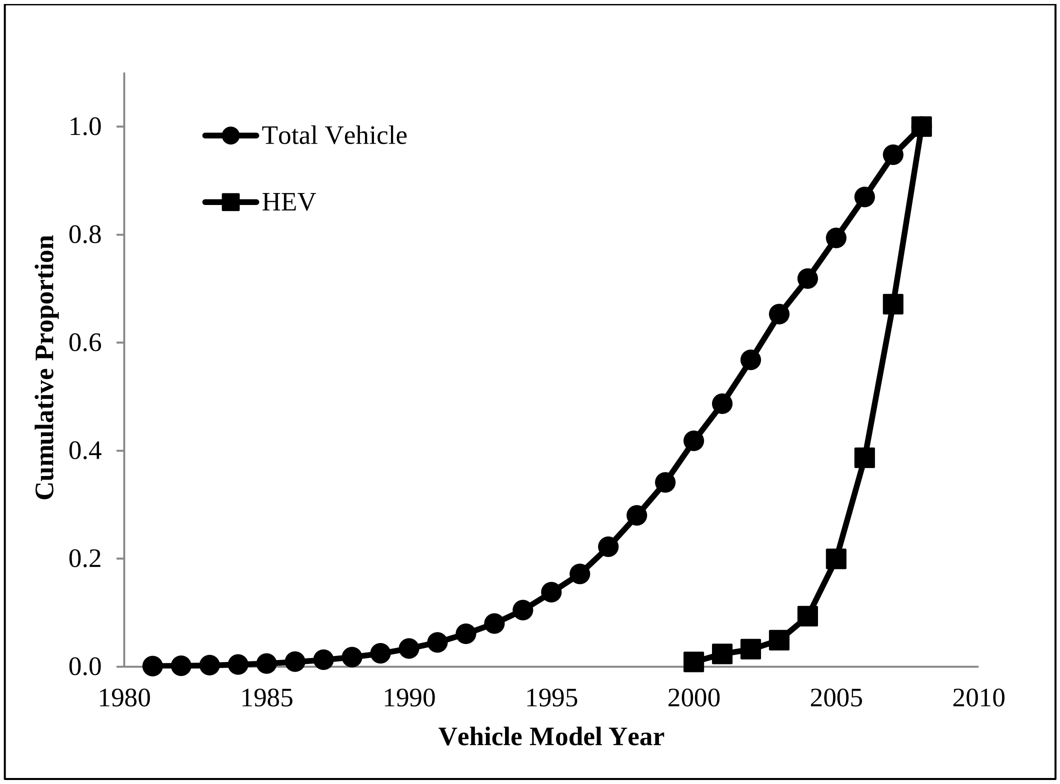


Figure 3.8: Cumulative proportions for total vehicle and HEV counts

3.2.2 2006 Canadian Census Data

The second data used in this study were 2006 Canadian census. Every five years, census questionnaires are delivered to all dwellings in Canada. These questionnaires are to be filled out by the residents of all households in Canada as well as Canadians working abroad for the federal and provincial governments, Canadian embassies, or the Canadian Armed Forces. The demographic, social and economic characteristics information collected through census on people and housing units in Canada are used by all levels of governments as well as many researchers. (Statistics Canada, 2011)

While the census data were available in different levels of aggregation, the one used for this study was at the census tract (CT) level for two reasons. CT was used as the level of aggregation in the vehicle registration data and it was also used to derive the Traffic Analysis Zones (TAZs) used in traffic flow simulation, explained in a later section. The census data can be divided into descriptive and sample count types. The descriptive type data have one value per CT and is not divided into subclasses. This includes among others: population, area, population density (derived from population and area of CTs), median household income, and average number of household members. The sample count type data provide number of residents or households that fall within a subclass of a category. Examples for this are: male population between ages of ten and fourteen, number of households with one child, and number of households living in a single-detached dwelling for each CT. The descriptive type data were used as is or converted into binary categorical data; 1 if the CT is in a given range, 0 otherwise. On the other hand, the count data were converted to proportional data; number of residents or households in a subclass divided by total response for that category.

From the vast range of information available through census, those found to have use in regression modeling had to be selected. In order to do this, previous research in potential market penetration of HEVs and AFVs were reviewed. Those studies used as references were focused on the socio-economics and demography of the subjects making the vehicle purchase choice. The list of variables thought to be relevant is shown in Table 3.1 with their sources if applicable. This list of variables was used as a guide in the selection of attributes from census data. For some variables used in the referenced studies, the equivalent information was not available in census due to those studies being disaggregate survey based. These variables included: number of licensed drivers, number of cars owned, and race. There were 94 variables derived from the census data to replicate the variables listed in Table 3.1. These 94 variables and their bivariate regression results from the negative binomial method against HEV count per CT are listed in Table 8.2. The variables are grouped in order of descriptive type data first, followed by count type data.

Table 3.1: List of Potential Variables for Regression Model

Variables	Sources
Age	Hess and Ong 2002
Income	Bhat and Pulugurta 1998; Roorda et al 2000; Chu 2002; Hess and Ong 2002; Potoglou and Kanaroglou 2008
Household Size	Roorda et al 2000; Hess and Ong 2002
Household Density	Hess and Ong 2002
Education	Roorda et al 2000; Potoglou and Kanaroglou 2008
Male vs. Female	Roorda et al 2000; Dagsvik et al 2002; Hess and Ong 2002
Number of Working Adults	Bhat and Pulugurta 1998; Hess and Ong 2002; Potoglou and Kanaroglou 2008
Single-Family Residential Housing	Bhat and Pulugurta 1998; Chu 2002; Hess and Ong 2002
Residential Location (Urban vs. Suburban)	Bhat and Pulugurta 1998
Number of Licensed Drivers	Roorda et al 2000; Chu 2002; Potoglou and Kanaroglou 2008
Number of Cars Owned	Roorda et al 2000; Potoglou and Kanaroglou 2008
Number of Children in a Household	Chu 2002; Hess and Ong 2002; Potoglou and Kanaroglou 2008
Race	Hess and Ong 2002
Exposure to Vehicle Types	Struben and Sterman 2008
Distance to Work	
Population Density	

3.3 Methodologies

This thesis was carried out in four major steps. First, the vehicle registration data for the Hamilton CMA were used to predict the future development patterns and market penetration of HEVs. Second, by combining the predicted HEV market penetration with the urban traffic simulation, the traffic volumes were assigned to the road links of the network. Third, the traffic emissions were calculated from traffic volume outputs of the traffic modeling and the emission factors from current literatures and emission models. Finally, whether the distribution of HEVs in the city of Hamilton and typical daily use would result in measurable changes in the pollution emissions was assessed. This section provides a brief overview of the software components used followed by detailed explanation on the creation of future market penetration models.

3.3.1 Traffic Flow and Emission Analysis Software

The general framework of the modeling used for simulating on-road link traffic flows and associated emissions is shown in Figure 3.9. There are three integrated programs developed to carry out this task: M6, TRAFFIC and LINK EMISSIONS. As described at the beginning of this chapter, these three software components were created for a series of previous projects at CSpA, aimed to estimate traffic emissions in several major Canadian cities. In the series, the Hamilton CMA was the first study area and since then, these programs have gone through updates and further modifications to fit the needs of this project and others. The following sections contain brief descriptions of each program and the changes made specifically for this project.

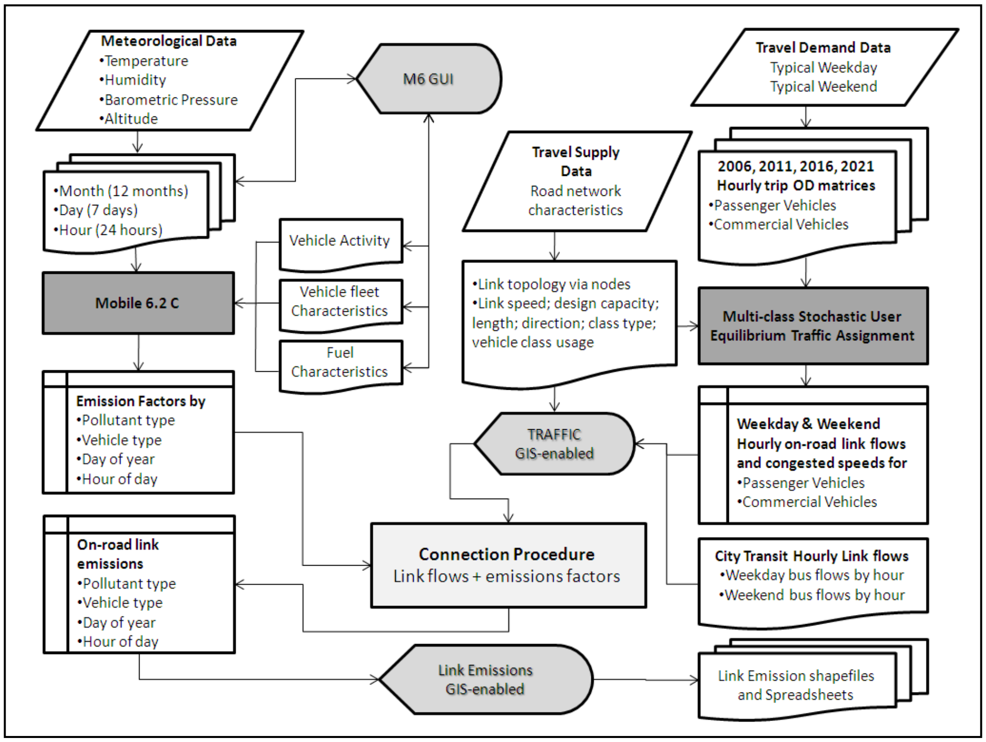


Figure 3.9: Modeling framework for estimating on-road link emissions (CSpA, 2009)

3.3.1.1 M6

M6 is a Graphical User Interface (GUI) based program developed to provide interactive input and to generate tabular outputs from MOBILE6.2C. MOBILE6.2C is a version of MOBILE6 originally developed by U.S. Environmental Protection Agency (EPA) and modified by Environment Canada to reflect the Canadian fleet of vehicles and Canadian conditions. MOBILE6.2C predicts emission factors for each hour of a day in grams or grams per kilometer for pollutants under various conditions for calendar years between 1952 and 2050 for a suite of gasoline, diesel, and natural-gas-fueled cars, trucks, buses, and motorcycles (USEPA, 1994; CSpA, 2009). It can generate emission factors for 19 different pollutants including: Hydrocarbons (HC), Carbon monoxide (CO), Oxides of nitrogen (NOx), Carbon dioxide (CO_2), nine types of particulate matters (PM), and six air toxics. M6 processes the emission estimates from MOBILE6.2C and produces the emission factors needed to estimate the on-road link emissions in combination with the link flows in tables summarizing for each vehicle type (CSpA, 2009).

The meteorological conditions and the vehicle fleet and its activities influence the emission factors produced by MOBILE6.2C. The meteorological variables used as inputs for MOBILE6.2C includes temperature, humidity, and barometric pressure (USEPA, 2003). These data were extracted from Environment Canada (2009) website for every hour of every day in 2006, as this was the original base year (CSpA, 2009). Since neither years of 2006 or 2008 included any extreme weather conditions, the data for 2006 were also used in this project. Input variables for the characteristics and activities of motorized vehicles include: vehicle activity, vehicle fleet characteristics (e.g. age distribution per vehicle type) and fuel characteristics (USEPA, 2003).

While MOBILE6.2C calculates the emission factors for 28 types of motorized vehicles under different travel speeds, for the purpose of the previous projects, only 26 of the 28 vehicle types are considered (Table 3.3). These 26 vehicle types were derived by separating gasoline and diesel engine vehicles in 16 vehicle classifications based on Gross Vehicle Weight Rating (GWVR) and Loaded Vehicle Weight (LVW), as seen in Table 3.2. The 26 vehicle types were then collapsed into five major vehicle classes, as shown in Table 3.3, to match the number of vehicle classes of the utilized travel data, the Transportation Tomorrow Survey (TTS) (CSpA, 2009). The five main classes and their acronyms were: Light duty passenger vehicles (LDPV), Light duty commercial vehicles (LDCV), Medium duty commercial vehicles (MDCV), Heavy duty commercial vehicles

(HDCV) and bus transit vehicles (CTRV) (CSpA, 2009). Since the detailed data on the vehicle fleet characteristics were available for LDPV and LDCV in the vehicle registration data, the default values were modified to simulate the vehicle makeup in the Hamilton CMA in 2008.

Table 3.2: 16 vehicle classifications based on GVWR and LVW

1	LDV	Light-Duty Vehicles (Passenger Cars)
2	LDT1	Light-Duty Trucks 1 (0-6,000 lbs. GVWR, 0-3750 lbs. LVW)
3	LDT2	Light Duty Trucks 2 (0-6,001 lbs. GVWR, 3751-5750 lbs. LVW)
4	LDT3	Light Duty Trucks 3 (6,001-8500 lbs. GVWR, 0-3750 lbs. LVW)
5	LDT4	Light Duty Trucks 4 (6,001-8500 lbs. GVWR, 3751-5750 lbs. LVW)
6	HDV2b	Class 2b Heavy Duty Vehicles (8501-10,000 lbs. GVWR)
7	HDV3	Class 3 Heavy Duty Vehicles (10,001-14,000 lbs. GVWR)
8	HDV4	Class 4 Heavy Duty Vehicles (14,001-16,000 lbs. GVWR)
9	HDV5	Class 5 Heavy Duty Vehicles (16,001-19,500 lbs. GVWR)
10	HDV6	Class 6 Heavy Duty Vehicles (19,501-26,000 lbs. GVWR)
11	HDV7	Class 7 Heavy Duty Vehicles (26,001-33,000 lbs. GVWR)
12	HDV8a	Class 8a Heavy Duty Vehicles (33,001-60,000 lbs. GVWR)
13	HDV8b	Class 8b Heavy Duty Vehicles (>60,000 lbs. GVWR)
14	HDBS	School Busses
15	HDBT	Transit and Urban Busses
16	MC	Motorcycles (All)

(USEPA, 2003)

For this thesis project, these five classes (Table 3.3) were modified in this project to accommodate for the introduction of another vehicle class, Hybrid-Electric Vehicles (HEV). LDPV and LDCV were combined together into one class, Light Duty Vehicles (LDV), by adding the emission factors after they were calculated. The fractions of LDPV and LDCV in the Hamilton CMA from the 2008 vehicle registration data were used in merging of the series of emission factor tables from each vehicle class, 0.6251 and 0.3749. To keep the current traffic assignment iteration procedure, explained in the following section, LDV replaced LDCV and the new vehicles class HEV was introduced in place of LDPV.

Table 3.3: Five Vehicle Classifications Used for TTS

Vehicle Type	Mobile6.2c Fleet Number	Mobile 6.2c Description
Light duty passenger vehicles (LDPVs)	1	LDGV Light-Duty Gasoline Vehicles (Passenger Cars)
	14	LDDV Light-Duty Diesel Vehicles (Passenger Cars)
Light duty commercial vehicle (LDCVs)	2	LDGT1 Light-Duty Gasoline Trucks 1
	3	LDGT2 Light-Duty Gasoline Trucks 2
	4	LDGT3 Light-Duty Gasoline Trucks 3
	5	LDGT4 Light-Duty Gasoline Trucks 4
	15	LDDT12 Light-Duty Diesel Trucks 1and 2
	28	LDDT34 Light-Duty Diesel Trucks 3 and 4
Medium duty commercial vehicles (MDCVs)	6	HDGV2b Class 2b Heavy-Duty Gasoline Vehicles
	7	HDGV3 Class 3 Heavy-Duty Gasoline Vehicles
	8	HDGV4 Class 4 Heavy-Duty Gasoline Vehicles
	9	HDGV5 Class 5 Heavy-Duty Gasoline Vehicles
	10	HDGV6 Class 6 Heavy-Duty Gasoline Vehicles
	11	HDGV7 Class 7 Heavy-Duty Gasoline Vehicles
	12	Class 8a Heavy-Duty Gasoline Vehicles
	16	HDDV2b Class 2b Heavy-Duty Diesel Vehicles
	17	HDDV3 Class 3 Heavy-Duty Diesel Vehicles
	18	HDDV4 Class 4 Heavy-Duty Diesel Vehicles
	19	HDDV5 Class 5 Heavy-Duty Diesel Vehicles
	20	HDDV6 Class 6 Heavy-Duty Diesel Vehicles
	21	HDDV7 Class 7 Heavy-Duty Diesel Vehicles
	22	HDDV8a Class 8a Heavy-Duty Diesel Vehicles
Heavy duty commercial vehicle (HDCVs)	13	HDGV8b Class 8b Heavy-Duty Gasoline Vehicles
	23	HDDV8b Class 8b Heavy-Duty Diesel Vehicles
Transit buses (CTRVs)	25	Gasoline Buses (School, Transit and Urban)
	26	HDDBT Diesel Transit and Urban Buses

This table excludes motorcycles and diesel school busses. (CSpA, 2009)

To calculate the emission factors for the newly added HEV class, "gasoline vehicles only" scenario for LDPV and LDCV were ran in MOBILE6.2C and combined. In this case, the fractions of gasoline engine vehicles in each of LDPV and LDCV, 0.6182 and 0.3818, were used to create the emission factor tables of $LDV_{gasoline}$. Based on Frey et al. (2009), an emission factor reduction table (Table 3.4) was produced to simulate a reduction in tailpipe emissions seen by using HEVs in place of gasoline vehicles. Since the reduction factor data were only available for HC, CO, NOx, and CO_2 from Frey et al. (2009), all other emissions and particulate matter were considered to be unchanged. The values in Table 3.4 represent the proportion of the emission factors for HEV compared to that of $LDV_{gasoline}$.

Table 3.4: The reduction factors used to reduce gasoline vehicle emission factors

Speed		HC	CO	NOx	CO2
km/h	**mph**				
0.0-20.0	0.0-12.4	0.128	0.195	0.289	0.252
20.1-30.0	12.5-18.6	0.209	0.345	0.524	0.441
30.1-40.0	18.7-24.8	0.290	0.500	0.760	0.630
40.1-50.0	24.9-31.1	0.302	0.590	0.806	0.643
> 50.1	> 31.2	0.287	0.475	0.760	0.586

(Frey et al. 2009)

3.3.1.2 TRAFFIC

To determine emissions levels at the road link level in the Hamilton CMA, the traffic flow estimates for each vehicle class for a typical weekday and weekend for a given year must be calculated and combined with the emission factors calculated in M6. This was accomplished in TRAFFIC, a GIS-based Stochastic User Equilibrium (SUE) traffic assignment program with some basic GIS capabilities to map and export tables of simulated traffic flows (CSpA, 2009). TRAFFIC uses Origin-Destination (OD) matrices as inputs and simulates traffic flows in a study area. The OD matrices correspond to a particular zoning system, 223 Traffic Analysis Zones (TAZ) for he Hamilton CMA, linked together by the road network (CSpA, 2009). The emissions on a particular link is calculated by combining the estimated link flows, link congested speeds, link length, and the emission factor generated in M6 program as per Anderson et al. (1996).

The 223 zones in the Hamilton CMA are connected through total of 831 network links. The 831 links include 223 pseudo links which connects the centroid of each TAZ to the main network of the Hamilton CMA. Each of these network links contain a set of attributes including: posted speed, length, the design capacity, link direction (one-way or two-ways), class type (freeway or arterial), and truck usage. Some of these attributes were modified from the original version to create more detailed and up-to-date network system for the Hamilton CMA. In the original network, some links (e.g. Cannon Street) in the study area were not included because classifications for these links were non-major links. Since the local residents consider these links as major streets, they were included to the network for this thesis project. There were some changes to the direction (one-way or two-way) and the truck routing since the street network was originally created. These changes were also reflected in the updated network. For example, two major streets running parallel to each other the through downtown core of Hamilton (James Street and John Street) became two-way streets while Stone Church Road that was formerly available for truck use are no longer in use by trucks.

The OD matricces for passenger and commercial vehicles were derived from household travel surveys for the passenger trips or estimated from spatial interaction models for the commercial trips. The 2006 TTS data, collected and maintained by University of Toronto, were used for passenger vehicles. The OD matrices for light, medium, and heavy duty commercial vehicles from the city of Calgary for 2006 were used to estimate OD matrices for the commercial vehicles in the Hamilton CMA. A regression analysis with population, dwelling, and employment patterns was used to calculate the growth in travel demand and OD matrices in the future. (CSpA, 2009)

TRAFFIC was designed to simultaneously assign the trips generated by different vehicle classes on the road network. Since the traffic assignment uses link design capacity measures in passenger car units, OD matrices for LDCV, MDCV and HDCV are expressed in passenger car equivalency (PCE) units. Typical PCE values for light, medium, and heavy duty commercial vehicles are 1.0, 2.0 and 2.5, respectively (Kanaroglou and Buliung 2008). The multiclass traffic assignment algorithm proceeds to estimate link flows by defining free flow travel times for all links, then starting iteration for all vehicle classes in order of HDCV, MDCV, LDCV, and LDPV until convergence is reached. Once the convergence has been achieved, assigned flows for heavy, medium and light commercial vehicles are converted back via PCE values and congested speeds can be calculated for each link (CSpA, 2009).

Introducing another vehicle class, on top of the existing four classes, to the traffic assignment algorithm process was a complicated procedure. To avoid lengthy software modifications and validation of the traffic assignment results, LDPV and LDCV were combined to create a new class of Light Duty Vehicles (LDV). These two classes have the same PCE values and have no restrictions on use of road network links unlike MDCV and HDCV. By treating LDPV and LDCV as one vehicle class, the iteration order was modified to HDCV, MDCV, LDV, and HEV. The LDV OD matrices were created through simple cell by cell addition for all 24 hours of weekday and weekend. The OD matrices required for the new HEV class was created based on an assumption that a fraction of trips made by LDV from a given zone *i* to another zone *j* is made by HEVs. This fraction was called “Reduction Proportion (RP)” for it is multiplied against LDV OD matrices and outputs another set of OD matrices with its number of trips reduced. For example, if there were 100 trips made by LDV from zone *i* to zone *j* originally and RP indicate 5% of these were made by HEVs, the new trip count for LDV and HEV are 95 and 5, respectively. For 20 out of 24 hours in a day, the RP was applied to number of trips originating from zone *i*. For the afternoon rush hour (3:00pm-6:59pm), when those vehicles left its registered location to the usual work location are returning, the RP was applied to trips ending in zone *j*. Section 3.3.2 explains how the RP was created to simulate different levels of HEV market penetration influences the traffic related emissions.

3.3.1.3 LINK EMISSIONS

LINK EMISSIONS is a program used as a database manager program that can visualize and map the estimated link emissions on the road network. This program was used to extract results of calculations from M6 and TRAFFIC. LINK EMISSIONS generates either tabular information or a spatial output in the form of GIS shapefiles on the link. It can produce outputs of emission levels in either grams or grams per km, the latter being the standardized form with respect to length of the road link. The only modification made to this program was the same road network changes seen in TRAFFIC.

3.3.2 Scenarios

The goal of this study was to evaluate the changes in overall traffic emission in the Hamilton CMA with increased use of HEVs. To accomplish this goal, the travel pattern for all vehicle types including HEVs must be determined. Unlike the passenger vehicles or the commercial vehicles, HEV did not have any previous data on travel patterns. In order to create OD matrices for HEV class, existing OD matrices for other vehicle classes had to be modified as described in the previous section. In this section, the steps taken from determination of HEV distribution pattern to the creation of OD matricies are explained. Figure 3.10 outlines the steps taken.

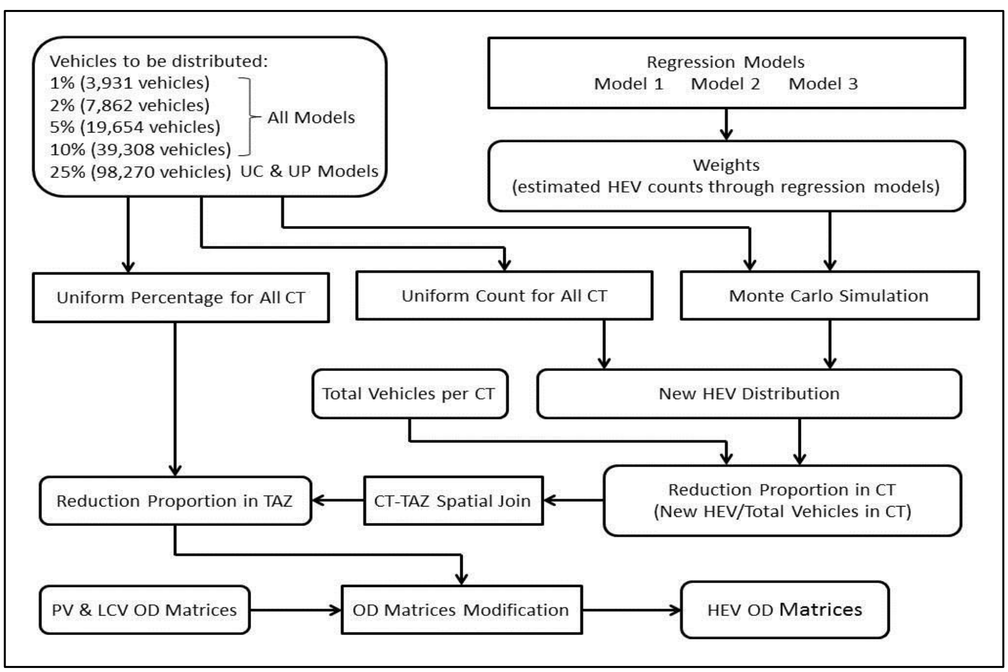


Figure 3.10: Flow chart representing steps taken for scenario creations

3.3.2.1 Models

The first task was to calculate the potential distribution pattern of HEVs at CT level. The simplest methods were to assume that each census tract will obtain equal number of HEVs or equal HEV-to-ICE ratio. Another way was to estimate the distribution by mathematical modeling based on current HEV distributions found in 2008 Vehicle Registration data as well as socioeconomic and demographic characteristics found in Canadian census 2006. The distribution of HEV by equal counts and by equal HEV-to-ICE ratio were called Uniform Count (UC) Model and Uniform Percentage (UP) Model, respectively. These two models were created by dividing the number of HEVs to be distributed by the number of CTs or assigning the same HEV-to-ICE ratios to all CTs.

Three regression models were created based on current HEV distributions and socioeconomic and demographic characteristics: Model 1, Model 2, and Model 3. In these distribution models, the HEV count was used as the dependent variable and the variables listed in Table 8.2 were used as independent variables, with each model using different combinations of independent variables. The type of regression model chosen for this was the negative binomial regression. In the following sections, creation and use of each model is outlined.

Originally, the logistic regression model with HEV proportion in each CT were considered as the primary method. This was soon rejected as the variation between HEV proportions were very small, ranging from 0 to 0.0125. The use of HEV count per CT was chosen instead, where the Poisson regression model (PRM) or negative binomial reression model (NBRM) are often used as the basic models for count data analysis (Park, 2005). A unique feature and the strict rule of the PRM is that the mean and the variance of the data should be equal, a relationship termed equidispersion (Hilbe, 2007). In the case of the Hamilton CMA, the HEV count data have a mean of 4.90 and the variance of 36.59. This condition, where the variance is greater than the mean, is called overdispersion (Park, 2005). As can be seen in Figure 3.4, there was an abundance of CTs with zero HEV count, which contributed to overdispersion. To adjust for this overdispersion, one of NBRM or zero-inflated negative binomial model (ZINB) can be used instead of PRM (Park, 2005; Hilbe 2007). In the LIMDEP statistical software used in this thesis, the Voung's statistics test was available to compare the preference for NBRM or ZINB. ZINB is preferred if the Voung's statistic value V is greater than 1.96 while NBRM is preferred if V is less than -1.96 (Park, 2005). During the model synthesis, the value of V fell between -1.96 and 1.96, which suggested either of NBRM or ZINB is suitable for this data (Park, 2005; Hilbe, 2007). For the modeling for this thesis, NBRM was chosen over ZINB.

In the census 2006, the cities of Hamilton and Burlington had 135 and 38 census tracts, respectively, to make up the total of 173. Of these 173 CTs, three were omitted from regression analysis for lack of census information. These CTs were 5370018, 5370036, and 5370072.01. For CT 5370018, none of census information or vehicle registration data were available while CT 5370036 only had basic census information and none of detail socio-economic information. CT 5370072.01 had very small population count which likely lead to information, such as income, being supressed.

MODEL1: VEHPHHLD, FM1CHLD, POSTSECU

For the development of Model 1, those independent variables considered to be significant in bivariate regression were divided into 11 subgroups of similar traits. Within each subgroup, combinations of independent variables that produced the best log-likelihood value were thought out. When the variables were highly correlated to each other, the variable with best log-likelihood from bivariate regression was taken to avoid multicollinearity. This process reduced the number of independent variables to 17 from 94. The list of 17 independent variables and the result of its first multivariate regression can be seen in Table 3.5.

Table 3.5: List of starting 17 independent variables for Model 1

Variables	Definitions	Coeff.	t-stats
Constant		1.210	0.521
POPDEN	Population Density	0.000	-1.539
AVEPHHLD	Average number of household members in a dwelling	0.421	0.307
VEHPHHLD	Average number of vehicles per private dwelling	0.619	2.978
X2PHHLD	Number of dwellings with 2 people in a household	3.916	0.863
X45PHHLD	Number of dwellings with 4 or 5 people in a household	2.706	0.439
SFAMHHLD	Number of single family household	-6.223	-1.536
MLTIHHLD	Number of multi-family household	0.825	0.092
FM1CHLD	Number of female lone parent with 1 child	-7.082	-2.331
FM3UCHLD	Number of female lone parent with 3 or more children	-0.091	-0.012
MA1CHLD	Number of male lone parent with 1 child	-8.765	-1.390
MA2CHLD	Number of male lone parent with 2 children	-11.767	-1.103
MAWRKCSD	Proportion of make workers travelling outside of CSD to usual place of work	0.333	0.585
FMWRKDRV	Number of female workers travelling to work as a driver in a private vehicle	-0.367	-0.244
MAWRKPAS	Number of male workers travelling to work as a passenger in a private vehicle	2.756	0.986
POSTSECC	Population with post-secondary education other than University	0.933	0.455
POSTSECU	Population with post-secondary education from University	4.906	3.337
EFIN80U	Number of economic family with after-tax income $80,000+	0.818	0.578

From the independent variables in Table 3.5, variables were eliminated one at a time for either its insignificance or the sign of the coefficient being opposite of a priori expectation. First four variables (POSTSECC, FM3UCHLD, MLTIHHLD, and FMWRKDRV) were eliminated for their insignificance in the model. After the removal of some variables, MAWRKPAS has become a significant variable in the model. It was removed, however, for its sign being opposite of bivariate regression result and also a priori understanding that those travelling to work as a passenger are less likely to invest in AFVs, especially in men (Dagsvik et al., 2002). Even though all studies relating to automobile ownership indicated income as an important indicator, in this combination of variables EFIN80U was not significant. This could have been that it conflicts with other variables related to high income such as POSTSECU. One of the household variables, AVEHHLD, was eliminated for its insignificance also likely to have been influenced by X2PHHLD and X45PHHLD. Then, SFAMHHLD was removed for its sign being opposite of literature interpretation, the single family household increases the chance of HEV ownership by investing for more vehicles (Chu, 2002; Hess and Ong, 2002).

Table 3.6: Mid-process independent variables for Model 1

Variables	Coeff.	t-stats	P-value
Constant	1.343	2.141	0.032
POPDEN	0.000	-1.494	0.135
VEHPHHLD	0.583	2.803	0.005
X2PHHLD	-2.355	-1.290	0.197
X45PHHLD	-3.825	-3.604	0.000
FM1CHLD	-7.220	-2.682	0.007
MAWCHLD	-6.387	-1.306	0.192
MAWRKCSD	0.557	1.059	0.290
POSTSECU	5.542	7.707	0.000

After the number of independent variables was reduced to half of what was at start, a minor adjustment was made to the lone parent variable combination. The combination of FM1CHLD, MA1CHLD, and MA2CHLD was replaced with FMWCHLD and/or MAWCHLD to look for the combination that increased the log-likelihood. This was possible because FMWCHLD and FM1CHLD had high correlation as well as MAWCHLD to MA1CHLD and MA2CHLD. After a few trial-and-errors, FM1CHLD and MAWCHLD combination was used (Table 3.6). From this point on, MAWRKCSD, MAWCHLD, and X2HHLD were eliminated in order for their insignificant contribution to the model. Then, X45PHHLD was excluded because studies indicate that larger households have more vehicles (Hess and Ong, 2002). This was followed by removal of POPDEN for insignificance to the model. The final model included three independent variables: VEHPHHLD, FM1CHLD, and POSTSECU (Table 3.9).

MODEL2: AFVPROP, VEHPHHLD, X1PHHLD, X2PHHLD, HHIN8099, HHIN100U, DOWNTOWN

For Model 2, all independent variables that resembled the variables in Table 3.1 were selected. These 23 variables selected included variables that were indicated as not having significant relationship in bivariate regression. Predictably, these variables were eliminated in the first few steps. Compared to Model 1, elimination of independent variables in this model was much simpler. Of the 23 variables selected, 13 were taken out of the model based on its insignificant contribution to the model, though not done in one process (Table 3.7). These 13 variables were: MALE014, MALE1529, MALE3444, MALE4564, MALE65U, FEM014, FEM1529, FEM3044, FEM65U, X1CHLD,

X2CHLD, X3UCHLD, HHIN6079, HHLDDEN, SFAMHHLD, and WORKOCSD. This process left seven independent variables (Table 3.8).

Table 3.7: List of starting 23 independent variables for Model 2

Variables	Definitions	Coeff.	t-stats
Constant		50.343	3.003
HHIN6079	Household After Tax Income $60,000-79,999	1.002	0.341
HHIN8099	Household After Tax Income $80,000-99,999	7.664	2.805
HHIN100U	Household After Tax Income $100,000+	5.328	4.136
AVEPHHLD	Average number of household members in a dwelling	-0.901	-0.871
HHLDDEN	Household density (number of dwellings per km^2)	0.000	-0.328
SFAMHHLD	Number of single family household	-3.170	-1.025
DOWNTOWN	Downtown area = 1, Elsewhere = 0	-0.266	-1.050
X1CHLD	Number of families with 1 child	-3.345	-1.584
X2CHLD	Number of families with 2 children	-3.218	-1.093
X3UCHLD	Number of families with 3 or more children	-4.752	-1.084
VEHPHHLD	Average Number of Vehicles per Private Dwellings	0.450	2.719
AFVPROP	AFV proportion to total vehicle count in a CT	64.895	3.891
WORKOCSD	Proportion of all workers travelling outside of CSD to their usual place of work	-0.449	-0.657
MALE014	Male population between ages 0 and 14	-13.583	-1.284
MALE1529	Male population between ages 15 and 29	-17.034	-1.413
MALE3044	Male population between ages 30 and 44	-30.916	-2.839
MALE4564	Male population between ages 45 and 64	-25.320	-2.107
MALE65U	Male population age 65 and up	-22.695	-2.060
FEM014	Female population between ages 0 and 14	-24.981	-1.968
FEM1529	Female population between ages 15 and 29	-23.460	-1.616
FEM3044	Female population between ages 30 and 44	-19.519	-1.240
FEM4564	Female population between ages 45 and 64	-25.005	-1.926
FEM65U	Female population age 65 and up	-22.084	-1.641

Once the number of variables was reduced, interchanging variables with one or more variables not originally in the list was conducted to search the best combination. This process showed that inclusion of X1PHHLD and X2PHHLD together produces better results than AVEPHHLD. Following this process, FEM4564 was removed for having opposite sign for its coefficient than its bivariate regression result. The final model was produced with seven independent variables (Table 3.9).

Table 3.8: Mid-process independent variables for Model 2

Variables	Coeff.	t-stats	P-value
Constant	2.659	3.476	0.001
HHIN8099	5.864	2.699	0.007
HHIN100U	4.681	6.002	0.000
AVEPHHLD	-1.375	-5.239	0.000
DOWNTOWN	-0.398	-1.956	0.050
VEHPHHLD	0.388	2.272	0.023
AFVPROP	77.619	6.633	0.000
FEM4564	-3.030	-1.713	0.087

MODEL3: SECONDRY, MLTIHHLD, X1CHLD, WORKOCSD, AVFAMIN1, AVFAMIN4, PDEN1, PDEN2, PDEN3, PDEN4, PDEN5

In the case of Model 3, the selection of the independent variables was carried out by process of inclusion rather than elimination. First, the descriptive variables for the density and the income were selected by trial-and-errors. Different combinations of the population density or household density and one of average household income, median household income, average economic family income, and median economic family income were tried to search for the best log-likelihood value. Once population density (PDEN) and average economic family income (AVFAMIN) were chosen to be the base for this model, selection for other variables was carried out.

Since PDEN and AVFAMIN were already selected, other variables related to density and income were excluded to avoid multicollinearity. The variables already used in the first two models were also excluded to capture factors yet to be seen in previous models. With 30 variables still to be considered, the variables were grouped into six subgroups, and were considered one group at a time in the model. The six subgroups were household members, place of work, household structure, number of children, age and sex, and education. From the bivariate analysis, the education variables were found to be one of the most significant explanatory variables of all. This group was then left until the end to be introduced into the model to reduce its influence.

First group was number of household members. All variables in this group changed its coefficient sign once introduced into the model, suggesting possible multicollinearity with variables already in use. Therefore none of these variables were used in the model. Second group was related to trips to usual place of work. Within this group, three variables without distinction of sex were considered first. Of the WRKOCSD, TRWRKDRV, and TRWRKPAS, the best log-likelihood value was obtained by using WRKOCSD. The three variables that describes place of work outside of his/her place of residence all had high correlation to each other. The variable WRKOCSD was included in the model since there was no need to specify the sex. In the third group on type of household structure, MLTIHHLD was the only one that was both significant and had the coefficient sign consistent with that of bivariate regression.

In the group for number of children in the households, X1CHLD, MAWCHLD, and MA2CHLD were significant when introduced one variable at a time. Of these three variables, X1CHLD was chosen to be included based on log-likelihood value. From the age and sex of population group, none were found to be significant in this model and was not included. Finally, the education variable was introduced into the model. Between PRIMARY and SECONDRY, the latter was chosen for two reasons. First, like many other variables chosen, SECONDRY produced higher log-likelihood of the model than PRIMARY. Secondly, PRIMARY includes those who are currently enrolled into secondary education. Therefore, to capture those who have decided not to obtain post-secondary education, for various reasons, SECONDRY was chosen. This left four variables along with seven binary descriptive variables, total of 11 independent variables, in the final model (Table 3.9).

Table 3.9: Summary of NBRM-based HEV Distribution Models

Model 1			Model 2			Model 3		
Variables	**Coeff.**	**t-stats**	**Variables**	**Coeff.**	**t-stats**	**Variables**	**Coeff.**	**t-stats**
Constant	-0.332	-0.689	Constant	-3.705	-5.752	Constant	4.596	5.028
VEHPHHLD	0.520	3.003	AFVPROP	74.513	6.117	SECONDRY	-8.705	-3.095
FM1CHLD	-5.117	-2.029	VEHPHHLD	0.368	2.129	MLTIHHLD	-17.312	-2.463
POSTSECU	6.095	9.142	X1PHHLD	4.902	4.543	X1CHLD	-2.857	-1.318
			X2PHHLD	2.408	1.936	WORKOCSD	1.328	2.266
			HHIN8099	7.109	3.341	AVFAMIN1	-0.824	-3.365
			HHIN100U	4.360	5.673	AVFAMIN4	0.396	1.623
			DOWNTOWN	-0.416	-1.964	PDEN1	0.228	1.018
						PDEN2	-0.337	-1.519
						PDEN3	0.010	0.042
						PDEN4	0.035	0.119
						PDEN5	-0.887	-1.936

	Model 1	**Model 2**	**Model 3**
Restricted Log-Likelihood (RLL)	-455.639	-455.639	-455.639
Unrestricted Log-Likelihood (ULL)	-392.196	-383.162	-394.822
Rho (1-(ULL/RLL))	0.1392	0.1591	0.1335
LR (2*(ULL-RLL))	126.886	144.954	121.634
Chi-squared (significance level)	167.092 (0.000)	128.205 (0.000)	188.053 (0.000)
Number of observations = 170			

The goodness-of-fit measures for NBRM through the results were not definitive in providing fit of the models to HEV counts, unlike R^2 value in Liner Regression. The predicted HEV counts from each model were contrasted against the observed count to calculate the pseudo-R^2 values (Figure 3.11). These values provided an estimate on how the models fit the observed counts. These pseudo-R^2 values indicates the best model out of the three created can only explain 47% of HEV ownership.

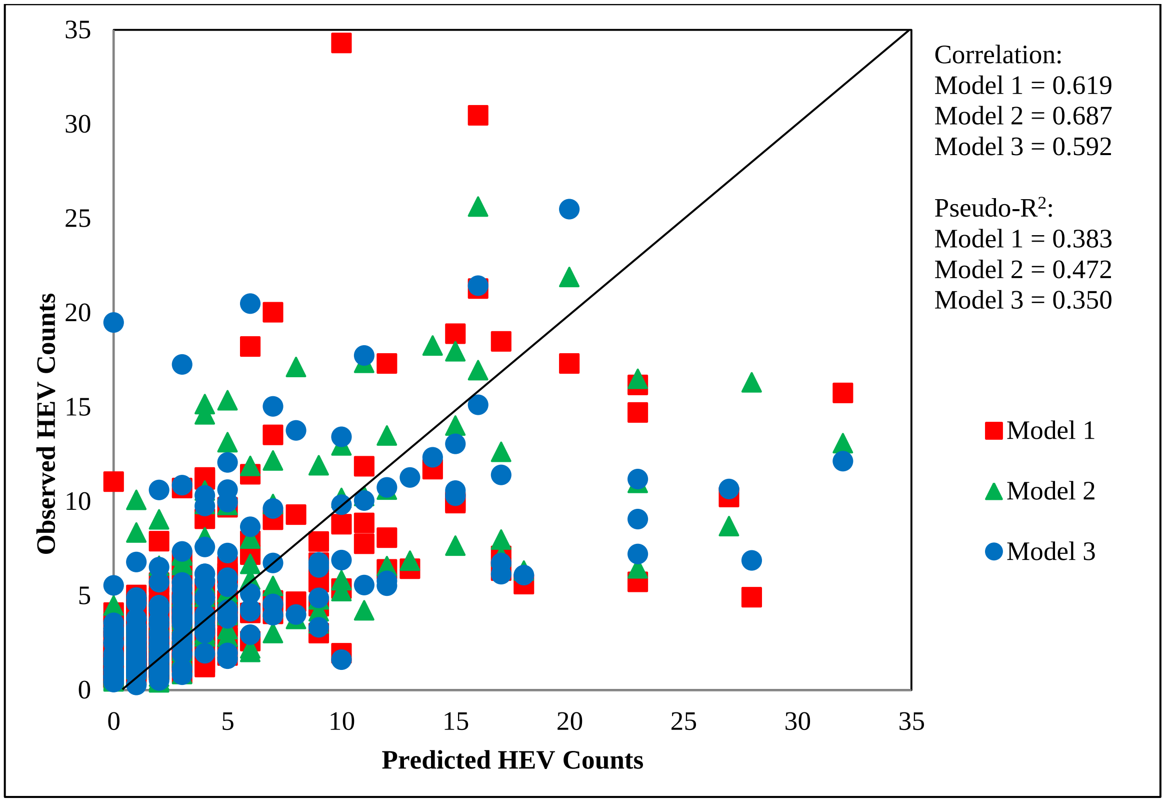


Figure 3.11: Correlation between observed and predicted HEV counts

In each of the models, most of the variables used were either direct or indirect indication of income levels. The fit of the models by pseudo-R^2 suggests that these models with mostly income related variables have 35% to 47% explanatory rate. The education level of a consumer can be a variable for their awareness of environmental issues or the jobs they are qualified. The lower number of people in a household can indicate a higher expendable income than those in multi-family household. From the non-income related variables used in other studies, the age and sex variables were not significant in any of the models and number of licenced drivers was not available through census data. Despite the weak to moderate fit, the predicted HEV count values from these models were used as the distribution patterns of HEV in 2021 with estimated sprawl type population growth in the Hamilton CMA.

3.3.2.2 Establishing OD matrices for HEV

There are two approaches to estimate future distribution of HEVs by using the regression models. First approach is to estimate the values for all independant variables used in regression models in 2021 and calculate the HEV count. For example, estimate the average vehicles per household, number of female lone parents with one child, and number of residents with post-secondary education from a university in each of the census in 2021 and apply these to Model 1. This method is very complicated since many of the variables used in the regression models are not driven by policies made and published by governments. The second approach is to use predicted or esimated HEV counts from the regression models as weights in distribution of predetermined number of HEVs in the future. This method assumes that the tendency of residents of the Hamilton CMA to purchase HEV stays the same as seen in 2008. Since the estimation is limited to the number of HEVs introduced, it is simpler than the first approach. Therefore the second approach was used in this study. The number of vehicles to be distributed were set to be 1%, 2%, 5%, and 10% of all registered passenger and light truck vehicles in Hamilton in 2008. The different level of proportions were set to simulate the changing levels of market penetrations.

When running the negative binomial regression model, the LIMDEP software was able to produce three sets, one for each of the three models, of predicted counts of HEVs based on 2006 values for the independent variables used (Figure 3.12 through Figure 3.14). The sum of the predicted values were 869.58, 851.64, and 852.75 for models 1 through 3, respectively. The predicted HEV count in each CT divided by the total number of HEVs was used as its probability weights in running the Monte Carlo simulation.

Of the three CTs omitted from the process of model construction, 5370036 and 5370072.01 were assigned the probability weights based on its neighbouring CTs sharing common boaders. Both of 5370036 and 5370072.01 shared boarder with seven other CTs. An average for each set of seven CTs were calculated for both CTs. The third CT omitted, 5370018 was given a probability weight of zero. The Monte Carlo simulations were executed using the predetermined number of HEVs that are being distributed. Once the distribution of HEVs was completed, the HEV counts were converted into proportions by dividing the counts by the total registered vehicles in each CT. After the first set of vehicles were distributed, the number of HEVs assigned to CT 5370016 was found to exceed the number of total vehicles in that CT. The probability weight for this CT was adjusted to zero with a consideration that there was no HEV in 2008 in this CT based on the Vehicle Registration data. The predicted counts and probability weight for each CT for all three models can be seen in Table 8.1 in Appendix.

Once the proportions of HEVs in CTs were established, these values had to be converted into TAZ used in the TRAFFIC software to which the OD matrices were fed into. This conversion was completed by overlapping CTs and TAZ through spatial join in ArcGIS. There were 32 TAZ that included more than one CT in its boundary. For these CTs, the averages of the proportions from all CTs in its boundary were used. There were multiple TAZ that belonged to the same CT. In these cases, the same proportion value was given to all TAZ belonging to the same CT. The proportions in TAZ level was used to scale down the OD matrices. Since the HEV penetration in the future was the focus of this study, the OD matrices of 2021 were modified. The OD matrices for the future years were created based on population and employment growth. These were done as a part of previous project already mentioned for years of 2011, 2016, and 2021.

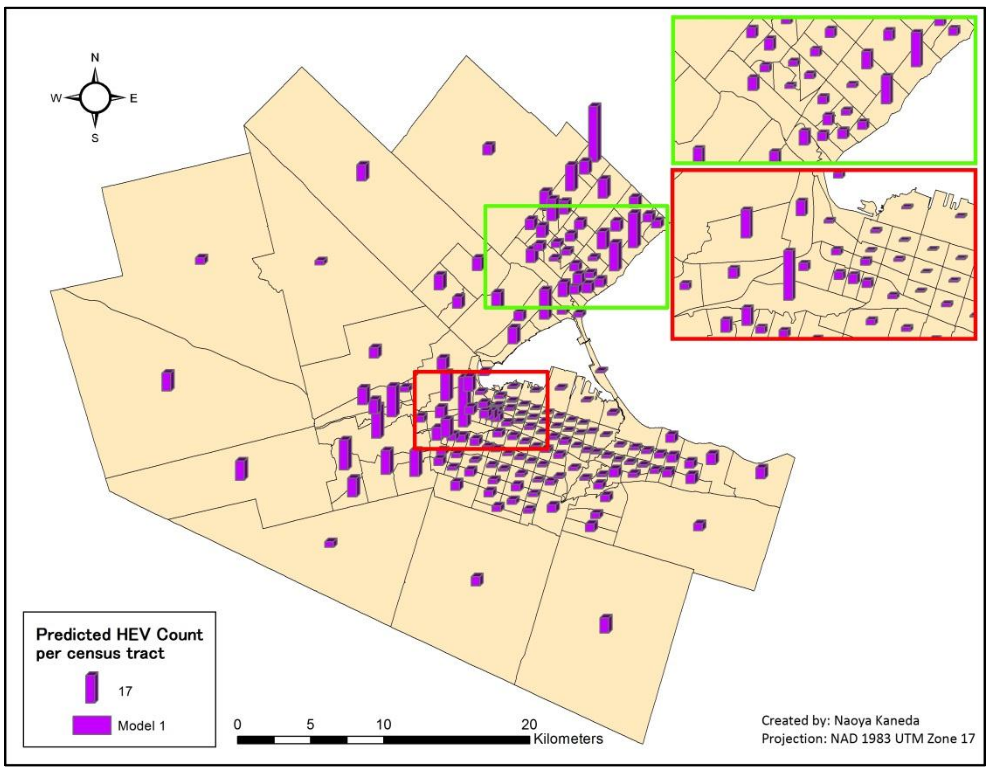


Figure 3.12: Predicted HEV distribution by regression for Model 1

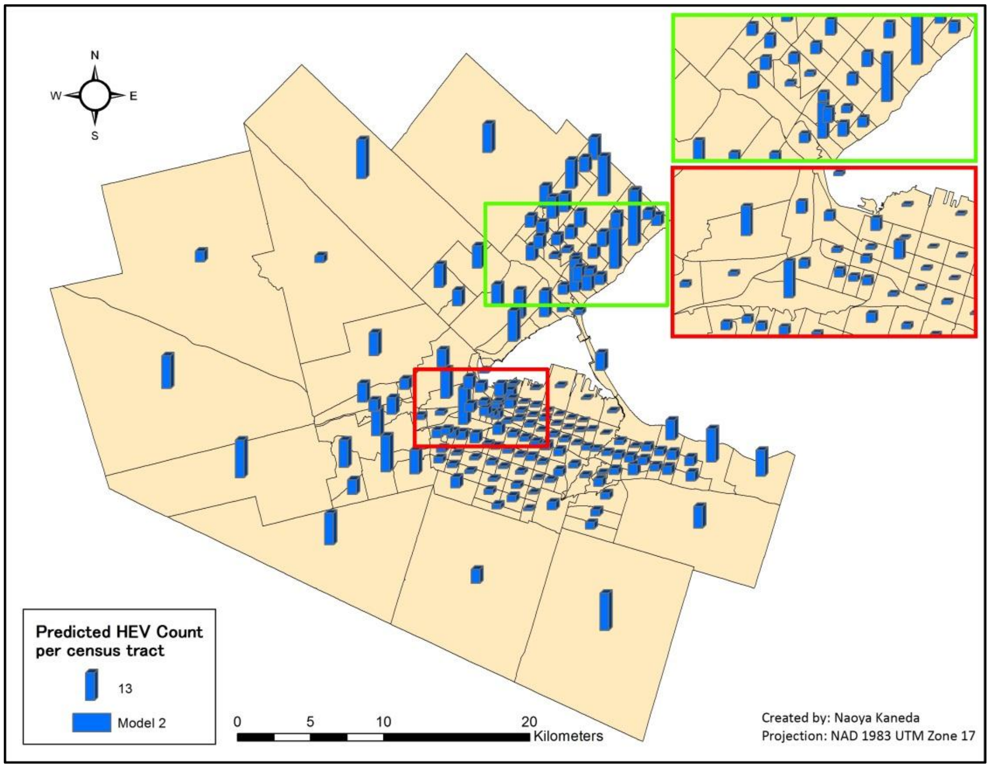


Figure 3.13: Predicted HEV distribution by regression for Model 2

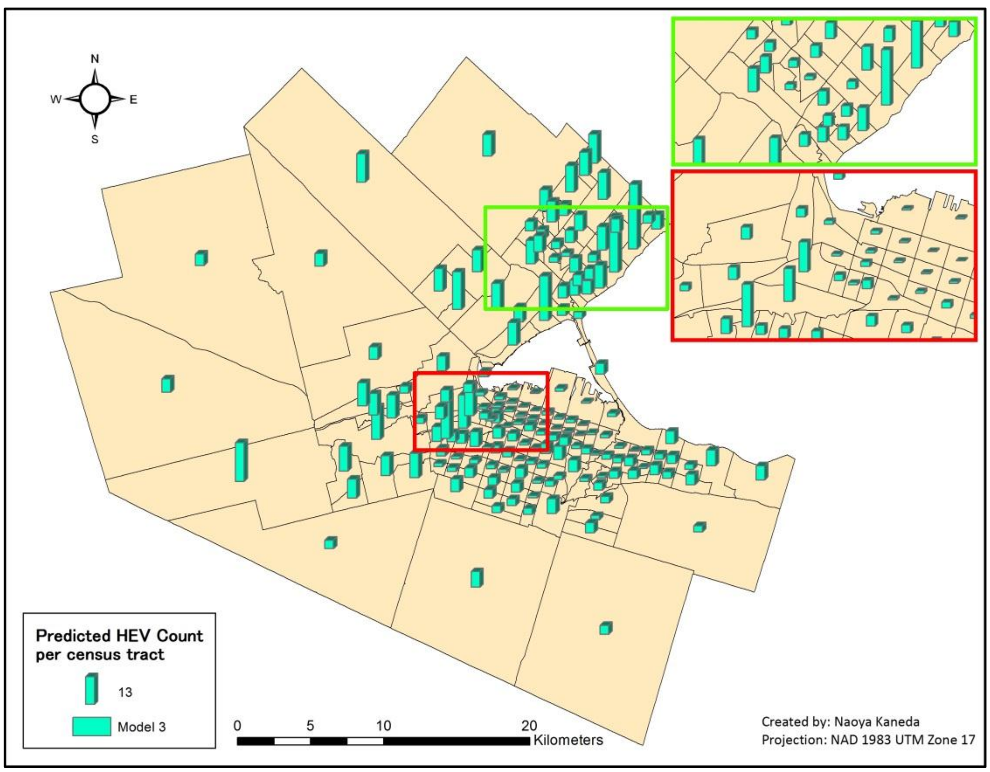


Figure 3.14: Predicted HEV distribution by regression for Model 3

3.3.2.3 Possible Electric Vehicle (EV) Scenario

Based on the simulation structure for this study, a quick review was conducted of the effect of EV implementation into the market. As discussed previously, this simulation model can only process four vehicle types. For this analysis, EV replaced HEV class. Since EV produces no tailpipe emissions (USEPA, 2003), all emission outputs from the simulation with HEVs were converted to a value of zero. This method was used for simulating traffic emissions in the morning peak hour (8:00am) in January.

4 Results

For this thesis, the year 2006 was selected for the present scenario and 2021 for the future scenario. The present scenario was estimated using: 2006 meteorological data from Environment Canada, 2006 TTS travel data, and 2008 vehicle registration data as outlined in section 3.3.1. The future scenario included business-as-usual (BAU) scenario and five models with differing market penetration levels. Traffic emission estimates are available for 24 hours in 365 days in 2006 and 2021, although, morning and afternoon rush hour (8am and 4pm) data from a weekday in winter and summer (January 15th/Day 15 and July 15th/Day 196) were selected for the purposes of comparison.

4.1 HEV OD Matrices Validation

First, the method used to calculate OD matrices and traffic flows for HEV and LDV was validated. It was assumed that LDPV and LDCV were equivalent in traffic flow assignment due to their road restriction and PCE being equal. These two classes were combined into one class then partitioned to create LDV and HEV. For this assumption to be true, the sum of all trips and the total vehicle kilometer travelled (VKT) must be equal across all models. The comparison of VKTs from each scenario to the BAU scenario is displayed in Table 4.1. The divergence from BAU was insignificant in all cases with the largest difference being 1.008% between BAU and Uniform Percentage at 1% (UP 1%) for 4:00pm. This confirmed that VKTs were equal for all scenarios and the effectiveness of the method used to create a new vehicle class and its OD matrices. Remaining parts of this chapter outline the traffic flows and emission estimates for each model, with a discussion of the comparison between models in Chapter 5.

Table 4.1: VKT comparisons against BAU for all models (in 1000km) in 2021

Models	8am				4pm			
	HEV	LDV	Total	Change %	HEV	LDV	Total	Change %
BAU	0.00	940.64	940.64	0.000	0.00	945.91	945.91	0.000
M1 1%	9.79	930.85	940.64	0.001	9.78	936.21	946.00	0.009
M1 2%	19.98	920.80	940.77	0.014	20.14	925.87	946.01	0.010
M1 5%	49.52	891.64	941.16	0.055	49.58	896.45	946.03	0.012
M1 10%	99.29	841.86	941.15	0.054	99.42	846.60	946.02	0.011
M2 1%	10.67	929.97	940.64	0.000	11.00	935.00	946.00	0.009
M2 2%	21.32	919.51	940.84	0.021	21.78	924.23	946.01	0.010
M2 5%	53.22	887.91	941.13	0.052	54.56	891.49	946.05	0.014
M2 10%	106.42	834.81	941.23	0.063	108.94	837.10	946.04	0.013
M3 1%	10.23	930.38	940.61	-0.003	10.33	935.66	945.99	0.008
M3 2%	20.14	920.71	940.86	0.023	20.60	925.40	946.00	0.010
M3 5%	50.56	890.57	941.12	0.052	51.62	894.41	946.03	0.012
M3 10%	101.36	839.84	941.20	0.060	102.99	843.04	946.03	0.013
UC 1%	9.70	930.91	940.61	-0.003	10.30	935.69	946.00	0.009
UC 2%	19.45	921.27	940.72	0.008	20.66	925.36	946.02	0.011
UC 5%	48.65	892.37	941.02	0.041	51.64	894.40	946.03	0.013
UC 10%	97.32	843.70	941.02	0.041	103.27	842.62	945.89	-0.003
UC 25%	243.52	697.88	941.40	0.081	258.29	687.60	945.89	-0.003
UP 1%	9.40	940.68	950.08	1.004	9.45	946.00	955.45	1.008
UP 2%	18.81	921.91	940.72	0.008	18.91	927.10	946.01	0.011
UP 5%	47.04	893.99	941.03	0.042	47.27	898.77	946.05	0.014
UP 10%	94.04	847.13	941.17	0.056	94.55	851.52	946.06	0.016
UP 25%	235.33	706.03	941.37	0.078	236.53	709.49	946.02	0.012

M1: Model 1, M2: Model 2, M3: Model 3, UC: Uniform Count, UP: Uniform Percentage

4.2 Business-as-usual (BAU) Scenario

Results of the BAU scenario for years 2006 and 2021 are presented. The scenario in year 2006 was the base for all scenarios, while the 2021 BAU scenario was the basis for comparison between different HEV market penetration models. BAU scenarios established that changes in VKTs and traffic emissions associated with the estimated population and employment development in the Hamilton CMA in the 15-year period. The difference in traffic emissions between the base year and 2021 was used as a reference when comparing other scenarios to determine the reduction as a result of using HEVs. The following tables (Table 4.2 and Table 4.3) summarize the changes between 2006 and 2021 using BAU scenario.

Table 4.2: VKT change for BAU 2006 vs. 2021

Hour	Vehicle Type	Aggregate VKT		Change
		2006	2021	
8am	LDV	735562.02	940638.97	27.88%
	MDCV	57949.73	60810.01	4.94%
	HDCV	21789.48	18380.90	-15.64%
	Total	815301.22	1019829.88	25.09%
4pm	LDV	768988.20	945913.05	23.01%
	MDCV	43749.98	47196.07	7.88%
	HDCV	6812.92	5794.47	-14.95%
	Total	819551.10	998903.59	21.88%

For both morning and afternoon rush hours, the VKT for LDV and MDCV increased, while HDCV declined significantly (Table 4.2). The most likely cause of the significant increase of VKT observed in LDV was the projected future development pattern of the Hamilton CMA. While the cities of Hamilton and Burlington have different developing patterns, a strong case of suburbanization and urban sprawl of population and new dwellings from 2006 to 2021 was predicted in the city of Hamilton, which comprises a major portion of the study area (CSpA, 2009). The employment growth model based on known employment, landuse, and socioeconomic data indicated growths in service, retail trade, and primary industries while manufacturing industries, wholesale trade and transport declined (CSpA, 2009). The large decline estimated in the manufacturing industry (-28%) was likely the most influential factor in the VKT decline for HDCV.

The percent change in VKTs between 2006 and 2021 closely resemble the changes in aggregate traffic emissions for each of the four traffic emissions: HC, CO, NOx, and CO_2 (Table 4.3). Since previous studies indicate that traffic emissions are not directly proportional to VKT (Frey et al., 2006), these similarities were investigated for validity. To investigate the relationship between the VKT change and the emissions changes, other outputs were also examined. The aggregate emissions were calculated by simple summation of the traffic emissions estimated for each of the 831 links. The traffic emissions for each of the network links were calculated based on the amount of vehicle flow and the flow speed (CSpA, 2009). Over the 15-year period, the total number of trips made by each vehicle class changed, resulting in changes in VKTs. Since the number of vehicles travelling in each class and flow speeds were inconsistent across link network, the similarities between VKT and aggregate emissions changes were not directly related. The percent change in total NOx aggregate emission was significantly different from that of VKT for morning and afternoon rush hours in January and July, in addition to CO_2 for morning rush hours in January and July. These results support a non-direct but positive relationship.

In Table 4.3, the percent differences for each pollutant between two years with respect to 2021 are also shown for LDV. This was done to show the amount of reduction necessary to offset the traffic emission growth projected in next 15 years. There were no significant differences in the estimation results for MDCV and HDCV classes in VKT, the aggregate emissions, and the link based emissions for all scenarios in 2021. This consistency was due to unaltered OD matrices and the traffic assignment order, allowing for these two classes to be assigned to the network unaffected by changes in LDV and/or HEV. The remaining sections focus on LDV and HEV classes.

Table 4.3: Aggregate Emissions for BAU Scenario in 2006 and 2021

Month	Vehicle Type	HC	CO	NOx	CO_2 (t)	HC	CO	NOx	CO_2 (t)
		2006				2021			
Morning Rush Hour (8am)									
Jan	LDV	290.64	9,004.36	886.89	162.32	369.98	11,500.10	1,133.78	207.57
	MDCV	21.55	629.52	334.12	39.93	22.61	658.63	349.75	41.90
	HDCV	4.59	184.01	107.60	9.22	3.91	154.73	90.13	7.78
	Total	316.79	9,817.89	1,328.61	211.47	396.50	12,313.46	1,573.66	257.25
Jul	LDV	261.44	5,237.55	528.92	162.52	332.62	6,684.38	676.01	207.83
	MDCV	19.12	506.16	314.80	39.89	20.07	529.57	329.50	41.85
	HDCV	4.06	151.02	102.57	9.20	3.46	127.00	85.91	7.76
	Total	284.62	5,894.74	946.29	211.61	356.15	7,340.95	1,091.41	257.45
Afternoon Rush Hour (4pm)									
Jan	LDV	296.49	8,784.16	899.51	169.69	363.48	10,768.94	1,103.62	208.74
	MDCV	15.89	463.36	250.80	30.14	17.06	499.23	270.91	32.52
	HDCV	1.41	56.22	33.43	2.88	1.21	47.71	28.26	2.45
	Total	313.79	9,303.74	1,183.74	202.72	381.74	11,315.88	1,402.78	243.71
Jul	LDV	312.41	7,584.21	550.21	169.90	382.95	9,287.61	674.49	209.00
	MDCV	16.67	492.74	229.28	30.11	17.89	530.90	247.66	32.48
	HDCV	1.46	60.09	31.13	2.88	1.25	50.99	26.31	2.45
	Total	330.53	8,137.04	810.62	202.89	402.10	9,869.49	948.47	243.93
Change 2006 to 2021 (2021 to 2006)									
		8am				4pm			
Jan	LDV	27.3% (-21.4%)	27.7% (-21.7%)	27.8% (-21.8%)	27.9% (-21.8%)	22.6% (-18.4%)	22.6% (-18.4%)	22.7% (-18.5%)	23.0% (-18.7%)
	MDCV	4.9%	4.6%	4.7%	4.9%	7.4%	7.7%	8.0%	7.9%
	HDCV	-14.9%	-15.9%	-16.2%	-15.6%	-14.2%	-15.1%	-15.5%	-14.9%
	Total	25.2%	25.4%	18.4%	21.7%	21.7%	21.6%	18.5%	20.2%
Jul	LDV	27.2% (-21.4%)	27.6% (-21.6%)	27.8% (-21.8%)	27.9% (-21.8%)	22.6% (-18.4%)	22.5% (-18.3%)	22.6% (-18.4%)	23.0% (-18.7%)
	MDCV	4.9%	4.6%	4.7%	4.9%	7.3%	7.7%	8.0%	7.9%
	HDCV	-14.9%	-15.9%	-16.2%	-15.6%	-14.1%	-15.1%	-15.5%	-14.9%
	Total	25.1%	24.5%	15.3%	21.7%	21.7%	21.3%	17.0%	20.2%

The units for HC, CO, and NOx are in kilograms (kg) while CO_2 is in tonnes (t).

4.3 HEV Flows

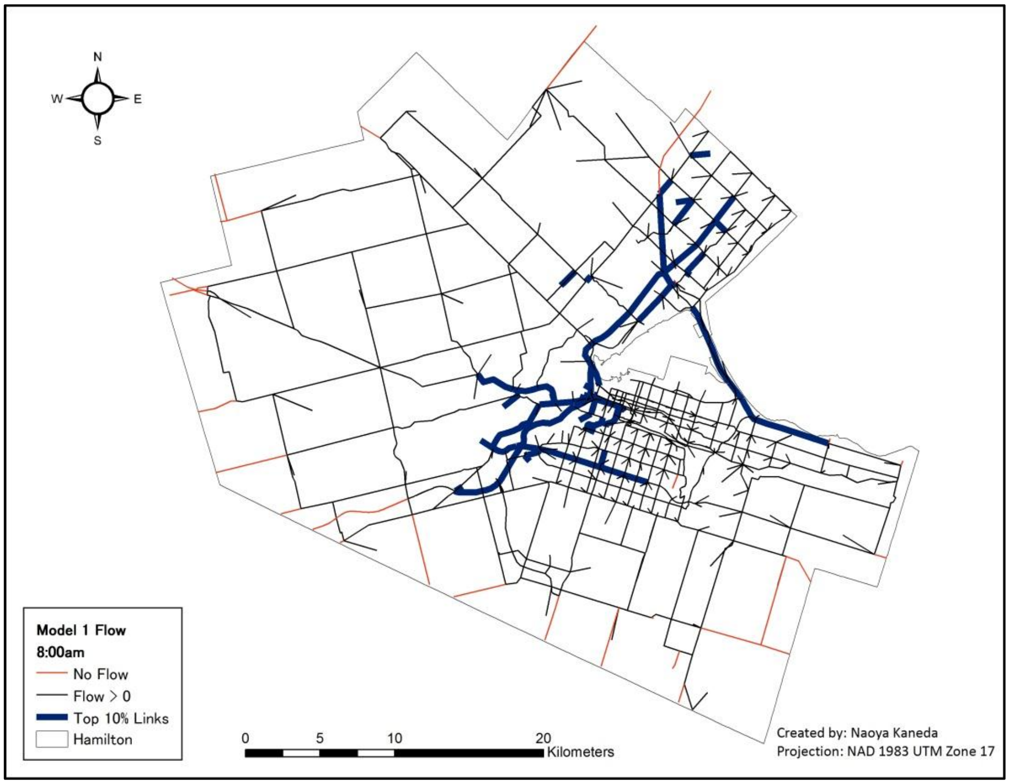
For all models, there were between 36 and 41 links out of 831 not travelled by HEVs. Most of these links were located at the edges of the study area. Since the traffic assignment model only calculates the intra-zonal trips and does not account for trips to or from outsize of the study area, these links cannot carry any traffic flow. All pseudo links carried some flow of HEVs except for 1810544 in the afternoon rush hour and 2090279 for both morning and afternoon rush hours. This was a result of HEV OD matrices calculations, which predicted that no trip would be made into or out of these two TAZs at these times. The variations in the number of links not travelled by HEVs were based on the market penetration levels across different models.

The most travelled links by HEVs in all models were the major highways and the large arterial roads given their higher capacity to carry more vehicles on the road. The following figures (Figure 4.1 through Figure 4.5) display a spatial pattern of link usage by HEVs at 10% market penetration. The links calculated in the top 10% for the highest HEV flows (approximately 250+ HEV flows per hour) are displayed in the thick blue lines. All other links with some HEV flow are displayed in black, while the links without HEV flow are in red. As each model distributed HEVs differently, minor differences in the resulting traffic flow were seen.

In Model 1 (Figure 4.1), links with high volumes of HEV flow in both morning and afternoon peak periods include parts of Hwy 403, Lincoln M. Alexander Parkway (Linc), and QEW over Burlington Skyway Bridge. These links contain high volumes of traffic flow due to their importance as major highways in the study area. The major differences between the two peak periods include use of Hwy 407, QEW between Centennial Parkway and Fruitland Road, and Red Hill Valley Parkway (RHVP). There were high volumes of HEV traffic in the morning on Hwy 407 and QEW, while RHVP was used heavily in the afternoon.

As seen in Model 1, most travelled links by HEVs in Model 2 (Figure 4.2) were also the major highways and arterial roads with higher capacity to carry more vehicles on the road. In contrast to Model 1, differences between the highest flows in the morning and afternoon rush hours were less apparent in Model 2. Other than the northern half of RHVP, which is heavily used for both peak hours, much of the other major links with heavy HEV traffic were the same as Model 1. These include: Hwy 403, the Linc, and QEW from Burlington Skyway Bridge to Fruitland Road. The differences in the use of Hwy 407 and southern half of RHVP between the morning and afternoon peaks also resembled HEV flow in Model 1.

Traffic on Hwy 407 decreased for both morning and afternoon rush hours compared to the previous two models discussed in Model 3 (Figure 4.3). The changes in the traffic flows on the Linc, RHVP, and QEW closely resembled those of Model 1 and 2. The heavy use of QEW in Burlington, Hwy 403 through Hamilton, and the west half of the Linc consistent across all models, including Uniform Count (UC) and Uniform Percentage (UP) models. For UC (Figure 4.4) and UP (Figure 4.5) models, fewer differences between two time periods were observed. The entire loop (the network of major highways circling Hamilton) carried high HEV volume for both morning and afternoon rush hours in UC and UP models. The difference between these two models and the first three models was higher volume in the arterial road in central Hamilton.



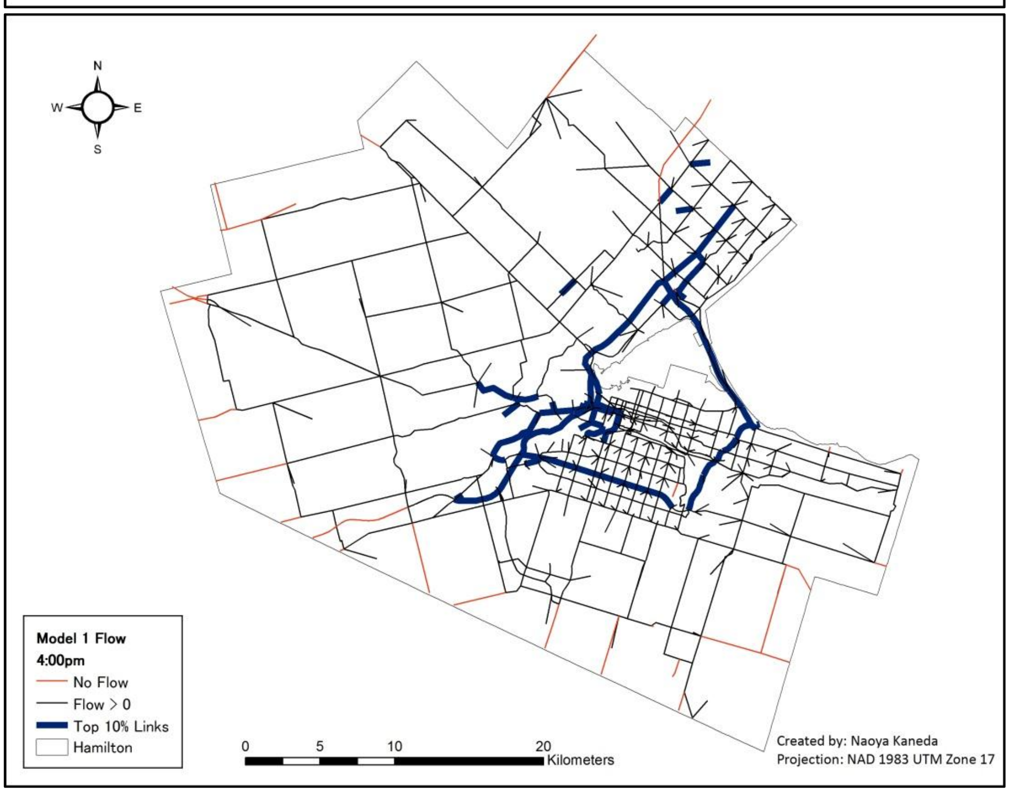


Figure 4.1: Link use by HEV for Model 1 at 8:00 am (top) and 4:00pm (bottom)

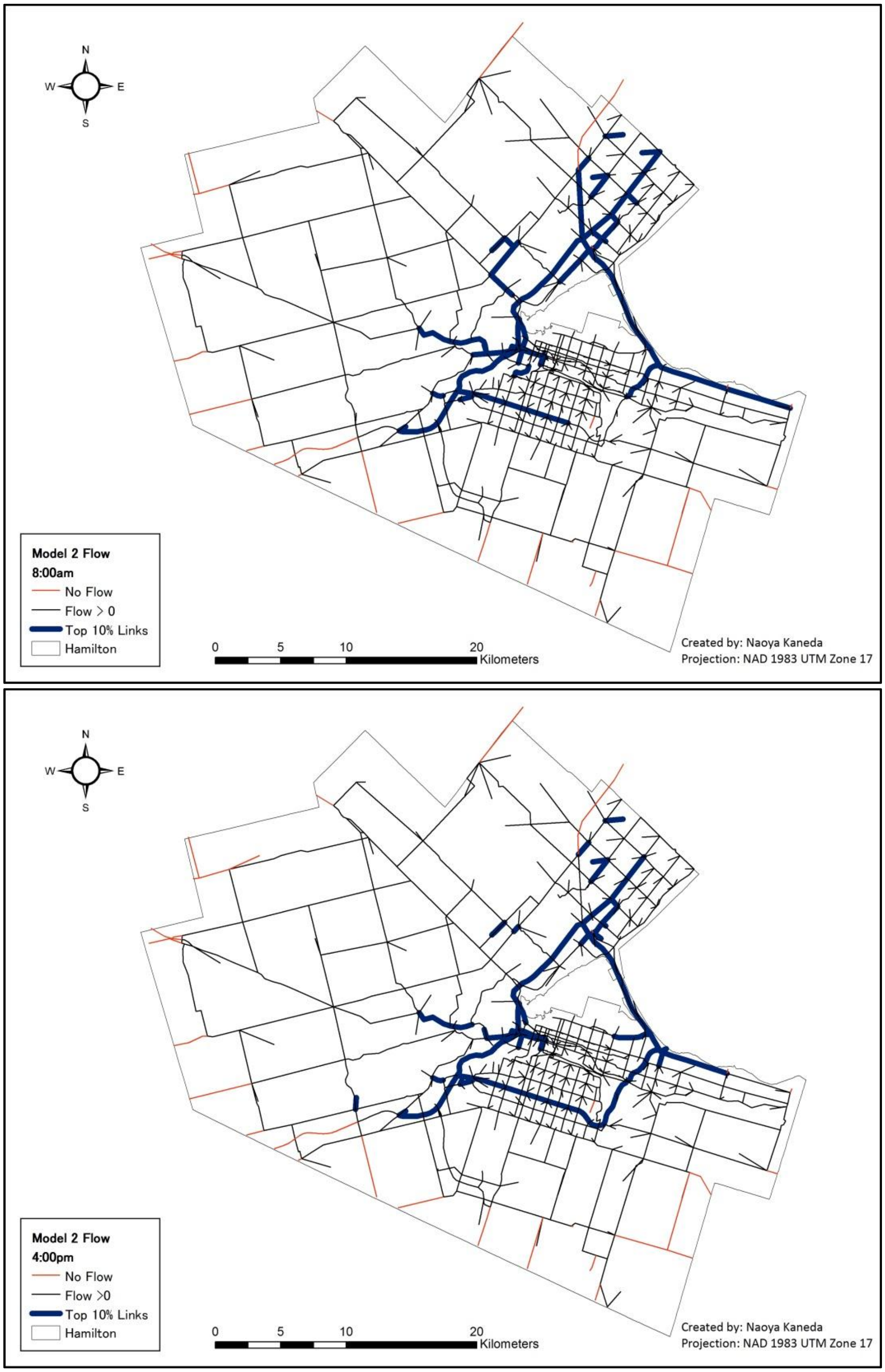
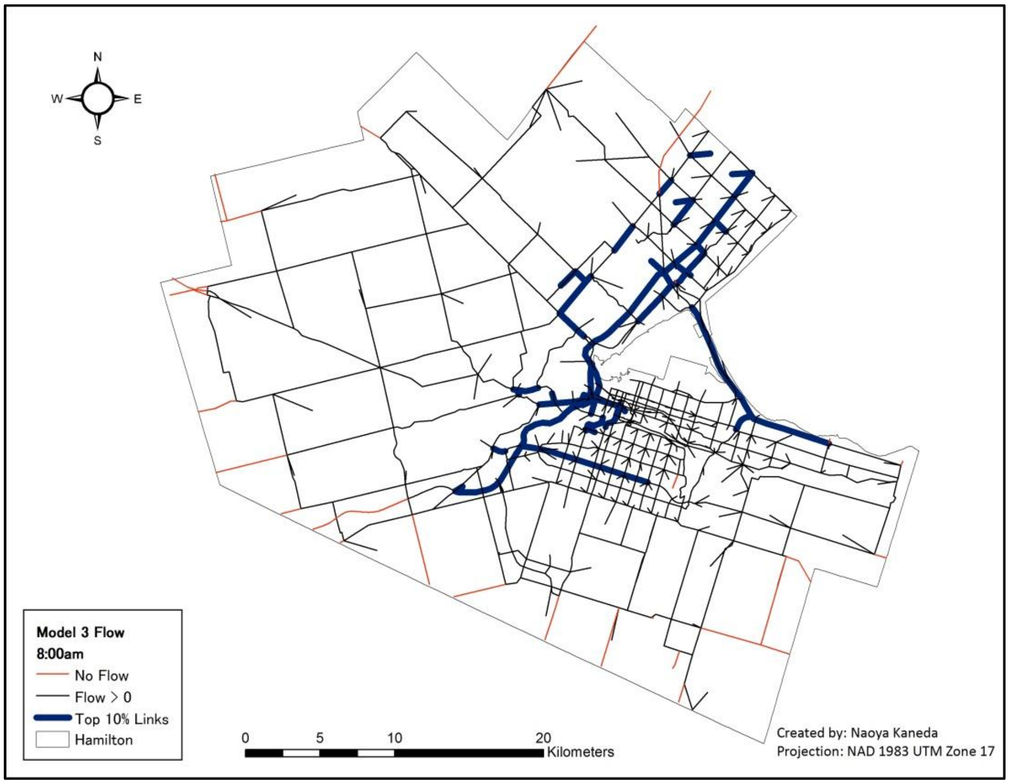


Figure 4.2: Link use by HEV for Model 2 at 8:00 am (top) and 4:00pm (bottom)



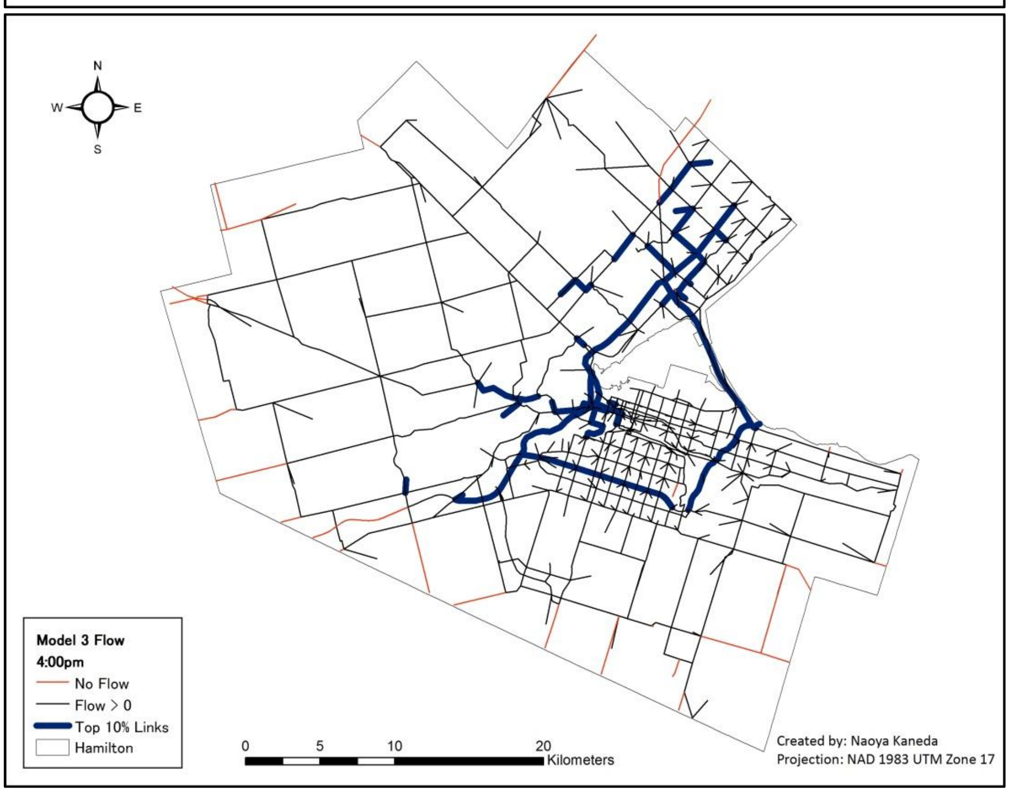


Figure 4.3: Link use by HEV for Model 3 at 8:00 am (top) and 4:00pm (bottom)

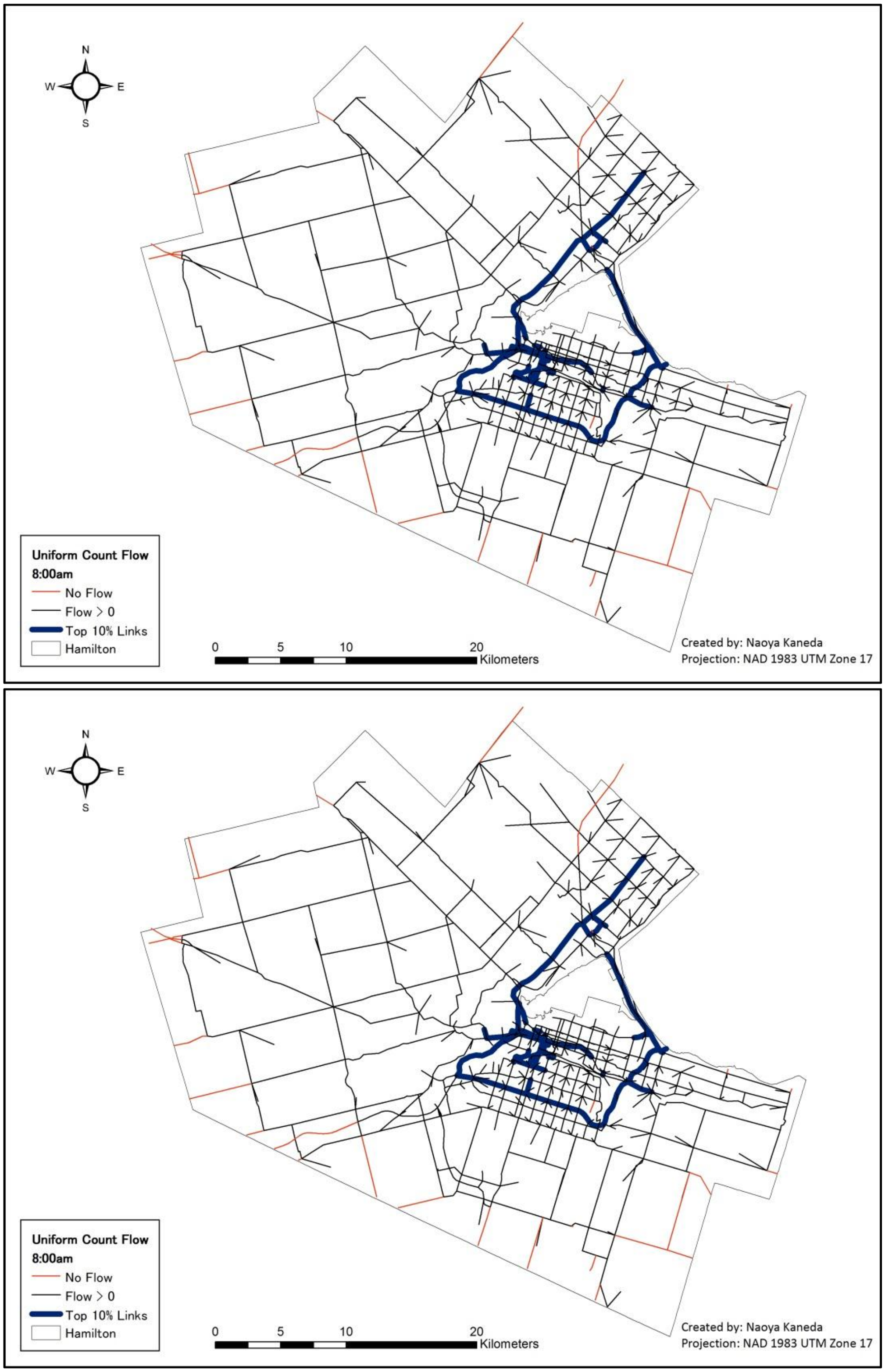


Figure 4.4: Link use by HEV for Uniform Count Model at 8:00 am (top) and 4:00pm (bottom)

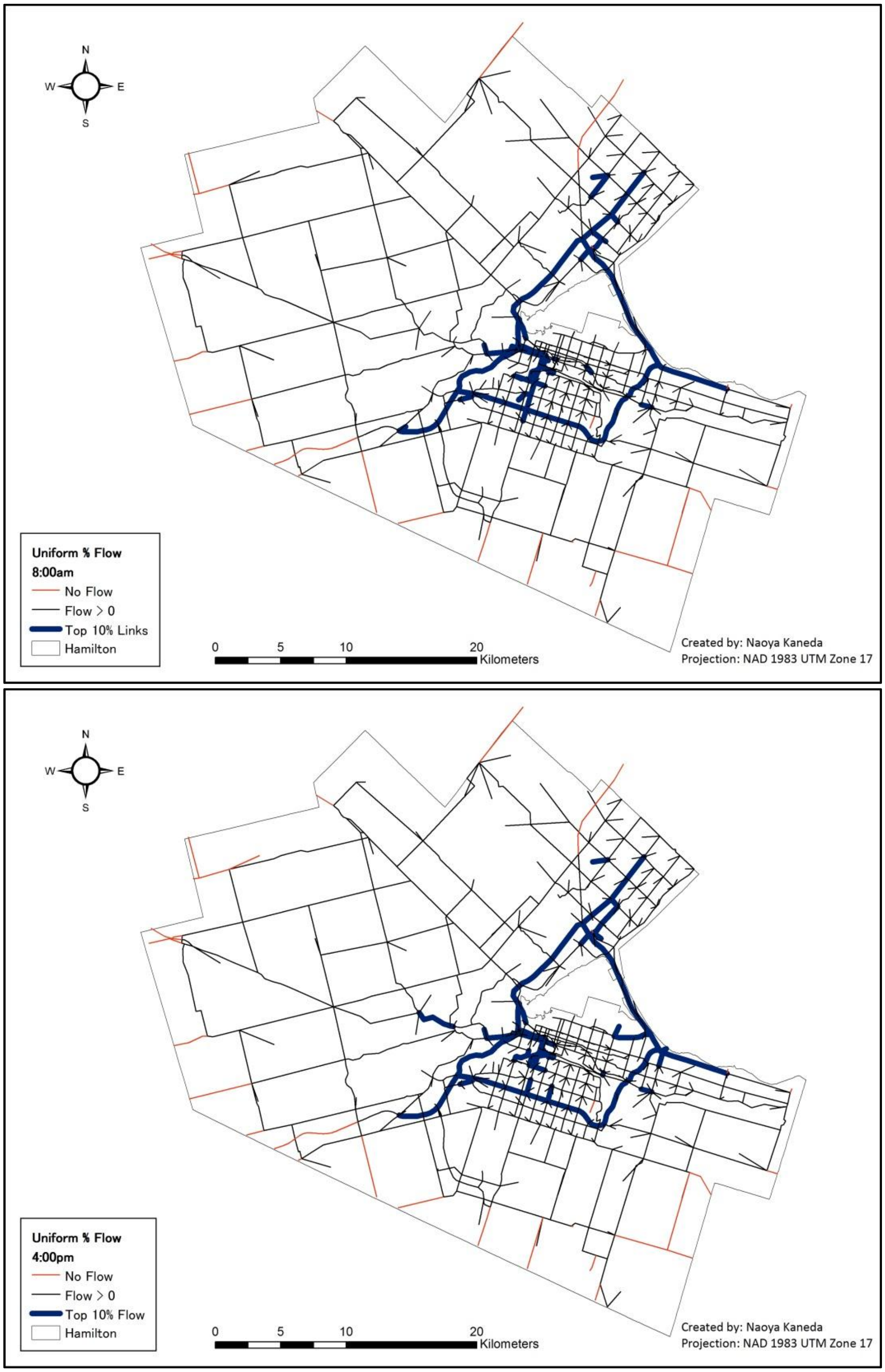


Figure 4.5: Link use by HEV for Uniform Percentage Model at 8:00 am (top) and 4:00pm (bottom)

4.4 Aggregate Emissions

Table 8.3 and Table 8.4 in the Appendix list the results of aggregated traffic emissions from each level of market penetrations (1%, 2%, 5%, and 10%) for all models, including BAU. From Table 8.3 and Table 8.4, the decreasing traffic emissions at all market penetration levels across all models, compared to the BAU scenario at an aggregate level are evident. The difference in each model in contrast to the BAU scenario cannot be observed directly with raw values. The percent changes from the BAU scenario to all models are shown in Table 4.4 and Table 4.5, which are separated for the months of January and July.

These tables show that at the aggregate level, a reduction in traffic emission was significant (more than 5% change) only for HC and CO when the 10% of the total light duty vehicles in the Hamilton CMA was HEVs. Despite the difference in distributions of HEV across the models, percent change did not differ greatly between the models, although the most significant reductions with HC exist at approximately 8%, followed by CO in the range of 6.5%. The reductions for NOx and CO_2 at 10% HEVs were around 3.4% and 4%, respectively. While the values for NOx and CO_2 fell short at the 5% significance level, it shows that increased use of HEVs does make a difference. Although the 25% HEV level was not used for non-uniform models due to difficulty in the distribution method, the two uniform models show the potential for reduction by increasing the number of HEVs. At 25% HEV, all four traffic emissions illustrated significant reductions with HC exceeding 20%.

Between BAU 2021 and Base 2006 emissions, the baseline emissions were lower by 21% in the morning and 18% in the afternoon rush hours (Table 4.3). Contrasting the percent reductions in each model approximately 35%, 30%, 16%, and 21% of emission growth in HC, CO, NOx, and CO_2 can be offset by use of 10% HEVs.

Table 4.4: Percent aggregate emission reduction contrasted to BAU in January

Models	8am				4pm			
	HC	CO	NOx	CO_2	HC	CO	NOx	CO_2
M1 1%	-0.80%	-0.65%	-0.35%	-0.43%	-0.79%	-0.63%	-0.33%	-0.42%
M1 2%	-1.62%	-1.29%	-0.68%	-0.86%	-1.63%	-1.31%	-0.69%	-0.87%
M1 5%	-3.96%	-3.22%	-1.71%	-2.11%	-4.05%	-3.25%	-1.73%	-2.15%
M1 10%	-8.02%	-6.58%	-3.56%	-4.29%	-8.07%	-6.54%	-3.51%	-4.32%
M2 1%	-0.86%	-0.71%	-0.38%	-0.47%	-0.89%	-0.71%	-0.37%	-0.47%
M2 2%	-1.69%	-1.39%	-0.74%	-0.91%	-1.75%	-1.42%	-0.75%	-0.94%
M2 5%	-4.24%	-3.49%	-1.87%	-2.28%	-4.42%	-3.58%	-1.91%	-2.36%
M2 10%	-8.54%	-7.08%	-3.85%	-4.60%	-8.79%	-7.19%	-3.87%	-4.73%
M3 1%	-0.84%	-0.68%	-0.37%	-0.45%	-0.83%	-0.66%	-0.35%	-0.44%
M3 2%	-1.61%	-1.30%	-0.69%	-0.86%	-1.66%	-1.33%	-0.70%	-0.89%
M3 5%	-4.05%	-3.30%	-1.76%	-2.16%	-4.19%	-3.38%	-1.80%	-2.24%
M3 10%	-8.18%	-6.72%	-3.64%	-4.38%	-8.34%	-6.77%	-3.64%	-4.47%
UC 1%	-0.80%	-0.64%	-0.34%	-0.43%	-0.84%	-0.66%	-0.34%	-0.44%
UC 2%	-1.59%	-1.27%	-0.67%	-0.84%	-1.69%	-1.33%	-0.69%	-0.89%
UC 5%	-3.95%	-3.17%	-1.70%	-2.08%	-4.25%	-3.36%	-1.78%	-2.23%
UC 10%	-7.99%	-6.44%	-3.49%	-4.21%	-8.48%	-6.77%	-3.62%	-4.49%
UC 25%	-19.99%	-15.87%	-8.76%	-3.95%	-21.15%	-17.19%	-9.34%	-11.21%
UP 1%	0.24%	0.35%	0.64%	0.59%	0.24%	0.36%	0.65%	0.60%
UP 2%	-1.52%	-1.22%	-0.65%	-0.81%	-1.54%	-1.22%	-0.64%	-0.81%
UP 5%	-3.79%	-3.07%	-1.64%	-2.01%	-3.86%	-3.07%	-1.62%	-2.04%
UP 10%	-7.64%	-6.22%	-3.36%	-4.05%	-7.69%	-6.18%	-3.30%	-4.09%
UP 25%	-19.19%	-15.87%	-8.76%	-3.56%	-19.26%	-15.73%	-8.53%	-10.27%

Table 4.5: Percent aggregate emission reduction contrasted to BAU in July

Models	8am				4pm			
	HC	CO	NOx	CO_2	HC	CO	NOx	CO_2
M1 1%	-0.78%	-0.62%	-0.31%	-0.43%	-0.79%	-0.63%	-0.27%	-0.42%
M1 2%	-1.59%	-1.24%	-0.59%	-0.86%	-1.63%	-1.30%	-0.56%	-0.87%
M1 5%	-3.89%	-3.09%	-1.51%	-2.11%	-4.04%	-3.24%	-1.42%	-2.15%
M1 10%	-7.88%	-6.36%	-3.18%	-4.29%	-8.04%	-6.53%	-2.90%	-4.32%
M2 1%	-0.85%	-0.68%	-0.34%	-0.47%	-0.88%	-0.71%	-0.30%	-0.47%
M2 2%	-1.66%	-1.34%	-0.66%	-0.91%	-1.74%	-1.41%	-0.61%	-0.94%
M2 5%	-4.16%	-3.36%	-1.66%	-2.28%	-4.40%	-3.58%	-1.58%	-2.37%
M2 10%	-8.39%	-6.85%	-3.46%	-4.60%	-8.75%	-7.18%	-3.21%	-4.74%
M3 1%	-0.82%	-0.66%	-0.33%	-0.45%	-0.83%	-0.66%	-0.28%	-0.44%
M3 2%	-1.57%	-1.25%	-0.61%	-0.86%	-1.66%	-1.33%	-0.57%	-0.89%
M3 5%	-3.97%	-3.17%	-1.56%	-2.16%	-4.18%	-3.37%	-1.48%	-2.24%
M3 10%	-8.03%	-6.50%	-3.27%	-4.38%	-8.31%	-6.77%	-3.01%	-4.48%
UC 1%	-0.79%	-0.61%	-0.30%	-0.43%	-0.84%	-0.66%	-0.27%	-0.44%
UC 2%	-1.56%	-1.21%	-0.59%	-0.84%	-1.69%	-1.32%	-0.56%	-0.89%
UC 5%	-3.88%	-3.05%	-1.50%	-2.08%	-4.25%	-3.35%	-1.45%	-2.23%
UC 10%	-7.86%	-6.22%	-3.12%	-4.21%	-8.46%	-6.75%	-2.98%	-4.49%
UC 25%	-19.68%	-15.86%	-8.11%	-10.56%	-21.08%	-17.23%	-7.82%	-11.22%
UP 1%	0.25%	0.36%	0.66%	0.59%	0.24%	0.35%	0.70%	0.60%
UP 2%	-1.49%	-1.17%	-0.57%	-0.81%	-1.53%	-1.21%	-0.52%	-0.81%
UP 5%	-3.72%	-2.96%	-1.46%	-2.02%	-3.86%	-3.07%	-1.33%	-2.04%
UP 10%	-7.51%	-6.00%	-3.00%	-4.06%	-7.67%	-6.16%	-2.71%	-4.10%
UP 25%	-18.88%	-15.36%	-7.84%	-10.22%	-19.18%	-15.75%	-7.14%	-10.28%

4.5 Link Based Emissions

While for the objective of this research was to illustrate reductions in emissions, seven to eight links highlighted significant (more than 5% change) increases, as compared to the BAU scenario in one or more of the situations (a combination of a market penetration level, a month, and a time). With regards to these links, all four pollutants had significant increases, with one or two pollutants falling just short of 5% cut-off in some cases. Table 4.6 displays the links with significant increases in traffic emissions and their situations.

Of those with significant increases in traffic emissions, four links (3410313, 4940495, 5000484, and 5000501) were common across all models. The rest were made up of two links (3320335 and 4800583) appearing in four models, another two links displayed in two models (3340335 and 3210301), and two more links (4480597 and 5970413) appearing only in one of the models. Out of these links, three showed percent traffic emission increase into the double digits. The links 3320335 and 3340335 displayed over 20% and 10% increases, respectively, in Model 1 and Model 2 and the link 3210301 displayed over 10% increase in Model 3 and UC model. There was, however, a link (480583) which showed duality: a significant increase for morning rush hours at 2% HEVs in four models and over 20% reduction in afternoon rush hours at 5% and 10% HEVs in all five models.

Table 4.6: Links with significant traffic emission increase situations (% = HEV level)

Models	LINKID	Street Names	Jan		Jul	
			8am	4pm	8am	4pm
M1	3320335	Mountain Brow Road	10%		10%	
	3340335	Mohawk Road	10%		10%	
	3410313	Maple Avenue	2% 5%		2% 5%	
	4570445	Hwy 403 exit to Main St	2%		2%	
	4940495	Southcote Road		1% 2%		1% 2%
	5000484	Carluke Road	2%		2%	
	5000501	Fiddlers Green Road	2%		2%	
M2	3320335	Mountain Brow Road	10%		10%	
	3340335	Mohawk Road	10%		10%	
	3410313	Maple Avenue	2% 5%		2% 5%	
	4800583	Stone Church Road	2%		2%	
	4940495	Southcote Road		1% 2%		1% 2%
	5000484	Carluke Road	2%		2%	
	5000501	Fiddlers Green Road	2%		2%	
M3	3200578	King Street East	1%		1%	
	3210301	Lawrence Road	1%		1%	
	3410313	Maple Avenue	2% 5%		2% 5%	
	4800583	Stone Church Road	2%		2%	
	4940495	Southcote Road		1% 2%		1% 2%
	5000484	Carluke Road	2% 5%		2% 5%	
	5000501	Fiddlers Green Road	2% 5%		2% 5%	
UC	3200578	King Street East	1%		1%	
	3210301	Lawrence Road	1%		1%	
	3320335	Mountain Brow Road	25%		25%	
	3410313	Maple Avenue	2% 5%		2% 5%	
	4800583	Stone Church Road	2%		2%	
	4940495	Southcote Road		1% 2%		1% 2%
	5000484	Carluke Road	2% 5%		2% 5%	
	5000501	Fiddlers Green Road	2% 5%		2% 5%	
UP	3320335	Mountain Brow Road	25%	1%	25%	1%
	3410313	Maple Avenue	2% 5% 10%		2% 5% 10%	
	4480597	York Boulevard	1%		1%	
	4800583	Stone Church Road	2%		2%	
	4940495	Southcote Road		2%		2%
	5000484	Carluke Road	2%		2%	
	5000501	Fiddlers Green Road	2%		2%	
	5970413	York Boulevard	1%		1%	

On the opposite end of the scale the number of links with significant reduction in traffic emissions for each model and situation are highlighted in Table 4.7 and Table 4.8. The difference between the values for each pollutant resembles that of a percent decrease in aggregate emissions (Table 4.4 and Table 4.5) where HC and CO have larger values than NOx or CO_2. The difference between morning and afternoon peak periods were also similar to that of aggregate emissions. Largely, there were more links with significant traffic emission reductions in the afternoon than in the morning. Unlike the aggregate emissions, the number of links with significant emission reductions does not coincide with HEV proportions linearly, but shows rapid increase, particularly for HC and CO. The tables display that more than 600 links with significant reductions can only account for approximately 8% reduction in the aggregate emissions in HC at 10% HEV for Models 1, 2, and 3.

Across the models, there were differences in the way the number of links with a significant increase changed from one HEV market penetration level to the next. The rate of change from 1% to 2% to 5% HEV levels was greater in Model 2 and UC model than in Model 1 and Model 3. Each of these model pairs displayed similar values in the number of links at corresponding market penetration levels. The pattern of emission increase seen in the number of links for UP was not observed in any other models. In the UP model, the values at 5% market penetration levels were comparable to that of 2% market penetration in other models, while the values at 10% market penetration matched those of other models at the same market penetration level.

At 25% HEV market penetration in UC and UP models, the number of links with a significant reduction exceeds 700. With nearly 40 of those links not carrying HEV flow, these values show that significant traffic emission reduction can be observed on almost all of the links, especially those emissions with more than 790 links. This result coincides with significant reductions seen at the aggregate level for these two models at 25% HEV.

Table 4.7: Number of links with significant (>0.05) emission reductions in January

Models	8am				4pm			
	HC	CO	NOx	CO_2	HC	CO	NOx	CO_2
M1 1%	0	0	0	0	1	1	1	1
M1 2%	7	5	1	1	8	6	1	1
M1 5%	164	92	16	19	181	106	24	25
M1 10%	617	483	144	160	642	527	164	183
M2 1%	0	0	0	0	2	2	1	1
M2 2%	20	11	2	2	21	11	2	2
M2 5%	229	135	34	37	258	155	51	54
M2 10%	626	545	211	221	659	585	227	246
M3 1%	6	6	6	6	1	1	1	1
M3 2%	10	4	2	2	10	6	1	1
M3 5%	174	109	22	27	201	141	33	43
M3 10%	632	490	176	187	656	527	191	204
UC 1%	6	6	6	6	1	1	1	1
UC 2%	9	7	2	2	5	4	1	1
UC 5%	251	105	11	10	268	103	21	26
UC 10%	699	615	240	252	721	655	234	254
UC 25%	789	776	723	728	794	784	747	753
UP 1%	0	0	0	0	1	1	0	0
UP 2%	4	4	2	2	4	3	1	1
UP 5%	33	23	6	6	48	29	15	14
UP 10%	769	748	58	54	789	773	63	60
UP 25%	794	794	788	790	794	794	789	791

Table 4.8: Number of links with significant (>0.05) emission reductions in July

Models	8am				4pm			
	HC	CO	NOx	CO_2	HC	CO	NOx	CO_2
M1 1%	0	0	0	0	2	3	1	2
M1 2%	7	5	1	1	9	9	1	2
M1 5%	160	87	13	19	178	112	15	25
M1 10%	607	468	120	160	637	538	110	185
M2 1%	0	0	0	0	3	4	1	2
M2 2%	19	11	2	2	21	11	2	2
M2 5%	220	133	27	37	254	158	35	54
M2 10%	621	534	163	221	655	588	158	246
M3 1%	6	6	6	6	1	1	1	1
M3 2%	10	4	2	2	11	8	1	2
M3 5%	169	106	16	27	199	147	16	43
M3 10%	628	472	142	191	650	536	143	204
UC 1%	6	6	6	6	1	1	1	1
UC 2%	8	6	2	2	6	6	1	2
UC 5%	239	99	9	10	258	115	17	26
UC 10%	693	604	184	254	717	661	123	254
UC 25%	789	776	718	729	793	784	713	753
UP 1%	0	0	0	0	1	1	0	0
UP 2%	4	3	2	2	5	5	1	2
UP 5%	33	23	6	6	48	31	11	14
UP 10%	767	747	48	54	788	773	42	60
UP 25%	794	794	782	790	794	794	776	791

5 Discussions

This chapter is divided into four parts. The first two sections review the results found in each of aggregate and disaggregate level. The aggregate emissions section compare and contrast the results from this study to previous literatures. The disaggregate emission section discusses this study's main benefit; to consider the spatial variation in emission changes with varying HEV market penetration models. The latter two sections consider a hypothetical EV scenario and make suggestions for improvements and future studies. An overview of possible 5% EV scenario, in accordance with a plan by the government of Ontario, is assessed in EV scenario section. In the last section on the future improvements, the effectiveness of and improvements that could be made to each of the traffic assignment program and HEV distribution models are discussed.

5.1 Aggregate Emissions

Along with an indication that 10% HEV can achieve significant reductions in HC and CO emissions, a linear trend was evident between the percent reductions of aggregated traffic emissions and the increasing HEV proportions for all models (Table 4.4 and Table 4.5). This trend suggests that if HEVs were distributed according to the models, the overall traffic emission reductions obtained from 100% vehicle replacement with HEVs would be approximately 80% for HC, 60%-70% for CO, 30%-35% for NOx, and 40% for CO_2. It was also observed that NOx and CO_2 will reach a significant level of reduction at 15% and 12% HEV proportions, respectively. Although this finding seems simplistic, previous studies have not performed small incremental changes in the HEV proportions as seen in this study. In recent studies examining traffic patterns and HEV replacement, only one alternative vehicle scenario was used with a predetermined HEV proportion. Frey et al. (2009) included 9.9% HEV, 9.9% E85, 5.9% diesel, 1.2% CNG, and 0.1% EV/Fuel Cell with 73% Gasoline vehicles as their alternative vehicle scenario, while Stone et al. (2009) replaced all vehicles with 100% hybridization.

Across the two inputs with direct influence on the traffic emission results (fleet vehicle makeup and OD matrices), only the OD matrices for LDV and HEV were altered from one scenario to another. The method used to create LDV and HEV OD matrices was validated to produce no significant changes in total VKT between scenarios, as seen in Table 4.1. This suggests that the overall traffic volume on each link remained constant and the LDV volume was replaced by increasing HEV volumes. Therefore the reductions in traffic emissions are directly related to the differences of the tailpipe emissions between LDV and HEV. Replacing LDVs on roads with more HEVs can lead to a higher reduction in traffic emissions. Altering of the HEV distribution patterns between the models changes the number of trips made by HEVs originating and/or ending in each TAZ. This would change the links used by HEVs and volume of HEVs on each link, as discussed in Section 4.3. The emission factors were calculated based on vehicle travel speed. Therefore, changing the links used and applying an average travel speed to each links helps to account for the variations in the percent reductions between the models.

Contributions

There were some differences between these results and those of previous studies involving traffic pattern and HEV replacement. In Frey et al. (2009), the future scenario with 33% VMT growth and 27% AFV market penetration was illustrated to result in large reductions in HC, CO, and NOx emissions compared to baseline scenario in 2005, while CO_2 emission increased significantly. In a study by Stone et al (2009), the implementation of HEVs to completely replace LDVs was estimated to offset the emission growth by 97%. These differences are discussed below.

First, the total emission reduction in alternative scenario was calculated with AFVs in all vehicle types (cars, trucks, and busses) (Frey et al., 2009) whereas no AFVs were included in trucks or busses in this study. Frey et al. (2009) have also incorporated a more complex combination for the AFV make up for cars which included E85, CNG, EV, and Fuel Cell vehicles. Secondly, Frey et al. (2009) accounted for the technological advancements from 2005 to 2030, such as the average fuel economy increase of 16% in LDV and vehicle turnover as a result of stricter emission codes. Thirdly, the impact of VMT growth estimated on the overall flow speed in the network differs between the studies. The 33% VMT growth was estimated to reduce the overall average trip speed of the network by 28%, which caused a significant increase in the CO_2 emission (Frey et al., 2009). In contrast, the calculations for the Hamilton CMA resulted in zero links with a significant decrease in average speed from 2006 to 2021 even though the total VKT increased by 25% (Table 4.2).

In Stone et al. (2009), three different landuse development patterns were contrasted, each with and without HEV fleet implementation for 11 metropolitan areas in the United States. The BAU scenario showed median VMT increases of 63.5% from 2000 to 2050, accompanied by 22.8% CO_2 emission increase with use of conventional ICE vehicles. It was estimated that implementation of complete hybridization of the LDVs would limit the CO_2 emission growth to 0.7% (Stone et al., 2009). Between the BAU scenarios with and without HEVs in 2050, CO_2 emission was reduced by 18% with HEVs. For the Hamilton CMA, 25% growth in VKT was accompanied by 28% and 23% increases in CO_2 emissions for morning and afternoon peaks, respectively, without HEVs. With the implementation of 10% HEVs, the CO_2 emission growth was limited to 23% (morning) and 18% (afternoon). A complete hybridization of LDV fleet in the Hamilton CMA was estimated to result in a 40% reduction in CO_2 emissions, as discussed previously. Consistent with Frey et al. (2009), the technological advancements in vehicles were also accounted for in Stone et al. (2009). It was projected that the fuel economy would increase from 19.5 MPG in 2000 to 25.6 MPG in 2050. They have also included 5.8% VMT increase as the “rebound effect”, an approximately 2 % increase in VMT for every 10% increase in MPG (Stone et al., 2009).

These differences point to the need for more complex strategic scenario building in terms of fuel type, vehicle class, and vehicle technology change in the Hamilton CMA. In this study, only three fuel types (gasoline, diesel, and hybrid-electric) were considered even though six fuel types were currently in use in the Hamilton CMA in 2008. This limitation stems partly from to the limited ability of the traffic assignment software. The traffic assignment software used in this study is currently only able to handle four vehicle classes, (HDCV, MDCV, LDV, and HEV) and bus transit; therefore, it cannot compute more than one AFV type. A software update to assign six or more vehicle classes is necessary to simulate a gradual transition from ICE to EV and/or Fuel Cell vehicles through HEV. Finally, the advancement of vehicle technologies as more fuel efficient vehicles are being developed by manufacturers every year is an important piece of information to consider. Use of Mobile6.2C emission factors with the same inputs are convenient and allow for an observation of emission changes by vehicle class alone. However, to see true technological advancement, improvement of fuel economy must be considered.

5.2 Disaggregate Emissions

At the aggregate level, the estimated traffic emissions showed a linear trend with the HEV market penetration level. Variations between models and between types of pollutants in the number of links with a significant emission reduction were also discussed (Table 4.7). In this section, investigations of traffic emission at the link level, the emission reduction trends between links, and spatial patterns of links with significant changes are discussed. The discussions and figures use HC during morning rush hour in January with 10% HEV as an example since the patterns for CO, NOx, and CO_2 were generally consistent with HC.

The focus of this study was to investigate the reduction in traffic emissions by use of HEVs in the fleet. To compare the emissions on each link, the volume of emissions had to be normalized with its length (grams per kilometer or g/km). In the BAU scenario, the links with highest traffic emission per kilometer included sections of QEW in Burlington, Burlington Skyway, Hwy 403, James Street South, and sections of King Street West and Main Street West between downtown and Cootes Drive. The example of BAU HC emission and its distribution can be seen in Figure 5.1.

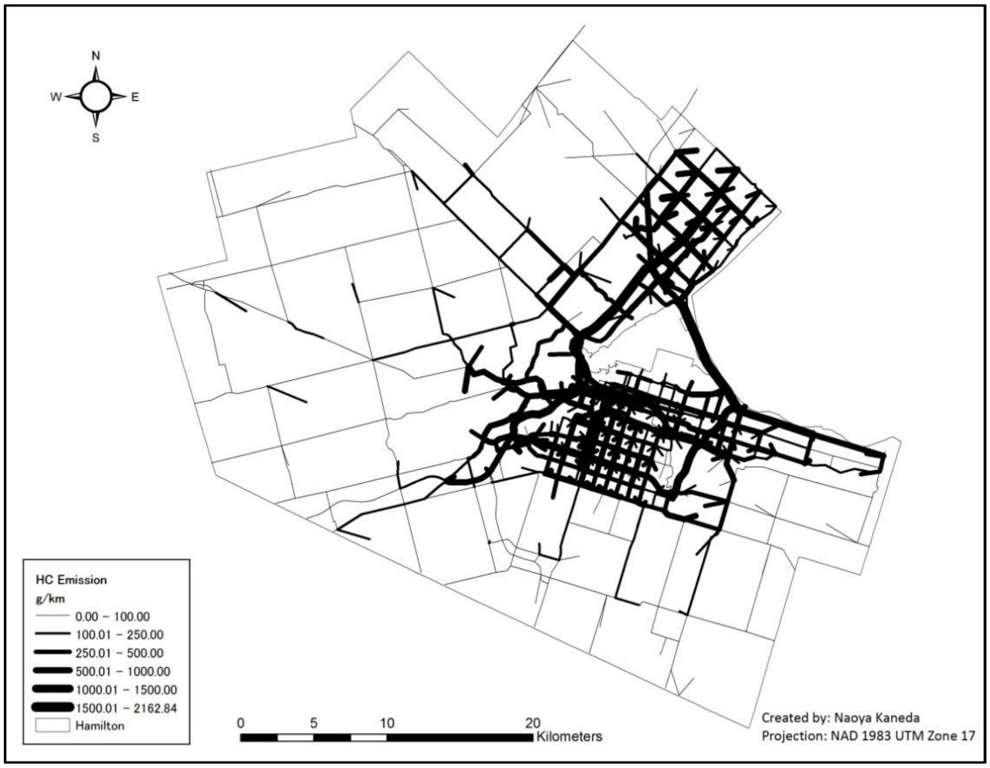


Figure 5.1: Business-as-Usual scenario HC emissions in 2021

Including those already listed, many of the links with high emissions were major highways in the study area. High vehicle speed and high vehicle flow help to explain high emissions on these links. Depending on the type of emission, the speed at which the vehicle produces a minimum amount of tailpipe or the optimum running speed changes. Mobile6.2C calculated the optimum speed is between 52.5 and 55mph (84.5 to 88.5km/h) for HC emission, 35mph or 56.3km/h for CO emission, and between 25 to 35mph for NOx depending on the type of road. This suggests that reducing the vehicle travel speed does not necessarily result in reduction of all traffic emissions.

Artificially reducing the speed limits on the major highways down to 70km/h prior to running the traffic assignment yielded roughly the same emissions outputs. This result was due to the nature of the trip stochastic user equilibrium used in the TRAFFIC program where travel time is minimized for all alternative routes. With an artificially reduced speed limit to simulate rush hour congestion, where alternative routes to major highways are also congested, the program rather simply replaced vehicles from the major highways to alternative arterial roads. To maximize the effectiveness of HEV on the traffic emission, the average speed must be reduced to between 40 and 50km/h throughout the network by limiting speed or increase the traffic volume to create congestion. Although approximately 80% of the links follow the similar linear trend in the traffic emission reductions at the aggregate level, there were links with different patterns. A number of examples of these links were mentioned in Table 4.6 in the previous chapter. Figure 5.2 shows the HC emission reduction trends for some sample links along with the aggregate emission trend. The variations from one HEV market penetration level to another are displayed clearly with the trend lines in Figure 5.2. The label “linear” trend can also be misinterpreted for the change from -1.48% to -14.37% on one link (2920285: Walkers Line) is as linear as -0.50% to -4.48 on another link (2940288: Upper Centennial Parkway). The linear trend seen at the aggregate level is an average of all these variations.

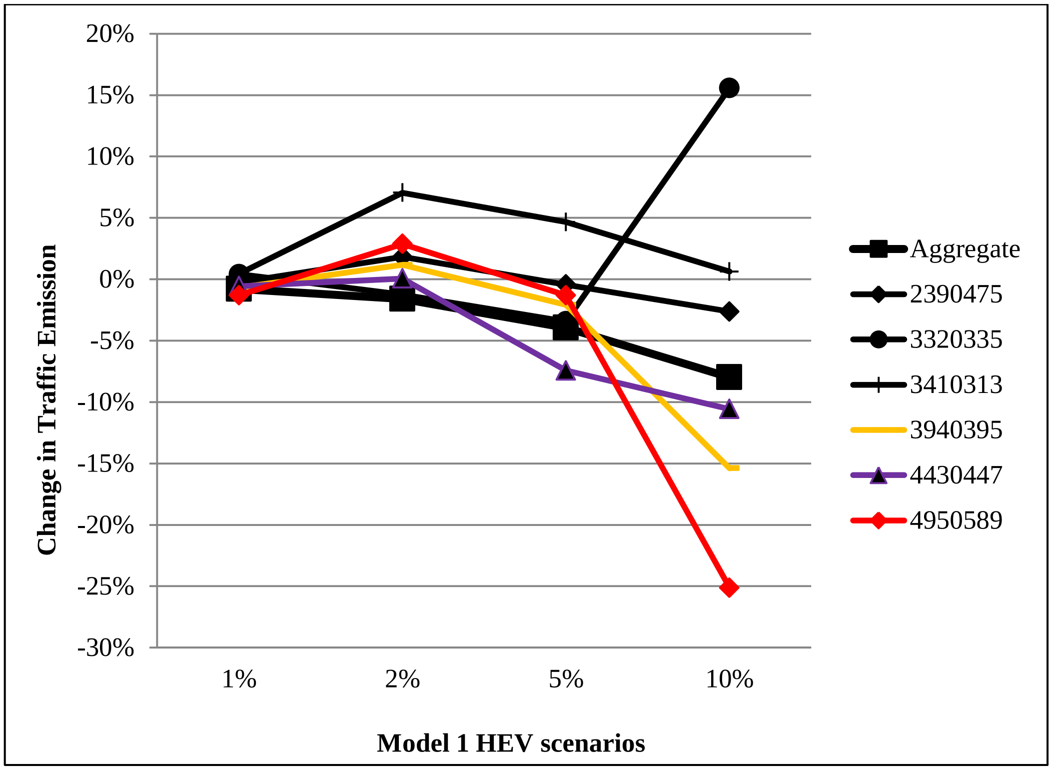


Figure 5.2: Sampled percent changes in HC emission in January at 8:00am

The percent reduction also varied over space and from model to model. The following series of maps have the links classified into: a “significant increase” (>+5%), “no change” (±0.01-4.99%), a “significant reduction” (-9.99%- -5%), and a “large reduction” (<-10%). Differences in spatial patterns for the links in each class and variation between the models are evident. The number of links that fall in each class for all five models can be seen in Table 5.1. For the scenarios with 10% HEV level, there were 36 links out of 831 that carried no traffic flow. These 36 links produced no HC or any other emission outputs.

Between the three models created through negative binomial regression, there were similarities and differences. In the three models, the proportions of links that had at least

5% reduction in HC emission ranged from 77.6% to 79.5% (Table 5.1). The number of links that fell in the "significant reduction" class was similar for Model 1 and Model 3, while Model 2 had fewer links in this class, but more in a "large reduction" class.

Table 5.1: HC emission change classes and number of links

Models	≥ 5% increase	No change (±<5%)	5 - 9.99% decrease	≥10% decrease
M1	2	174	460	157
M2	2	167	396	230
M3	0	163	450	182
UC	0	96	447	252
UP	0	26	743	26

The spatial patterns of links in each category corresponded to how the HEVs were distributed for each model in 10% HEV scenario. The links with "large reductions" were seen in the zones that received HEVs that were more than 10% of its total vehicle count for each model. For all three models, some links were evident in these areas with high HEV proportions but did not have "large reductions". The variations in the number of links in "large reduction" class are the likely the result of the continuity of high HEV zones in each of the three models. In Model 1 (Figure 5.3) and Model 3 (Figure 5.5), there were gaps between clusters of high HEV zones. On the other hand, in Model 2 (Figure 5.4), there were two large clusters of high HEV zones. One of these two clusters spans from the western half of the study area between Ancaster and North Burlington.

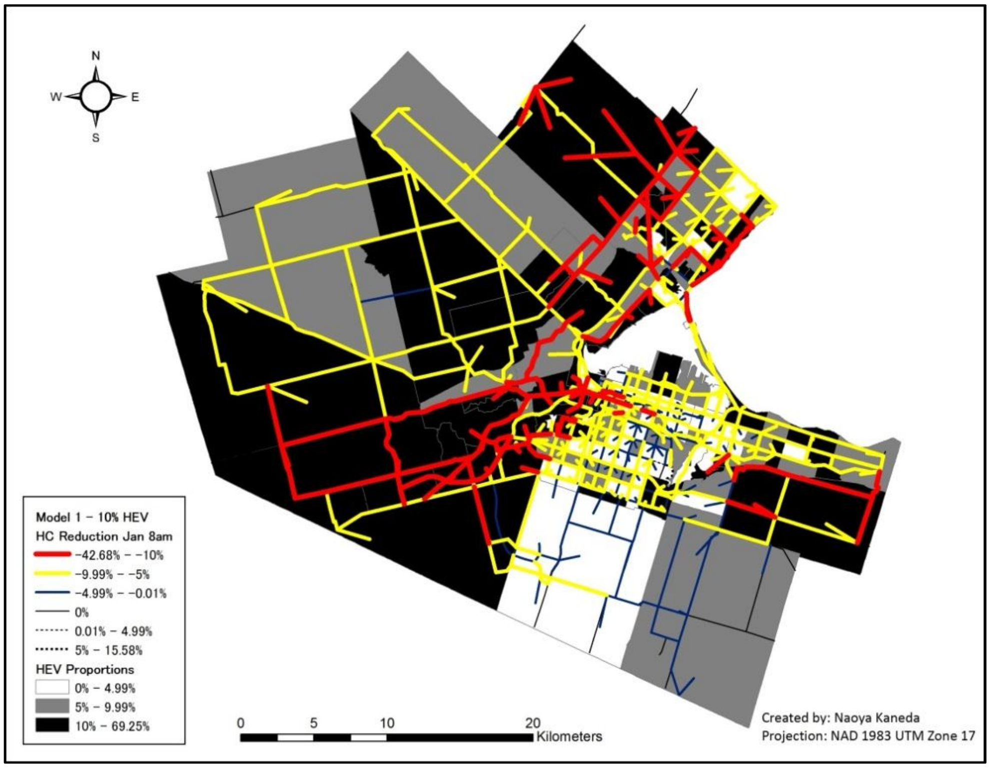


Figure 5.3: Model 1 HC reductions and HEV proportions

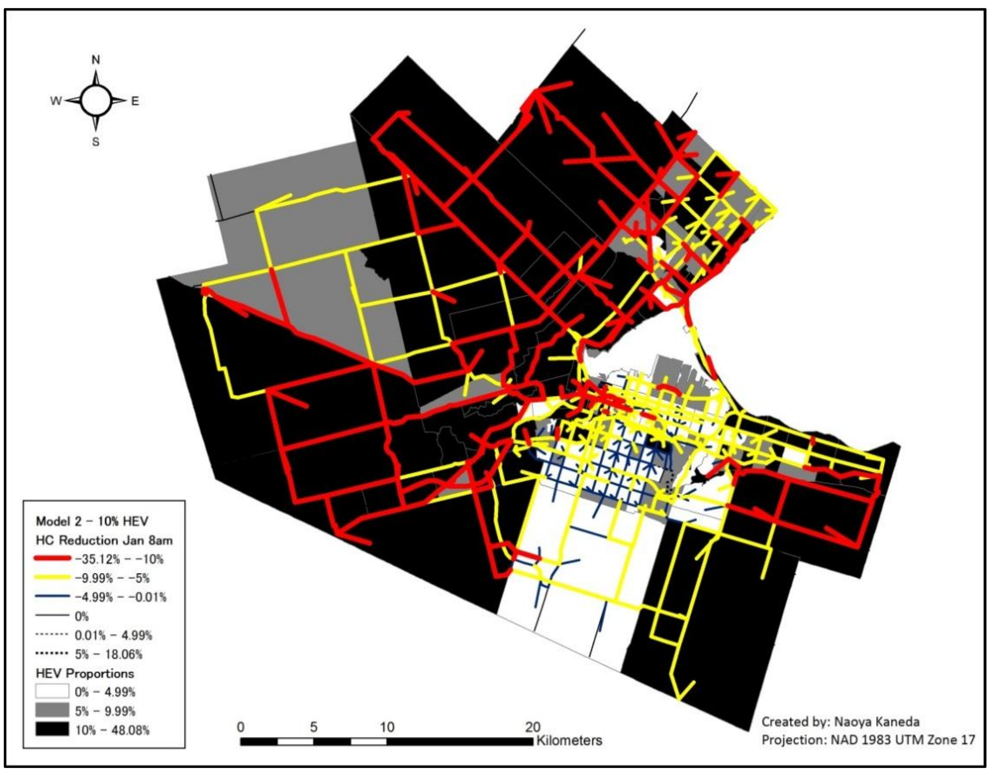


Figure 5.4: Model 2 HC reductions and HEV proportions

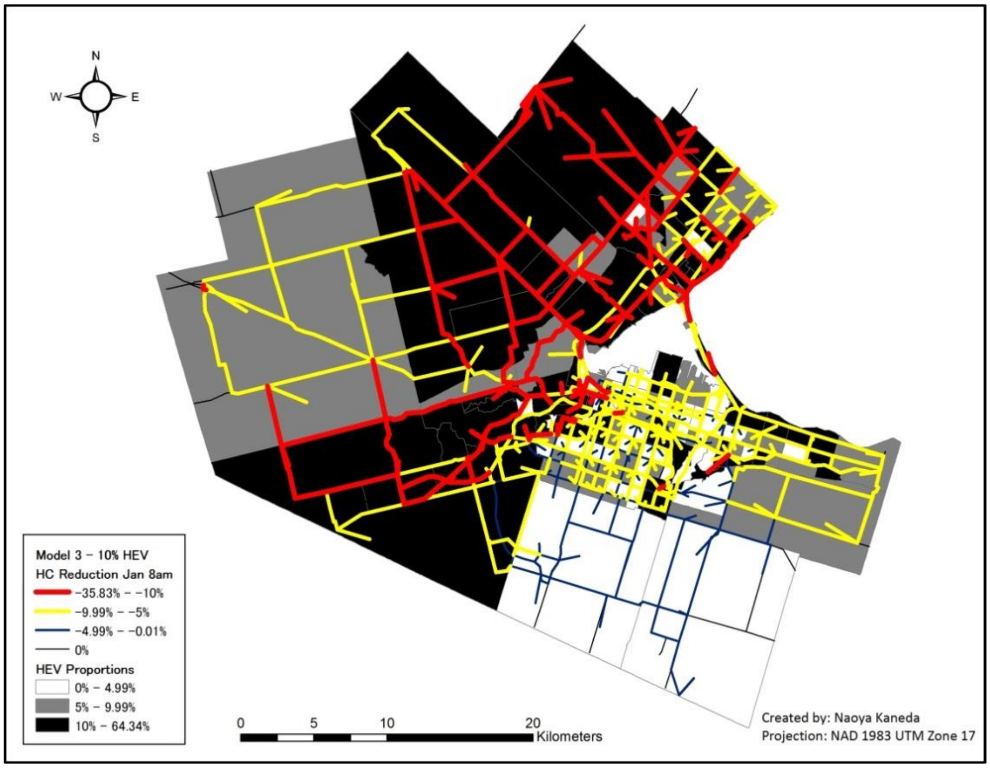


Figure 5.5: Model 3 HC reductions and HEV proportions

The spatial patterns for UC and UP models differed from each other and from the three models created through negative binomial regressions. The proportions of trips made by HEVs to and from each zone in both UC and UP models were influenced more by the total number of vehicles in each TAZ than the other three models. In the UC model, zones with a lower total vehicle count had higher proportions of HEV trips and vice versa since each zone had the same number of HEVs. The results of are evident in Figure 5.6, where a majority of the links in lower Hamilton, Flamborough, and downtown Burlington, and north Burlington showed “large reductions”. Thirty-two percent of all links were associated with the zones of lower total vehicle counts (Figure 3.2), and therefore had higher HEV proportions than zones with high total vehicle counts. Of the 795 links that carried traffic flow, 56% showed a “significant reduction” of HC emission in UC model.

These links were distributed across the study area except for the areas near very high total vehicle count zones such as Mount Hope, Binbrook, and Flamboro. The links associated with these zones showed neither significant increases nor reductions.

In the case of the UP model, HEVs were distributed according to the total vehicle. Therefore, each zone carried an equal proportion of HEVs. An equal HEV distribution resulted in a similar proportion of trips made to and from each TAZ. This resulted in to most links (93%) belonging to the same class, and "significant reductions" and fewer links with "large reductions" (3%) than other four models (Figure 5.7).

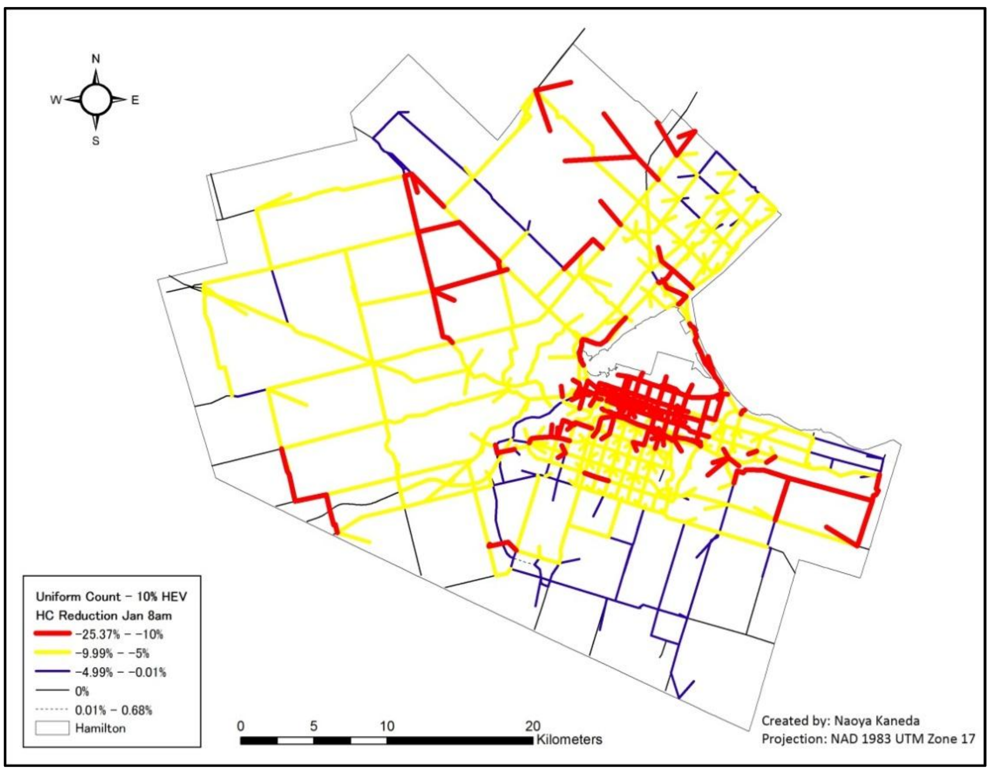


Figure 5.6: Uniform Count model HC reductions

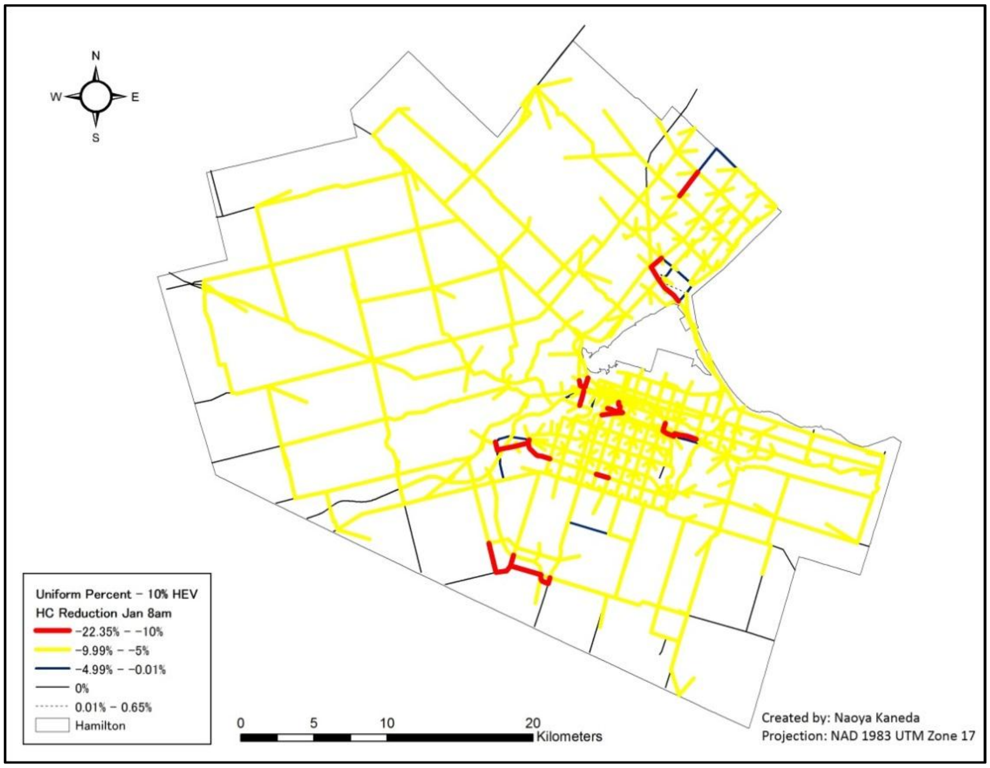


Figure 5.7: Uniform Percentage model HC reductions

All of the major highways in the study area have “significant reductions” in all five models, with some sections of King Street West and Main Street West having “large reductions”. Since these links had very high traffic emissions, even a “significant reduction” of 5% to 9.99% is large compared to changes seen in other minor roads in the area in actual grams per kilometer.

The perfect scenario is that these links with a high volume of traffic, high vehicle speed, and high traffic emissions see much larger reduction through the use of HEVs. However, previous literature questions HEV’s performance as a cleaner vehicle while travelling at high speeds (Alessandrini et al., 2009; Frontaras et al., 2008; An and Sauer, 2004). HEV best showcase its potential as a clean vehicle is when driven in heavy congestions leading at a decreased average speed such as in stop-and-go traffic jam (Emadi et al., 2005; Frontaras et al., 2008). The traffic assignments calculated that even during the morning and afternoon rush hours, the Hamilton CMA does not have enough trips to cause this situation. Of the five models, the three models created through NBRM illustrated the realistic potential of future HEV distributions and its effect on the traffic emissions. The UC model displayed the most optimal distribution of HEVs to reduce the traffic emissions.

5.3 Possible EV scenario

By 2020, the Government of Ontario aims to have one in every 20 passenger vehicle on the roads be an electric vehicle (OPO, 2009). After more than a decade since the release of first mass produced HEV, it has yet to reach 1% of the total fleet in the Hamilton CMA. To achieve a market penetration of 5% in a decade with a vehicle type that is yet to be available in mass production from major companies in Canada, is unrealistic.

Nissan has produced one of the first mass-produced EVs called LEAF. It is now available for purchase starting December 3rd, 2010 in Japan with its price starting at ¥3,760,000JPN ($44,250CAN @ $1CAN = ¥85JPN). Although this may seem costly, the Japanese government has an eco-car tax reduction to lower to the cost for consumers to ¥2,990,000 (or approximately $35,200CAN[i]) (Nissan Japan, 2010). It is available in the US starting at $35,200US and may be as low as $27,700US with federal tax savings (Nissan USA, 2011). In Canada, around 600 of the 2012 models are expected to be

[i] Rate as of December, 2010. In November 2011, $1CAN = ¥75JPN; ¥3,760,000JPN = $50,130CAN

released starting at $38,395CAN. Once it is available, the consumers in Ontario are eligible for a tax rebate up to $8,500CAN (Nissan Canada, 2011). Other companies, such as Chevrolet, are following this example and also planning to release EVs in the near future.

Electric cars are thought to replace combustion engine vehicles given that they lack any tailpipe emissions. While this is true, EVs are not completely pollution free. They still use the same rubber tires and breaking systems as other vehicles which can produce particulate matter (USEPA, 2003). Unlike HEVs or hydrogen vehicles, EVs are incapable of generating electricity internally. They have to be plugged into a socket, which is connected to an electric power plant elsewhere. These electric power plants can produce higher levels of GHG. Therefore, in order for EVs to be emission free, they have to be plugged into solar or wind powered electric generators (Chiumiento et al., 2008).

The percent change in aggregated emissions follows a linear trend, as seen in Table 5.2. The difference between EV and HEV is that the percent change is approximately equal across all four emission types and the percent reduction is directly related to the proportion of EVs in the fleet. From this analysis the introduction of 5% EV into the fleet, as the government of Ontario aims to do, will produce approximately 5% reduction in traffic emissions. While it is unrealistic to assume that there will be no HEVs as transitional technologies from ICE to EVs within the next 10 years, this result can be used as the best case scenario of rapid transition.

Table 5.2: Aggregate Emission Estimates with Electric Vehicles in 2021

Models	Aggregated Emission				Change from BAU 2021			
	HC (kg)	CO (t)	NOx (kg)	CO_2 (t)	HC (kg)	CO (t)	NOx (kg)	CO_2 (t)
BAU 2021	369.98	11.50	1133.78	207.57	-	-	-	-
M1 1%	366.15	11.38	1122.30	205.41	-1.03%	-1.01%	-1.01%	-1.04%
M1 2%	362.20	11.27	1110.75	203.19	-2.10%	-2.03%	-2.03%	-2.11%
M1 5%	350.85	10.92	1076.40	196.76	-5.17%	-5.06%	-5.06%	-5.21%
M1 10%	331.38	10.32	1017.26	185.78	-10.43%	-10.27%	-10.28%	-10.50%
M2 1%	365.83	11.37	1121.24	205.22	-1.12%	-1.10%	-1.11%	-1.13%
M2 2%	361.80	11.25	1109.01	202.91	-2.21%	-2.18%	-2.18%	-2.25%
M2 5%	349.52	10.87	1071.76	195.94	-5.53%	-5.46%	-5.47%	-5.61%
M2 10%	328.85	10.23	1008.42	184.22	-11.12%	-11.03%	-11.06%	-11.25%
M3 1%	365.97	11.38	1121.77	205.31	-1.09%	-1.06%	-1.06%	-1.09%
M3 2%	362.23	11.26	1110.53	203.18	-2.09%	-2.05%	-2.05%	-2.12%
M3 5%	350.47	10.91	1075.15	196.52	-5.27%	-5.17%	-5.17%	-5.32%
M3 10%	330.62	10.30	1014.90	185.33	-10.64%	-10.47%	-10.49%	-10.72%
UC 1%	366.12	11.39	1122.48	205.43	-1.04%	-1.00%	-1.00%	-1.03%
UC 2%	362.34	11.27	1111.29	203.30	-2.07%	-1.99%	-1.98%	-2.06%
UC 5%	350.93	10.93	1077.44	196.92	-5.15%	-4.97%	-4.97%	-5.13%
UC 10%	331.53	10.35	1020.06	186.18	-10.39%	-10.04%	-10.03%	-10.31%
UC 25%	273.79	8.58	846.58	154.00	-26.00%	-25.36%	-25.33%	-25.81%
UP 1%	370.01	11.50	1133.81	207.58	0.01%	0.00%	0.00%	0.00%
UP 2%	362.66	11.28	1111.98	203.44	-1.98%	-1.92%	-1.92%	-1.99%
UP 5%	351.71	10.95	1079.13	197.28	-4.94%	-4.82%	-4.82%	-4.96%
UP 10%	333.21	10.38	1023.78	186.94	-9.94%	-9.70%	-9.70%	-9.94%
UP 25%	277.66	8.68	855.34	155.80	-24.95%	-24.55%	-24.56%	-24.94%

5.4 Possibilities for the Future

Four suggestions for improvement to the traffic assignment program and HEV distribution models are discussed in this section. First, an update of the emission factor calculation software from current MOBILE6.2C to Motor Vehicle Emission Simulator (MOVES). A second and third improvement pertains to the TRAFFIC software: inclusion of more vehicle classes and inter-regional traffic. Lastly, the HEV distribution models were created under the assumption that the relationship between the HEVs distribution in 2008 and the socio-demographic characteristics in 2006 census will stay consistent. There are two paths to improving these models: collection of disaggregate data and use of longitudinal or multiple cross sectional data.

As vehicle technology changes with time, so does the software to account for these changes and its influences on emission. MOVES is an upgrade from MOBILE6.2C incorporating substantial emissions test data, and can account for changing vehicle technology and regulations. It allows the user to answer "what if" questions where a wide range of user-defined conditions can be tested (USEPA, 2010). MOVES has options that allow users to modify the vehicle fuels and technologies fractions in each model year and/or to enter information on retrofitted diesel trucks and buses to meet emission control regulations. Although it does not separately model HEVs, it does include them as part of average vehicles (USEPA, 2010). An update to software such as MOVES could produce more accurate emission estimates based on more detailed information of the region.

The methods used to include HEV as its own class was described in Chapter 3, followed by its limitations in Chapter 5. The conversion of LDPV and LDCV into LDV and HEV was possible only because these vehicle classes shared common characteristics within the traffic assignment program. However, current TRAFFIC software is unable to process splitting of HDCV or MDCV into two classes to simulate new vehicle technologies or using three LDV equivalent classes (ICE, HEV, and EV) for a transitional stage simulation. Although it may be time consuming, an update to include more vehicle classes are recommended as newer technologies become available for medium and heavy commercial vehicles in the future and for more complex scenarios to be executed.

An important improvement to TRAFFIC would be the inclusion of inter-regional traffic. In the original project, the vehicle flow validation showed approximately 70% accuracy in the Hamilton CMA network (CSpA, 2009). This leaves 30% of the traffic volume unaccounted for by trips made between TAZ in the study area, or intra-regional traffic. The major highways in the Hamilton CMA carry a large volume of traffic, moving people and commercial goods through the area on a daily basis. These additional vehicles on the road cause daily congestion on these major highways.

When investigating the average link speed calculated for the Hamilton CMA, the links did not produce significant changes from the set speed limits even during the busiest times of the day. This suggests that the number of trips made in the Hamilton CMA is not enough to saturate the network and cause bumper-to-bumper congestion. Since HEVs performance in emission reduction is seen in situations where battery powered motor is used, such as that in a congested traffic, simulating accurate traffic volume and its effect is very important.

An alternative to including inter-regional traffic in the Hamilton CMA case would be to choose a study area carrying high intra-regional volume, such as the Greater Toronto Area (GTA). In a major city such as Toronto, the inclusion of surrounding cities, would lead to congestion in many parts of the GTA. By considering the GTA as a group of smaller regions, a simulation of inter-regional traffic is possible. It is also possible to merge the Hamilton CMA and the GTA into one study area (the Greater Toronto

Hamilton Area or GTHA) or include both metropolitan areas in the Golden Horseshoe. A drawback to the expansion of the study area is the large increase in time and complexity of the computations.

The data collection in a study such as this is limited by time and monetary resources. The best way to learn why consumers choose to buy HEV or AFV is to ask the question directly to those who have already purchased one. This is a revealed preference survey method that can collect detailed disaggregate data on the reasons for vehicle purchase, as well as socio-demographic data of the buyer. It is also possible to inquire about conventional ICE vehicles purchase and the reasons recent buyers did not to choose a type of AFV. This data collection method could be conducted by the dealership during the purchasing process, and could possibly be funded by the government.

These data are cross-sectional, even in the revealed preference survey questionnaires. The state of buyers' preference and socio-demographic characteristics could change before and after the purchase. While it is almost impossible to obtain real longitudinal data, a useful alternative is a series of cross-sectional data such as using the vehicle registration data from multiple years. This would allow for analyses on the number of HEV growth in the area and would reveal possible relationships between fluctuations of vehicle purchase and local or world events, including the period prior to and following the financial crisis of 2008.

In Japan, the number of Toyota Prius sold annually was 58,315 in 2007 and 73,110 in 2008, averaging 5,343 vehicles per month until April, 2009. In May, 2009, monthly sales of Prius surpassed 10,000 vehicles and have remained at the top of the domestic vehicle sales, to date, selling 208,876 in 2009, 315,669 in 2010, and 195,366 vehicles between January and October of 2011 (JADA, 2011). On a much smaller scale, this trend can be observed in the Hamilton CMA in the last three years. The knowledge of such trend in the study area can improve the regression model by using the number of HEVs or AFVs in the previous years as an independent variable.

An investigation into purchasing behaviour across different regions of the world for HEV or AFV would be useful. HEVs have successfully penetrated the market in Japan, consistently at the top of the sales ranking. It has been argued that monetary incentive programs are helpful; however, this strategy needs to be sustained for a long period of time to be effective (Diamond, 2009; Struben and Sterman, 2008; Flynn, 2002; Moore et al, 1998). Although consumers can benefit from "eco-car" tax reduction incentives, there may be other reasons why HEV has been successful in Japan. With the gasoline price higher in the UK (216.3¢/L[ii]) than in Japan (190.3¢/L[ii]), it is easy to question the lack of increase in HEV sales in the UK. A survey in different locations of the world would provide useful purchasing information.

[ii] Prices of gasoline in Canadian dollar as of mid-November, 2011 (BBC, 2011; NHK, 2011)

6 Conclusions

In this study, the effect of HEVs on traffic related pollution was assessed in the Hamilton CMA. Research in traffic involving alternative fuel vehicles has been carried out in separate fields, including the areas of market penetration and vehicle performance. This thesis aimed to combine findings from these two fields in a traffic simulation procedure. By introducing the HEVs in incremental levels to the vehicle travel pattern of more than 700,000 people in the study area, changes occurring in traffic related pollution at different levels were modeled.

Five models were created for the hypothetical HEV spatial distribution patterns. Three of these five models were derived through NBRM based on 2006 census data and 2008 vehicle registration data. The areas with the highest probabilities of HEV distributions were located in the suburban areas of the Hamilton CMA, where ongoing residential and commercial developments are evident. The distribution of a predetermined number of HEVs throughout the Hamilton CMA was completed via these five models and results were used to modify input OD matrices for the TRAFFIC program. The link-based emissions were calculated in combination with traffic emission factors for HEV.

The results indicated that converting 10% of the total fleet into HEVs was needed to make significant reductions to the HC and CO aggregate emissions in all five models. At this level of HEV implementation, emission growths from 2006 to 2021 in business-as-usual scenario can be offset by approximately 35%, 30%, 16%, and 21% for HC, CO, NOx, and CO_2, respectively. The distribution pattern created by Model 2 produced the highest reduction in traffic related pollution, while the spatial distributions from all models produced slightly different spatial patterns in the links with significant reductions. An important finding with the incremental HEV penetration levels was the approximately linear trend between the percent reduction in the traffic emissions and the percent of HEVs in the total fleet. This trend allows calculations of approximate traffic emission reduction expected with any HEV level.

The results illustrating links with more than 10% reduction in traffic emissions indicated that HEV technology as an effective method in dealing with environmental concerns. On the other hand, the lack of congestion on the major highways during rush hour illustrated that traffic simulation does not include a portion of trips within the Hamilton CMA. An improvement to the traffic simulation model to correctly simulate daily congestions seen in the Hamilton CMA can illustrate greater reductions in the traffic emission by use of HEVs.

Relocating the study area to a more densely populated area where current programs can replicate daily congestion, would be beneficial. In addition, including the vehicle registration and socio-economic data from various years in NBRM would help improve the HEV distribution model. Interesting research exists is in consumer opinion difference between countries where HEV or AFV has been successfully introduced, and where they have not. Findings would help illustrate policies that increase consumers' willingness-to-pay for cleaner vehicles in real world.

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8 Appendix

Table 8.1: Predicted HEV counts and Probability Weights

CTUID	2008	Predicted			Probability Weight		
	Count	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
5370001.01	1	4.56	3.54	6.77	0.242%	0.188%	0.359%
5370001.02	2	2.77	1.16	2.94	0.101%	0.042%	0.107%
5370001.04	5	3.87	2.20	3.95	0.125%	0.071%	0.128%
5370001.05	2	2.67	1.34	3.47	0.136%	0.068%	0.176%
5370001.06	6	4.07	2.19	4.28	0.138%	0.074%	0.145%
5370001.07	1	2.07	0.76	1.06	0.125%	0.046%	0.064%
5370001.08	4	2.96	2.86	3.19	0.091%	0.088%	0.099%
5370001.09	0	3.54	2.20	3.08	0.224%	0.140%	0.195%
5370002.01	2	3.98	1.43	4.25	0.179%	0.064%	0.191%
5370002.02	4	5.37	4.92	5.77	0.104%	0.095%	0.112%
5370002.03	2	1.98	1.77	1.87	0.126%	0.112%	0.119%
5370002.04	1	4.40	2.56	1.72	0.157%	0.091%	0.061%
5370003.01	9	7.86	3.52	6.76	0.251%	0.112%	0.216%
5370003.02	2	3.13	2.26	3.71	0.166%	0.120%	0.197%
5370003.03	2	2.68	1.12	1.24	0.178%	0.075%	0.082%
5370003.04	3	1.67	1.35	1.91	0.057%	0.046%	0.065%
5370004.01	0	1.66	1.82	1.90	0.094%	0.103%	0.107%
5370004.02	1	1.53	1.10	1.25	0.078%	0.056%	0.064%
5370005.01	2	2.02	1.53	4.45	0.068%	0.051%	0.150%
5370005.02	0	1.45	0.85	1.39	0.078%	0.046%	0.075%
5370005.03	0	2.64	1.52	2.51	0.114%	0.066%	0.108%
5370006	4	1.44	3.01	1.93	0.055%	0.114%	0.074%
5370007	1	1.44	1.34	1.94	0.085%	0.079%	0.114%
5370008	2	1.17	2.42	1.66	0.088%	0.182%	0.125%
5370009	0	1.61	1.24	0.90	0.089%	0.068%	0.050%
5370010	1	1.50	1.81	3.14	0.084%	0.102%	0.176%
5370011	3	2.09	1.82	3.55	0.155%	0.135%	0.263%
5370012	1	1.80	1.49	1.48	0.248%	0.206%	0.204%
5370013	7	4.02	4.38	6.73	0.243%	0.265%	0.407%
5370014	2	4.22	3.61	4.49	0.261%	0.223%	0.277%
5370015	3	4.04	3.51	4.21	0.668%	0.581%	0.696%
5370016**	0	*0.00*	*0.00*	*0.00*	7.566%	2.050%	13.337%
5370017	16	30.47	16.94	15.12	1.564%	0.870%	0.776%
5370019	3	3.41	4.29	4.75	0.173%	0.218%	0.242%
5370020	0	2.56	2.12	3.55	0.118%	0.098%	0.164%
5370021	3	1.42	2.06	1.11	0.059%	0.086%	0.046%
5370022	0	0.99	1.92	0.67	0.040%	0.077%	0.027%
5370023	1	2.32	3.05	4.61	0.170%	0.223%	0.338%
5370024	4	2.83	3.03	6.15	0.201%	0.216%	0.437%
5370025	0	2.02	2.07	5.54	0.120%	0.124%	0.331%
5370026.01	2	1.62	1.87	2.26	0.082%	0.095%	0.115%
5370026.02	2	1.17	2.60	2.34	0.130%	0.289%	0.259%
5370026.03	1	5.02	2.66	3.34	0.365%	0.193%	0.243%
5370026.04	1	3.40	3.42	3.27	0.341%	0.344%	0.329%
5370026.05	2	1.60	1.34	1.56	0.075%	0.063%	0.074%
5370026.06	1	1.46	0.78	0.98	0.060%	0.032%	0.040%
5370027	0	0.98	1.39	0.71	0.142%	0.203%	0.104%

CTUID	2008 Count	Predicted Model 1	Predicted Model 2	Predicted Model 3	Probability Weight Model 1	Probability Weight Model 2	Probability Weight Model 3
5370028	1	1.54	1.91	2.72	0.098%	0.122%	0.173%
5370029	0	1.15	0.99	1.50	0.054%	0.046%	0.070%
5370030	1	2.68	1.67	3.79	0.118%	0.073%	0.167%
5370031	1	2.04	1.58	2.66	0.199%	0.155%	0.261%
5370032	0	0.93	0.73	1.62	0.073%	0.058%	0.128%
5370033	3	2.06	1.73	2.74	0.158%	0.132%	0.211%
5370034	1	2.43	1.51	0.80	0.123%	0.076%	0.041%
5370035	1	0.97	1.39	1.32	0.083%	0.118%	0.113%
5370036*	14	*2.13*	*2.91*	*1.60*	0.133%	0.181%	0.100%
5370037	1	3.73	2.97	2.16	0.442%	0.352%	0.256%
5370038	4	4.44	3.45	3.99	0.315%	0.245%	0.283%
5370039	2	5.68	2.57	1.10	0.264%	0.119%	0.051%
5370040	3	4.67	3.73	2.85	0.554%	0.442%	0.338%
5370041	1	3.50	2.00	1.07	0.490%	0.280%	0.150%
5370042	8	4.67	3.76	13.76	0.329%	0.266%	0.971%
5370043	3	6.36	1.67	5.69	0.420%	0.110%	0.376%
5370044	3	3.77	2.18	2.70	0.156%	0.090%	0.112%
5370045	12	17.30	13.49	5.52	1.250%	0.975%	0.399%
5370046	7	9.02	5.50	3.96	0.625%	0.381%	0.274%
5370047	5	1.82	3.97	1.65	0.094%	0.206%	0.086%
5370048	1	1.03	1.46	1.17	0.176%	0.251%	0.201%
5370049	1	1.70	8.35	1.03	0.195%	0.958%	0.118%
5370050	0	0.64	1.21	0.74	0.052%	0.098%	0.060%
5370051	1	1.12	0.82	0.95	0.085%	0.062%	0.072%
5370052	1	1.37	1.73	0.78	0.098%	0.124%	0.056%
5370053	0	0.96	0.84	0.41	0.071%	0.062%	0.030%
5370054	0	0.61	0.74	0.63	0.050%	0.061%	0.053%
5370055	0	0.82	0.80	0.58	0.050%	0.049%	0.036%
5370056	0	1.41	0.89	1.06	0.073%	0.046%	0.054%
5370057	0	0.62	0.55	0.64	0.042%	0.037%	0.044%
5370058	0	0.62	0.50	1.41	0.061%	0.049%	0.139%
5370059	2	1.10	0.51	0.92	0.079%	0.037%	0.066%
5370060	0	0.84	0.45	1.67	0.089%	0.047%	0.178%
5370061	1	0.77	1.09	0.26	0.044%	0.063%	0.015%
5370062	0	0.72	0.66	0.42	0.055%	0.051%	0.032%
5370063	3	0.88	0.83	0.80	0.070%	0.066%	0.063%
5370064	10	1.94	5.81	1.60	0.243%	0.726%	0.200%
5370065	2	3.06	1.49	2.61	0.220%	0.107%	0.188%
5370066	2	1.18	1.05	0.77	0.054%	0.048%	0.036%
5370067	0	1.03	0.93	0.65	0.114%	0.103%	0.072%
5370068	1	1.51	1.19	1.49	0.215%	0.170%	0.212%
5370069	0	1.20	0.76	0.75	0.187%	0.119%	0.117%
5370070	0	1.77	0.94	1.63	0.094%	0.050%	0.086%
5370071	2	1.05	0.40	1.50	0.039%	0.015%	0.055%
5370072.01*	1	*2.25*	*2.61*	*2.17*	0.244%	0.283%	0.235%
5370072.02	0	1.17	1.84	1.06	0.065%	0.102%	0.058%
5370072.03	2	1.72	0.70	0.49	0.067%	0.027%	0.019%
5370072.04	1	2.28	2.83	2.41	0.116%	0.144%	0.123%
5370073	4	1.21	8.09	4.88	0.160%	1.071%	0.647%
5370080.01	1	4.42	10.07	2.90	0.280%	0.639%	0.184%
5370080.03	4	3.99	2.82	3.00	0.133%	0.094%	0.100%

CTUID	2008	Predicted			Probability Weight		
	Count	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
5370080.04	5	3.36	2.80	1.96	0.081%	0.067%	0.047%
5370080.05	7	4.75	3.01	4.55	0.128%	0.081%	0.123%
5370081	3	2.55	4.95	3.83	0.204%	0.397%	0.307%
5370082	3	1.47	2.96	3.71	0.076%	0.152%	0.191%
5370083	1	1.54	3.22	0.77	0.127%	0.264%	0.063%
5370084.01	1	2.89	2.54	2.42	0.155%	0.136%	0.130%
5370084.02	2	2.48	2.79	4.48	0.133%	0.150%	0.242%
5370084.03	0	4.09	3.75	2.93	0.284%	0.260%	0.203%
5370084.04	2	4.89	9.04	5.71	0.221%	0.408%	0.257%
5370084.05	3	4.58	3.85	3.93	0.236%	0.198%	0.202%
5370085.01	9	5.71	4.17	4.88	0.187%	0.136%	0.160%
5370085.02	3	4.27	3.90	2.30	0.105%	0.096%	0.057%
5370085.03	5	6.55	15.35	7.26	0.239%	0.559%	0.264%
5370086	9	6.75	11.91	6.49	0.141%	0.249%	0.136%
5370100	8	9.28	17.12	4.00	0.128%	0.236%	0.055%
5370101	23	5.73	6.44	7.20	0.070%	0.079%	0.088%
5370120.01	23	16.17	10.98	11.17	0.314%	0.213%	0.217%
5370120.02	4	3.50	14.61	3.82	0.231%	0.964%	0.252%
5370121	11	11.86	17.35	17.73	0.670%	0.980%	1.002%
5370122.01	6	11.44	6.67	8.64	0.364%	0.212%	0.275%
5370122.02	17	18.47	12.61	11.39	0.510%	0.348%	0.315%
5370123	23	14.70	16.49	9.06	0.315%	0.353%	0.194%
5370124	7	20.02	12.17	15.02	0.918%	0.558%	0.689%
5370130.02	15	18.88	7.65	10.57	0.757%	0.307%	0.424%
5370130.03	10	8.78	5.23	9.82	0.467%	0.278%	0.522%
5370131	17	7.09	7.97	6.72	0.210%	0.236%	0.199%
5370132	9	3.01	4.80	3.32	0.178%	0.284%	0.197%
5370133	27	10.23	8.68	10.64	0.175%	0.148%	0.182%
5370140.02	11	7.74	10.27	10.03	0.146%	0.193%	0.189%
5370140.03	4	9.06	10.56	10.32	0.276%	0.322%	0.314%
5370140.04	3	6.87	7.20	17.25	0.558%	0.585%	1.402%
5370141	12	6.39	10.61	5.77	0.240%	0.398%	0.216%
5370142.01	4	11.16	15.15	6.14	0.274%	0.372%	0.151%
5370142.02	3	4.12	4.94	5.35	0.135%	0.162%	0.175%
5370143	5	2.77	3.21	5.95	0.282%	0.327%	0.606%
5370144	15	9.99	17.95	13.05	0.195%	0.351%	0.255%
5370200	5	9.68	9.80	12.07	0.631%	0.639%	0.787%
5370201	10	5.37	12.96	6.88	0.195%	0.470%	0.249%
5370202	15	9.90	14.02	10.29	0.295%	0.418%	0.307%
5370203	6	18.21	11.87	20.47	1.093%	0.712%	1.229%
5370204	4	2.75	2.31	3.72	0.101%	0.085%	0.137%
5370205.01	11	8.85	4.21	5.56	0.322%	0.153%	0.202%
5370205.02	6	2.59	2.01	2.93	0.114%	0.089%	0.129%
5370206	28	4.92	16.30	6.86	0.172%	0.571%	0.240%
5370207.01	12	8.07	6.55	10.73	0.185%	0.150%	0.246%
5370207.02	5	6.19	5.18	4.24	0.146%	0.122%	0.100%
5370207.03	6	7.17	5.84	4.17	0.259%	0.211%	0.151%
5370207.04	4	4.23	5.63	7.58	0.287%	0.382%	0.514%
5370208	0	2.15	1.81	2.46	0.114%	0.096%	0.131%
5370209	0	3.27	4.47	3.23	0.289%	0.395%	0.286%
5370210	1	3.24	1.91	1.81	0.237%	0.140%	0.132%

CTUID	2008	Predicted			Probability Weight		
	Count	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
5370211	2	4.50	4.16	6.50	0.190%	0.176%	0.274%
5370212	3	6.14	6.74	4.90	0.667%	0.732%	0.532%
5370213	18	5.60	6.32	6.09	0.255%	0.287%	0.277%
5370214	1	3.26	3.00	4.90	0.199%	0.183%	0.299%
5370215	5	4.75	4.32	10.61	0.326%	0.297%	0.730%
5370216	20	17.31	21.88	25.49	0.651%	0.824%	0.959%
5370217.01	4	2.26	5.13	3.42	0.074%	0.168%	0.112%
5370217.02	3	10.70	6.60	10.85	0.385%	0.238%	0.390%
5370218	17	6.32	7.07	6.12	0.117%	0.131%	0.113%
5370219	16	21.27	25.62	21.43	0.673%	0.811%	0.678%
5370220	9	4.43	4.82	6.71	0.115%	0.125%	0.175%
5370221	5	4.76	4.04	3.80	0.244%	0.207%	0.195%
5370222	13	6.41	6.85	11.27	0.099%	0.106%	0.174%
5370223.01	5	4.55	4.97	5.47	0.193%	0.211%	0.232%
5370223.02	3	5.30	7.11	7.34	0.184%	0.247%	0.255%
5370223.05	4	11.26	9.86	9.76	0.521%	0.456%	0.451%
5370223.06	7	13.52	9.85	9.62	0.469%	0.342%	0.334%
5370223.07	6	7.90	8.01	5.09	0.242%	0.245%	0.156%
5370223.09	10	34.29	10.18	13.41	0.672%	0.200%	0.263%
5370223.1	2	7.88	6.58	10.61	0.682%	0.569%	0.917%
5370223.11	32	15.74	13.08	12.13	0.173%	0.144%	0.133%
5370223.12	14	11.70	18.25	12.33	0.204%	0.318%	0.215%
5370224	5	5.98	13.13	9.96	0.460%	1.010%	0.766%
Total	847	862.92	854.17	837.06			

* Predicted weight calculated based on surrounding CTs.
** Predicted weight reduced to zero.

Table 8.2: List of Variables created from Census 2006 data

Variables	Definitions	Coefficient	t-stats	P-value	Log- Likelihood
POPDEN	Population density (population per km^2)	0.000	-6.81	0.000	-441.34
PDEN0	Popden less than 999 per km^2 (reference variable)				
PDEN1	Popden 1,000 - 1,999 per km^2	0.772	2.92	0.004	-448.50
PDEN2	Popden 2,000 - 2,999 per km^2	-0.183	-0.89	0.376	-455.35
PDEN3	Popden 3,000 - 3,999 per km^2	-0.283	-1.28	0.200	-454.87
PDEN4	Popden 4,000 - 4,999 per km^2	-0.673	-2.88	0.004	-453.21
PDEN5	Popden 5000+ per km^2	-1.610	-3.85	0.000	-443.84
HHLDDEN	Household density (number of dwellings per km^2)	0.000	-6.16	0.000	-446.56
HDEN0	Household density less than 249 per km^2 (reference variable)				
HDEN1	HHLDDEN 250 - 499 per km^2	0.630	1.68	0.093	-453.32
HDEN2	HHLDDEN 500 - 749 per km^2	0.607	2.12	0.034	-452.10
HDEN3	HHLDDEN750 - 999 per km^2	0.108	0.43	0.669	-455.57
HDEN4	HHLDDEN 1,000 - 1,249 per km^2	-0.323	-0.61	0.540	-454.99
HDEN5	HHLDDEN 1,250 - 1,499 per km^2	-0.669	-1.84	0.066	-453.12
HDEN6	HHLDEN 1,500 - 1,999 per km^2	-0.630	-3.38	0.001	-453.10
HDEN7	HHLDDEN 2000+ per km^2	-0.961	-4.65	0.000	-450.42
MDFAMINC	Median Economic Family Income After Tax	0.000	7.11	0.000	-424.59
AVFAMINC	Average Economic Family Income After Tax	0.000	8.13	0.000	-421.44
MDHHINC	Median Household Income After Tax	0.000	6.65	0.000	-432.10
AVHHINC	Average Household Income After Tax	0.000	7.10	0.000	-427.84
MDFAMIN0	MDFAMINC less than $39,999 (reference variable)				
MDFAMIN1	MDFAMINC $40,000-59,999 = 1	-0.893	-5.69	0.000	-444.29
MDFAMIN2	MDFAMINC $60,000-79,999 = 1	0.300	1.55	0.121	-454.26
MDFAMIN3	MDFAMINC $80,000+ = 1	1.021	3.17	0.002	-445.07
AVFAMIN1	AVFAMINC Less Than $59,999 = 1	-1.616	-9.28	0.000	-424.87
AVFAMIN2	AVFAMINC $60,000-79,999 = 1	-0.064	-0.35	0.726	-455.58
AVFAMIN3	AVFAMINC $80,000-99,999 = 1	0.690	2.40	0.017	-450.19
AVFAMIN4	AVFAMINC $100,000+ = 1	1.132	2.34	0.019	-447.13
MDHHIN0	MDHHINC less than $39,999 (reference variable)				
MDHHIN1	MDHHINC $40,000-59,999 = 1	-0.495	-2.91	0.004	-452.12
MDHHIN2	MDHHINC $60,000-79,999 = 1	0.623	2.59	0.010	-450.11
MDHHIN3	MDHHINC $80,000+ = 1	1.056	2.38	0.018	-448.46
AVHHIN0	AVHHINC less than $39,999 (reference variable)				
AVHHIN1	AVHHINC $40,000-59,999 = 1	-29.594	0.00	1.000	-453.99
AVHHIN2	AVHHINC $60,000-79,999 = 1	0.274	1.33	0.182	-454.58
AVHHIN3	AVHHINC $80,000-99,999 = 1	0.905	1.96	0.050	-448.23
AVHHIN4	AVHHINC $100,000+ = 1	1.040	1.91	0.056	-451.17
AVEPHHLD	Average number of household members per dwelling	0.450	2.28	0.022	-453.45
VEHPHHLD	Average Number of Vehicles per Private Dwellings	1.001	5.57	0.000	-438.95

Variables	Definitions	Coefficient	t-stats	P-value	Log- Likelihood
DOWNTOWN	Downtown area = 1, Elsewhere = 0	-0.757	-4.76	0.000	-449.70
MALE014	Male population between ages 0 and 14	2.099	1.06	0.291	-455.12
MALE1529	Male population between ages 15 and 29	-6.140	-2.90	0.004	-452.54
MALE3044	Male population between ages 30 and 44	-2.569	-1.49	0.137	-454.72
MALE4564	Male population between ages 45 and 64	3.292	1.53	0.126	-454.51
MALE65U	Male population age 65 and up	1.033	0.56	0.578	-455.44
FEM014	Female population between ages 0 and 14	0.897	0.48	0.634	-455.54
FEM1529	Female population between ages 15 and 29	-5.888	-3.34	0.001	-452.35
FEM3044	Female population between ages 30 and 44	-0.342	-0.16	0.870	-455.63
FEM4564	Female population between ages 45 and 64	3.414	1.67	0.096	-454.27
FEM65U	Female population age 65 and up	0.061	0.05	0.961	-455.64
X1PHHLD	Number of dwellings with 1 person per household	-1.891	-3.07	0.002	-452.09
X2PHHLD	Number of dwellings with 2 people per household	4.612	2.27	0.023	-452.47
X3PHHLD	Number of dwellings with 3 people per household	-2.551	-0.89	0.373	-455.16
X45PHHLD	Number of dwellings with 4 or 5 people per household	2.416	2.83	0.005	-452.36
X3UHHLD	Number of dwellings with 3+ people per household	1.020	1.66	0.098	-454.45
X6UHHLD	Number of dwellings with 6+ people per household	0.374	0.07	0.945	-455.64
SFAMHHLD	Number of single family household	2.031	3.54	0.000	-450.93
MLTIHHLD	Number of multi-family household	-18.823	-1.88	0.060	-453.02
NFAMHHLD	Number of non-family household	-1.801	-3.14	0.002	-451.74
DWELLOWN	Number of dwellings owned	1.532	4.26	0.000	-448.67
SNGLDWEL	Number of single detached dwelling	0.452	1.27	0.203	-454.85
X1CHLD	Number of families with 1 child	-11.390	-6.57	0.000	-434.57
X2CHLD	Number of families with 2 children	2.374	1.74	0.082	-454.25
X3UCHLD	Number of families with 3 or more children	1.045	0.49	0.627	-455.53
CPL1CHLD	Number of couples with 1 child	-1.419	-0.40	0.690	-455.55
CPL2CHLD	Number of couples with 2 children	5.075	4.00	0.000	-449.55
CPL3UCHLD	Number of couples with 3+ children	5.063	2.27	0.024	-453.41
FMWCHLD	Total number of female lone parent with a child	-10.680	-8.95	0.000	-429.48
FM1CHLD	Number of female lone parent with 1 child	-15.900	-6.79	0.000	-431.32
FM2CHLD	Number of female lone parent with 2 children	-13.239	-5.64	0.000	-449.17
FM3UCHLD	Number of female lone parent with 3+ children	-30.352	-3.42	0.001	-445.30
MAWCHLD	Total number of male lone parent with a child	-26.538	-3.60	0.000	-444.31
MA1CHLD	Number of male lone parent with 1 child	-27.625	-3.51	0.001	-448.08
MA2CHLD	Number of male lone parent with 2 children	-43.509	-3.07	0.002	-449.66
MA3UCHLD	Number of male lone parent with 3 or more children	-34.264	-1.42	0.155	-454.60
WORKOCSD	Proportion of all workers travelling outside of CSD to their usual place of work	2.939	3.81	0.000	-444.84
MAWRKCSD	Proportion of male workers travelling outside of CSD to usual place of work	2.920	4.19	0.000	-444.18
FMWRKCSD	Proportion of females workers travelling outside of CSD to usual place of work	2.639	3.55	0.000	-446.51

Variables	Definitions	Coefficient	t-stats	P-value	Log- Likelihood
TRWRKDRV	Number of workers travelling to work as a driver in a private vehicle	3.867	5.12	0.000	-444.80
TRWRKPAS	Number of workers travelling to work as a passenger in a private vehicle	-15.540	-4.09	0.000	-446.31
MAWRKDRV	Number of male workers travelling to work as a driver in a private vehicle	3.486	3.77	0.000	-449.14
MAWRKPAS	Number of male workers travelling to work as a passenger in a private vehicle	-12.268	-3.91	0.000	-448.20
FMWRKDRV	Number of female workers travelling to work as a driver in a private vehicle	3.637	6.00	0.000	-441.27
FMWRKPAS	Number of female workers travelling to work as a passenger in a private vehicle	-9.283	-2.92	0.004	-450.43
EFIN019	Economic Family After Tax Income $0-19999	-10.880	-4.25	0.000	-439.68
EFIN2039	Economic Family After Tax Income $20,000-39,999	-7.354	-7.44	0.000	-427.62
EFIN4059	Economic Family After Tax Income $40,000-59,999	-8.667	-6.27	0.000	-434.73
EFIN6079	Economic Family After Tax Income $60,000-79,999	0.294	0.14	0.890	-455.63
EFIN80U	Economic Family After Tax Income $80,000+	4.506	8.16	0.000	-419.18
HHIN019	Household After Tax Income $0-19,999	-5.956	-5.91	0.000	-438.19
HHIN2039	Household After Tax Income $20,000-39,999	-5.911	-6.55	0.000	-438.27
HHIN4059	Household After Tax Income $40,000-59,999	-9.030	-4.76	0.000	-444.11
HHIN6079	Household After Tax Income $60,000-79,999	5.384	2.41	0.016	-452.47
HHIN8099	Household After Tax Income $80,000-99,999	10.889	5.38	0.000	-438.44
HHIN100U	Household After Tax Income $100,000+	5.317	6.73	0.000	-429.52
PRIMARY	Population that without secondary education	-9.448	-15.31	0.000	-411.60
SECONDRY	Population with secondary education as the highest education level	-14.041	-4.60	0.000	-441.47
POSTSECC	Population with post-secondary education from other than University	-2.811	-1.35	0.176	-454.47
POSTSECU	Population with post-secondary education from University	7.419	9.91	0.000	-410.07

Table 8.3: Aggregated emissions for all models in January, 2021

Models	8am				4pm			
	HC (kg)	CO (t)	NOx (kg)	CO_2 (t)	HC (kg)	CO (t)	NOx (kg)	CO_2 (t)
BAU	369.98	11.50	1133.78	207.57	363.48	10.77	1103.62	208.74
M1 1%	367.04	11.43	1129.81	206.68	360.59	10.70	1099.99	207.87
M1 2%	364.00	11.35	1126.06	205.79	357.55	10.63	1096.03	206.93
M1 5%	355.31	11.13	1114.39	203.19	348.77	10.42	1084.58	204.26
M1 10%	340.32	10.74	1093.44	198.67	334.16	10.06	1064.91	199.72
M2 1%	366.79	11.42	1129.43	206.60	360.26	10.69	1099.51	207.75
M2 2%	363.71	11.34	1125.37	205.68	357.12	10.62	1095.34	206.78
M2 5%	354.28	11.10	1112.61	202.84	347.43	10.38	1,082.50	203.81
M2 10%	338.38	10.69	1090.12	198.03	331.53	9.99	1060.92	198.86
M3 1%	366.89	11.42	1129.59	206.64	360.44	10.70	1099.80	207.82
M3 2%	364.04	11.35	1125.95	205.79	357.43	10.63	1095.85	206.88
M3 5%	355.01	11.12	1113.84	203.09	348.23	10.41	1083.77	204.07
M3 10%	339.73	10.73	1092.46	198.49	333.16	10.04	1063.48	199.40
UC 1%	367.01	11.43	1129.87	206.69	360.41	10.70	1099.86	207.82
UC 2%	364.11	11.35	1126.13	205.83	357.35	10.63	1095.97	206.89
UC 5%	355.38	11.14	1114.53	203.25	348.02	10.41	1084.01	204.08
UC 10%	340.42	10.76	1094.24	198.84	332.67	10.04	1063.65	199.37
UC 25%	296.02	9.67	1034.41	199.37	286.59	8.92	1000.53	185.34
UP 1%	370.86	11.54	1141.01	208.80	364.34	10.81	1110.76	209.98
UP 2%	364.36	11.36	1126.38	205.88	357.90	10.64	1096.58	207.04
UP 5%	355.98	11.15	1115.13	203.39	349.43	10.44	1085.68	204.48
UP 10%	341.73	10.78	1095.71	199.16	335.51	10.10	1067.23	200.19
UP 25%	298.98	9.67	1034.41	200.19	293.48	9.08	1009.48	187.31

Table 8.4: Aggregated emissions for all models in July, 2021

Models	8am				4pm			
	HC (kg)	CO (t)	NOx (kg)	CO_2 (t)	HC (kg)	CO (t)	NOx (kg)	CO_2 (t)
BAU	332.62	6.68	676.01	207.83	382.95	9.29	674.49	209.00
M1 1%	330.02	6.64	673.91	206.94	379.92	9.23	672.69	208.12
M1 2%	327.34	6.60	671.99	206.04	376.73	9.17	670.71	207.18
M1 5%	319.67	6.48	665.80	203.44	367.49	8.99	664.93	204.50
M1 10%	306.42	6.26	654.49	198.90	352.17	8.68	654.94	199.96
M2 1%	329.80	6.64	673.70	206.86	379.57	9.22	672.45	208.01
M2 2%	327.09	6.59	671.58	205.93	376.27	9.16	670.36	207.03
M2 5%	318.77	6.46	664.79	203.09	366.10	8.95	663.84	204.05
M2 10%	304.71	6.23	652.60	198.27	349.45	8.62	652.85	199.09
M3 1%	329.89	6.64	673.79	206.89	379.76	9.23	672.61	208.07
M3 2%	327.38	6.60	671.90	206.04	376.60	9.16	670.63	207.14
M3 5%	319.41	6.47	665.48	203.33	366.94	8.97	664.52	204.32
M3 10%	305.90	6.25	653.92	198.72	351.13	8.66	654.20	199.63
UC 1%	330.00	6.64	673.95	206.94	379.72	9.23	672.65	208.08
UC 2%	327.44	6.60	672.00	206.08	376.50	9.17	670.72	207.14
UC 5%	319.72	6.48	665.84	203.50	366.68	8.98	664.70	204.33
UC 10%	306.47	6.27	654.92	199.08	350.56	8.66	654.38	199.61
UC 25%	267.17	5.62	621.22	185.89	302.24	7.69	621.72	185.54
UP 1%	333.45	6.71	680.51	209.06	383.89	9.32	679.20	210.24
UP 2%	327.66	6.61	672.13	206.14	377.08	9.17	671.01	207.30
UP 5%	320.26	6.49	666.15	203.64	368.18	9.00	665.54	204.73
UP 10%	307.66	6.28	655.71	199.39	353.57	8.72	656.21	200.43
UP 25%	269.82	5.66	622.98	186.59	309.51	7.82	626.36	187.51