Estimating the contribution of commercial vehicle movement to mobile emissions in urban areas

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Abstract

Metropolitan scale studies of transport-based air pollution have emphasized inputs from the passenger vehicle fleet, with minimal attention given to the role of urban goods movement. Furthermore, little is known about the spatial distribution of transport related emissions. This study uses an integrated urban land use and transport model (IMULATE) for Hamilton, Canada, to examine the contribution of trucking to the spatial distribution of mobile emissions in urban areas. Using tube data and intersection counts for commercial vehicles, we produce an origin-by-destination matrix of commercial trips. The transportation module of IMULATE was adjusted to estimate the differential traffic volume, due to the presence of commercial trips, in all the links of the transport network. These estimates are then translated into emissions of carbon monoxide (CO), nitrogen oxides (NOx), hydrocarbons (HC) and particulates. The results demonstrate the need to control for urban commercial vehicle movement when attempting to estimate mobile emissions in urban areas.

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1. Introduction

Public perception concerning the impact of trucking on North American roadways typically focuses on the issues of road safety and congestion. Empirical data suggest that urban commercial vehicle movements (UCVM) account for roughly 6–18% of total urban travel (Cambridge Systematics, 2004; Hunt et al., 2004; Stefan et al., 2005). Despite this relatively small contribution when compared with non-commercial travel, UCVM exerts substantial influence on traffic flow, road surface conditions, and environmental emissions (Hallmark and Isebrands, 2005; Kanaroglou et al., 2000; Stefan et al., 2005). Recognition of the contribution of UCVM to local and regional economies, the impact of UCVM in cities, and the unique set of conditions and behaviours that facilitate and characterize UCVM have lead to increased research activity over the last decade.

This study uses the transport component of an integrated urban land use and transport model (IMULATE), developed for the Census Metropolitan Area of Hamilton, Canada, to examine the contribution of
UCVM to mobile emissions in urban areas. The methodology proposed has minimal data requirements, but estimates can improve if detailed data are available. Furthermore, the modeling requirements are modest and the system can be adapted to other metropolitan areas. Pollutants most often associated with motor vehicles include Nitrogen Oxides (NO$_x$), Carbon Monoxide (CO), Hydrocarbons (HC) and Particulate Matter (PM). These pollutants have been linked, either in isolation or in combination, to negative ecosystem and human health effects. In addition, there is increasing interest in particulate matter (PM), associated usually with heavy-duty gasoline and diesel trucks. Research suggests that such matter can be detrimental to human health (Burnett et al., 1999).

A secondary objective of this paper is to review what is known about UCVM data availability and modeling. To this end, in the next section we review the relevant literature. We then describe the study area and the model we use for the analysis presented in this paper. This is followed by a detailed description of the methods used to evaluate the contribution of emissions from trucks during the morning peak period in the Hamilton Census Metropolitan Area (CMA). The results are discussed in the following section. We end the paper with concluding comments and a discussion of future research directions in estimating UCVM emissions in urban areas.

2. Background

Despite increasing recognition of the impacts of UCVM on urban travel conditions, regular data collection and commercial vehicle modeling has not become a routine planning activity of US MPOs or similar organizations in Canada. This brief review examines UCVM survey design and data collection, key behavioural findings, and approaches to modeling UCVM flows in urban areas.

2.1. Survey design and data collection

Data availability has proven to be one of the key challenges in gaining insight into the contribution of trucking to environmental externalities at the urban scale. Reviews covering approaches and issues surrounding data collection are available elsewhere (e.g., Cambridge Systematics, 2004; JFA, 1997; Jessup et al., 2004). This section provides a synthesis of recommendations and conclusions from these reports. With respect to survey design, four approaches are commonly discussed: (1) telephone interview, (2) mailout-back, (3) roadside interview or highway intercept, and (4) mixed-methods combining aspects of the first three. Detail and quality concerning origin–destination flows, land use at stops, commodity type, weight, vehicle type/technology, timing of stops, and volume vary across survey approaches (e.g., roadside interview, highway intercept, mail/fax) (Jessup et al., 2004). For example, the mail/fax questionnaire approach generally suffers from low response rates and very general spatial detail, while roadside interviews can achieve success in identifying inter- and intra-regional routing (Jessup et al., 2004; Kanaroglou and Taylor, 1999).

Two common issues influencing successful implementation of trucking surveys are (1) multi-stakeholder participation to improve survey response, and (2) matching survey methods to outcomes of interest (e.g., directed flows at the regional scale) (JFA, 1997; Jessup et al., 2004). The geography of survey design and implementation (e.g., weigh-in-motion stations, toll plazas, ports, warehouses, establishment locations) is also a challenge, influencing the type and quality of contextual detail and respondent information. Overall, establishment surveys targeting commercial activities by sector and vehicle type have been identified as an approach to advancing the state of the art in UCVM modeling (Cambridge Systematics, 2004). Recent work carried out in Alberta, Canada (Hunt et al., 2004; Stefan et al., 2005), Oregon State (Donnelly et al., 1999; ODoT, 2002), and California (e.g., Golob and Regan, 2003) has yielded insights into the behaviour of commercial vehicle fleets in urban areas. Policy-based questions have largely emphasized infrastructure supply, maintenance, and performance, with less attention given to environmental impacts.

2.2. Behavioural findings

While similarities exist with respect to the behaviour of commercial vehicle fleets across urban areas, unique conditions may give rise to distinct behaviours. The most basic evidence supporting this claim concerns the
wide-range reported for the percentage of urban travel comprised of commercial vehicles (6–18%). This suggests that it may be difficult to generalize findings from one study to several areas, and that “local” data collection initiatives are required to support local planning of commercial movement strategies. With this in mind, it is useful to describe the characteristics that set UCVM apart from other activities carried out in urban areas. In doing so, the focus here will be on travel and fleet characteristics, and spatiotemporal dimensions of UCVM.

Data on commercial vehicle miles traveled (CVMT) suggest that urban freight distribution, service vehicles (private and public), and rental cars make the greatest contribution to urban vehicle miles traveled (VMT) next to auto-use for personal travel (Cambridge Systematics, 2004). Results for Calgary and Edmonton suggest that roughly 12% of weekday VMT is taken up by commercial vehicles, with at least 60% of stops being made by light-duty vehicles (e.g., cars, vans, pick-ups, SUVs) (Stefan et al., 2005). This finding is critical, pointing to requirements for UCVM models that recognize the contribution of light vehicles to commercial activities (Stefan et al., 2005). A different picture emerges for other facility types (e.g., highways). Data for Calgary suggest that more than 70% of the trucks traveling on the highway system are heavy trucks (e.g., semi-trailer) (City of Calgary, 2001).

With respect to the spatial qualities of UCVM, recent data for Calgary and Edmonton suggest that a relatively small proportion of UCVM involves through-traffic (external-external flows), with the majority of stops distributed throughout the city as opposed to having a CBD or regional focus (City of Calgary, 2001; Stefan et al., 2005). These data also point to orthogonal directional bias in the distribution of trucking volumes over space. For example, in Calgary, trucking is heavily concentrated in the north-end (the Edmonton side of the city), while the converse is true for Edmonton. Parameter estimates from a tour-based micro-simulation of UCVM flows also point to directional trends in vehicular movement with differences in spatial behaviour reported across sectors (e.g., goods, service) (Hunt et al., 2003).

Looking into temporal characteristics, the literature is fairly consistent in reporting differential peaks in travel when comparing commercial with personal activities (Kanaroglou and Taylor, 1999; Stefan et al., 2005). Data for Calgary and Edmonton demonstrate a lag-effect with the peak in commercial travel following the a.m. peak for personal/work travel. In addition, daily peaks in personal travel occur over much shorter time periods than is the case for trucking, indicating a relatively sustained commercial vehicle flow throughout the core of the regular workday. Moreover, the late afternoon peak in personal travel is unmatched by a similar peak in commercial travel. Findings from other studies also indicate that temporal characteristics vary across the vehicle fleet and by route type (Kanaroglou and Taylor, 1999; Stefan et al., 2005). For example, heavy-duty trucks (such as semi-one or two trailers) are more likely to take their first trip before 6:00 a.m. when compared with light-duty trucks, and through traffic tends to occur outside the regular peak period associated with personal travel (City of Calgary, 2001; Kanaroglou and Taylor, 1999).

2.3. Modeling approaches and issues

At the core of UCVM analysis are essentially two modeling problems. The first involves the conceptualization and estimation of UCVM as independent flows between discrete origins and destinations or, as has been done more recently, as tours beginning and ending at a commercial establishment (e.g., Hunt and Stefan, 2003; Hunt et al., 2003; Hunt and Stefan, 2005). The second problem involves the assignment of flows, modeled as trips or tours, to urban road networks. Procedures for modeling UCVM as origin/destination flows have been around for some time and include, matrix expansion methods, four-stage models and related approaches (e.g., Quick Response Freight Manual (QRFM) – Cambridge Systematics et al., 1996; Freidrich et al., 2003), spatially disaggregate input–output analysis, and supply chain models (e.g., Boerkamps et al., 2000). Review of the state-of-practice and the more recent tour-based stochastic and behavioural microsimulation approaches can be found elsewhere (Cambridge Systematics, 2004; Hunt, 2001; JFA, 1997; ODoT, 2002; Stefan and Hunt, 2004).

With respect to network assignment, several challenges arise when attempting to allocate UCVM flows to digital road networks. These challenges arise due to intrinsic behavioural differences across passenger vehicle, public (buses), and commercial movements, and the influence of macro-level conditions (e.g., policy) on UCVM. Because commercial and non-commercial vehicle activities essentially compete for the use of network
facilities throughout the day, it is desirable to simultaneously account for these activities in network assign-
ment procedures (e.g., Freidrich et al., 2003). With respect to macro-level conditions, municipal bylaws place
restrictions on the use of certain vehicle types on specific roadway facilities, and time-of-day restrictions are
also enforced, regulating pickup/delivery activities (Kanaroglou et al., 2000; Stefan and Hunt, 2004). Network
assignment procedures require a mechanism to control for such restrictions.

Behavioural realism and policy sensitivity increase with migration from the matrix expansion method and
its oversimplification of fleet characteristics and behaviours, to state of the art microsimulation. Augmentation
of behavioural content requires extensive data collection. A heavy computational cost can also be associated
with modeling the commercial tours of a population of vehicles (Hunt et al., 2003). While advances in behav-
ioural modeling are emerging, less attention has been given to modeling the environmental externalities of
trucking at the urban scale. Recent survey of the literature suggests that some work has been done to develop
mobile emissions models capable of producing inputs to pollutant dispersion models (e.g., Bachman, 1998;
Bachman et al., 2000; Potoglou and Kanaroglou, 2005). Other research has produced coupled systems with
capabilities for emissions and dispersion modeling (e.g., Gualtieri and Tartaglia, 1998; Jensen et al., 2001;
Kinne et al., 1997; McHugh et al., 1997; Rakha et al., 2004). With notable exceptions (e.g., Rakha et al.,
2004), the inclusion of goods movement has been uneven at best.

The case for modeling environmental externalities is supported by recent data indicating that trucking
activities disproportionately impact facility operating conditions (Al-Kaisy et al., 2002; Al-Kaisy et al.,
2005; ICF, 2005; Webster and Elefteriadou, 1999). Moreover, research suggests the existence of a passenger
car/trucking differential in emissions under various operating conditions (Hallmark et al., 2004; Hallmark
and Isebrands, 2005). Progress in the analysis and modeling of commercial vehicle emissions, at the urban
scale, has likely been hampered by the lack of UCVM data.

Taking account of the difficulties in collecting detailed UCVM data, as described in this section, in what
follows we describe a methodology for estimating the contribution of UCVM to traffic and emissions, and
we apply this method to the Census Metropolitan Area (CMA) of Hamilton, Ontario, Canada. The approach
is based on data that are routinely collected in most metropolitan areas. The modeling methodology could be
considered state-of-practice as it is based on origin–destination matrices and aggregate, trip-based techniques.
The method is amenable to considerable estimation improvement if appropriate data become available.

3. Imulate – general structure

The Census Metropolitan Area (CMA) of Hamilton is located on the west shore of Lake Ontario, approxi-
mately 75 km southwest from the city of Toronto. The CMA is divided into eight municipalities, as shown in
the map. In 2005, the estimated population of the CMA was about 600,000, mainly concentrated in the City of
Hamilton, and the municipalities of Dundas, Burlington, and Stoney Creek. The traditional economic base of
the city has been the heavy steel industry, located by the harbour in the City of Hamilton. In recent years, the
service sector is successfully competing with, and has surpassed, the manufacturing sector in terms of employ-
ment. The presence of heavy industry partially explains the relatively poor air quality of Hamilton within the
Canadian context (Hamilton Air Quality Initiative, 1997). The Niagara escarpment separates the city into the
lower and the upper part (known also as the mountain). Both parts of the city are relatively flat, with access
from one to the other provided by five major transport links.

Given an appropriate set of OD matrices by vehicle type, the methodology proposed here requires only a
traffic assignment algorithm coupled with a vehicle emissions model. For the purposes of this study, however,
we make use of an integrated urban model, called IMULATE that allows us to estimate an OD matrix for
passenger vehicles in Hamilton and for the time period of interest. Apart from that, we make use of only cer-
tain components of the integrated model.

IMULATE was designed to predict traffic loads on links of the transport network for the morning peak
period (7:00 to 8:00am) in the Hamilton CMA. The initial conception and operationalization of the model
are described in detail in Anderson et al. (1994). The general structure of IMULATE is illustrated in
Fig. 3.1. It consists of three main modules. The first is the land-use module, made up of two sub-modules;
POPMOB that handles intraurban population mobility, affected by a host of urban characteristics, including
the availability and price of housing, and; EMPLOC that determines the location of firms in the urban area as
places of employment. POBMOB and EMPLOC work in tandem to produce a place of residence to place of work matrix and a place of residence to place of school (university/college) matrix within a system of 151 zones (census tracts).

Second is the transport module, which operates on the output of the land-use module. It consists of two sub-modules; TRANDEM that uses multinomial logit models to estimate the number of work and school trips by mode, and a doubly constrained gravity model to estimate motorized discretionary (i.e., shopping, recreational) trips, and; TRAFFIC ASSIGNMENT that uses a stochastic user equilibrium algorithm to assign interzonal automobile trips (from TRANDEM) to the CMA’s road network. The latter consists of about 1100 nodes and 1500 links. The stochastic user equilibrium algorithm we use is an implementation of the method of successive averages described in Sheffi (1985, pp. 324–331). The feedback between the transport and land use modules ensures that land use changes are reflected in the estimated traffic volumes. Furthermore, the feedback loop within the transport module ensures appropriate modal splits for the travel times encountered in the city network.

The third module of IMULATE uses link flows and average link speeds produced by the transport module and estimates emissions of CO, HC and NOx for each link. For this purpose, a formal link has been developed with MOBILE5.C, the Canadian version of the US Environmental Protection Agency’s (EPA) mobile source emissions model. Average link speeds are used as indicators of roadway congestion. Link speeds lower than those under free flow are considered representative of the driving cycle that automobiles face in congested roadways. MOBILE5.C allows creation of a functional relationship between average link speeds and emissions of CO, HC and NOx.

For the purposes of this study, IMULATE was run from the base period (1986–1991) to the simulation period of interest 1996–2001. The land-use module generated OD matrices for work and school trips for the time period of interest that were fed as input into the transport module. The modal split component (TRANDEM) of the transport module generated OD matrices for motorized work and school trips, as well as an OD matrix of discretionary trips. The three matrices were added to create one OD matrix of motorized trips that was provided as input to the traffic assignment sub-module. The resulting travel times were used as
input into TRANDEM through a feedback loop, so that modal splits can be adjusted and the process was repeated until equilibrium was reached. In what follows, the resulting OD matrix from this process is an estimate of passenger trips and is referred to as \( P \).

4. Methodology and data

This study proceeds in four steps. First, an origin-by-destination matrix of commercial vehicle trips, \( C \), at the census tract level was acquired from the City of Hamilton. Second, the concept of passenger car equivalency (PCE – number of passenger cars that correspond to a typical truck) is discussed and a method is developed for the determination of a representative mean value for it, \( E \), in the study area. In the third step, we combine the origin-by-destination matrix of commercial vehicle trips \( C \) with the estimated \( E \) value to produce an origin-by-destination matrix of passenger cars that is equivalent to the commercial vehicle matrix. Since \( E \) is a scalar, the matrix sought is the product \( EC \). In step four, the derived matrix is added to the passenger cars origin-by-destination matrix \( P \), estimated within the transport module of IMULATE, to produce \( T = P + EC \), which is used as input to a stochastic user equilibrium routine that determines the traffic flow on the network. After equilibrium is achieved, the estimated traffic flows are passed to the emissions sub-module of IMULATE to produce estimates of HC, CO, and NO\(_x\) emissions by link, and for the study area as a whole. Since emission factors for the determination of PM emissions are not included in IMULATE, a separate procedure has been developed and is discussed later in this section. One can examine several scenarios by varying the passenger car equivalency scalar value of \( E \). In particular, we are interested in examining the sensitivity of the results to the value of \( E \). A time step, or the simulation period for IMULATE is five years. The simulation period for this study is 1996–2001.

4.1. The commercial vehicle trips matrix

IMULATE’s transportation model has been adjusted to include an origin–destination matrix of morning peak hour (7:00–8:00am) urban commercial vehicle flows within the Hamilton CMA. This matrix was generated from data collected during the 1998 Hamilton Commercial Vehicle Survey. The collected data included tube data and intersection counts. Bi-proportional updating was used to transform the count data into the matrix \( C \). Commercial vehicles in this context include anything identified by an observer as being a vehicle used for commercial purposes. As a result, heavy and light-duty gas and diesel-powered vehicles ranging from pick-up trucks to trucks with six or more axles are included in the matrix. Trip-ends within the municipalities of Burlington and Grimsby have not been included due to incomplete enumeration.

Ideally, estimation of mobile emissions related to the movement of goods or passengers should control for heterogeneity in fleet characteristics (e.g., combustion process, vehicle type), operating conditions, supply-side characteristics (e.g., capacity, travel cost), and the temporal dynamics of demand. Using the exogenously determined aggregate trucking flow matrix \( C \) contributes to uncertainty around the estimation of link and system-wide emission. Developing a clearer understanding of the flow of vehicles by type is a matter left to future research and, in particular, will require an alternative approach to trucking data collection in the study area. The approach we introduce can, however, be used to shed light on spatial patterns of competition for network resources that can give rise to congestion, and as a consequence, higher levels of certain types of mobile emissions.

4.2. Passenger car equivalency (PCE)

Passenger car equivalencies were introduced to the literature in the *Highway Capacity Manual* (HCM) of 1965, and defined as: “The number of passenger cars displaced in the traffic flow by a truck or a bus, under the prevailing roadway and traffic conditions”. In other words, PCEs measure the number of base vehicles (usually passenger cars) removed from traffic due to the presence of heavy vehicles (Al-Kaisy et al., 2005; Elefteriadou et al., 1997; Sumner et al., 1984). There has been little change to the PCE definition since the 1960s (see TRB, 1965; TRB, 2000), and PCE values are still used to evaluate the impact of heavy vehicles on traffic operations under free-flow conditions (Al-Kaisy et al., 2005; Elefteriadou et al., 1997).
PCE estimation procedures can be distinguished by the travel characteristic used to define an equivalency criterion. Past research has used vehicle headway, delay, platoon formation, speed, vehicle hours, travel-time, density, and queue discharge flow (QDF) (see Al-Kaisy et al., 2005; Elefteriadou et al., 1997). While the HCM publishes PCE measures for various facility-types (e.g., 2-lane and multilane highways and freeways), classified by grade and heavy vehicle type (Truck, RV); free-flow operating conditions are assumed.\footnote{Buses are treated the same as trucks under the assumption that they have a similar impact on the traffic stream.} Traffic simulation studies provide some contrast to the HCM approach, indicating variation in PCEs by heavy vehicle type, road grade and facility type, volume, vehicle mix, and traffic conditions (Al-Kaisy et al., 2002; Al-Kaisy et al., 2005; Elefteriadou et al., 1997; TRB, 2000). For example, Webster and Elefteriadou (1999) reported increases in PCE values with traffic flow, free-flow speed, and segment length/grade, and decreasing PCEs with number of lanes and truck percentage.

More recently, understanding of the impact of heavy vehicles on traffic flow, under variable conditions – i.e., operating within the congested or uncongested regime, has become more sophisticated (e.g., Al-Kaisy et al., 2005; Webster and Elefteriadou, 1999). The latest evidence suggests that the effect of heavy vehicles during congested conditions is much greater than under free-flow conditions (Al-Kaisy et al., 2002). Using a mixture of field observation, empirical evidence, and traffic micro-simulation, Al-Kaisy et al. (2005) reported across the board increases in freeway PCEs over those published in the HCM. These data raise concerns with respect to the application of free-flow PCEs to the evaluation of traffic operations under congested travel conditions (Al-Kaisy et al., 2005). The current emphasis of research on freeway operating conditions, suggests an opportunity exists to revisit the PCE concept as it applies to heavy vehicle operation, under the congested regime, along lower capacity facilities such as urban arterials and two-lane highways.

Within our framework, since we use an integrated model and congestion is estimated by link, it is conceivable to take account of congestion in determining the PCE values by link, provided one accepts a functional relationship between the two. In the absence of such a relationship, we assume that PCE values are invariant to congestion, implying a potential underestimation of emissions. Using the speed-flow PCEs estimated by Elefteriadou et al. (1997), we assign representative PCEs to network segments according to link type. Commercial vehicles within the Hamilton CMA are restricted, by law, to a subset of links in the road network, as shown in Fig. 4.1. This subset consists of 805 links.

Values are assigned to links by type according to the following scheme: Freeways, two-lane highways, and arterials with four lanes are given a PCE value of 2, while arterials with two lanes are given a PCE value of 5. The latter type of arterials does not provide an opportunity for passing, and therefore the impact of heavy vehicles is more pronounced. The mean PCE value over the 805 truck route links was found to be 2.48. This value implies that, on average, two and half passenger cars are displaced from the traffic flow for every individual commercial vehicle. The upper and lower bounds of a 90% confidence interval were 2.54 and 2.42, respectively. Since our estimate of PCE is rather crude, we decided to perform some sensitivity analysis by allowing the PCE to attain the values 0, 1, 2, 2.42, 2.48, 2.54, 3, 4 and 5. The value of 0 implies the absence of commercial vehicles in the network, corresponding to a “passenger cars only” scenario.

The aggregate nature of the exogenous commercial vehicle matrix does not allow taking account of the commercial vehicle type in the determination of PCE values. Furthermore, we ignore the grade of the links. As discussed earlier, the upper and lower parts of the Hamilton CMA are relatively flat, justifying the assumption of ignoring the grade for links that are in each one of them. There are five links, however, that connect the lower with the upper part of the CMA, for which the grade is substantially different than zero. Trucks are allowed to use three of those links. Given, however, that those links are arterials with four to six lanes, and that they constitute a small proportion of the total number of links, we felt that ignoring the link grade is justified. Our framework, however, is capable of handling different link grades.

4.3. PM estimation

The MOBILE5.C emissions model does not estimate particulates. In this sub-section, we present a methodology for the estimation of PM at the link and aggregate levels. Particulate emissions come from a variety of
sources including combustion exhaust, tire wear, brake wear, idle emissions, and fugitive dust. In this study, IMULATE is combined with EPA PM emission factors to generate PM estimates from combustion exhaust, tire wear, and brake wear. Data limitations do not allow PM estimation from idling and fugitive dust.

The total exhaust particulate emission factor is calculated from the sum of lead, direct sulfate, and a carbon emission factor which includes soluble organics and other remaining carbon (USEPA, 1985). Carbon is the primary element of diesel and gas powered mobile source combustion. Lack of detailed information on the Hamilton CMA vehicle fleet prohibits the use of lead and direct sulfate emission factors.

To address the contribution of urban commercial vehicles to PM emissions we require information on the type of vehicles and emissions from those vehicles. Since these data are not available, we resort to evaluating the average type of urban commercial vehicle and the frequency of its appearance in links within the Hamilton network during the morning peak period. While lack of information concerning fleet characteristics in the flow matrix \( C \) limits the accuracy of our results, we are able to demonstrate the impact of trucking on base-level emissions that result from the use of privately owned vehicles (POVs). At the time of collection of the traffic counts that were used to generate the origin-by-destination matrix of commercial vehicle trips, a separate vehicle classification was done at 28 randomly selected intersections of the network. The classification scheme employed is shown in Table 4.1, along with the percentage frequency of appearance of the different vehicle types. Interestingly, these data substantiate results reported for other cities (e.g., Calgary, Edmonton), with light vehicles taking up the largest percentage of observed commercial vehicle types during the peak period.

An additional challenge in matching trucking flows to particulate emission factors is the absence of a consistent approach to vehicle classification. The US EPA classifies trucks by weight, while the Ontario Ministry of Transportation (MTO) and the Regional Municipality of Hamilton-Wentworth classify trucks by axle (Kanaroglou and Taylor, 1999). To address this issue, we have drawn empirical connections across vehicle fleet data from the Hamilton survey, the PCE literature, and the USEPA classification schema. Data from the Hamilton survey indicate that the highest ranked class, strictly limited to trucks, is Vehicle Class 3 (2-axle light truck), comprising 10.7% of the total vehicle flow over the sampled intersections. On this basis, we considered for our purposes Vehicle Class 3 the average or representative type of commercial vehicle for

Fig. 4.1. Hamilton CMA trucking routes.
the Hamilton fleet. This can be compared with a ‘Single Unit Truck (SUT), with a length of 12.2 m and a weight-to-horse power ratio of 300' defined in Elefteriadou et al. (1997). Also, the EPA defines this SUT as a light duty diesel truck (LDDT) (USEPA, 1993). The sum of all truck vehicle classes is 14.24% of all vehicles. This is consistent with the percent of trucks in traffic flow reported in Elefteriadou et al. (1997). For our purposes, in what follows, we consider a rough estimate of 15% of commercial vehicles, including buses.

4.3.1. Selecting PM emission factors

As discussed earlier, this study is limited to estimating PM exhaust emissions through the carbon emission factor. Model year and the technology type of trucks and cars affect the carbon emission factor (USEPA, 1985; USEPA, 1993). Average age of the Hamilton CMA vehicle fleet (model year) was approximated from US data, collected by the Polk Data Company (1998).

The average model year for both the car and truck fleet was estimated to be 1990 as follows. As mentioned earlier, the simulation period for this study was 1996–2001. The midpoint of this period would be half way through 1998. In 1996, the average age of cars was 8.3 years (The Polk Data Company, 1998). Subtracting the average age (roughly eight and a half years) from the year of estimation left a model year of 1990.

The nearest EPA age category for passenger cars (LDGVs) was 1981 and newer. The PM exhaust emission factor for this category is EE\textsubscript{LDGV} = 0.0043 g/mile. To determine the amount of PM of certain particle sizes, a Particle Size Cutoff (PSC) is applied to this emission factor (USEPA, 1985). The PSC is defined as the maximum aerodynamic diameter of the particles in the emission factors (USEPA, 1985). PM\textsubscript{10} includes particles of 10 \(\mu m\) or less in aerodynamic diameter, and is of particular concern due to its association with cardio-respiratory hospitalisations (Burnett et al., 1999) and other health effects (Hamilton Air Quality Initiative, 1997). In this study a PSC for PM\textsubscript{10} is determined from tables provided by the USEPA (1985). For catalyst equipped LDGVs, 1981 and newer, using unleaded fuel, the fraction of particles less than or equal to 10 \(\mu m\) in diameter, PSC\textsubscript{LDGV} = 0.98.

To determine the exhaust emissions factor and the PSC for light duty diesel trucks (LDDT), we follow the same procedure as for the passenger cars. In 1996, the average age of trucks was 8.6 years (The Polk Data Company, 1998). Subtracting the average age (roughly eight and a half years) from the year of estimation left a model year of 1990. The PM exhaust emission factor for this category is EE\textsubscript{LDDT} = 0.291 g/mile. To determine the PSC for particles less than 10 \(\mu m\) in diameter we note that for all model years of all diesel vehicles, including 1990 LDDT, the value is PSC\textsubscript{LDDT} = 1.00 (USEPA, 1985).
4.3.2. Calculation of PM emissions

For the purpose of estimating PM, the road network in this study is broken into links that are part of truck routes and links that are not part of truck routes. The PM exhaust (PME) estimate for a truck route link $i$ is calculated as

$$\text{PME}_i = 0.15 f_i l_i E_{\text{LDTT}} \text{PSC}_{\text{LDTT}} + 0.85 f_i l_i E_{\text{LDGV}} \text{PSC}_{\text{LDGV}}$$  \hspace{1cm} (1)

where, $f_i$ is the total traffic volume on link $i$, and $l_i$ is the length of link $i$. The factors .15 and .85 reflect our estimate that 15% of the flow on a truck route link $i$ is from trucks and the remaining 85% from passenger vehicles. The PM exhaust estimate for a non-truck route link $j$ is calculated as

$$\text{PME}_j = f_j l_j E_{\text{LDGV}} \text{PSC}_{\text{LDGV}}$$  \hspace{1cm} (2)

where, $f_j$ is the total traffic volume on link $j$, and $l_j$ is the length of link $j$.

Assuming that we have $n$ truck route links and $m$ non-truck route links, PM from combustion exhaust for the entire system is given by

$$\text{PME}_{\text{TOTAL}} = \sum_{i=1}^{n} \text{PME}_i + \sum_{j=1}^{m} \text{PME}_j$$  \hspace{1cm} (3)

The PM tire wear emission factor for all vehicle categories and model years is $E_{\text{tire}} = 0.002$ g/mile/tire, while the particle size cut-off for all vehicles is $\text{PSC}_{\text{tire}} = 1.00$ (USEPA, 1985). Since the emission factor is per tire, one needs the average number of tires per vehicle, which is $\text{ANOT}_r = 4$ (USEPA, 1985). Obviously, the tire wear emission factor does not vary by the type of link. So the tire-wear emission $\text{PMTW}_k$ for any link $k$ is given by

$$\text{PMTW}_k = f_k l_k E_{\text{tire}} \text{PSC}_{\text{tire}} \text{ANOT}_r,$$  \hspace{1cm} (4)

and the PM tire wear emissions for the entire system are given by

$$\text{PMTW}_{\text{TOTAL}} = \sum_{k=1}^{n+m} \text{PMTW}_k$$  \hspace{1cm} (5)

The PM brake wear emission factor for all vehicle categories and model years is $E_{\text{brake}} = 0.0128$ g/mile, while the average particle size cut-off over all vehicles and model years is $\text{PSC}_{\text{brake}} = 0.98$. Since there is no variation by link type, the PM brake wear emission $\text{PMBW}_k$ for any link $k$ is given by

$$\text{PMBW}_k = f_k l_k E_{\text{brake}} \text{PSC}_{\text{brake}},$$  \hspace{1cm} (6)

and the PM brake wear emissions for the entire system are given by

$$\text{PMBW}_{\text{TOTAL}} = \sum_{k=1}^{n+m} \text{PMBW}_k$$  \hspace{1cm} (7)

Total PM for the entire system, then, is the sum of PM emissions from combustion exhaust, brake wear, and tire wear.

$$\text{PMTOTAL} = \text{PME}_{\text{TOTAL}} + \text{PMTW}_{\text{TOTAL}} + \text{PMBW}_{\text{TOTAL}}$$  \hspace{1cm} (8)

5. Results and discussion

Establishing the contribution of commercial vehicles to mobile emissions requires an initial estimation of network flows from passenger vehicles only. As discussed earlier, this is achieved by letting $E = 0$, in which case $T = P$. That is, the matrix passed to the stochastic equilibrium routine of TRANDEM is equivalent to the matrix of passenger cars only. This is followed by a series of estimations, where $T = P + EC$ and $E$ attains non-negative values, as discussed in the methodology section of this paper. The results of each of these estimations are compared to the results of the passenger vehicles only scenario, allowing the assessment of changes in link and total emissions for the study area. The rationale for the selection of values for $E$ is
discussed in detail in the methodology section. The procedure allows assessing the sensitivity of emission estimates to subtle variations in equivalency values.

5.1. Aggregate level results

The results for the whole of the study area are summarized in Table 5.1. The first column displays the passenger car equivalency values used in the simulations. In the discussion that follows, estimates of emissions for \( E = 0 \) are used as a base case for comparison. Aggregate emissions are simply summations of emission estimates across all links in the road network. The last column in the table reflects the percent increase in passenger vehicle trips beyond the base case.

Increasing the PCE value is equivalent to increasing the volume of vehicle traffic loaded onto the network. The additional traffic serves as a proxy for the presence of commercial vehicles in the network. Loading additional base vehicles onto the network leads to increased traffic on network links. For certain links, especially those on truck routes, the result is increased congestion and lower average speeds. When interpreting the emissions results, it is important to remember that within this study HC, NO\(_x\), and CO emissions are functionally linked to the average speed (or driving cycle) in each one of the links. As the PCE value increases from 0 to 2.48 (the estimated average), the number of trips increases by 11.9%, while HC and CO emissions increase by 23.4 and 24.1, respectively. So, the behavior of those two pollutants is very similar. On the other hand, NO\(_x\) behaves differently. The same increase in PCE and number of trips results in a 10.9% increase in NO\(_x\) emissions. The difference is in the functional relationship of emissions factors to link speed (Anderson et al., 1996). While for HC and CO the emission factors drop rapidly as average link speed increases, NO\(_x\) emission factors tend to initially marginally decrease with speed, but then remain stable until about 30 miles/h, increasing with speed from then on.

Unlike the other pollutants, PM emissions are not affected by congestion and the average speed on a link, but by vehicle-miles traveled (strictly speaking this might not be true - congestion and stop and go will augment brake-use, and brake dust emissions). This is evident in the PM emission figures shown in Table 5.1. What is important in those figures is the increase in particulate matter emissions when commercial vehicles are introduced at all, that is when the PCE value changes from 0 to 1. For a 4.8% increase in the number of trips, PM emissions increase by 111.3%. To understand better this relationship, it is important to examine the source of emissions. Table 5.2 provides a breakdown of emission estimates for brake wear, tire wear, and exhaust for this particular case.

The first striking result in Table 5.2 is that the introduction of commercial vehicles causes the vehicle-miles traveled (VMT) by passenger cars to decrease from 1,900,288 to 1,807,957. This decrease is the response of passenger car drivers to the disutility of the extra congestion introduced with the commercial vehicles, which entails changing mode of travel or not taking the trip at the morning peak period. Perhaps the most important result reported in Table 5.2 is that the exhaust system represents the primary source of PM emissions introduced by commercial vehicles. Out of the 54.6 kg of particulate matter produced by commercial vehicles, 51 kg

### Table 5.1

<table>
<thead>
<tr>
<th>PCE</th>
<th>HC</th>
<th>%a</th>
<th>CO</th>
<th>%a</th>
<th>NO(_x)</th>
<th>%a</th>
<th>PM</th>
<th>%a</th>
<th>Trips</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td>kg</td>
<td>%a</td>
<td>kg</td>
<td>%a</td>
<td>kg</td>
<td>%a</td>
<td>kg</td>
<td>%a</td>
<td>n</td>
</tr>
<tr>
<td>0.00</td>
<td>12,929</td>
<td>0.0</td>
<td>1,37,556</td>
<td>0.0</td>
<td>9476</td>
<td>0.0</td>
<td>47</td>
<td>0.0</td>
<td>1,74,996</td>
</tr>
<tr>
<td>1.00</td>
<td>14,035</td>
<td>8.6</td>
<td>1,49,563</td>
<td>8.7</td>
<td>9877</td>
<td>4.2</td>
<td>99</td>
<td>111.3</td>
<td>1,83,452</td>
</tr>
<tr>
<td>2.00</td>
<td>15,275</td>
<td>18.1</td>
<td>1,63,174</td>
<td>18.6</td>
<td>10,299</td>
<td>8.7</td>
<td>104</td>
<td>121.7</td>
<td>1,92,297</td>
</tr>
<tr>
<td>2.42</td>
<td>15,865</td>
<td>22.7</td>
<td>1,69,707</td>
<td>23.4</td>
<td>10,478</td>
<td>10.6</td>
<td>106</td>
<td>125.9</td>
<td>1,95,851</td>
</tr>
<tr>
<td>2.48</td>
<td>15,955</td>
<td>23.4</td>
<td>1,70,700</td>
<td>24.1</td>
<td>10,507</td>
<td>10.9</td>
<td>107</td>
<td>126.5</td>
<td>1,96,396</td>
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<tr>
<td>2.54</td>
<td>16,033</td>
<td>24.0</td>
<td>1,71,560</td>
<td>24.7</td>
<td>10,534</td>
<td>11.2</td>
<td>107</td>
<td>127.2</td>
<td>1,96,960</td>
</tr>
<tr>
<td>3.00</td>
<td>16,641</td>
<td>28.7</td>
<td>1,78,250</td>
<td>29.6</td>
<td>10,733</td>
<td>13.3</td>
<td>109</td>
<td>131.9</td>
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<td>4.00</td>
<td>18,071</td>
<td>39.8</td>
<td>1,93,956</td>
<td>41.0</td>
<td>11,181</td>
<td>18.0</td>
<td>114</td>
<td>142.4</td>
<td>2,09,798</td>
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<tr>
<td>5.00</td>
<td>19,592</td>
<td>51.5</td>
<td>2,10,879</td>
<td>53.3</td>
<td>11,634</td>
<td>22.8</td>
<td>119</td>
<td>152.9</td>
<td>2,18,686</td>
</tr>
</tbody>
</table>

a Denotes percent increase over the ‘passenger cars only’ scenario.
originates at the tailpipe. These results indicate that to reduce particulate matter emissions in urban areas, one has to pay close attention to commercial vehicles in general and their exhaust systems in particular.

5.2. Results at the link level

In this sub-section we focus on the spatial concentration of congestion and emissions through a selected set of figures. Fig. 5.1 depicts the ratio of flow to capacity when PCE is $E = 2.48$. Thicker link lines are associated with ratio values greater than 1, meaning that traffic flow exceeds capacity (volume to capacity ratio), rendering the link congested. Qualitative comparison with Fig. 4.1 indicates that the congestion occurs primarily on truck routes.

With respect to emissions, Figs. 5.2 and 5.3 show spatial variation in link-based estimates of HC. The first of the figures is based on estimates from passenger cars alone, while the second includes commercial vehicles with PCE value $E = 2.48$. In these figures, a thicker link line is associated with a higher emission level for HC. The effect of the inclusion of commercial vehicles in the system is shown clearly. As expected, the effect appears to be stronger along the truck routes shown in Fig. 4.1.

Similar figures for CO and NOx show a pattern almost identical to that for HC, so they are not shown here. It is interesting, however, to examine the results for particulate matter, shown in Figs. 5.4 and 5.5. Again,

<table>
<thead>
<tr>
<th>Source</th>
<th>PCE $E = 0.00$</th>
<th>PCE $E = 1.00$</th>
<th>Increase (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Car</td>
<td>Truck</td>
<td>Total</td>
</tr>
<tr>
<td>VMT</td>
<td>1,900,288</td>
<td>0.0</td>
<td>1,900,288</td>
</tr>
<tr>
<td>Brake wear (kg)</td>
<td>23.8</td>
<td>0.0</td>
<td>23.8</td>
</tr>
<tr>
<td>Tire wear (kg)</td>
<td>15.2</td>
<td>0.0</td>
<td>15.2</td>
</tr>
<tr>
<td>Exhaust (kg)</td>
<td>8.0</td>
<td>0.0</td>
<td>8.0</td>
</tr>
<tr>
<td>Total (kg)</td>
<td>47.0</td>
<td>0.0</td>
<td>47.0</td>
</tr>
</tbody>
</table>

Fig. 5.1. Ratio of link flows to link capacity, PCE value $E = 2.48$. 
thicker link lines are associated with higher levels of emissions, given in g/mile. From our earlier discussion on PM emission factors, we know that the number of trips on a link, rather than the level of congestion or the average link speed, affects the level of PM emissions. With the inclusion of commercial vehicles in the network, and the trips they contribute confined only to certain routes, the effect on PM is more pronounced particularly along trucking routes.

Fig. 5.2. Emissions of HC for passenger cars, PCE value $E = 0$.

Fig. 5.3. Emissions of HC with commercial vehicles, PCE value $E = 2.48$. 
The results suggest that not controlling for the presence of commercial vehicles results in low estimates of link emissions within certain parts of the Hamilton CMA. Exposure to mobile source pollutants or estimates of ground level ozone would potentially be understated under such conditions.
6. Conclusions

A procedure for evaluating the contribution of trucks to mobile source emissions within urban areas has been presented. The proposed method has modest data requirements and makes use of models that are widely used. Although in this paper the method is demonstrated for the Census Metropolitan Area of Hamilton, Canada, it has wide applicability. We demonstrate that the procedure produces plausible results with respect to spatial patterns of mobile emissions, and the impact of trucking beyond a baseline scenario involving privately owned vehicles. The contribution of urban commercial vehicle movements (UCVM) to emissions of HC, CO, NO\textsubscript{x}, and PM has been addressed at the aggregate and link levels. Emission estimates demonstrate sensitivity to passenger car equivalency (PCE) values. With respect to HC and CO, a percentage increase in number of trips due to the presence of trucks induces twice as high a percentage increase in emissions. The additional trips decrease average speed on the network causing a disproportional increase in emissions because of the non-linearity in the relationship between link speed and emissions. This is not the case, however, for NO\textsubscript{x} emissions that tend to increase with link speed.

The presence of trucks is shown to produce a dramatic increase in particulate matter emissions as well. The analysis indicates that this increase is mainly due to combustion exhaust emissions from trucks, as opposed to tire and break wear. Overall, a 4.4% increase in vehicle miles traveled because of the presence of trucks can produce a 111% increase in PM emissions. For all pollutants, link level changes tend to be focussed along trucking routes.

While the results are encouraging, the potential of this procedure for generating accurate estimates is limited by the resolution of the observed trucking data. Another limitation is that only trips with origins and destinations within the Hamilton CMA are included. The contribution of trucks passing through the CMA is not dealt with. In the presence of current data on inter-city trucking, we anticipate that the contribution of external flows to emissions could be relatively small (e.g., City of Calgary, 2001). Furthermore, the current focus of the model is the morning peak period traffic volumes and related emissions, while the majority of truck trips in urban areas take place outside this period.

Having looked extensively into the literature, some further recommendations can be made with respect to future work. Data describing heterogeneity in fleet characteristics and behaviours are required to move beyond aggregate origin/destination UCVM matrices. Data of this sort will reduce uncertainty in the emissions estimation process. Moreover, while data are available for some urban regions (e.g., Edmonton, Calgary, Oregon), planning organizations have not adopted regular freight data collection and updating as a routine activity. Surveys should cover inter and intra-regional flows by sector and vehicle type, and should be proposed within a multi-objective framework that will be of interest to a wide-range of private and public sector stakeholders. The availability of disaggregate data could be matched with current research into dynamic microscopic emissions modeling, e.g., CEMEM – Barth et al. (2000); VT-Micro – Rakha and Ahn (2004); Rakha et al. (2004), providing a micro-level emissions capability to be interfaced with microsimulation models of land use/transport and environment interactions.

Looking more broadly at goods movement, trucking has become the dominant mode of transport by weight and value in much of the developed world. Recent data for the US indicate that trucking accounts for approximately 64% of freight tonnage, and 75% of freight shipment value (ICF, 2005), while Class 1 rail accounts for the largest share of domestic ton-miles (47%). Similar data have been reported for other G7 nations (e.g. Canada) while in Europe, trucking is even more dominant, accounting for the largest share of ton-miles (EC, 2000). Despite producing a smaller share of overall VMT, trucking appears to disproportionately impact facilities and the environment when compared with other modes of road transport (Al-Kaisy et al., 2005; ICF, 2005). Moreover, and as this study has shown, there appears to be some heterogeneity in the distribution of effects across facilities and over space.

Policymakers face a clear challenge with respect to addressing trade-offs between the essential role of trucking in the economy and our daily lives, and negative externalities associated with on-road goods movement. While recent policy in the US, for example, pursues technological solutions to the emissions problem (ICF, 2005), less attention has been given to the spatial distribution of impacts and the demand side of trucking. For example, the presence of spatial variation in patterns of environmental emissions raises concerns around the equitable distribution of externalities across urban areas. Moreover, increasing demand for trucking could
give rise to greater system-wide emissions despite per capita reductions resulting from technological policy and innovation.

References


