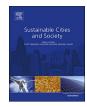


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Automated, electric, or both? Investigating the effects of transportation and technology scenarios on metropolitan greenhouse gas emissions



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ARTICLE INFO	A B S T R A C T
<i>Keywords:</i> Emission inventory Regional Passenger transportation Automated vehicles Emission intensity	The anticipated impacts of automated transportation are numerous. Of importance are the effects on energy consumption and greenhouse gas (GHG) emissions. Can automation promote low carbon transportation? Another question often raised relates to the appropriateness of current tools. Will existing tools become irrelevant in the face of the disruptive changes or can we extend the capabilities of our models to broadly capture the effects of automated transportation? This study presents an approach to estimate fuel-cycle GHG emissions, integrated within an activity-based travel demand model for the Greater Toronto and Hamilton Area. The model chain is used to evaluate different shares of automated vehicles (AV), and the effects of electrification of AVs. Daily operating GHG emissions were estimated at 29,000 t in CO_{2eq} with 96% attributed to private vehicles and 4% to transit. While sharing a minor portion of emissions, the public transit system carries 32% of daily passenger kilometers traveled. When accounting for fuel-cycle emissions, the daily total was estimated to be over 36,000 t for private vehicles. With the introduction of AVs, higher vehicle kilometers travelled (3.6%–5.4%) and GHG emissions (2.5%) are expected. However, electrification of AVs can reduce regional GHG emissions (5%), and emission intensities of all vehicles (11%).

1. Introduction

Developing an up-to-date greenhouse gas (GHG) emission inventory is a widely adopted exercise to regulate, monitor, and understand energy usage and emissions on a national or regional level. For regulatory purposes, various metropolitan areas in North America have established reliable regional GHG emission inventory archives that record historical emission data and estimate current and future trends. On-road transportation, especially passenger transportation emission inventories have become a research hotspot due to their ever-changing nature and close relationship with travel behavior and lifestyles.

Generally, two different approaches ("top-down" and "bottom-up") have been adopted when calculating GHG emissions from on-road vehicles. For example, the Mid-Hudson Region (north of New York City), Chicago Metropolitan Region, and member states of the EU make use of fuel-consumption based ("top-down") methods (European Environment Agency, 2016; ICF International, 2012; Mcgraw et al., 2010). On the other hand, the regions of New Jersey (Newark and proximity), Delaware Valley (Philadelphia metropolitan area), and Dallas-Fort Worth employ local vehicle activity data and emission factors per distance traveled ("bottom-up") (Delaware Valley Regional Planning Commission, 2009; North Central Texas Council of Goverments, 2015; North Jersey Transportation Planning Authority, 2011). Both methods have also been extensively used in many studies in Europe (Guevara et al., 2017), North and South America (Brond et al., 2012; Rojas et al., 2017), and Asia (Fu et al., 2013). "Top-down" models are generally able to capture the full macro-economic impacts of policies while "bottomup" models are more sensitive to intra-urban fluctuations in demand and technology uptake (Dai et al., 2016).

Automated vehicles (AV) are expected to drastically change individual lifestyles and travel behavior. Their impacts on regional GHG emissions and energy consumption are still unclear. Some studies argue that AVs will decrease on-road emissions due to smoother driving cycle and ability to eco-drive (Fagnant & Kockelman, 2014). Meanwhile, other studies caution against potential increases in emissions due to increases in vehicle kilometers traveled (VKT) (Harper et al., 2016). Few studies have investigated the effects of AVs on regional GHG emissions (Childress et al., 2015).

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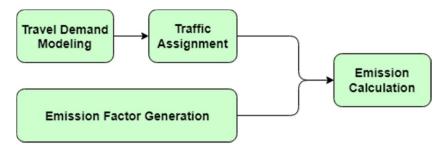


Fig. 1. Conceptual Framework for Regional Emission Inventory.

Our study focuses on developing a GHG emission inventory for passenger transportation in the Greater Toronto and Hamilton Area (GTHA). An activity-based travel demand model with up-to-date travel survey data serves as our core method to generate travel demand in the GTHA. The model is extended with capability to estimate the emissions and energy consumption of all passenger modes (private vehicles and all forms of transit), both during vehicle operation and over the fuel production process. A number of scenarios for AV adoption were tested for their impacts on travel demand, vehicle operating GHG emissions, fuel production GHG emissions, and energy consumption (comparing electric vs. conventionally-fueled AVs). Four scenarios of electricity generation mixes that explored emission potential of marginal power generation sources were also evaluated with respect to the current mix.

2. Methodology

2.1. Operating GHG emissions for passenger vehicles and public transit

The emission estimation framework incorporates four main parts: travel demand modeling, traffic assignment, emission factor generation, and emission estimation (Fig. 1).

2.1.1. Travel demand and traffic assignment

Our emission inventory is integrated within the GTAModel V4.0, a travel demand model developed at the University of Toronto. It is an activity-based model using the 2011 Transportation Tomorrow Survey (TTS), a comprehensive travel survey conducted every 5 years in the GTHA. It contains demographic and travel information for all members of a surveyed household in a typical workday (Travel Modeling Group, 2015). Traffic assignment was conducted using the EMME4 platform, a user equilibrium-based traffic assignment model currently used by all major planning agencies in the GTHA. It uses trip data in the form of Origin Destination matrices and applies a user equilibrium traffic assignment to generate average travel speeds and travel times for passenger vehicles as well as all forms of public transportation in the network (transit buses, streetcars and light rail, intercity buses, and regional rail). A typical weekday was divided into four periods: A.M. (6-9 A.M.), Midday (9 A.M.-3 P.M.), P.M. (3-7 P.M.), and Evening (7 P.M.-12 A.M.). Trips were aggregated over the four periods. Traffic assignment was conducted for only one peak hour in each time period and then expanded using peak hour factors (0.437; 0.167; 0.385; 0.2 for A.M., Midday, PM., and Evening, respectively). The peak hour factors are determined as a proportion of the highest hourly demand in each period; such that, the period volume equals the 1-hour volume divided by the peak hour factor.

2.1.2. Emission modeling

Regional GHG emissions (in CO_2eq) and energy consumption were estimated as the sum of vehicle operating emissions for all passenger transportation modes.

Emission factors (EFs) for GHGs and energy consumption rates for passenger cars, passenger trucks, intercity buses and transit buses were estimated based on EPA's MOtor Vehicle Emission Simulator (MOVES). Fourteen speed bins were identified (from 2.5 mph to 67.5 mph) with three different road types (urban unrestricted, urban restricted, and rural unrestricted). A database of EFs and energy consumption rates by vehicle type, age, speed, and road type, was generated.

For private vehicles, age and type distributions were obtained from the Ontario Ministry of Transportation (MTO) vehicle registry. EFs were then weighted according to the model year and type distributions. As only 2.9% light vehicles are diesel-powered (Office of Energy Efficiency, 2009), all private vehicles were assumed to be gasoline fueled. For buses, fleet age and type distributions were obtained from the Toronto Transit Commission (TTC) and GO Transit (the two largest transit service providers in the area); all buses are diesel-fueled. The fleet composition is shown in Fig. 2. Both private and public vehicle fleet data refer to the year 2016, such that age 0 refers to model year 2016. For locomotives, their EF does not depend on speed (15.35 kg $CO_2eq/$ train-km) (Marin et al., 2010). It is the product of fuel consumption per locomotive kilometer travelled (5 L/train-km) and average emission rate of local diesel fuel (3.07 kg CO_2eq/L).

Emissions from private vehicles and transit buses were estimated

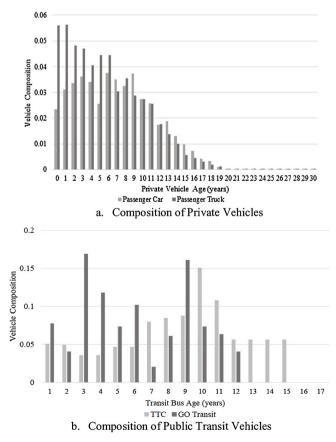


Fig. 2. Ontario Fleet Composition Based on 2016 Data for a. Private Vehicles; b. Transit Buses.

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