DISAGGREGATE LEVEL SIMULATION OF PUBLIC TRANSIT EMISSIONS IN A LARGE URBAN REGION

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ABSTRACT

In this study, we demonstrate the development of a methodology for simulating transit bus ridership and GHG emissions (in CO₂ equivalent) across a network of 200 buses in the city of Montreal, Canada. Our simulation allows us to estimate emissions for individual buses while running and idling at bus stops. The disaggregate level simulation process allows us to incorporate for each bus along every route the specificities such as vehicle type, age, fuel, and passenger load. Using MOVES2014, we estimated average-speed emission factors first by assuming that the MOVES default drivecycles are representative of the Montreal buses, and then by embedding operating mode distributions computed based on local drivecycles. The latter were derived from a data collection campaign conducted on-board eight transit buses. We observe that systemwide GHG emissions are about 15 percent lower when the MOVES default drivecycles are used. This difference could be higher on specific routes. We also investigated the effect of a 20 percent systemwide increase in ridership and observed a 1.7% increase in total emissions and a 28% decrease in per capita emissions. Finally, we estimated the effects of decreasing the frequency of low occupancy buses and increasing the frequency of high occupancy buses. These frequency changes were associated with proportional changes in emissions.

Keywords: bus emissions, MOVES, air pollution, greenhouse gases, transit ridership, emission modeling
INTRODUCTION

Overdependence on automobiles for travel has resulted in a vast array of negative consequences including congestion, poor health outcomes, traffic crashes, smog, air pollution and greenhouse gas (GHG) emissions (Santos et al., 2010a). Development of an efficient intermodal public transportation system comprised of railways (commuter rail, light rail, high-speed rail, inter-urban rail), metro (underground subway), buses (regular buses, articulated buses), and ferries offer a unique and promising solution for mitigating the different road traffic externalities (Santos et al., 2010b). Therefore, not surprisingly, many urban regions are either enhancing or considering improvements to public transportation infrastructure to address the private vehicle use challenge (for example see transportation plans of Montreal (Ville de Montreal, 2008) and Toronto (Get Toronto Moving, 2014)). Positive impacts of public transit, particularly, in the reduction of harmful emissions such as CO\textsubscript{2} have been reported in the literature (Givoni et al., 2009; Chester and Horvath, 2009; Lau et al., 2011). It has also been investigated that if public transit’s mode share could be increased by a few percentage points, it would lead to considerable GHG reductions (Bailey, 2007). Moreover, mass transit systems in larger cities of USA have been reported to encourage more resource efficient land use and personal activity patterns (Bailey et al., 2008).

This current study contributes to a burgeoning literature on public transit emissions by developing an urban regional level micro-simulation model for transit bus emissions. While transit in general is an environmentally friendly and sustainable transportation mode, owing to the variations in passenger load, service type, fuel type, weather, time of the day, road grade, vehicle configuration and type, and vehicle age, the emissions output varies substantially (Alam et al., 2014; Lau et al., 2011). A major portion of the transit bus emission results from the combustion of fuels during vehicle operation. These include: (1) combustion of fuel during transport of passengers between destinations (via bus stops); (2) combustion of fuel while idling (allowing for boarding and alighting of passengers); and (3) combustion of fuel while driving with an empty vehicle, where such driving is a direct result/requirement of transporting passengers such as arriving from the bus depot to the bus route starting point. However, there is a paucity of literature that attempts to quantify and understand the emissions generated by public transit at the level of an entire system. In our study, we attempt to improve the methodology for bus emission evaluation by undertaking disaggregate level analysis of bus transit emissions in Montreal, Canada.

The overall methodology involves the development of a microsimulation platform that considers bus emissions for all bus routes and all scheduled trips by simulating boarding and alighting at each stop allowing us to simulate passenger ridership at the finest resolution. Disaggregate boarding information augmented with vehicle type and configuration, vehicle age and fuel type allows us to identify accurate emission factors (EFs) for emission computation. The proposed framework is employed to evaluate bus emissions for all bus routes in the Montreal region. Further, based on ridership numbers and emissions computed, several useful emission indicators are developed. Further, to illustrate the value of the proposed simulator, several scenario analyses were considered: (a) effect of fixed percentage (20\%) increase in ridership on emissions, (b) effect of reducing transit bus frequency in low use bus lines, and (c) effect of increasing transit bus frequency in high use bus lines.
The rest of the paper is organized as follows. Section 2 provides a brief literature review. In Section 3, study area, data source and methodology are described in detail. The estimation results are presented in Section 4. Section 5 concludes the paper and presents directions for future research.

LITERATURE REVIEW

Traffic-related air pollution is a byproduct of the combustion process that occurs in the majority of automobiles, buses and trucks, producing a host of pollutants such as particulate matter, nitrogen oxides (NO\(_x\)), volatile organic compounds (VOC), and more. A significant amount of research over the past few years has linked exposure to the aforementioned pollutants with a host of chronic and acute health effects (Brauer et al., 2008; Gan et al., 2012; Selander et al., 2009). Thus, there is growing acceptance in transportation and health communities of the importance of improving urban air quality. Towards improving air quality, an accurate quantification of emissions is absolutely critical. The transportation field has made substantial progress in recent years in developing quantitative frameworks that estimate disaggregate level automobile emissions accounting for the influence of travel patterns, vehicle characteristics (such as age, type and fuel type), and land use patterns on automobile emission outputs (see Sider et al., 2013; Sider et al., 2014; Beckx et al., 2013; Beckx et al., 2010; Dons et al., 2011). Surprisingly, there has been fewer research attempts at quantifying public transit emissions on an urban regional level.

A summary of earlier studies relevant to our research is presented below. In a majority of the studies, researchers investigated operational or lifecycle GHG emissions of transit buses – with Chan et al. (2013) reporting that operational emissions make up the largest part of the lifecycle emissions. An early attempt at inventorying the operating transit bus fleet emission was carried out by Regie Autonome des Transports Parisiens, the major transit agency in Paris. Using static instrumentation system, installed in 400 buses (10% of the fleet) they evaluated the effects of changes in bus type, fuel, age, mileage, and other bus-dependent conditions on operating emissions (Dolidze, 2007). Studies dealing with operational GHG emissions were mostly conducted for the peak traffic periods (morning or afternoon or both) to capture the effect of ridership loads as well as the surrounding vehicular traffic. For instance, Lau et al. (2011) modeled exhaust emissions for transit buses operated by Toronto Transit Commission (TTC), Canada. The methodology involved linking of micro simulated transit assignment results with EFs to develop link-based, route-based, and stop based emissions for individual buses under varying combinations of age, fuel type, and Sulphur content. Quite intuitively, the busiest routes were associated with the highest total emissions and the highest dwell emissions were observed at intermodal transfer stations. On average, bus trips were found to be three times more fuel efficient than car trips. However, the highlight of the research findings relates to the sensitivity of transit emissions to occupancy rates; a finding which is also documented by Chester and Horvath (2009). In another study, Alam and Hatzopoulou (2014a) observed that emissions decreased by 5% with each additional passenger for a less crowded bus as compared to 1.2% for a crowded bus.

Almost all the studies tested a range of emission scenarios to glean a better understanding of the factors which affect transit bus emissions. The most common scenario evaluated by the
researchers were the effect of different fuel types on emissions. A common consensus was reached among the researchers on the potential of alternative fuels as opposed to conventional diesel to reduce transit emissions, particularly CNG. For instance, Alam and Hatzopoulou (2014b) found that CNG buses reduce emissions by 8–12% in uncongested conditions; the percentage increases to 16% in congested traffic situation. Similar positive environmental implications of alternative fuels were documented by Nanaki et al. (2014). Chan et al. (2013) and McKenzie and Durango-Cohen (2012) reported reduced lifecycle emission of alternative fuels as well. However, McKenzie and Durango-Cohen (2012) also concluded that alternative fuel buses reduce operating costs and emissions but increase life cycle costs.

In addition to fuel types, some researchers attempted to quantify the impact of different traffic control and operation techniques on emissions. Amongst others, transit signal priority was reported to reduce GHG emissions by 14% in congested conditions (Alam and Hatzopoulou, 2014b) while Alam et al. (2014) observed that bus lanes and express bus services also reduce emissions significantly and use of smart card reduces idling emissions. Among other studies, Maghelal (2011) conducted a study to observe the effects of fuel price on transit ridership and CO\textsubscript{2} emissions. Specifically, a negative binomial regression model was used to study transit ridership and ordinary least squares (OLS) model was utilized to estimate CO\textsubscript{2} emissions. It was observed that an increase in fuel price increases transit ridership and decreases emissions.

An interesting study was conducted by Diana et al. (2007) where they compared the emissions of demand responsive transit service with conventional fixed route transit service by making use of hypothetical scenarios composed of varying road networks, service quality, and demand densities. It was observed that the demand responsive transit service had lower emissions especially under lower demand densities. Use of hypothetical scenarios for estimation and visualization of emissions by conventional diesel buses was also suggested by Li et al. (2009). Another study indicated that the implementation of bus rapid transit system in Mexico City, Mexico resulted in a 20% to 70% reduction of carbon monoxide (CO), benzene, and particulate matter (PM\textsubscript{2.5}) due to the lower emission rates of the buses and the reduction in commute times (Wohrnschimmel et al., 2008). A set of research studies have developed algorithms for optimal fleet allocation of alternative fuel vehicles to obtain better environmental benefits (for example see Beltran et al., 2009, and Li and Head, 2009).

Current Study in Context
Our review indicates that transit bus emissions are receiving more attention from the emission research community in recent years. Evidently, there is a need to quantify the environmental impact and performance of the existing public transit systems, so that better deployment, operation, and routing strategies can be formulated. Most of the studies conducted in the field of public transit emissions are either at a micro level i.e. bus/route/corridor level studies or macro i.e. aggregate transit system level studies. The micro level studies conducted at bus, route or corridor level, while very insightful, provide no information on the overall system; thus it is very hard to generalize findings from one bus route to the system level. On the other hand, at a macro level the data used to evaluate the performance of the system is aggregated resulting in ignoring the effects of various
factors at a disaggregate level. The current study aims to bridge the gap between the micro and macro level studies by estimating ridership and emissions at a micro level i.e. disaggregate stop level for 24 hours of a typical weekday for all the bus lines (and their trips) in the bus network of Montreal, Canada. To the best of the authors’ knowledge, this is the first attempt to develop such a disaggregate system to evaluate the emissions of a public transit system in a large urban metropolitan region using detailed stop level boardings and alightings.

STUDY REGION AND RESEARCH METHODS

Our study is set in Montreal, which is the second most populous metropolitan area in Canada with 3.7 million residents. According to the 2008 Montreal Origin-Destination (OD) survey (AMT, 2008), 67.8% of trips are undertaken by car, 21.4% by public transit, and 10.8% by active transportation (walking and bicycling). The annual transit trips made by the residents of Montreal are higher than those made in most major American cities. The higher share of public transit trips can be attributed to the multimodal transit system of Montreal which includes 4 metro lines, 5 commuter train lines, and over 200 bus lines managed by different travel agencies (Chakour and Eluru, 2015). In the last 15 years, the transit patronage (bus, metro, train) has increased by over 25% for the Montreal Metropolitan Region. The Société de transport de Montreal (STM), which serves bus and metro on the Island of Montreal, has reached a record transit ridership in 2011 with 405 million trips, exceeding the previous record of the year 1945 (STM, 2011). Thus, the Montreal metropolitan region with its unique public transit characteristics and culture of the region forms an ideal test bed for our analysis.

Our methodology is divided into the following three modules: (a) ridership simulation for boarding and alighting, (b) bus occupancy determination, and (c) emission estimation. In the following sub-sections, we describe each of the components in detail.

Module 1: Stop Level Boarding and Alighting

At the core of Module 1 is an object oriented programming code using JAVA developed to predict boardings and alightings at a stop level for the entire metropolitan region. The program predicts hourly boardings and alightings based on a stop level regression model developed for the bus system. The data employed for the model development is drawn from data collected by STM. Specifically, three stop level regression models for low, medium, and high ridership are estimated. The categorization is based on the overall daily ridership (boarding + alighting) at the stop. The stops with daily ridership of less than 50 are characterized as low stops; stops with daily ridership between 50 and 250 are characterized as medium stops, and stops with daily ridership more than 250 are classified as high stops. Then a separate model for each stop category is developed (see Chakour and Eluru, 2015 for more details on modeling approach) considering the influence of a whole range of transit accessibility, transport infrastructure, and built environment factors. Eventually, these models are employed to predict the expected number of boardings and alightings at every bus stop for every hour of the day. Considering a uniform rate of arrival in the hour, these boardings and alightings are converted to per minute arrivals. In cases with multiple buses arriving at the same stop, the boardings and alightings are pro-rated based on frequency of the buses.
Module 2: Bus Occupancy Determination

The stop level boarding and alighting information is available across all stops for 24 hours from the first module. In the second module, these boardings and alightings are assigned to actual buses. The occupancy module starts for a bus route and its first trip as per the bus schedule. Based on the vehicle fleet information of STM bus service, a bus type is probabilistically allocated for this instance of bus route. Now this bus begins its service from the starting origin on schedule. Based on the stop level model, people waiting at the stop, board the bus and the bus occupancy is updated accordingly. As the bus arrives at the next stop, based on the stop level boardings and alightings predicted, we update the bus occupancy. The calculation of occupancy is done in the following manner. Say, a bus with 10 people on board arrived at a stop. According to the ridership model, the predicted number of boardings and alightings are 4 and 2, respectively. Hence, the occupancy of the bus until the next stop is 10+4−2=12. The boardings and alightings at each stop are saved so as to calculate the time for idling at the stop. The procedure is repeated at each stop thus updating bus occupancy, boardings and alightings at every stop.

While these steps are repeated across all stops in the leg, several consistency checks are incorporated. For example, if the bus is at capacity (determined as 75 for a regular bus and 115 for an articulated bus) when it arrives at a particular stop, the passengers are forced to wait for the next bus with space. If the bus has no passengers, no alightings are allowed. The reader would note that the same bus type is employed for the entire leg of the tour. The process is repeated across all legs of the bus route based on its schedule. Once a single bus route has been analyzed, the second bus route is chosen for simulation and so on until all buses in the Montreal system are covered. The outputs from the ridership module include detailed information on bus occupancy at every stop for every route and every leg. The information also includes detailed stop level boarding and alighting numbers.

Module 3: Emission Estimation

In this module, GHG emissions (in CO₂ equivalent) are calculated for each bus line by time of day by linking the results of module 2 to EFs. The module connects the bus lines directly to the emissions and further computes both active and idle emissions for each bus line at each bus stop.

Emission Factor (EF) Generation

Bus EFs were generated using MOVES2014 (Motor Vehicle Emission Simulator), the latest emissions inventory model developed by the US Environmental Protection Agency (USEPA, 2010). MOVES has an enriched database for estimating passenger vehicle emissions for both average and instantaneous speeds. But in the case of transit buses, it has many limitations (see Alam and Hatzopoulou, 2015 for more details). Specifically, when only average speeds are available, the MOVES database lacks transit bus specific data and as a result, the estimated emissions might be under/over predicted compared to a local context. In light of this fact, an effort was made to quantify the extent of the difference between emission estimates using MOVES default data and emission estimates generated after embedding local data into the MOVES database.
Towards that end, the MOVES embedded drive cycles were updated using manually collected Montreal specific transit data along eight routes. Local data along these routes were collected during a 6-week campaign in 2013 with GPS devices installed on-board transit buses. Repeated observations were conducted at different times of day; each bus route was monitored 6 times in each direction (3 trips in the morning and 3 trips in the afternoon periods). To embed our own drive cycles into the MOVES database we considered only the drives cycles that were collected for zero-grade links. In our data, a total of 1,998 link observations were found having zero grade (1,389 for regular buses and 609 for articulated buses) and we grouped them into 25 speed categories with average speeds ranging from 1 to 25 mph. For speeds between 3 and 17 mph, at least 50 observations were found in each category, while for the other categories at least 10 observations were found.

For each link-level observation, a cumulative operating mode (opmode)\(^1\) distribution was developed considering the second-by-second speed profile and onboard passenger number. Later, within each speed category the variations among different link-specific cumulative opmode distributions were carefully observed. For each average speed category, a median cumulative opmode distribution was identified to represent the drive cycle characteristics of all the observations in that category. It was calculated using the cumulative opmode distribution of all individual drive cycles within this category. Then, in each speed category, one drive cycle was selected in such a way that the calculated opmode distribution of that selected drive cycle was the closest to the median opmode distribution. Root mean square error (RMSE)\(^2\) for each drive cycle was calculated. For each average speed category the drive cycle having the lowest RMSE was selected as the representative drive cycle of that category. Then the selected 25 drive cycles for 25 average speed categories were assigned a drivescheduleID. Using the MySQL platform, three files in the MOVES2014 database were modified to incorporate this drivescheduleID.

**Generating Emission Estimates**

Once the EFs are generated, bus transit emissions are estimated at the stop level for each bus line for 24 hours of the day using outputs from module 2. The distances between stops for each bus line is calculated using ArcGIS network distance and the time taken to travel between the stops is calculated from the difference between the scheduled arrival times (provided by STM) of the buses at the stops under consideration. Then, the operating speed of the bus between each bus stop is computed by simply dividing the distance by the travel time. Although the speed calculated ignores

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\(^1\) An opmode distribution provides the amount of time that the vehicle has spent under different opmode categories. Each opmode is characterized by the combination of vehicle specific power (VSP) and speed. VSP is defined as the engine power output per vehicle unit mass and indicates the tractive power needed to haul the vehicle. It is a function of instantaneous speed, acceleration, vehicle weight, and road grade as shown in equation 1. Please see Alam et al., (2014) for more details.

\(^2\) RMSE = \(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}\); where, \(y_i\) is the opmode fraction of the drive cycle at opmodeID ‘i’; \(\hat{y}_i\) is the opmode fraction of the median opmode distribution at opmodeID ‘i’; ‘i’ is the opmodeID, and \(n\) is the number of total opmodeID which is 23 as MOVES has a total of 23 opmodes.
direct traffic congestion, it is dependent on the realistic time which the bus takes to travel from one stop to another (since the arrival times of buses at the stops are set up considering peak and off-peak hour traffic conditions). In fact, it varies by time of day depending upon the traffic conditions or other variables affecting the travel time between the bus stops. However, congestion or delay due to traffic signal or road networks are not taken into account. The bus type is chosen in Module 2 and given the STM bus model distribution, a model year is also probabilistically selected for each bus line. Finally, roadway grade and type are then calculated using both GIS and GPS.

The EF tables contain factors both in grams/mile for running emission and grams/hour for idle emissions separated by speed, bus type, bus model year, road type, and bus occupancy. We considered zero grade due to relatively flat topography of the island and meteorology data of only summer season. Two EF look-up tables were generated: (1) based on the MOVES default drive cycles associated with different average speeds, and (2) based on the local drive cycles embedded into MOVES to replace the default distributions. Each look-up table includes EFs for two types of buses (regular and articulated), two types of road categories (urban restricted and urban unrestricted), 72 average speed categories with in increment of 1 mph, 30 model years of buses ranging from 1983 to 2013, 75 onboard passenger loads for regular buses, and 125 onboard passenger load for articulated buses. A total of 864,000 EFs were generated for all identified combinations.

Given this information, an EF is selected from the EF look up tables described above. Total emissions include the sum of both the moving emissions given by the EFs and the idling emissions given by idling time. The idling time is considered a function of number of people boarding and alighting. However, to ensure the randomness of the process, we assume each boarding (alighting) to follow a normally distributed time in seconds with mean of 3 (2) and standard deviation of 3 (2). The alighting process is likely to take less time as there is no need to swipe or pay for the ticket. Based on the normal random draws, the total times for boarding and alighting are computed. Thehigher of the alighting or boarding time is considered as idling time. The emissions procedure is repeated from one stop to another to cover all stops in the leg, all instances of a bus route in a day and all bus routes in the region. The process provided as outputs: (1) total emissions in the region, (2) total emissions by bus route, and (3) emission information that is related to time of day and bus occupancy.

**Performance Measures**

Based on our micro simulation exercise, we can estimate emissions by bus line as well as by time of day. With disaggregate boarding information, more useful emission indicators can be computed. To understand the overall emission values, we generate a host of system level indicators. The total system level emissions are obtained by aggregating the emissions from all bus lines during the time period of interest. Specifically, we compute emissions for the entire day, AM peak period (from – to), off peak period, PM peak period and off peak night period. In addition, we also compute the per capita emissions (defined as total emissions/total boardings), per km emissions (total emissions/total kms travelled) and per person km emissions (total emissions/total person kms travelled on transit). The last indicator requires the knowledge of bus occupancy between each
stop. The person kms are computed as a sum of (total occupancy * distance between stops) across the entire system. This metric allows us to come up with a comparable number to emissions from automobile users. The indicators developed above can also be generated at a bus route level or time of day level for identifying inefficiencies in the system.

RESULTS AND ANALYSIS
In this section, the base case analysis results are presented first followed by the outcomes of the scenario analysis. Our entire emission analysis is based on the output of the ridership model embedded in the emission estimation code. Hence, prior to moving on with the emission analysis, we validated our ridership model using observed ridership. The accuracy of ridership prediction is paramount since it affects the emission calculations directly. Based on our observed ridership from operator data and predicted ridership difference for boardings is 18.4% and for alightings is 11.5%. For such a large micro-simulation process these errors are reasonable.

Base Case Results
For the base case, we computed the emission indicators based on two sets of EFs from MOVES: default and local. The default emissions rely on the MOVES default values while the local emissions correspond to the customized EFs discussed in the previous section. The comparison of emissions measures (in CO₂ equivalent) - total and average for the entire bus network of Montreal indicates that the use of local EFs instead of default MOVES distributions results in an estimate of emissions that is approximately 15 percent higher. Given the observed differences, it is recommended that EFs be customized for the local jurisdiction whenever possible.

In order to better understand the spatial and temporal variation of emissions in the region, the total computed emissions for AM and PM peak periods are plotted using kernel density function which is a spatial analysis function to identify the hot spots. Figure 1 represents the plot. It can be observed that the city center of Montreal has high value of emissions as compared to the rest of city. One plausible explanation for the trend is that more bus lines are serving the downtown area because of high ridership. Higher values of emissions were also observed close to intermodal transfer points – particularly, metro-bus transfer points. Presumably, increased number of boardings and alightings takes place at this intermodal junctions, resulting in high emission from buses. Furthermore a reduction in the emissions can be seen in the suburban areas as compared to the downtown.

To provide better insight into the base case scenario, we prepared some additional figures. Figure 2 presents the total emissions, boardings, and distance traveled by the transit buses categorized by specific time period of the day. It can be observed that the off peak night (OPN) time period contributes a major part of the total emissions to the system even with the lowest number of per hour boardings. This can be attributed towards the fact that the distance traveled by buses during the OPN time period is almost the same as off peak day. So, the buses have to operate in order to provide service to riders even though the ridership drops from 82,085 persons per hour for PM peak to 15,143 for the OPN time period. Clearly, the operation of buses during OPN needs to be studied carefully in order to reduce the emissions generated by the bus network. However,
the highest total emissions were observed during OPD time period which is due to the highest value of distance traveled by buses during the said time period.

Figure 3 presents the three emission indicators categorized by time of day. It can be observed that increase in distance reduces the emissions per kilometer. Similarly the emissions per person are reduced by an increase in the total boardings. The lowest average emissions per person km were observed during the PM peak which is due to the highest ridership and least distance traveled. Moreover, we also checked the variation in total emissions and the three emission indicators over the time period of the day and found that there was little or no variation between emissions per km and emission per person km throughout the time of the day. However, due to decreased ridership at night, the emission per capita increase during the OPN period from 1 AM to 5 AM even though the total emissions during that time period decreased. It can also be observed that the total emissions increased during AM and PM peak periods.

Scenario Analysis
To demonstrate the applicability of the platform developed in terms of policy analysis, we computed the proposed emission indicators for three policy scenarios. For the first scenario, we increased the overall ridership; while for the second and third scenarios, we varied the bus frequencies.

Scenario 1: Increase in Ridership
In order to study the effect of changes in ridership on emissions, the ridership at all the bus stops was increased by 20% and emissions were generated at the bus stop level. Afterwards, the emissions estimated at the stop level were aggregated at a system level. We observed that the increase in ridership resulted in an increase in systemwide emissions. Table 1 provides a comparison between total systemwide emissions before and after the increase in ridership. From the table, we can see that the total emissions for the day increased by 1.7 percent with a 20 percent increase in systemwide boardings and alightings. Also, the average emissions per km increased by the same percentage. However, average emissions per capita and average emissions per person per km decreased by about 28% and 17%, respectively. Clearly, although the increase in transit ridership increases total emissions, it enhances the performance of the system by reducing per capita emissions in addition to decreasing private vehicle emissions presumably resulting from the change in mode choice of additional transit riders.

Scenario 2: Effects of Change in Bus Frequency
In order to evaluate the effect of change in bus frequencies on emissions, low and high occupancy buses in the network were identified. The occupancy for each bus line was calculated by dividing the total number of individuals on bus by the capacity of the bus. Later on, the occupancy of the buses was determined at the disaggregate stop level and then aggregated by bus line. The bus lines were then categorized as low or high occupancy buses based on the aggregated sum of occupancy at the bus line level. The scenario was based on the intuition that the frequency of low occupancy buses need to be decreased and the frequency of high occupancy buses need to be increased in
order to reduce emissions. The obtained results are presented in Table 2.

**Decreasing bus frequency for low occupancy buses**
Route 21 was found to be the bus line with the lowest occupancy. Note that it is a morning peak period bus that connects the Lasalle metro station to Bell campus with an average headway of 30 minutes. The total boardings for the morning peak period observed for seven roundtrips is 12 as compared to a capacity of 75. In this scenario, the effect of increasing the headway from 30 minutes to 60 minutes is investigated. Doing so increased the ridership twice. The emissions were estimated for the said scenario of decreasing the bus frequency and doubling the headway. Table 2 presents the emission details as well as a comparison of total emissions for before and after the increase in ridership owing to a decrease in the frequency of buses. We observe that the decrease in bus frequency resulted in a 50% decrease in emissions.

**Increasing bus frequency for high occupancy buses**
Based on the occupancy values, Route 18 was one of the high occupancy buses. We found that during the PM peak it runs at capacity for 60 percent of the bus stops. Obviously, there is a need to increase the frequency of this bus line in order to improve its service. Note that Route 18 is a major bus line that runs during all 24 hours of the day and connects Honore Beaugrand metro station to Saint Laurent. It contributes almost 2% of the total bus emissions in Montreal. Again, from Table 2, we can see that increasing the frequency by 25% led to a decrease in bus ridership at the cost of increasing total emissions by ~24%. While the total emissions have increased, the intangible parameters such as comfort, seat availability and lower waiting time (as less likelihood of a full bus arriving at a stop) are the positive impacts of such frequency increase.

**CONCLUSION**
Estimating transit bus emissions is an important step towards the improvement of transit’s carbon footprint in urban areas. While transit is considered a more environmentally friendly mode of transportation, buses could be as polluting as private cars on a per passenger basis under low ridership situations. Similarly, busy transit corridors going through dense urban neighborhoods may become characterized by poor air quality due bus emissions especially when fueled with conventional diesel.

In this study, we demonstrate the development of a method for estimating transit emissions over a large network of 200 bus lines, at the level of the individual bus. This method allows us to incorporate bus and route characteristics in the emission modeling process. This in turn will make it feasible to investigate the effects of changing ridership, frequencies, and ultimately bus types and fuels. Such a systems perspective to transit bus emissions is crucial in the evaluation of planning strategies both at the network level and at a corridor level. With this tool, we can help address questions relating to the allocation of buses based on type, size, and technology while keeping GHG emissions at the forefront of planning decisions. The applicability of the emissions platform was evaluated for a base condition and two scenarios. The results from these exercise offered intuitive and useful insights.
In terms of future research, the simulation platform will be updated to incorporate traffic congestion (as opposed to schedule-based speeds) in emission calculation. Further refinements to boarding and alighting models will also need to be investigated.

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FIGURE 1 Emission for AM and PM peak
FIGURE 2 Total distance, ridership and emissions categorized by time period of day
FIGURE 3 Emission indicators categorized by time of day
### TABLE 1 Comparison of emissions after increase in ridership

<table>
<thead>
<tr>
<th>Emission indicator</th>
<th>Before increase in ridership</th>
<th>After 20% increase in ridership</th>
<th>Percentage change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total emissions for the day (grams)</td>
<td>313,783,768</td>
<td>319,182,928</td>
<td>1.721</td>
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<tr>
<td>Average emissions per capita (grams/person)</td>
<td>349.849</td>
<td>251.857</td>
<td>-28.010</td>
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<tr>
<td>Average emissions per km (grams/km)</td>
<td>1475.707</td>
<td>1501.099</td>
<td>1.721</td>
</tr>
<tr>
<td>Average Emissions per person per km (grams/person km)</td>
<td>109.927</td>
<td>90.944</td>
<td>-17.269</td>
</tr>
</tbody>
</table>
### TABLE 2 Comparison of emissions after decrease/increase in frequency of buses

<table>
<thead>
<tr>
<th>Time period</th>
<th>No of buses</th>
<th>Average headway (mm:ss)</th>
<th>Average trip time (mm:ss)</th>
<th>Trip distance (km)</th>
<th>Base case emissions</th>
<th>Modified emissions</th>
<th>% decrease</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Scenario: Decrease in Frequency (50%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AM PEAK</td>
<td>13</td>
<td>30:00</td>
<td>13:00</td>
<td>4.208</td>
<td>68,825.40</td>
<td>34,569.525</td>
<td>49.77</td>
</tr>
<tr>
<td><strong>Scenario: Increase in Frequency (25%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AM PEAK</td>
<td>61</td>
<td>02:51</td>
<td>48:39</td>
<td>11.04</td>
<td>1,129,326</td>
<td>1,406,673</td>
<td>24.56</td>
</tr>
<tr>
<td>OFF PEAK DAY</td>
<td>108</td>
<td>03:20</td>
<td>49:39</td>
<td>11.04</td>
<td>2,156,153</td>
<td>2,573,453</td>
<td>19.35</td>
</tr>
<tr>
<td>PM PEAK</td>
<td>58</td>
<td>03:03</td>
<td>50:50</td>
<td>11.04</td>
<td>1,223,355</td>
<td>1,554,996</td>
<td>27.11</td>
</tr>
<tr>
<td>OFF PEAK NIGHT</td>
<td>85</td>
<td>14:45</td>
<td>42:25</td>
<td>11.04</td>
<td>1,570,348</td>
<td>1,993,420</td>
<td>26.94</td>
</tr>
<tr>
<td>TOTAL</td>
<td>312</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>6,079,183</td>
<td>7,528,542</td>
<td>23.84</td>
</tr>
</tbody>
</table>