Eco-driving for transit: An effective strategy to conserve fuel and emissions

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HIGHLIGHTS

• We analyzed real-world transit bus operations data to assess potential eco-driving benefits.
• We proposed a new eco-driving algorithm tailored for transit buses.
• We compared eco-driving benefits to those expected from the conversion to a CNG fleet.
• Eco-driving proved a cost-effective strategy to conserve fuel and emissions for transit.

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ABSTRACT

Eco-driving is one of the many options to reduce fuel consumption and emissions from transit operations. However, it is not yet clear how effective eco-driving is for different transit service and fuel types. As policymakers consider implementing eco-driving, they also need comparisons of eco-driving against other fuel-conserving strategies, such as purchasing alternative fuel vehicles. Using a case study of transit operations in Atlanta, Georgia, United States, this paper evaluated eco-driving for two very different service types – local urban service and express service. The authors simulated the implementation of transit eco-driving strategies using an innovative, streamlined algorithm designed to minimize fuel consumption by limiting instantaneous vehicle specific power while maintaining average speed and conserving total distance. Fuel consumption and fuel-cycle emissions were compared across the monitored driving cycles and their modified eco-driving cycles. The savings from eco-driving were also compared to fuel and emissions reductions expected via the conversion of the transit fleets to compressed natural gas (CNG), another popular fuel conservation strategy. The results showed that eco-driving would be a potentially very cost-effective strategy for local and express bus transit operations.

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1. Introduction

Transit agencies are always seeking opportunities to conserve fuel (which typically provides simultaneous emissions reductions) to lower operating costs. Strategies range from making wise new vehicle purchase decisions, such as alternative propulsion/fuel buses, to making operational improvements, such as implementing anti-idle policies and eco-driving training. Each emissions reduction option offers different return-on-investment (ROI), depending upon the local conditions and operational characteristics of each agency. Further complicating the evaluation is the fact that emissions reductions from strategies are not necessarily additive. In selecting a set of emissions reduction strategies to implement, transit agencies need to evaluate multiple options simultaneously, under agency-specific operating characteristics.

Concerning operational improvements, eco-driving is a much-talked-about but often overlooked strategy to combat climate change [1]. Even though some researchers have suggested that transit operators should adopt eco-driving to reduce emissions and improve fuel economy [2], others have pointed out that benefits of eco-driving are unclear [3]. Alam and McNabola [3] argue that driver assistance technologies that do not account for real-world driving conditions limit the effectiveness of eco-driving. To this end, this paper presents a transit bus eco-driving algorithm that utilizes second-by-second GPS data to provide real-time feedback. We derive the potential reductions in fuel consumption from operational improvements achieved through driver behavior modification, predominantly limiting vehicle acceleration rates and top speeds. To assist transit agencies in deciding whether to adopt eco-driving policies, we evaluate fuel and emissions savings from the
aforementioned eco-driving algorithm based upon real-world operations data collected from two transit agencies in Atlanta, Georgia, United States. One agency, the Metropolitan Atlanta Rapid Transit Authority (MARTA), provides local urban service, featuring low speed and frequent stops. The other agency, the Georgia Regional Transportation Authority (GRTA), provides regional express bus service, featuring high-speed operations.

In addition to operational improvements, such as eco-driving, transit agencies have also shown increasing interest in the deployment of alternative fuel buses as a strategy to lower total fuel costs [4]. Compressed natural gas (CNG) is a particularly popular choice of alternative fuel, especially in light of recent decreases in CNG prices due to increased fracking activity. For example, in the United States alone, as of 2014, more than 10,000 buses in the United States are running on CNG, compared to about 4000 hybrid diesel buses (National Transit Database, 2014). Therefore, this paper not only evaluates eco-driving as a stand-alone strategy but also puts the savings from eco-driving into perspective by independently and simultaneously estimating fuel and emissions savings from converting the existing fleets to CNG. Because switching to alternative fuels may result in unintended life-cycle impacts [5], the analyses in this paper extend beyond fuel consumption and tailpipe emissions. Any reduction in fuel consumption at the vehicle also reduces fuel consumption and emissions along the entire fuel chain: harvesting fuel feedstocks, refining and processing the feedstocks into fuels, and distributing the fuels. The analyses that follow will report “pump-to-wheel” (occurring at the vehicle) fuel consumption, greenhouse gas (GHG) emissions, and criteria pollutant emissions and “well-to-wheel” GHG and criteria air pollutant emissions (associated with the entire fuel chain).

The paper first provides a literature review on eco-driving as a fuel consumption and emissions control strategy for surface transportation in general and transit operations in particular. The collection of the data employed in this study is then described and summary statistics of the data are presented. The development of the eco-driving algorithm used in the analysis of potential benefits is then outlined. The comparative fuel consumption and emission reduction results that could be achieved with eco-driving intervention for the monitored data are then summarized and compared to the benefits that could be obtained from fleet conversion to CNG. Conclusions on the effectiveness of eco-driving for transit and the innovativeness of the algorithm developed herein are presented at the end.

2. Literature review

Eco-driving training is well-known as a likely strategy to decrease fuel consumption and emissions. Eco-driving encompasses the following driving tactics [6]: anticipating traffic, limiting high-speed operations, avoiding hard acceleration, shifting to the highest available gear rpm will allow, maintaining a steady speed, and limiting idling. There is a large body of literature regarding the effectiveness of eco-driving, and its implementation strategies. Table 1 summarizes the results from the variety of studies identified and reviewed in this research effort.

Existing studies have evaluated the benefits of eco-driving through real-world implementation, through simulated vehicle activity data, or through a combination of both. In real-world implementations, the observed fuel savings range from 2% to 14% [7–15]. Also, Rolim et al. [16] reported that drivers with instant in-cab voice feedback showed much more reductions in hard accelerations compared to drivers who only received in-class eco-driving training, although the paper did not report the actual fuel savings from these two eco-driving strategies compared to a baseline condition. In simulated vehicle studies, estimated eco-driving benefits exhibit higher variability than observed in real-world implementations, ranging from 8% to about 35% in fuel savings and CO2 reduction [7,17–21].

Eco-driving studies based on simulations have devised a range of driving strategies to represent the implementation of eco-driving objectives. Most studies simulate eco-driving strategies through modifying vehicle speed and acceleration. Barth and Borboonsomsin [7] devised a dynamic eco-driving system that provided drivers with suggested speeds based on average traffic speed and the freeway link level-of-service (LOS). Mensing et al. [22] created a numerical model of the velocity trajectory of a vehicle operating according to eco-driving principles and real-life traffic constraints. Using simulated traffic data, Qian and Chung [19] evaluated fuel consumption and CO2 emissions of eco-driving by reducing the maximum acceleration rates by 10% and 20% in a simulation. Suzdaleva and Nagy [21] developed a data-based Bayesian approach to identify and modify the speed to optimize fuel consumption for conventional vehicles. Zhao et al. [23] developed an eco-driving support system based on driving simulator and achieved about 5% reduction in CO2 emissions and fuel consumption. Hu et al. [24] developed an eco-driving strategy for hybrid vehicles operating on rolling terrain based on simulation, and the results indicated an improvement in fuel efficiency from 5.0% to 8.9% on mild slopes and from 15.7% to 16.9% on steep slopes. The literature search revealed three research gaps. First, despite the large body of research on the benefits of eco-driving, quantitative assessments performed for heavy-duty vehicles, in general, and transit fleets, in particular, are few. In the three papers that focused on buses, one did not provide any information regarding driving cycles or service type, and the remaining two [12,15] were limited to a single route. As such, little is known about the varying degree of fuel and emissions reduction eco-driving can achieve for different service types. The lack of evidence for the effectiveness of
<table>
<thead>
<tr>
<th>Source</th>
<th>Vehicle type</th>
<th>Before data</th>
<th>After data</th>
<th>Methodology</th>
<th>Time scope</th>
<th>Fuel savings (CO₂ reduction/pollutant reduction)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beusen et al. [8]</td>
<td>Light-duty vehicles</td>
<td>Real-world vehicle activity data</td>
<td>Real-world vehicle activity data</td>
<td>Four-hour training: ten drivers At least 100 km of driving per month</td>
<td>Two months of data collection: ten months for ten drivers during real-life conditions, monitored weekly</td>
<td>Fuel saving: 5.8% with large differences between individuals</td>
</tr>
<tr>
<td>Dib et al. [9]</td>
<td>EV</td>
<td>Real-world vehicle activity data</td>
<td>Real-world vehicle activity data</td>
<td>Participants drove EV in fixed route Energy comparison was made before and after eco training</td>
<td>N/A</td>
<td>Fuel savings: 14% for EV</td>
</tr>
<tr>
<td>Ho et al. [10]</td>
<td>Light-duty vehicles</td>
<td>Real-world vehicle activity data</td>
<td>Real-world vehicle activity data</td>
<td>116 participants Classroom training</td>
<td>Pre-test of drivers 30–45 min training sessions re-test drivers right after training</td>
<td>Fuel saving and carbon emissions: more than 10%</td>
</tr>
<tr>
<td>Hu et al. [24]</td>
<td>Light-duty hybrid electric vehicles</td>
<td>Simulated vehicle activity data</td>
<td>Simulated vehicle activity data</td>
<td>Simulating hybrid vehicle activities in different terrain profile Applying optimization methods to achieve ecological vehicle operations</td>
<td>N/A</td>
<td>Fuel savings 5.0–8.9% on mild slopes and from 15.7–16.9% on steep slopes</td>
</tr>
<tr>
<td>Jeffreys et al. [17]</td>
<td>Light-duty vehicles</td>
<td>Real-world vehicle activity data</td>
<td>Real-world vehicle activity data</td>
<td>1056 private drivers 853 received eco-driving education, 203 as control group</td>
<td>Seven months</td>
<td>Reduction in fuel use of 4.6%, or 0.51 L per 100 km</td>
</tr>
<tr>
<td>Mensing et al. [18]</td>
<td>Light-duty vehicles</td>
<td>Simulated vehicle activity data</td>
<td>Simulated vehicle activity data based on the optimization method</td>
<td>Simulating a conventional passenger vehicle Applying optimization methods to achieve ecologically and economically optimal vehicle operations</td>
<td>N/A</td>
<td>Economic cycle Fuel saving: 2.5 L/100 km CO₂ reduction: 31.9% NOx reduction: 16.4% Ecologic cycle Fuel saving: 2.3 L/100 km CO₂ reduction: 26.8% NOx reduction: 54.5% HC reduction: 7.4%</td>
</tr>
<tr>
<td>Qian and Chung [19]</td>
<td>Light-duty vehicles</td>
<td>Simulated vehicle activity data</td>
<td>Simulated vehicle activity data</td>
<td>Traffic microsimulation model Different traffic condition, penetration rates of eco-drivers, and acceleration rates</td>
<td>N/A</td>
<td>Scenarios of heavy congestion and 25% penetration impact traffic and environmental performance negatively Moderate and smooth accelerations save 11% fuel without major increase in travel time</td>
</tr>
<tr>
<td>Rutty et al. [11]</td>
<td>Light-duty vehicles</td>
<td>Real-world vehicle activity data</td>
<td>Real-world vehicle activity data</td>
<td>11 gasoline vehicles Four hybrid vehicles 40 km per day Goal-directed feedback</td>
<td>Post-training data collection: one month Training: one month Post-training data collection: one month</td>
<td>Fuel savings: 0.48L per gasoline vehicle per day 0.3 L per hybrid vehicle per day CO₂ reduction: 1.1 kg per gasoline vehicle per day; 0.6 kg per hybrid vehicle per day. Baseline data not reported</td>
</tr>
<tr>
<td>Schall and Mohnen [20]</td>
<td>Light commercial vehicles</td>
<td>Real-world vehicle activity data</td>
<td>Real-world vehicle activity data</td>
<td>86 drivers from German logistics company</td>
<td>Baseline: three months Test period: three months</td>
<td>Reduction of fuel consumption of 5%</td>
</tr>
<tr>
<td>Strömberg and Karlsson [12]</td>
<td>Buses</td>
<td>Real-world vehicle activity data</td>
<td>Real-world vehicle activity data</td>
<td>54 bus drivers, divided into Three groups: control, eco-driving feedback only, and eco-driving feedback supplemented with training</td>
<td>Baseline: three weeks Test period: three weeks</td>
<td>6.8% reduction in fuel consumption between the eco-driving groups and control group; no significant difference between the two eco-driving groups</td>
</tr>
<tr>
<td>Study</td>
<td>Type of Vehicle</td>
<td>Deployment Method</td>
<td>Pre-training 1</td>
<td>Post-training 1</td>
<td>Fuel Savings</td>
<td></td>
</tr>
<tr>
<td>-------</td>
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<td>---------------</td>
<td>----------------</td>
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<td></td>
</tr>
<tr>
<td>Sozdanov and Nagy [21]</td>
<td>Light-duty vehicles</td>
<td>Real-world vehicle activity data</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>Wahlberg [14]</td>
<td>Buses</td>
<td>Real-world vehicle activity data</td>
<td>Pre-test of drivers after one year</td>
<td>2000–2003</td>
<td>Fuel savings: 5.5% overall</td>
<td></td>
</tr>
</tbody>
</table>
| Zarkadoula et al. [15] | Buses | Real-world vehicle activity data | 3.1. Overview | 3. Methodology | eco-driving for transit vehicles makes it difficult for transit operators to make informed decisions on fuel-conserving strategies. Second, there is a gap between theoretical research in eco-driving algorithms and the implementation among transit agencies. Transit agencies are often motivated to pilot eco-driving programs (e.g., [15]), but the eco-driving algorithms identified in literature were designed for light-duty vehicles. Given the differences in vehicle dynamics between light- and heavy-duty vehicles, it is likely that the real-world implementation of eco-driving strategies will differ, and that bus drivers will need specific instructions during their daily operations. An easily implementable algorithm for heavy-duty vehicles is necessary to bridge the gaps between research, development, and implementation of eco-driving in support of energy conservation. Finally, as concluded by de Abreu e Silva et al. [25] after a comprehensive literature search, previous studies focused on evaluating the impact of either vehicle-related factors or driver’s behavior separately, instead of addressing the impact altogether. In other words, the potential benefits of eco-driving have not been compared against alternative fuel strategies such as CNG. The varying degrees of benefits attributable to a transit agency’s type of service have also not been discussed. This paper fills these gaps by proposing a new algorithm founded on modeled fuel and emissions relationships specific to transit buses, evaluating the extent to which fuel and emissions can be reduced through such a bus-specific eco-driving algorithm, and exploring the effectiveness of eco-driving when compared against and deployed with an alternative fuel bus fleet.

3. Methodology

This paper utilized second-by-second transit operations data collected from local urban transit services and regional express buses in Atlanta, Georgia, United States. For local transit services, Metropolitan Atlanta Rapid Transit Authority (MARTA) operations data were collected on 13 buses for 381 days (June 28, 2004, to Oct 24, 2005) using the GT Trip Data Collector [26]. For express buses, data were collected via spot sampling (typically two- to three-day deployments between August 6, 2013, and March 3, 2014). Qstarz BT-Q1000eX GPS loggers were temporarily installed on Georgia Regional Transportation Authority (GRTA) express buses in this sampling effort. In all, second-by-second real-world transit operations data were collected for more than 109 thousand kilometers from 26 buses. The following sections first describe the general workflow and then provide detailed descriptions of the theoretical foundation and the implementation approach of the new eco-driving algorithm.

3.1. Overview

Fig. 1 depicts the general process of the study method. The first column describes the necessary steps to cleanse the raw GPS data, including (Supplementary Information describes these steps in detail):

1. Applying a Kalman filter to remove erroneous GPS points, typically occurring at low speeds and in urban street canyons [27].
2. Using a spline process to interpolate missing data.
3. Conducting geographic information system (GIS) network mapping to identify the facility type (freeway, arterial, or bus yard) for each time point in the bus operation. Distinguishing between freeway from non-freeway operations is a major step for subsequent analysis because the eco-driving strategies for freeways and non-freeways differ substantially.
4. Identifying potential extended idle to be excluded from this analysis by setting different idle speed cutoffs were set for
MARTA and GRTA operations given the differences in precision levels of the GPS devices [28]. Because neither the GT Trip Data Collector nor the Qstarz GPS loggers had the ability to detect whether the engine was on, which would require an oil pressure sensor [29] or OBD connection, there was no feasible way to determine whether a bus was idling when the speed values were near zero. As such, the team elected to exclude the potential benefits of idle reduction in this paper. Nevertheless, idle reduction is another viable strategy that can be implemented to reduce emissions [30,29].

5. Breaking the continuous data streams from the logging devices into trip segments, separated by gaps in data at trip ends, and where gaps resulted from missing data. Only those trip segments longer than 30 s with an average speed of 8 km per hour (kph) or greater were retained for subsequent eco-driving analysis. Table 2 summarizes the final analytical dataset.

The two right columns in Fig. 1 then show the parallel fuel and emissions analysis for the observed duty cycles and the simulated eco-driving cycles. After initial processing of the raw data obtained from transit monitoring devices, the observed driving cycles went through a two-step process for life-cycle energy and emissions estimation [31]. The duty cycles were first linked to onroad emission rates to estimate pump-to-wheel fuel and emissions. The onroad fuel and emission rates were matched by fleet age distribution and operating mode distribution to MOVES-Matrix [32], a large emission rate lookup matrix developed from the U.S. Environmental Protection Agency’s MOtor Vehicle Emission Simulator (MOVES) (EPA, 2014). To estimate the emissions and fuel consumptions for the entire fleet, this paper employed the fleet size and annual distance information from the National Transit Database (NTD) (2014). The NTD does not provide information of operating distance on different road types but does differentiate between revenue and non-revenue (also known as deadhead) distance. Therefore, proportions of freeway and non-freeway distance were estimated separately for revenue and deadhead operations, using spatial analysis in ArcGIS (details are provided in Supplementary Information). The onroad fuel consumption was then aggregated to estimate well-to-pump fuel consumption and emissions using the Greenhouse gases, Regulatory Emissions, Energy, and Transportation (GREET) model, a publicly available, process-based life-cycle model [33]. The observed driving cycles were processed to generate the eco-driving cycles using the algorithm as described later. The eco-driving cycles were also linked to MOVES and GREET to estimate comparative fuel consumption and emissions.

3.2. Theoretical foundation of eco-driving cycle development

The basic approach to eco-driving is to limit engine power demand so as to conserve fuel and reduce emissions. Power demand is a non-linear function of speed and acceleration; hence, the proposed algorithm manages engine load by controlling top speeds (for wind resistance) and acceleration rates (for all load parameters). Engine load is high during acceleration from stopping, so minimizing stop-and-go activity is a goal of eco-driving. However, because engine load involves the product of speed and acceleration, it is more important to ensure that hard acceleration conditions do not occur at moderate- and high-speed operations.

A variety of emission rate models has been developed to predict emissions from heavy-duty vehicle operations. Models that predict emissions as a function of operating mode (speed/acceleration conditions) are commonly known as “modal models.” These modal models range from high-resolution engine load models that predict second-by-second emissions as a function of predicted instantaneous engine load [34–36], to models that predict second-by-second emission rates (or average emission rates for a roadway) as a function of some surrogate for engine load. The wide range of potential benefits eco-driving noted in the literature arises in part from the application of a variety of modeling approaches. The eco-driving strategy, i.e. optimal change in driving cycle to achieve emissions reductions, is, therefore, a direct function of the model employed in the analysis.

The eco-driving analyses reported in this study used the modal emissions modeling framework in the U.S. Environmental Protection Agency (EPA)’s MOtor Vehicle Emission Simulator (MOVES). The MOVES model uses scaled tractive power (STP) as a surrogate for engine load, where STP is a function of vehicle speed, acceleration, and vehicle mass. MOVES employs a binning approach, such that higher STP values within specific operating speed bins are

| Table 2
| Summarized analytical dataset.
<table>
<thead>
<tr>
<th>Type of operation</th>
<th>Local transit</th>
<th>Express service</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agency</td>
<td>MARTA</td>
<td>GRTA</td>
</tr>
<tr>
<td>Number of buses</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>Number of trips</td>
<td>9984</td>
<td>852</td>
</tr>
<tr>
<td>Total distance (km)</td>
<td>98,567</td>
<td>5853</td>
</tr>
<tr>
<td>Total duration (h)</td>
<td>3716</td>
<td>84</td>
</tr>
<tr>
<td>Average speed (kph)</td>
<td>26.5</td>
<td>69.7</td>
</tr>
</tbody>
</table>
linked to higher fuel consumption, \( \text{CO}_2 \) emissions, and criteria pollutant emissions. Fig. 2 presents the fuel rate for model year (MY) 2010 transit buses of each operating mode bin (defined by speed and STP ranges) extracted from MOVES. High speeds and hard accelerations at moderate or high speeds push the onroad activity into higher STP values and yield higher fuel consumption and emissions. In developing the strategy to generate eco cycles for 2010 transit buses of each operating mode bin (defined by speed and total distance), the goal was to modify each vehicle’s trajectory to minimize activity in higher STP bins, while preserving average speed and total distance.

This study proposes a new method for optimizing each vehicle trajectories based on the structure of the MOVES STP operating mode bins. The methodology conserved cycle distance, maintained overall average speed, but prevented instantaneous STP from increasing significantly by setting acceleration limits within each MOVES speed grouping.

STP is calculated as:

\[
STP = \frac{A}{M} v + \left( \frac{B}{M} \right) v^2 + \left( \frac{C}{M} \right) v^3 + \left( \frac{m}{M} \right) (\text{acc + sin } \theta) v
\]  

(1)

where

- \( \nu = \text{second} - \text{by} - \text{second velocity} \ (\text{m/s}) \)
- \( \text{acc} = \text{second} - \text{by} - \text{second acceleration} \ (\text{m/s}^2) \)
- \( m = \text{vehicle mass} \ (\text{metric tonne}) \)
- \( A = \text{rolling resistance} \ (\text{kW s/m}) \)
- \( B = \text{rotating resistance} \ (\text{kW s}^2/\text{m}^2) \)
- \( C = \text{aeodynamic drag} \ (\text{kW s}^3/\text{m}^3) \)
- \( M = \text{fixed mass factor} \)
- \( \theta = \text{road grade}. \)

A, B, C, and M are fixed parameters for each vehicle type modeled in MOVES. The values can be found in “sourceustype” table in the MOVES database (providing in Supplementary Information). For simplification, all of the analyses in this report assumed zero road grade (\( \sin \theta = 0 \)). STP increases monotonically with speed and acceleration. The first step in the eco-driving process was to set an STP limit value (STPL). For each speed \( \nu \), the acceleration limit \( \text{acc} \), that prevented STP from exceeding \( \text{STPL} \) would be:

\[
\text{acc} = \left( \frac{STP \cdot M}{m \nu} \right) - \left( \frac{A}{m} \right) - \frac{B}{m} \nu - \left( \frac{C}{m} \right) v^2
\]  

(2)

In the MOVES operating mode classification, each speed level includes different STP levels. Based on the STP categories (see Table 6), we set STPL to different levels: STPL-1 = 30, STPL-2 = 24, STPL-3 = 18, STPL-4 = 12, STPL-5 = 9, STPL-6 = 6, and STPL-7 = 3. From STPL-1 to STPL-7, for a given speed, the acceleration limit became more stringent, as illustrated in Fig. 3.

The principle of the computational method was to read each second of vehicle activity and adjust the acceleration rate downward when the STP reaches or exceeds the STPL. The acceleration rate was adjusted downward enough to lower the STP of the next data point to the median value of the STP range that met the STP limit. For example, if the STP limit was STPL-4 = 12, the acceleration would be adjusted downward until the calculated STP for that data point equaled 10.5 (the median STP value for the 9–12 STP bin, which meets the STPL) when STP reached or exceeded 12.

It is important to set appropriate STP limits by driving cycle. If the rules are too lenient, the rules will not significantly fuel consumption and emissions. However, if the rules are too stringent, the average speed of the trace will be too slow for drivers to accept. Furthermore, a reduction in average speed leads to increased

![Fig. 2. Fuel rate (MJ/h) for each operating mode bin for 2010 MY transit buses (MOVES2014 output).](image1)

![Fig. 3. Acceleration limit for each speed level at each STP limit level.](image2)
driving time, offsetting some of the fuel and emissions savings. In this study, the research team established different STP limits by road type and speed after iterative testing. Table 3 summarizes the resulting STP limits.

### 3.3. Implementation of eco-driving cycle modification

To implement the eco-driving strategy, the proposed algorithm applied three iterative steps to each vehicle trajectory:

1. **Maintaining Status Quo:** When the STP of the original cycle did reach or exceed STPL, no modification of the cycle was required. The next data point in the eco-cycle would be the same as the data point from the original cycle.

2. **Smoothing:** When the STP of the original cycle reached or exceeded the STPL, the acceleration rate was adjusted downward such that the resulting STP for the data point equaled the median value for the STP bin that did not exceed the STP limit. As the acceleration rate decreased, the speed of the next data point in the eco-cycle would be slightly lower than the speed at that point in the original cycle. The acceleration rates for subsequent points in the cycle were also set to achieve the median STP value for that STP bin. Smoothing of acceleration continued until the speed of eco cycle matched that of the original cycle.

3. **Conservation of Distance:** Once the speed of eco cycle and original cycle aligned, the distance covered by the eco cycle was less than that of the original cycle (due to the implementation of lower acceleration rates). To conserve travel distance, the algorithm extended the eco cycle cruise speed until the distance traversed by the eco cycle matched that of the original cycle. This step assumed that a slower-moving vehicle was not in the path of the vehicle of interest.

**Table 3**

<table>
<thead>
<tr>
<th>Road type</th>
<th>Speed level (kph)</th>
<th>STP limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local road</td>
<td>0–40</td>
<td>≤6</td>
</tr>
<tr>
<td></td>
<td>40–80</td>
<td>≤6</td>
</tr>
<tr>
<td></td>
<td>≥80</td>
<td>≤6</td>
</tr>
<tr>
<td>Freeway</td>
<td>0–40</td>
<td>≤6</td>
</tr>
<tr>
<td></td>
<td>40–80</td>
<td>≤9</td>
</tr>
<tr>
<td></td>
<td>≥80</td>
<td>≤12</td>
</tr>
</tbody>
</table>

**Fig. 4.** Eco cycle development example.

**Fig. 5.** Example of an observed cycle and corresponding eco cycle.

Fig. 4 illustrates the results of the three steps applied to short driving cycle. In this figure, the initial trajectories of eco and original cycle are the same (status quo) because the early portion of the cycle does not exceed STPL. Once the vehicle power exceeds STPL, smoothing begins and the acceleration rates of the eco cycle are set lower than those observed. Smoothing is usually followed by conservation of distance to ensure that the vehicle traverses the same distance in the eco cycle as in the observed cycle. Fig. 5 presents an example of an observed cycle and its corresponding eco cycle. The modified eco cycle smoothed the sharp acceleration, especially during high-speed operations. Fig. 6 provides the full flowchart describing the implementation of the eco-driving algorithm and iteration processes.

Fig. 7 shows the speed-acceleration (acceleration >0 mph/s) scatter plots from the observed cycles and eco cycles. The hard acceleration rates in observed cycles have been reduced to keep the STP below the STP limit in the eco cycle. The dashed lines in Fig. 7 correspond to the acceleration limits for each speed level at STP threshold 6, 9, and 12 in Fig. 3. After the modification, the overall distance increased by 0.05%, and the overall speed reduced by 3.07%. The corresponding highway and local speed reductions were 1.93% and 3.13%, respectively.
Cycle Optimization

1-steady status: \( \text{STP} < \text{STP}_L \)

\[ \text{EcoSpeed}(i) = \text{OriginalSpeed}(i) \]

\[ \text{EcoAcc}(i) = \text{OriginalSpeed}(i) \]

Next second \( (i = i + 1) \)

No

2-smoothing status:

\[ \text{EcoAcc} = \text{Acc} \text{ L} \]

\[ \text{EcoSpeed}(i) = \text{EcoSpeed}(i-1) + \text{EcoAcc}(i-1) \]

Yes

3-conserving distance status:

\[ \text{EcoSpeed}(i) = \text{EcoSpeed}(i-1) \]

\[ \text{EcoAcc} = 0 \]

Next second \( (i = i + 1) \)

Yes

No

Selection STP Limit Level

<table>
<thead>
<tr>
<th>( \text{STPL}_1 )</th>
<th>( \text{STPL}_2 )</th>
<th>( \text{STPL}_3 )</th>
<th>( \text{STPL}_4 )</th>
<th>( \text{STPL}_5 )</th>
<th>( \text{STPL}_6 )</th>
<th>( \text{STPL}_7 )</th>
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</thead>
<tbody>
<tr>
<td>( 30 )</td>
<td>( 24 )</td>
<td>( 18 )</td>
<td>( 12 )</td>
<td>( 9 )</td>
<td>( 6 )</td>
<td>( 3 )</td>
</tr>
</tbody>
</table>

Average speed of eco cycle significantly smaller than original cycle

Fuel/emission of interest from eco cycle does not change much compared with original cycle

Optimization Complete

Yes, Choose a less strict rule

Yes, Choose a more strict rule

Fig. 6. Algorithm flow chart.

Observed Speed-Acceleration

Eco Speed-Acceleration

Fig. 7. Speed-acceleration scatter plot (10,000-s sample).
4. Results

In this section, we present fuel and emissions results for three scenarios. Scenario 1 evaluates the implementation of the eco-driving cycles with the existing fleet, denoted as eco-driving. Scenario 2 assesses the purchase of new CNG vehicles to replace the current fleet, denoted as CNG. Scenario 3 combines the two strategies and implements eco-driving with a new CNG fleet purchase, denoted as eco-driving + CNG. These scenarios are compared against the baseline scenario comprised of observed driving behavior, as revealed through the GPS data samples, and existing fleet and annual distance (see Table 4). We summarized the annual fuel usage and fuel cycle emissions of MARTA and GRTA given the existing fleet and driving behavior. Among air pollutants, we only present NOx and PM2.5 because heavy-duty vehicles have relatively low HC and CO emissions.

4.1. Eco-driving scenario

The speed and acceleration modifications resulted in a shift of operation mode bin distributions. As shown in Fig. 8 for the MARTA sample and Fig. 9 for the GRTA sample, most of the operation points with high STP values have been adjusted downward to lower STP values by limiting the acceleration rate.

The eco-driving scenario assumed that all drivers would follow the eco cycle for all distance traveled. In this scenario, the fleet composition was assumed to be the same as the existing fleet. When these operating mode bin distributions were applied to the entire 508-bus MARTA fleet, eco driving would reduce fuel consumption by about 999 billion joules (5%) per year. The MARTA fuel savings translated to an annual reduction of about 3930 metric tons (5%) in fuel cycle carbon dioxide equivalent (CO2e) emissions. Regarding criteria air pollutants, eco-driving implementation in

<table>
<thead>
<tr>
<th>Transit agency</th>
<th>Annual distance (1000 km)</th>
<th>Deadheading percent (%)</th>
<th>Number of buses</th>
<th>CNG fleet percent (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MARTA</td>
<td>41,602</td>
<td>12</td>
<td>508</td>
<td>69</td>
</tr>
<tr>
<td>GRTA</td>
<td>7566</td>
<td>44</td>
<td>166</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 4
Distance and fleet information [39].

Fig. 8. Operating mode bin distributions of observed and eco cycles in the MARTA sample.

Fig. 9. Operating mode bin distributions of observed and eco cycles in the GRTA sample.
the MARTA fleet would reduce annual NOx emissions by 14 metric tons (4%), and annual PM2.5 emissions by 0.8 metric tons (7%).

For the GRTA fleet, annual fuel savings amounted to about 993 billion joules, a 7% reduction. CO2e emissions reduced by about 700 metric tons per year. NOx reductions would amount to 2 metric tons (5%), and the annual PM2.5 reductions would be 0.1 metric tons (7%) per year.

4.2. CNG fleet purchase scenario

In this hypothetical scenario, MARTA and GRTA were assumed to replace their existing diesel buses with new CNG buses (MY 2015). MARTA was assumed to retain their current CNG buses, so this strategy would affect 31% of the fleet (see Fig. 10 and Table 4). The age distributions of the existing fleets are summarized in Fig. 10 for MARTA and Fig. 11 for GRTA. The CNG scenario assumed no changes in the current driving style.

Compared to the base scenario, new CNG buses slightly increased onroad energy consumption. Annual total fuel consumption increased by 823 billion joules for MARTA and 831 billion joules for GRTA. However, due to the lower well-to-pump CO2e emission rate of CNG as compared to diesel, the well-to-wheel CO2e emissions did not increase, despite the increase in fuel consumption. The annual total CO2e emissions stayed about the same for MARTA and decreased by about 800 metric tons for GRTA. A CNG fleet would significantly reduce NOx and PM2.5 emissions. After MARTA’s assumed replacement the 158 existing diesel buses with new CNG buses, the fuel cycle NOx emissions reduced by 112 metric tons (30%) per year, and PM2.5 emissions reduced by nine metric tons (85%) per year. If GRTA replaced all of its 166 diesel buses with CNG buses, its annual fuel cycle NOx emissions would decrease by 29 metric tons (70%), and annual fuel cycle PM2.5 emissions would reduce by two metric tons (95%).

4.3. Eco-driving with CNG fleet purchase scenario

In this scenario, we combined the changes in driving style with the changes in fleet composition. For both MARTA and GRTA fleets, all existing diesel buses were assumed to be replaced with new CNG buses. Eco cycles were applied to the agencies’ entire annual distance. Table 5 summarizes the results for the combined eco-driving and CNG fleet scenario. For MARTA, the combined strategy reduced annual fuel consumption by 199 billion joules (1%). Fuel cycle CO2e emissions decreased by 3780 metric tons (5%) per year. The all-CNG fleet with eco cycles showed significant reductions in

Table 5
Summary of annual fuel consumption and fuel cycle emissions across scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Transit agency</th>
<th>Fuel $10^6$ MJ</th>
<th>GHGs metric tons</th>
<th>NOx metric tons</th>
<th>PM2.5 metric tons</th>
</tr>
</thead>
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<tr>
<td>Baseline</td>
<td>MARTA</td>
<td>855</td>
<td>81,233</td>
<td>371</td>
<td>10.5</td>
</tr>
<tr>
<td></td>
<td>GRTA</td>
<td>102</td>
<td>9511</td>
<td>41</td>
<td>1.9</td>
</tr>
<tr>
<td>Eco-driving</td>
<td>MARTA</td>
<td>814</td>
<td>77,304</td>
<td>356</td>
<td>9.8</td>
</tr>
<tr>
<td></td>
<td>GRTA</td>
<td>94</td>
<td>8809</td>
<td>39</td>
<td>1.7</td>
</tr>
<tr>
<td>CNG</td>
<td>MARTA</td>
<td>890</td>
<td>81,349</td>
<td>258</td>
<td>1.5</td>
</tr>
<tr>
<td></td>
<td>GRTA</td>
<td>108</td>
<td>8704</td>
<td>12</td>
<td>0.1</td>
</tr>
<tr>
<td>Eco-driving + CNG</td>
<td>MARTA</td>
<td>847</td>
<td>77,453</td>
<td>246</td>
<td>1.3</td>
</tr>
<tr>
<td></td>
<td>GRTA</td>
<td>98</td>
<td>7884</td>
<td>11</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Numbers in parentheses indicate percent changes compared to baseline.
fuel cycle NOX and PM2.5 reduction, by 124 metric tons (34%) and nine metric tons (87%), respectively. The GRTA fleet exhibited even more fuel savings and emission reductions. Annual fuel consumption fell by 4%, amounting to 520 billion joules. The fuel cycle emissions in CO2e, NOx, and PM2.5 decreased by 1628 (17%), 30 (73%), and 2 (96%) metric tons, respectively.

Table 5 summarizes the onroad fuel consumption and fuel cycle emissions from the baseline and the three scenarios described above.

4.4. Overall comparison and discussion

The reductions in fuel consumption and fuel cycle emissions presented in this paper reflect each agency’s fleet size and extent of operations. In this section, the results are presented on a per km basis, which will shed light on generalized fuel and emissions impacts for local and express services. Figs. 12–15 provide comparisons across scenarios and operation types for fuel economy, fuel cycle CO2e, NOx, and PM2.5 emission rates, respectively. In general, eco-driving is more effective in express service, improving fuel economy by 8%, than local transit service where the fuel economy improvement is 5%. Eco-driving reduces more fuel cycle CO2e emissions than the CNG fleet purchase. Combining eco-driving with new CNG fleet purchase can provide added benefits in fuel cycle energy savings and emissions reduction. In the case of fuel cycle CO2e emissions in express bus service, the reduction achieved by the combined CNG and eco-driving strategy is more than the sum of reductions achieved by the eco-driving scenario and CNG.

Fig. 12. Fuel consumption comparison across scenarios and types of operation.

Fig. 13. CO2e emission rate comparison.
fleet purchase scenario. This compounded reduction shows that eco-driving can be especially effective as a fuel conserving strategy for agencies that provide express service with a CNG fleet.

5. Conclusions

This paper evaluated potential fuel and emissions savings from the implementation of eco-driving in an urban local transit fleet and an express bus fleet in Atlanta, Georgia, United States. The analyses employed real-world operations data collected from these two fleets as baseline operating conditions, and eco-driving duty cycles developed through an algorithm that modified speed and acceleration. The eco-driving algorithms reduce fuel consumption and emissions by limiting engine load, as indicated by scaled traction power (STP) in the modal modeling scheme employed by the USEPA’s MOVES model, while still conserving total distance and average speed. The benefits of the eco-driving strategy were compared to CNG fleet conversion, another popular transit fuel strategy. This paper also assessed the simultaneous effects of eco-driving and CNG fleet purchase. Changes in total annual fuel consumption and emissions for the three strategies were compared for the two agencies, as well as fuel and emission rates on a per-km basis.

5.1. Effectiveness of eco-driving

This paper has added evidence to the body of literature that eco-driving is an effective fuel and emission reduction strategy for transit for a variety of service and fuel types. The evaluation has a few innovative features. First, eco-driving was examined in
the context of broader energy conserving strategies. That is, the paper compared eco-driving to new CNG fleet purchase as a competing strategy, and also evaluated eco-driving as a complementary strategy to a CNG fleet. By doing so, this paper lays a clear case to assist informed policy making in transit operations. Second, the analyses employed more than 100,000 km of real-world bus operations data from two very different service types, one providing local urban service with frequent stops, and the other providing express service with sustained high speeds. Prior studies on eco-driving for buses have not differentiated service types in their evaluations. The results have shown that, assuming the existing fleet composition of the case study fleets in Atlanta, Georgia, United States, eco-driving can reduce fuel consumption by 5% in local transit service, and 7% in express bus service. Although the percentage decrease is larger for the express bus fleet (freeway benefits are large), the actual fuel savings per year is greater for buses in the local transit fleet in the case study, given the number of kilometers driven per bus each day. By comparison, a new CNG fleet would slightly increase fuel consumption, albeit keeping the fuel cycle CO₂e emissions about the same as the baseline conditions. Eco-driving was also found to be an effective strategy for reducing fuel consumption and emissions for CNG fleets. For the GRTA express bus service, eco-driving conserved a larger percentage of fuel in the hypothetical CNG fleet than in the existing diesel fleet.

Eco-driving can prove a very cost-effective strategy for transit agencies seeking to reduce fuel consumption and emissions. For example, the fuel savings that GRTA can achieve amount to about 208,200 L of diesel, translating to about $132,000 in annual fuel savings (about $800/bus/year), assuming a diesel fuel price of $2.40 per gallon ($0.63/L). Unlike the purchase of an alternative fuel bus fleet, eco-driving does not require significant capital investment. Once buses are monitored, eco-driving is easy to implement, only requiring the development of driver reports, training, and feedback. Based on the research team’s prior experience with fleet monitoring [29], preliminary cost estimates show that implementing eco-driving would cost an agency about $650/bus/year, inclusive of equipment, communications, driver incentives, and data analysis. For fleets that are not currently monitoring transit speed/acceleration activity, the fuel savings is sufficient to pay for such monitoring. Fuel savings in the MARTA fleet amount to about 322,500 L of diesel plus 956,000 L of gasoline equivalent for CNG. Assuming a diesel price of $2.40/gallon ($0.63/L) and a CNG price of $1.20 per gasoline gallon equivalent [37], the cost savings for the MARTA fleet amount to about $1000/bus/year. Not only will fleet monitoring enable real-time feedback to drivers, which has been shown to provide added fuel savings than in-class training [16], but it will also provide asset management and driver safety assessment benefits.

5.2. Methodological innovation

From a methodological standpoint, this paper has contributed a new eco-driving algorithm tailored for transit buses. This algorithm would be used to train drivers and assess their onroad performance of eco-driving interventions (i.e., to evaluate if there is still room for improvement for the driver after intervention). The eco-driving algorithm developed for this study utilizes the modal modeling framework of USEPA’s MOVES model. The advantages are two-fold. First, the algorithm is not computationally demanding; nor does it interact with surrounding traffic or infrastructure, as some of the more sophisticated dynamic models do (e.g., [7,24]). The gain from this streamlined approach is that the resulting algorithm can be readily used in real-time or near-real-time driving advising housed on mobile devices. In an on-going project, the research team has already integrated the algorithm with the Commute Warrior smartphone application [38]. As shown in Fig. 16, the smartphone interface simply shows a green1 dot when the vehicle is operating at a moderate STP level, and a red dot when the vehicle is operating at a high STP level, as indicated in Fig. 3.

Work is ongoing to deploy Commute Warrior equipped smartphones with local transit agencies to provide real-time eco-driving feedback to bus drivers. Second, MOVES is a widely accessible tool with peer-reviewed technical documentation. It is the USEPA’s approved model for regulatory use and is available for free anywhere from the world on the USEPA’s website. As such, using the MOVES framework allows a unified platform for fuel and emissions estimation. However, the disadvantage of the analytical approach is that the algorithm is limited by uncertainties and emissions averaging inherent in the MOVES model, especially those related to the lack of resolution for high-speed, high-power operating mode bins for heavy-duty vehicles. In future work, the authors plan to refine the eco-driving algorithm using high-fidelity vehicle simulation models and road grade information without compromising on computational efficiency.

The analyses presented in this paper serve as a point of departure for debating the benefits of eco-driving for transit operations, and the initial assessment of benefits appear significant and are likely to be very cost-effective. Because eco-driving training is relatively easy to implement when speed/acceleration activity is monitored, and because fuel savings can pay for monitoring expenses, this paper concludes that eco-driving strategies are a reasonable approach to reducing fleet emissions in local and express bus transit operations.

Acknowledgment

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1 For interpretation of color in Fig. 16, the reader is referred to the web version of this article.
Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2016.09.101.

References