

ECO-DRIVING FOR TRANSIT

April 2016

A White Paper from the National Center
for Sustainable Transportation

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**National Center
for Sustainable
Transportation**



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Acknowledgments

This study was funded by a grant from the National Center for Sustainable Transportation (NCST), supported by USDOT through the University Transportation Centers program. The author would like to thank the NCST and USDOT for their support of university-based research in transportation, and especially for the funding provided in support of this project. The authors would like to thank reviewers at the California Air Resources Board, Georgia Regional Transportation Authority, and Pedal Logic LP for providing comments on preliminary versions of this white paper.

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Eco-driving for Transit

EXECUTIVE SUMMARY

Eco-driving has significant potential to reduce fuel consumption and emissions from transit operations. Analyses were conducted of 68 thousand miles of real-world operations data from 26 buses, collected from local transit service provided by the Metropolitan Atlanta Rapid Transit Authority (MARTA), and express bus service provided by the Georgia Regional Transportation Authority (GRTA). The analysis utilized second-by-second operations data collected via global positioning system (GPS) devices from buses operated by these transit agencies. The researchers simulated the implementation of transit eco-driving strategies, based on the modal emissions modeling framework employed by the MOtor Vehicle Emission Simulator (MOVES) designed to reduce engine load and emissions. This algorithm seeks to minimize fuel consumption by limiting instantaneous vehicle specific power (VSP), 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 against expected fuel and emissions reductions via conversion of the transit fleets to compressed natural gas (CNG), which is another popular fuel conservation strategy.

The transit eco-driving strategy showed a 5% reduction in fuel consumption and fuel cycle greenhouse gas (GHG) emissions for MARTA's 508-bus fleet (~35% diesel/65% CNG), and a 7% reduction in fuel consumption for GRTA's 166-bus diesel fleet. The fuel savings translate to about 300,000 gallons of diesel fuel equivalent per year for MARTA and 55,000 gallons of diesel per year for GRTA. Eco-driving was also shown to reduce fuel use and emissions for CNG fleets. Eco-driving training can readily be implemented if speed/acceleration activity is monitored. Because eco-driving does not require significant capital investment it is a potentially very cost-effective strategy for local and express bus transit operations.

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 alternative 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.

This paper focuses on transit fuel and emissions savings from eco-driving for two transit agencies. The analyses in this report are based upon real-world operations data collected from the Metropolitan Atlanta Rapid Transit Authority (MARTA), a local transit agency, and the Georgia Regional Transportation Authority (GRTA), which provides regional express bus services. The potential reductions in fuel consumption are derived from operational improvements achieved through driver behavior modification, predominantly limiting vehicle acceleration rates and top speeds. The potential benefits are quantified using a new eco-driving algorithm developed for this project. The analyses 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).

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 (TCRP, 2010). 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. As of 2014, more than 10,000 buses in the United States are running on CNG, compared to about 4,000 hybrid diesel buses (National Transit Database, 2014). Therefore, this project evaluates eco-driving as a stand-alone strategy, but the savings from eco-driving is also put into perspective by independently and simultaneously evaluating fuel and emissions savings from converting the existing fleets to CNG.

The paper first provides a literature review on eco-driving, as a fuel consumption and emissions control strategy for transit operations. 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. This algorithm would be used to train drivers and assess their onroad performance of eco-driving interventions

(i.e. after intervention, is there still room for improvement for the driver). The comparative fuel consumption and emission reduction results that could be achieved with eco-driving intervention for the monitored data are then summarized, and then compared to the benefits that could be obtained from fleet conversion to CNG. Assuming that the monitored data are roughly representative of fleet operations, transit eco-driving could yield a 5% reduction in fuel consumption for MARTA's fleet and a 7% reduction in fuel consumption for GRTA's Xpress bus fleet (more freeway operations). The reductions translate to about 300,000 gallons of diesel fuel per year for MARTA and 55,000 gallons of diesel per year for GRTA. Eco-driving can also reduce fuel use and emissions from CNG fleets. Because eco-driving training is relatively easy to implement when speed/acceleration activity is monitored, and because monitoring can be paid for through fuel savings, the research team concludes that eco-driving strategies are a reasonable approach to reducing fleet emissions in local and express bus transit operations.

Literature Review

Eco-driving training is well-known as a feasible strategy to decrease fuel consumption and emissions. It is generally accepted that eco-driving encompasses the following driving tactics (Intelligent Energy Europe, 2013): 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.

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% (Barth and Boriboonsomsin, 2009; Beusen, et al., 2009; Dib, et al., 2014; Ho, et al., 2015; Ruttu, et al., 2013; Strömberg and Karlsson, 2013; Transport Canada, 2004; Wåhlberg, 2007; Zarkadoula, et al., 2007). In addition, Rolim, et al. (2014) 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 actual fuel savings from these two eco-driving strategies compared to a baseline condition was not reported. Estimated eco-driving benefits through simulated vehicle data exhibit higher variability than the benefits observed in real-world implementation, ranging from 8% to about 35% in fuel savings and CO₂ reduction (Barth and Boriboonsomsin, 2009; Mensing, et al., 2014; Qian and Chung, 2011; Suzdaleva and Nagy, 2011).

Eco-driving studies based on simulations have devised a range of driving strategies to represent the implementation of eco-driving objectives. In most studies, eco-driving strategies are realized through modifying vehicle speed and/or acceleration. Barth and Boriboonsomsin (2009) devised a dynamic eco-driving system through which drivers are provided with suggested speeds based on average traffic speed and level-of-service (LOS) for the freeway section on which the vehicle was operating. Mensing, et al. (2013) 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 (2011) evaluated fuel consumption and CO₂ emissions of eco-driving by reducing the maximum acceleration rates by 10% and 20% in simulation. Suzdaleva and Nagy (2011) developed a data-based Bayesian approach to identify and modify the speed to optimize fuel consumption for conventional vehicles. However, all of these algorithms were designed for light-duty vehicles. Table 1 summarizes the results from the variety of studies identified and reviewed in this research effort.

Table 1. Summary of Eco-Driving Benefit Research

Source	Vehicle Type	Before Data	After Data	Methodology	Time Scope	Fuel Savings /CO ₂ Reduction /Pollutant Reduction
Barth and Boriboonsomsin, 2009	Light-duty vehicles	Real-world vehicle activity data	Simulated vehicle activity data and real-world vehicle activity data	Static recommended speed to drivers; Simulation modeling tools and real-world vehicle experimentation	3 probe vehicles on freeways September 2005, May 2006, and March 2007	Fuel savings: 13% (real-world), 37% (simulated) CO ₂ reduction: 12% (real-world), -35% (simulated) Savings depend on congestion
Beusen, et al., 2009	Light-duty vehicles	Real-world vehicle activity data	Real-world vehicle activity data	Four-hour training; 10 drivers; At least 100km of driving per month	Two months of data collection; 10 months for 10 drivers during real-life conditions, monitored weekly	Fuel saving: 5.8% with large differences between individuals
Dib, et al., 2014	EV	Real-world vehicle activity data	Real-world vehicle activity data	Participants drove EV in fixed route. Energy comparison were made before and after eco training	N/A	Fuel savings: 14% for EV
Ho, et al., 2015	Light-duty vehicles	Real -world vehicle activity data	Real-world vehicle activity data	116 participants; Classroom training	Pre-test of drivers; 30 to 45 min training sessions; Re-test drivers right after training	Fuel saving and carbon emissions: in excess of 10%
Mensing, et al., 2014	Light-duty vehicles	Simulated vehicle activity data	Simulated vehicle activity data based on the optimization method	Simulating a conventional passenger vehicle; Applying optimization methods to achieve ecologically and economically optimal vehicle operations	N/A	Economic cycle Fuel saving: 2.5 L/100km CO ₂ reduction: 31.9% NO _x reduction: 16.4% Ecologic cycle Fuel saving: 2.3 L/100km CO ₂ reduction: 26.8% NO _x reduction: 54.5%

Source	Vehicle Type	Before Data	After Data	Methodology	Time Scope	Fuel Savings /CO ₂ Reduction /Pollutant Reduction
						HC reduction: 7.4%
Qian and Chung, 2011	Light-duty vehicles	Simulated vehicle activity data	Simulated vehicle activity data	Traffic micro-simulation model; Different traffic condition, penetration rates of eco-drivers, and acceleration rates	N/A	Scenarios of heavy congestion and 25% penetration impacts traffic and environmental performance negatively; Moderate and smooth acceleration saves 11% fuel without major increase in travel time
Rutty, et al., 2013	Light-duty vehicles	Real-world vehicle activity data	Real-world vehicle activity data	11 gasoline vehicles, 4 hybrid vehicles; 40 km per day Goal-directed feedback	Post-training data collection: 1 month Training: 1 month Post-training data collection: 1 month	Fuel savings: 0.48L per gasoline vehicle per day; 0.3L per hybrid vehicle per day CO ₂ reduction: 1.1 kg per gasoline vehicle per day; 0.6 kg per hybrid vehicle per day. Baseline data not reported
Strömberg and Karlsson, 2013	Buses	Real-world vehicle activity data	Real-world vehicle activity data	54 bus drivers, divided into 3 groups: control, eco-driving feedback only, and eco-driving feedback supplemented with training	Baseline: 3 weeks Test period: 3 weeks	6.8% reduction in fuel consumption between the eco-driving groups and control group; no significant difference between the two eco-driving groups
Suzdaleva and Nagy, 2011	Light-duty vehicles	Real-world vehicle activity data	Simulated vehicle activity data	Bayesian approach to identify and modify the speed in order to optimize fuel consumption	N/A	Fuel savings: 8.2% overall
Transport Canada, 2004	Light-duty vehicles	Real-world vehicle activity data	Real-world vehicle activity data	Approximately 1,000 corporate employees were identified; Training, 2-hour classroom and 2-hour on-road	Pre-test of drivers; 4-hour training; Re-test drivers after one year	Fuel savings: 5.5% overall
Wählberg, 2007	Buses	Real-world vehicle activity	Real-world vehicle activity	Phase 1: practical eco-driving training; 247 trained	2000 to 2003	Training provided 2% fuel reduction;

Source	Vehicle Type	Before Data	After Data	Methodology	Time Scope	Fuel Savings /CO ₂ Reduction /Pollutant Reduction
		data	data	drivers vs. 147 untrained drivers; Phase 2: 28 buses were equipped with feedback devices		feedback provided another 2% fuel reduction
Zarkadoula, et al., 2007	Buses	Real-world vehicle activity data	Real-world vehicle activity data	3 drivers, 2 buses; Fixed 15km route Training seminar	Pre-training 1.5 months; Post-training 2 months	Fuel savings: 10.2% during training, 4.35% in actual condition

Data

To evaluate the potential emissions and fuel consumptions associated with eco-driving for transit operations in the Atlanta metropolitan area, second-by-second transit operations data were collected from local transit operations and regional express buses. For local transit operations, 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 Georgia Tech (GT) Trip Data Collector (Ogle, et al., 2006). 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 68 thousand miles from 26 buses.

The GPS data underwent quality assurance/quality control (QA/QC) and post processing before being used in the analyses. First, an initial screening was performed to remove trips shorter than one-minute and data points with invalid latitude and longitude information. Second, speed values were treated with a Kalman filter algorithm to replace low-validity GPS speeds (typically at low speeds and in urban street canyons) with location-inferred speed, using a spline algorithm to fill in data gaps. After these data processing steps, the data were overlaid on base GIS maps to identify the type of facility (i.e. freeway, non-freeway, or off-network) on which a bus was operating for each second of the driving record. Distinguishing between freeway from non-freeway operations is an important step for subsequent analysis because the eco-driving strategies for freeways and non-freeways differ substantially.

The onroad and off-network distinction is used to identify and eliminate extended idle. 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 (Xu, et al., 2013a) or on-board diagnostics (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 ignore the potential benefits of idle reduction in this paper. Some jurisdictions assume that buses should not idle for more than 10 minutes onroad, and should not idle for more than 30 seconds off-network. Different idle speed cutpoints are set for MARTA and GRTA operations given the differences in device precision levels (Xu, et al., 2013b). Nevertheless, idle reduction is another viable strategy that can be implemented to reduce emissions (Shancita, et al., 2014; Xu, et al., 2013a).

Finally, trip files recorded by the data collection devices were broken 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 seconds with an average speed of 5 miles per hour (mph) or greater were retained for subsequent eco-driving analysis. Table 2 summarizes the final analytical data set. Step-by-step descriptions of the data processing procedures are provided in Appendix I.

Table 2. Summary of Analytical Data Set

Type of Operation	Local Transit	Express Service
Agency	MARTA	GRTA
Number of Buses	13	13
Number of Trips	9,984	852
Total Distance (miles)	61,247	3,637
Total Duration (hours)	3,716	84
Average Speed (mph)	16.5	43.3

Methodology

Following QA/QC processing and data preparation, the observed driving cycles from MARTA and GRTA were modified to reflect the implementation of eco-driving strategies. For comparison purposes, the modified driving cycles are referred to as eco-cycles. The observed cycles and eco-cycles were then employed in fuel and emissions analysis in parallel to assess the energy and environmental benefits of eco-driving. Figure 1 depicts the general process of the study method. After initial processing of the raw data obtained from transit monitoring devices, the observed driving cycles are linked to emission rates from the U.S. Environmental Protection Agency’s MOtor Vehicle Emission Simulator (MOVES) to estimate fuel consumption and emissions, and also to the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model (GREET) model to estimate well-to-pump fuel consumption and emissions (Argonne National Laboratory 2013; EPA, 2014; Xu, et al., 2015; Guensler, et al., 2016; Guensler, et al., 2015). The observed driving cycles are then post-processed to generate the eco-cycles, as described later, and then also linked to MOVES and GREET to estimate comparative fuel consumption and emissions.

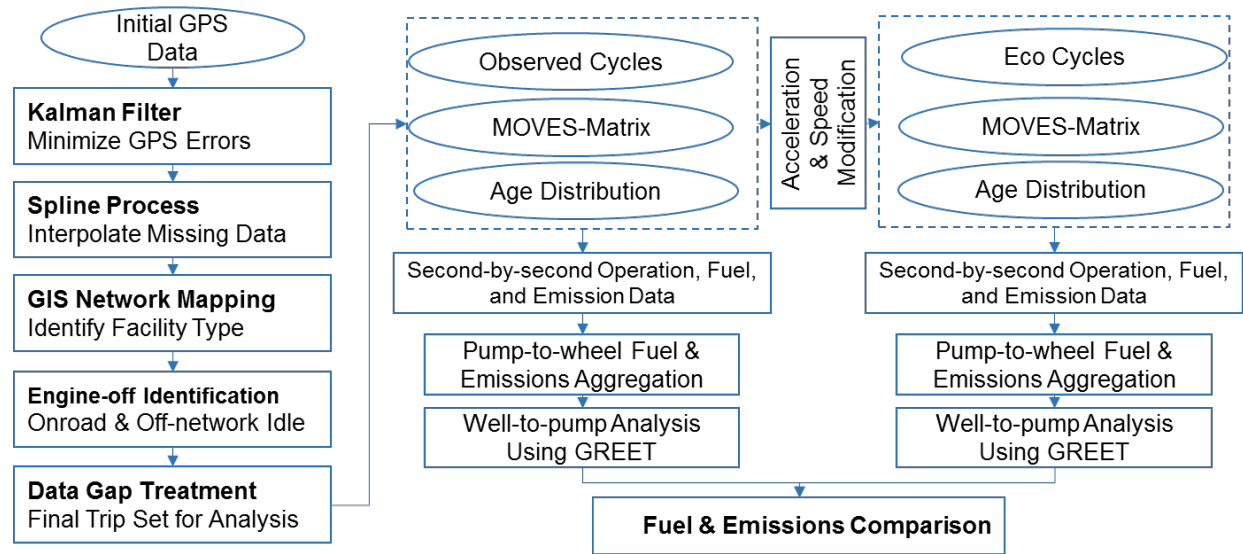


Figure 1. Methodology Flow Chart

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, managing engine load is typically accomplished by managing top speeds (for wind resistance) and acceleration rates (for all load parameters). Engine load is also high during lugging operations (acceleration from the stop line), 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 even more important to ensure that hard acceleration conditions do not occur at moderate and high speed operations.

As indicated in the literature review, a variety of emission rate models have 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 (Barth, et al., 1996; Feng, et al., 2007; Guensler, et al., 2005), 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 in potential benefits eco-driving noted in the literature arises in part from the application of a wide range 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 employ the modal emissions modeling framework in the U.S. EPA’s MOVES model. 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 linked to higher fuel consumption, CO₂ emissions, and criteria pollutant emissions. Figure 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 use with MOVES, the goal is to modify each vehicle’s trajectory to minimize activity in higher STP bins, while preserving average speed and total distance.

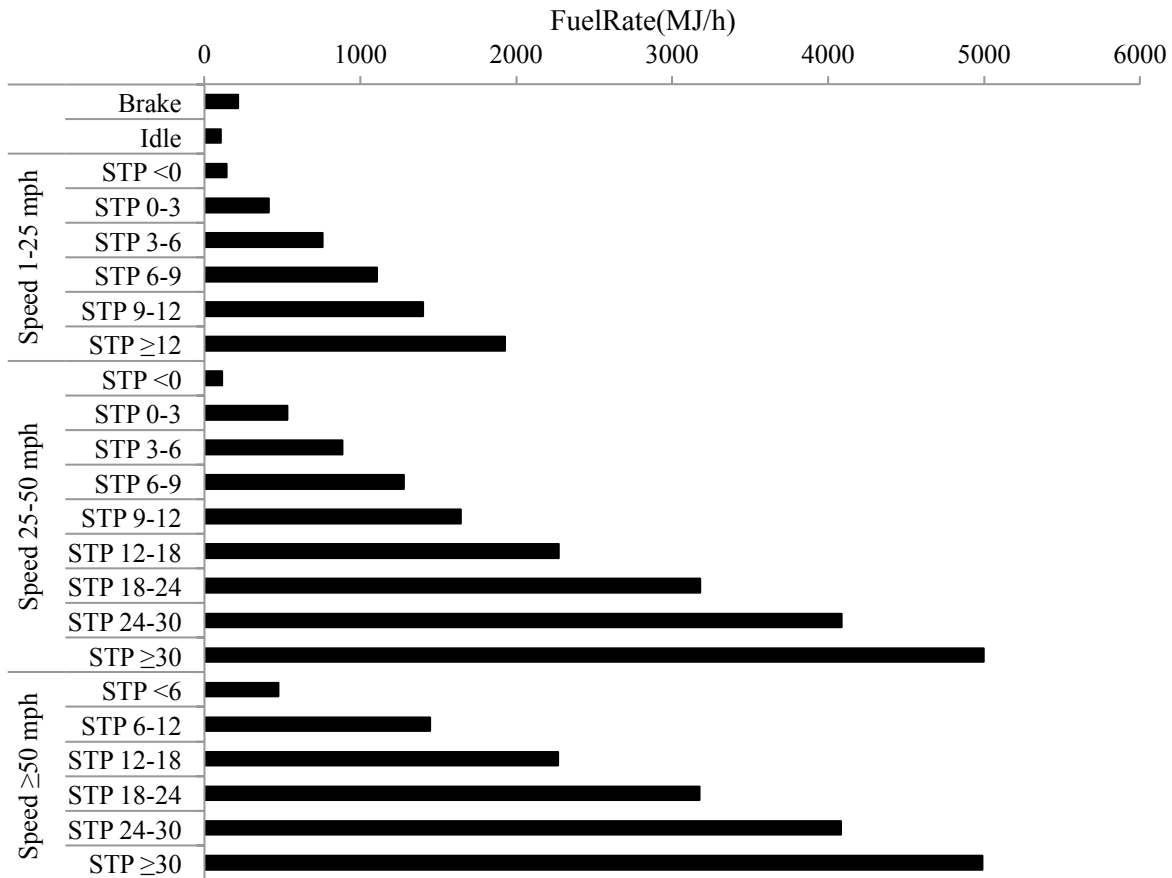


Figure 2. Fuel Rate (MJ/h) for each Operating Mode Bin for 2010 MY Transit Buses (MOVES2014 Output)

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

STP is calculated as:

$$STP = \left(\frac{A}{M}\right) v + \left(\frac{B}{M}\right) v^2 + \left(\frac{C}{M}\right) v^3 + \left(\frac{m}{M}\right) (acc + g * \sin \theta)v \quad (1)$$

where:

- A = the rolling resistance coefficient (kW s/m)
- B = the rotational resistance coefficient (kW s²/m²)
- C = the aerodynamic drag coefficient (kW s³/m³)
- m = vehicle mass (metric tonnes)
- M = fixed mass factor (unitless)
- v = instantaneous vehicle velocity at time t (m/s)
- a = instantaneous vehicle acceleration (m/s²)
- g = gravitational acceleration with the value 9.8 (m/s²)
- θ = road grade (radians or degrees, as required by the sin calculation algorithm)

A, B, C, and M are fixed parameters for each vehicle type modeled in MOVES. The values can be found in “sourceusertype” table in the MOVES database (provided in Appendix II). For simplification, all of the analyses in this report assume zero road grade (sin θ = 0). STP increases monotonically with speed and acceleration. The first step in the eco-driving process is to set a STP limit value (STP_L). For each speed v, the acceleration limit acc_L that prevent STP from exceeding STP_L is:

$$acc_L = \left(\frac{STP_L M}{mv} \right) - \left(\frac{A}{m} \right) - \left(\frac{B}{m} \right) v - \left(\frac{C}{m} \right) v^2 \quad (2)$$

From the MOVES operating mode classification, each speed level includes different STP levels. Based the STP categories (see Table 11), we can set STP_L to different levels: STP_{L-1}=30, STP_{L-2}=24, STP_{L-3}=18, STP_{L-4}=12, STP_{L-5}=9, STP_{L-6}=6, and STP_{L-7}=3. From STP_{L-1} to STP_{L-7}, for a given speed, the acceleration limit becomes more stringent, as illustrated in Figure 3.

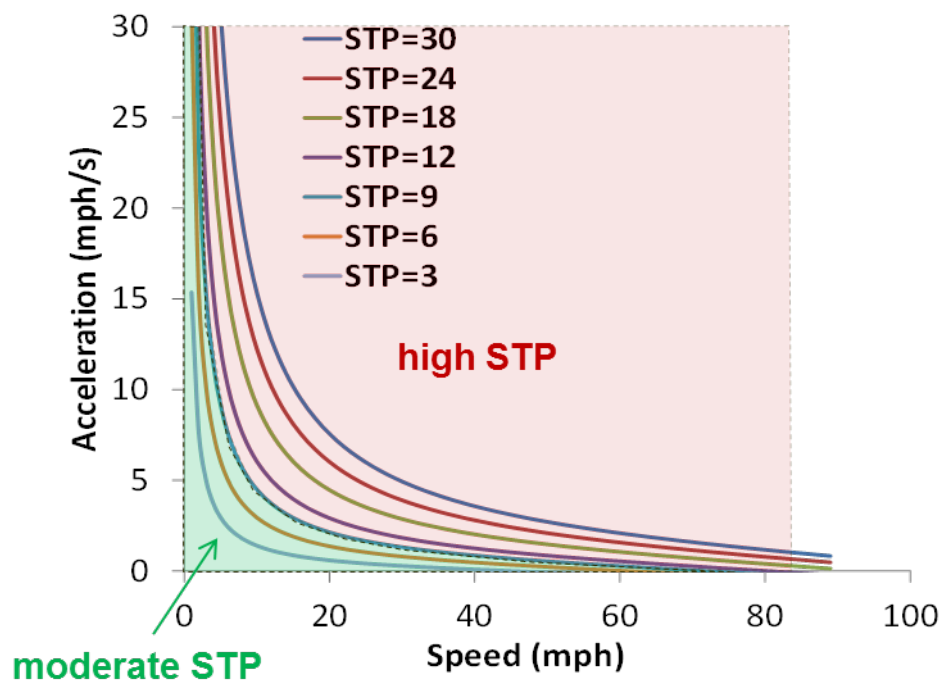


Figure 3. Acceleration Limit for each Speed Level at each STP Limit Level

The principle of the computational method is to read each second of vehicle activity and adjust the acceleration rate downward when the STP reaches or exceeds the STP_L . The acceleration rate is adjusted downward enough to lower the STP of the next data point to the median value of the STP range that meets the STP limit. For example, if the STP limit is set as $STP_{L-4}=12$, when STP reaches or exceeds 12, the acceleration will be adjusted downward until the calculated STP for that data point equals 10.5 (the median STP value for the 9 to 12 STP bin, which meets the STP_L).

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 significantly lower, which may be difficult for drivers to accept. Furthermore, a reduction in average speed leads to increased 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. The resulting STP limits are summarized in Table 3.

Table 3. STP Limits for Local Roads and Freeways Employed in This Analysis

Road Type	Speed Level	STP Limit
Local Road	0~25 mph	≤ 6
	25~50 mph	≤ 6
	≥ 50 mph	≤ 6
Freeway	0~25 mph	≤ 6
	25~50 mph	≤ 9
	≥ 50 mph	≤ 12

Implementation of Eco-driving Cycle Modification

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

- 1 Maintaining Status Quo: When the STP of original cycle doesn't reach or exceed STP_L , no modification of the cycle is required. The next data point in the eco-cycle is the same as the data point from the original cycle.
- 2 Smoothing: When the STP of original cycle reaches or exceeds the STP_L , the acceleration rate is adjusted downward such that the resulting STP for the data point equals the median value for the STP bin that does not exceed the STP limit. Because the acceleration rate decreases, the speed of the next data point in the eco-cycle will be slightly lower than the speed for that point in the original cycle. The acceleration rates for subsequent points in the cycle are also set to achieve the median STP value for that

STP bin. Smoothing of acceleration continues until the speed of eco-cycle matches that of the original cycle.

- 3 Conservation of Distance: Once the speed of eco-cycle and original cycle align, the distance covered by the eco-cycle is less than that of the original cycle (due to the implementation of lower acceleration rates). To conserve distance traveled, the eco-cycle cruise speed is extended until the distance traversed by the eco-cycle matches that of the original cycle. This step assumes that the vehicle is not limited by the presence of a slower-moving vehicle in its path.

Figure 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 exactly the same (status quo) because the early portion of the cycle does not exceed STP_L . Once the STP_L is exceeded, smoothing begins and the acceleration rates of the eco-cycle is set lower than those observed. Smoothing is normally followed conservation of distance to ensure that the vehicle traverses the same distance in the eco-cycle as in the observed cycle. An example of an observed cycle and its corresponding eco-cycle is presented in Figure 5. The modified eco-cycle smoothed the sharp acceleration, especially during high speed operations. Figure 6 provides the full flowchart describing the implementation of the eco-driving algorithm and iteration processes.

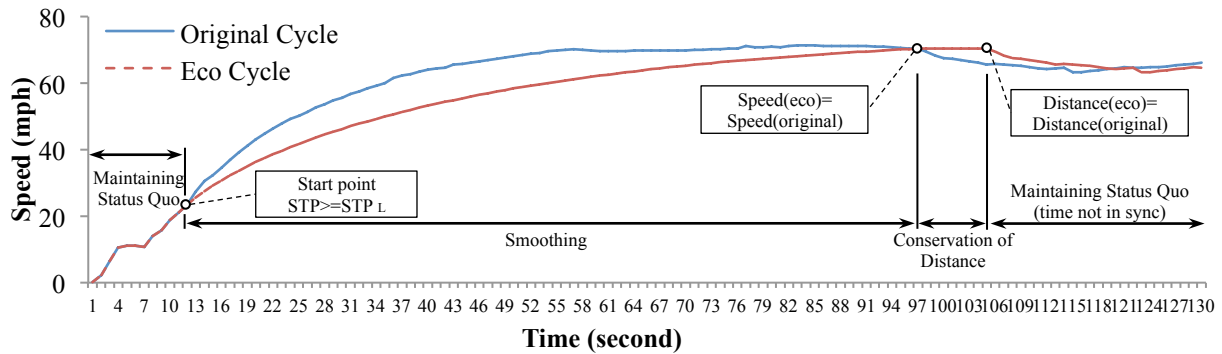


Figure 4. Eco-cycle Example

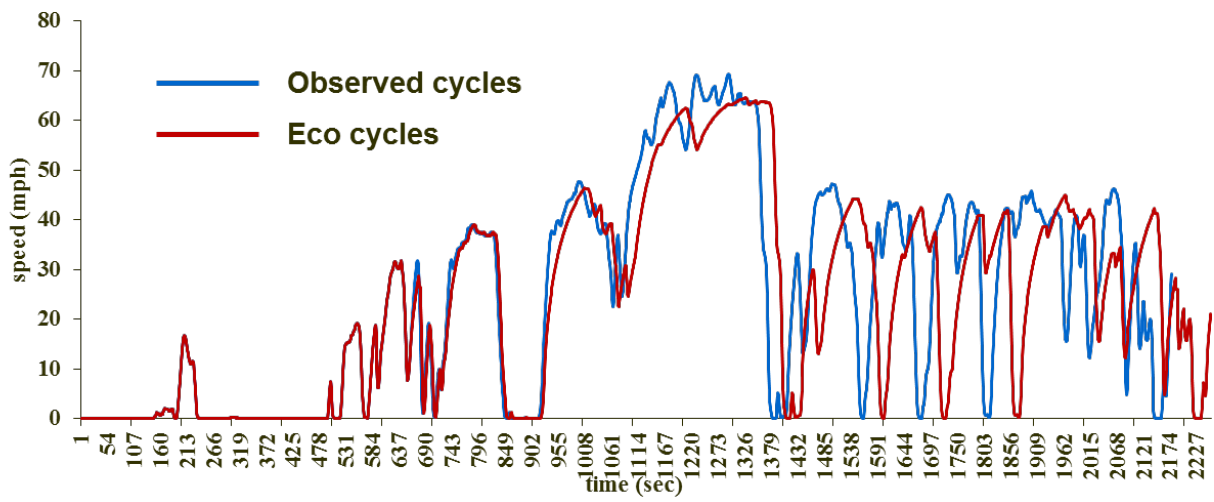


Figure 5. Example of an Observed Cycle and Corresponding Eco-cycle

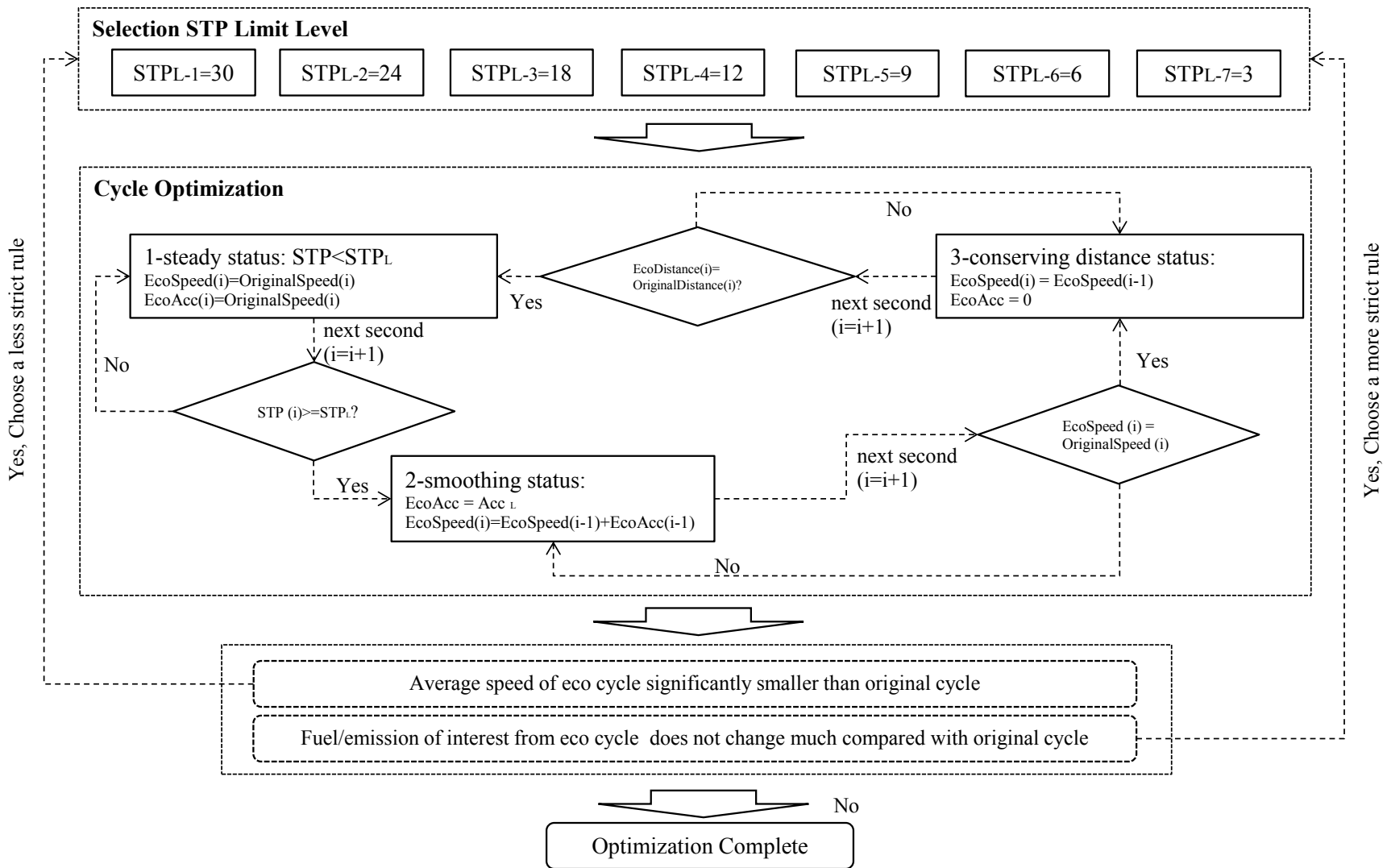


Figure 6. Algorithm Flow Chart

Figure 7 shows the speed-acceleration (acceleration > 0 mph/sec) 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 Figure 7 correspond to the acceleration limits for each speed level at STP threshold 6, 9, and 12 in Figure 3. After the modification, the overall distance increases by 0.05%, and the overall speed reduction is 3.07%, within which the highway and local speed reduction is 1.93% and 3.13% respectively.

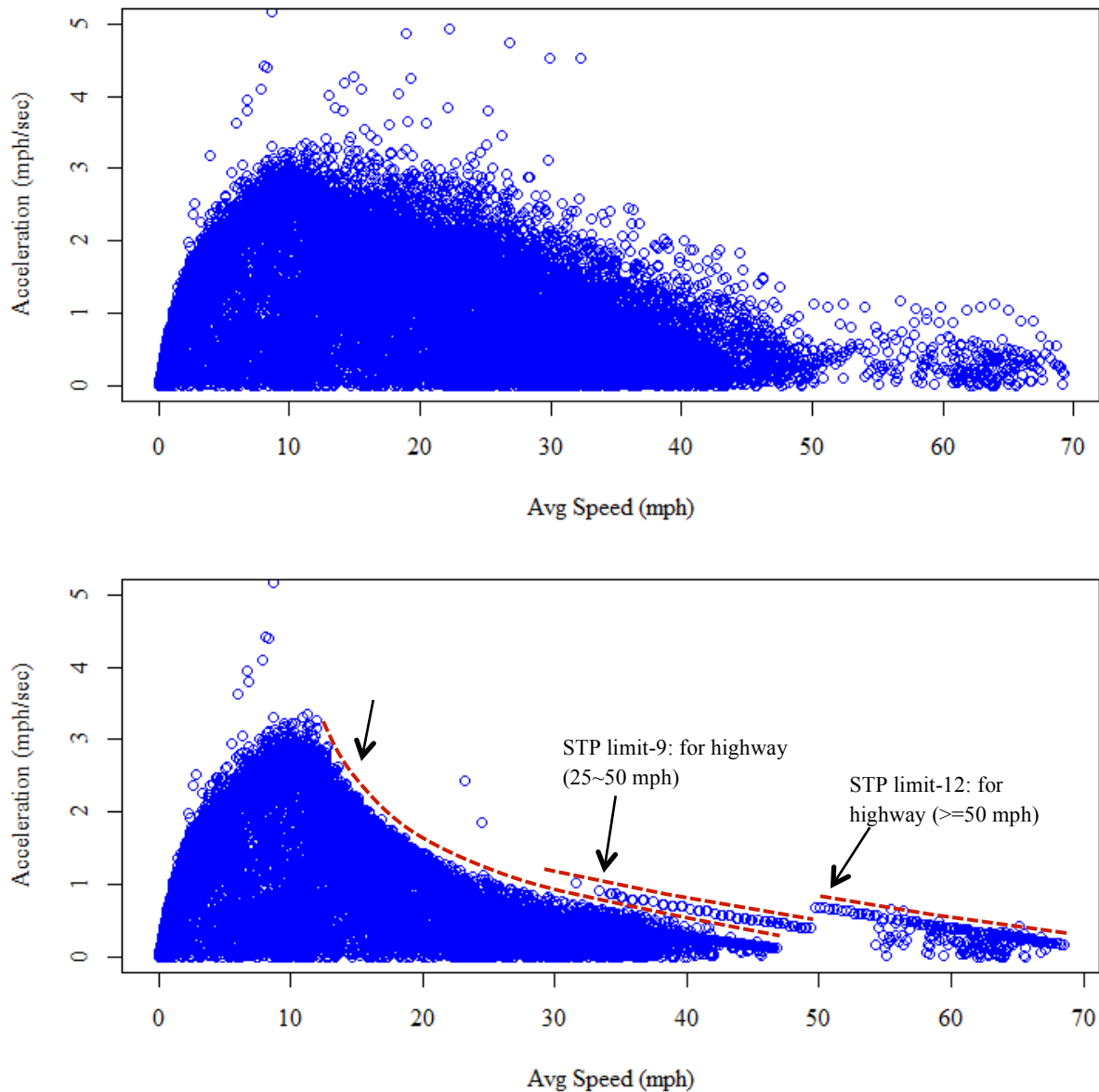


Figure 7. Speed-Acceleration Scatter Plot (10,000-second Sample)

Fuel and Emissions Analysis

The goal of the fuel and emissions analysis is to assess the impact of the eco-driving and other fuel saving strategies at the transit agency level. To do so, real-world operations data collected from MARTA and GRTA buses are used and applicable fuel consumption and emission rates are applied as if the entire fleet experiences the observed operating conditions. To provide a fair comparison between diesel and CNG, we evaluated the full fuel cycle (i.e. well-to-wheel emissions) following the approach adopted in the Fuel and Emissions Calculator for Transit Fleets (Xu, et al., 2015). Pump-to-wheel emissions were estimated using MOVES-Matrix (Guenster, et al., 2015), a multi-dimensional emission rate look up table derived directly from millions of MOVES emission rate runs for Atlanta. The detailed settings for the MOVES runs are listed in Appendix III. Well-to-pump emissions were estimated using the GREET model (Argonne National Laboratory, 2015).

To estimate the emissions and fuel consumptions for the entire fleet, fleet size and annual mileage information was taken from the National Transit Database (NTD) (2014). The NTD does not provide information of operating mileage on different road types, but does differentiate between revenue and non-revenue (also known as deadhead) mileage. Therefore, proportions of freeway and non-freeway mileage were estimated separately for revenue and deadhead operations, using spatial analysis in ArcGIS (details are provided in Appendix I). Table 4 summarizes the pump-to-wheel emission rates for local transit service and **Table 5** summarizes the pump-to-wheel emission rates for express bus service. Well-to-pump emissions (emissions to harvest feedstock, process feedstock into fuel, and deliver fuel to the pump) were estimated for the predicted pump-to-wheel fuel consumption.

Table 4. Pump-to-wheel Emission Rates for Local Transit Based for MARTA Buses

Fuel	Duty Cycle	Revenue/ Deadhead	Road Type	Duration (seconds)	Avg. Speed (mph)	Distance (miles)	Emission Rate (g/mile/vehicle; MJ/mile/vehicle for fuel)						
							HC	CO	NOx	PM _{2.5}	CO ₂	GHGs	Fuel
Diesel (Existing)	Observed	Deadhead	Local	4,545,040	16.9	21,390	1.72	6.27	16.54	1.07	2,142	2,142	29.1
			Freeway	301,994	54.7	4,591	0.68	3.42	9.25	0.46	1,341	1,341	18.2
		Revenue	Local	19,090,668	16.5	87,424	1.72	6.27	16.54	1.07	2,142	2,142	29.1
			Freeway	172,750	54	2,589	0.68	3.42	9.25	0.46	1,341	1,341	18.2
	Eco	Deadhead	Local	4,686,687	16.4	21,344	1.82	6.49	16.02	1.01	2,032	2,032	27.6
			Freeway	310,210	53.8	4,636	0.69	3.53	9.07	0.47	1,327	1,327	18.0
		Revenue	Local	19,711,963	16.0	87,463	1.82	6.49	16.02	1.01	2,032	2,032	27.6
			Freeway	178,599	52.7	2,613	0.69	3.53	9.07	0.47	1,327	1,327	18.0
CNG (Existing)	Observed	Deadhead	Local	4,545,040	16.9	21,390	24.80	15.45	11.28	0.05	2,104	2,682	35.6
			Freeway	301,994	54.7	4,591	7.33	9.52	7.71	0.08	1,237	1,407	21.0
		Revenue	Local	19,090,668	16.5	87,424	24.80	15.45	11.28	0.05	2,104	2,682	35.6
			Freeway	172,750	54.0	2,589	7.33	9.52	7.71	0.08	1,237	1,407	21.0
	Eco	Deadhead	Local	4,686,687	16.4	21,344	23.61	14.06	10.81	0.04	2,003	2,553	33.9
			Freeway	310,210	53.8	4,636	7.42	9.48	7.43	0.07	1,203	1,375	20.4
		Revenue	Local	19,711,963	16.0	87,463	23.61	14.06	10.81	0.04	2,003	2,553	33.9
			Freeway	178,599	52.7	2,613	7.42	9.48	7.43	0.07	1,203	1,375	20.4
CNG (New)	Observed	Deadhead	Local	4,545,040	16.9	21,390	3.32	6.00	1.93	0.00	1,975	2,054	33.5
			Freeway	301,994	54.7	4,591	0.73	2.99	1.31	0.00	1,161	1,178	19.7
		Revenue	Local	19,090,668	16.5	87,424	3.32	6.00	1.93	0.00	1,975	2,054	33.5
			Freeway	172,750	54.0	2,589	0.73	2.99	1.31	0.00	1,161	1,178	19.7
	Eco	Deadhead	Local	4,686,687	16.4	21,344	3.05	5.00	1.70	0.00	1,879	1,952	31.8
			Freeway	310,210	53.8	4,636	0.78	3.11	1.27	0.00	1,129	1,148	19.1
		Revenue	Local	19,711,963	16.0	87,463	3.05	5.00	1.70	0.00	1,879	1,952	31.8
			Freeway	178,599	52.7	2,613	0.78	3.11	1.27	0.00	1,129	1,148	19.1

Table 5. Pump-to-wheel Emission Rates for Express Service Based for GRTA Buses

Fuel	Duty Cycle	Revenue/Deadhead	Road Type	Duration (seconds)	Avg. Speed (mph)	Distance (miles)	Emission Rate (g/mile/vehicle; MJ/mile/vehicle for fuel)						
							HC	CO	NOx	PM _{2.5}	CO ₂	GHGs	Fuel
Diesel (Existing)	Observed	Deadhead	Local	143,802	32.2	1,285	0.59	2.41	9.56	0.50	1,891	1,892	25.7
			Freeway	123,346	59.6	2,041	0.37	1.82	7.33	0.29	1,523	1,523	20.7
		Revenue	Local	87,694	20.3	494	0.89	3.04	11.36	0.60	2,139	2,140	29.0
			Freeway	225,294	55.6	3,482	0.39	1.88	7.41	0.30	1,525	1,526	20.7
	Eco	Deadhead	Local	160,670	28.5	1,271	0.72	2.86	8.31	0.43	1,543	1,544	20.9
			Freeway	126,231	58.2	2,042	0.37	1.92	6.78	0.27	1,430	1,430	19.4
		Revenue	Local	92,628	18.9	486	1.01	3.40	10.41	0.53	1,847	1,849	25.1
			Freeway	228,780	54.7	3,476	0.39	1.97	6.85	0.28	1,427	1,428	19.4
CNG (New)	Observed	Deadhead	Local	143,802	32.2	1,285	2.23	5.89	1.86	0.00	1,738	1,791	29.4
			Freeway	123,346	59.6	2,041	0.74	2.87	1.37	0.00	1,270	1,287	21.5
		Revenue	Local	87,694	20.3	494	3.12	6.31	2.04	0.00	1,988	2,063	33.7
			Freeway	225,294	55.6	3,482	0.83	3.08	1.38	0.00	1,281	1,301	21.7
	Eco	Deadhead	Local	160,670	28.5	1,271	2.00	4.65	1.33	0.00	1,478	1,525	25.0
			Freeway	126,231	58.2	2,042	0.72	2.72	1.25	0.00	1,160	1,177	19.7
		Revenue	Local	92,628	18.9	486	2.77	4.86	1.58	0.00	1,736	1,802	29.4
			Freeway	228,780	54.7	3,476	0.79	2.87	1.25	0.00	1,165	1,184	19.7

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. Scenario 2 evaluates the purchase of new CNG vehicles to replace the existing fleet. Scenario 3 combines the two strategies and implements eco-driving with a new CNG fleet purchase. 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 mileage (see Table 6). Table 7 summarizes the annual fuel usage and fuel cycle emissions of MARTA and GRTA given the existing fleet and driving behavior. This is the base scenario against which the aforementioned three scenarios will be compared. Among air pollutants, we only present NO_x and PM_{2.5} because heavy-duty vehicles have relatively low HC and CO emissions.

Table 6. Mileage and Fleet Information (National Transit Database, 2014; GRTA, 2015)

Transit Agency	Annual Mileage (1,000 Miles)	Deadheading Percent (%)	Number of Buses	CNG Fleet Percent (%)
MARTA	25,850	12	508	69
GRTA	4,701	44	166	0

Table 7. Annual On-road Fuel Consumption and Fuel Cycle Emissions of Base Scenario

Transit Agency	Fuel (1,000 GGE)	GHGs (metric tons)	NO _x (metric tons)	PM _{2.5} (metric tons)
MARTA	7,226	81,233	371	10.5
GRTA	859	9,511	41	1.9

Eco-driving Scenario

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

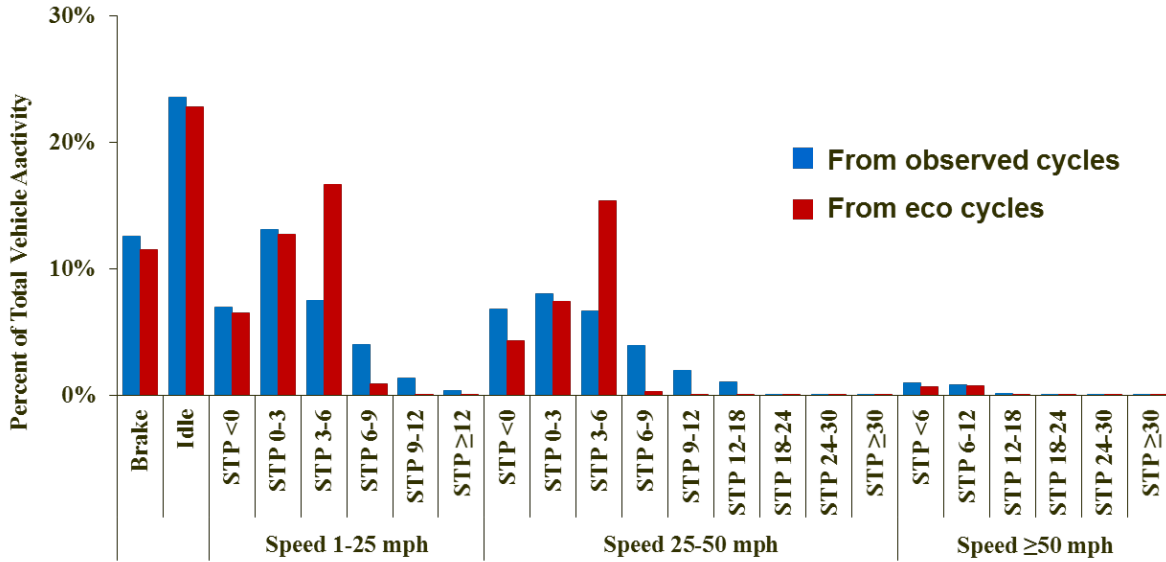


Figure 8. Operating Mode Bin Distributions of Observed and Eco-cycles in the MARTA Sample

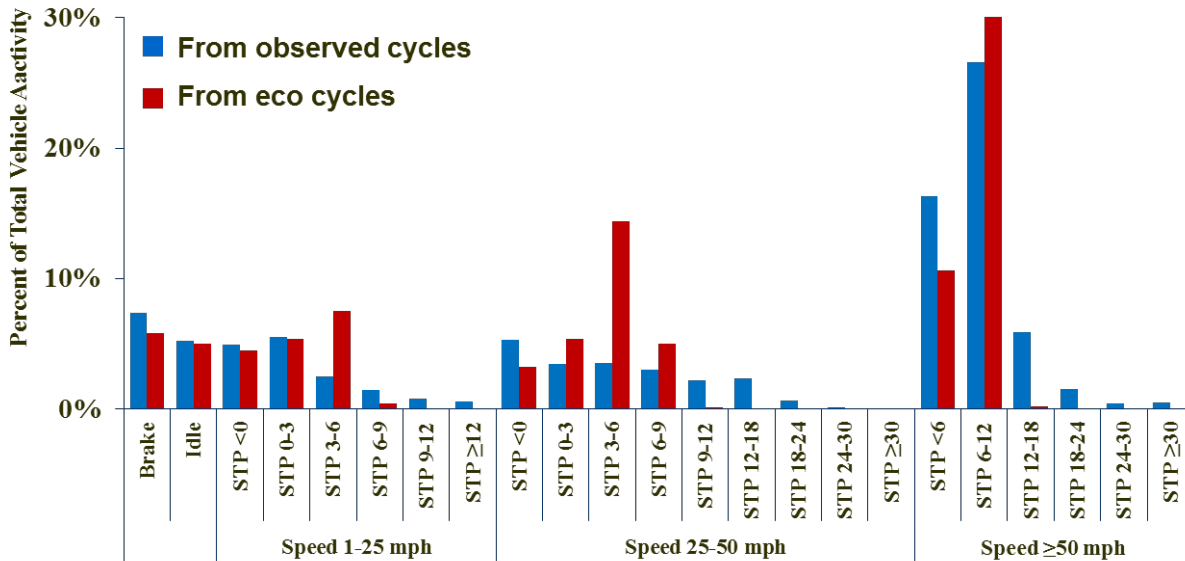


Figure 9. Operating Mode Bin Distributions of Observed and Eco-cycles in the GRTA Sample

Table 8 summarizes annual total fuel consumption and emissions results under the eco-driving scenario, in which all drivers are assumed to follow the eco-cycle for all miles traveled. In this scenario, fleet composition is 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 351,000 gallons per year, measured in standard gasoline gallon equivalent (GGE). Hence, MARTA could save about 309,000 gallons per year of diesel fuel

equivalent given the higher energy content of diesel. The MARTA fuel savings translates to an annual reduction of about 3,930 metric tons (5%) in fuel cycle carbon dioxide equivalent (CO₂e) emissions. In terms of criteria air pollutants, eco-driving implementation in the MARTA fleet would reduce annual NO_x emissions by 14 metric tons (4%), and annual PM_{2.5} emissions by 0.8 metric tons (7%).

For the GRTA fleet, annual fuel savings amounted to about 63,000 GGEs. This translates to a savings of about 55,000 gallons of diesel fuel per year a 7% reduction. Greenhouse gas CO₂e emissions are also reduced by about 700 metric tons per year. NO_x reductions would amount to 2 metric tons (5%), and the annual PM_{2.5} reductions would be 0.1 metric tons (7%) per year.

Table 8. Eco-driving Scenario Annual Fuel Consumption and Fuel Cycle Emissions

Transit Agency	Fuel (1,000 GGE)	GHGs (metric tons)	NO _x (metric tons)	PM _{2.5} (metric tons)
MARTA	6,875	77,304	356	9.8
GRTA	796	8,809	39	1.7

CNG Fleet Purchase Scenario

In this hypothetical scenario, MARTA and GRTA are assumed to replace their existing diesel buses with new CNG buses (model year 2015). MARTA is assumed to retain their existing CNG buses, so this strategy affects 31% of the fleet (see Figure 10 and Table 6). The age distributions of the existing fleets are summarized in Figure 10 for MARTA and Figure 11 for GRTA. The CNG scenario assumed no changes in the existing driving style.

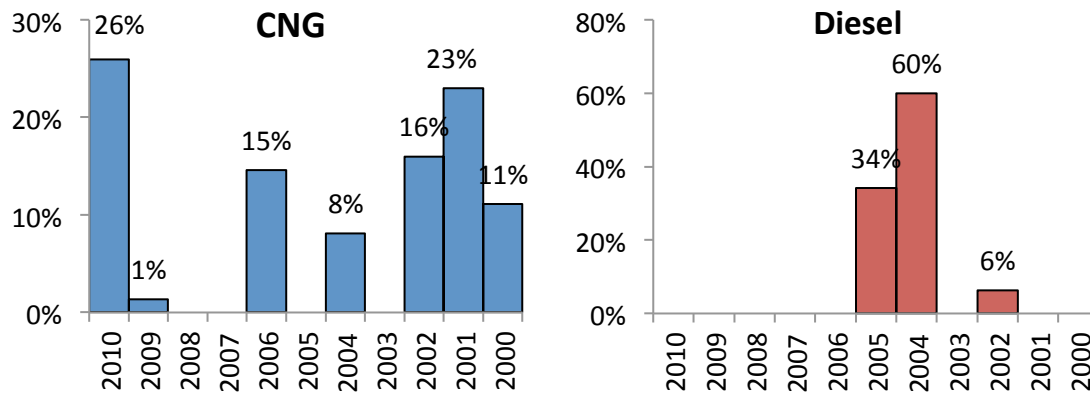


Figure 10. Age Distribution of Current MARTA Mixed Diesel and CNG Fleet

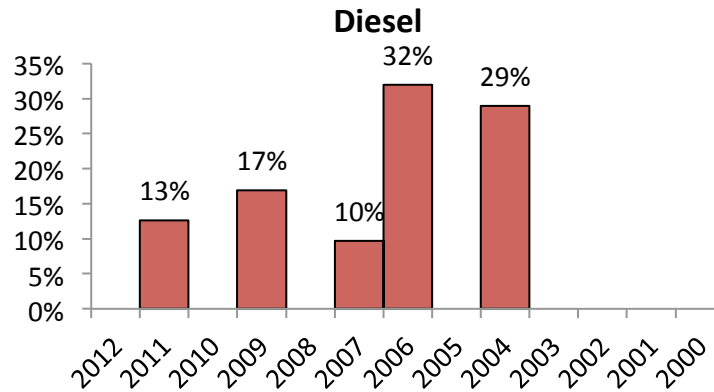


Figure 11. Age Distribution of Current GRTA Diesel Fleet

Table 9 summarizes fuel and emissions results of the CNG fleet purchase scenario. Compared to the base scenario, new CNG buses slightly increased on-road energy consumption. Annual total fuel consumption increased by 289,000 GGEs for MARTA, and 53,000 GGEs for GRTA. However, due to the lower well-to-pump CO₂e emission rate 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 NO_x and PM_{2.5} emissions. After MARTA’s assumed replacement the 158 existing diesel buses with new CNG buses, the fuel cycle NO_x emissions reduced by 112 metric tons (30%) per year, and PM_{2.5} emissions reduced by 9 metric tons (85%) per year. If GRTA replaced all of its 166 diesel buses with CNG buses, its annual fuel cycle NO_x emissions would decrease by 29 metric tons (70%), and annual fuel cycle PM_{2.5} emissions would decrease by 2 metric tons (95%).

Table 9. CNG Fleet Purchase Scenario Annual Fuel Consumption and Fuel Cycle Emissions

Transit Agency	Fuel (1,000 GGE)	GHGs (metric tons)	NO _x (metric tons)	PM _{2.5} (metric tons)
MARTA	7,515	81,349	258	1.5
GRTA	912	8,704	12	0.1

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 mileage. Table 10 summarizes the results for the combined eco-driving and CNG fleet scenario. For MARTA, the combined strategy reduced annual fuel consumption by 70 GGEs (1%). Fuel cycle CO₂e emissions decreased by 3,780 metric tons (5%) per year. The all-CNG fleet with eco-cycles showed significant reductions in fuel cycle NO_x and PM_{2.5} reduction, by 124 metric tons (34%) and 9 metric tons (87%), respectively. The GRTA fleet exhibited even more fuel savings and emission reductions. Annual fuel consumption fell by 4%, amounting to 33 GGEs. The fuel

cycle emissions in CO₂e, NO_x, and PM_{2.5} decreased by 1,628 (17%), 30 (73%), and 2 (96%) metric tons, respectively.

Table 10. CNG and Eco-driving Scenario Annual Fuel Consumption and Fuel Cycle Emissions

Transit Agency	Fuel (1,000 GGE)	GHGs (metric tons)	NO_x (metric tons)	PM_{2.5} (metric tons)
MARTA	7,156	77,453	246	1.3
GRTA	826	7,884	11	0.1

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 mile basis, which will shed light on generalized fuel and emissions impacts for local and express services. Figure 12 through Figure 15 provide comparisons across scenarios and operation types for fuel economy, fuel cycle CO₂e, NO_x, and PM_{2.5} 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 fleet purchase scenario. This shows that eco-driving can be especially effective as a fuel conserving strategy for agencies that provide express service with a CNG fleet. In terms of NO_x and PM_{2.5}, the additional emissions reduction from eco-driving in a CNG fleet is marginal, since a CNG fleet already has very low NO_x and PM_{2.5} emissions.

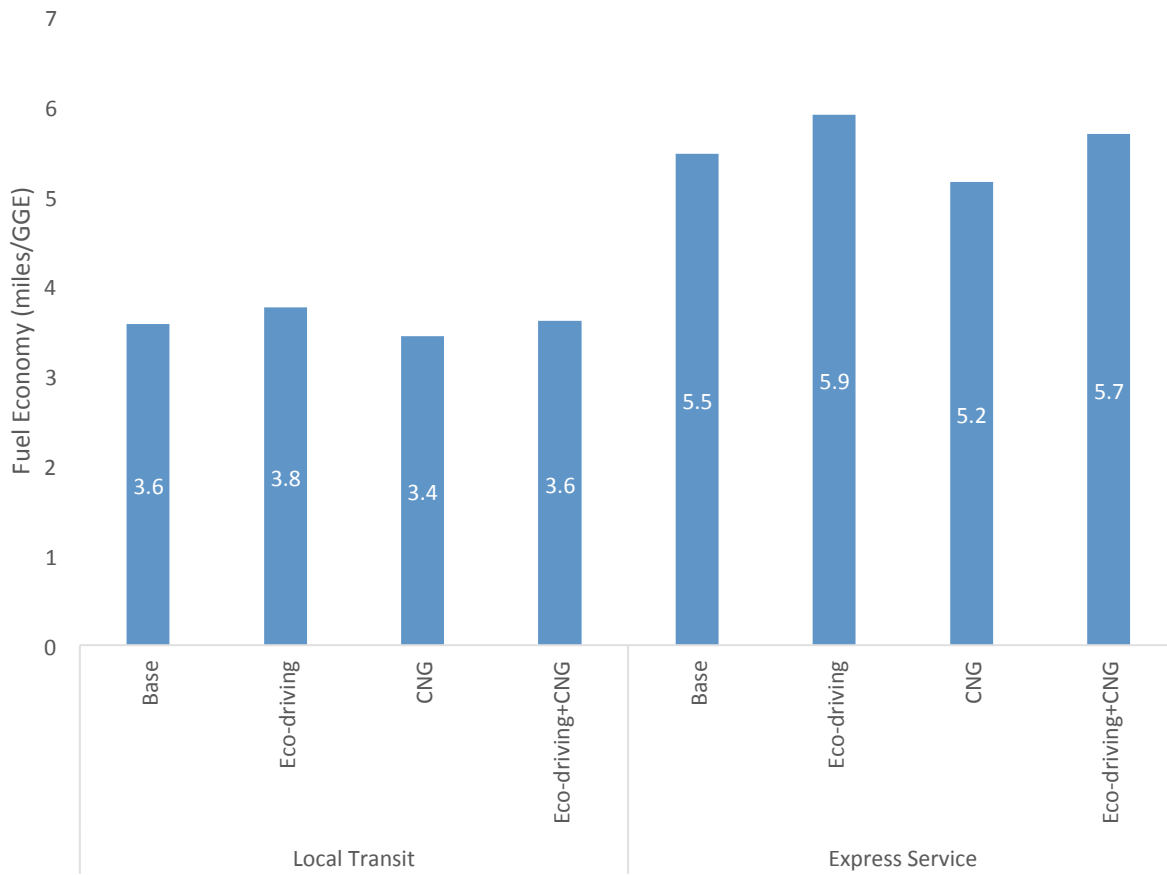


Figure 12. Fuel Economy Comparison across Scenarios and Types of Operation

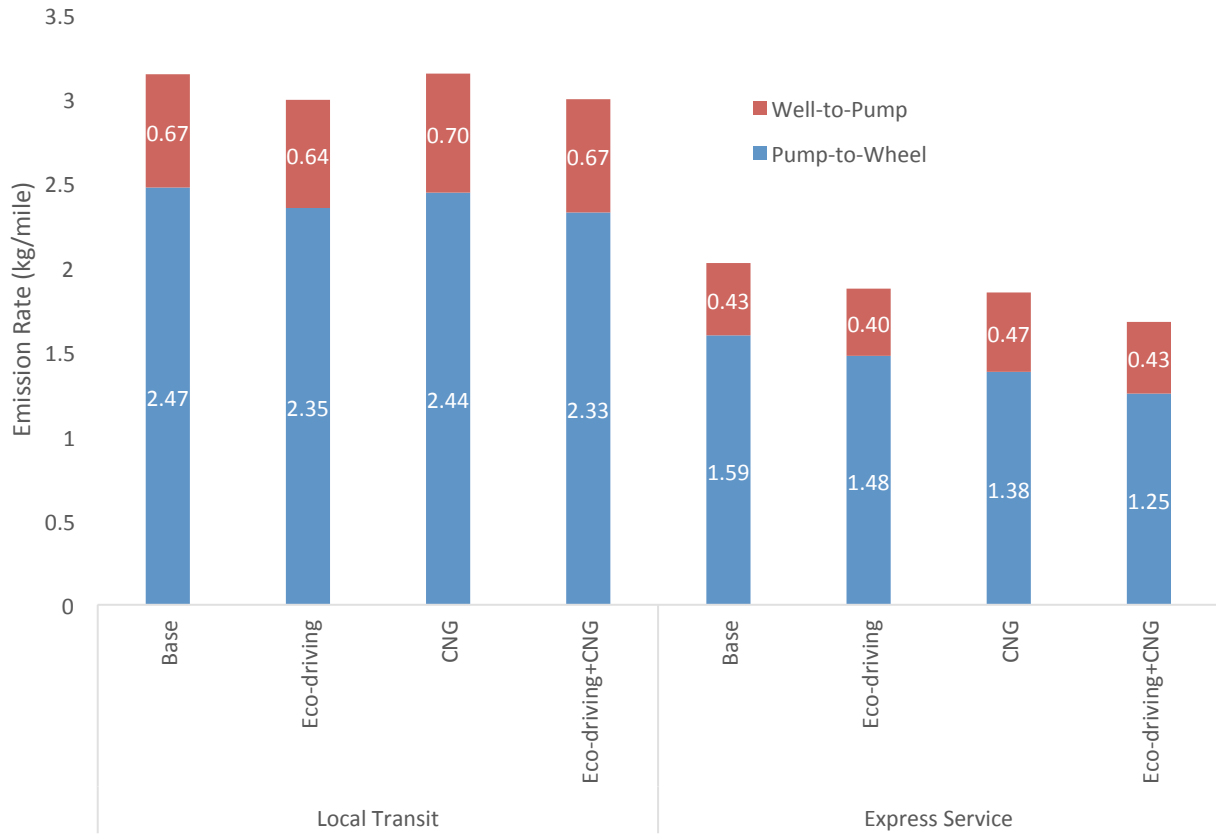


Figure 13. CO₂e Emission Rate Comparison

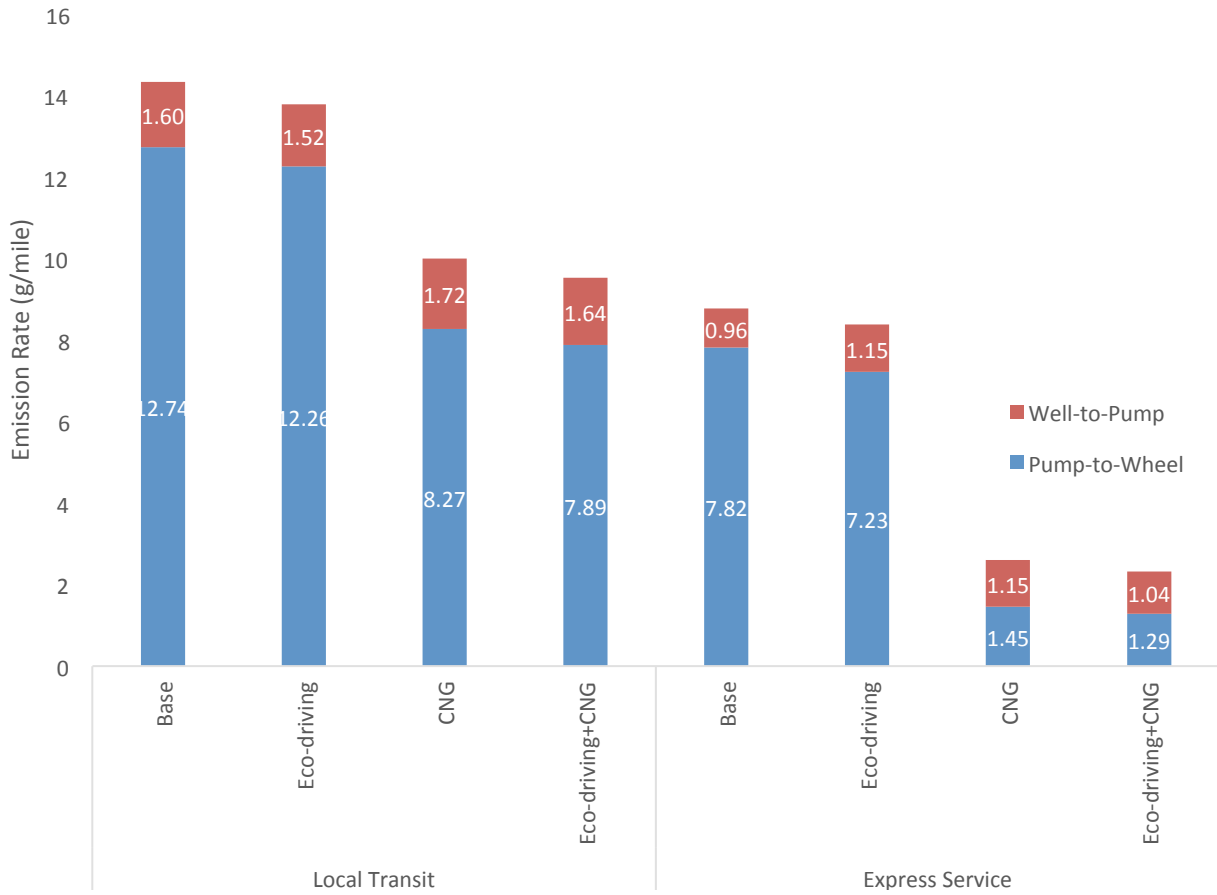


Figure 14. NO_x Emission Rate Comparison

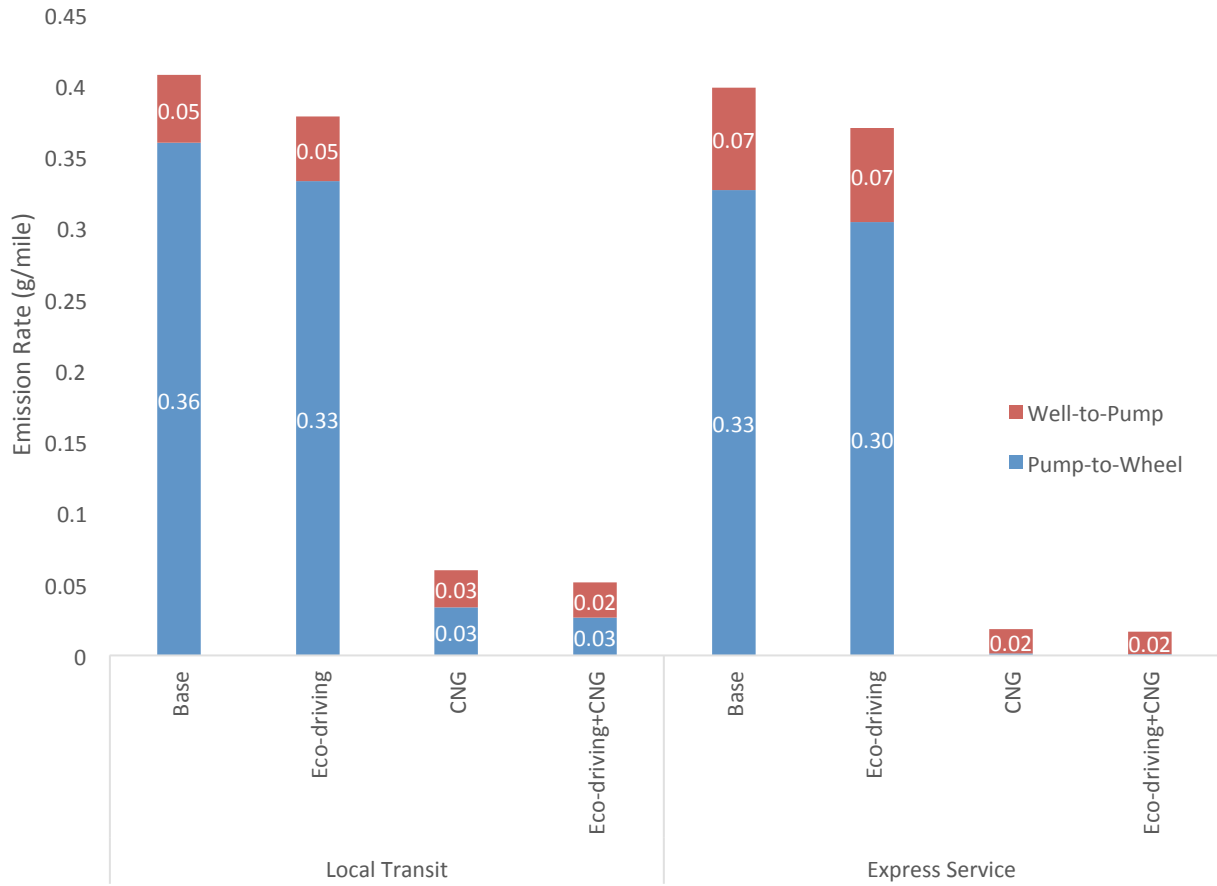


Figure 15. PM_{2.5} Emission Rate Comparison

Conclusions

This paper evaluated potential fuel and emissions savings from the implementation of eco-driving in Atlanta's MARTA local transit and GRTA express bus fleets. The analyses employed real-world operations data collected from these two fleets as baseline operating conditions, and eco-driving duty cycles developed through a speed and acceleration modification algorithm. The eco-driving algorithms reduce fuel consumption and emissions by limiting engine load, as indicated by STP in the MOVES modeling scheme, 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 reduction strategy. The simultaneous effects of eco-driving and CNG fleet purchase were also assessed. 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-mile basis.

Assuming the existing fleet composition of MARTA and GRTA, 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 MARTA fleet given the number of miles 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 55,000 gallons of diesel, translating to about \$132,000 in annual fuel savings (about \$800/bus/year), assuming a diesel fuel price of \$2.40/gallon. For MARTA's mixed CNG and diesel fleet, fuel savings from eco-driving amounted to about 300,000 gallons of diesel fuel equivalent (85,200 gallons of diesel fuel plus 252,500 gasoline gallons equivalent of CNG) per year. Assuming a diesel price of \$2.40/gallon (\$0.63/liter) and a CNG price of \$1.20 per gasoline gallon equivalent (Skelton, 2015), the cost savings for the MARTA fleet amount to translating to about \$720,000 in annual fuel savings, or \$1,000/bus/year.

Unlike the purchase of an alternative fuel bus fleet, eco-driving does not require significant capital investment. Once buses are being monitored, eco-driving is easy to implement, requiring only development of driver reports, training and feedback. Based on the research team's prior experience with fleet monitoring (Xu et al., 2013a), 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. Not only will fleet monitoring enable real-time feedback to drivers, which has been shown to provide added fuel savings than in-class training (Rolim, et al., 2014), but it will

also provide ancillary benefits, such as asset management, on-time performance assessment, and driver safety assessment.

The eco-driving algorithm developed for this study utilizes the modal modeling framework of U.S. EPA's MOVES model. The advantages are three-fold. First, MOVES is not computationally demanding, and therefore can be used in real-time or near-real-time driving advising for future applications. Second, using the MOVES framework allows a unified platform for fuel and emissions estimation. Third, MOVES is the U.S. EPA's approved model for regulatory use. However, the disadvantage in 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. 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. In future work, the authors plan to expand data collection to all MARTA and GRTA routes, and refine the eco-driving algorithm using high-fidelity vehicle simulation models.

Appendix I

Data QA/QC Procedures

GPS position and speed traces collected from moving transit vehicles underwent a series of QA/QC and post processing routines to ensure data validity, accuracy, and continuity, before using the data in the emissions analysis described in this paper. The data processing procedures included Kalman filtering to eliminate problematic data points, spline fitting to infill missing data, mapping of data to roadways, identification of off-network activity, elimination of parked vehicle data (parked vehicle in non-idle conditions), and treatment of large data gaps. Each process is described in detail below, and summary figures describe any data losses at each processing step.

Kalman Filtering

The quality of any GPS data strongly depends on GPS signal condition, which is a function of number of satellites and positional dilution of precision (PDOP) values. Although GPS receivers employ proprietary data filtering algorithms in their embedded chipset firmware to help correct data on-the-fly prior to delivery to the user, it is still necessary to further process the data. The proprietary GPS chipset filtering algorithms do not identify and eliminate all data outliers, as can be seen in random errors in the GPS output data stream. The modified discrete Kalman filter algorithm is proved to effectively enhance its capability of controlling GPS random errors (Jun, et al., 2005). The Kalman filter is used to correct the GPS speed with the Kalman Gain Matrix and the difference between the estimated and the measured speeds. The Kalman Gain Matrix is generated based on the GPS quality criteria, the number of satellites and PDOP values. If the number of satellites is below 4 and the PDOP is above 8, the quality of the speed is determined to be poor; therefore, estimated speed values are used in place of measured GPS speed values. Considering the data availability, the modified discrete Kalman filter algorithm is implemented to MARTA operations data to minimize the random errors from GPS loggers. The Kalman filter routine was not implemented on GRTA data due to the lack of GPS parameters provided by the Qstarz data loggers.

Spline Data Infill Process

Missing segments exist in almost all the trip files due to various factors, such as obstruction and signal interference. Missing segments of short duration can be reasonably interpolated to generate a continuous speed profile for emission modeling. A cubic spline algorithm is implemented for all of the trip files to interpolate missing segments of no longer than three seconds. If the gap of the missing segment is no longer than three seconds, i.e., single second or two or three consecutive seconds are missing, this segment will be candidate segments to be splined; otherwise, segments longer than 3 seconds are not splined or further used for modeling because interpolating such long missing segments may be inaccurate or unreliable if the vehicle is not in a steady cruise mode. To spline infill a missing segment, six good speeds (i.e., speed was collected successfully) are needed; three seconds before the start missing segment but no earlier than 10 seconds, and three seconds after end of the missing segment but no later than 10 seconds. If sufficient good speed data cannot be found within the 20 seconds wrapping the candidate segment, this segment is identified as missing and is not spline infilled.

GIS Network Mapping

Facility Type

To identify the facility type on which the vehicle is operating, the GIS shapefile of restricted roadways (highways and freeways) is used. Two steps are conducted to identify whether the traces are on restricted highway or unrestricted arterial:

Step1: Overlay GPS Data with the Restricted Roadway Layer

A 72-foot buffer is created for each centerline of the restricted roadway on each direction. This buffer layer is then overlaid with the operations data to identify the portions of traces running on restricted highways. Figure 16 illustrates the facility type identification process.

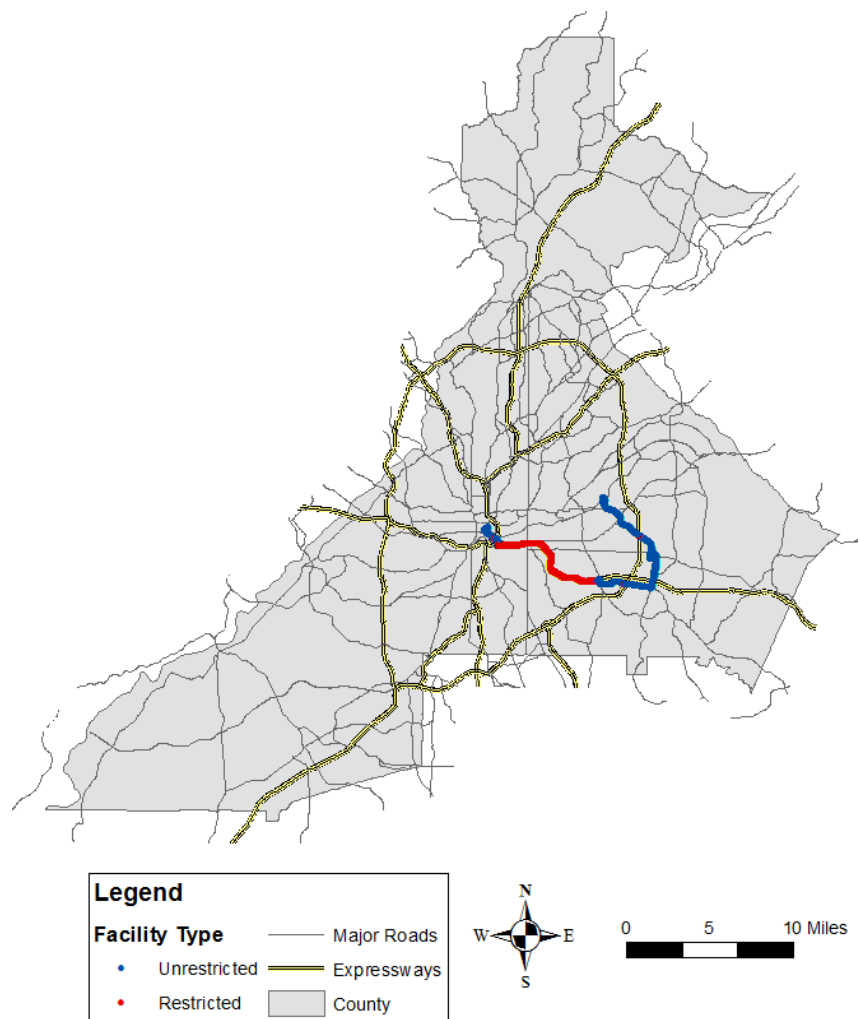


Figure 16. Example of Facility Type Identification

Step 2: Filter Roadway Classification Results

The direct processing of GPS traces can lead to incorrect identification of facility type under certain conditions. For example when a bus on an arterial passes beneath a freeway, via an

arterial underpass, a portion of the trip may be identified as operating on the restricted highway for a short duration. . Therefore, post-processing and filtering is needed to ensure correct roadway classification identification. Because consecutive freeway exits are normally set one or more miles apart, the researchers implemented a filtering rule that employs duration (consecutive seconds) of operation on restricted highway. If the vehicle does not operate for more than one minute on a restricted highway facility, the data are linked back to the unrestricted arterial. Two scenarios are described below and illustrated in Figure 17.

- 1) Some GPS points fall within the buffer and are determined as “restricted” in the “spatial overlay,” as the bus passes along or below the roads that are intersecting with the freeway. These points are changed back to “unrestricted” in this step
- 2) Some points fall out of the buffer and are determined as “unrestricted” in the “spatial overlay. These points are changed back to “restricted” in this step

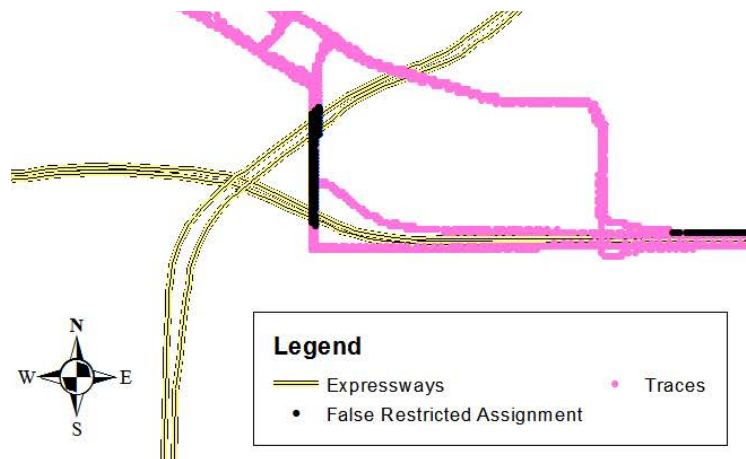


Figure 17. Example of Filtering Facility Type Results

Engine-off Identification

Once a bus driver stops their vehicle and turns off the engine, fuel consumption and emissions no longer occur. The equipment employed by the research team does not monitor engine on status. Hence, the researchers are not able to confirm whether the engine is off under what would normally be defined as idle conditions (speed<1mph for MARTA operations, and speed<3mph for GRTA operations, given the equipment sensitivity) from GPS data directly.

For these fleets, drivers are supposed to turn off engine if they need to stop the bus for an extended period. For the purposes of this study, engine idle idling activity is defined based upon idling time and location. The engine is treated as off (i.e. no engine idle) under the following two circumstances and excluded from fuel consumption and emissions analysis:

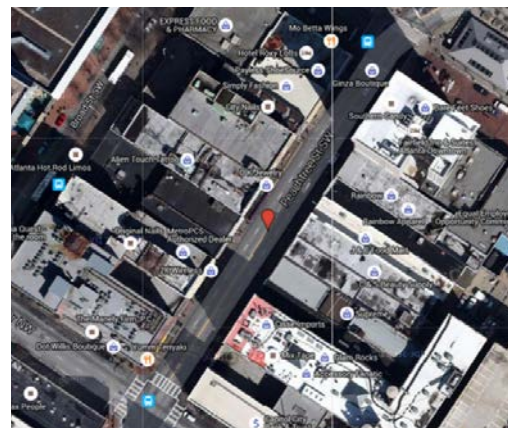
- 3) Onroad: When the length of continuous idling speed (speed<=1mph for MARTA operations, and speed<=3mph for GRTA operations) exceeds 10 minutes.

- 4) Off Network: When the length of continuous idling speed (speed \leq 1mph for MARTA operations, and speed \leq 3mph for GRTA operations) exceeds 30 seconds.

To assess the engine off threshold, the researchers examined 35 engine-off operations with idling duration between 10 and 15 minutes, and 35 identified engine-on operations with idling duration between 5 and 10 minutes. These engine-off operations typically occurred in remote parking lot locations (not MARTA maintenance yards) or in the middle of a roadway. In the example shown in Figure 18(b), the bus stayed at the location of the left and right red marker for 845 and 690 seconds, respectively, and then headed into revenue service. There is no reason to believe that the bus idled for that period in violation of MARTA operations policy (although a driver may have done so), so the activity was considered to be an engine stop and trip end location. In the example shown in Figure 18(b), the bus stopped in the middle of the street for 855 seconds. This on-street location was neither at a bus stop nor an intersection. There is no way to know what the bus was doing at this mid-street location. The delay may have resulted from road construction, the driver may have parked the vehicle to use a restroom, or the driver may have stopped for some other reason. In any case, there is no reason to believe that the bus was idling for 855 seconds in violation of transit agency policy. For the purposes of the analysis, the location was deemed a trip end and engine off location. Neither of the two scenarios described above are part regular bus service activity. Without evidence to the contrary (monitoring of engine on status), activity at these locations are not identified as extended idle activity and are therefore excluded from the assessment of eco-driving for MARTA revenue operations. On the other hand, for the locations adjacent to existing bus stops, as shown in Figure 19, , and where the stop durations are shorter than 10 minutes, the stop is deemed part of regular revenue operations and becomes part of the eco-driving assessment.



(a)



(b)

Figure 18. Example of Identified Engine-Off Conditions (Parking Lots and Midblock)



Figure 19. Example of Engine-On Condition (Transit Stops)

Breaking GPS Data into Trips for Eco-Driving Analysis

The data processing routines described above identify trip end locations, where the engine is presumed to have been turned off. In addition, there are still gaps in the data stream where the research team did not allow the spline function to infill data. These stop locations and data gaps were used to break the monitored data into trips for eco-driving analysis. However, some of the trips that result from the data processing are very short, typically associated with choppy periods of GPS data loss. To ensure trip quality and applicability, trips were included in the analysis only if: 1) the length of cycle is longer than 30 seconds; and 2) the average speed of the cycle is greater than 5 mph.

Data Processing Results

Figure 20 and Figure 21 summarize the data processing procedures for the MARTA and GRTA data, respectively. Figure 22 and Figure 23 show the geographic coverage of MARTA and GRTA operations as reflected in the final analytical data set.

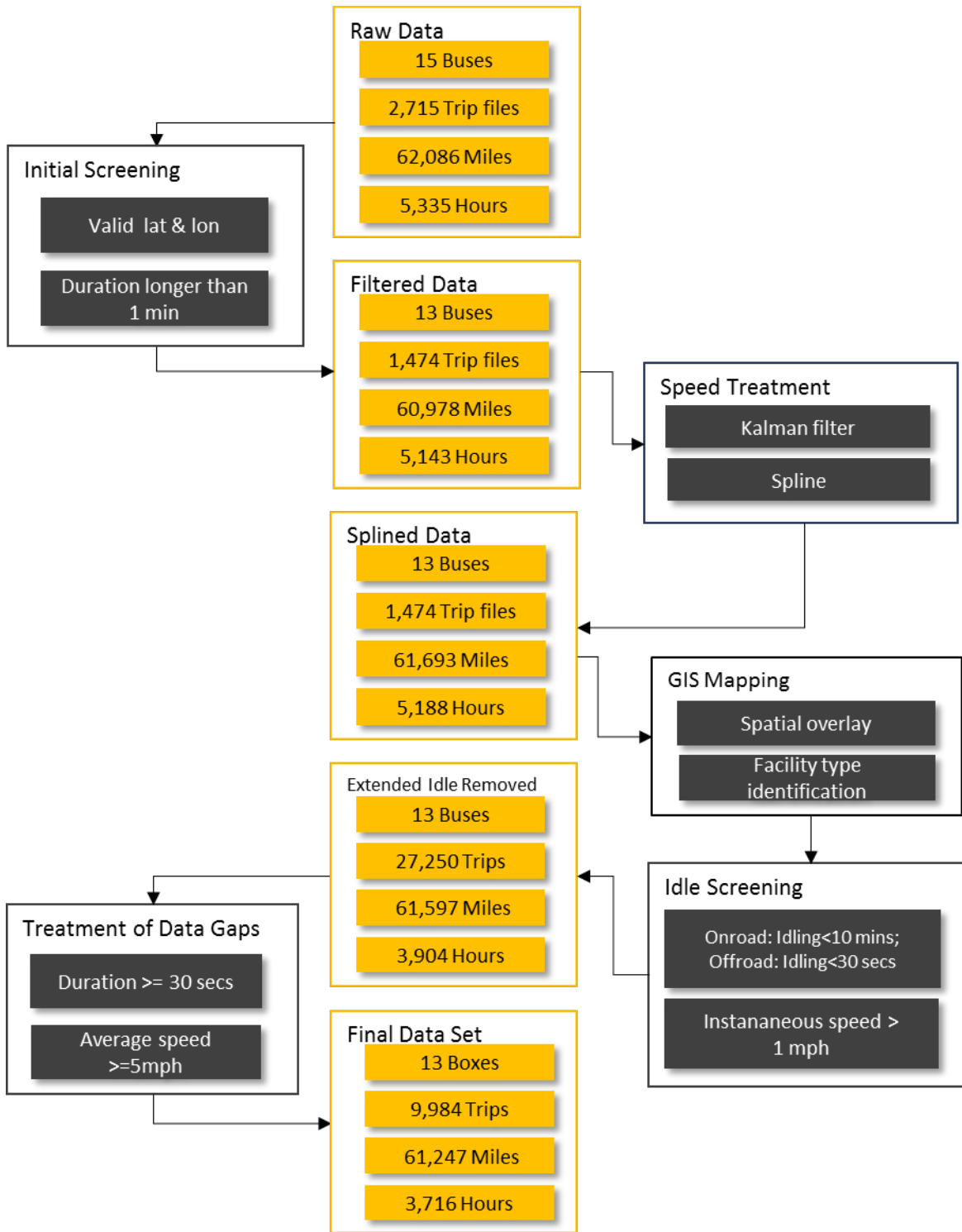


Figure 20. Processing steps for MARTA data

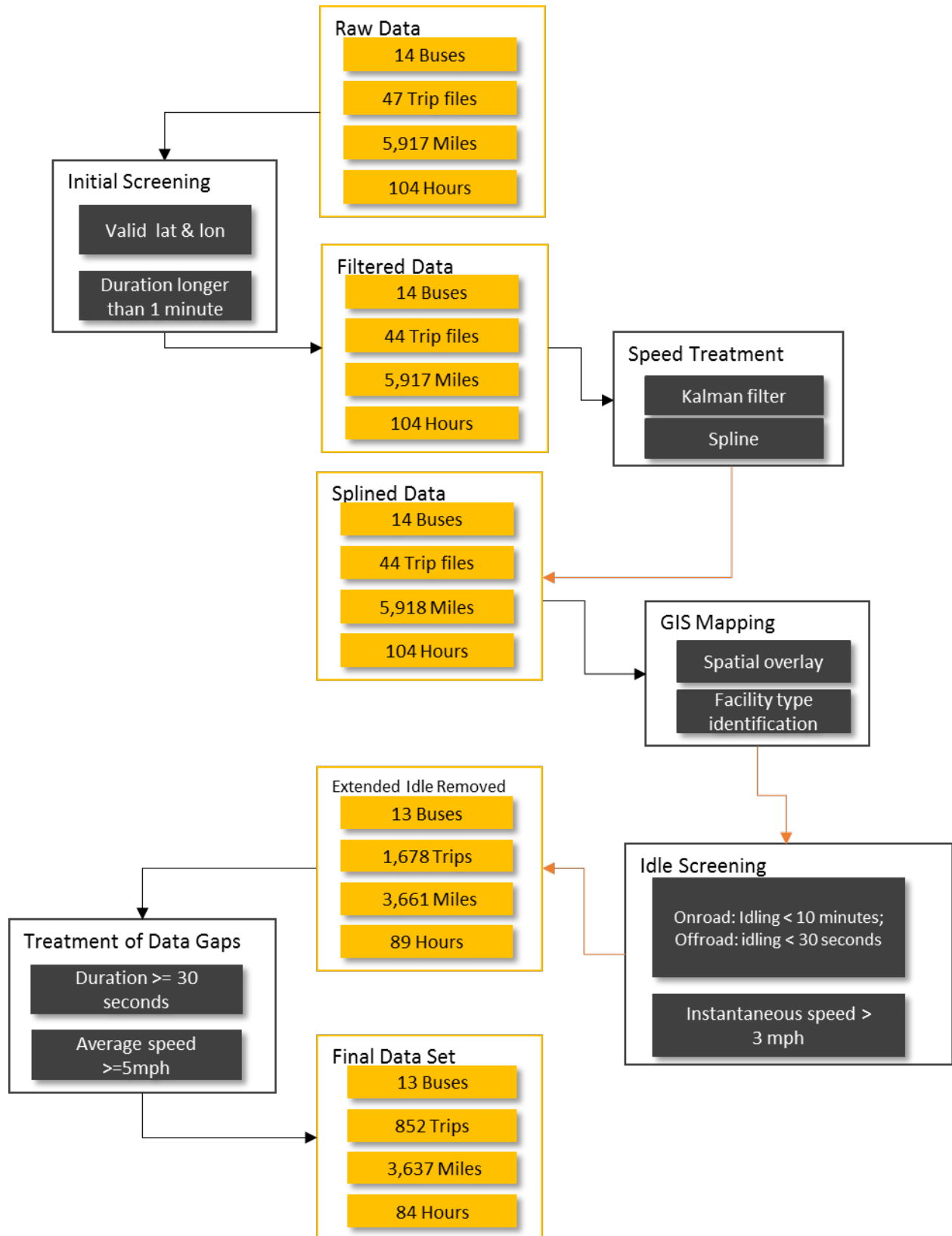


Figure 21. Processing steps for GRTA data

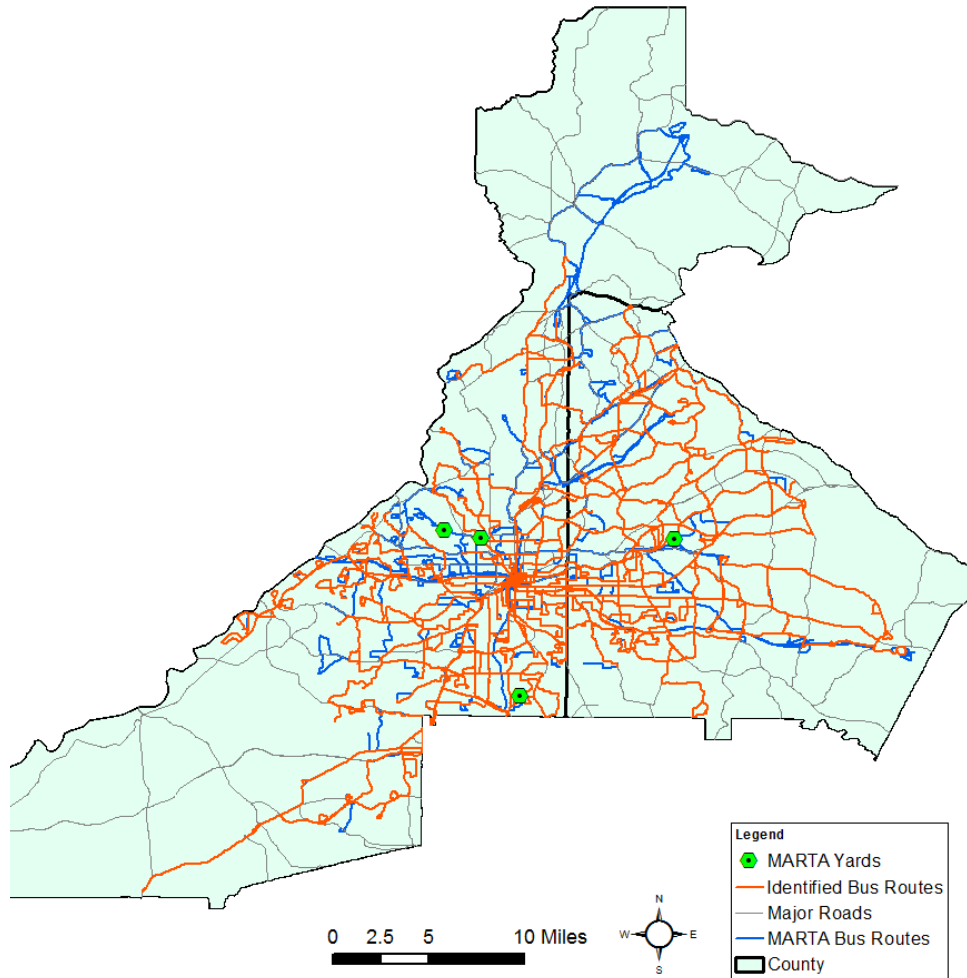


Figure 22. Geographic Coverage of MARTA Bus Routes

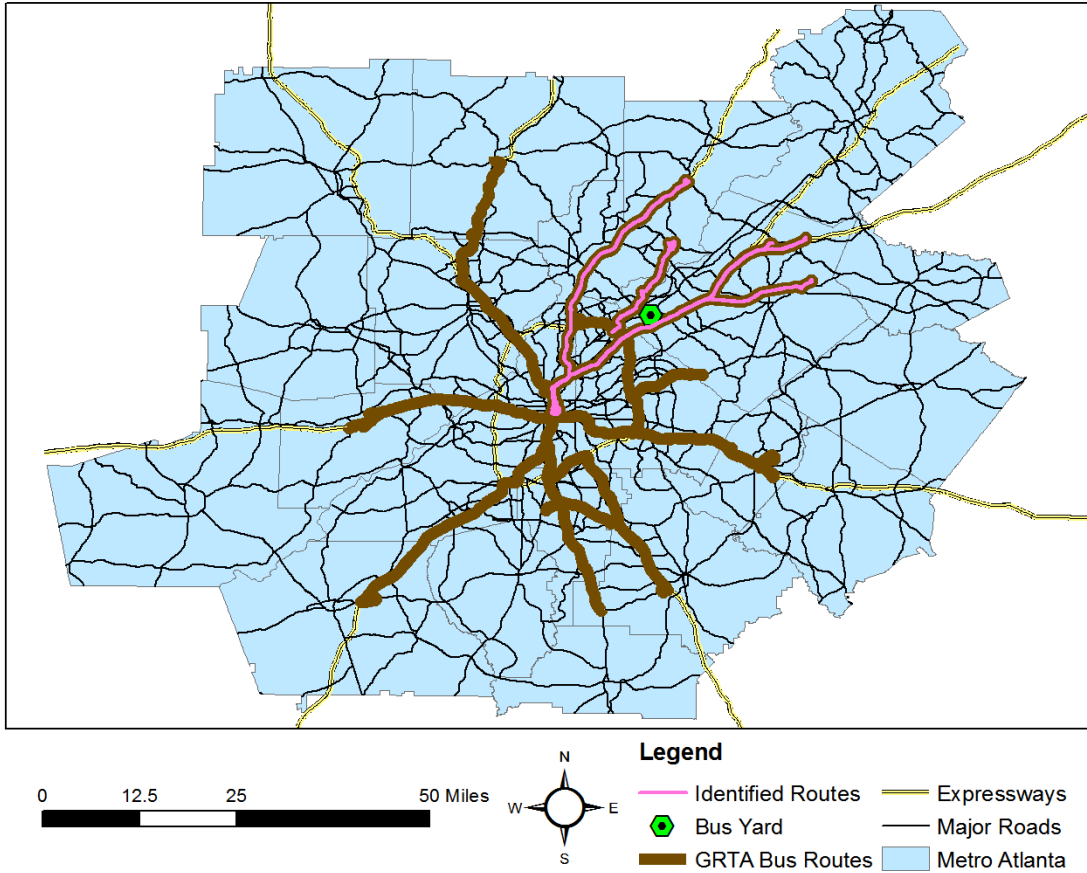


Figure 23. Geographic Coverage of GRTA Bus Routes

Appendix II MOVES Background

Table 11. Definitions of STP Operating Mode Bins in MOVES

Operating Mode ID	Operating Mode	Scaled Tractive Power	Vehicle Speed	Vehicle Acceleration
	Description	(STP _t , kW)	(v _t , mph)	(a _t , mph/sec)
0	Deceleration/Braking			$a_t \leq -2.0$ OR ($a_t < -1.0$ AND $a_{t-1} < -1.0$ AND $a_{t+2} < -1.0$)
1	Idle		$-1.0 \leq v_t < 1.0$	Any
11	Coast	$STP_t < 0$	$0 \leq v_t < 25$	Any
12	Cruise/Acceleration	$0 \leq STP_t < 3$	$0 \leq v_t < 25$	Any
13	Cruise/Acceleration	$3 \leq STP_t < 6$	$0 \leq v_t < 25$	Any
14	Cruise/Acceleration	$6 \leq STP_t < 9$	$0 \leq v_t < 25$	Any
15	Cruise/Acceleration	$9 \leq STP_t < 12$	$0 \leq v_t < 25$	Any
16	Cruise/Acceleration	$12 \leq STP_t$	$0 \leq v_t < 25$	Any
21	Coast	$STP_t < 0$	$25 \leq v_t < 50$	Any
22	Cruise/Acceleration	$0 \leq STP_t < 3$	$25 \leq v_t < 50$	Any
23	Cruise/Acceleration	$3 \leq STP_t < 6$	$25 \leq v_t < 50$	Any
24	Cruise/Acceleration	$6 \leq STP_t < 9$	$25 \leq v_t < 50$	Any
25	Cruise/Acceleration	$9 \leq STP_t < 12$	$25 \leq v_t < 50$	Any
27	Cruise/Acceleration	$12 \leq STP_t < 18$	$25 \leq v_t < 50$	Any
28	Cruise/Acceleration	$18 \leq STP_t < 24$	$25 \leq v_t < 50$	Any
29	Cruise/Acceleration	$24 \leq STP_t < 30$	$25 \leq v_t < 50$	Any
30	Cruise/Acceleration	$30 \leq STP_t$	$25 \leq v_t < 50$	Any
33	Cruise/Acceleration	$STP_t < 6$	$50 \leq v_t$	Any
35	Cruise/Acceleration	$6 \leq STP_t < 12$	$50 \leq v_t$	Any
37	Cruise/Acceleration	$12 \leq STP_t < 18$	$50 \leq v_t$	Any
38	Cruise/Acceleration	$18 \leq STP_t < 24$	$50 \leq v_t$	Any
39	Cruise/Acceleration	$24 \leq STP_t < 30$	$50 \leq v_t$	Any
40	Cruise/Acceleration	$30 \leq STP_t$	$50 \leq v_t$	Any

Table 12. STP Parameters from MOVES2014

	Source	Rolling	Rotating	Drag	Source Mass	Fixed Mass
Source Type	Type ID	Term	Term	Term	Metric	Factor
Name	ID	A	B	C	Tonnes	M
Intercity Bus	41	1.29515	0	0.00371491	19.5937	17.1
Transit Bus	42	1.0944	0	0.00358702	16.556	17.1

Appendix III

MOVES Input Settings

General settings are listed below, and the specific settings are listed in Table 13.

- Region:
 - Fulton County, Georgia
- Calendar Year:
 - 2015
- Month:
 - January
- Date and Time:
 - Weekday, 7:00-8:00AM
- I/M Strategy:
 - Default 2015 I/M strategy from MOVES2014
- Meteorology (default value determined by time and region from MOVES):
 - Temperature: 30 F
 - Humidity: 75%
- Fuel Supply and Fuel Formulation:
 - Default winter fuel supply and fuel share from MOVES
- Source Type:
 - Transit bus (source type ID = 42) for MARTA local transit buses
 - Intercity bus (source type ID = 41) for GRTA express buses
- 23 Links:
 - To generate an emission rate for a mode of operation, each link is assigned 100% fraction of one operating mode bin
 - Time is scaled to one hour of operation using link length and link average speed

Table 13. Emission Rates with Specific Settings

Type of Operation	Scenario Setting	Fuel Type	Age Distribution	Cycle
Local Transit	Current fleet, current driving style	Diesel and CNG	Current MARTA fleet age distribution (Figure 10)	Observed Driving Cycle
	New fleet, current driving style	CNG	Age=0	
	Current fleet, eco-driving	Diesel and CNG	Current MARTA fleet age distribution (Figure 10)	Eco-cycle
	New fleet, eco-driving	CNG	Age=0	
Express Bus Service	Current fleet, current driving style	Diesel	Current GRTA fleet age distribution (Figure 11)	Observed Driving Cycle
	New fleet, current driving style	CNG	Age=0	
	Current fleet, eco-driving	Diesel	Current GRTA fleet age distribution (Figure 11)	Eco-cycle
	New fleet, eco-driving	CNG	Age=0	

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