UCR | College of Engineering- Center for Environmental Research & Technology

FINAL TECHNICAL REPORT

Federal Grant Number	DE-EE0005448
Project Title	Next Generation Environmentally-Friendly Driving Feedback Systems Research and Development
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Recipient Organization	The Regents of the University of California on behalf of its Riverside Campus
Consortium Member Organizations	Automatiks Beat the Traffic California Department of Transportation Earthrise Technology Esri NAVTEQ Riverside Transit Agency Transportation Sustainability Research Center at the University of California Berkeley

Acknowledgements

The research team acknowledges the funding support from the National Energy Technology Laboratory, the U.S. Department of Energy (DOE). We are grateful for the program support from David Ollett, John Hatfield, Yury Kalish, Leo Breton, and Adrienne Riggi of DOE during the course of the project.

The principal investigators (PIs) acknowledge the cost shares from Beat the Traffic, the California Department of Transportation, Earthrise Technology, Esri, NAVTEQ, the Riverside Transit Agency, and the College of Engineering at the University of California (UC) Riverside. We are also thankful for the contribution of several members of the consortium member organizations, including:

- Automatiks – Steve Wollenberg
- Beat the Traffic – Andre Gueziec, Edgar Rojas
- California Department of Transportation – Srikanth Balasubramanian, Lisa Kunzman
- Earthrise Technology – Jim DiSanto
- Esri – Wolfgang Hall, Buyang Cao
- NAVTEQ – Kevin Moran, David Ko
- Riverside Transit Agency – Virginia Werly, Luciano Rose
- Transportation Sustainability Research Center at UC Berkeley – Susan Shaheen, Elliot Martin, Nelson Chan, Kate Yu, Rachel Finson

In addition, the PIs acknowledge the contribution of many staff members and students at the College of Engineering – Center for Environmental Research and Technology, UC Riverside. These include Alexander Vu, Daniel Sandez, Michael Todd, Peng Hao, Umesh Moghariya, Deepanshu Madan, Qichi Yang, Junhyuk Kang, Shawn Miata, Min Ho Kang, Sultan Khan, Nicholas Jarak, and Steven Em.

Executive Summary

The objective of this project is to design, develop, and demonstrate a next-generation, federal safety- and emission-complaint driving feedback system that can be deployed across the existing vehicle fleet and improve fleet average fuel efficiency by at least 2%.

The project objective was achieved with the driving feedback system that encourages fuel-efficient vehicle travel and operation through: 1) *Eco-Routing Navigation* module that suggests the most fuel-efficient route from one stop to the next, 2) *Eco-Driving Feedback* module that provides sensible information, recommendation, and warning regarding fuel-efficient vehicle operation, and 3) *Eco-Score and Eco-Rank* module that provides a means for driving performance tracking, self-evaluation, and peer comparison. The system also collects and stores vehicle travel and operation data, which are used by *Algorithm Updating* module to customize the other modules for specific vehicles and adapts them to specific drivers over time.

The driving feedback system was designed and developed as an aftermarket technology that can be retrofitted to vehicles in the existing fleet. It consists of a mobile application for smart devices running Android operating system, a vehicle on-board diagnostics connector, and a data server. While the system receives and utilizes real-time vehicle and engine data from the vehicle's controller area network bus through the vehicle's on-board diagnostic connector, it does not modify or interfere with the vehicle's controller area network bus, and thus, is in compliance with federal safety and emission regulations.

The driving feedback system was demonstrated and then installed on 45 vehicles from three different fleets for field operational test. These include 15 private vehicles of the general public, 15 pickup trucks of the California Department of Transportation that are assigned to individual employees for business use, and 15 shuttle buses of the Riverside Transit Agency that are used for paratransit service. Detailed vehicle travel and operation data including route taken, driving speed, acceleration, braking, and the corresponding fuel consumption, were collected both before and during the test period. The data analysis results show that the fleet average fuel efficiency improvements for the three fleets with the use of the driving feedback system are in the range of 2% to 9%.

The economic viability of the driving feedback system is high. A fully deployed system would require capital investment in smart device ($150-$350) and on-board diagnostics connector ($50-$100) as well as paying operating costs for wireless data plan and subscription fees ($20-$30 per month) for connecting to the data server and receiving various system services. For individual consumers who already own a smart device (such as smartphone) and commercial fleets that already use some kind of telematics services, the costs for deploying this driving feedback system would be much lower.

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1. Introduction

1.1. Overview

In the FY 2011 Vehicle Technologies Program Wide Funding Opportunity Announcement by the National Energy Technology Laboratory, the U.S. Department of Energy, it was recognized that "the variation in fuel consumption due to driver differences can be as high as 25%. Developing a means of improving driver behavior to maximize fuel economy is a significant opportunity to reducing fuel consumption in existing fleets. One of the most promising approaches involves providing immediate information to the driver about the effect of driving behavior on fuel consumption. It is the intent of this Driver Feedback Technology subtopic to undertake research and development project(s) that would result in simple and inexpensive means of providing feedback to the driver on instantaneous fuel consumption."

Specifically, the following criteria were set forth:

1. "An innovative and cost effective technical approach to reduce fleet average fuel consumption by at least 2% via driver feedback technology;
2. Compliance with federal safety and emissions regulations; and
3. Ability to deploy the technology across the existing vehicle fleet."

In this project, the University of California at Riverside (UCR) along with its partners develops a next generation environmentally-friendly driving feedback system that builds on current vehicle routing technology and on-board driving feedback systems to create new capabilities for helping drivers as well as fleet dispatchers and managers reduce fuel consumption and greenhouse gas emissions from their vehicle operations. The project includes:

1. Research and development of algorithms to determine operating conditions that are optimal for fuel efficiency and those that need improvement;
2. Development of communications methods and interfaces to notify the driver when changes in operating mode will be beneficial;
3. Demonstration of the technology in passenger car and commercial vehicle fleets; and
4. Knowledge and technology transfer leading to implementation of the technology.

The project has a performance period of three years where the first two years were focused on research, development, and demonstration of the driving feedback system. The last year of the project was used for field operational test and system evaluation. The project was successfully completed in December 2014.

1.2. Project Objectives

The objective of this project is to design, develop, and demonstrate a next-generation, federal safety and emission complaint driving feedback system with four advanced modules: Eco-Routing Navigation, Eco-Driving Feedback, Eco-Score and Eco-Rank, and Algorithm Updating that will improve fuel efficiency of fleet average fuel consumption by at least 2%. The driver feedback technology will be deployable across the existing vehicle fleet.

1.3. System Components

The next generation environmentally-friendly driving feedback system consists of several components or modules that are integrated into a comprehensive driving feedback system solution. These modules provide different types of feedback to drivers that can reduce vehicle fuel consumption and emissions. The individual reductions from each module can add up to result in a greater sum of fuel consumption and emissions reduction. These different modules of the driving feedback system are depicted in Figure 1-1 and are briefly described:

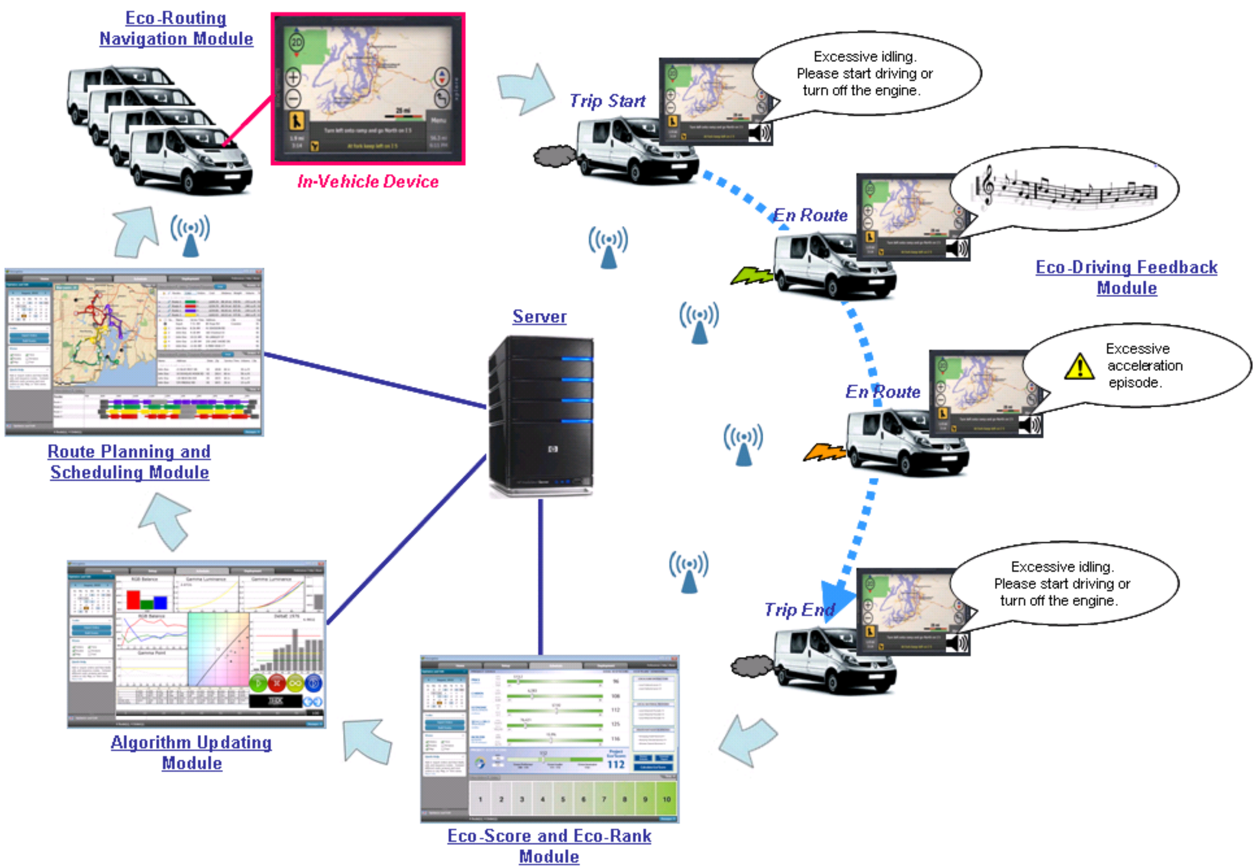

Figure 1-1. Components of the next generation environmentally-friendly driving feedback system

- **Eco-Route Planning and Scheduling Module** – One of the eco-driving practices is to plan driving trips in advance. This module provides trip feedback to fleet operation by finding the minimum cost path between a set of stops or destinations by incorporating time schedules and road networks into a solution. The module can also account for driver and vehicle costs, vehicle capacity, and other constraints. Pre-planning trips help reduce time, fuel consumption, and the need for vehicle maintenance.

- **Eco-Routing Navigation Module** – Current navigation systems can determine the shortest-distance or shortest-time route for any trips. However, it has been shown that these routes are not necessarily the most fuel efficient route[1]. Potential fuel savings range from 5% to 15% with the help of fuel-optimized navigation systems[2]. This eco-routing navigation module provides route feedback by calculating the most fuel-efficient route for each of the pre-planned trips, given that the time schedules are still met.

- **Eco-Driving Feedback Module** – Once a trip is underway, eco-driving feedback can be used to further reduce fuel consumption and emissions. It has been shown that providing instantaneous fuel economy feedback to drivers can positively influence driving behavior towards fuel economy improvements; one study showed improvements of 6% on city roads and 1% on highways[3]. This proposed module goes beyond providing simple instantaneous fuel economy to include specific driving feedback on items such as excessive speed, acceleration, or idling under different driving situations. The feedback is selectively provided through various means (such as audio tones or messages) in an effort to reduce driver distraction.

- **Eco-Score and Eco-Rank Module** – This module analyzes the driving data of each driver to determine how eco-friendly the driver is with respects to the different driving modes (i.e. cruising, accelerating, braking, and idling). The module determines a score for each driving mode and explains the underlying reasons for the score. The module also generates reports with specific recommendation feedback for improving the scores. These scores can be compared across the different driving modes for the same driver so that (s)he can prioritize the areas for improvements. The scores can also be used to rank multiple drivers.

- **Algorithm Updating Module** – This module allows many of the underlying algorithms in other modules to be customized for specific vehicles and drivers, and continually updated over time based on measured vehicle and driver performance.

- **System Server** – The system server integrates all the modules together. It provides data communication, storage, and processing capabilities to the system. It also provides computational power to support the system applications.

The next generation environmentally-friendly driving feedback system is applicable to both fleet vehicles and consumer vehicles. For multi-vehicle fleet operation, the system includes the eco-route planning and scheduling module that optimizes routes and schedules of multiple vehicles at the same time, as shown in Figure 1-2. The individual system modules function as an application that works cooperatively with other applications. The eco-routing navigation and eco-driving feedback applications are client applications that operate on an in-vehicle device and interface directly with the driver. The other applications are server applications that run on the system server.

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[1] Barth, M., Boriboonsomsin, K., and Vu, A. (2007). Environmental-friendly navigation. Proceedings of the 10th International IEEE Conference on Intelligent Transportation Systems, Seattle, WA, September 30 – October 3.

[2] Boriboonsomsin, K., Barth, M., Zhu, W., and Vu. A. (2012). "ECO-routing navigation system based on multi-source historical and real-time traffic information." *IEEE Transactions on Intelligent Transportation Systems*, 99, 1-11.

[3] Boriboonsomsin, K., Vu, A., and Barth, M. (2011). Evaluation of driving behavior and attitude towards eco-driving: A Southern California case study. Proceedings of the 90th Annual Meeting of the Transportation Research Board, Washington, DC, January 23-27.

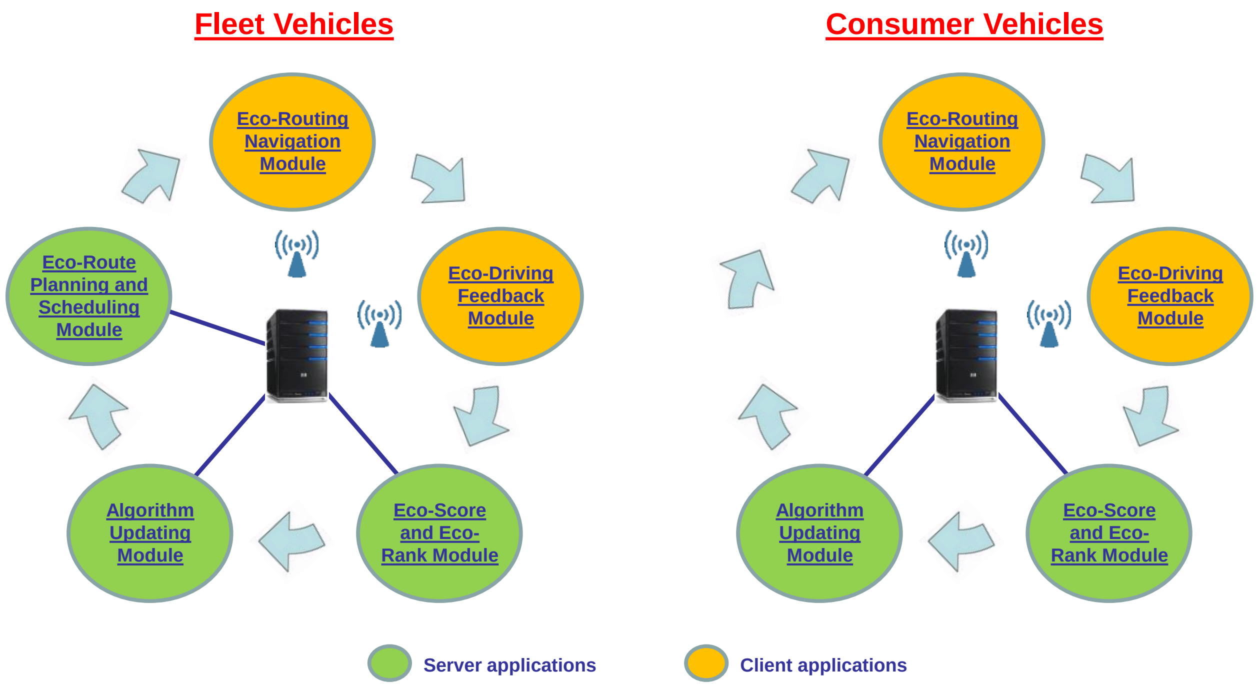


Figure 1-2. System applications for fleet and consumer vehicles

1.4. Report Organization

This report is organized in a way that aligns with project tasks where one chapter summarizes project activities of one task as follows:

- Chapter 2 presents the research and development of the Eco-Routing Navigation module.
- Chapter 3 describes project activities related to the Eco-Driving Feedback module.
- Chapter 4 discusses the underlying algorithms of the Eco-Score and Eco-Rank module.
- Chapter 5 presents the methodology developed for the Algorithm Updating module.
- Chapter 6 describes the integration of the different modules into the driving feedback system. In addition to the software integration, this chapter also discusses the hardware selection and configuration as well as the setup of data communication with the system server.
- Chapter 7 presents the details of the field operational test of the system.
- Chapter 8 discusses the methods and results of system evaluation using the data collected during the field operational test.
- Finally, Chapter 9 lists the research products and technology transfer activities of this project.

2. Eco-Routing Navigation Module

2.1. Overview

The eco-routing navigation module is built upon UCR's existing eco-routing technology that has the ability to: 1) determine an eco-route that is the most fuel-efficient and/or lowest-emission for a vehicle by accounting for distance and traffic conditions; and 2) update the eco-route for the vehicle based on real-time traffic information. The eco-routing navigation module has new capabilities that include:

- Accounting for road type (e.g., freeways versus surface streets) and road grade in eco-route calculation
- Accounting for turning movements and delays at intersections in eco-route calculation

The system architecture of the eco-routing navigation module is depicted in Figure 2-1 and described briefly below.

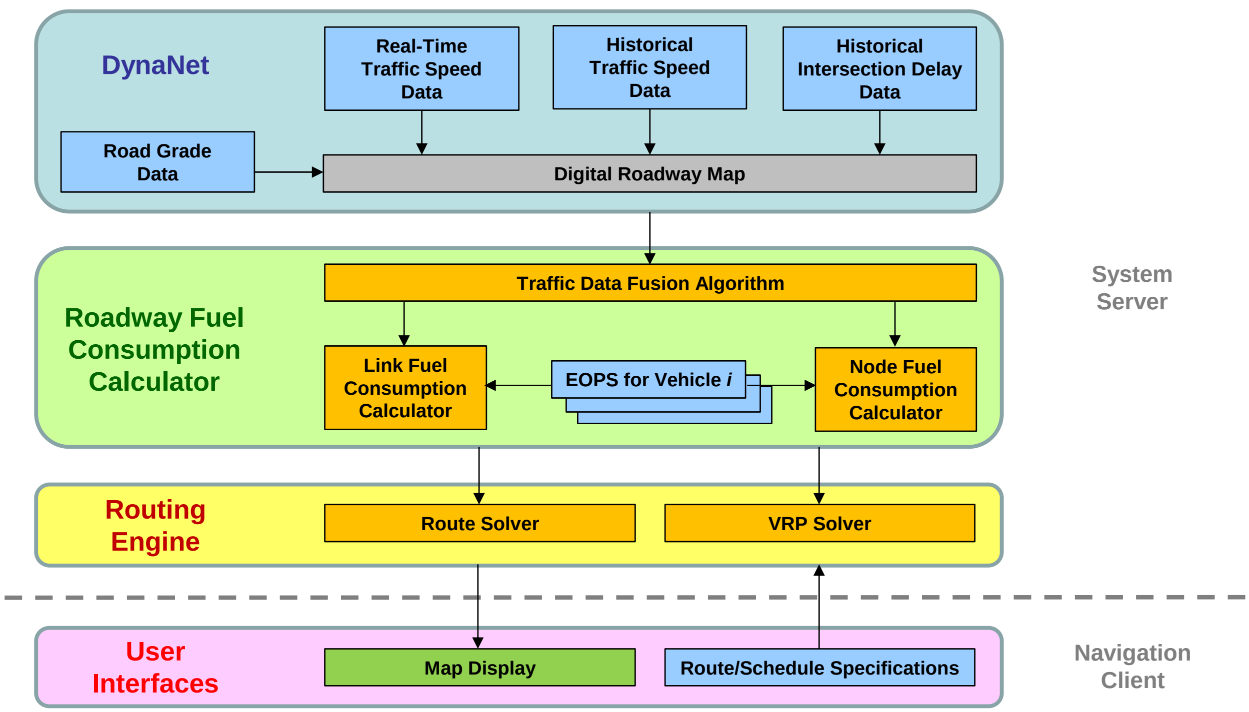


Figure 2-1. System architecture of Eco-Routing Navigation module

- **DynaNet** – Dynamic Roadway Network (DynaNet) Database is a digital roadway map that has been enhanced by various kinds of roadway-related data. The underlying digital roadway map in DynaNet is NAVSTREETS from NAVTEQ. Data that have been added to DynaNet include road grade, historical traffic speed, real-time traffic speed, and historical intersection delay.

- **Roadway Fuel Consumption Calculator** – This compoment takes the various traffic data stored in DynaNet and fuse them together to result in the best representative of traffic conditions at that point in time. The fused traffic data are then used to estimate fuel consumption needed for vehicles to traverse individual roadway links (i.e., road segments) and nodes (i.e., intersections). The fuel consumption calculators for both links and nodes are calibrated for individual specific vehicles by Energy Operational Parameter Set (EOPS).

- **Routing Engine** – The routing engine includes a shortest path algorithm for calculating an optimal route from Point A to Point B in terms of fuel efficiency, time, and distance.

- **User Interfaces** – The user interfaces allow the driver to specify an origin and a destination as well as select the routing criteria (i.e., minimizing distance, travel time, or fuel consumption). The user interfaces also display the calculated routes along with their associated costs (i.e., distance, travel time, and fuel consumption) to the driver. In addition, the user interfaces provide voice-guided, turn-by-turn directions to the driver upon request.

2.2. Dynamic Roadway Network Database Upgrade

At the heart of any route planning or roadway navigation tools are digital roadway maps. These digital roadway maps are usually created in a Geographic Information System (GIS) database, which stores static information regarding the characteristics (e.g., length, functional class, speed limit, etc.) of each roadway link as a data layer. More data layers can be added to include time-varying data such as historical traffic conditions on the roadway links. They can also be updated periodically to store real-time traffic information for use in route calculation or map display.

The research team has developed a Dynamic Roadway Network (DynaNet) database for Southern California in a MySQL environment. It uses NAVSTREETS as the underlying digital roadway map, and incorporates traffic performance data—both historical and real-time—from multiple sources as additional data layers (see Figure 2-2). Historical data include those obtained from travel demand models, traffic simulation models, as well as traffic monitoring systems. The main source for real-time traffic information on freeways is the California Department of Transportation (Caltrans)'s Freeway Performance Measurement System or PeMS[4], which gathers traffic measurements from thousands of loop detectors on California freeways. Data from PeMS are acquired by DynaNet at five-minute intervals or on demand. In addition to PeMS, DynaNet also receives speed data from probe vehicles traveling on both freeways and surface streets through traffic data vendors. These traffic data can be displayed on the connected Google Earth or Google Maps interfaces.

All traffic performance data received by DynaNet are processed and combined by data fusion algorithms. The first part of the data fusion involves determining traffic performance measures for each roadway link in the underlying roadway map. This step is handled differently for data from different sources. For instance, PeMS provides point measurements of traffic performance at the locations of its sensors. Thus, traffic performance measurements at each sensor need to be projected onto the roadway links in the underlying roadway map. With the knowledge of the distances between the adjacent pairs of sensors, a set of virtual links i whose spatial coverage is l_i is created (see Figure 2-3). Then, each link in the roadway network is assigned a traffic performance value of the overlapping virtual link(s) weighted by the overlapping distance. For the example in Figure 2-4, $E_1 = (3/4)E_L + (1/4)E_M$; $E_2 = (3/7)E_M + (4/7)E_N$; $E_3 = E_O$; and so forth.

[4] http://pems.dot.ca.gov/

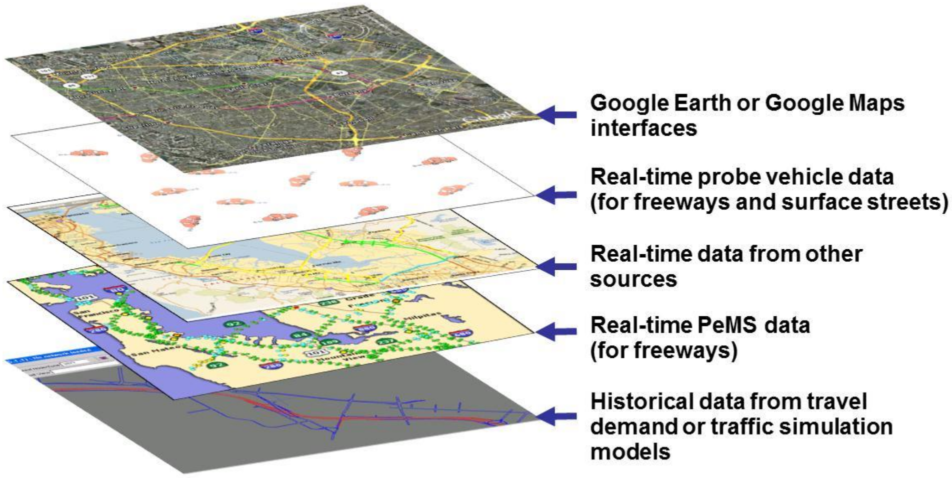


Figure 2-2. Dynamic Roadway Network Database

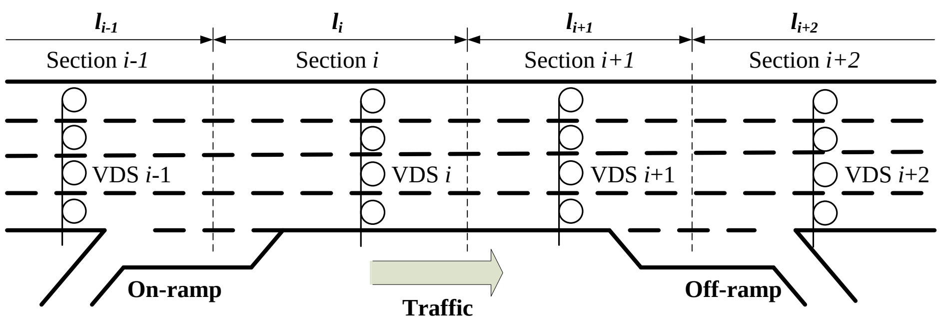


Figure 2-3. Spatial coverage of traffic sensors

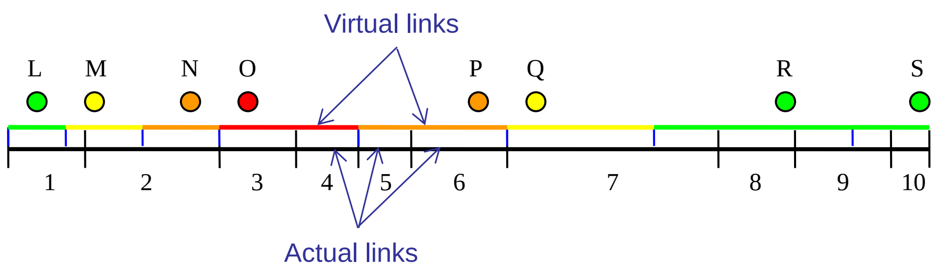


Figure 2-4. Projection of point measurements to continuous measurements

For other traffic data sources that provide traffic performance measurements or estimates on a roadway link basis, the processing of the data into DynaNet is straightforward. Figure 2-5 shows a data table in DynaNet that associates real-time traffic speed data with each roadway link.

Time_Stamp	Edge_ID	Speed
2012-04-25 15:30:00	391248	38.49
2012-04-25 15:30:00	392140	38.49
2012-04-25 15:30:00	1603378	57.52
2012-04-25 15:30:00	1690055	57.52
2012-04-25 15:30:00	2686653	57.52
2012-04-25 15:30:00	2686654	57.52
2012-04-25 15:30:00	2686657	64.62
2012-04-25 15:30:00	2925408	64.62
2012-04-25 15:30:00	2925409	64.62
2012-04-25 15:30:00	2925414	64.41
2012-04-25 15:30:00	2925415	64.41
2012-04-25 15:30:00	385182	63.27
2012-04-25 15:30:00	2921665	60.05
2012-04-25 15:30:00	1603518	31.65
2012-04-25 15:30:00	1690058	31.65
2012-04-25 15:30:00	1690059	31.65
2012-04-25 15:30:00	381671	21.3

Figure 2-5. Real-time traffic speed data table in DynaNet

The NAVSTREETS digital roadway map is a two dimensional (2D) map on a ground plane; there is no elevation information. In this project, the research team has integrated road grade data from NAVTEQ into DynaNet so that it can be accounted for when estimating vehicle fuel consumption. The integration method is illustrated in Figure 2-6. Link B in the 2D map is bounded by the starting and ending nodes. When considering the roadway elevation on this link, there are three distinct road grade levels as separated by the two inflection points, thus breaking this link into three sublinks. Each sublink is defined in the DynaNet road grade data table by its sequence in the link and the distance from the starting node of the link, as shown in Figure 2-7.

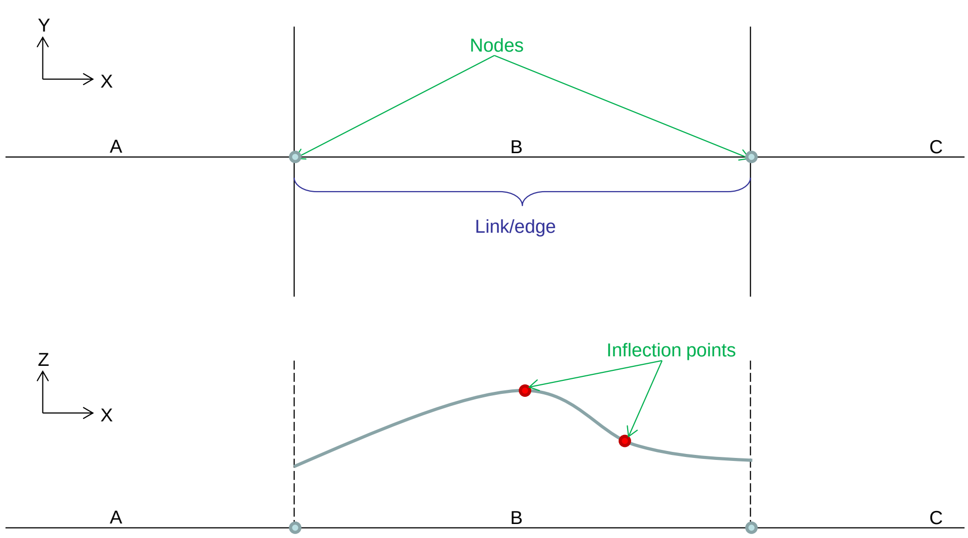


Figure 2-6. Integrating road grade data into digital roadway map

Link_ID	Sequence_Number	Distance	Grade
23593103	1	10.106039718...	537
23593103	2	26.005687704...	524
23593103	3	62.582112643...	377
23593560	1	67.28965307	-2391
23593562	1	29.981222438...	-1491
23593562	2	37.464598654...	-2333
23593563	1	14.948617045...	-5553
23593563	2	12.955798930...	-4963
23593563	3	40.951709691...	-3987

Figure 2-7. Road grade data table in DynaNet

2.3. Method for Estimating Intersection Delays from Probe Data

As pointed out earlier, the eco-routing navigation module developed in this project has several new and unique capabilities. One of them is the ability to account for turning movements and delays at intersections in eco-route calculation. In order to do this, estimates of delay and fuel consumption associated with each turning movement at intersections in the network are needed. In this project, these estimates were based on smartphone-based probe data provided by Beat the Traffic who is one of the project partners. Beat the Traffic collects location and speed data from millions of its smartphone app users, and use these data to derive and display real-time traffic speed information back to the users. These data have an interval of 20 seconds, which is typical for crowdsourcing traffic data applications. One of the tasks in this project is to develop a method for estimating intersection delays using such probe data so that fuel consumption associated with these delays can be estimated and incorporated into the eco-route calculation.

The method consists of two major parts. The first part is to reconstruct second-by-second trajectory (i.e., position and speed) of vehicles based on their 20-second probe data. Then, in the second part the reconstructed vehicle trajectories can be used to quantify the amount of delays associated with each turning movement at intersections. This section describes the method in detail.

2.3.1. Modal Activity Based Vehicle Dynamic State Model

We model the state of a probe vehicle in a stochastic manner to find an optimal vehicle dynamic state with maximize likelihood. First, we create a sampling pool that consists of all possible modal activity sequences and time/distance of each modal activity under basic assumptions of traffic operation. Then, we focus on those valid vehicle dynamic states that satisfy some specific conditions derived from the data. Finally, the vehicle trajectory is reconstructed from the valid vehicle dynamic state with maximum likelihood.

Modal Activity Sequence

When a vehicle is traveling on an arterial, it experiences stop-and-go behavior repetitively due to traffic control devices and congestion. It can be safely assumed that modal activities of the vehicle evolve with a certain pattern, e.g., idling (“1”) – acceleration (“2”) – cruising (“3”) – deceleration (“4”) – idling (“1”) periodically. Here, we use numbers 1-4 to represent the type of the modal activities. Let M_s (starting mode) and M_e (ending mode) be the modal activities at two consecutive data points. M_p is defined as the number of full modal activity periods. It is one less than the maximum number that one modal activity could appear in a sequence. Therefore, a modal activity sequence between two consecutive data points can be uniquely determined by a tuple (M_s, M_e, M_p). For example, M_s=2, M_e=4, M_p=0 represents an acceleration-cruising-deceleration pattern, and M_s=4, M_e=1, M_p=1 represents a deceleration-idling-acceleration-cruising-deceleration-idling pattern. The total number of modal activities (denoted as K) between two data points can be determined by M_s, M_e and M_p, as

$$K = \begin{cases} M_e - M_s + 4M_p + 1 & \text{if } M_e \geq M_s \\ M_e - M_s + 4M_p + 5 & \text{otherwise} \end{cases} \tag{2-1}$$

In real-world traffic, vehicles do not change their modal activities too frequently. Within certain sampling time interval, it is assumed that there is an upper bound for the number of modal activities (denoted as K_{max}). Here, we consider the case where the time interval between two consecutive data points is no more than 30 seconds, so the number of full modal activity period can only be 0 or 1 if we assume that a full modal activity period takes at least 15 seconds. Then, K_{max} is 8. As a result, there are 32 different modal activity sequences when selecting M_s and M_e from the four modal activities, and M_p from either 0 or 1. If the sampling time interval is longer, one can increase K_{max} accordingly to introduce more possible modal activity sequences, but the computational load will also be increased.

The modal activity sequence could also be presented in another form. We use M_i (i = 1, 2, 3… K_{max}) to represent the i^{th} modal activity between two data points. By definition, $M_1 = M_s$, $M_K = M_e$, and $M_i = 0$ if $K < i \leq K_{max}$. The gathering of all M_i's, denoted as **M**, is a vector of multiple integers ranged from 0 to 4. For example, if M_s=4, M_e=1, M_p=1, then $\mathbf{M} = [4,1,2,3,4,1,0,0]^T$. As **M** is uniquely mapped from (M_s, M_e, M_p), it can also have 32 possible values when K_{max} is 8. We define Ω_M as the set of those values. Then, Ω_M is the sample space of the modal activity vector **M**. The a priori distribution of **M** could be converted to a joint probability distribution of M_s, M_e, and M_p. Here, we assume that the a priori probabilities of M_s and M_e are independent of each other and can be determined from the arrival speed and departure speed, respectively. If the arrival speed is zero, the probability is 1 for M_s=1 (idling mode) and 0 for M_s>1. If the arrival speed is around the free flow speed, the probability that M_s=3 (cruising mode) is about 1. If the vehicle arrives with a speed in between, the probability that M_s is 2 (acceleration) or 4 (deceleration) is high. For the ending mode, M_e is derived in a similar way. We use probability mass function f_M (m, u, v) to represent the probability that a vehicle is in mode m if the vehicle speed is v and the free flow speed is u. Note that in this paper the free flow speed is defined as the average speed when a vehicle is traveling under the cruising mode. The detailed expression and parameters of the function f_M (m, u, v) are provided later. Then, we have the a priori probability of the starting and ending modes in (2-2), assuming that the free flow speed of each vehicle on each link is u_0.

$$\begin{aligned} P(M_s = m_1) &= f_M(m_1, u_0, v_1) \\ P(M_e = m_K) &= f_M(m_K, u_0, v_2) \end{aligned} \tag{2-2}$$

where v_1 and v_2 represent instant speeds of two data points.

The number of full modal activity periods, M_p, is assumed to be independent of M_s and M_e, and follow the integer uniform distribution. Every possible value of M_p has equal probability of $4/K_{max}$. Therefore, the a priori distributions of **M** are estimated by solving (2-3):

$$
\begin{aligned}
&P(\mathbf{M}=\mathbf{m}) \\
&= P(M_s = m_1, M_e = m_K, M_p = \lfloor K/4 \rfloor) \\
&= P(M_s = m_1)P(M_e = m_K)P(M_p = \lfloor K/4 \rfloor) \\
&= f_M(m_1, u_0, v_1) \cdot f_M(m_K, u_0, v_2) \cdot \frac{4}{K_{\max}}
\end{aligned}
\tag{2-3}
$$

where $\lfloor K/4 \rfloor$ represents the integer part of $K/4$.

In the following sections, we first present the basic model that assumes the free flow speed of each vehicle on each link to be a predefined constant. Then, we further discuss the extended model with variable free flow speed.

Valid Vehicle Dynamic State

In the developed modal activity based model, the vehicle dynamic state between two consecutive GPS points is determined by the modal activity sequence (i.e., **M)**, along with the travel time (denoted as T_i) and distance (denoted as X_i) of each mode. We use **T**, a K_{max}-element vector, to represent the set of modal travel times. The i^{th} element of **T** is the travel time of the i^{th} mode. Similarly, we use another K_{max}-vector set, **X**, to represent the set of modal distances. The values of random vectors **T** and **X** (denoted as **t**, **x**) correspond to a valid vehicle dynamic state if and only if the following rules are satisfied.

1. Sample space. As the total number of valid modal activities is *K*, the first *K* elements of **t** and/or **x** are non-negative, and the other elements of **t** and/or **x** are zero. Thus **T** and **X** are defined in the sample space Ω_T and Ω_X, respectively, which are formulated in (2-4).

$$
\begin{aligned}
\Omega_T &= \left\{ \mathbf{t} \middle| t_1 \ge 0, \ldots t_K \ge 0, t_{K+1} \ldots = t_{K_{\max}} = 0 \right\} \\
\Omega_X &= \left\{ \mathbf{x} \middle| x_1 \ge 0, \ldots x_K \ge 0, x_{K+1} \ldots = x_{K_{\max}} = 0 \right\}
\end{aligned}
\tag{2-4}
$$

   where t_i represents the i^{th} element of **t**, and x_i represents the i^{th} element of **x**.

2. Constraint from data. The sum of travel times for all modal activities between two consecutive data points is the sampling time interval Δt. The sum of distances for all modal activities between two consecutive data points is Δx, the distance between the two data points. That is

$$
\sum_{i=1}^{K_{\max}} t_i = \Delta t, \sum_{i=1}^{K_{\max}} x_i = \Delta x \tag{2-5}
$$

Then, the following equation is formulated to estimate the conditional probability of vehicle dynamic state {**m**, **t**, **x**} given sample time interval Δt and sample distance Δx.

$$
\begin{aligned}
&P\left(\mathbf{M}=\mathbf{m}, \mathbf{T}=\mathbf{t}, \mathbf{X}=\mathbf{x} \middle| \sum_{i=1}^{K_{\max}} T_i = \Delta t, \sum_{i=1}^{K_{\max}} X_i = \Delta x \right) \\
&= \alpha P\left(\mathbf{M}=\mathbf{m}, \mathbf{T}=\mathbf{t}, \mathbf{X}=\mathbf{x}, \sum_{i=1}^{K_{\max}} T_i = \Delta t, \sum_{i=1}^{K_{\max}} X_i = \Delta x \right)
\end{aligned}
\tag{2-6}
$$

where the normalization factor α is given as $\alpha = \dfrac{1}{P\left(\sum_{i=1}^{K_{\max}} T_i = \Delta t, \sum_{i=1}^{K_{\max}} X_i = \Delta x\right)}$.

For a valid vehicle dynamic state {**m**, **t**, **x**}, due to the data constraint $\sum_{i=1}^{K_{\max}} t_i = \Delta t, \sum_{i=1}^{K_{\max}} x_i = \Delta x$, the fourth and fifth events of (2-6) always hold. The conditional probability in (2-6) is hence reduced to $\alpha P(\mathbf{M} = \mathbf{m}, \mathbf{T} = \mathbf{t}, \mathbf{X} = \mathbf{x})$. Otherwise, the probability is 0 as there are two null events in the expression. In the next section, we will estimate the probability of a valid vehicle dynamic state.

Vehicle Dynamic State Probability Estimation

For a valid vehicle dynamic state that satisfies the data constraint on time and distance, we aim to estimate $\alpha P(\mathbf{M} = \mathbf{m}, \mathbf{T} = \mathbf{t}, \mathbf{X} = \mathbf{x})$, a joint probability of $3K_{\max}$ (e.g., 24 if $K_{\max}$ is 8) events. If we want to investigate the correlation between those events solely using machine learning techniques, a large amount of training data and heavy computation load are required. Therefore, it is necessary to decompose this large problem into several sub-problems based on vehicle kinematics knowledge.

We first take a deeper look at the four types of modal activities. For the idling mode, the vehicle does not move and the idle time is affected by the signal and the queue. To quantify the idling process, we assume that the idle time follows a uniform distribution.

The time and distance of the cruising mode mainly depend on the distance between the intersections and the queue lengths. We consider the cruising time to be uniformly distributed with the average speed equal to the free flow speed. Thus, the modal distance is also uniformly distributed.

The acceleration and deceleration modes are less impacted by signal timing and intersection spacing. Thus, we could use historical data to create time/distance distributions based on the vehicle speeds at the beginning and the end of the mode (details provided in Section III). Here, we assume that the acceleration pace (i.e., the reciprocal of the average acceleration rate) follows a Gaussian distribution. Meanwhile, the distance that the vehicle has traveled during acceleration mode follows another Gaussian distribution factored by the modal travel time and speed. Similarly, we can formulate and parameterize two other Gaussian distributions to model the travel time and distance of the deceleration mode.

In summary, the modal travel time T_i is independent of the time and distance of other modes for a given modal type M_i. The activity distance X_i is independent of the time and distance of other modes for given M_i and T_i. As **t** and **x** are continuous variables, the general form of the conditional probability density function for T_i and X_i are:

$$\begin{aligned} &P\left(T_i = t_i \middle| M_i = m_i\right) = f_T(m_i, u_0, v_1, v_2) \\ &P\left(X_i = x_i \middle| T_i = t_i, M_i = m_i\right) = f_X(t_i, m_i, u_0, v_1, v_2) \end{aligned} \tag{2-7}$$

The vehicle dynamic state probability is then reformulated as the product of probabilities of multiple independent events as follows:

$$
\begin{aligned}
&\alpha P(\mathbf{M}=\mathbf{m},\mathbf{T}=\mathbf{t},\mathbf{X}=\mathbf{x}) \\
&=\alpha P(\mathbf{X}=\mathbf{x}|\mathbf{T}=\mathbf{t},\mathbf{M}=\mathbf{m})P(\mathbf{T}=\mathbf{t}|\mathbf{M}=\mathbf{m})P(\mathbf{M}=\mathbf{m}) \\
&=\alpha\prod_i P(X_i=x_i|T_i=t_i,M_i=m_i) \\
&\quad\cdot\prod_i P(T_i=t_i|M_i=m_i)\cdot P(\mathbf{M}=\mathbf{m})
\end{aligned}
\tag{2-8}
$$

The probability mass or density functions in (2-3) and (2-7) are substituted in (2-8) to derive $f_{M,T,X}$, the joint probability density of a certain vehicle dynamic state {**m**, **t**, **x**}.

$$
\begin{aligned}
f_{M,T,X} =&\alpha\prod_i f_X(t_i,m_i,u_0,v_1,v_2)\cdot\prod_i f_T(m_i,u_0,v_1,v_2) \\
&\cdot f_M(m_1,u_0,v_1)\cdot f_M(m_K,u_0,v_2)\cdot\frac{4}{K_{\max}}
\end{aligned}
\tag{9}
$$

Extended Model with Variable Free Flow Speed

The aforementioned model assumes that the free flow speed of each vehicle on each link is a predefined constant u_0. This may not be the case in the real world. First, the speed limits of roadway links may vary, so the free flow speed should not be considered as a constant. Even for the same link, the free flow speeds of different vehicles may not be the same due to variable traffic conditions and driving behaviors. To address the variability of the free flow speed, we introduce a new vehicle dynamic state variable, U, which represents the free flow speed. Then, the conditional probability of vehicle dynamic state {**m**, **t**, **x**, u} given a sample time interval Δt and a sample distance Δx is formulated based on (2-6):

$$
P\left(\mathbf{M}=\mathbf{m},\mathbf{T}=\mathbf{t},\mathbf{X}=\mathbf{x},U=u\middle|\sum_{i=1}^{K_{\max}}T_i=\Delta t,\sum_{i=1}^{K_{\max}}X_i=\Delta x\right)
\tag{10}
$$

If the data constraints $\sum_{i=1}^{K_{\max}}t_i=\Delta t,\sum_{i=1}^{K_{\max}}x_i=\Delta x$ are satisfied, the problem in (2-10) is converted to αP(**M** = **m**, **T** = **t**, **X** = **x**, U = u). Due to the independency assumptions discussed in the previous part, it is extended as follows:

$$
\begin{aligned}
&\alpha P(\mathbf{M}=\mathbf{m},\mathbf{T}=\mathbf{t},\mathbf{X}=\mathbf{x},U=u) \\
&=\alpha\prod_i P(X_i=x_i|T_i=t_i,M_i=m_i,U=u) \\
&\quad\cdot\prod_i P(T_i=t_i|M_i=m_i,U=u) \\
&\quad\cdot P(\mathbf{M}=\mathbf{m}|U=u)\cdot P(U=u)
\end{aligned}
\tag{11}
$$

In (2-11), $P(U = u)$ is the a priori probability of the free flow speed which is directly estimated from the test dataset before the vehicle dynamic state estimation. We first use the starting, ending, and average speeds as filters to preliminarily select trips that are under cruising mode. Then, we assume that the free flow pace (i.e., the reciprocal of the free flow speed, denoted as w) follows a truncated Gaussian distribution with lower bound w_l and upper bound w_u. The mean value, μ, and standard deviation, σ, can be trained from the observed free flow pace data. The probability density function of the free flow speed is then formulated as follows:

$$f_U(u)=\frac{\frac{1}{\sigma}\phi(\frac{1/u-\mu}{\sigma})}{\Phi(\frac{w_u-\mu}{\sigma})-\Phi(\frac{w_l-\mu}{\sigma})} \tag{12}$$

where $\phi(\cdot)$ is the probability density function of the standard Gaussian distribution and $\Phi(\cdot)$ is its cumulative distribution function.

$P(\mathbf{M} = \mathbf{m} \mid U = u)$ is the probability of the modal activity vector given the free flow speed. According to the discussions in Section II-A, we can compute the conditional probability by replacing u_0 in (2-2) with u. Therefore, we can rewrite (2-3) into

$$P\left(\mathbf{M}=\mathbf{m}\middle|U=u\right)=f_M(m_1,u,v_1)\cdot f_M(m_K,u,v_2)\cdot\frac{4}{K_{\max}} \tag{13}$$

Similarly, the conditional probability density functions in (2-7) are reformulated to adapt to the variable free flow speed as follows:

$$\begin{aligned}&P\left(T_i=t_i\middle|M_i=m_i,U=u\right)=f_T(m_i,u,v_1,v_2)\\&P\left(X_i=x_i\middle|T_i=t_i,M_i=m_i,U=u\right)=f_X(t_i,m_i,u,v_1,v_2)\end{aligned} \tag{14}$$

We then substitute (2-12), (2-13), and (2-14) in (2-11) to calculate the probability density function of vehicle dynamic state {**m**, **t**, **x,** u}.

$$\begin{aligned}f_{M,T,X,U}=&\alpha\prod_i f_X(t_i,m_i,u,v_1,v_2)\cdot\prod_i f_T(m_i,u,v_1,v_2)\\&\cdot f_M(m_1,u,v_1)\cdot f_M(m_K,u,v_2)\cdot f_U(u)\cdot\frac{4}{K_{\max}}\end{aligned} \tag{15}$$

Note that we only present a descriptive characterization of modal activities in this section. The numerical formula and parameters for f_X, f_T, and f_M are calibrated in the next section.

2.3.2. Modal Calibration

In this section, we calibrate the distribution parameters for the vehicle trajectory estimation model proposed in Section II. Before the calibration, we first discuss what we can learn from historical data in a traffic model. Unlike many other phenomena, traffic flow is a non-stationary process. The behavior of a vehicle in traffic flow is impacted by the surrounding traffic condition, upcoming signal, road geometry, weather, and many other factors. The use of historical data from one environment to estimate or predict traffic flow in a different environment will likely result in estimation or prediction errors. In order to reduce the biases due to the environment as much as possible, we need to make some assumptions.

Here, we assume acceleration and deceleration to be stationary processes as they are less impacted by the environment, and calibrate them using the NGSIM dataset from Lankershim Blvd in Los Angeles, California[5]. We extract the second-by-second vehicle trajectories (during the period from 8:30 a.m. to 8:45 a.m.) from the dataset and use them to calibrate the three probability mass functions: f_M for modal activity identification, f_T for modal travel time, and f_X for modal distance.

Modal Activity Identification

As discussed earlier, the probability that a data point is under a certain mode is determined by the vehicle speed *v* and the free flow speed *u*. We first consider the low speed and high speed cases. If the speed of the vehicle is zero or very low (e.g., less than 1 ft/s), the probability is set to 1 for the idling mode (*m*=1) and 0 for the other modes. In Section II-A, we define the free flow speed as the average speed for the cruising mode, so the actual speed of a vehicle in a data point may exceed the free flow speed. For those high-speed cases (i.e., above the free flow speed), the probability is 1 for the cruising mode (*m*=3) and 0 for the other modes.

If the vehicle is traveling with a speed right below the free flow speed, the modal activity is not that easy to determine. It could still be in the cruising mode as the speed may be fluctuating below the free flow speed when cruising. It could also be at the beginning of a deceleration process or at the end of an acceleration process. Estimating the probability of any of those three modal activities is non-trivial. When the speed is lower than that, the probability of acceleration or deceleration increases and the probability of cruising drops. If the speed is below a critical value, the probability of cruising becomes zero--the vehicle is either accelerating or decelerating. Here, we assume that this critical speed value is proportional to the free flow speed, i.e., βu, where $0<\beta<1$ is the proportional coefficient. Therefore, the probability of cruising increases linearly from 0 to 1 when the speed changes from βu to *u*. Thus, the probability function of the cruising mode (*m*=3) is estimated via (2-16).

$$f_M(3,u,v)=\begin{cases}1 & \text{if } v\geq u\\ 1-\dfrac{u-v}{u(1-\beta)} & \text{if } \beta u\leq v<u\\ 0 & \text{otherwise}\end{cases} \tag{16}$$

The proportional coefficient β is calibrated based on NGSIM data. In the training dataset, we use second-by-second vehicle trajectories to compute the average free flow speed for each cruising period of each vehicle, and mark each data point with its observed modal activity. The observed frequency table of the cruising mode given the speed and free flow speed is then generated based on the training dataset. On the other hand, we can also estimate the frequency table via (2-16) for any given proportional coefficient β. As the mean absolute error (MAE) of the frequency estimation is minimized when β is 0.57, we take 0.57 as the calibrated coefficient in (2-16).

If the vehicle speed is between βu and *u*, the probability that the vehicle is in either acceleration or deceleration mode is $\frac{u-v}{u(1-\beta)}$. If the speed is between 1 ft/s and β *u*, the total probability of both acceleration and deceleration modes is 1. We assume that the probability of acceleration (*m*=4) and deceleration mode (*m*=2) are equal, so their probability mass functions are

[5] Next Generation SIMulation, http://ngsim-community.org/. Accessed Nov 20, 2014.

$$f_M(2,u,v){=}f_M(4,u,v)=\begin{cases}0.5 & \text{if } 1\le v<\beta u\\ \dfrac{u-v}{2u(1-\beta)} & \text{if } \beta u\le v<u\\ 0 & \text{otherwise}\end{cases} \tag{17}$$

Figure 2-8 illustrates the probability of the four modes as a function of vehicle speed. In this figure, each mode covers a specific region, and the vertical length of the region at a certain speed is the probability of that mode at that speed.

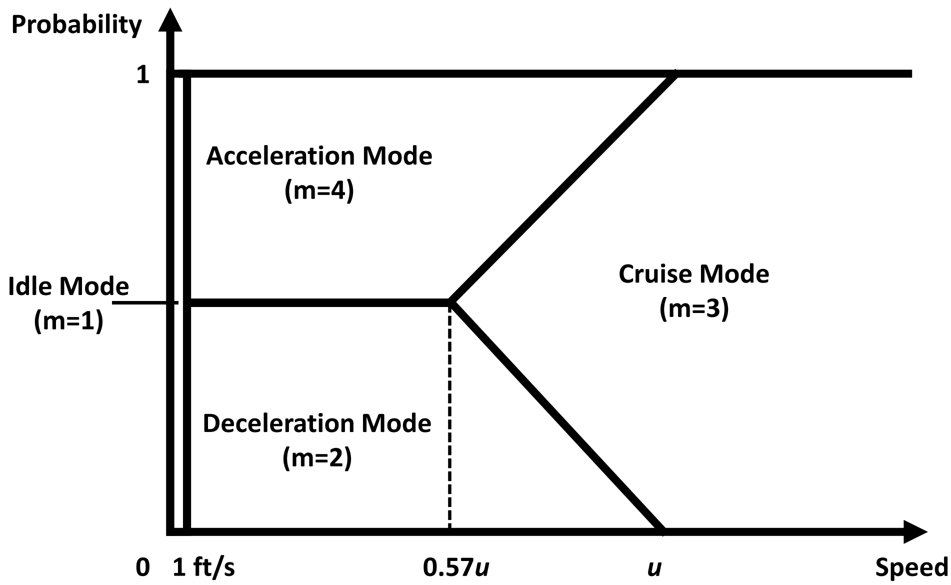


Figure 2-8. Modal probability mass function vs. vehicle speed

Mode Travel Time and Distance

According to (2-14), the conditional probability density functions of modal travel time and distance, f_T and f_X, are mode-specific. We first calibrate these functions for the acceleration and deceleration modes. As stated earlier, we assume that the acceleration pace follows a Gaussian distribution, so the travel time t that a vehicle has spent in the acceleration mode is the product of speed variation v'_2- v'_1 and a Gaussian-distributed factor.

$$t{=}(v'_2-v'_1)\phi_1 \quad \text{where } \phi_1 \sim N(\mu_1,\sigma_1^2) \tag{18}$$

In (2-18), v'_1 and v'_2 are vehicle speeds at the beginning and the end of the acceleration mode. If acceleration is the first mode for the data point pair, then v'_1 is equal to the speed at the first data point v_1 and v'_2 is the free flow speed u. If it is the last mode for the data point pair, then we have v'_1=0 and v'_2=v_2. If acceleration is neither the first nor the last mode, it is a complete acceleration process with speed increasing from 0 to u.

In the training dataset, second-by-second vehicle speed profiles are available. This provides sufficient acceleration data to determine travel time and speed variation. The parameters μ_1 and σ_1 of the Gaussian distribution $N(\mu_1,\sigma_1^2)$ could then be fitted via the Maximum Likelihood Estimation (MLE) method using sample acceleration paces derived from the time and speed information. Here, we categorize the training dataset into two groups and fit them separately. The low speed group includes sample acceleration paces from zero speed to any other speeds. The high speed group includes sample acceleration paces from any speed to the free flow speed. The mean and standard deviation of each group are listed in Table 2-1. The units of distance, time, and speed are feet, seconds and feet/second, respectively. The acceleration paces is higher at the end of the acceleration process because the acceleration rate is reduced in the adjustment phase when the vehicle is approaching the free flow speed. Similarly, the parameters for deceleration processes are also learned from the training dataset. Table 2-1 shows that deceleration is also slowed down in the adjustment phase right before the stop.

Table 2-1. Parameters for acceleration and deceleration

	Acceleration Pace φ_1		**Deviation Factor φ_2**	
	Mean	**S.D**	**Mean**	**S.D**
Acceleration (low speed)	0.2347	0.0843	0.5090	0.1049
Acceleration (high speed)	0.2923	0.1223	0.5170	0.0483
Deceleration (low speed)	0.2659	0.1061	0.4511	0.1096
Deceleration (high speed)	0.2369	0.1144	0.5086	0.0505

We then assume that the distance x a vehicle travels in the acceleration mode follows

$$x = t(v'_2 + v'_1)\phi_2 \quad \text{where } \phi_2 \sim N(\mu_2, \sigma_2^2) \tag{19}$$

If the acceleration process follows a constant acceleration motion, we have $x = t(v'_1 + v'_2)/2$. ϕ_2 is another Gaussian multiplier that measures how far the acceleration process is deviated from the constant acceleration motion. The parameters μ_2 and σ_2 of the Gaussian distribution $N(\mu_2,\sigma_2^2)$ can also be fitted using the MLE. Correspondingly, we can estimate the parameters for the deceleration process following the same steps. The last four rows of Table I show the basic statistics of deviation factor distribution of both processes in this model. The mean values for all cases are around 0.5, but the standard deviation is much higher at lower speed as the acceleration/deceleration rate is more heterogeneous at lower speed.

For the idling and cruising modes, the mode times mainly depend on the signal plan, traffic condition, and intersection spacing. In this model, we suppose that the signal plan and map information are not available, so the idling and cruising modal travel times are assumed to be uniformly distributed, ranging from zero to the sampling time interval. As the average speed for the cruising mode equals the free flow speed, the cruising modal distance is also uniformly distributed. Then, we could formulate the modal travel time function f_T and modal distance function f_X for given mode and speed variables. They are substituted in (2-15) with f_M to derive the probability density for any vehicle dynamic state {**m**, **t**, **x,** u}.

2.3.3. Vehicle Trajectory Reconstruction

Based on the proposed vehicle dynamic state model and the calibrated probability functions, the probability density for a certain modal activity sequence, given mode time/distance and free flow speed, is calculated via (2-15). To compute the probability values efficiently, we further discretize the temporal, spatial, and speed domains with appropriate steps, e.g., 1 s, 5 ft, and 1 ft/s, respectively.

Figure 2-9 illustrates the process to estimate the probability of a certain vehicle dynamic state. The sample time interval is 20 seconds and the distance between the two samples is 320 ft. The arrival speed is 33 ft/s and the departure speed is 36 ft/s. For this scenario, the modeled modal activity sequence is deceleration-idling-acceleration. Given the free flow speed of 47 ft/s, the probability is 0.34 for deceleration at the first data point, and 0.27 for acceleration at the second point based on (2-17). The time of each mode is 9/2/9 seconds, respectively. The distance of each mode is 145/0/175 ft, respectively. We can compute the conditional probability of mode time and distance via (2-14). Notice that we discretize the temporal and spatial domains in this problem, so the probability shown in Figure 2-9 is actually the integration of all probability densities around this state. Finally, the probability of this specific vehicle dynamic state is the product of all conditional probabilities.

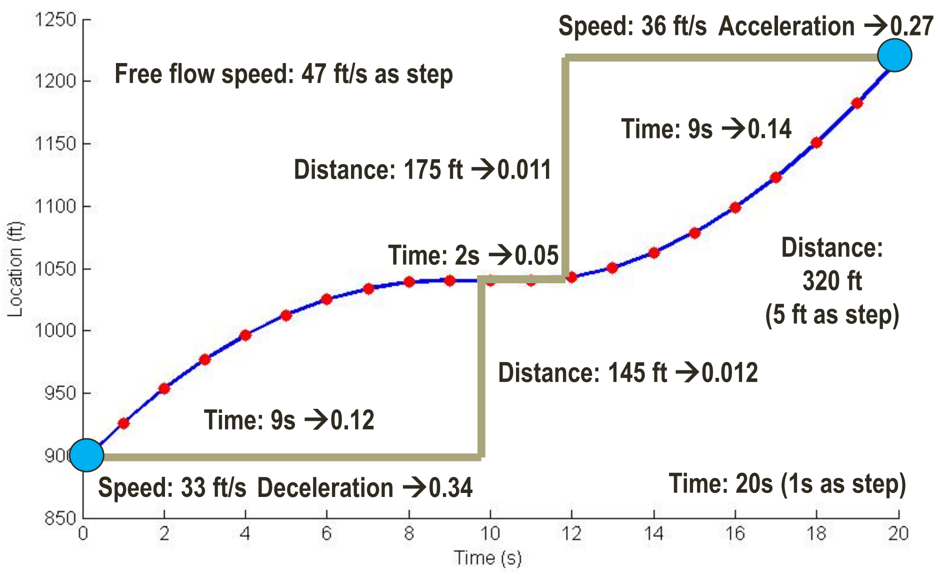


Figure 2-9. Vehicle state probability estimation

Based on the probability estimation results of all the vehicle dynamic states, we first find the optimal mode sequence which maximizes the marginal likelihood of **M** under the condition of the data constraint (2-5).

$$\begin{aligned}\mathbf{m}^* &= \arg\max_{\mathbf{M}} P\left(\mathbf{M} \middle| \sum_{i=1}^{K_{\max}} T_i = \Delta t, \sum_{i=1}^{K_{\max}} X_i = \Delta x\right) \\ &= \arg\max_{\mathbf{M}} \sum_{\mathbf{T}} \sum_{\mathbf{X}} \sum_{U} P\left(\mathbf{M}, \mathbf{T}, \mathbf{X}, U \middle| \sum_{i=1}^{K_{\max}} T_i = \Delta t, \sum_{i=1}^{K_{\max}} X_i = \Delta x\right)\end{aligned} \tag{20}$$

Then we find the best scenario under the optimal mode sequence $\mathbf{m}^*$. Here the best scenario is defined as a combination of **T**, **X**, and *U* that maximizes the conditional probability

$$\arg\max_{\mathbf{T},\mathbf{X},U} P\left(\mathbf{T}, \mathbf{X}, U \middle| \mathbf{M} = \mathbf{m}^*, \sum_{i=1}^{K_{\max}} T_i = \Delta t, \sum_{i=1}^{K_{\max}} X_i = \Delta x\right) \tag{21}$$

The vehicle trajectory reconstruction method is then applied to this scenario by computing the location and speed at each second. For the acceleration/deceleration mode, we consider the acceleration rate as a linear function of time such that the time, distance, and start/end speed of each mode would be consistent with each other.

The model above is applicable to a vehicle that has two data points. If there are more than two data points, we have to introduce another condition in (2-10) to guarantee that the mode at the end of the previous data pair and the mode at the beginning of the next data pair are the same. If a vehicle has N data points, the optimal modal activity sequence is the one that maximize the product of the conditional mode probabilities of all N-1 data point pairs. As more data point pairs provide more constraints to the problem, the estimation performance could be enhanced.

Numerical Experiments

The proposed model is also validated using the NGSIM Lankershim Blvd dataset but for a different time period. We use the data from 8:45 a.m. to 9:00 a.m. as the test dataset. As shown in Fig. 4, there are 5 links and 4 intersections in the study corridor. The raw data are processed into mobile sensor data form with 20-second sampling interval. There are totally 894 vehicles and 2,744 data point pairs in the test dataset.

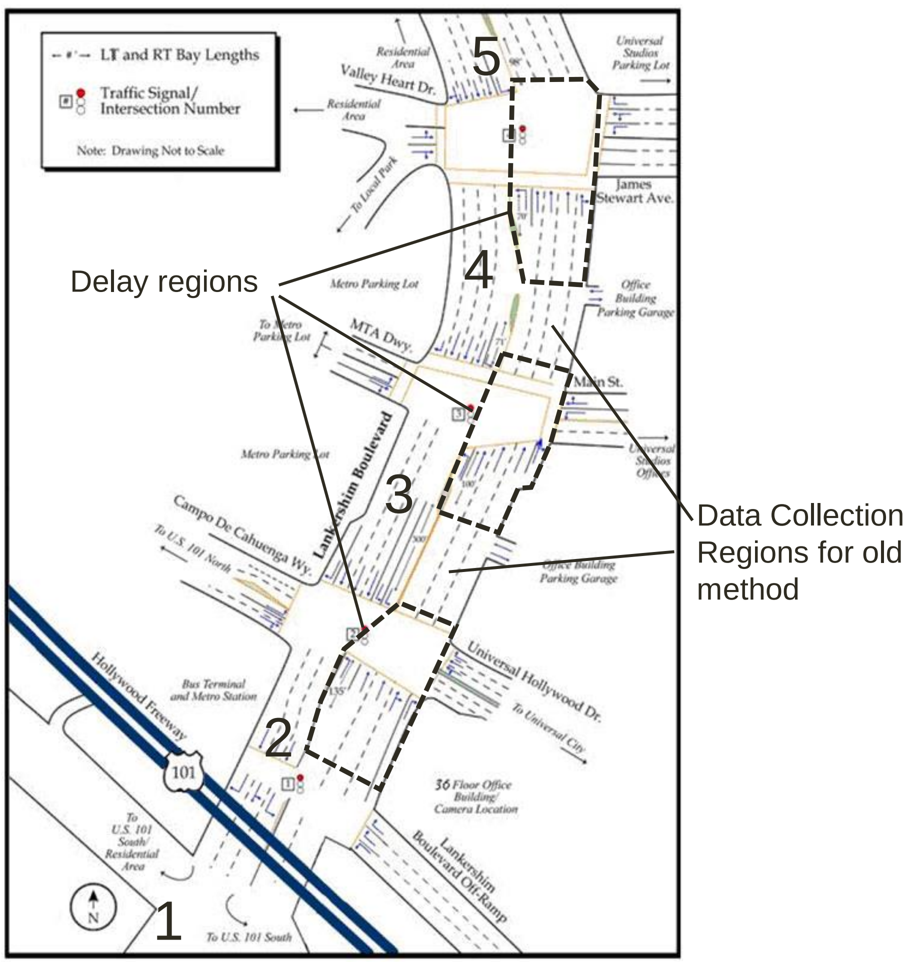


Figure 2-10. Lankershim Blvd corridor in NGSIM

Figure 2-11 shows the estimation results of vehicle trajectories. We plot the observed and estimated time-space trajectories of all vehicles in a signal cycle at one of the intersections. The smooth red solid curves represent the observations, and the blue curves with dots represent the estimates. As shown in this figure, the observed and estimated curves match well with each other for most of the times. For a few vehicles, the mode sequences are correctly estimated but the estimated trajectories are slightly deviated from the ground truth.

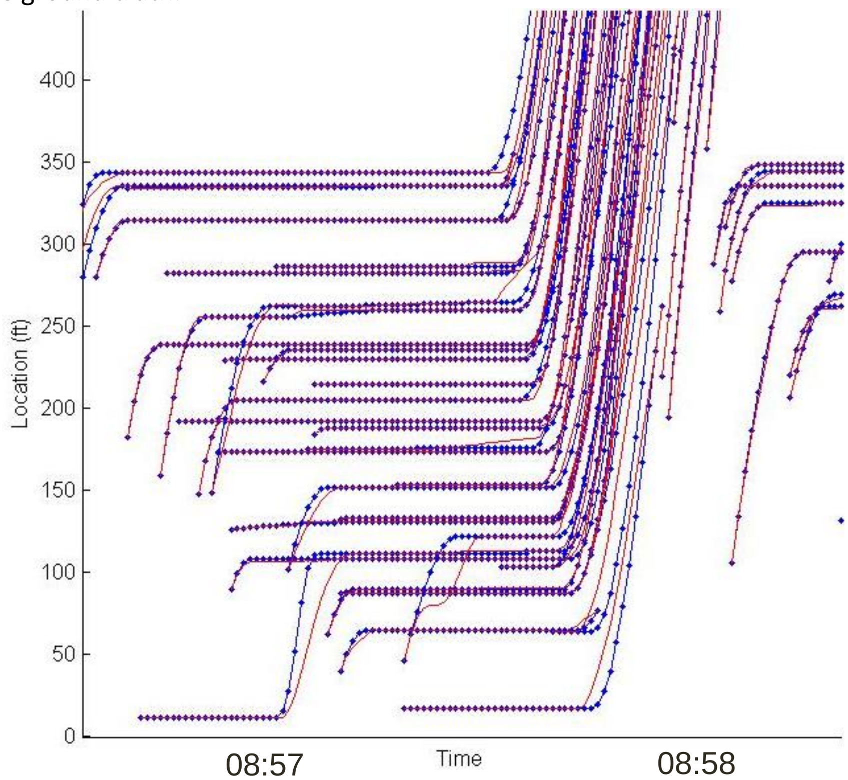


Figure 2-11. Results of vehicle trajectory estimation in NGSIM

For the entire test dataset, the proposed model is successfully applied to all data point pairs. The Mean Absolute Error (MAE) of the second-by-second location estimation is 9.5 ft. The model is also able to estimate the vehicles' modal activities at each second correctly for 79.7%. As 25.9% of the data point pairs are idling pairs (i.e., the vehicles do not move during the 20 seconds), the estimation performance might be overestimated by including them in the result. If we only consider non-idling data point pairs, the MAE of vehicle location estimation increases to 12.6 ft, and the percentage of correct mode estimation becomes 72.7%.

To put the estimation performance of the proposed method in context, we compare the results above with those from a baseline method which creates vehicle trajectories by linear interpolation. As the MAE of vehicle location estimation for the baseline method is 30.6 ft, the proposed method reduces the error by 69.0%. When considering only non-idling data point pairs, the MAE for the baseline method is 41.2 ft, so the MAE for the proposed method is reduced by 69.4%. These comparisons show that the proposed method significantly improves the vehicle trajectory estimation performance over the baseline method.

The Mean Absolute Percentage Error (MAPE) is also computed based on the estimated vehicle trajectories. For each second of each vehicle, we calculate the relative error by dividing the absolute error by the distance that the vehicle traveled between two data points. The MAPE is the mean value of all the relative errors for all non-idling data point pairs. The idling pairs are not included as the distance for the idling mode is or around zero. For the entire test dataset, the MAPE is 4.3% for the proposed method and 20.1% for the baseline method.

We further show the variations of MAPE as a function of the distance between two data points. In Figure 2-12, the blue solid curve represents the MAPE for the proposed method while the red dashed curve represents that for the baseline method. We choose 50 ft as the distance increment. The estimation errors are aggregated from the data pairs whose distance is within each interval. Then, the MAPE for each interval is calculated and plotted with dot in the middle of the interval in Fig. 6. For the proposed method, the MAPE curve oscillates around 5% for the distance between data points of less than 600 ft, and drops to around 1.5% for a longer distance. For the baseline method, the MAPE is very high in the case of short distance, e.g., above 30% for the distance of less than 200 ft. The MAPE curve for the baseline method approaches that for the propose method as the distance gets longer. This is because the vehicles are more likely to be in cruising mode where the estimated vehicle trajectories by both methods are just straight lines.

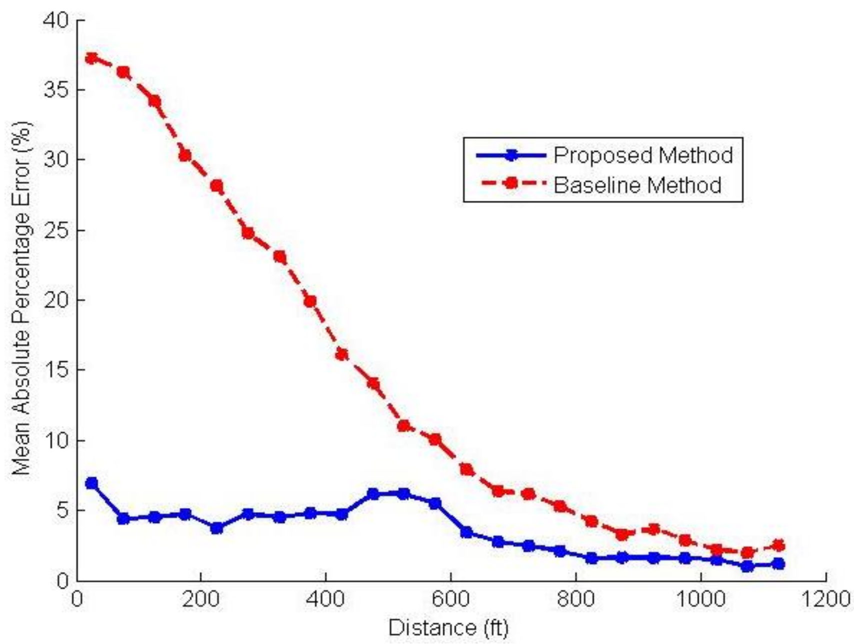


Figure 2-12. MAPE vs. distance of two data points

These results indicate that the estimation performance of the proposed method is promising, and it outperforms the baseline method significantly. Additionally, the proposed model is applicable to varying traffic conditions without the knowledge of signal plan or map information. Although we only use arterial roads as examples in the calibration and validation of the proposed model, it should also work for freeways in detecting congestion regions and periods. This model requires much less training data than a typical machine learning based model as it incorporates well-established knowledge on vehicle kinematics.

Application to a Large-scale Network in Los Angeles, CA

The proposed vehicle trajectory estimation model and its application to arterial travel time distribution estimation have been validated by the NGSIM dataset. Next, we apply the proposed method to a large-scale dataset for Los Angeles, California, obtained from Beat the Traffic. This dataset contains about 5 million GPS data records on more than 177,000 links for a period between June 2011 and August 2013. In this dataset, most vehicles are sampled every 20 seconds, but some of them have smaller or larger sampling intervals. As the GPS data have already been well map-matched, we directly input them into the proposed model to estimate the vehicle trajectories between data points. A dictionary-based method is used to deal with the large-scale dataset efficiently. First, we categorize the data point pairs into 60,886 cases by the sampling interval, distance, and speed. For each case, we estimate the optimal vehicle trajectory using the proposed model that is trained by the NGSIM dataset from Lankershim Blvd, which is also located in Los Angeles, California. Thus, we do not need to repeat all the modeling steps for each data point pair. Instead, we just search the dictionary for the applicable case and adopt the optimal vehicle trajectory for that case.

The estimated vehicle trajectories can then be used in many traffic analyses. For example, we show the hourly variation of average link delay of three typical links in Figure 2-13. The average delay curve for Link A has a significant increase around 5 p.m. as the link is congested during the PM peak period. Link B, on the contrary, has an AM peak but no PM peak. Link C has both AM and PM peaks as well as a midday peak between 11 a.m. and 1 p.m. Figure 2-13 shows that mobile sensor data can help measure or estimate traffic conditions, even under low penetration rate and sampling rate. The dictionary-based approach also provides an efficient way to deal with crowd-sourced big data not only from mobile sensors but also from other tracking techniques such as Bluetooth Mac address matching, wireless magnetic sensors, and Connected Vehicles technology.

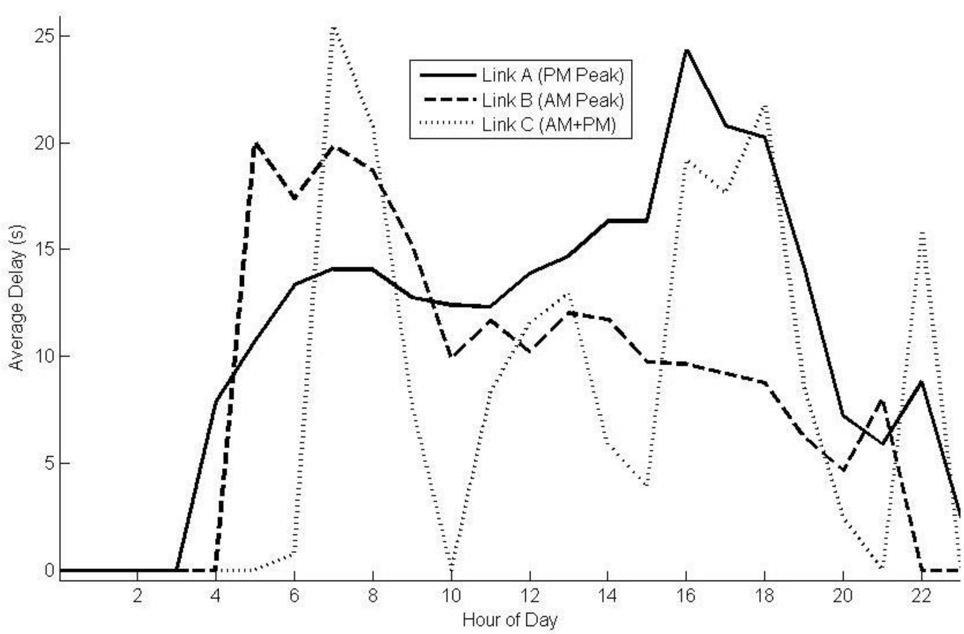


Figure 2-13. Hourly variation of average link delay

3. Eco-Driving Feedback Module

3.1. Overview

The eco-driving feedback module is a client application running on the in-vehicle device. It provides various types of driving feedback to the driver in a way that balances between driver's acceptance and driver's distraction. The system architecture of the eco-driving feedback module is depicted in Figure 3-1 and described briefly below.

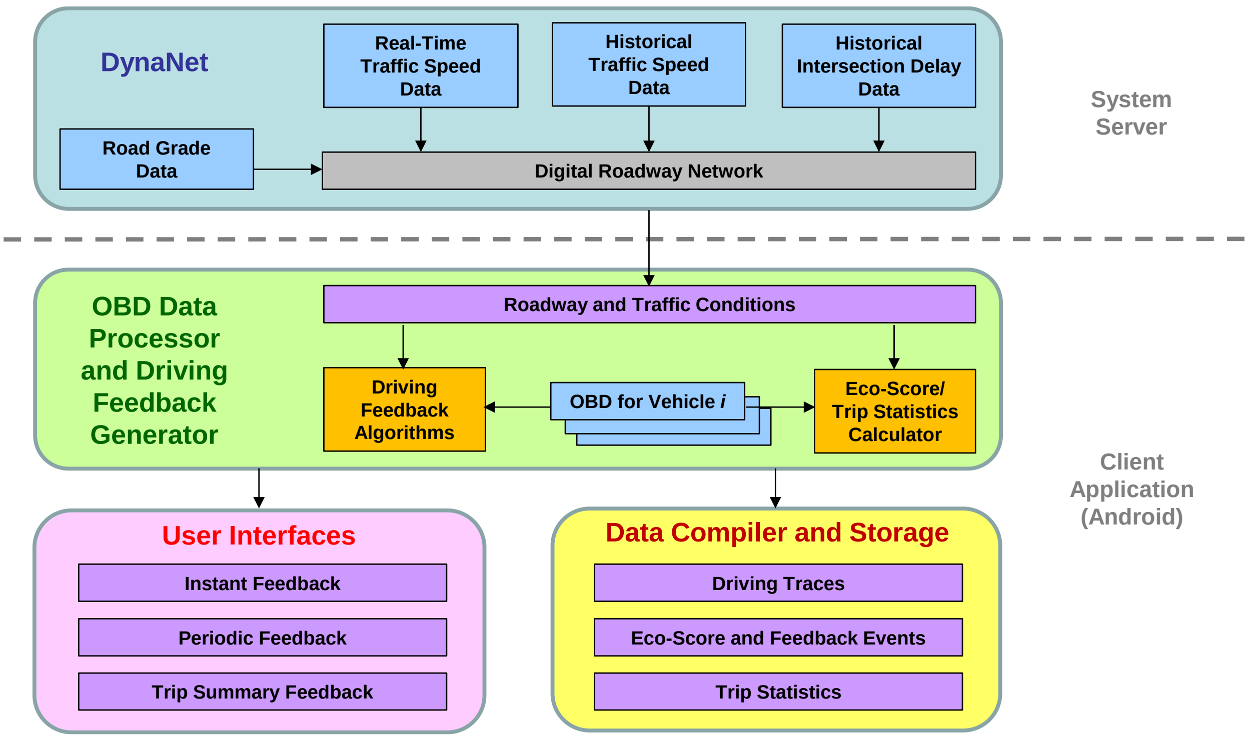


Figure 3-1. System architecture of Eco-Driving Feedback module

- **DynaNet** – Dynamic Roadway Network Database is a digital roadway map that has been enhanced by various kinds of roadway-related data. The underlying digital roadway map in DynaNet is NAVSTREETS from NAVTEQ. Roadway-related data that have been added to DynaNet includes road grade, historical traffic speed, and real-time traffic speed, all from NAVTEQ. Work is being done to generate historical intersection delay data to be added to DynaNet.

- **OBD Data Processor and Driving Feedback Generator** – This component takes the OBD data from the vehicle along with road grade and traffic data from DynaNet, and then processes them through driving feedback algorithms as well as Eco-Score and trip statistics calculator to generate driving feedback for the driver.

- **User Interfaces** – The user interfaces present the different types of driving feedback (i.e., instant, periodic, and trip summary) to the driver in various forms.

- **Data Compiler and Storage** – This component compiles and temporarily stores driving traces of the driver, Eco-Score and feedback given to the driver, as well as the calculated trip statistics before sending these data to the system server.

3.2. Review of Eco-Driving Feedback

3.2.1. Literature Review

In the project, literature related to eco-driving feedback design was reviewed. Among all the reviewed studies, the most relevant one was the study on fuel economy driver interfaces (FEDIs) sponsored by the National Highway Traffic Safety Administration (NHTSA)[6, 7]. The study consisted of three main tasks. Task 1 was to catalogue existing FEDIs. Task 2 was to conduct focus group of vehicle owners to assess their driving habits and opinions about the usefulness and potential for distraction of FEDI designs. Finally, Task 3 was to develop interface recommendations based on usability evaluation and driving simulation evaluation. As an example, the FEDI designs evaluated for usability are shown in Figure 3-2.

Key findings from the NHTSA study include:

- FEDIC designs that presented multiple types of fuel economy information or behavioral information (e.g., acceleration) within a simple display aligned best with user-needs.
- Horizontal bars and/or simple representations (i.e., pictures) of fuel economy information are preferred to text representation.
- Participants made significant improvements in fuel economy just by being asked to drive fuel efficiently, even without the presence of a FEDIC.

The NHTSA study provides the following recommendations regarding the design of FEDIs:

- Present more than one fuel economy information type
- Use horizontal bar and/or symbolic representations of fuel economy information
- Set reference points on fuel economy bars or symbols that indicate “good” versus “poor” performance
- Display fuel economy information during slower-speed or stop-and-go driving
- Limit the amount of attention required to view and understand the information presented

Another relevant study was conducted by the National Renewable Energy Laboratory (NREL)[8] to assess various driver feedback approaches. Key recommendations from this study are given below. In addition, the study presents a simple way for retrofitting existing speedometer with reference points for efficient driving, as shown in Figure 3-3.

- Provide simple and effective instruction on how to drive more efficiently
- Provide useful reference points
- Provide incentives to drivers

[6] James W. Jenness, Jeremiah Singer, Jeremy Walrath, and Elisha Lubar (2009). Fuel Economy Driver Interfaces: Design Range and Driver Opinions. Report No. DOT HS 811 092, National Highway Traffic Safety Administration, August.

[7] Michael P. Manser, Michael Rakauskas, Justin Graving, James W. Jenness (2010). Fuel Economy Driver Interfaces: Develop Interface Recommendations. Report No. DOT HS 811 319, National Highway Traffic Safety Administration, May.

[8] Jeffrey Gonder, Matthew Earleywine, and Witt Sparks (2011). Final Report on the Fuel Saving Effectiveness of Various Driver Feedback Approaches. Report No. NREL/MP-5400-50836, National Renewable Energy Laboratory, March.

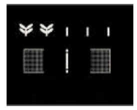
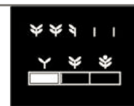
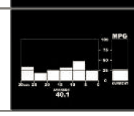
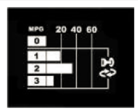
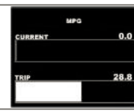
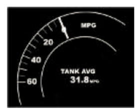
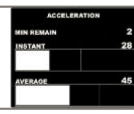
CS01		Intensity-changing light + Text MPG
CS02		Representative picture + Acceleration/ Deceleration Bar
CS03		Representative picture + Horizontal MPG Bar
CS04		Vertical Graph of Instantaneous + Trip MPG
CS05		Horizontal Graph of Trip + Horizontal Graph of Average MPG
CS06		Horizontal Graph of Instantaneous + Trip
CS07		Leftward Dial + Text MPG
CS09t[2]		Acceleration & Smoothness training exercises
CS010t		Fiat post-drive training exercises

Figure 3-2. Fuel economy driver interface designs evaluated for usability in the NHTSA study

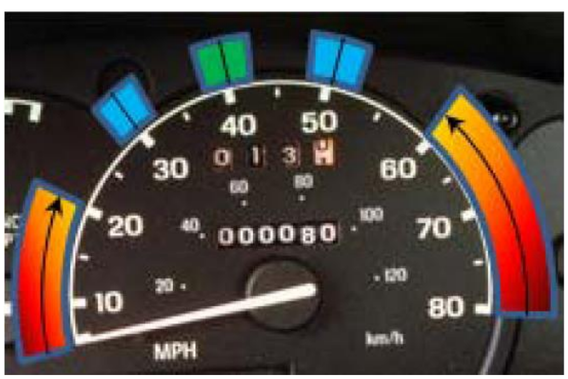


Figure 3-3. Retrofitting of existing speedometer for efficient driving as proposed by the NREL study

3.2.2. Technology Review

Several eco-driving feedback systems have been developed by vehicle manufacturers and made available initially in their hybrid-electric vehicle (HEV) models. Examples include Toyota Prius and Ford Fusion Hybrid as displayed in Figure 3-4. These feedback systems have similar features and characteristics. They are comprised of fuel level indicator as typically found in all vehicle models, battery level indicator which shows the state of charge of the battery, and power indicator which presents the instantaneous power requirement placed on the engine. The power indicator in these HEV models is associated with both acceleration and braking of the vehicle. When accelerating, the required power from the engine is increased and the power indicator moves towards the high power zone. The goal for the driver is therefore to accelerate mildly so that the power indicator stays away from the high power zone. This type of feedback can be regarded as indirect acceleration advice. It discourages aggressive acceleration, which consumes a large amount of fuel.

Figure 3-4. Eco-driving feedback interfaces in Toyota Prius (top) and Ford Fusion Hybrid (bottom)

In addition to the auto-manufacturers, there are also several eco-driving feedback systems that have emerged onto the consumer electronics market. These systems come in various forms and have different functionalities. Most of them are capable of providing dynamic feedback to users while driving. The feedback is given in a variety of ways such as instantaneous fuel economy bar/gauge as well as real-time and summary eco-score/indicator, which are based on how the driver drives.

As an example, there are now several eco-driving applications (apps) on smartphones (see Figure 3-5). Typically, these apps measure vehicle speed and acceleration from the embedded accelerometer and/or GPS chipset. Then, a set of eco-driving scores/indicators is determined based on the measured speed/acceleration and displayed to drivers both in real-time and at trip end. The major drawback of these eco-driving apps is that the given feedback is not based on direct measurements of vehicle fuel consumption. Rather, it is determined from surrogate variables (i.e., vehicle speed and acceleration) and the generic relationships between these variables and vehicle fuel consumption. However, it has been shown that vehicle fuel consumption is a function of not only vehicle speed and acceleration but also several other factors such as road gradient. Thus, these eco-driving apps can give misleading feedback to drivers under a variety of driving conditions. For instance, an eco-score for a 60 mph cruise will remain the same when on a flat road and on a steep hill.

Figure 3-5. Example eco-driving apps for smartphones

The drawback mentioned earlier has been addressed by some commercially available eco-driving systems such as Eco-Way and ecoRoute HD, shown in Figure 3-6. These eco-driving systems are integrated into personal navigation devices (PNDs) and are connected to the vehicle computer system. For instance, Eco-Way consists of a PND, an on-board diagnostic II (OBD-II) module, and an OBD-II cable. The OBD-II cable is connected to the vehicle's OBD-II port, accessing messages from the controller area network (CAN) bus. It also draws electrical power from the vehicle to supply the device. The OBD-II module is a firmware that decodes the received CAN messages including mass air flow rate that can be used to accurately compute vehicle fuel economy. It also houses a GPS chipset that is programmed to log the position (i.e., latitude and longitude) and speed of the vehicle. The data from the CAN bus and the GPS chipset are synchronized before being forwarded to the PND. The PND of Eco-Way serves as an input/output interface to the driver. It has several features including Eco:Drive which displays real-time fuel economy and carbon dioxide (CO_2) emission in a color scheme.

Similar to Eco-Way, ecoRoute HD also receives actual vehicle and engine data from the vehicle's CAN bus through OBD-II connection. These data are used to improve the credibility of its eco-score over its previous version, which is based on vehicle speed and acceleration measured from the GPS alone. In ecoRoute HD, separate eco-scores are given for speed, acceleration, and braking. These individual scores are also combined to result in an overall score.

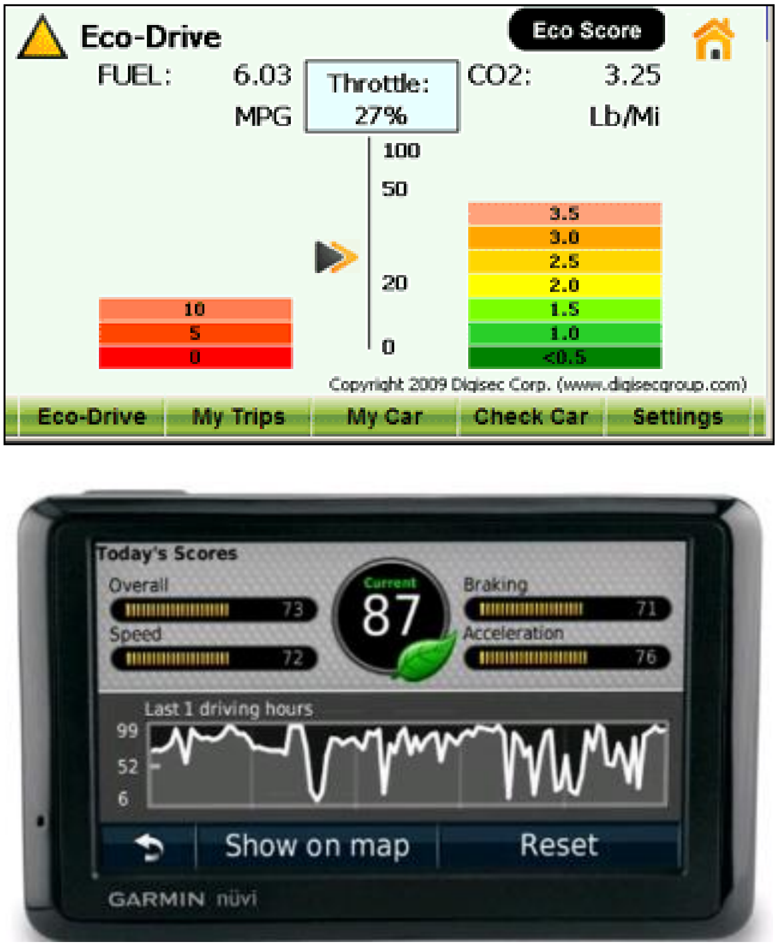


Figure 3-6. Eco-Way (top) and ecoRoute HD (bottom)

3.3. Expert Interview

As part of the efforts to gather inputs to guide the design of the Eco-Driving Feedback module, the research team conducted a telephone interview of experts from both public and private sectors in order to gain an understanding of the type of information that would be most useful in an eco-driving feedback system. The interview addressed respondents' professional background, perception on eco-driving, incentives to adopt eco-driving, mechanisms to convey eco-driving feedback, and driving data transmission, storage, and privacy.

The respondents included 11 experts from the following organizations with their primary responsibility area noted in the brackets:

- California Department of Transportation [fleet management]
- Daimler Trucks [research and development]
- Environmental Protection Agency (2 experts) [policy]
- Environmental systems Research Institute [research and development]
- General Motors [research and development]
- National Renewable Energy Laboratory [research and development]

- Riverside Transit Agency [fleet management]
- Westat [consulting]
- University of Minnesota, HumanFIRST Program [research and development]
- U.S. Department of Transportation [policy]

The interview responses were synthesized and the key findings are provided below. Details of the interview results are provided in Appendix A.

Perception on Eco-Driving

All respondents believed that eco-driving has the potential to reduce fuel consumption. However, opinions varied on the potential impact it could have (from 2-3% to more than 20%). There was a consensus that more empirical studies on the benefits of eco-driving are required, especially examining large-scaled study across a diverse population, short-term versus long-term benefits, and impact of external factors such as fuel prices. Several interviewees believed that eco-driving feedback can be useful for fleet operations in several ways:

- Feedback can help coach individual drivers.
- Driver performance can be measured against their past performance and their peers (but needs to be fair).
- Driver performance can also be used as a basis for rewarding high-performing drivers.
- Vehicle health information from the eco-driving feedback system is a side benefit to fleet managers.

Incentives to Adopt Eco-Driving

All believed that eco-driving should be promoted by incentivizing drivers to voluntarily change their behavior. Some incentives such as monetary savings in fuel and vehicle maintenance costs are directly a byproduct of eco-driving. Indirect incentives may be in the form of employee recognition and peer pressure such as in a fleet's internal competition or on social network. Other ways to promote eco-driving include education/outreach campaigns (similar to ant idrunk-driving) and emphasizing environmental co-benefits such as reducing harmful emissions and combating climate change.

Mechanisms to Convey Feedback

Several respondents mentioned a need for government policies encouraging manufacturers to alter the design of their vehicles to facilitate eco-driving (e.g., real-time fuel economy displays that are pre-installed in all vehicles). In terms of eco-driving feedback displays, it was suggested that they should not be over-detailed and only include small amounts of pertinent information. And these information should be located where drivers are already looking at, such as near the speedometer, to mitigate distraction. There were varying opinions regarding the type of feedback whether instantaneous vs. summary, numerical vs. symbolic, and current vs. target.

Driving Data Transmission and Privacy

It was generally agreed that the system would involve wireless data transfer to back-end server with web interfaces as front-end application. In terms of privacy, it was suggested that fleet drivers would reasonably expect a certain loss of privacy when they are operating a company vehicle. However, they should only be able to access their own information and system-wide aggregates, but not that of other drivers. For private drivers, they should be able to choose which type of data they want to be centrally available (e.g., fuel economy data), and which they do not (e.g., GPS data).

3.4. User Interfaces

Based on the findings from the expert interviews as well as the review of existing eco-driving feedback devices and systems, the research team designs the eco-driving feedback interface as shown in Figure 3-7. It is purposefully designed to look similar to the typical vehicle dashboard so that it can be used in place of the dashboard (the tablet will be placed in front of the dashboard). This is aimed to reduce the length of "eyes off road" time, which is one of the measures of driver's distraction, when glancing at the interface. In this simple and intuitive design, although there is still a speedometer, the tachometer is replaced by a fuel economy gauge. Other features on the interface are:

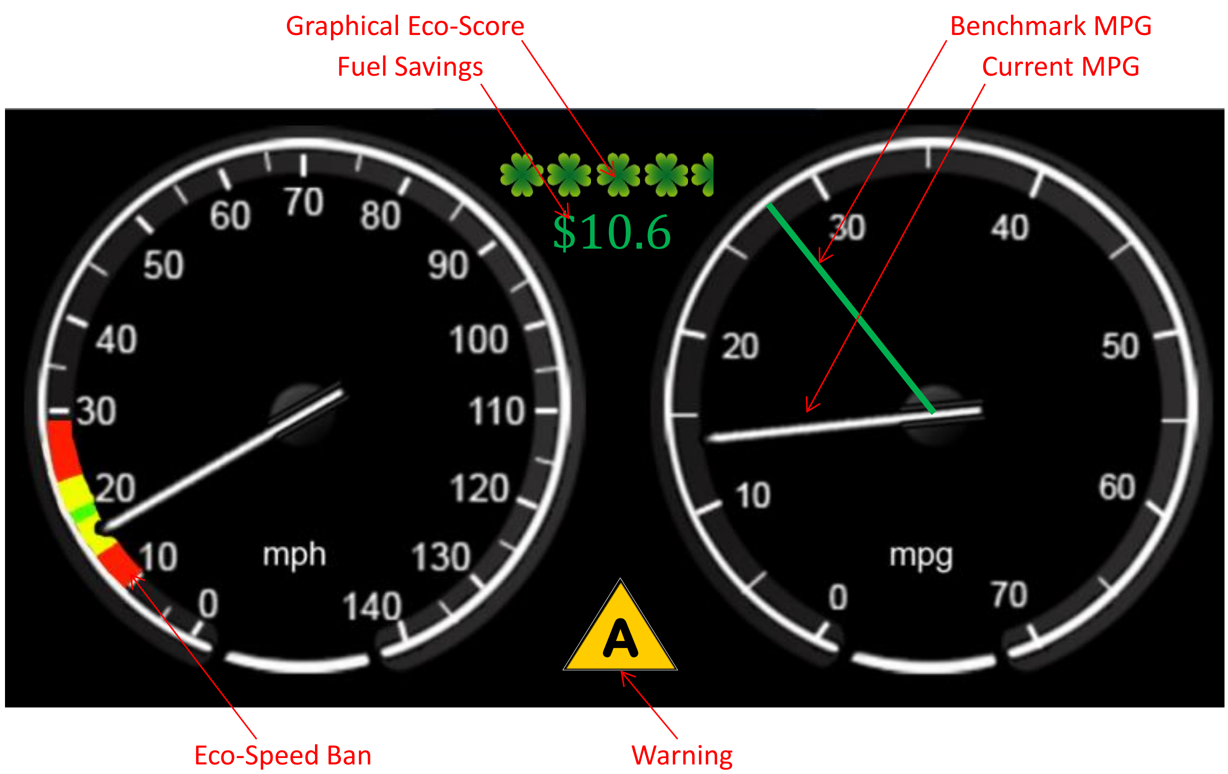


Figure 3-7. Design of eco-driving feedback interface in this project

- **Eco-speed band** – The location and width of the different colors on this speed ban are dynamically changed depending on the prevailing traffic speed and road grade on the current roadway link. The goal for the driver is to stay in green or yellow.

- **Warning** – This multi-purposed warning sign pops up when accelerating too aggressively (A), braking too abruptly (B), or idling for too long (i). The driver or fleet manager can set to have the warning sign be accompanied by a beep sound if desirable.

- **Benchmark MPG** – The benchmark value is customizable. It can be the average MPG value over the lifetime, last day, last 5 minutes, etc. Or, it can be a value entered by the driver or fleet manager (e.g., the U.S. Environmental Protection Agency's fuel economy rating for the vehicle, the fleet-wide target fuel economy for the vehicle).

- **Current MPG** – This is also customizable. The driver can elect to show the average MPG value over the last 5 minutes, last 30 seconds, etc. The goal for the driver is to stay on the right side of the benchmark MPG as much as possible.

- **Graphical Eco-Score** – It converts a 100-point Eco-Score to a 5-point graphical scale. The Eco-Score to be shown can be the average score over the lifetime, last day, last 5 minutes, or for the current trip.

- **Fuel savings** – These fuel savings are calculated based on the benchmark and the current MPG values as well as the average fuel price in the area the vehicle is operating. This feature directly presents an economic incentive for eco-driving.

3.5. Feedback Algorithms

There are four types of feedback provided to the driver through the eco-driving feedback interface. These are: 1) Eco-Speed band, 2) aggressive acceleration warning, 3) hard braking warning, and 4) excessive idling warning. The algorithms for each of them are described below.

3.5.1. Eco-Speed Band

Eco-Speed is first determined based on real-time average traffic speed. Then, it is adjusted based on road grade. Real-time average traffic speed is available on a link-by-link basis and is updated every 2 minutes. The underlying logic of the Eco-Speed is that to reduce fuel consumption a vehicle should travel at a constant speed around the average traffic speed to avoid unnecessary acceleration and braking, especially in congestion where traffic is often stop-and-go. Given an average traffic speed of the roadway link the vehicle is on (v_{avg}), the Eco-Speed (v_{eco}) is calculated as:

$$v_{eco} = 0.8538v_{avg} + 10.89 \tag{3-1}$$

This equation is a linear fit of data from a traffic simulation study previous conducted by the research team[9]. The data and the linear fit are shown in Figure 3-8. It is observed that for any average traffic speed lower than 75 mph, the Eco-Speed will always be higher than the average traffic speed. This is because the driver is unlikely to be able to keep a constant speed throughout the link, especially in congestion. Recommending a higher Eco-Speed value will help ensure that the impact on travel time is minimal.

After the Eco-Speed has been determined based on real-time average traffic speed, it will be adjusted based on road grade. The adjustment will vary depending on the fuel consumption characteristics of individual vehicles. For example, Figure 3-9 shows fuel consumption curves of a 2007 Nissan Altima for different road grade values from -8% to 8%. Each curve represents fuel consumption rate as a function of average vehicle speed. It can be observed that the “sweet spot” speed for this vehicle is different for the different road grade values. These fuel consumption curves and the associated sweet spot speeds are likely to be different for other vehicles.

[9] Servin, O., Boriboonsomsin, K., and Barth, M. (2008). “A preliminary design of speed control strategies in dynamic intelligent speed adaptation system for freeways.” Proceedings of the 87th Annual Meeting of the Transportation Research Board (DVD), Washington, DC, January 13-17.

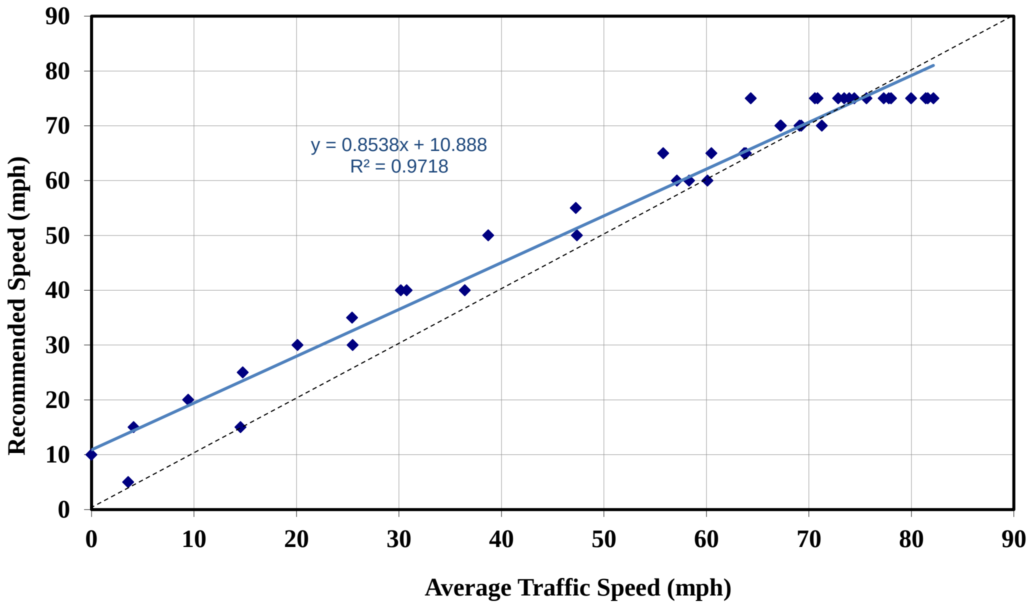


Figure 3-8. Average traffic speed versus eco-speed

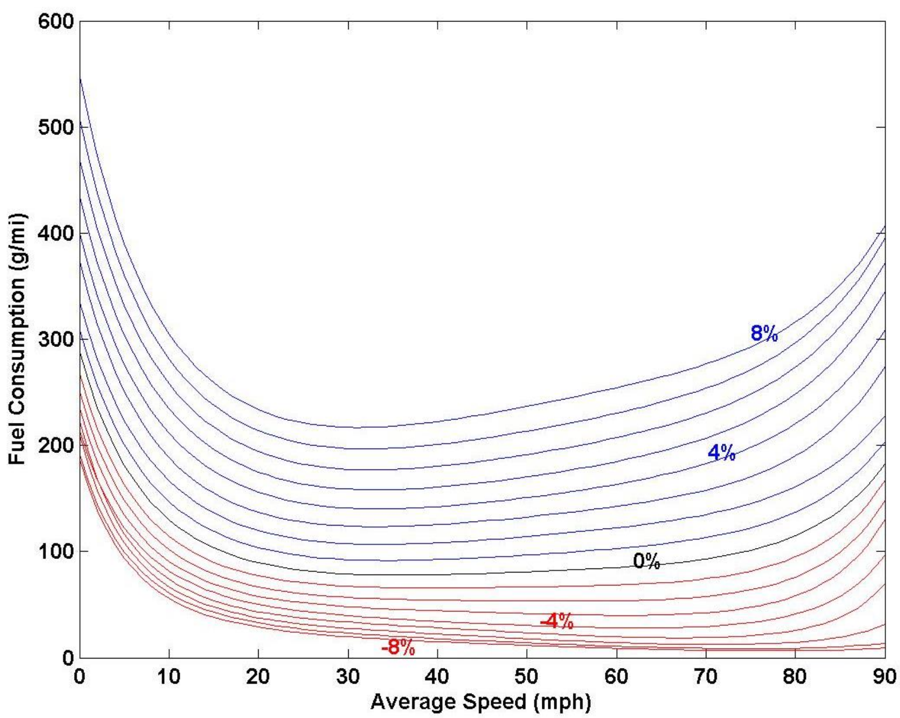


Figure 3-9. Fuel consumption rates as a function of average speed and road grade

Given a set of fuel consumption curves for a vehicle, the adjustment to the Eco-Speed is performed in the following steps:

1. Determine road grade of the roadway link the vehicle is on, and select the corresponding fuel consumption curve.
2. Create a 10-mph speed window of [v_{eco} – 5 mph, v_{eco} + 5 mph].
3. Search for a speed value within the speed window whose fuel consumption rate is the lowest.

After the adjustment based on road grade has been made, the Eco-Speed will be checked to see whether it exceeds the speed limit of the link. If so, it will be changed to the speed limit. Finally, the Eco-Speed band will be constructed around the Eco-Speed as follows:

- The green portion in the middle is +/- 2.5 mph of the Eco-Speed.
- The yellow portions on each side of the green extend the band for 2.5 mph each.
- The red portions on each outer side of the yellow extend the band for another 2.5 mph each.

In total, the Eco-Speed band covers a speed range of 15 mph. The driver is encouraged to stay within the green portion of the band as much as possible.

3.5.2. Aggressive Acceleration Warning

Aggressive acceleration requires higher power from the engine, and thus consumes more fuel. In the Eco-Driving Feedback module, such driving behavior is discouraged by providing graphical (and optionally audio) warning when the vehicle's acceleration rate exceeds a threshold. The threshold for prompting the aggressive acceleration warning varies by vehicle speed. This is because the typical acceleration rate (e.g., mean) for any drivers and its variation (e.g., standard deviation) also vary by vehicle speed, as shown in Figure 3-10 and Figure 3-11, respectively.

The plots in Figure 3-10 and Figure 3-11 were created from 220 hours of driving data collected from a test vehicle in another project that aims to evaluate the impact of eco-driving technology on driving behavior. The same types of plots (and the associated data table) can be created for any vehicle using vehicle speed data collected from the vehicle's OBD-II port. Then, the threshold for prompting the aggressive acceleration warning for that vehicle can be calculated as:

$$T_i^a(v) = \mu_i^a(v) + k^a \cdot \sigma_i^a(v) \qquad \forall\, i = 1, 2, \ldots, \frac{80}{n} \tag{3-2}$$

where $T^a_i(v)$ is the aggressive acceleration threshold for vehicle speed in bin i; $\mu^a_i(v)$ is the mean acceleration rate for vehicle speed in bin i; $\sigma^a_i(v)$ is the standard deviation of acceleration rate for vehicle speed in bin i; and n is the size of speed bins with a default value of 1 mph. The strictness parameter for acceleration, k^a, has a default value of 2 but can be changed by the driver or fleet manager.

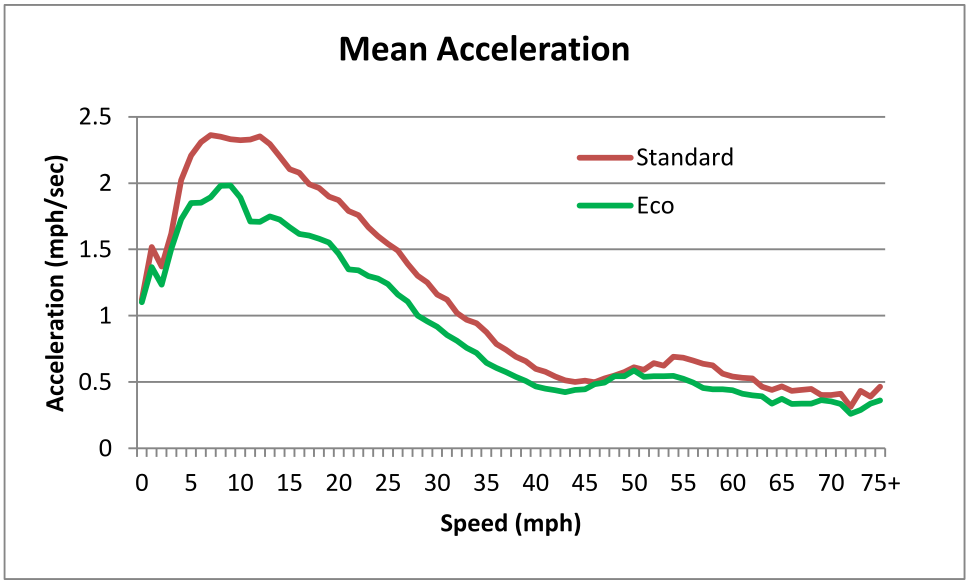


Figure 3-10. Mean acceleration as a function of vehicle speed

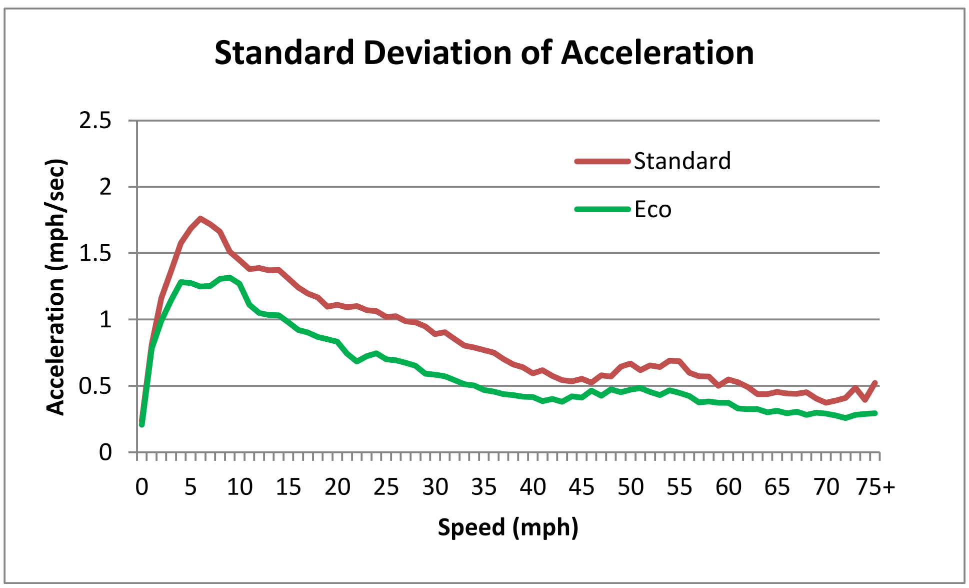


Figure 3-11. Standard deviation of acceleration as a function of vehicle speed

3.5.3. Hard Braking Warning

Hard braking is an inefficient driving behavior as it turns vehicle kinetic energy that is generated by burning fuel into heat waste. Vehicle consumes fuel to build up kinetic energy, which allows it to travel a certain distance. By applying a brake, the distance that can be achieved is shortened and the vehicle will have to accelerate again, and thus consume additional fuel, to complete the original distance. Although braking is an important part of safe driving, drivers can avoid unnecessarily hard braking by anticipate traffic flow or signal ahead. In the Eco-Driving Feedback module, hard breaking is discouraged by providing graphical (and optionally audio) warning when the vehicle's deceleration rate exceeds a threshold. Similar to the aggressive acceleration warning, the threshold for prompting the hard braking warning also varies by vehicle speed. This is because the typical deceleration rate (e.g., mean) for any drivers and its variation (e.g., standard deviation) vary by vehicle speed, as shown in Figure 3-12 and Figure 3-13, respectively.

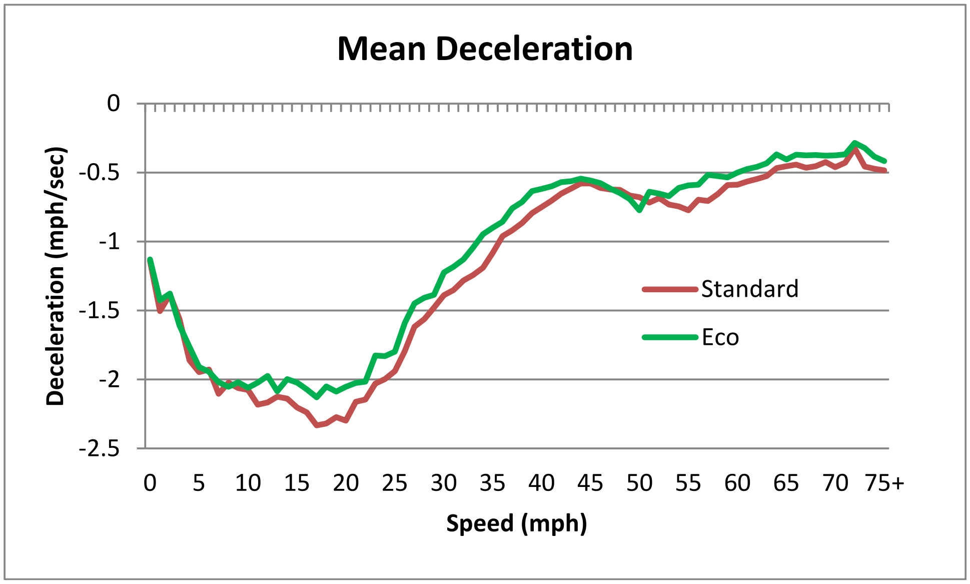


Figure 3-12. Mean deceleration as a function of vehicle speed

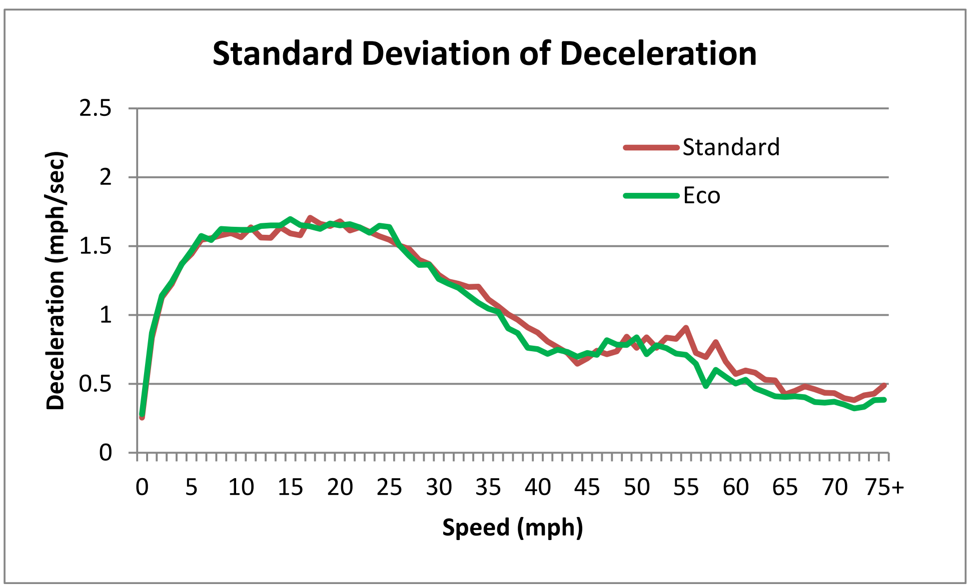


Figure 3-13. Standard deviation of deceleration as a function of vehicle speed

The plots in Figure 3-12 and Figure 3-13 were created from the same dataset that is used to create Figure 3-10 and Figure 3-11. The same types of plots (and the associated data table) can be created for any vehicle using vehicle speed data collected from the vehicle's OBD-II port. Then, the threshold for prompting the hard braking warning for that vehicle can be calculated as:

$$T_i^b(v) = \mu_i^b(v) - k^b \cdot \sigma_i^b(v) \qquad \forall\ i = 1, 2, \ldots, \frac{80}{n} \tag{3-3}$$

where $T^b_i(v)$ is the hard braking threshold for vehicle speed in bin i; $\mu^b_i(v)$ is the mean deceleration rate for vehicle speed in bin i; $\sigma^b_i(v)$ is the standard deviation of deceleration rate for vehicle speed in bin i; and n is the size of speed bins with a default value of 1 mph. The strictness parameter for deceleration, k^b, has a default value of 2 but can be changed by the driver or fleet manager. Note that the strictness parameter for acceleration and deceleration can be set differently, allowing the driver or fleet manager to focus on improving one behavior at a time or to emphasize one behavior over the other.

3.5.4. Excessive Idling Warning

Idling wastes fuel as the vehicle consumes fuel without achieving any distance towards completing its trip. Thus, excessive idling is an undesirable driving behavior and should be discouraged. Like accelerating and braking, idling is part of driving and some idling events are unavoidable such as when stuck in traffic or at red light. However, these idling events are unlikely to be for an extended period. For example, even when traffic is heavily congested, vehicles would still creep along the road from time to time. In another example, a typical maximum cycle length of traffic signals is 120 seconds, and thus, vehicles stopping at signalized intersections are unlikely to idle for longer than that. Therefore, in the Eco-Driving Feedback module the graphical (and optionally audio) warning for excessive idling will be prompted when the vehicle idles for longer than 120 seconds. After that, the module will continue to prompt the warning every 10 seconds until the vehicle is turned off or starts moving. These threshold values are customizable by the driver or fleet manager.

Figure 3-14 shows an idling event of a vehicle at a signalized intersection that lasts 85 seconds. This idling event will not prompt the excessive idling warning. Most of the excessive idling events occur at activity locations, either before trip starts or after trip ends. Figure 3-15 shows an idling event of the same vehicle at an activity location that lasts 268 seconds. In this case, the excessive idling warning will be prompted many times.

3.5.5. Graphical Eco-Score

Graphical eco-score consists of 5 leaves, representing a range of eco-score from 0 to 100. Therefore, each leave represent 20 points of eco-score. The graphical eco-score changes in real-time based on the average eco-score from the beginning of the trip to that point in time.

3.5.6. Fuel Savings

The fuel savings display represent the dollar-equivalent of fuel saved (positive) or wasted (negative) for the trip. It changes in real-time based on the cumulative fuel use from the beginning of the trip to that point in time. The fuel saved or wasted is determined in relative to the expected amount of fuel use based on the pre-set benchmark MPG. Then, it is converted to a dollar term using a pre-set gasoline price or a real-time gasoline price for the area.

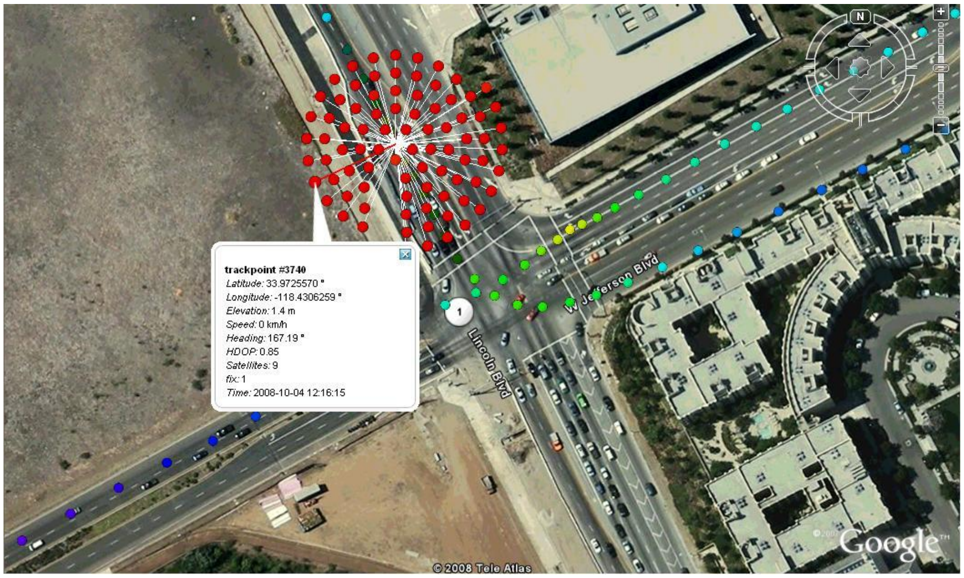


Figure 3-14. 85-second idling at a signalized intersection

Figure 3-15. 268-second idling at an activity location

4. Eco-Score and Eco-Rank Module

4.1. Overview

Given the real-time vehicle operation data (e.g., speed, acceleration) available through the connection with the vehicle's OBD-II data bus as well as the driving situation information (e.g., road type, speed limit) derived from the vehicle's position obtained though GPS, this module calculates Eco-Scores on a second-by-second basis. Individual scores are calculated for four driving modes (i.e., cruising, accelerating, braking, and idling), which indicate how fuel-efficient the driver is with respect to each driving mode. The individual scores are also combined into an overall score. Second-by-second individual and overall scores can be aggregated for a trip or a time period (e.g., five minutes, one week, or one month). Then, the aggregated scores can be compared between different driving modes for the same driver so that (s)he can prioritize the areas for improvements, or across different drivers so that they can be ranked against each other.

While miles per gallon (MPG) is a widely used metric for vehicle fuel economy, it is varied not only by driving behaviors, but also vehicle type, travel route, weather, loaded weight, tire pressure, usage of accessories (e.g., air conditioning), etc. Thus, MPG cannot be used to fairly compare driving performance between drivers or of the same driver over time. In contrast, Eco-Scores are intended to serve as metrics for fuel-efficient *driving behaviors* that are independent of other factors affecting vehicle fuel consumption.

There are existing devices and systems in the market that provide similar information to Eco-Score, as shown in Figure 4-1 and Figure 4-2. These devices and systems are all proprietary and there is no publically available information regarding how the different scores in these products are determined. Therefore, the research team purchased and test drove the two devices shown in Figure 4-2, namely Kiwi Drive Green and Garmin's Mechanic. The two products in Figure 4-1 are geared toward fleets and not available for purchase in the consumer market. After the test drives, the following observations were made:

- Getting multiple real-time scores is overwhelming.

- These real-time scores need to be interpreted. They tell how good or bad the driving is, but they do not tell what to do to improve the driving. Interpreting the scores while driving also increases mental workload. In contrast, providing real-time driving feedback targeted at specific driving behaviors may be more user-friendly and effective.

- Driving scores should be provided after the trip is complete to reflect overall driving performance. They are probably better used as a tool for evaluating driving performance over time and comparing the performance between drivers.

Figure 4-1. Existing systems that provide driving score information

Figure 4-2. Existing devices that provide driving score information

4.2. Calculation Algorithms

The Eco-Scores developed in this project consist of: 1) speed score, 2) acceleration score, 3) braking score, 4) idling score, and 5) overall score. Each score is represented by a point, which ranges from 0 (worst) to 100 (best). The calculation algorithms of these scores and their logics are described below.

4.2.1. Speed Score

In general, vehicles are most fuel-efficient when operating at moderate speeds around 40-50 mph. Thus, one might want to give the maximum point to the driver who drives within this speed range, and deduct some points when driving outside of the speed range. However, driving at a lower speed than 40 mph is usually not by choice but rather because of traffic congestion. Although the Eco-Driving Feedback module provides a range of recommended driving speed that is most fuel efficient for any driving conditions including when under traffic congestion, it is not possible for the driver to stay within the recommended speed range all the time. For instance, sometimes the driver may have to slow down significantly as another vehicle cuts in from the adjacent lane. Therefore, no point should be deducted from the Speed Score under this circumstance.

Similarly, driving above 50 mph may sometime be necessary especially on highways. In fact, when traffic is moving at highway speed (e.g., 65 mph), driving at a significant lower speed is unsafe and considered a hazard to other vehicles. Therefore, no point should be deducted from the Speed Score under this circumstance as well. Therefore, the Speed Score will be the maximum possible of 100 as long as the vehicle speed stays within the speed limit (v_{limit}).

On the other hand, excessive speed is always a safety concern and speeding is illegal. In addition, driving at a speed exceeding speed limits on highways is mostly not fuel efficient. Therefore, in the Speed Score calculation algorithm, points will be deducted from the maximum possible of 100 whenever the vehicle speed exceeds the speed limit. The amount of point deduction is a function of speed threshold, which can be set by the driver or fleet manager. Figure 4-3 shows the Speed Score curve for a maximum speed threshold of 10 mph above the speed limit. The Speed Score will be 100 when the vehicle speed is lower than or equal to the speed limit. Then, it will decrease linearly as the vehicle speed increases towards the speed threshold. Beyond the threshold, the Speed Score will be zero.

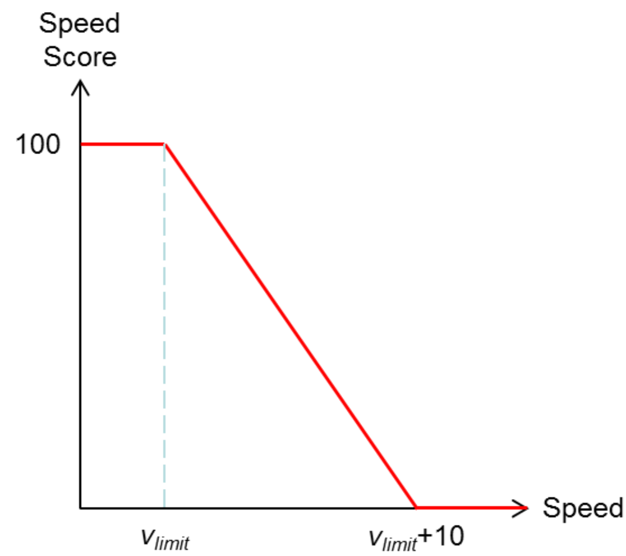


Figure 4-3. Speed score curve

4.2.2. Acceleration Score

As described earlier, the typical acceleration rate (e.g., mean) for any drivers and its variation (e.g., standard deviation) vary by vehicle speed. Equation 1-2 then presents a calculation of the threshold for prompting the aggressive acceleration warning in the Eco-Driving Feedback module. A similar concept is applied to the calculation of the Acceleration Score. Given the mean (μ) and standard deviation (σ) of acceleration rate for any vehicle speed bin, the range of vehicle acceleration rate can be divided into three regions: 1) desirable, 2) acceptable, and 3) unacceptable.

Taking Figure 4-4 as an example, a vehicle acceleration rate is *desirable* if it is less than or equal to μ-σ. In this region, the Acceleration Score will be the maximum possible of 100. A vehicle acceleration rate is *acceptable* if it is greater than μ-σ but less than μ+2σ. In this region, the Acceleration Score will decrease linearly from 100 to 0 as the vehicle acceleration rate increases from μ-σ towards μ+2σ. Finally, a vehicle acceleration rate is *unacceptable* if it is equal to or greater than μ+2σ. In this case, the Acceleration Score will be zero. Note that the thresholds of the acceptable acceleration rate region can be set by the driver or fleet manager. Also, when the vehicle is not in acceleration, the score will be 100.

4.2.3. Braking Score

The calculation of the Braking Score is similar to that of the Acceleration Score. Given the mean (μ) and standard deviation (σ) of deceleration rate for any vehicle speed bin, the range of vehicle deceleration rate can also be divided into three regions: 1) desirable, 2) acceptable, and 3) unacceptable. Note that arithmetically, the value of vehicle deceleration rates is negative.

Based on Figure 4-5, a vehicle deceleration rate is *desirable* if its value is higher than or equal to μ+σ. In this region, the Deceleration Score will be the maximum possible of 100. A vehicle deceleration rate is *acceptable* if its value is lower than μ+σ but higher than μ-2σ. In this region, the Deceleration Score will decrease linearly from 100 to 0 as the value of vehicle deceleration rate decreases from μ+σ towards μ-2σ. Finally, a vehicle deceleration rate is *unacceptable* if its value is equal to or lower than μ-2σ. In this case, the Deceleration Score will be zero. Note that the thresholds of the acceptable deceleration rate region can be set by the driver or fleet manager. Also, when the vehicle is not in deceleration, the score will be 100.

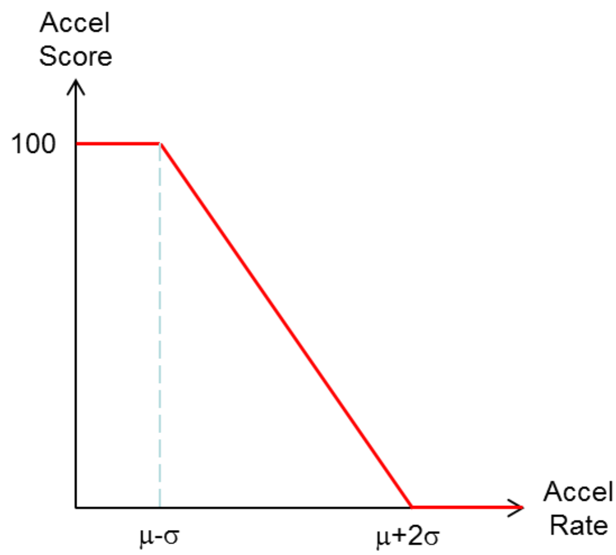


Figure 4-4. Acceleration score curve

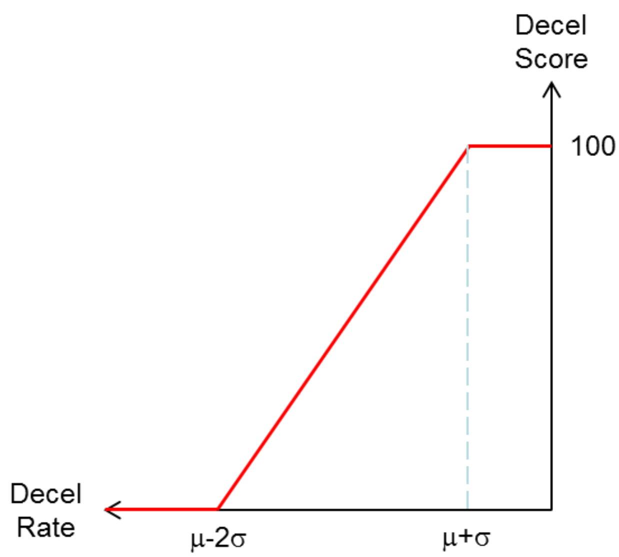


Figure 4-5. Braking score curve

4.2.4. Idling Score

As pointed out earlier, some idling events such as when stuck in traffic or at red light are unavoidable, and the Eco-Driving Feedback module will not prompt excessive idling warning if the vehicle has not idled for longer than 120 seconds. Based on this logic, the Idling Score will be the maximum possible of 100 as long as the vehicle has not idled for longer than 120 seconds. After the vehicle has idled for longer than that limit, the Idling Score will decrease linearly from 100, and it will reach zero once the vehicle has idled for equal to or longer than the maximum acceptable idling period (i_{max}), as depicted in Figure 4-6. The maximum acceptable idling period can be set by the driver or fleet manager.

Note that all the scores are calculated on a second-by-second basis. In the case of the Idling Score, when the vehicle is not in idle, the score will be 100. Once the vehicle enters the idling mode, the score will remain 100 for the first 120 seconds. Then, the score for the 121st second and onward will keep decreasing and it will become zero at the i_{max} second. After the 120th second but before the i_{max} second, if the vehicle starts moving, then the Idling Score will revert back to 100 as it is no longer in idle.

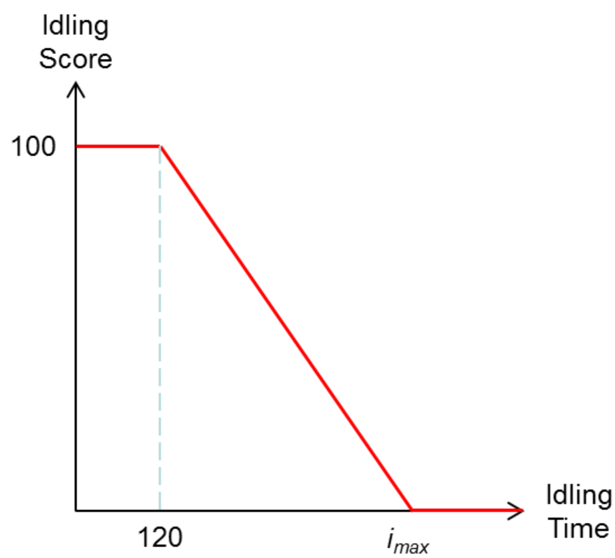


Figure 4-6. Idling score curve

4.2.5. Overall Score

The Overall Score is an aggregation of the four modal scores into one score. This is useful for evaluating the overall driving performance in all aspects. The Overall Score (s_o) is calculated as a weighted average of the four modal scores, as written in Equations (4-1) and (4-2).

$$s_o = w_s s_s + w_a s_a + w_b s_b + w_i s_i \quad (4\text{-}1)$$

$$w_s + w_a + w_b + w_i = 1 \quad (4\text{-}2)$$

where s_s, s_a, s_b, and s_i are the Speed Score, Acceleration Score, Braking Score, and Idling Score, respectively; w_s, w_a, w_b, and w_i are the corresponding weights for the Speed Score, Acceleration Score, Braking Score, and Idling Score, respectively. The default weights are 0.25 each, but they are customizable, allowing the driver or fleet manager to emphasize one behavior over another. For example, one may give more weight to the Acceleration Score than the Braking Score as acceleration behavior has a greater impact on vehicle fuel consumption than braking behavior.

Similar to other scores, the Overall Score is also calculated on a second-by-second basis. Thus, it can be aggregated for any time period (e.g., 5 minutes) by calculating the simple average of the score values over that time period. The same method can be applied to the four modal scores as well. The aggregated scores are used to rank drivers in the Eco-Rank application. The aggregated Overall Score is also converted into a graphic and displayed to the driver in real-time through the Eco-Driving Feedback module's graphical user interface, as shown in Figure 3-7.

4.3. Web Application

As described earlier, all the driving data are collected by the in-vehicle device and sent to the system server. The server stores these data and also uses them to drive the Eco-Score and Eco-Rank web application. This web application allows drivers and fleet managers to review past driving records on a trip-by-trip basis and the associated driving performance in the form of Eco-Scores. The driving traces of individual trips can be viewed on a map where they can be colored based on different metrics, such as vehicle speed, Speed Score, Acceleration Score, Braking Score, Idling Score, or Overall Score. This allows for the identification of locations where scores are low and improvements in driving performance can be made.

In addition, the web application also shows Eco-Rank, which is a ranking of drivers (or vehicles) based on the Eco-Scores. The ranking can be done weekly, monthly, etc., and can be performed separately for subgroups (e.g., drivers in the same region, drivers of similar vehicles). Appendix B provides example screenshots of the Eco-Score and Eco-Rank web application.

5. System Evaluation

5.1. Field Operational Test

After the driving feedback system had been demonstrated and tested internally by the research team, it was prepared for a field operational test (FOT) by potential users. The goal of the FOT was to collect real-world driving data from potential users to support the evaluation of the system's effectiveness. The FOT was designed to consist of two data collection periods: 1) *without* the driving feedback system (baseline period) where the drivers operated their vehicles as they would normally do, and 2) *with* the driving feedback system (feedback period) where the system was made available to the drivers. Each data collection period lasted approximately two to three months although this was varied from one driver to another.

Note that during the first data collection period, the driving feedback system was not made available to the drivers but a data collection system was installed on the vehicles to collect baseline driving data. The research team designed and developed the data collection system based on the same hardware and configured it to collect the same type of data in the same format as the driving feedback system in order to prevent measurement biases in the data.

5.1.1. Test Fleets

Originally, the FOT was planned for 30 vehicles. With the cost savings due to the changes in system configuration, the FOT was expanded to include 15 additional vehicles for a total of 45 vehicles. These vehicles were split equally among three different fleets as follows:

1. **15 paratransit shuttles of the Riverside Transit Agency (RTA)** – RTA is one of the project partners. It provides public transit services in the County of Riverside, California. One of the services is Dial-A-Ride, which is a non-fixed-route paratransit service. Riders make requests for pick up and drop off in advance and will be given a time window for each pick up and drop off. The 15 vehicles participating in the FOT were converted from 2012 Ford E-450 van with gasoline engine as shown in Figure 5-1. They were usually in operation 8-12 hours a day on weekday.

2. **15 pickup trucks of the California Department of Transportation (Caltrans)** – Caltrans is also one of the project partners. It owns and maintains a variety of vehicles that are used for various purposes. The 15 vehicles participating in the FOT were 2008 Chevy Silverado C15 pickup trucks as shown in Figure 5-2. They are assigned to individual employees for business use such as visiting construction sites. The drivers keep the vehicles with them and only bring them in to base stations for maintenance and repair.

3. **15 private vehicles of general public** – Private drivers were recruited via Internet to participate in the FOT. Eligibility requirements include being 21 years old or more, possessing valid driver license and auto insurance, and being the only driver of the vehicle that is determined to work with the driver feedback system (typically model years 1996 and newer). Therefore, the 15 participating vehicles have varied make, model, and model year as listed in **Error! Reference ource not found.**. The demographic of the drivers are also varied.

Figure 5-1. RTA's paratransit shuttles

Figure 5-2. Caltrans' pickup trucks

The driving feedback system consisting of an on-board diagnostic (OBD-II) connector and a tablet was installed in the participating vehicles. During the baseline period, the tablet was hidden and only used to collect baseline driving data. During the feedback period, the tablet was installed in the cabin where the drivers could see it and used its different features. Figure 5-3 shows the driving feedback system installed in a RTA shuttle.

Figure 5-3. Driving feedback system installed in RTA shuttle

5.1.2. Data

Second-by-second data of vehicle and engine operation parameters were collected and sent to the data server. These data were filtered and processed into the system database. The database was then used to populate the various pages of the web application.

Throughout the FOT, there were various issues with the data logging. These included malfunction devices, lost connection between the OBD connector and the tablet, insufficient battery power for the tablet, etc. The amount of data loss due to these issue varies by fleet and by vehicle. For instance, since the RTA shuttles were in operation for many hours a day, the tablets on these vehicles never had the issue of insufficient battery power. On the other hand, this was a major issue with the Caltrans and private vehicles as they were not in operation as much. The Caltrans and private drivers were asked to periodically charge the battery of the tablet in their home or office as they would do with their smartphone, but the response varied and was out of our control.

Thus, we had to exclude some vehicles from the study if there were not sufficient data. At the end of the FOT, we determined that there were 15 RTA vehicles, 12 Caltrans vehicles, and 6 private vehicles that provide sufficient data for further analyses. Their data are summarized in Table 5-1 for the RTA fleet, Table 5-2 for the Caltrans fleet, and Table 5-3 for the private fleet, respectively.

Table 5-1. Data summary for RTA fleet

Veh ID	Baseline Period[1]						Feedback Period[2]					
	No. of Trips	Dist. (mi)	Time (hr)	Fuel (gal)	Speed (mph)	FE (mpg)	No. of Trips	Dist. (mi)	Time (hr)	Fuel (gal)	Speed (mph)	FE (mpg)
306	298	2,605	159	368	16.4	7.1	405	3,313	194	474	17.1	7.0
312	418	4,617	304	789	15.2	5.8	442	5,569	339	940	16.4	5.9
313	352	4,327	242	572	17.9	7.6	383	2,974	174	393	17.1	7.6
314	310	3,372	206	466	16.3	7.2	393	5,257	298	721	17.6	7.3
320	377	4,349	233	620	18.6	7.0	314	2,100	139	306	15.1	6.9
321	250	2,863	172	405	16.6	7.1	477	3,920	244	541	16.1	7.2
323	367	4,058	263	525	15.4	7.7	298	2,949	180	377	16.4	7.8
325	292	3,683	222	467	16.6	7.9	602	7,272	437	1,002	16.6	7.3
326	260	2,873	175	418	16.4	6.9	338	3,350	203	483	16.5	6.9
328	405	4,320	243	562	17.8	7.7	785	7,731	419	1,016	18.5	7.6
329	317	3,755	247	557	15.2	6.7	458	3,549	235	550	15.1	6.5
330	190	2,356	139	334	17.0	7.1	93	585	35	78	16.8	7.5
331	281	3,010	168	397	18.0	7.6	629	7,626	406	990	18.8	7.7
336	381	4,547	281	619	16.2	7.3	550	5,695	331	767	17.2	7.4
338	148	1,868	118	263	15.8	7.1	378	4,451	277	691	16.1	6.4
Fleet	*4,646*	*52,604*	*3,172*	*7,362*	*16.6*	*7.1*	*6,545*	*66,340*	*3,910*	*9,328*	*17.0*	*7.1*

[1] April - July, 2014

[2] August - November, 2014

Table 5-2. Data summary for Caltrans fleet

Veh ID	Baseline Period[1]						Feedback Period[2]					
	No. of Trips	Dist. (mi)	Time (hr)	Fuel (gal)	Speed (mph)	FE (mpg)	No. of Trips	Dist. (mi)	Time (hr)	Fuel (gal)	Speed (mph)	FE (mpg)
942	40	725	17	38	43.8	18.9	94	1,853	44	98	42.5	18.9
945	19	701	13	39	54.4	18.0	226	4,484	102	247	43.8	18.1
948	125	301	18	24	16.4	12.4	138	245	14	19	17.2	12.9
957	209	3,162	93	195	34.1	16.2	37	545	13	32	40.7	17.0
950	38	403	13	27	30.5	15.1	17	158	6	9	27.6	16.7
956	174	2,492	55	139	45.4	17.9	34	342	12	21	29.0	16.3
959	63	1,015	40	65	25.4	15.7	94	662	25	37	26.2	18.0
949	94	693	39	48	17.7	14.5	35	300	12	19	24.2	15.5
955	269	1,338	70	89	19.0	15.0	27	86	7	24	12.5	3.7
958	48	368	10	22	35.7	16.7	43	132	5	10	28.3	13.4
922	58	1,008	25	55	40.5	18.2	16	98	3	6	36.6	17.6
951	53	805	58	66	14.0	12.2	40	543	43	43	12.7	12.5
Fleet	*1,190*	*13,012*	*451*	*808*	*28.9*	*16.1*	*801*	*9,448*	*286*	*565*	*33.1*	*16.7*

[1] March - June, 2014

[2] July - October, 2014

Table 5-3. Data summary for private fleet

Veh ID	Baseline Period[1]						Feedback Period[2]					
	No. of Trips	Dist. (mi)	Time (hr)	Fuel (gal)	Speed (mph)	FE (mpg)	No. of Trips	Dist. (mi)	Time (hr)	Fuel (gal)	Speed (mph)	FE (mpg)
16	186	1,481	59	46	25.2	32.0	260	2,171	82	69	26.3	31.6
22	121	534	23	19	23.2	28.5	48	102	6	4	17.2	25.3
23	158	758	41	35	18.5	21.4	196	1,297	59	56	22.0	23.3
25	87	609	24	21	25.4	28.7	26	201	8	7	26.1	28.8
26	83	431	18	16	24.3	26.8	225	1,598	60	58	26.7	27.6
30	220	2,929	84	80	35.0	36.6	443	5,180	159	144	32.6	35.9
Fleet	*855*	*6,742*	*248*	*218*	*27.2*	*30.9*	*1,198*	*10,548*	*374*	*338*	*28.2*	*31.2*

[1] February - June, 2014

[2] June - October, 2014

5.2. System Effectiveness

After the real-world driving data had been collected from both baseline and feedback periods, the evaluation of the system was carried out. The evaluation spanned multiple aspects including effectiveness (at reducing fuel consumption), driver acceptance, and cost. In terms of effectiveness, the primary focus was on whether the driving feedback system meets the project objective of reducing fleet average fuel consumption by at least 2%, based on the collected driving data. For driver acceptance, a pair of driver surveys was conducted—one before the start of the FOT and the other after the completion of the FOT. The before survey was to gauge the drivers' knowledge about fuel-efficient driving and attitude towards driving feedback systems. The after survey was to obtain the drivers' opinions about their experience with the driving feedback system developed in this project. Lastly, the cost of the driving feedback system was analyzed to determine the economic viability of the system. Each of the three evaluation aspects is described in this chapter.

5.2.1. Variation in Real-World Fuel Economy

During the FOT, there were a number of factors that could affect the vehicles' real-world fuel economy. If these factors were not the same during the data collection periods without and with the driving feedback system, then the real-world fuel economy numbers would be biased. Some of these factors are discussed below:

- **Vehicle factors –** A vehicle carrying more weight requires more energy to run, thus directly affecting its fuel economy. Tire pressure also has a significant effect on fuel economy. If an extra weight was put on the vehicle or the tire pressure was low for some parts of the FOT, then the fuel economy during those times would be lower than it should.

- **Road factors** – Climbing a steep road grade requires higher power from the engine to overcome the added gravitational force. This can put the engine in a power enrichment mode, which reduces the vehicle fuel economy. Driving on rough road surface also results in lower fuel economy.

- **Weather factors** – Weather affects vehicle fuel economy, both directly and indirectly. For instance, headwind reduces vehicle fuel economy as the vehicle needs additional power from the engine to combat the wind drag. Hot weather induces the use of air conditioning, which places accessory load requirement on the engine.

- **Traffic factors** – Stop-and-go driving in congested traffic wastes fuel. So, the vehicle fuel economy degrades significantly under this traffic condition.

It is impossible to control for all these factors throughout the data collection periods without and with the driving feedback system. For example, an RTA shuttle carried no passenger at the beginning of the day but then could carry up to 14 passengers at some points. The extra weight of passengers would certainly lower fuel economy of the shuttle. As another example, an RTA shuttle that picked up a passenger on a hill would have worse fuel economy on the way up when going uphill than on the way down albeit using the same road. In addition, because the baseline data collection period occurred mostly in spring while the feedback data collection period occurred mostly in summer, the drivers were more likely to turn on air conditioning during the second period, resulting in lower fuel economy.

Therefore, it is important to remove these biases from the real-world fuel economy numbers as much as possible so that the resulting *normalized fuel economy* numbers without and with the driving feedback system can be fairly compared. Then, the change in normalized fuel economy can be attributed primarily to driving behavior changes as a result of using the driving feedback system. The method for normalizing fuel economy developed in this project consists of multiple steps as described in the following subsections.

5.2.2. Normalizing Fuel Consumption Rate

The normalization of fuel consumption rate is based on characterizing vehicle specific power (VSP) of vehicle operation on a second-by-second basis. VSP has been shown to be a strong descriptor of vehicle fuel consumption and emissions. It is used by the U.S. Environmental Protection Agency to characterize vehicle operating modes in its regulatory emission model, MOVES (Motor Vehicle Emission Simulator), as shown in Table 5-4. VSP is defined as the power per unit mass (kW/metric ton) to overcome road grade, inertial acceleration, and rolling and aerodynamic resistances:

$$VSP = \frac{A}{m} \cdot v + \frac{B}{m} \cdot v^2 + \frac{C}{m} \cdot v^3 + (a + g \cdot sin\,\theta) \cdot v \qquad (8\text{-}1)$$

where A is road load coefficient for rolling resistance ($\mathrm{kW \cdot s/m}$)
B is road load coefficient for rotating resistance ($\mathrm{kW \cdot s^2/m^2}$)
C is road load coefficient for aerodynamic drag ($\mathrm{kW \cdot s^3/m^3}$)
v is vehicle speed (m/s)
m is fixed mass factor for the vehicle type (metric ton)
a is vehicle acceleration (m/s^2)
g is acceleration due to gravity (9.8 m/s^2)
sin θ is fractional road grade

As an example, typical values for passenger cars are *A* = 0.156461, *B* = 0.00200193, *C* = 0.000492646, and *m* = 1.4788. By assuming that road grade is zero, VSP for each second of driving is then a function of speed and acceleration alone.

Table 5-4. Definition of vehicle operating modes in MOVES model

Operating Mode	Operating Mode Description	Vehicle-Specific Power (VSP*t*, kW/tonne)	Vehicle Speed (v_t,mi/hr)	Vehicle Acceleration (*a*, mi/hr-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		$-1.0 \leq v_t < 1.0$	
11	Coast	$VSP_t < 0$	$0 \leq v_t < 25$	
12	Cruise/Acceleration	$0 \leq VSP_t < 3$	$0 \leq v_t < 25$	
13	Cruise/Acceleration	$3 \leq VSP_t < 6$	$0 \leq v_t < 25$	
14	Cruise/Acceleration	$6 \leq VSP_t < 9$	$0 \leq v_t < 25$	
15	Cruise/Acceleration	$9 \leq VSP_t < 12$	$0 \leq v_t < 25$	
16	Cruise/Acceleration	$12 \leq VSP_t$	$0 \leq v_t < 25$	
21	Coast	$VSP_t < 0$	$25 \leq v_t < 50$	
22	Cruise/Acceleration	$0 \leq VSP_t < 3$	$25 \leq v_t < 50$	
23	Cruise/Acceleration	$3 \leq VSP_t < 6$	$25 \leq v_t < 50$	
24	Cruise/Acceleration	$6 \leq VSP_t < 9$	$25 \leq v_t < 50$	
25	Cruise/Acceleration	$9 \leq VSP_t < 12$	$25 \leq v_t < 50$	
27	Cruise/Acceleration	$12 \leq VSP < 18$	$25 \leq v_t < 50$	
28	Cruise/Acceleration	$18 \leq VSP < 24$	$25 \leq v_t < 50$	
29	Cruise/Acceleration	$24 \leq VSP < 30$	$25 \leq v_t < 50$	
30	Cruise/Acceleration	$30 \leq VSP$	$25 \leq v_t < 50$	
33	Cruise/Acceleration	$VSP_t < 6$	$50 \leq v_t$	
35	Cruise/Acceleration	$6 \leq VSP_t < 12$	$50 \leq v_t$	
37	Cruise/Acceleration	$12 \leq VSP < 18$	$50 \leq v_t$	
38	Cruise/Acceleration	$18 \leq VSP < 24$	$50 \leq v_t$	
39	Cruise/Acceleration	$24 \leq VSP < 30$	$50 \leq v_t$	
40	Cruise/Acceleration	$30 \leq VSP$	$50 \leq v_t$	

In this project, VSP was calculated for each second of the collected data, which also include instantaneous fuel consumption rate (grams/s). This allows the relationship between VSP and fuel consumption rate to be established. In our method, the VSP values were binned in 1 kW/metric ton increments and the average fuel consumption rate for each bin was calculated. Figure 5-3 shows an example of the relationship between VSP and fuel consumption rate for a 2007 Ford Expedition based on the data from both baseline and feedback periods. The blue dots represent the average fuel consumption rate and the error bars represent its 95% confidence interval. The black vertical bars represent the amount of data in each VSP bin that was used to calculate the average fuel consumption rate for that VSP bin.

In Figure 5-3, the variation in fuel consumption rate of each VSP bin as represented by the error bars is an indication of the varying conditions (e.g. vehicle, road, weather, traffic) under which fuel consumption data was obtained during the data collection periods. The variation is high for the VSP bins in the high end partly because the number of data samples in those bins is small. Also, those VSP bins are for vehicle operating under high power demand and the impact of uncontrolled factors (such as road grade) on instantaneous fuel consumption rate is more pronounced. Therefore, by taking the average fuel consumption rates of these VSP bins and assigning them to the second-by-second driving data based on their calculated VSP values essentially normalize the effects of every other factors except for speed and acceleration, which depend largely on driving behaviors. Note that the average fuel consumption rates assigned to each second of the driving data may be different from the actual fuel consumption rates obtained from the vehicle. This is because the actual fuel consumption rates may be affected by other factors not related to driving behaviors.

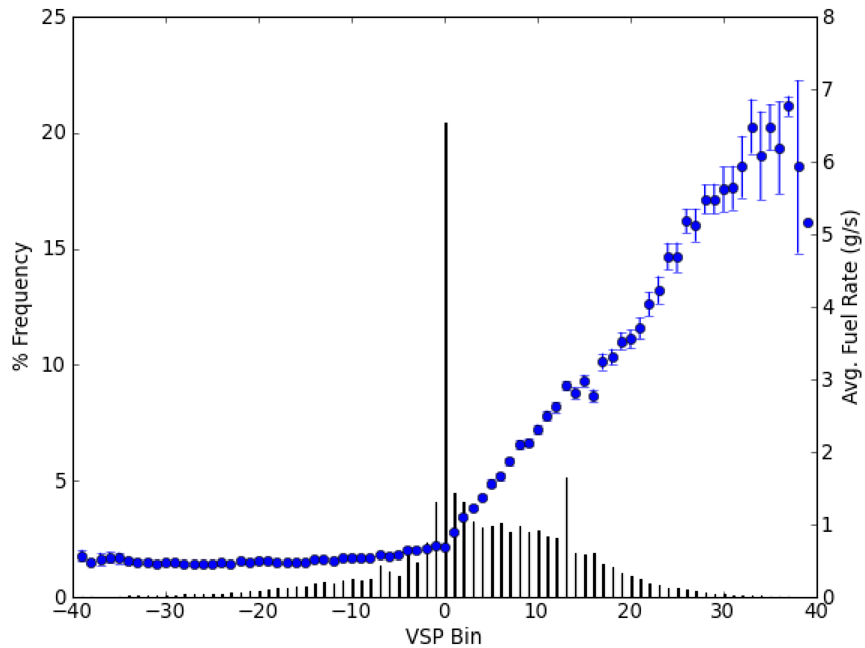


Figure 5-4. Example of VSP versus fuel consumption rate relationship

5.2.3. Adjustments for Differences in Travel Patterns

Although the use of VSP-based fuel consumption rates has removed several biases (e.g., loaded weight, tire pressure, air conditioning usage), there remain other biases that still need to be taken care of. The remaining biases are mostly due to the differences in travel patterns between the two data collection periods. For instance, if a vehicle operated more on highways during the baseline period while it was driven more on city streets during the feedback period, then the change in fuel economy for this vehicle during the feedback period might not be due to the effect of the driving feedback system alone as for a typical gasoline-engine vehicle, fuel economy is usually better in the case of highway driving. Similarly, the differences in travel patterns could result in the vehicle experiencing a different amount of steep road grade, head wind, traffic congestion, etc. between the two data collection periods.

To make adjustments for the differences in travel patterns, we adopted a similar approach to the Eco-Score algorithms where we considered four driving behaviors individually, including accelerating, braking (decelerating), idling, and speeding. We analyzed the impact of each driving behavior on vehicle fuel economy as if the vehicle was subject to the same travel pattern without and with the driving feedback system. This allowed for non-biased determination of the change in fuel economy as a result of the driving feedback system. The detailed methodology is described below, using one of the RTA shuttles (ID 312) as an example.

Acceleration and Braking Behaviors

First of all, we defined driving scenarios under which the vehicles would experience. Since vehicle fuel economy differs greatly based on road type (highway versus city) and varies by vehicle speed, we defined 16 driving scenarios as listed in Table 5-5. They are made up of two road types and eight speed ranges. Note that although driving scenarios 15 and 16 are very unlikely, we keep them for consistency.

Table 5-5. Definition of driving scenarios

Driving Scenario	Road Type	Speed Range (mph)
1	Highway	<7.5
2	Highway	7.5-17.5
3	Highway	17.5-27.5
4	Highway	27.5-37.5
5	Highway	37.5-47.5
6	Highway	47.5-57.5
7	Highway	57.5-67.5
8	Highway	>67.5
9	City Street	<7.5
10	City Street	7.5-17.5
11	City Street	17.5-27.5
12	City Street	27.5-37.5
13	City Street	37.5-47.5
14	City Street	47.5-57.5
15	City Street	57.5-67.5
16	City Street	>67.5

Next, we assigned each second of the collected driving data to one of the 16 driving scenarios based on a combination of road type and instantaneous speed. Then, we calculated the average value of the VSP-based fuel consumption rate for each driving scenario. This calculation was performed separately for data from the baseline period and the feedback period. The results are shown in Figure 5-5 for highway driving scenarios and Figure 5-6 for city driving scenarios. It can be observed that for most of the scenarios the average fuel rate during the feedback period is lower than that during the baseline period. This is mainly due to the milder acceleration and deceleration with which this shuttle was operated during the feedback period, as shown in Figure 5-7 through Figure 5-10. For instance, the acceleration rates while driving at speed between 5 and 35 mph on highway were much lower on average during the feedback period compared to the baseline period. The same was true for the deceleration rates. These result in the notably lower average fuel rates during the feedback period for driving scenarios 2, 3, and 4. For this shuttle, the changes in average acceleration and deceleration were not as much in other driving scenarios but almost all of them are in the positive direction (i.e., being milder). It is reasonable to assume that these changes are attributable to the driving feedback system.

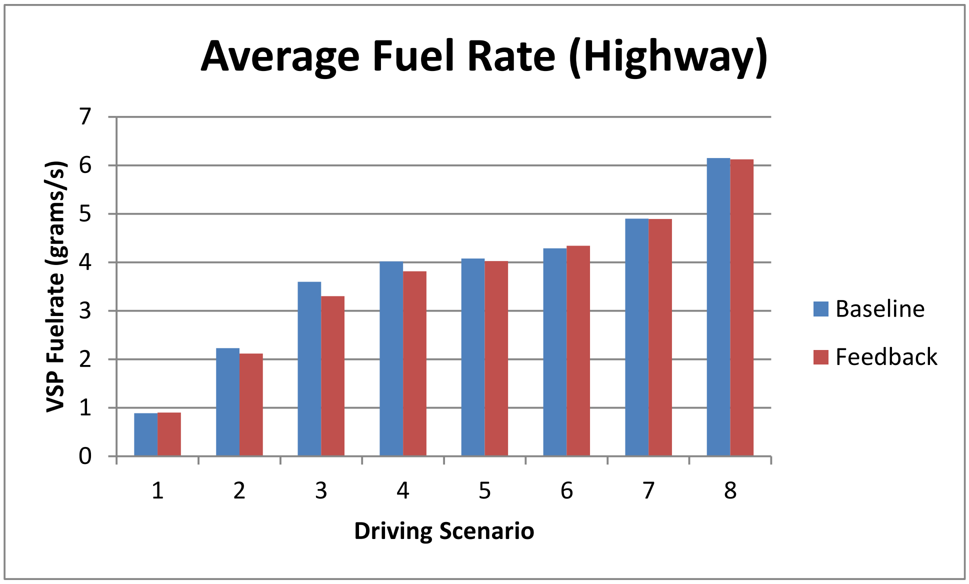


Figure 5-5. Average fuel consumption rate under each highway scenarios

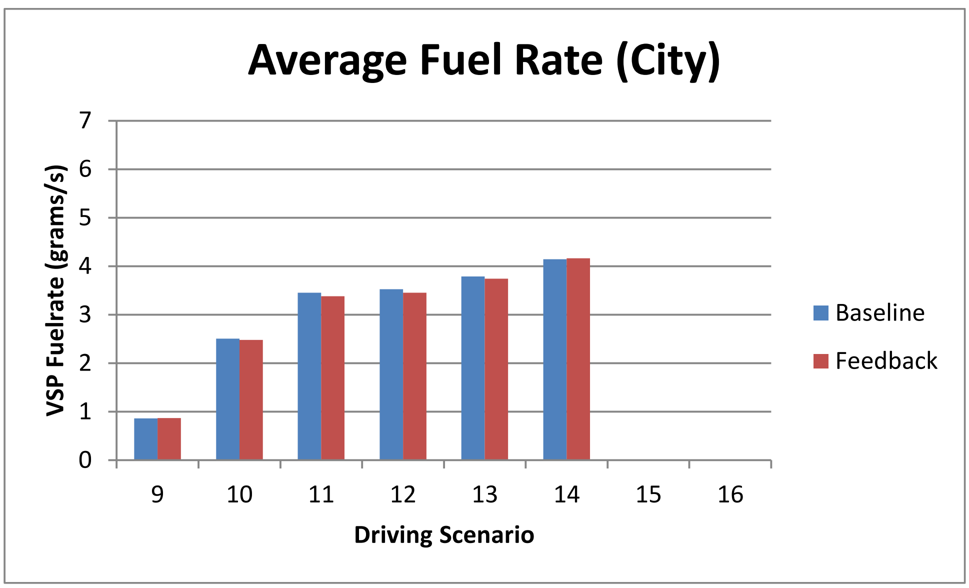


Figure 5-6. Average fuel consumption rate under each city scenarios

In order to estimate the impact of changes in acceleration and deceleration rates on vehicle fuel consumption, we combined the driving data from both baseline and feedback periods, and then determined the proportion of driving time the vehicle was operated under each of the 16 driving scenarios. The results are presented in Figure 5-11 for highway driving scenarios and Figure 5-12 for city driving scenarios. After that, we calculated the total fuel consumption without and with the use of the driving feedback system as

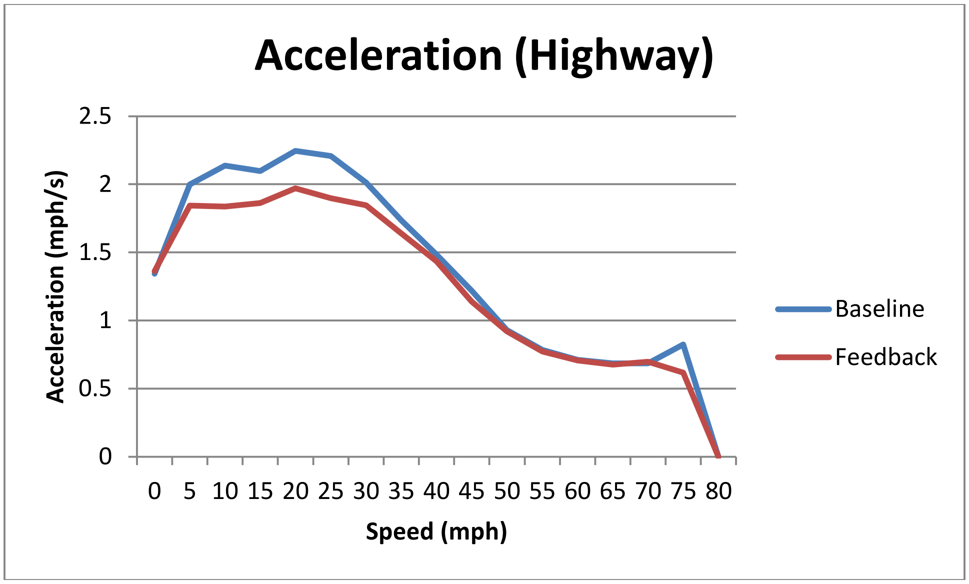


Figure 5-7. Average acceleration profile during highway driving

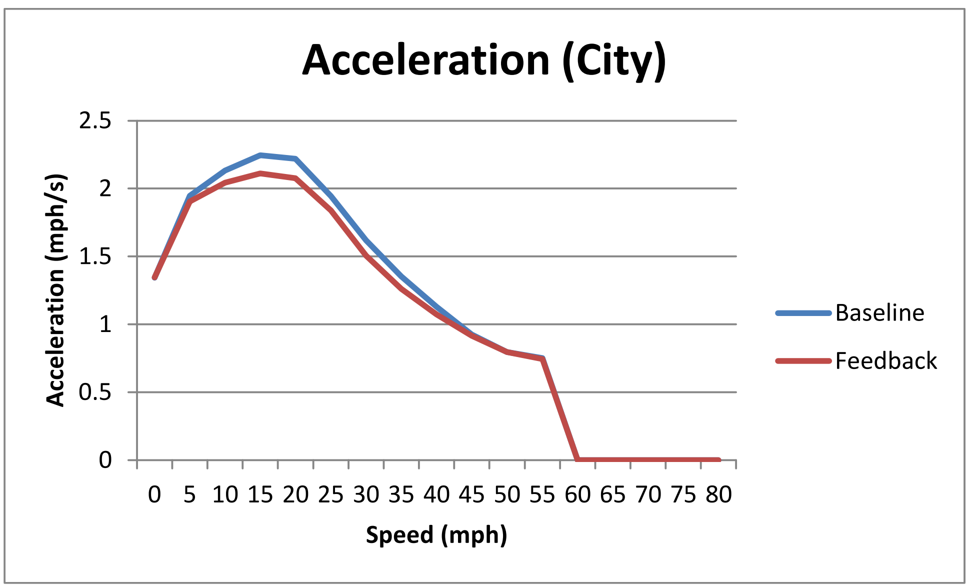


Figure 5-8. Average acceleration profile during city driving

$$F(a,b)_j = \sum_{i=1}^{16}(f_{i,j}.t_i) \qquad (8\text{-}2)$$

where *F(a,b)* is total fuel consumption adjusted for accelerating and braking behaviors (grams)
f is average fuel consumption rate (grams/s)
t is driving time from both periods combined (s)
i is driving scenario; *i* = {1, 2, 3, ..., 16}
j is use of driving feedback system; *j* = {without, with}

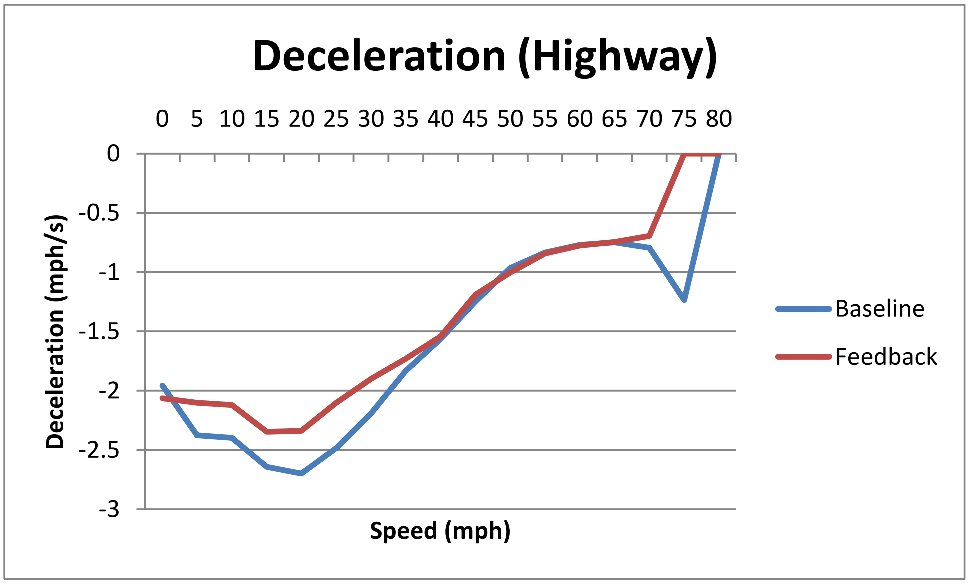


Figure 5-9. Average deceleration profile during highway driving

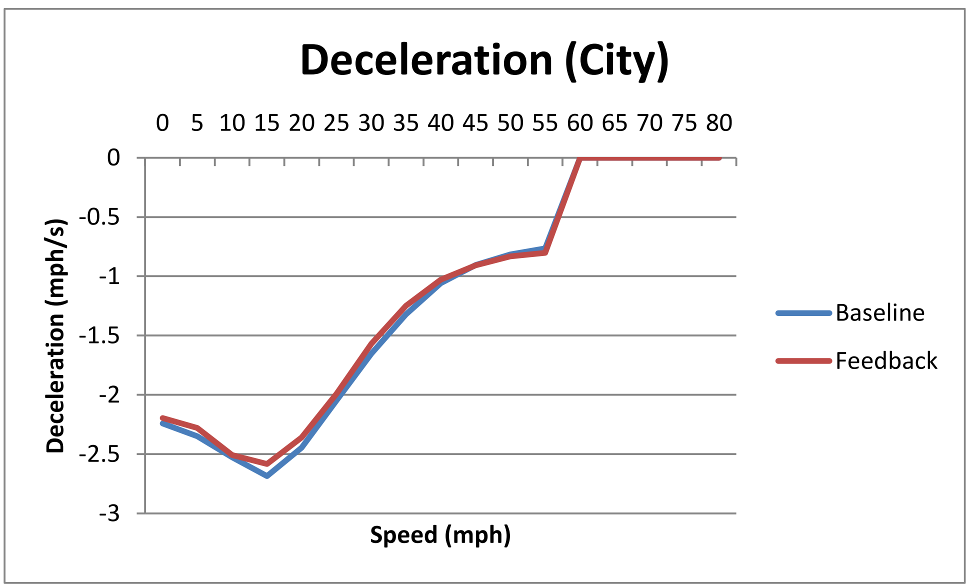


Figure 5-10. Average deceleration profile during city driving

The calculation above assumes that the vehicle was subjected to the same travel pattern during the periods without and with the driving feedback system as the same driving time distribution is used for both periods. It ensures that the difference in the calculated total fuel consumption between the two periods is due to the differences in average fuel rates, and thus, acceleration and deceleration profiles. Therefore, it can be claimed that the difference in the total fuel consumption calculated in this step reflects the changes in accelerating and braking behaviors of the driver as influenced by the driving feedback system.

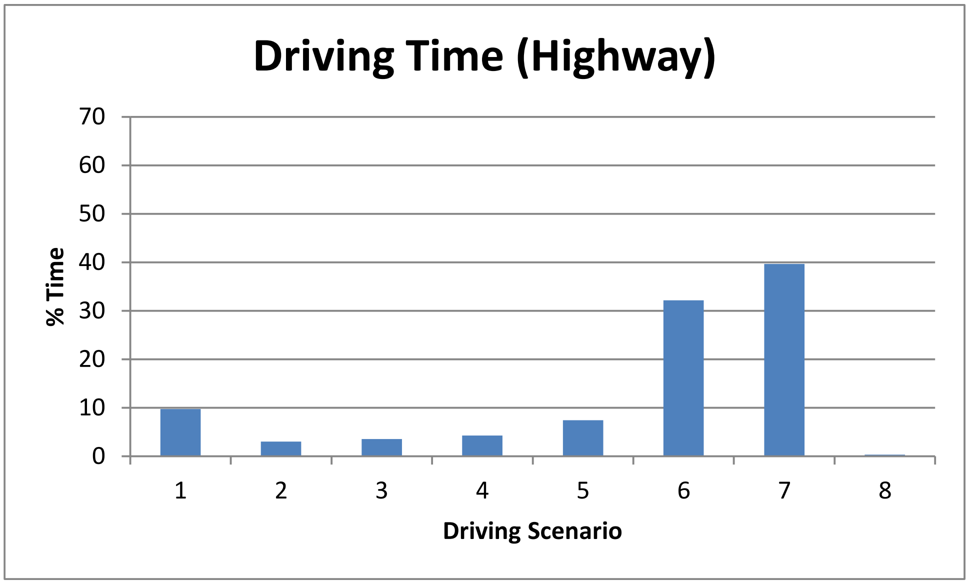


Figure 5-11. Percent driving time under each highway scenario

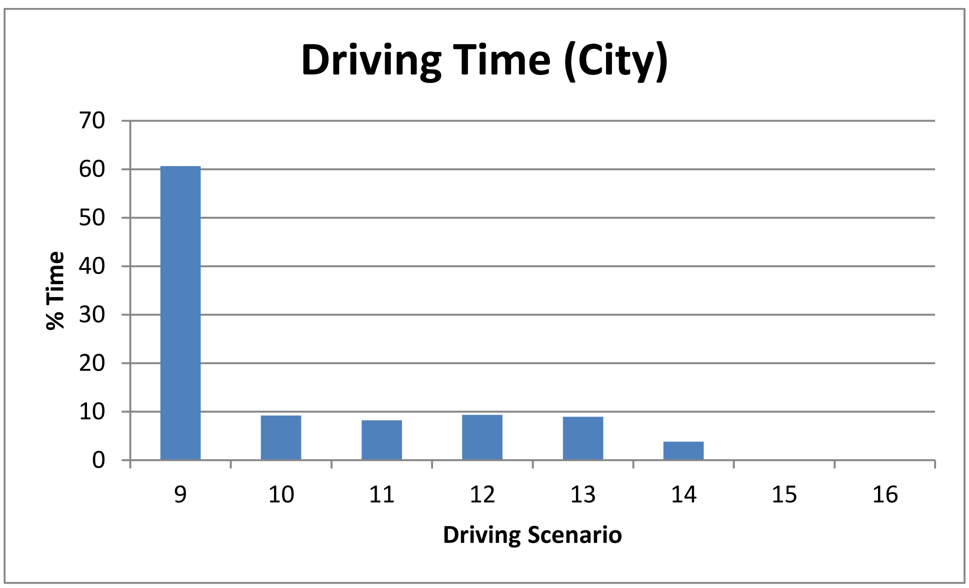


Figure 5-12. Percent driving time under each city scenario

Idling Behavior

Although idling is sometime unavoidable, unnecessarily long idling is not desirable and discouraged by the driving feedback system. A warning sign will be flashed (and accompanied by a warning sound if set by the driver) if the vehicle has been idling for longer than a threshold. To account for the effect of changes in idling behavior on total fuel consumption, we applied a method revolving around an *unnecessary idling rate*, defined as the total idling time beyond the threshold (e.g., 5 minutes) per hour of vehicle operation time. Figure 5-13 shows the frequency of all idling events by idling period, and Figure 5-14 shows the unnecessary idling rates for two example threshold values. According to Figure 5-13, while the majority of the idling events during the baseline period was shorter than 2.5 minutes, the idling events during the feedback period were more evenly distributed. When examining Figure 5-14, it is observed that the unnecessary idling rates during the feedback period were lower, presumably due to the influence of the driving feedback system.

To account for the changes in unnecessary idling rate on total fuel consumption, we performed the following calculations.

$$uF = f^{VSP=0} \cdot \sum_j uT_j \tag{8-3}$$

$$uF'_j = f^{VSP=0} \cdot uR_j \cdot \sum_j VOT_j \tag{8-4}$$

$$F(a,b,i)_j = F(a,b)_j - uF + uF'_j \tag{8-5}$$

where *uF* is actual fuel consumption due to unnecessary idling in both periods combined (grams)
$f^{VSP=0}$ is idling fuel consumption rate which is when VSP is 0 (grams/s)
uT is total unnecessary idling time beyond the threshold (s)
uF' is adjusted fuel consumption based on period-specific unnecessary idling rate (grams)
uR is unnecessary idling rate (s/hr)
VOT is vehicle operating time (hr)
F(a,b) is total fuel consumption adjusted for accelerating and braking behaviors (grams)
F(a,b,i) is total fuel consumption adjusted for accelerating, braking, and idling behaviors (grams)
j is use of driving feedback system; *j* = {without, with}

Equation (8-3) determines how much fuel was actually consumed while idling unnecessarily during both baseline and feedback periods. Equation (8-4) then determines how much fuel would have been consumed while idling unnecessarily if the period-specific unnecessary idling rates had been applied throughout the entire vehicle operating time in both periods. Finally, Equation (8-5) subtracts the actual fuel consumption and adds the adjusted fuel consumption to the total fuel consumption previously adjusted for accelerating and braking behaviors. The result is the total fuel consumption adjusted for accelerating, braking, as well as idling behaviors.

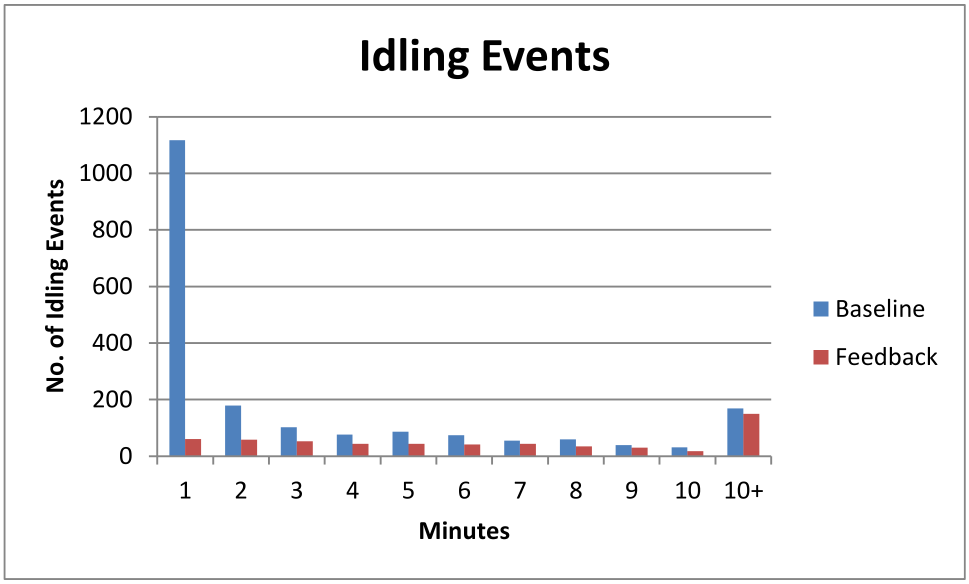


Figure 5-13. Number of idling events by idling period

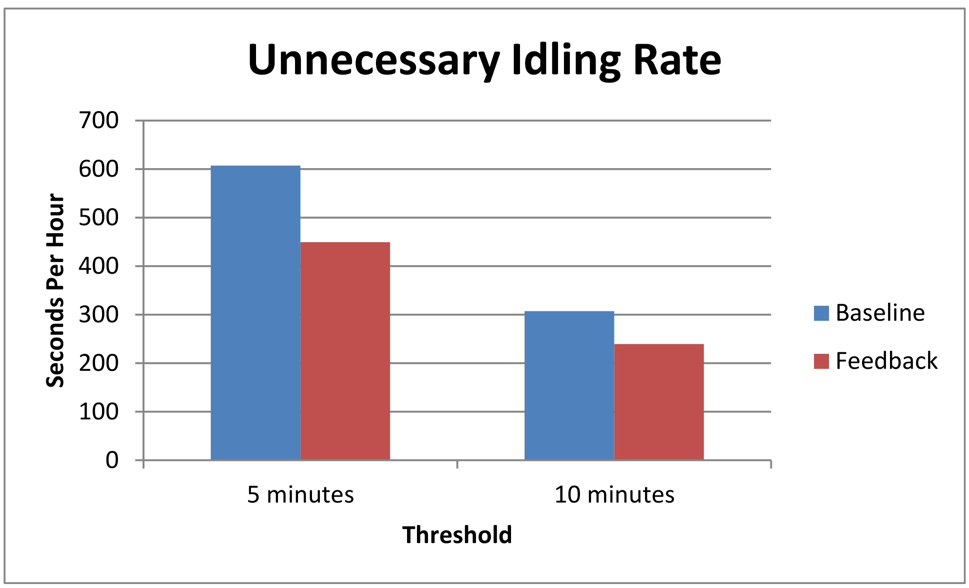


Figure 5-14. Unnecessary idling time per hour of vehicle operation time

Speeding Behavior

A vehicle usually has a range of speed in which it is most fuel efficient. This "sweet-spot" speed range varies from one vehicle to another as well as by road type. Figure 5-15 shows the relationship between speed and fuel consumption per unit distance for the example RTA shuttle (ID 312) using data collected from both periods. For city driving the fuel consumption rate starts to bottom out at around 45 mph and stays flat through 55 mph. This is because traveling at those speeds on city streets[10] involves mostly cruising. For highway driving, the sweet-spot speed range is around 50-60 mph. While traveling at speeds above 50 mph on freeways involves mostly cruising, the vehicle needs more power to overcome the higher aerodynamic drag at speeds beyond 60 mph.

Although driving at speeds below the sweet-spot speeds will incur higher fuel consumption, it is often difficult to maintain these speeds because of traffic congestion. Similarly, driving above 55 mph on highway but still below the speed limit may sometime be necessary. In fact, when traffic is moving at or around the speed limit (e.g., 65 mph), driving at a significant lower speed is unsafe and considered a hazard to other vehicles. Therefore, no point is deducted in the Speed Score of the driving feedback system under these circumstances.

On the other hand, excessive speed is always a safety concern and speeding is illegal. In addition, driving at a speed exceeding speed limits on highways is usually not fuel efficient. Therefore, in the Speed Score calculation algorithm, points are only deducted from the maximum possible of 100 whenever the vehicle speed exceeds the speed limit. Also, the driving feedback system will flash a warning sign (and provide a warning sound if set by the driver) to encourage the driver to slow down. Therefore, in the normalization of fuel consumption for speed behavior, we focused on the effect of change in the amount of speeding beyond the speed limit.

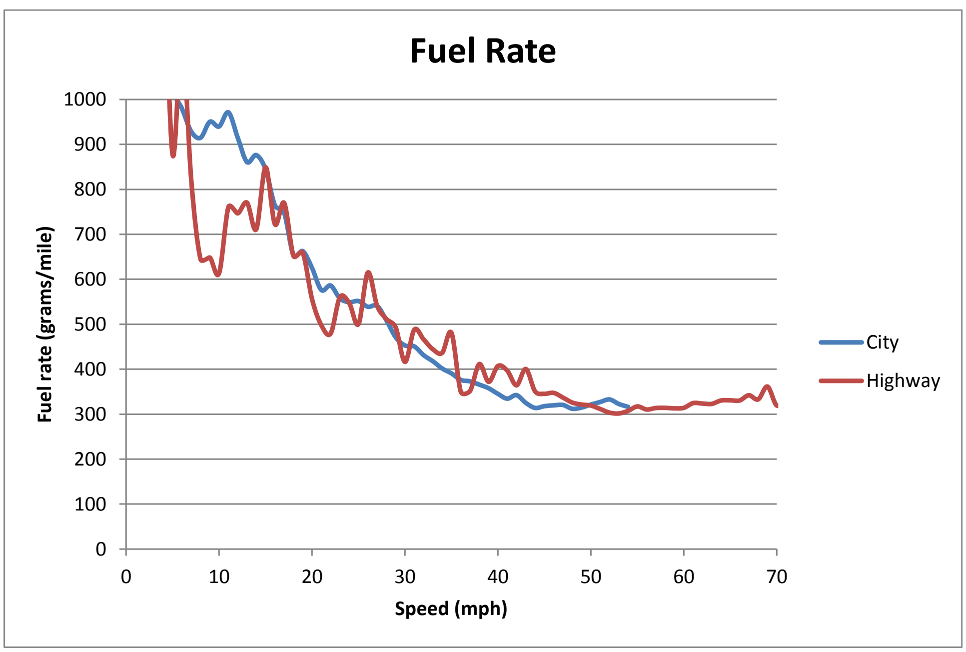


Figure 5-15. Fuel consumption per mile for RTA shuttle ID 312

[10] City streets here are referred to all non-freeway roads with unrestricted access. These include some major arterials and signalized highways with speed limit as high as 50 mph.

The method to account for the effect of change in speeding behavior on total fuel consumption revolves around a *speeding rate*. Since all freeways in the study area have a speed limit of 65 mph, the speeding rate for highway driving is defined as the ratio of total driving time above 65 mph to total driving time above 55 mph. The rationale is that when driving at speeds above 55 mph, it is likely not (or minimally) affected by traffic congestion. When provided with such speed choice freedom, a fuel-efficient driver will keep the driving speed below the speed limit of 65 mph. For city driving, it is more difficult to define the speeding rate as the speed limits on city streets vary greatly. In the context of fuel efficiency and according to Figure 5-15, the speeding rate for city driving is defined as the ratio of total driving time above 55 mph to total driving time above 45 mph. Figure 5-16 and Figure 5-17 show the speed distributions of the example vehicle for highway driving and city driving, respectively.

To account for the change in speeding rate on total fuel consumption, we performed the following calculations.

$$sF = \sum_{i,j}(f_{i,j}.t_i\,)\,; i = \{8,15,16\} \tag{8-6}$$

$$\begin{aligned} sF'_j = &\left[\frac{t_{8,j}}{\sum_{i=7}^{8} t_{i,j}} \times \sum_{i=7}^{8} \sum_j t_{i,j} \times f_{8,j}\right] \\ &+ \left[\frac{t_{15,j}}{\sum_{i=14}^{16} t_{i,j}} \times \sum_{i=14}^{16} \sum_j t_{i,j} \times f_{15,j}\right] + \left[\frac{t_{16j}}{\sum_{i=14}^{16} t_{i,j}} \times \sum_{i=14}^{16} \sum_j t_{i,j} \times f_{16,j}\right] \end{aligned} \tag{8-7}$$

$$F(a,b,i,s)_j = F(a,b,i)_j - sF + sF'_j \tag{8-8}$$

where *sF* is actual fuel consumption due to speeding in both periods combined (grams)
f is average fuel consumption rate (grams/s)
t is driving time from both periods combined (s)
sF′ is adjusted fuel consumption based on period-specific speeding rate (grams)
F(a,b,i) is total fuel consumption adjusted for accelerating, braking, and idling behaviors (grams)
F(a,b,i,s) is total fuel consumption adjusted for accelerating, braking, idling, and speeding behaviors (grams)
i is driving scenario; *i* = {1, 2, 3, …, 16}
j is use of driving feedback system; *j* = {without, with}

Equation (8-6) determines how much fuel was actually consumed while speeding during both baseline and feedback periods. Equation (8-7) then determines how much fuel would have been consumed while speeding if the period-specific speeding rates had been applied throughout the driving time with speed choice freedom. In this equation, the first bracket is for highway driving and the other two brackets are for city driving. In each bracket, the first term is the speeding rate, the second term is the total driving time with speed choice freedom, and the last term is the average fuel consumption rate. Finally, Equation (8-8) subtracts the actual fuel consumption and adds the adjusted fuel consumption to the total fuel consumption previously adjusted for accelerating, braking, and idling behaviors. The result is the total fuel consumption adjusted for accelerating, braking, idling, as well as speeding behaviors.

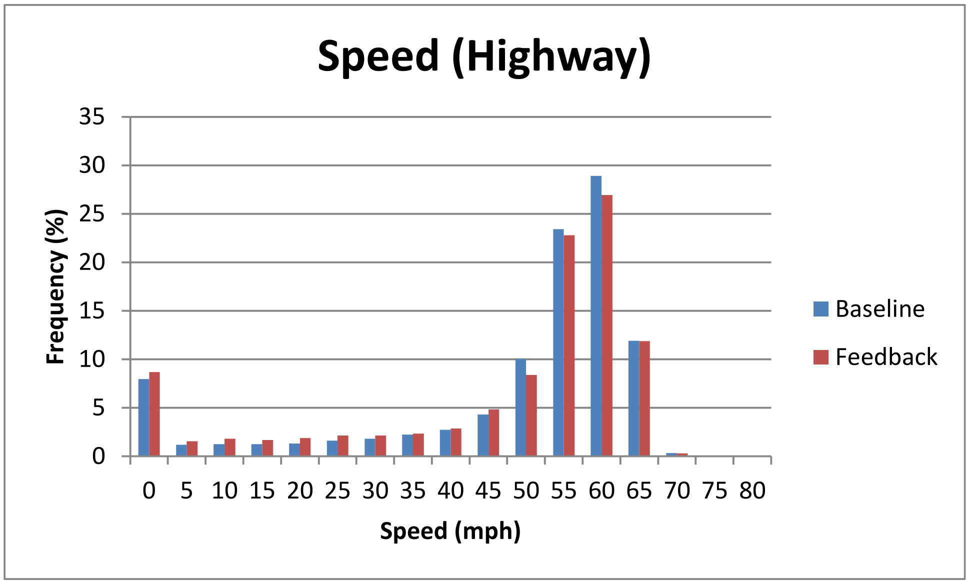


Figure 5-16. Speed distribution during highway driving

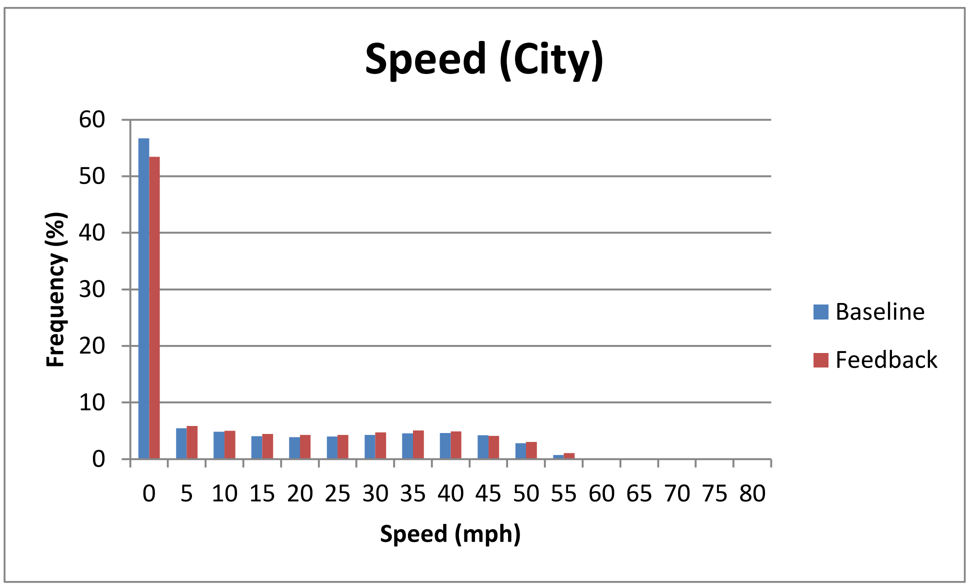


Figure 5-17. Speed distribution during city driving

5.2.4. Results

After completing the normalization of fuel consumption rates and the adjustments of fuel consumption for differences in travel patterns, we calculated the normalized fuel economy numbers without and with the use of driving feedback system as

$$nFE_j = 2790.7 \times \sum_j Dj / F(a,b,i,s)_j \tag{8-9}$$

where *nFE* is normalized fuel economy (miles per gallon, MPG)
D is total travel distance (miles)
F(a,b,i,s) is total fuel consumption adjusted for accelerating, braking, idling, and speeding behaviors (grams)
j is use of driving feedback system; *j* = {without, with}

The constant 2790.7 is for converting the unit of fuel consumption from grams to gallon. These normalized fuel economy numbers were used to determine the effectiveness of the driving feedback system at improving fuel efficiency, both at the vehicle level as well as at the fleet level, for each of the three fleets.

RTA Fleet

Table 5-6 presents the fuel economy results for the RTA fleet. In this table, FE stands for fuel economy, nFE normalized fuel economy, and nFuel normalized fuel consumption. The normalized fuel consumption is back-calculated based on the normalized fuel economy and distance. The last two columns of the table are the changes in fuel economy and normalized fuel economy during the feedback period compared to the baseline period.

Table 5-6. Fuel economy results for RTA fleet

Veh ID	Baseline Period					Feedback Period					Change in	
	Dist. (mi)	Fuel (gal)	FE (mpg)	nFuel (gal)	nFE (mpg)	Dist. (mi)	Fuel (gal)	FE (mpg)	nFuel (gal)	nFE (mpg)	FE (%)	nFE (%)
306	2,605	368	7.1	373	7.0	3,313	474	7.0	469	7.1	-1.4	1.3
312	4,617	789	5.8	793	5.8	5,569	940	5.9	935	6.0	1.7	2.3
313	4,327	572	7.6	574	7.5	2,974	393	7.6	391	7.6	0.0	0.9
314	3,372	466	7.2	466	7.2	5,257	721	7.3	721	7.3	1.4	0.6
320	4,349	620	7.0	634	6.9	2,100	306	6.9	294	7.1	-1.4	4.1
321	2,863	405	7.1	409	7.0	3,920	541	7.2	537	7.3	1.4	4.2
323	4,058	525	7.7	526	7.7	2,949	377	7.8	377	7.8	1.3	1.5
325	3,683	467	7.9	492	7.5	7,272	1,002	7.3	978	7.4	-7.6	-0.7
326	2,873	418	6.9	421	6.8	3,350	483	6.9	481	7.0	0.0	2.0
328	4,320	562	7.7	569	7.6	7,731	1,016	7.6	1,008	7.7	-1.3	0.9
329	3,755	557	6.7	578	6.5	3,549	550	6.5	529	6.7	-3.0	3.3
330	2,356	334	7.1	331	7.1	585	78	7.5	81	7.2	5.6	1.2
331	3,010	397	7.6	395	7.6	7,626	990	7.7	992	7.7	1.3	1.0
336	4,547	619	7.3	620	7.3	5,695	767	7.4	766	7.4	1.4	1.3
338	1,868	263	7.1	284	6.6	4,451	691	6.4	670	6.6	-9.9	1.0
Fleet	*52,604*	*7,362*	*7.1*	*7,464*	*7.0*	*66,340*	*9,328*	*7.1*	*9,229*	*7.2*	*-0.5*	*2.0*

According to Table 5-6, the fleet average change in fuel economy is negative, meaning that the fuel efficiency during the feedback period was lower than that during the baseline period. But as pointed out earlier in this chapter, that can be due to the variation in real-world fuel economy caused by a variety of factors as well as the differences in travel patterns between the two data collection periods. On the other hand, the fleet average normalized fuel economy increased by 2.0% during the feedback period, indicating that the driving feedback system helped improve the overall fuel efficiency of the fleet. When looking at the results for the individual vehicles, it was found that all but one shuttle had a higher normalized fuel economy, ranging from 0.6% to 4.2%.

To determine where the improvements in normalized fuel economy come from, we refer to the eco-scores results for the RTA fleet presented in Table 5-7. In this table, ESA is eco-score for acceleration, ESD eco-score for deceleration (braking), ESS eco-score for speed, ESI eco-score for idling, and ES overall eco-score. The table presents the eco-scores for each data collection period as well as the changes in eco-scores. The changes in eco-scores are colored in gradient from red (negative values) to no color (zero) to green (positive values). This allows for a quick observation of patterns in the changes in eco-scores.

According to the color pattern in Table 5-7, it is observed that the most improvement is in the eco-score for idling, indicating that during the feedback period most drivers committed less excessive idling. Especially, vehicles 321 and 329 which have the highest values of change in eco-score for idling (7.1% and 7.3%, respectively) also rank among the top three vehicles with the greatest improvement in normalized fuel economy (4.2% and 3.3%, respectively) according to Table 5-6. It is noted that the RTA vehicles have already been instrumented with a safety-camera system where the camera will record a video clip of the driver and inside the vehicle when triggered by an event deemed unsafe (e.g., aggressive acceleration, hard braking). Thus, the drivers have already practiced safe driving, which translates to mild acceleration and braking as well as moderate speed, without the use of the driving feedback system. On the other hand, excessive idling events are not recorded by the safety-camera system and reported to the fleet manager. Therefore, it is logical that the driving feedback system brings about the most improvements in idling behavior.

Table 5-7. Eco-score results for RTA fleet

	Baseline Period					Feedback Period					Change (%)				
Veh ID	ESA	ESD	ESS	ESI	ES	ESA	ESD	ESS	ESI	ES	ESA	ESD	ESS	ESI	ES
306	92.4	94.1	99.4	95.2	95.3	92.8	94.5	99.3	95.1	95.4	0.4	0.4	-0.1	0.0	0.2
312	93.3	94.3	97.9	88.0	93.4	93.2	94.2	98.0	89.9	93.8	-0.1	-0.1	0.1	2.2	0.5
313	92.4	94.2	99.2	93.7	94.9	92.5	94.4	99.4	93.8	95.0	0.2	0.2	0.2	0.1	0.2
314	92.5	93.9	99.4	93.5	94.8	92.1	93.8	99.4	93.6	94.7	-0.5	-0.1	0.0	0.1	-0.1
320	92.4	93.9	98.8	95.3	95.1	93.7	95.7	99.6	94.3	95.8	1.4	1.9	0.8	-1.0	0.7
321	93.2	94.5	98.8	88.0	93.6	93.3	94.6	99.4	94.3	95.4	0.1	0.1	0.6	7.1	1.9
323	93.3	94.2	99.3	92.1	94.7	92.9	93.9	99.5	93.9	95.1	-0.3	-0.3	0.2	1.9	0.3
325	93.1	94.2	99.4	89.8	94.1	92.4	93.6	99.1	90.0	93.8	-0.8	-0.6	-0.3	0.3	-0.4
326	92.5	93.9	99.1	92.3	94.5	92.8	94.0	99.4	94.6	95.2	0.3	0.1	0.3	2.5	0.8
328	92.8	94.3	99.5	94.1	95.2	92.0	94.1	99.6	95.4	95.3	-0.9	-0.2	0.1	1.3	0.1
329	93.7	94.5	99.2	86.2	93.4	93.5	94.4	99.1	92.5	94.9	-0.2	-0.1	-0.1	7.3	1.6
330	92.8	94.3	99.1	90.9	94.3	93.2	94.6	99.4	90.8	94.5	0.4	0.4	0.4	-0.1	0.2
331	92.7	93.7	99.2	95.0	95.1	92.3	93.7	98.8	95.3	95.0	-0.4	0.0	-0.4	0.4	-0.1
336	93.2	94.7	99.5	91.4	94.7	92.7	94.3	99.6	94.5	95.3	-0.5	-0.4	0.1	3.4	0.6
338	93.5	94.2	99.4	89.5	94.2	93.5	94.3	99.2	90.0	94.2	0.0	0.1	-0.3	0.6	0.1

Caltrans Fleet

In the same fashion as for the RTA fleet, Table 5-8 presents the fuel economy results and Table 5-9 presents the eco-score results for the Caltrans fleet. According to Table 5-8, the fleet average normalized fuel economy increased by 9.3% during the feedback period, which is quite substantial. When looking at the changes in normalized fuel economy for the individual vehicles, it was found that the results vary greatly, ranging from -20.4% to 23.0%.

Table 5-8. Fuel economy results for Caltrans fleet

	Baseline Period					Feedback Period					Change in	
Veh ID	Dist. (mi)	Fuel (gal)	FE (mpg)	nFuel (gal)	nFE (mpg)	Dist. (mi)	Fuel (gal)	FE (mpg)	nFuel (gal)	nFE (mpg)	FE (%)	nFE (%)
942	725	38	18.9	37	19.7	1,853	98	18.9	100	18.5	0.0	-5.8
945	701	39	18.0	42	16.8	4,484	247	18.1	244	18.4	0.6	9.5
948	301	24	12.4	23	12.9	245	19	12.9	20	12.3	4.0	-5.0
957	3,162	195	16.2	196	16.2	545	32	17.0	32	17.1	4.9	5.7
950	403	27	15.1	27	15.2	158	9	16.7	10	16.4	10.6	8.0
956	2,492	139	17.9	136	18.3	342	21	16.3	23	14.5	-8.9	-20.4
959	1,015	65	15.7	66	15.4	662	37	18.0	35	18.9	14.6	23.0
949	693	48	14.5	46	14.9	300	19	15.5	20	14.7	6.9	-1.9
955	1,338	89	15.0	106	12.6	86	24	3.7	7	12.8	-75.3	1.8
958	368	22	16.7	23	15.7	132	10	13.4	8	15.8	-19.8	0.4
922	1,008	55	18.2	55	18.3	98	6	17.6	6	17.2	-3.3	-5.7
951	805	66	12.2	67	12.1	543	43	12.5	42	12.8	2.5	5.5
Fleet	*13,012*	*808*	*16.1*	*824*	*15.8*	*9,448*	*565*	*16.7*	*547*	*17.3*	*3.8*	*9.3*

Table 5-9. Eco-score results for Caltrans fleet

	Baseline Period					Feedback Period					Change (%)				
Veh ID	ESA	ESD	ESS	ESI	ES	ESA	ESD	ESS	ESI	ES	ESA	ESD	ESS	ESI	ES
942	94.0	94.5	91.9	96.3	94.2	95.1	95.6	91.5	91.3	93.4	1.2	1.1	-0.4	-5.3	-0.9
945	94.7	94.8	79.9	99.4	92.2	93.9	94.0	84.2	97.0	92.3	-0.8	-0.8	5.3	-2.4	0.1
948	92.3	92.9	99.0	87.9	93.0	93.5	94.3	98.7	80.5	91.7	1.3	1.5	-0.3	-8.4	-1.4
957	94.0	94.3	86.9	87.2	90.6	92.7	93.0	84.9	90.5	90.3	-1.4	-1.4	-2.3	3.9	-0.4
950	93.1	93.5	89.3	84.7	90.2	94.9	95.2	94.7	85.9	92.7	1.9	1.8	6.0	1.4	2.8
956	92.1	92.9	86.9	96.8	92.2	96.3	96.8	88.6	69.3	87.8	4.6	4.2	2.0	-28.4	-4.8
959	95.2	95.7	94.9	76.7	90.7	95.0	95.6	98.1	83.8	93.1	-0.3	-0.1	3.4	9.2	2.7
949	94.4	94.9	98.4	67.7	88.8	92.1	92.9	96.4	79.8	90.3	-2.5	-2.1	-2.0	17.9	1.6
955	94.9	95.2	98.4	73.4	90.5	96.4	96.6	99.5	68.9	90.4	1.6	1.5	1.1	-6.2	-0.1
958	91.6	92.7	92.7	97.1	93.5	90.8	93.6	94.9	89.5	92.2	-0.9	1.0	2.5	-7.8	-1.4
922	91.6	92.4	90.6	96.9	92.9	92.5	93.1	90.0	92.0	91.9	0.9	0.8	-0.7	-5.1	-1.1
951	96.5	96.6	95.0	46.5	83.6	96.9	96.8	96.9	46.9	84.3	0.4	0.2	2.0	0.9	0.9

It is observed that five out of 12 vehicles had degraded normalized fuel economy during the feedback period. Based on the results in Table 5-9, for four of these five vehicles the degraded normalized fuel economy was primarily attributable to having worse idling behavior. In fact, more than half of the fleet had much worse idling behavior during the feedback period. A possible explanation is that the feedback period for this fleet overlapped mostly with summer months where the air temperature could be over

100 °F in the area where these vehicles were operated (Inland Empire region of Southern California). Also, these vehicles were used for outdoor activities such as visiting construction sites and field work. Therefore, there was sometime an urge for the drivers to idle the vehicles for cooling purposes. Unlike the RTA drivers who are employed as a professional driver and their driving performance monitored and evaluated by the fleet manager, the Caltrans drivers are engineering professionals who use the agency's vehicles to facilitate their job responsibilities. Thus, they might prioritize creating a work environment that allows them to perform their primary functions over saving fuel.

On the other hand, the significant improvement in normalized fuel economy for the Caltrans fleet was brought about primarily by improvements in acceleration, braking, and speed behaviors. Unlike the RTA vehicles, the Caltrans vehicles have not been instrumented with any monitoring system, and thus, the Caltrans drivers had not previously been monitored for their driving behaviors. That may be why they improve acceleration, braking, and speed behaviors with the use of the driving feedback system.

Private Fleet

Table 5-10 presents the fuel economy results and Table 5-11 presents the eco-score results for the private vehicle fleet. According to Table 5-10, the fleet average normalized fuel economy increased by 2.1% during the feedback period. The changes in normalized fuel economy for the individual vehicles show that four out of six vehicles increased their normalized fuel economy, one of them substantially. For this particular vehicle (ID 22), the increase in normalized fuel economy is driven mainly by the improvement in speed behavior. When examining the color pattern in Table 5-11, it is observed that most of the changes in eco-scores are modest, in the range of +/-1%.

Table 5-10. Fuel economy results for private fleet

	Baseline Period					Feedback Period					Change in	
Veh ID	Dist. (mi)	Fuel (gal)	FE (mpg)	nFuel (gal)	nFE (mpg)	Dist. (mi)	Fuel (gal)	FE (mpg)	nFuel (gal)	nFE (mpg)	FE (%)	nFE (%)
16	1,481	46	32.0	47	31.8	2,171	69	31.6	69	31.7	-1.3	-0.5
22	534	19	28.5	19	27.8	102	4	25.3	3	32.1	-11.3	15.6
23	758	35	21.4	33	22.8	1,297	56	23.3	58	22.5	9.1	-1.3
25	609	21	28.7	21	28.6	201	7	28.8	7	29.1	0.4	1.7
26	431	16	26.8	16	27.2	1,598	58	27.6	58	27.5	3.1	1.2
30	2,929	80	36.6	82	35.7	5,180	144	35.9	142	36.4	-1.9	1.7
Fleet	*6,742*	*198*	*34.0*	*198*	*34.0*	*10,548*	*304*	*34.7*	*304*	*34.7*	*2.0*	*2.1*

Table 5-11. Eco-score results for private fleet

	Baseline Period					Feedback Period					Change (%)				
Veh ID	ESA	ESD	ESS	ESI	ES	ESA	ESD	ESS	ESI	ES	ESA	ESD	ESS	ESI	ES
16	91.9	89.8	99.4	98.8	95.0	91.9	89.8	99.3	99.1	95.0	0.0	0.0	-0.2	0.3	0.0
22	90.6	91.6	95.0	96.5	93.4	91.3	92.2	98.7	97.0	94.8	0.8	0.7	3.8	0.5	1.5
23	90.2	90.4	98.4	100.0	94.8	90.3	90.3	97.7	99.1	94.4	0.1	-0.1	-0.7	-0.9	-0.4
25	89.3	88.8	96.1	99.9	93.5	89.3	88.7	96.1	100.0	93.5	0.0	-0.1	0.0	0.1	0.0
26	89.0	89.4	97.7	99.9	94.0	89.6	89.9	96.3	100.0	93.9	0.6	0.6	-1.5	0.0	-0.1
30	91.9	90.3	97.7	98.8	94.7	91.7	90.0	98.5	98.4	94.7	-0.3	-0.3	0.8	-0.4	0.0

5.2.5. Discussion

Effect of Gas Prices

The modest changes in eco-scores for the private fleet might be due to the effect of gas prices. Figure 5-18 illustrates the gasoline prices in the study areas (Riverside and Los Angeles, California) between 2010 and 2014. The project began in the fall of 2011 in response to the big surge in gasoline prices earlier in the year. While there had been fluctuation, the prices remained relatively high until the summer of 2014, after which they plunged rapidly. Figure 5-18 also highlights the baseline period in light blue and the feedback period in light yellow. It can be seen that the baseline period overlapped with the last surge in gasoline prices before the great drop in gasoline prices while the feedback overlapped directly with it.

For private drivers who have freedom on how they want to drive, the main motivation for using the driving feedback system would probably be to save fuel cost. The research team observed that while many drivers were excited to learn about fuel saving technology and participate in the study when we first met them in early 2014 to install the baseline data collection system, the excitement seemed to cool down when installed the driving feedback system in the summer and provided technical support throughout the feedback period.

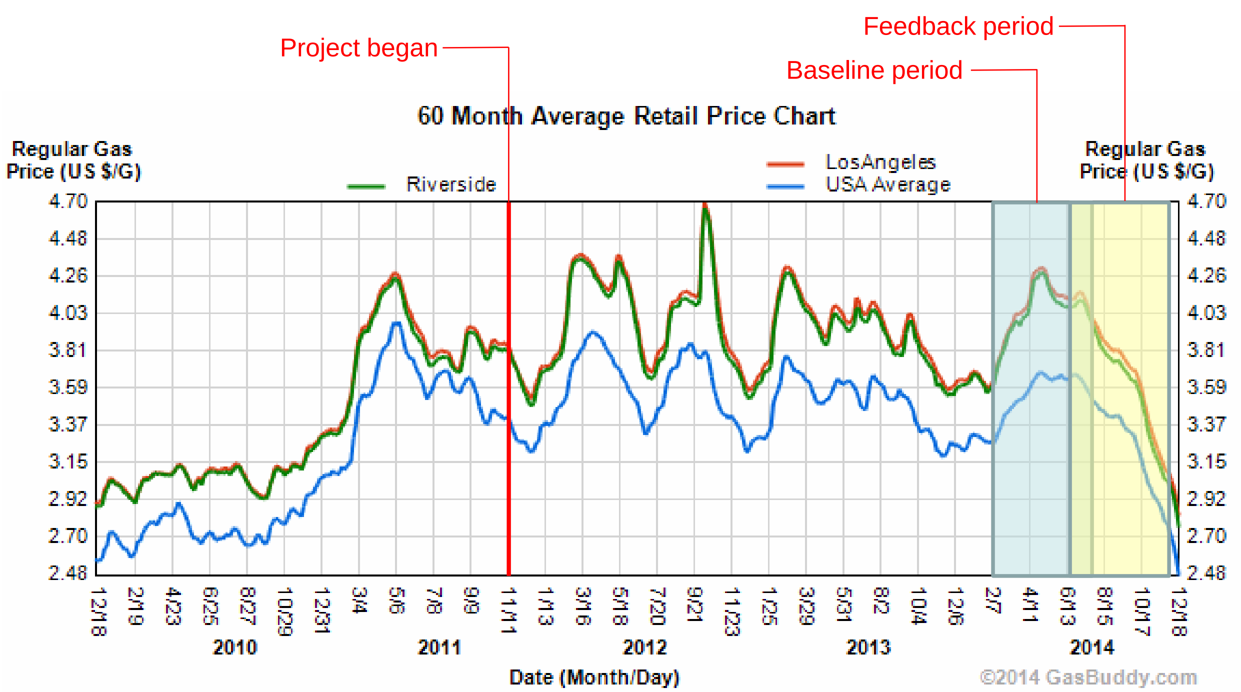


Figure 5-18. Historical gasoline prices between 2010 and 2014

Effect of Incentives

During the feedback collection period, while the driving feedback system was made available to the drivers, the decision to use it or not was at the discretion of the individual drivers. Such decision could significantly be influenced by incentives. One would make an extra effort to use the system if there is a strong incentive for that person to do so. In order not to bias the results, the research team did not provide any special incentives to the drivers beyond those that would be available to them under normal circumstances. Specifically:

- In the case of private drivers, while they would receive a $200 gift card after completing the FOT, it was for their time and participation. No incentive was tied to how much they used the driving feedback system or how much improvement in fuel economy they achieved. The research team just encouraged the drivers verbally to use the system when demonstrating the system to them.

- In the case of Caltrans and RTA drivers, the drivers did not receive any compensation for participation. The research team just encouraged the drivers verbally to use the system when demonstrating the system to them. The fleet managers also encouraged the drivers to use the system, but they were not ready to tie fuel-efficient driving performance to any formal reward or consequence during this initial FOT just yet.

5.2.6. Potential Fuel Savings from Eco-Routing

The fuel efficiency benefits of the driving feedback system discussed earlier are due to better driving *behaviors,* inspired by the Eco-Driving Feedback module and the Eco-Score and Eco-Rank module. Additional benefits can be gained from taking more fuel-efficient driving *routes* as suggested by the Eco-Routing Navigation module. These eco-routes are usually direct, with few turns and steep climbs, on which traffic is traveling at speed close to the sweet-spot speed for the vehicle.

The evaluation of the real-world fuel efficiency benefits of eco-routing is difficult. This is because the vehicles did not always make the same trips during the baseline and feedback periods. Even when they did, the trips occurred on different days and times, and thus, the traffic conditions were not the same. During the feedback period, while the Eco-Routing Navigation module was made available to the drivers, overall it was rarely used. This might be due in part to the drivers not needing route guidance for their trips (they already know a route to take for the trip) and not wanting to spend extra time executing the module (since they already have a route in mind, they want to start driving right away). The low usage of the module makes it even more difficult to evaluate the real-world benefits of eco-routing.

Therefore, we took a semi-simulation approach for the evaluation. It is still based on real-world trips that were made. However, for each trip we estimated the fuel consumption for the route actually taken as well as for the eco-route based on the fuel consumption model of the vehicle before comparing them. Note that the actual fuel consumption was not used in the comparison because it depended on driving behaviors during the trips, which would result in bias. Instead, using estimated values based on the same fuel consumption model provided a more appropriate basis for the evaluation of the route effect on trip fuel consumption.

The fuel consumption model is calibrated for individual vehicles based on their real-world fuel consumption. Aside from vehicle characteristics, the model is also a function of average traffic speed, road type, and road grade on each roadway link. Average traffic speed is a key variable of the model, and it is based on real-time traffic information that is updated every 2 minutes. Therefore, in the estimation of trip fuel consumption, we traced the position and time of the vehicle along the route and used the corresponding average traffic speeds of the roadway links as input to the fuel consumption model. That is, the average traffic speed on a roadway link at a point in time was used to calculate the fuel consumption on that roadway link as well as the arrival time at the next roadway link. The calculation was repeated until the destination was reached. This estimation process was very time-consuming to implement but provided more realistic estimates of trip fuel consumption for both the actual route and the eco-route.

In the evaluation with the semi-simulation approach, we used real-world trips that the RTA vehicles made in a week during the feedback period that has the most complete dataset. For each trip, we calculated the eco-route and compared it to the actual route taken. Two examples are given in Figure 5-19 where the actual route taken is displayed in blue while the eco-route is in green.

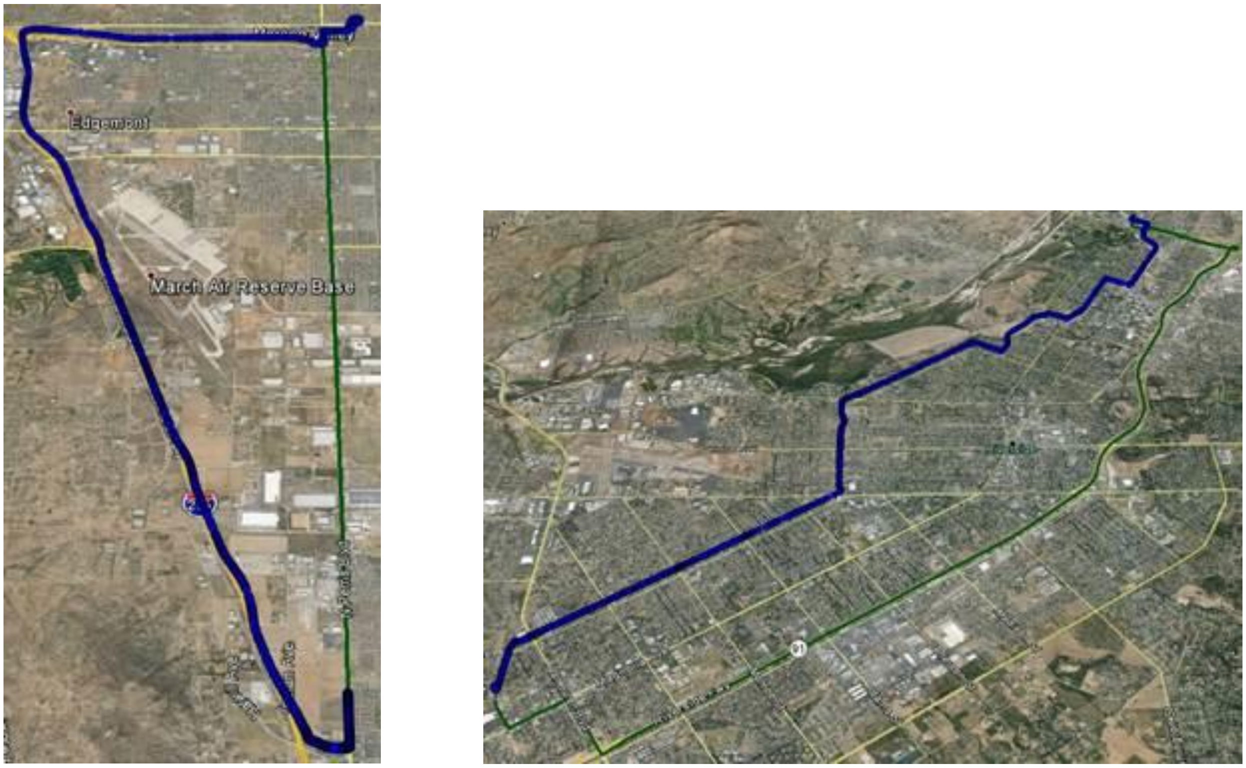


Figure 5-19. Actual route taken (blue) and eco-route (green)

During the week of May 9-15, 2014, the 15 RTA vehicles made a total of 2,233 trips. Out of these trips, 509 have complete GPS and OBD data from the start to the end. Three vehicles do not have any trip with complete data. For each of the 509 good trips, potential fuel savings from taking the eco-route was estimated using the semi-simulation approach. The results are summarized in Table 5-12

where aDist, aTime, and aFuel are actual distance, travel time, and fuel consumption, respectively, as determined from the recorded GPS and OBD data;

eDist, eTime, and eFuel are estimated distance, travel time, and fuel consumption, respectively, for the actual route taken as determined from the digital map and the fuel consumption model of the vehicle;

ecoDist, ecoTime, and ecoFuel are estimated distance, travel time, and fuel consumption, respectively, for the eco-route as determined from the digital map and the fuel consumption model of the vehicle; and

% Reduction in Dist and Fuel are percent reduction in distance and fuel consumption of the eco-route as compared to the actual route taken.

According to Table 5-12, the fuel savings from taking the eco-route ranges from 6% to 15% for individual vehicles with the fleet average of 11%. The fuel savings is due to the eco-route having shorter distance (7.3% on average) and more favorable traffic conditions for fuel efficiency (e.g., moderate traffic speed).

Table 5-12. Summary of potential fuel savings from taking eco-route

Vehicle ID	# of Good Trips	aDist (mi)	aTime (min)	aFuel (gal)	eDist (mi)	eTime (min)	eFuel (gal)	ecoDist (mi)	ecoTime (min)	ecoFuel (gal)	% Reduction in Dist	% Reduction in Fuel
11306	74	347	858	43.3	360	711	46.6	336	630	42.5	6.6	8.8
11312	14	60	146	9.1	62	124	10.1	56	104	8.5	8.7	15.4
11313	56	275	645	32.3	284	537	37.0	260	472	32.6	8.3	11.9
11314	14	89	205	10.3	93	162	12.6	83	149	10.9	11.2	13.5
11320	90	526	1,107	68.1	536	969	71.6	492	854	63.9	8.3	10.8
11323	35	216	491	24.0	223	395	24.6	212	360	22.8	4.9	7.3
11325	20	111	219	11.9	114	207	13.8	111	189	12.9	2.7	6.3
11326	28	109	273	14.9	112	229	15.2	101	210	13.7	9.7	9.7
11328	16	74	172	8.6	76	149	9.7	68	132	8.5	10.4	12.2
11329	14	83	177	9.8	85	149	10.8	81	135	10.1	4.3	6.9
11336	80	384	906	45.5	389	760	46.1	367	677	42.5	5.5	7.7
11338	68	406	960	48.7	387	710	56.7	353	594	48.7	8.8	14.1
Total	*509*	*2,680*	*6,160*	*326.6*	*2,720*	*5,103*	*354.5*	*2,521*	*4,507*	*317.4*	*7.3*	*10.5*

5.3. Driver Survey Results

The survey results probed the response of study participants to the device through a pre- and post-exposure framework. The survey sample was broken into three sub-samples defining separate cohorts that used the device under different circumstances. They included the “Private” cohort, the “Bus” cohort, and the “Caltrans” cohort. The Private cohort was defined as participants recruited from the general public and use the device within their own personal cars. The Bus cohort consisted of drivers for the Riverside Transit Agency (RTA), and the Caltrans cohort consisted of Caltrans employees. The demographics of the study participants is shown in Table 5-13.

Table 5-13 shows that participants had incomes between $25K and $100K. However, this distribution is mostly representative of the Private cohort, as a large share of the Bus cohort declined to respond and the Caltrans cohort was not asked the income question. The education distribution had a similar spread. The Private was generally educated, with 80% having a Bachelor’s degree or more. The distribution of education among the Bus cohort was slightly lower and had a small sample size, while the question was not asked of the Caltrans cohort. The age distribution showed a fair among of spread with the Private and Caltrans cohort. Unfortunately, non-response was also observed with high frequency among the Bus cohort, and so we have limited information pertaining to this age distribution. The racial distribution found to be relatively diverse across racial/ethnic classifications, with no one race/ethnicity in the majority of any cohort. The gender distribution showed a 60/40 split among the Private cohort, whereas the Bus and Caltrans cohort were at close to 60% male or higher.

Figure 5-20 shows a pre- and post-self assessment of driving efficiency among study participants among each of the cohorts. The results of Figure 5-20 show the before-and-after shift of self-assessed driving efficiency among the three cohorts. The results show on balance an overall improvement in the self-assessed efficiency of driving within two of three cohorts. The Bus driver cohort was the only one that exhibited a shift towards a value of “About Average”. The Private and Caltrans cohort exhibited a modest increase in the share of participants reporting that they drove at least somewhat more efficiently.

The post-survey asked questions about the utility of various features of the driving feedback system, including the ability of it to:

1. Provide the most efficient route to save fuel
2. Recommend speeds based on real-time traffic information
3. Provide real-time fuel economy while driving
4. Provide audio/visual warnings to the driver for accelerating too hard
5. Provide audio/visual warnings to the driver for braking too hard
6. Provide audio/visual warnings to the driver for idling too long
7. Providing a summary of the driver's performance at the end of the trip

For each of these questions, the survey asked the participant how useful the feature was, and also asked how often the feature was used.

Table 5-13. Survey demographics

Income	Private	Bus	Caltrans	Education	Private	Bus	Caltrans
< $10k	0%	0%	NA	Grade school	0%	0%	NA
$10k-$15k	0%	0%	NA	Graduated high school	0%	14%	NA
$15k-$25k	0%	0%	NA	Some college	7%	29%	NA
$25k-$35k	13%	29%	NA	2-year degree	13%	14%	NA
$35k-$50k	0%	0%	NA	Bachelor's degree	53%	0%	NA
$50k-$75k	33%	0%	NA	Master's degree	27%	0%	NA
$75k-$100k	40%	0%	NA	Juris Doctorate degree (JD)	0%	0%	NA
$100k-$500k	0%	0%	NA	Doctorate Degree (PhD, EdD, etc.)	0%	0%	NA
$150k-$200k	7%	0%	NA	Medical degree (MD)	0%	0%	NA
>$200k	0%	0%	NA	Decline to respond	0%	29%	NA
Decline to respond	7%	71%	NA	Other, please specify:	0%	14%	NA
Total N	15	7	NA	Total N	15	7	NA

Age	Private	Bus	Caltrans	Race	Private	Bus	Caltrans
21 to 30	27%	13%	0%	Caucasian	40%	0%	30%
31 to 40	27%	0%	27%	Hispanic	20%	14%	40%
41 to 50	27%	0%	45%	African-American	13%	29%	0%
51 to 60	13%	13%	27%	Asian	13%	14%	30%
61 to 70	0%	6%	0%	Indian or Pakistani	7%	0%	10%
71 to 80	7%	0%	0%	Middle Eastern or Arab	7%	0%	10%
				Native American or Alaskan Native	0%	0%	0%
Gender	**Private**	**Bus**	**Caltrans**	Hawaiian or Pacific Islander	0%	0%	0%
Male	40%	57%	73%	Mixed Race (two or more)	0%	0%	10%
Female	60%	36%	27%	Decline to respond	0%	29%	0%
Decline to respond	0%	7%	0%	Other, please specify:	0%	14%	0%
Total N	15	16	11	Total N	15	7	10

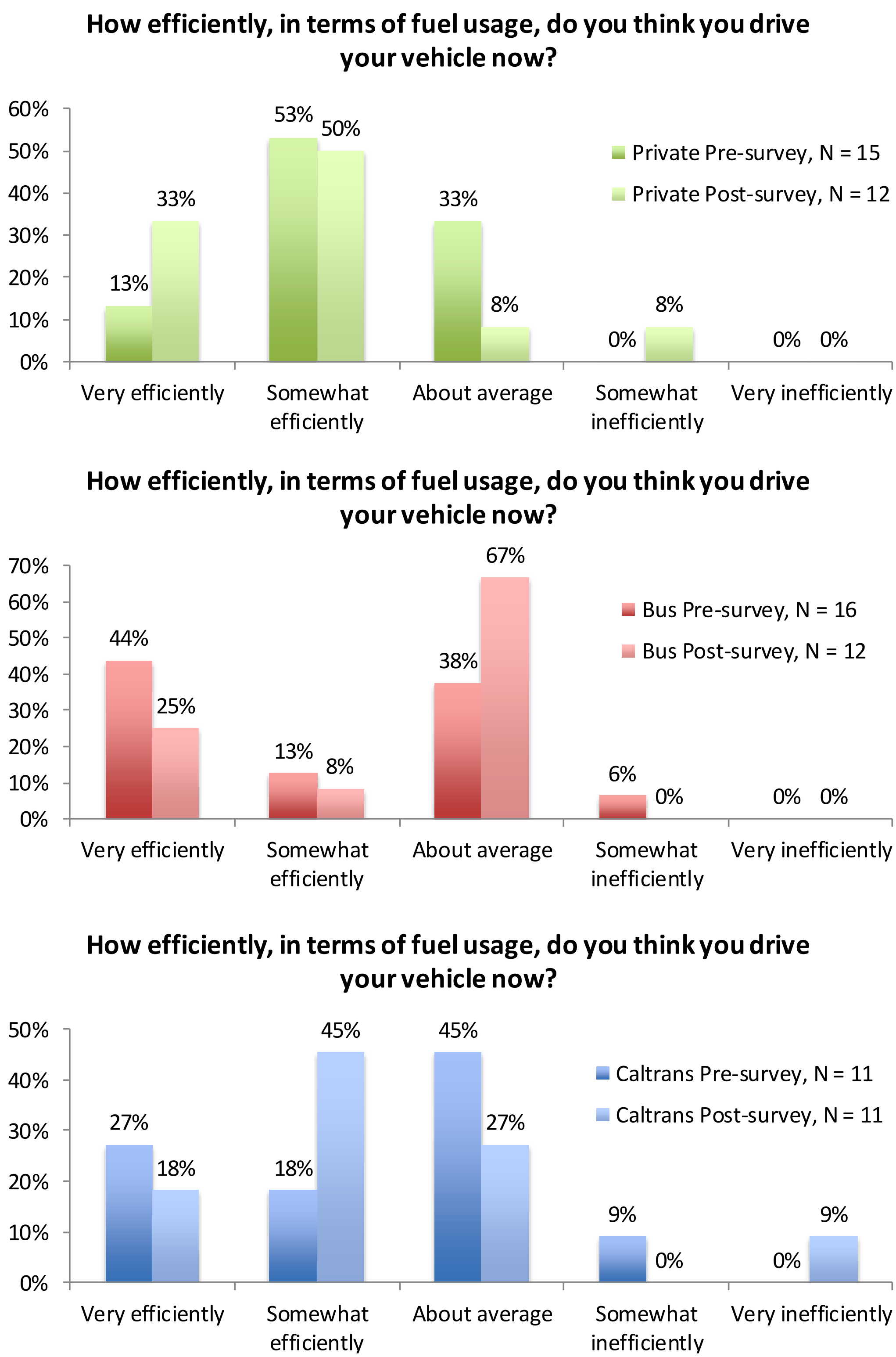
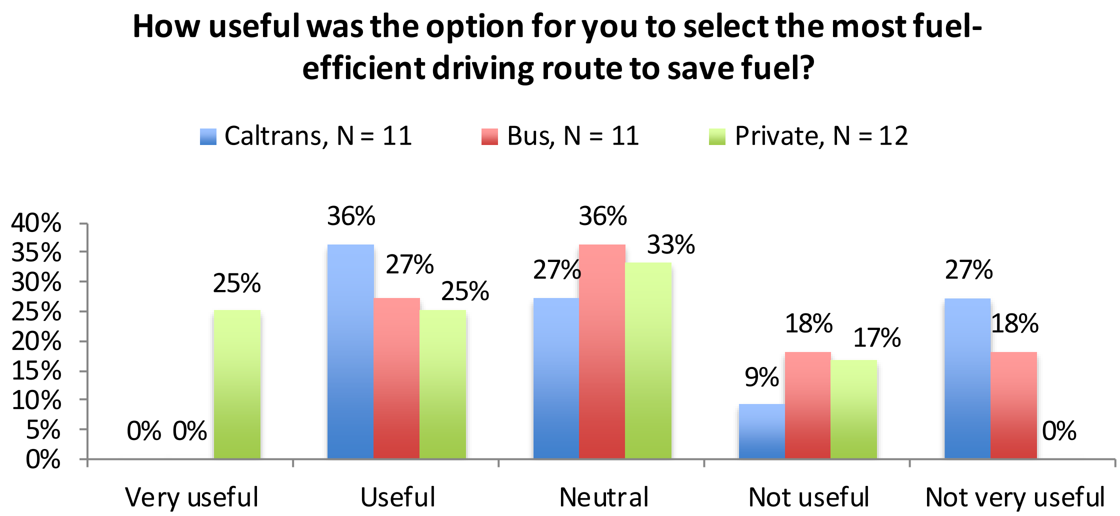


Figure 5-20. Comparative self-assessment of driving efficiency

Figure 5-21 presents the first of these results, assessing the utility of suggesting the most efficient route to save fuel to the study participants. It shows that 50% of the Private cohort felt that the feature was useful or very useful. About 36% or Caltrans drivers and 27% of bus drivers felt that the feature was useful. The responses further showed that the feature was used somewhat infrequently. About 50% of the Private cohort used it at least sometimes, whereas the majority of Bus and Caltrans cohorts used it rarely or never.



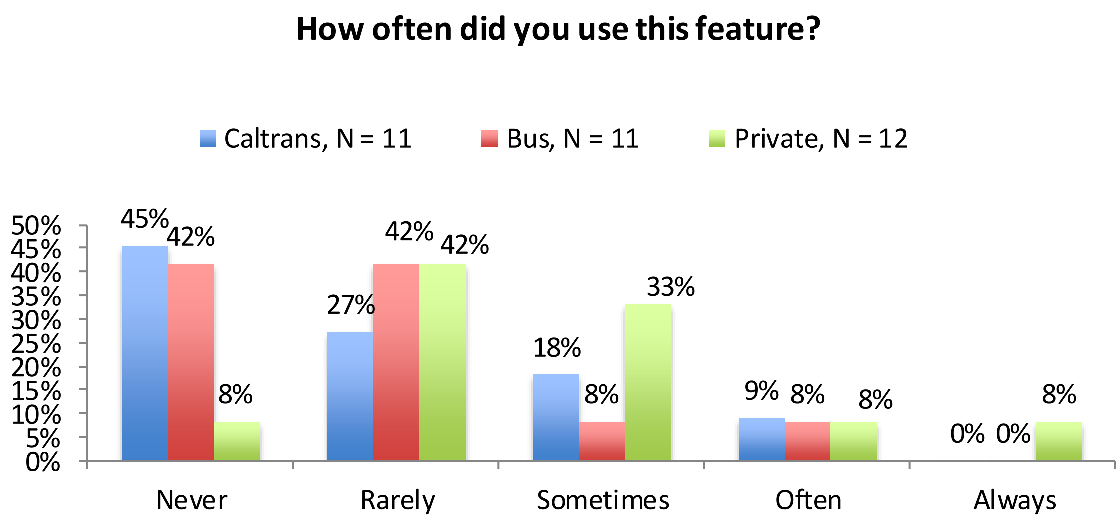


Figure 5-21. Utility of selecting fuel efficient route

Figure 5-22 asks the same set of questions for the device feature that recommended speeds based on the real-time traffic conditions ahead. This feature provided drivers with input on how fast they should drive to avoid large swings in speed within congestion (stop and go). As in Figure 5-21, Figure 5-22 shows that 50% of the Private cohort found the feature to be useful. A greater share of the Caltrans cohort (45%) and the RTA bus drivers (36%) found it to be useful. As with Figure 5-21, over 50% of the Private cohort used it at least sometimes, whereas it was used infrequently by the Caltrans and Bus cohort.

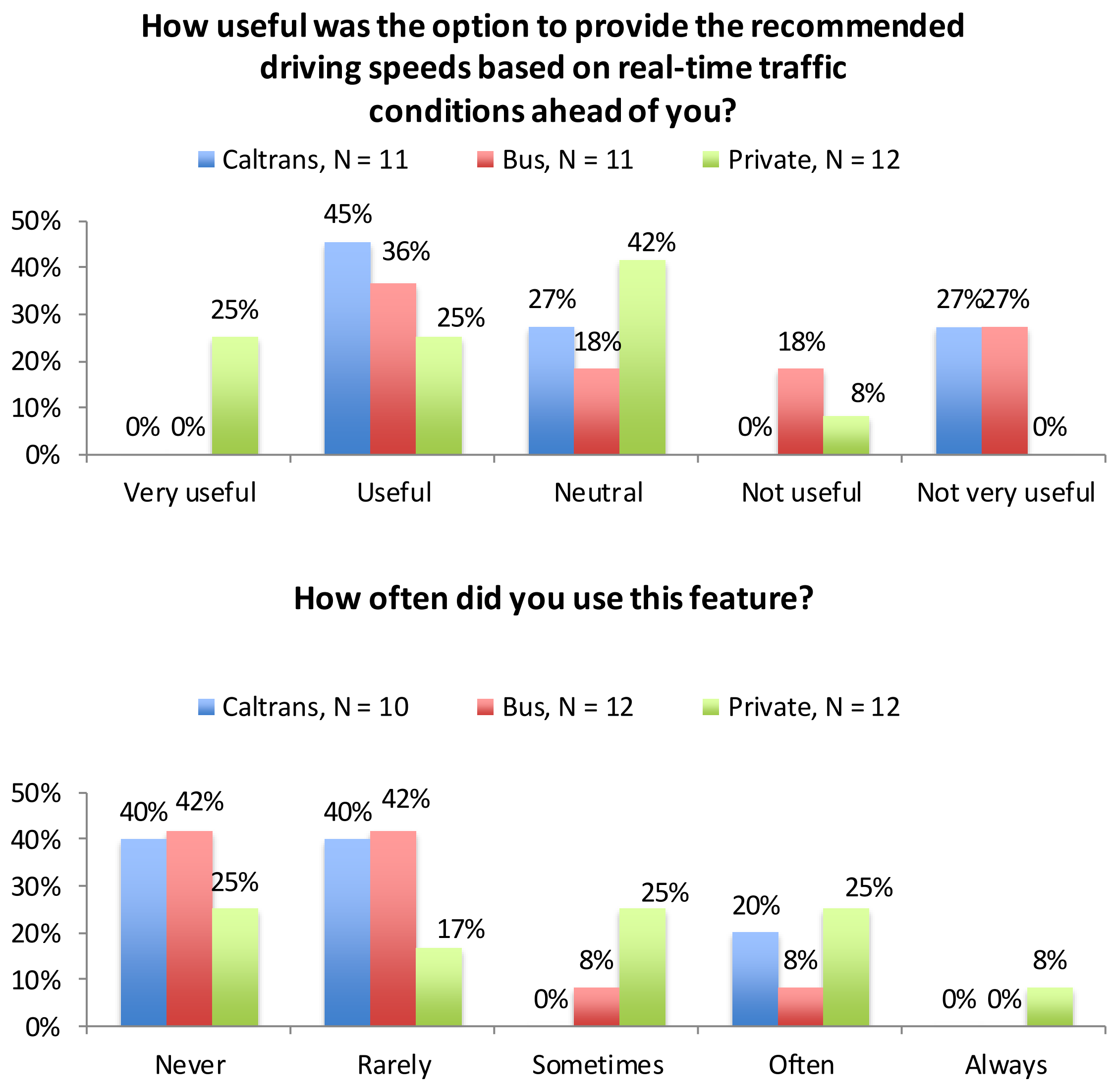


Figure 5-22. Utility of recommended speeds based on traffic conditions

Figure 5-23 shows the reported utility of the provision of real-time fuel economy information while driving. It shows that the provision of real-time fuel economy was considered to be useful or very useful by 83% of the Private cohort, by 64% of the Caltrans cohort, and 36% of the Bus cohort. Figure 5-23 also shows that the feature was regularly used by a majority of the Private cohort, and at least sometimes by the entire Private sample. The frequency of use was notably less however by the Bus and Caltrans cohort.

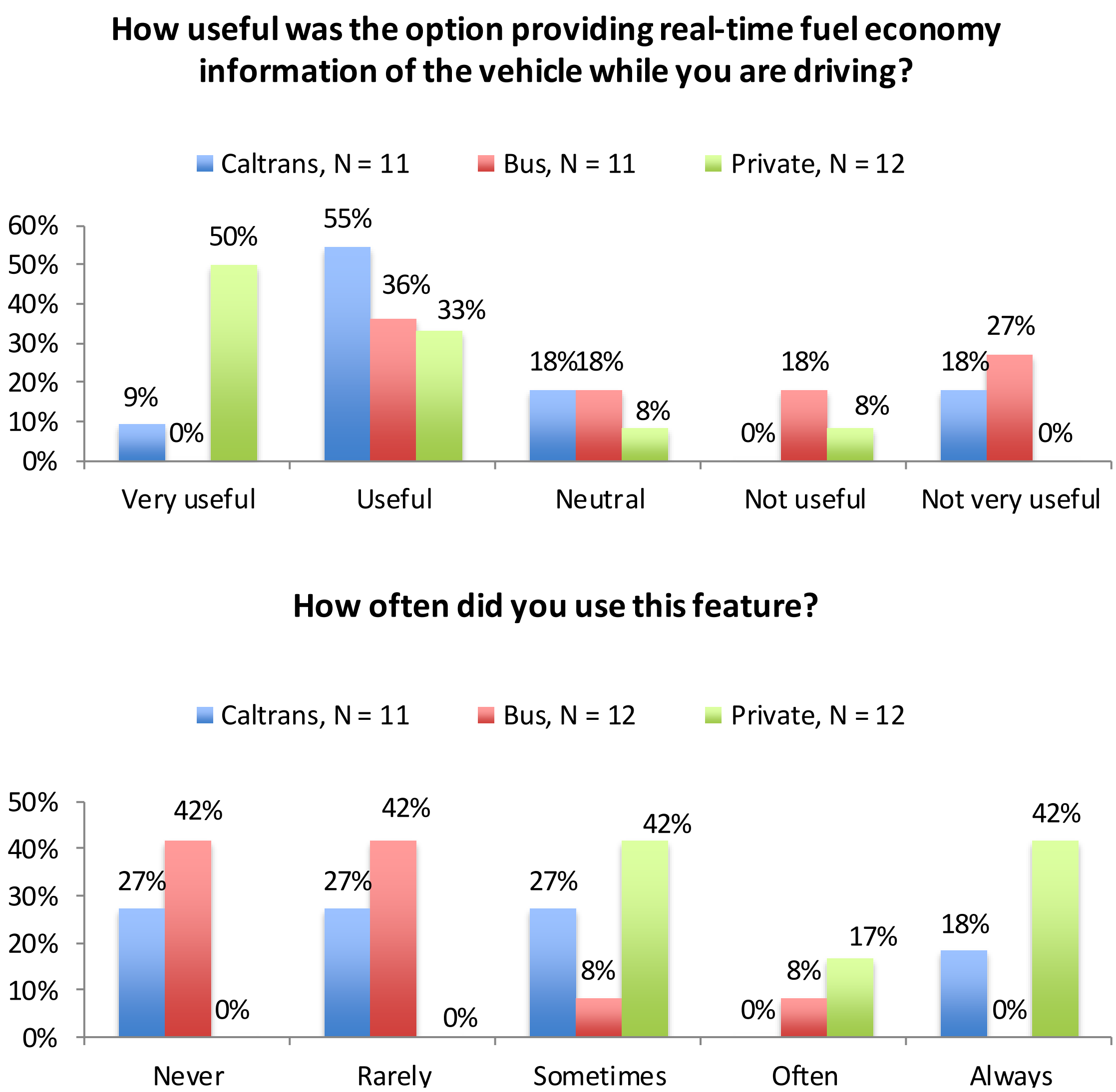


Figure 5-23. Utility of provision of real-time fuel economy

Figure 5-24 shows the distribution of reported utility of the warning that the device gave when the participant accelerated too rapidly. The results showed that similar proportions of the Caltrans and Private cohort felt that the warning was useful or very useful. About 30% of the Bus cohort also felt that the warning was useful. As with previous results presented thus far, the Private cohort used the warning with the greatest frequency. About 16% of the Bus cohort used the warning at least sometimes, and 20% of the Caltrans cohort used it often or always.

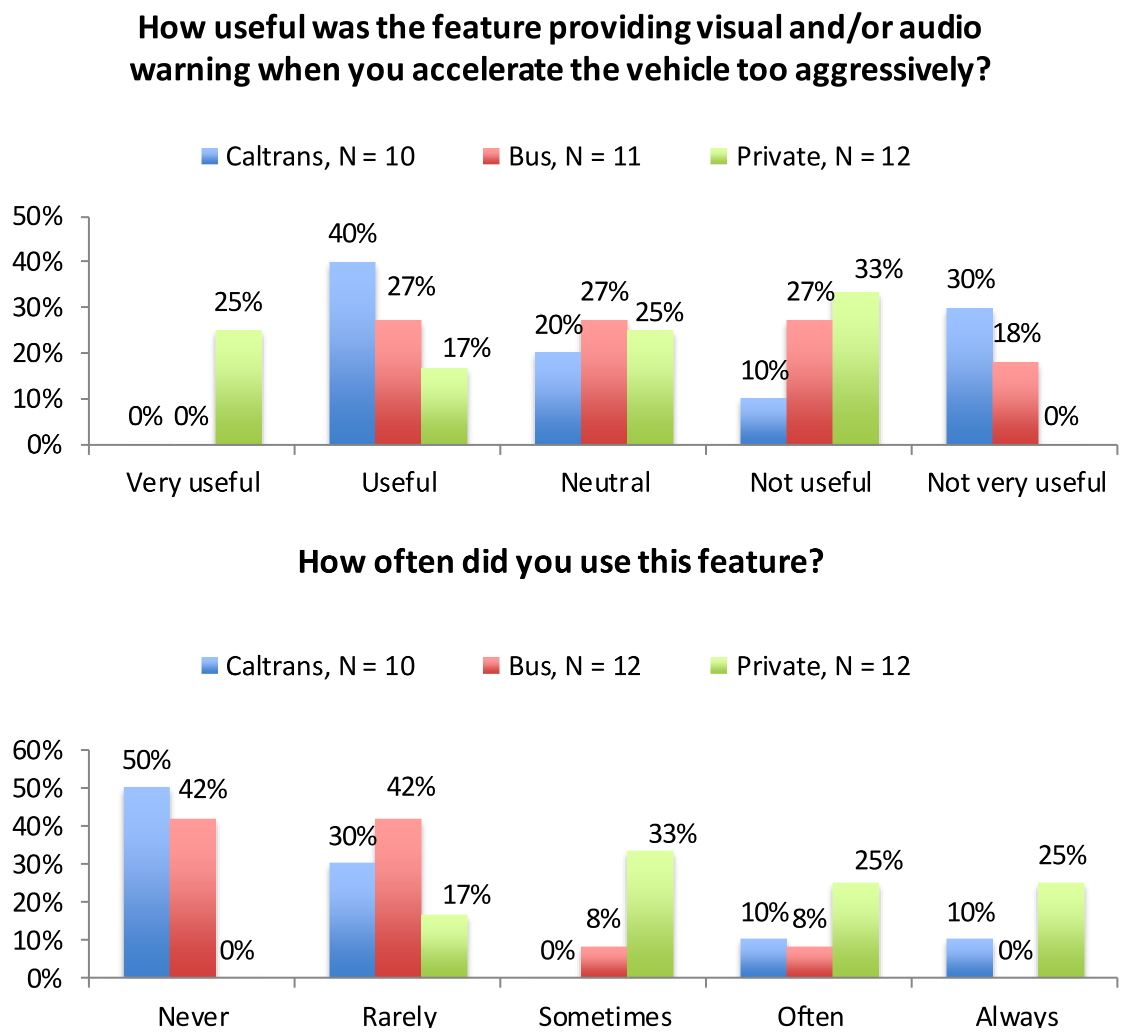


Figure 5-24. Utility of aggressive acceleration warning

Figure 5-25 shows the distribution of response to a warning given to participants for braking too hard. The results show that 50% of the Private cohort considered the warning useful or very useful, whereas about 20% of the Caltrans and Bus cohort considered the warning useful. In terms of frequency of use, a notable distinction is the high percentage of the Private cohort that used the warning often or always (~64%). The warning was used sometimes or more frequently by about 20% of the Caltrans and Bus sample.

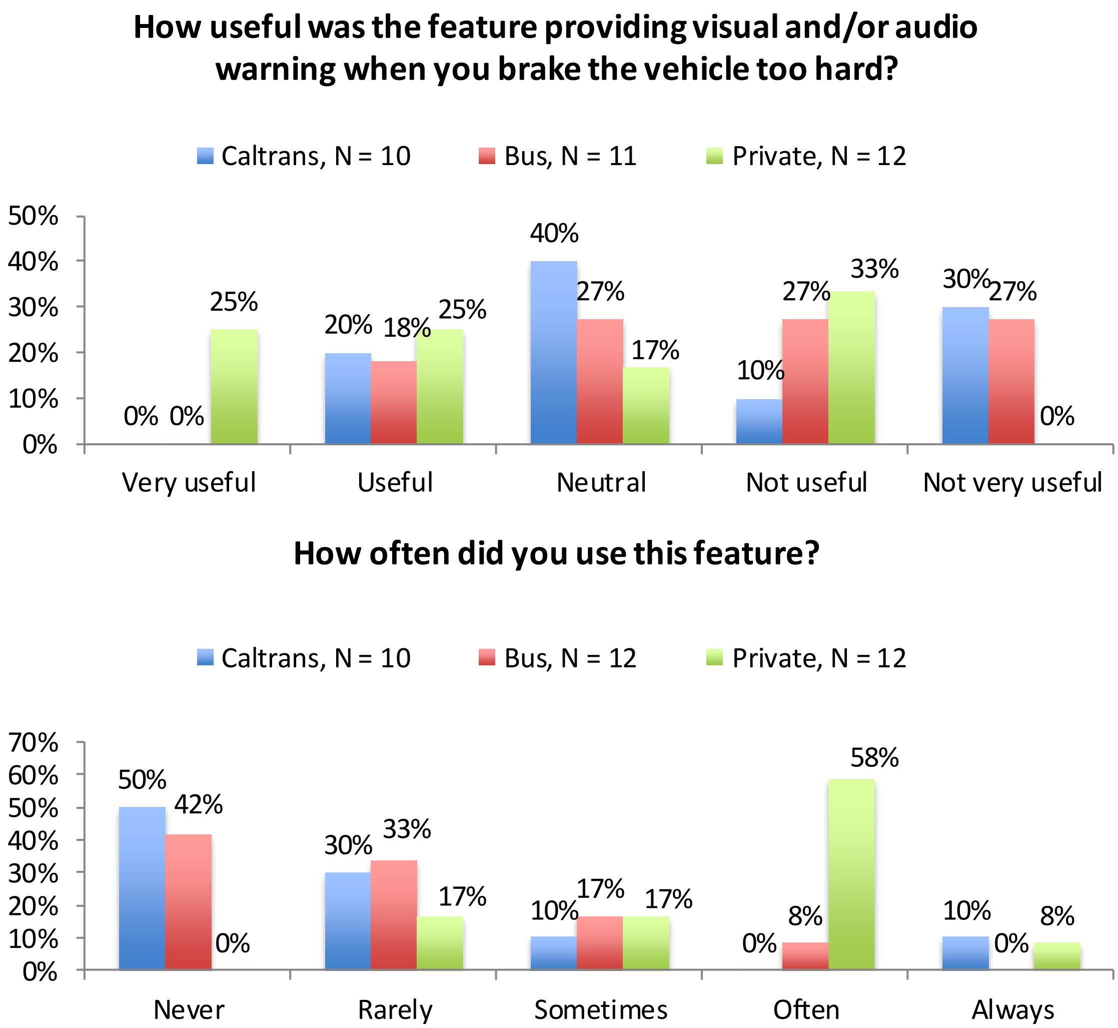


Figure 5-25. Utility of hard braking warning

Figure 5-26 shows the distribution of reported utility of the warning for idling the vehicle too long. A higher percentage of all cohorts considered this warning to be useful or very useful. Half of the Private cohort considered the warning to be useful, and 40% of the Caltrans cohort agreed, while 27% of the Bus cohort considered the warning useful. Over 50% of the Private cohort used the feature at least sometimes or more frequently, while again, about 20% of the Caltrans and bus sample used the warning at least sometimes.

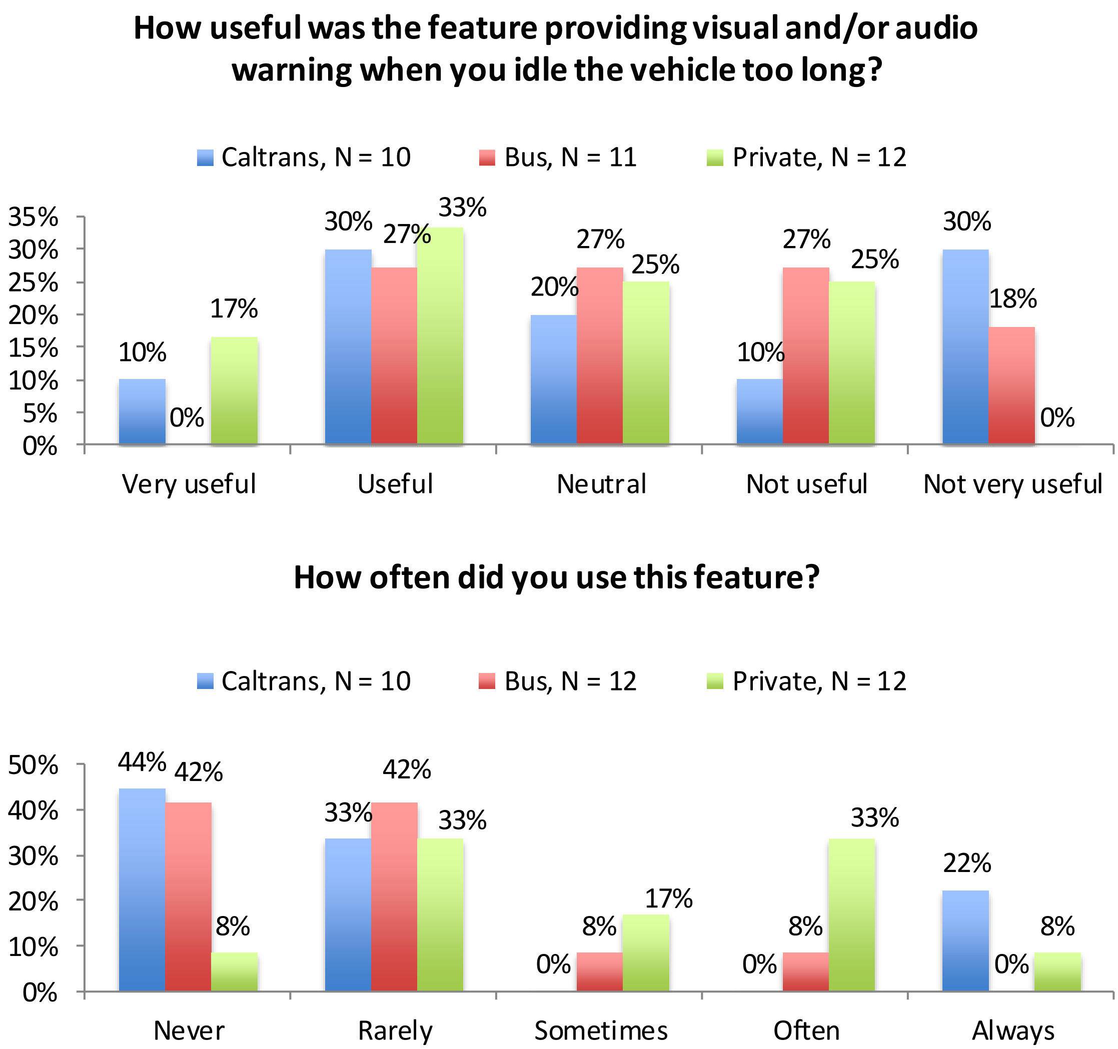


Figure 5-26. Utility of excessive idling warning

Figure 5-27 shows the reported utility of providing driving performance at the end of each trip. It shows that over 50% of the private cohort found the driving performance report to useful. Notably nearly 40% of the Bus cohort also believed that the report was useful, as did 45% of the Caltrans cohort. The report was also used by sizable shares of each cohort, with 72% of the Private cohort using the report at least sometimes, while 45% of the Caltrans cohort and 42% of the Bus cohort also used the report at least sometimes.

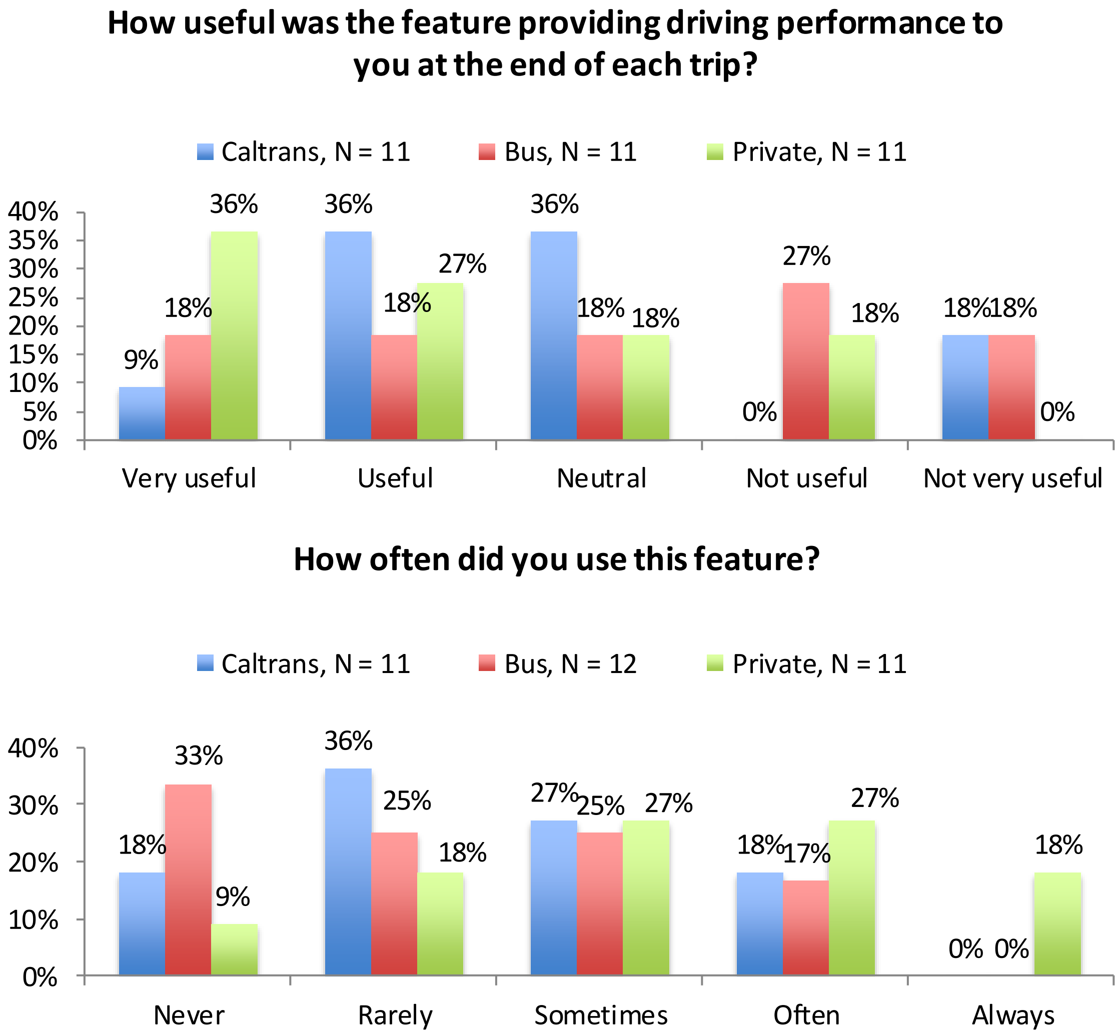


Figure 5-27. Utility of driving performance summary

Figure 5-28 shows the response to two causal questions assessing the impacts of the device on driving behavior. The questions ask “As a result of feedback from the device, I…” following some stated action. The possible responses include “Much more often”, “More often”, “About the same (no difference)”, “Less often”, and “Much less often”. When relevant, participants could also select “I have changed, but not because of the device”, and “I never did <this behavior>, before or after using the device”.

The results in Figure 8 24 suggest that the device helped some respondents maintain a steady speed more often. About 75% of the Private cohort indicated that the maintained steady speeds more often as a result of the device, whereas roughly 60% of the Caltrans cohort indicated the same. The Bus cohort reported 25% (3) participants indicating that they maintained steadier speeds due to the device. A similar was found with respect to the device’s ability to reduce the frequency of rapid starts and stops. Nearly 60% of the Private cohort reported that they would make rapid starts and stops less often, while the device reported to be effective also for Caltrans and Bus cohort. About 67% of the Caltrans cohorts reported making rapid starts and stops less often, and 43% of the Bus cohort reported the same.

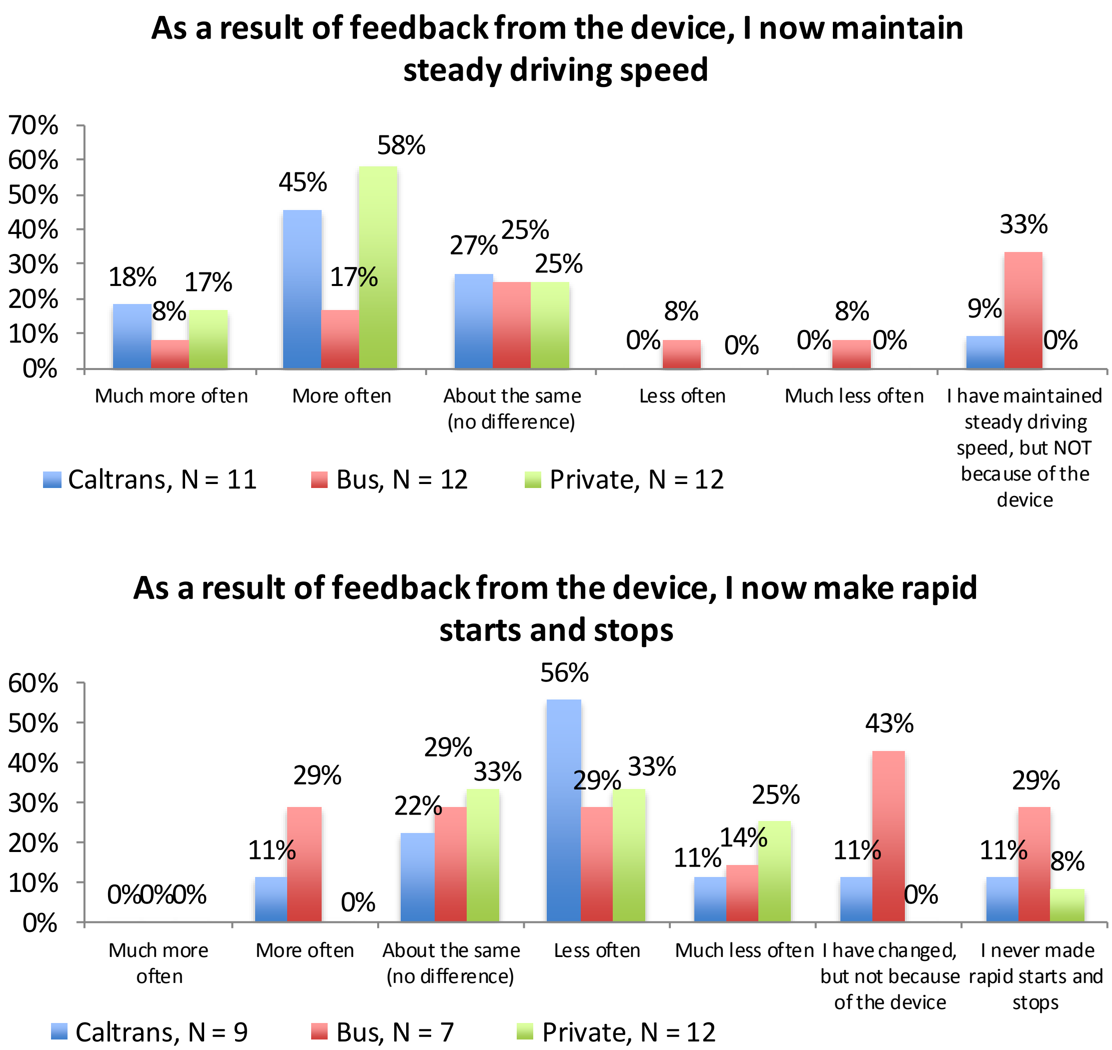


Figure 5-28. Impact of driving feedback on speed, accelerating, and braking behaviors

Figure 5-29 presents the results of a similarly structured question on idling the vehicle and assesses the perception of overall fuel economy improvement. It suggests that modest percentages (between 37% and 44%) of all three cohorts idled their vehicle less as a result of the device. Further, 83% of the Private cohort stated that they noticed a modest improvement in fuel economy, while 60% of the Caltrans cohort, and a third of the Bus cohort also noticed some improvement in fuel economy.

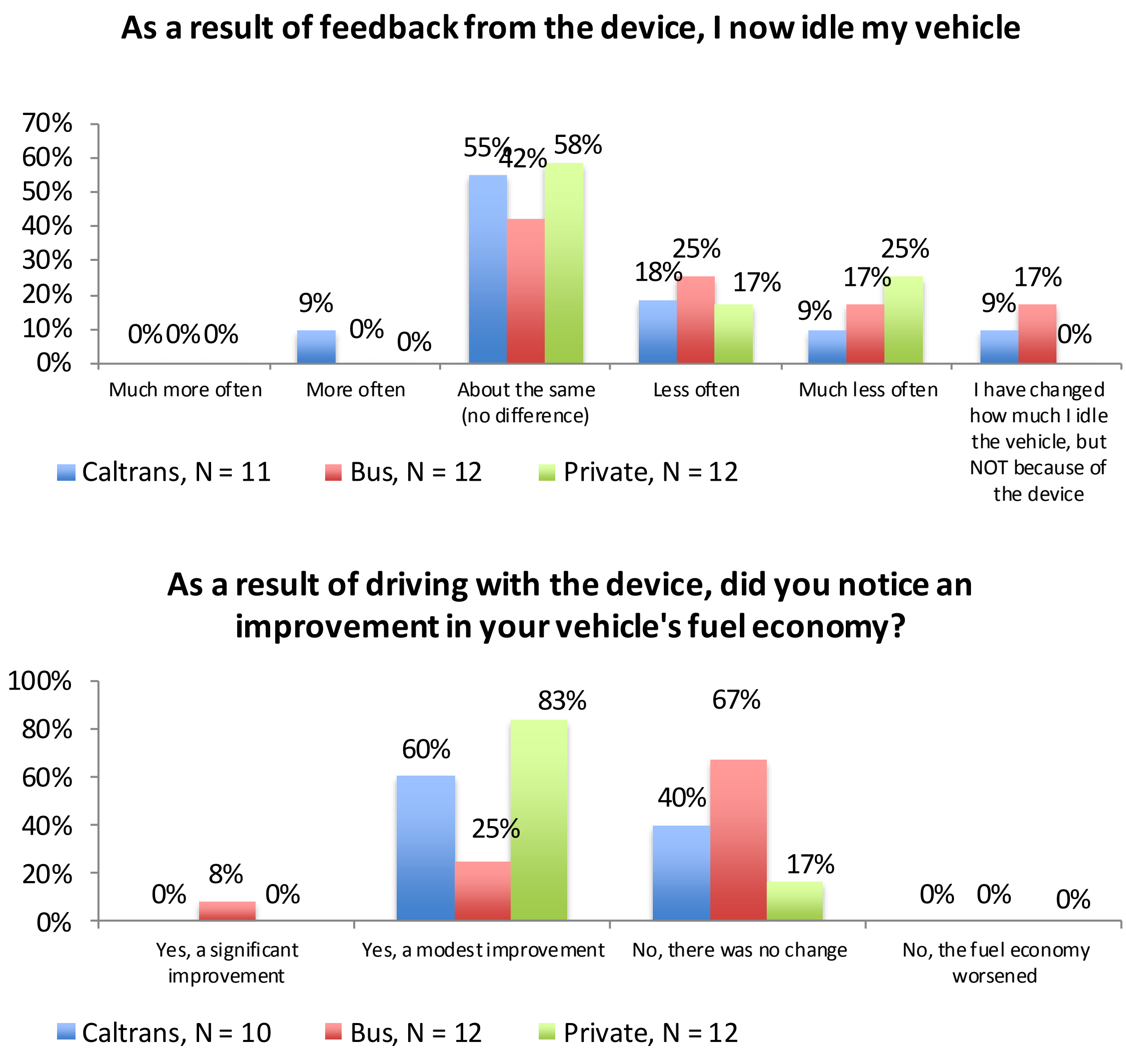


Figure 5-29. Impact of driving feedback on idling behavior and fuel economy improvement

Overall, based on the survey results, the device seemed to be most effective with the Private cohort, followed by the Caltrans cohort and then the Bus cohort. Members of each cohort reported being responsive to the device and finding its feedback useful, but the Private cohort consistently reported this in the greatest numbers. The reason for these results are not clear directly from these responses. One possible explanation is the Private drivers had greater freedom in their driving behavior and activity to respond to the input from the device, whereas bus drivers, who are focused on mainly different inputs and constraints, could adjust their behavior the least. These and other considerations may support improvements future iterations of the device design.

5.4. System Costs

A fully deployed driving system developed in this project would require capital investment in Android-based smart device ($150-$350) and on-board diagnostics connector ($50-$100) as well as paying operating costs for wireless data plan and subscription fees ($20-$30 per month) for connecting to the data server and receiving various system services. For individual consumers who already own a smart device (such as smartphone) and commercial fleets that already use some kind of telematics services, the costs for deploying this driving feedback system would be much lower.

As has been observed over the project period, the prices of smart devices and on-board diagnostics connectors have been dropping at a significant rate. This trend indicates that the capital costs of the driving feedback system would continue to go down. In the long term, the main costs of the system will likely be in the wireless data plan and service subscription fees, which are ongoing costs typically on a monthly basis. How much these operating costs will be depend on the business model of the technology provider as well as the fuel prices. It would be expected by the system users that the operating costs are fully, or at least mostly, covered by the savings in fuel cost with the use of the system.

6. Products and Technology Transfer Activities

6.1. Publications

Boriboonsomsin, K. and Barth, M. (2015). Context-sensitive fuel-efficient driving performance scores. In preparation.

Hao, P., Boriboonsomsin, K., Wu, G., and Barth, M. (2015). Modal activity based stochastic model for estimating vehicle trajectories from sparse mobile sensor data. Submitted to *IEEE Transactions on Intelligent Transportation Systems*.

Yang, Q., Wu, G., Boriboonsomsin, K., and Barth, M. (2015). Modified Gaussian Mixture Model (MGMM) based arterial travel time model and its application to energy/emissions estimation. Submitted to *Transportation Research Part C*.

Boriboonsomsin, K., Dean, J., and Barth, M. (2014). Examination of attributes and value of ecologically friendly route choices. *Transportation Research Record*, 2427, 13-25.

Hao, P., Boriboonsomsin, K., Wu, G., and Barth, M. (2014). "Probabilistic model for estimating vehicle trajectories using sparse mobile sensor data." Proceedings of the 17th International IEEE Conference on Intelligent Transportation Systems, Qingdao, China, October 8-11

Boriboonsomsin, K. and Barth, M. (2014). Context-sensitive eco-driving scores. Proceedings of the 21st World Congress on Intelligent Transportation Systems, Detroit, MI, September 7-11.

Boriboonsomsin, K., Dean, J., and Barth, M. (2014). An examination of the attributes and value of eco-friendly route choices. Proceedings of the 93rd Annual Meeting of the Transportation Research Board, Washington, DC, January 12-16.

Yang, Q., Wu, G., Boriboonsomsin, K., and Barth, M. (2013). Arterial roadway travel time distribution estimation and vehicle movement classification using a modified Gaussian mixture model. Proceedings of the 16th International IEEE Conference on Intelligent Transportation Systems, The Hague, Netherlands, October 6-9.

Jarak, N., Boriboonsomsin, K., and Barth, M. (2013). Method for self-constructing/updating vehicle fuel consumption models based on real-time fuel consumption data. Presented at 2013 University of California Transportation Center Research Conference, Los Angeles, CA, March 1-2.

Yang, Q., Kang, J., Boriboonsomsin, K., and Barth, M. (2013). Estimating intersection delays and associated fuel consumption based on mobile sensor data. Presented at 2013 University of California Transportation Center Research Conference, Los Angeles, CA, March 1-2.

Barth, M. and Boriboonsomsin, K. (2012). Next generation environmentally-friendly driving feedback systems research and development. Presented as part of ITS America Webinar Series on Driver Behavior and Vehicle Technology: Understanding the Impact of Eco-Driving, October 31.

6.2. Collaborations

6.2.1. Within the Project

Esri, Redland, CA

Esri provided ArcLogistics and other related GIS software packages that optimize route planning and scheduling of fleet operators as well as individual travelers for use in the project as a cost share. Esri also provided technical support in the integration of its software products with other components of the driving feedback system.

NAVTEQ, Chicago, IL

NAVTEQ provided 3D digital street map, real-time and historical traffic data, as well as continuing technical support at no cost to the project.

Beat the Traffic, Santa Clara, CA

Beat the Traffic partially provided access to GPS data from its smart phone app users at no cost to the project. Beat the Traffic also worked with UCR to develop methods to detect and model intersection delays on arterial and local roads using these GPS data.

Earthrise Technology, Palo Alto, CA

Earthrise Technology provided to the project its vehicle interface and telematics devices as well as software development and support services, both at reduced costs.

Automatiks, Palo Alto, CA

Automatiks provided support in the areas of system development and configuration of the in-vehicle device and software development of the voice-guided turn-by-turn navigation feature for the driving feedback system.

Riverside Transit Agency, Riverside, CA

Riverside Transit Agency allowed a subset of its paratransit fleet to be equipped with the driving feedback system and provided staff support during the field operation test of the system at no cost to the project.

California Department of Transportation, Sacramento, CA

The California Department of Transportation allowed selected pickup trucks from its fleets to be equipped with the driving feedback system and provided staff support during the field operation test of the system at no cost to the project.

University of California, Berkeley, CA

The University of California at Berkeley gathered inputs for the design of the driving feedback system through a series of expert interviews, and evaluated drivers’ perception towards the system through before-and-after surveys.

6.2.2. Outside the Project

Nissan Motor Company

UCR researchers have been working with Nissan to develop methods for quantifying fuel saving/greenhouse gas reduction benefits of eco-driving technologies.

Expert Interview

As part of the efforts to gather inputs to guide the design of the Eco-Driving Feedback module, the research team interviewed 11 domain experts from both public and private sectors in order to gain an understanding of the type of information that would be most useful in an eco-driving feedback system. These experts are from a variety of organizations listed below. Their primary responsibility area noted in the brackets:

- California Department of Transportation [fleet management]
- Daimler Trucks [research and development]
- Environmental Protection Agency (2 experts) [policy]
- Environmental systems Research Institute [research and development]
- General Motors [research and development]
- National Renewable Energy Laboratory [research and development]
- Riverside Transit Agency [fleet management]
- Westat [consulting]
- University of Minnesota, HumanFIRST Program [research and development]
- U.S. Department of Transportation [policy]

6.2.3. Coordination with Other Research Programs

In addition to the various forms of collaboration mentioned above, the research team also coordinated the research efforts in this project with other relevant research programs that the research team has been involved. One of them is the Eco-Driving research of the University of California's Multi-campus Research Program and Initiative (MRPI). This MRPI research seeks to improve understanding of the effectiveness of and driver's attitude toward various eco-driving tools and policies. Another research program is the Applications for the Environment: Real-Time Information Synthesis (AERIS) research of the Federal Highway Administration. It is aimed at developing and evaluating applications enabled by vehicle-to-vehicle and vehicle-to-infrastructure communication technology that reduce energy consumption and emissions from roadway transportation. The coordination among these research programs includes sharing knowledge and resources, conducting research in topics that are complementary to each other, etc.

6.3. Technologies and Techniques

As described in the earlier chapters of this report, several technologies and techniques were developed during the course of this project. The key overarching technology developed in this project is the next generation environmentally friendly driving feedback system. It encompasses several novel techniques or methods as listed below.

- Method for estimating intersection movements and delays from sparse mobile sensor data
- Method for determining fuel-efficient route with consideration of intersection delays

- Method for self-constructing/updating vehicle fuel consumption models based on real-time fuel consumption data
- Method for determining recommended driving speed based on local real-time traffic condition
- Method for calculating fuel-efficient driving performance scores that are customizable
- Method for adjusting real-world fuel economy for factors not related to driving behaviors

6.4. Inventions and Patent Applications

The research team has neither disclosed any inventions nor filed any patent applications based on the work performed in this project. However, we may consider doing so in the future.

6.5. Other Products

Another product of this research project is the driving data collected during the field operation test of the driving feedback system. The dataset includes second-by-second data of vehicle position, speed, acceleration, fuel consumption, and many other parameters from 45 participating vehicles for several months. The dataset has been processed and stored in a server database and can be accessed via a web application, both developed as part of this project.

Appendix A:

Expert Interview Summary

Background

Between April and May 2012, researchers conducted 11 expert interviews to gain an understanding of the information that would be most useful in the design of a next generation environmentally-friendly driving feedback system. Researchers developed a questionnaire to address key topics including: respondents' professional background; eco-driving and intelligent transportation systems (ITS); incentives to adoption; mechanisms to convey eco-driving feedback; as well as Information transmission, storage, and privacy. Subject populations included fleet managers, engineers, and state and federal regulators. The interview results will assist researchers in designing an environmentally-friendly driving feedback device and subsequent "before" and "after" surveys.

A semi-structured questionnaire was used as the method of data collection to enable the interviewer to collect comparable qualitative data while maintaining the flexibility to probe respondents on relevant topics. Questionnaires were provided prior to administration so that experts could formulate answers before being interviewed. Interviews lasted for approximately 30 minutes to one hour and were recorded and transcribed for analysis purposes.

The eleven experts came from diverse fields including automobile manufacturing, academia, scientific research, consulting and in government agencies at the federal, state and regional levels. Two worked in research and development roles at major automobile manufacturing companies. Five respondents were involved in government - three worked for the federal government in transportation and environmental policy, one worked in transportation consulting at a federal contractor, and one at a state transportation agency. Two worked in transportation research, one at a federal laboratory and one headed a research program at a major public university. One was a geodata software company employee who also had a longtime personal interest in eco-driving, and one was a contract operations manager at a regional transit agency. Most had been in the transportation industry for at least five years and almost all held leadership positions within their organizations. All were based in the United States. The experts worked at the following organizations:

- California Department of Transportation
- Daimler Trucks
- Environmental Protection Agency (2 experts)
- Environmental systems Research Institute
- General Motors
- National Renewable Energy Laboratory
- Riverside Transit Agency
- Westat
- University of Minnesota, HumanFIRST Program
- U.S. Department of Transportation

Eco-driving and Intelligent Transportation Systems (ITS)

Nearly all respondents were familiar with the term 'eco-driving.' Asked to describe their understanding of the term, all interview subjects agreed that eco-driving involves behavior modification that results in reduced gasoline consumption; several pointed out that it also may decrease greenhouse gas (GHG) emissions and provide positive environmental impacts. Four respondents highlighted the role of drivers in voluntarily altering their behavior, while two emphasized the use of real-time feedback from an in-vehicle monitoring device to help drivers adjust their behavior. One expert included reducing fossil-fuel dependency through the use of alternative energy sources as an aspect of eco-driving.

All respondents believed that eco-driving has the potential to reduce fuel consumption, however, opinions varied on the potential impact it could have:

- A researcher at an automobile manufacturer believed eco-driving could have a “huge impact” because 80% of the variability between the published fuel economy and that experienced by the driver can be attributed to driving style.

- One respondent was able to improve personal miles per gallon (MPG) by at least 20% through eco-driving, sometimes resulting in a higher MPG than what was quoted by the manufacturer.

- Another respondent estimated a 15%-20% reduction in fuel consumption.

- A transit agency fleet manager said fuel costs were the second highest cost of operations (after labor) and so reduced fuel consumption could be highly beneficial, especially with funding reductions in recent years. This individual believed that more fuel-efficient equipment and driving behavior would improve public perception of transit.

- One subject said that based on personal experience, eco-driving only reduced fuel use by about 2-3%. However, due to the large number of automobiles in the U.S., this individual believed that eco-driving would still have a significant impact if adopted on a large scale.

- Two respondents cautioned that it might be difficult for drivers to adopt eco-driving practices, while a third emphasized that drivers needed motivation in addition to awareness in order to adopt eco-driving practices.

- One engineer at an automobile manufacturer stated that while vehicles could be engineered to become more efficient, driving style adds an additional layer of efficiency, and true eco-driving involved both aspects.

Interviewees evaluated the importance of eco-driving feedback from a fleet management perspective. While not all respondents had direct experience in this field, most were currently working in leadership or supervisory positions.

- One respondent imagined a more hands-off management style and felt it could be difficult to attribute behavior to specific drivers within the fleet, especially as drivers are often assigned to different vehicles within a limited period of time.

- Two participants said information such as engine health or overall vehicle health would be more useful for the fleet manager or the maintenance staff, but less so for the individual operator who does not perform the maintenance.

- Two interviewees felt fleet managers would value navigation and maintenance information more than individual drivers, due to labor and maintenance costs.

- Two individuals involved in fleet management said data on performance indicators was helpful in coaching sessions with individual drivers because it helps illustrate the impact of their driving behavior, and suggested that drivers be measured not only against their peers, but also their past performance. However, one cautioned against micromanaging.

- Two suggested rewarding high-performing drivers based on collected data.

- Regarding the issue of privacy, several respondents felt that drivers reasonably expect a certain loss of privacy when they are operating a company vehicle.

- One emphasized the need for fairness, as some drivers may be assigned more fuel-intensive routes. Drivers are paid on a per-mile basis, so are not incentivized to eco-drive.

- Interestingly, two interviewees likened parents of young drivers to fleet managers, saying that information would be useful to individuals who were paying for another's vehicle.

All respondents agreed that eco-driving could reduce greenhouse gas emissions. One respondent commented that while eco-driving has theoretical benefits, more empirical studies are required to demonstrate its actual impacts. Another advised against using the term "climate change" to avoid generating controversy related to global warming. However, this individual believed that it is worthwhile to reduce greenhouse gas emissions even if unrelated to climate change.

Interview subjects provided their assessment on the short and long term effectiveness of eco-driving. While reactions were mixed, several respondents pointed out that for eco-driving to be impactful; it required widespread behavioral change over the long-term. They agreed that this would be difficult because it requires sustained behavioral change across a diverse population. Respondents noted that individual motivations would fluctuate depending on external factors such as gasoline prices.

- Two interview subjects cited societal views as an important factor. One believed peer pressure could encourage previously reluctant individuals to adopt eco-driving practices, and one believed the younger generation, referred to as the "hybrid driving generation," would be more willing to adopt eco-driving practices.

- Two stated environmental factors were not the only determinants of driving behavior and other considerations might affect the operating decisions of drivers.

- A few believed there would always be a portion of the population that would refuse to alter their behavior, but most would be open to suggestions.

- One cautioned against the so-called rebound effect, where people might start driving more because they feel they are driving more efficiently.

Incentives to Adoption

Participants shared ideas for strategies to promote eco-driving. All agreed that eco-driving should not be made mandatory, with a government regulator stating that people tended not to follow mandates unless it was life-threatening, citing the example of seatbelt laws. Two noted that increased fuel prices in the past had motivated people to value fuel efficiency or purchase vehicles that have integrated displays. A federal employee believed eco-driving should be voluntary, but noted it was difficult to ensure funds would be available for non-compulsory programs.

All participants believed that eco-driving should be promoted by incentivizing drivers to voluntarily change their behavior, rather than penalizing those who do not. Interviewees had differing opinions on the best ways to achieve this:

- Almost all alluded to monetary savings as a prime motivator. Several mentioned the price of fuel, and two mentioned gas taxes or mileage-based road pricing. A few suggested tax breaks for those who voluntarily adopt eco-driving technology.

- One cited the need for a cultural shift to encourage alternatives to single-occupancy vehicles, such as public transit and cycling.

- One interviewee, who did not work for the government, cited past federal successes in changing driver behavior, such as drunk-driving initiatives. This individual suggested that an energy independence initiative could be effective in reducing fuel consumption.

- Several respondents mentioned a need for government policies encouraging manufacturers to alter the design of their vehicles to facilitate eco-driving. Two mentioned a need for real-time fuel economy displays that are pre-installed in all vehicles.

- A transit fleet manager cited past experience in implementing a new smart-drive system. Initially seen as intrusive, it was well-received after drivers were educated about the benefits and provided incentives to adopt the new system.

Experts provided ideas for promoting eco-driving. All believed that friendly competition would be effective, and that social media would be extremely useful in promoting eco-driving.

- One interviewee mentioned peer pressure; if an individual saw that others in his/her social network were all eco-driving then they would be more likely to ecodrive as well.

- Several suggested using Facebook or iPhone applications as a platform, with two stating that while they personally did not use social media, most of their social circle did.

- Two respondents said that a fair competition required comparisons with others who drove the same vehicle, and one cited an example of a successful program by a European manufacturer where all drivers could record their usage online.

- A few interviewees suggested that competition be within social networks. However, another suggested aggregating statistics and displaying them to individual drivers.

- Several interviewees liked the idea of an overall “ecorank”, however one felt that miles-per-gallon would suffice, particularly because it was a well-understood concept.

- One stated it was important to provide easily understood information to drivers, such as publicizing that the most fuel-efficient speeds are 30-55mph.

Interviewees were then asked about the incentives needed for promoting eco-driving. While some felt that bragging rights or personal satisfaction might be enough, others, particularly those with commercial backgrounds, felt demonstrable monetary savings were more important. Asked about the viability of an adjustable display (where individuals could choose to display either environmental or financial measurements), a respondent said he believed that most people would either be unaware of or unwilling to use this function.

Respondents mentioned other incentives for eco-driving:

- One said that smoother or slower driving was more enjoyable and relaxing. However, being too didactic about eco-driving could be a turnoff.

- Several suggested increasing the cost of driving. One interviewee suggested mile-based road pricing or tolls, while another suggested increasing the price of gas. Others preferred financial incentives for buying fuel-efficient cars and maintaining cars to operate at a fuel-efficient level. An automaker employee suggested manufacturer credits.

- Two suggested utilizing employee recognition measures, such as priority in shift choice, to encourage eco-driving among commercial drivers.

Most interviewees believed that if ecodrive units are demonstrated to be effective, fleet operators would be more likely than individuals to purchase them since fuel is one of their largest operating costs. While increasing gasoline prices might cause more individuals to be interested in such devices, several felt individual consumers would have a lower reservation price than business clients, and one respondent said she felt the "greenie" market was very small.

Mechanisms to Convey Eco-driving Feedback

Researchers then sought to assess how feedback and ITS can help inform drivers on how to implement eco-driving practices. While all agreed on the importance of feedback, particularly instantaneous feedback, many cautioned against such information becoming a distraction for drivers. Several felt that over-detailed displays would not only cause drivers to pay less attention to road conditions, but also make them frustrated and impatient. While acknowledging that drivers should keep their eyes on the road as much as possible, most felt that audio alerts would either be too distracting, or drivers would tune out and completely ignore them. In particular, the subject from the transit agency was "adamantly opposed" to audible alerts because it could create panic among the passengers. Thus, respondents preferred displaying small amounts of pertinent information, with one suggesting that the information be located where drivers are already looking at, such as by the rearview mirror or near the speedometer. One noted that while eco-driving was not the most critical feature in vehicle safety, drivers would refer to it frequently and so it should be placed in a convenient location. Many suggested displaying instantaneous fuel economy. Two preferred a comprehensive "eco-score" that incorporated elements of driver behavior, route choices and vehicle maintenance. One interviewee noted it was important to display numerical data, rather than symbols that do not convey real information. While one interviewee suggested displaying both a 'current' and a 'target' miles-per-gallon ratio, another felt this would be too didactic. Several felt judging acceleration or braking behavior would be dangerous as drivers might modify their behavior in ways that are not conducive to road safety.

Several respondents said navigation systems that suggested travel routes based on real-time traffic conditions would be helpful; however one said an effective system required a significant network of infrastructure and sensors that was not currently present. A few mentioned the importance of maintenance practices, particularly tire pressure, which needs to be modified depending on the season and thus required frequent checks by individuals.

Respondents differed on the most effective platform for the feedback device. A majority preferred for it to be part of the vehicle, because it would be integrated into the vehicle display, unobtrusive and available to all drivers. A public transit manager also said it would be easier from an administrative standpoint if the cost for the device was included in the cost of the bus. However, one cited the low turnover rate for vehicles that would slow adoption of the device.
Another suggested smartphones as a testing ground, and if successful, the concept could be included in future new vehicles. However, one cautioned against encouraging the use of a cellphone while driving.

Information Transmission, Storage, and Privacy

Participants discussed safety considerations with designing feedback devices. All felt distraction would be the main problem and cautioned against overly detailed displays that drew attention away from the road. Most suggested brief, factual displays that did not trigger anger or panic. Two suggested periodic summation, such as a trip-based data display at the end of each journey, or displays during refueling. Two also said that real-time feedback would be most effective in achieving behavior change, with a third saying he believed few drivers would willingly access the data after the trip in question. However, one interviewee warned that real-time displays could cause drivers to be so focused on their own eco-driving that they neglect road safety.

One expert suggested an audio system, where a particular sound might be played when the driver is engaging in undesirable behavior. However, three said that audio responses were annoying or distracting. All agreed that drivers should have the option of turning off audio reminders, while acknowledging that this might cause drivers to disable the option by default.

Most interviewees suggested that information be wirelessly transferred to fleet managers, because vehicles are often not brought back to a central location, and devices that require a direct connection are prone to failure and tampering. One respondent noted that fleet managers only need to look at the information on a limited basis (e.g. weekly or monthly), so the mode of transmission should be selected based on the manager's needs. Most suggested a web interface for managers to access this information. The transit operator was already using wireless transmission and aggregating the information on a web portal.

Most experts felt that privacy was not a significant issue, however two were concerned about how collected information might be used by legal or commercial entities such as insurance companies. A transit agency manager said drivers could access their own information and system-wide aggregates, but not that of other individuals. She believed that for fleets, privacy is easily overcome through the use of ID numbers rather than names. Two experts felt that consumers should be able to choose if they want the data to be centrally available. Another stated it would depend on the type of data that was collected; for example fuel efficiency measures would be much more acceptable than detailed route choices or destinations. Two said individuals should be in control of their own data.

Conclusion

Respondents believed that widespread, long-term adoption of eco-driving practices could significantly reduce fuel consumption and greenhouse gas emissions. Most felt eco-driving should not be required by law, but rather promoted as a financially positive practice that saves money for the adoptee. In addition to driver education, several suggested tax incentives, rebates or road pricing. Subjects also suggested using social media networks to promote eco-driving. Interviewees agreed that real-time feedback would be most effective, but cautioned that eco-driving feedback units should not distract drivers from road conditions. A majority preferred simple visual displays and advised against audio feedback. Several felt fleet managers would be more likely to use eco-driving feedback devices than individuals as fuel is one of the largest costs in the transportation industry, and real-time data attributed to individuals could allow managers to appropriately reward or train employees. Most interviewees felt that privacy was not a significant concern as long as collected data was controlled by the individual driver and not accessible by legal or commercial entities, such as automobile insurance companies. However, several felt that commercial drivers expect a loss of privacy when operating a company vehicle and so managers would be justified in using driver performance data in individual assessments.

Appendix B:

Eco-Score and Eco-Rank Web Application

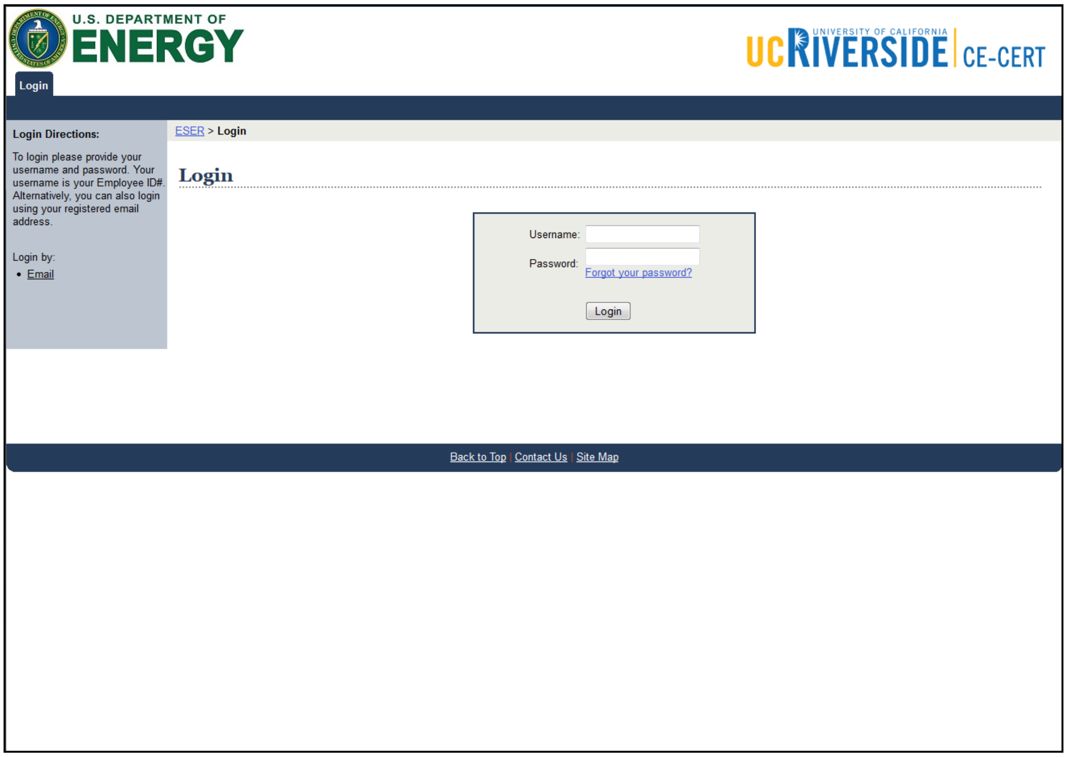


Figure B-1. Login page

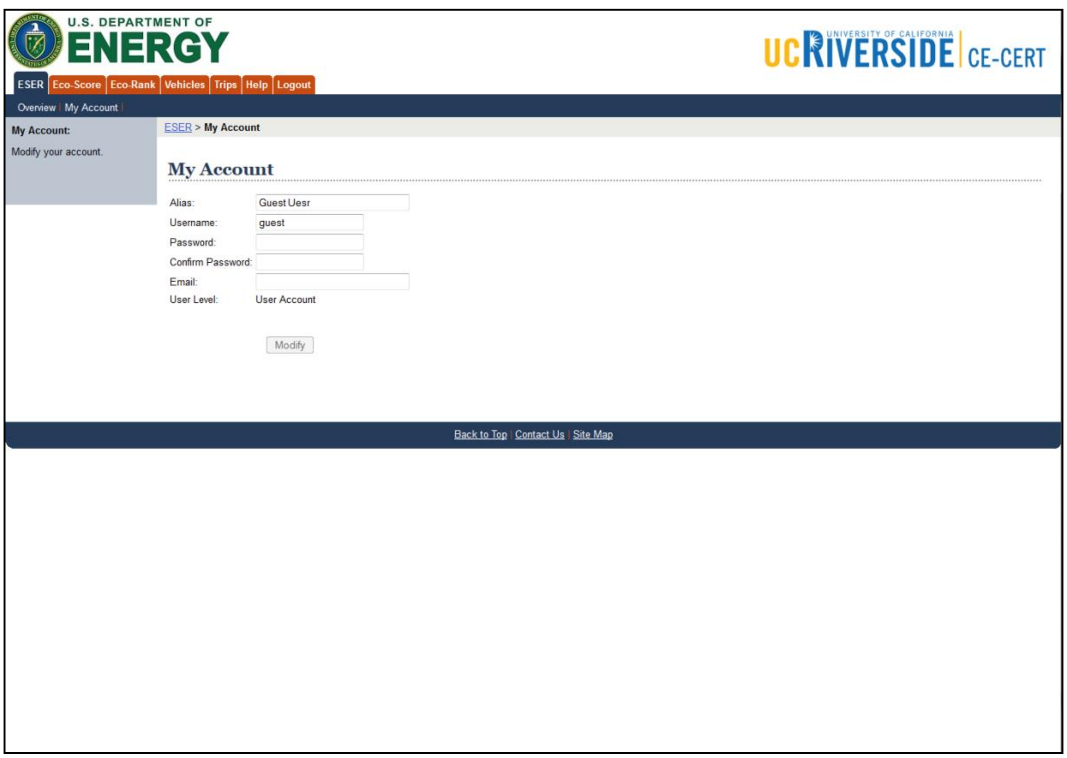


Figure B-2. Account management page

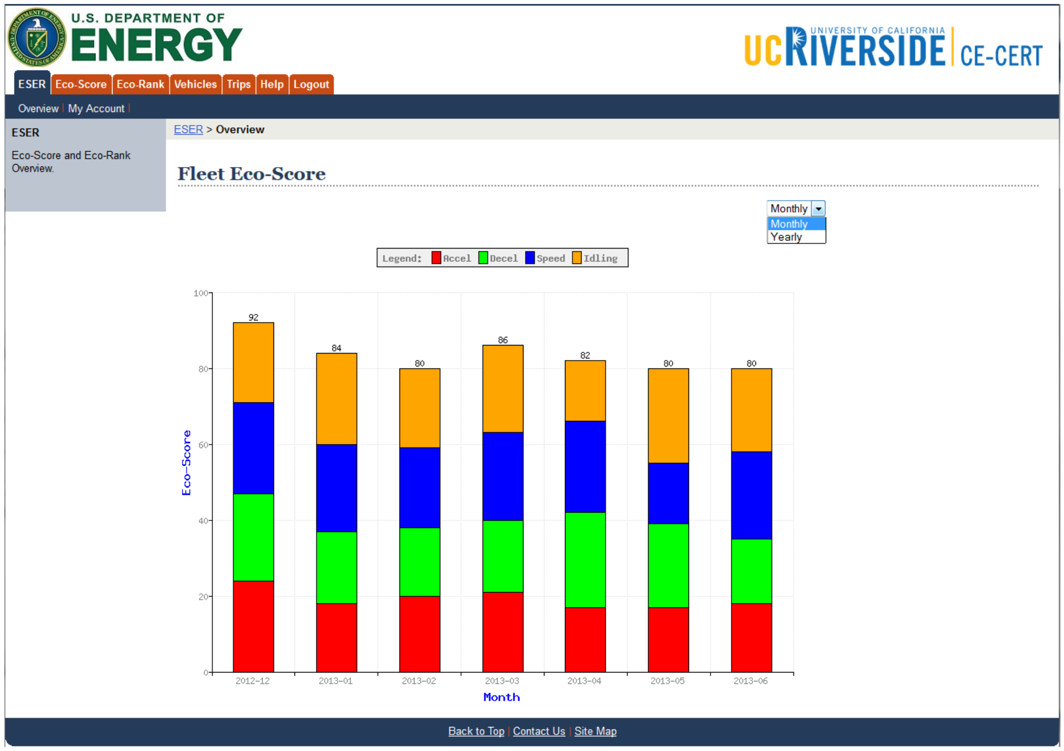


Figure B-3. Fleet average Eco-Score page

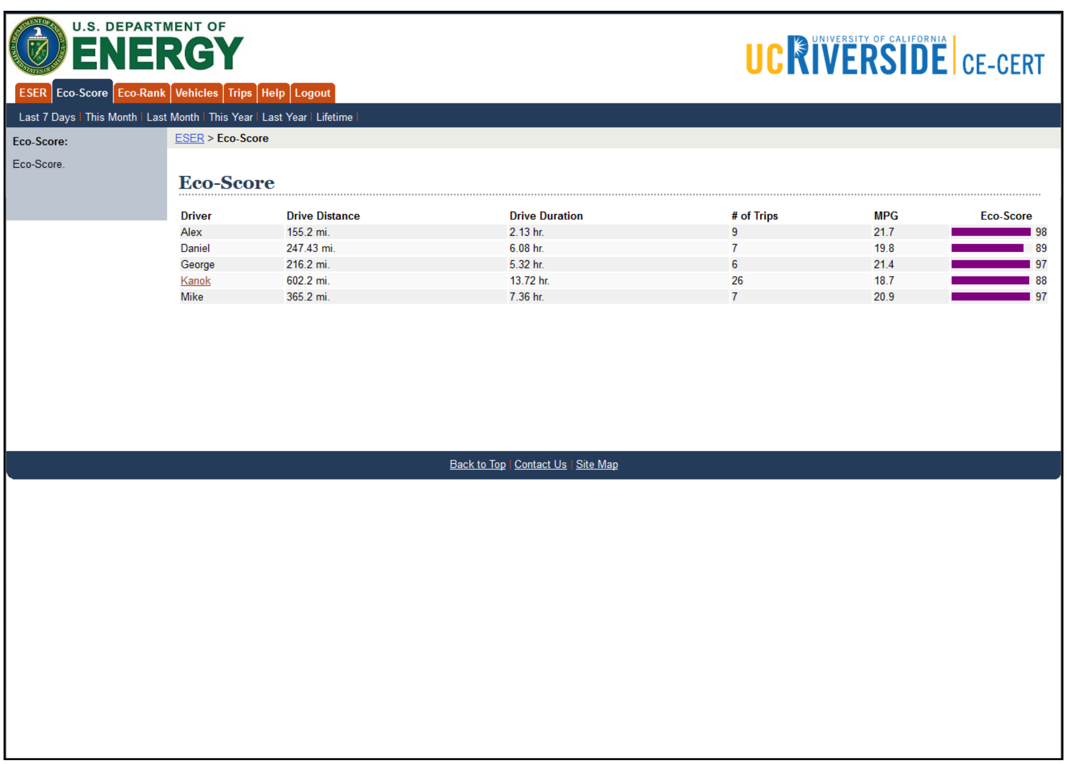


Figure B-4. Driver summary page

Figure B-5. Individual driver information page

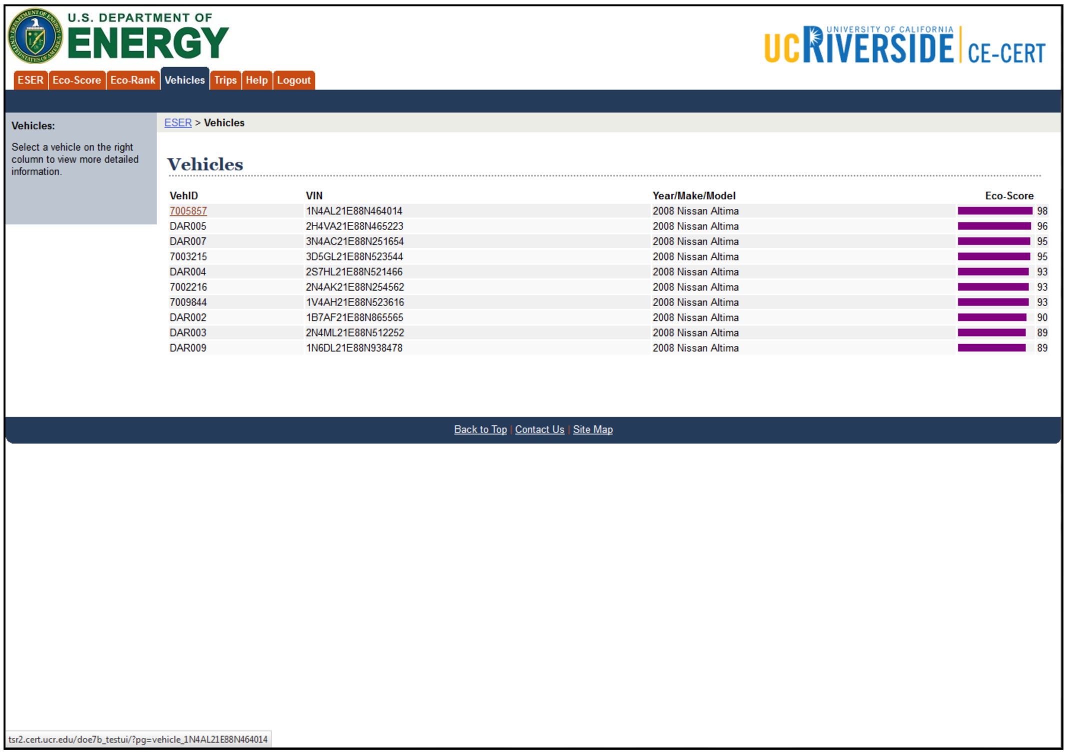


Figure B-6. Vehicle summary page

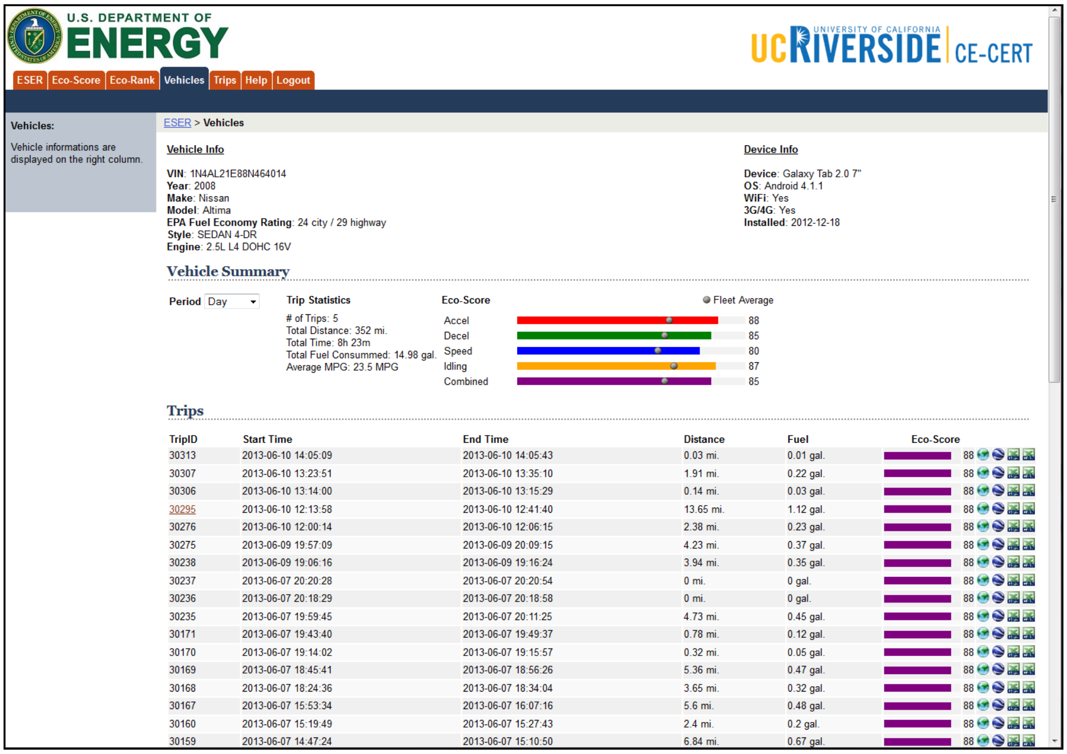


Figure B-7. Individual vehicle information page

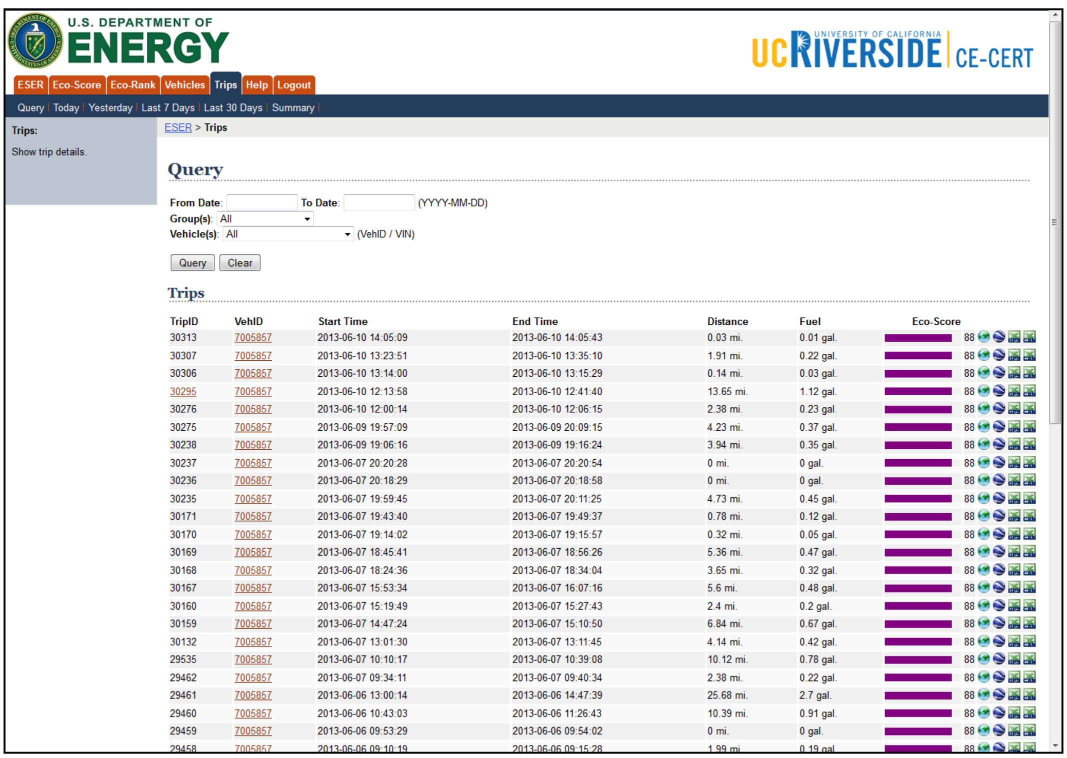


Figure B-8. Trip summary page

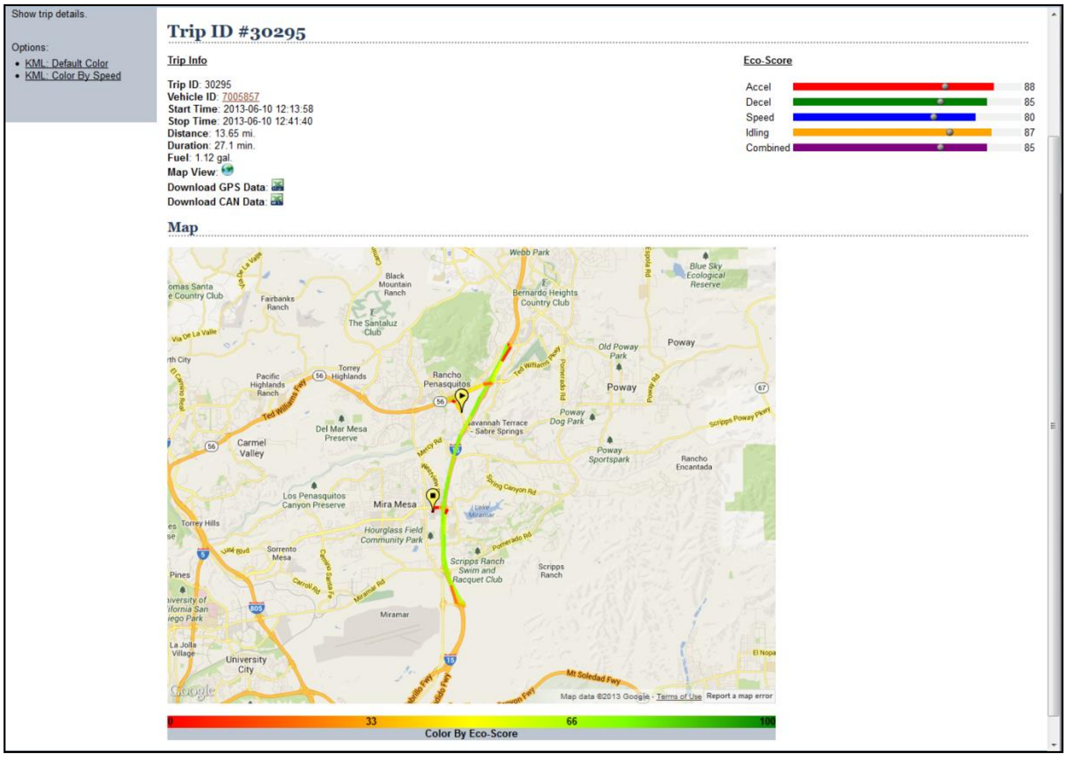
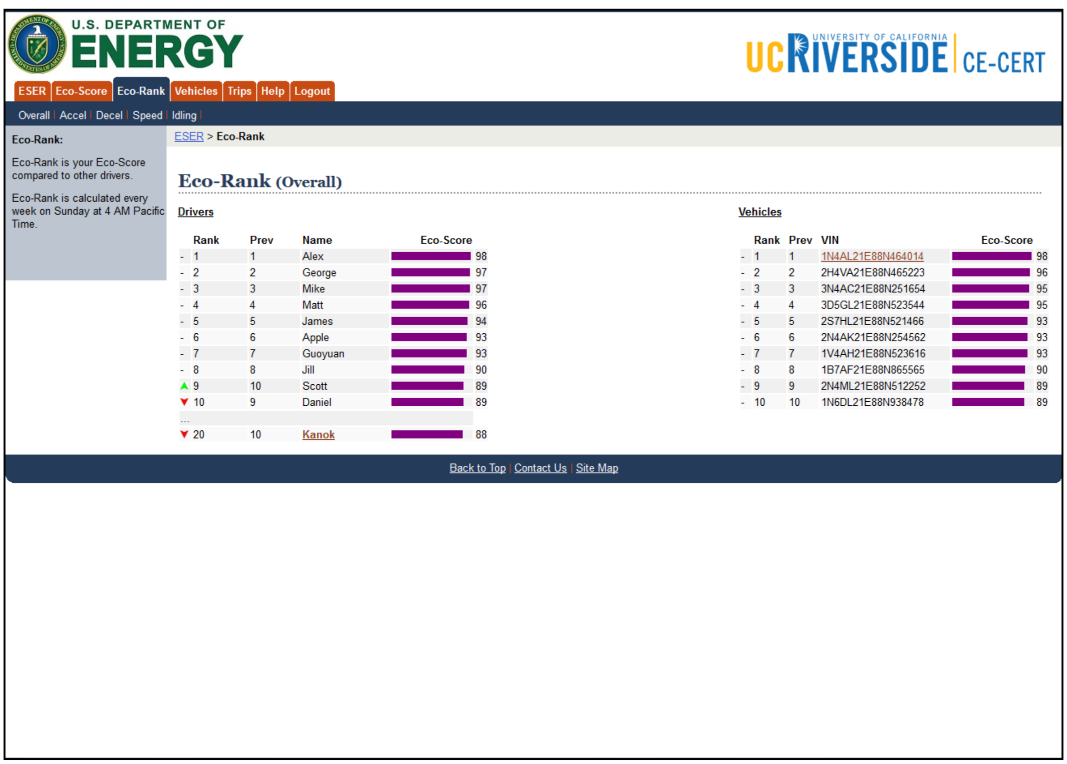


Figure B-9. Individual trip information page



	Rank	Prev	Name	Eco-Score
-	1	1	Alex	98
-	2	2	George	97
-	3	3	Mike	97
-	4	4	Matt	96
-	5	5	James	94
-	6	6	Apple	93
-	7	7	Guoyuan	93
-	8	8	Jill	90
▲	9	10	Scott	89
▼	10	9	Daniel	89
...				
▼	20	10	Kanok	88

	Rank	Prev	VIN	Eco-Score
-	1	1	1N4AL21E88N464014	98
-	2	2	2H4VA21E88N465223	96
-	3	3	3N4AC21E88N251654	95
-	4	4	3D5GL21E88N523544	95
-	5	5	2S7HL21E88N521466	93
-	6	6	2N4AK21E88N254562	93
-	7	7	1V4AH21E88N523616	93
-	8	8	1B7AF21E88N865565	90
-	9	9	2N4ML21E88N512252	89
-	10	10	1N6DL21E88N938478	89

Figure B-10. Eco-Rank summary page