Navigation Application Programming Interface Route Fuel Saving Opportunity Assessment on Large-Scale Real-World Travel Data for Conventional Vehicles and Hybrid Electric Vehicles

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ABSTRACT

The green routing strategy instructing a vehicle to select a fuel-efficient route benefits the current transportation system with fuel-saving opportunities. This paper introduces a navigation application programming interface (API) route fuel-saving evaluation framework for estimating fuel advantages of alternative API routes based on large-scale, real-world travel data for conventional vehicles (CVs) and hybrid electric vehicles (HEVs). Navigation APIs, such as Google Directions API, integrate traffic conditions and provide feasible alternative routes for origin–destination pairs. This paper develops two link-based fuel-consumption models stratified by link-level speed, road grade, and functional class (local/non-local), one for CVs and the other for HEVs. The link-based fuel-consumption models are built by assigning travel from many global positioning system driving traces to the links in TomTom MultiNet and road grade data from the U.S. Geological Survey elevation data set. Fuel consumption on a link is computed by the proposed model. This paper envisions two kinds of applications: 1) identifying alternate routes that save fuel, and 2) quantifying the potential fuel savings for large amounts of travel. An experiment based on a large-scale California Household Travel Survey global positioning system trajectory data set is conducted. The fuel consumption and savings of CVs and HEVs are investigated. At the same time, the trade-off between fuel saving and travel time due to choosing different routes is also examined for both powertrains.

INTRODUCTION

Emerging intelligent transportation system technologies, such as connected and automated vehicles, can be implemented and provide positive effects on mobility, fuel consumption, and greenhouse gas emissions (*1, 2*) in the near future. One particular interest in connected and automated vehicle technology is to provide vehicles with guidance to achieve better fuel efficiency during driving, which includes two types of tactics. One type is called "eco-driving," offering operational feedback to drivers, such as maintaining a steady speed and smoothing acceleration (*3*). The second type is guiding drivers to choose more fuel-efficient routes, referred to as "green routing." The selected ideal route considers road features and the traffic conditions, which are dominant factors in driving behavior (*4*) and fuel efficiency. A study by Nie and Li revealed that when the route is chosen, the operational tactics seem to have relatively small impacts on operating speed and fuel efficiency (*5*). Therefore, if the estimated fuel consumption of each alternative route is known before departure, the driver will potentially save fuel and reduce greenhouse gas emissions for that trip by choosing the most fuel-efficient route.

The green routing algorithms find the most fuel-efficient route for an origin and destination (OD) pair (*6, 7*). The fuel-saving opportunities of green routing strategies have been extensively studied recently. A comprehensive performance study of current eco-routing methods showed that an average saving of 12.5% could be achieved under ideal assumptions (*8*). A study in Lund, Sweden, on potential reduction of fuel consumption and carbon dioxide emissions through an eco-routing navigation system (*9*) was applied to 109 trips. The results indicated an average 8.2% fuel saving by choosing the greenest route. A navigation service "GreenGPS" uses participatory sensing data that allow the driver to find the most fuel-efficient route (*6*), which can save about 10% of fuel. A similar tool, Eco-Routing Navigation System developed by researchers at the University of California at Riverside (*10*), requires an extensive traffic database and accurate model inputs. A green-routing environmental benefit evaluation study in the greater Buffalo–Niagara, New York (*11*), proposed a "green-user equilibrium" concept. The TRansportation ANalysis SIMulation System (TRANSIMS)–Motor Vehicle Emission Simulator (MOVES) framework carries out the potential environmental benefit analysis. These studies are applied either on a small travel data set (e.g., a small number of trips or mileages) or on simulation data to prove the concept. They are restricted by quality traffic and network data requirements and the accurate pre-trip fuel consumption estimation model applicable to large-scale real-world travel data.

Therefore, assessing the route choice fuel-saving potential for a large-scale, real-world travel data set is not easy. First, hosting and maintaining a routing server for route choice is costly and requires detailed and quality traffic and network (*12-14*) and other data, such as GPS trajectories (*10, 13*). Second, a pre-trip fuel consumption estimation model that accurately predicts fuel consumption of a route before it is taken for different vehicle powertrains is desired.

To overcome the rigorous traffic and network data requirements, studies utilize the outputs of traffic simulation tools such as TRANSIMS (*11*) or Dynamic Urban Systems in Transportation (DynusT) (*15*). However, establishing a traffic simulation application is challenging due to the efforts of model calibration and the lack of computational resources. Also, their link cost attributes can be relatively simplistic in the area of energy estimation. Moreover, the simulation and traffic assignment results, either user equilibrium or system optimal, do not reflect traffic in the real world. Hence, the fuel-saving analysis based on simulation solutions may not be accurate and persuasive. In that case, an efficient and effective way of applying real-world travel data to find the possible green route options is needed.

Routing application programming interfaces (APIs), such as Google Maps Directions API (*16*), provide feasible route solutions for any OD pair by considering typical traffic conditions. The API offers quality routes conveniently because of the industry-level high-quality network and real-time traffic data. Although the API routes may not be exhaustive in presenting all possible routes for an OD pair, it is reasonable that the API routes are logical alternatives when considering both ease of following the routes and travel time. They may offer a fuel-saving opportunity for an actual route by comparing its estimated fuel consumption to alternative API routes.

With actual routes and API alternative routes, pre-trip fuel consumption estimation methods evaluate actual and API routes' fuel consumption based on the correlation of fuel consumption and influencing factors about trips, vehicles, and drivers. Macroscopic models assume experimentally fixed fuel consumption rate values for particular powertrain models. Microscopic-level vehicle models, such as the Future Automotive Systems Technology Simulator (FASTSim) (*17*) and Autonomie (*18*), consider vehicle driving and road details to provide a fuel-consumption estimation. The mesoscopic-level model is a compromise between macroscopic and microscopic models. Mesoscopic-level models do not need complete driving cycles and consider various fuel economy impact factors, such as traffic conditions, trip road features, offering acceptable estimation results. The present mesoscopic-level studies (*19-21*) mainly rely on the average speed of a trip to estimate the trip fuel consumption rate. Except for aggregated traffic conditions, the mesoscopic fuel consumption estimation models also need a vehicle's powertrain information. A hybrid electric vehicle (HEV) is a type of vehicle that "combines a conventional internal combustion engine system with an electric propulsion system" (*22*). The partially electric powertrain can achieve better fuel economy than a conventional vehicle (CV).

This study applies the enhanced pre-trip fuel consumption estimation models for CVs and HEVs. The model was trained and developed using millions of driving cycle global positioning system (GPS) trajectory point data and considering the route traffic conditions, functional class, and road grade factors. The advantages of the models are that they do not need complete trip drive cycles and can provide accurate fuel consumption rate estimations for both powertrains for a route that has not yet been driven.

In that case, a fuel-saving opportunity assessment framework using a routing API and the pre-trip fuel consumption rate estimation models for large-scale, real-world travel data is proposed. The framework has the capability to quantify fuel-saving opportunities for a large-scale, real-world travel data set by comparing the API routes to the actual routes for all OD pairs, which is enabled by the automated similarity comparison between the actual route GPS trajectories and the alternative API routes. Meanwhile, the trade-off between fuel saving and travel time saving is also investigated. The contributions of the proposed route choice fuel-saving assessment method include but are not limited to:

- Quantifying and analyzing potential fuel consumption and savings in a large-scale, real-world travel data set for both CVs and HEVs for the first time.

- The API (Google Directions) method provides alternative route options and is easy to implement and compatible with any cities that have travel data.
- The enhanced pre-trip fuel consumption rate estimation models for CVs and HEVs evaluate the route fuel use and enable pre-trip green route selection.

METHODOLOGY

The proposed framework consists of several modules:

1) Initialization
2) API query
3) Map matching
4) Route fuel consumption estimation
5) Route similarity assessment
6) Fuel saving analysis.

Initialization

An initialization procedure deals with the raw GPS trajectories and abstracts the real driving routes from a large-scale, real-world travel data set (*23, 24*) generated by GPS-instrumented vehicles within a region. A pre-processing procedure is used to cleanse raw GPS data (*25*) to remove the stationary points and outliers. The actual routes are segregated from the raw GPS trajectories by the time and distance gaps in the GPS data. Meanwhile, the actual route OD locations are extracted from the first and last GPS point coordinates of the route. The trip departure time is directly read from the timestamp of the origin GPS point. The actual route point-based speed sequence (speed profile) is used as a proxy to indicate the route's traffic condition (*26*). The actual route length is computed by summing the coordinate distances among all consecutive GPS point pairs.

API Query

The navigation API (e.g., Google Directions API) provides routes for a specific OD pair and departure time. Google Directions API responds with the route topology, length, and duration in traffic. The traffic model of Google Directions API is obtained by providing an additional input parameter, "departure_time," in the API request URL. Then, the API returns the "duration in traffic" feature in the response. The "duration in traffic" feature is the route travel time under traffic conditions at a typical future time with the same time-of-day and day-of-week information as the actual route. Although the typical future time is not the historical time when the actual route occurred, the typical traffic conditions at the time with the similar temporal feature (e.g., time of day, day of week) as the actual route time is still meaningful in general cases (except for accidents or unexpected events). The API route is composed of a sequence of shape nodes with coordinates.

However, the API cannot offer the route speed profile, which reflects detailed driving operation and traffic conditions. Nevertheless, the segmented traffic data are considered as a surrogate for the speed profile. First, the API query obtains multiple consecutive route segments (legs). Then, the second-level API query is conducted to fetch the polyline (i.e., shape node sequence), duration in traffic, and distance features for each route segment. The average speed of the segment is calculated by the distance over the duration on the segment, and then the speed is assigned to each shape node on the segment. After that, the combination of the ordered shape nodes of all segments form the route topology; the point-based speed sequences of all segments compose the route speed profile.

Map Matching

The map-matching procedure (*25, 27, 28*) matches all routes onto a common road network (*13, 21*) to procure the additional road attributes for the routes according to route location. After map matching, each GPS point in the actual routes or each shape node in the API routes is associated with a link identification, which can be used to retrieve link functional class and elevation (grade). The link functional class and road grade are used for estimating route-based fuel consumption, which will be explained in the fuel estimation model.

Route Fuel Consumption Estimation

With detailed road link information, the enhanced fuel consumption rate estimation model estimates the route fuel usage for CVs and HEVs. The model uses link-level average speed, road grade, and a local and non-local road classifier based on functional road class, rather than detailed second-by-second speed profiles, as input to provide accurate energy estimates for one route. The FASTSim model (*17*) is used in conjunction with real-world driving data, made available by the Transportation Secure Data Center at the National Renewable Energy Laboratory (*23*), to obtain FASTSim-estimated fuel economy data as the ground truth for nearly 1 million miles of driving in the United States. The driving data are used as the feedstock for developing a trip-level fuel estimation model, which does not require second-by-second drive cycles. The raw GPS points may cause drive-cycle profiles to be noisy, so the drive cycles are cleansed and filtered via the National Renewable Energy Laboratory's standard processing (*25*) to make them more suitable for the powertrain simulation model. As a part of the processing, the U.S. Geological Survey Digital Elevation Model is used to append road grade to the drive-cycle data, and the GPS points are matched to a road network with the map-matching procedure.

FASTSim is run for all cleansed drive cycles to determine the second-by-second fuel consumption for the drive cycle. The FASTSim fuel consumption results for the HEV and CV powertrain models are taken to be the ground truth for the model development. Since FASTSim returns fuel consumption estimations for each point in the drive cycle provided as an input, the resulting resolution is too fine for the link-based energy estimation model. Therefore, the point-based FASTSim results are aggregated to the link level as the total fuel consumption on the link, defined as the sum of all point-based FASTSim fuel consumption estimations on the link. Therefore, the link level results include total fuel consumption, functional class (local (such as urban major/minor arterials, local streets, etc.) or non-local (such as freeways)), road grade, and average speed of travel. The functional class attribute is directly obtained from the road network attributes. The road grade is computed as a ratio of "rise" to "run," in which run is the horizontal distance and rise is the vertical distance—the result is taken as a percentage. The average speed of the link is calculated by averaging all speed points on the link.

The link-based result data are grouped into "bins" by average link speed, functional class, and road grade. Average fuel consumption rate for each bin is calculated from the link-level

FASTSim results, and this generates the estimation model. The model is a three-dimensional lookup table. FIGURE 1(a) shows fuel consumption rate (gallons per 100 miles) for each speed and functional class bin in the model. FIGURE 1(b) has fuel consumption rates as a function of road grade and functional class. Each figure shows the results for the HEV and CV powertrains on local and non-local road links. Overall, the accuracy of the model is computed from the modeled to the ground-truth error in estimated fuel consumption (gallons) for a trip. The normalized averaged absolute error for all trips used to generate this model is approximately 5.7%. The fuel economy of HEVs outperforms that of CVs in all situations. In particular, FIGURE 1(a) indicates that the HEV has more fuel use benefits on low-speed ranges, partially due to the HEV's fuel-efficient performance on urban streets. For example, when cruising at low speed or stopping at a traffic signal, an HEV is likely under full electric power and thus has a better fuel economy.

The fuel consumption rate of a route comprised of links can be estimated by looking at the model tables through the link average speed, functional class, and road grade attributes. Link fuel consumption in gallons is computed by the link length (in miles) multiplied by the fuel consumption rate. The fuel consumption for the entire route is the sum of all links' fuel consumption quantities on the route.

Route Similarity Assessment

Given the routes' estimated fuel consumption, if a route matches one of the API routes, the fuel consumptions of the matched API route and the actual route are assumed to be the same. Before studying the fuel-saving opportunity, the similarity relationship of the actual routes, the API routes, and the green route have to be examined. The route similarity is described by a longest common sub-sequence (LCS)-based similarity score (ranging between 0 and 1) (*25, 29, 30*). The LCS similarity score usually represents the overlapping level of two trajectories. The LCS model can match two sequences by allowing them to stretch without changing the order of elements in the sequences but allowing some parts to be unmatched (*29*). In that case, an API route matched to the actual route can be found when the API route similarity score is the maximum one among all alternative API routes and is greater than a predefined similarity threshold (for example, maximum score > threshold of 0.7).

The predefined similarity score threshold affects the performance of route matching. For a large threshold, such as 1, the tightest constraint makes it very hard to find matching cases. A small threshold, such as 0.1, implies that almost all actual routes can find a matched API route. Both cases are not favorable for the fuel-saving study in different route similarity situations. The similarity score threshold of 0.7 used in this study is an empirically derived value, obtained from a route-matching study in the literature (*25*) to define a reasonable route-matching case.

Fuel Saving Analysis

In the fuel-saving analysis module, the actual routes are first separated as "follow API" and "non-follow API," according to whether a route matches one of the API routes. For the "follow API" group, the estimated fuel consumption of the actual route is replaced by the fuel consumption estimation of the matched API route. The reason for doing that is that the two matched routes are not fully identical due to the similarity threshold setting. A small discrepancy between two matched routes (the actual route and its corresponding API route, as "a matched route pair") leads to a fuel consumption difference by using a common fuel estimation model. Therefore, it is better to choose a comparable route from the matched route pair to compare with other API routes. Since all API routes share the same Google routing engine, the matched API route is more comparable to other API routes in light of path choice logic. Using the matched API route instead of the actual route to estimate fuel saving, the adverse impact of the fuel consumption difference between the actual route and the matched API route might be diminished in the fuel comparison procedure.

If the fuel consumption of the matched API route is higher than any other API route, the route is not the green one. Thus there is fuel-saving potential, and the actual route is categorized as having an "API saving route." Otherwise, it is denoted as "API greenest route."

For the "non-follow API" group, the estimated fuel consumption of the actual route and the API routes are directly compared. If the fuel consumption of the actual route is less than or equal to (outperforms) that of all API routes, the actual route is called "Actual outperform route." Otherwise, the actual route has fuel-saving potential, and the actual route is defined as "Actual saving route." Ultimately, the actual routes are divided into four groups: *1) API greenest route, 2) API saving route, 3) Actual saving route, and 4) Actual outperform route.*

To understand the total fuel saving, the cumulative fuel consumption of those four groups are calculated. According to the definitions, the fuel-saving amount is derived from the fuel consumption differences of the actual routes and their green API routes for the potential fuel saving groups, including 2) *API saving route,* and 3) *Actual saving route*.

The fuel consumption and saving patterns of the two powertrain models—CV and HEV—are investigated respectively. In addition to the quantitative study of fuel savings, the fuel-saving and travel time relationship study reveals the changes of fuel saving and travel time for specific potential fuel-saving routes.

EXPERIMENT AND RESULTS DISCUSSION

The California travel data set in the Transportation Secure Data Center is used in the experiment. The data set has 44,805 OD pairs containing 4,265,064 GPS points, which are extracted from 111,096 miles of driving by Californian travelers from 2010–2012. There are 100,031 API routes procured by the Google Directions API queries. Using TomTom MultiNet as the underlying road network layer and U.S. Geological Survey elevation data for all routes in the map-matching procedure, the additional link attributes are appended to the routes.

The framework processing efficiency was assessed. The computational time for processing one OD pair is impacted by many factors, such as route length and internet speed. The API query takes on average about 1 second for an OD pair. The map-matching module takes about 8 seconds for an average length trip. One OD pair may have two to three API routes and one actual route. So, the map-matching may take about 28 seconds. And, considering the time costs of other modules, the overall computational time for computing a green route and comparing its fuel consumption will take about 30 seconds.

Fuel Saving Quantitative Analysis

Overall Actual Route Ratio Distribution

The ratio distribution of the four actual route groups for CVs and HEVs are illustrated in FIGURE 2. From the figure, similar distribution patterns for CVs and HEVs are observed. In FIGURE 2(a), for CVs, 31% of actual routes have fuel-saving potential (all blue slices) while 69% of actual routes (all green slices) do not. In FIGURE 2(b), for HEVs, 39% of actual routes have fuel-saving potential while 61% of actual routes do not. In that case, HEVs have a larger number of potential fuel saving routes (39%) than CVs have (31%).

For the subset of cases that follow API routes (dark blue and dark green slices, 78% of all actual routes), most of them (58% for CVs and 55% for HEVs) followed the greenest API route so do not have fuel saving potential.

Cumulative Fuel Consumption and Saving

The cumulative fuel consumption of potential fuel-saving routes and no fuel-saving routes for CVs and HEVs are demonstrated in FIGURE 2 (c) and (d). The columns marked as "actual" and "green" denote the actual routes and their corresponding green routes (either actual route itself or its greener API route). The red bars in the "actual" column represent the cumulative estimated fuel consumption of potential fuel-saving actual routes. The red bars in the "green" column illustrate the cumulative fuel consumption of the green routes corresponding to the potential fuel-saving actual routes. The blue bars in the "actual" columns indicate the cumulative fuel usage of no-fuel-saving actual routes, which is identical to that of the corresponding green routes, marked with the blue bars in the "green" columns.

The cumulative fuel consumption difference between CVs and HEVs is significant, and HEVs always outperform CVs. For the actual routes' fuel consumption perspective, HEV cumulative fuel consumption is roughly half of that for CVs. Thus, considerable fuel-saving potential exists for HEVs compared to CVs, though this requires vehicle switching which is more costly and complicated than route switching.

For the CV case, the total potential fuel saving derived from the fuel use difference between actual routes and their green routes is 476 gallons (3,896 – 3,420 gallons), which is 12.2% of the cumulative fuel consumption of the actual routes with potential fuel-saving. For the HEV case, the total fuel saving amount is 472 gallons, which accounts for 17.8% of the potential fuel saving actual routes' cumulative fuel consumption. Although the absolute fuel saving amounts of CVs and HEVs are very close, the fuel-saving ratio of the HEVs is higher in this analysis.

The percentages of the local and non-local roads (functional class attribute) on an actual route may impact the estimated fuel consumption and fuel saving. For CVs, 84% of actual routes with fuel-saving potential are on local roads, and 16% of actual routes with fuel-saving potential are on non-local roads (i.e., freeway). For HEVs, 78% of the potential fuel-saving routes are on local roads, and 22% of the potential fuel-saving routes are on non-local roads. Considering the comparable ratios of potential fuel saving actual routes for two powertrains (HEV–39% vs. CV–31%), the non-local routes are more likely to have fuel-saving potential for HEVs compared to that for CVs.

Trade-Off between Fuel Saving and Travel Time

For the actual routes with fuel-saving potential, the time penalties or savings of green alternative routes are uncertain. Scatter diagrams in FIGURE 3 illustrate fuel-saving and travel time differences of potential fuel-saving actual routes for CVs (a), and HEVs (b). Each actual route is represented as a colored dot, and the color of the dot describes the *actual route duration* in seconds, which ranges from 15 to 10,800 seconds (3 hours). The actual route duration minus the green route duration yields the *travel time difference*.

The actual routes are separated into two classes according to time savings and penalties. The actual routes with both time and fuel savings are the **more desirable routes**, which are located above the zero time difference line (dashed line). The colored dots located below the zero time difference line with fuel saving and without travel time saving represent **less desirable routes**. The statistics of more desirable and less desirable routes for CVs and HEVs are illustrated in TABLE 1. The fuel saving is described by the fuel saving amount in gallons and as a percentage, calculated by the fuel-saving amount of the category over the total fuel saving amount. From the table, HEVs have fewer more desirable routes (as compared to CVs) that save both fuel and travel time. For the less desirable routes category, it follows that the HEV case has more actual routes than the CV case with time penalties (negative time savings) that accompany the fuel savings. These differences are also visible from the point scattering trend of FIGURE 3 (a) and (b). For the CV case, more dots are located above the zero-time difference line, while for the HEV case more dots are below the zero line.

TABLE 2 summarizes statistics of actual route attributes for both the CV and HEV, including route duration (seconds), length (miles), and road classification (local/non-local), broken out between the more desirable and less desirable route designations. For the CV cases, the mean values of length and duration for the more desirable route group are statistically higher than those of the less desirable route group. On the other hand, the splits between local and non-local road classes are very similar between the more and less desirable route options for the CV—in both cases, the number of local routes is significantly larger than the number of non-local routes.

For the HEVs, the duration attribute has a similar pattern to the CV case, while the pattern for length flips (the mean length value of the most desirable route group is smaller than that of the less desirable route group). This implies that green routes that save both fuel and travel time for an HEV are more likely to be found for shorter routes with relatively longer travel time. The road classification attribute again shows more green routing opportunities overall for local roads than non-local roads, though the percentage skews higher toward non-local roads for the less desirable HEV green route options.

CONCLUSIONS

The proposed navigation API route fuel-saving opportunity assessment framework provides a feasible way to assess the potential fuel saving for a large-scale, real-world travel data set for CVs and HEVs. The API methods do not need rigorous network and traffic data to provide the possible green routes for OD pairs in the target research area. The framework using large-scale, real-world travel data rather than simulation-based or small-scale travel data can better reflect the traffic patterns, and the estimated aggregate fuel saving results of route choice are more reliable and convincing.

In the experimental data set of 44,805 OD pairs, 31% of actual routes for CVs and 39% of actual routes for HEVs show opportunities for fuel savings by choosing a different route. Of those actual routes, the total estimated fuel saving is 476 gallons for the CV case, which is 12.2% of potential fuel-saving actual routes fuel consumption. For the HEV case, the overall fuel saving estimation is very similar (472 gallons), and accounts for 17.8%.

Due to the overall better fuel efficiency performance of HEVs, if HEVs drive all the routes, the total fuel consumption could be cut in half relative to the CV cases, although this would require full vehicle replacement rather than simply alternative route selection. From the perspective of fuel vs. travel time trade-offs, the analysis indicates that a given green route alternative for a CV is more likely to save time as well as fuel, whereas a given HEV green route is more likely to trade off an increase in travel time against the decrease in fuel consumption.

The proposed framework is transferable and can be applied to any city with real-world travel data and road networks. The findings are promising and convincing, thanks to the use of the large-scale, real-world GPS trajectory data.

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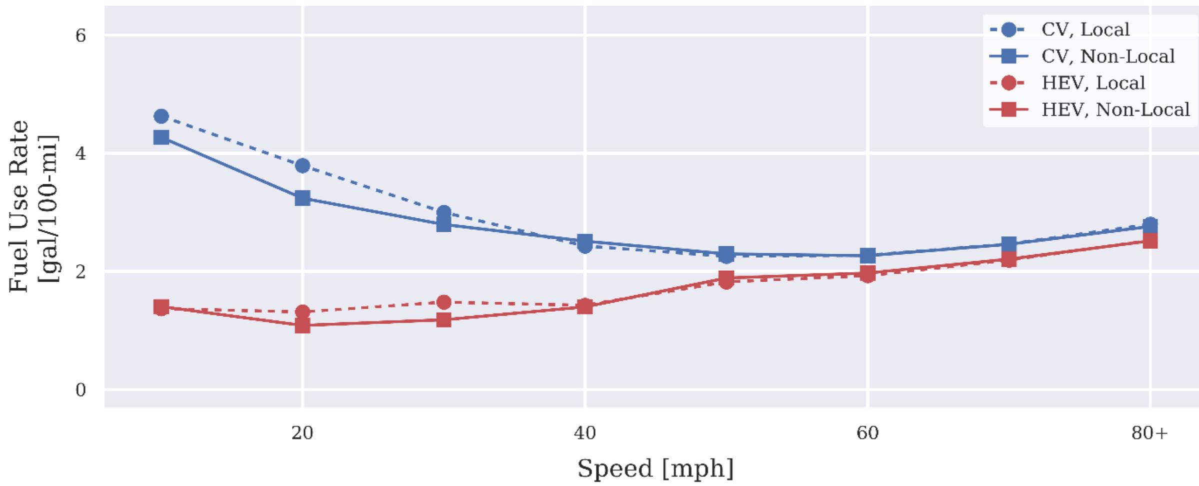
TABLE 1 Statistical Summary of Most Desirable and Less Desirable Routes

	Most desirable routes			**Less desirable routes**		
	# of actual routes	**Fuel saving (gal. / %)**	**Time-saving (hours)**	**# of actual routes**	**Fuel saving (gal. / %)**	**Time-saving (hours)**
CV	6,831	315 / 66.2%	438	7,059	161 / 33.8%	-263
HEV	6,005	170 / 36.0%	347	11,397	302 / 64.0%	-712

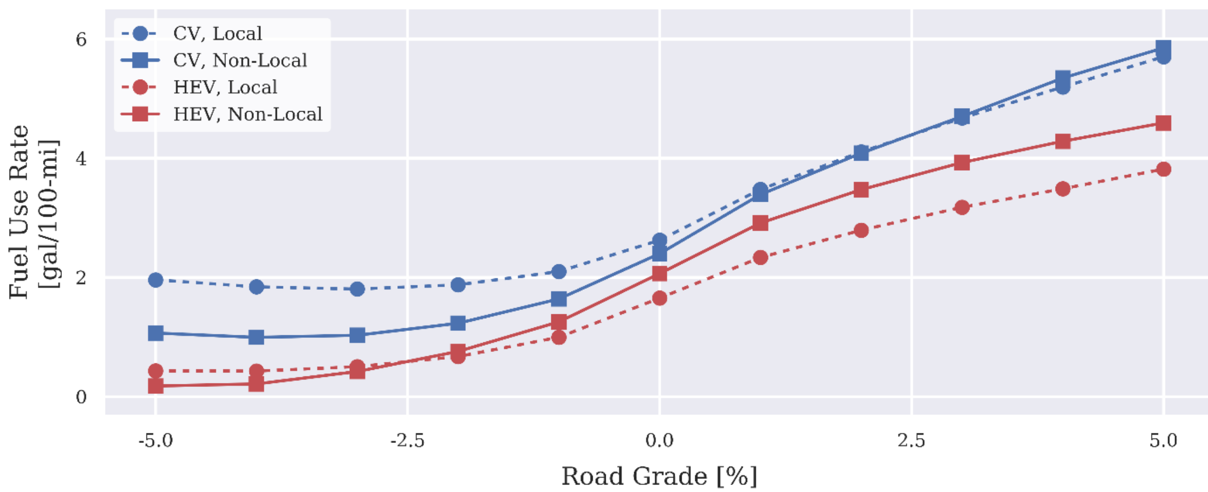
TABLE 2 Statistical Summary of Route Attributes for CVs and HEVs

CV	**Length**		**Mean**	**Std.**	**p-value**	**t-value**
		Most desirable	8.32	14.23	0.01[a]	2.62
		Less desirable	7.64	16.10	–	–
	Duration		**Mean**	**Std.**	**p-value**	**t-value**
		Most desirable	1,079.14	1,202.44	0.0[a]	16.80
		Less desirable	763.10	1,005.16	–	–
	Functional Class		**# of Local**	**# of Non-Local**	**Local%**	**Non-Local%**
		Most desirable	5,833	1,018	85%	15%
		Less desirable	5,873	1,206	83%	17%
HEV	**Length**		**Mean**	**Std.**	**p-value**	**t-value**
		Most desirable	7.97	13.78	0.00[a]	-4.47
		Less desirable	8.97	14.41	–	–
	Duration		**Mean**	**Std.**	**p-value**	**t-value**
		Most desirable	1,074.55	1,171.95	0.00[a]	9.74
		Less desirable	903.10	962.36	–	-
	Functional Class		**# of Local**	**# of Non-Local**	**Local%**	**Non-Local%**
		Most desirable	5,173	832	86%	14%
		Less desirable	8,470	2,927	74%	26%

[a] significance level of 0.05



(a)



(b)

FIGURE 1 Fuel consumption estimation model: (a) fuel consumption rate as a function of link average speed and functional class; (b) fuel consumption rate as a function of road grade and functional class.

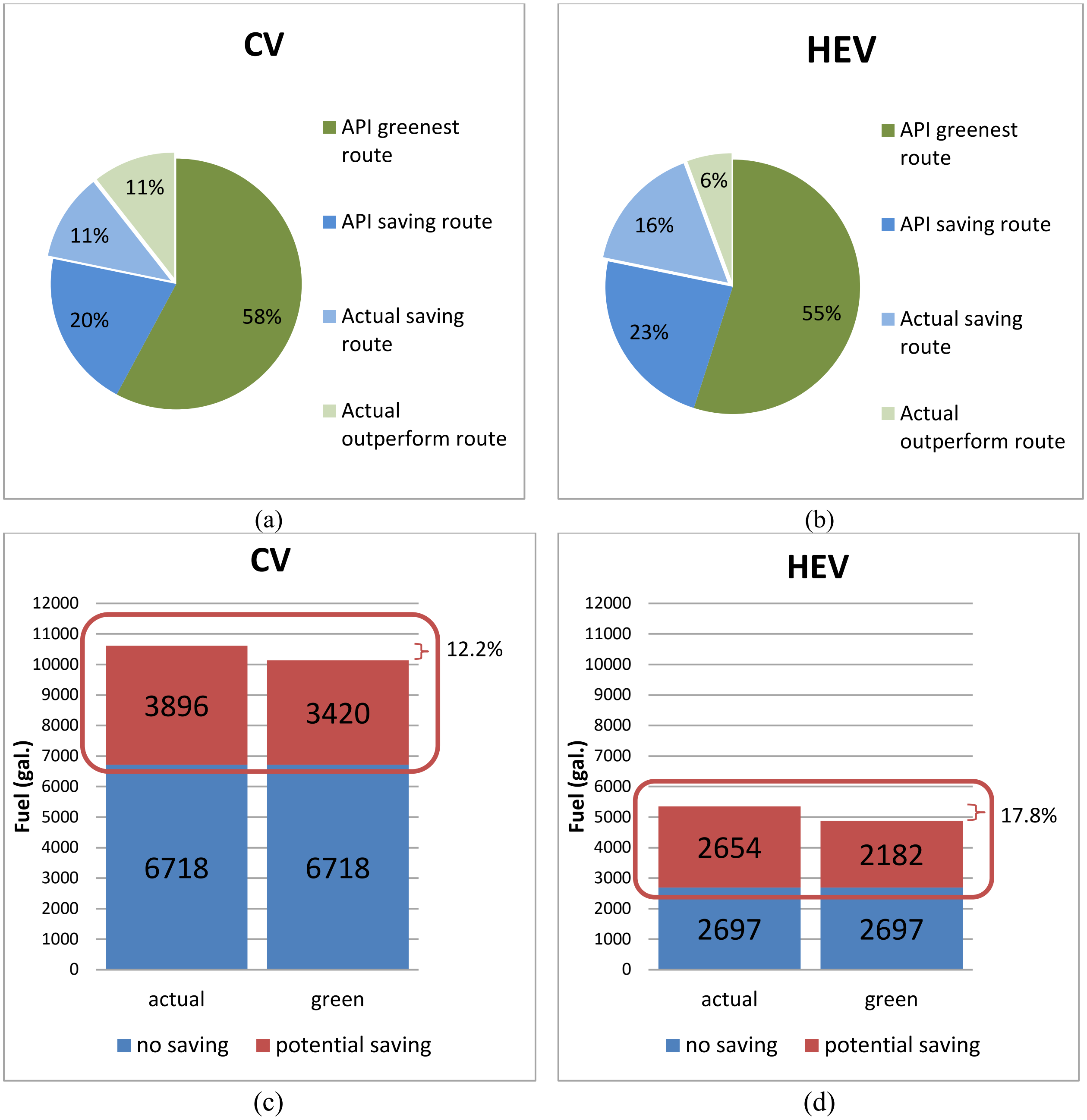
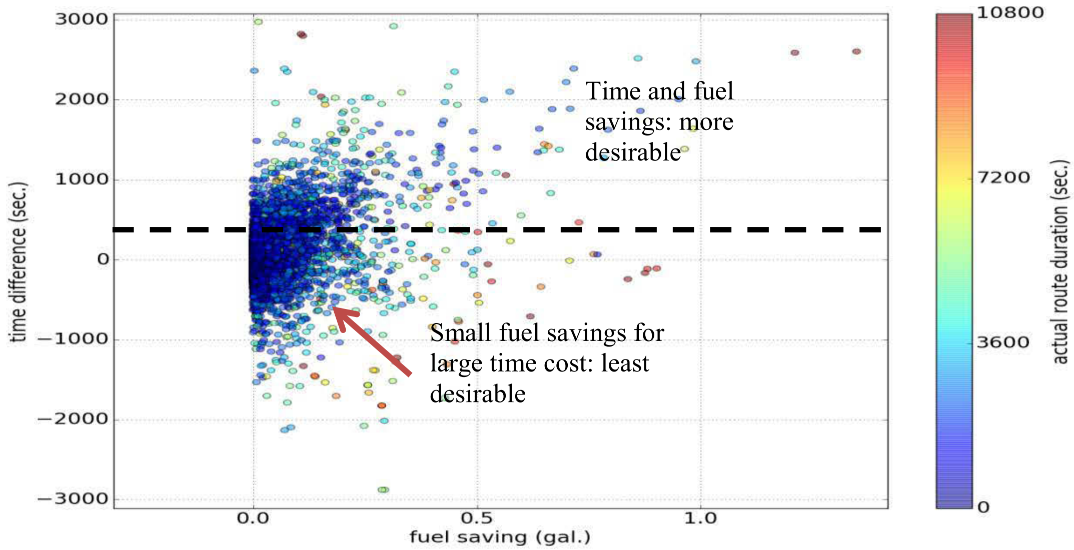
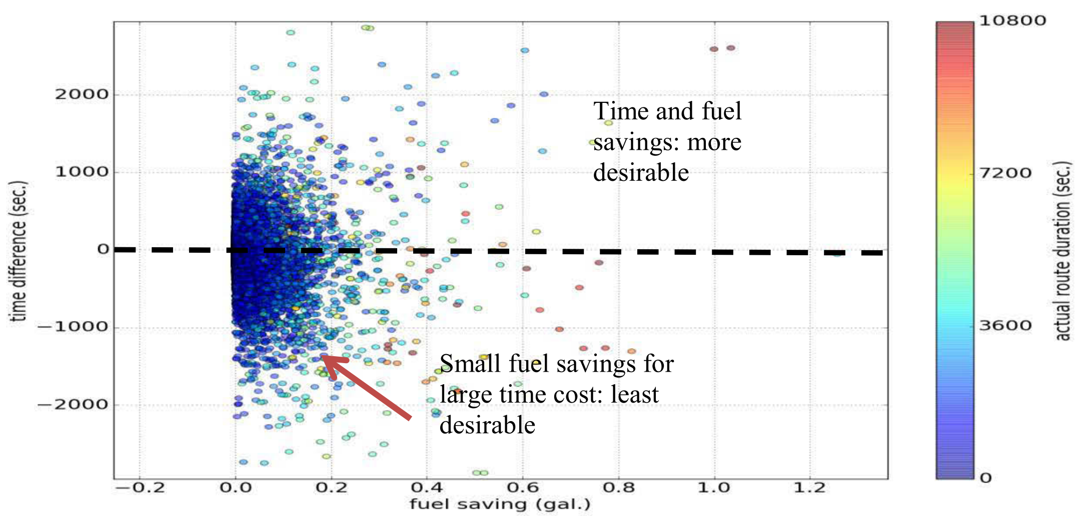


FIGURE 2 Ratio distribution of actual routes for CVs (a) and HEVs (b) and cumulative fuel consumption for actual routes for CVs (c) and HEVs (d).



(a)



(b)

FIGURE 3 Fuel saving vs. time difference for potential fuel-saving actual routes for CVs (a) and HEVs (b).