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

Preprint

Lei Zhu, Jacob Holden, and Jeffrey Gonder
National Renewable Energy Laboratory

To be presented at Transportation Research Board (TRB) 97th Annual Meeting
Washington, DC
January 7-11, 2018

NOTICE

The submitted manuscript has been offered by an employee of the Alliance for Sustainable Energy, LLC (Alliance), a contractor of the US Government under Contract No. DE-AC36-08GO28308. Accordingly, the US Government and Alliance retain a nonexclusive royalty-free license to publish or reproduce the published form of this contribution, or allow others to do so, for US Government purposes.

This report was prepared as an account of work sponsored by an agency of the United States government. Neither the United States government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States government or any agency thereof.

Cover Photos by Dennis Schroeder: (left to right) NREL 26173, NREL 18302, NREL 19758, NREL 29642, NREL 19795.

NREL prints on paper that contains recycled content.

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

Lei Zhu, Corresponding Author

National Renewable Energy Laboratory

15013 Denver West Parkway, Golden, CO 80401

Tel: 303-275-3194; Email: lei.zhu@nrel.gov

Jacob Holden

National Renewable Energy Laboratory

15013 Denver West Parkway, Golden, CO 80401

Tel: 303-275-4985; Email: Jacob.Holden@nrel.gov

Jeffrey Gonder

National Renewable Energy Laboratory

15013 Denver West Parkway, Golden, CO 80401

Tel: 303-275-4462; Email: Jeff.Gonder@nrel.gov

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 a large number of global positioning system driving traces to the links in TomTom MultiNet as the underlying road network layer and road grade data from a U.S. Geological Survey elevation data set. Fuel consumption on a link is calculated by the proposed fuel consumption 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 for choosing different routes is also examined for both powertrains.

Keywords: Navigation API, fuel-saving assessment, GPS travel data, hybrid electric vehicles

INTRODUCTION

Emerging intelligent transportation system technologies, such as connected and automated vehicles, can be implemented in the near term and provide positive effects on mobility, fuel consumption, and greenhouse gas emissions (*1, 2*). One particular interest of 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," which offers detailed 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 or "greener" 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 consumptions of all alternative routes are known before departure, the driver will potentially save fuel and reduce greenhouse gas emissions for that trip by choosing the most fuel-efficient route as a "green route."

The green routing algorithm is a route-choice method to 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 the best result, 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 has been presented (*9*). This study was applied to 109 trips, and the results indicated an average 8.2% fuel saving by choosing the greenest route. A navigation service, "GreenGPS," uses participatory sensing data that allows drivers to find the most fuel-efficient routes (*6*). The 1,000-mile travel data experiment indicates that the "GreenGPS" navigation service can save about 10% of fuel. Another tool is the Eco-Routing Navigation System, developed by researchers at the University of California at Riverside (*10*). The system requires an extensive traffic database and accurate model inputs. A green routing environmental benefits evaluation study in the greater Buffalo–Niagara, New York, region (*11*) proposed a "green-user equilibrium" concept, and the TRANSIMS-MOVES framework that was used can carry out the potential environmental benefit analysis. These studies are applied either on a small travel data set (a small number of trips or mileages) or on the simulation data to prove the concept. They are restricted by the detailed 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 by different vehicle powertrains is desired.

To overcome the rigorous traffic and network data requirement, some studies use the outputs of traffic simulation tools, such as TRansportation ANalysis SIMulation System (TRANSIMS) (*11*) or Dynamic Urban Systems in Transportation (DynusT) (*15*). However, implementing a traffic simulation application is challenging due to the efforts of model

3

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, are not the real-world traffic conditions. Hence, the fuel-saving analysis based on simulation solutions may not be accurate. 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 is able to offer reliable 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.

Pre-trip fuel consumption estimation methods evaluate the route's 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 detailed vehicle driving and road details to provide accurate fuel-consumption estimation. The mesoscopic-level model is a compromise between macroscopic and microscopic models. Mesoscopic-level models do not need full driving cycles and consider different fuel economy impact factors, such as trip road features, offering better estimation results than the macroscopic models. The present mesoscopic-level studies (*19-21*) mainly rely on the average speed of a trip to determine the trip fuel consumption rate. Except for the aggregated traffic conditions, the mesoscopic fuel consumption estimation models also need the 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 condition, functional class, 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 of quantifying fuel-saving opportunities for a large-scale, real-world travel data set by comparing the API routes to the actual route, which is enabled by the automated similarity comparison between the actual route GPS trajectories and the alternative API routes. Meanwhile, the trade-off of 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 fuel savings in a large-scale, real-world travel data set for both CVs and HEVs for the first time. Previous fuel-saving opportunity studies only applied to either simulation or small-scale travel data. The fuel-saving analysis on large-scale, real-world travel data provides convincing and reliable results.
- The API (Google Directions API) 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.

The Methodology section elaborates the details of the route choice fuel-saving-potential assessment framework. The experiment on large-scale, real-world California travel survey data and the fuel-saving analyses are discussed in the Experiment and Results Discussion section. The Conclusions section summarizes the whole paper and demonstrates the findings of this study.

METHODOLOGY

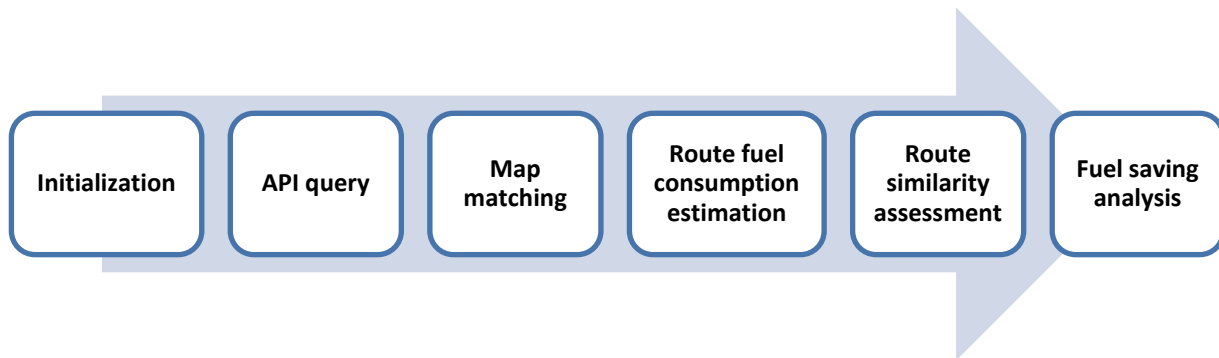The framework is shown in Figure 1.

FIGURE 1 Navigation API route fuel saving opportunity assessment framework.

In the beginning, an **initialization** procedure deals with the raw GPS trajectories and abstracts the real driving routes from a large-scale, real-world travel data set. The start and end GPS trajectory points of an actual route compose an origin-destination (OD) pair. The **API query** procedure queries the directions API for each OD pair, and then the API alternative routes, including topology and traffic data, are obtained. An OD pair only has one actual route and may have one or more API routes. A **map-matching** procedure matches all routes onto a common road network to obtain their road attributes. After that, in the **route fuel consumption estimation** procedure, the proposed enhanced pre-trip fuel consumption estimation model calculates the fuel consumption for all routes for conventional gasoline and hybrid electric powertrains. Next, a **route similarity assessment** procedure evaluates the similarity relationship of the actual route and the API route. If the actual route matches one API route, it indicates the vehicle drove on the API-suggested route. At the same time, it determines the green route for the OD pair. In the end, the **fuel-saving analysis** procedure first picks up the actual routes with fuel-saving potential from all actual routes and investigates cumulative fuel use and travel time. Then the potential fuel-saving analyses are able to be conducted.

Initialization

The large-scale, real-world travel GPS trajectories (*23, 24*) generated by GPS-instrumented vehicles within a region are needed. A pre-process procedure is used to cleanse raw GPS data (*25*) to remove the stationary points and outliers. After that, it detects the actual route GPS trajectory segments from the raw GPS trajectories by considering the time and distance gaps. When the actual routes are determined, the route OD locations are extracted from the first and the last route GPS trajectory segment point coordinates. The trip departure time is directly read from the timestamp of the first 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) can provide routes for specific OD locations and departure times. Google Directions API responds with the route topology, length, and duration in traffic. The traffic model of Google Directions API is used by providing an additional input parameter, "departure_time," in the API request URL, and 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 and 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 gets multiple consecutive route segments (legs). Then, the second-level API query is conducted to fetch the polyline (i.e., shape nodes sequence), duration in traffic and distance features for each route segment. The average speed of the segment is calculated by the segment distance over the segment duration, and then the speed is assigned to each segment shape node. After that, the combination of the ordered shape nodes of all segments is the API route topology, which is composed of shape nodes; the point-based speed sequences of all segments compose the API 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 point-based location information. After map matching, each GPS point in the actual routes or each shape node in the API routes is associated with a link ID, which can be used to retrieve link functional class and elevation (grade). The functional class and elevation/grade are used for estimating route-based fuel consumption.

Route Fuel Consumption Estimation

With detailed road link information, the enhanced fuel consumption rate estimation model can estimate the route fuel usage for CVs and HEVs separately. The model uses link-level average speed, road grade, and a local/non-local road classifier based on functional road class, rather than

6

detailed second-by-second speed profiles, as input to provide accurate energy estimates for one route. The model evaluates the fuel economy estimates for all routes (actual routes and API routes), and then the greenest route for each OD pair can be determined by comparing the routes' fuel consumption estimates.

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 fuel estimation model that does not require second-by-second drive cycles to accurately predict fuel economy at the trip level.
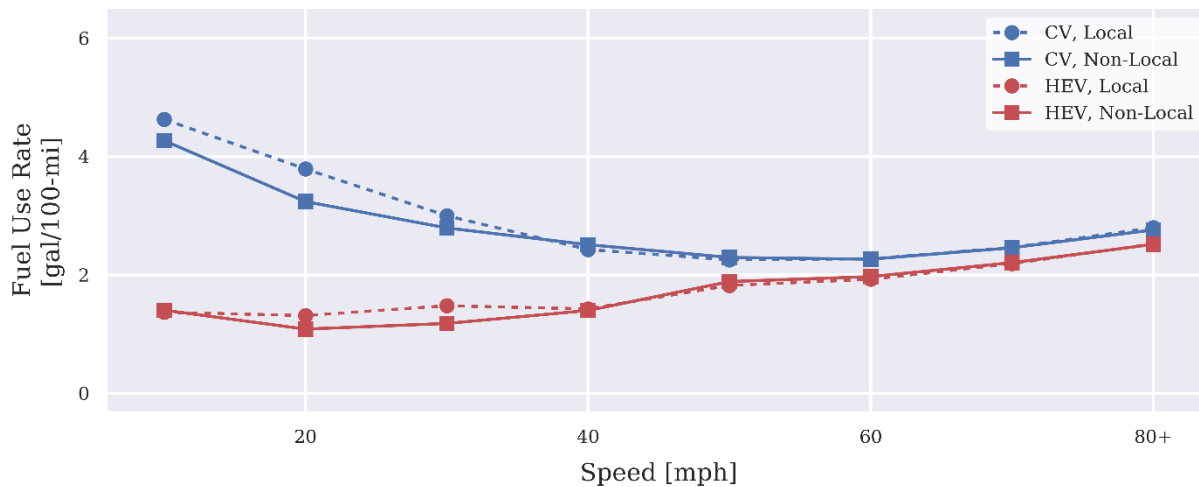
Fuel Consumption Rate Estimation Methodology
The Transportation Secure Data Center contains nearly 150 million GPS spatial points from real drivers acquired at a 1-Hz frequency. The raw GPS points may cause drive-cycle profiles to be noisy, so the drive cycles are cleansed and filtered via the National 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 backward-facing FASTSim model allows for rapid results and can model a range of stock vehicles and powertrain configurations. For this work, the FASTSim fuel consumption results from the HEV and the CV powertrain models are taken to be the ground truth for the model development. FASTSim returns fuel consumption estimations for each point in the drive cycle provided as an input. However, the resulting resolution is too fine for the energy estimation model in this work. It is desired to estimate fuel consumption down to the road network link level because the link level is the finest resolution that traffic and road attributes can be reliably obtained on a large scale. Therefore, the point-based FASTSim results are aggregated to the link level as the total fuel consumption on the link. All points located on the same link are grouped, and 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 total fuel consumption on a link is defined as the sum of all point-based FASTSim fuel consumption estimations on the link. 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-level results are used to build the fuel consumption rate estimation model. Results 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 2(a) shows fuel consumption rate (gallons per 100 miles) for each speed and functional class bin in the model. Figure 2(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 ground-truth error in

7

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. Particularly, Figure 2(a) indicates that HEV earns more fuel use benefits on low-speed ranges, partially due to HEV's fuel-efficient performance for urban street conditions. For example, when cruising at low speed or stopping at a signal, an HEV is likely under full electric power.

(a)
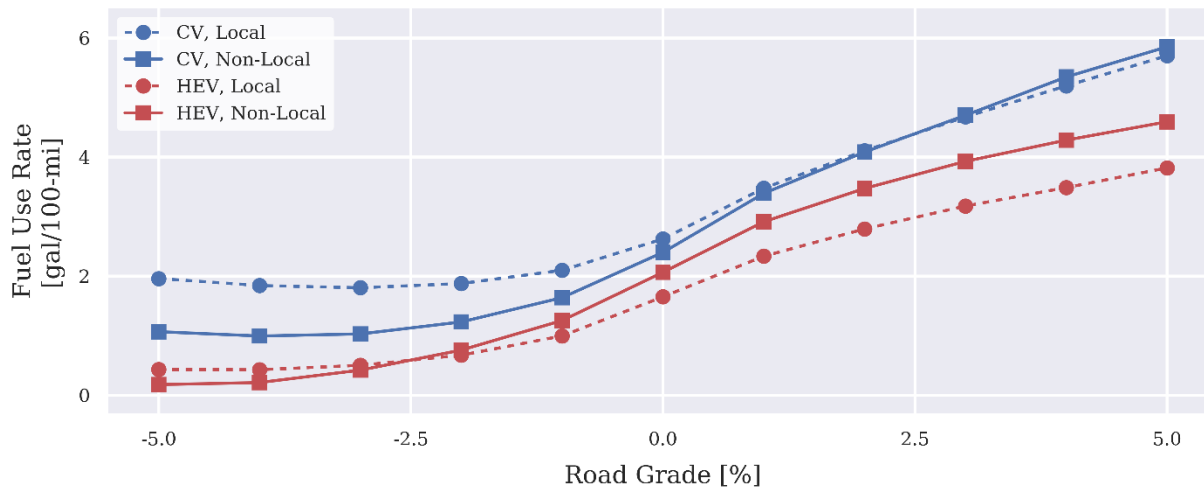
(b)

FIGURE 2 Fuel consumption estimation model for CVs and HEVs: (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.

According to the fuel consumption estimation models, the fuel consumption rate of a route can be estimated by looking at the model tables through the link average speed, functional class, and road grade attributes. Hence, links are the basic units for obtaining the fuel consumption rate estimates. 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.

8

Route Similarity Assessment

After fuel consumption has been estimated for all routes, a fuel-saving opportunity appears when the actual routes use more fuel than alternative routes. In this study, if a route matches one of its 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 need to be examined. It is described by a longest common subsequence (LCS)-based similarity score system. 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*). The details of the LCS similarity score are introduced in (*25, 30*). 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, max score > threshold of 0.7).

The predefined similarity score threshold affects the performance of route matching. For a large threshold, such as 1, the tight 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

The fuel-saving analysis will quantify the routes' fuel consumption and potential fuel saving and discover fuel saving and travel time penalty relationships for CVs and HEVs, respectively. The actual routes are first separated as "follow API" and "non-follow API," according to whether a route matches one of 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 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 (or actual route) is higher than any other API route, the route is not the green route. Thus it has 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.*

9

To understand the total fuel saving, the cumulative fuel consumptions 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*. Additionally, the fuel consumption and saving patterns of the two powertrain models—CV and HEV—are also investigated. 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

This section introduces a potential fuel-saving analysis concerning route choice based on a large California travel data set in the Transportation Secure Data Center. 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.

The initialization step processes raw GPS trajectory data and extracts actual routes. Google Directions API provides the API routes for all OD pairs. 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. Next, the routes' fuel consumptions are predicted by the pre-trip fuel consumption models for CVs and HEVs. Meanwhile, the route similarity assessment procedure calculates the similarity score of actual routes and their API routes for all OD pairs. Then, the fuel-saving analyses based on the large-scale real-world travel data can be conducted.

The computational time for processing one OD pair may be impacted by many factors, such as route length and internet speed. However, the average computational time for this procedure can be estimated. Generally, the API query takes on average about 1 second for an OD pair. The map-matching step 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 step may take about 28 seconds. Therefore, considering the other time costs, 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
As previously discussed, the actual routes are categorized into four groups. There are a total of 78% of actual routes following any one of the API routes with the same OD pair. The ratio distribution of the four actual route groups for CVs and HEVs are illustrated in Figure 3.
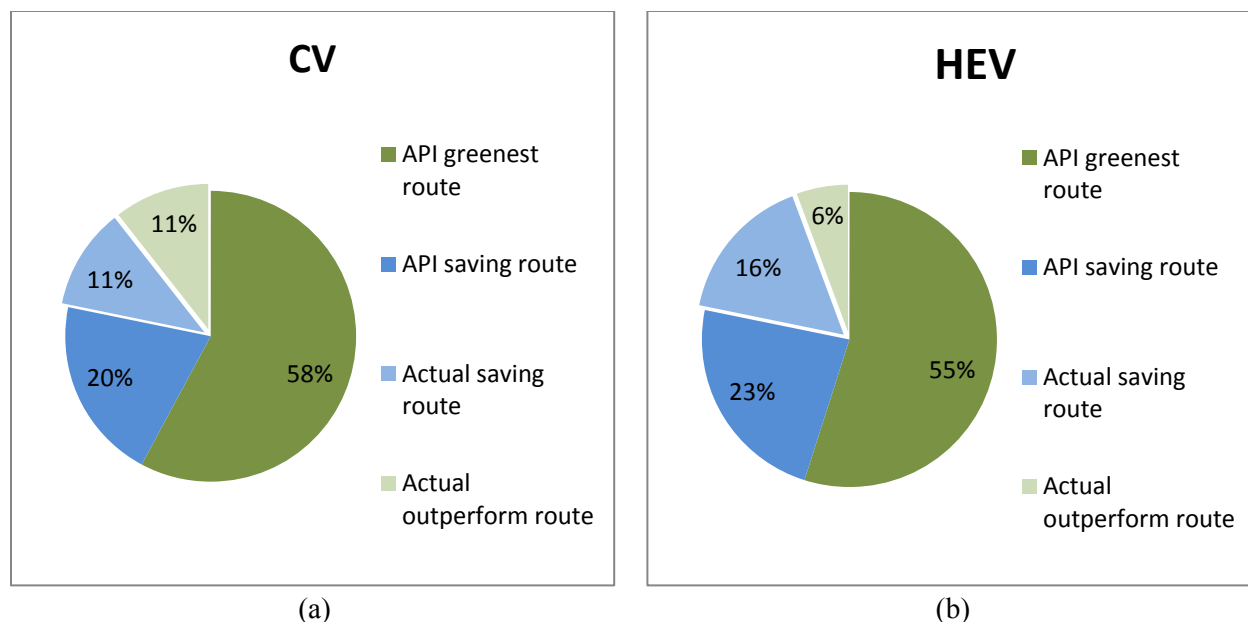
FIGURE 3 Ratio distribution of actual routes for CVs (a) and HEVs (b).

From the figure, similar distribution patterns for CVs and HEVs are observed. In Figure 3(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 3(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 4. For those plots, the column "actual" and "green" denote the actual routes and their corresponding green routes. The red bar in the "actual" column represents the cumulative estimated fuel consumption of potential fuel-saving actual routes. The red bar in the "green" column illustrates the cumulative fuel consumption of the green routes corresponding to the potential fuel-saving actual routes. The blue bar in the "actual" column represents the cumulative fuel usage of no-fuel-saving actual routes, which is identical to the accumulated fuel consumption of their corresponding green routes, marked with a blue bar in the "green" column.

The cumulative fuel consumption difference between CVs and HEVs is significant. For all types of actual routes, HEVs always outperform CVs with respect to fuel usage. 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%

11

of the cumulative fuel consumption of the potential fuel-saving actual routes. For the HEV case, the total fuel saving amount is 472 gallons, which accounts for 17.8% of the potential fuel saving of the 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.
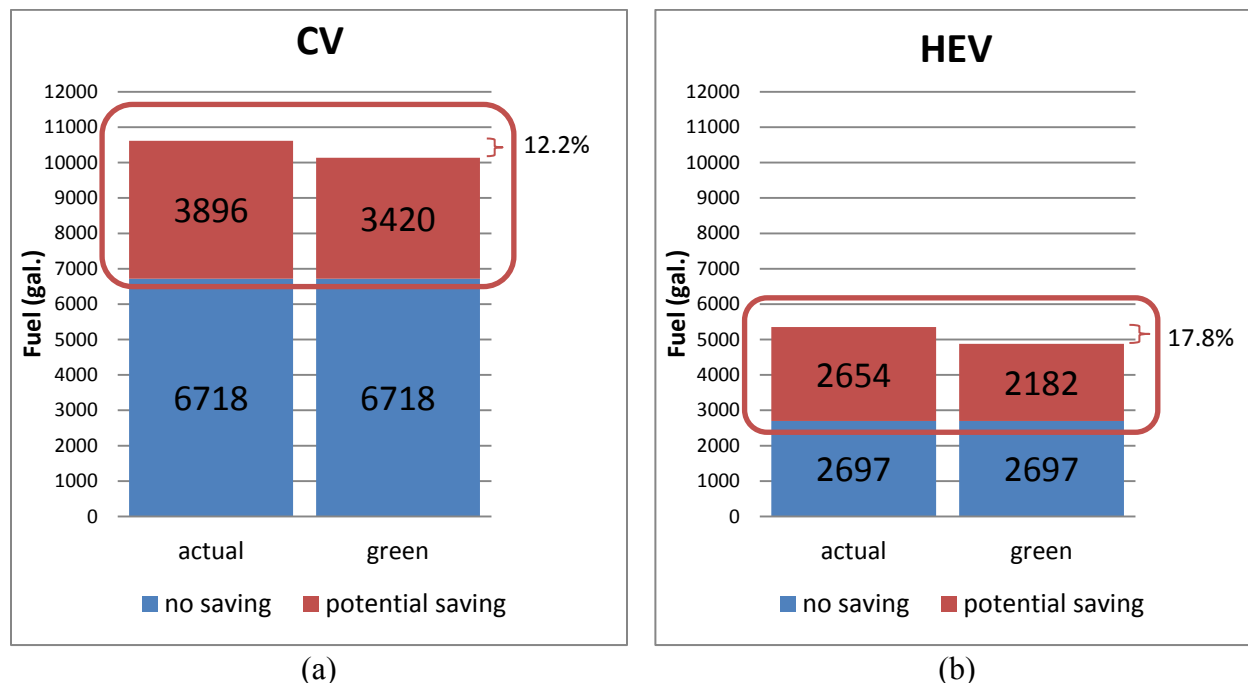

(a)   (b)

**FIGURE 4 Cumulative fuel consumption bar charts for actual routes for CVs (a) and HEVs (b).**

The percentages of the local/non-local roads (functional class attribute) on an actual route may impact the estimated fuel consumption and fuel saving. For CVs, 84% of total actual routes are on local roads and 16% of total actual routes are on non-local roads. The percentages do not change between the no-fuel-saving and the potential-fuel-saving groups. For HEVs, 88% of the no-fuel-saving routes are on local roads, while 78% of the potential fuel-saving routes are on local roads. In other words, 12% of the no-fuel-saving routes are on non-local roads and 22% of the potential fuel-saving routes are on non-local roads. It means that the non-local (i.e., freeway) routes are more likely to have fuel-saving potential for HEVs compared to that for CVs.

Trade-Off between Fuel Saving and Travel Time
The actual routes with fuel-saving potential are the targets for fuel-saving and travel time-saving trade-off analyses. The green alternative routes sometimes provide time penalties while sometimes they offer time savings. Scatter diagrams for fuel-saving and travel time differences of potential fuel-saving actual routes for CVs (a), and HEVs (b) are shown in Figure 5. In the figure, each actual route is represented by a colored circle, and the color of the circle indicates the *actual route duration* in seconds, which ranges from 15 to 10,800 seconds. The actual route duration minus the green route duration yields the *travel time difference*.

12
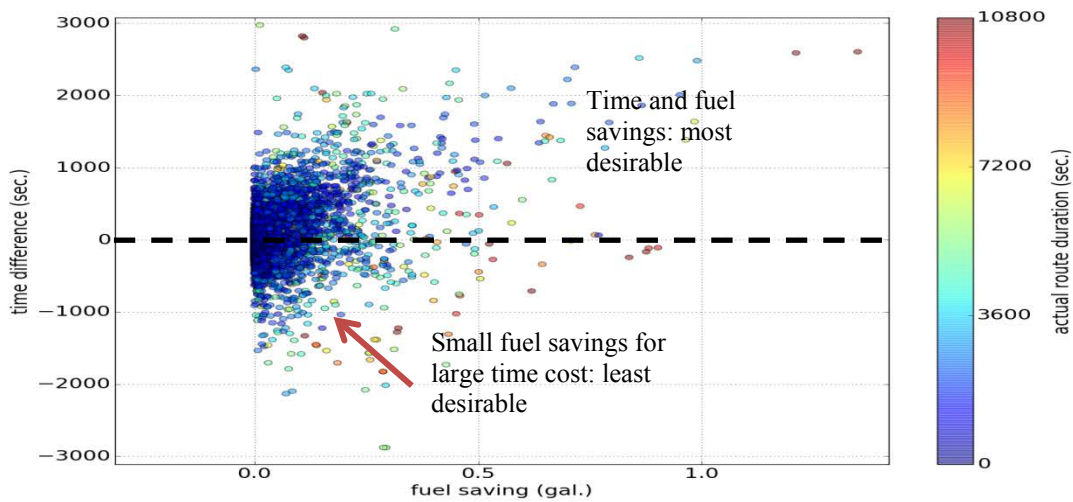
(a)
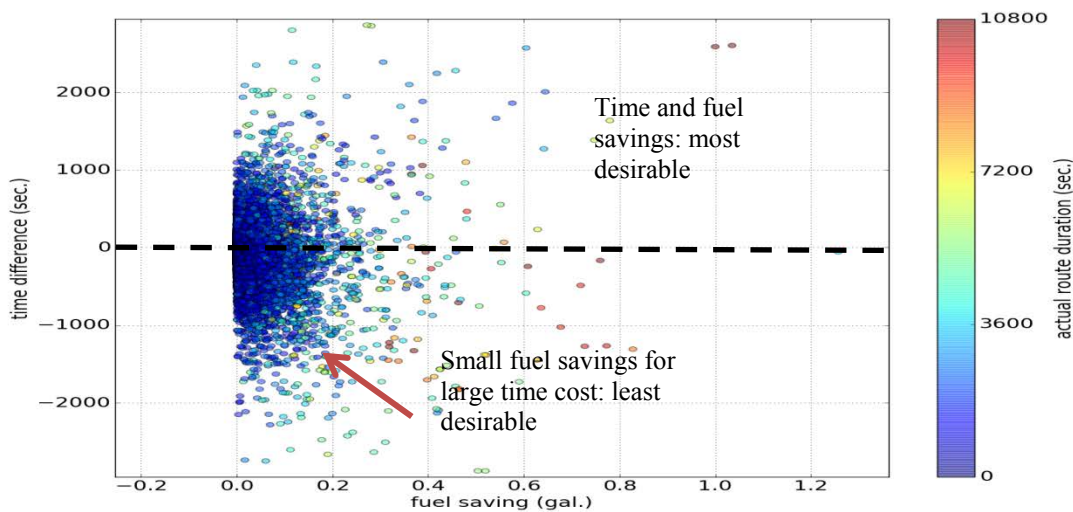
(b)

FIGURE 5 Fuel saving vs. time difference for potential fuel-saving actual routes for CVs (a) and HEVs (b).

From these diagrams, considering time savings and penalties, the actual routes are separated into two classes. The actual routes with both time and fuel savings are the **most desirable routes**, which are located above the zero-time difference line. The actual routes located below the zero-time difference line with fuel saving and without travel time saving are **less desirable routes**. The statistics of most desirable and less desirable routes for CVs and HEVs are illustrated in Table 1. The fuel saving is described by fuel saving amount in gallons and as a percentage. The percentage is calculated by the fuel-saving amount of the category over the total fuel saving amount. From the table, for the most desirable routes, HEVs have fewer actual 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

13

visible from the point scattering trend of Figure 5(a) and (b). For the CV case more points are located above the zero-time difference line, while for the HEV case more points are below the zero line.

TABLE 1 Statistical Summary of Most Desirable and Less Desirable Green 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 summarizes statistics for both CV and HEV actual route attributes, including route duration (seconds), length (miles), and road classification (local/non-local), broken out between the most desirable and less desirable route designations. For the CV cases the mean values of length and duration for the most 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 most 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 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.

TABLE 2 Statistical Summary of Route Attributes for CVs and HEVs

			Mean	Std.	p-value	t-value
CV	**Length**	Most desirable	8.32	14.23	0.01^a	2.62
		Less desirable	7.64	16.10	–	–
			Mean	**Std.**	**p-value**	**t-value**
	Duration	Most desirable	1,079.14	1,202.44	0.0^a	16.80
		Less desirable	763.10	1,005.16	–	–
			# of Local	**# of Non-Local**	**Local%**	**Non-Local%**
	Functional Class	Most desirable	5,833	1,018	85%	15%
		Less desirable	5,873	1,206	83%	17%

			Mean	Std.	p-value	t-value
HEV	**Length**	Most desirable	7.97	13.78	0.00^a	-4.47
		Less desirable	8.97	14.41	–	–
			Mean	**Std.**	**p-value**	**t-value**
	Duration	Most desirable	1,074.55	1,171.95	0.00^a	9.74
		Less desirable	903.10	962.36	–	-

14

		# of Local	# of Non-Local	Local%	Non-Local%
Functional Class	Most desirable	5,173	832	86%	14%
	Less desirable	8,470	2,927	74%	26%

[a] : significance level of 0.05

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 any OD pairs in the target research area. The framework using large-scale, real-world travel data rather than simulation or small-scale travel data can better reflect the real-world 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 routes fuel consumption. For the HEV case, the overall fuel saving estimation is very similar (472 gallons), and accounts for 17.8% of fuel consumption for potential fuel-saving actual routes.

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, though 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 use of the large-scale, real-world GPS trajectory data.

ACKNOWLEDGMENTS

REFERENCES

1.   Ahn, K. and H. Rakha, The effects of route choice decisions on vehicle energy consumption and emissions. *Transportation Research Part D: Transport and Environment*, Vol. 13, No. 3, 2008, pp. 151–167.

2.   Manzie, C., H. Watson, and S. Halgamuge, Fuel economy improvements for urban driving: Hybrid vs. intelligent vehicles. *Transportation Research Part C: Emerging Technologies*, Vol. 15, No. 1, 2007, pp. 1–16.

3.   Boriboonsomsin, K., A. Vu, and M. Barth, Eco-driving: pilot evaluation of driving behavior changes among us drivers. *University of California Transportation Center*, 2010.

4.   Hu, X., Y.-C. Chiu, and L. Zhu, Behavior insights for an incentive-based active demand management platform. *International Journal of Transportation Science and Technology*, Vol. 4, No. 2, 2015, pp. 119-133.

5.   Nie, Y. and Q. Li, An eco-routing model considering microscopic vehicle operating conditions. *Transportation Research Part B: Methodological*, Vol. 55, 2013, pp. 154–170.

6.   Ganti, R.K., N. Pham, H. Ahmadi, S. Nangia, and T.F. Abdelzaher. GreenGPS: a participatory sensing fuel-efficient maps application. in *Proceedings of the 8th international conference on Mobile systems, applications, and services*. ACM, 2010.

7.   Zhu, L., J. Holden, E. Wood, and J. Gender. Green routing fuel saving opportunity assessment: a case study using large-scale real-world travel data. in *Intelligent Vehicles Symposium (IV), 2017 IEEE*. 2017. IEEE.

8.   Kubicka, M., J. Klusacek, A. Sciarretta, A. Cela, H. Mounier, L. Thibault, and S.I. Niculescu. Performance of current eco-routing methods. in *2016 IEEE Intelligent Vehicles Symposium (IV)*. 2016.

9.   Ericsson, E., H. Larsson, and K. Brundell-Freij, Optimizing route choice for lowest fuel consumption–potential effects of a new driver support tool. *Transportation Research Part C: Emerging Technologies*, Vol. 14, No. 6, 2006, pp. 369–383.

10.   Boriboonsomsin, K., M.J. Barth, W. Zhu, and A. Vu, Eco-routing navigation system based on multisource historical and real-time traffic information. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 13, No. 4, 2012, pp. 1694–1704.

11.   Guo, L., S. Huang, and A.W. Sadek, An Evaluation of Environmental Benefits of Time-Dependent Green Routing in the Greater Buffalo–Niagara Region. *Journal of Intelligent Transportation Systems*, Vol. 17, No. 1, 2013, pp. 18–30.

12.   Zhu, L., Y.-C. Chiu, and Y. Chen. *Traffic Analysis Network Abstraction Approach: Framework and Numerical Analysis*. Transportation Research Board,Washington, D.C., 2017.

13.   Zhu, L. and Y.-C. Chiu, Transportation Routing Map Abstraction Approach: Algorithm and Numerical Analysis. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2528, 2015, pp. 78–85.

14.   Zhu, L., Routing Map Topology Analysis and Application. Dessertation, University of Arizona, 2014.

15.   Lin, J., Y.-C. Chiu, S. Vallamsundar, and S. Bai. Integration of MOVES and dynamic traffic assignment models for fine-grained transportation and air quality analyses. in *Integrated and Sustainable Transportation System (FISTS), 2011 IEEE Forum on*. 2011. IEEE.

16.   Svennerberg, G., *Beginning Google Maps API 3*. 2010: Apress.

17.   Brooker, A., J. Gonder, L. Wang, E. Wood, S. Lopp, and L. Ramroth. FASTSim: A Model to Estimate Vehicle Efficiency, Cost and Performance. 2015, SAE Technical Paper.

18.   Halbach, S., P. Sharer, S. Pagerit, A.P. Rousseau, and C. Folkerts. Model architecture, methods, and interfaces for efficient math-based design and simulation of automotive control systems. 2010, SAE Technical Paper.

19. Barth, M., F. An, J. Norbeck, and M. Ross, Modal emissions modeling: A physical approach. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1520, 1996, pp. 81–88.

20. Sugawara, S. and D. Niemeier, How much can vehicle emissions be reduced?: exploratory analysis of an upper boundary using an emissions-optimized trip assignment. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1815, 2002, pp. 29–37.

21. Zhu, L., Y.-C. Chiu, and Y. Chen, Road network abstraction approach for traffic analysis: framework and numerical analysis. *IET Intelligent Transport Systems*, Vol. 11, No. 7, 2017, pp. 424–430.

22. Hybrid Electric Vehicle. Wikipedia, 2017 [cited 2017 10 July 2017 20:57 UTC]; Available from: https://en.wikipedia.org/w/index.php?title=Hybrid_electric_vehicle&oldid=789980728.

23. Zhu, L., J. Gonder, and L. Lin, Prediction of individual social-demographic role based on travel behavior variability using long-term GPS data. *Journal of Advanced Transportation*, Vol. 11, No. 7, 2017, pp. 424–430.

24. Holden, J., E.W. Wood, L. Zhu, and J.D. Gonder. Development of a Trip Energy Estimation Model Using Real-World Global Positioning System Driving Data: Preprint. 2017, National Renewable Energy Laboratory (NREL), Golden, CO (United States).

25. Zhu, L., J.R. Holden, and J.D. Gonder. *A Trajectory Segmentation Map-Matching Approach for Large-Scale, High-Resolution GPS Data*. Transportation Research Board,Washington, D.C., 2017.

26. Hu, X., Y.-C. Chiu, Y.-L. Ma, and L. Zhu, Studying Driving Risk Factors using Multi-Source Mobile Computing Data. *International Journal of Transportation Science and Technology*, Vol. 4, No. 3, 2015, pp. 295–312.

27. Wang, M., X. Bao, L. Zhu, and Y.L. Bao, A Map-Matching Method Using Intersection-Based Parallelogram Criterion. *Advanced Materials Research*, Vol. 403, 2012, pp. 2746–2750.

28. Zhu, L., Y. Bao, S.-G. Wang, Q. Zhou, and X. Bao, *Map-Matching Compatible with Junction Adjusting in Vehicle Navigation System*, in Recent Advances in Computer Science and Information Engineering. Springer. 2012, pp. 451-457.

29. Vlachos, M., G. Kollios, and D. Gunopulos. Discovering similar multidimensional trajectories. in *Data Engineering, 2002. Proceedings. 18th International Conference on*. 2002. IEEE.

30. Kim, J. and H.S. Mahmassani, Spatial and temporal characterization of travel patterns in a traffic network using vehicle trajectories. *Transportation Research Part C: Emerging Technologies*, Vol. 59, 2015, pp. 375–390.