Trip Energy Estimation Methodology and Model Based on Real-World Driving Data for Green Routing Applications

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TRIP ENERGY ESTIMATION METHODOLOGY AND MODEL BASED ON REAL-WORLD DRIVING DATA FOR GREEN ROUTING APPLICATIONS

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INTRODUCTION

To increase the energy efficiency of the transportation sector, which accounts for 28% of total U.S. energy consumption (*1*), and reduce greenhouse gas production, new technologies and models informed by real-world driving data are necessary. Optimal strategies to minimize energy use vary by powertrain and level of vehicle automation. A method to accurately predict the energy required for individual trips is key to vehicle design and routing for energy optimization (*2*). Accurate trip energy estimation can also be applied to regional- or national-level transportation energy analyses, where trips (i.e., origin-destination pairs) are known, but real and detailed driving data are unavailable.

Typically, transportation energy models are considered to be macroscopic, mesoscopic, or microscopic in scale (*3*). There are very few or no models that can accurately predict energy consumption across a spectrum of levels, where only low-resolution data (origin, destination, and routing only) are available. At the microscopic level, authors have demonstrated energy and emissions sensitivities to attributes such as road grade, vehicle speed, and congestion (*4*) (*5*) (*6*) (*7*) (*8)*. These models are often customized to a particular vehicle type and set of road/driving conditions and make simplifying assumptions about vehicle powertrains. There is a need to predict trip energy consumption for different vehicle powertrains and driving behaviors because the vehicle fleet and driver population are highly diverse in energy use characteristics.

A data-informed model to predict energy use for a proposed vehicle trip has been developed, leveraging roughly 1 million miles of real-world driving data to generate the model. Driving is categorized at the sub-trip level by average speed, road grade, and road network geometry, then aggregated by category. The averaged results generate a multi-dimensional energy rate look-up table. Proposed vehicle trips are then categorized in the same manner, and estimated energy rates are appended from the look-up table. The methodology is robust and applicable to almost any type of driving data. The model has been trained on vehicle global positioning system (GPS) data from the Transportation Secure Data Center (TSDC) and validated against on-road fuel consumption data from testing in Phoenix, Arizona. The estimation model has demonstrated a relative trip energy error of 9.1% for a conventional vehicle powertrain. The resulting model can be used to inform control strategies in routing tools, such as change in departure time, alternate routing, and alternate destinations to reduce energy consumption. This work provides a highly extensible framework that allows the model to be tuned to a specific driver or vehicle type.

METHODOLOGY

The framework used for the energy estimation tool is largely covered by the authors in a previous work (*9*). Modifications to the methodology were made for the present work to use a different input data set of real-world drive cycles. On-road fuel consumption data were also acquired from instrumented vehicles to benchmark the performance of the energy estimation tool.

The Data

The approach requires a large quantity of real-world driving data to develop a robust model. The source is a collection of vehicle GPS data from across the United States. The survey data are made available in the TSDC at the National Renewable Energy Laboratory (NREL) (*10*). The TSDC contains about 150 million vehicle GPS points collected at 1-Hz frequency. The data are summarized in Table 1.

TABLE 1 Summary of the TSDC Drive Cycles Used to Inform the Energy Estimation Model

Feature	Value
# of Trips	185,588
# of Drivers	10,417
# of Points	133,914,065
Reporting Frequency	1 Hz

On-road fuel consumption data were acquired from testing in Phoenix, Arizona, in early 2017. Three different powertrain types were tested. For each powertrain in the testing, two identical vehicles drove from the same origins to the same destinations at the same time of day over different routes. The three powertrains tested were a 2014 Mazda 3 conventional vehicle, a 2015 Honda Accord hybrid electric vehicle, and a 2016 Chevrolet Volt plug-in hybrid electric vehicle. The findings presented here will focus primarily on the conventional vehicle to establish the framework for validating the energy estimation methodology. Each phase of testing consisted of 24 trips over 3 days, for a total of 430 driving miles.

Energy Estimation Overview

The TSDC drive cycles were used in combination with a digital road map and the Future Automotive Systems Technology Simulator (FASTSim), NREL's powertrain simulation package (*11*). The fuel consumption for a particular vehicle powertrain model was simulated over all the drive cycles in the TSDC. The drive cycles were also matched to the digital road map to obtain attributes for different segments of driving, such as predicted speeds and road geometries. The drive cycle fuel consumption results were then aggregated by road and driving attributes: speed, road grade, and road link orientation. The aggregated bins all have an average fuel consumption rate associated with the bin. This multi-dimensional fuel consumption rate look-up table is the result of the model. The resulting table can be used to estimate trip fuel consumption for a proposed route. Figure 1 summarizes the model generation process graphically.

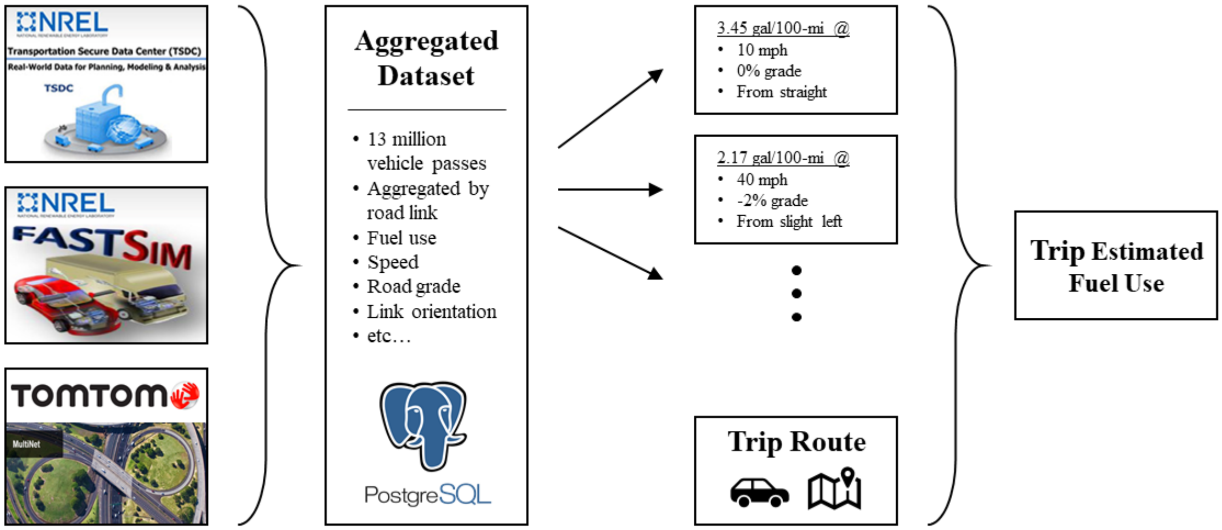

FIGURE 1 From left to right: the data pre-processing and powertrain simulation steps, the results of which are aggregated into a large data set from which an energy estimation look-up table for that particular vehicle model can be generated. Trip fuel use is estimated by combining the model results with a proposed trip route.

FINDINGS

Aggregating the simulated fuel consumption results from the TSDC drive cycles showed the dependence of fuel consumption rate on various road and driving attributes. Figure 2 shows a selection of the attributes that were explored in generating the model. Included are all three attributes that were used in the final look-up table, and the next link orientation to demonstrate an attribute that was investigated but not included. Figure 2b shows the road grade fuel use rate relationship. The behavior from -2% to -6% grade where a slight increase in fuel use rate is unexpected and likely attributed to an anomaly in the powertrain simulation and the aggregation of results. Figure 2c and Figure 2d show the fuel use rate dependence on the orientation of the previous link to the current link, and the current link to the next link. The previous turn angle has a much more significant impact on fuel use than the coming turn angle. This is because accelerating on the current link after a turn has a much more substantial energy impact than slowing down on the current link to prepare for a coming turn.

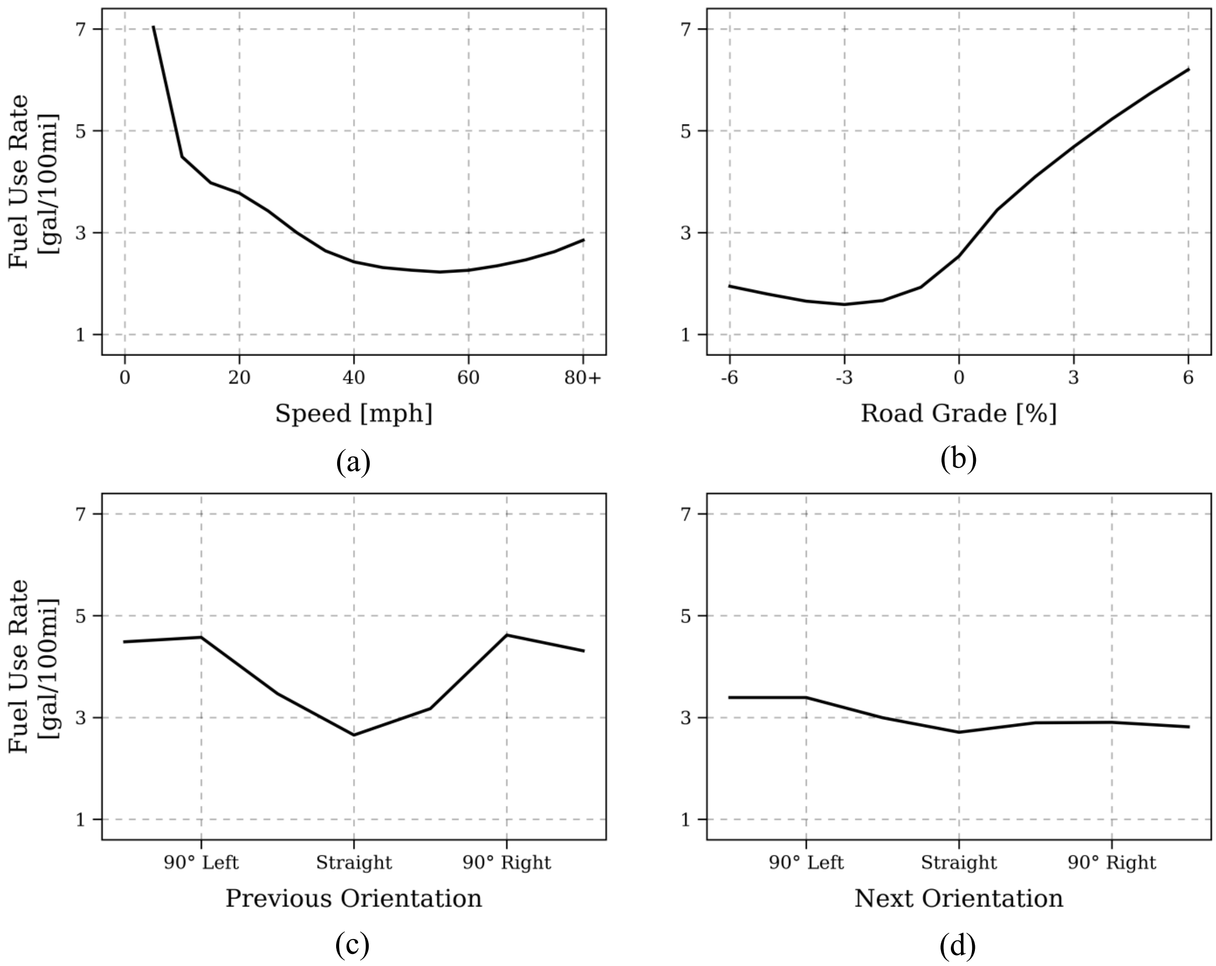

FIGURE 2 Driving and road network attributes plotted against vehicle fuel use rate for a conventional vehicle to determine the most important attributes to include in the energy estimation model. (a) Vehicle average speed over a pass vs. fuel use rate, (b) link average road grade vs. fuel use rate, (c) severity of turn from the previous link to the current vs. fuel use rate on the current link, and (d) severity of turn from the current link to the next link vs. fuel use rate on the current link.

As described above, the on-road test program had two identical vehicles traversing different routes between the same origin and destination. One route was highway dominant, and the other was surface road dominant. Since one of the most significant applications of the energy estimation model is in green routing, it was desired to quantify the model's ability to accurately predict the energy savings between the two routes and select the "greener" route. Error was calculated as a normalized difference between the ground truth (calibrated signal from the engine controller) ratio of highway-route to surface-route fuel consumption and the energy estimation predicted fuel consumption ratio.

The results are shown in Table 2, where A denotes a surface route, and B denotes a highway route. FASTSim simulated fuel consumption ratios were also validated for reference. The “FS” subscript indicates the FASTSim simulated energy results, and the “EE” subscript indicates the energy estimation model predicted energy consumption. Both ratios are compared to the fuel consumption reported by the engine controller to calculated error. However, to make the energy predictions, FASTSim is using the high-resolution GPS drive cycle data, and the energy estimation model is simply using the sequence of links that the trip will traverse and various attributes on each of those links.

TABLE 2 Calculated root mean square values of the trip errors (RMSE) in relative energy ratios. A is a surface route, and B is the highway route. FS indicates FASTSim simulated consumption, and EE indicates energy estimation predicted consumption.

$\frac{A_{FS}}{B_{FS}}$ **RMSE**	$\frac{A_{EE}}{B_{EE}}$ **RMSE**
5.9%	9.1%

In addition to the error value, the energy estimation model’s ability to select the greener route was also tested. It successfully selected the greenest route on 12 of 12 trips for the 2014 Mazda 3 model. The model’s RMSE of 9.1% in energy ratios indicates a high likelihood of correctly selecting the greener route when the predicted energy ratio is beyond 9.1% in either direction, and when the energy difference is less, the likelihood of selecting the greener route varies based on a probability curve.

CONCLUSION

A robust, data-driven vehicle trip energy estimation technique has been described, demonstrated, and validated. The energy estimation technique is computationally inexpensive to apply, and in addition, the methodology for generating the model is generally agnostic to powertrain type. The model has demonstrated an accurate estimation of relative trip energy consumption for a conventional vehicle powertrain with a relative fuel consumption RMSE of 9.1% when benchmarked against calibrated, on-road fuel consumption data.

From the literature reviewed, this energy estimation technique is the first of its kind to be generated from such a large quantity of real-world driving data. The contributions of this technique are two-fold. One is a working model that can accurately estimate trip fuel consumption and can be expanded to a broad range of powertrain types. The second is a general methodology to use real-world GPS trajectories to train an energy estimation model for various mobility choices. The methodology is highly extensible—it could generate a model by aggregating simulation data by various explicit attributes, or it could employ more advanced machine learning techniques to infer attributes beyond those that can be explicitly pulled from the road network, driver, or vehicle information, to inform vehicle energy consumption. The potential result of using advanced techniques would be to generate a more accurate energy estimation model while maintaining a major benefit of this methodology—namely, that deploying the model requires only a simple, computationally inexpensive look-up process. Green routing is the deployment application for which the energy estimation method has been validated here; however, it is also fit for range estimation, regional energy analyses, and mobility behavior modelling.

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