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Connectivity-Enhanced Route Selection and Adaptive Control for the Chevrolet Volt

Jeffrey Gonder[1], Eric Wood[1] and Sai Rajagopalan[2]

1. National Renewable Energy Laboratory, Golden CO 80401, USA

2. General Motors R&D, Warren MI 48090, USA

Abstract: The National Renewable Energy Laboratory and General Motors evaluated connectivity-enabled efficiency enhancements for the Chevrolet Volt. A high-level model was developed to predict vehicle fuel and electricity consumption based on driving characteristics and vehicle state inputs. These techniques were leveraged to optimize energy efficiency via green routing and intelligent control mode scheduling, which were evaluated using prospective driving routes between tens of thousands of real-world origin/destination pairs. The overall energy savings potential of green routing and intelligent mode scheduling was estimated at 5% and 3%, respectively. These represent substantial opportunities considering that they only require software adjustments to implement.

Key words: ITS (intelligent transportation systems), green routing, vehicle drive cycles/profiles, route-based/adaptive powertrain control, vehicle telematics/navigation, vehicle energy use prediction.

1. Introduction

Energy security, fuel cost and air quality concerns have led to increased powertrain electrification in new vehicles. At the same time, the ubiquitous availability of advanced vehicle telematics systems, such as OnStar, has made real-time information on driving routes, traffic and road topology readily accessible. Together, these trends offer the potential for increased powertrain efficiency, particularly in vehicles with both a traction battery and a combustion engine. Such vehicles can leverage route-specific information to anticipate road loads and schedule power flows in the most efficient manner possible.

Significant research exists in the literature exploring pathways for increasingly connected vehicles to optimize modern transportation systems. Some example applications include:

- routing algorithms that leverage digital maps to make drive cycle predictions with the goals of minimizing travel time, energy use and/or emissions [1-4];
- vehicle speed advisory programs targeted at encouraging efficient driving habits, such as gradual accelerations and intermediate travel speeds [5-8];
- predictive powertrain controls that employ drive cycle predictions for optimal energy management in hybrid electric and plug-in hybrid electric vehicles [9-19].

As a contribution to this growing field of research, the NREL (National Renewable Energy Laboratory) and General Motors, in collaboration with the U.S. Department of Energy, evaluated connectivity-enhanced route selection and adaptive control techniques to further increase energy efficiency in the Chevrolet Volt platform. The project included both simulation and chassis dynamometer testing to develop energy prediction algorithms applied to the Volt over multiple real-world driving profiles. The algorithms were used to implement and evaluate green routing and adaptive intelligent control mode scheduling for the Volt over predicted travel routes.

Corresponding author: Jeffrey Gonder, senior engineer, supervisor, research fields: real-world travel, optimal vehicle design and control, impact of drive cycle and intelligent transportation technologies on fuel efficiency.

2. Approach

Fig. 1 illustrates the overall methodology for developing the energy predictions that serve as the basis for the green routing and adaptive control energy efficiency enhancements. The process begins by identifying candidate routes for traveling between a given (or predicted) O/D (origin and destination) pair. Each route is divided into segments characterized by road type information and that may also take real-time traffic and driver aggression predictions as inputs. A drive cycle model (developed as part of this project) then makes predictions of drive cycle characteristics expected over each driving segment. Based on these cycle metrics, as well as road grade and the current vehicle/battery state, a look-up table model (also developed for this project specific to the Volt powertrain) estimates the vehicle's segment-by-segment fuel and electricity consumption.

This methodology, particularly the drive cycle and Volt PT (powertrain) models illustrated in Fig. 1, was very computationally heavy to develop, involving processing, analyzing and simulating hundreds of thousands of drive cycles. However, the resultant look-up table models become quite computationally light to implement in a vehicle by eliminating the need for predicting a second-by-second speed trace or for real-time simulation using a computationally intensive vehicle model.

3. Results

3.1 Cycle Metric Prediction

After establishing one or more potential driving routes between a given O/D pair (including map matching each segment of the route to an underlying road layer from a provider, such as HERE or TomTom), the project team drew on information, such as road segment type (FC (functional class), speed category, etc.) from the underlying road layer to predict representative cycle metrics (such as average speed, acceleration, road grade and stops per mile) over each segment of the driving route. A data-driven correlation between road type and drive cycle characteristics was established by analyzing thousands of second-by-second real-world driving profiles collected with global positioning system devices and archived in NREL's TSDC (Transportation Secure Data Center) [18]. After map-matching the TSDC driving profiles to the underlying road layer (as described above), the driving profiles were subdivided into smaller increments, such as the 0.1-mile "nanotrips" illustrated in Fig. 2.

The speed and acceleration characteristics for these nanotrips were then correlated to the road functional class being traversed (FC = 1 corresponds to high-throughput interstate travel, and FC = 5 corresponds to low-throughput neighborhood streets). As illustrated in Fig. 3, this resulted in reasonable predictions of average speed and acceleration characteristics simply given information on the functional class of the current and the previous 0.1-mile segment of the given driving route. Further precision would be obtained by factoring in additional inputs, such as real-time traffic speeds over the given driving segment.

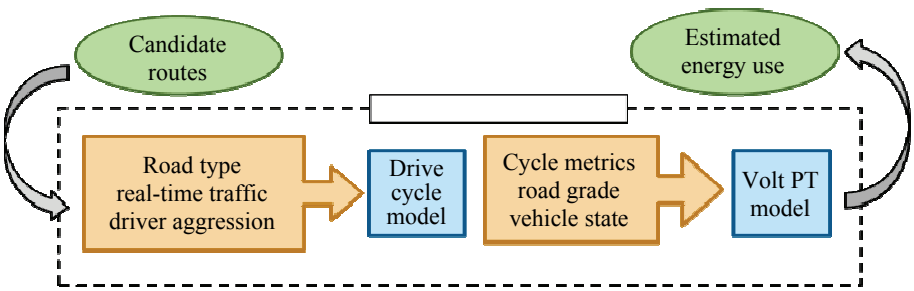

Fig. 1 Overall energy use estimation methodology that provides the basis for green routing and adaptive control efficiency enhancements.

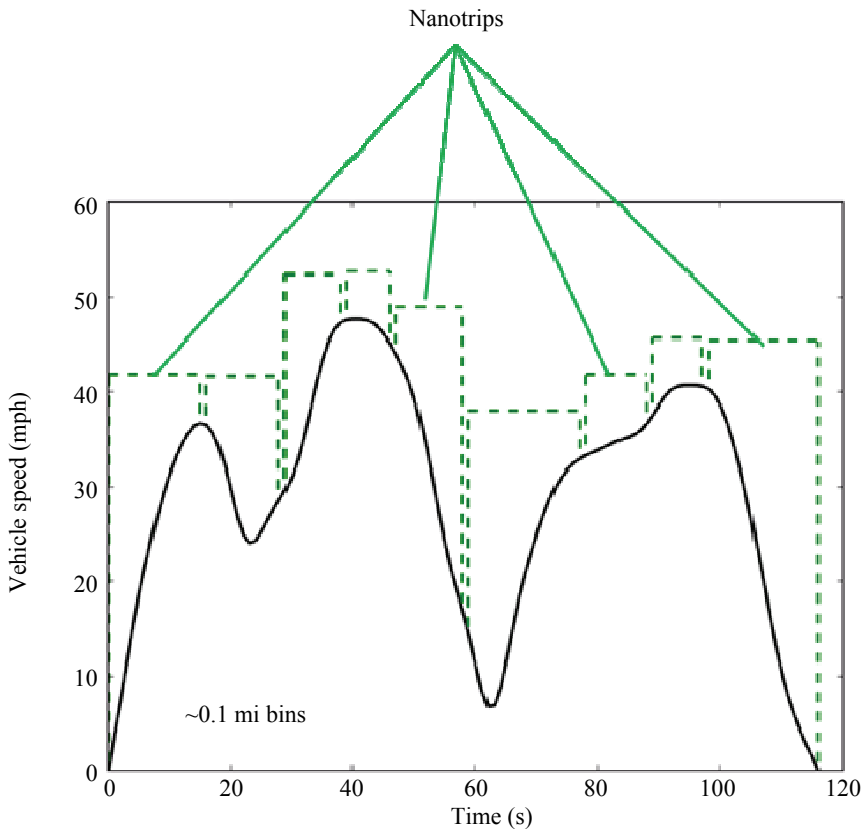

Fig. 2 Illustrative division of real-world driving "microtrip" (profile starting and ending at zero speed) into smaller "nanotrip" distance intervals.

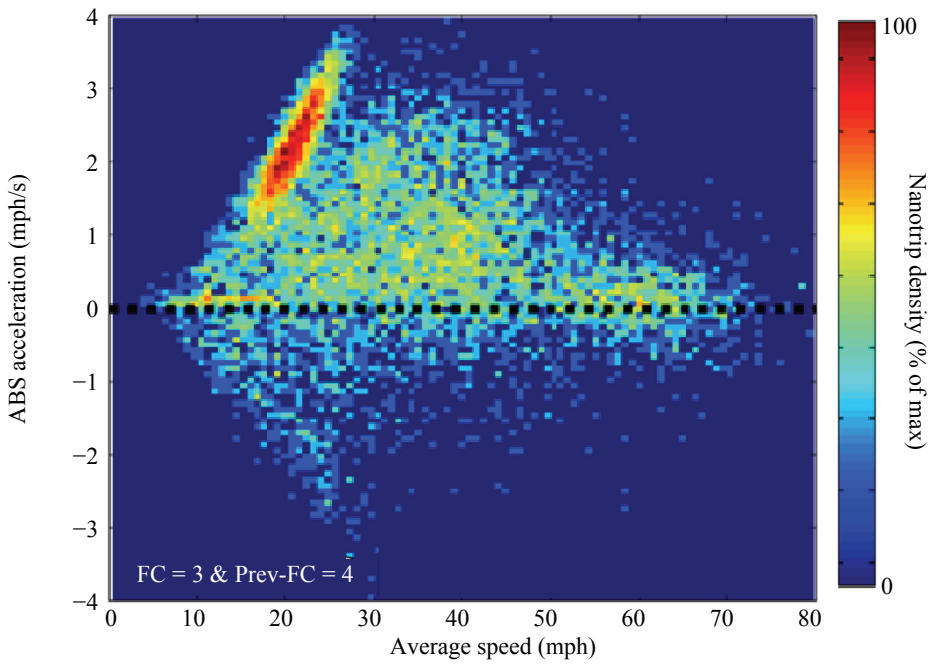

Fig. 3 Significant concentration of nanotrip data around hard accelerations when transitioning from an FC-4 to an FC-3 road segment (i.e., to a higher speed/capacity roadway).

3.2 Energy Use Prediction

In the next component of the project, estimated cycle metrics (such as average speed, acceleration, road grade, etc.) were converted into vehicle energy use predictions over a given route. The method developed to accomplish this involved generating detailed energy use maps for the vehicle using detailed simulations (complemented by physical vehicle data collection) over tens of thousands of drive cycles. As mentioned in Section 2, these energy use maps are computationally heavy to develop, but once they are built, they are computationally light to implement for a green routing or dynamic control application.

For the Chevrolet Volt powertrain used in this study, the energy use maps included both electricity and fuel consumption relationships, and considered CD (charge depleting) operation, CS (charge sustaining) operation and the need to track vehicle SOC (state of charge) via the electricity consumption relationships to determine the correct operating mode. The effort relied primarily upon simulations using an internal General Motors powertrain model and secondarily on test data collected from a Chevrolet Volt that had been modified to allow on-the-fly initiation of CS operation even at a high vehicle battery SOC. It should be noted that the results shown here omit proprietary data values specific to the Volt powertrain, but nonetheless convey the relative trends and overall steps employed in the analysis.

The simulation and test results were post-processed into nanotrips using the methods described in Fig. 1. In addition to the previously mentioned cycle characteristic categorization (average speed, acceleration, etc.), the simulation and testing permitted associating each nanotrip with values for electricity and fuel consumption (each value referenced as well to the battery SOC at the start of the nanotrip). Fig. 4 illustrates a discretized look-up map of engine-off electric rate in the average speed and acceleration space. This map was derived from all the engine-off nanotrip simulation results, which showed consistent electric consumption rates for nanotrips with similar speed and acceleration characteristics. Once again, due to the proprietary nature of the Volt powertrain data, the precise consumption rate values have been excluded but the general trends are apparent.

Fig. 5 provides a similar visualization of the electric consumption rate while the vehicle engine is on, this time organized in a space defined by the SOC of the nanotrip (where the CS hold mode was engaged at a

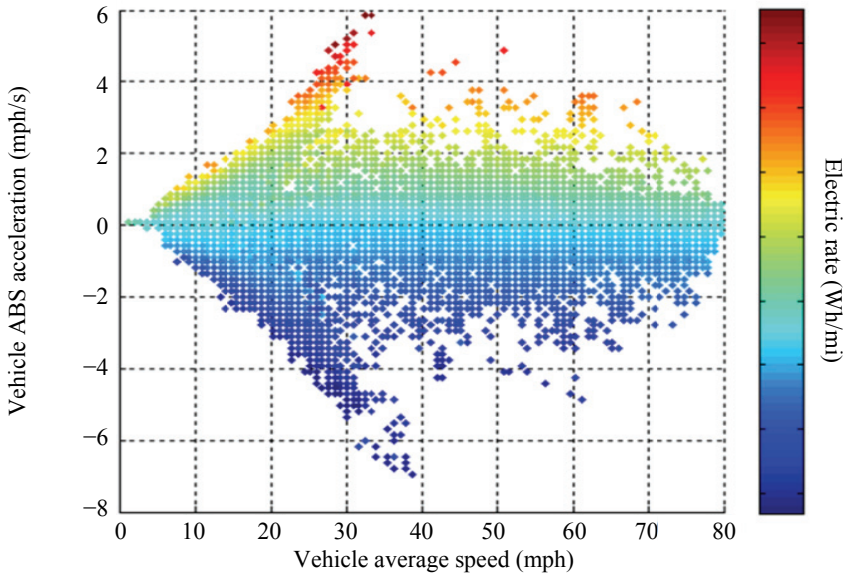

Fig. 4 Discretized correlation between cycle characteristics and electric consumption rate generated from detailed simulation results when the Volt engine was off.

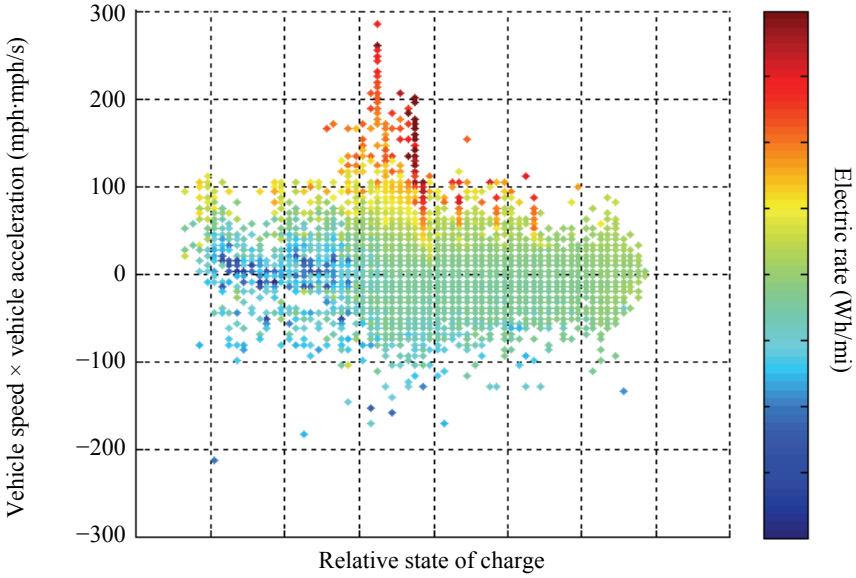

Fig. 5 Discretized correlation between cycle characteristics, SOC, and electric consumption rate generated from detailed simulation results when the Volt engine was on.

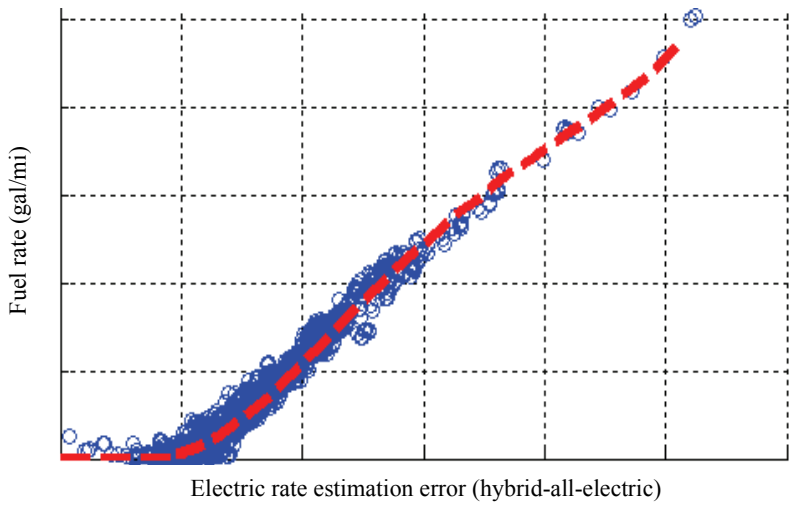

Fig. 6 Engine-on fuel rate estimates correlate with the difference or "error" between the hybrid (engine-on) electric rate and the all-electric (engine-off) electric rate estimates.

target SOC around the middle of the figure) and the product of the average speed and acceleration characteristics of the nanotrip. Consistent results within this space for nanotrips with similar characteristics again enable discretization of the data into a look-up map as illustrated by Fig. 5. The engine-on fuel rate relationship was found to correlate well with the difference between the engine-on and engine-off electric rate estimates (as provided by the cycle-characteristic-based look-up maps in Figs. 4 and 5). Fig. 6 illustrates the resulting correlation established as compared to the actual results from the detailed simulation.

The described look-up maps/correlations define everything needed to predict energy use (fuel and electricity consumption) from speed and acceleration cycle characteristics. The predictions can be further refined by establishing similar correlations for additional cycle segment characteristics, such as road grade. Fig. 7 illustrates the translation model (trained by the detailed simulation and test data over cycles with different baseline (Wh/mi) demands run at different

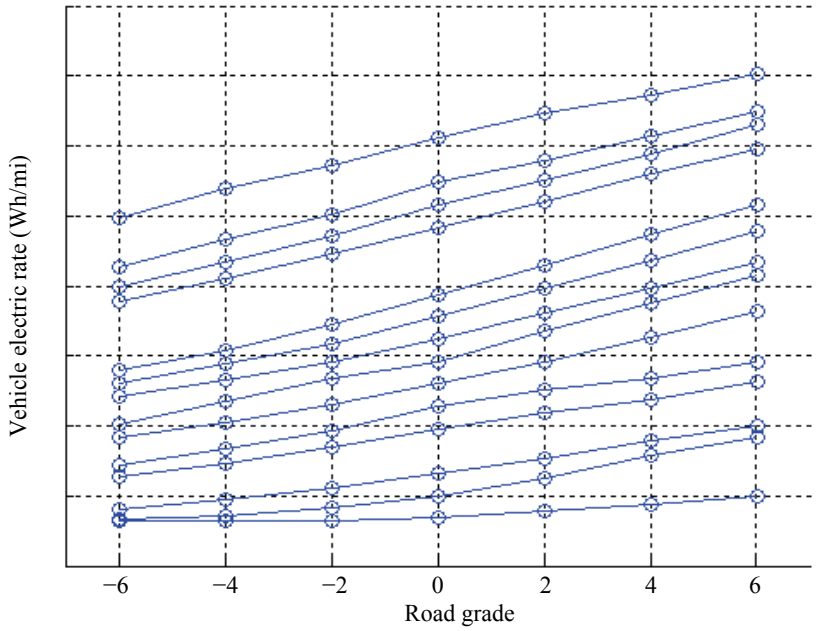

Fig. 7 Grade-based electric rate translation model created to adjust the zero-grade look-up maps described in Figs. 4-6 to account for driving segment grade.

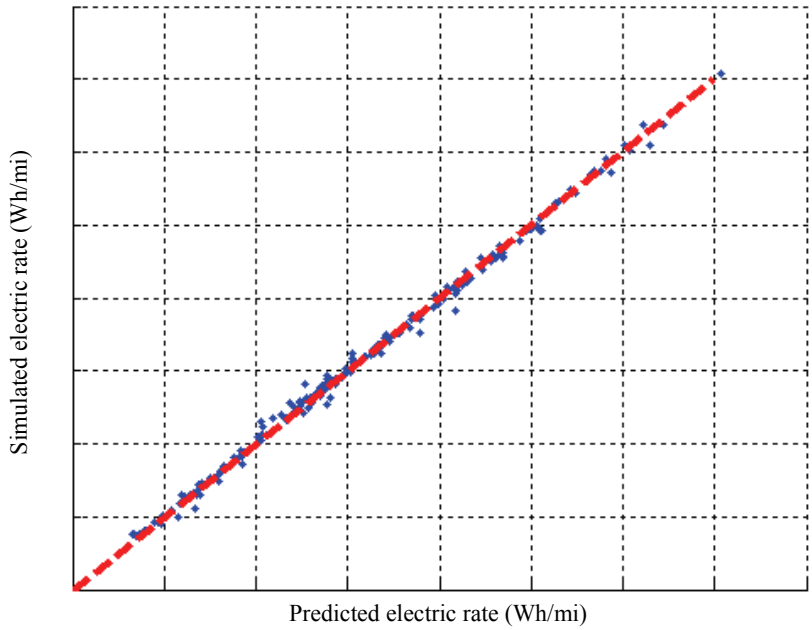

Fig. 8 The grade translation model agrees well with individual electric rate adjustments observed from simulation and test data over similarly characterized nanotrips at different road grades.

grades) to estimate electric rate impact as a function of road grade for similarly characterized nanotrips. As shown in Fig. 8, the grade-based translation model shows a very good ability to predict the grade-adjusted electric consumption rates based only on the zero-grade electric rate as an input.

As a point of validation, the energy prediction maps (trained on simulation data) were evaluated against test data from an instrumented Chevrolet Volt run on a vehicle dynamometer over a comprehensive range of driving conditions including combinations of speed/acceleration characteristics, positive and negative

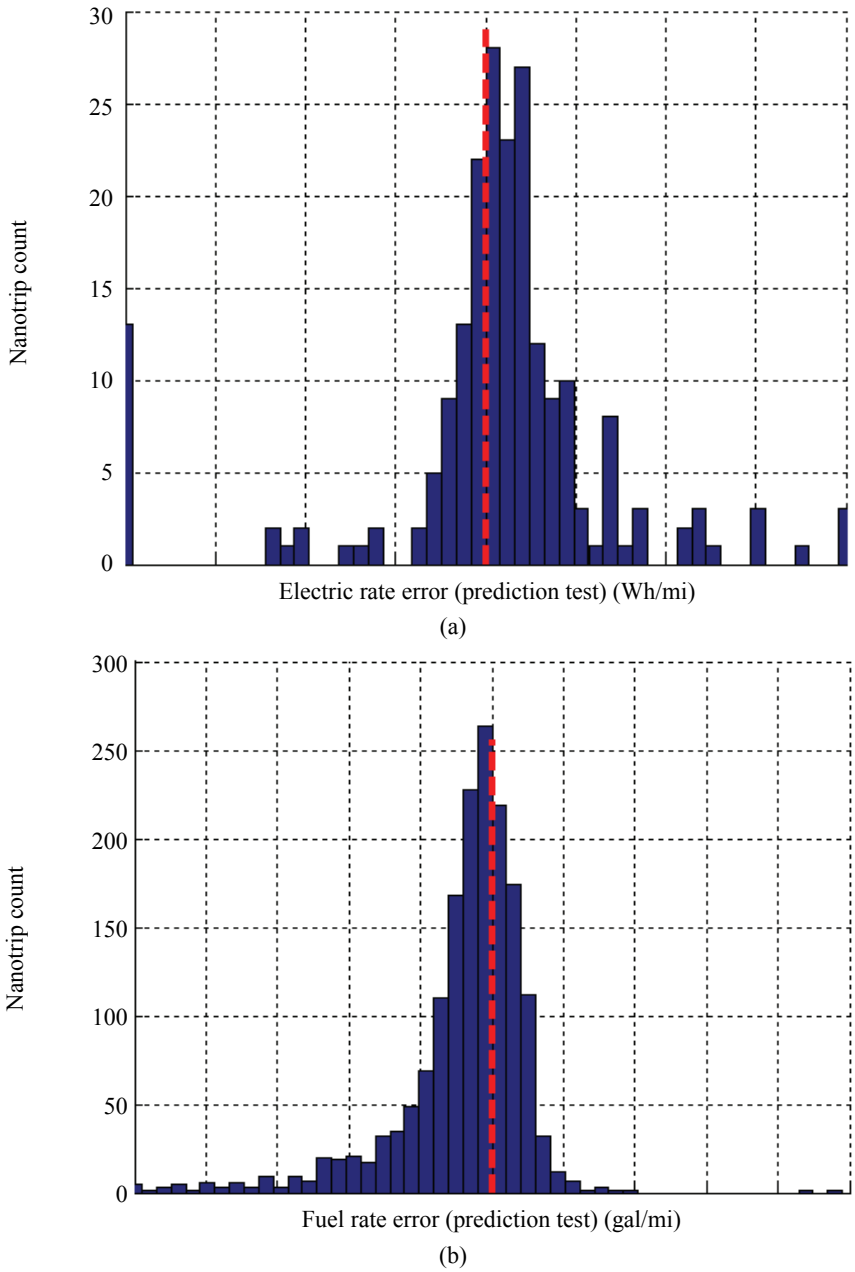

Fig. 9 Distributions when comparing energy estimation maps to dynamometer test data: (a) modeled electric; (b) fuel rate errors.

Red dashed line represented zero error.

road grades, control modes (CD/CS), and battery SOCs. Fig. 9 provides a snapshot of these comparisons by showing distributions of model error (energy prediction map minus measured test data) for both electric and fuel use rates. Model error distributions can be seen to center around zero (represented by the red dashed lines). Further evaluation of model error will be an important part of future work, to include assessing fuel and electricity consumption impacts when the driving type predictions turn out to be incorrect.

3.3 Green Routing

Evaluation of the connectivity-enabled green routing

and route-based control enhancements again involved leveraging the TSDC—specifically the large set of real O/D locations contained in the database. NREL leveraged Google Maps' application programming interface to generate route options between each O/D pair and applied the cycle metric and fuel/electricity prediction approach outlined above to evaluate each route. Fig. 10 categorizes the results for the nearly 43,000 O/D pairs and highlights that for many O/D pairs Google's routing software either recommends only one route, or the fastest recommended route also turns out to be the most energy efficient route. However, 37% of the time the fastest route does not correspond with the greenest route, so that fraction of driving trips is taken to be the potential opportunity where green routing could result in energy-saving benefits (relative to the fastest route being the assumed default).

Under this set of assumptions, any green routing energy savings will come at a cost of increased travel time. Fig. 11 explores this tradeoff by arranging the results as a function of the vehicle operator's hypothetical

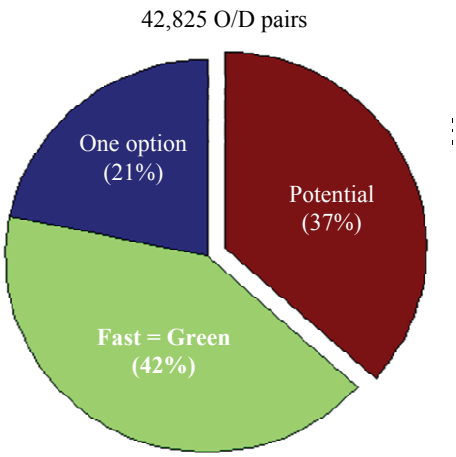

Fig. 10 Results for the 42,825 O/D pairs.

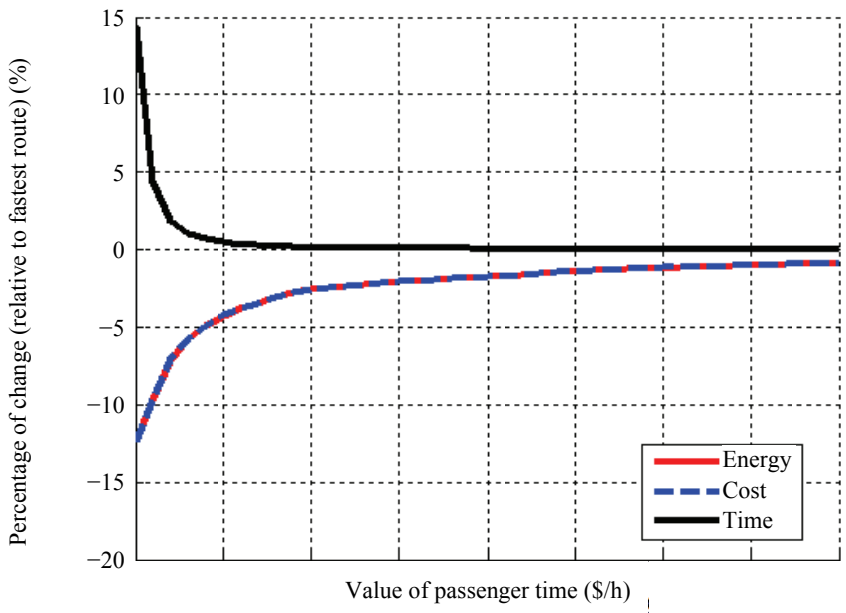

Fig. 11 Trade-off between aggregate energy/cost savings and total increases in travel time as a function of passenger/driver value of time (for the 37% of O/D pairs where the least energy-consuming route prediction was not the fastest route).

monetary value of time spent in the vehicle. The top line in the plot corresponds to total percent increased travel time, and the bottom line corresponds to total percent energy (and resulting energy cost) reductions provided by the "greenest" routes.

To facilitate interpretation, consider two example vertical slices on this plot. In the first example, the points intersecting the y-axis represent the extreme scenario with no value of time penalty counted against increased time requirements by the green routes. The aggregate results represented by this scenario could realize a 12.3% reduction in energy use and cost, but a 14.4% increase in travel time. The second example considers the vertical slice at a time value of $35/h. For this scenario, the qualifying alternative green routes could decrease overall energy use and cost by 1.0% with a negligible increase in travel time.

3.4 Control Mode Scheduling

The intelligent CD vs. CS mode scheduling evaluation involved similar large-scale analysis, specifically, of over 100,000 potential routes identified from the TSDC O/D database. The evaluation required first adding an extra analysis layer to compare the default mode schedule (CD followed by CS) as compared to the optimal (least fuel consuming) mode schedule. As a simplified overview, the methodology included in the added layer begins by assuming that all driving could be accomplished in CD mode (initially ignoring energy limits of the vehicle battery). It then incrementally substitutes driving segments from CD to CS operation, until the final trip SOC equals that from the default CD followed by CS operation. Trip segments are prioritized for substituting from CD to CS control based on minimizing the cost/benefit ratio of doing so, where the cost is defined as the increased fuel use incurred by the substitution, and the benefit is defined as the decreased electric depletion rate.

The top plot in Fig. 12 shows an example of a nominal vs. optimal battery SOC depletion profile generated by the methodology described above. It should be noted that when evaluating this project's high-level CD vs. CS mode scheduling opportunity, each trip considered was assumed to begin at an initial

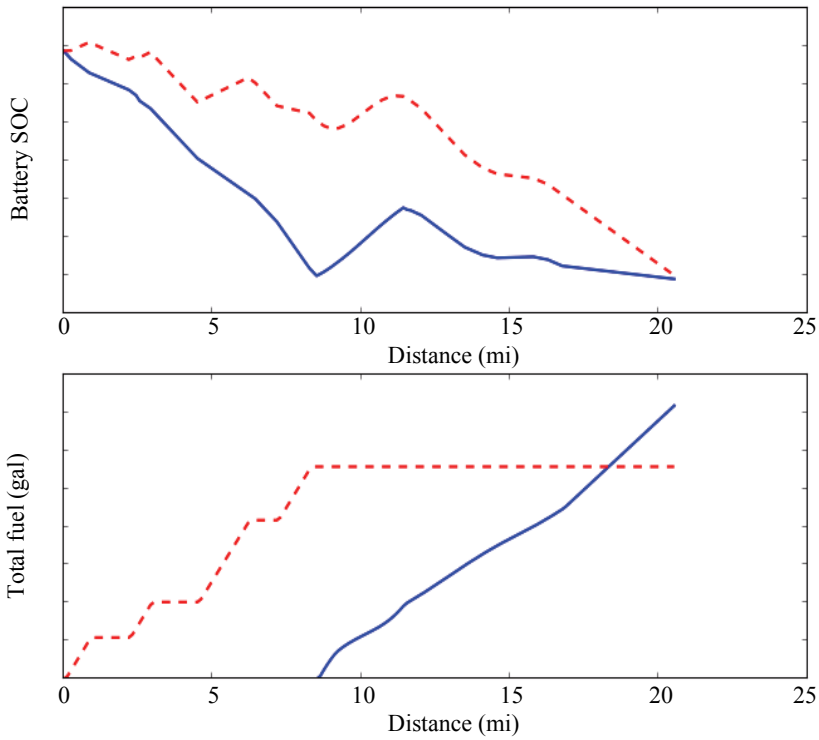

Fig. 12 Nominal (solid blue line) vs. optimal (dashed red line) battery SOC and fuel use profiles for one example route.

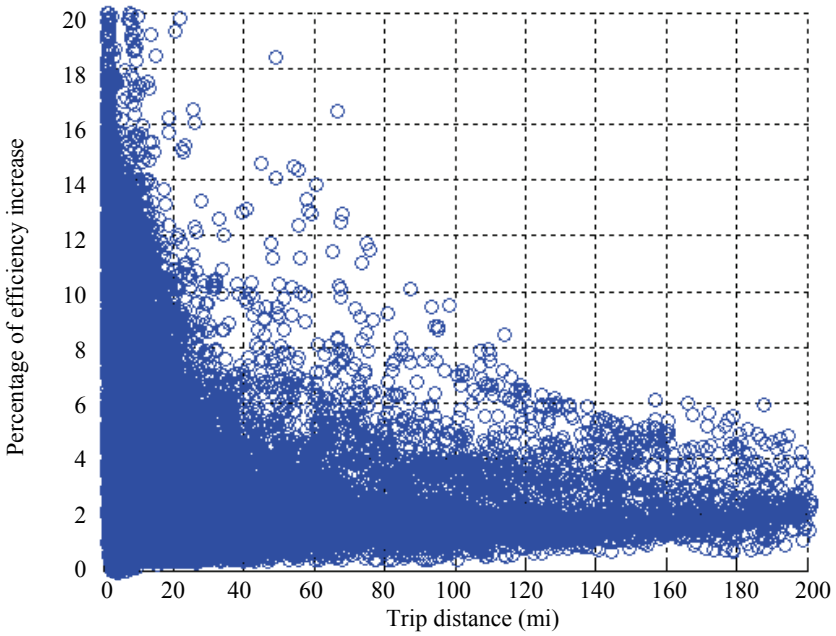

Fig. 13 Efficiency improvements from control mode scheduling optimization evaluated across over 100,000 representative driving routes.

SOC such that 50% or more of the trip was completed in CS mode. The bottom plot in Fig. 12 shows the corresponding fuel consumption profile for the nominal vs. optimal control mode scheduling over the example profile. In this example, fuel consumption was reduced 25% by scheduling CS operation during highway driving segments in the first half of the route and saving CD operation for the city driving anticipated at the end of the route.

Fig. 13 shows the scatter of fuel savings opportunity from optimal mode scheduling applied to over 100,000 trips. These results indicated that very large percent fuel savings results predominantly occur at short driving distances, which may be an artifact of the reduced starting SOC approach applied for these shorter trips. However, a number of trips (even longer than 30~40 miles in length) realize fuel savings on the order of 10%, and the average fuel savings across all trips exceeds 3%.

4. Conclusions

Under this project, NREL collaborated with General Motors to evaluate connectivity-enabled efficiency enhancements for the Chevrolet Volt. Project accomplishments included developing and demonstrating the ability to estimate drive cycle characteristics over anticipated driving routes. The project team further developed a high-level model to predict vehicle fuel and electricity consumption based on driving characteristic and vehicle state inputs. The team combined and leveraged these techniques in pursuit of energy efficiency optimization via green routing and intelligent control mode scheduling.

The green routing and intelligent control mode scheduling enhancements were evaluated using prospective driving routes between tens of thousands of real-world O/D pairs. Considering the aggregate green routing benefit multiplied by the fraction of O/D pairs where the default (fastest) route consumed more fuel, the overall green routing fuel savings opportunity could approach 5% (assuming a low value of passenger time). The average efficiency benefit from intelligent high-level scheduling of CS vs. CD control showed a similar magnitude—a little over 3% potential fuel savings on trips that require some mix of CS and CD operation. An 8% fuel savings (when taken as additive benefits) represents a substantial opportunity especially considering that only software adjustments

are required to realize this efficiency gain.

Future work efforts could include adding route-based optimization to lower-level controls (in addition to the high-level CD vs. CS control mode scheduling), formally incorporating real-time traffic/congestion information to further improve cycle metric predictions, and evaluating result sensitivity to various conditions and erroneous predictions. Additional options could include implementing, refining and more robustly testing both green routing and adaptive control approaches in a development vehicle, and/or considering additional vehicle platforms/powertrains.

Acknowledgments

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