Future Automotive Systems Technology Simulator (FASTSim) Validation Report

Jeffrey Gonder, Aaron Brooker, Eric Wood, and Matthew Moniot

National Renewable Energy Laboratory

NREL is a national laboratory of the U.S. Department of Energy
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July 2018

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Preface

The National Renewable Energy Laboratory's Future Automotive Systems Technology Simulator (FASTSim) captures the most important factors influencing vehicle power demands and performs large-scale fuel efficiency calculations very quickly. These features make FASTSim well suited to evaluate a representative distribution of real-world fuel efficiency over a large quantity of in-use driving profiles, which have become increasingly available in recent years owing to incorporation of global positioning system data collection into various travel surveys and studies. In addition, by being open source, computationally lightweight, freely available, and free from expensive third-party software requirements, analyses conducted using FASTSim may be easily replicated and critiqued in an open forum. This is highly desirable for situations in which technical experts seek to reach consensus over questions about what vehicle development plans or public interest strategies could maximize fuel savings and minimize adverse environmental impacts with an evolving vehicle fleet. While FASTSim continues to be refined and improved on an on-going basis, this report compiles available runs using versions of the tool from the past few years to provide illustrative comparison of the model results against measured data.

Acknowledgments

The core development and use of FASTSim have been funded for many years by the Vehicle Systems Program and the Analysis Program at the Vehicle Technologies Office in the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy. The authors would particularly like to thank the U.S. Department of Energy's David Anderson, Lee Slezak, Jacob Ward, and Rachael Nealer for their support and feedback.

List of Acronyms

A/C	air conditioning
ADOPT	Automotive Deployment Options Projection Tool
ANL	Argonne National Laboratory
APRF	Advanced Powertrain Research Facility
CARB	California Air Resources Board
DOE	U.S. Department of Energy
EPA	U.S. Environmental Protection Agency
EV	electric vehicle
FASTSim	Future Automotive Systems Technology Simulator
HEV	hybrid electric vehicle
HWFET	Highway Fuel Economy Test
mpg	miles per gallon
MPGGE	miles per gasoline gallon equivalent
mph	miles per hour
NREL	National Renewable Energy Laboratory
PHEV	plug-in hybrid electric vehicle
RMSE	root-mean-square error
UDDS	Urban Dynamometer Driving Schedule

Executive Summary

The National Renewable Energy Laboratory (NREL) has been developing and using the Future Automotive Systems Technology Simulator (FASTSim) for more than a decade in support of the U.S. Department of Energy's (DOE's) transportation research goals. FASTSim produces very rapid estimates of vehicle efficiency, performance, cost, and battery life in conventional and advanced-powertrain technologies, enabling completion of such analyses using only a few publicly available vehicle parameters. This simplified approach provides accurate results for many types of analysis while increasing speed, ease, and accuracy related to finding required inputs, running the model, and interpreting results. FASTSim can also use customized inputs to represent specific vehicles even more precisely if detailed input data are available.

As with any model, the most critical aspect of FASTSim is its ability to reflect reality accurately. This is the purpose of validation—the comparison of modeled results versus results measured during vehicle or component operation in the laboratory or on the road. This report begins by describing FASTSim and its role within the continuum of available modeling tools, and then it focuses on the validation of FASTSim.

FASTSim occupies a "sweet spot" along the continuum of modeling tools based on each tool's tradeoff between accuracy and complexity, where "complexity" includes the required number of input parameters, availability of required input data, time required to obtain the inputs and perform calibration, software requirements, and computational overhead to run (Figure ES-1). FASTSim is designed to balance predictive accuracy with model complexity across a wide range of analytical tasks. Across its range of capabilities, FASTSim is particularly well suited for quickly and conveniently conducting large numbers of simulations over representative real-world driving distributions and/or myriad vehicle design variations. In such analyses, the uncertainties and efficiency impacts from the broad spectrum of operating conditions or design variants far exceed small uncertainties resulting from modeling simplifications within FASTSim.

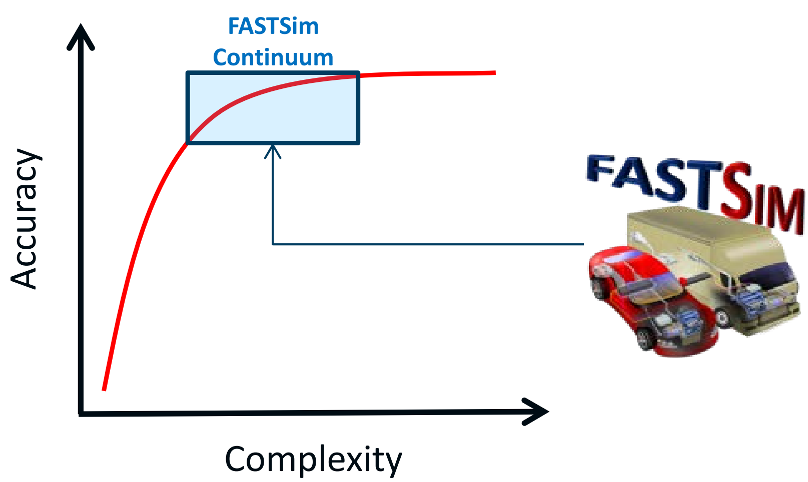

Figure ES-1. Conceptual illustration of the FASTSim continuum on the vehicle-modeling continuum

FASTSim's continuum of modeling capabilities—illustrated by the box in Figure ES-1—can be divided conceptually into three levels (Table ES-1). The standard option is suitable for large-scale simulation of hundreds or even thousands of vehicles. It employs generally representative default power-versus-efficiency maps for each of the components, which are then scaled based on the component power ratings for a particular modeled vehicle. Thus, the standard option has the fastest calibration, only requiring a small amount of publicly available vehicle information, and it still captures most important factors for high-level vehicle comparisons. However, for some targeted studies, more component data details may be available on specific vehicles of interest and/or the studies may seek to investigate scenarios sensitive to factors such as operating temperature or gear selection. For these situations, FASTSim enables further customization and the addition of modeling extensions, moving the model up the accuracy-versus-complexity tradeoff curve.

Table ES-1. FASTSim Continuum: Modeling Levels and Their Strengths and Limitations

Level of Modeling	Strengths	Limitations
Standard Option		
• Default power versus efficiency maps for each component • Maps scaled based on component power ratings for modeled vehicle	• Fastest to calibrate: requires small amount of public vehicle information • Suitable for large-scale simulation/evaluation of thousands of vehicle designs	• Captures most important factors for high-level comparisons but lacks detail for focused studies
Customized Option		
• Vehicle-specific component calibration	• Provides more precise model of specific vehicle(s)	• Larger calibration burden: requires detailed component-level data from manufacturer or testing
Potential Extensions for Targeted Investigations		
• Temperature dependence • Torque versus speed disaggregation • Shift schedules	• Even more detail for studies that need it • Precise validation in numerous dimensions and conditions	• Further increases calibration burden • Still not suitable for applications requiring real-time control (e.g., hardware-in-the-loop testing)

At the standard-option level, FASTSim's power-based engine model is a well-validated reduction of more computationally intense torque-versus-speed models, which are higher on the accuracy-complexity continuum. A single FASTSim efficiency-power engine map scales well to various engine sizes, as demonstrated in Figure ES-2. FASTSim's power-based approach works similarly well for electric motor modeling.

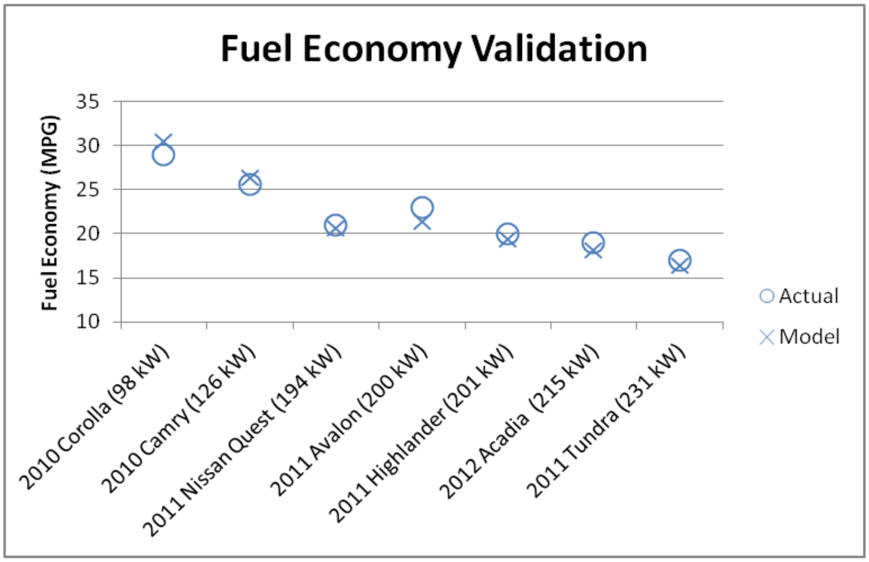

Figure ES-2. FASTSim fuel economy validation against U.S. Environmental Protection Agency (EPA) window-sticker data (combined UDDS and HWFET drive cycles)[1] for vehicles with engines of different sizes

At the vehicle level, road-load and energy consumption results generated using FASTSim's standard option validate well against chassis dynamometer data for conventional gasoline vehicles, hybrid electric vehicles, plug-in hybrid electric vehicles, and electric vehicles. Figure ES-3 is an example of the fit between measured and modeled results for a Chevrolet Volt over sections of the high-speed, high-acceleration US06 drive cycle.

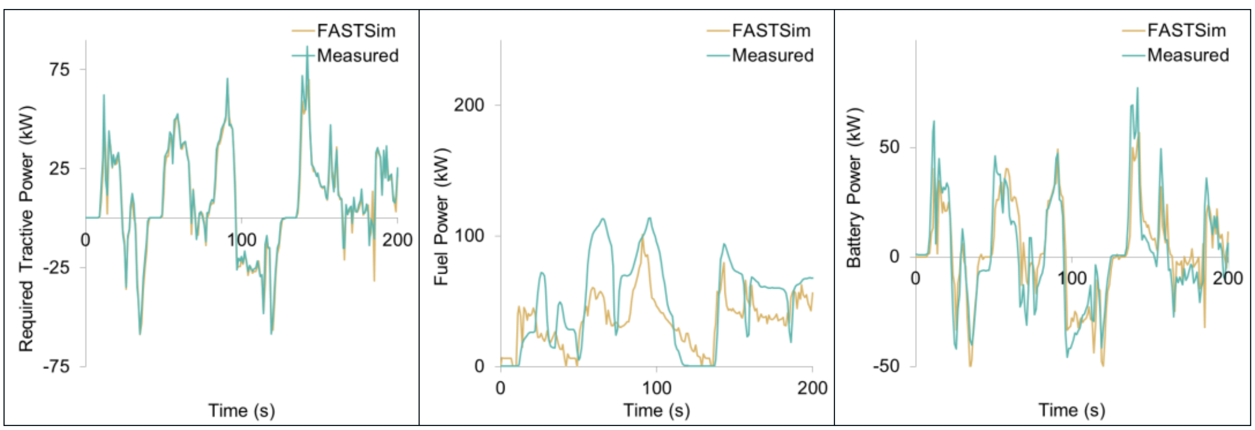

Figure ES-3. Time series validation: 2012 Chevrolet Volt, US06

While the second-by-second validation results for FASTSim's standard option do not agree exactly, they do provide reasonable overall agreement, and the corresponding full-cycle-level fuel economy and performance results validate well.[2] NREL has vetted the inputs for select recent vehicles, and in the comparisons made for this report, modeled results for fuel economy,

[1] HWFET = Highway Fuel Economy Test; UDDS = Urban Dynamometer Driving Schedule.
[2] The fuel economy validation shown here calibrates FASTSim's vehicle aerodynamic drag, rolling resistance, and test mass to EPA-reported values, and results are compared with EPA window-sticker data derived from combined fuel economy (UDDS + HWFET drive cycles) dynamometer testing. For performance validation, FASTSim-simulated acceleration is compared with acceleration data from the website www.zeroto60times.com.

electricity consumption, and acceleration are within 5% of measured data for most vehicles and within 10% for all vehicles. Figure ES-4 shows the fuel economy validation for 12 recent conventional, hybrid, and fuel cell vehicles with NREL-vetted input data. Figure ES-5 shows the FASTSim acceleration validation for 12 vehicles with vetted input and acceleration rating data.

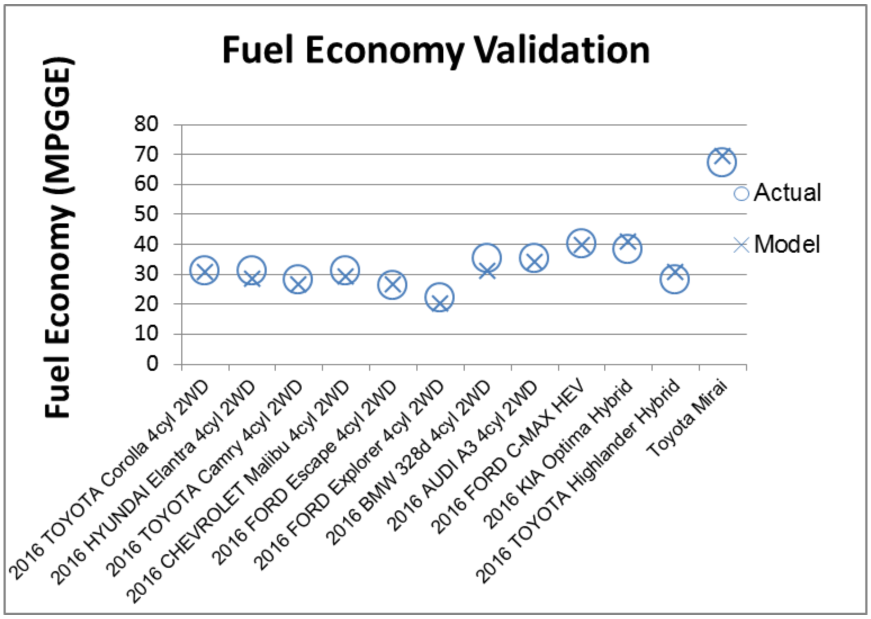

Figure ES-4. FASTSim fuel economy validation versus EPA window-sticker data for select recent vehicles with vetted inputs

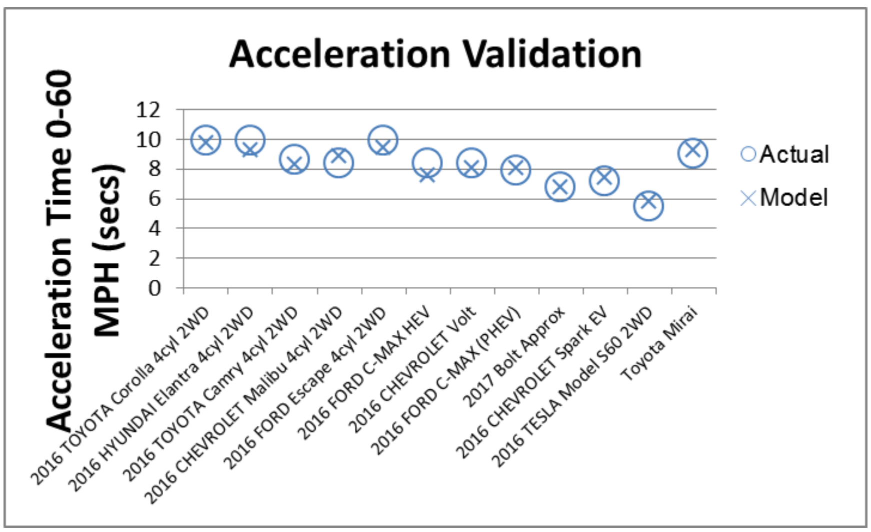

Figure ES-5. FASTSim acceleration validation versus Zero to 60 Times website data for select recent vehicles with vetted inputs

NREL continues vetting the inputs for a much larger group of recent vehicles. Even when using only the partially vetted inputs, however, FASTSim-modeled fuel economy/electricity consumption are within 5%–10% of the measured dynamometer data for most vehicles, and modeled acceleration validates reasonably well.

The results summarized above focus on component- and vehicle-level modeling and validation within FASTSim's standard option. FASTSim's customized option with potential extensions for select components has also been validated, notably against detailed test data collected by NREL and Argonne National Laboratory (ANL) on a highly-instrumented 2011 Ford Fusion. Chassis dynamometer data were used to calibrate a customized FASTSim model of the Fusion, which included estimating impacts from engine oil viscosity and fuel enrichment using lumped thermal root-mean-square error (RMSE) models for engine oil/coolant and exhaust catalyst—producing an engine efficiency model sensitive to both engine power and thermal state. The resulting model calculates fuel consumption to within 2.4% RMSE on the chassis dynamometer test cycles (and within the range of cycle-to-cycle dynamometer test uncertainty). NREL and ANL next performed on-road testing of the highly instrumented Ford Fusion. Figure ES-6 shows the validation of the customized FASTSim model against the on-road data. Overall, the model matches the measured results within a 5.6% RMSE, showing that FASTSim trained on a limited set of dynamometer cycles can perform well over a broad range of real-world conditions (over which trip level fuel economy varies by over +/-50% from the average for the vehicle).

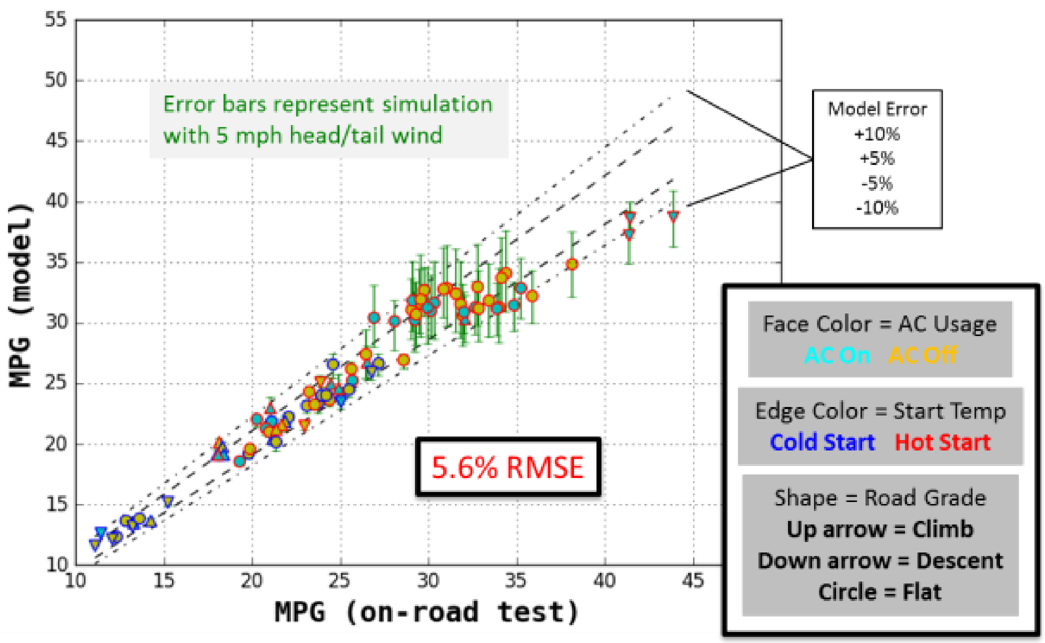

Figure ES-6. Validation of FASTSim-modeled versus measured fuel economy over on-road driving

This report also summarizes the widespread referencing of FASTSim in the literature. Most of the numerous studies that use FASTSim are from NREL, but additional users include DOE, other national laboratories, automakers, the California Air Resources Board, and American and foreign universities and research centers. The publicly released beta version of FASTSim has been robust, with more than 2,700 unique downloads and no reports of major errors or inaccuracies.

Finally, public sponsorship and open-source code add transparency and credibility to FASTSim, making it well suited for analyses that must be shared and understood among multiple stakeholders such as automakers and regulatory agencies. In this capacity, it can be a powerful tool for building large-scale future scenarios of the type that might support public-interest discussions related to vehicle fuel economy and design.

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1 Introduction

The National Renewable Energy Laboratory (NREL) transportation research team possesses decades of experience with vehicle powertrain modeling. This extensive history includes development of the ADVISOR Advanced Vehicle Simulator from 1994 to 2004. ADVISOR has been one of the most frequently used vehicle modeling software packages in the United States and abroad. Even after NREL ended formal development of ADVISOR, the tool spun off into an open-source development community and has been downloaded thousands of times each year.

Since 2004, NREL has built on the foundational work with ADVISOR to develop, use, and refine the Future Automotive Systems Technology Simulator (FASTSim) in support of the U.S. Department of Energy's (DOE's) transportation research goals. FASTSim produces very rapid estimates of vehicle efficiency, performance, cost, and battery life in conventional and advanced-powertrain technologies. The tool enables completion of such analyses using only a few publicly available vehicle parameters, such as peak power output of the engine and hybrid/electric components, vehicle mass, frontal area, and rolling resistance. This simplified approach provides accurate results for many types of analysis while increasing speed, ease, and accuracy related to finding required inputs, running the model, and interpreting results. When appropriate, FASTSim also can use customized inputs to represent specific vehicles even more precisely if detailed input data are available.

In addition, FASTSim has the advantage of being publicly accessible and transparent. FASTSim's graphical user interface steps users through selecting a vehicle to run, choosing drive cycles to simulate, and viewing the results. Although many simulations do not require it, FASTSim's open-source approach allows for customization to capture temperature-dependent characteristics, component speed-related variations, and other detailed aspects. The publicly released beta version has been robust, with more than 2,700 unique downloads and no reports of major errors or inaccuracies.

Primary applications of FASTSim include evaluating the impact of technology improvements on efficiency, performance, cost, and battery life in conventional vehicles, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and all-electric vehicles (EVs). FASTSim helps answer questions such as:

- Which battery sizes are most cost effective for a PHEV or EV?
- At what battery prices do PHEVs and EVs become cost effective?
- On average, how much fuel does a PHEV with a 30-mile electric range save compared with a conventional vehicle?
- How much fuel does an HEV save compared with a conventional vehicle over a given drive cycle?
- How do lifetime costs and petroleum use compare for conventional vehicles, HEVs, PHEVs, fuel cell vehicles, and EVs?

FASTSim models vehicle components at as high a level as possible while maintaining accuracy. Simulations over standard city and highway time-versus-speed fuel economy drive cycles take less than 1 second for most vehicles. FASTSim is also capable of running a large number of drive cycles at once. It has been used to estimate the benefits of changing a fleet of vehicles to an advanced powertrain and to capture a more realistic representation of light-duty vehicle real-world driving by using data sets from NREL's Transportation Secure Data Center (NREL 2017). More information about FASTSim is available from Brooker et al. (2015) and www.nrel.gov/transportation/fastsim.html.[3]

As with any model, the most critical aspect of FASTSim is its ability to reflect reality accurately. This is the purpose of validation—the comparison of modeled results versus results measured during vehicle or component operation in the laboratory or on the road. FASTSim's high-level vehicle simulation results have been validated against test data for hundreds of different vehicles and most existing powertrain options. In addition, detailed validation of individual vehicles has been performed via both chassis dynamometer and on-road testing of highly instrumented vehicles.

This report focuses on the validation of FASTSim. Section 2 explains FASTSim's place in the continuum of vehicle-modeling options and discusses the continuum of capabilities within FASTSim itself. Sections 3 and 4 analyze modeling and validation of FASTSim at the component and vehicle levels. Section 5 details on-road/real-world validation. Section 6 describes how various users have applied FASTSim, and Section 7 summarizes the report's findings.

[3] This website also links to the latest publicly available version of FASTSim.

2 FASTSim in the Vehicle Modeling Continuum

This section describes the continuum of vehicle-modeling options, FASTSim's place within that continuum, and the continuum of capabilities within FASTSim itself.

2.1 The Vehicle-Modeling Continuum

Many software tools have been developed for vehicle/powertrain modeling. For example, Mahmud and Town (2016) reviewed 125 tools available for EV modeling, yet even their long list is not comprehensive, and it excludes the many proprietary tools developed by automakers and others.

Modeling tools can be categorized conceptually into a continuum based on each tool's tradeoff between accuracy and complexity, where "complexity" includes the required number of input parameters, availability of required input data, time required to obtain the inputs and perform calibration, software requirements, and computational overhead to run. Figure 1 shows a qualitative, illustrative representation of the modeling continuum. Importantly, the relationship between accuracy and complexity shown here is non-linear: the greatest returns in accuracy are gained with the initial advances in complexity, whereas further marginal increases in accuracy come at the cost of greatly increasing complexity, which entails increased data discovery, setup, calibration, computational, and runtime requirements.

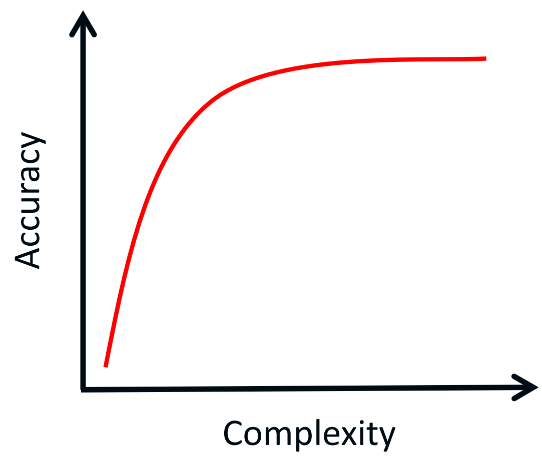

Figure 1. Conceptual illustration of the vehicle-modeling continuum

Approaches at the low-complexity/accuracy end of the full vehicle-modeling continuum include simply taking vehicles' U.S. Environmental Protection Agency (EPA) "window sticker" composite fuel economy ratings and multiplying these by the number of miles the vehicles are driven to estimate the total fuel consumed by each vehicle. One step up the accuracy/complexity curve is to consider each vehicle's "city" and "highway" fuel economy ratings and multiply these by the driving conducted on roads categorized as "city" and "highway." These approaches may give fair estimates of total fuel consumption by a large population of vehicles, but they are inadequate for studies seeking to represent the distribution of fuel efficiency for a given vehicle technology over a range of customer driving profiles, weather conditions, and (for electrified vehicles) charging behaviors.

Approaches at the high-complexity/accuracy end of the full vehicle-modeling continuum include models that call for hundreds of input specifications per vehicle, multidimensional efficiency maps for each component, and computational time steps on the order of 1/100th of a second throughout a vehicle's exact driving profile. Such approaches can provide accurate representations of vehicle operating behavior and are useful for applications requiring real-time computations, such as development of control code to implement in a production vehicle or completion of hardware-in-the-loop testing. However, the modeling complexity and computational burden for these approaches can be unnecessary for a variety of applications, limiting the breadth of different operating characteristics and vehicle configurations that could otherwise be explored as a result. In short, the suitability of tools across this continuum depends on the analytical task being performed.

2.2 The FASTSim Continuum

FASTSim occupies a "sweet spot" along the vehicle-modeling continuum. It is designed to balance predictive accuracy with model complexity (including data, calibration, computation, and runtime requirements) across a wide range of analytical tasks. Figure 2 locates FASTSim along the continuum. As shown, FASTSim encompasses a sizable segment of the curve—its own continuum—providing moderately high accuracy with low complexity (for standard, high-level analyses) on one end to providing high accuracy with moderate complexity (for customized vehicle-specific analyses) on the other. Across this full range, FASTSim is particularly well suited for quickly and conveniently conducting large numbers of simulations over representative real-world driving distributions and/or myriad vehicle design variations. In such analyses, the uncertainties and efficiency impacts from the broad spectrum of operating conditions or design variants far exceed any small uncertainties resulting from modeling simplifications within FASTSim.

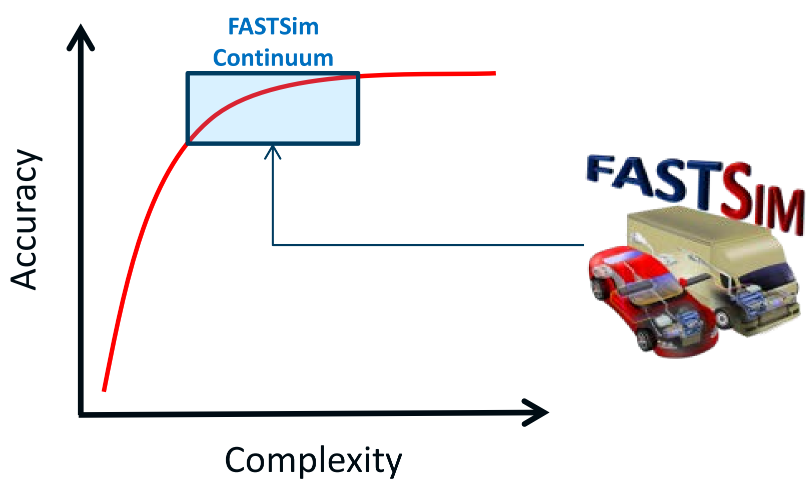

Figure 2. Conceptual illustration of the FASTSim continuum on the vehicle-modeling continuum

Several elements are common to FASTSim across its continuum of capabilities and requirements:

- Backward/forward calculation structure[4]
    - Requires a full driving trajectory but can run using 1-second time steps (enabling fast run times)
- Modeling performed over a variety of drive-cycle simulations
    - Certification test cycles (with and without standard adjustments to improve "real-world" representativeness)
    - Best-effort acceleration tests
    - Real-world simulations (leveraging Transportation Secure Data Center data and/or on-road testing)
- Different user interface options
    - Microsoft Excel (simple and user friendly; has been externally posted for many years)
    - Python (scripting language for even faster run times and streamlined large database integration; becoming externally posted)
- Variety of model validation examples
    - Some coverage in existing publications
    - More comprehensive presentation in this report

Beyond those common elements, FASTSim can be used across a continuum of modeling levels (Table 1). FASTSim's standard option is suitable for large-scale simulation of hundreds or even thousands of vehicles. It employs generally representative default power-versus-efficiency maps for each of the components (such as the standard gasoline engine map shown in Figure 3), which are then scaled based on the component power ratings for a particular modeled vehicle. Thus, the standard option has the fastest calibration, only requiring a small amount of publicly available vehicle information, and it still captures most important factors for high-level vehicle comparisons. However, for some targeted studies, more component data details may be available on specific vehicles of interest, or the studies may seek to investigate scenarios sensitive to factors such as operating temperature or gear selection. For these situations, FASTSim enables further customization and the addition of modeling extensions—moving the model up the accuracy-versus-complexity tradeoff curve.

[4] The backward/forward calculation structure starts with power requirements at the vehicle's wheels as dictated by the road-load equation for a particular driving trajectory, then moves backwards up the driveline to confirm that each component can satisfy the required power before moving forward back down the driveline to apply the identified operating points for each component.

Table 1. FASTSim Continuum: Modeling Levels and Their Strengths and Limitations

Level of Modeling	Strengths	Limitations
Standard Option		
• Default power versus efficiency maps for each component • Maps scaled based on component power ratings for modeled vehicle	• Fastest to calibrate, requires small amount of public vehicle information • Suitable for large-scale simulation/evaluation of thousands of vehicle designs	• Captures most important factors for high-level comparisons but lacks detail for focused studies
Customized Option		
• Vehicle-specific component calibration	• Provides more precise model of specific vehicle(s)	• Larger calibration burden, requires detailed component-level data from manufacturer or testing
Potential Extensions for Targeted Investigations		
• Temperature dependence • Torque versus speed disaggregation • Shift schedules	• Even more detail for studies that need it • Precise validation in numerous dimensions and conditions	• Further increases calibration burden • Still not suitable for applications requiring real-time control (e.g., hardware-in-the-loop testing)

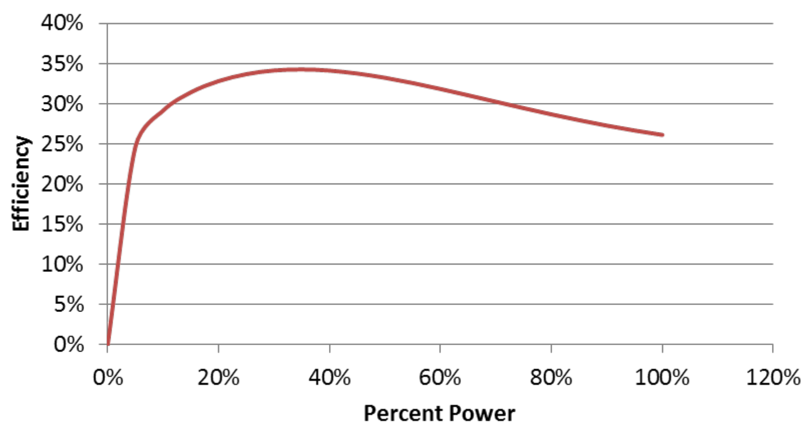

Figure 3. Example default gasoline engine efficiency map for FASTSim's standard option

The customized option provides more precise modeling of a specific vehicle or vehicles. The vehicle-specific component calibration (Figure 4) entails a larger calibration burden because detailed component-level data from the manufacturer or from testing are required.

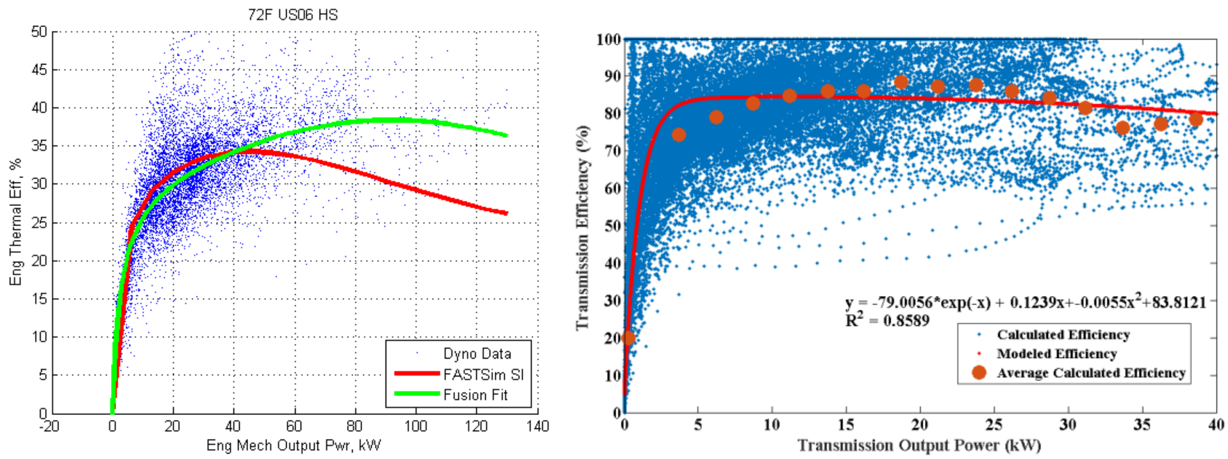

Figure 4. Examples of custom engine and transmission efficiency maps for 2011 Ford Fusion (dynamometer tested), for FASTSim's customized option

Finally, the customized option can accept extensions for targeted investigations, accounting for factors such as the temperature dependence of efficiency maps for the engine and/or other components, torque-versus-speed disaggregation for select components, and consideration of shift schedules and torque converter lock-up (Figure 5, Figure 6). Such extensions can provide even more detail for studies that require it and offer precise validation in numerous dimensions and conditions (Figure 7), although at the cost of higher input data requirements and calibration burden.

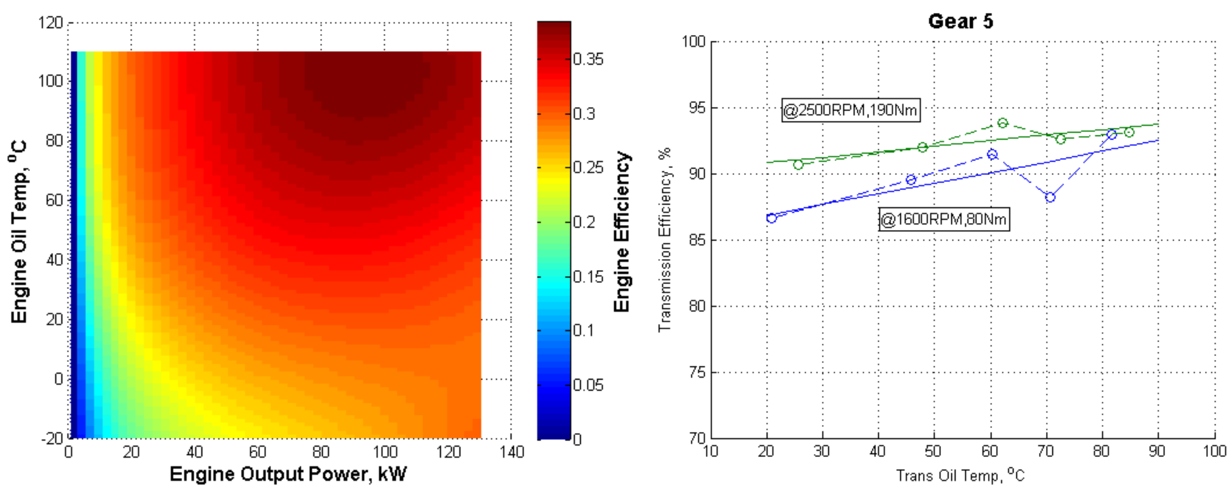

Figure 5. Examples of thermally sensitive engine and transmission maps for FASTSim's customized option with extensions for select components

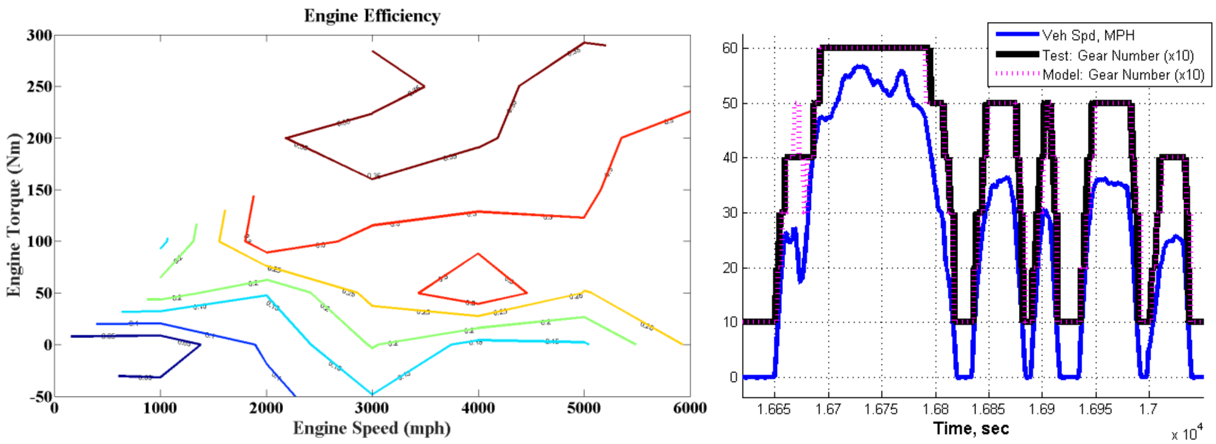

Figure 6. Examples of torque-speed component map and shift schedule for FASTSim's customized option with extensions for select components

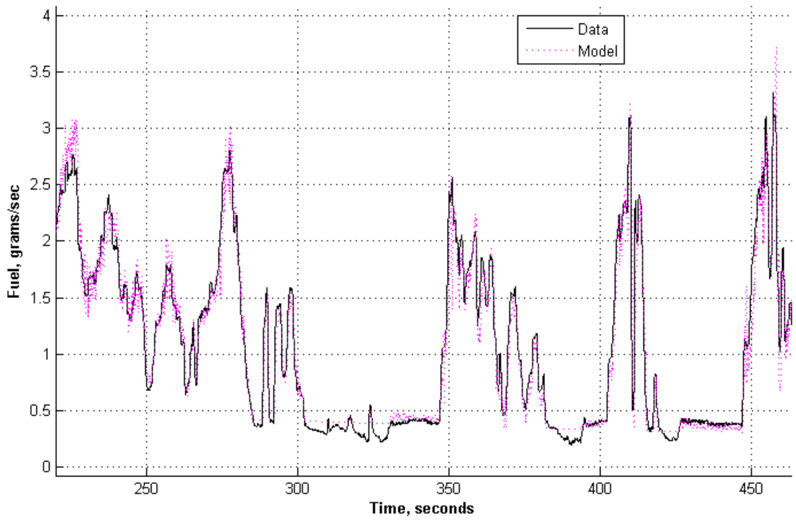

Figure 7. Example of precise fuel consumption calibration enabled by FASTSim's customized option with extensions for select components

3 Component-Level Modeling and Validation

This section focuses on component-level modeling and validation within FASTSim's standard option (see Table 1). FASTSim's standard power-based engine model is a well-validated reduction of more computationally intense torque-versus-speed models (that are higher on the accuracy-complexity continuum). By design, modern automatic transmissions with high gear counts limit engine operation to a relatively narrow band of torque/speed combinations (Figure 8). Within the band of typical engine operation, contours of constant efficiency and constant power tend to be well aligned (particularly at low power, where the engine predominantly operates). Limited operational bands and the alignment of engine power and efficiency make FASTSim's power-based model of engine efficiency an effective approximation (Figure 9, Figure 10).

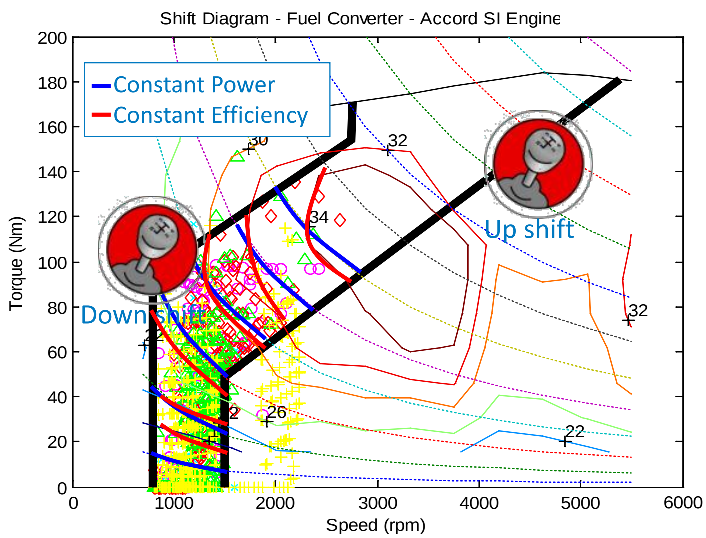

Figure 8. Torque-speed engine map with shift schedule showing alignment of constant power and efficiency curves

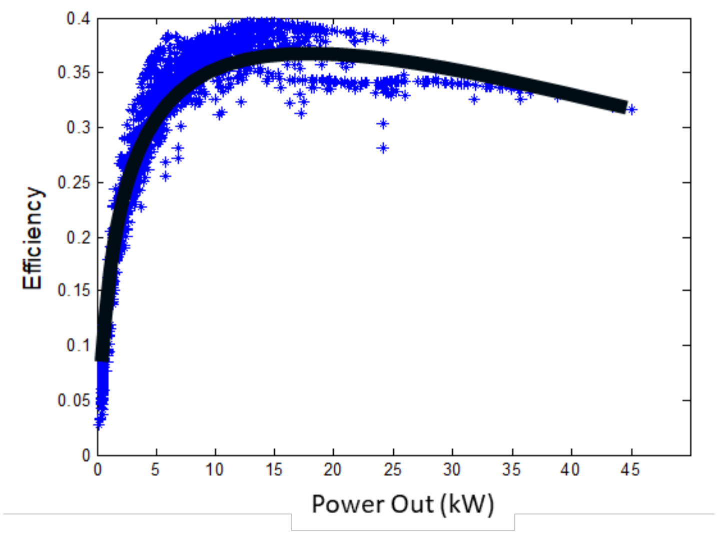

Figure 9. FASTSim efficiency-power engine map (black line) developed from torque-speed map operating points (blue stars) transferred from Figure 8

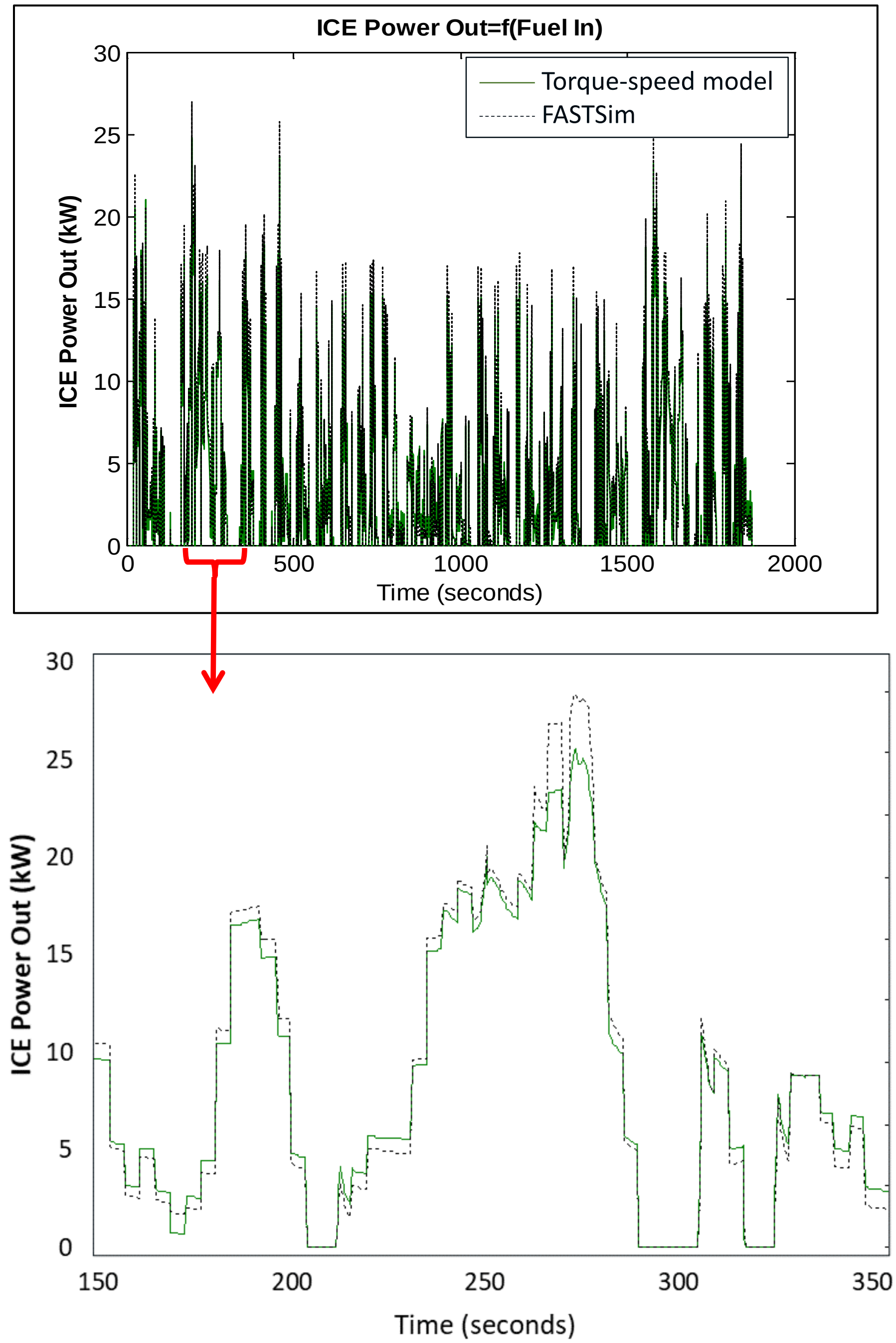

Figure 10. Validation of simplified FASTSim engine model against a torque-speed model

The single FASTSim efficiency-power engine map scales well to various engine sizes. Figure 11 shows the engine map superimposed on data points from a torque-speed model for a 100-kilowatt (kW) and a 125-kW engine, demonstrating a good fit for both. The effectiveness of FASTSim's engine-scaling approach translates well into fuel economy validation for vehicles with engines of different sizes. Figure 12 shows good matches between FASTSim's modeled fuel economy results and EPA window-sticker data for vehicles with engines sizes ranging from 98 to 231 kW.

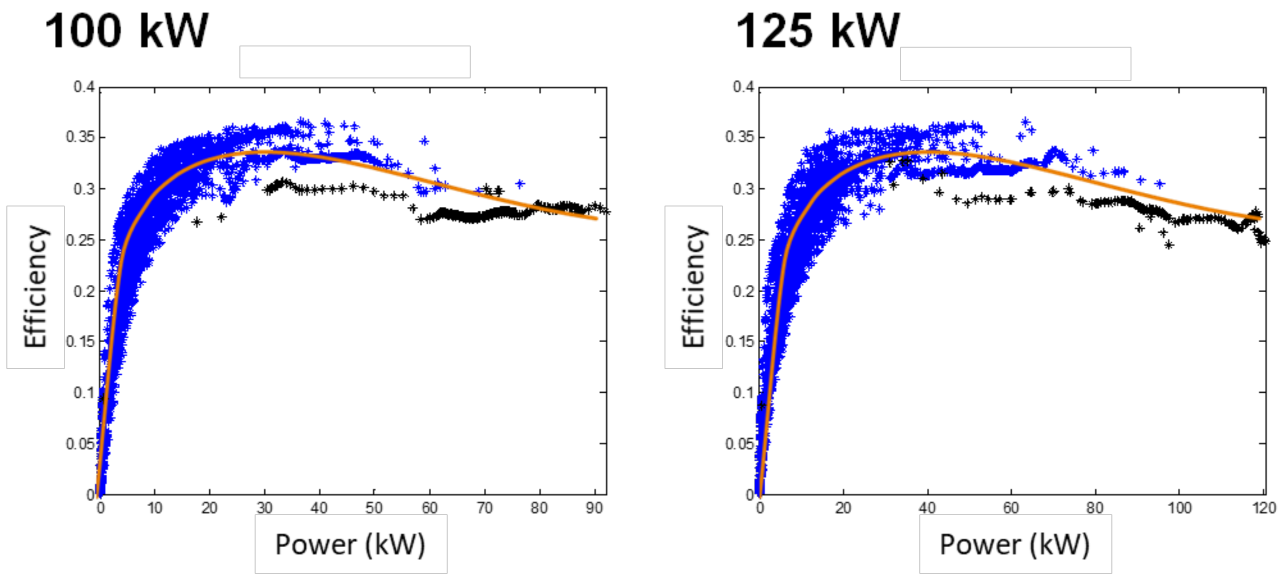

Figure 11. FASTSim efficiency-power engine maps (orange lines) showing fit with torque-speed model (blue and black stars) for engines of various sizes

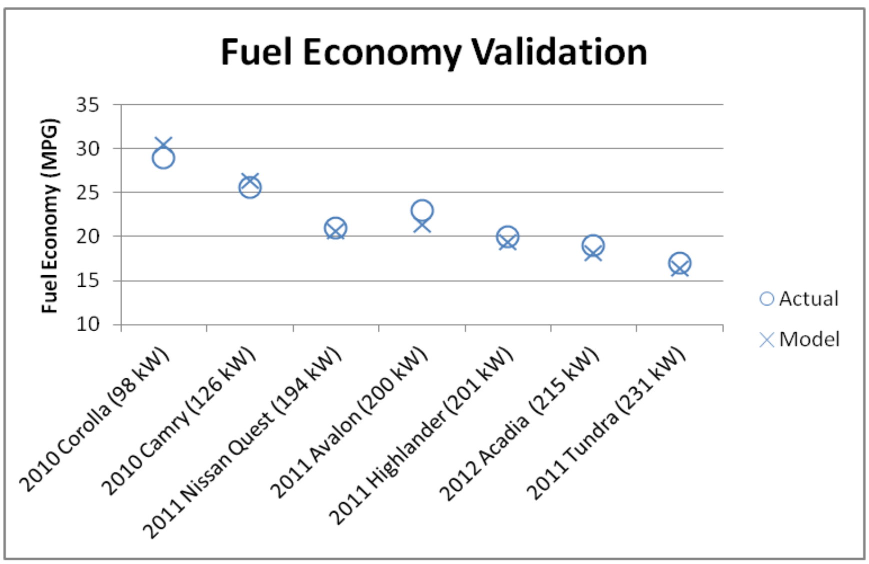

Figure 12. FASTSim fuel economy validation against EPA window-sticker data (combined UDDS and HWFET drive cycles)[5] for vehicles with engines of different sizes

FASTSim's power-based approach works similarly well for electric motor modeling. Figure 13 shows a torque-speed electric motor map for the Nissan Leaf. Figure 14 demonstrates a good fit between FASTSim's efficiency-power approximation and published Nissan Leaf torque-speed data. Finally, Figure 15 shows that FASTSim's simplified efficiency-versus-power model matches well with the torque-speed model.

[5] HWFET = Highway Fuel Economy Test; UDDS = Urban Dynamometer Driving Schedule.

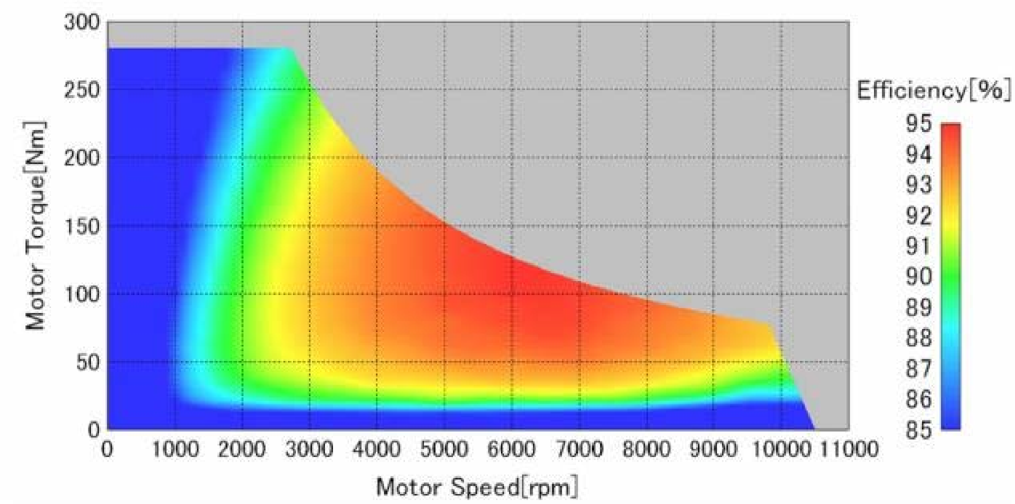

Figure 13. Torque-speed electric motor map

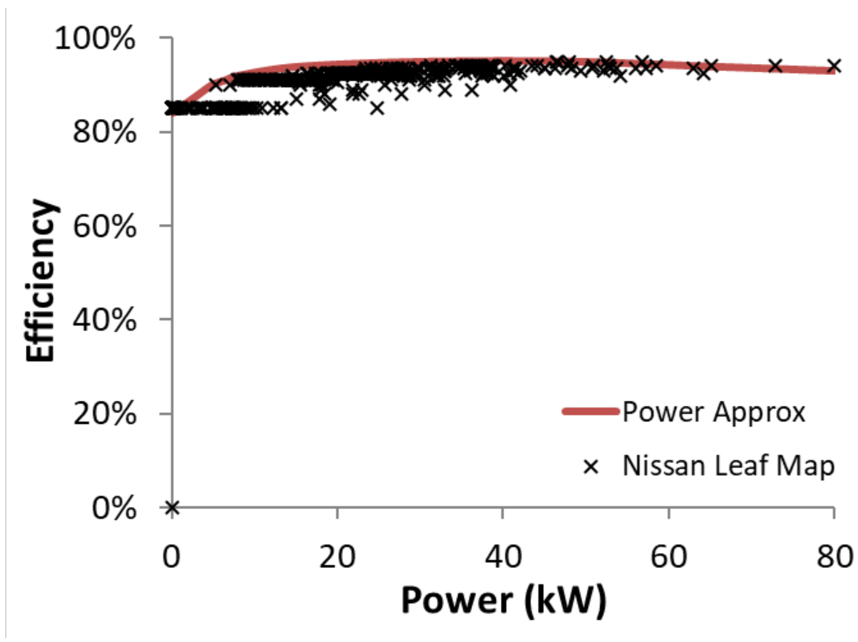

Figure 14. Comparison of FASTSim efficiency-power electric motor map with published Nissan Leaf torque-speed map (98% inverter efficiency)

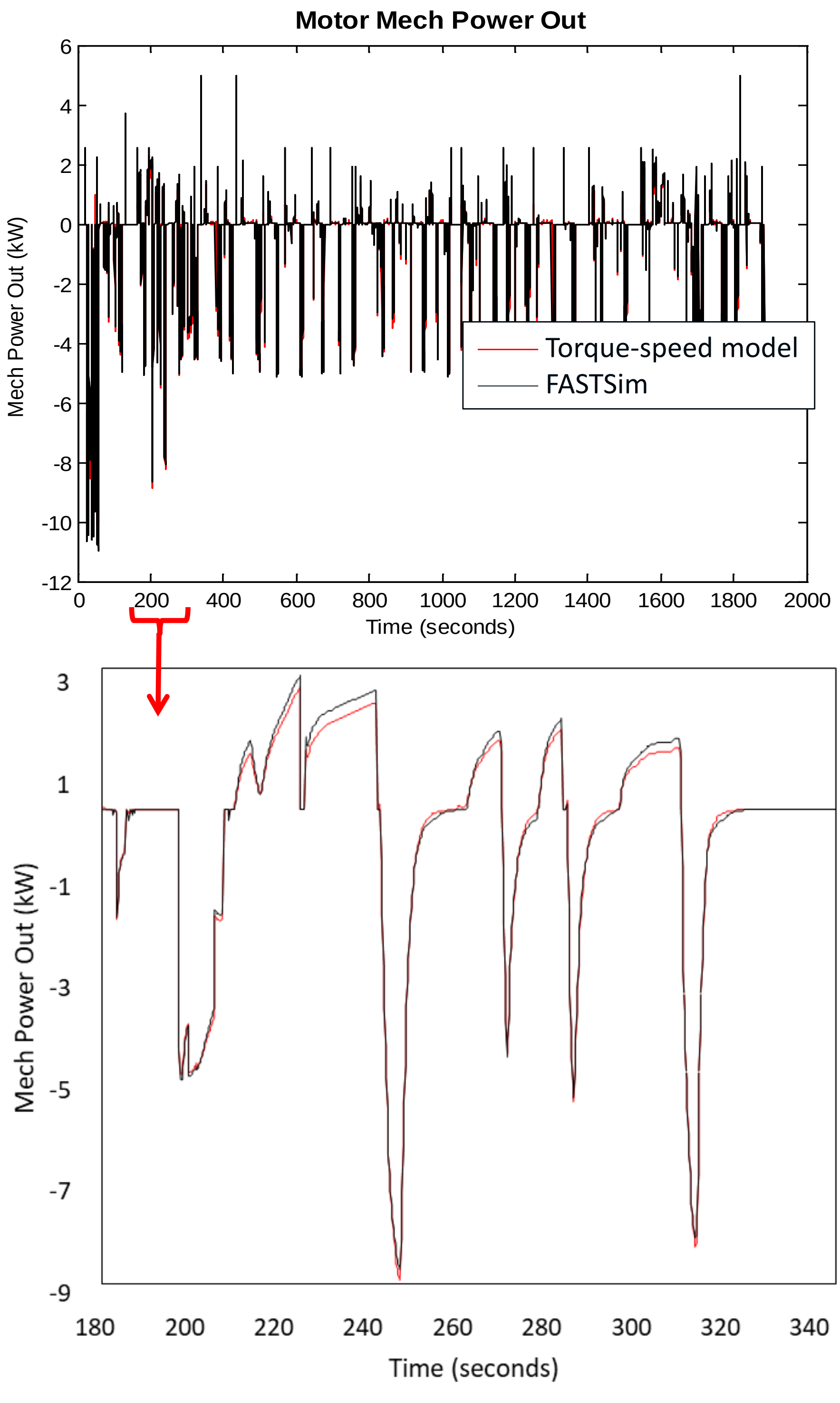

Figure 15. Validation of FASTSim electric motor model against torque-speed model

4 Vehicle-Level Modeling and Validation

This section focuses on vehicle-level modeling and validation within FASTSim's standard option (see Table 1). Section 4.1 addresses vehicle-level time series validation. Section 4.2 addresses fuel economy and performance validation.

4.1 Vehicle-Level Time Series Validation

The time series validations shown here compare FASTSim road-load and energy consumption rates (fuel power and battery power, both in kilowatts) against data from Argonne National Laboratory (ANL) chassis dynamometer testing. All time series are shown over sections of the high-speed, high-acceleration US06 drive cycle.

Figure 16 and Figure 17 show results for the mid-size Ford Fusion and the compact Chevrolet Cruze conventional gasoline vehicles. Both demonstrate good FASTSim fits to measured data for required tractive power and fuel power over time.

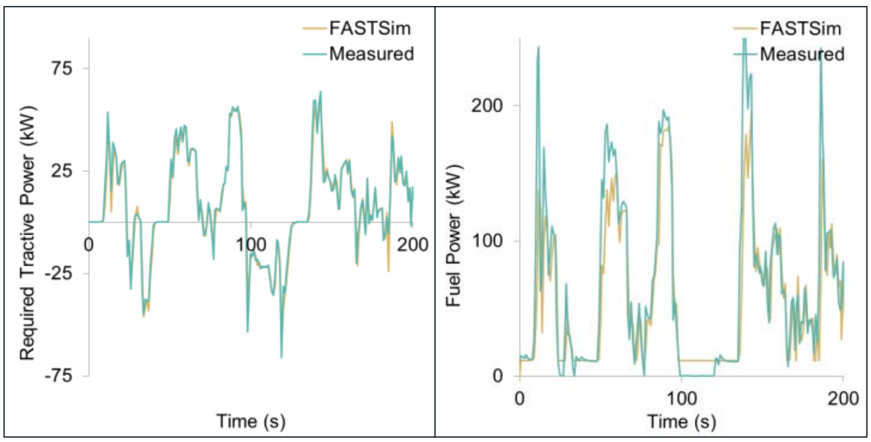

Figure 16. Time series validation: 2012 Ford Fusion, US06

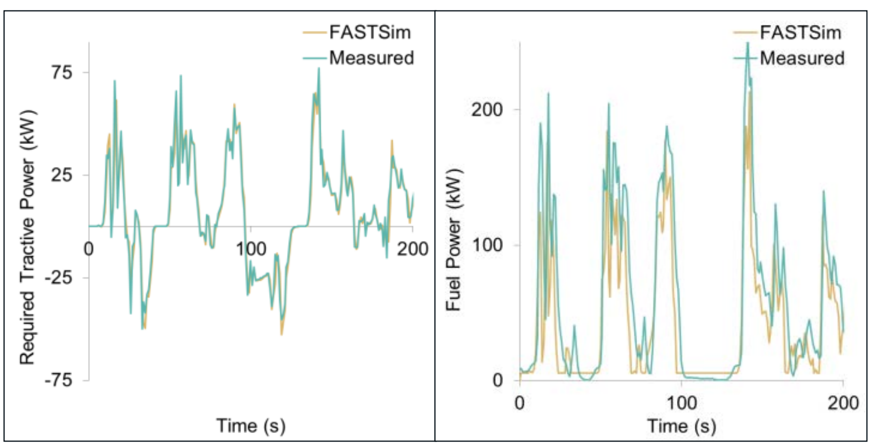

Figure 17. Time series validation: 2014 Chevrolet Cruze, US06

HEV and PHEV results are shown in Figure 18 (Toyota Prius), Figure 19 (Toyota Prius Plug-in), and Figure 20 (Chevrolet Volt), which also include battery power results. FASTSim's time series matches for these advanced vehicles are generally good. Finally, strong FASTSim fits for EVs are shown in Figure 21 (Nissan Leaf) and Figure 22 (Volkswagen eGolf).

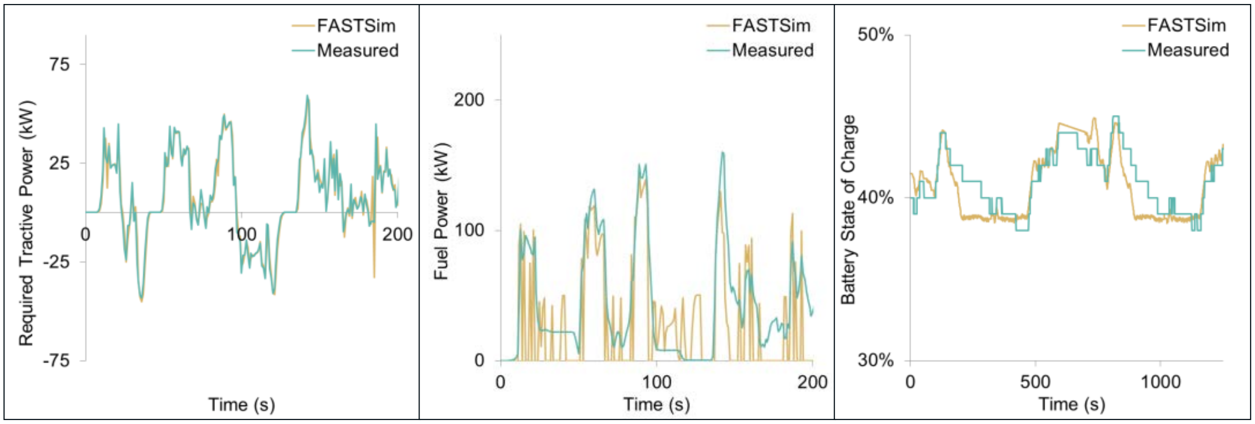

Figure 18. Time series validation: 2010 Toyota Prius, US06

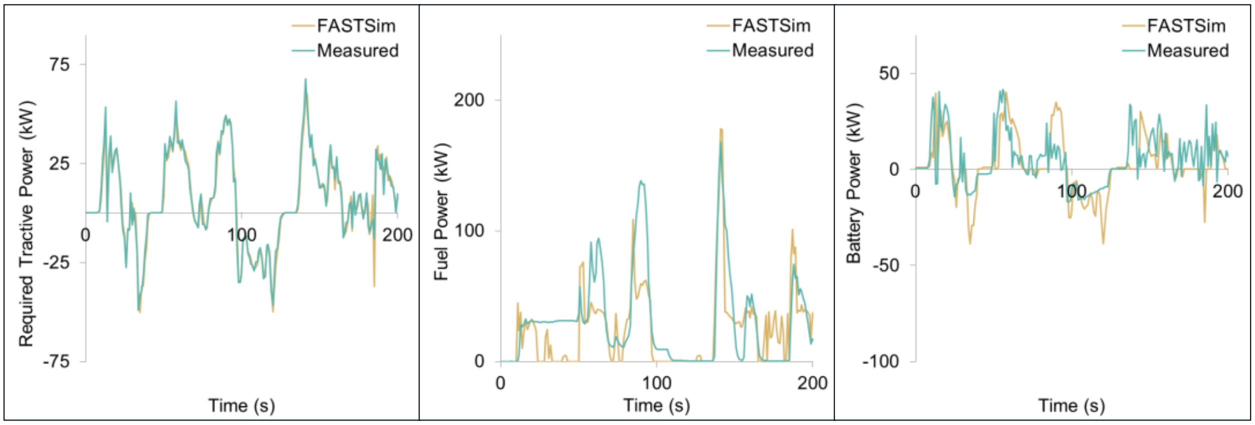

Figure 19. Time series validation: 2013 Toyota Prius Plug-in, US06

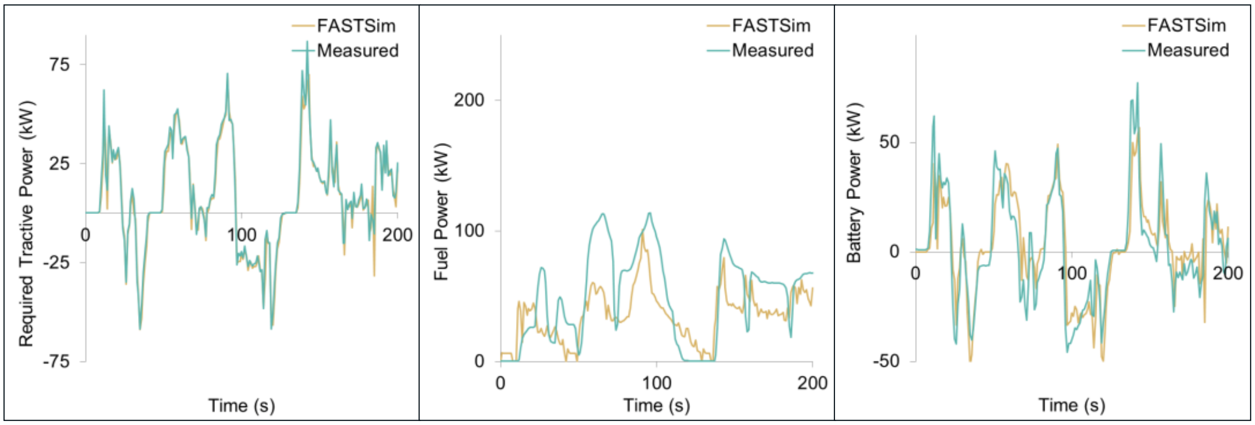

Figure 20. Time series validation: 2012 Chevrolet Volt, US06

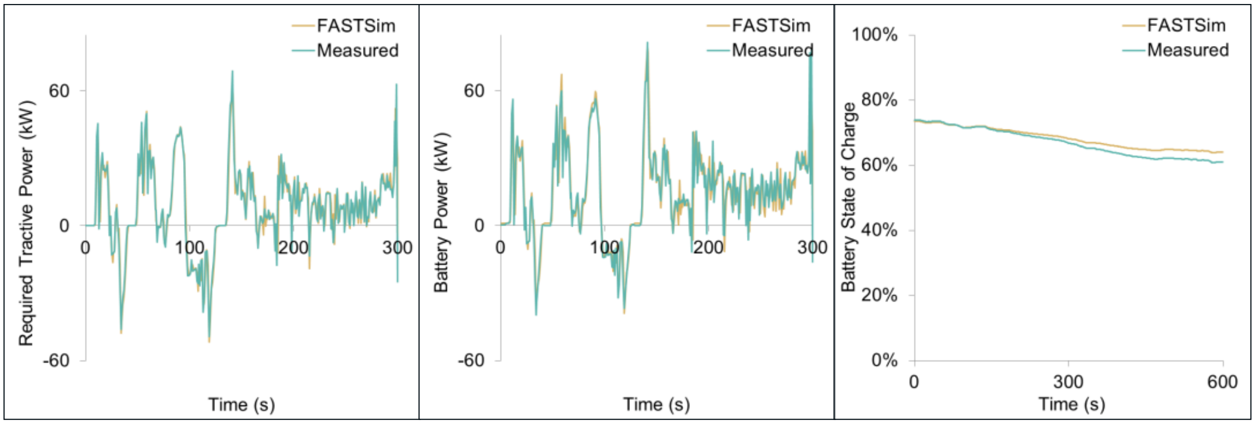

Figure 21. Time series validation: 2013 Nissan Leaf, US06

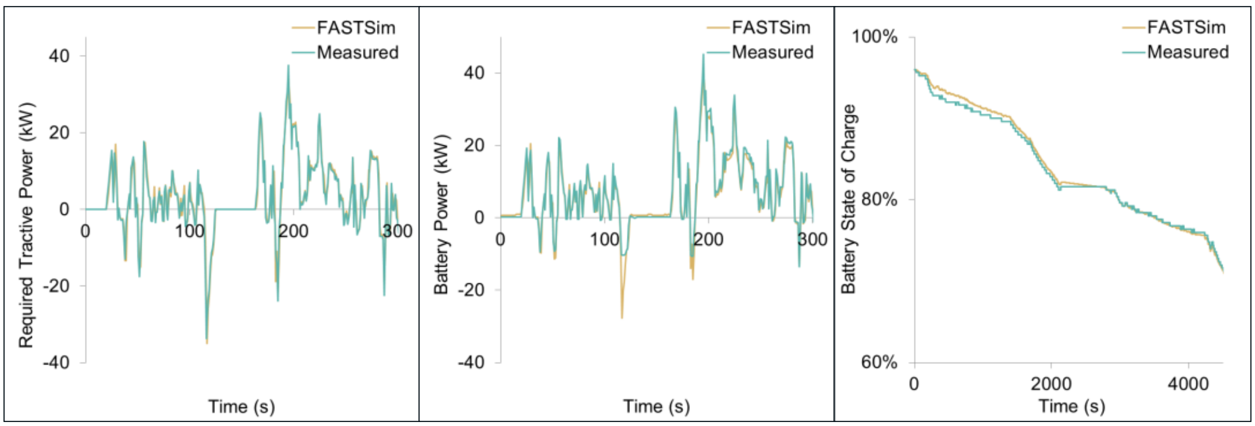

Figure 22. Time series validation: 2015 Volkswagen eGolf, US06

4.2 Fuel Economy and Performance Validation

For fuel economy validation, the FASTSim modeling in this section calibrates vehicle aerodynamic drag, rolling resistance, and test mass to EPA-reported values. FASTSim results are compared with EPA window-sticker data derived from combined fuel economy (UDDS + HWFET drive cycles) dynamometer testing.

For performance validation, FASTSim-simulated acceleration is compared with acceleration data from the website Zero to 60 Times (http://www.zeroto60times.com/). This website aims to compile credible 0-to-60 mph acceleration times and average the results.

Section 4.2.1 presents validation results on select recent vehicles for which NREL has vetted their input data (vetting continues for a much larger group of recent vehicles). Section 4.2.2 presents sample results for the larger group of recent vehicles, which should be considered preliminary pending full vetting of inputs, and Appendix A contains comprehensive results.

4.2.1 Validation Results for Vehicles with Vetted Inputs

Figure 23 shows the FASTSim fuel economy validation for 12 recent conventional, hybrid, and fuel cell vehicles with NREL-vetted input data, and Figure 24 shows the electricity consumption validation for six recent PHEVs and EVs with NREL-vetted input data. For most of the vehicles, the FASTSim-modeled fuel economy/electricity consumption value is within 5% of the measured value, and the modeled value is within 10% for all vehicles (Figure 25). The 2017 Chevrolet Bolt shows the largest deviation, although its input data were not fully finalized in this comparison.

Figure 26 shows the FASTSim acceleration validation for the 12 vehicles with NREL-vetted input data. Again, the modeled and actual results are very close. For three-quarters of the vehicles, the FASTSim-modeled acceleration value is within 5% of the measured value, and the modeled value is within 10% for all vehicles (Figure 27).

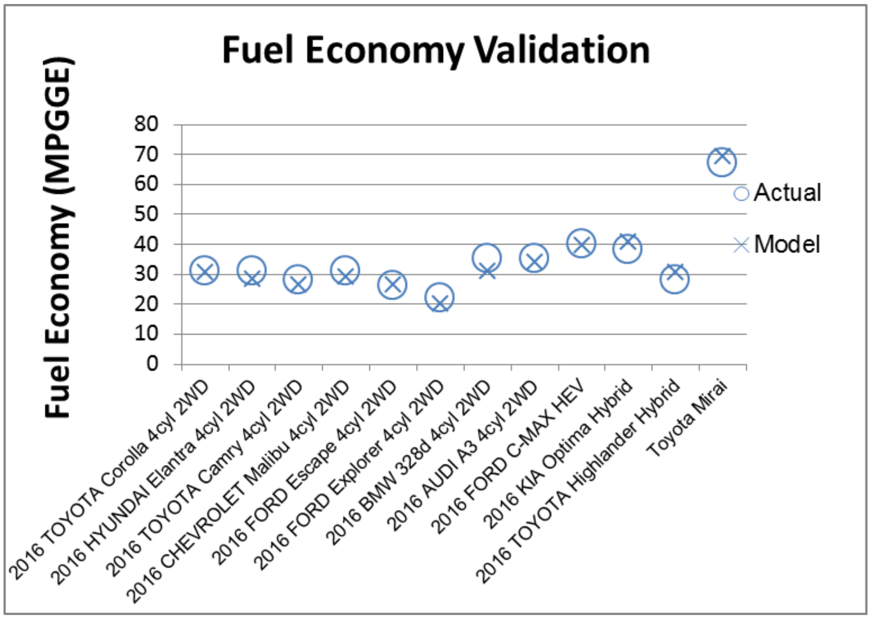

Figure 23. FASTSim fuel economy validation versus EPA window-sticker data for select recent vehicles with vetted inputs

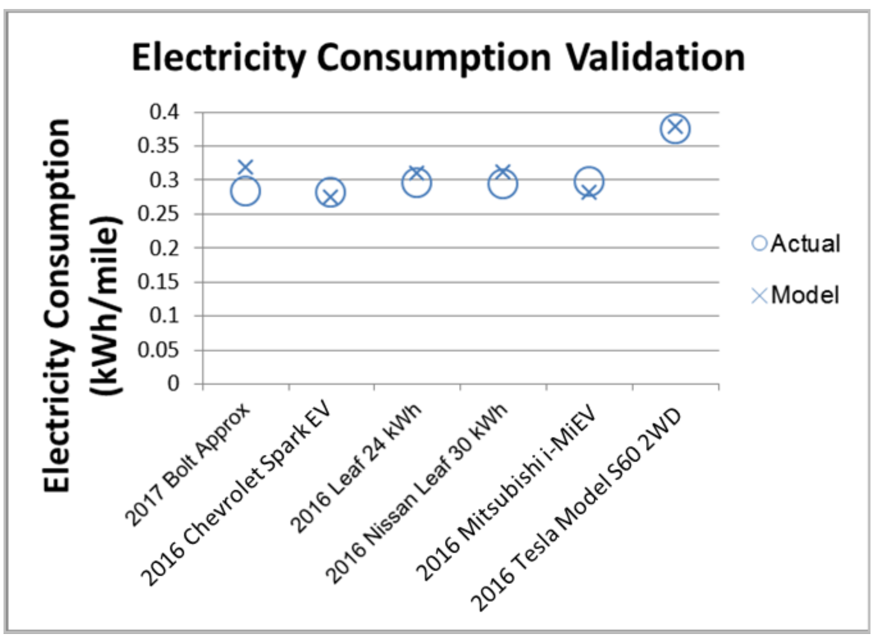

Figure 24. FASTSim electricity consumption validation versus EPA window-sticker data for select recent vehicles with vetted inputs

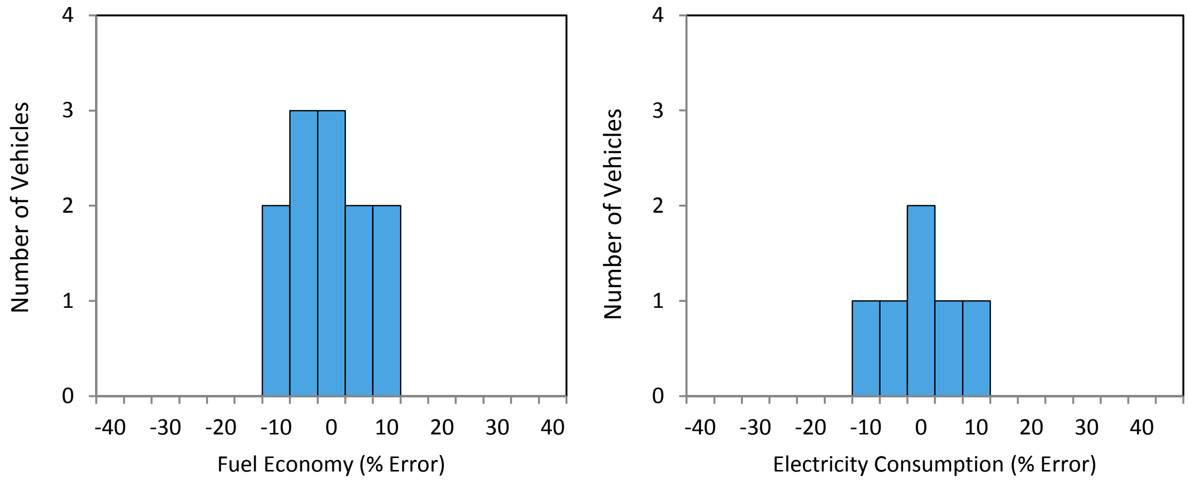

Figure 25. Histograms of error (difference between FASTSim-modeled and measured results) for fuel economy and electricity consumption, for NREL-vetted vehicles

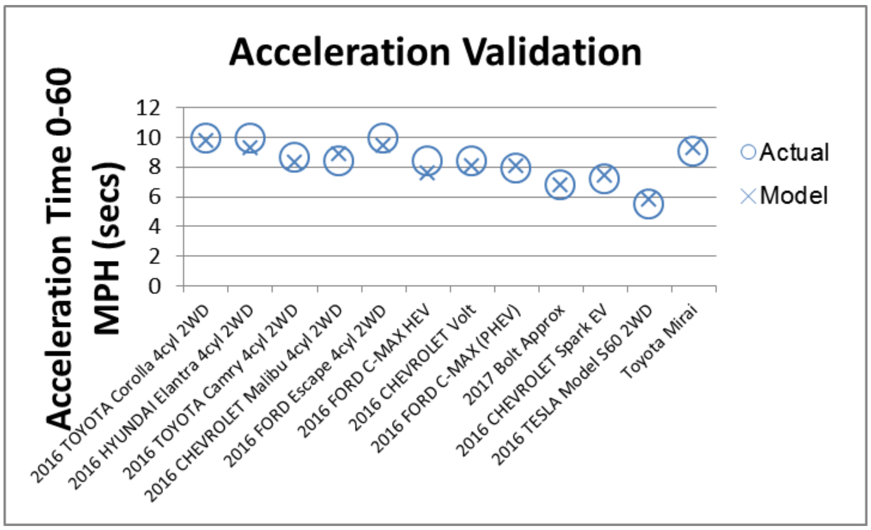

Figure 26. FASTSim acceleration validation versus Zero to 60 Times website data for select recent vehicles with vetted inputs

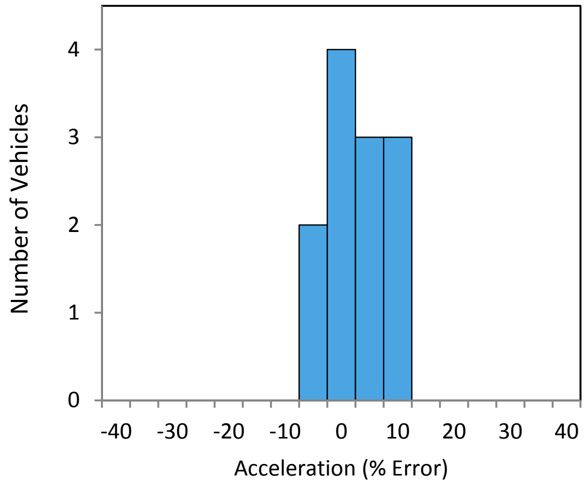

Figure 27. Histogram of error (difference between FASTSim-modeled and measured results) for acceleration, for NREL-vetted vehicles

4.2.2 Preliminary Validation Results for Vehicles with Partially Vetted Inputs

NREL includes information for more than 700 vehicles in its vehicle choice model, ADOPT (the Automotive Deployment Options Projection Tool). Currently the input data for these vehicles are being evaluated using factors such as the presence of turbocharging (affects efficiency and acceleration), two- versus four-wheel drive (affects efficiency and acceleration), and front- versus rear-wheel drive (center of gravity affects acceleration). Thus, the results shown here and the full set of results in Appendix A are preliminary, and many show greater differences between FASTSim-modeled results and measured results than are present in the vetted vehicles discussed in Section 4.2.1.

For example, Figure 28 provides modeled and measured fuel economy and acceleration results for a sample of partially vetted conventional gasoline vehicles, showing significant disparities for a few vehicles. Still, for the vast majority of vehicles in the partially vetted group, the FASTSim-modeled fuel economy is within 10% of measured fuel economy, and the modeled acceleration is within 1 second of measured acceleration. Figure 29 shows these fits in histograms of fuel consumption and acceleration errors for the top-selling vehicles in our partially vetted data set.

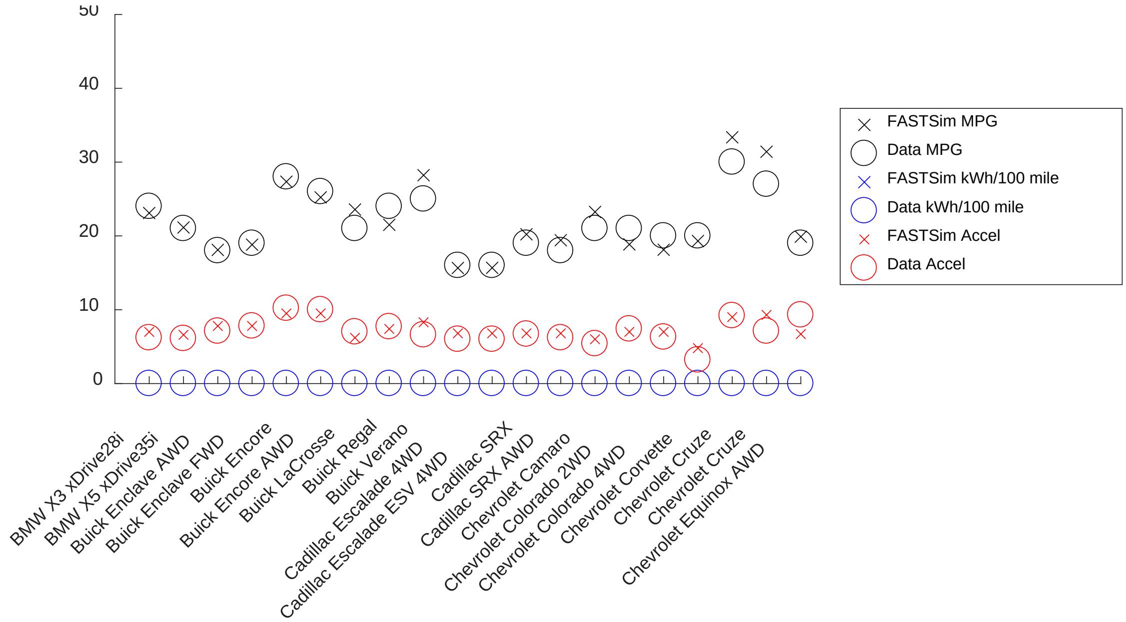

Figure 28. Example of FASTSim fuel economy (versus EPA window-sticker data) and acceleration (versus Zero to 60 Times website data) validation for recent conventional gasoline vehicles with partially vetted inputs[6]

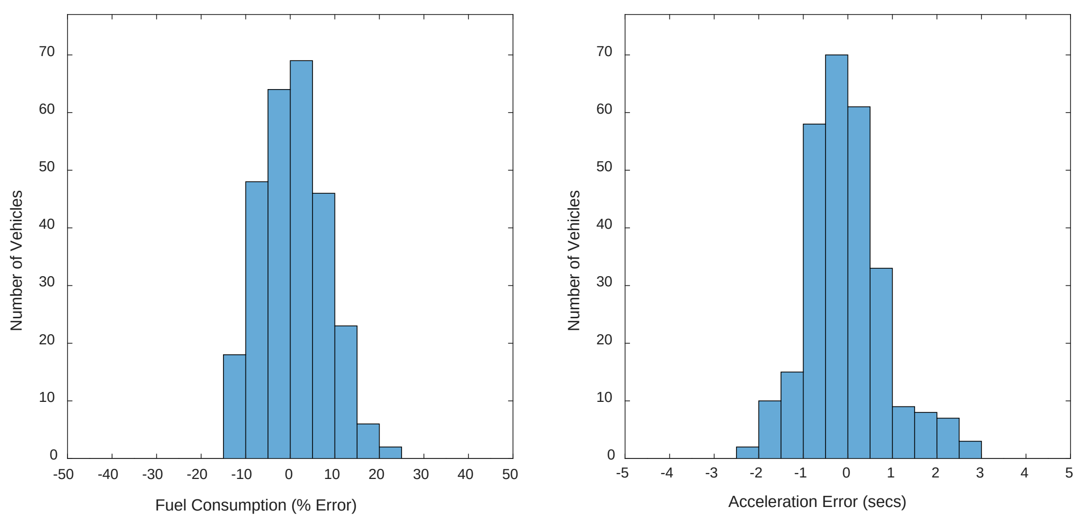

Figure 29. Histograms of error (difference between FASTSim-modeled and measured results) for fuel consumption and acceleration, for partially vetted conventional gasoline vehicles

Overall accuracy is reasonably high for partially vetted advanced powertrain vehicles as well. Figure 30 shows the fuel economy and acceleration validation results for HEVs that sold more than 10,000 vehicles in 2015. For most of these vehicles, the FASTSim-modeled fuel economy is within 10% of the measured fuel economy; the spread of error in the modeled acceleration is somewhat larger (Figure 31).

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[6] Electricity consumption for these conventional vehicles is zero; electricity consumption points are plotted here merely for consistency with other similar figures.

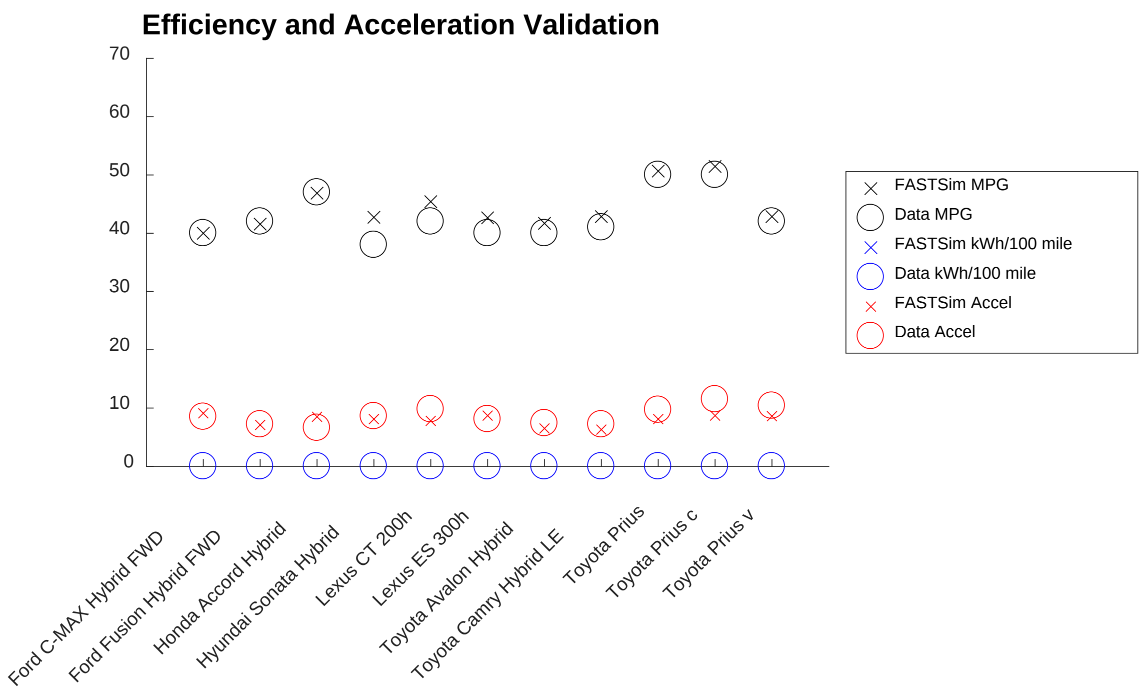

Figure 30. FASTSim fuel economy (versus EPA window-sticker data) and acceleration (versus Zero to 60 Times website data) validation for recent HEVs (with 2015 sales of more 10,000 vehicles) with partially vetted inputs

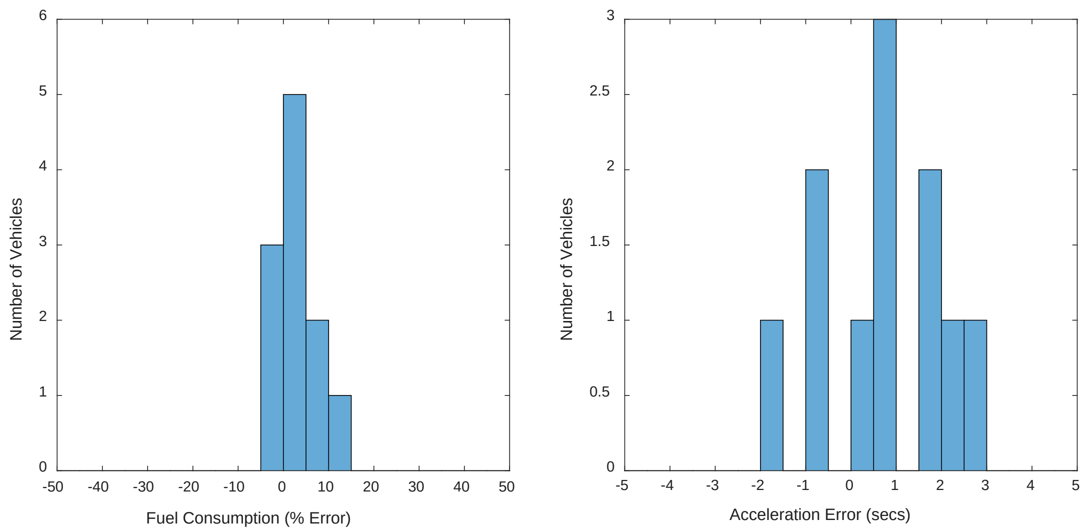

Figure 31. Histograms of error (difference between FASTSim-modeled and measured results) for fuel consumption and acceleration for partially vetted HEVs

Finally, Figure 32 shows the electricity consumption and acceleration validation results for EVs that sold more than 1,000 vehicles in 2015. For all these vehicles, the FASTSim-modeled electricity consumption is within 5% of the measured electricity consumption whereas the spread of error in the modeled acceleration is somewhat larger (Figure 33).

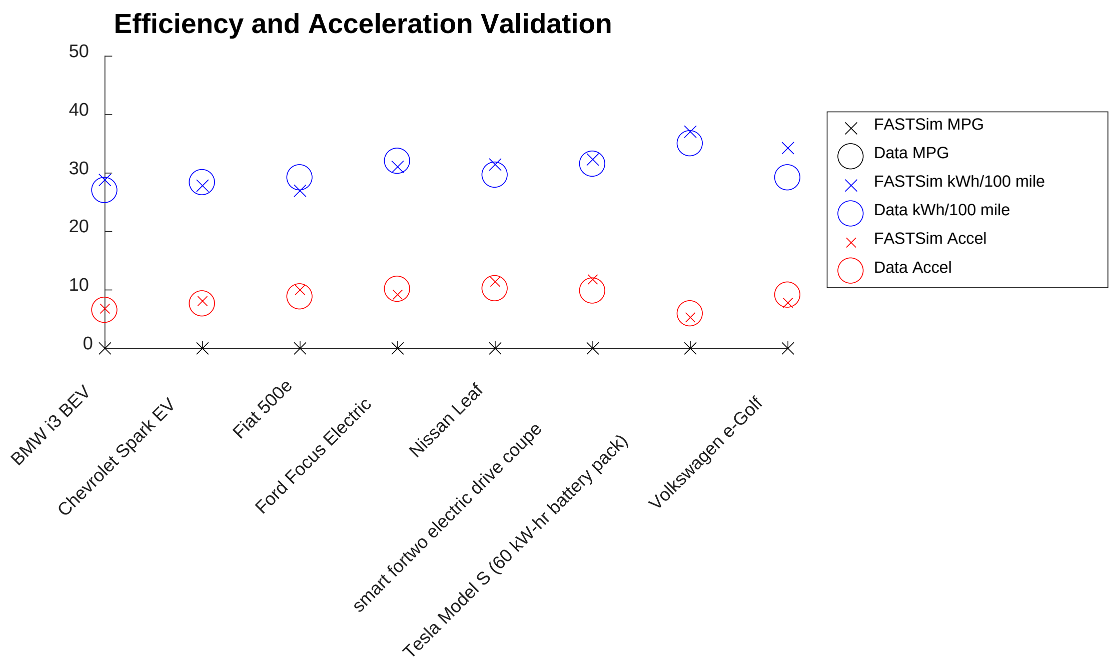

Figure 32. FASTSim electricity consumption (versus EPA window-sticker data) and acceleration (versus Zero to 60 Times website data) validation for recent EVs (with 2015 sales of more 1,000 vehicles) with partially vetted inputs

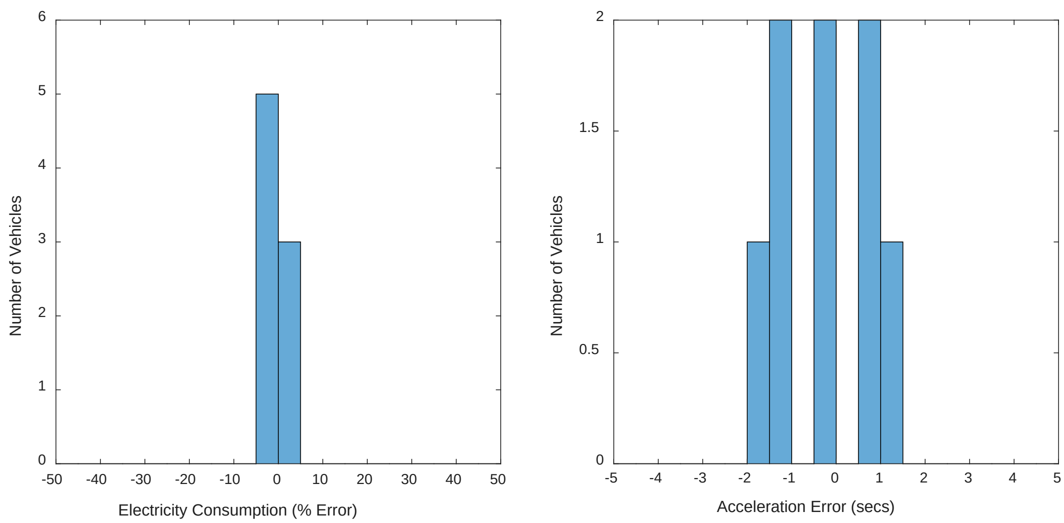

Figure 33. Histograms of error (difference between FASTSim-modeled and measured results) for electricity consumption and acceleration for partially vetted EVs

5 On-Road/Real-World Validation

The previous two sections focus on component- and vehicle-level modeling and validation within FASTSim's standard option. This section explores the more detailed end of the FASTSim continuum—the customized option with extensions (see Table 1). Specifically, it summarizes the calibration of FASTSim to an individual vehicle using chassis dynamometer data over standard drive cycles, followed by validation of the model against data collected during on-road operation of the vehicle. See Wood et al. (2017) for additional details.

First, chassis dynamometer data were collected from a four-cylinder, six-speed 2011 Ford Fusion—which is representative of a modern mid-size vehicle—at ANL's Advanced Powertrain Research Facility (APRF). Instrumentation of the vehicle included more than 27 channels of thermal data (Figure 34). The vehicle was exercised over a matrix of 16 dynamometer tests characterized by different drive cycles, initial thermal conditions, and ambient temperatures (Table 2).

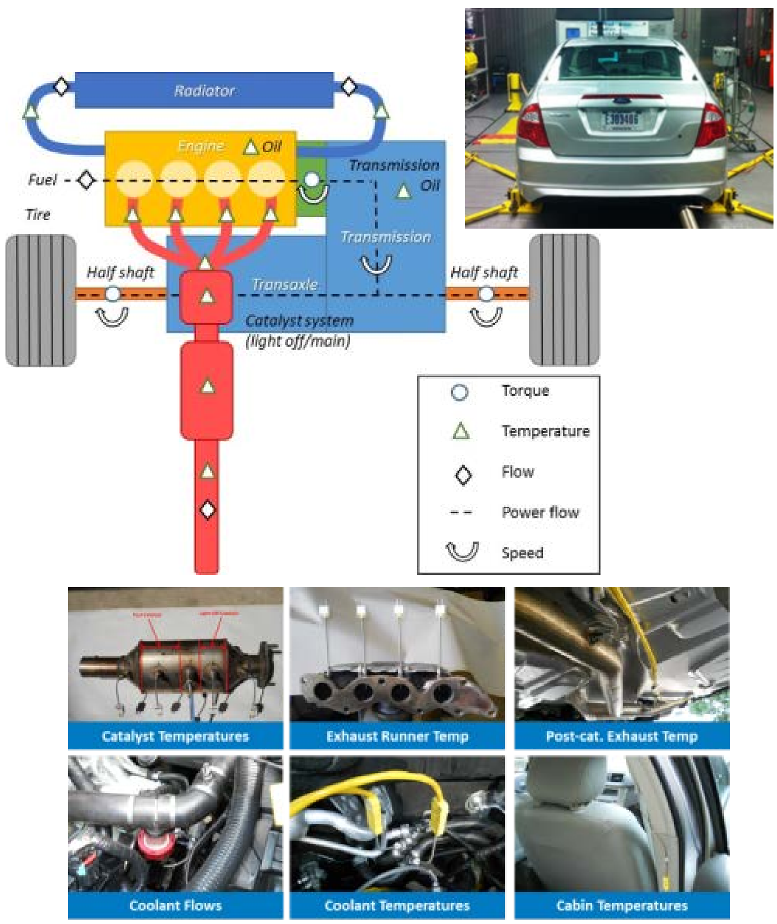

Figure 34. Instrumentation of Ford Fusion test vehicle

Photo credit: Forrest Jehlik, ANL

Table 2. Matrix of Dynamometer Tests

Variable	Values
Drive Cycle	UDDS x 2, US06 x 2
Start Condition	Hot start, cold start
Test Cell Temperature	-17°C, -7°C, +20°C, +35°C

The dynamometer data were then used to calibrate a customized FASTSim model of the Ford Fusion. This calibration included estimation of engine oil viscosity and fuel enrichment using lumped thermal models for engine oil/coolant and exhaust catalyst as well as modeling of mechanical losses relative to power and thermal state. The resulting model calculates fuel consumption to within 5.2% of measured data under all 16 test conditions, with a 2.4% root-mean-square error (RMSE); these differences are within the range of cycle-to-cycle dynamometer test uncertainty (Figure 35). For model validation, EPA 5-cycle testing was conducted at APRF, including the Federal Test Procedure (FTP), HWFET, US06, SC03, and Cold FTP, and the modeled fuel economy was within 3.0% of the measured data. To capture the impacts of cabin air-conditioning (A/C) use, a simplified cabin model was calibrated to APRF test data over the SC03 cycle, which showed 19.6 miles per gallon with the A/C on and 26.0 miles per gallon with the A/C off.

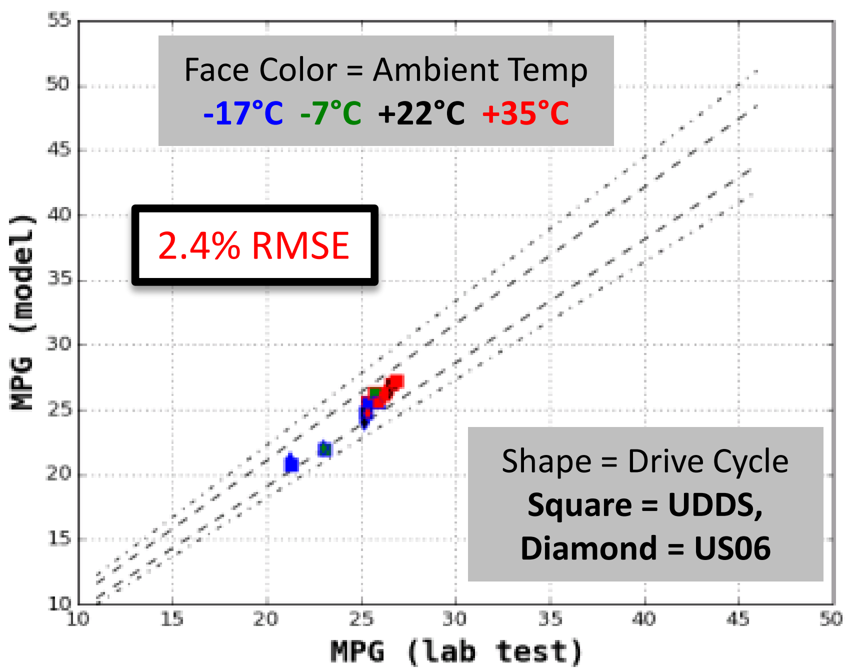

Figure 35. Calibration of FASTSim-modeled Ford Fusion fuel economy to dynamometer data

Next, NREL and ANL performed on-road testing of the Ford Fusion, retaining most of the instrumentation from the dynamometer testing but with some reconfiguration for mobile data collection. Important new elements included a global positioning system device for measuring vehicle position and a highly accurate inline fuel flow meter. The global positioning system device also enabled calculation of elevation via cross-referencing latitude/longitude data with a third-party elevation map and NREL-developed filtering routines. Overall, most of the instrumentation was customized for the testing, with less reliance on controller area network data. The driving of the instrumented vehicle represented a mix of various conditions known to impact fuel economy (Table 3).

Table 3. On-Road Testing Characteristics

Data-collection period	August–September 2015
Trip count	85
Total distance	2,843 miles
Trip average speeds	15 – 75 mph
Trip types	36 “highway” (≥ 40 mph avg. speed), 49 “city” (< 40 mph)
–Initial oil temps	20°C – 100°C (68°F – 212°F) 32 “hot” start (≥ 80°C), 53 “cold” start (< 80°C) trips
Ambient temps	17°C – 38°C (63°F – 100°F)
A/C status	31 trips with A/C on, 54 trips with A/C off
Elevation range	535 – 11,100 ft
Trips with elevation change of ± 3,000 ft	6

Figure 36 shows the validation of the customized FASTSim model against the on-road data. The shape and colors of the symbols signify various conditions as noted in the legend. Wind was not directly accounted for during the testing, but weather data suggested that winds of 5 – 10 mph were typical; thus, the figure includes error bars representing fuel economy impacts from 5-mph head/tail winds. Overall, the modeled and measured results match well, with an RMSE of 5.6%, showing that FASTSim trained on a limited set of dynamometer cycles can perform well over a broad range of real-world conditions (over which trip level fuel economy varies by over +/-50% from the average for the vehicle).

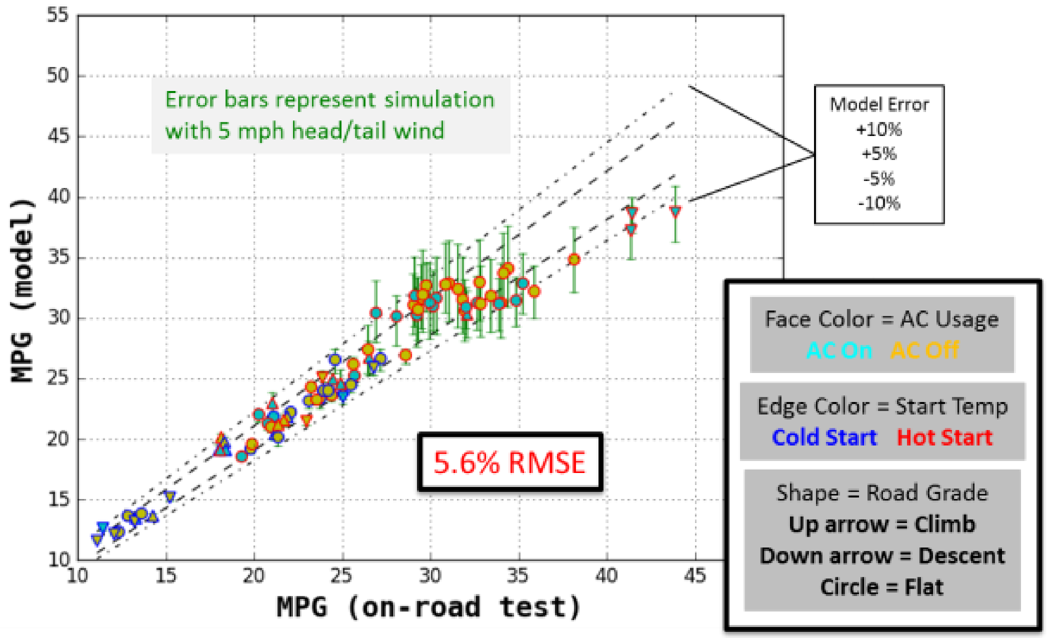

Figure 36. Validation of FASTSim-modeled versus measured fuel economy over on-road driving

Finally, Figure 37 breaks out the effects on the fit between FASTSim modeled and measured results due to the incorporation of various vehicle and environmental conditions. The baseline model produces considerably more variation, with an RMSE of 16.8%.[7] The largest improvements come from considering the thermal sensitivity of vehicle components and estimating road grade. Adjusting for air density improves the fit further, and accounting for cabin A/C load results in the final model with a 5.6% RMSE. Clearly effects not captured on a dynamometer are important for estimating real-world fuel economy. Further enhancements may include investigation of wheel set thermal sensitivities and the significance of wind on aerodynamic loads.

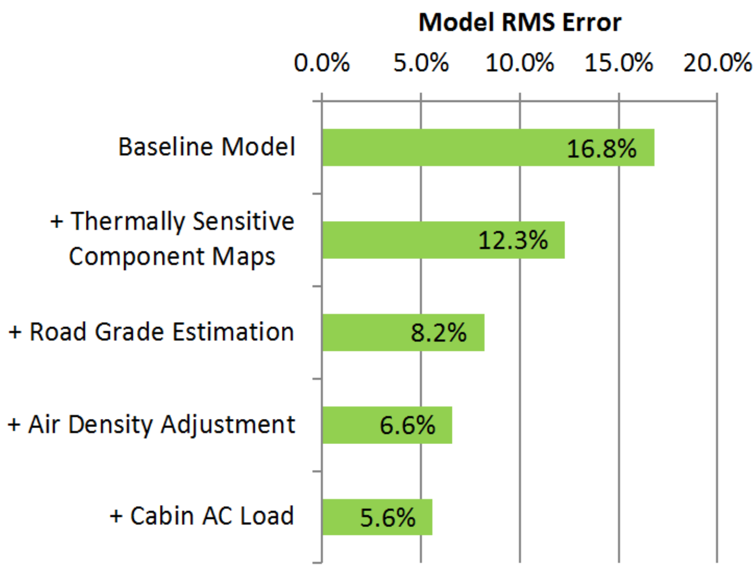

Figure 37. Effects on RMSE of incorporating various vehicle and environmental conditions into the FASTSim model

[7] The baseline includes Ford Fusion-specific engine mapping but assumes hot starts for each trip.

6 FASTSim Applications and Publications

A basic search of the peer-reviewed literature, using variations of FASTSim and NREL as search terms, yielded dozens of relevant publications. Most are from NREL, but the list also includes contributions from DOE, other national laboratories, automakers, the California Air Resources Board (CARB), and American and foreign universities and research centers. Figure 38 categorizes the FASTSim-related publications by investigating organization/sponsor. Appendix B lists all the publications. Several interesting examples are summarized below.

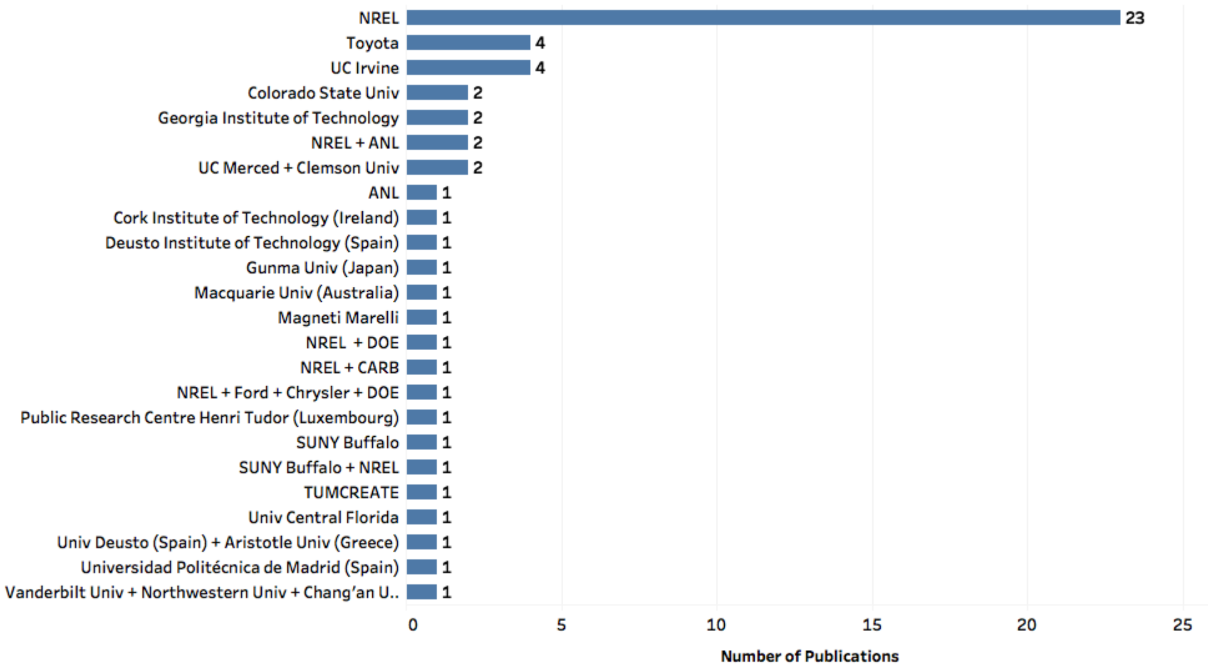

Figure 38. Number of FASTSim-related publications by investigating organization/sponsor

"Aerodynamic Drag Reduction Technologies Testing of Heavy-Duty Vocational Vehicles and a Dry Van Trailer"

Author/sponsor: NREL, CARB

Publication: NREL technical report

Publication year: 2016

Summary: On-road testing of commercial vehicles equipped with aerodynamic devices was used to calibrate FASTSim models, which were simulated over real-world drive cycles. This study complements EPA work on greenhouse gas regulations for commercial vehicles.

"Updating United States Advanced Battery Consortium and Department of Energy Battery Technology Targets for Battery Electric Vehicles"

Author/sponsor: NREL, Ford, Chrysler, DOE

Publication: *Journal of Power Sources*

Publication year: 2014

Summary: The United States Advanced Battery Consortium updated EV technology targets with the support of NREL modeling, including FASTSim. The result was an aggressive target, implying that (as of 2012) batteries needed considerable advancement to make EVs competitive.

“A Cluster Analysis Study of Opportune Adoption of Electric Drive Vehicles for Better Greenhouse Gas Reduction”

Author/sponsor: Toyota

Publication: ASME Design Automation Conference

Publication year: 2016

Summary: FASTSim was used to model real-world fuel economy from California global positioning system driving traces. The results suggest that the benefits of advanced technology vehicles are maximized when applied to specific driving patterns.

“The Importance of Grid Integration for Achievable Greenhouse Gas Emissions Reductions from Alternative Vehicle Technologies”

Author/sponsor: University of California – Irvine

Publication: *Energy*

Publication year: 2015

Summary: FASTSim was used within a larger framework to investigate California's Executive Order S-21-09 goal of achieving an 80% greenhouse gas reduction in light of EV interactions with the electric grid.

7 Summary

The primary advantage of FASTSim is its useful balance of modeling accuracy and complexity. It captures the most important factors influencing vehicle fuel economy and performance using simplified efficiency maps, 1-second time steps, and low data requirements for standard calibration. Little effort is required to set up and run numerous simulations.

At the same time, FASTSim is well validated. Its simplest modeling option with generic component maps provides good large-scale agreement. For most vehicles with fully vetted inputs, modeled results for fuel economy, electricity consumption, and acceleration are within 5% of measured data, and modeled results are within 10% of measured data for all vehicles. Even when using only partially vetted inputs, FASTSim-modeled fuel economy/electricity consumption is within 5%–10% of measured data for most vehicles, and modeled acceleration validates reasonably well. In addition, complexity can be added to FASTSim to accurately capture a range of real-world considerations such as road grade, A/C use, component thermal sensitivity, and air density as validated via detailed on-road testing.

FASTSim is also widely referenced. Of the numerous studies that use FASTSim, most are from NREL, but additional users include DOE, other national laboratories, automakers, CARB, and American and foreign universities and research centers.

Finally, public sponsorship and open-source code add transparency and credibility to FASTSim, making it well suited for analyses that must be shared and understood among multiple stakeholders such as automakers and regulatory agencies. In this capacity, it can be a powerful tool for building large-scale future scenarios of the type that might support public-interest discussions related to vehicle fuel economy and design.

References

Brooker, A., J. Gonder, L. Wang, E. Wood, S. Lopp, and L. Ramroth. 2015. "FASTSim: A Model to Estimate Vehicle Efficiency, Cost and Performance." SAE Technical Paper 2015-01-0973, doi:10.4271/2015-01-0973. http://www.nrel.gov/docs/fy15osti/63623.pdf.

Mahmud, K., and G. Town. 2016. "A Review of Computer Tools for Modeling Electric Vehicle Energy Requirements and Their Impact on Power Distribution Networks." *Applied Energy* 172: 337–359. http://dx.doi.org/10.1016/j.apenergy.2016.03.100.

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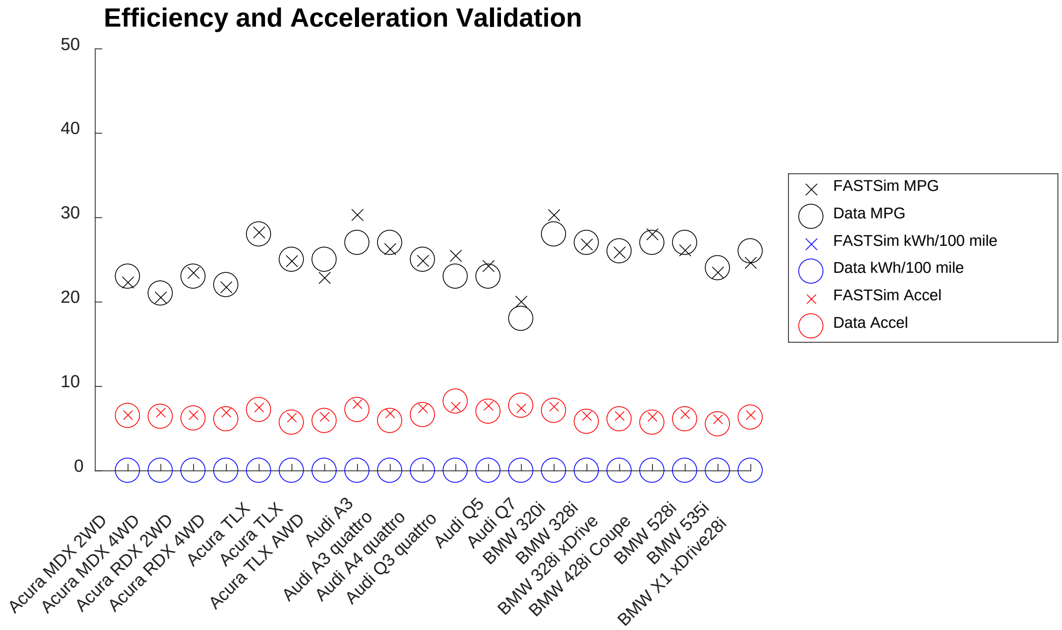
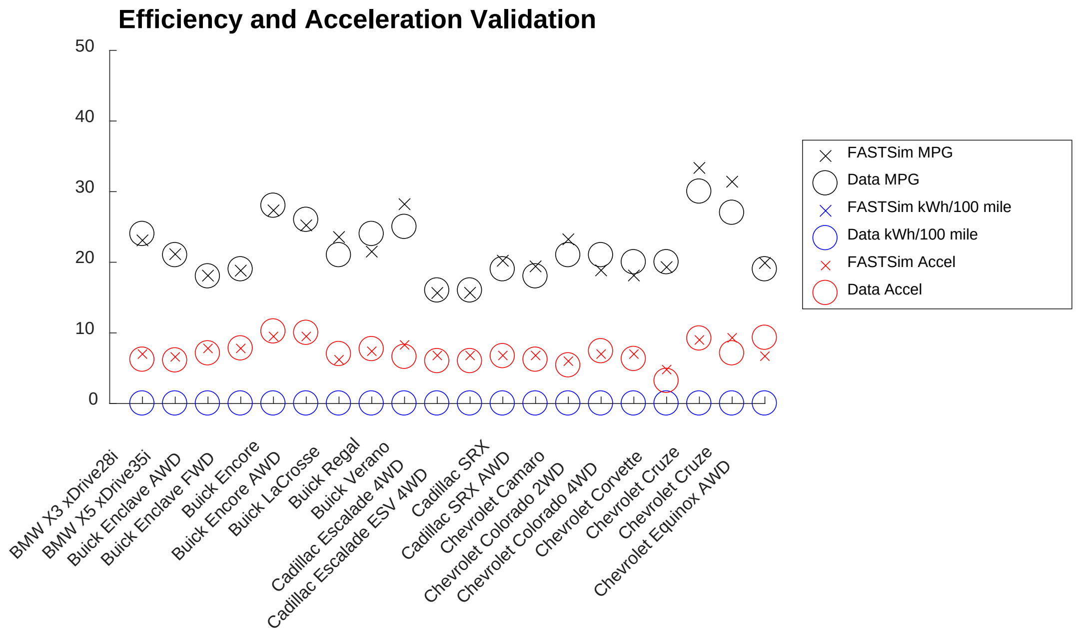
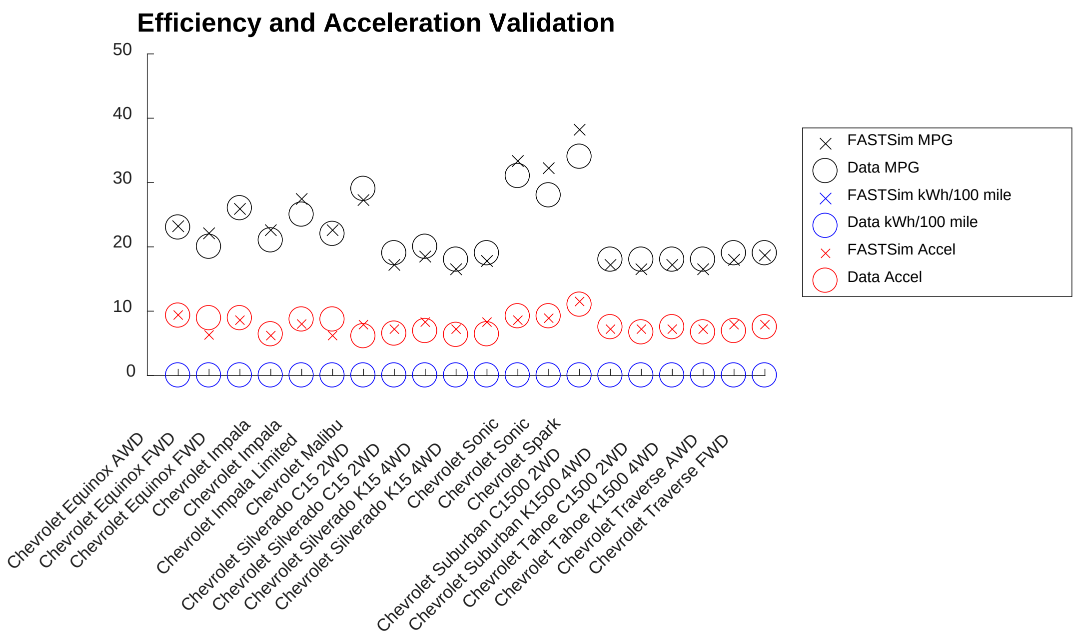
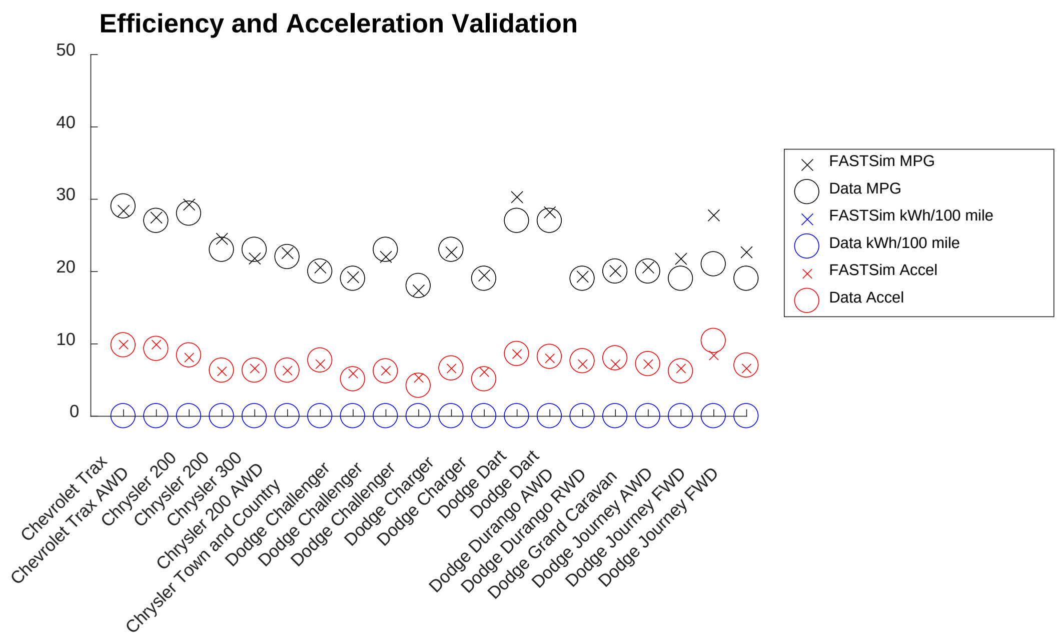
Appendix A: Partially Vetted Vehicle Validation Results

NREL includes information for more than 700 vehicles in its vehicle choice model, ADOPT. Currently the input data for these vehicles are undergoing quality assurance evaluation. Thus, the results shown here for the top-selling vehicles in the supporting data set are preliminary, and many show greater differences between FASTSim-modeled results and measured results than are present in the vetted vehicles discussed in Section 4.2.1. Duplicated vehicle labels represent the same vehicle with different options (4 cylinder versus 6 cylinder, for instance).






Efficiency and Acceleration Validation
50
40
30
20
10
0
FASTSim MPG
Data MPG
FASTSim kWh/100 mile
Data kWh/100 mile
FASTSim Accel
Data Accel
Chevrolet Equinox AWD
Chevrolet Equinox FWD
Chevrolet Equinox FWD
Chevrolet Impala
Chevrolet Impala
Chevrolet Impala Limited
Chevrolet Malibu
Chevrolet Silverado C15 2WD
Chevrolet Silverado C15 2WD
Chevrolet Silverado K15 4WD
Chevrolet Silverado K15 4WD
Chevrolet Sonic
Chevrolet Sonic
Chevrolet Spark
Chevrolet Suburban C1500 2WD
Chevrolet Suburban K1500 4WD
Chevrolet Tahoe C1500 2WD
Chevrolet Tahoe K1500 4WD
Chevrolet Traverse AWD
Chevrolet Traverse FWD


Efficiency and Acceleration Validation
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40
30
20
10
0
FASTSim MPG
Data MPG
FASTSim kWh/100 mile
Data kWh/100 mile
FASTSim Accel
Data Accel
Chevrolet Trax
Chevrolet Trax AWD
Chrysler 200
Chrysler 200
Chrysler 300
Chrysler 200 AWD
Chrysler Town and Country
Dodge Challenger
Dodge Challenger
Dodge Challenger
Dodge Charger
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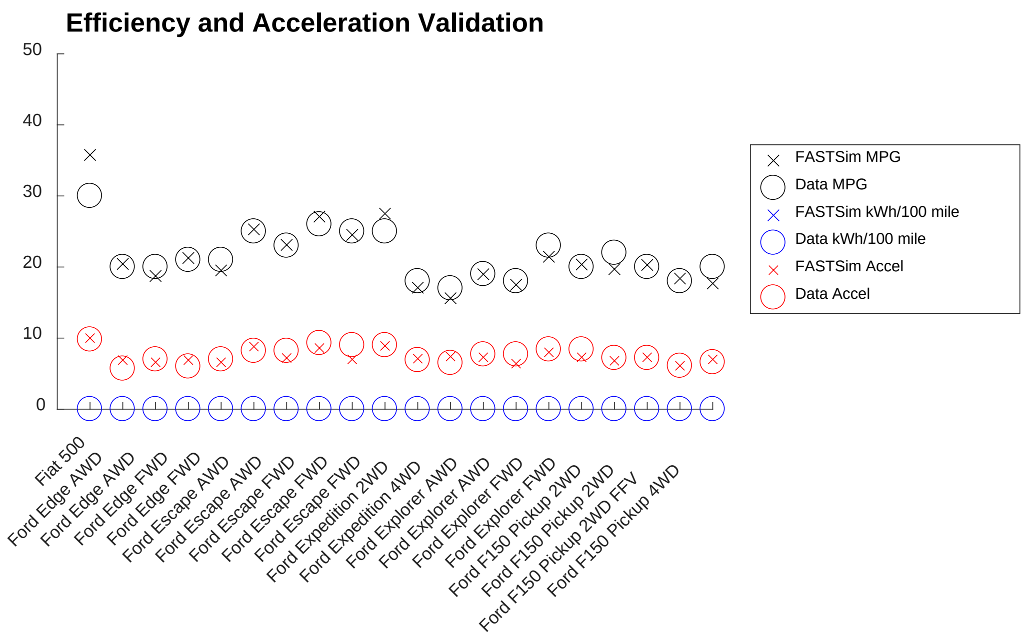
Dodge Journey FWD
Dodge Journey FWD



Efficiency and Acceleration Validation
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30
20
10
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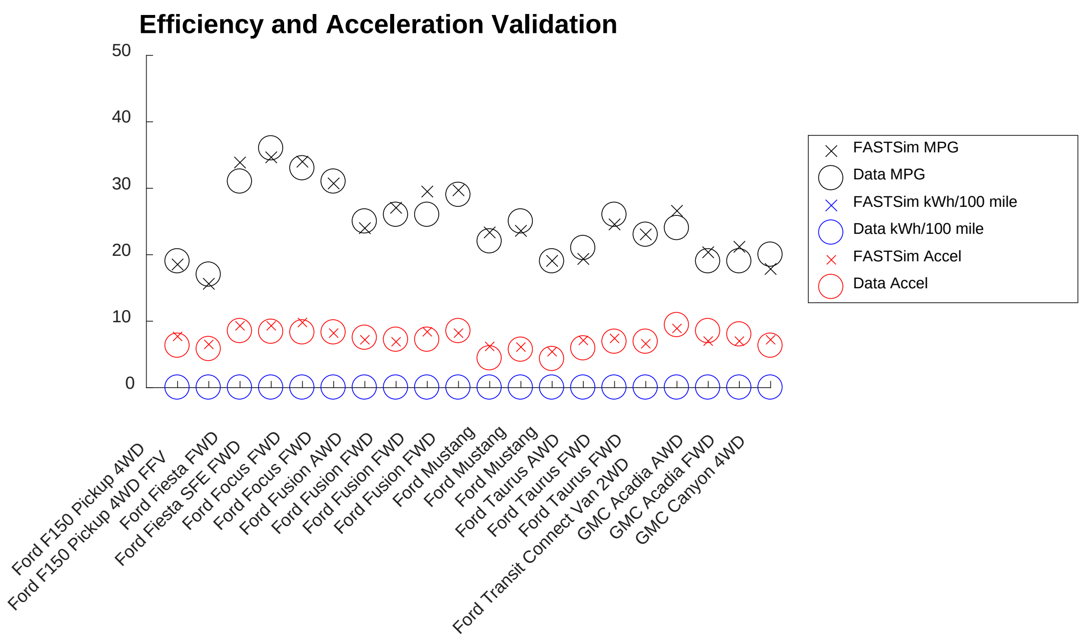
FASTSim MPG
Data MPG
FASTSim kWh/100 mile
Data kWh/100 mile
FASTSim Accel
Data Accel
Fiat 500
Ford Edge AWD
Ford Edge AWD
Ford Edge FWD
Ford Edge FWD
Ford Escape AWD
Ford Escape AWD
Ford Escape FWD
Ford Escape FWD
Ford Escape FWD
Ford Expedition 2WD
Ford Expedition 4WD
Ford Explorer AWD
Ford Explorer AWD
Ford Explorer FWD
Ford Explorer FWD
Ford F150 Pickup 2WD
Ford F150 Pickup 2WD
Ford F150 Pickup 2WD FFV
Ford F150 Pickup 4WD



Efficiency and Acceleration Validation
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40
30
20
10
0
FASTSim MPG
Data MPG
FASTSim kWh/100 mile
Data kWh/100 mile
FASTSim Accel
Data Accel
Ford F150 Pickup 4WD
Ford F150 Pickup 4WD FFV
Ford Fiesta FWD
Ford Fiesta SFE FWD
Ford Focus FWD
Ford Focus FWD
Ford Fusion AWD
Ford Fusion FWD
Ford Fusion FWD
Ford Fusion FWD
Ford Mustang
Ford Mustang
Ford Mustang
Ford Taurus AWD
Ford Taurus FWD
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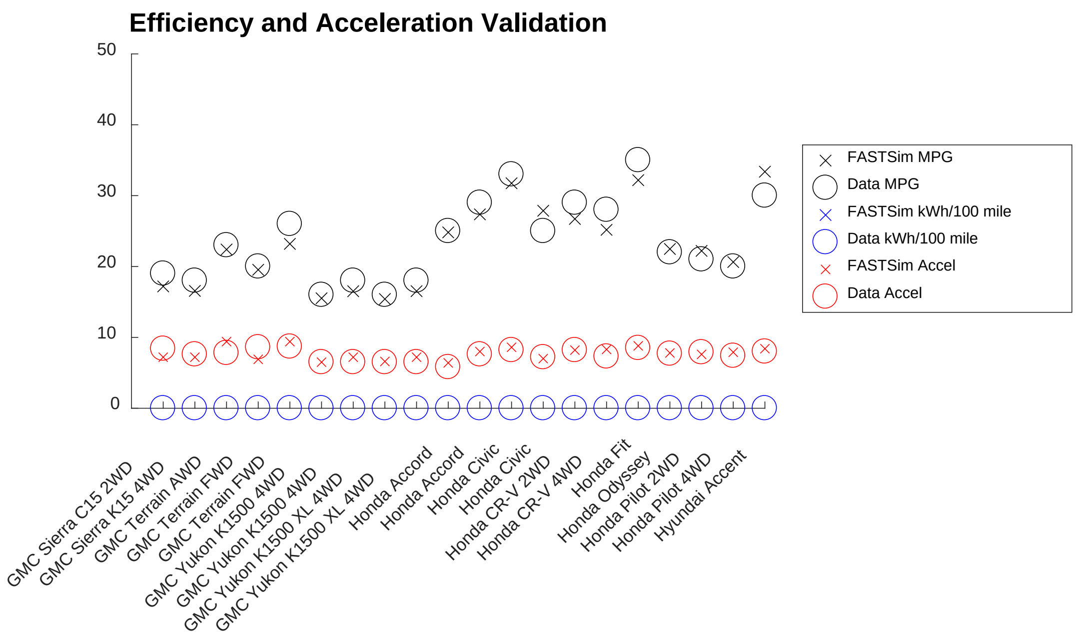
Ford Transit Connect Van 2WD
GMC Acadia AWD
GMC Acadia FWD
GMC Canyon 4WD



Efficiency and Acceleration Validation
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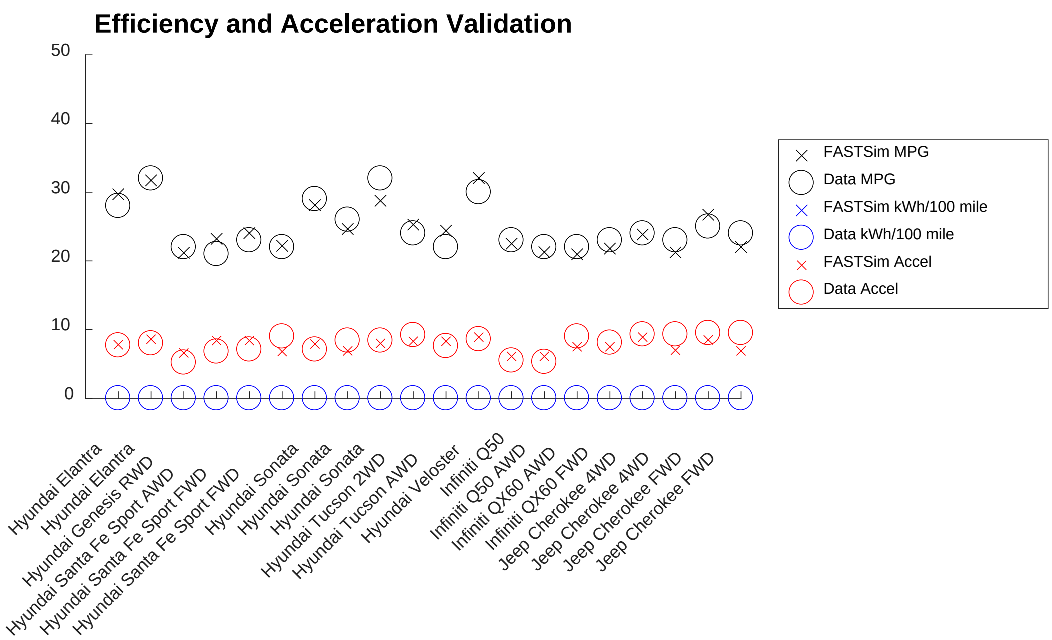
40
30
20
10
0
FASTSim MPG
Data MPG
FASTSim kWh/100 mile
Data kWh/100 mile
FASTSim Accel
Data Accel
GMC Sierra C15 2WD
GMC Sierra K15 4WD
GMC Terrain AWD
GMC Terrain FWD
GMC Terrain FWD
GMC Yukon K1500 4WD
GMC Yukon K1500 4WD
GMC Yukon K1500 XL 4WD
GMC Yukon K1500 XL 4WD
Honda Accord
Honda Accord
Honda Civic
Honda Civic
Honda CR-V 2WD
Honda CR-V 4WD
Honda Fit
Honda Odyssey
Honda Pilot 2WD
Honda Pilot 4WD
Hyundai Accent



Efficiency and Acceleration Validation
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20
10
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Data MPG
FASTSim kWh/100 mile
Data kWh/100 mile
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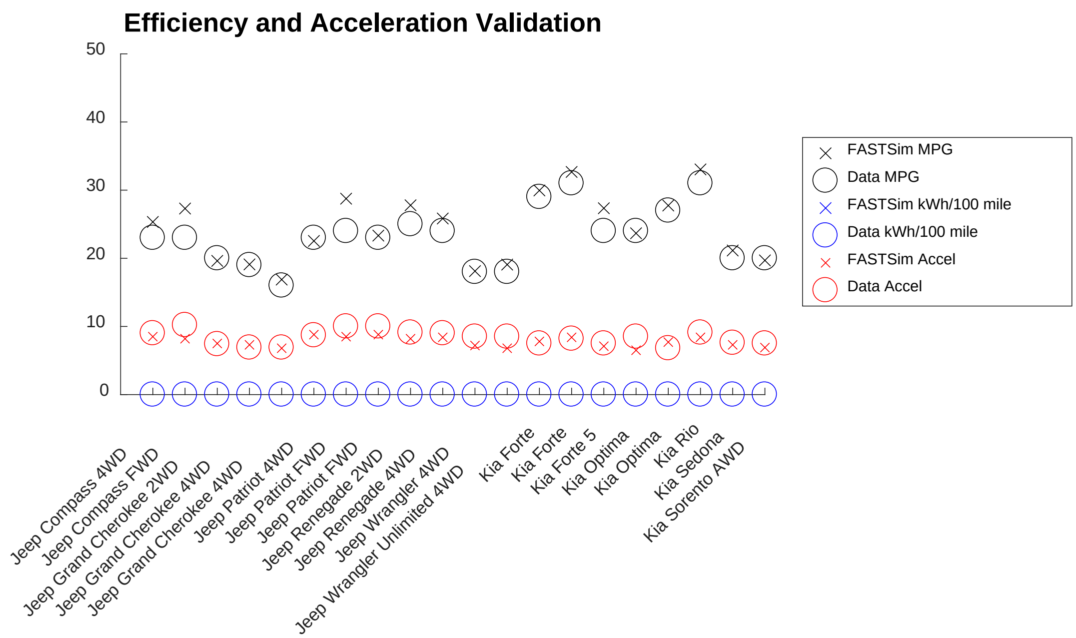
Data Accel
Hyundai Elantra
Hyundai Elantra
Hyundai Genesis RWD
Hyundai Santa Fe Sport AWD
Hyundai Santa Fe Sport FWD
Hyundai Santa Fe Sport FWD
Hyundai Sonata
Hyundai Sonata
Hyundai Sonata
Hyundai Tucson 2WD
Hyundai Tucson AWD
Hyundai Veloster
Infiniti Q50
Infiniti Q50 AWD
Infiniti QX60 AWD
Infiniti QX60 FWD
Jeep Cherokee 4WD
Jeep Cherokee 4WD
Jeep Cherokee FWD
Jeep Cherokee FWD



Efficiency and Acceleration Validation
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40
30
20
10
0
FASTSim MPG
Data MPG
FASTSim kWh/100 mile
Data kWh/100 mile
FASTSim Accel
Data Accel
Jeep Compass 4WD
Jeep Compass FWD
Jeep Grand Cherokee 2WD
Jeep Grand Cherokee 4WD
Jeep Grand Cherokee 4WD
Jeep Patriot 4WD
Jeep Patriot FWD
Jeep Patriot FWD
Jeep Renegade 2WD
Jeep Renegade 4WD
Jeep Wrangler 4WD
Jeep Wrangler Unlimited 4WD
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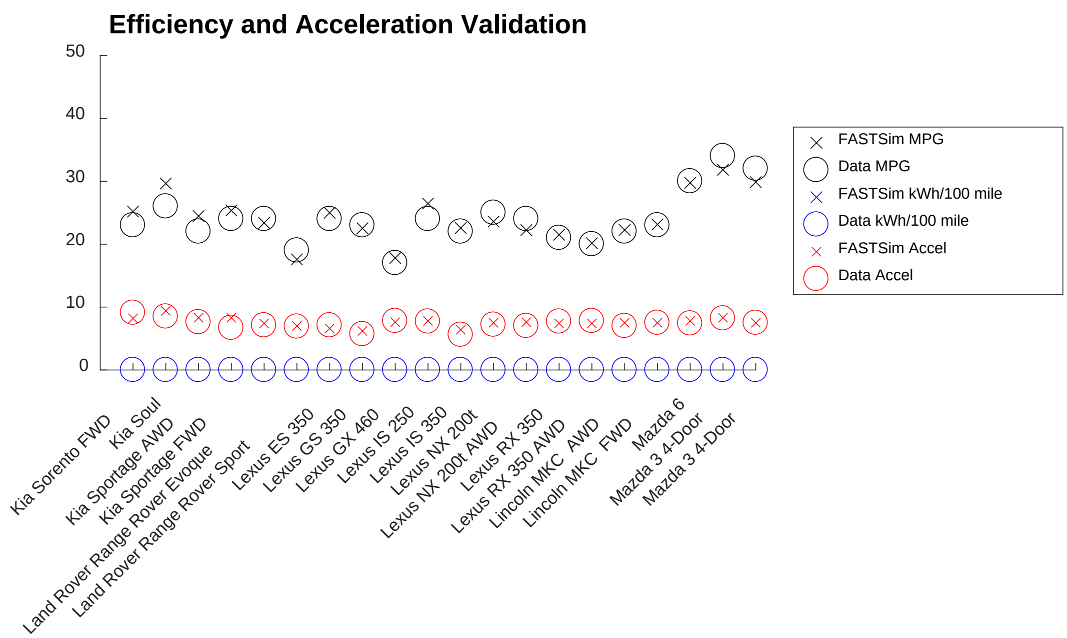
Kia Forte
Kia Forte 5
Kia Optima
Kia Optima
Kia Rio
Kia Sedona
Kia Sorento AWD



Efficiency and Acceleration Validation
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40
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FASTSim MPG
Data MPG
FASTSim kWh/100 mile
Data kWh/100 mile
FASTSim Accel
Data Accel
Kia Sorento FWD
Kia Soul
Kia Sportage AWD
Kia Sportage FWD
Land Rover Range Rover Evoque
Land Rover Range Rover Sport
Lexus ES 350
Lexus GS 350
Lexus GX 460
Lexus IS 250
Lexus IS 350
Lexus NX 200t
Lexus NX 200t AWD
Lexus RX 350
Lexus RX 350 AWD
Lincoln MKC AWD
Lincoln MKC FWD
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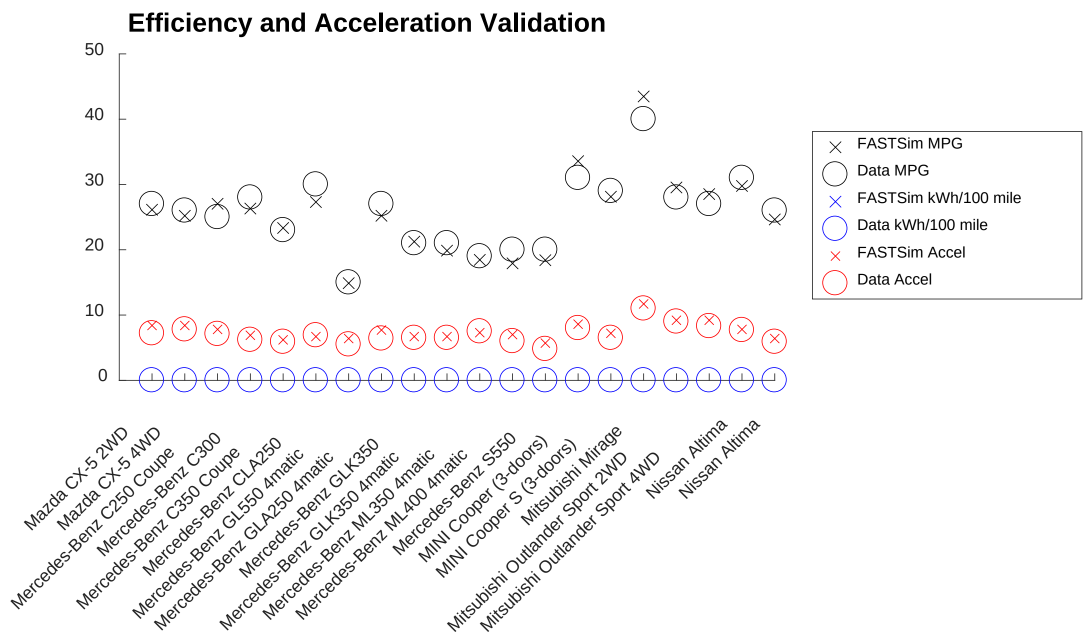
Mazda 3 4-Door
Mazda 3 4-Door


Efficiency and Acceleration Validation
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10
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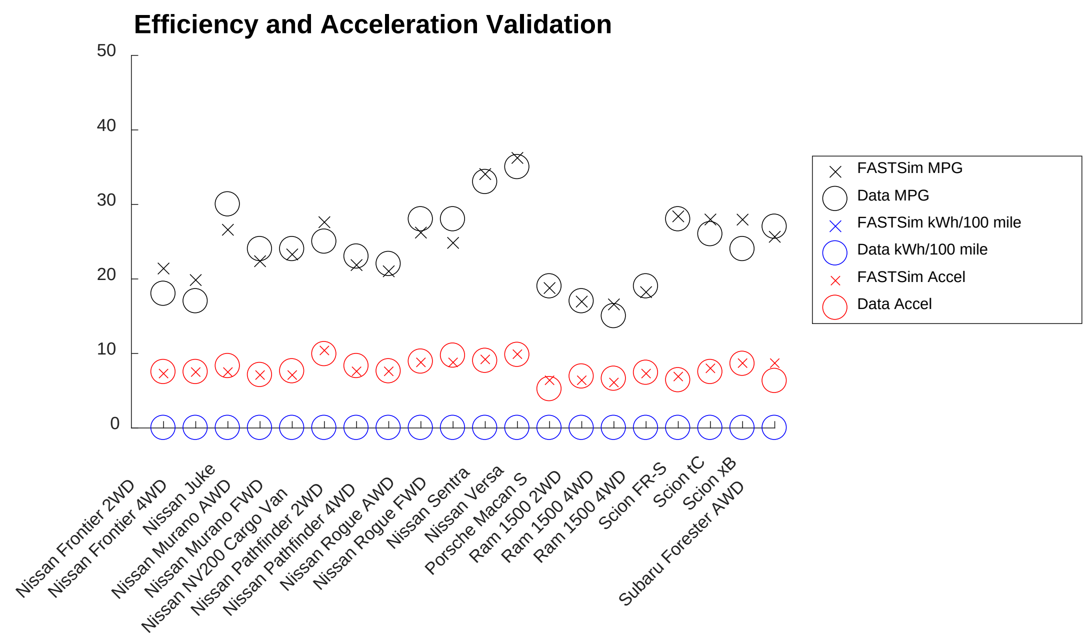
Data MPG
FASTSim kWh/100 mile
Data kWh/100 mile
FASTSim Accel
Data Accel
Mazda CX-5 2WD
Mazda CX-5 4WD
Mercedes-Benz C250 Coupe
Mercedes-Benz C300
Mercedes-Benz C350 Coupe
Mercedes-Benz CLA250
Mercedes-Benz GL550 4matic
Mercedes-Benz GLA250 4matic
Mercedes-Benz GLK350
Mercedes-Benz GLK350 4matic
Mercedes-Benz ML350 4matic
Mercedes-Benz ML400 4matic
Mercedes-Benz S550
MINI Cooper (3-doors)
MINI Cooper S (3-doors)
Mitsubishi Mirage
Mitsubishi Outlander Sport 2WD
Mitsubishi Outlander Sport 4WD
Nissan Altima
Nissan Altima


Efficiency and Acceleration Validation
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FASTSim kWh/100 mile
Data kWh/100 mile
FASTSim Accel
Data Accel
Nissan Frontier 2WD
Nissan Frontier 4WD
Nissan Juke
Nissan Murano AWD
Nissan Murano FWD
Nissan NV200 Cargo Van
Nissan Pathfinder 2WD
Nissan Pathfinder 4WD
Nissan Rogue AWD
Nissan Rogue FWD
Nissan Sentra
Nissan Versa
Porsche Macan S
Ram 1500 2WD
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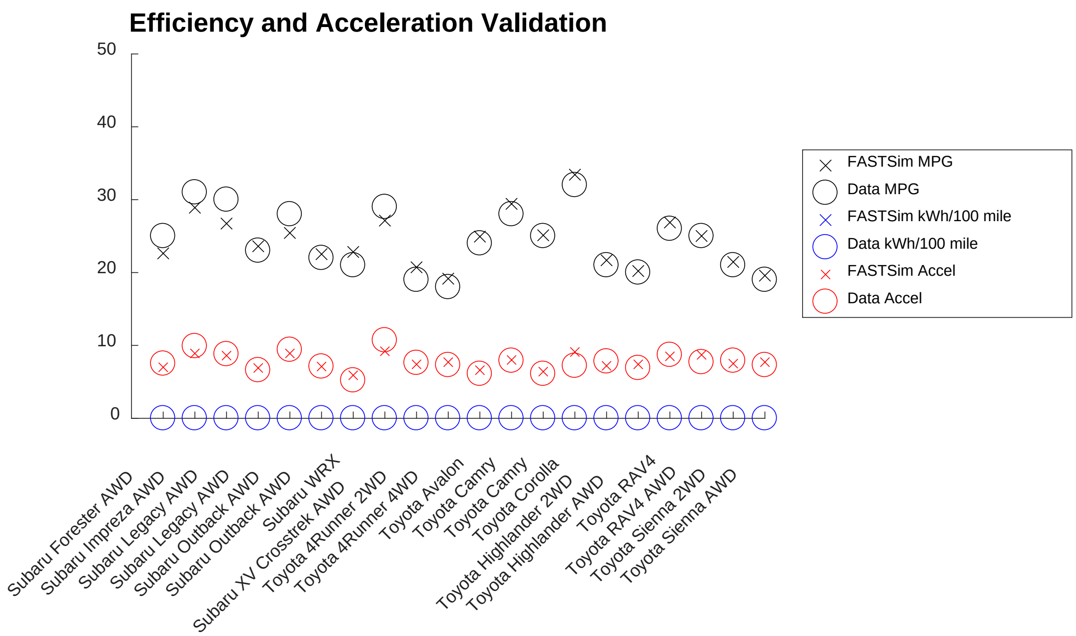
Ram 1500 4WD
Scion FR-S
Scion tC
Scion xB
Subaru Forester AWD



Efficiency and Acceleration Validation
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Data MPG
FASTSim kWh/100 mile
Data kWh/100 mile
FASTSim Accel
Data Accel
Subaru Forester AWD
Subaru Impreza AWD
Subaru Legacy AWD
Subaru Legacy AWD
Subaru Outback AWD
Subaru Outback AWD
Subaru WRX
Subaru XV Crosstrek AWD
Toyota 4Runner 2WD
Toyota 4Runner 4WD
Toyota Avalon
Toyota Camry
Toyota Camry
Toyota Corolla
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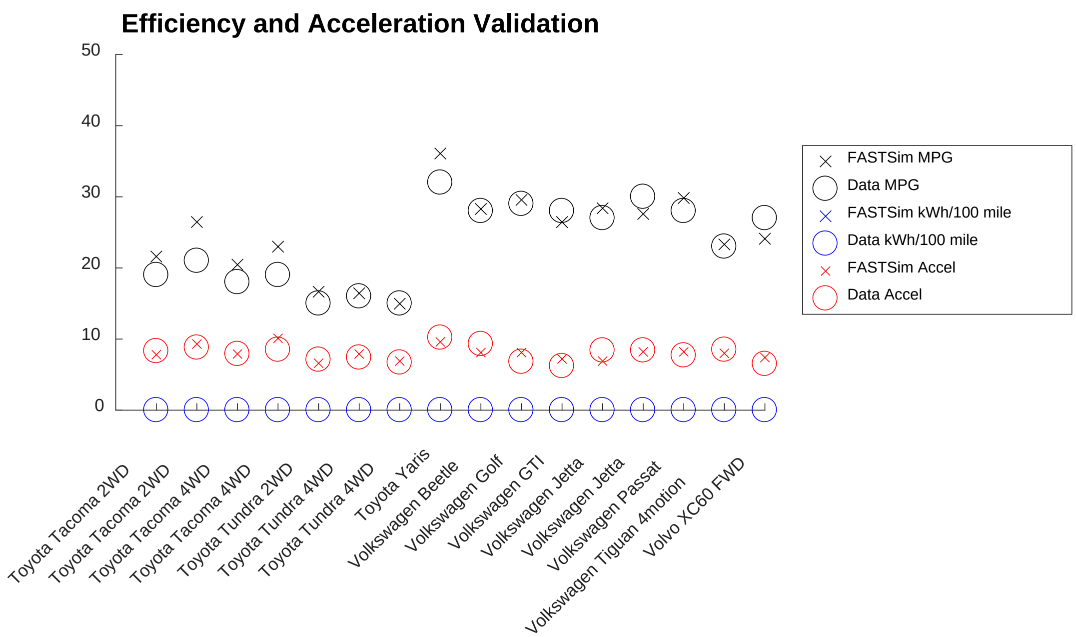
Toyota RAV4
Toyota RAV4 AWD
Toyota Sienna 2WD
Toyota Sienna AWD



Efficiency and Acceleration Validation
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20
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FASTSim MPG
Data MPG
FASTSim kWh/100 mile
Data kWh/100 mile
FASTSim Accel
Data Accel
Toyota Tacoma 2WD
Toyota Tacoma 2WD
Toyota Tacoma 4WD
Toyota Tacoma 4WD
Toyota Tundra 2WD
Toyota Tundra 4WD
Toyota Tundra 4WD
Toyota Yaris
Volkswagen Beetle
Volkswagen Golf
Volkswagen GTI
Volkswagen Jetta
Volkswagen Jetta
Volkswagen Passat
Volkswagen Tiguan 4motion
Volvo XC60 FWD

Appendix B: Studies Using FASTSim

Title	Authors	Affiliation	Year	Publication
Quantifying Uncertainty in Vehicle Simulation Studies	Geller and Bradley	Colorado State University	2012	SAE World Congress
Increasing the Fuel Economy of Connected and Autonomous Lithium-Ion Electrified Vehicles	Asher et al.	Colorado State University	2018	Behaviour of Lithium-Ion Batteries in Electric Vehicles
Analysis of Electric Vehicle Powertrain Simulators for Fuel Consumption Calculations	Davis and Hayes	Cork Institute of Technology	2016	Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference
Regression Based Emission Models for Vehicle Contribution to Climate Change	Pijoan et al.	Deusto Institute of Technology	2016	Advances in Intelligent Systems and Computing
Assessment of Alternative Fuel and Powertrain Transit Bus Options using Real-World Operations Data: Life-Cycle Fuel and Emissions Modeling	Yanzhi et al.	Georgia Institute of Technology	2015	Applied Energy
Optimization of Fuel Economy of Hybrid Electric Vehicles using Set Based Dynamic Programming	Ramaswamy and Sadegh	Georgia Institute of Technology	2014	ASME Dynamic Systems and Control Conference
Impact of Powertrain Electrification, Vehicle Size Reduction and Lightweight Materials Substitution on Energy Use, CO_2 Emissions and Cost of a Passenger Light-Duty Vehicle Fleet	González Palencia et al.	Gunma University (Japan)	2015	Energy
A Review of Computer Tools for Modeling Electric Vehicle Energy Requirements and Their Impact on Power Distribution Networks	Mahmud and Town	Macquarie University (Australia)	2016	Applied Energy
Technology Comparison for Spark Ignition Engines of New Generation	De Cesare et al.	Magneti Marelli	2017	SAE International Journal of Engines
Green Routing Fuel Saving Opportunity Assessment: A Case Study Using Large-Scale Real-World Travel Data	Zhu et al.	NREL	2017	IEEE Intelligent Vehicles Symposium

Title	Authors	Affiliation	Year	Publication
Modeling Control Strategies and Range Impacts for Electric Vehicle Integrated Thermal Management Systems with MATLAB/Simulink	Titov and Lustbader	NREL	2017	SAE World Congress
Sensitivity of Battery Electric Vehicle Economics to Drive Patterns, Vehicle Range, and Charge Strategies	Neubauer et al.	NREL	2012	Journal of Power Sources
Sensitivity of Plug-In Hybrid Electric Vehicle Economics to Drive Patterns, Electric Range, Energy Management, and Charge Strategies	Neubauer et al.	NREL	2013	Journal of Power Sources
A Cost Effectiveness Analysis of Quasi-Static Wireless Power Transfer for Plug-In Hybrid Electric Transit Buses	Wang et al.	NREL	2015	IEEE–Vehicular Power and Propulsion Conference
ADOPT: A Historically Validated Light Duty Vehicle Consumer Choice Model	Brooker et al.	NREL	2015	SAE World Congress & Exhibition
Aerodynamic Drag Reduction Technologies Testing of Heavy-Duty Vocational Vehicles and A Dry Van Trailer	Ragatz and Thornton	NREL	2016	NREL Technical Report
An Opportunistic Wireless Charging System Design for an On-Demand Shuttle Service	Doubleday et al.	NREL	2016	IEEE Transportation Electrification Conference
Analysis of In-Route Wireless Charging for the Shuttle System at Zion National Park	Meintz et al.	NREL	2016	2016 IEEE PELS Workshop on Emerging Technologies
Assessing the Battery Cost at which Plug-In Hybrid Medium-Duty Parcel Delivery Vehicles Become Cost-Effective	Ramroth et al.	NREL	2013	SAE World Congress & Exhibition
Combined Fluid Loop Thermal Management for Electric Drive Vehicle Range Improvement	Leighton	NREL	2015	SAE World Congress & Exhibition
Contribution of Road Grade to the Energy Use of Modern Automobiles across Large Datasets of Real-World Drive Cycles	Wood et al.	NREL	2014	SAE World Congress
Evaluating the Impact of Road Grade on Simulated Commercial Vehicle Fuel Economy using Real-World Drive Cycles	Lopp et al.	NREL	2015	SAE Commercial Vehicle Engineering Congress

Title	Authors	Affiliation	Year	Publication
FASTSim: A Model to Estimate Vehicle Efficiency, Cost and Performance	Brooker et al.	NREL	2015	SAE World Congress & Exhibition
Measuring the Benefits of Public Chargers and Improving Infrastructure Deployments using Advanced Simulation Tools	Wood et al.	NREL	2015	SAE World Congress and Exhibition
Modeling Heavy/Medium-Duty Fuel Consumption based on Drive Cycle Properties	Wang et al.	NREL	2015	SAE Commercial Vehicle Engineering Congress
Overcoming the Range Limitation of Medium-Duty Battery Electric Vehicles through the Use of Hydrogen Fuel-Cells	Wood et al.	NREL	2013	SAE Commercial Vehicle Engineering Congress
Quantifying the Effect of Fast Charger Deployments on Electric Vehicle Utility and Travel Patterns via Advanced Simulation	Wood et al.	NREL	2015	SAE World Congress and Exhibition
Quantitative Effects of Vehicle Parameters on Fuel Consumption for Heavy-Duty Vehicle	Wang et al.	NREL	2015	SAE Commercial Vehicle Engineering Congress
Technology Improvement Pathways to Cost-Effective Vehicle Electrification	Brooker et al.	NREL	2010	SAE World Congress
The Evaluation of the Impact of New Technologies for Different Powertrain Medium-Duty Trucks on Fuel Consumption	Wang et al.	NREL	2016	SAE Technical Paper
Thru-life Impacts of Driver Aggression, Climate, Cabin Thermal Management, and Battery Thermal Management on Battery Electric Vehicle Utility	Neubauer and Wood	NREL	2014	Journal of Power Sources
Variability of Battery Wear in Light Duty Plug-In Electric Vehicles Subject to Ambient Temperature, Battery Size, and Consumer Usage	Wood et al.	NREL	2012	International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium 26
Will Your Battery Survive a World with Fast Chargers?	Neubauer and Wood	NREL	2015	SAE World Congress & Exhibition
On-Road Validation of a Simplified Model for Estimating Real-World Fuel Economy	Wood et al.	NREL + ANL	2017	SAE World Congress Experience

Title	Authors	Affiliation	Year	Publication
Simulated Real-World Energy Impacts of a Thermally Sensitive Powertrain Considering Viscous Losses and Enrichment	Wood et al.	NREL + ANL	2015	SAE World Congress and Exhibition
Assessing the Energy Impact of Traffic Management and Vehicle Hybridization	Karbowski et al.	ANL	2016	International Journal of Complexity in Applied Science and Technology
Lightweighting Impacts on Fuel Economy, Cost, and Component Losses	Brooker et al.	NREL + DOE	2013	SAE World Congress & Exhibition
Updating United States Advanced Battery Consortium and Department of Energy Battery Technology Targets for Battery Electric Vehicles	Neubauer et al.	NREL + Ford + Chrysler + DOE	2014	Journal of Power Sources
Combining Agent-Based Modeling and Life Cycle Assessment for the evaluation of mobility policies	Florent and Enrico	Public Research Centre Henri Tudor (Luxembourg)	2015	Environmental Science & Technology
Suitability of Synthetic Driving Profiles from Traffic Micro-Simulation for Real-World Energy Analysis	Hou et al.	SUNY Buffalo + NREL	2015	22nd ITS World Congress
Design and Evaluation of Cyber Transportation Systems	Hou	SUNY Buffalo	2016	PhD Dissertation
A Study of Greenhouse Gas Emissions Reduction Opportunity in Light-Duty Vehicles by Analyzing Real Driving Patterns	Laberteaux and Hamza	Toyota	2017	SAE World Congress
Highlighting the Differential Benefit in Greenhouse Gas Reduction via Adoption of Plugin Hybrid Vehicles for Different Patterns of Real Driving	Laberteaux and Hamza	Toyota	2017	SAE World Congress
A Cluster Analysis Study of Opportune Adoption of Electric Drive Vehicles for Better Greenhouse Gas Reduction	Hamza and Laberteaux	Toyota	2016	ASME Design Automation Conference
An Energy Reallocation Model for Estimation of Equivalent Greenhouse Gas Emissions of Various Charging Behaviors of Plugin Hybrid Electric Vehicles	Hamza and Laberteaux	Toyota	2016	SAE International Journal of Alternative Powertrains
Methodology to Evaluate the Operational Suitability of Electromobility Systems for Urban Logistics Operations	Teoh et al.	TUMCREATE	2016	Transportation Research Procedia

Title	Authors	Affiliation	Year	Publication
Modelling the Effect of Driving Events on Electrical Vehicle Energy Consumption Using Inertial Sensors in Smartphones	Jiménez et al.	Universidad Politécnica de Madrid	2018	Energies
Assessing the Stationary Energy Storage Equivalency of Vehicle-to-Grid Charging Battery Electric Vehicles	Tarroja et al.	University of California Irvine	2016	Energy
Plug-in Fuel Cell Electric Vehicles: A California Case Study	Lane et al.	University of California Irvine	2017	International Journal of Hydrogen Energy
Charging a Renewable Future: The Impact of Electric Vehicle Charging Intelligence on Energy Storage Requirements to Meet Renewable Portfolio Standards	Forrest et al.	University of California Irvine	2016	Journal of Power Sources
The Importance of Grid Integration for Achievable Greenhouse Gas Emissions Reductions from Alternative Vehicle Technologies	Tarroja et al.	University of California Irvine	2015	Energy
Optimal Design and Techno-Economic Analysis of a Hybrid Solar Vehicle: Incorporating Solar Energy as an On-Board Fuel toward Future Mobility	Abdelhamid et al.	University of California, Merced + Clemson University	2016	ASME International Conference on Advanced Vehicle Technologies
Impacts of Adding Photovoltaic Solar System On-Board to Internal Combustion Engine Vehicles towards Meeting 2025 Fuel Economy CAFE Standards	Abdelhamid et al.	University of California, Merced + Clemson University	2016	SAE International Journal of Alternative Powertrains
Electric Vehicle Cost, Emissions, and Water Footprint in the United States: Development of a Regional Optimization Model	Noori et al.	University of Central Florida	2015	Energy
A Computationally Efficient Simulation Model for Estimating Energy Consumption of Electric Vehicles in the Context of Route Planning Applications	Genikomsakis and Mitrentsis	University of Deusto (Spain), Aristotle University of Thessaloniki (Greece)	2017	Transportation Research Part D: Transport and Environment
In-Use Energy and CO2 emissions Impact of a Plug-In Hybrid and Battery Electric Vehicle based on Real-World Driving	Chen et al.	Vanderbilt University	2017	International Journal of Environmental Science and Technology

Title	Authors	Affiliation	Year	Publication
Quantifying Uncertainty in Vehicle Simulation Studies	Geller and Bradley	Colorado State University	2012	SAE World Congress
Increasing the Fuel Economy of Connected and Autonomous Lithium-Ion Electrified Vehicles	Asher et al.	Colorado State University	2018	Behaviour of Lithium-Ion Batteries in Electric Vehicles
Analysis of Electric Vehicle Powertrain Simulators for Fuel Consumption Calculations	Davis and Hayes	Cork Institute of Technology	2016	Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference
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A Review of Computer Tools for Modeling Electric Vehicle Energy Requirements and Their Impact on Power Distribution Networks	Mahmud and Town	Macquarie University (Australia)	2016	Applied Energy
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Green Routing Fuel Saving Opportunity Assessment: A Case Study Using Large-Scale Real-World Travel Data	Zhu et al.	NREL	2017	IEEE Intelligent Vehicles Symposium

Title	Authors	Affiliation	Year	Publication
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Sensitivity of Plug-In Hybrid Electric Vehicle Economics to Drive Patterns, Electric Range, Energy Management, and Charge Strategies	Neubauer et al.	NREL	2013	Journal of Power Sources
A Cost Effectiveness Analysis of Quasi-Static Wireless Power Transfer for Plug-In Hybrid Electric Transit Buses	Wang et al.	NREL	2015	IEEE–Vehicular Power and Propulsion Conference
ADOPT: A Historically Validated Light Duty Vehicle Consumer Choice Model	Brooker et al.	NREL	2015	SAE World Congress & Exhibition
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