

Extended Modeling, Calibration and Validity Assessment of Vehicle Models in Future Automotive Systems Technology Simulator via Real-World Driving Data

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Abstract

Software simulation tools for vehicle fuel economy/energy efficiency can play an important role in strategic decisions about advanced powertrains. One such tool that has been developed by the National Renewable Energy Laboratory (NREL) is known as FASTSim. The philosophy of FASTSim aims to strike a difficult balance between simplifying the task of creating/editing vehicle models, fast computation time and high-fidelity simulation results. In the “baseline” version of FASTSim, which is open-source and freely available in Python or Excel, the instantaneous efficiency of an engine, motor or fuel cell is estimated via reference curves as function of power demand. The reference efficiency curve for each powertrain subsystem (e.g. for a spark-ignition engine) in baseline FASTSim has the same profile irrespective of what vehicle is being modelled, which is a compromise in accuracy in favor of ease of modeling. This paper utilizes an open-source Java implementation of FASTSim with capability for custom efficiency curves for engine and motor, along with a large dataset of real-world vehicle trips to calibrate and validate FASTSim vehicle models for three Battery Electric Vehicles (BEVs), four Plug-in Hybrid Electric Vehicles (PHEVs), one non-plug-in Hybrid Electric Vehicle (HEV) and one conventional internal combustion engine (ICE) vehicle. An ultimate goal in vehicle modeling, is for the simulation results to closely match the real-world trip data for every trip, but such a goal is difficult due to many uncertainties in real-world trips. Instead, results show that it is possible to achieve high fidelity for an aggregate of several trips, and the modeling fidelity improves with less uncertainty in trips information, such as when road slope and cabin heating/cooling loads are known.

Introduction

A wide variety of approaches and software tools exist for modeling of vehicle fuel economy/energy efficiency. From a categorical [1] standpoint, it may be useful to distinguish between approaches that attempt to model and replicate the performance of individual powertrain components, also referred to as physics-based approaches (or “White box” in [1]), empirical approaches that are primarily data-inference based (referred to as “Black box” in [1]), and hybrid approaches or “Gray box” [1], which attempt to combine traits of both physics-based and data inference approaches. Black-box models have the advantage in being grounded to real-world data when estimating average vehicle performance across many owners,

however, such models may be less accurate when considering unconventional cases that are off the typical norm. Moreover, real-world data for calibration of such models often lags by up to a few years. A simple and commonly used example black-box model is the US Environmental Protection Agency (EPA) fuel economy labels [2], where the fuel economy of a vehicle can be one of three numbers corresponding to “city”-like driving, “highway”-like driving or “combined”. Other black-box type models in utilization by US government agencies include MOVES [3] and EMFAC [4]. Among several physics based models for vehicle fuel economy simulation, two of which are endorsed by the US Department of Energy [5]; Autonomie [6] and FASTSim [7], both of which have been utilized in peer-reviewed work in the literature [8-13]. Furthermore, both Autonomie and FASTSim have been utilized in studies/reports that aim to gauge/shape the future of transportation in the US [14-16]. With such an important topic in discussion, it is beneficial to continuously conduct assessments and validation of the fuel economy simulation models.

As a general rule of thumb in physics-based models, higher degree of detail in modeling the powertrain components and vehicle generally leads to better accuracy in the simulation results, but that usually comes at the expense of higher computational resources requirement [17]. To the authors’ understanding, the development FASTSim philosophy had been to aim for a good trade-off between fast computations that are still capable of providing reasonable accuracy [13], a modeling strategy that is very beneficial for studies that involve the simulation of a large number of trips, such as some of the authors’ past work [18, 19]. More recently, FASTSim has become a key component in a partnership between the National Renewable Energy Laboratory (NREL) and Google, which aims at developing Eco-friendly routing for Google Maps [20]. Previous work by the authors in [21] had attempted a hybrid (or “gray box”) calibration approach for FASTSim by introducing three additional tuning parameters that present correction terms to traction power, vehicle mass and auxiliary power, with the ultimate goal of reducing the difference in simulation results compared to a dataset of real-world trip data. And although the approach in [21] successfully improved the fidelity of FASTSim models compared to “baseline” FASTSim for select test cases, it seemed like the tuning setup in [21] was trying to accomplish two things at once; i) accounting for unknown variations in real-world trips (such as number of passengers, cargo load, wind speed and direction), and ii) accounting for modeling idealizations of the powertrain. This paper presents an extension of the previous work in [21] by incorporating some additional detail of

the powertrain components, akin to some of the more detailed versions of FASTSim (per discussions with NREL researchers). Furthermore, since some of the tuning parameters are tied to the type of information available (or not) in the real-world trips data, proper setting of the tuning parameters is dependent on such information. For example, tuning a FASTSim vehicle model so that the simulated energy consumption for a trip matches the real-world dictates different values for the auxiliary power correction term, depending on whether (or not) the heating ventilation and air conditioning (HVAC) power information is incorporated within the FASTSim simulation. Such dependency on real-world trip information availability is also explored in this work.

This paper started with a motivation and brief review of relevant work in the literature. The rest of the manuscript is organized as follows: next section provides an overview of the extended calibration approach for FASTSim, which involves two parts: i) physics-based model, and ii) calibration for real-world trips. The section that follows showcases results of the first part (physics-based model tuning), with subsequent sections showing an overview of real-world trips and utilizing them for calibration. The paper then concludes with a summary and brief discussion of future work.

Approach Overview

In “baseline” FASTSim [7], powertrain components such as the engine and motor have one-dimensional efficiency curves with a pre-set profile that relates the instantaneous efficiency of the engine or motor to its relative power input/output, with the relative power being the ratio between instantaneous power and the maximum rated power. In other words, a user of baseline FASTSim conducting modeling work, may adjust the maximum power of the engine or motor, but they do not control the profile of the efficiency curve, which is automatically selected by FASTSim based on type of the engine (Spark ignition, Atkins, Diesel, ...etc.) or maximum power of the motor (smaller motors have efficiency curves scaled down compared to the default curve utilized in baseline FASTSim). This setup of baseline FASTSim is mainly intended for ease of use by the general public, yet more advanced users may wish to modify the efficiency curves and/or utilize two-dimensional torque-speed efficiency maps. The work in the current paper utilizes a Java implementation of FASTSim (following closely the code flow of Excel and python version of baseline FASTSim [7]) that has been contributed and open-sourced by the authors [22]. The Java-implementation adheres to the default efficiency curves of baseline FASTSim, but also permits user input modification of (i.e. use of “custom” curves for) the efficiency curves for engine and motor.

Overview of the overall scheme for calibration and verification of FASTSim vehicle models is shown in Fig. 1. First stage of vehicle model calibration (bounded by a red rectangle in Fig. 1) is to adjust the physical parameters (such as size and weight, tire coefficient, maximum power of various components, battery storage capacity and state of charge limits, ...etc.) as well as the efficiency curves of engine and/or motor. The goal for adjusting the physics-based model is to match (within reasonable error limits) the observed performance of the vehicle under the controlled conditions of dynamometer tests that have known results from the EPA. This includes both road-load dynamometer coefficients [23], as well as EPA label values [2].

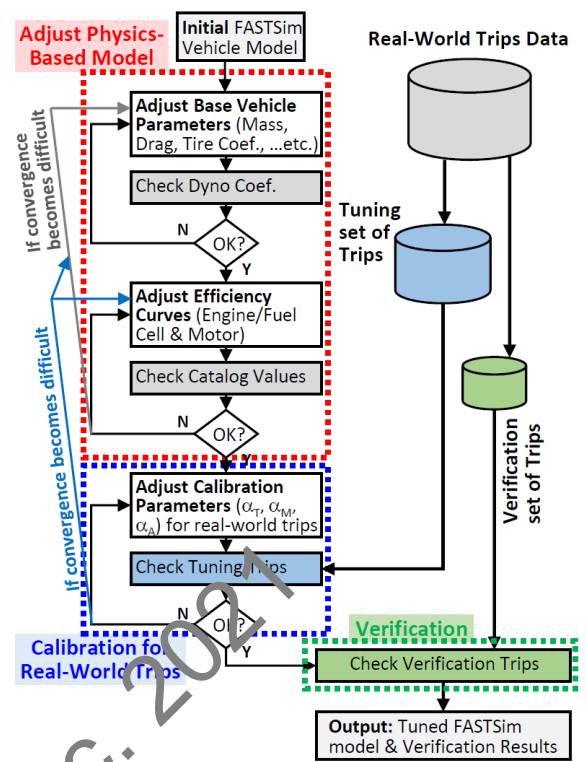


Figure 1. Overview of the approach for FASTSim vehicle models calibration and verification.

After generating reasonable physics-based models from first stage, a second stage (bounded by a blue rectangle in Fig. 1) begins. In the second stage, FASTSim simulations of real-world trips, modified by three tuning/calibration parameters (α_T , α_M , α_A), are compared to the known values for energy and/or fuel consumption of the real-world trips, with values of the calibration parameters continuously adjusted via an optimization process that aims to minimize the average error between FASTSim simulations and the real-world trips. Interested readers may refer to [21] for details about the reasoning and derivation of the tuning parameters, but for convenience, a brief summary of their effect is explained as follows:

- α_T is a scaling factor (dimensionless) for the vehicle traction power. A value of 1.0 for this parameter implies “no adjustment” which is usually the favored case during the model calibration process, though sometimes a value less/greater than (but still close to) 1.0 may be used
- α_M is a correction term to the vehicle mass (in kg), mainly aimed to account for things like unknown number of passengers or cargo load in the real-world trips
- α_A is a correction term to auxiliary power (in kW), mainly aimed to account for things like unknown HVAC power

After generating real-world-calibrated FASTSim vehicle models via the second stage, the models are checked via another set of real-world trips (which we refer to as “Verification trips”) that have not been included in the process of optimizing the values of (α_T , α_M , α_A). Results for the verification trips are regarded as the metric for performance.

Physics-Based Model of Vehicles

Nine vehicle models are considered in this work including three BEVs (Bolt, Leaf, Model S), four PHEVs (C-Max Energi, Pacifica Hybrid, Prius Prime, Volt), one HEV (Prius) and one conventional ICE (CR-V). Results of the first stage of the vehicle models tuning (red rectangle in Fig. 1) are shown in Table 1 and Table 2. Custom efficiency curves for engine and motor to achieve those results are shown in Fig. 2, with full listing of the vehicle modeling parameters provided in a publicly accessible shared storage at [24]. In current work, we set a target of $\pm 10\%$ error margin for vehicle mass and equivalent dynamometer coefficients in the FASTSim model compared to EPA test values [23], which was successfully achieved for all the considered vehicle models in Table 1. Likewise, we also set a target of $\pm 10\%$ error margin for FASTSim simulation of the vehicle models' equivalent EPA label values, compared to the standard catalogue label value [2], and this was also successfully achieved, as observed in Table 2. We note that the custom efficiency curves (Fig. 2) and vehicle physical parameter settings via this process [24] may not necessarily be the only, nor necessarily the best settings to arrive at such result. However, with the first stage being a precursor to calibrating the vehicle models versus real-world trips (main focus of this work), we consider these results of the first stage sufficient.

Real-World Driving Data

Real-world trips data (anonymized to include only speed, road slope, HVAC power, energy and fuel consumption) in this study were obtained from the eVMT survey [25]. While only a subset of the eVMT survey dataset, the analyzed trip data comes several 3-10 vehicle owners for each of the considered vehicle models, with the total number of trips per vehicle model constituting at least several hundred, as shown in Fig. 3. Trips from each vehicle model in the analyzed data were split via a randomized procedure into a set of tuning trips (approx. 85% of trips) that will be used for calibration of (α_T , α_M , α_A) values, and a set of verification trips (approx. 15% of trips). Aside from showing the split between tuning and verification trips, a main purpose of Fig. 3 is to show the variations in energy and fuel consumption (as recorded via OBD logging in the eVMT survey data) across different owners of same vehicle model, and even across different trips by the same owner. This variation is visualized via box plots in Fig. 3 for the electric energy intensity (in kWh/mile) for BEVs, and gasoline intensity (in gal/mile) for HEV and conventional ICE. For PHEVs, whose trips may include both electric energy and gasoline consumption, we converted fuel amounts to equivalent electric energy at a conversion rate corresponding to the EPA combined cycle rating [2] kWh/mile and MPG values.

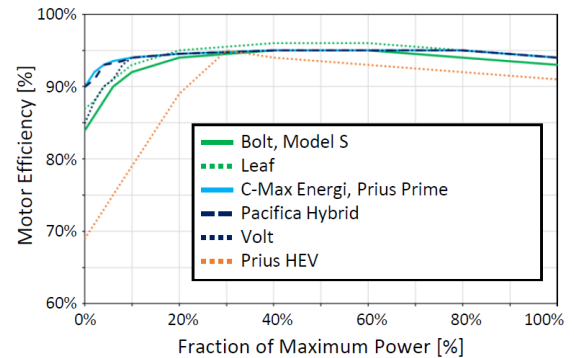
In the box plots of Fig. 3, the bottom and top limits of the box respectively represent the 25th and 75th percentiles, while the horizontal line within the box represents the median value (50th percentile). The extension lines respectively represent the 5th and 95th percentiles, while the diamond shape marks the non-outlier average value (average of the values between the 5th and 95th percentiles). Also marked in Fig. 3 (via dotted line) is EPA combined cycle label. We observe that individual trips, or the average for individual vehicle owners may deviate a lot from the EPA rating, but the average for a large number of trips by different owners (diamond shape in the darker tone box-plots in Fig. 3) remains within $\pm 15\%$ from the EPA combined cycle rating. Though in comparison, tuned FASTSim models in [21] (without custom curves) achieved $\pm 4\%$ error margin.

Table 1. Error margins in vehicle mass and dynamometer coefficients in vehicle models

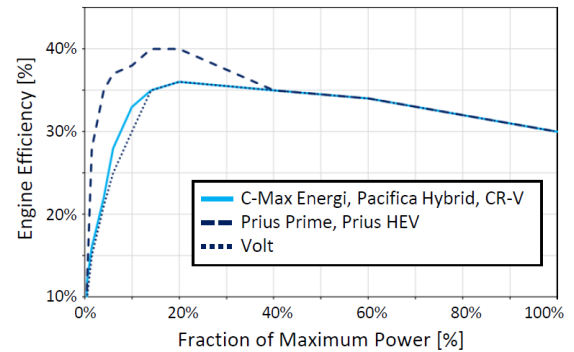
Vehicle Model	Relative Error [%] for		
	Vehicle Mass	Dyno Coeff A	Dyno Coeff C
Bolt	+8.8%	-8.6%	-7.9%
Leaf	+7.3%	-2.5%	+0.2%
Model S	+0.1%	-2.2%	+8.8%
C-Max	+4.9%	-6.2%	+9.6%
Pacifica	+8.5%	-2.2%	-4.5%
Prius Prime	+6.9%	-4.2%	+2.2%
Volt	+9.4%	+8.1%	+2.6%
Prius	+8.3%	+6.4%	-9.6%
CR-V	+9.5%	+7.9%	+1.2%

Table 2. Error margins for standard dynamometer drive cycles simulations of the vehicle models compared to EPA label values

Vehicle Model	Relative Error [%] in					
	Electric Intensity (kWh/mile) for			Fuel Economy (MPG) for		
	City	Hwy	Comb	City	Hwy	Comb
Bolt	+9.5%	+5.8%	+8.7%			
Leaf	+5.3%	+3.7%	+3.9%			
Model S	+2.4%	+9.4%	+7.5%			
C-Max			-6.5%	-7.9%	+6.5%	-1.3%
Pacifica			+0.4%	-9.3%	+9.0%	-2.6%
Prius Prime			+6.5%	-4.5%	+9.9%	+2.0%
Volt			-3.0%	-9.6%	-0.3%	-6.6%
Prius				-8.8%	+8.9%	+0.1%
CR-V				-9.9%	+4.9%	-3.2%



(a) Custom Curves for Motor Efficiency



(b) Custom Curves for Engine Efficiency

Figure 2. Custom efficiency curves for vehicle models.

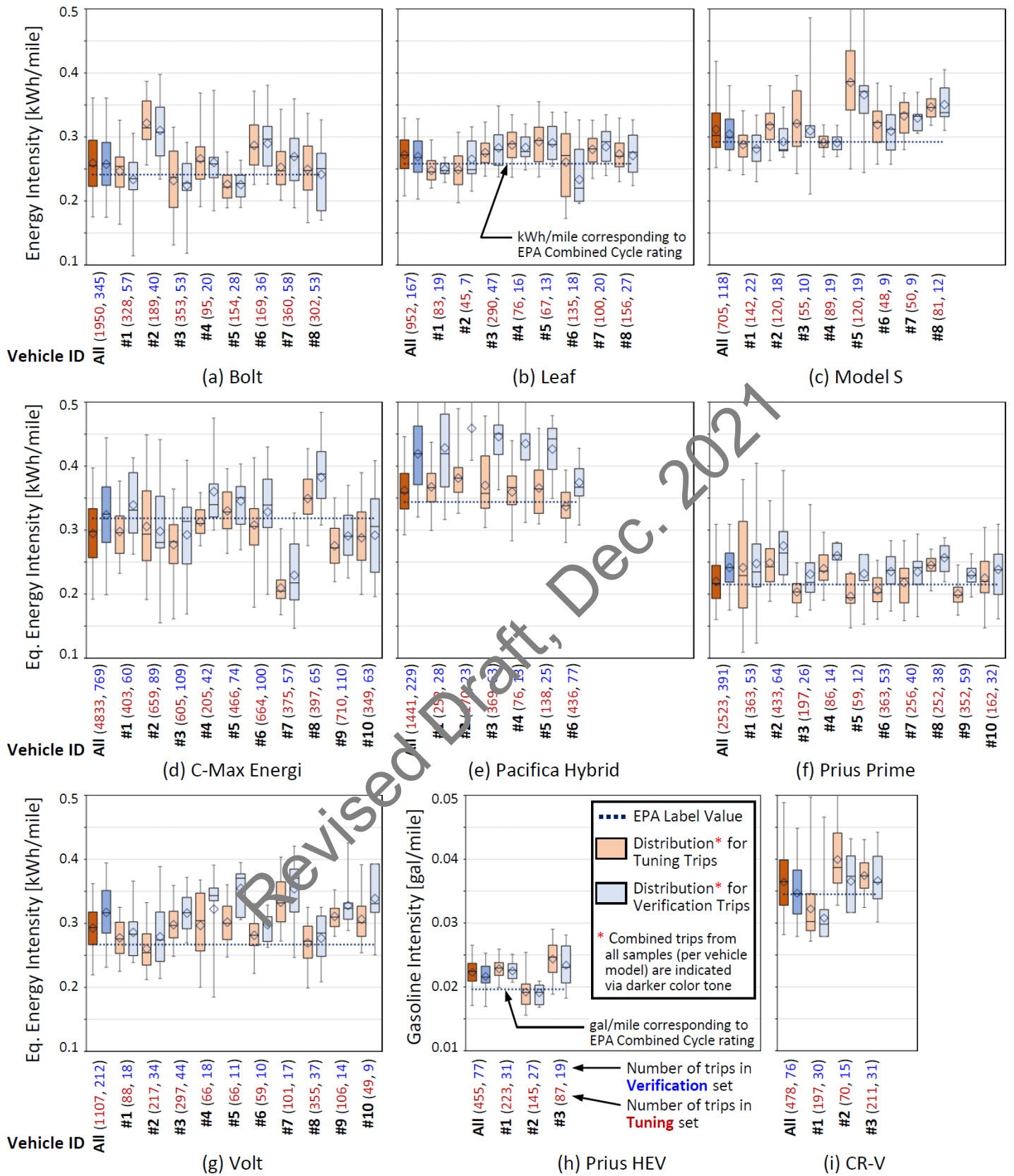


Figure 3. Summary of real-world energy efficiency for vehicle models in current study.

Results and Discussion

We first examine adjusting the three tuning parameters (α_T , α_M , α_A) with the objective of getting the average value for relative error in trip energy consumption to be within $\pm 0.1\%$ for the tuning set of trips (this process corresponds to the blue rectangular boundary in Fig. 1). In doing so, we use all the available information (speed, road slope and HVAC power) of the real-world trips within the FASTSim simulations. The corresponding (α_T , α_M , α_A) values are listed in Table 3. Noting however that if the purpose of creating the tuned FASTSim vehicle models is to conduct simulations for other real-world trip datasets (ones that may not have fuel/energy, nor slope/HVAC information) such as the travel datasets hosted at NREL's Transportation Secure Data Center (TSDC) [26], then another set of (α_T , α_M , α_A) values are needed in order to compensate for the unavailable trip information. Those re-adjusted values are listed in Table 4 and Table 5 for respectively datasets that include slope but not HVAC power, and datasets that include neither slope nor HVAC power. We note that the real-world data obtained for Model S, Volt, Prius and CR-V did not include HVAC power, and thus, the corresponding (α_T , α_M , α_A) values could not be generated in Table 4. Error in trip energy FASTSim simulation in the tuning set of trips are shown in Fig. 4.b for the appropriately set (α_T , α_M , α_A) values. We also explore the effect of *inappropriate* setting of (α_T , α_M , α_A) values in Fig. 4.a, if the tuning parameter values from Table 3 (and Table 4 for Model S, Volt, Prius and CR-V) were to be used for FASTSim simulation of trips that did not include road slope and/or HVAC information.

By examining the box plots in Fig. 4.a, one may gain some insights into how real-world trip information interacts with fuel economy simulations. In general, a FASTSim vehicle model that is tuned (via α_T , α_M , α_A values) to provide the "correct answer" when road slope and HVAC are provided to FASTSim (green tone box plots in Fig. 4.a), will generally underestimate trip energy (pink tone box plots in Fig. 4.a) if the simulation used only the trip speed, which would be akin to driving on a perfectly flat terrain with no heating/cooling. Comparing the average values (diamond marker) of green tone and yellow tone box plots in Fig. 4.a implies that the error in trip energy estimation due to missing HVAC power information is between 2% to 6%. Similarly, comparing the average values of yellow tone and pink tone box plots in Fig. 4.a implies that the error in trip energy estimation due to missing road slope information is another 2% to 7%. When utilizing the proper tuning parameter values (Fig. 4.b), the average relative error in FASTSim simulations for the tuning trips was within $\pm 0.1\%$ when road slope and HVAC power are included in the simulated trips data (green tone box plots in Fig. 4.b), within $\pm 0.4\%$ when road slope is included but not HVAC power (yellow tone box plots in Fig. 4.b), and within $\pm 1.2\%$ when neither road slope nor HVAC power are included (pink tone box plots in Fig. 4.b).

To check the capability of tuned FASTSim models for generalization however, we examine their performance for the set of verification trips, which were not included in the process of tuning the (α_T , α_M , α_A) values. The results of this are shown in Fig. 5. We observe that the average relative error in trip energy remained within $\pm 1.5\%$ when road slope information is included (green and yellow tone box plots

in Fig. 5), which is an improved result compared to $\pm 4\%$ in previous work [21], likely owing to modeling improvements via the custom efficiency curves. We also observed that tuned models without road slope nor HVAC power (not attempted in previous work) were able to achieve average relative error within $\pm 4\%$ (pink tone box plots in Fig. 5). Furthermore, aside from the average value for relative error, there is a fairly clear improvement in the fidelity of simulation results in Fig. 5 (in terms of narrower band between 25th to 75th percentile and/or 5th to 95th percentiles) as one observes the pink, yellow and green tone box plots for each of the vehicle models (with the exception of Pacifica Hybrid, where they are mostly similar). This is perceived to attest to the importance of including road slope and HVAC power within simulations when such information is available.

Table 3. Tuning parameter values for real-world trips that include both slope and HVAC power information

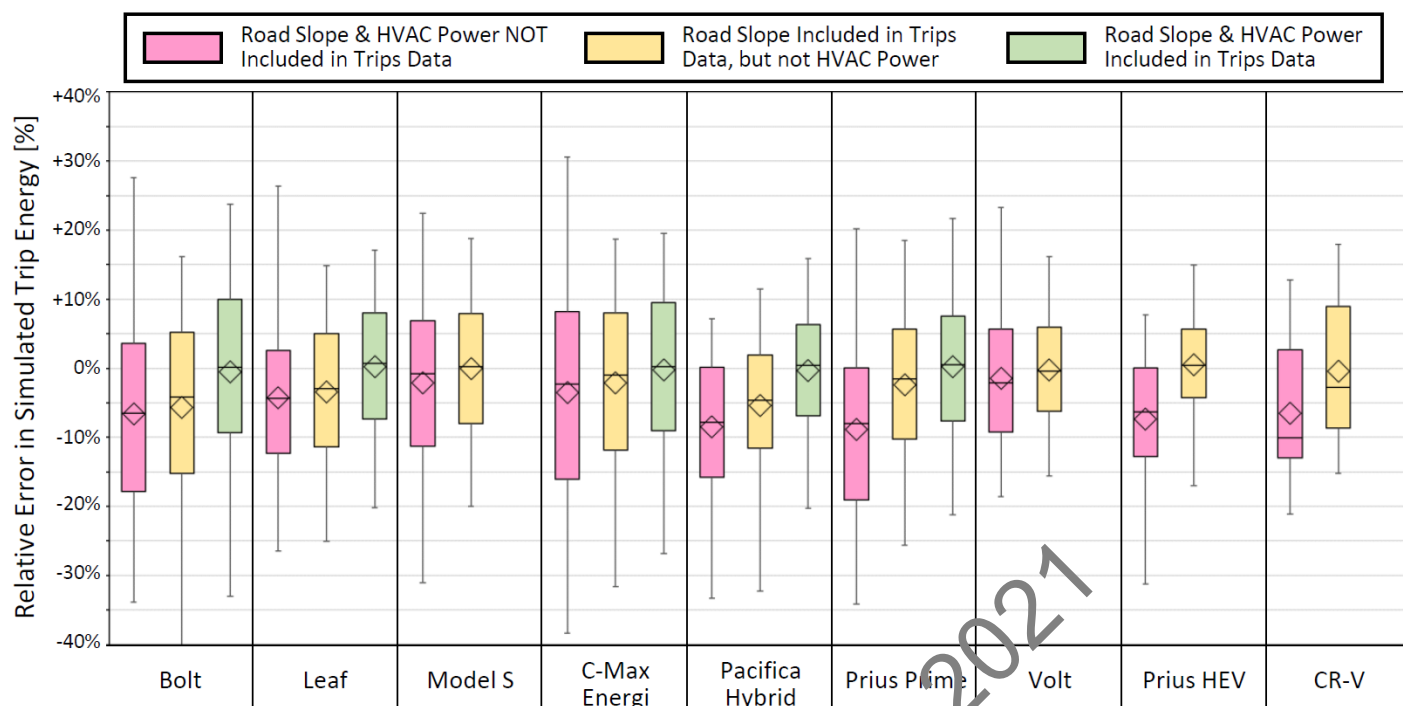
Vehicle Model	α_T	α_M [kg]	α_A [kW]
Bolt	1.000	40	0.00
Leaf	1.000	50	0.20
C-Max	0.965	0	0.00
Pacifica	1.000	100	0.20
Prius Prime	0.960	0	0.00

Table 4. Tuning parameter values for real-world trips that include slope but not HVAC power information

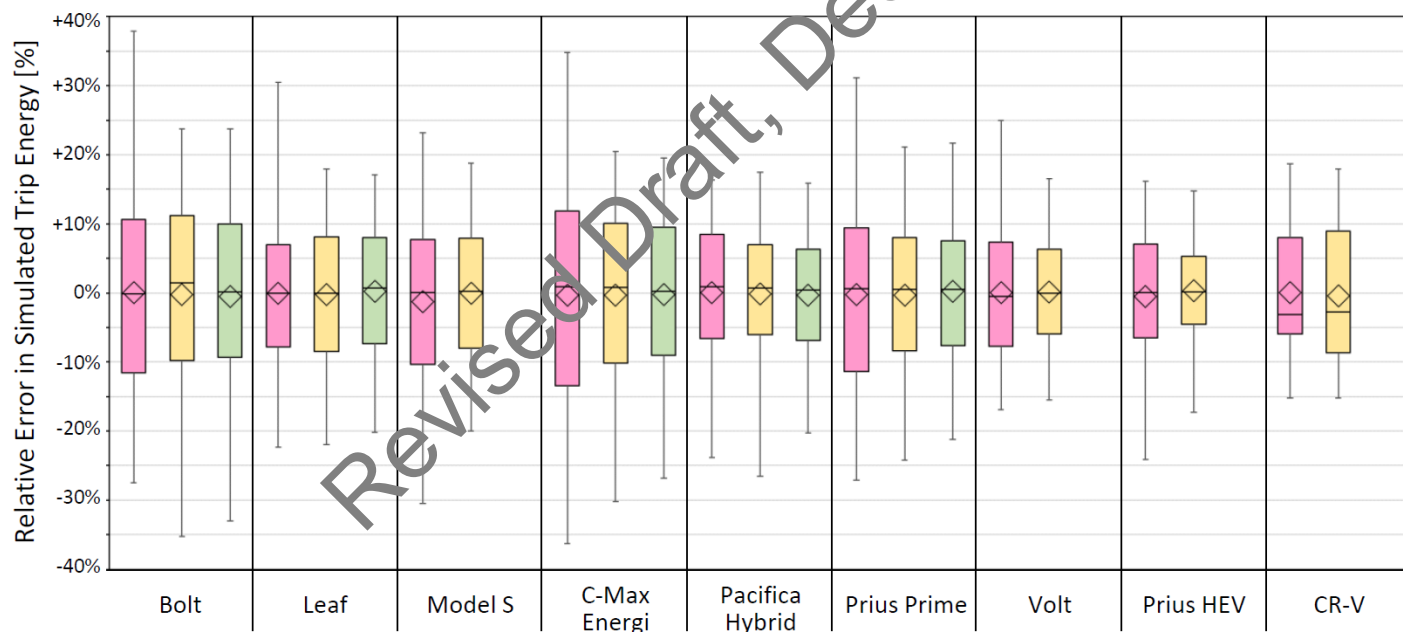
Vehicle Model	α_T	α_M [kg]	α_A [kW]
Bolt	1.000	150	0.30
Leaf	1.000	170	0.30
Model S	1.000	50	0.10
C-Max	0.970	0	0.00
Pacifica	1.000	260	0.70
Prius Prime	0.970	0	0.00
Volt	1.000	220	1.20
Prius	0.960	30	0.00
CR-V	1.000	150	0.50

Table 5. Tuning parameter values for real-world trips that do not include slope or HVAC power information

Vehicle Model	α_T	α_M [kg]	α_A [kW]
Bolt	1.000	100	0.50
Leaf	1.000	210	0.35
Model S	1.000	100	0.10
C-Max	0.980	45	0.00
Pacifica	1.000	475	0.90
Prius Prime	1.000	50	0.25
Volt	1.000	300	1.20
Prius	1.000	50	0.25
CR-V	1.000	350	0.70



(a) Before adjusting the Tuning Parameters to compensate for excluded trip data



(b) After adjusting the Tuning Parameters to compensate for excluded trip data

Figure 4. Results for FASTSim tuning trips with both HVAC and Road Slope data (green), Road Slope data only (yellow), and neither (red) included (a) using three-parameter tuning values corresponding to when slope and HVAC information is included, and (b) after re-adjusting the tuning to compensate for the excluded data.

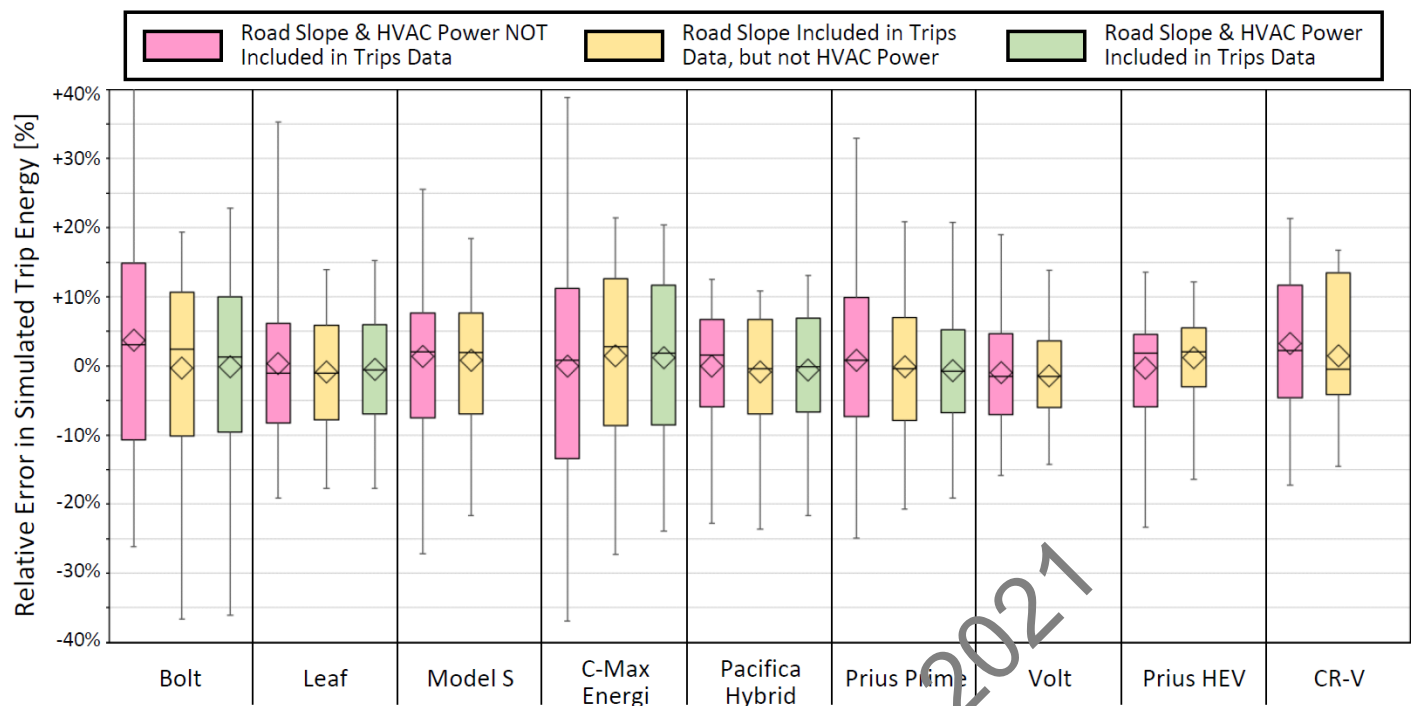


Figure 5. Results for FASTSim verification trips with both HVAC and Road Slope data (green), Road Slope data only (yellow), and neither (red) included.

Conclusion & Future Work

This paper presented an extension of previous work that aimed at improving the fidelity of energy efficiency/fuel economy simulation results of FASTSim via a two-stage model tuning process, with the first stage focusing on adjusting the physical parameters of vehicle model (including custom efficiency curves for engine and motor), and the second stage focusing on tuning of energy adjustment parameters that aim to account for uncertainties in real-world driving. Tuned FASTSim vehicle models were generated for nine high-duty vehicles were generated including three BEVs, four PHEVs, one HEV and one conventional ICE. Where feasible, up to three variants of the tuned models were generated depending on whether the available information in the real-world trips to be simulated includes only the vehicle speed, speed and road slope, or speed, road slope and HVAC power. Verification test simulations of the tuned models attained average relative error in trip energy estimation within $\pm 1.5\%$ when road slope information is included, and within $\pm 4\%$ when neither road slope nor HVAC power information are included. Future extensions of this work may include repeating the study on a larger scale (more vehicle models, more vehicles and trips per vehicle model), and/or consideration for automation procedures for optimal tuning of the custom-curves and other tuning parameters.

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