



# 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

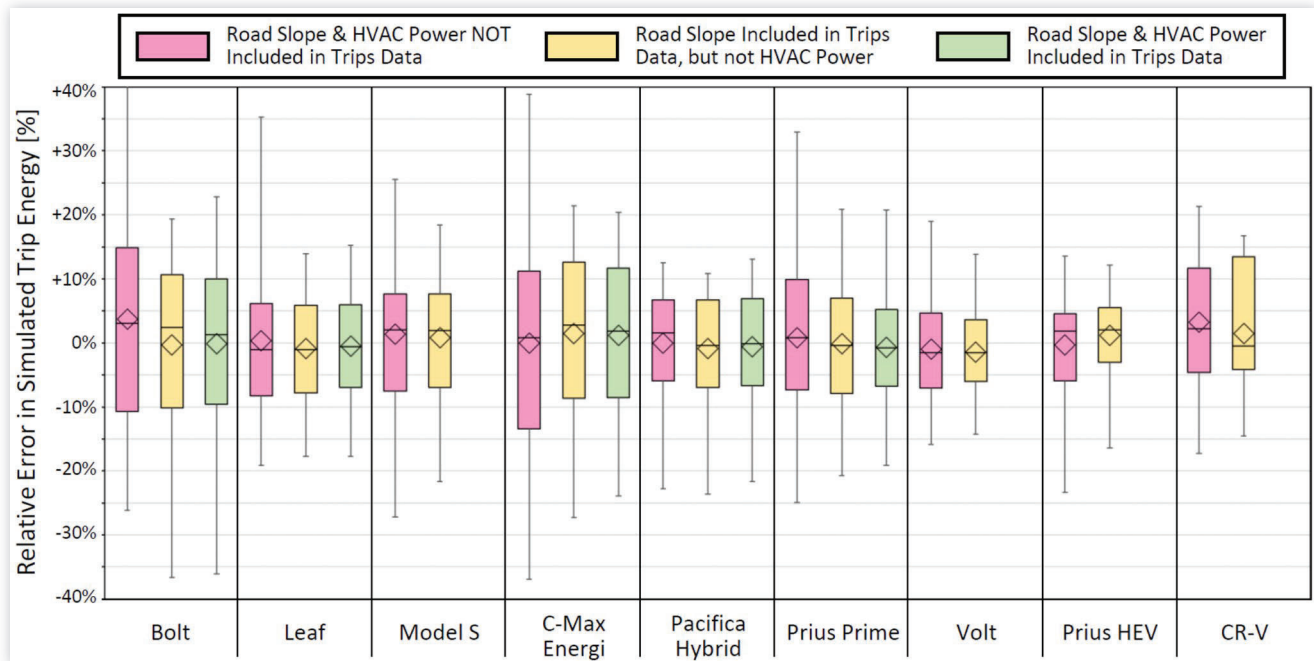
compromise in accuracy in favor of ease of modeling. This paper utilizes an open-source Java implementation of FASTSim with capability for custom efficiency curves for engine and motor, along with a large dataset of real-world vehicle trips to calibrate and validate FASTSim vehicle models for three Battery 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.

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



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.

## 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 light-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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