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

Karim Hamza Toyota Motor North America Inc.

Peter Benoliel University Of California Davis

Kang-Ching Chu and Ken Laberteaux Toyota Motor North America Inc.

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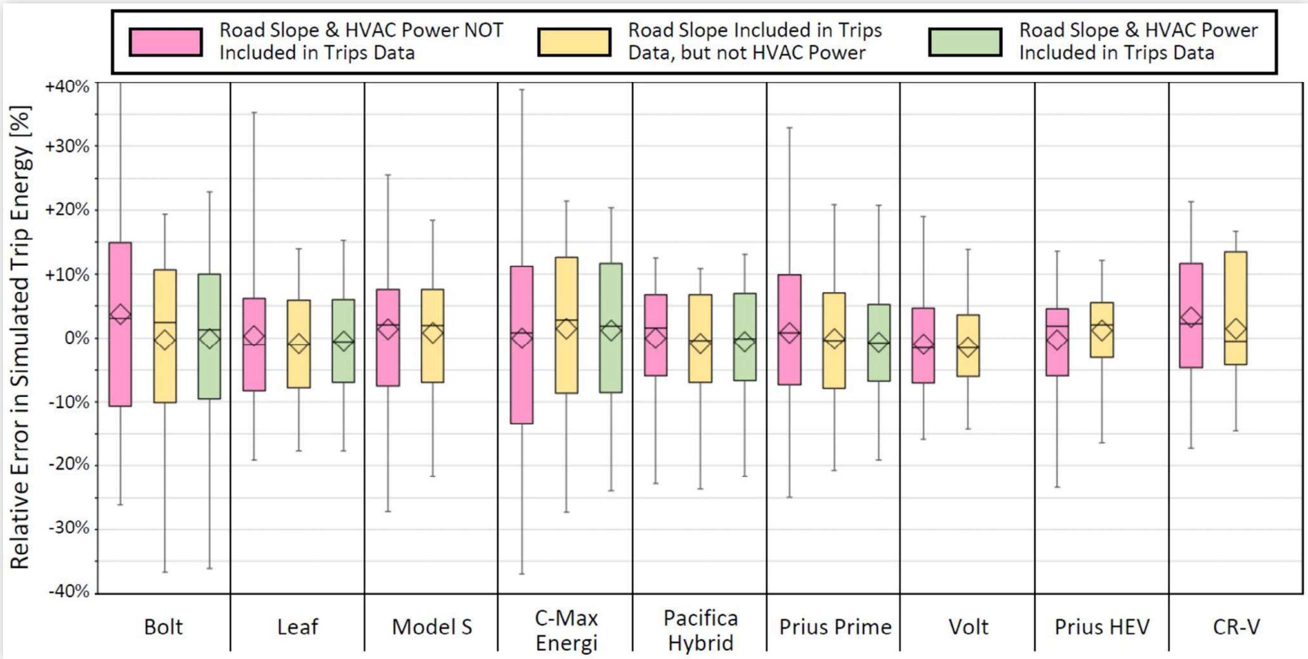
Abstract

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 ±1.5% when road slope information is included, and within ±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.

References

1. Zhou, M., Jin, H., and Wang, W., "A Review of Vehicle Fuel Consumption Models to Evaluate Eco-Driving and Eco-Routing," *Transportation Research Part D* 49 (2016): 203-218.
2. US Department of Energy, accessed October 2021, https://www.fueleconomy.gov/feg/printGuides.shtml.
3. US Environmental Protection Agency, accessed October 2019, https://www.epa.gov/moves.
4. California Air Resources Board, accessed October 2019, https://ww2.arb.ca.gov/our-work/programs/mobile-source-emissions-inventory/msei-modeling-tools.
5. US Department of Energy, Vehicle Technologies Office, https://energy.gov/eere/vehicles/vehicle-technologies-office-modeling-and-simulation.
6. Argonne National Laboratory, "Autonomie: Automotive System Design," accessed October 2021, https://www.autonomie.net/.
7. National Renewable Energy Laboratory, "FASTSim: Future Automotive Systems Technology Simulator," 2018, accessed October 2021, https://www.nrel.gov/transportation/fastsim.html.
8. Kim, N., Rousseau, A., and Rask, E., "Autonomie Model Validation with Test Data for 2010 Toyota Prius," in *SAE World Congress*, Detroit, MI, 2012.
9. Karabasoglu, O. and Michalek, J., "Influence of Driving Patterns on Life Cycle Cost and Emissions of Hybrid and Plug-In Electric Vehicle Power Trains," *Energy Policy* 60 (2013): 445-461.
10. Karbowski, D., Sokolov, V., and Rousseau, A., "Vehicle Energy Management Optimisation through Digital Maps

and Connectivity," in *22nd ITS World Congress*, Bordeaux, France, 2015.

11. Kim, N., Moawad, A., Shidore, N., and Rousseau, A., "Fuel Consumption and Cost Potential of Different Plug-In Hybrid Vehicle Architectures," *SAE International Journal of Alternative Powertrains* 4, no. 1 (2015): 88-99.
12. Neubauer, J. and Wood, E., "Accounting for Driver Aggression in the Simulation of Conventional and Advanced Vehicles," in *SAE World Congress*, Detroit, MI, 2013.
13. Brooker, A., Gonder, J., Wang, L., Wood, E. et al., "FASTSim: A Model to Estimate Vehicle Efficiency, Cost and Performance," in *SAE World Congress*, Detroit, MI, 2015.
14. Vijayagopal, R., Prada, D.N., and Rousseau, A., "Fuel Economy and Cost Estimates for Medium- and Heavy-Duty Trucks," ANL/ESD-19/8, 2019.
15. Islam, H., Moawad, A., Kim, N., and Rousseau, A., "Energy Consumption and Cost Reduction of Future Light-Duty Vehicles through Advanced Vehicle Technologies: A Modeling Simulation Study through 2050," ANL/ESD-19/10, 2020.
16. Hunter, C., Penev, M., Reznicek, E., Lustbader, J. et al., "Spatial and Temporal Analysis of the Total Cost of Ownership for Class 8 Tractors and Class 4 Parcel Delivery Trucks," NREL/TP-5400-71796, 2021.
17. Zhu, D., Pritchard, E.G.D., and Silverberg, L.M., "A New System Development Framework Driven by a Model-Based Testing Approach Bridged by Information Flow," *IEEE Systems Journal* 12, no. 3 (2016): 2917-2924, doi:10.1109/JSYST.2016.2631142.
18. Laberteaux, K., Hamza, K., and Willard, J., "Optimizing the Electric Range of Plug-In Vehicles via Fuel Economy Simulations of Real-World Driving in California," *Transportation Research Part D* 73 (2019): 15-33.
19. Hamza, K., Willard, J., Chu, K.C., and Laberteaux, K., "Modeling the Effect of Power Consumption in Automated Driving Systems on Vehicle Energy Efficiency for Real-World Driving in California," *Transportation Research Record* 2673, no. 4 (2019): 339-347.
20. National Renewable Energy Laboratory, 2021, accessed October 2021, https://www.nrel.gov/news/program/2021/google-taps-nrel-expertise-to-incorporate-energy-optimization-into-google-maps-route-guidance.html.
21. Hamza, K., Chu, K.C., Favetti, M., Benoliel, P. et al., "Validity Assessment and Calibration Approach for Simulation Models of Energy Efficiency of Light-Duty Vehicles," in *SAE World Congress*, Detroit, MI, 2020.
22. FASTSim-Java on GitHub, 2021, accessed June 2021, https://github.com/khamza075/FASTSim-Java.
23. US Environmental Protection Agency, "Data on Cars used for Testing Fuel Economy," 2020, accessed June 2021, https://www.epa.gov/compliance-and-fuel-economy-data/data-cars-used-testing-fuel-economy.
24. FASTSim Vehicle Models Archive, 2021, accessed October 2021, https://drive.google.com/drive/folders/1W55AkmcqBY-RnkslUmY31ysZRCzXqwdf?usp=sharing.
25. University of California-Davis, Institute of Transportation Studies, accessed October 2019, https://phev.ucdavis.edu/project/evmt-project/.
26. National Renewable Energy Laboratory Transportation Secure Data Center, "California Household Travel Survey," 2013, accessed October 2021, https://www.nrel.gov/transportation/secure-transportation-data/tsdc-cleansed-data.html.

Contact Information

Toyota Motor North America-R&D (FRD)
1555 Woodridge Avenue, Ann Arbor, MI 48105
Tel: 734-546-2423 Fax: 734-995-4200
Email: karim.hamza@toyota.com