I Modeling and Simulation

I.1 ParaChoice Model

Camron Proctor, Principal Investigator
Organization: Sandia National Laboratories
Address: 7011 East Avenue
Livermore, CA 94550
E-mail: cproct@sandia.gov

Jacob Ward, DOE Program Manager
U.S. Department of Energy
E-mail: Jacob.Ward@ee.doe.gov

Start Date:FY14 End Date:Project continuation determined annually
Project Funding : $1,330k DOE share: $1,330k Non-DOE share: $0

Project Introduction

Sandia National Laboratories' (SNL's) Parametric Choice Model (ParaChoice) supports the U.S. Department of Energy Vehicle Technologies Office (VTO) mission. Using early-stage research as input, ParaChoice supports the informed development of technology that will improve affordability of transportation, while encouraging innovation and reducing dependence on petroleum. Analysis with ParaChoice enables exploration of key factors that influence consumer choice, as well as projecting the effects of technology, fuel, and infrastructure development for the vehicle fleet mix. Because of the distinct differences between requirements, needs, and use patterns for light duty vehicles (LDVs) relative to heavy duty vehicles (HDVs), this project separately models the dynamics of each of these segments to accurately characterize the factors that influence technology adoption.

Objectives

The overall project objective is to assess the evolving integration potential of LDV and HDV technologies, fuels, and infrastructure and their contributions to lowering emissions and petroleum consumption. We leverage existing LDV and build HDV ParaChoice capability to conduct parametric analyses that explore the trade-space for key factors that influence consumer choice and technology, fuel and infrastructure development. ParaChoice provides the unique capability to examine tipping points and tradeoffs, and can help quantify the effects of and mitigate uncertainty introduced by data sources and assumptions.

LDV analysis goal: Determine the potential for alternative fuel LDVs to penetrate the market, reduce LDV petroleum consumption and emissions, and impact energy use for two scenarios to support the Benefits Analysis low and high technology cases.

HDV analysis goal: Provide the capability to model PHEVs, BEV, and FCEVs to reflect the changing technology space for HDVs, and evaluate the potential for alternative fuel heavy duty vehicles (AFHDVs) to penetrate the market, increase freight hauling efficiency and reduce pollution.

Approach

ParaChoice is a system dynamics model incorporating energy sources, fuels, and LD or HD vehicles; see Figure 1. Simulations begin with today's energy, fuel, and vehicle stock and projects out to 2050. At each time step, vehicles compete for share in the sales fleet based on value to consumers. The simulation assesses

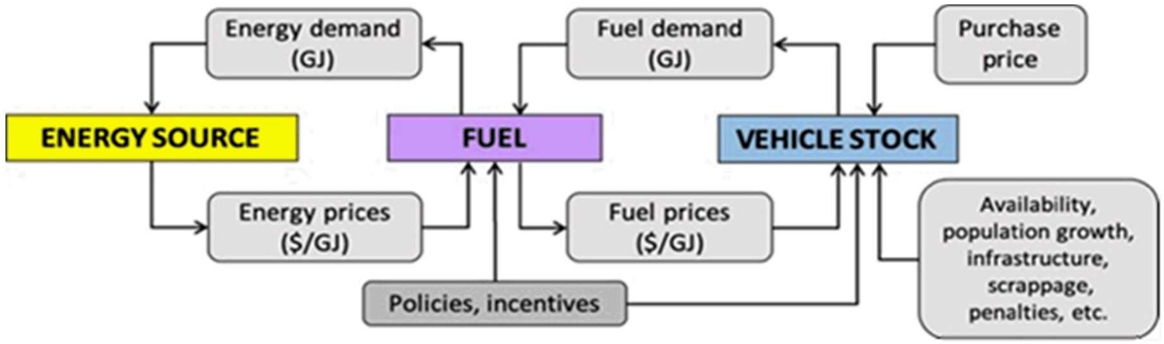


Figure 1 Schematic of ParaChoice systems dynamices model structure that indicates how energy, fuel, and vehicle-stock effect each other iteratively. The model allows for incentives and policy options to act as functions of time.

generalized vehicle cost for each vehicle at every time step. A nested multinomial logit choice function assigns sales fractions based on these costs and updates the vehicle stock accordingly [1, 2].

ParaChoice is designed to enable parameterization that can be used to explore uncertainty and trade spaces, allowing identification of tipping points and system sensitivities. Uncertainty analyses include trade space analyses where two parameters are varied, generating hundreds of scenarios; and sensitivity analyses where many parameters are varied at once, generating thousands of scenarios. Parameter ranges are selected to explore plausible and "what if" regimes, and provide thorough coverage of possible future states. Analysis products using ParaChoice provide insights into: (1) perspectives in uncertain energy and technology futures; (2) sensitivities and tradeoffs between technology investments, market incentives, and modeling uncertainty; and (3) the set of conditions that must be true to reach performance goals.

Vehicles, fuels, and populations are segmented to study the competition between powertrains and market niches; see Figure 2. Baseline inputs into the ParaChoice model include the following data and modeling sources: GREET 2016 [3] (emissions & fuel cost); NHTS [4] (LDV fleet segmentation); Polk [5] (HDV fleet segmentation & price projections); Autonomie 2018 [6] (price projections); AFDC [7] (2010-2017 fueling stations and policies by state); VIUS 2002 [8] (VTMT); APTA 2019 [9] (VTMT); 2018 FHWA FAF4 [10] (VTMT); NPC ATATP 2012 [11] (efficiency); EPA-NHTSA [12] 2016(efficiency); EIA AEO 2018 [13] (fuel costs); HDSAM 2015 [14] (fuel costs); H2A 2015 [15] (fuel costs); Foothill Transit Agency 2018 [16] (price projections); and ICCT 2017 [17] (price projections).

Results

In FY19 we added three alternative fuel powertrains to the ParaChoice Truck (HDV) model—battery electric (BEV); plug-in hybrid electric (PHEV), and fuel cell electric (FCEV) vehicles—and demonstrated the capability for a subset of the HDV segment. Results from the LDV analysis supporting the Benefits Analysis will be published in FY20 due to delays in receiving the inputs before the end of the FY.

To inform HDV model development and which vehicle segment to demonstrate this year, we conducted a gaps analysis that incorporates an in-depth literature review to determine whether or not data is available and sufficient to answer specific analysis questions. A multistep process was used beginning with identifying relevant analsysis questions that can be addressed using ParaChoice; the associated data needed, its availability and quality; and given the quality, what questions of interest can we credibly pursue. The analysis identified (1) specific data gaps that limit the vehicles types and powertrains we can study in the near term; (2) specific data gaps around HDV consumers that create uncertainty in projections; and (3) inconsistencies in data aggregation across vehicle types, weights, powertrains, duty cycles, and vocation that may introduce further uncertainty into the analysis results.

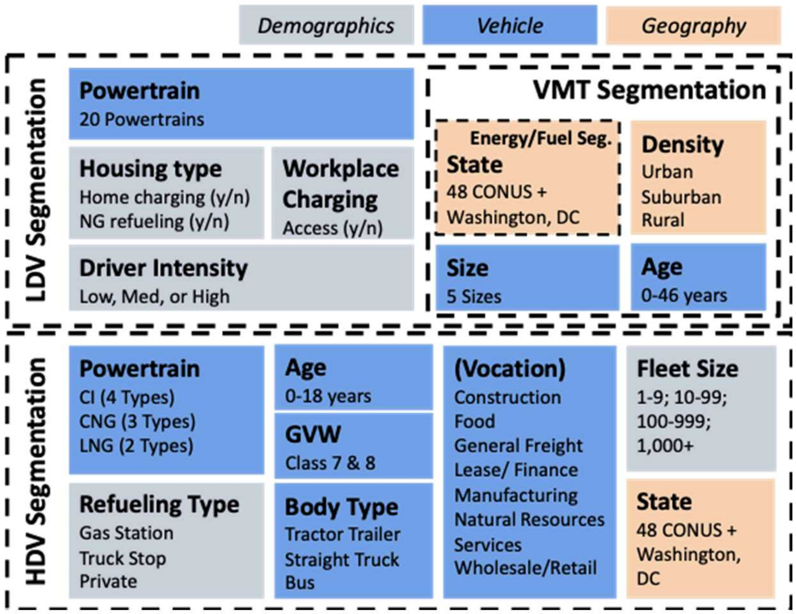


Figure 2 LDV and HDV segmentations grouped into themes of buyer demographics (e.g., access to workplace charging or truck stop versus gas station refueling), vehicle options (e.g., powertrain or body type) and geography (e.g., state or population density).

Based on the gaps analysis and our FY18 market segmentation analysis that indicated tractor trucks comprise almost half of Class 7 & 8 HDVs and travel approximately three-quarters of the total annual miles and consume three-quarters of fuel, we selected long haul tractor trucks to demonstrate the ParaChoice Truck modeling capability this FY.

The Parachoice Truck modeling capability built on previous work [18] to provide choice among the following powertrains, with nesting according to fuel types (Figure 3): compression ignition diesel (CI), mild hybrid CI integrated start generator (CI-ISG), hybrid CI (CI-HE), compressed natural gas (CNG), hybrid CNG (CNG-HE), liquified natural gas (LNG), battery electric (BE), plugin hybrid CI (CI-PHE), plugin hybrid CNG (CNG-PHE) and fuel cell (FC). Note that BEV and the PHEVs falls under the plugin electric (PEV) category and will be referred to as such in the subsequent sections of this report.

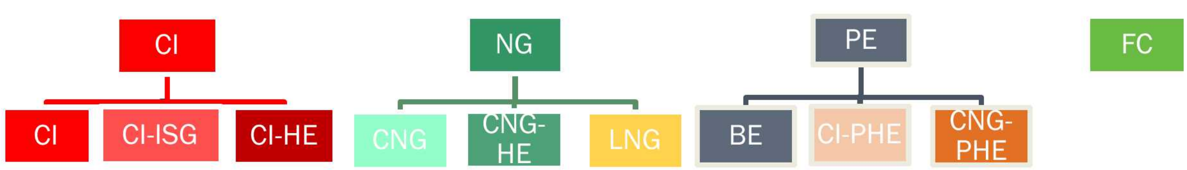
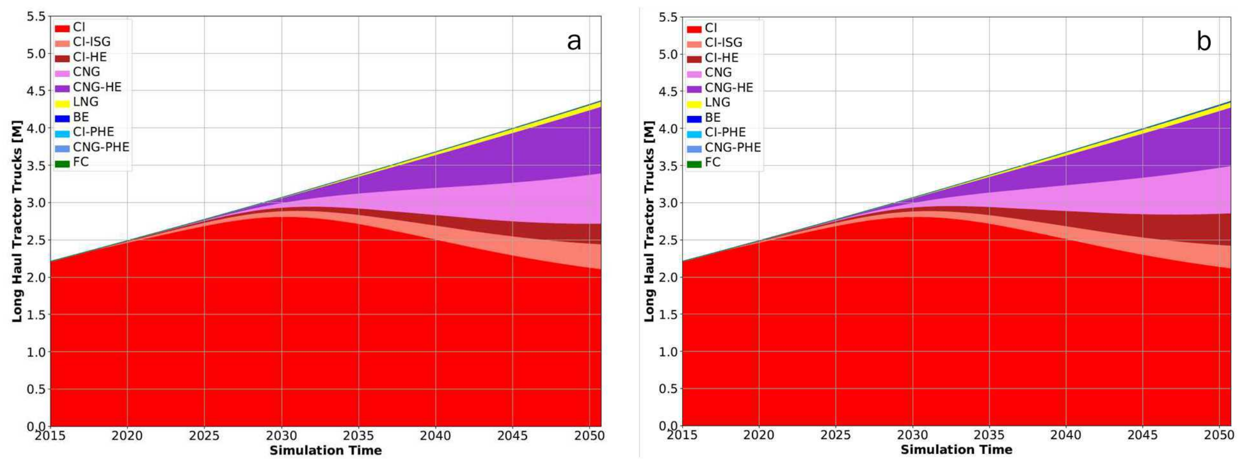


Figure 3 Nesting method for HDV vehicles was added in conjuction with the addition of BE, PHE, and FCE vehicles

Because of variability in data values from different sources, as well as the finding that not all sources had data for all the powertrains of interest, some adjustments to the data were needed for use in the model. For example, fuel efficiency data from Autonomie are slightly different than from EPA-NHTSA, and NPC provides NG vehicle efficiencies while Autonomie does not. To minimize data error, these sources were normalized to one source by applying relative proportions derived from one source to another; e.g. relative efficiency of CNG vs CI was derived from NPC and applied to CI efficiency from Autonomie. As more refined data becomes available and is added to the model, specific results from projections will become more valuable. The addition of more single source data and recent vehicle stock would further mitigate errors and allow for model calibration.

The baseline analysis for low technology and high technology cases (as defined by ANL/Autonomie) show that there is negligible adoption of AFHDVs out to 2050. Figure 4 shows the population of long haul tractor trucks by powertrain out to 2050, with fleet stock represented mainly by CI, NG and their hybrids. Based on the model cost and efficiency input trends, CNG and CNGHE appear to reach cost parity with CI around the year 2030 and begin to take a significant share of the vehicle stock. Comparison of the low and high



technology cases suggests improved penetration of
CI-HE, but AFHDVs continue to comprise only a small fraction of the fleet.

To understand what factors are suppressing adoption of the alternative powertrains, a sensitivity study using 2560 Monte Carlo samples (latin hypercube method) was conducted across input parameters. The results indicate carbon cost, acting as a cost modifier due to greenhouse gas (GHG) emissions, is the most impactful factor across all powertrains and should be viewed as a potential instrument for promoting AFHDVs with less GHG emission intensity than diesel.

For AFHDVs, FCEV and PEV purchase costs are the driving factor for adoption, suggesting purchase incentives and/or further cost reductions are needed to spur adoption of AFHDVs (Figure 5). Without these changes, AFHDVs rest at a valley where CI, NG and their hybrid counterparts dominate. There are clear cost tipping points for these vehicles: ~\$150k for FCEV and ~\$180k for PEV (2018 \$ value). Below these points, FCEV and PEV begin to compete among one another (lower left corners in Figure 5). The lower cost requirement for FC is attributed to higher cost of H_2 per unit energy than electricity and lower FCV efficiency p

Figure 4 ParaChoice projections of long haul tractor truck stock for the (a) low technology and (b) high technology case scenarios identified by ANL/Auotnomie

Key findings from the long haul tractor truck analysis:

- AFHDVs have a negligible effect on the sales fraction of conventional CI powertrains projected to 2050. Adoption of AFHDVs is closely tied to the initial purchase cost of the vehicle. There is an apparent tipping point for adoption of these vehicles between \$150k-\$180k. Incentive and financing options may be needed to promote adoption of these vehicles.

- NG vehicles appear to significantly displace conventional powertrains as driven by lower purchase cost and lower fuel costs relative to the AFHDVs. They appear to readily compete in the baseline case, thus investments should be targeted towards the alternative fuel powertrains.

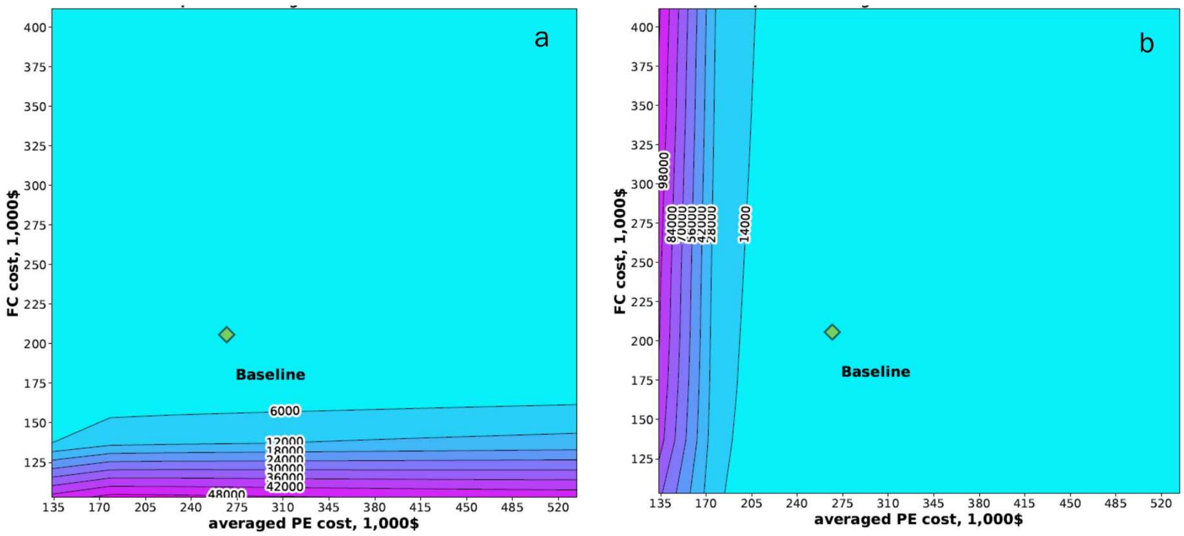


Figure 4 - Tradespace analysis showing the numbe of (a) FCEVs and (b) PEVs at the end of analysis period (2050). The conditions for the baseline conditions are noted by the diamond marker.

Conclusions

ParaChoice is a system-level model of the dynamics existing among vehicles, fuels, and infrastructure. It leverages other DOE models and inputs to simulate fuel production pathways that scale with demand from vehicles. It is designed for parametric analysis in order to understand and mitigate uncertainty introduced by data sources and assumptions. Native parametric capabilities are also useful for identifying trade spaces, tipping points and sensitivities. Acquisition of more recent vehicle and VMT data is needed for further ParaChoice Truck model refinement. Incorporation of additional efficiency and cost data covering relevant permutations of tractor trucks, box trucks, buses and vocational vehicles is planned for FY20.

References

1. Levinson, R., Manley, D., and West, T., *History v. Simulation: An Analysis of the Drivers of Alternative Energy VehicleSales.* 2016. **5**(2).

2. Barter, G.E., et al., *Parametric analysis of technology and policy tradeoffs for conventional and electric light-duty vehicles.* Energy Policy, 2012. **46**: p. 15.

3. *GREET® Model - The Greenhouse gases, Regulated Emissions, and Energy use in Transportation Model*. 2016, Argonne National Laboratory: https://greet.es.anl.gov/.

4. *Vehicle Survivalibility and Travel Milage Schedules*. 2006, NHTSA National Center for Statistics and Analysis: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/809952.

5. *IHS Markit (formerly Polk Automotive)*. IHS: https://ihsmarkit.com/btp/polk.html.

6. *Autonomie Vehicle System Simulation Tool*. 2018, Argonne National Laboratory: https://www.anl.gov/es/autonomie-vehicle-system-simulation-tool.

7. *Alternative Fuel Data Center*. Department of Energy: https://afdc.energy.gov/data/. .

8. *Vehicle Inventory and Use Survey*. 2002, United States Census Bureau: https://www.census.gov/library/publications/2002/econ/census/vehicle-inventory-and-use-survey.html.

9. *Public Transportation Fact Book* 2019, American Public Transportation Association: https://www.apta.com/wp-content/uploads/APTA_Fact-Book-2019_FINAL.pdf.

10. *Freight Analysis Framework V4*. 2019, Oak Ridge National Laboratory: https://faf.ornl.gov/fafweb/.

11. *Advancing Technology for America's Transportation Future*. 2012, National Petroleum Council: https://www.npc.org/reports/trans-future_fuels_summary-2012-lowres.pdf.

12. *Final Rule for Greenhouse Gas Emissions and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles - Phase 2*. 2016, United States Environmental Protection Agency: https://www.epa.gov/regulations-emissions-vehicles-and-engines/final-rule-greenhouse-gas-emissions-and-fuel-efficiency.

13. *Annual Energy Outlook*. 2018, United States Energy Information Administration: https://www.eia.gov/outlooks/aeo/.

14. *Hydrogen Delivery Scenario Analysis Model*. 2015, Argonne National Laboratory: https://hdsam.es.anl.gov/index.php?content=hdsam.

15. *H2A: Hydrogen Analysis Production Models*. 2015, National Renewable Energy Laboratory: https://www.nrel.gov/hydrogen/h2a-production-models.html.

16. Eudy, L.J., M. , *Battery Electric Bus Progress*, in *NREL/PR-5400-72209*. 2019, Foothills Transit Agency May 2019.

17. Moultak, M., Lutsey, N, Hall, D. , *Transitioning to Zero-Emissions Heavy-Duty Freight Vehicles*. ICCT White Paper: September 2017.

18. Askin, A.C., et al., *The heavy-duty vehicle future in the United States: A parametric analysis of technology and policy tradeoffs*. Energy Policy, 2015. **81**: p. 13.

Acknowledgements

We would like to recognize Steven Wiryadinata for his invaluable contributions to this effort. Especially the adaptions to the HDV ParaChoice capability.