Comparison of Vehicle Choice Models

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Comparison of Vehicle Choice Models

prepared by:
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<th>Abbreviation</th>
<th>Description</th>
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<td>AEO</td>
<td>Annual Energy Outlook</td>
</tr>
<tr>
<td>Argonne</td>
<td>Argonne National Laboratory</td>
</tr>
<tr>
<td>ARRA</td>
<td>American Recovery and Reinvestment Act</td>
</tr>
<tr>
<td>BEV</td>
<td>battery electric vehicle</td>
</tr>
<tr>
<td>CAFE</td>
<td>Corporate Average Fuel Economy</td>
</tr>
<tr>
<td>CD</td>
<td>charge-depleting</td>
</tr>
<tr>
<td>CI</td>
<td>compression-ignition</td>
</tr>
<tr>
<td>CNG</td>
<td>compressed natural gas</td>
</tr>
<tr>
<td>CNGV</td>
<td>compressed natural gas vehicle</td>
</tr>
<tr>
<td>Conv</td>
<td>conventional</td>
</tr>
<tr>
<td>CS</td>
<td>charge-sustaining</td>
</tr>
<tr>
<td>CVCC</td>
<td>Consumer Vehicle Choice Component</td>
</tr>
<tr>
<td>CY</td>
<td>calendar year</td>
</tr>
<tr>
<td>DOE</td>
<td>U.S. Department of Energy</td>
</tr>
<tr>
<td>EERE</td>
<td>Energy Efficiency and Renewable Energy</td>
</tr>
<tr>
<td>EIA</td>
<td>Energy Information Administration</td>
</tr>
<tr>
<td>EPA</td>
<td>U.S. Environmental Protection Agency</td>
</tr>
<tr>
<td>EREV</td>
<td>extended-range electric vehicle</td>
</tr>
<tr>
<td>FCTO</td>
<td>Fuel Cell Technologies Office</td>
</tr>
<tr>
<td>FCV</td>
<td>fuel cell vehicle</td>
</tr>
<tr>
<td>ft³</td>
<td>cubic foot (feet)</td>
</tr>
<tr>
<td>GHG</td>
<td>greenhouse gas</td>
</tr>
<tr>
<td>HEV</td>
<td>hybrid electric vehicle</td>
</tr>
<tr>
<td>HWFET</td>
<td>Highway Fuel Economy Test</td>
</tr>
<tr>
<td>ICE</td>
<td>internal combustion engine</td>
</tr>
<tr>
<td>kg</td>
<td>kilogram(s)</td>
</tr>
<tr>
<td>kWh</td>
<td>kilowatt hour(s)</td>
</tr>
<tr>
<td>LAVE-Trans</td>
<td>Light-Duty Alternative Vehicle Energy Transitions</td>
</tr>
<tr>
<td>LDV</td>
<td>light-duty vehicle</td>
</tr>
<tr>
<td>LPG</td>
<td>liquefied petroleum gas</td>
</tr>
<tr>
<td>MA³T</td>
<td>Market Acceptance of Advanced Automotive Technologies</td>
</tr>
<tr>
<td>mi</td>
<td>mile(s)</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Definition</td>
</tr>
<tr>
<td>--------------</td>
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</tr>
<tr>
<td>mpgge</td>
<td>mile(s) per gallon of gasoline equivalent</td>
</tr>
<tr>
<td>mph</td>
<td>miles per hour</td>
</tr>
<tr>
<td>MSRP</td>
<td>Manufacturer’s Suggested Retail Price</td>
</tr>
<tr>
<td>NEMS</td>
<td>National Energy Modeling System</td>
</tr>
<tr>
<td>NPC</td>
<td>National Petroleum Council</td>
</tr>
<tr>
<td>NRC</td>
<td>Natural Research Council</td>
</tr>
<tr>
<td>NREL</td>
<td>National Renewable Energy Laboratory</td>
</tr>
<tr>
<td>ORNL</td>
<td>Oak Ridge National Laboratory</td>
</tr>
<tr>
<td>PEV</td>
<td>plug-in electric vehicle</td>
</tr>
<tr>
<td>PHEV</td>
<td>plug-in hybrid electric vehicle</td>
</tr>
<tr>
<td>s</td>
<td>second(s)</td>
</tr>
<tr>
<td>SI</td>
<td>spark-ignition</td>
</tr>
<tr>
<td>SNL</td>
<td>Sandia National Laboratories</td>
</tr>
<tr>
<td>SUV</td>
<td>sport utility vehicle</td>
</tr>
<tr>
<td>UDDS</td>
<td>Urban Dynamometer Driving Schedule</td>
</tr>
<tr>
<td>VTO</td>
<td>Vehicle Technologies Office</td>
</tr>
<tr>
<td>Wh</td>
<td>watt-hour(s)</td>
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ACKNOWLEDGMENTS

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COMPARISON OF VEHICLE CHOICE MODELS

by

Thomas S. Stephens, Rebecca S. Levinson, Aaron Brooker, Changzheng Liu, Zhenhong Lin, Alicia Birky, and Eleftheria Kontou

ABSTRACT

Five consumer vehicle choice models that give projections of future sales shares of light-duty vehicles were compared by running each model using the same inputs, where possible, for two scenarios. The five models compared — LVCFlex, MA³T, LAVE-Trans, ParaChoice, and ADOPT — have been used in support of the Energy Efficiency and Renewable Energy (EERE) Vehicle Technologies Office in analyses of future light-duty vehicle markets under different assumptions about future vehicle technologies and market conditions. The models give projections of sales shares by powertrain technology. Projections made using common, but not identical, inputs showed qualitative agreement, with the exception of ADOPT. ADOPT estimated somewhat lower advanced vehicle shares, mostly composed of hybrid electric vehicles. Other models projected large shares of multiple advanced vehicle powertrains. Projections of models differed in significant ways, including how different technologies penetrated cars and light trucks. Since the models are constructed differently and take different inputs, not all inputs were identical, but were the same or very similar where possible.

Projections by all models were in close agreement only in the first few years. Although the projections from LVCFlex, MA³T, LAVE-Trans, and ParaChoice were in qualitative agreement, there were significant differences in sales shares given by the different models for individual powertrain types, particularly in later years (2030 and later). For example, projected sales shares of conventional spark-ignition vehicles in 2030 for a given scenario ranged from 35% to 74%. Reasons for such differences are discussed, recognizing that these models were not developed to give quantitatively accurate predictions of future sales shares, but to represent vehicles markets realistically and capture the connections between sales and important influences.

Model features were also compared at a high level, and suggestions for further comparison of models are given to enable better understanding of how different features and algorithms used in these models may give different projections.
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1 INTRODUCTION

The U.S. Department of Energy (DOE) Vehicle Technologies Office (VTO) analysis team uses projections of market penetration of advanced-technology powertrains in light-duty vehicles (LDVs) to assess potential energy and emissions impacts and to understand how future conditions such as fuel prices, policies, and technology advancement might influence consumer adoption of these powertrain technologies. Likewise, the Fuel Cell Technologies Office (FCTO) uses such projections to analyze potential adoption of fuel cell vehicles under different assumptions about fuel cell and hydrogen storage, production, and delivery technologies.

Since approximately 2010, VTO and FCTO have funded the development and use of several consumer vehicle choice models to give such projections. Five of these models were compared by running each of them on two scenario cases with, to the extent allowed by the diversity of the models, mutually agreed upon inputs for critical parameters such as future fuel costs, technology prices and efficiencies, and infrastructure growth. The models gave different market share projections. Comparing some of the features and algorithms used in the different models reveals some reasons to expect different projections and highlights the different approaches taken by model developers.

This document describes the inputs used to define the two scenarios, the market shares projected by each model for these scenarios, and some of the similarities and differences between the five vehicle choice models. Finally, some recommendations are given for further work to elucidate differences in model algorithms and sensitivities.

Section 2 describes the five vehicle choice models compared, compares the main features of the models, briefly describes some applications of these models, and describes how models were calibrated or benchmarked. In Section 3, the types of inputs and how they were developed are described, and the values of selected inputs and how they were used in the models for the two scenarios are also given. The projections of the five models are discussed in Section 4. Section 5 gives a summary and conclusions. References used in support of this document are provided in Section 6.
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2 VEHICLE CHOICE MODELS EXAMINED

2.1 MODEL FEATURES AND CHARACTERISTICS

Five vehicle choice models have been used for VTO and FCTO analysis activities. The following models were developed with different assumptions, and each represents the LDV market somewhat differently:

- LVCFlex model, developed by Energetics Incorporated (Birky, 2015)
- Light-Duty Alternative Vehicle Energy Transitions (LAVE-Trans) model, developed by ORNL (Liu, 2015; NRC, 2013)
- ParaChoice model, developed by Sandia National Laboratories (SNL) (Manley et al., 2015; Levinson et al., 2016)
- ADOPT model, developed by the National Renewable Energy Laboratory (NREL; Brooker, 2015; Brooker et al., 2015a)

The LVCFlex model (Birky, 2015) was derived from the LVChoice model (Argonne, 2014), both of which were based on the Consumer Vehicle Choice Component (CVCC) in the Energy Information Administration’s (EIA’s) National Energy Modeling System (NEMS) used to develop the Annual Energy Outlook (AEO). LVCFlex models consumer choice in five size classes: small cars, large cars, small sport utility vehicles (SUVs), large SUVs, and pickups. The model is configured to allow flexible specification of up to 16 powertrain types, with defaults provided for the 14 technologies included in AEO 2014 (EIA 2014). For this study, the following technologies were included: gasoline spark-ignition (SI) and diesel compression-ignition (CI) conventional (Conv) powertrains; a hybrid electric vehicle (HEV) with SI gasoline engine; two plug-in hybrid electric vehicle (PHEV) platforms with SI engines; two battery electric vehicle (BEV) platforms; and a hydrogen fuel cell vehicle (FCV). Sales shares of each size class are specified by the user; in this case, the shares by size class and total vehicle sales were specified to be consistent with the AEO 2014 Reference Case (EIA 2014). There is a single consumer preference specification for each vehicle size class (no segmentation of consumers).

In the MA3T model, consumers are segmented with more dimensions, including state, area type (urban or rural), new technology attitude, driving pattern, and availability of electric charging at home and at work (Lin, 2015). Powertrain choices include Conv SI, Conv CI, HEV, PHEV, BEV, FCV, fuel cell PHEV (FC PHEV), and compressed natural gas SI vehicle (CNGV). In particular, multiple PHEVs and BEVs with different electric driving ranges are represented to account for consumer choices of optimal ranges based on heterogeneous driving patterns.

Multiple variants within each powertrain choice are also included to reflect the trade-off between attributes such as efficiency and incremental cost, which is important for analysis of market-
driven-compliance to fuel economy standards (Xie and Lin, 2017). Five size classes are included: small cars, midsize cars, car-based SUVs, truck-based SUVs, and pickup trucks. The MA\textsuperscript{3}T model estimates total LDV sales and vehicle population (stock), and sales shares by size class, powertrain type, variant, and state endogenously. Recently, ORNL has released the MA\textsuperscript{3}T MiniTool (http://teem.ornl.gov), which provides a simpler process of utilizing MA\textsuperscript{3}T. It is currently being expanded to (1) MA\textsuperscript{3}T-MC (Mobility Choice), which includes choices such as automated vehicles, ridesharing, transit, and shared vehicles (Lin, 2017); (2) MA\textsuperscript{3}T-China, which is an adaptation of MA\textsuperscript{3}T to the China market and funded by Aramco; and (3) MA\textsuperscript{3}T-Global, which is an adaptation to the global market.

The LAVE-Trans model gives sales shares for two vehicle classes — cars and light trucks — and represents two segments of consumers: early adopters and majority adopters. The main difference between the two segments is the value consumers place on newness or maturity of technology (Liu, 2015). Early adopters more readily adopt vehicles with advanced technologies, such as plug-in electric vehicles (PEVs) and FCVs, while the majority of consumers are averse to these vehicles. As more of these new vehicles are purchased, both the preference for them by early adopters and the aversion by the majority of consumers will decrease. This is calculated in LAVE-Trans, which tracks the on-road populations of these vehicles.

The ParaChoice model was heavily influenced by the Transitional Alternative Fuels and Vehicles (TAFV) model (Greene, 2001) and thus shares many structural similarities with MA\textsuperscript{3}T, though it has some simplifications (Manley et al., 2015; Levinson et al., 2016). However, it is integrated with an energy sector model and has built-in parametric capability allowing for sensitivity analyses. In the ParaChoice model used in the analysis reported here, powertrain choices included Conv SI and CI, SI HEV, two PHEVs, a BEV, and FCV. However, the model is capable of including other powertrain choices as well, such as FlexFuel Conv and HEV, CI HEVs and PHEVs, CNG (dedicated) HEV and PHEV, CNG/bifuel Conv, and BEVs of multiple ranges. Three size classes of cars and two size classes of light trucks are modeled, with sales shares of each size class specified as inputs.

The ADOPT model represents vehicles by using existing vehicle options and creates new options in the future based on technology improvements, consumer preferences, and market conditions. ADOPT simulations start with the nearly 1,000 existing vehicle makes, models, and trim levels, unlike the other models in this study that used vehicle attributes generated by Autonomie simulations to represent vehicle options and technology improvements over time (Moawad et al., 2016). The attributes are represented by their actual price, acceleration, size, efficiency, and range. While the vehicle options are different, ADOPT uses the same technology improvement assumptions that were used by the Autonomie model (Argonne, 2017). In ADOPT, the technology improvements are applied over time to adjust the vehicle attributes using a vehicle powertrain model FASTSim (Brooker et al., 2015b). ADOPT also uses the FASTSim tool to generate new vehicle options over time based on consumer preferences and market conditions.

Another difference between the five vehicle choice models is the level of aggregation of the powertrain types. Table 1 provides a summary of the key characteristics of the vehicle choice models as used in this analysis.
<table>
<thead>
<tr>
<th></th>
<th>LVCFlex</th>
<th>MA³T</th>
<th>LAVE-Tran</th>
<th>ParaChoice</th>
<th>ADOPT</th>
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<tr>
<td>Reference</td>
<td>Birky, 2015; Argonne,</td>
<td>Lin, 2015; Lin and Greene,</td>
<td>Liu, 2015; NRC, 2013</td>
<td>Manley et al., 2015; Levinson et al., 2016</td>
<td>Brooker, 2015; Brooker et al., 2015a</td>
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<td>Model type</td>
<td>Nested multinomial logit</td>
<td>Nested multinomial logit</td>
<td>Nested multinomial logit</td>
<td>Nested multinomial logit</td>
<td>Mixed multinomial logit</td>
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<td>Vehicle size classes modeled</td>
<td>Sm car, Lg car, Sm SUV, Lg SUV, Pickup</td>
<td>Sm car, Lg car, Sm SUV, Lg SUV, Pickup</td>
<td>Car, Light truck</td>
<td>Sm car, Lg car, Sm SUV, Lg SUV, Pickup</td>
<td>All sizes</td>
</tr>
<tr>
<td>Vehicle powertrain choices</td>
<td>SI Conv, E85 FlexFuel Conv, CI Conv, CNG, LPG, SI HEV, CI HEV, PHEV10 &amp; 40, H2 FCV, BEV100, 200, &amp; 300, CNG bifuel, LPG bifuel</td>
<td>SI Conv, FlexFuel Conv, CI Conv, Conv CNG, SI HEV, CI HEV, CNG HEV, PHEV10, 20, &amp; 40, EREV10, 20, &amp; 40, FCV, BEV100, 200, &amp; 300, CI PHEV10, 20, &amp; 40, FC PHEV10, 20, &amp; 40</td>
<td>SI Conv, HEV, PHEV10, PHEV40, FCV, BEV</td>
<td>SI Conv, FlexFuel Conv, CI Conv, CNG Conv, SI HEV, CI HEV, FlexFuel HEV, CNG HEV, SI PHEV10 &amp; 40, CI PHEV10 &amp; 40, FlexFuel PHEV10 &amp; 40, FCV, BEV75, 100, 150, &amp; 225, CNG Bifuel</td>
<td>All existing makes, models, and trim levels, plus future FCVs</td>
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<tr>
<td>Total LDV sales</td>
<td>Exogenous</td>
<td>Endogenous</td>
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<td>Exogenous</td>
<td>Endogenous or Exogenous</td>
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<td>Maint. cost per yr (−)</td>
<td>Acceleration (−)</td>
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<td>Range (+)</td>
<td>PEV Batt. repl. cost (−)</td>
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<tr>
<td>Acceleration (−)</td>
<td>Luggage space (+)</td>
<td>Luggage space (+)</td>
<td>Luggage space (+)</td>
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<td>PEV Batt. repl. cost (−)</td>
<td>Make/model diversity (+)</td>
<td>Make/model diversity (+)</td>
<td>Make/model diversity (+)</td>
<td>Make/model diversity (+)</td>
<td></td>
</tr>
<tr>
<td>Luggage space (+)</td>
<td>Range (+)</td>
<td>Range (+)</td>
<td>PEV charger costs (−)</td>
<td>PEV charger costs (−)</td>
<td></td>
</tr>
<tr>
<td>Make/model availability or diversity (+)</td>
<td>Home/workplace/public charging availability (+)</td>
<td>Home/workplace/public charging availability (+)</td>
<td>Home/workplace/public charging availability (+)</td>
<td>Home/workplace/public charging availability (+)</td>
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<tr>
<td>Multi-fuel utility (+/−)</td>
<td>Refueling travel time (−)</td>
<td>Refueling travel time (−)</td>
<td>Refueling travel time (−)</td>
<td>Refueling travel time (−)</td>
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</tr>
<tr>
<td>Home PEV recharge (+)</td>
<td>Function of previous 3 years sales</td>
<td>Function of previous year sales</td>
<td>Function of previous year sales</td>
<td>Function of previous year sales</td>
<td></td>
</tr>
<tr>
<td>Make/model diversity</td>
<td>Function of previous 3 years sales</td>
<td>Function of previous year sales</td>
<td>Function of previous year sales</td>
<td>Modeled by “evolving” high-selling makes/models</td>
<td></td>
</tr>
<tr>
<td>Consumer segmentation</td>
<td>None (one segment per vehicle size class)</td>
<td>Segmented by: Annual driving distance</td>
<td>Segmented by: Annual driving distance</td>
<td>Segmented by: Annual driving distance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Segment by: New technology attitude</td>
<td>Function of stock and consumer segment</td>
<td>Function of stock and consumer segment</td>
<td>Function of stock and consumer segment</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Segment by: Population density</td>
<td>Exogenous, based on powertrain introduction year</td>
<td>Exogenous, based on powertrain introduction year</td>
<td>Exogenous, based on powertrain introduction year</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Segment by: U.S. Census Div. and State Home charging convenience</td>
<td>Function of stock and consumer segment</td>
<td>Function of stock and consumer segment</td>
<td>Function of stock and consumer segment</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Segment by: Workplace charging availability</td>
<td>Exogenous, based on powertrain introduction year</td>
<td>Exogenous, based on powertrain introduction year</td>
<td>Exogenous, based on powertrain introduction year</td>
<td></td>
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<tr>
<td></td>
<td>Segment by: Income</td>
<td>Exogenous, based on powertrain introduction year</td>
<td>Exogenous, based on powertrain introduction year</td>
<td>Exogenous, based on powertrain introduction year</td>
<td></td>
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<tr>
<td></td>
<td>Segment by: Can also segment consumers by preference for acceleration, size, fuel cost</td>
<td>Exogenous, based on powertrain introduction year</td>
<td>Exogenous, based on powertrain introduction year</td>
<td>Exogenous, based on powertrain introduction year</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Segment by: Endogenous; capacity increases in response to sales</td>
<td>Exogenous, based on powertrain introduction year</td>
<td>Exogenous, based on powertrain introduction year</td>
<td>Exogenous, based on powertrain introduction year</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Segment by: Exogenous</td>
<td>Exogenous, based on powertrain introduction year</td>
<td>Exogenous, based on powertrain introduction year</td>
<td>Exogenous, based on powertrain introduction year</td>
<td></td>
</tr>
<tr>
<td>Consumer risk aversion</td>
<td>No</td>
<td>Function of stock and consumer segment</td>
<td>Function of stock and consumer segment</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>Fuel availability (alt. fuels, electricity)</td>
<td>Exogenous or endogenous, as a function of estimated vehicle stock</td>
<td>Exogenous or endogenous, as a function of estimated vehicle stock</td>
<td>Exogenous or endogenous, as a function of estimated vehicle stock</td>
<td>Exogenous or endogenous, as a function of estimated vehicle stock</td>
<td></td>
</tr>
</tbody>
</table>

Note: Table entries represent significant vehicle attributes, with arrows indicating trends (− for decrease, + for increase).
<table>
<thead>
<tr>
<th></th>
<th>LVCFlex</th>
<th>MA³T</th>
<th>LAVE-Tran</th>
<th>ParaChoice</th>
<th>ADOPT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle price</td>
<td>Exogenous</td>
<td>Uses user inputs, but can adjust prices endogenously as a function of sales and stock.</td>
<td>Uses user inputs, but can adjust prices endogenously as a function of sales and stock.</td>
<td>Uses user inputs, but can be parameterized.</td>
<td>Exogenously reflects current prices, but are adjusted endogenously based on evolved component size variations and technology improvements.</td>
</tr>
<tr>
<td>endogenous/</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>exogenous</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Special features</td>
<td>Market penetration can be exogenously limited to represent supply-side constraints</td>
<td>Market penetration can be exogenously limited to represent supply-side constraints. Range anxiety cost is a function of driving pattern, daily range limitation value, and range.</td>
<td>Market penetration can be exogenously limited to represent supply-side constraints. Hydrogen prices can be endogenous (function of hydrogen demand).</td>
<td>Hydrogen production pathway and prices determined endogenously as a function of cost and demand. Electricity grid evolves endogenously. Built-in parameterization of uncertain variables.</td>
<td>Captures all current makes, models, and trims. CAFE standards can be implemented as a constraint with supply-side assumptions.</td>
</tr>
<tr>
<td>Incentives</td>
<td>Subtracted from vehicle price</td>
<td>Can be modeled by state. User can specify if incentive is worth less than the face value.</td>
<td>Subtracted from vehicle price</td>
<td>Can be modeled by state</td>
<td>Can be modeled by state, county, or zip code.</td>
</tr>
<tr>
<td></td>
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<td></td>
</tr>
</tbody>
</table>
2.2 MODEL APPLICATIONS

The five vehicle choice models compared here have been used in a range of applications for VTO analyses and other studies. Many of these studies are summarized below; the references cited provide additional details.

The LVCFlex model was developed by Energetics Incorporated from the LVChoice model (Argonne, 2014), originally developed by TA Engineering, Inc., for use in the National Petroleum Council’s Future Transportation Fuels Study (NPC, 2013), and subsequently modified and updated. LVCFlex is based on the EIA’s NEMS consumer choice methodology used to develop light-duty market projections in the AEO. Though more simplistic, LVCFlex can be used to approximate the NEMS consumer choice model behavior and allows users to quickly develop NEMS-like LDV technology sales share projections without running the NEMS model. Being a stand-alone model, it does not have links to economic or industry sectors as does NEMS; however, it is much simpler to use. The primary application of LVCFlex has been to estimate future market shares of advanced-technology LDVs for the DOE’s VTO prospective benefits analysis (see, e.g., Stephens et al., 2016).

The MA³T was developed to examine the potential market adoption of advanced-technology vehicles under various conditions and policies, in particular technology cost and performance (Lin and Greene, 2010). In addition to VTO prospective benefits analysis, MA³T has been used to analyze numerous technology and policy studies, including those led by ORNL and third-party institutions, as listed below:

- Sensitivity of hydrogen vehicle sales to consumers’ preferences (Greene et al., 2013a),
- Impacts of DOE technical targets on market acceptance and societal benefits (Lin et al., 2013),
- Distribution of cost-effective BEV electric ranges for U.S. consumers (Lin, 2014),
- Distribution of cost-effective PHEV electric ranges for U.S. consumers (Lin, 2012),
- Role of public and workplace charging on PEV sales (Lin and Greene, 2011),
- Potential impact of dynamic wireless charging on PEV sales (Lin et al., 2014)
- Global transportation technology transition (McCollum et al., 2016),
- Market-driven compliance of the Corporate Average Fuel Economy/greenhouse gas (CAFE/GHG) standards (Xie and Lin, 2017),
• Uncertainty of future PEV adoption (Liu and Lin, 2017), and

• Biogas electricity incentives to stimulate PEV sales (Podkaminer et al., 2017).

The above studies include funding support from multiple DOE offices or programs (VTO, FCTO, Bioenergy Technology Office, Office of Policy, and EIA), with VTO being the original and main sponsor.

Also, MA³T has been expanded to the China vehicle market with funding support by Aramco Services Company and to the global context with funding support by the International Institute for Applied Systems Analysis.

The LAVE-Trans model was originally developed and used for the National Research Council (NRC) study, Transitions to Alternative Vehicles and Fuels (NRC, 2013). It has been used to examine the barriers to and dynamics of transitions to advanced vehicle technologies and alternative fuels under different policy scenarios, including various subsidies and other incentives (NRC, 2013), and the California zero emission vehicles mandates (Greene et al., 2013b; Greene et al., 2014a). LAVE-Trans was also used in a study of the sensitivity of a transition to electric-drive vehicles to network externalities and various uncertainties (Green et al., 2014b).

The ParaChoice model was initially developed with SNL Laboratory Directed Research and Development (LDRD) funds in order to model and understand the dynamics between the transportation and energy sectors. The model is constructed to enable stochastic or parametric studies of sensitivities to different inputs (Barter et al., 2012). ParaChoice has been used in VTO prospective benefits analysis. It also has been used to assess which factors most strongly influence sales (Barter et al., 2013; Levinson et al., 2016). Peterson et al. (2014) used ParaChoice to examine the impact of natural gas vehicles in competition with PEVs and conventional vehicles, and they examined sensitivity to natural gas prices, public refueling infrastructure, and other variables. Barter et al. (2015) used ParaChoice to assess the sensitivity of future BEV adoption to battery costs and internal combustion engine (ICE) vehicle efficiency, and how different approaches to representing non-cost barriers, such as limited driving range, impacts projected adoption levels and sensitivities.

The ADOPT model was developed as an alternative approach to estimating the technical target improvements needed for advanced-technology vehicle market success. Other approaches used representative vehicles by powertrain and size class. ADOPT starts with the diverse set of acceleration and other attributes of the actual market, and then creates a diverse set of future options by optimizing vehicle component sizes for the market. This approach helps to capture many of the most successful advanced-technology vehicles, such as the Toyota Prius, Nissan Leaf, and Tesla Model S, which do not have typical characteristics. These vehicles are successful in part due to their combinations of acceleration, price, and fuel cost (in addition to incentives). Including all the existing vehicle options enables other unique capabilities. One, it provides vehicle footprint data needed to model and enforce the Light-Duty Vehicle Greenhouse Gas Emissions standards and CAFE standards, which historically have dictated vehicle fuel economy. And two, including all the existing vehicle options enable a data-driven calibration of
the value of vehicle attributes, which results in robust and detailed validation. Finally, ADOPT is very spatially explicit and can provide sales projections by zip code (LVCFlex provides national estimates and MA3T and ParaChoice estimate sales by state). ADOPT was chosen for these unique capabilities for several projects, including estimating trade-offs in component sizes for FCVs, VTO technology target impacts on sales, technology target pathways to FCVs, high octane fuel analysis (Johnson et al., 2015), and PEV impacts on the electric grid.

2.3 COMPARISON OF MODEL STRUCTURES AND SENSITIVITIES

Four of the models — LVCFlex, MA3T, LAVE-Trans, and ParaChoice — are nested, multinomial logit models; however, the nesting hierarchy is different. The nesting hierarchy constrains substitution patterns; that is, how changes in sales shares of different vehicle alternatives are correlated. Vehicle choices within the same nest are better substitutes (their shares are more strongly and negatively correlated) than choices in different nests (Train, 2009). The ADOPT model uses no nesting and is a mixed multinomial logit model, which has distributions of values of coefficients in the utility function. The nesting structures of LVCFlex, MA3T, LAVE-Trans, and ParaChoice are shown in Figures 1 through 4, respectively. It should be noted that each of these models is continually being upgraded, and the nesting hierarchy is subject to change by the developers. LVCFlex includes three levels of nesting within each size class, as shown in Figure 1, which reflects the NEMS structure for AEO 2015. However, the technology group assignment is specified by the user. The hierarchy used for this study was consistent with that in Figure 1, but technologies not included in this study (ethanol [EtOH] and CNG) were omitted.

All five models use a utility function to relate vehicle attributes and other inputs to a measure of utility. Sales shares are estimated on the basis of utility, and, in some models, additional factors, as discussed below. However, the utility of alternatives is relative; there is no absolute scale for utility. Therefore, utility values from different models cannot be compared directly. However, a generalized cost can be calculated that is comparable. The function representing the utility of a vehicle choice in each of the above models contains a term that

![FIGURE 1 Nesting Hierarchy of the LVCFlex Model (Technologies not included in this study were omitted.)](image-url)
FIGURE 2 Nesting Hierarchy of the MA$^3$T Model

FIGURE 3 Nesting Hierarchy of the LAVE-Trans Model

FIGURE 4 Nesting Hierarchy of the ParaChoice Model
includes the vehicle price. If a consumer places a value of $1 on a $1 decrease in the price of a vehicle, the coefficient on the vehicle price term in the utility equation is the marginal utility of $1. By forming the ratios of the marginal or incremental utilities of other terms in the utility equation (representing the contributions of other attributes and factors), the relative influence of these other factors can be expressed in dollars. These marginal costs are often called “generalized costs” (Greene, 2001).

For example, the generalized costs of incremental changes in some vehicle attributes appearing in earlier versions of the MA³T, LAVE-Trans, and LVCFlex (the LVChoice model) models were estimated. A 10% change in each of the following attributes was made, and the resulting generalized costs were approximately evaluated:

- Fuel cost per mile: from 0.10 to 0.11 $/mi
- BEV range: from 100 to 110 mi
- Maintenance cost: from 500 to 450 $/yr
- Luggage space: from 91% to 100% of a conventional vehicle
- Make/model diversity (as a ratio of the number of BEV models to Conv SI models): from 0.1 to 0.11
- Public charging availability: from 10% to 11% (relative to gas stations)

Figure 5 shows the magnitudes of the generalized costs associated with these changes. For the MA³T model, approximate ranges are shown for values of vehicle range and availability of public chargers, since these vary widely between different consumer segments in that model (values were not estimated for all the segments).

The generalized costs shown in Figure 5 are only approximate and were estimated from earlier versions of the models that were used in the market share projections presented in Section 4; they should not be taken as definitive comparisons of the sensitivities of the models to the different attributes. This example shows a possible approach which may provide some insight into the assumed value to consumers of different attributes in each of the models, for different consumer segments. The ADOPT model allows the user to generate generalized costs showing the relative importance of different factors that influence vehicle choices (Brooker et al., 2015a).

However, differences in generalized costs estimated from different models cannot be used to predict differences in sales shares, since sales shares depend on utility in a highly nonlinear way. A large change in utility of a given vehicle alternative may or may not result in a large change in sales share of that vehicle, since it is relative utility that influences sales shares. Sensitivity studies such as those conducted by Liu and Lin (2017) of the MA³T model and regularly conducted using the ParaChoice model (Barter et al., 2012, 2013; Peterson et al., 2014; Westbrook et al., 2014) are another possible approach. Both Barter et al. (2012, 2013) and Liu and Lin (2017) used Monte Carlo simulation to evaluate the sensitivity of sales shares of PEVs to...
FIGURE 5 Comparison of Generalized Costs Estimated for a 10% Improvement in Selected Inputs for Three Vehicle Choice Models

various inputs. Monte Carlo or stochastic simulation techniques would be useful if assumed variations in the inputs to be studied can be standardized across models. This type of sensitivity analysis is straightforward for many inputs that are used in similar ways by different models, but it requires care for other inputs. A stochastic simulation approach could be used to evaluate many different sensitivity metrics, including cross-elasticities (how changes in one vehicle alternative’s attributes affect the sales shares of other vehicle alternatives).

Care should also be taken in comparing the influence of factors that may be calculated endogenously and therefore may be in a feedback loop. For example, make/model diversity of advanced-technology vehicles (e.g., PHEVs, BEVs, and FCVs) is estimated in some models from previous years’ sales, which reflects automakers expanding the diversity of models in which an advanced powertrain is offered as the model matures and sales grow. This creates a feedback that can amplify market penetration of a new vehicle several years after market introduction. Another feedback present in MA3T and LAVE-Trans is change in consumer risk aversion (new technology attitude), which depends on the stock of advanced-technology vehicles and represents the decrease in loss aversion as more of these vehicles are in the on-road stock and consumers become more familiar with them. Sensitivities to make/model diversity or risk aversion should be assessed from the response over several years, or by evaluating different scenarios with stronger or weaker feedbacks.

Some models also include limits on growth in sales or on sales shares of advanced-technology vehicles. For example, LVCFlex permits users to specify a maximum market
penetration curve, depending on the year of introduction and other parameters. Analogous limits can be set by users in MA³T, LAVE-Trans, and ADOPT. ADOPT can also have constraints that represent automakers’ responses to CAFE standards.

Future comparisons of these models should include a structured study of sensitivities to factors that the models have in common, including many vehicle attributes, fuel prices, and policy-related variables such as alternative fuel and electricity charging availability. Standardized ranges of variation of inputs, all defined consistently across models, could be specified, and changes in sale shares of all vehicle alternatives could be evaluated. This would generate a large number of sensitivity metrics, and a systematic approach to evaluating and comparing them would be needed. However, evaluating the factors that Liu and Lin (2017) found to be influential for PEV sales shares, as given by the MA³T model, would be a good starting point.

Another approach to comparing models is to document how each input is used in each model, starting with how the utility is influenced by each input, and the values of coefficients used in the utility and shares calculations, including the alternative-specific constant. Additional limits or adjustments (e.g., limits on shares growth) and endogenous calculations, such as make/model diversity, should also be documented to allow transparency and easy comparison of model algorithms. Several of the models have been at least partially documented, but more complete and up-to-date documentation is needed for several models.

2.4 MODEL CALIBRATION AND VALIDATION

Each of the five models has been calibrated and validated or benchmarked. Calibration consists of choosing model parameters to give sales shares and sensitivities to inputs that match historical sales (or to AEO projections in the case of LVCFlex) and known market trends. Validation typically relies on comparison of model output with additional information. Benchmarking consists of comparing the output of a model (e.g., LVCFlex) with that of the model it is intended to approximate (in the case of LVCFlex, the NEMS Consumer Vehicle Choice Submodule output reported in the AEO).

2.4.1 LVCFlex Calibration and Benchmarking

Since the LVCFlex model was developed to approximate the CVCC in NEMS, the coefficients in the model for consumer utility and other parameters were developed from analogous parameters in NEMS. Since NEMS models 12 LDV size classes, and LVCFlex models 5, the values from several size classes in NEMS were combined to give 5 sets of parameters for the 5 size classes in LVCFlex. The model includes CVCC calibration factors which are implemented using a constant term in the utility equation, specified annually for each technology. LVCFlex also incorporates within-nest limits to market shares of PEVs, which are applied separately from the consumer utility calculation, consistent with the CVCC.
To benchmark LVCFlex, vehicle and fuel attributes were extracted from the AEO 2014 Reference Case and used to develop model inputs. The resulting market shares were then compared with AEO. Note that the AEO output tables do not report acceleration times by powertrain type within size classes, annual values for make/model availability (diversity), or annual values of alternative fuel availability. Acceleration time was estimated using an approach consistent with algorithms in NEMS but without adjustments required to comply with CAFE standards. At this time, the LVCFlex make/model and fuel availability algorithms have not been validated against NEMS due to the lack of intermediate output from NEMS.

Figure 6 shows the market shares of advanced-technology cars and light trucks as projected by LVCFlex and in the AEO 2014 Reference Case. The shares given by LVCFlex are quite similar to those from the AEO, but LVCFlex gives slightly higher HEV shares of car sales after 2030 and slightly lower shares of alternative-fueled light trucks compared to AEO. These slight differences may be due to estimation of parameter and vehicle attribute values required for aggregated size classes and differences in vehicle make/model and fuel availability calculations. In addition, LVCFlex is implemented at the national level, while NEMS is implemented on a regional level and reflects geographic differences in fuel price, vehicle sales, and other factors.

2.4.2 MA³T Calibration and Validation

The MA³T model has undergone two rounds of validation. The first round included calibration to historical sales data between 2005 and 2011, using historical prices and fuel economies. The constants of the utility equations were the only parameters that were calibrated, thus the calibration result was unique, subject to pre-defined numerical precision. The calibrated constants were intended to capture systematic bias from implicit factors (factors not included in the model). Constants varied from year to year, as expected, and were averaged over the seven calibration years to form a set of static constants used for projection. With the static constants, the model is informed by history. It should be pointed out that, in the first round, differences between states had not been fully reflected in MA³T. Although the share of driver type, the share of city driving, and energy prices had been estimated to vary between states, important factors such as state-specific policies and income have not been disaggregated by state. The effect of such calibration on projection accuracy was unknown, but it was expected that such a calibration is more likely to contribute to short-term projection accuracy than the long-term accuracy. In terms of validation, the calibrated MA³T was then used to back-cast the market shares of light-duty trucks, passenger cars, and HEVs (Figure 7). Another validation step was to test the model against actual market shares for calendar year (CY) 2012, for passenger cars, light-duty trucks, PHEVs, and BEVs (Figure 8). The model appeared to underestimate HEV shares for 2007 and 2009 and overestimate them for 2011 and 2012. The predicted market share of passenger cars also appeared a little lower than the actual number. But overall, the errors were small, and the model appeared reasonably accurate for near-term projection. Its accuracy for long-term projection was unknown, even if all the inputs were predicted accurately.

More recently, ORNL has conducted a second round of validation of MA³T. Simulated sales were compared with actual sales for 2014. Figure 9 shows the comparisons of 2014 sales of Conv SI, HEV, PHEV40 and BEV100 (MA³T was calibrated to match historical sales in
FIGURE 6 Comparison of LVCFlex Advanced-Technology Vehicle (AV) Sales Shares Projections against AEO 2014 Reference Case Projections: (a) Cars, (b) Light Trucks (Note that FCV methanol and gasoline technology slots were not populated in AEO 2014 but are retained as placeholders for future use.)
FIGURE 7 Validation of MA$^3$T against 2005–2011 Market Shares: (a) Car Share of LDVs, (b) HEV Share among Cars (Historical data from the ORNL Transportation Energy Data Book, Argonne PEV Sales Database, and WardsAuto.)

FIGURE 8 Validation of MA$^3$T against CY 2012 Market Shares (Historical data from ORNL Transportation Energy Data Book, Argonne PEV Sales Database, and WardsAuto.)
FIGURE 9 Comparison of Historical (Actual) Sales, MA³T Calibration (2013 and prior years), and MA³T Projections of Annual Sales (for 2014) of (a) Conv SI, (b) Hybrid, (c) Plug-in Hybrid, and (d) Electric Vehicles (Historical data from Argonne PEV Sales Database, WardsAuto, and R.L. Polk.)

2010–2013). These results generally show reasonably good matches between model results and actual data. One exception is the PHEV40 comparison. As shown, the difference in sales is very significant for 2014, which is likely due to the Osborne effect, in which the announcement of an upgraded product reduces demand for the existing model (Rao and Turut, 2014). General Motors, producer of the main PHEV40 product Volt, offered a $5,000 price cut in the summer of 2014 and also announced imminent availability of the newer version of Volt that is much superior to, but almost priced the same as, the current version. The combining effect is a surprisingly slight decrease in Volt sales. The current MA³T model does not consider the Osborne effect, which is more relevant to short-term company marketing interests than to policy analysis.

In addition, system dynamics validation methods were used as outlined in Barlas (1989) and Senge and Forrester (1980), where model validity is defined as “usefulness with respect to some purpose” (Barlas, 1989, p. 184). These methods include a set of validation procedures, as summarized in Table 2. Extreme condition tests were conducted to test whether the model gives the expected responses to extreme changes in certain parameters. For example, great
TABLE 2 Validation Procedures Used for the MA³T Model

<table>
<thead>
<tr>
<th>Formal Validation Procedures</th>
<th>Examples, specific to project</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Direct Structure Tests</strong></td>
<td></td>
</tr>
<tr>
<td>(qualitative; without simulation)</td>
<td></td>
</tr>
<tr>
<td>Empirical Tests: comparison with real system knowledge</td>
<td>Survey data; price elasticity data</td>
</tr>
<tr>
<td>Theoretical Tests: comparison with literature knowledge</td>
<td>Compare to literature elasticity estimates</td>
</tr>
<tr>
<td><strong>Structure Oriented Tests</strong></td>
<td></td>
</tr>
<tr>
<td>(quantitative; with simulation)</td>
<td></td>
</tr>
<tr>
<td>Extreme condition tests</td>
<td>Set range anxiety value to zero</td>
</tr>
<tr>
<td>Behavior sensitivity tests</td>
<td>Monte-Carlo simulation</td>
</tr>
<tr>
<td>Modified behavior prediction</td>
<td>Validation with real market datasets</td>
</tr>
<tr>
<td><strong>Behavior pattern test</strong></td>
<td>Scenarios analyses</td>
</tr>
</tbody>
</table>

uncertainties are involved in estimating the range anxiety value, measured in dollars per day, which represents a monetized value of the disutility of forgone trips that are infeasible due to limited BEV range. When the range anxiety daily value is set as high as $10,000/day, it represents the case in which consumers who travel distances longer than the range of the BEV will not adopt this vehicle. However, as shown in Figure 10, noticeable market sales of BEVs still occur (shown in purple), mainly thanks to the modest drivers who still prefer BEVs as they do not drive long distances. While little effect is seen when it is decreased from $10,000/day to $1,000/day (green area), a larger effect is seen when it is reduced to $50/day (blue area), and larger still when assumed to be $0/day, which represents a negligible penalty cost for range anxiety (red area). Under this assumption, BEV users can freely choose alternative travel modes if the trip cannot be made with BEVs. A significant increase in BEV sales is expected for this optimistic case, as the model indicated. A causal relationship test was conducted on the U.S. federal PEV incentive policy. The results are presented in Figure 11 and show higher early sales and earlier policy expiration due to an increase in the rebate value while holding all other policy parameters unchanged.

2.4.3 ParaChoice Calibration and Validation

In order to test the ability of the ParaChoice model to capture the dynamics of consumer choice, Levinson et al. (2016) conducted a validation study comparing sales data for alternative energy vehicles simulated using the ParaChoice model to historical sales data from January 2010 to June 2015. The simulation was run using historically accurate values for oil prices, with values for all years provided by the AEO report of the subsequent year, with the exception of 2015, for which the 2015 report values were used. Autonomie 2015 technology cost and efficiency projections for 2010 were used and held constant throughout the simulation. Historically accurate incentives were used in the simulation and varied annually on a state-by-state level. In addition, vehicle model availability was set to reflect historically accurate values by vehicle class size, with vehicle model year determining the year of availability to consumers in the simulation. Diesel vehicles, HEVs, PHEV10s, PHEV40s, BEV75s, and BEV100s were all analyzed.
Extreme scenario: Range anxiety impact

FIGURE 10 Extreme Scenario Test of the MA³T Model Showing the Impact of Range Anxiety Value on BEV Sales (range anxiety value: penalty cost in dollars per day if BEV trip cannot be fulfilled with limited range) (Colored areas represent differences in cumulative sales with the indicated changes in the range penalty cost.)

FIGURE 11 Causal Relationship Test of the MA³T Model Showing the Impacts of Rebate Value
Figure 12 shows the resulting simulated U.S. LDV sales fractions for diesel vehicles, alongside vehicle sales fractions reported by hybridcars.com. As one would expect, the simulation does not capture the monthly variations in sales seen in actual data. However, it does capture the longer-term trends seen in the historical data, including the following:

1. The slow upward trend in sales from 2010 to 2013;

2. The jump in sales, which can be attributed to the large increase in vehicle model availability that occurs in summer 2013 in the historical data when the 2014 models are released, but 2014 in the simulation when the models appear in the simulation;

3. The dip in sales from 2014 into 2015; and


All sharp discontinuities in the simulated data can be attributed to changes in vehicle model availability. Similar analyses are performed for hybrids, PHEVs, and BEVs and can be found in Levinson et al. (2016). The work serves as validation of the ParaChoice’s simulation logic pertaining to consumer choice, and also an analysis of areas for simulation improvement.

FIGURE 12  Fraction of Diesel Sales Compared to Total Vehicle Sales from 2010 to Mid-2015 (Historically accurate reported by month (red xs) and simulated using the ParaChoice model (black dots). Lines are smoothed data.) (Source: Levinson et al., 2016)
2.4.4 ADOPT Calibration and Validation

ADOPT parameters were calibrated and validated in key dimensions for estimating petroleum use and GHG emissions. ADOPT does not use the constant term in the utility equation to adjust its vehicle-attribute-based sales estimates to match historical sales. Instead, the consumer preferences for the different vehicle attributes were calibrated for one year, and then held constant for other years and regions. It is not calibrated to Autonomie-generated vehicles, but to the actual available vehicle options. In order to match historical sales well, the consumer preference for each attribute had to vary non-linearly over each attribute’s range, and by income, where higher income consumers were less concerned with fuel cost and vehicle price, as shown in Figure 13.

ADOPT is focused on aggregate petroleum use and GHG emissions, thus most of the validation is done by comparing the related aggregate data. Specifically, the model sales estimates were compared to actual sales for relevant key metrics, including the distribution of sales by powertrain, fuel economy, acceleration, price, and class size, as shown for 2008 vehicles in Figure 14. Since ADOPT uses the actual vehicle options, its sales estimates are for vehicles that have attributes consistent with those of the actual sales. Without recalibration, ADOPT also matched well in 2012, as shown in Figure 15. Furthermore, it matched well in these dimensions and others for all the years and specific regions examined, including 2000 to 2013, and 2015. Some of the additional validation is presented in Brooker et al. (2015a).
FIGURE 14  Comparison of 2008 Historical Sales and ADOPT Estimates of (a) HEV Sales Share and Sales by (b) Fuel Economy, (c) Acceleration Time, (d) MSRP, and (e) Size Class

FIGURE 15  Comparison of 2012 Historical Sales and ADOPT Estimates of (a) HEV Sales Share and Sales by (b) Fuel Economy, (c) Acceleration Time, (d) MSRP, and (e) Size Class
2.4.5 LAVE-Trans Calibration and Validation

Key parameters in LAVE-Trans include price slopes and constant terms in the generalized cost equation. Price slopes are based on literature on new vehicle demand, taking into consideration the theoretical constraint that price slopes at disaggregated levels (e.g., vehicle class level) should be larger than the slopes at more aggregated levels (e.g., buy/no-buy level). Constant terms are calibrated to market sales in the baseline scenario. Specifically, constant terms for the buy/no-buy level are calibrated to AEO 2014 projections of total LDV sales, and constants for the car/truck level are calibrated to AEO 2014 projections of car/truck shares. Constants at the vehicle technology level (e.g., the choice of buying a gasoline vehicle versus buying a BEV) are calibrated to the available historical data. For later years, constants are assumed to be the average values of all historical constants.

The LAVE-Trans model is validated through backcasting. The model is first calibrated to historical data for 2010–2013. Then constant terms in 2014 are assumed to be the mean of 2010–2013 constants. The model is used to predict 2014 market shares. The predicted values are compared against actual 2014 market shares. This comparison is illustrated in Figure 16.

**FIGURE 16 LAVE-Trans Model Validation: Predicted 2014 Market Shares vs. Actual Values**
3 SCENARIOS AND INPUTS USED FOR MODEL COMPARISON

3.1 TYPES OF INPUTS DEFINED FOR THE SCENARIOS

Inputs for each of the models were provided for 2015 through 2050. These were based on two scenarios developed for prospective benefits analysis of the DOE VTO and FCTO programs (Stephens et al., 2016):

1. “No Program” scenario, which assumes there is no technology improvement or cost reduction due to the DOE VTO Program, and

2. “Program Success” scenario, which assumes that there are technology improvements and cost reductions that meet DOE VTO Program goals.

Attributes of light-duty passenger vehicles were estimated for 2015, 2020, 2025, 2030, 2035, and 2050 using Autonomie, with inputs based on experts from DOE and Argonne’s original equipment manufacturer (OEM) partners.

Vehicle attributes for the Program Success scenario were established based on VTO and FCTO program goals and relevant vehicle data available in the Autonomie library. Similarly, the attributes for the No Program scenario were established with input from VTO and FCTO for a counterfactual future scenario with no further investment in vehicle technologies by VTO or FCTO.

Vehicle attributes were defined for LDVs of five size classes: compact car, midsize car, small SUV, midsize SUV, and pickup truck — each having the following types of powertrains:

• Conv SI (gasoline);

• Conv CI;

• Hybrid electric (HEV, gasoline);

• PHEV electric, with SI engines, with nominal charge-depleting (CD) ranges of 10 and 40 mi (PHEV10, PHEV40);

• Hydrogen FCV; and

• BEV, with batteries sized for ranges of 100 and 300 mi (BEV100, BEV300).

Vehicle attributes were developed for the Program Success and No Program scenarios using the Argonne Autonomie toolkit (Argonne, 2017). Component-level inputs for these simulations were established in collaboration with VTO and FCTO program managers and analysts. Inputs for the Program Success scenario were based on VTO program goals in 2015, 2020, 2025, 2030, and 2045. A 5-year lag was assumed between the attainment of VTO and
FCTO program goals at the component level and successful commercialization of the vehicles. Inputs for the No Program scenario were also established with VTO and FCTO, assuming no further investment by the program offices in vehicle or fuel cell technologies. These inputs were less optimistic; that is, performance increased more slowly, and costs decreased more slowly than in the Program Success scenario. Again, a 5-year lag was assumed between the time that the components were assumed to reach a given cost and performance level, and the time of commercialization of vehicles with these components. In estimating costs, fully learned manufacturing costs were assumed. The retail price equivalent (RPE) was calculated from the estimated vehicle manufacturing price by applying a constant factor of 1.5. All prices were given in 2010$.

Vehicles were simulated over standard drive cycles to give fuel economy values for the Urban Dynamometer Driving Schedule (UDDS) for city fuel economy, and the Highway Fuel Economy Test (HWFET) for highway fuel economy. Standard practices developed by SAE were used for PHEV fuel economy and electricity consumption under CD and charge-sustaining (CS) modes. Vehicle simulations are described in more detail in Moawad et al. (2016).

The following vehicle attributes were provided:

• Vehicle manufacturing cost;
• Fuel economy, UDDS, HWFET, mi per gallon of gasoline equivalent (mpgge);
• Electricity consumption by PEVs, CD mode, Wh/mi;
• Fuel economy in CD mode (for PHEV10);
• CD range (of PHEVs, mi);
• Acceleration time (0 to 60 mph, s);
• Vehicle mass (as used in drive cycle simulations, kg);
• Gross vehicle mass (used in gradability simulations, kg);
• Usable battery pack energy (PEVs, Wh);
• Battery pack cost (HEVs and PEVs, $);
• Fuel cell cost (FCVs);
• Fuel tank capacity (for liquid-fueled vehicles, gal); and
• Fuel tank capacity, usable fuel (for CNG vehicles and FCVs-fueled vehicles, kg).
For each vehicle in each scenario, three vehicle prices were given, representing a high, medium, and average price, in order to give an estimate of the uncertainty of prices. The low (optimistic) price was used for the Program Success scenario, the high (pessimistic) price was used for the No Program scenario, and the low price was not used in this comparison.

Other vehicle attributes, which were not estimated using Autonomie but were used as inputs to some of the vehicle choice models, were defined by assuming typical values for currently available vehicles in each size class. Values for luggage/cargo space (ft³) were taken from the defaults of the MA³T model. Maintenance costs were assumed to be zero (or identical for all vehicle types). No inputs were defined for make/model diversity, since different models used different algorithms to calculate this.

Inputs in addition to vehicle attributes included fuel prices and availability and the total sales of LDVs in each year. Total LDV sales and fuel prices used for both scenarios were taken from the AEO 2014 Reference Case, except for hydrogen. Hydrogen prices were provided by FCTO analysts for the two scenarios. Public charging infrastructure assumptions were based on scenarios in the NRC’s Transitions to Alternative Vehicles and Fuels study (NRC, 2013). Assumptions about the numbers of hydrogen stations were developed in consultation with FCTO analysts. Since the FCTO is investing in technologies for producing and distributing hydrogen, more hydrogen fuel station availability was assumed for the Program Success scenario than in the No Program scenario. Hydrogen availability was quantified as a percentage, relative to the availability of gasoline; that is, 100% implies that hydrogen is as ubiquitous as gasoline. Values for these inputs for the two scenarios are presented in Section 4.

Vehicle choice modelers used these inputs, to the extent possible, given constraints in the representation of vehicles and other variables. Some differences in use of inputs or implementation details were impossible to avoid, such as differences in make/model diversity, as noted above.

Other differences included on-road adjustment of fuel economy values. LVCFlex fuel economies were adjusted in accordance with the procedure used for VTO prospective benefits as documented in Stephens et al. (2013). This procedure is based on the adjustment used in U.S. Environmental Protection Agency (EPA) fuel economy labeling, with a slight difference for PHEVs with blended operation in CD mode. The fuel economy adjustment in MA³T, LAVE-Trans, and ParaChoice was done in accordance with the method used by the EPA prior to model year 2009. This method applies constant factors (0.90 for city and 0.78 for highway) to the UDDS and HWFET fuel economy values, respectively.

The fuel economy values in ADOPT were also different. At the start of the simulation, they reflect the current EPA label fuel economy for each make, model, and trim. Future fuel economy values were adjusted using NREL’s FASTSim model which is integrated with ADOPT. ADOPT runs also included CNGVs, whereas the other models did not. Another difference in the ADOPT model runs was the use of low-production volume costs for FCVs, based on the price of the Toyota Mirai FCV. This was needed to accurately represent the high starting price of the Mirai at $57,500, while still being consistent with technical target prices as sales volumes increased. Similar to fuel economy, other vehicle attributes used in ADOPT
started with the actual existing vehicle attributes, and were then adjusted using FASTSim to reflect component-level cost and performance improvements consistent with those used in the Autonomie simulation. Specifically, there were components for which VTO and FCTO have program goals, including batteries, engine efficiency, fuel cells, hydrogen tanks, and lightweight materials. However, vehicle attributes used in ADOPT may have differed significantly from those used in the other vehicle choice models. For example, acceleration differed significantly in ADOPT. By including all existing makes, models, and trims, it has a large variety in acceleration reflecting those vehicles. The sales-weighted average acceleration also changes over time endogenously based on market conditions, as shown in Figure 17. The changes arise from technology improvements, such as lightweighting, a change in sales mix, and from vehicle evolution. When ADOPT creates new vehicle model options, it optimizes the component sizes to maximize sales, which impacts acceleration. For example, ADOPT may increase the engine size when fuel prices are low, because the improved acceleration is worth the increase in price and fuel cost. The result is that ADOPT uses technology improvements to improve both acceleration and efficiency.

There were also differences in how size classes were represented and how vehicle attributes were assigned to different classes. Since the classes for which vehicle attributes were provided were similar to those for which the LVCFlex and ParaChoice models were designed, attributes of each size class were used. MA³T, however, was developed to represent size classes based on EPA classification, with size classes cars: car SUV, truck SUV, and pickup. Attributes assigned to these were values supplied for midsize car, small SUV, midsize SUV, and pickup, respectively. In the LAVE-Trans model, car and light truck are the only size classes, so attributes of midsize car and midsize SUV were used.
3.2 “PROGRAM SUCCESS” AND “NO PROGRAM” SCENARIOS

Vehicle retail price equivalents for midsize cars, estimated as described above, are shown in Figure 18 for the No Program scenario, and in Figure 19 for the Program Success scenario. Vehicle prices in 2015 were the same in both scenarios, but tend to be lower in the Program Success scenario for future years.

FIGURE 18 Midsize Car Retail Price Equivalents in 2010$ for the No Program Scenario

FIGURE 19 Midsize Car Retail Price Equivalents in 2010$ for the Program Success Scenario
Federal tax credits for PEVs were assumed, consistent with the American Recovery and Reinvestment Act (ARRA), which specifies a tax credit of $2,500 for PEVs with at least 4 kWh total battery capacity, plus $417 for each kWh in excess of 4 kWh, for the first 200,000 units produced per manufacturer. For modeling, eight manufacturers were assumed. However, in all models except ParaChoice, it was assumed that on average, this had a value of 55% of the nominal value, since not all consumers realize the full value of this tax credit, and because it is not awarded at the point of sale, it presumably has a smaller influence on vehicle choice than a point-of-sale cash discount.

Figures 20 and 21 show the fuel economies for the No Program scenario and Program Success scenario, respectively. Combined, unadjusted fuel economies, with a 55/45 city/highway weighting are shown. For PHEVs, the fuel economy in CS mode is shown.

Future fuel prices were assumed to be those in the AEO 2014 Reference Case, extrapolated to 2050 on the basis of the trend from 2035 to 2040, and future hydrogen prices in the No Program and Program Success scenarios were supplied by the Energy Efficiency and Renewable Energy (EERE) FCTO. While, as noted above, the ParaChoice model used endogenously estimated hydrogen prices, the evolution of fixed costs for hydrogen production was parametrically tuned to most closely match the FCTO’s hydrogen cost projections for these scenarios. Fuel prices used here are shown in Figure 22.
Assumptions about the availability of charging stations were based on the “PEV and FCV Emphasis” scenario in the NRC’s Transitions to Alternative Vehicles and Fuels study (NRC, 2013). The number of charging stations over time was assumed to be the same in both the No Program and Program Success scenarios. The number of Level 2 and DC fast chargers assumed is plotted in Figure 23.
Hydrogen availability was quantified as a percentage relative to the availability of gasoline; that is, 100% implies that hydrogen is as ubiquitous as gasoline. The hydrogen availability assumed in the two scenarios is plotted in Figure 24. Although in the ParaChoice model the number of hydrogen stations was calculated endogenously, station growth rates were set so that the number of hydrogen stations throughout the simulation was in agreement with the hydrogen availability assumed in the other models.
Sales share projections of new LDVs, by powertrain technology, were estimated for 2010 through 2050 by using the five LDV choice models described above using the inputs for the No Program and Program Success scenarios. Projections from the five vehicle choice models are shown below; first, sales shares of LDVs, then sales shares of cars, and then sales shares of light trucks, all by powertrain type. For models that project market shares by multiple size classes, different size classes were included in cars and light trucks, but shares shown below are consolidated to cars, light truck, and LDV shares. Shares of all powertrain types, except Conv SI, are shown as colored areas, with Conv SI shares indicated by the white area above the other areas (shares sum to 100%). Sales shares of all LDVs are weighted averages over all size classes.

4.1 LVCFlex PROJECTIONS

Figure 25 shows LVCFlex LDV sales share projections for the No Program and Program Success scenarios. Figure 26 shows the LVCFlex sales share projections for cars, and Figure 27 shows sales share projections for light trucks. Cars in LVCFlex included the size classes compact car and midsize car, and light trucks included compact SUV, midsize SUV, and pickup. The sales share of each size class was taken from aggregated sales by size class in the AEO 2014 Reference Case. These shares are shown in Table 3 and were the same in the No Program and Program Success cases.
FIGURE 26 Car Sales Share by Powertrain Type for the No Program Scenario (left) and the Program Success Scenario (right) Projected by the LVCFlex Model

FIGURE 27 Light Truck Sales Share by Powertrain Type for the No Program Scenario (left) and the Program Success Scenario (right) Projected by the LVCFlex Model

TABLE 3 Sales Shares by Size Class Used as Input to the LVCFlex Model

<table>
<thead>
<tr>
<th></th>
<th>2015</th>
<th>2020</th>
<th>2025</th>
<th>2030</th>
<th>2035</th>
<th>2040</th>
<th>2045</th>
<th>2050</th>
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<tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compact car</td>
<td>0.256</td>
<td>0.268</td>
<td>0.275</td>
<td>0.284</td>
<td>0.29</td>
<td>0.283</td>
<td>0.275</td>
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</tr>
<tr>
<td>Midsize car</td>
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<td>0.274</td>
<td>0.279</td>
<td>0.283</td>
<td>0.285</td>
<td>0.3</td>
<td>0.315</td>
</tr>
<tr>
<td>Light truck</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compact SUV</td>
<td>0.191</td>
<td>0.189</td>
<td>0.185</td>
<td>0.179</td>
<td>0.176</td>
<td>0.173</td>
<td>0.17</td>
<td>0.167</td>
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<tr>
<td>Midsize SUV</td>
<td>0.149</td>
<td>0.149</td>
<td>0.145</td>
<td>0.141</td>
<td>0.139</td>
<td>0.136</td>
<td>0.133</td>
<td>0.13</td>
</tr>
<tr>
<td>Pickup</td>
<td>0.128</td>
<td>0.127</td>
<td>0.122</td>
<td>0.121</td>
<td>0.119</td>
<td>0.116</td>
<td>0.114</td>
<td>0.113</td>
</tr>
</tbody>
</table>
LVCFlex projected significant penetration by HEVs in the No Program scenario, but very rapid penetration of HEVs and PHEV40s in the first few years (2016–2020) of the Program Success scenario. Conv CI penetrates to a lesser extent in both scenarios, but somewhat earlier in the Program Success scenario; Conv CI shares then decrease as other powertrains penetrate. Penetration by FCVs occurs in later years, after 2035, and is significantly higher in the Program Success scenario. In general, sales shares of HEVs, PHEV40s, and FCVs are higher in the Program Success scenario. BEV300 sales shares are low in both scenarios, but BEV100 shows modest shares in both scenarios, with market penetration occurring earlier in the Program Success scenario.

LVCFlex projections for cars are quite different from those for light trucks, as seen by comparing Figures 26 and 27. HEVs, PHEVs, and BEV100s penetrate the car market, but not the light truck market. This is likely due to calibration factors taken from NEMS. Conv CI and FCVs penetrate light trucks much more than cars.

4.2 MA³T PROJECTIONS

Figure 28 shows MA³T LDV sales shares projections. Rapid and large penetrations by powertrains other than Conv SI are seen in both scenarios. Conv CI penetrates significantly in the Program Success scenario, but after 2020, Conv CI shares decrease as other shares increase. BEV100 sales shares reach a large fraction of all LDV sales in both scenarios. BEV300 shows some market share growth in the late years in the Program Success scenario. FCVs gain a significant share in both scenarios after 2025, but reach a higher sales share in the Program Success scenario, and FCVs appear to compete with PHEV10 and BEV100 for market share in years after 2035.

FIGURE 28  LDV Sales Share by Powertrain Type for the No Program Scenario (left) and the Program Success Scenario (right) Projected by the MA³T Model
Cars in MA³T included midsize car and compact SUV, and light trucks included midsize SUV and pickup. Sales shares of cars projected by MA³T qualitatively resemble the LDV shares, but Conv CI shares are lower in cars, as seen in Figure 29. Light truck shares projected by MA³T are shown in Figure 30, which shows Conv CI penetrating rapidly to a large market share by the year 2020, then rapidly decreasing as BEV100 shares increase. Little penetration by BEV300 in light trucks is seen in either scenario. FCVs show growing light truck sales share after 2030, slightly later than in cars. FCV light truck shares grow faster in the Program Success scenario than in the No Program scenario.

**FIGURE 29** Car Sales Share by Powertrain Type for the No Program Scenario (left) and the Program Success Scenario (right) Projected by the MA³T Model

**FIGURE 30** Light Truck Sales Share by Powertrain Type for the No Program Scenario (left) and the Program Success Scenario (right) Projected by the MA³T Model
4.3 LAVE-Trans PROJECTIONS

Figure 31 shows LDV sales shares projected by LAVE-Trans. Only one BEV and one PHEV were modeled in LAVE-Trans, and no CI vehicles were modeled. CI Conv shares can be considered to be included in SI Conv shares. In both scenarios, advanced-technology vehicles reach high market shares, with more rapid market penetration in the Program Success scenario. PHEVs, and especially FCVs, reach much higher sales shares in the Program Success scenario than in the No Program scenario, while shares of Conv, BEV, and HEV are lower in the Program Success scenario.

LAVE-Trans sales shares in cars show little qualitative difference from the LDV shares, as seen by comparing Figures 31 and 32. Light truck shares projected by LAVE-Trans are shown in Figure 33, which shows higher shares of HEVs and BEVs in light trucks than in cars. In light trucks, advanced powertrains displace nearly all Conv powertrains in the Program Success scenario.

FIGURE 31  LDV Sales Share by Powertrain Type for the No Program Scenario (left) and the Program Success Scenario (right) Projected by the LAVE-Trans Model
4.4 ParaChoice PROJECTIONS

Figure 34 shows sales shares of LDVs projected by ParaChoice for the two scenarios. Note that BEVs included only BEV100 in ParaChoice, and as with the other models, no flex fuel, CNG, or hybrid diesel vehicles were included. In these projections, advanced powertrains displace Conv SI fairly rapidly in both scenarios, and Conv CI gains large shares until 2025 to 2030, after which PHEV and especially FCV gain market share. Conv SI loses market share more rapidly in the Program Success scenario, and HEV gains market share more quickly in early years. In years after 2030 in the Program Success scenario, FCVs rapidly gain market share, reaching a much larger share than in the No Program scenario.
Cars in the ParaChoice model included size classes compact car, midsize car, and compact SUV, and light trucks included midsize SUV and pickup. Table 4 shows sales shares by size class. These were the same in the No Program and Program Success cases.

**TABLE 4**  Sales Shares by Size Class Used as Input to the ParaChoice Model

<table>
<thead>
<tr>
<th></th>
<th>2015</th>
<th>2020</th>
<th>2025</th>
<th>2030</th>
<th>2035</th>
<th>2040</th>
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<td></td>
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<tr>
<td>Compact car</td>
<td>0.18</td>
<td>0.18</td>
<td>0.18</td>
<td>0.18</td>
<td>0.18</td>
<td>0.18</td>
<td>0.18</td>
<td>0.18</td>
</tr>
<tr>
<td>Midsize car</td>
<td>0.188</td>
<td>0.188</td>
<td>0.188</td>
<td>0.188</td>
<td>0.188</td>
<td>0.188</td>
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<tr>
<td>Light truck</td>
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<td></td>
</tr>
<tr>
<td>Compact SUV</td>
<td>0.143</td>
<td>0.143</td>
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<td>0.143</td>
<td>0.143</td>
<td>0.143</td>
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</tr>
<tr>
<td>Midsize SUV</td>
<td>0.254</td>
<td>0.254</td>
<td>0.254</td>
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<td>Pickup</td>
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<td>0.235</td>
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</tr>
</tbody>
</table>

Sales shares of cars and light trucks are similar, with slightly higher HEV penetration in light trucks, as can be seen in Figures 35 and 36, respectively.
4.5 ADOPT PROJECTIONS

Figure 37 shows sales shares of LDVs (sales-weighted averages of all vehicles of a given powertrain type) projected by the ADOPT model for the two scenarios. A large penetration by HEVs is projected, with smaller gains for other powertrains. While the projections for the two scenarios are similar, the Program Success scenario shows faster advanced-technology vehicle market penetration.
The HEVs sold well, even in the Program Success scenario, due to the combination of lightweighting, engine efficiency improvement, and battery cost reductions. The 2035 VTO lightweighting targets decreased vehicle glider mass by 24%, improved the Atkinson peak engine efficiency from 38% to 47%, and reduced the HEV battery cost by more than half by 2030. These assumptions enabled the best-selling HEVs to achieve high fuel economy and fast acceleration at a relatively low price, as shown in Figure 38. The stacked bar heights represent the relative generalized costs, or relative price penalties, for the vehicle attributes. Lower stacks, corresponding to lower penalties, lead to greater sales, as represented by the wider bars. Starting from the bottom of the stacked penalties, the HEV’s price is higher than the conventional vehicle, but lower than that of the PHEV. Next, the CAFE penalties are zero for all, because for this analysis CAFE was neglected. The tax credits for all vehicles are zero, because the 200,000 vehicles per manufacturer caps are depleted by 2035. Next, the HEV has a fuel cost and acceleration advantage compared to the conventional vehicle, allowing it to take the lead. The PHEV has an even greater fuel cost advantage, but since both have very low fuel cost, the impact is only enough to overcome the small vehicle price difference. Next, the HEV takes a slight lead over the PHEV with larger interior volume and range. Because both vehicles evolve from the same vehicle option, they have the same preference value, which represents all the non-powertrain vehicle attributes. Finally, the fueling penalty is negligible, even for the FCV, which assumes that infrastructure is rolled out to meet demand. In total, the HEV and PHEV penalties are almost equal, resulting in similar best-selling vehicle sales. However, the HEV sells much better overall because having the best sales, especially earlier on, increases the number of vehicle options, which then increases sales. The slightly less desirable PHEV only achieved 19 vehicle options compared to 124 HEV options.
FIGURE 38  Best-Selling 2035 Vehicle Sales (Wide Blue Bar) and Attribute Value Breakdown Indicating Relative Price Penalties (Narrow Colored Bars) for the Program Success Scenario
5 SUMMARY AND CONCLUSIONS

Five light-duty consumer vehicle choice models used to support EERE VTO analysis of LDV markets were compared:

- LVCFlex model, developed by Energetics Incorporated (Birky, 2015)
- LAVE-Trans model, developed by ORNL (Liu, 2015; NRC, 2013)
- ParaChoice model, developed by SNL (Manley et al., 2015; Levinson et al., 2016)
- ADOPT model, developed by NREL (Brooker, 2015; Brooker et al., 2015a)

Table 1 presented a high-level comparison of the main features of each model, including vehicle alternatives, salient vehicle attributes, other influencing factors, and special features of the five models to permit a quick comparative overview.

Methods for more in-depth comparison of models were discussed, including comparison of generalized costs derived from the utility equation used in the models, sensitivity studies to directly evaluate sensitivity of shares to selected inputs, and comparison of model algorithms. Each of these gives different insights into the models. While generalized cost does not give sensitivity to shares, it permits comparison of the effects of inputs on consumer utility in each model. Direct sensitivity evaluations of sales share with respect to different inputs would enable a more exhaustive comparison. The stochastic or Monte Carlo techniques, as used by Liu and Lin (2017) with MA³T, could be applied to other models, which would allow quantitative comparison of sensitivities of sales to selected inputs, if variations and evaluation techniques are standardized.

Market share projections were made using the five models with the same inputs for two scenarios — Program Success, with optimistic vehicle attributes (high fuel efficiency and low vehicle prices), and No Program, with less optimistic vehicle attributes.

Projections of four of the models generally showed qualitative agreement, with the exception of ADOPT. ADOPT estimated that approximately half of the market changed to advanced-technology vehicles, mostly HEVs. The other models projected larger market shares of advanced vehicles, including HEVs, PEVs, and FCVs, with greater penetration of these for the scenario with more optimistic assumptions (lower prices and higher efficiency). The vehicle attributes and choices used in ADOPT were different from those used in the other models, which may account for some of the differences in the projections from ADOPT compared to those of the other models. The projections of other models differed in significant ways, including how different technologies penetrated cars and light trucks, with some models (LVCFlex and MA³T)
showing very different market penetrations by certain powertrain vehicles in cars from light trucks, while others (LAVE-Trans, ParaChoice) showed similar shares in both cars and light trucks.

Projections by all models were in close agreement only in the first few years. Although the projections from LVCFlex, MA$^3$T, LAVE-Trans, and ParaChoice were in qualitative agreement, there were significant differences in sales shares given by the different models for individual powertrain types, particularly in later years (2030 or later). For example, projected sales shares of Conv SI vehicles of LDV sales in 2030 for a given scenario ranged from 35% to 54%. Part of the discrepancy was due to differences in projected market penetration rate by individual powertrain technologies, so that even though some models gave similar long-term market share for a given powertrain type, the shares in some intermediate year could differ widely. In this way, models could be in qualitative agreement, but not in close quantitative agreement. It is important to recognize that these models were not developed to give quantitatively accurate predictions of future sales shares, but to represent the vehicle market realistically and capture the connections between sales and important factors.

Complete documentation of model algorithms and assumptions is desirable. Some models are publicly available and at least partially documented. As models are further developed, newer versions should be made available and documentation updated.
6 REFERENCES


