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Analytic Tool to Support the Implementation of Electric Vehicle Programs

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Analytic Tool to Support the Implementation of Electric Vehicle Programs

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Abstract

This project developed a lifecycle cost of ownership (LCO) model to support the deployment of plug-in vehicles (PEV) in California. The model is incorporated into a dynamic analytic tool that can be used to understand questions related to LCO. The model uses information from a variety of sources. Detailed drive cycle data was recorded from various routes in the Sacramento and San Francisco regions. The drive cycle data was input to a dynamic vehicle model, Advisor, which calculated fuel economy values (both electric Wh/mi and gasoline gallons/mi) for the various drive cycles. The fuel economy outputs were then input to the LCO model along with relevant parameters such as fuel prices, vehicle cost incentives, costs for insurance, parking, and maintenance. The fuel and electricity prices were stochastically varied to simulate expected future increases and uncertainties. The output of the model is not a fixed cost but rather a distribution of expected costs that can have significant variation. The model includes results for three vehicle types – vehicles similar to the Nissan Leaf, the GM Volt, and the Chevy Cruze. The Advisor model runs showed that increased accessory loads from heating or cooling can have a large effect on fuel economy and range for vehicles operating in electric mode. The LCO varied up to 15% based on the choice of drive cycle.

Key Words: electric vehicles, vehicle efficiency, lifecycle cost of ownership, vehicle simulations, drive cycles

Executive Summary

Introduction

While several groups have published LCO analyses, the analyses suffer from a variety of shortcomings such as not including risks and uncertainties, excluding time effects in key variables, assuming hypothetical vehicle configurations and general vehicle drive cycles rather than ones specific to regions, or excluding real world factors (road grades, traffic conditions, ambient conditions, etc.). Since LCO analyses are useful in comparing battery electric and plug-in hybrid vehicle ownership costs to those of conventional vehicles, a LCO model which eliminates these shortcomings can be especially useful to policy researchers, fleet owners, and other people interested in the comparisons on lifecycle ownership costs of PEVs. The overarching goal of this study was to offer stakeholders rigorous, context-specific knowledge about factors that affect the purchase and cost of owning PEVs relative to other vehicle platforms.

Project Objectives and Outcomes

The project had six objectives. The objectives are listed below along with the corresponding results.

1. Develop a list of variables identified in the literature to affect vehicle cost of ownership and develop a model that includes at least this set of variables.

   Discussions with stakeholders, such as automakers and fleet managers, as well as review of other LCO models allowed the researchers to settle on the input parameters chosen for the vehicle simulation and cost models. Critical parameters are location specific drive cycles, auxiliary loads for heating and cooling, battery SOC range, capital cost, incentives, taxes, insurance, parking, maintenance, depreciation, average trip length, annual mileage, fuel and electricity prices, and discount rate. The two models used in this project, a dynamic vehicle simulation and a cost of ownership tool, incorporate these variables.

2. Collect five hours of GPS driving data for each of seven days in at least two metropolitan areas in the state of California.

   Location specific drive cycles with grade were recorded by driving in specified regions. Drive cycles were recorded for both urban and regional trips in both Sacramento and San Francisco. Specific trips include Sacramento urban, Sacramento-Davis round trip, Sacramento-Auburn round trip, Sacramento-Truckee round trip, Davis urban, Davis-Napa round trip, San Francisco urban, San Francisco-Fairfield round trip, San Francisco-San Raphael round trip, and San Francisco-Palo Alto round trip.

3. Complete a round of consultations with at least one representative of each of the a) car manufacturers with plug-in electric vehicle offerings in the market at the time of starting this project, b) transportation agency with jurisdiction in the metropolitan areas where we collect driving data.

   A key uncertainty in the analysis is the depreciation of PEVs. Since PEVs have been in the market for only a few years, getting useful depreciation values for specific vehicle types was not possible. The automaker researchers spoke with suggested that PEV depreciation would be roughly similar to that of conventional vehicles so the tool could use conventional vehicle data to estimate PEV depreciation.

Stakeholders agreed that location specific drive cycles and grades along with estimates of the auxiliary loads added to the usefulness of the LCO model.

4. Perform one set of simulations for each of the driving cycles for which data is collected in task 2. For each set, simulations will be performed for a) cold and hot ambient temperatures b) average speeds higher and lower than speeds recorded in task 2 to understand the effect of variation is driving speeds. Validate simulation results for vehicle electric range and energy consumption with DOE available test data (city and highway).

   Researchers used the dynamic vehicle simulation model, Advisor, to estimate range and energy use for various vehicles on the measured drive cycles. Appendices I and II show results for the range and energy use including results for higher auxiliary loads to handle hot and cold temperatures. Simulations for the drive cycles with higher and lower speeds indicate that the energy consumption very roughly tracks the average speeds. The researchers compared simulation results from the Advisor model with EPA test data for 3 vehicles – Chevy Cruze, Honda Civic, and Hybrid Civic. The most difficult parameters to model for vehicles are the engine (manufacturer engine fuel efficiency maps are generally not publically available) and the auxiliary loads. The simulation results, shown in Table 10, match EPA results reasonably well for the EPA FUDS and Highway tests.

5. Continue runs of the stochastic model until the estimates of vehicle lifecycle cost of ownership converge to within 0.1% marginal change.

   Since the LCO model included stochastic fuel and electricity pricing, individual cost outputs varied. Each "run" of the model consists of a large number of individual iterations. These "runs" output a spread of ownership costs with a mean value. Depending on the number of iterations, the spread in means can vary significantly. Researchers verified that given enough iterations the marginal change remains within 0.1% marginal change.

6. Format analytical tool in a way such that the tool provides estimates of vehicle lifecycle cost of ownership with the need of not more than 15 input values.

   Researchers have produced a cost of ownership tool to estimate vehicle lifecycle cost of ownership. The tool includes many variables, but the inputs required from the user are the following.

   - Vehicle type
   - Level of the use of heating and air conditioning
   - Drive cycle
   - Location where the vehicle is registered
   - Expected duration of ownership
   - Average and expected maximum trip length
   - Expected average annual mileage
   - Expected use of parking facilities and toll roads

Conclusions

The dynamic vehicle modeling demonstrated a large potential effect of heating and cooling accessory loads. Using a heater in cold weather or air conditioning in warn weather can increase the fuel use of a battery electric vehicle by up to 100% in urban driving and up to 30% in highway driving. The range of the vehicle can be reduced by roughly 50% in urban driving and up to 30% in highway driving. This potential range reduction can have a large effect on its perceived utility. Plug-in hybrid vehicles also show significant variation in vehicle performance based on changes in speed, grade, and accessory loads. These variations have a significant effect on both vehicle energy use and range. The vehicle simulations showed clearly that to characterize the performance of a plug-in vehicle based on testing at a standard, fixed ambient temperature such as 70 degrees F and on a specific driving cycle such as the FUDS and/or the Federal Highway cycle will not yield an accurate description of the PEV performance in real-world driving.

The variation in fuel economy and range for both battery electric vehicles and plug-in hybrids can have large effects on the LCO. The LCO for specific vehicles can vary up to 15% based on the choice of drive cycle. The stochastic treatment of fuel and electricity prices resulted in standard deviations in the LCO of 2-5% depending of the gasoline usage of the vehicle. If other parameters such as drive cycle, trip length, accessory loads were treated in a stochastic manner, the resulting variation in LCO would be much greater.

Recommendations

The LCO tool would benefit from additional work to refine and extend the modeling and formulations on which the tool is based in order to increase its functionality, scope, and benefits for potential users. Potential refinements and extensions are:

1. Additional locations/drive cycles

   The present tool includes the Sacramento and San Francisco regions in California. The tool could be expanded to include other regions in California (e.g. Los Angeles and San Diego) as well as elsewhere in the US.

2. Additional vehicles

   The present tool includes data for vehicles similar to the Nissan Leaf, GM Volt, and Chevy Cruze. There are many other PEVs that fleets or consumers will wish to compare to conventional vehicles. The Advisor model and the LCO tool could be modified to include data for these other vehicles.

3. Inclusion of other stochastic parameters in the LCO Tool

   Fuel and electricity prices are represented in the tool using a stochastic model that recognizes uncertainties in future pricing thus leading to a spread of potential ownership costs. Other parameters such as annual mileage, average trip length and route, ambient conditions and heating and cooling loads could also be represented in a stochastic manner. The addition of these parameters would result in a more realistic and larger spread of ownership costs.

4. More realistic modeling of the effect of ambient temperature and HVAC operation on PEV energy consumption.

   While the tool incorporates the effect of heating and cooling loads, only two values of accessory loads were used (400 and 4000W). Additional work to model the heating and cooling of the vehicle could result in more accurate estimates of fuel use and vehicle range. These two parameters can significantly affect the overall ownership cost.

5. More extensive calculations using the LCO Tool

With the improved auxiliary load model and the inclusion of additional stochastic variables, the LCO Tool can be run for a large number of vehicles, regions, and economic conditions to determine the effect of the various parameters on the economic attractiveness of different PEV designs to consumers having different needs.

Public Benefits to California

Present markets for PEVs are limited by their higher cost and lower perceived utility compared to conventional ICE vehicles. As the sales of PEVs expand, more customers will need to evaluate the utility and economics of the increasing number of PEV options. The LCO Tool, after further refinement, will allow potential PEV consumers (both fleet managers and individuals) to gain better information about the various PEV options in the market. This improved information will help to expand the PEV market in California and the other States. Increased information can result in more PEV sales in California and less difficulty in meeting the ZEV Mandate for 2015 and beyond.

Based on projected sales of EVs in California over the next 3 years, the researchers estimate that the information from this tool could add roughly 5000 additional EV sales in California for an accumulated cost of ownership savings of roughly $35 million.

Introduction

Understanding the lifecycle cost of ownership (LCO) for advanced technology vehicles is critical to the eventual penetration of these technologies into fleets and consumer markets. Several groups have developed methods and models to estimate vehicle LCO. Examples are given below.

Automobile manufacturers have developed their own estimates of PEV LCO and purchase decision factors, though naturally these analyses are not public. A Nissan spokesperson, for example, said the lifecycle cost of ownership of the Leaf is $28,180. Their estimate includes the cost of the vehicle, the charging station, and the electricity over a period of five years [1}.

The Rocky Mountain Institute [2] developed a relatively flexible online calculator that estimates the total vehicle cost of ownership. RMI's calculator accounts for variations in the price of electricity across states and permits the comparison of the LCO of two vehicle models at a time. Their calculator is essentially cross sectional and does not account for uncertainties. It also assumes a fixed electricity mix (and, consequently, carbon emissions) and vehicle fuel economy is taken from EPA's ratings [3].

Simpson [4] used dynamic vehicle simulation software to perform a cost-benefit analysis of plug-in hybrid electric vehicles. He analyzed a number of hypothetical degrees of vehicle hybridizaton for plug-in platforms, looking at the interaction between retail price increases from higher hybridization and reductions in operation costs from petroleum fuel savings. He also attempts a simple estimation of lifecycle costs of ownership, including only retail price and fuel costs.

Probably the most comprehensive analysis of the lifecycle costs of electric vehicles is that of Delucchi et al. [5]. Cuenca et al. [6] did a similarly thorough analysis. Technology, however, has evolved significantly since these studies were done. As an example, these studies assumed electric vehicles would be equipped mostly with lead-acid and nickel metal hydride batteries, and that these batteries would have a life of four to six years. Electric vehicles presently being marketed are equipped with lithium ion batteries having a stated useful life of ten years or more.

Conclusions about the economic competitiveness of plug-in vehicles have differed widely in the various studies. For example, Deloitte [7] argues that the cost of batteries needs to be reduced by 40% for the LCO of an EV to be comparable to that of conventional vehicles. Lee and Lovellette [8] found that the cost of purchasing and operating a battery electric vehicle is $4,815 higher than that of a conventional vehicle. A recent ITS-Davis study [9], which included comparisons of the initial costs and breakeven gasoline prices of PEVs and conventional vehicles, indicated the circumstances under which PHEVs have favorable economics.

Most efforts to estimate the PEV LCO have some combinations of the following shortcomings:
- Not being comprehensive;
- Not including time effects in the key variables;
- Relying heavily on hypotheses (about vehicle configuration, etc.);
- Being out of date;
- Not being adaptable to specific regional contexts;
- Not accounting for real world factors (ambient conditions, road grades, typical traffic conditions, battery degradation, etc.);
- Not accounting for risk and uncertainties;
- Not accounting for integration of the PEV with the grid;

- Not incorporating stakeholders' perspectives;
- Not designed to be incorporated into program development.

The present study has extended the work done to date in the following ways:

- **Focused on EV-support program development**: The focus centered on vehicles in the market for which sufficient information is available rather than hypothetical vehicles. The study incorporated new information on PEV technology such as updated battery models and data on vehicle accessory loads.
- **Accounted for risk and temporal effects**: Most studies to date have relied on point estimates for all or some of the key variables that affect LCO, such as fuel prices, technology innovation, traffic conditions, and others. This analysis incorporates variation in input variables, specifically electricity and fuel costs, into the LCO estimates.
- **Focus on California markets**: The study inputs variables that characterize key regions within the state.
- **Utilized advanced vehicle dynamics simulations**: The analysis used validated dynamic vehicle models for the simulation of energy consumption of real (as opposed to hypothetical) vehicle configurations. In addition the models incorporate actual drive cycles measured from real world driving in the Sacramento and San Francisco regions.
- **Incorporated stakeholder input**: The study team communicated with key stakeholders for guidance in general analysis direction and to incorporate policy and regulatory variables.

Project Objectives

The overarching goal of the study is to offer stakeholders rigorous, context-specific knowledge about the factors that affect the purchase and cost of owning a plug-in vehicle, relative to other vehicle platforms. With this knowledge, stakeholders such as electric utilities, state agencies, local governments, and consumers can make decisions and implement programs to support the adoption of plugin vehicles consistent with extant policy and regulatory frameworks. By using real-world data specific to key regions in the state of California, the study will enable stakeholders to develop programs tailored to their areas and that target vehicles currently in the market or near production.

The objectives of the project are:

1. Develop a list of variables identified in the literature to affect vehicle cost of ownership and develop a model that includes at least this set of variables.

   The intent of the project was to improve LCO models to give fleet owners and other users a better assessment of vehicle lifecycle costs. Including correct variables that affect the cost increases the effectiveness of the model.

2. Collect five hours of GPS driving data for each of seven days in at least two metropolitan areas in the state of California.

   Improving LCO models require acquiring drive cycle data for the vehicle efficiencies in order to properly input energy efficiencies into the tool.

3. Complete a round of consultations with at least one representative of each of the a) car manufacturers with plug-in electric vehicle offerings in the market at the time of starting this project, b) transportation agency with jurisdiction in the metropolitan areas where we collect driving data.

   Discussions with automakers and other stakeholders helped determine aspects of the analysis such as likely market locations in California, PEV resale value, battery performance and lifetime.

4. Perform one set of simulations for each of the driving cycles for which data is collected in task 2. For each set, simulations will be performed for a) cold and hot ambient temperatures b) average speeds higher and lower than speeds recorded in task 2 to understand the effect of variation is driving speeds. Validate simulation results for vehicle electric range and energy consumption with DOE available test data (city and highway).

   Vehicle simulations provide vehicle fuel economies and range which are important parameters for the LCO model. Comparing the model outputs with test data ensures that the model matches vehicle performance.

5. Continue runs of the stochastic model until the estimates of vehicle lifecycle cost of ownership converge to within 0.1% marginal change.

The LCO model does not output a fixed lifecycle ownership cost. The model includes stochastic representations of the fuel prices so individual runs of the model will output different means and standard deviations of the cost. Determining that the model is repeatable is important in verifying the model usefulness.

6. Format analytical tool in a way such that the tool provides estimates of vehicle lifecycle cost of ownership with the need of not more than 15 input values.

   The tool must be simple enough to use such that fleet managers and individual consumers can utilize the tool without too much difficulty.

Project Approach

Task 1: Design Analysis

Model/Tool design analysis
In order to properly estimate the LCO for vehicles, it is necessary to identify a critical set of input variables for the model. The researchers reviewed the literature on LCO studies to help determine the necessary input variables[1,2,4,5,6,7,8,9]. These variables included direct cost parameters such as vehicle sales price, incentives, fuel price, and taxes. In addition there is a set of parameters that impact the vehicle fuel energy consumption (electricity and gasoline) and related costs. These include the vehicle energy use Wh/mi , miles traveled and the price of energy.

While many factors influence energy use, the critical factors included in the present study were the drive cycle, weather conditions, road grade, and battery state-of-charge (SOC). The project addressed these factors, but in some cases significant further work could enhance the results. A discussion of further work is given in the Recommendations section.

Task 2: Collect Data

Most of the data needed for the model/tool was available from the literature and/or contacts with stakeholders. The primary new data generated as part of this project consisted of determining driving cycles appropriate for various trips in the Sacramento and San Francisco regions. This was done using a GPS to collect 3-dimensional position versus time data along real world driving routes and conditions. In general, routes consisted of round trips between the city and various suburbs or between two inter-city locations. The specific drive cycles for the two regions are shown below:

Sacramento - Davis urban cycle, Davis-Napa regional cycle, Davis-Sacramento interurban cycle, Sacramento urban cycle, Sacramento-Auburn interurban cycle, Sacramento-Truckee regional cycle

San Francisco - San Francisco urban, San Francisco-Fairfield interurban cycle, San Francisco-Palo Alto interurban cycle, and San Francisco-San Raphael interurban cycle.

The recorded road data were processed to create drive cycle input files to be used in the dynamic vehicle simulations. These input files included the vehicle speed versus time along with the road grade vs. distance for every second during the driving. Since the individual data points had uncertainties that would result in driving cycles that had sudden transitions from second to second, the data were smoothed to eliminate unreasonable vehicle speed changes (accelerations).

Task 3: Communicate with Stakeholders

The research team discussed electric and plug-in hybrid vehicles in conference calls with representatives from several automotive companies. The intent was to better understand features of the vehicles that affect the lifecycle cost. In addition researchers spoke with representatives of public agencies in order to understand how regulators viewed the potential use of the tool.

Task 4: Perform vehicle dynamics simulation

The researchers performed simulations of plug-in electric vehicles (PEVs) similar to vehicles currently on the market to determine their energy consumption and range for appropriate driving cycles, ambient conditions, accessory loads, road grades, and traffic conditions. These results are needed as inputs to the economic ownership analyzes (LCO) discussed in later sections of the report. The approach taken was to obtain realistic estimates of vehicle energy consumption and range that reflect the conditions specific to particular regions of California. This permitted the analysis of the ownership costs for those regions. Earlier analyses [10-17] have used standard EPA driving cycles used for the fuel economy ratings of conventional ICE cars and EPA ratings for electric vehicles.

As part of this project, the simulations were improved by including the effects of real-world cycles (speed and grade), vehicle accessories (heating and air-conditioning) and ambient temperature (air density and tire pressure). Special attention was given to the effects of the various factors on the energy consumption (Wh/mi) and range of the PEVs. Initial experience with both the Volt and Leaf demonstrate that consumers have concerns about the variability of vehicle range with use patterns and driving conditions. Quoting a universal range value (e.g. 100 miles) for a PEV is a poor indicator of real-world performance and results in significant consumer dissatisfaction. To enable the development of effective PEV support programs/tools, our simulations focus on estimates of real-world vehicle range and energy consumption.

A number of driving cycles have been used for the evaluation of PEVs. In the United States, the driving cycles used most often for testing and simulations are the Federal Urban (FUDS) and Federal Highway cycles. These cycles specify vehicle speed as a function of time (V vs t) - all at level grade. In the real world, elevation changes (grade) are always present and should be included in prescribing the driving conditions. This has been done in the present study. Both the appropriate driving cycle and grade are specific to a particular region and trip. In the present study, trip data were obtained for the Sacramento and San Francisco regions. The specific trips for the two regions are shown in Table 1. As noted previously, this was done by driving a conventional ICE car between specific locations with a GPS unit connected to a laptop computer to record the appropriate data, which was processed to determine the driving cycle in the form required by Advisor. The speed and elevation vs. time from the GPS data logger were smoothed with an 8-second moving average. The distance was calculated from the smoothed speed and time. The road grade was calculated from the filtered elevation and the calculated distance. Typical speed and elevation data for a trip between Auburn and Sacramento are shown in Figure 1. A summary of the trip driving cycle data is given in Appendix I. *Grade* is input into Advisor as *grade* vs. distance. Most of the trip driving occurred on highways except for the indicated urban areas in Davis and San Francisco.

Table 1. List of drive cycle trips in the Sacramento and San Francisco regions.

Region	Trip
Sacramento	Davis urban
	Davis – Sacramento
	Davis-Napa
	Sacramento urban
	Sacramento - Auburn
	Sacramento - Truckee
San Francisco	San Francisco urban
	San Francisco – San Raphael
	San Francisco – Palo Alto
	San Francisco – Fairfield

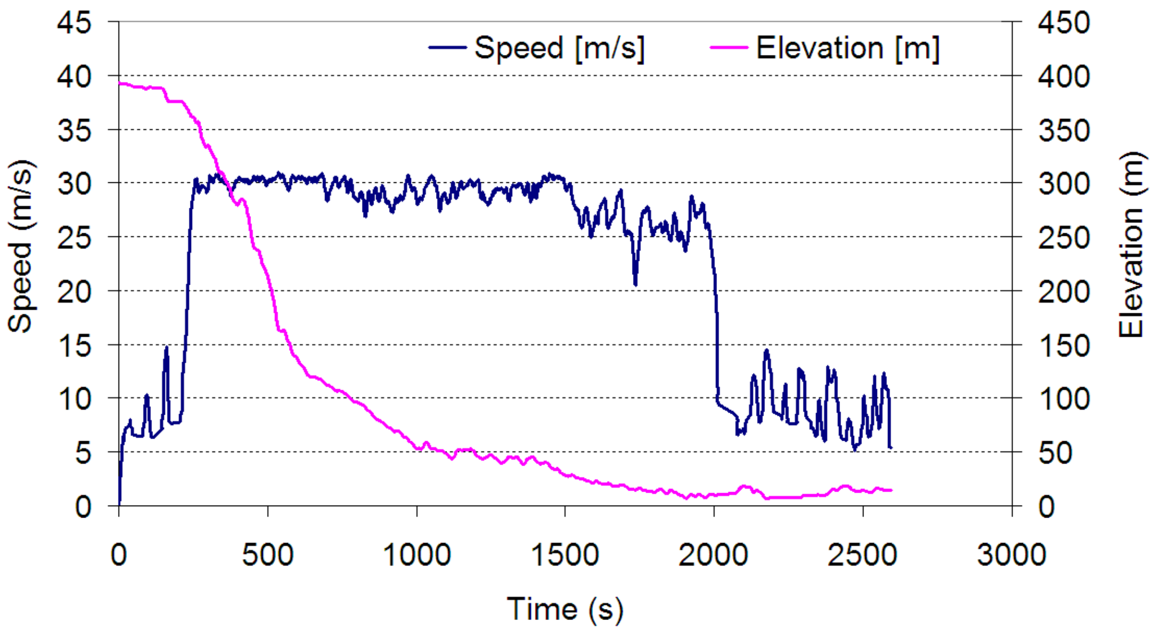


Figure 1: Speed and elevation profile of the Auburn – Sacramento Trip

Getting information concerning ambient conditions and utilizing it to vary the vehicle accessory loads in the various seasons is not as straight forward as obtaining driving cycle information, because the operation of the climate control system in the vehicle varies with time as the demand on the system changes. This can result in large changes in the accessory load for nearly constant ambient conditions. The simplest approach is to determine an average value for the accessory load for a specified ambient condition. Analyzes of the load for air-conditioning and heating for electric and hybrid vehicles are given in [18-20]. Based on those analyses, researchers altered the accessory loads input to **Advisor** as follows: the baseline accessory load was 400W and the heating and cooling load was 4000W. This is consistent with the NREL study discussed in [5].

The road load for the vehicles consists of the aerodynamic drag and the tire rolling resistance. The ambient temperature affects the air density (proportional to 1/ T) and the tire pressure (proportional to T). Since the aerodynamic drag increases with higher density and the rolling resistance increases as the tire pressure decreases [21, 22], both the aerodynamic drag and tire rolling resistance are higher at low ambient temperatures (cold weather) than at the baseline temperature of 25 degrees C used for most vehicle testing. In addition, the powertrain friction is higher at low temperatures which increases the effective rolling resistance of the vehicle. This combination of effects will significantly increase the effective road load at low ambient temperatures and thus reduce the vehicle range. These effects have been included in the Advisor simulations by increasing the input air density and rolling resistance values in the low temperature runs. The air density was increased up to 9% and the rolling resistance up to 10% in the simulations compared to the values at 25 degrees C.

The vehicle simulation program used in this study was the UC Davis version of ADVISOR developed initially at the National Renewable Energy Laboratory (NREL). Researchers at UC Davis have modified the NREL version to accommodate the various hybrid driveline arrangements and control strategies being marketed by the various auto companies [23, 24]. In addition, UC Davis has added files to describe lithium batteries using various chemistries based on testing of cells/modules of those batteries in the Battery Laboratory at UC Davis. The UC Davis simulation program (UCD-ADVISOR) has been validated using fuel economy data published by the U.S. Department of Energy (DOE) in their Fuel Economy Guide [23, 24]. Some of the recent UC Davis work includes simulations of the GM Volt plug-in hybrid vehicle and the Nissan Leaf and Honda EV Fit electric vehicles. Comparisons of the simulation results with published characteristics of those plug-in vehicles also show good agreement.

The power requirements for the heating and air-conditioning systems in electric plug-in vehicles are discussed in [20, 21]. The reports concluded that the power required for these accessories is 4-6 kW. In the present study, the normal (baseline) accessory load was taken to be 400W and the HVAC (heating and air-conditioning) load was set at 4 kW. The effect of ambient temperature was investigated by including its effect on ambient air density (increased drag) and the rolling resistance of the tires (decreased tire pressure).

The researchers ran simulations for a Leaf-like electric vehicle for a number of driving cycles and ambient temperatures. The vehicle characteristics are given in Table 2. The baseline driving cycles are the Federal Urban and highway cycles. These are the cycles for which the energy consumption (Wh/mi) and range are given in the literature based on testing done at EPA. Simulations have also been run for driving cycles pertinent to the Sacramento and San Francisco areas. As discussed previously, these cycles (speed and elevation) were determined by actually driving between selected destinations and logging speed and position with a GPS. These cycles are used to illustrate the effect of a real-world driving cycle on energy consumption and range.

Table 2: Characteristics of a Leaf-like EV

Vehicle parameter	
Test weight (kg)	1666
Drag coefficient C_D	.285
Frontal area (m^2)	2.25
Rolling resistance (kg/kg)	.008
Wheel radius (m)	.35
Overall gear ratio	7.0
Electric motor (kW)	81
Lithium battery (360V, 75Ah)	26 kwh (complete disch.)

Simulations were also run for a Volt-like plug-in hybrid vehicle. The Volt was simulated as a series hybrid. The vehicle characteristics used in the simulations are shown in Table 3. Runs were made for both the Sacramento and San Francisco areas using the appropriate driving cycles.

Table 3: Characteristics of the Volt-like PHEV

Vehicle parameter	
Test weight (kg)	1855
Drag coefficient C_D	.285
Frontal area (m^2)	2.44
Rolling resistance (kg/kg)	.007
Wheel radius (m)	.406
Overall gear ratio	6
Electric motor (kW)	110
Lithium battery (310V, 50Ah)	10 kWh used
Engine power (kW)	64

The results of the simulations are discussed in Section 4 and tables of the detailed simulation results are given in Appendix II.

<u>*Task 5: Perform stochastic analysis*</u>

For the economic valuation of vehicle platforms, the researchers used a model developed by Logios, 2012 that advances the state of the art and current practice. Indeed, the approach to modeling of the lifecycle costs of ownership (LCO) of the different vehicle platforms is one of the key advances of this project over previous studies of vehicle cost of ownership. The researchers take an asset valuation approach that accounts for uncertainties and risk. The researchers move beyond the typical approach to assume fixed values for given cost variables and recognize that the value of some of these variables will change over time and may be relatively uncertain.

Further, by using data specific to regions of interest, the researchers recognize that the value of cost variables, and ultimately the relative cost of owning a given vehicle, will be affected by local conditions. The researchers find that the impact of such local conditions on cost of ownership can be significant. Local variables include local temperatures (and the use of heating and air conditioning), topography, driving conditions, electricity prices, etc.

As a consequence of using stochastic variables, the output of the model will be also stochastic. In other words, results are presented in terms of probability distributions, with mean values, spreads, etc. This is important to appropriately assess the economics of investments. With this more granular and context-specific information, stakeholders such as electric utilities, state agencies, and local governments can implement programs to support the adoption of plug-in vehicles consistent with extant policy and regulatory frameworks.

As discussed in the Introduction, the researchers conducted a thorough review of the literature and the state of the art and identified areas where our contribution may be most useful. All previous studies, except for Henry and Lovellette (2011) carried out deterministic analyses, meaning that they assigned all variables a point (fixed) value. Stochastic analyses instead recognize that some of the factors affecting LCO are bound to variation and uncertainty. One aspect where this tool improves over Lee and Lovellette (2011) is in the substantiation of the selection of particular probability distributions by looking at data and/or by consultation with relevant stakeholders. The researchers will also improve over the cited reference by incorporating temporal effects. For example, the price of gasoline, electricity rates, generation mix, and other variables are expected to vary over the time span of vehicle ownership.

As a modeling technique, the researchers use a Monte Carlo simulation. Ideally, one would carefully specify the probability distributions for the random variables. For the time being, the researchers use Gaussian distributions because of the capability offered by Excel, which is the software platform of our tool. Future iterations of our model will be based on more flexible platforms that allow for more case-specific probability distributions. The variables that are used in Logios' model to estimate the lifecycle cost of ownership include:

Outputs from UCD-Advisor:

- Vehicle average fuel efficiency (Wh/mi and mpg)
- Vehicle range (mi)

User input:

- Vehicle type
- Level of the use of heating and air conditioning
- Drive cycle
- Location where the vehicle is registered
- Expected duration of ownership
- Average and expected maximum trip length
- Expected average annual mileage
- Expected use of parking facilities and toll roads

Fixed variables:

- Vehicle MSRP
- Vehicle battery size (kWh)
- Charging station efficiency
- Onboard charger efficiency
- Initial price of electricity and gasoline
- Fuel price volatility
- Discount rate (6% for this project)
- Fiscal incentives, state and federal
- Owner tax credit appetite
- Sales taxes
- Local taxes and fees
- Carbon price
- Vehicle resale value at the end of ownership
- Local prices for parking and toll roads
- Other costs: insurance, vehicle destination & handling, maintenance

After identifying the factors that affect the vehicle lifecycle cost of ownership and obtained data on these factors for the regions of interest in the state of California, the researchers proceeded to perform a stochastic analysis using those data. The researchers use a Monte Carlo simulation approach. One aspect in which the researchers improved over Lee and Lovellette (2011) is in incorporating temporal effects. For example, the prices of gasoline and electricity rates are expected to vary over the time span of vehicle ownership. Some other variables are expected to vary with uncertainty over time, but the researchers did not have reliable information to assign to them probability distributions (e.g. the effect of battery degradation on PEV efficiency and range). For this study, the only variables that are modeled as stochastic are the prices of gasoline and electricity.

The output of LCO tool is the lifecycle cost of ownership of a variety of vehicles, expressed as probability distributions of net present value, as a function of the variables that affect this cost. Forecasting the price of oil and gasoline is extremely challenging. Many factors affect the international price of oil, including reservoirs, costs, demand, recovery technology, storage, the behavior of markets, and the level of geopolitical stability in supply regions. Since most of these factors are stochastic, the instantaneous price, the equilibrium level, the trend, the variance (or volatility), and the jumps are all essentially stochastic. On the grounds of economic fundamentals, researchers have considered modeling oil prices as an Ornstein-Uhlenbeck mean-reverting process. However, it has been shown oil prices are a non-stationary process and that if mean reversion exists, it takes place in a time scale of a century or more and that for problems of practical relevance the equilibrium price can be modeled as a geometric Brownian Motion. The researchers choose to model the price of oil and gasoline in this manner.

Task 6: Modify analytic tool

While some of the methods used in our estimation of vehicle LCO are not simple, the researchers focused on preparing a tool that would be user friendly, yet personalized. For the purposes of this project, the researchers used MS Excel, which though simpler is more familiar to most users. Once initial experience is gained with the Excel tool, it can be upgraded to more advanced platforms.

Project Outcomes

1. Develop a list of variables identified in the literature to affect vehicle cost of ownership and develop a model that includes at least this set of variables.

The input parameters used for this project are shown below along with a description.

<u>*Model/Tool Input Parameters*</u>:
Vehicle capital cost – The MSRP for a particular model.
Vehicle Incentives – State and federal incentives available at the time of purchase specific to the vehicle type and location.
Vehicle taxes – Taxes on the purchase price.
Vehicle insurance, parking, and maintenance – Yearly insurance, parking, and expected maintenance for specific vehicle types operating in specific locations.
Discount rate – The discount rate used to calculate present value.
Vehicle depreciation – The percentage of the MSRP that the used vehicle is worth after a set number of years.
Drive cycle and road grade – The speed versus time and grade for real world driving in specific regions.
Auxiliary power – Vehicles need electrical power for various auxiliary systems on board such as power steering, vehicle computer, and lights. The most significant variation in auxiliary power comes from the use of air conditioning and vehicle heating.
Battery SOC range – The battery SOC range (maximum and minimum) affects the vehicle electric range, battery cycle life, and vehicle and charging efficiencies.

Past LCO studies have assumed fixed values for all the input variables. The present study includes the effects of uncertainties and temporal changes in some of the variables; in particular, the costs of energy (both gasoline and electricity) were used as stochastic variables assuming normal distributions that are time (year) dependent. Other variables such as annual mileage and average trip length could also be treated as stochastic variables in future studies within the framework of the LCO tool developed. In general, the list of input and output variables for the LCO tool are thought to be both useful and adequate for determining the life cycle costs of electric vehicles of various classes.

This objective was met.

2. Collect five hours of GPS driving data for each of seven days in at least two metropolitan areas in the state of California.

Researchers collected drive cycle data for 10 specific routes in the Sacramento and San Francisco regions. These routes consisted of either urban driving or regional driving from a city to a surrounding suburb or other city. In general the region driving cycles consisted of round trip data. Details of the driving cycles are given in Appendix I.

The GPS data used to determine driving cycles for the various regions in California were taken using a conventional ICE vehicle during March-August 2013. Driving was done on arterial streets and highways such as I-80. All trips were taken in both directions to and from selected locations (see Table 1). Particular attention was given to changes in elevation (grade) for each of the trips. Repeated trips reflecting different traffic conditions were not made, but the trips in the different regions and between different locations in the regions did reflect different traffic conditions in those regions. The ambient conditions of the GPS trips were those found in Spring and Summer in Northern California. As shown in Appendix I, there is a significant variation in drive cycle characteristics (distance, average and peak speed, grade). Other locations in California or elsewhere in the US may show somewhat different characteristics that could translate into differing vehicle ownership costs.

This objective was met.

3. Complete a round of consultations with at least one representative of each of the a) car manufacturers with plug-in electric vehicle offerings in the market at the time of starting this project, b) transportation agency with jurisdiction in the metropolitan areas where we collect driving data.

The discussions with automakers focused on the battery life and battery second life, vehicle depreciation, and California markets. The relevant conclusions are given below.

Battery life and second life – Battery warranties are expected to be in the 8-10 year range or possibly up to 150,000 miles. The second use market is rather uncertain. Presently there are no specified markets, and there are reasons to be skeptical of significant savings due the present period of rapid changes in battery technology and cost.

Vehicle depreciation – After conversations with several automakers the research team concluded that the vehicle depreciation for PEVs would be similar to that of conventional vehicles.

Markets – The main California markets are Southern California, San Francisco region, and the Sacramento regions.

The discussion with public stakeholders focused on the potential for disseminating the tool for use with fleets and consumers. The researchers determined that the stochastic nature of the tool likely will require more education for stakeholders not familiar with modeling. In particular, researchers might have to explain the causes and significance of the outputs for LCO results (means and standard deviations).

Although the researchers did meet with the majority of OEMs, they were unable to meet with a representative of every automaker. The researchers believe that the information obtained from the meetings was sufficient to create a useful tool.

4. Perform one set of simulations for each of the driving cycles for which data is collected in task 2. For each set, simulations will be performed for a) cold and hot ambient temperatures b) average speeds higher and lower than speeds recorded in task 2 to understand the effect of variation is driving speeds. Validate simulation results for vehicle electric range and energy consumption with DOE available test data (city and highway)

The results of the simulations for the Leaf-like EV, the Volt-like vehicle, and the ICE conventional Chevy Cruze used in the LCO Tool calculations are given in Tables 4-6 for various driving cycles. Complete summaries of the Advisor calculations for the various vehicles, ambient temperatures, and driving cycles are given in Appendix II. The large effects of the driving cycle and HVAC accessory load on both the energy consumption and range are shown in the results given in the Appendix. .

Table 4: Leaf-like vehicle on various driving cycles

	400W			**4000W**	
Cycle	Wh/mi battery	Range mi		Wh/mi battery	Range mi

FUDS	219	93		403	51
HW	235	90		312	66
SF-SanRaf	263	81		328	64
SanRaf-SF	296	73		367	56
SF-Fairfield	250	87		348	59
Fairfield-SF	289	72		367	57
SF-urban1	174	117		372	54
SF-urban2	204	101		446	46
Aub-Sac	222	93		295	69
Sac-Aub	330	62		399	52
Davis-Sac	258	81		343	60
Sac-Davis	264	76		347	60
Davis-urban	168	121		337	61
Sac-Truckee	373	56		428	48
Truckee-Sac	210	98		257	80

Table 5: Chevy Volt-like vehicle on various driving cycles

	CD* 400W			CD 4000W			CS* 400W	CS 4000W
Cycle	Wh/mi battery	Range mi		Wh/mi battery	Range mi		mpg	mpg
FUDS	226	46		396	25		36.6	20.0
HW	221	49		286	35		41.2	30.4
SF-SanRaf	261	41		357	30		34.5	23.5
SanRaf-SF	296	36		372	28		31.7	23.8
SF-Fairfield	277	37		360	29		34.5	24.8
Fairfield-SF	316	34		398	27		30.1	23.9
SF-urban1	161	60		410	26		46.6	22.3
SF-urban2	193	50		493	21		38.0	18.1
Aub-Sac	308	33		353	26		43.7	32.3
Sac-Aub	189	54		267	37		27.4	23.8
Davis-Sac	235	46		332	30		37.8	27.0
Sac-Davis	217	49		333	32		36.7	26.8
Davis-urban	169	61		341	30		49.0	25.0
Sac-Truckee	339	31		385	27		26.0	22.0
Truckee-Sac	173	62		259	41		52.3	40.3

*CD charge depleting mode: CS charge sustaining mode

Table 6: Fuel economy for the Chev. Cruze on various cycles

Cycle	mpg 400W	mpg 4000W
FUDS	25.5	19.9

HW	37.3	31.2
SF-SanRaf	29.9	25.4
SanRaf-SF	30.0	26.2
SF-Fairfield	32.3	27.3
Fairfield-SF	31.8	27.9
SF-urban1	28.4	21.1
SF-urban2	25.1	17.7
Aub-Sac	39.1	33.0
Sac-Aub	31.3	27.2
Davis-Sac	34.7	28.8
Sac-Davis	34.5	29.0
Davis-urban	32.8	23.9
Sac-Truckee	28.6	25.3
Truckee-Sac	39.5	34.7

Note in Tables 4 and 5 that the EV has about a 100 mile range on the FUDS cycle and the Highway cycle with the HVAC off, but a much different ranges on other cycles with the HVAC on or off. The effect of the ambient conditions is much smaller than that of the driving cycle and whether the HVAC is on/off. Hence in describing the energy consumption and range of an EV, it is not accurate to quote a single value and it is important to know the driving conditions under which the vehicle will operate.

The GPS data was used to develop driving cycles (speed vs time, grade vs. distance) for input into the ***Advisor*** vehicle simulation program. No attempt was made to relate the actual driving conditions (traffic and ambient temperature), under which the GPS data was taken, to the driving cycle to be used in the vehicle simulations. Information was not available to attempt to do that. What was done was to average the energy use for trips to and from a location to determine the energy usage for that trip (driving cycle).

General discussion of the simulation results

There have been a number of studies [10-16] of the real-world operation of electric and hybrid vehicles. These studies have involved both chassis dynamometer testing [10-13] and computer simulations [14-16] of vehicles. The present study involves computer simulations so the available test data on vehicles will be used to compare with and validate our simulation results. Until recently the only test data available to characterize electric and hybrid vehicles like the Nissan Leaf and the Chevy Volt were taken by EPA as part of their fuel economy program [17]. Those data were taken on a chassis dynamometer at 25 degrees C (about 75 degrees F) using the Federal Urban (FUDS) and Highway driving cycles with the HVAC system off. The data are useful for comparing vehicles, but not for determining the energy use and range in real-world conditions for which the ambient temperature can be much different than 25 degrees C and the HVAC system is in use. In addition, the driving cycles are not good representations of real world driving for many vehicle owners. One of the objectives of the present study is to project the operation of electric vehicles in real world conditions. This has been done via computer simulations and the examination of recent vehicle dynamometer test data taken under conditions more appropriate for real world driving. Much of this data [10, 11] was taken at the Argonne National Laboratory (ANL) with the support of the United States Department of Energy. The chassis dynamometer used in the ANL testing is housed in an insulated temperature chamber with the capability to simulate solar flux. The testing was done at temperatures of 20, 72, and 95 degrees F (-7, 22, 35 degrees C) with the HVAC system set at 72 degrees F for all the testing. The driving cycles used in the testing were the Federal urban (FUDS), Federal highway, and the US06 cycles. The vehicles included in the ANL testing included the

Nissan Leaf and the Chevy Volt. The ANL test results for the effect of ambient conditions and HVAC accessory loads on vehicle energy use are summarized in Table 7.

Table 7: Percent increase in energy use and decrease in electric range based on the ANL test data

Vehicle	**ICE Focus**	**Leaf Wh/mi**	**Leaf Range mi**	**Volt Wh/mi CD**	**Volt Range mi CD**	**Volt mpg CS**
FUDS						
Cold (HT)**	7	95	48	95	*	23
Hot (AC)**	28	24	17	38	25	64
HW						
Cold (HT)	4	40	30	60	*	8
Hot(AC)	14	5	6	20	14	20

***Volt could not make even one FUDS cycle at cold condition without the engine coming on**

** Cold (HT) was with the heater at 20 degrees F; Hot (AC) was with air-conditioning at 95 degrees F

The test results in Table 7 indicate the effect of operation of the heater in the Leaf and Volt is large for both the urban FUDS and highway HW cycles. The large increase in energy consumption results in a significant reduction in the electric range of both vehicles. The operation of the air-conditioning also results in increased energy consumption and reduced range, but the changes are less than for heating. In general, the magnitudes of the effect of the accessory loads are much higher for the electric drive vehicles than for the conventional ICE Focus. This is especially true of operation with the heater at low ambient temperature.

The simulation results for the Leaf and the Volt have been given in Tables 4 and 5 and in Appendix II. The effect of the heater or AC on the energy consumption and range can be determined by comparing the results for accessory loads of 400W and 4000W. These comparisons are summarized in Tables 8 and 9.

Table 8: Percentage changes in the energy consumption and range of the Leaf from changes in ambient temperature and accessory load

Cycle	**Ambient temperature**	**Accessory load (W)**	**% increase in Wh/mi**	**% decrease in range miles**
FUDS	25	400 to 4000	92	48
FUDS	25 to 0	400	3	3
FUDS	25 to 0	400 to 4000	102	49
HW	25	400 to 4000	34	25
HW	25 to 0	400	5	5
HW	25 to 0	400 to 4000	40	29

Aub-Sac	25 to 0	400 to 4000	35	26
Sac-Aub	25 to 0	400 to 4000	25	20
Davis -urban	25	400 to 2000	44	30
SF-SanRaf	25 to 0	400 to 4000	40	30
SanRaf-SF	25 to 0	400 to 4000	29	24
SF-urban1	25 to 0	400 to 2000	56	36
SF-urban2	25 to 0	400 to 2000	58	36

Table 9: Percentage changes in the energy consumption and range of the Volt from changes in accessory load

		CD mode		**CS mode**
Cycle	**Accessory load (W)**	**% increase in Wh/mi**	**% decrease in range miles**	**% decrease in mpg**
FUDS	400 to 4000	75	45	45
HW	400 to 4000	29	29	26
Aub-Sac	400 to 4000	15	21	26
Sac-Aub	400 to 4000	41	32	13
Davis -urban	400 to 4000	102	51	49
SF-SanRaf	400 to 4000	37	27	32
SanRaf-SF	400 to 4000	26	22	25
SF-urban1	400 to 4000	154	57	52
SF-urban2	400 to 4000	155	58	52

The effect of ambient temperature and accessory load for the Leaf-like EV are given in Table 8. The results have been converted to percentage changes relative the baseline case – ambient temperature of 25 degrees C and an accessory load of 400W. Note from the table that changes due to the effect of ambient temperature on the road load are small (only a few percent), but changes due to the effect of the heating or cooling load (2000-4000W) are large being as high as 100% in Wh/mi and 50% in range. The magnitude of the changes are largest for driving cycles with low average speed and many stops (FUDS and urban cycles) and significantly smaller for driving cycles with higher average speed (Highway and Aub-Sac). In the latter cases, the average power of the cycle is higher and the accessory load is a smaller fraction of the average power.

Comparison of the simulation results with 400W and 4000W accessory loads for the Volt are shown in Table 8. The comparisons indicate that the energy consumption from the battery and the all-electric range of the PHEV vary significantly with the driving cycle and the accessory load. Use of the Highway values to describe the Volt-like PHEV can be misleading even for a driving cycle that is primarily highway driving. The all-electric range on the FUDS cycle is 48 miles, but it is sensitive to the accessory load. The charge sustaining fuel economy (mpg) of a PHEV for a given driving distance is sensitive to the all-electric range for that driving cycle and accessory load. Hence in assessing the energy use (fuel and electricity) of a PHEV it is critical to know the all-electric range and electricity use for the driving conditions of the trip.

Comparing the simulation results in Tables 8 and 9 with the test results from Argonne National Laboratory in Table 7, one finds good agreement for the large effect of the heating on the energy consumption and electric range. However, the test data indicate the effect of the cooling loads are much less than the heating loads for both the Leaf and Volt. Apparently, the operation of the HVAC in the cooling mode is much more sensitive than in the heating mode to variations in the required load after the passenger cabin has reached the desired temperature (72 degrees F in the case of the ANL tests). The variation in the HVAC loads is not included in the present heating/cooling model.

Simulations were also performed for conventional ICE vehicles and non-plug hybrid-electric vehicles. The results for the fuel economy of several vehicles are given in Table 10. Test data from ANL [10,112] for several hybrids are given in Table 11. Of particular interest is the effect of ambient temperature and accessory load on the fuel economy of the vehicles. This effect is expressed quantitatively as the % change/decrease in fuel economy referenced to the fuel economy for 72 degrees F with the HVAC off.

Table 10: Simulation results for the fuel economy of the ICE and hybrid vehicles

Vehicle	**accessory load 400W**	**accessory load 3000W**	**% decrease in mpg**
Chev. Cruze EPA 25/36			
FUDS	25.5	19.9	22
HW	37.3	31.2	16
SF-SanRaf	29.9	25.4	15
Honda Civic EPA 30/39			
FUDS	32.7	26.4	19
HW	46.4	39.8	14
SF-SanRaf	36.3	31.5	13
Hybrid Civic EPA 44/47			
FUDS	57.7	33.7	42
HW	60.3	47.4	21
SF-SanRaf	53.9	39.8	26

Table 11: Test data from ANL for the fuel usage and mpg on the FUDS cycle for mild and full hybrid vehicles with climate control and simulated solar flux [2]

	12 deg F with heating	**12 deg F with no heating**	**72 deg with no heating or AC**	**95 deg with no AC**		**95 deg with AC**
VEHICLE **						

		Liters of fuel use for on FUDS cycle				
Honda Insight HEV	.818	.764	.595			.745
Prius HEV	.764	.564	.445	.418		.70
VW Jetta HEV	.891	.760	.627			.90
	mpg * 12 deg F with heating	**% increase in fuel used compared to 72 deg**	**mpg 72 deg F with no heating or AC**	**mpg 95 deg with no AC**	**mpg 95 deg F with AC on**	**% increase in fuel use compared to 72 deg**
Honda Insight HEV	34.9	27.3	48.0		38.4	20.0
Prius HEV	37.4	41.7	64.2	68.3	40.8	36.4
VW Jetta HEV	32.1	36.6	50.7		31.8	37.2
Ford Focus ICE		15				22

* mpg = (Liters fuel /3.81/7.5) $^{-1}$

**All tests were done on the FUDS cycle – 7.5 miles. Cold start for all the tests. Tests at 72 deg F had climate control off and other tests had climate control set to 72 deg F.

Tables 10 and 11 indicate that the effect of ambient temperature and accessory load is significantly smaller for conventional ICE vehicles than for hybrid vehicles and that the differences are largest for the strong hybrids like the Prius. Hence the more efficient the driveline of the hybrid, the more sensitive the fuel economy of the vehicles is to the accessory load. The simulation results (Table 10) are in general in good agreement with the test data (Table 11), but additional work on the simulation models is needed to be able to differentiate between the effects of heating and cooling on the fuel economy penalty from the respective accessory loads. This is the case because the present simulation models do not account for changes in the accessory load as the temperature inside the vehicle changes from the ambient value. This appears to be a more important effect for cooling than for heating. Nevertheless, the simulation results show that real-world driving involving changes in ambient conditions and the need for heating or cooling can have a large effect on vehicle energy consumption for all vehicle types- ICE, EV, and PHEV.

In order to understand the effect of drivers who might drive faster or slower than the speeds in the recorded drive cycles, the researchers modified drive cycles to increase and decrease the speeds. New drive cycles were created that had the speeds increased by 5% and decreased by 5% and 10%.

The simulations (Table 12 below) for the Leaf indicate that the change in energy consumption (Wh/mi) of electric vehicles on the FUDS driving cycle tracks closely the velocity factor, which is the ratio of the velocity at any time to the specified velocity on the FUDS cycle at the same time. Hence it seems reasonable to adjust the range on the driving cycle by the velocity factor.

Table 12: Effect of the velocity factor on the energy consumption of the Leaf

Velocity factor	SF-Fairfield	Fairfield-SF
.90	.916	.90
.95	.95	.963
1.0	1.0	1.0
1.05	1.063	--

The objective was met.

5. Continue runs of the stochastic model until the estimates of vehicle lifecycle cost of ownership converge to within 0.1% marginal change.

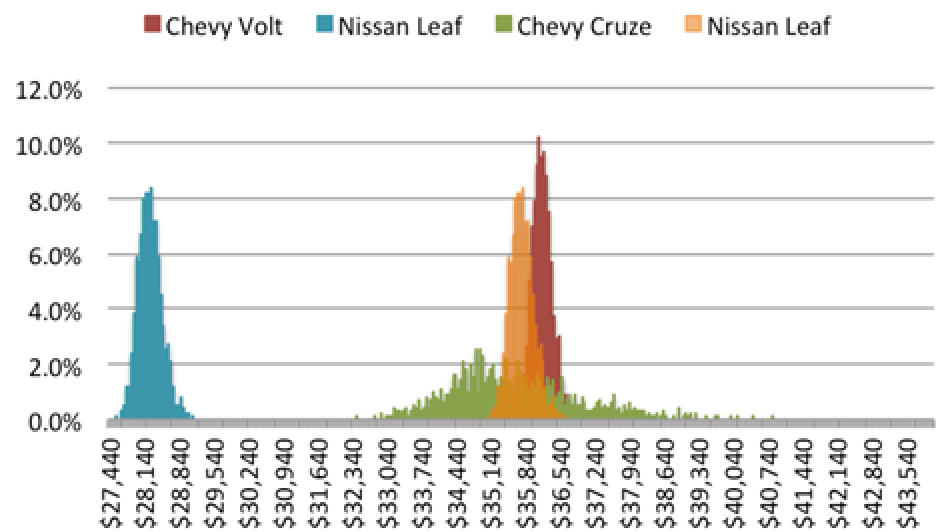
The LCO tool has been run for four vehicle cases: (1) Leaf with full incentives (Federal plus California $10K), (2) Leaf with only the California incentive $2.5K, (3) Chevy Volt with a $9K incentive, (4) Chevy Cruze as the baseline conventional ICE vehicle. The set of vehicles was run for five driving cycles – three for the Davis/Sacramento area and two for the San Francisco area. Runs were made for accessory loads of 400W and 4000W and for a combined accessory load. In the case of the Davis/Sacramento area, it was assumed the 4000W accessory was on 36% of the time and for the San Francisco area the 4000W accessory was on 12% of the time, because it is much warmer in the summer in Davis than in San Francisco. Calculations were made for a 5 year period for 12, 0000 miles per year. The energy use values used in the calculation are taken from the vehicle simulation results discussed in the previous section. The primary outputs of the LCO tool are the accumulated cost of ownership and the standard deviation of the cost. The results of the calculations are shown in Table 13.

Table 13: Accumulated ownership cost/ standard deviation of cost for a 5 year period

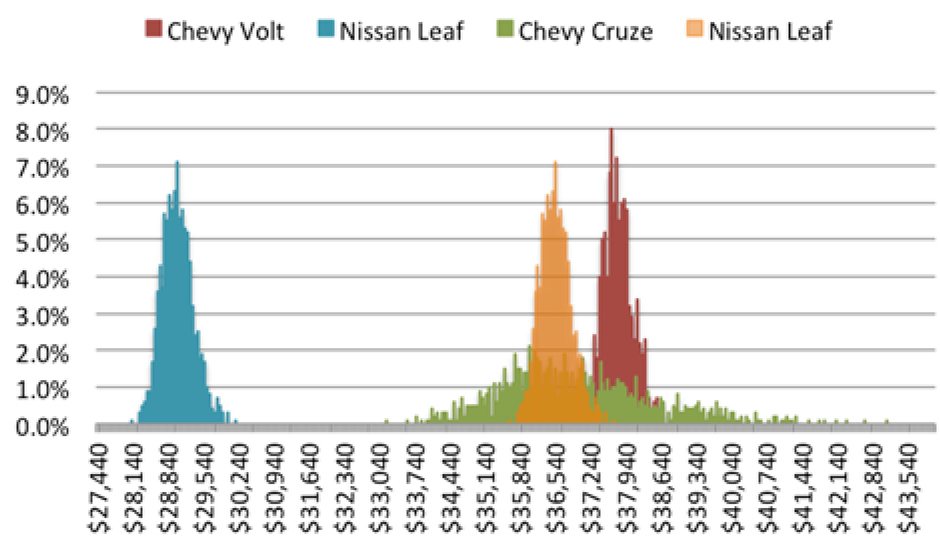
Vehicle/trips	**400W accessory load- 5 yr ***	**Combined accessory load- 5 yr ***
Leaf		
Davis-urban	27101/152	27845/224
Davis-Sac	28750/291	29134/327
Sac-Auburn	31764/304	32150/342
SF-urban	30563/182	32296/349
SF-SanRF	31128/233	31648/282
Volt		
Davis-urban	35457/153	36212/226
Davis-Sac	37267/266	38398/385
Sac-Auburn	40299/282	41442/402
SF-urban	38854/173	43313/672
SF-SanRF	39502/231	40968/332
Cruze		
Davis-urban	35660/1358	37219/1643
Davis-Sac	36144/1364	36857/1488
Sac-Auburn	39202/1351	39922/1475
SF-urban	40979/1709	44357/2307
SF-SanRF	39379/1449	40837/1671

* 5 yr, 60,000 miles

Graphic presentations of the results of the LCO tool are shown in Figure 2 for the Davis-Sacramento trip. The consequences of the stochastic character of the electricity and gasoline cost inputs are shown in the distribution of the ownership costs. The results given in Table 13 indicate the magnitude of the standard deviation can vary significantly for the various driving cycles and different vehicles.



Davis-sac 400W accessory load 60K miles



Davis-sac 4000W accessory load 60K miles

Figure 2: Graphic presentations of the LCO tool outputs showing the distributions of ownership costs

A summary of the total ownership costs obtained using a simpler and much less comprehensive approach than the LCO tool is shown in Table 14. The costs are broken into component contributions as indicated in the table. Results are shown using inputs from the UCD LCO tool and EPRI 2014 studies of ownership costs. The cost breakdowns are shown for the same three vehicles for which LCO results are given in Table 13. The cost of the vehicle to the owner is calculated based on a 5% interest loan for 5 years. No residual value of the vehicle is used, because it is assumed the owner will continue to own the vehicle in the future. The maintenance cost was pro-rated from the EPRI study which was done over 150K miles of ownership. All the costs in Table 14 seem to be self-consistent for the 60K miles of the calculations and are in reasonable good agreement with the LCO Tool results. Hence this simple exercise acts as a validation of the results from the UCD LCO tool and shows good agreement with the EPRI 2014 results.

Table 14: Summary of the total ownership costs and cost breakdowns

Vehicle	Purchase price including incentives, sales tax, finance chg.	Cost of electricity	Cost of gasoline	Maintenance	Simple approach Total cost of ownership for 60000 miles	Software calculated cost of ownership
2013 Leaf						
UCD	23635	2096		317	26048	28750
EPRI *	32860	2088		317	35265	
EPRI **	32860	1500+1328***		317	36005	
2014 Volt						
UCD	32292	1668	998	860	34958	37267
EPRI *	34946	2152	998	860	38996	
EPRI **	34946	1567	978	860	38391	
2014 Cruze						
UCD	28297		7240	1563	37100	36144
EPRI	30345		7240	1563	39148	

* EPRI does not include incentives in purchase prices, UCD includes an incentive of $10k for the Leaf and $9K for the Volt
**the energy costs shown are those in the EPRI 2014 report, the other energy costs are calculated from the Wh/mi and mpg, electricity $.12/kWh, gasoline $3.62/gal
*** Vehicle replacement cost used in the EPRI calculations of the ownership cost of EVs

The summary of the LCO tool results are given Table 13 and Figure 2. The results for the several trip/driving cycles indicate that the driving patterns and distances can make a significant difference in the ownership cost for all the vehicles. However, the trip/driving cycles does not affect the relative economic attractiveness of the vehicles. For example, the Leaf with the incentives is more attractive than either the Volt or Cruze for all the trip/driving cycles and the Volt and Cruze have nearly the same ownership costs for the respective trip/driving cycles. The effect of the accessory load can be relatively small on the total operating costs as shown in Figure 3. This is somewhat surprising as the effect of the accessory load on the electricity use and fuel economy in the case of the Volt was found to be significant. However, the effect of higher energy consumption on the total ownership costs due to the use of the heater and/or air-conditioner depends on the split between urban and highway driving and that was not included in the present study. It could be included in the LCO tool in further work.

The LCO model includes stochastic representations of the fuel prices so individual runs of the model will output different means and standard deviations of the cost. Determining that the model is repeatable is important in verifying the model usefulness. The researchers verified that repeated runs with many iterations showed means and standard deviations that were very similar. In particular, the means of repeated runs converged as the number of iterations increased.

The objective was met.

6. Format analytical tool in a way such that the tool provides estimates of vehicle lifecycle cost of ownership with the need of not more than 15 input values.

In its current format, the tool allows for the simultaneous analysis of four vehicles. Inputs that apply to all vehicles being modeled are in cells in the upper left corner of the setup sheet. The only user-defined input specific to each vehicle is the retail price, and it is input in the center column of the section corresponding to each vehicle. All input variables are indicated with a light blue cell background.

The setup sheet shows in green cells values that are either fixed in the tool (e.g. charger efficiency) or derived from user input or from intermediate variables. For example, the size of the onboard battery is derived from the vehicle model chosen by the user, and in turn helps calculate the maximum eligibility for federal tax incentives. The setup sheet also shows, in the upper right corner, for each vehicle and for each auxiliary load operating mode, the LCO values obtained in the first Monte Carlo run. This is displayed only for reference and should not be used to make conclusions concerning the lifecycle cost.

The tool includes output sheets with results and histograms as shown in Figure 3 below.

Nissan Leaf	Driving Cycle	Davis-Davis		
	Tax credit claimed	10000		
	Auxiliary loads	400W	4000W	Combined
	Mean	$27,101	$28,685	$27,845
	Std Dev	152.41	305.72	224.44
	Skew	0.26	0.26	0.26
	Kurtosis	-0.02	-0.02	-0.02
	Min	$26,582	$27,645	$27,081
	Max	$27,704	$29,896	$28,734

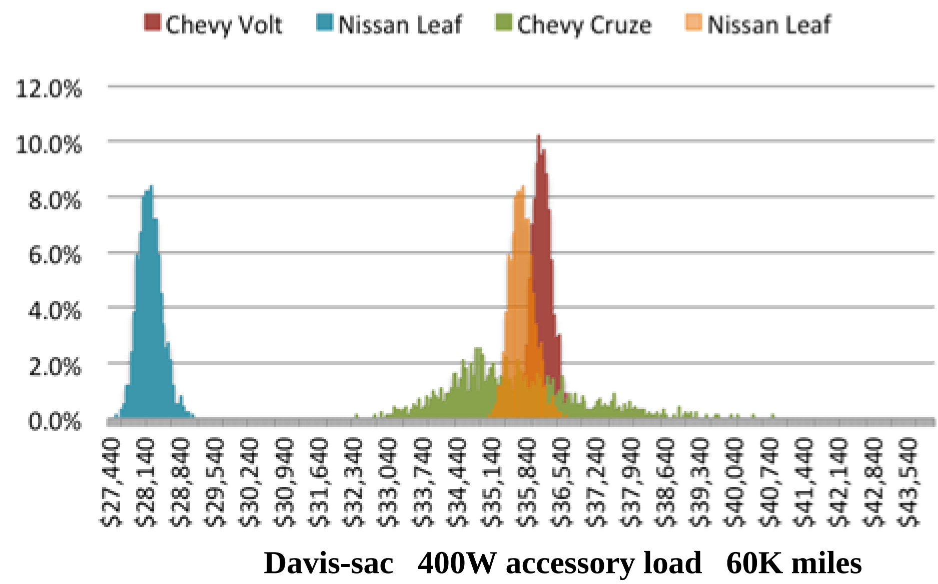


Figure 3. Output sheet for LCO tool.

The table shows for each vehicle modeled the probabilistic characteristics (most importantly the mean and the standard deviation) of the LCO for each mode of operation of the auxiliary loads. The plot gives the histograms of the Monte Carlo simulations, each of which shows the percentage of times that a given LCO range was obtained in Monte Carlo runs.

The objective was met.

Summary and Conclusions

1. Develop a list of variables identified in the literature to affect vehicle cost of ownership and develop a model that includes at least this set of variables.

Through reviewing the literature on LCO models, the researchers were able to define a set of relevant variables that capture aspects of driving that contribute significantly to the lifecycle cost of ownership. These variables include vehicle capital cost, vehicle Incentives, vehicle taxes, vehicle insurance, parking, and maintenance, discount rate, vehicle depreciation, drive cycle and road grade, auxiliary power for heating and cooling, and battery SOC range.

2. Collect five hours of GPS driving data for each of seven days in at least two metropolitan areas in the state of California.

To adequately estimate lifecycle cost of ownership for vehicles in specific regions, a critical input variable is the vehicle drive cycle. Drive cycles should be recorded for expected driving patterns along both urban and regional routes. The drive cycles must include road grade in order to properly estimate the energy requirements.

3. Complete a round of consultations with at least one representative of each of the a) car manufacturers with plug-in electric vehicle offerings in the market at the time of starting this project, b) transportation agency with jurisdiction in the metropolitan areas where we collect driving data.

Battery warranties are likely to last a significant portion of the vehicle life, for example 8-10 years or possibly up to 150,000 miles. After use in a vehicle, batteries may be sold into a second life application, but this possibility is rather uncertain especially in the near term.

Vehicle depreciation for PEVs is likely to be similar to that of conventional vehicles.

The stochastic nature of the tool likely will require more education for stakeholders not familiar with the tool outputs of means and standard deviations.

4. Perform one set of simulations for each of the driving cycles for which data is collected in task 2. For each set, simulations will be performed for a) cold and hot ambient temperatures b) average speeds higher and lower than speeds recorded in task 2 to understand the effect of variation is driving speeds. Validate simulation results for vehicle electric range and energy consumption with DOE available test data (city and highway).

The researchers found that the driving cycle, grade, and accessory loads can have a large effect on the electric energy consumed from the battery in an EV and the fuel economy of both conventional ICE and hybrid vehicles. It was found that Wh/mi of an electric vehicle can increase close to 100% with full heater or air conditioner operation in urban driving and by 25-30% in highway driving. The range of the EV can be reduced by about 50% in urban driving and 15-20% on the highway. To customers the reduction in range is particularly significant. There were also significant variations in plug-in vehicle performance due to changes in driving condition of speed and grade appropriate for specific trips. These variations have significant effect on both vehicle energy use and range. The changes in Wh/mi, range, and mpg can be large-both being larger and smaller depending on ambient temperature, average speed, and grade for the trip in the plug-in vehicle. The magnitude of these changes is comparable to that calculated for variations in accessory loads. The vehicle simulations showed clearly that to characterize the performance of a plug-in vehicle based on testing at a standard, fixed ambient temperature like 70 degrees F and on a specific driving cycle like the FUDS and/or the Federal Highway cycle will not yield an accurate description of the PEV performance in real-world driving.

5. Continue runs of the stochastic model until the estimates of vehicle lifecycle cost of ownership converge to within 0.1% marginal change.

Repeated runs of many iterations show convergence of the mean output. The effect of changes in the trip/driving cycle and accessory load on the AOC distributions seemed realistic in that they were consistent with prior expectations and not excessively large. For a particular vehicle and set of inputs other than trip/drive cycle and accessory load which were varied the differences were 5-10% in most cases. Larger differences would be expected if other variables such as trip length were given stochastically rather than as fixed values. Further development of the LCO tool seems justified based on the phase one results.

6. Format analytical tool in a way such that the tool provides estimates of vehicle lifecycle cost of ownership with the need of not more than 15 input values.

The LCO tool is based on an Excel platform. A user can display and compare the lifecycle cost of ownership for several vehicles types within specific regions in California. The number of user inputs are modest and they are well defined.

General Conclusions

The overarching goal of this study was to offer stakeholders rigorous, context-specific knowledge about factors that affect the purchase and cost of owning a plug-in vehicle,(PEVs) relative to other vehicle platforms. With this knowledge, stakeholders such as electric utilities, state agencies, local governments, and consumers can make decisions and implement programs to support the adoption of plugin vehicles consistent with extant policy and regulatory frameworks. By using real-world data specific to key regions in the state of California, the study will enable stakeholders to develop programs tailored to their areas and that target vehicles currently in the market or near production.

Commercialization and Marketing potential

The LCO tool is not intended as a commercial product. The intent is to offer the tool to appropriate stakeholders such that they may benefit from the additional information the tool provides. The researchers have discussed the tool with a variety of California stakeholders including fleet managers, non-profit organizations, and governmental organizations. The goal is to eventually make the tool available either directly or perhaps on websites where it could be utilized.

Based on initial discussions, the researchers have determined that the tool may require targeted education in order to ensure that the outputs and potential benefits are understood.

Recommendations

The research described in this report will give stakeholders such as fleet managers and other potential purchasers of PEVs better information on vehicle performance and life cycle costs than are presently available allowing them to make more informed decisions concerning their vehicle purchase. In particular, the research demonstrates that several factors, such as drive cycle, location, recharging times, vehicle incentives, and weather, can have significant impacts on the lifecycle cost of ownership and vehicle functionality. Cold weather, for example, can significantly reduce the range of PEVs and increase energy costs. The LCO tool developed in this project addresses these issues, but there is additional work needed to refine and extend the modeling and formulations on which the tool is based that would increase its functionality, scope, and benefits for potential users. These extensions and improvement are discussed below.

Additional locations/drive cycles
The present work includes information for the Sacramento, CA and San Francisco, Ca regions. Drive cycle data were collected for those regions only. Since the drive cycle determines the vehicle energy consumption (electricity and gasoline), it is a critical input to the lifecycle cost of ownership. The tool could be expanded to include other regions in California (such as the Los Angeles and San Diego regions) and elsewhere in the United States.

To expand the tool for other regions, urban and regional routes could be driven collecting the vehicle speed and elevation versus time data. This data could then be converted into drive cycles appropriate for those regions. The Advisor model could then use those drive cycles to calculate the energy consumption and range for a variety of PEVs. These energy use and range values , specific to various regions, would then be available for use with the tool to calculate lifecycle cost of ownership in additional regions.

Additional vehicles
The tool presently includes data for vehicles similar to the Nissan Leaf, GM Volt, and Chevy Cruze. There are, however, many other conventional and plug-in or electric vehicles that fleets or consumers will want to compare. The tool could be expanded to include other vehicle models similar to those becoming available on the market. The **Advisor** input models would be updated to include these additional PEVs with other vehicle parameters. Additional runs would then yield their fuel economies and ranges for appropriate drive cycles. That data could then be included in the cost tool to allow comparisons for a wider range of vehicles.

Inclusion of other stochastic parameters in the LCO Tool
The present LCO tool includes stochastic representations of the fuel prices (both gas and electricity). This variation yields a spread of potential ownership costs for a given vehicle in a specific region. Other variables, such as annual mileage, average trip length and route, vehicle initial price, ambient conditions and heating and cooling loads, are represented with fixed inputs. People do not drive a single drive cycle throughout the year, and the pattern of the use of heating or cooling is the same for all drivers. These parameters could be modified such that they are no longer characterized by fixed inputs but rather with stochastic representations. Adding additional variation to the input parameters would allow the tool to estimate ownership costs that more accurately reflect actual vehicle use.

More realistic modeling of the effect of ambient temperature and HVAC operation on PEV energy consumption
The present project showed clearly the large effect of ambient conditions and HVAC operation on the energy consumption of PEVs and the corresponding effect on the life cycle cost of ownership of the vehicles. The effect of the auxiliary loads also influences the useable range of the PEVs. The present analysis assumes a

fixed value for the auxiliary load meant to represent the average value of the load over the driving cycle. Additional work is needed to model the heating and cooling of the vehicle including the effect of changing cabin temperature in response to the operation of the HVAC unit and the heat gain or loss to the ambient environment as the vehicle moves along the road. This improved model will yield a variable auxiliary load depend on trip length and cycle, ambient temperature, cabin temperature set point, vehicle thermal design and HVAC unit efficiency characteristics. Combining this model with the **Advisor** simulation program will permit more reliable predictions of the energy consumption and range of PEVs in regions having different climate conditions.

More extensive calculations using the LCO Tool

In the present project, only limited use of the LCO tool was made. For example, calculations were made for only single values of tax incentives and only for single ranges of energy costs. With the improved auxiliary load model and the inclusion of additional stochastic variables, the LCO Tool can be run for a large number of vehicles, regions, and economic conditions to determine the effect of the various parameters on the economic attractiveness of different PEV designs to consumers having different needs.

Public Benefits to California

This work has added to a better understanding of PEV ownership in California and in other States following the California Zero Emission Vehicle (ZEV) Mandate. The present markets for PEVs are limited to early adopters who are willing to purchase PEVs in spite of their higher cost and limited utility compared to conventional ICE vehicles. As the sales of PEVs expand into the mass market, it will be necessary for more customers to be able to evaluate the utility and economics of the increasing number of PEV options. The LCO Tool developed in the present project is intended to be a valuable tool for potential PEV consumers (both fleet managers and individuals) which can help to expand the PEV market in California and the other States. This should result in more PEV sales and lower vehicle emissions in California and less difficulty in meeting the ZEV Mandate for 2015 and beyond.

Several groups have projected EV sales in California over the next few years [25, 26]. Table 14 shows a summary of those estimates along with the value of those sales assuming $25,000 per EV. While it's difficult to project the effect of the tool on consumer decisions and thus sales, fleet managers and individual consumers having access to better cost of ownership information are likely to purchase more plug-in vehicles.

Table 15: Estimated number of EV sales per year in California and the value of those sales.

Year	Projected annual sales of EVs (vehicles/yr.) *	Projected value of sales ($Billion/yr) based on $25,000 per vehicle
2015	27,000	0.67
2016	33,000	0.83
2017	42,000	1.05
2018	57,000	1.43
2019	84,000	2.1

*To date about 1/3 of the EVs sold in the United States are sold in California

Assuming that the added information increases the number of EVs sold over the 3 year period from 2015 – 2017 by 5%, roughly 5000 additional vehicles would be sold in California. The value of these sales would be about $125 million. Using the LCO results in Table 12, the 5-year cost savings of a Leaf purchaser would be about $7000 compared to owning a Cruze. Hence additional sales of EVs would result in a total ownership savings of about $35 million over the 5-years in California.

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Glossary

AC – air conditioning
ANL – Argonne National Laboratory
AOC – accumulated ownership cost
EPA – Environmental Protection Agency
EPRI – Electric Power Research Institute
EV – electric vehicle
GPS – global positioning system
HVAC – heating, ventilation, and air conditioning
ICE – Internal Combustion Engine
kWh – kilowatt hours
LCO – Lifecycle Cost of Ownership
MSRP – manufactures suggested retail price
NREL – National Renewable Energy Laboratory
PEV – plug-in vehicle
PHEV – plug-in hybrid vehicle
RMI – Rocky Mountain Institute
SOC – state of charge
UCD – University of California, Davis
Wh – watt hours

Appendix I: Summary of the GPS speed-grade driving cycle characteristics

Driving cycle	Distance miles	Average speed mph	Maximum speed mph	Average grade up %	Average grade down %
FUDS	7.45	19.6	56.7	0	0
FedHW	10.26	48.2	59.9	0	0
Sac area					
Sac-Davis	16.4	44.1	67.8	.4	.3
Davis-sac	15.4	42.2	68.8	.3	.3
Sac-auburn	37.4	56.5	69.1	.9	.3
Auburn-sac	36.0	50.0	69.3	.3	.9
Davis urban	10.2	21.4	38.5	.4	.4
Davis-Napa	46.9	53.2	69.4	.5	.5
Napa-Davis	47.1	53.1	69.3	.5	.5
Sac-Truckee	100.6	59.5	69.3	2.3	1.7
Truckee-sac	100.3	60.0	69.5	1.6	2.2
Bay area					
SF-urban1	9.07	18.3	34.2	2.1	1.9
SF-urban2	8.8	14.9	29.2	1.7	1.1
SF-Farfield	49.4	37.3	68.8	1.5	1.6
SF-San Raphael	31.7	39.3	69.0	2	2
SF-San Raphael	38.9	49.7	69.1	2.1	2
Palo-alto-SF	15.2	48.7	69.4	2.4	2.5

Appendix II: Summaries of the Advisor simulations for PEVs for various driving cycles and ambient temperatures

Advisor results for a Leaf-like EV for various driving cycles and ambient temperatures

Driving cycle	Accessories (W)	Ambient temp.	Wh/mi	Range (miles)* to SOC=.2
Aub-sac	4000	25 deg C	283	73
Aub-sac	400	25	210	99
Sac-aub	4000	25	384	55
Sac-aub	400	25	321	65
FUDS	4000	25	381	55
FUDS	400	25	198	105
FEDHW	4000	25	294	71
FEDHW	400	25	219	95
Davis-urban	400	25	171	120
Davis-urban	2000	25	246	85
Aub-sac	4000	10 degC	292	71
Aub-sac	400	10	218	95
Sac-aub	4000	10	395	52
Sac-aub	400	10	329	63
FUDS	4000	10	384	54
FUDS	400	10	200	104
FEDHW	4000	10	300	69
FEDHW	400	10	225	92
Aub-sac	4000	0 degC	297	70
Aub-sac	400	0	223	93
Sac-aub	4000	0	400	52
Sac-aub	400	0	335	62
FUDS	4000	0	389	54
FUDS	400	0	204	102
FEDHW	4000	0	306	68
FEDHW	400	0	230	90

*does not account for the effect of temperature on the battery kWh capacity

Advisor results for an EV (Leaf-like) on various driving cycles and ambient temperatures (San Francisco Bay area)

Driving cycle	Accessories (W)	Ambient temp. deg C	Wh/mi	Range (miles)* to SOC=.2
FUDS	400	25	197	111
FEDHW			220	100
SF-urban1			158	138
SF-urban2			188	114
SF-Fairfield			228	96
SF-SanRaf			238	93
SanRaf-SF			267	83
PaloAlto-SF			263	84
SF-urban1			158	135

SF-urban2			188	114
FUDS	2000	25	280	79
FEDHW			254	87
SF-urban1			246	89
SF-urban2			297	73
SF-Fairfield			272	79
SF-SanRaf			276	79
SanRaf-SF			298	75
PaloAlto-SF			291	77
SF-urban1			246	89
SF-urban2			297	73
FUDS	4000	25	380	58
FEDHW			296	87
SF-urban1			356	61
SF-urban2			429	51
SF-Fairfield			329	66
SF-SanRaf			333	65
SanRaf-SF			344	63
PaloAlto-SF			338	61
FUDS	6000	25	486	45
FEDHW			338	65
SF-urban1			468	47
SF-urban2			566	39
SF-Fairfield			398	54
SF-SanRaf			388	56
SanRaf-SF			388	55
PaloAlto-SF			388	55

*does not account for the effect of temperature on the battery kWh capacity

Advisor simulation results for the VOLT-like PHEV for various driving cycles

Driving cycle	Ambient Temp. degC	Accessories (W)	Wh/mi from battery	Electric range (miles)	Fuel economy (mpg)
Sac-aub	25	400	308	33	232
Sac-aub	25	4000	353	26	119
Aub-sac	25	400	189	54	No fuel used
Aub-sac	25	4000	267	37	No fuel used
FEDHW	25	400	206	49	No fuel used
FEDHW	25	4000	286	35	No fuel used

FUDS	25	400	207	48	No fuel used
FUDS	25	4000	396	25	No fuel used
FUDS	25	4000	396 up to 25 mi	48	45
SF-urban1	25	400	161	60	144mpg for 100 miles
SF-urban1	25	4000	410	26	29 mpg for 100 miles
SF-urban2	25	400	193	50	93 mpg for 100 miles
SF-urban2	25	4000	493	21	23 mpg for 100 miles
SF-Fairfield	25	400	10.5 kWh from the battery		491 mpg for 49 miles 1-way 87 mpg for 99 miles (2-way)
SF-Fairfield	25	4000	10.5 kWh from the battery		51 mpg for 49 miles 1-way 32 mpg for 99 miles (2-way)
FUDS	0	400W	244	40	No fuel used
FUDS	0	4000W	434	24	No fuel used
Aub-Sac	0	4000W	307	33	No fuel used
Sac-Aub	0	4000W	396	27	No fuel used
SF-Fairfield	0	4000W	360	29	No fuel used
SF-Fairfield	0	4000W	10.5 kWh from the battery		108 miles, 30 mpg
SF-Fairfield	0	4000W	10.5 kWh from the battery		286 miles, 25.4 mpg
			400W		**4000W**
			Mpg in charge sustaining mode		**Mpg in charge sustaining mode**
FUDS	25		36.6		20.0
HW	25		41.2		30.4
SF-SanRaf	25		34.5		23.5
SanRaf-SF	25		31.7		23.8
SF-Fairfield	25		34.5		24.8
Fairfield-SF	25		30.1		23.9
Sac-Davis	25		36.7		26.8
Davis-Sac	25		37.8		27.0
SF-urban1	25		46.6		22.3
SF-urban2	25		38.0		18.1
Aub-Sac	25		43.7		32.3
Sac-Aub	25		27.4		23.8
Davis-urban	25		49.0		25.0

Development Status Questionnaire

California Energy Commission Energy Innovations Small Grant (EISG) Program **PROJECT DEVELOPMENT STATUS**	**Questionnaire**

Answer each question below and provide brief comments where appropriate to clarify status. If you are filling out this form in MS Word the comment block will expand to accommodate inserted text.

Please Identify yourself, and your project: **PI Name** __Andrew Burke________**Grant** # 11-02TE ___________

Overall Status	
Questions	**Comments:**
1) Do you consider that this research project proved the feasibility of your concept?	*Yes, the researchershave developed and demonstrated the LCO Tool for meaningful examples.*
2) Do you intend to continue this development effort towards commercialization?	*The researchers plan to enhance the LCO tool as funding is available. Presently the LCO tool is used for research at ITS-Davis and for consulting. No commercialization of the tool is presently planned*
Engineering/Technical	
3) What are the key remaining technical or engineering obstacles that prevent product demonstration?	*None.*
4) Have you defined a development path from where you are to product demonstration?	*The tool can be demonstrated presently.*
5) How many years are required to complete product development and demonstration?	*None.*
6) How much money is required to complete engineering development and demonstration?	*None, but further money would be necessary to enhance the tool..*
7) Do you have an engineering requirements specification for your potential product?	*No.*
Marketing	
8) What market does your concept serve?	*NGOs, public and private fleets, consumers, policymakers*
9) What is the market need?	*Having the tool available on appropriate sites along with educating stakeholders about the tool is all that is necessary.*
10) Have you surveyed potential customers for interest in your product?	*Stakeholders.*
11) Have you performed a market analysis that takes external factors into consideration?	*No.*
12) Have you identified any regulatory, institutional or legal barriers to product acceptance?	*None.*
13) What is the size of the potential market in California for your proposed technology?	*NA*

14) Have you clearly identified the technology that can be patented?	*None.*
15) Have you performed a patent search?	*No*
16) Have you applied for patents?	*No*
17) Have you secured any patents?	*No*
18) Have you published any paper or publicly disclosed your concept in any way that would limit your ability to seek patent protection?	*No*
Commercialization Path	
19) Can your organization commercialize your product without partnering with another organization?	*NA*
20) Has an industrial or commercial company expressed interest in helping you take your technology to the market?	*NA*
21) Have you developed a commercialization plan?	*NA*
22) What are the commercialization risks?	*NA*
Financial Plan	
23) If you plan to continue development of your concept, do you have a plan for the required funding?	*Not yet*
24) Have you identified funding requirements for each of the development and commercialization phases?	*Development would require similar additional funds to this project depending on the details of the enhancements*
25) Have you received any follow-on funding or commitments to fund the follow-on work to this grant?	*No*
26) What are the go/no-go milestones in your commercialization plan?	*NA*
27) How would you assess the financial risk of bringing this product/service to the market?	*NA*
28) Have you developed a comprehensive business plan that incorporates the information requested in this questionnaire?	*NA*
Public Benefits	
29) What sectors will receive the greatest benefits as a result of your concept?	*NGOs, public and private fleets, consumers, policymakers*
30) Identify the relevant savings to California in terms of kWh, cost, reliability, safety, environment etc.	*Additional sales of PEVs due to enhanced knowledge .*
31) Does the proposed technology reduce emissions from power generation?	*Additional PEVs will reduce emissions from vehicles*
32) Are there any potential negative effects from the application of this technology with regard to public safety, environment etc.?	*No. There are no safety or environmental issues related to the development or use of the LCO tool and use of the tool should improve the prospects for the sale of electric vehicles, which are environmentally friendly.*
Competitive Analysis	

33) What are the comparative advantages of your product (compared to your competition) and how relevant are they to your customers?	*Location specific (very relevant), addition of auxiliary loads and their effect on ownership cost (relevant), Stochastic handling of parameters (potentially relevant)*
34) What are the comparative disadvantages of your product (compared to your competition) and how relevant are they to your customers?	*Additional complexity of outputs. Customers must be educated on the value of this tool.*
Development Assistance	
The EISG Program may in the future provide follow-on services to selected Awardees that would assist them in obtaining follow-on funding from the full range of funding sources (i.e. Partners, PIER, NSF, SBIR, DOE etc.). The types of services offered could include: (1) intellectual property assessment; (2) market assessment; (3) business plan development etc.	
35) If selected, would you be interested in receiving development assistance?	*NA*