CHARGING CHOICES AND FUEL DISPLACEMENT IN A LARGE-SCALE PLUG-IN HYBRID ELECTRIC VEHICLE DEMONSTRATION

Stephen Zoepf**
Engineering Systems Division
Massachusetts Institute of Technology
77 Massachusetts Ave. Bldg. 31-141
Cambridge, MA 02139
Telephone: 617-452-4771 Email: szoepf@mit.edu

Co-Author:
Don MacKenzie
Engineering Systems Division
Massachusetts Institute of Technology
77 Massachusetts Ave. Bldg. 31-141
Cambridge, MA 02139
Telephone: 617-452-4771 Email: dwm@mit.edu

Co-Author:
David Keith, Ph.D
Sloan School of Management
Massachusetts Institute of Technology
100 Main St. Bldg. E62-366
Cambridge, MA 02141
Telephone: 617-452-4771 Email: dkeith@mit.edu

Co-Author:
William Chernicoff
Toyota Motor North America, Inc.
601 13th Street, NW - Suite 910 South
Washington, DC 20005
Telephone: 202-463-6813 Email: wchernicoff@tma.toyota.com

**Corresponding Author:
Word Count: 5,739 + 7(250) figures = 7,489

ABSTRACT

As relatively few plug-in hybrid electric vehicles (PHEVs) have been deployed to date, existing analyses of the effects of PHEVs on gasoline and electricity demand have relied on travel patterns of conventional vehicles and assumption-driven charging scenarios. This paper presents a comprehensive analysis of a real-world fleet of 125 instrumented PHEV prototypes deployed in the United States over a one-year period. First, the trial is introduced and the patterns of travel, charging behavior and energy consumption observed are analyzed. Second, a mixed logit model of the decision to charge at the end of each trip is estimated. The results indicate that charging is most likely after the day's last trip, when ending at home, and when there are more than 3 hours before the next trip, although significant heterogeneity exists between drivers. To the authors' knowledge this is the first application of a discrete choice model to the empirical analysis of plug-in vehicle charging. Third, the performance of this fleet assuming different vehicle designs and charging patterns is simulated. Aggressive opportunistic charging after every trip would result in approximately the same fuel savings as increasing the battery size by a factor of five. However, fast charging would provide only marginal changes in energy use given the observed utilization patterns.

1. INTRODUCTION

Gasoline and diesel, derived from petroleum, fuel the vast majority of light-duty vehicles globally. Growing concern over the long-term availability of petroleum and the environmental impact of its combustion products has led to the development of various alternative fuel vehicle technologies. Electric vehicles (EVs) hold the potential for deep cuts in emissions when recharged with clean electricity. However, EV batteries are expensive and have low energy density at present, limiting the range and appeal of EVs compared with conventional gasoline-powered equivalents.

Plug-in hybrid electric vehicles (PHEVs) overcome these limitations, incorporating an internal combustion engine, an electric drivetrain and charging apparatus that allow them to be powered by both gasoline and electricity. PHEVs offer a number of benefits: they use smaller and less expensive batteries than pure EVs, they offer both the range of gasoline vehicles and the low operating costs and emissions of EVs, and are well-suited to the typical trip distribution comprising many shorter trips and relatively few longer ones. (*1*) However, PHEV performance depends strongly on vehicle design and control strategies, driving patterns (acceleration, speed and distances) and charging patterns (time, rate, duration and frequency).

Due to limited market penetration, most existing knowledge of PHEV usage and energy consumption, such as the impact of battery size and the grid impact of recharging, is based on analysis of known mobility patterns, surveys, and retrofitted hybrid vehicles (*2*,*3*). Various efforts have attempted to develop more realistic assessments of how PHEVs will perform in the real world. Vehicle-level simulation has been used to model the effects of design attributes and control strategies (*1,4*), while survey data and, more recently, GPS-based datalogging are used to characterize driving patterns. (*4,5*,*6*,*10*) The validity of these approaches requires an assumption that driving behavior will be the same for PHEVs as for conventional vehicles.

Charging behavior is an area of even greater uncertainty. Due to a lack of real-world data, charging behavior in existing work has been largely assumption-driven (*6*) or based on small samples. Axsen and Kurani (*7*) surveyed respondents about possible charging behavior, based on availability and perceived importance. Davies and Kurani (*8*) reported results from a study of 40 vehicles for a one-week period during which the authors identified a mean of one daily charge, including two participants that did not recharge at all. Williams et al. (*9*) noted the paucity of real-world information on recharging behavior, and presented the results of one prototype PHEV vehicle rotated among twelve households over one year to gather more information on real-world charging behavior. Using small samples to predict fleet-wide impact generates substantial uncertainty. (*10*)

This paper expands this body of knowledge by analyzing the driving and charging behavior observed during a large, long-term, geographically diverse deployment of 125 prototype PHEVs in the United States. First, concepts used in the analysis of PHEV usage are defined, and the details of the PHEV trial being studied are introduced A range of vehicle performance measures are investigated, including gasoline consumption in charge-sustaining (CS) and charge-depleting (CD) modes, electricity consumption in CD mode, effective electricity consumption per electrified km, real-world effective electric range and utility factors and petroleum displacement factors at a fleet and vehicle level. Second, a mixed logit model of the probability of charging at the end of a trip is estimated, conditional on characteristics of the completed trip and time until the next trip. The results show that PHEV charging is most likely after the day's last trip, when the trip ends at home, and when the next trip is more than 3 hours away, although significant heterogeneity exists between drivers. Third, the fleet impact of vehicle and behavioral changes on the consumption of gasoline and electricity is simulated. Opportunistic charging after every trip greatly increases PHEV fuel savings. In contrast, fast charging is found to result in only marginal changes in energy use.

2. PHEV CONCEPTS

PHEVs may operate in three modes: charge-sustaining (CS), all-electric (EV), or blended. In CS mode, the battery's state of charge (SoC) fluctuates within a limited range like that of a regular HEV, but exhibits no long-term trend, so the vehicle is considered to use only gasoline. When using only electricity a PHEV is operating in EV mode, and when using both gasoline and electricity a PHEV is operating in blended mode. Both EV mode and blended mode are charge-depleting (CD) modes, because SoC trends downward over time.

PHEVs are commonly designated PHEV-x, where x is some measure of electric range. However, there is ambiguity as to the exact meaning of this term. Kurani et al. (*11*) identify at least three published interpretations of the PHEV-x designation: x = equivalent miles of gasoline displaced by electricity (the interpretation preferred in this work), x = distance before the engine first turns on, or x = distance that the vehicle travels in CD mode.

Two other important PHEV-related concepts are utility factor (UF) and petroleum displacement factor (PDF). UF, as defined by SAE Standard J2841, is the ratio of the distance the vehicle travels in CD mode to the total distance traveled, and PDF is the ratio of distance attributable to the non-petroleum fuel (i.e. grid electricity) to total distance traveled. PDF depends on vehicle design, driving patterns, and charging behavior: (*1*,*12*,*13*,*14*)

$$UF = \frac{Dist_{CD}}{Dist_{Total}}$$

$$PDF = \frac{Dist_{Electrified}}{Dist_{Total}}$$

These two concepts – UF and PDF – are functionally equivalent for vehicles that do not use blended mode. However, for vehicles that do use blended mode, UF will overestimate fuel displacement because a portion of the tractive force during CD mode is petroleum-derived. This work reports estimates for both UF and PDF.

To calculate PDF when blended mode is used, electrified distance is defined as the amount by which the distance traveled in CD mode exceeds the distance that can be explained by the amount of gasoline consumed in CD mode. The latter is taken to be the CD mode gasoline usage ($Gasoline_{CD}$) divided by the CS mode fuel consumption rate (FC_{cs}):

$$Dist_{Electrified} = Dist_{CD} - \frac{Gasoline_{CD}}{FC_{CS}}$$

There are potential problems imputing gasoline distance in CD mode based on fuel consumption in CS mode, since systematic differences in the driving patterns that characterize each mode may exist. These risks are partially mitigated by calculating the CS mode fuel consumption separately for each vehicle in the trial, and using that vehicle's specific CS mode fuel consumption to impute its gasoline miles in CD mode. However, bias may remain if, for instance, trips that occur soon after a charge have different speed, acceleration, or accessory load profiles than those occurring later. It should be possible to adjust for these differences using more disaggregated data from each mode, but such adjustments are not considered in this analysis.

3. DESCRIPTION OF THE TRIAL

The test fleet studied here consisted of 125 pre-production Toyota Prius PHEVs deployed in the U.S. from approximately April, 2011 to April, 2012. The deployment was part of a global fleet evaluation and learning program to test the real-world usage of the vehicles against intended and expected usage and performance. The evaluation also provided a platform for assessing the potential merits of changing the availability and accessibility of level 1 (110V) or 2 (220V) at-home charging, work place charging, and other vehicle-grid interactions. A final objective was to disseminate information on the driving patterns, charging habits, and other factors related to the real-world operation of PHEVs.

Vehicle Specifications

The powertrain configuration of the vehicles was a prototype, adapted from the 2010 Toyota Prius. It was not representative of current or future production PHEVs from the manufacturer. Key specifications for the vehicle included:

- 5.4 kWh Li-ion battery, estimated 21 km range (EPA test cycle);
- Permanent magnet synchronous motor (maximum 60 kW / 207 Nm);
- 1.8-liter internal combustion engine (maximum 73 kW / 142 Nm);
- Maximum combined output 100 kW.

Vehicle Operation & Charging

The PHEVs in this trial operate in three modes: All-electric, blended, and charge-sustaining. The selection of operating mode is dictated by battery SoC and power demands from driver inputs and accessory loads.

The vehicle operates in EV mode with sufficient SoC and low-moderate loads consistent with typical operation and accessory loads. If power requirements exceed battery limits as a result of throttle input, HVAC settings, or vehicle speed exceeding 100 km/h, the vehicle enters blended mode. Additionally, as the battery nears a state of discharge, the vehicle may enter blended mode in order to reduce the current flow from the battery to extend battery life. When SoC is low, the PHEV operates like a conventional HEV, and uses a limited portion of the battery capacity for regenerative braking and supplemental torque.

Each vehicle was supplied with a compact, readily portable level 1 charger using a standard 15 A household outlet, though it is unknown whether participants carried the chargers with the vehicles or used them in a fixed location. Other permanent and semi-permanent level 1 and level 2 charging facilities were available in some locations. The vehicles were not compatible with level 3 charging.

Participant Selection

Participants for the trial in the U.S. were a variety of corporate, governmental, and educational partner institutions, selected to meet the following primary objectives according to Future Fuels and Environmental Strategy Manager Jaycie Chitwood:

- A range of operational use cases and conditions including personal, business, and demonstration fleets.
- Geographic distribution that provide wide coverage, but clustered to minimize the cost of support organizations.
- Some preference was given to partner organizations with an existing relationship with the manufacturer, and to those with known outreach capabilities.

Data Collection and Processing

All vehicles were equipped with proprietary data loggers collecting more than 100 channels of data with 1-second resolution. The data were cached, periodically transmitted via cellular modem to the data logger manufacturer, and then transferred to the vehicle manufacturer. The data available to researchers included time, speed, location, temperature, battery SoC, operating mode (CS/CD), and information on HVAC and regenerative braking use. Researchers at the National Renewable Energy Laboratory (NREL) aggregated the second-by-second data into 59,287 individual trips.

4. GASOLINE AND ELECTRICITY CONSUMPTION OF VEHICLES IN THE TRIAL

The performance of the PHEVs in this trial was characterized according to several common figures of merit. When operating in CS mode, the gasoline consumption was similar to that of the standard Prius HEV. In CD mode, the gasoline consumption was approximately halved, as grid electricity provided a portion of the vehicles' power demands. The use of blended mode complicates the attribution of distance traveled to either gasoline or electricity, so a simple method for assigning CD mode travel to each fuel was established, as described in Section 2.

For each vehicle in the trial, average fuel consumption in CS mode was calculated by dividing total gasoline consumption by total distance traveled in CS mode. Nearly all of the vehicles returned average CS mode fuel consumption between 4.0 and 6.0 l/100 km (39 – 59 mpg), as shown in FIGURE 1. The overall average was 4.90 l/100 km (48.0 mpg), which is close to the 4.70 l/100 km (50 mpg) EPA rating of the standard 2010 Prius HEV.

When operating in charge-depleting mode, the average rate of gasoline consumption was approximately halved, to an average of 2.48 l/100 km (94.6 mpg). Most of the vehicles returned rates between 1.0 and 4.0 l/100 km. The variance in gasoline consumption was higher in CD mode than in CS mode, reflecting the wider range of variables that may influence gasoline consumption in CD mode.

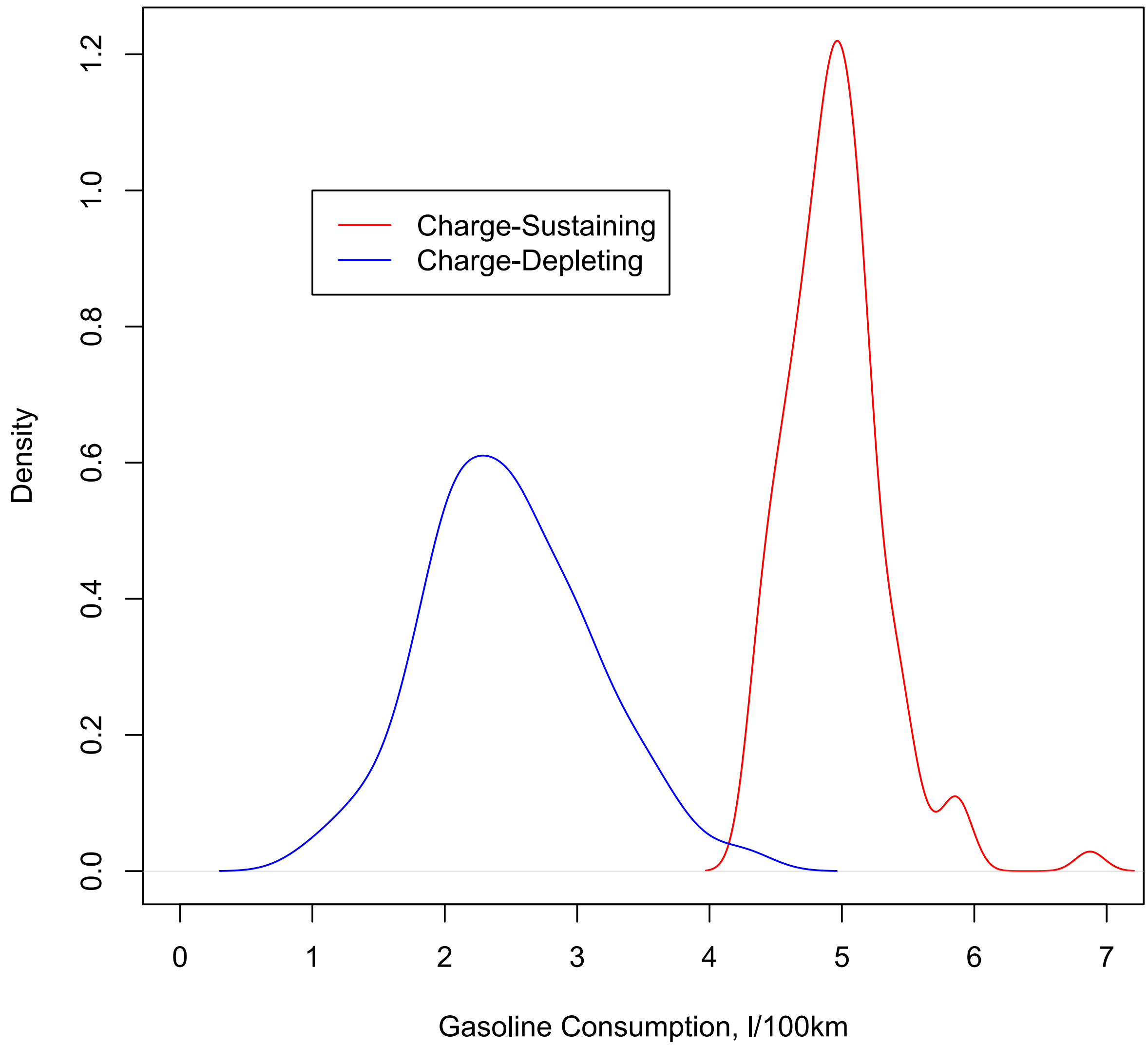

FIGURE 1 Density plots of fuel consumption in CD and CS modes.

The effective electricity consumption rate per electric kilometer was calculated as the distance attributed to grid electricity divided by the total electricity consumed in CD mode (FIGURE 2). The large majority of vehicles used between 150 and 350 Wh for each additional kilometer of travel beyond that explained by their gasoline usage. The overall mean across all vehicles in the trial was 218 Wh/km, which is similar to the EPA's electricity consumption ratings for the Nissan Leaf EV and Chevrolet Volt PHEV (213 and 225 Wh/km, respectively). For 3 kWh of working capacity in CD mode, the distribution of electricity consumption rates implies a distribution of electric range values; on average, the vehicles in this trial gained 13.8 km of electrified travel from a 3 kWh charge.

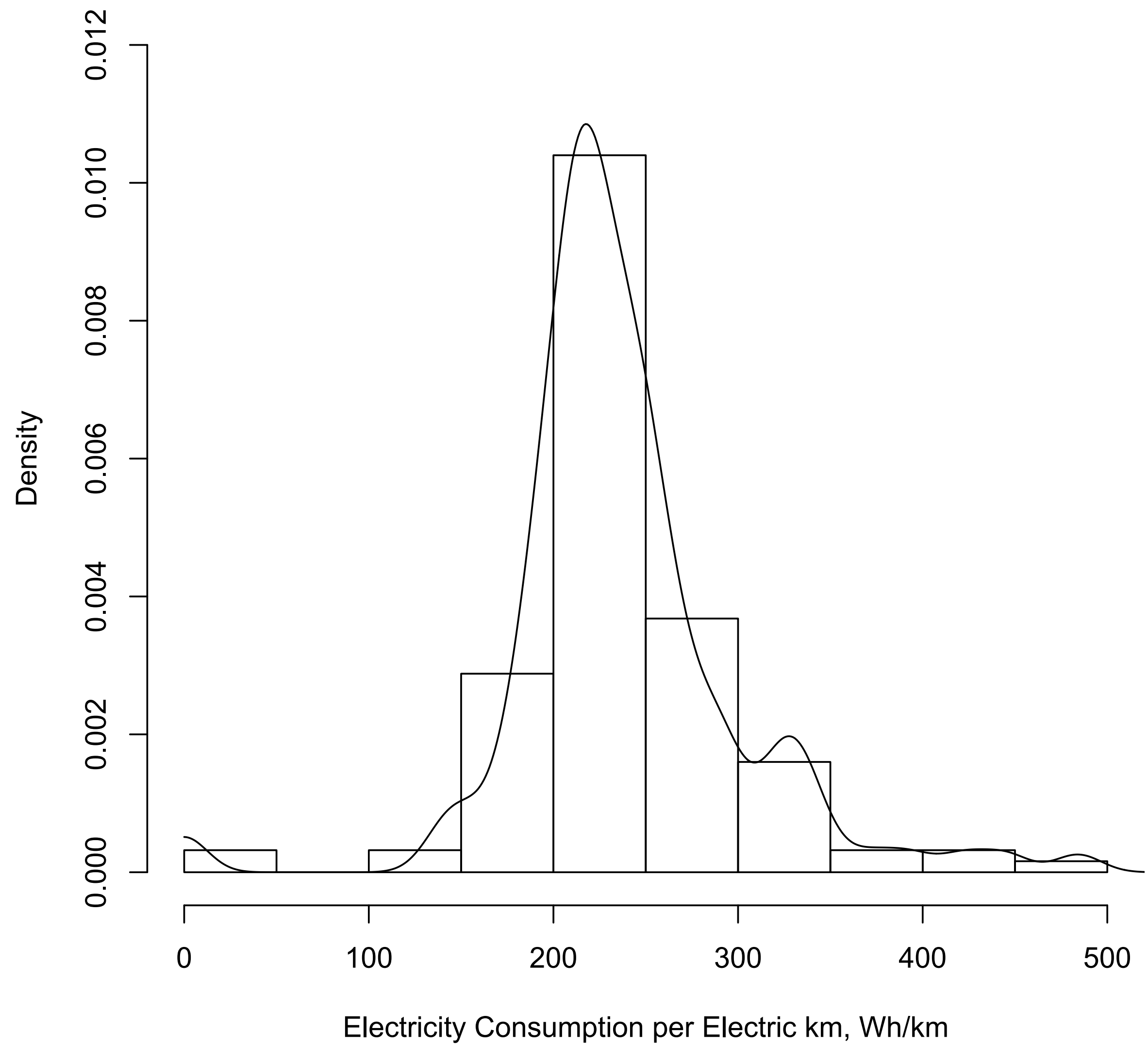

FIGURE 2 Distribution of Electricity Consumption

Operation in blended mode means that vehicles generally drive further than their effective electric range in order to fully deplete their CD battery capacity. Although the vehicles used an average of 218 Wh for each electric km, the actual rate of electricity consumption in CD mode averaged 107 Wh/km. Thus, even in CD mode, gasoline was providing approximately half the vehicles' energy requirements on average, and it took an average of 28 km before a fully charged vehicle exited CD mode. This pattern will tend to reduce the PDF, since the vehicle must be driven further in order to fully exploit the battery's stored electricity. Put differently, the finding that gasoline still accounts for half the distance traveled in CD mode effectively puts an upper limit of 50% on the PDF, although it could be higher if driving habits were adjusted to increase pure EV mode usage.

The PDF was calculated as the ratio of the distance attributed to grid electricity to the total distance traveled. The distribution of PDF values is shown FIGURE 3, and the overall average in this trial was found to be 13.7%. Also shown is the distribution for UFs across the vehicles in this trial, which averaged 28.1% overall. The PDFs and UFs observed in this trial are lower than predicted by the SAE J2841 standard for UF, a discrepancy that is further explored below.

There was a very wide spread in the values of these metrics across different vehicles. The highest PDF was 59%, showing that the right combination of driving patterns and charging habits can make very effective use of even a small battery to displace gasoline. On the other hand, five of the 125 vehicles in the study had PDFs of less than 1%, indicating that they derived almost none of their energy usage from grid electricity. Another 16 vehicles had PDFs between 1% and 5%, typically coincident with infrequent charging.

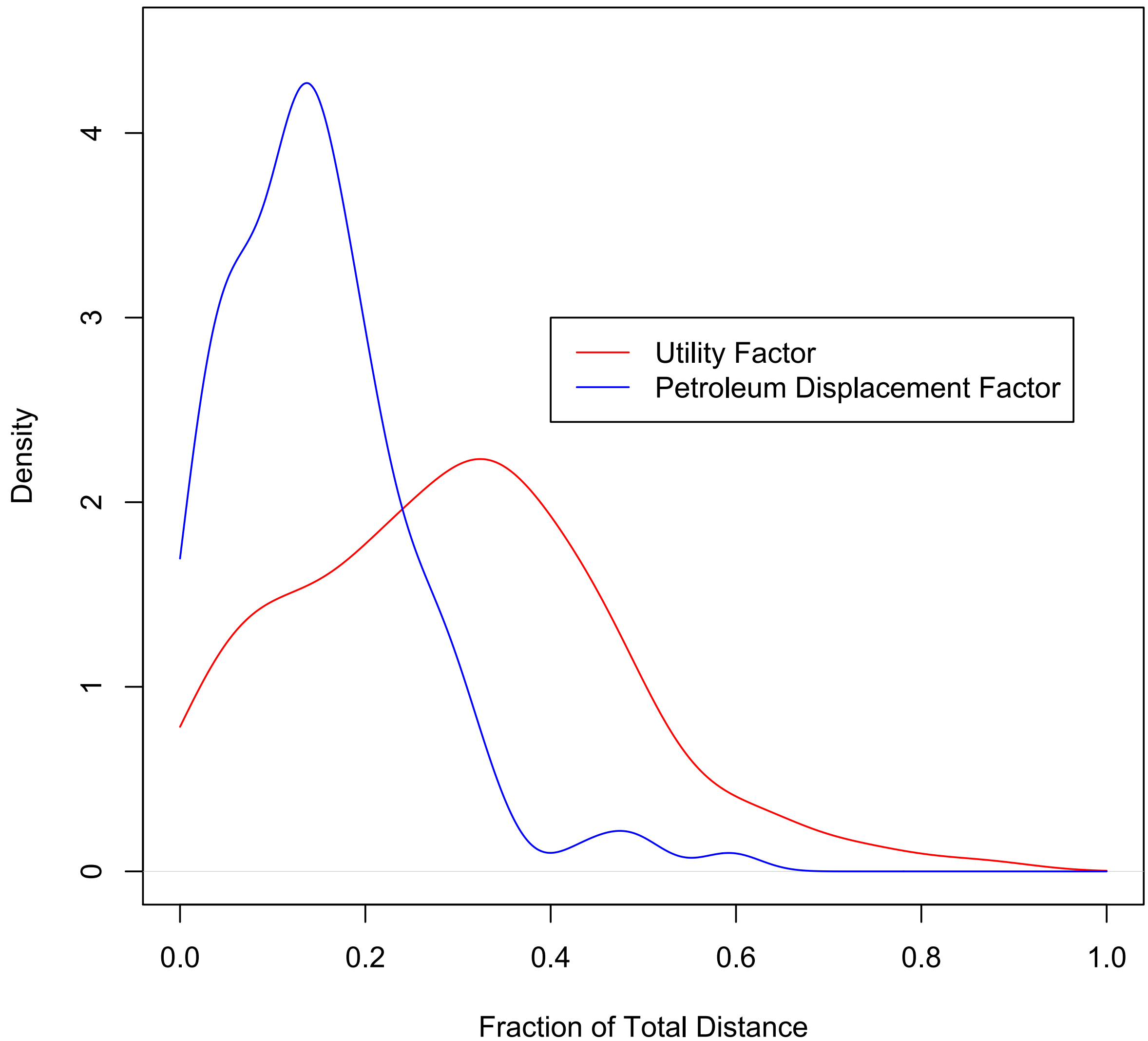

FIGURE 3 Density Plot of UF and PDF

5. ANALYSIS OF TRIPS, VMT AND CHARGING BEHAVIOR

Trips and Daily Distance

To help assess the generalizability of the trial data, the distribution of daily travel distances from the trial was compared with that observed in the 2001 National Household Transportation Survey (NHTS). The distribution of daily distances observed in this trial is positively skewed, with more low-mileage days (FIGURE 4). The distribution of individual trip lengths in this trial was also positively skewed when compared with NHTS 2001.

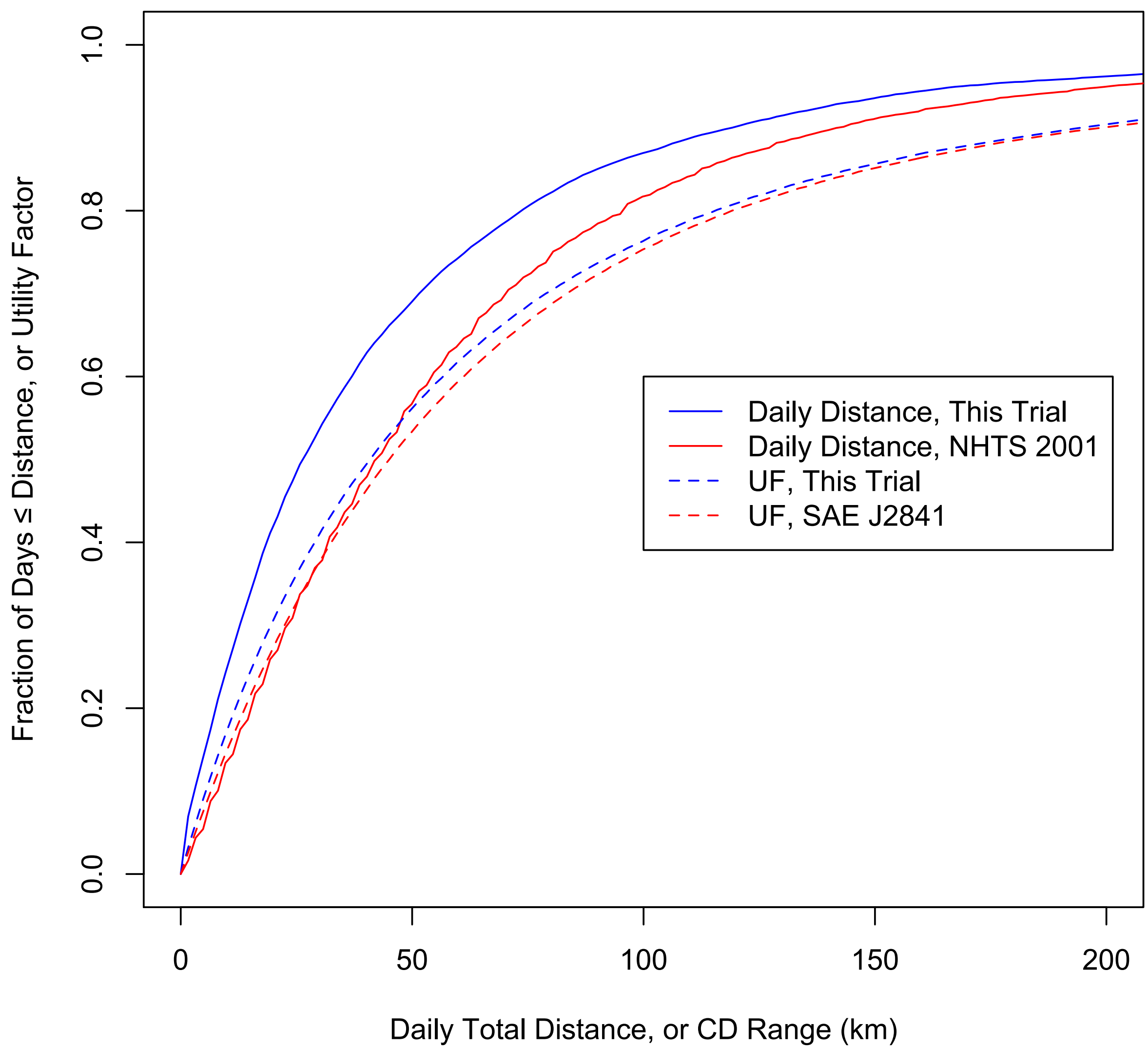

FIGURE 4 Cumulative distribution of Daily Travel Distance and corresponding UF curves

The daily distance distribution from the trial was used to calculate the fleet utility factor (FUF) using the method described in SAE standard J2841. (12) The resulting FUF curve is shown in FIGURE 4 along with the FUF curve from SAE J2841 (which is based on NHTS 2001). The FUF from this trial predicts that a fleet of PHEVs with a 28 km CD range would drive 42% of its overall distance in CD mode, assuming each vehicle is fully charged each night and only at night. In contrast, SAE J2841 predicts that such a fleet would cover 36% of its overall distance in CD mode. The larger UF predicted for this trial is a result of the bias toward shorter daily total distances in this trial when compared with NHTS 2001.

As discussed in Section 4, the 3 kWh of charge-depleting battery capacity is estimated to provide an equivalent electric range of 13.8 km. If the vehicles' control strategy strictly preferred electric operation when in CD mode (i.e. if the vehicles did not have a blended mode), then the predicted PDF and the FUF for this 13.8 km range would be 20% (based on SAE J2841) or 23% (based on the daily distance distribution from this trial).

The actual UF averaged across all vehicles in this trial was 28.1%, and the average PDF was 13.7%. Both of these values are lower than the respective predictions based on SAE J2841 and on the theoretical FUF based on the trip distribution in this work. This appears to be due both to between-days variation in distance traveled, and to vehicles being charged less than once per day. (5)

Aggregate Charging Behavior

The trial reported here provides important insights into the charging habits of actual drivers who used PHEVs on a regular basis. Because the action of plugging the vehicle in was not actually logged, a charge was deemed to have occurred whenever the SoC between the end of one trip and the beginning of the next trip increased by at least 5 percentage points. The rationale for this condition is to avoid misclassifying as a charging event mere drifts in SoC resulting from changes in temperature or other conditions that can influence the measured SoC of the battery.

FIGURE 5 shows the distribution of charging start times across all charging events identified in the trial. Charging was assumed to start immediately at the end of the trip preceding the charging period, a reasonable assumption since the vehicles were not equipped with smart chargers. The most common times for the start of a charge were between 2:00 PM and 4:00 PM, and the initialization of new charging events fell off abruptly after 6:00 PM. This is somewhat surprising but may be due to the way in which the cars were deployed in this trial. If the cars were used mainly in corporate fleets, then the afternoon peak in charging may reflect them being plugged in after the last work-related trip rather than after an evening commute.

Approximately half of the charging events observed in this study involved nearly a full charge (i.e. a charge of more than 2.5 kWh for the 3 kWh battery pack), indicating that the battery was fully discharged before charging and was allowed to charge fully before being unplugged. The other half of the charging events were uniformly distributed between 0 and 2.5 kWh.

More than 40% of the days on which a vehicle was driven in the trial saw no charging, while a similar number saw one charge. Just 10% saw two charges, and smaller numbers saw more. Thus nearly half the time, the PHEVs were not being charged even once on days when they were driven, even though the overall average rate was 0.75 charges per day per vehicle.

Differences in charging behavior were apparent between different vehicles. For example, one vehicle in the study was never charged, one charged an average of 1.7 times per day over the course of the trial, while the others were broadly dispersed between 0 and 1.25 charges per day. These observations tend to discredit the simplistic assumption that each vehicle charges once and only once each day, which is commonly employed in PHEV analyses. Not only was observed charging behavior different than commonly assumed, it also varied substantially between vehicles, suggesting differences in drivers' preferences, incentives, or abilities to plug in.

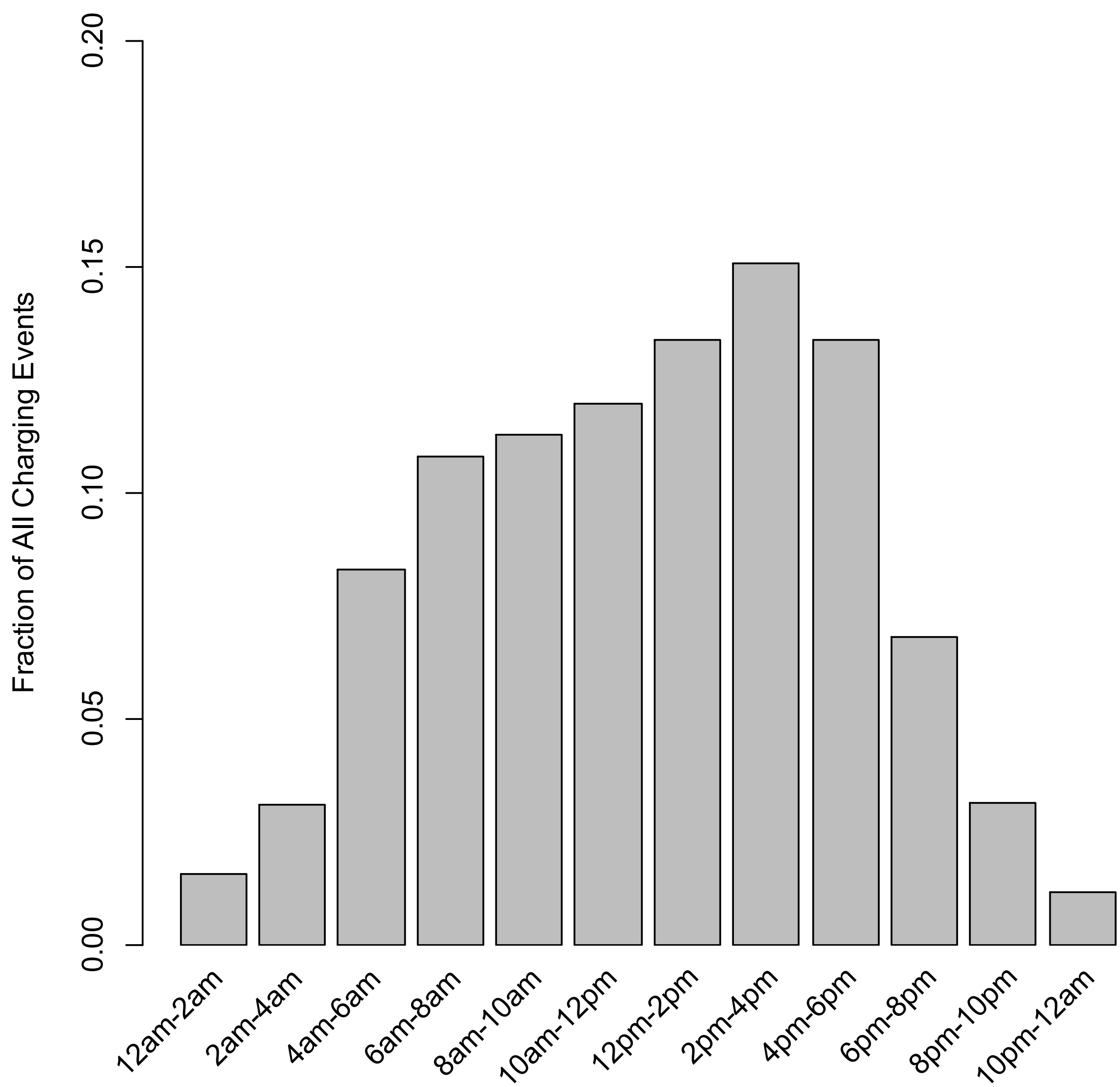

FIGURE 5 Distribution of charging start times

A Model of Individual Charging Choices

The dataset used in this work was sufficiently detailed to permit empirical testing of common assumptions about charging behavior. Although PHEV analyses are increasingly grounded in real-world driving patterns, there has been very little data collected on charging behavior, because of the dearth of PHEVs and BEVs in real-world service. As a result, assessments of these vehicles to date have relied on assumptions about how people might charge their vehicles. In this section, a mixed effects logistic regression model is presented, with results that tend to validate the belief that overnight charging is the most likely charging behavior. However, the results also show significant heterogeneity in the relationship between various predictors and the probability of charging for different vehicles.

The mixed-effects logit specification is shown below:

$$P(Charge_{it}) = \frac{e^{V_{it}}}{1 + e^{V_{it}}}$$

Where $Charge_{it}$ is a binary variable indicating whether vehicle i was charged at the end of trip t, and V_{it} can be interpreted as the observable portion of the utility of charging U_{it}. (Since there is no information on whether a charging point is available at each stop, what is modeled here is the probability of locating and using a charging point.)

$$U_{it} = V_{it} + \varepsilon_{it} = X_{it}\beta + Z_{it}b_i + \varepsilon_{it}$$

In the second expression above, X_{it} is a vector of variables characterizing the conditions encountered by vehicle i at the end of trip t, and β is a vector of fixed effects and coefficients capturing the average effect of those variables on the utility of charging. Z_{it}, which may be the same as X_{it}, is a vector of variables whose effect on the utility varies over the vehicles in the sample, and b_i is a vector of independent, normally distributed random effects which capture heterogeneity in the effects of the variables in Z. Both X_{it} and Z_{it} contain constant terms which capture, respectively, the average utility of charging and the variation in this average from one vehicle to the next. The final term, ε_{it}, represents the unobserved utility and is assumed to be independently, identically distributed (i.i.d.) with extreme value distribution. The utility of not charging is normalized to zero by assumption.

The model tested the dependence of charging on the battery's SoC at the end of the trip, characteristics of the completed trip, the time before the next trip, and the day and time at which the trip was completed. Initially, both fixed and random effects were estimated for all of the independent variables. Random terms relating to the hours before the next trip were dropped from the model after initial analyses indicated that they would have no practical significance. State of charge was included linearly, along with dummy variables indicating that the battery was fully charged or depleted, with the expectation that the probability of charging would increase as the battery is depleted. The length of the completed trip was included, since longer trips might make drivers more aware that the battery is depleted (alternatively, longer trips might leave a driver more fatigued and less likely to plug in). Also included were dummy variables indicating if the trip was the last trip of the day, or ended at the same place the vehicle started the day, both of which would tend to be associated with overnight stops. Finally, dummy variables were defined to identify the approximate time the trip ended, and whether it ended on a weekend or a weekday.

The results of the model estimation, which was done using the *lme4* package in R, are presented in TABLE 1. The parameter estimates and associated standard errors are presented for the fixed effects / constant coefficients in the first column. The estimated standard deviations of the random parameters are presented in the second column. Because of the asymmetry in the sampling distribution of the random parameters, standard errors are not reported and significance testing was not based on t-tests. Instead, significance of each random parameter was assessed using likelihood ratio tests on restricted versions of the model in which the random parameter in question had been dropped. The test statistic for the likelihood ratio test is provided in parentheses for each random parameter; under the null hypothesis these will be χ^2-distributed with 1 degree of freedom.

Looking first at the fixed effects, the time before the next trip is strongly related to whether a vehicle is charged at the end of a trip. For times up to three hours, the probability of charging increases with the waiting time. However, above three hours, there is essentially no change in the probability of charging. There are at least two possible explanations for this result. First, three hours is the approximate time needed for a full charge in these vehicles, so it is possible that drivers only want to plug in when they know they have enough time for a full charge. Alternatively, it is possible that three hours' worth of charging is the minimum that drivers are willing to accept in return for the inconvenience of plugging in. Distinguishing between these hypotheses would be more practical with charging data from some other types of plugin vehicles.

A trip being the last trip of the day, and ending at the location where the day began, are each strongly correlated with a higher probability of charging. Combined with the substantial effect of a stop being longer than three hours, these results suggest that the probability of charging overnight is going to be relatively high, since overnight stops are likely to be longer than three hours, the last trip of the day, and to occur at the same place where the vehicle's day began. Trip length had a small effect, and weekends had no significant effect on the probability of charging.

The fixed effect estimate for SoC has the expected sign, indicating that the vehicles were less likely to be plugged in when the SoC was higher. When the battery was already full, the vehicles were much less likely to be plugged in. Surprisingly, an empty battery was associated with a lower probability of charging; it is possible that this is due to empty batteries being more common when vehicles are away from their usual charging infrastructure. Although statistically significant, this effect is relatively small compared with the effects discussed above. The fixed effects for times after noon were significant, indicating a modest reduction in the probability of charging after a trip that ends in the afternoon or, especially, in the late evening.

Turning to the random effects, there is heterogeneity evident in the effects of most variables on the probability of charging, which is significant in both statistical and practical terms. Interestingly, for some variables (ending on weekend, and several time-of-day dummies) there is no fixed effect, but there is a significant random effect. This indicates that although there is no effect of these variables on the probability of charging on average, the effect for some vehicles was positive and for other vehicles was negative.

TABLE 1 Parameter Estimates of Logit Model

	FIXED EFFECTS, β (standard error)	RANDOM EFFECTS, σ (LRT statistic on nested model)
Intercept	-3.635 ***	0.594 ***
	(0.113)	(60.3)
Battery State		
Battery SoC	-0.0148 ***	0.009 ***
(percentage points SoC)	(0.0015)	(50.3)
Full battery	-2.762 ***	0.948
(>90% SoC)	(0.278)	(2.5)
Empty battery	-0.342 ***	0.329 ***
(<10% SoC)	(0.064)	(15.8)
Next Trip		
Hours until next trip	1.007 ***	
	(0.028)	
>3 hours until next trip	2.774 ***	0.558 ***
	(0.081)	(70.3)
(Hours until next trip) *	-1.007 ***	
(>3 hours until next trip)	(0.028)	
Current Trip		
Distance (miles)	-0.003 **	0.003
	(0.001)	(0.3)
Last trip of day	0.972 ***	1.143 ***
	(0.117)	(690.3)
Ends at day's starting point	0.655 ***	0.840 ***
	(0.088)	(376.5)
Ends on weekend	-0.035	0.542 ***
	(0.067)	(71.3)
Trip End Time		
4 AM – 8 AM	0.053	0.551 ***
	(0.092)	(52.7)
8 AM – Noon	-0.075	0.365 ***
	(0.082)	(17.3)
Noon – 4 PM	-0.206 *	0.395 ***
	(0.086)	(22.8)
4 PM – 8 PM	-0.202 *	0.477 ***
	(0.096)	(22.6)
8 PM - Midnight	-0.285 +	0.864 ***
	(0.152)	(40.9)
Model Summary Statistics		
Null Log-Likelihood L(0)	-37344	
Model Log-Likelihood L(β)	-16447	
Adjusted ρ^2	0.559	

+ significant at 0.1 level * 0.05 level ** 0.01 level *** 0.001 level

6. SIMULATION ANALYSIS

The gasoline and electricity consumption in this trial result from specific charging and driving behaviors applied to one vehicle design. This section reports on simulations of the electricity and gasoline consumption when small, one factor at a time (OFAT) changes are made to the vehicle design or charging logic, assuming that all trips remained the same. These scenarios are described below, and results are summarized in the subsequent section.

Scenarios

Each scenario used original trip cycles with new CD and CS percentages calculated based on the parameters of the scenario, such as battery size and new charging schedules. In all cases vehicle-level average values of CD and CS gasoline and electricity consumption were used.

Charged Once Daily

To simulate once-daily charging, SoC for each vehicle was reset to 100% at the start of each new calendar day. Battery capacity was unchanged. This assumption is present in existing UF definitions and embodies the common-sense assumption that PHEVs will be charged primarily overnight at home.

Opportunistic Charging

The Opportunistic Charging case simulates a scenario in which PHEV users charge their vehicles whenever they will be parked longer than a given time threshold. This assumes ubiquitous availability of 110V charging facilities. The study was conducted at nine time thresholds from 0 – 8 hours. Zero hours represents a limiting case in which the vehicle is plugged in immediately whenever switched off.

Fast Charging

The Fast Charging scenario simulates the same vehicle fleet, charged at exactly the same times and for the same duration but charged at higher rates. In theory this should primarily impact short charge cycles that are not capacity-limited.

Alternative Battery Capacity

Alternative Battery Capacity cases apply different battery pack sizes to the same vehicle, which permits a higher SoC and longer CD driving distances. This scenario considers the impact of battery capacity only through the mechanism of extending CD range. A larger pack size will also increase vehicle weight and decrease overall efficiency, but this effect is not considered.

Strictly Prefer EV mode

The Strictly Prefer EV Mode scenario models the effect of an alternative vehicle control strategy in which blended mode is not used and vehicles operate strictly on electric power until the battery pack is exhausted, then reverting to CS operation.

Scenario Outcomes

The results of these scenarios are summarized in TABLE 2 and compared against an actual UF of 28.1% and PDF of 13.7% With daily charging, the PDF improves to 18.2%, similar to the 19.1% achieved under opportunistic charging with an 8-hour threshold. With more aggressively opportunistic charging, improvement continues until a maximum of 28.3% is reached at zero hours, simulating performance if each vehicle is charged at every stop. As noted in Section 5, the probability of charging for the average driver falls off when stop time drops below 3 hours.

As expected, increasing battery capacity would increase petroleum displacement, but with diminishing marginal returns. Quadrupling CD capacity would have increased PDF to approximately 27%, but increasing by a factor of ten would only have increased this to 33.7% (assuming that driving and charging patterns remained unchanged).

Other scenarios yielded only minimal changes. Deployment of rapid charging alone, even at rates up to 8x as fast as current 110V charging, left the PDF substantially unchanged at 14.2%, offsetting only 203 additional liters of gasoline. Eliminating blended mode via the Strictly Prefer EV Mode scenario yielded a PDF of 15.5%, saving an additional 642 liters of gasoline.

TABLE 2 Charging & Design Scenarios: Summarized Results

	kWh	Fuel (L)	Liters saved*	PDF	UF
Actual Fleet Performance					
	21804	31328	4908	0.137	0.281
Charged Once Daily					
	30947	29534	6703	0.186	0.382
Opportunistic Charging (Charge if parked N hours)					
N = 8	31784	29351	6885	0.191	0.392
N = 7	32694	29148	7088	0.196	0.404
N = 6	33524	28960	7277	0.201	0.416
N = 5	34659	28707	7530	0.208	0.430
N = 4	36403	28315	7922	0.219	0.452
N = 3	38580	27839	8398	0.232	0.480
N = 2	41403	27234	9003	0.249	0.514
N = 1	44580	26559	9678	0.268	0.553
N = 0	47154	26012	10224	0.283	0.584
Fast Charging					
1 kWh / hour**	22451	31346	4891	0.137	0.280
2 kWh / hour	23055	31216	5020	0.140	0.288
4 kWh / hour	23310	31161	5075	0.142	0.291
8 kWh / hour	23399	31142	5094	0.142	0.292
Alternative Battery Capacity					
0 kWh	0	36237	0	0.000	0.000
1.5 kWh	13357	33330	2907	0.081	0.166
3 kWh**	22451	31346	4891	0.137	0.280
6 kWh	33534	28928	7309	0.204	0.420
12 kWh	44490	26571	9666	0.270	0.556
18 kWh	49991	25403	10833	0.303	0.624
24 kWh	53396	24684	11552	0.323	0.666
30 kWh	55851	24168	12068	0.337	0.696
Strictly Prefer EV mode					
	25644	30687	5550	0.155	0.155

(* = Liters vs. simulation of HEV, ** = Approximates actual performance)

7. CONCLUSIONS

This paper summarizes findings from the largest fully instrumented, real-world trial of prototype PHEV vehicles thus far.

The results of this analysis highlight the important role blended mode plays in the operation of this type of PHEV and consequently the importance in distinguishing between UF and PDF. While this fleet returned an in-use UF of 28% the PDF was just half, at 14%, due to the use of gasoline in blended mode.

Scenario analysis indicates that deployment of fast charging with a small battery capacity brings little benefit, but ubiquitous use of conventional 110V chargers more than doubles UF and PDF. Increasing battery capacity decreases gasoline consumption, but most benefits are realized by increasing effective electric range to 55 km. Charging the vehicles in this study every time they are stopped for 3 hours or more would increase PDF to 23%, the same level expected from increasing electric range to 41km.

When charging, more than half of all charge events result in a charge delivered of at least 2.5 kWh. On days that they were used, 40% of vehicles were charged only once and 40% were not charged at all. A mixed logit model for the decision to charge at the end of a trip indicated that the probability of charging was higher when there was more than three hours before the next trip, when the completed trip was the last one of the day, and when the trip ended at the day's starting point. Charging probability was slightly lower later in the day, all else equal. Although the generalizability of this sample is questionable, these results tend to confirm the common assumption that overnight charging is a likely scenario.

However, even under the most favorable conditions, the probability of charging is slightly over 50%. Significant heterogeneity was also found in the effects of many variables on the charging probability. This, and the finding that many vehicles were not charged at all on travel days, indicates that caution is warranted when assuming homogeneous, daily charging behavior.

Implications

Under the right conditions, PHEVs with a relatively small battery can achieve significant reductions in petroleum usage – reductions of up to 60% below a comparable HEV were observed in this work. However, average petroleum displacement was 14% (and was below 5% for one-sixth of vehicles) and discrete choice analysis revealed significant heterogeneity in charging preferences between drivers. This suggests that policymakers may wish to reinforce selection of PHEVs by those most likely to charge them, and avoid incentivizing PHEV purchases by those lacking an incentive to plug in.

For the driving and charging patterns observed in this work, increasing CD range and increasing charging frequency can raise PDF by similar amounts. Policymakers should bear in mind that petroleum displacement does not scale linearly with battery size or charging frequency, and that interactions between battery size and charging patterns may be significant in the real world. This suggests that if petroleum displacement is the goal, then PHEV policies should carefully weigh the costs of enabling more frequent charging against the costs of subsidizing larger batteries. Discrete choice analysis revealed that charging probability was highest when stopping for more than 3 hours, suggesting that Level 1 or 2 charging infrastructure development may be most effective if it targets locations where stops at least this length are common.

8. ACKNOWLEDGEMENTS

The authors thank Toyota Motor North America and Toyota Motor Sales for sharing the raw data underlying this report. General results pertaining to driving and charging patterns can be found at http://www.toyota.com/esq/#. We offer our sincere gratitude to Chris Ainscough and Sam Sprik of National Renewable Energy Laboratory for support and assistance in data processing. We encourage interested researchers to visit http://www.nrel.gov/hydrogen/cdp_topic.html to view more of NREL's vehicle data collected through real-world demonstration programs.

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