Charging Choices and Fuel Displacement in a Large-Scale Demonstration of Plug-In Hybrid Electric Vehicles

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Because 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 been based on the travel patterns of conventional vehicles and assumption-driven charging scenarios. A comprehensive analysis of a real-world fleet of 125 instrumented PHEV prototypes deployed in the United States over a 1-year period—likely the first application of a discrete choice model to the empirical analysis of plug-in vehicle charging—is presented. First, the trial is introduced, and the patterns of travel, charging behavior, and observed energy consumption are analyzed. Then, a mixed logit model of the decision to charge at the end of each trip is estimated. Results indicate that charging usually is done after the day's last trip when ending at home and when the next trip will occur in more than 3 h, even though significant heterogeneity exists between drivers. Finally, the performance of this fleet is simulated with different vehicle designs and charging patterns. Results indicate that aggressive opportunistic charging after every trip results in approximately the same fuel savings as increasing the battery size by a factor of five. However, fast charging provides only marginal changes in energy use for the observed use patterns.

Derived from petroleum, gasoline and diesel fuel most 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 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, limiting the range and appeal of EVs compared with their gasoline-powered equivalents.

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

Because of limited market penetration, most existing knowledge about PHEV usage and energy consumption (e.g., effect of battery size and grid impact of recharging) is based on the analysis of known mobility patterns, surveys, and retrofitted hybrid vehicles (*2, 3*). Various efforts have attempted to realistically assess real-world PHEV performance. Vehicle-level simulation has been used to model the effects of design attributes and control strategies (*1, 4*), whereas survey data and, more recently, GPS-based data logging have been used to characterize driving patterns (*4–7*). 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. Because of a lack of real-world data on charging behavior, existing work has been driven largely by assumptions or based on small samples (*6*). Axsen and Kurani surveyed respondents about possible charging behavior according to availability and perceived importance (*8*). In a 1-week study of 40 vehicles, Davies and Kurani identify a mean of one daily charge and two participants who did not recharge at all (*9*). Williams et al. note the paucity of real-world information on recharging behavior and present the results of one prototype PHEV vehicle rotated among 12 households over 1 year to gather information on real-world charging behavior (*10*). The use of small samples to predict fleetwide impact generates substantial uncertainty (*7*).

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 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 kilometer, real-world effective electric range, and utility factors (UFs) and petroleum displacement factors (PDFs) at the fleet and the 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. Results show that PHEVs usually are charged after the day's last trip when the trip ends at home and when the next trip will occur in more than 3 h, even though significant heterogeneity exists between drivers. Third, the fleet impact of vehicle and behavioral changes on the consumption of gasoline and

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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.

PHEV CONCEPTS

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

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

Two important PHEV-related concepts are UF and PDF. As defined by Society of Automobile Engineers (SAE) Standard J2841, UF is the ratio of the distance the vehicle travels in CD mode (dist_{CD}) to the total distance traveled (dist_{total}), and PDF is the ratio of distance attributable to the nonpetroleum fuel such as grid electricity ($\text{dist}_{electrified}$) to total distance traveled (*12*). PDF depends on vehicle design, driving patterns, and charging behavior (*1, 13, 14*):

$$\text{UF} = \frac{\text{dist}_{CD}}{\text{dist}_{total}}$$

$$\text{PDF} = \frac{\text{dist}_{electrified}}{\text{dist}_{total}}$$

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, the UF will overestimate fuel displacement because a portion of the tractive force during CD mode is derived from petroleum. This work reports estimates for both UF and PDF.

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

$$\text{dist}_{electrified} = \text{dist}_{CD} - \frac{\text{gasoline}_{CD}}{\text{FC}_{CS}}$$

Imputing CD-mode gasoline distance based on CS-mode fuel consumption presents potential problems because the driving patterns that characterize each mode may have systematic differences. 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 with more disaggregated data from each mode, but such adjustments are not considered in this analysis.

TRIAL DESCRIPTION

The test fleet studied here consisted of 125 preproduction 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 (110-V) or Level 2 (220-V) at-home charging, workplace 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

- A 5.4-kW-h lithium-ion battery with an estimated range of 21 km [U.S. Environmental Protection Agency (EPA) test cycle],
- A permanent magnet synchronous motor (maximum 60 kW/207 N-m),
- A 1.8-L internal combustion engine (maximum 73 kW/142 N-m), and
- A maximum combined output of 100 kW.

Vehicle Operation and Charging

The PHEVs in this trial operate in three modes: EV, blended, or CS. 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-to-moderate loads consistent with typical operation and accessory loads. If power requirements exceed battery limits as a result of throttle input; heating, ventilating, and air conditioning (HVAC) settings; or vehicle speed exceeding 100 km/h, then the vehicle enters blended mode. Also, as the battery nears a state of discharge, the vehicle may enter blended mode to reduce the current flow from the battery to extend battery life. When the 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 for a standard 15-A household outlet; however, it is unknown whether participants carried chargers with the vehicles or used chargers at fixed locations. Other permanent and semipermanent 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 were various corporate, governmental, and educational partner institutions in the United States selected to meet the following primary objectives (personal communication from Jaycie Chitwood, Future Fuels and Environmental Strategy Manager, Toyota Motor Sales, July 19, 2012):

- A range of operational use cases and conditions, including personal, business, and demonstration fleets, and
- Geographic distribution that provides wide coverage but is 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 that collected more than 100 channels of data with 1-s resolution. The data were cached, periodically transmitted via cellular modem to the data logger manufacturer, then transferred to the vehicle manufacturer. The data available to researchers included time, speed, location, temperature, battery SOC, operating mode (CS or CD), and HVAC and regenerative braking information. Researchers at the National Renewable Energy Laboratory (NREL) aggregated the second-by-second data into 59,287 individual trips.

CONSUMPTION OF TRIAL VEHICLES

PHEV performance in this trial was characterized according to several common figures of merit. Gasoline consumption was similar to that of the standard Prius HEV in CS mode, but that amount was approximately halved (because grid electricity provided a portion of the vehicles' power demands) in CD mode. The use of blended mode complicates the attribution of distance traveled to gasoline or electricity, so a simple method for assigning CD mode travel to each fuel was established (described later).

For each vehicle in the trial, average CS-mode fuel consumption was calculated by dividing total gasoline consumption by total distance traveled in CS mode. The average CS-mode fuel consumption of most vehicles was 4.0 to 6.0 L/100 km (39 to 59 mpg) (Figure 1). The overall average was 4.90 L/100 km (48.0 mpg), which is close to the EPA rating for the standard 2010 Prius HEV [4.70 L/100 km (50 mpg)]. The average rate of CD-mode gasoline consumption was approximately one-half of the average CS-mode value [2.48 L/100 km (94.6 mpg)]; most vehicles used 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.

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

Operation in blended mode means that a vehicle generally drives farther than its effective electric range to deplete its CD battery capacity fully. Even though the vehicles used an average of 218 W-h for each electric kilometer, the average rate of electricity consumption in CD mode was 107 W-h/km. Thus, even in CD mode, gasoline provided approximately one-half of the vehicles' energy requirements

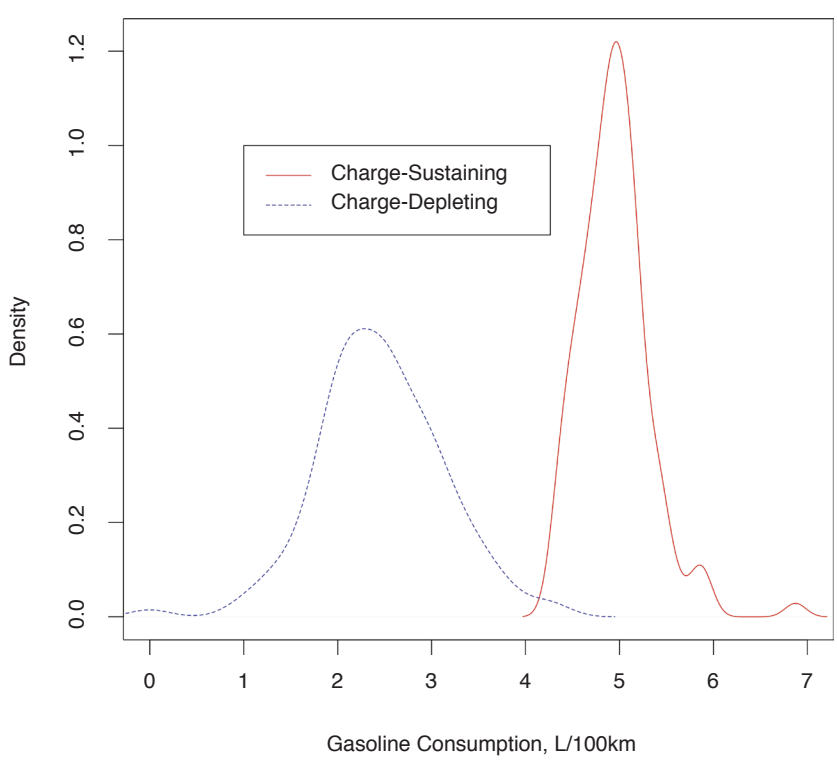

FIGURE 1 Density plots of fuel consumption in CD and CS modes.

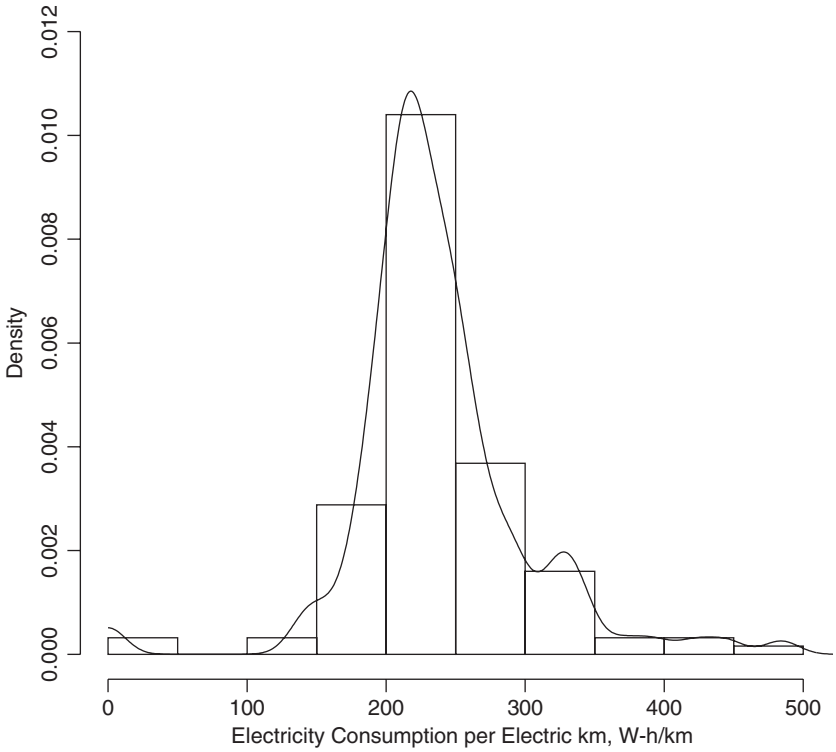

FIGURE 2 Distribution of electricity consumption.

on average, and a fully charged vehicle took an average of 28 km to exit CD mode. This pattern tends to reduce the PDF because the vehicle must be driven farther to fully exploit the battery's stored electricity. In other words, the finding that gasoline still accounts for one-half the distance traveled in CD mode effectively limits the PDF to 50%—higher if driving habits were adjusted to increase usage in pure EV mode.

The PDF was calculated as the ratio of the distance attributed to grid electricity to the total distance traveled. The overall average in this trial was 13.7%; the PDF distribution is shown in Figure 3, which also shows the distribution of UFs across the vehicles in this trial (on average 28.1% overall). The PDFs and UFs observed in this trial are lower than predicted by SAE J2841 for UF, a discrepancy that is explored in detail later.

The values of these metrics were spread wide across vehicles. The highest PDF was 59%, indicating that the right combination of driving patterns and charging habits can make effective use of even a small battery to displace gasoline. However, five of the 125 studied vehicles had PDFs of less than 1%, which indicated that they derived almost none of their energy usage from the grid. Another 16 vehicles had PDFs between 1% and 5%, typical of infrequent charging.

ANALYSIS OF TRIPS, VEHICLE MILES TRAVELED, 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 2001; *15*). The distribution of daily distances observed in this trial is positively skewed toward more low-mileage days (Figure 4). The distribution of individual trip lengths in this trial also was skewed positively compared with NHTS 2001 data.

Daily distance distribution from the trial was used to calculate the fleet utility factor (FUF) according to the method described in SAE J2841 (*12*). The resulting FUF curve is compared with the SAE J2841 FUF curve [which is based on NHTS 2001 (*15*)] in Figure 4. The FUF from this trial predicts that a fleet of PHEVs with a 28-km range in CD mode would drive 42% of its overall distance in CD mode if it is assumed that 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 than in NHTS 2001 (*15*).

As discussed earlier in the section about the consumption of the trial vehicles, the 3 kW-h of CD 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 FUF for this 13.8-km range would be 20% (according to SAE J2841) and 23% (according to the daily distance distribution from this trial), respectively.

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

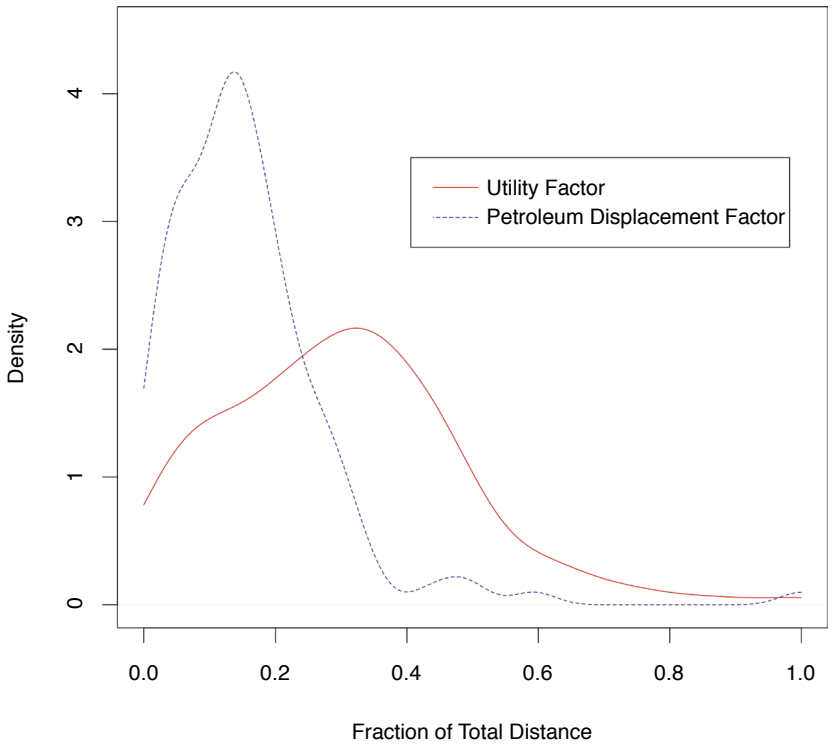

FIGURE 3 Density plot of UF and PDF.

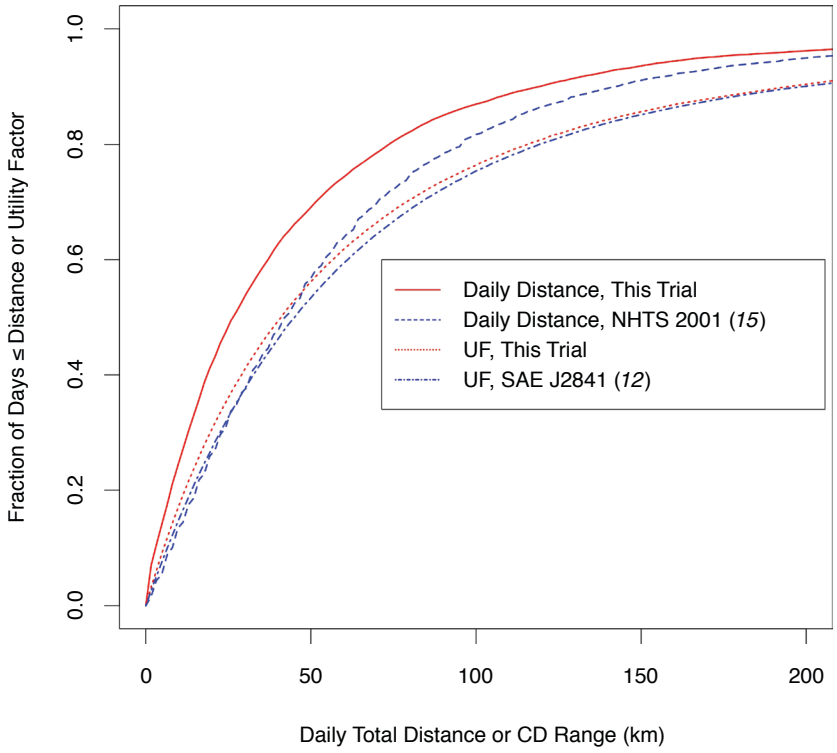

FIGURE 4 Cumulative distribution of daily travel distance and corresponding UF curves.

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 in the vehicle was not logged, a charge was deemed to have occurred whenever the SOC increased by at least 5 percentage points between the end of one trip and the beginning of the next. The rationale for this condition is to avoid misclassifying mere drifts in SOC (which result from temperature changes and other conditions that can influence the measured SOC of the battery) as a charging event.

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 because the vehicles were not equipped with smart chargers. The most common times to start a charge were between 2:00 p.m. and 4:00 p.m., and the initialization of new charging events fell off abruptly after 6:00 p.m. This finding is somewhat surprising but may reflect how cars were deployed in this trial; if the cars were used mainly in corporate fleets, then the afternoon peak in charging may reflect their being plugged in after the last work-related trip rather than after an evening commute.

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

Of the days on which a vehicle was driven in the trial, more than 40% of the vehicles were not charged and a similar percentage were charged once. Only 10% were charged twice, and smaller percentages were charged 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 vehicles. For example, one vehicle in the study was never charged, one was charged an average of 1.7 times per day over the course of the trial, and others ranged broadly from 0 to 1.25 charges per day. These observations tend to discredit the simplistic assumption commonly used in PHEV analyses (i.e., that each vehicle charges once and only once each day). Not only was observed charging behavior different from commonly assumed; it also varied substantially between vehicles, suggesting differences in drivers' preferences, incentives, and abilities to plug in.

Model of Individual Charging Choices

The data set was sufficiently detailed to permit the empirical testing of common assumptions about charging behavior. Even though PHEV analyses are increasingly grounded in real-world driving patterns, little data have been collected on charging behavior because of the dearth of PHEVs and battery electric vehicles 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.

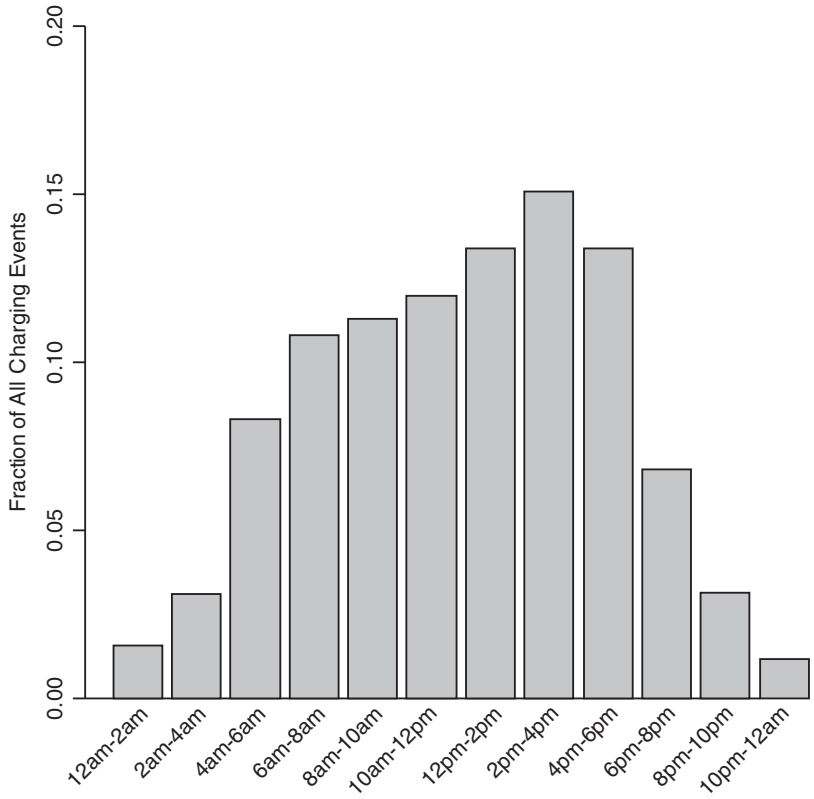

FIGURE 5 Distribution of charging start times.

The mixed-effects logit specification is

$$P(\text{charge}_{it}) = \frac{e^{V_{it}}}{1+e^{V_{it}}}$$

where charge_{it} is a binary variable indicating whether vehicle i was charged at the end of trip t and V_{it} is the observable portion of the utility of charging. (Because no information indicates whether a charging point is available at each stop, the probability of locating and using a charging point is modeled here.) The utility of charging is

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

where

ε_{it} = unobserved utility (assumed to be independently, identically distributed with extreme value distribution),
X_{it} = vector of variables characterizing conditions encountered by vehicle i at the end of trip t,
β = vector of fixed effects and coefficients capturing the average effect of those variables on the utility of charging,
Z_{it} = vector of variables whose effect on the utility varies over the vehicles in the sample (may be the same as X_{it}), and
b_i = vector of independent, normally distributed random effects that capture heterogeneity in the effects of the variables in Z.

Both X_{it} and Z_{it} contain constant terms that capture the average utility of charging and the variation in this average from one vehicle to the next, respectively. 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, the 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 independent variables. Random terms related to the hours before the next trip were dropped from the model after initial analyses indicated that they would have no practical significance. The SOC was included linearly with dummy variables indicating that the battery was fully charged or depleted, expecting that the probability of charging would increase as the battery was depleted. The length of the completed trip was included because long trips might make drivers more aware that the battery is depleted (or, alternatively, more fatigued and less likely to plug in). Also included were dummy variables indicating whether the trip was the last trip of the day or ended at the same place the vehicle started the day, both of which 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.

Model estimation was done using the lme4 package in R; results are presented in Table 1. The parameter estimates and associated standard errors are presented for the fixed effects and constant coefficients as well as the estimated standard deviations of the random parameters. 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, the significance of each random parameter was assessed with 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 they are χ^2-distributed with 1 degree of freedom.

For 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 3 h, the probability of charging increases with the waiting time; however, at more than 3 h, the probability of charging is essentially unchanged. Two possible explanations for this result are that 3 h of charging is (*a*) the approximate time needed for a full charge in these vehicles, so drivers want to plug in only when they know they have enough time for a full charge, or (*b*) the minimum time 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 plug-in vehicles.

A trip being the last trip of the day and a trip ending at the location where the vehicle's day began are each strongly correlated with a higher probability of charging. Combined with the substantial effect of a stop being longer than 3 h, these results suggest that the probability of charging overnight is going to be relatively high because overnight stops are likely to be longer than 3 h, the last trip of the day, and 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.

TABLE 1 Parameter Estimates of Logit Model

Variable	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 h until next trip	2.774***	0.558***
	(0.081)	(70.3)
(hours until next trip) ×	–1.007***	—
(>3 h 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		
4–8 a.m.	0.053	0.551***
	(0.092)	(52.7)
8 a.m.–noon	–0.075	0.365***
	(0.082)	(17.3)
Noon–4 p.m.	–0.206*	0.395***
	(0.086)	(22.8)
4–8 p.m.	–0.202*	0.477***
	(0.096)	(22.6)
8 p.m.–midnight	–0.285[a]	0.864***
	(0.152)	(40.9)

NOTE: Model summary statistics: null log likelihood L(0) = –37,344, model log likelihood L(β) = –16,447, and adjusted ρ^2 = .559; LRT = likelihood ratio test; — = random effects not included for this variable.
[a]Significant at 0.1 level.
*p < .05 level; **p < .01 level; ***p < .001 level.

The fixed-effect estimate for SOC has the expected sign, indicating that vehicles were less likely to be plugged in when the SOC was high. 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, possibly because empty batteries are more common when vehicles are away from their usual charging infrastructure. Although statistically significant, this effect is relatively small compared with the effects discussed earlier. 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.

For the random effects, heterogeneity is evident for most variables on the probability of charging, which is significant in both statistical and practical terms. Some variables (ending on weekend and several time-of-day dummies) have no fixed effect but a significant random effect, indicating that even though on average these variables have no effect on the probability of charging, the effect was positive for some vehicles and negative for others.

SIMULATION ANALYSIS

The gasoline and electricity consumption in this trial results from specific charging and driving behaviors applied to one vehicle design. This section reports on simulations of electricity and gasoline consumption when small, one-factor-at-a-time changes are made to the vehicle design or charging logic but all trips are assumed to remain the same. These scenarios are described later, and results are summarized in the subsequent section.

Scenarios

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

Charged Once Daily

The SOC for each vehicle was reset to 100% at the start of each calendar day to simulate once-daily charging; battery capacity was unchanged. This scenario reflects the common-sense assumption (as in existing UF definitions) that PHEVs usually are charged overnight at home.

Opportunistic Charging

In the opportunistic charging scenario, PHEV users charge vehicles whenever they will be parked longer than a given time threshold. It assumes ubiquitous availability of 110-V charging facilities. The study was conducted at nine time thresholds from 0 to 8 h. 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 durations but at higher rates. In theory, it primarily should affect short charge cycles that are not capacity limited.

Alternative Battery Capacity

The alternative battery capacity scenario applies different battery pack sizes to the same vehicle, permitting a higher SOC and longer CD-mode driving distances. It considers the impact of battery capacity only through the mechanism of extending CD range. A larger pack size also increases vehicle weight and decreases 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; vehicles operate strictly on electric power until the battery pack is exhausted and then change to CS mode.

Outcomes

Results of the scenarios are summarized in Table 2 and compared with an actual UF of 28.1% and a PDF of 13.7%. With daily charging, the PDF increases to 18.2%, similar to the 19.1% achieved under opportunistic charging with an 8-h threshold. With more aggressive opportunistic charging (i.e., each vehicle is charged at every stop), the increase continues to a maximum of 28.3% reached at zero hours. As noted earlier, for the average driver, the probability of charging falls off when stop time drops below 3 h.

As expected, increasing battery capacity would increase petroleum displacement, but with diminishing marginal returns. Quadrupling CD capacity would increase PDF to approximately 27%, and increasing by a factor of 10 would increase it to only 33.7% (assuming that driving and charging patterns remain unchanged).

Other scenarios yield only minimal changes. Deployment of rapid charging alone, even at rates up to eight times as fast as current 110-V charging, left the PDF substantially unchanged at 14.2%, offsetting only 203 additional liters of gasoline. Eliminating blended mode in this scenario yielded a PDF of 15.5%, saving an additional 642 L of gasoline.

CONCLUSIONS AND IMPLICATIONS

This paper summarizes findings from the largest fully instrumented, real-world trial of prototype PHEV vehicles to date. Results of this analysis highlight the important role that blended mode plays in the operation of this type of PHEV and, consequently, the importance of distinguishing between the UF and the PDF. Even though this fleet had an in-use UF of 28%, the PDF was just one-half that value (14%) because of gasoline use in blended mode.

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

TABLE 2 Summarized Results for Charging and Design Scenarios

Scenario	kW-h	Fuel (L)	Liters Saved[a]	PDF	UF
Actual fleet performance	21,804	31,328	4,908	0.137	0.281
Charged once daily	30,947	29,534	6,703	0.186	0.382
Opportunistic charging (charge if parked *N* hours)					
N = 8	31,784	29,351	6,885	0.191	0.392
N = 7	32,694	29,148	7,088	0.196	0.404
N = 6	33,524	28,960	7,277	0.201	0.416
N = 5	34,659	28,707	7,530	0.208	0.430
N = 4	36,403	28,315	7,922	0.219	0.452
N = 3	38,580	27,839	8,398	0.232	0.480
N = 2	41,403	27,234	9,003	0.249	0.514
N = 1	44,580	26,559	9,678	0.268	0.553
N = 0	47,154	26,012	10,224	0.283	0.584
Fast charging					
1 kW-h/h[b]	22,451	31,346	4,891	0.137	0.280
2 kW-h/h	23,055	31,216	5,020	0.140	0.288
4 kW-h/h	23,310	31,161	5,075	0.142	0.291
8 kW-h/h	23,399	31,142	5,094	0.142	0.292
Alternative battery capacity					
0 kW-h	0	36,237	0	0.000	0.000
1.5 kW-h	13,357	33,330	2,907	0.081	0.166
3 kW-h[b]	22,451	31,346	4,891	0.137	0.280
6 kW-h	33,534	28,928	7,309	0.204	0.420
12 kW-h	44,490	26,571	9,666	0.270	0.556
18 kW-h	49,991	25,403	10,833	0.303	0.624
24 kW-h	53,396	24,684	11,552	0.323	0.666
30 kW-h	55,851	24,168	12,068	0.337	0.696
Strictly prefer EV mode	25,644	30,687	5,550	0.155	0.155

[a]Liters versus simulation of HEV.
[b]Approximates actual performance.

More than one-half of all charge events result in a delivered charge of at least 2.5 kW-h. On days that vehicles 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 the next trip would be in more than 3 h, when the completed trip was the last trip 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. Even though the generalizability of this sample is questionable, 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 more than 50%. Heterogeneity was significant in the effects of many variables on the charging probability. This finding, and the fact that many vehicles were not charged at all on travel days, indicates that caution is warranted when homogeneous daily charging behavior is assumed.

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

For the driving and charging patterns observed in this work, increasing CD-mode range and increasing charging frequency raise the PDF by similar amounts. Policy makers 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. 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 reveals that the charging probability was highest when the vehicle was stopped for more than 3 h, suggesting that the development of Level 1 or 2 charging infrastructure may be most effective if it targets locations where stops of at least this length are common.

General results pertaining to driving and charging patterns can be found on the Toyota website (*16*). Interested researchers are encouraged to visit the NREL website (*17*) to view more of the vehicle data collected through real-world demonstration programs.

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