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Updating Utility Factor (UF) Calculations in SAE J2841: Analyzing Charging Behaviors and Other Real-World Impacts on PHEV UF

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Executive Summary

Recent studies have shown that the Utility Factor (UF) of Plug-in Hybrid Electric Vehicles (PHEVs), as defined by SAE J2841, tends to overestimate real-world electric usage. A major contributor to this discrepancy appears to be less frequent charging behavior than the daily charging assumed in the standard. However, additional real-world factors—including driving patterns of PHEV users compared to the broader vehicle fleet, blended engine operation, ambient weather conditions, and others—also reduce electric utility. This paper presents a preliminary analysis aimed at quantifying how these real-world impacts affect the UF curve. Building upon the established travel survey foundations of J2841, the study introduces a multi-dimensional human behavior charging model to capture variability in charging practices. Other factors such as driving pattern differences, blended operation, and environmental influences are also explored, with the goal of developing an updated UF framework that better represents real-world conditions. These findings are part of an ongoing collaborative effort to update SAE J2841, and are presented to foster discussion and gather insights from the international PHEV research community, to help guide future refinements of the UF methodology.

Keywords: Plug-in Hybrid Vehicles, Trends & Forecasting of e-mobility, Standardization, Environmental Impact, Consumer behavior

1 Introduction

The growing adoption of Plug-in Hybrid Electric Vehicles (PHEVs) presents both opportunities and challenges for accurately assessing vehicle efficiency and environmental impact. Key to this assessment is the ability to predict how effective a PHEV will displace fuel usage by instead consuming off-board electrical energy, a balance that depends heavily on user behavior and charging patterns. The Utility Factor (UF), as defined by SAE J2841, provides a standardized method for estimating this balance based on a vehicle's all-electric range and assumed driving behavior. However, emerging real-world data suggests that actual usage patterns may diverge from these assumptions, raising questions about the accuracy of current UF estimates. This paper examines these discrepancies by analyzing real-world data, reviewing existing literature, and proposing updated modeling approaches to better capture the factors influencing PHEV utility.

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1.1 Background

The UF is a key concept used to estimate the proportion of distance traveled by a PHEV in charge-depleting (CD) mode versus charge-sustaining (CS) mode over typical driving patterns. In the context of regulatory testing and vehicle energy consumption assessment, UF provides a standardized method for combining results from charge-depleting (mostly electric) and charge-sustaining (hybrid) operating modes into a single, weighted metric.

The recommended practice for testing PHEVs is detailed in SAE J1711. The testing involves running separate CD and CS tests and weighting them together using the appropriate UF. Details on the derivation and application of UF methodology is defined in SAE J2841, which is built upon driving pattern data from large-scale travel surveys data from the US Department of Transportation National Household Travel Survey (NHTS)[1]. This approach enables the estimation in use off CD distance compared to CS distance based primarily on a vehicle's CD range, under the assumption that vehicles are charged regularly — typically, once per day — and that their usage aligns with patterns from the general driving population.

The UF plays a critical role in the testing and certification of PHEVs, influencing reported fuel economy, greenhouse gas emissions, and compliance with regulatory targets. By integrating test results from both operational modes, UF allows regulators, manufacturers, and consumers to understand the potential benefits of electrification under standardized conditions. However, as PHEV adoption grows and real-world usage patterns diverge from early assumptions, questions have emerged about the accuracy of the current UF in representing actual vehicle operation. Understanding and improving UF estimations is therefore essential for ensuring that policy targets and consumer information reflect the real-world performance of PHEVs.

1.2 Definitions of Key Terms

1.2.1 General PHEV Terms

CD, CS, and EV Modes

During driving, propulsion power can come from the battery, the fuel tank, or both. It is assumed that, once charged, all PHEVs will be in their CD mode until the off-board portion of battery energy is depleted and then switches to CS mode. It is assumed that all PHEVs operate with at least these two modes. CD mode and EV driving mode are sometimes conflated, but they are not necessarily the same. If the driver's power demand exceeds the electric-only capability of the PHEV, the engine may assist with propulsion even while the vehicle is operating in CD mode. This type of operation is referred to as a "blended" PHEV design. Conversely, vehicles capable of operating fully electrically throughout CD mode — without engine assistance — are sometimes referred to as Extended-Range Electric Vehicles (EREVs). Despite this distinction, both blended and EREV designs operate in CD mode as long as the vehicle is drawing down its battery charge.

1.2.2 J2841 Utility Factors

SAE J1711 and J2841 define UF curves as functions where vehicle range is the input and the output is a dimensionless fraction representing the proportion of driving distance in CD mode. These curves are derived from large datasets of daily driving distances. For any given vehicle range, the calculation estimates the total miles of driving expected in the daily driving set. The J2841 operating assumption is that at the beginning of each day, the battery is fully charged and the vehicle operates in CD mode for the rated range of a given PHEV.

The Fleet UF, shown in Equation 1, expresses the fleet-level share of charge-depleting distance traveled for a given PHEV range. It is calculated by dividing the total expected CD distance accumulated across all vehicles by the total distance traveled in the fleet. Fleet UF is sensitive to vehicle usage distribution, meaning that vehicles with consistently long daily driving distances can significantly lower the overall Fleet UF.

$$\text{Fleet UF} = \frac{\sum \text{CD distance of all vehicles}}{\sum \text{Total distance of all vehicles}} = \frac{\sum\limits_{v \in V} \min\left(d_v, R_{CD}\right)}{\sum\limits_{v \in V} d_v} \tag{1}$$

In contrast, the Individual UF, defined in Equation 2, is calculated as the average of vehicle-level utility factors. Each vehicle's UF is computed as its charge-depleting distance divided by its total distance traveled, and then these individual UFs are averaged across the fleet. This approach treats each vehicle equally, regardless of mileage, and provides insight into the typical behavior of individual PHEV users within the fleet.

$$\text{Individual UF} = \text{Average of}\left(\frac{\text{CD distance}_i}{\text{Total distance}_i}\right) = \frac{1}{nVehicles}\sum_{i=1}^{nVehicles}\frac{\sum_{j=1}^{nDays}\min\left(d_{i,j}, R_{CD}\right)}{\sum_{j=1}^{nDays} d_{i,j}} \tag{2}$$

1.2.3 Charging Frequency Definitions

The concept of a *Driving Day* is essential when analyzing daily charging behavior and evaluating plug-in hybrid electric vehicle (PHEV) utility. For the purposes of in-use data analysis, a consistent cutoff time is used to delineate one driving day from the next. Empirical driving pattern data show that the lowest frequency of trip starts occurs between 3:00 and 3:30 a.m. local time. Accordingly, a *Driving Day* is defined as all trips that begin between 3:00 a.m. on one calendar day and 2:59 a.m. on the following day.

Overnight Charging Frequency is defined as the proportion of Driving Days on which a PHEV starts with a fully charged battery. This metric quantifies the regularity of overnight recharging behavior and serves as a critical input for modeling real-world utility factors. It is calculated as the number of overnight charging events divided by the total number of Driving Days (Equation 3).

$$\text{Overnight Charging Frequency} = \frac{\text{Overnight Charging Events}}{\text{Total Driving Days}} \tag{3}$$

Daytime Charging Frequency refers to the proportion of Driving Days in which one or more daytime charging events occur between trips. It captures supplemental charging that can extend electric driving range beyond the initial morning state of charge. This metric is calculated by dividing the number of daytime charging events by the total number of Driving Days (Equation 4).

$$\text{Daytime Charging Frequency} = \frac{\text{Daytime Charging Events}}{\text{Total Driving Days}} \tag{4}$$

Finally, *Daytime Charging Energy Share* quantifies the contribution of daytime charging to total off-board energy. It is computed as the total energy received during daytime charging events divided by the total off-board charging energy (Equation 5). This metric helps evaluate the relative importance of daytime charging in real-world electric utility.

$$\text{Daytime Charging Energy Share} = \frac{\text{Daytime Charging Energy}}{\text{Total Charging Energy}} \tag{5}$$

1.2.4 Observed PHEV Utility Metrics to Compare to Utility Factors

Several metrics derived from in-use data can be compared to the theoretical UF. These metrics use observable quantities from real-world driving data, each metric provides a different perspective on electric utilization.

First, a direct analog to the Fleet UF can be calculated based on the total charge-depleting (CD) miles traveled relative to total miles traveled:

$$\text{Observed CD Driving Fraction} = \frac{\text{Miles}_{CD}}{\text{Miles}_{total}} \tag{6}$$

Another commonly reported metric is based on observed electric-only driving. However, caution is needed in interpreting this metric. Analysts sometimes look directly at EV miles as a proxy for electric utility, but this can be misleading. Specifically, PHEVs operating in CS mode may still accumulate some EV-only miles during low-load conditions. Therefore, to maintain conceptual consistency with UF, EV miles counted in this metric should be limited to those occurring only during CD mode operation:

$$\text{Observed EV Driving Fraction} = \frac{\text{Miles}_{EVinCD}}{\text{Miles}_{total}} \tag{7}$$

Finally, a fuel displacement-based metric can be used to quantify electric utility. This approach compares the vehicle's observed fuel consumption rate to its expected rate in charge-sustaining (CS) mode, reflecting the share of fuel displaced by electric operation. A greater reduction in overall fuel consumption—relative to CS operation—indicates higher electric utility.

$$\text{Observed Electric Utility} = 1 - \frac{(\text{Fuel}/\text{mi})_{\text{total}}}{(\text{Fuel}/\text{mi})_{\text{CS}}} \tag{8}$$

2 Discrepancies Between the J2841 UF and Real-World Observations

Studies of in-use PHEVs consistently show lower electric driving shares than those estimated from standard type-approval tests. A 2022 ICCT report analyzing on-road data from approximately 9,000 PHEVs in Europe found that private vehicles operated in electric mode only 45–49% of the time, and company cars just 11–15%—compared to the 70–85% electric driving assumed under the WLTP test cycle [2]. Other European studies, such as Plötz *et al.* [3], report real-world PHEV fuel consumption and CO_2 emissions several times higher than official values due to reduced electric usage. The primary reason is infrequent charging: many PHEV users plug in only a few times per week [4]. Additional factors include limited all-electric range, additional engine operation in CD mode triggered by high power demands or user behavior. This paper explores these contributing factors and presents methods to quantify their impact guided by real-world data.

2.1 California Bureau of Automotive Repair Data

The California Bureau of Automotive Repair (BAR) collects OBD-II diagnostic data from vehicles during smog checks, which are often conducted voluntarily or, in some cases, mandatorily during events such as changes of ownership or out-of-state registration. These data include accumulated fuel consumption, odometer readings, and—in some cases—extended diagnostic parameters such as engine runtime, electric motor usage, and battery-related statistics. The BAR data has played a central role in evaluating real-world performance of plug-in hybrid electric vehicles (PHEVs). The U.S. Environmental Protection Agency (EPA) cited BAR data in its initial ruling for including off-cycle adjustments in the greenhouse gas (GHG) compliance values for PHEVs [5], and the International Council on Clean Transportation (ICCT) used it extensively to estimate the real-world electric driving shares of PHEVs operating in California [4].

2.1.1 Exploring BAR OBD Data

The BAR data analyzed below were received by EPA and uploaded to their GHG rule making dockets on two occasions [6, 7]. Analyses can be performed at the individual-vehicle level or aggregated by model. Individual vehicle data reveal substantial variability in usage patterns and provide critical context for interpreting aggregated results. Figure 1 shows the proportion of charge-depleting (CD) or electric driving for two specific PHEV models under real-world conditions. Each point on the plot is a vehicle's lifetime driving distance (x-axis) and its cumulative charge-depleting (CD) distance (in orange) or engine-off CD distance (electric-only driving, in blue) on the y-axis.

The clusters of points in Figure 1 can be compared to their respective J2841 Fleet Utility Factor (FUF) curves, which are overlaid for reference. For both PHEV models, the data show that while some vehicles exceed the CD distances estimated by J2841 and others fall short, those with shorter electric driving tend to pull the overall trend downward, reducing the average electric utility across the fleet.

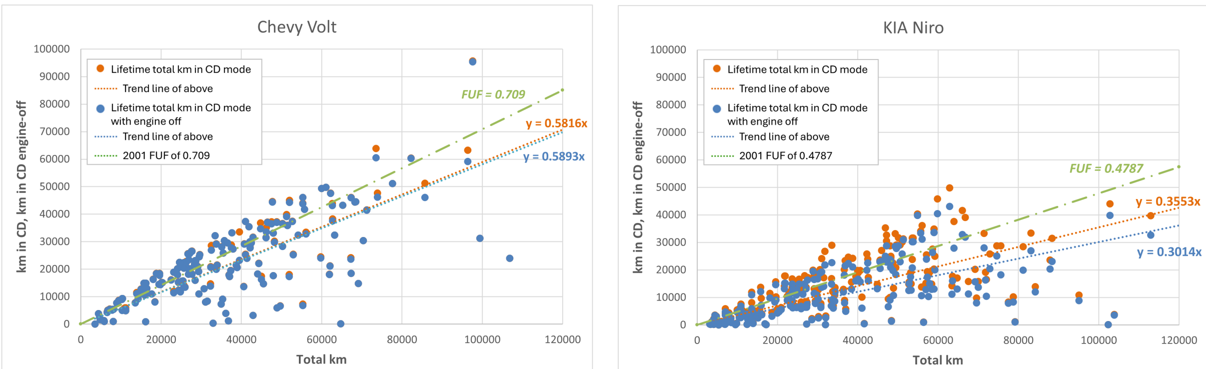


Figure 1: Individual vehicle data from in-use monitoring. (left) Chevy Volt; (right) KIA Niro

Note that for the Chevy Volt, the recorded distances in CD and EV modes are nearly identical, reflecting the vehicle's ability to operate fully in electric mode whenever under CD conditions. Compare this to the Niro data which like many other PHEV models, show a gap between CD-mode and EV driving distances. This difference reflects the amount of engine operation engaged during CD mode operation. This is due to the assistance of the engine during high load demands and operation under cold ambient conditions, where the engine is engaged during

CD mode to provide cabin heat or to reduce battery loads. It is worth mentioning that the trend lines are shown for reference and are not miles-weighted UF calculations.

Switching to an analysis of the observed aggregate data by PHEV model, several important comparisons can be made. Figure 2 presents results for a number of observational metrics defined in Equations 6, 7, and 8, sorted by the corresponding J2841 FUF value for each model. These metrics—derived from BAR data—include the observed CD-mode driving fraction, EV-mode driving fraction, and the fuel-based Electric Utility.

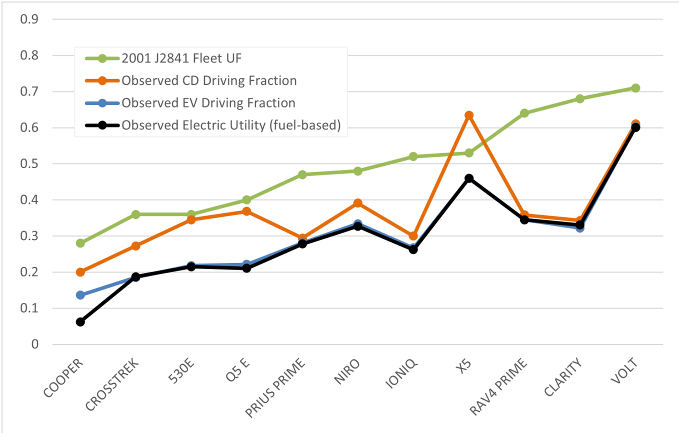


Figure 2: Comparison of J2841 UF to Observed Driving and Electric Utility Metrics by PHEV Model in BAR Data

As discussed previously, the Chevy Volt operates in distinct propulsion modes: it drives either fully electrically or in charge-sustaining (CS) mode. As a result, all three observed metrics are approximately equal for the Volt. In contrast, other PHEV models exhibit significant differences between the CD-mode driving fraction and the EV-mode driving fraction. This divergence is attributed to a higher degree of blended operation, where both the engine and motor contribute propulsion energy during CD mode. Notably, the Toyota RAV4 Prime and the Honda Clarity display only a small gap between these two fractions, indicating that their operational behavior is more similar to the Volt than to other blended PHEVs. Additionally, across nearly all models, the EV-mode driving fraction closely follows the Electric Utility calculated from fuel consumption. This alignment underscores the importance of understanding these distinctions when evaluating PHEV effectiveness and setting realistic expectations for vehicle electrification.

It is worth pausing to clarify the significance of these observed fractions. The J2841 FUF is often mistakenly interpreted as a proxy for overall electrification or Electric Utility. However, the FUF was originally designed to represent the expected fraction of miles traveled in CD mode—not necessarily the proportion of miles driven electrically. This distinction becomes critical when applied to blended PHEVs, where CD mode may still involve partial engine operation. Only for vehicles with full electric capability in CD mode—such as extended-range electric vehicles (EREVs) like the Volt—does the FUF approximate EV-mode usage.

The misinterpretation of FUF as a direct indicator of electrification stems in part from limitations in current U.S. PHEV certification test procedures. These procedures use fixed driving cycles that do not encompass the full range of power and speed demands encountered in real-world use. Consequently, translating laboratory results to in-use electric performance requires additional context and data not currently captured by the test. Moreover, the energy management strategies in blended PHEVs lead to complex interactions between fuel and electric energy usage. Depending on control design, a PHEV may appear to either *increase* or *decrease* its observed CD-mode range relative to the test procedure. These interactions, and their implications for utility factor calculation, are explored in more detail in Duoba *et al.* [8].

2.1.2 Limitations of BAR OBD Data

Any dataset of the extended OBD data (like the BAR dataset) provides a valuable baseline for evaluating the electric utility of PHEVs in real-world use. It is especially useful because it is collected independently of user participation, offering an unbiased snapshot of in-use operation. However, several structural limitations must be considered when interpreting aggregate results, including representativeness issues stemming from the conditions under which smog checks are either mandatory or voluntary.

California's Smog Check program requires most vehicles to undergo biennial emissions inspections, but PHEVs are exempt during their first eight years of operation. As a result, comprehensive OBD data for newer PHEV models begins to accumulate only once vehicles reach this age threshold. Although CARB proposed standardized PHEV-specific parameters as early as 2014, the relevant diagnostic standard (SAE J1979-3) was not finalized until 2023. The widespread implementation of these parameters, and thus the consistent capture of the electric mode usage metrics, will take several years to appear in the inspection data. Additional key limitations of the BAR dataset include the following:

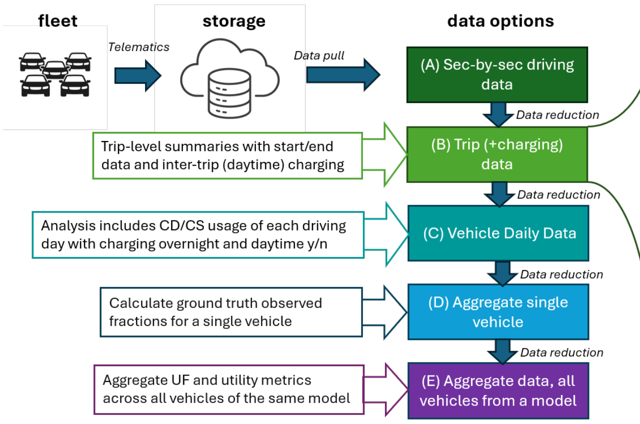
- It is limited to vehicles registered in California and may not represent national driving or charging behavior patterns.
- A significant portion of the dataset consists of off-lease vehicles, often returned to dealers within 1 to 2 years; this is shorter than typical lease periods and raises concerns about whether these vehicles reflect typical long-term ownership and usage patterns.
- Vehicles originating from out of state may have accumulated long relocation trips with limited or no charging, disproportionately affecting calculated electric driving fractions.
- Driving dynamics such as speed, acceleration, and trip timing are not available; only cumulative energy and fuel counters are recorded.
- There is no information on charging event frequency, timing, or energy per event, limiting the ability to analyze user charging behavior directly.
- Early data entries may reflect non-routine inspection cases such as out-of-state registration, change of ownership, voluntary smog checks, or repairs, potentially introducing selection bias.
- Inconsistencies exist between different batches of BAR data; the first batch included both pre- and post-filtered records, while later batches only reported post-filtered results, reducing transparency regarding data quality controls.

3 In-Use PHEV Data Needs

While the BAR dataset provides a valuable starting point for understanding in-use PHEV operation, its coarse resolution, geographic limitation to California, and delayed availability due to smog check exemptions limit its utility. To overcome these gaps and accurately quantify the UF under real-world conditions, more granular data are required.

To this end, we worked with stakeholders and SAE committees to define which data provides the best balance between detail and scalability. It was decided that trip-level data was the right fit. This level captures the contextual granularity needed to isolate and model key behavioral and technical factors, while remaining feasible for fleet-wide application. Figure 3 shows the various levels of telematics data and the associated tradeoffs, culminating in the selection of trip-level summaries as the preferred input format.

As part of this effort, we developed a standardized list of trip-level parameters to guide OEM data requests. These parameters are grouped into thematic categories—vehicle identifiers, consumption results, battery metrics, charging behavior, driving style, and ambient conditions—and are designed to support both high-level UF computation and deeper investigation of the distinct impacts contributing to UF shortfall. The right side of Figure 3 summarizes the recommended data fields.



Trip Data Needed for UF Analysis	
Vehicle Info	Model year, make/model, vehicle ID, home location info
Driving Data	Trip miles, CD/CS/EV mode miles, run time, idle time
Consumption Results	Fuel, kWh consumed in each mode (CS/CD)
Trip Metadata	Trip ID, start/end time, odometer, low-res GPS (or numbered location)
Charging Info (Pre-Trip)	Charge start/end time, SOC at start/end, peak power
Battery Info	SOC at trip start/end, DC Wh remaining
Route and Driving Style	Stops, average speed, speed and pedal histograms, wheel energy
Ambient Conditions	Temperature, rain, HVAC setpoint
Driver-Selectable Modes	Mode distance, fuel, and time breakdowns

Figure 3: Data hierarchy for in-use PHEV analysis. Trip-level data (B) was selected for its balance of detail and scalability.

4 Analysis and Proposed Models of Real-World Factors Affecting UF

The previous sections highlighted a consistent shortfall between the J2841 Utility Factor (UF) predictions and values observed from in-use PHEV data sources such as the BAR dataset. To better align the UF with real-world performance, this section identifies and models several key behavioral and technical factors that contribute to the observed discrepancies. Each factor represents a distinct mechanism that can shift electric usage away from the assumptions embedded in the original J2841 formulation.

Rather than proposing a single adjustment, we outline a modular modeling approach in which each real-world impact—such as altered driving distances, reduced charging frequency, or cold-weather effects—is explicitly represented. This enables incremental refinements that can be combined to produce an updated UF curve. Collectively, these modeled impacts provide a framework for improving the accuracy and policy relevance of the UF metric

4.1 Daily Driving Distances

One of the most fundamental influences on UF is the distribution of daily driving distances for PHEV users. This is the primary input variable used in the original J2841 Fleet UF Equation 1. The key question is whether PHEV drivers exhibit a noticeably different driving distance profile than the broader driving population represented in the National Household Travel Survey [9]. If PHEV owners consistently drive longer daily distances, the resulting in-use UF would naturally fall below the J2841 baseline—even in the absence of other effects.

Recent work by Hamza [10] highlights that real-world PHEV daily driving distances—particularly for models like the Toyota Prius Prime—may contribute to the observed Utility Factor (UF) shortfall. However, while these findings provide valuable insight into early PHEV usage patterns, they may reflect the behavior of early adopters or specific vehicle segments rather than universally applying to all PHEV models. Additional insights from industry sources suggest that factors such as vehicle class and intended use case may play a more significant role in determining daily mileage than powertrain type alone.

To explore whether publicly available data supports higher average use among PHEVs, we analyzed the most recent National Household Travel Survey (NHTS) dataset. PHEVs in the sample exhibited slightly lower average daily travel (24.4 miles) compared to conventional internal combustion engine (ICE) vehicles (32.0 miles) and hybrid electric vehicles (HEVs) (32.2 miles), and were also driven less than battery electric vehicles (BEVs), which averaged 37.2 miles per day. However, the limited number of PHEV entries in the dataset ($n = 56$) precludes definitive conclusions. Moreover, odometer-based averages serve only as rough proxies for the full distribution of daily driving distances that underpin J2841 UF calculations. Still, if a strong signal for increased PHEV usage were present, some indication might be expected even in a small sample.

Recent analysis of odometer readings across vehicle types found no strong evidence that PHEVs, by virtue of their powertrain, are driven longer distances than conventional vehicles. Zhao *et al.* [11] report that conventional gasoline cars average 11,642 miles annually, compared to 11,113 miles for PHEVs and 11,941 miles for HEVs—showing no systematic indication that PHEVs are driven more.

Although additional in-use data is needed to draw definitive conclusions about whether PHEV-specific daily driving distributions deviate meaningfully from the broader NHTS dataset, a placeholder for this potential real-world effect can be maintained. When sufficient data becomes available, it can be readily incorporated into the existing J2841 framework using Equations 1 and 2.

4.2 Charging Behavior

One of the most consequential real-world deviations from the assumptions underlying SAE J2841 relates to charging behavior. The original Utility Factor (UF) curve was constructed with the simplifying assumption that every plug-in hybrid electric vehicle (PHEV) begins each driving day with a fully charged battery. This assumption reflected expert consensus at the time—developed in the absence of any existing production PHEVs. Today, however, observational datasets reveal that real-world charging behavior is far more variable and complex than the original framework anticipated.

Accurately updating the UF methodology requires a model that goes beyond a single average charging rate. While it may seem reasonable to replace the current J2841 overnight charging frequency of 1.0 with better a better number taken from in-use data. Recent analysis has shown that this approach would fail to capture the complex interaction between population profiles and temporal profiles of charging with the daily driving distance profiles. Indeed a complex charging model must be developed.

The first layer of the model is the distribution of charging frequency across the vehicle population (instead of a single number). Figure 4 illustrates why a distribution needs to be determined by using two stylized examples, each with a nominal 90% overnight charging frequency. In one case, each vehicle charges 90% of the time in a randomized manner. In the other, 90% of vehicles always charge, while 10% never do. While both scenarios yield the same average charging rate, their differing profiles have significantly different impacts on the baseline UF curve. The "always charge" case reduces the whole UF curve by 10%, while the "random charge" case results in a higher UF due to the carryover of unused charge from one day to the next.

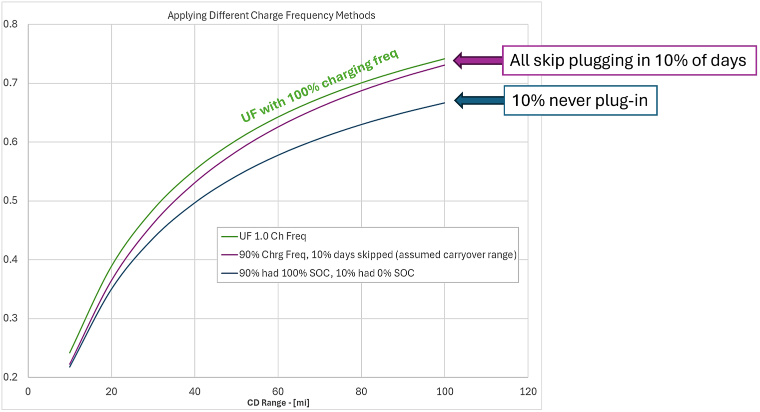


Figure 4: Impact of different charging frequency distributions on the Utility Factor (UF). Both scenarios have a nominal 90% overnight charging rate.

In addition to the population-level effects of charging frequency, the Hamza paper also highlights important temporal dimensions of real-world charging behavior. Specifically, it is not only the overall frequency of overnight charging (as defined in Equation 3) that matters, but also the sequence and timing of charging events for each individual vehicle. Hamza illustrates this with two stylized cases, both with a nominal 50% charging frequency. In one, vehicles charge every other night; in the other, vehicles charge every night during the first half of the observed days and never during the second half. While both scenarios have the same overall charging rate, the first produces a substantially higher UF due to the carryover of unused electric range from one day to the next. The second scenario results in many uncharged days later in the sequence, disproportionately reducing electric driving opportunities.

Motivated by this insight, we extended the analysis by examining real-world charging data from a set of PHEVs observed over roughly one year. If charging decisions are not random, what characterizes their timing? The critical feature influencing UF outcomes is the presence of clusters—consecutive days of charging or not charging—referred to here as streaks. To quantify this, we calculated the coefficient of variation (CV) of non-charging streak lengths and compared it to a randomized baseline (Figure 5). We found that real-world data exhibits significantly greater variability than the random case, indicating that non-charging streaks tend to be longer than expected under random behavior. This streakiness in user behavior diminishes as the overall charging frequency approaches 1.0, but remains an important factor at middle ranges of charge frequency.

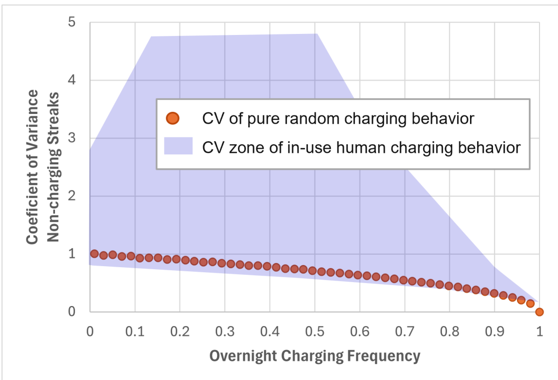


Figure 5: Coefficient of variation (CV) in non-charging streaks by charging frequency. Orange points show expected CV from random behavior; blue region shows observed CVs, indicating clustered real-world charging.

There is a high degree of diversity in the structure of non-charging streaks observed in the real-world data.

Figure 6 presents time-series plots for selected vehicles with similar average overnight charging frequencies (CF), but with the highest and lowest coefficients of variation (CV) in non-charging streaks. The upper examples (high CV) exhibit long, contiguous stretches without charging, interspersed with extended periods of consistent charging behavior—patterns suggestive of habit formation or situational constraints. In contrast, the lower examples (low CV) display more randomized, evenly spaced charging behavior.

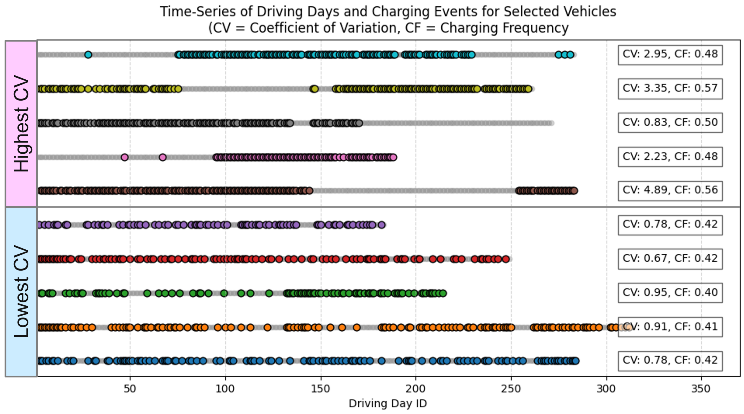


Figure 6: Time-series of driving and charging events showing clustered non-charging behavior in high-CV vehicles vs more evenly spaced charging in low-CV cases.

Human behavior often follows routines that shift with competing demands, leading to temporal variability in attention and decision-making. As Lenartowicz *et al.* [12] note, fluctuations in cognitive control are a fundamental aspect of real-world behavior. This supports the idea that simple random plug-in models fail to capture the true complexity of observed charging patterns.

For any given overnight charging frequency, there is an associated pattern of charging and non-charging streaks. To replicate this behavior, we developed a Markov-like simulation that alternates between charging states based on empirically derived probability histograms. The simulated outputs closely reproduce observed charging frequencies, coefficient of variation (CV), and deviations from randomness. This approach forms the foundation for modeling real-world charging behavior. Preliminary findings suggest charging patterns may be uncorrelated with daily driving distances, suggesting the model can be applied to other driving datasets, such as the NHTS. Our objective is to retain the NHTS dataset as the foundation for the UF curve, while sequentially layering in this and other real-world behavioral impacts to produce an updated Utility Factor

4.3 Blended Charge-Depleting Designs

While charging behavior is a dominant factor in explaining deviations from the original J2841 Utility Factor (UF), another major contributor is the vehicle's design—specifically, how a plug-in hybrid electric vehicle (PHEV) depletes its battery energy during charge-depleting (CD) operation. In contrast to EREV-type PHEVs like the Chevy Volt, many early PHEV models adopted a blended design where the internal combustion engine (ICE) assists in propulsion even when usable battery energy remains. These design choices can have significant implications on observed electric utility.

As described in Duoba *et al.* [8], the key factor is the rate at which the battery is depleted—driven by the maximum electric propulsion capability of the vehicle. A higher EV power limit enables more electric-only driving and faster depletion, but if the EV power limit is low, the ICE is invoked more frequently to meet common power demands. This slows depletion, effectively extending the CD range. While a longer CD range might seem advantageous, it can paradoxically lower the observed electric utility in real-world driving: short trips may not use much of the battery at all, leaving electric energy unused and fuel consumption higher than expected.

These interactions between blended operation, trip length, and energy usage reinforce the need to model charge-depleting behavior more precisely in the UF update. To account for blended effects, one possible approach is to compare the electric energy fraction observed during a high-power drive cycle, such as the US06, with in-use data to quantify the degree of engine assistance during charge-depleting mode for a specific PHEV model. Incorporating this comparison could help quantify where a vehicle falls on the spectrum between blended operation and extended-range electric behavior in real-world conditions.The electric energy share on the US06 cycle could be used to calculate a continuous metric that represents the degree of ”blendedness” for each PHEV model. As such, improvements to the J2841 methodology may include parameters that reflect this continuum, allowing for more representative UF curves that account for variations in vehicle control strategies and electric-only capability.

Fortunately, CARB's Advanced Clean Cars II (ACC II) regulation now incentivizes designs that are effectively extended-range EVs. To receive maximum zero-emission vehicle credit, a PHEV must demonstrate all-electric capability on the US06 test cycle and achieve a real-world electric range of at least 50 miles. As these requirements take effect, PHEVs will increasingly resemble EREVs in practice, reducing the blended operation effect and simplifying the modeling needed for UF updates. Indeed, in BAR data, the Volt—an EREV—showed no meaningful divergence between calculated CD, EV, and electric utility fractions, validating this design advantage.

4.4 Ambient Weather

Cold ambient temperatures significantly degrade PHEV efficiency and electric-only operation, leading to lower real-world UF values. At low temperatures, increased battery internal resistance and slower electrochemical kinetics reduce the usable battery energy and increase energy consumption per mile [13]. In addition, cabin heating and battery thermal management introduce further energy demands. Simulations from NREL indicate that climate-control use in severe cold can raise PHEV fuel consumption by up to 61%. Empirical tests have shown substantial range loss: one study found a 25% drop in all-electric range for a PHEV when ambient temperature fell from 23°C to –7°C with the cabin heater on (from 20 km to 15 km) [13]. For comparison, BEVs can lose up to 40% of their range at similar cold temperatures [14], highlighting the pronounced impact of cold on battery efficiency across electrified vehicles.

Unlike BEVs, which must always draw heating energy directly from the battery—thereby reducing driving range—many PHEVs are designed to invoke the engine for cabin heating once ambient temperatures fall below a certain threshold. This allows them to utilize waste heat from the internal combustion engine (ICE), meeting heating demands with minimal incremental fuel cost. However, this design introduces two distinct UF-lowering effects unique to PHEVs. First, like BEVs, cold weather reduces battery efficiency and increases energy consumption for thermal management. Second, engine operation triggered for cabin heat delays or eliminates opportunities to displace fuel with electricity—similar to the blended operation effect—thereby directly reducing electric driving share. Additionally, cold-start ICE use incurs its own penalties: Argonne measurements show 25–40% higher fuel consumption until the engine warms up [15]. As with blended operation, these temperature-driven effects are might be model-dependent and difficult to predict generically. Accurately extrapolating their real-world impact on UF may require specific laboratory test data for each vehicle to understand the control logic governing ICE use in cold weather.

4.5 User-Selectable Modes and Manual Overrides

Some PHEV models offer user-selectable modes that override the default CD strategy, such as a "Hold" or "Sustain" mode that preserves battery charge for later use. These modes are typically used for specific scenarios—such as preserving EV range for low-emission zones or enabling more efficient engine operation on highways. In other cases, drivers may intentionally trigger engine operation to improve cabin heating performance during cold weather. While such interventions may be infrequent, their cumulative effect can be significant in large datasets, reducing the observed electric utility across the fleet. The prevalence and impact of these behaviors vary by model and user awareness, but they highlight an important source of deviation from the assumptions embedded in standard UF calculations.

4.6 Other Impacts

In addition to the primary factors modeled above, there are other real-world behaviors that may reduce electric utility but are less frequently quantified. These include extended idling or HVAC use while parked—such as waiting to pick up children or staying warm while stationary—which can disproportionately trigger engine operation in PHEVs. Moreover, as more granular in-use data becomes available, additional edge cases and usage patterns may emerge that warrant further study. While difficult to generalize, these effects collectively underscore the value of real-world datasets in uncovering operational nuances not captured by standard test procedures.

5 Conclusions and Future Directions

This paper examined the discrepancy between real-world plug-in hybrid electric vehicle (PHEV) utility and the assumptions underlying the current SAE J2841 Utility Factor (UF) methodology. Using a combination of observational datasets, including California BAR data, we identified multiple behavioral and technical drivers of this shortfall—most notably infrequent charging behavior, longer or more variable daily driving distances, blended-mode operation, and cold-weather effects.

To address these limitations, we proposed a modular framework for refining the UF curve by applying individual real-world impact models on top of baseline driving patterns derived from NHTS data. Each component—charging frequency, driving behavior, vehicle-specific traits, and environmental conditions—can be modeled and calibrated independently, enabling both traceability and flexibility as new data sources emerge (Figure 7).

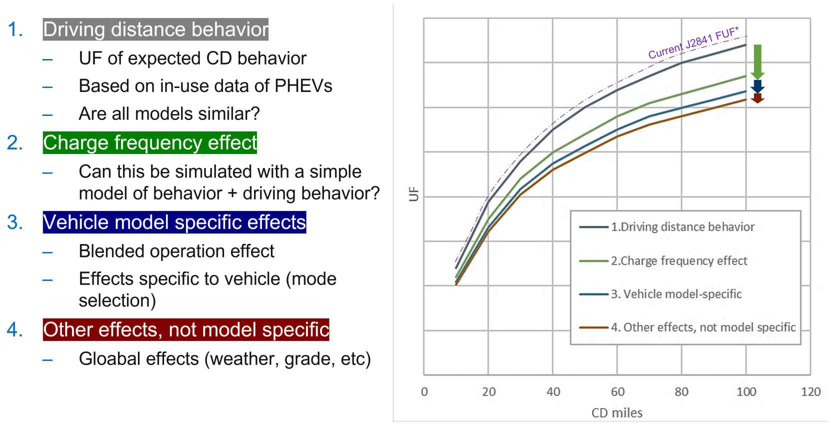


Figure 7: Stepwise modeling approach showing cumulative UF reductions from layered real-world impacts. The updated UF curve incorporates behavior, vehicle, and environmental effects.

This stepwise modeling strategy incrementally layers real-world effects onto the original J2841 UF curve to produce a more representative and adaptable Utility Factor. This modular structure ensures that individual influences can be studied and validated independently, and readily incorporated into future UF updates without requiring a complete methodological overhaul. It also supports ongoing SAE committee work and offers a transparent foundation for future regulatory and industry adoption.

Finally, a central purpose of this paper is to initiate broader engagement with the international research and regulatory community. As vehicle technologies, driver behaviors, and policy frameworks evolve, it is critical that the UF methodology also evolves to reflect real-world conditions. We invite collaboration, data-sharing, and methodological feedback to advance a globally harmonized understanding of PHEV utility and to support convergent policy outcomes that reflect the full complexity of in-use electrified vehicle performance.

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