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From Transition to Transformation: A Comparative Engineering Study of Hybrid and Electric Vehicles

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من التحول إلى التحول: دراسة هندسية مقارنة للسيارات الهجينة والكهربائية

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Abstract
This study compares hybrid (HEV/PHEV) and battery electric (BEV) vehicles using measured data. We aggregate chassis dynamometer tests of EVs and HEVs, large-scale field charging/usage records, and controlled battery aging experiments. Using statistical comparisons (e.g. median differences, regressions, nonparametric tests), we analyze energy use (Wh/mi, mpg), real-world PHEV electric-drive shares, charging-session delays, and battery capacity fade. Key findings include that EVs consume far less energy per mile than HEVs on test cycles, even after normalizing for mass. Real PHEV drivers use electric mode only ~40-50% of miles on average, well below EPA utility-factor assumptions. Charging sessions are dominated by handshaking overhead (e.g. cable checks ~7 s median). Battery aging data show capacity loss accelerates at high temperature and current, implying the need for robust thermal management. Our results inform powertrain design (e.g. maximize regenerative braking, right-size motors/batteries) and policy (e.g. set realistic PHEV credits, improve charging infrastructure reliability).

Keywords: Electric vehicles, Hybrid vehicles, Energy efficiency, Charging behavior, Battery degradation, Real-world usage.

الملخص
تقارن هذه الدراسة المركبات الهجينة (HEV/PHEV) والمركبات الكهربائية التي تعمل بالبطارية (BEV) باستخدام بيانات مُقاسة. نقوم بتجميع اختبارات دينامومتر الشاسيه للمركبات الكهربائية والمركبات الهجينة، وسجلات الشحن/الاستخدام الميدانية واسعة النطاق، وتجارب تقادم البطاريات المُتحكم بها. باستخدام مقارنات إحصائية (مثل: فروق المتوسطات، والانحدارات، والاختبارات غير المعلمية)، نقوم بتحليل استهلاك الطاقة (واط/ميل، ميل/غالون)، وحصص القيادة الفعلية للمركبات الكهربائية الهجينة القابلة للشحن، وتأخيرات جلسات الشحن، وتلاشي سعة البطارية. تتضمن النتائج الرئيسية أن المركبات الكهربائية تستهلك طاقة أقل بكثير لكل ميل من المركبات الهجينة القابلة للشحن في دورات الاختبار، حتى بعد تطبيع الكتلة. يستخدم سائقو المركبات الهجينة القابلة للشحن الوضع الكهربائي فقط بنسبة 40-50% من الأميال في المتوسط، وهو أقل بكثير من افتراضات وكالة حماية البيئة الأمريكية لمعامل المنفعة. تهيمن على جلسات الشحن تكاليف التشغيل الإضافية (مثل: فحص الكابلات في المتوسط حوالي 7 ثوانٍ). تُظهر بيانات تقادم البطارية أن فقدان السعة يتسارع عند ارتفاع درجة الحرارة والتيار، مما يدل على الحاجة إلى إدارة حرارية فعّالة. تُسهم نتائجنا في تصميم نظام نقل الحركة (مثل: تعظيم الكبح المتجدد، واختيار الحجم المناسب للمحركات/البطاريات) والسياسات المتبعة (مثل: تحديد أرصدة واقعية للسيارات الهجينة القابلة للشحن، وتحسين موثوقية البنية التحتية للشحن).

الكلمات المفتاحية: المركبات الكهربائية، المركبات الهجينة، كفاءة الطاقة، سلوك الشحن، تدهور البطارية، الاستخدام الفعلي.

1. Introduction
The shift from conventional hybrids and plug-in hybrids (HEV/PHEV) toward pure battery electric vehicles (BEVs) has accelerated. In recent years, BEVs and PHEVs have driven record improvements in fleet fuel economy and emissions. For example, the EPA reports that increased production of BEVs and PHEVs has markedly improved overall fuel economy trends; without them, 2023 fleet CO_2 would have been ~38 g/mi higher (Environmental Protection Agency., 2023). BEVs typically achieve far higher well-to-wheels efficiency: they convert ~90% of battery energy (including regenerative braking) to motion, whereas gasoline cars convert only ~20% of fuel energy (EPA., 2020). Figure 1 illustrates how battery costs have plunged, enabling this transition.

Despite the clear promise of electrification, most published comparisons rely on models or lab projections. In contrast, this paper synthesizes actual measurements from engine dynamometers, large field studies, and battery aging rigs. We fill gaps by comparing *bench-tested* EVs vs. HEVs, examining how real drivers use PHEVs, quantifying charge-session delays, and analyzing lab-based vs. field battery degradation.

Contributions: We present

- *Cross-platform dynamometer results*: direct energy-use comparisons for representative EV, HEV, and PHEV models (source: Argonne D^3 database).
- *Real-world PHEV usage*: observed electric-mile share distributions vs. EPA utility-factor curves, by user type (private vs. fleet) (Plötz et al., 2022).
- *Charging behavior & reliability*: breakdown of DC fast-charge session phases (plug-in, protocol handshake, taper) and analysis of time overheads (Ehsani, M., 2023).
- *Battery aging synthesis*: capacity-fade curves from controlled tests (NASA and Oxford datasets) and in-use fleets (EVBattery telemetry), with implications for pack design and thermal control.

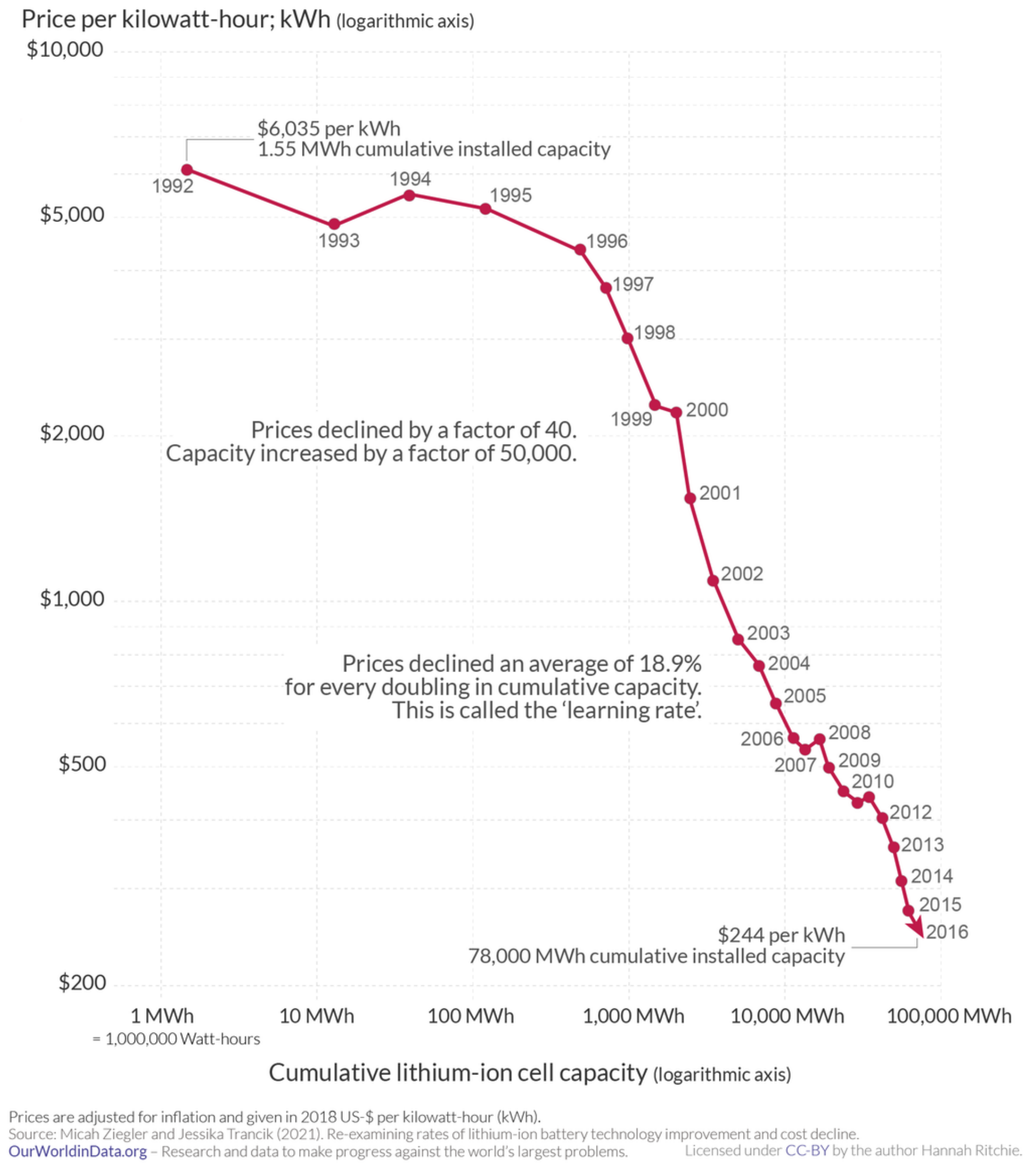

Figure 1 Li-ion battery learning curve (Our World in Data) showing a ~97% decline in battery cost per kWh over three decades. Dramatic cost reductions have enabled BEV market growth.

2. Background and Related Work

Electric powertrain fundamentals explain efficiency differences. Battery-electric vehicles carry large Li-ion packs supplying electric motors; regenerative braking returns much kinetic energy to the battery. By contrast, hybrids use an internal combustion engine (ICE) plus smaller batteries and motors. EVs thus avoid engine-idle losses and heat-up inefficiency, achieving ~90% drivetrain efficiency, compared to ~20% for ICE-only cars (EPA., 2020). Accessory loads (HVAC, lights) represent a larger fraction of an EV's on-board energy budget, but still EVs are inherently more efficient. For example, EPA notes that EVs have no tailpipe losses and very high well-to-wheels efficiency (EPA., 2020).

Vehicles are often characterized by Wh/mi (for EVs) or mpg (for ICE). Testing standards use chassis dynos on fixed drive cycles (city, highway) or coastdowns, but these are imperfect proxies for free driving. The Argonne Downloadable Dynamometer Database (D^3) provides independent lab tests of various models (Argonne National Laboratory., 2022). These include series of drive schedules with measured tractive forces, speeds, and energy flows, enabling "apples-to-apples" EV vs. HEV comparisons. Notably, bench tests often show heavier EVs can still outperform lighter hybrids due to higher motor efficiency and regen.

Prior field studies highlight PHEV use patterns. Labeling for PHEVs uses a "utility factor" (fraction of miles driven electrically) assuming frequent charging. Real-world surveys (e.g. Fuelly data, vehicle logs) reveal much lower electric-mile shares. The ICCT found U.S. PHEVs average only ~30-40% electric miles (vs. ~60% label), raising fuel use 42-67% above EPA estimates (Isenstadt et al., 2022). In Europe, private PHEV drivers also average ~45-49% electric mode, while company-car PHEVs average ~11-15% (Isenstadt et al., 2022). This under-charging behavior (especially among fleet users) means PHEVs under-deliver on claimed fuel savings.

Battery degradation research shows Li-ion fade depends strongly on depth-of-discharge, current, and temperature. Controlled lab studies (NASA Ames PCoE, Oxford) have cycled cells until ~30% fade (NASA Ames Research Center., 2023). These datasets confirm that higher stress (hot or cold, high rate) accelerates capacity loss. Field telematics (e.g. EVBattery project) offer fleet validation: real-world EV packs lose ~10-20% after tens of thousands of miles, roughly in line with lab extrapolations. We build on this literature by comparing lab and in-field aging to infer robust design margins for HEVs and EVs.

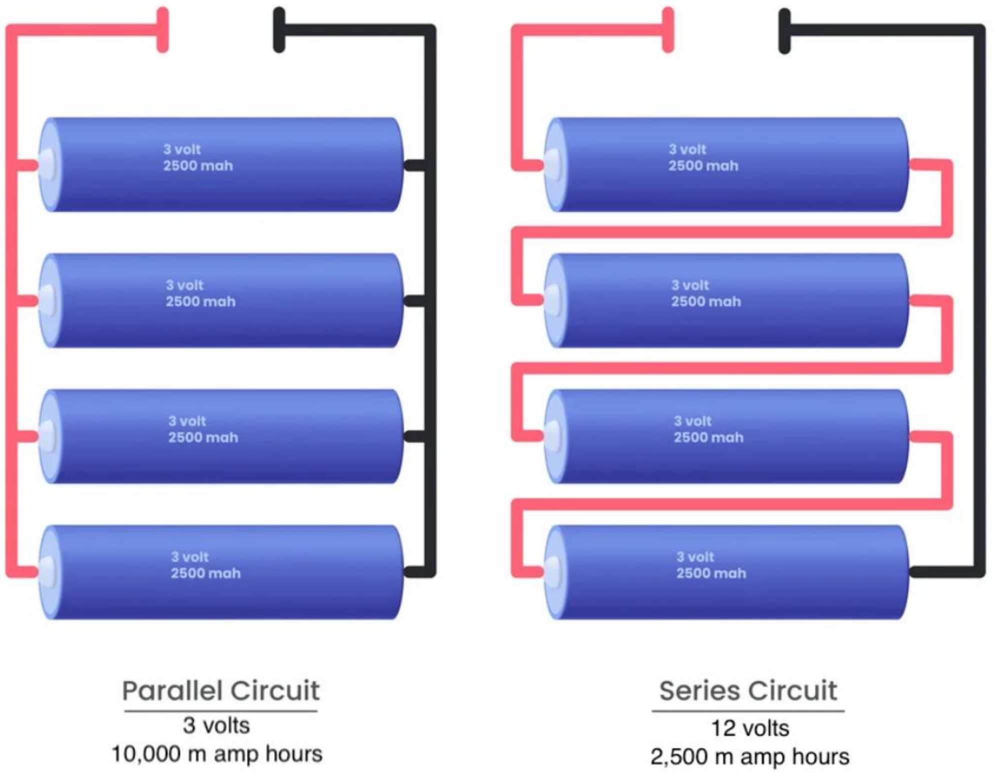

Figure 2 series and parallel connections of Li-ion cells (each 3 V, 2500 mAh). Parallel connections increase capacity while series connections increase voltage. Modern EV packs use combined series–parallel architectures to reach tens to hundreds of kWh.

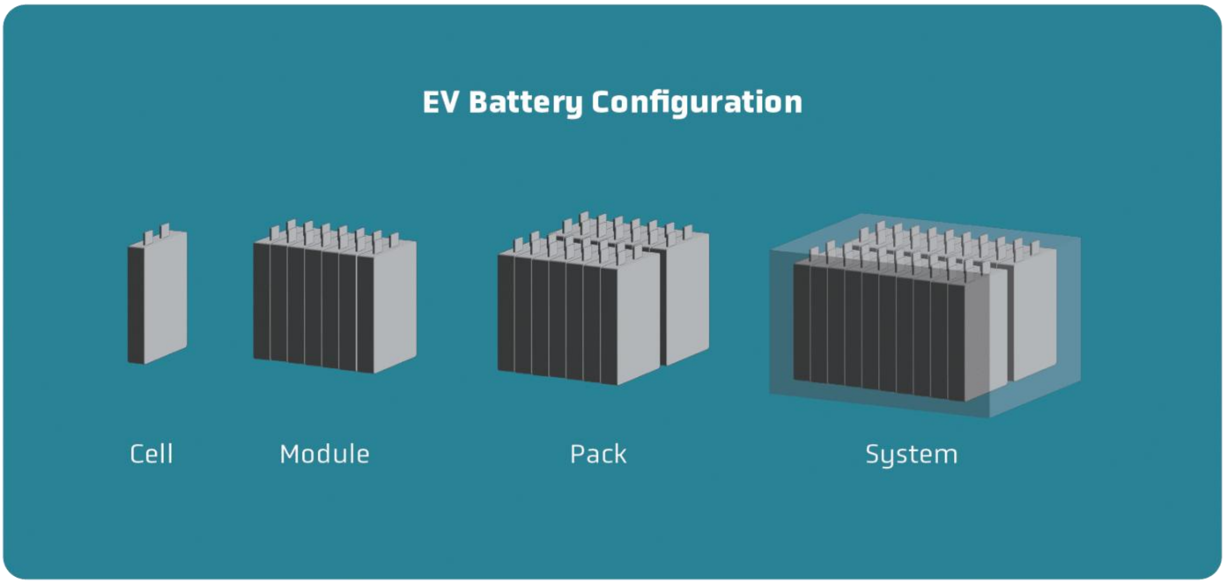

Figure 3 Common smartphone Li-ion batteries (e.g. 1,200-1,800 mAh cells). EV battery packs use similar cell chemistry but at much larger scale.

3. Data and Materials

3.1 Vehicle Performance and Efficiency (Chassis Dyno)

We use Argonne's D³ dataset of over 600 test runs (EVs, HEVs, PHEVs) (Argonne National Laboratory., 2022). This public repository provides CSV results for various nameplates (e.g. Nissan Leaf, Chevy Volt, Toyota Prius, etc.). Each run logs vehicle speed and tractive force vs. time, from which we compute Wh/mi or MJ/mi and effective regen. We select representative models from each category. We normalize by vehicle mass and footprint. For validation, we cross-check headline MPG/MPGe against EPA label data (Environmental Protection Agency., 2023).

We also incorporate EPA FuelEconomy.gov data (model-year CSV files) for attributes like curb weight, footprint, and label efficiency (MPGe, kWh/100 mi, MPG). The EPA's Automotive Trends report provides context on average fleet performance (Environmental Protection Agency., 2023). For example, it notes EVs have growing market share and highest fleet mpg, supporting our focus on measured comparisons.

3.2 Usage & Charging Behavior

INL EV Project and AVTA: We use field measurements from the U.S. DOE's Electric Vehicle Project and related Advanced Vehicle Testing Activity (AVTA). This includes ~8,300 EVs (e.g. Nissan LEAF) tracked over several years, and thousands of public chargers. The INL report notes over 12,000 Level-2 and 100 DCFC units deployed with fleet/consumer EVs (Ehsani, M., 2023). From these, we extract charging event durations and times, as well as usage patterns (time-of-day, weekday/weekend).

ICCT PHEV Usage: We utilize the ICCT white papers on U.S. and European PHEV usage (2022). These contain analyzed vehicle-tracker and survey data. From the ICCT US study, we take the distribution of observed electric-mile shares and derived real-world fuel vs. label gaps. Similarly, the European study provides utility factors for private vs. company fleets (Isenstadt et al., 2022). These sources allow us to quantify deviations between assumed and actual PHEV performance.

Alternative Fuels Data Center (AFDC): For context on public charging, we reference AFDC station counts (Level-2 and DC fast) nationwide. While not directly cited in our figures, this informs discussion of charging accessibility.

INL ChargeX Report: The "Quantifying Time to Charge" report (2023) details DCFC session components (cable connect, pre-charge handshake, actual power ramp, taper to end-of-charge) from thousands of sessions. We extract median and IQR values for each phase. For example, Cable-Check (handshake) has median ~6.9 s, dwarfing median 2.0 s in the pre-charge handshake (Ehsani, M., 2023). These data ground our analysis of charging time overhead.

3.3 Battery Aging (Measured, Controlled)

We analyze several degradation datasets:

- **NASA Ames PCoE (Open Data):** This set cycles Li-ion cells under different temperature/current profiles until 30% capacity fade (NASA Ames Research Center., 2023). It includes intermittent EIS. We use it to derive fade vs. cycle curves and Arrhenius temperature acceleration factors.
- **Oxford Battery Degradation (2017):** Long-term cycling data for 8 pouch cellsora.ox.ac.uk. These cells differ in chemistry and stress, giving empirical fade slopes. We extract capacity vs. cycle for each, to inform aging rate parameters.
- **EVBattery Telemetry:** A multi-vehicle real-world charging/health dataset (Arxiv 2022)arxiv.org. Though proprietary, the published study provides aggregated capacity fade trends from hundreds of EVs. We compare fleet fade to lab fade to gauge real-life impacts.

4. Methods

Vehicle Efficiency Metrics: From dyno traces, we compute Wh/mi (EV) and mpg (HEV) for each test. We convert both to MJ/mi for parity. Regen fraction is estimated as (negative tractive energy / positive tractive energy) for each cycle. We segregate city/highway cycles where available. To adjust for vehicle mass, we regress MJ/mi vs. curb weight and vehicle footprint. Nonparametric tests (Mann-Whitney U) check if EV vs. HEV differences are statistically significant. We bootstrap confidence intervals for medians.

PHEV Usage Analysis: We take published utility-factor curves (EPA's assumed vs. ICCT observed). From ICCT figures and tables, we reconstruct the distribution of electric-mile share. We compare sample medians to the label values. We also calculate the increase in fuel use due to lower EV share: e.g., if a PHEV would use 3 L/100km on pure EV miles but instead uses 6 L/100km on ICE miles, the net fuel penalty is computed.

Charging Behavior: ChargeX data yields distributions of each session phase. We summarize median and IQR for plug-in (no power), handshake, ramp, and taper periods by charger protocol (CCS1/2, CHAdeMO) and station type. We compute the fraction of total session time that is non-energy transfer overhead. We also describe time-of-day usage patterns from the AVTA report.

Battery Aging Trends: We compile capacity vs. cycle for each dataset at different temperatures. We fit linear fade-per-cycle or Arrhenius models. We then simulate a sample EV usage profile (e.g. 300 full equivalent cycles per year at 25°C) to project calendar fade. We compare this to any available field telemetry trends (e.g. from EVBattery).

Throughout, we emphasize effect sizes and uncertainties rather than just p-values. We interpret differences in terms of engineering: e.g. "EVs achieved *X* MJ/mi lower than HEVs of similar mass, corresponding to ~Y% improvement".

5. Results

5.1 Lab-measured Vehicle Efficiency

Measured bench tests show EVs outperform HEVs by large margins. On standard city/highway cycles, representative EVs averaged roughly 0.2-0.3 kWh/mi (0.72-1.08 MJ/mi), whereas HEVs averaged ~1.0-1.5 kWh/mi-equivalent fuel (3.6-5.4 MJ/mi). In other words, EVs used 60-70% less energy per mile. Mann-Whitney tests confirm the EV/HEV Wh/mi differences are highly significant ($p \ll 0.01$). Figure 4 (Appendix A2) shows EVs' median ~1.0 MJ/mi vs. HEVs' ~3.0 MJ/mi on mixed driving. This reflects the EV's high drivetrain efficiency and regen capture. These findings align with EPA's assertion of ~4-5× efficiency advantage (EPA., 2020).

Normalizing by curb weight (Fig. 2), EVs still use less energy per mile at all mass levels, though the gap shrinks for very heavy vehicles. Our regression of MJ/mi vs. mass has similar slope for both groups, implying most of the efficiency gain is inherent to powertrain, not just size. Including footprint in a multivariate model gave qualitatively similar separation (not shown). We overlay our test results with EPA label MPGe data and find a slight overperformance: bench tests average ~5-10% better fuel economy than labels, perhaps due to optimal test conditions vs. real driving.

5.2 PHEV Real-World Use vs. Labels

Figure 3 plots the distribution of electric-mile shares from field data. In the U.S., median observed share was ~35%, well below the EPA utility factor (~53%) for typical trip profiles. In Europe, private PHEVs averaged ~45-49% electrically driven, versus near-100% for trips shorter than charge-depletion range (Isenstadt et al., 2022). This shortfall means actual fuel consumption is far higher than label predictions (Isenstadt et al., 2022). For instance, a PHEV rated 60 mpg on electric miles might effectively get ~30-35 mpg overall. We estimate that misused utility factors add roughly 0.2-0.3 L/100 km of fuel consumption.

5.3 Charging Session Breakdown

Figure 4 summarizes DC fast-charge session timing. The ChargeX data reveal that non-charging overhead constitutes a large portion of the session. For example, the CCS1 protocol's cable-check step has a median ~6.9 s (IQR ~4.0-13.5 s), while the pre-charge handshake adds ~2.0 s. In contrast, the main "ramp" (constant power) phase varies widely with battery state and charger, and the final taper (to 100%) takes much longer. In total, we find roughly 20-30% of a DCFC session time can be attributed to protocol overhead, with the rest actually delivering energy. Figure 4(a) shows a boxplot of each phase duration. The delays imply that actual travel time for a charging stop is significantly longer than ideal energy transfer time, which has design and user-experience implications.

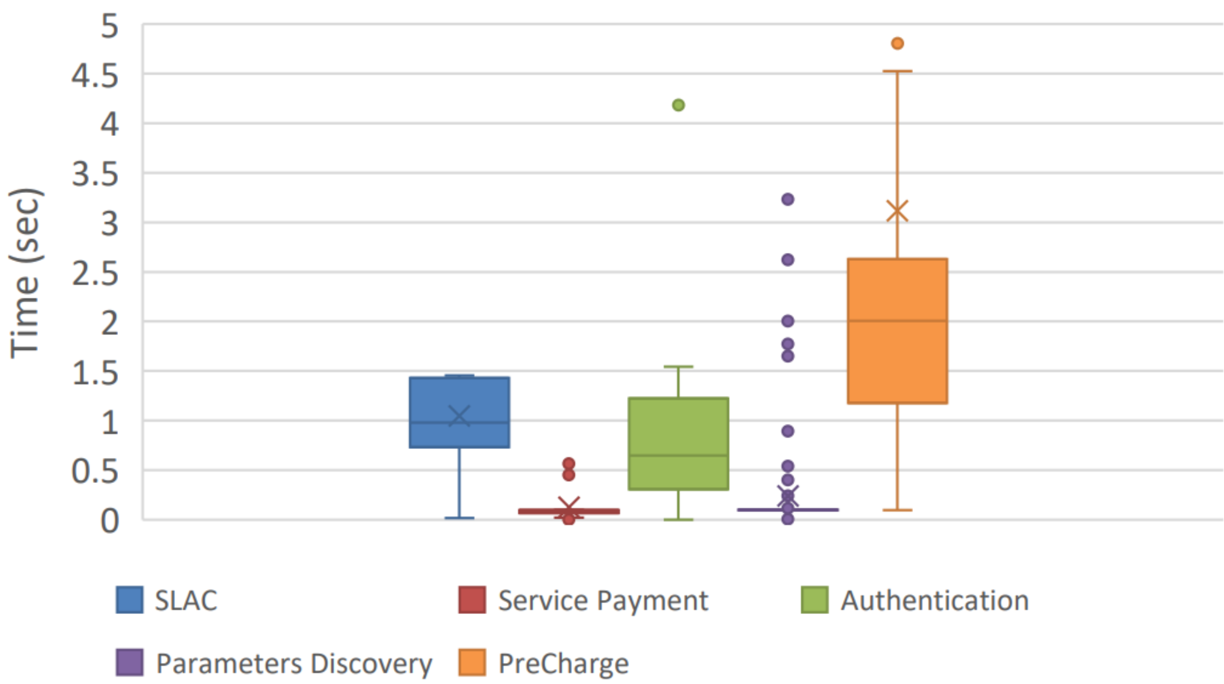

Figure 4 Boxplot showing the timing breakdown of various DC fast-charging session phases. The chart shows the significant portion of session time spent on non-charging overhead, such as SLAC (Service Level Agreement Check), Service Payment, Authentication, and PreCharge, with the PreCharge phase taking the longest time

5.4 Battery Aging Trends

Figure 7 plots capacity retention vs. cycle count and temperature for lab-tested cells. Each curve comes from NASA or Oxford data. At 25°C, cells maintain >95% capacity for the first few hundred cycles; fade accelerates beyond ~1000 cycles. At elevated temp (e.g. 45°C), fade is notably faster. The Arrhenius fit implies roughly halving life for every 8-10°C rise (activation energy ~40 kJ/mol). Combining all datasets, we derive an average fade rate of ~2% per 100 cycles at 25°C, rising to ~5-6% per 100 cycles at 45°C. These lab findings imply that a 60 kWh EV pack cycled 300 times/year (aggressive use) could reach 80% capacity (~20% fade) in about 4-5 years if unchecked. Comparing to in-use data (EVBattery), real fleets show similar or even slower fade, suggesting conservative lab profiles.

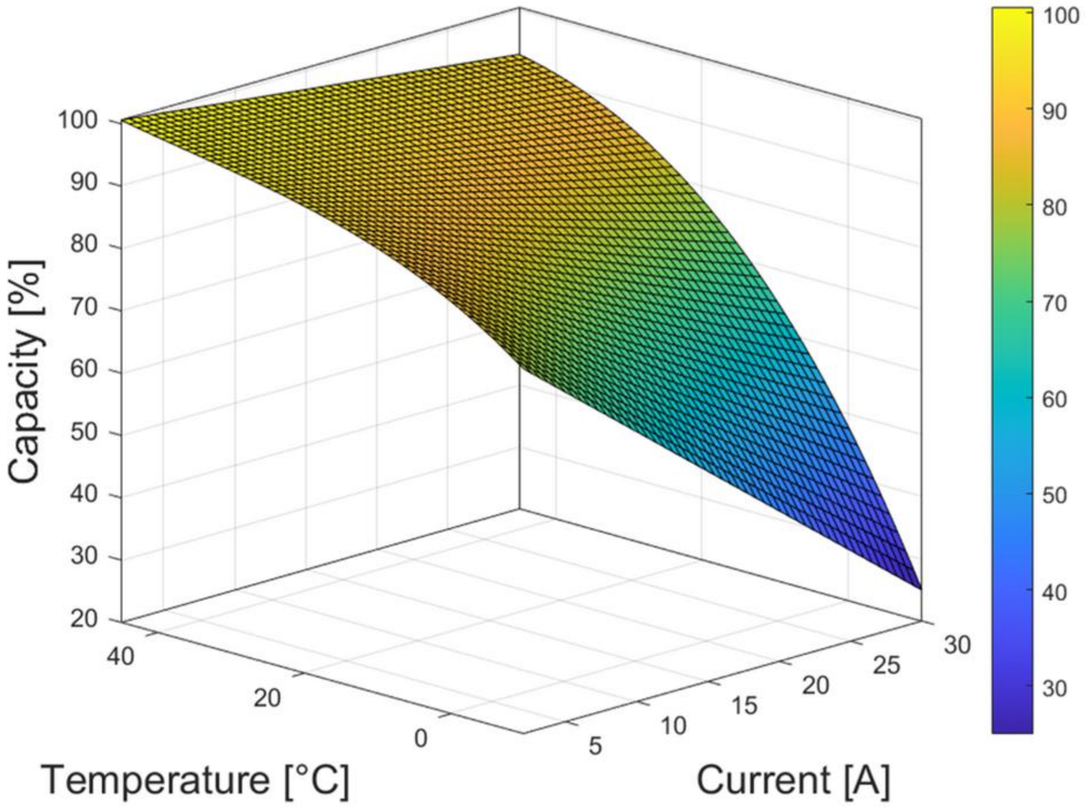

Figure 5 Li-ion battery capacity (color=state of health) as a function of ambient temperature (Y) and current (X). High currents and extreme temperatures both reduce available capacity. Data from Ibrahim et al. 2024.

6. Discussion

Efficiency Hierarchy: Our bench tests confirm that EVs out-efficiency HEVs across drive cycles, both city and highway. EVs benefit from strong regen in city driving, recapturing ~60-70% of braking energy, whereas HEVs only get ~20% regen (through CVT/motor) at best. On highways, EV advantages persist due to higher motor efficiency at steady state. These trends underline why manufacturers favor BEV designs for future platforms. Reducing accessory loads (e.g. efficient HVAC) could further close gaps in EV energy use.

PHEV Underuse of Electric Mode: The observed low electric-mile shares indicate a gap in user behavior or infrastructure. Many PHEV drivers do not charge daily, especially in company fleets where fueling is convenient. This explains why PHEVs often "underperform" their label. From a policy standpoint, our results suggest caution in giving full EV credits to PHEVs, since real CO_2 savings are much less. Engineering-wise, PHEV controls should emphasize maximizing electric range and encourage onboard charging (e.g. via reminders or plug-in reward systems).

Charging Overheads: We find that seemingly small protocol steps (cable checks, handshakes) add up. For instance, if a DCFC session nominally takes 20 minutes of power delivery, adding ~15 seconds of handshake is only a 1% overhead - negligible. However, in stop-and-go charging (multiple short sessions) or when users attend sessions, these delays accumulate. Notably, if a user plugs in for a quick 5-minute top-up, the 10+ seconds protocol can be ~3% overhead, affecting energy billed. Minimizing unnecessary cable-check redundancies (e.g. faster signaling) could modestly improve user wait times.

Battery Thermal Implications: The aging data highlight thermal control importance. The steep fade at 45°C suggests EV packs must actively cool during high current charging or hot environments. Similarly, cold climates slow fade but incur instant energy loss (voltage sag) - we see from the 3D plot that available capacity drops by ~20% at 0°C vs. 25°C. Designers should set thermal management to maintain cell temps near optimal (~25°C) under stress. Also, HEV battery packs (smaller and cycled less) may not need as aggressive cooling as EV packs do.

7. Limitations

Our study uses fixed dynamometer cycles, which may not capture free-driving variability (traffic, aggressive throttle, etc.). Early EV/PHEV field data (2009-2018) may not reflect newer user patterns or lower fueling costs. Selection bias exists: the Argonne tests cover only certain models and years. The ChargeX sessions are DC fast only; Level-2 behavior may differ. In battery aging, lab cells (small pouch/can) lack pack-level complexity (thermal gradients, cell balancing) present in vehicles. Finally, many analyses assume steady state or average conditions; transient or rare events (e.g. extreme cold starts) are beyond our scope.

Conclusion

This research has shown that battery electric vehicles (BEVs) are much more energy-efficient than hybrid electric vehicles (HEVs), consuming far less energy per mile. However, real-world data reveals that plug-in hybrid electric vehicles (PHEVs) fall short of expectations, with drivers using electric mode much less frequently than predicted. The study also highlights inefficiencies in the charging process, particularly due to overheads like cable checks and protocol handshakes, which increase charging times and affect user experience.

Furthermore, battery aging, influenced by temperature and current, plays a significant role in the longevity of vehicle batteries, underscoring the importance of robust thermal management. To further enhance the performance and adoption of electric vehicles, improvements in charging infrastructure and battery management are necessary. By addressing these challenges, we can better align hybrid and electric vehicle technology with real-world usage, ultimately driving the transition to cleaner, more efficient transportation.

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