

Commercial-EV Mobility-Feasible V2G Opportunity: Survey and BMS Evidence

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Abstract

Vehicle-to-grid (V2G) service requires a physical connection, which household travel surveys (HTS) do not observe. We therefore estimate *mobility-feasible opportunity*: dwell hours satisfying service-window, consecutive-dwell, and state-of-charge criteria, without a plug-state gate. We compare HTS proxies with battery-management-system (BMS) traces from 108 Korean electric vehicles—34 taxis, 37 light-freight vehicles, and 37 private vehicles—covering 175,102 trips over 14 months. For all-day Use Case C, the nominal HTS tier order recurs in only 15.3% of bootstrap replicates, whereas the Korean BMS private, freight, taxi order recurs in 99.9%. The US rideshare-equivalent/Korean-taxi median ratio is $2.33\times$ under the original, differently resolved estimators and $2.25\times$ (95% household/vehicle-cluster CI [2.00, 2.57]) under a common hourly temporal rule. It spans 2.11–2.57 across 12 SoC/dwell definitions. This cross-source ratio still mixes country and vehicle role. Climate derating of 5–8% in sampled KR/US locations and $\sim 1\%$ in sampled UK/NL locations is a scenario projection from Korean-only thermal regressions, not a cross-country validation; 72 of 107 region-mapped BMS vehicles are in Daegu. Fleet-specific validation is needed before translating dwell opportunity into V2G capacity.

Index Terms—Vehicle-to-grid, mobility-feasible opportunity, commercial electric vehicles, travel survey, battery management system, climate-conditioned derating.

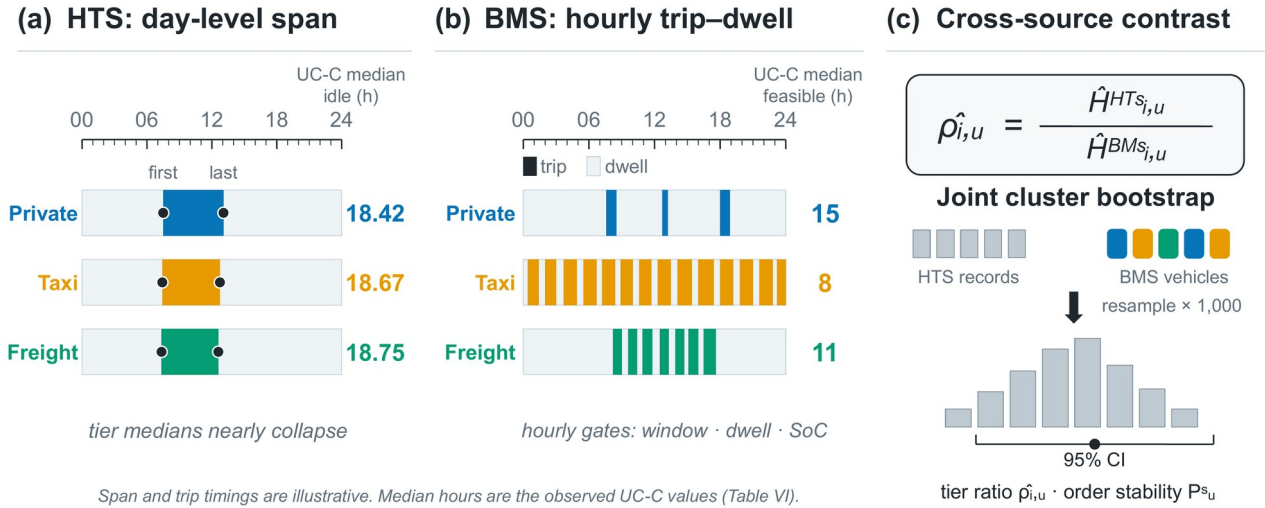


Fig. 1. BMS-anchored mobility-opportunity comparison. (a) HTS first/last-trip spans leave internal dwell unresolved. (b) BMS hourly trip-dwell patterns yield observed UC-C medians of 15, 8, and 11 h for private, taxi, and light-freight vehicles; stripe timing is illustrative. (c) Tier-specific HTS/BMS ratios follow Eq. 3; 1,000 joint cluster resamples give confidence intervals and tier-order stability.

I. Introduction

V2G planning requires fleet-specific idle opportunity, state-of-charge (SoC) headroom, a compatible physical connection, and adequate battery and grid capacity. Existing pipelines commonly transform household travel surveys (HTS) into synthetic mobility and battery trajectories [1], [2], [3]. Because the HTS records contain no observed connection state, this paper estimates mobility-feasible opportunity rather than connected or dispatchable V2G availability. Applying private-dominated survey categories to taxis and light-freight EVs can obscure operational differences; transferring a Korean thermal fit across climates is a separate scenario assumption.

We investigate these issues using 175,102 trips from 108 Korean EVs over 14 months. Three mobility Use Cases are reconstructed from BMS traces and compared with HTS person-day proxies; climate derating is evaluated separately as a UC-A modifier. Fig. 1 summarizes the estimator.

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The contributions are: (C1) evidence that the HTS proxy tiers have an unstable UC-C order while the observed Korean BMS tiers retain private, freight, taxi under clustered resampling; (C2) a common-hourly UC-C threshold test and a within-BMS check of how collapsing trip histories changes the result, alongside battery-parameter and proxy sensitivities; and (C3) UC-A climate scenarios obtained by applying Korean per-tier ambient-to-battery regressions to ERA5 data for KR, UK, US, DE, and NL. Revenue is downstream context; degradation and net-profit accounting are outside scope.

II. Background and Related Work

HTS-based EV models reproduce aggregate charging behavior [1] and support configurable battery simulation [2] and power-system studies [3]. Trip-chain models add arrival and SoC distributions [4], [5], [6], but still inherit mobility inputs from national surveys. Transfer studies address activity-model bias [7] or adapt charging predictors across sites [8], [9]; they do not validate commercial duty cycles against BMS traces.

Commercial-freight studies mainly examine grid flexibility, depot scheduling, or routing and charger siting [10], [11], [12]. Representative thermal studies quantify range, HVAC, battery management, and cold-charging effects [13], [14], [15], [16]; multi-country weather–mobility comparisons remain outside V2G opportunity analysis [17]. The unresolved need is a fleet-telemetry check on commercial mobility proxies, with climate transfer kept distinct from in-market validation.

III. Data

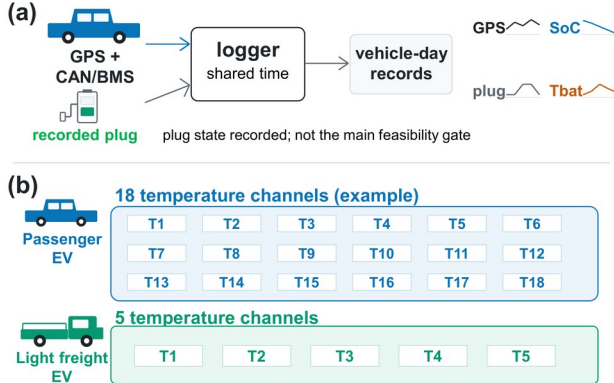


Fig. 2. Korean EV BMS measurement architecture. (a) GPS and CAN/BMS channels provide time-aligned position, SoC, plug state, and battery temperature; plug state does not gate the main estimator. (b) The passenger array is an 18-channel example; the retained passenger cohort spans 4–20 nominal channels and all freight vehicles have five. Geometry and positions are schematic.

A. Korean EV BMS

Fig. 2 documents the measurement channels and sensor architectures. Table I reports the distinct analysis subsets. The classified fleet comprises 114 EVs over 14 months (November 2024–December 2025). The three main operational tiers retain 108 vehicles after excluding 6 unclassified instances. Independently, 113 vehicles have GPS records; intersecting the main-tier IDs with the spatial join yields 107 region-mapped main vehicles for regional sensitivity. The main tier composition is:

- Private (37): Hyundai IONIQ5, Kia EV6, IONIQ6, EV9, etc.
- Taxi (34): the same passenger models operated in commercial passenger service.
- Light freight (37): PORTER2 ($n=24$) and BONGO3 ($n=13$), both 1-ton commercial delivery vehicles.

The dataset includes 40,255,460 GPS records, 175,102 trip-level start/end SoC records, and per-timestamp battery temperature. Thermal-cohort metadata show 4–20 nominal channels for 70 passenger vehicles (13 nominally exact-18) and five for all 37 light-freight vehicles. The raw-channel sensitivity includes 11 of those 13: one lacks a paper-cohort day in the local raw-retention overlap and one lacks local raw rows. At each timestamp, T_{mean} averages valid temperature1–temperature18 fields; nominally 20-channel vehicles therefore contribute at most 18. Channel coverage and unmapped physical locations are limitations (Sec. VII).

TABLE I. Vehicle subsets used for the distinct analyses.

Analysis subset	Vehicles	Vehicle-days
Classified/processed	114	–
Mobility reconstruction	108	23,756

Analysis subset	Vehicles	Vehicle-days
Thermal regression	107	25,763
GPS-bearing	113	–
Region-mapped main	107	–

The mobility and thermal-regression subsets are filtered independently. Mobility analysis requires a reconstructable trip day, whereas the regression requires valid daily battery temperature, a region assignment, and a matched ASOS weather day. Consequently, the regression retains 107 vehicles and 25,763 vehicle-days, while mobility analysis retains 108 vehicles and 23,756 vehicle-days.

B. UK NTS, US NHTS

The UK National Travel Survey (NTS) baseline pools the selected 2017–2019 and 2021–2024 survey years and contains 434,056 person-days [18]; 2020 is excluded to avoid pandemic-distorted travel behavior. The US 2022 National Household Travel Survey (NHTS) extract spans January 2022–January 2023 and contains 10,587 person-days [19]. Its vehicle-category information in *vehv2pub.csv* yields 8,999 private, 96 rideshare-equivalent, 203 delivery-equivalent, and 1,289 other commercial records. The primary category assigns a person-day to a commercial proxy when that household reports a vehicle of the corresponding type; it does not require the person’s trips to use that vehicle. These are household-exposure proxies, not observed Korean taxi or 1-ton delivery duty cycles. Official 2021 KTDB person-travel microdata and 2021 and 2025 census population margins—province-by-sex-by-five-year-age-group totals used as raking targets—were obtained after the revision analysis was frozen. Because the 2021 survey records pandemic-period travel, a Korean HTS comparator is deferred until trip-chain reconstruction, 2021 same-year reweighting, and pandemic-period sensitivity analyses are prespecified; 2025 margins will be used only for temporal-shift sensitivity. The noncontemporaneous survey and Korean BMS periods preclude an aligned-period comparison; Table IV records the mapping, and an operated-vehicle-linked and pooled-commercial sensitivity is reported in Sec. V-F.

C. Electricity markets

The monetary contextualization uses DE/NL day-ahead price files derived from ENTSO-E Transparency Platform data [20], the UK system sell price from Elexon BMRS [21], and Korean system marginal price from KPX

EPSIS [22]. The Korean price window is retained only as a contextual sensitivity because it is shorter than the European market records.

D. Ambient temperature

KMA Automated Synoptic Observing System (ASOS) hourly observations are joined to the Korean BMS records when fitting the ambient-to-battery regression [23]. Climate-regime projection then uses ERA5 hourly reanalysis [24] at representative grid cells (six in KR, four in the UK, five in the US spanning cold-continental Chicago to hot-humid Houston, two in DE, one in NL; exact coordinates are recorded in the analysis code) so that all country occupancies use the same reanalysis product. Per-country spatial coverage is a stated limitation (Sec. VII).

E. Data processing pipeline and reproducibility

The project scripts perform GPS extraction, regional joining, tier classification, BMS/HTS feasibility reconstruction, ambient-to-battery regression, and ERA5 projection. Cached aggregate tables and claim macros document the reported results. A complete independent rerun requires access to the original BMS trip series under the data-provider agreement, the UK NTS under its access terms, and the cited NHTS, ASOS, and ERA5 sources.

IV. Methodology

A. Use Case rules and mobility opportunity

Table III states the operational rules implemented for three mobility Use Cases. UC-B is a midday discharge window; UC-C is an all-day opportunity window, not an observation of dispatch frequency or frequency-regulation delivery. Climate derating is subsequently applied only to UC-A. The BMS analysis evaluates hourly trip, dwell, and SoC states; the HTS analysis uses a day-level active span and estimated average SoC. Thus the two sources have corresponding service windows and SoC cutoffs but different temporal resolution and feasibility rules; the original ratios do not use identical hourly rules. Because HTS lacks measured plug state, neither source is gated on

connection. The reported hours are modeled mobility opportunity, which can exceed connected hours under the same assumptions. Charger access, bidirectional capability, dispatch constraints, and degradation can reduce realizable service further. The recorded BMS plug signal is part of the acquisition inventory, not evidence that the reported hours were connected.

For each vehicle-day, feasibility is evaluated per hourly bin and summed to obtain $h_{v,u,d}^{BMS}$, the daily feasible hours of vehicle v for Use Case u on day d . For tier $i \in \{\text{private, taxi, freight}\}$, $\hat{H}_{i,u}^{BMS}$ is the median of $h_{v,u,d}^{BMS}$ across all vehicle-days assigned to that tier. Table II defines the notation used below.

TABLE II. Notation for the mobility and climate estimators.

Symbol	Meaning
i, u, d, v	Tier, Use Case, day, and BMS vehicle indices
S	Data source, HTS or BMS
$h_{v,u,d}^S$	Mobility-feasible hours for one vehicle-day (HTS analog uses one survey record)
$h_{S,d}^{(q,\ell,W)}$	Feasible hours under the common hourly rule for source S and day d
$\hat{H}_{i,u}^S$	Tier median of mobility-feasible hours
$\rho_{i,u}$	HTS-to-BMS ratio of tier medians
t	Hour-start index, $t \in \{0, \dots, 23\}$
$L_{S,d,t}$	Elapsed dwell at hour start t for source S and day d
$Q_{S,d,t}$	SoC at hour start t for source S and day d
b, B	Bootstrap replicate index and total replicates
$f_{i,c,r}$	Projected thermal-regime fraction for tier i , country C , regime r
d_r	Assumed fractional discharge-power derate in regime r
q, ℓ, W	UC-C SoC cutoff, consecutive-dwell threshold, and eligible hour set
a_i, β_i	Intercept and slope of the Korean tier- i thermal regression

B. BMS duty-cycle envelope reconstruction

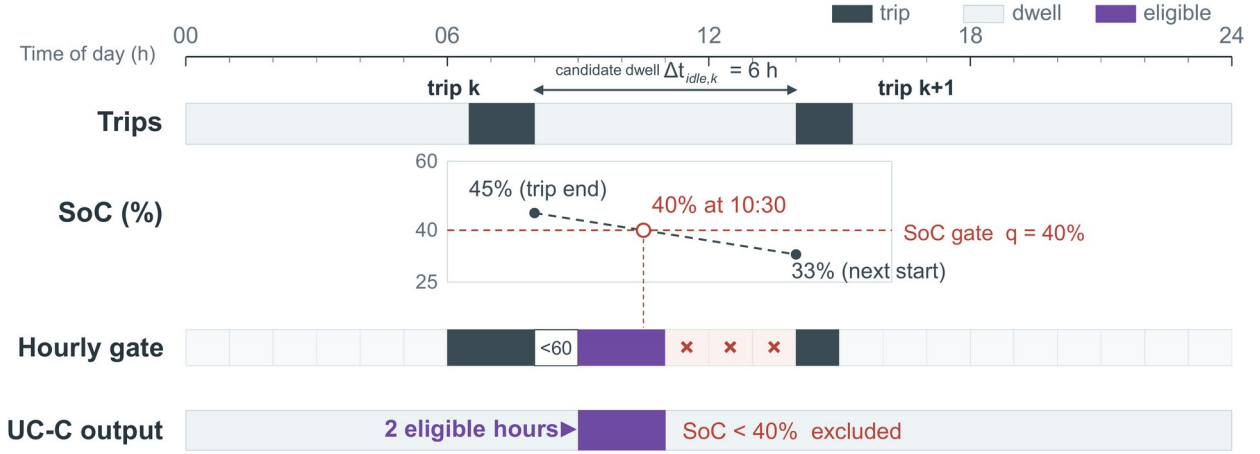


Fig. 3. Between-trip idle reconstruction and hourly UC-C screening. A 6-h candidate dwell separates trips k and $k+1$. The illustrative SoC path falls from 45% to 33% and crosses 40% at 10:30. The first bin fails the 60-min dwell rule, two hour starts pass both gates, and later bins fail the SoC gate. Values are illustrative.

Fig. 3 summarizes the reconstruction. We reconstruct each vehicle-day timeline from trip-level records ($t_{start,k}$, $t_{end,k}$, s_k , $SoC_{start,k}$, and $SoC_{end,k}$ for trip k), where s_k is trip distance. For hourly bin $h \in \{0, \dots, 23\}$, we determine (i) whether any trip intersects the closed hour interval, $t_{start,k} \leq h+1$ and $t_{end,k} \geq h$, and (ii) SoC by interpolation within a trip or between adjacent trip endpoints, evaluated at the hour start. Consecutive dwell (between-trip idle time) is the interval used in the main estimator; it is not asserted to be measured plug-in time. Battery temperature is extracted from the valid recorded channels and summarized by vehicle-day. The processing also forms architecture-dependent center and edge summaries, but these are not responses in the ambient-temperature regressions.

C. HTS day-level proxy reconstruction

For UK NTS and US NHTS person-day records, we use the tier proxies in Table IV. Assumed parameters are reported in Table V: starting SoC = 100%, consumption = 0.18 kWh/km, and pack capacity = 70 kWh. Idle hours are $24 - \text{active_span_min}/60$, where the active span is $\text{last_arrive} - \text{first_depart}$. End-of-day SoC is $\max(0, 100 - \text{total_dist}_{\text{km}} \times 0.18/70 \times 100)$, and the SoC gate uses the average of starting and end-of-day SoC. Unlike the hourly BMS reconstruction, the HTS UC-C rule credits all daily idle hours when total idle exceeds 1 h and average SoC meets the 40% cutoff. UC-A and UC-B assign the full window only if the survey active span lies entirely outside that window. Table III makes these differences explicit. The day-level estimator remains the

headline comparison because it is the implemented rule spanning both UK NTS and US NHTS and therefore retains the pooled private reference; the observed-trip common-hourly check is US-NHTS-only. Section IV-D reconstructs that additional common hourly temporal operator while retaining synthetic SoC and cross-population limitations.

D. Common hourly test and within-BMS aggregation check

To test the UC-C definition directly, we reconstruct 24 hourly trip/idle states from the original Korean BMS trip series and the observed US NHTS trip start/end times. At hour t , the common temporal operator is

$$h_{S,d}^{(q,\ell,W)} = \sum_{t=0}^{23} 1\{t \in W\} 1\{L_{S,d,t} \geq \ell\} 1\{Q_{S,d,t} \geq q\}, \quad (1)$$

where L is elapsed dwell since the last trip, Q is SoC, q is the SoC cutoff, ℓ is the consecutive-dwell threshold, and W is the eligible hour set. The same trip-hour overlap and elapsed-dwell rules are applied to both sources. BMS SoC is reconstructed from measured trip endpoints; NHTS SoC is synthetic, starting at 100% and declining by observed trip distance under the 70-kWh/0.18-kWh/km assumptions without within-day charging. NHTS rows describe a person's trips, potentially across transport modes, whereas BMS rows describe one vehicle; even a household with a flagged commercial vehicle does not guarantee those trips occurred in it. This is a matched *temporal* rule, not matched SoC measurement, vehicle

category, or country. We replay the original BMS UC-C result on every eligible vehicle-day before changing thresholds, then sweep $q \in \{30, 40, 50, 60\}\%$ and $\ell \in \{30, 60, 120\}$ min, with a separate service-window check at the baseline 40%/60 min. NHTS households and BMS vehicles are resampled as clusters, retaining their days and reusing the same bootstrap draw across estimator variants and thresholds.

To test the effect of discarding within-day trip timing on the same BMS days, we also collapse their original trips to the NHTS day-level fields (first departure, last arrival, total distance) and apply the NHTS synthetic-SoC UC-C formula. Writing $H_i^{H,D}$ and $H_i^{H,H}$ for the NHTS day-level and hourly medians, and $H_i^{B,C}$ and $H_i^{B,H}$ for the BMS collapsed-day and measured-hourly medians, respectively, gives the exact accounting identity

$$H_i^{H,D} - H_i^{B,H} = \underbrace{(H_i^{H,D} - H_i^{B,C})}_{\text{cross-population contrast}} + \underbrace{(H_i^{B,C} - H_i^{B,H})}_{\text{HTS day-to-hourly change}}. \quad (2)$$

The first term is a cross-population contrast under one day-level formula; the second changes representation within the same Korean BMS days. Separately, $H_i^{H,D} - H_i^{H,H}$ quantifies the HTS day-to-hourly change.

E. Cross-source ratio, tier-order stability, and bootstrap confidence intervals

The cross-source median ratio per tier i and Use Case u is

$$\rho_{i,u} = \frac{\widehat{H}_{i,u}^{HTS}}{\widehat{H}_{i,u}^{BMS}}, \quad (3)$$

F. Climate-conditioned derating

Climate is evaluated as a modifier of the UC-A peak-shaving result, not as a separate fourth Use Case. For every tier, the regression response is the vehicle-day mean T_{mean} across its valid recorded temperature channels; neither the center nor edge summary enters the fit or the climate projection. Per-tier ambient-to-battery temperature regression on KR ASOS hourly and BMS daily aggregates yields $\widehat{T}_{bat}^{(i)} = \alpha_i + \beta_i T_{air}$ for tier i . Battery temperature is classified into three regimes:

$$regime(\widehat{T}_{bat}) = \begin{cases} \text{cold,} & \widehat{T}_{bat} < 5^\circ \text{C} \\ \text{hot,} & \widehat{T}_{bat} > 25^\circ \text{C} \\ \text{mild,} & \text{otherwise.} \end{cases} \quad (5)$$

where $\widehat{H}_{i,u}^S$ is the tier median of feasible hours under source $S \in \{HTS, BMS\}$. Thus, the point estimate in Eq. 3 is the ratio of the two displayed medians, not a ratio involving a mean over bootstrap replicates. Because the sources represent different countries, vehicle-category proxies, and measurement systems, $\rho_{i,u}$ is a descriptive stress-test contrast; it does not identify a causal HTS measurement bias. UC-B has a zero HTS day-level median, so a ratio for that case is not interpreted.

Tier-order stability. Let $\pi_{u,0}^S = \text{rank}_i(\widehat{H}_{i,u}^S)$ denote the nominal tier order produced by source S for Use Case u . Because the three HTS UC-C medians are close, the evidential question is whether that nominal order is stable under HTS sampling uncertainty, rather than whether two fixed point-estimate orders differ.

Joint bootstrap. For each replicate b , HTS person-days are resampled with replacement within tier and BMS vehicles are resampled with replacement within tier while retaining all days belonging to each selected vehicle. The replicate statistics are

$$\rho_{i,u}^{(b)} \wedge \frac{\widehat{H}_{i,u}^{HTS,*(b)}}{\widehat{H}_{i,u}^{BMS,*(b)}}, \quad (4)$$

$$P_u^S(\pi_{u,0}^S) \wedge \frac{1}{B} \sum_{b=1}^B \mathbf{1}\{\pi_u^{S,*(b)} = \pi_{u,0}^S\}.$$

We use $B=1,000$ replicates. The 95% ratio CI is the $[Q_{0.025}, Q_{0.975}]$ percentile interval across joint replicates, and P_u^S reports the sampling stability of each source's own nominal tier order.

Assumed discharge-power derating per regime is $d_{cold}=0.30$, $d_{hot}=0.20$, and $d_{mild}=0$. The cold power derate represents a severe scenario motivated by the low-temperature capability reductions reviewed in [25]; it is not a fitted BMS parameter. The hot derate represents a protective BMS-throttle scenario, not an intrinsic battery-capability loss measured by this fleet. Both magnitudes are varied in the sensitivity of Sec. VI-B. The scenario-projected mean discharge-power derating for tier i and sampled country locations c is

$$\Delta_{i,c}^{lim} = \sum_{r \in \{cold, hot, mild\}} f_{i,c,r} d_r, \quad (6)$$

where $f_{i,c,r}$ is the country-level fractional occupancy of regime r for tier i obtained from ERA5 hourly reanalysis projected through the tier regression. Cutoff sensitivity (

$T < 0/5/10^{\circ}\text{C}$ cold thresholds; mild/default/severe

derating magnitudes) is reported in Sec. VI-B.

V. Results

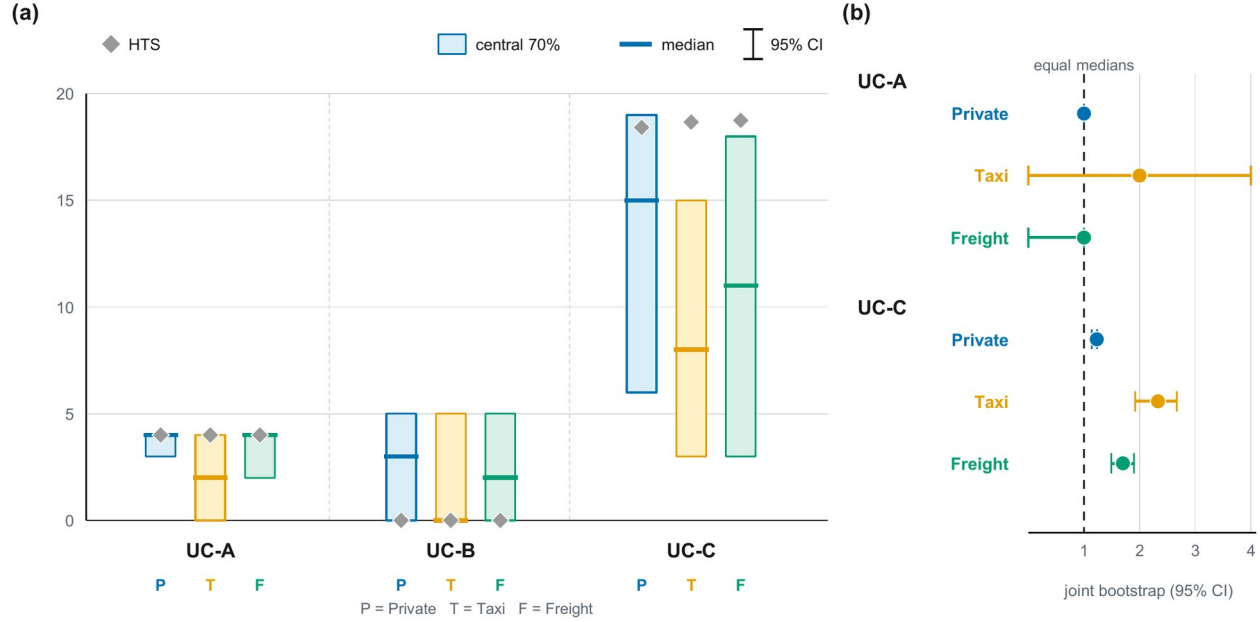


Fig. 4. Mobility-opportunity evidence and HTS/BMS ratios. (a) BMS vehicle-day feasible hours: boxes span the 15th–85th percentiles, colored segments are medians, black whiskers are vehicle-cluster 95% confidence intervals, and gray diamonds are HTS proxies. (b) UC-A/UC-C median ratios with joint HTS-person-day/BMS-vehicle-cluster 95% confidence intervals; $\rho = 1$ marks equal medians. UC-B is omitted because its HTS estimate is zero. The BMS subset has 108 vehicles and 23,756 vehicle-days.

A. Use Case mobility-opportunity contrasts

TABLE III. Use Case rules implemented in the BMS and HTS analyses. The shared SoC cutoff has different temporal support: hourly BMS SoC versus estimated day-average HTS SoC.

UC	Service	Window	SoC $\geq$	BMS hourly dwell rule	HTS day-level dwell rule
A	Peak shaving	17–21 h	30%	Count each unoccupied hour in window.	Credit 4 h only if active span avoids window.
B	Midday discharge	10–15 h	50%	Count each unoccupied hour in window.	Credit 5 h only if active span avoids window.
C	All-day discharge	00–24 h	40%	Count dwell hours after 60 min since last trip.	Credit total daily idle if it reaches 1 h.

TABLE IV. Dataset and HTS-to-tier proxy mapping. NHTS commercial counts are person-days in households reporting the vehicle category, rather than verified operated-vehicle days.

Tier (BMS)	HTS mapping	n vehicles (BMS)	n person-days (HTS)
private (passenger)	UK NTS + US NHTS private	37	434,056 + 8,999
taxi	US NHTS VEHCOM_RS (rideshare-equivalent)	34	96
freight (light)	US NHTS VEHCOM_DEL (delivery-equivalent)	37	203

TABLE V. Model parameters used in the BMS-anchored comparison. Bootstrap $B=1,000$ applies to the original estimator; proxy and hourly-definition checks use 2,000 household/vehicle-cluster resamples.

Parameter	Value
Pack capacity (assumption for HTS recon.)	70 kWh
Consumption rate (HTS)	0.18 kWh/km
Illustrative discharge setpoint (UC-A/B)	7.4 kW
Illustrative discharge setpoint (UC-C)	11 kW
Cold threshold (battery temp)	5°C
Hot threshold (battery temp)	25°C
Cold discharge derate	30%
Hot discharge derate	20%
Bootstrap replicates B	1,000

TABLE VI. Main per-Use-Case cross-source ratios. The point ratio is the displayed HTS median divided by the displayed BMS median; intervals jointly bootstrap HTS person-days and BMS vehicle clusters.

UC	Tier	$\hat{H}^{BMS}$	$\hat{H}^{HTS}$	ρ	95% CI
A	private	4	4	1.00	[1.00, 1.00]
	taxi	2	4	2.00	[0.00, 4.00]
	freight	4	4	1.00	[0.00, 1.00]
C	private	15	18.42	1.23	[1.14, 1.24]
	taxi	8	18.67	2.33	[1.92, 2.67]
	freight	11	18.75	1.70	[1.49, 1.90]

Table VI reports median per-Use-Case mobility-feasible hours under BMS trip-level reconstruction versus HTS day-level synthesis, with a three-tier decomposition. Fig. 4(a) shows the BMS vehicle-day distributions against the HTS proxies; Fig. 4(b) reports direct median ratios and joint-bootstrap intervals. The near-collapsed HTS UC-C proxy separates into private, freight, and taxi tiers under Korean BMS reconstruction. For taxi UC-C, the direct cross-source ratio is $2.33\times$ with joint-bootstrap 95% CI [1.92, 2.67].

B. Gross monetary consequence per market

For a market m and Use Case u with service window W_u , the reproducible gross-revenue contextualization is

$$R_{i,u,m} = 365 P_u \min \dot{c} \quad (7)$$

where P_u is an illustrative discharge setpoint and $\dot{p}_{m,h}$ is the market's mean price per kWh at hour h . The 7.4-kW (UC-A/B) and 11-kW (UC-C) settings in Table V are

scenario inputs, not measured or certified export limits of the study vehicles. IEC 61851-23 and ISO 15118-20 establish equipment and communication requirements for bidirectional power transfer [26], [27], but standards compliance alone does not establish V2G export capability for the study vehicles. The uniform-within-window allocation makes the HTS/BMS revenue ratio equal to the mobility-hour ratio when neither source saturates the window. Applying Eq. 7 to the displayed UC-C medians yields annual DE day-ahead gross-revenue contrasts of EUR 3,877/yr (taxi), EUR 2,817/yr (freight), and EUR 1,242/yr (private) per vehicle. These are cross-source scenario differences, not measured revenue overestimates. NL/UK/KR prices rescale the monetary difference but do not alter the underlying mobility-hour ratio. Degradation costs and aggregator fees remain out of scope.

C. Bootstrap confidence intervals

A joint bootstrap (1,000 replicates) yields disjoint UC-C 95% intervals across the operational tiers: private 1.23

[1.14, 1.24], freight 1.70 [1.49, 1.90], and taxi 2.33 [1.92, 2.67]. In contrast, the small NHTS rideshare baseline (96 person-days) makes the UC-A taxi interval [0.00, 4.00] and the freight interval [0.00, 1.00] too wide for a comparable separation claim. Pairwise separation is therefore a UC-C result, not a general property of every Use Case.

HTS tier non-separation. The UC-C HTS medians are nearly collapsed at 18.42 h (private), 18.67 h (rideshare-equivalent taxi), and 18.75 h (delivery-equivalent freight). Their nominal freight $\hat{< taxi$ private order recurs in only 15.3% of joint-bootstrap replicates. By comparison, the BMS private $\hat{< freight$ taxi order recurs in 99.9% of replicates. Equation 4 therefore supports the interpretation that HTS cannot stably distinguish these operational tiers, while BMS traces resolve a robust tier

order; it does not justify treating the fragile HTS point order as a deterministic ranking that is then “reversed.”

D. UC-C temporal-definition stability and within-BMS check

The original Korean trip series replays 23,756 reported BMS vehicle-days with 0 UC-C mismatches. The common hourly operator in Eq. 1 uses 10,587 observed US NHTS person-day trip sequences, including the small rideshare-equivalent subset, with synthetic NHTS SoC. Under the original day-level NHTS formula, the rideshare-equivalent/Korean-taxi median ratio is $2.33\times$. Applying the common hourly temporal rule to both sources yields $2.25\times$ (household/vehicle-cluster 95% CI [2.00, 2.57]); the corresponding ratios are 1.20 for the US private proxy and 1.64 for delivery-equivalent versus Korean freight.

TABLE VII. UC-C matched-hourly taxi proxy/Korean-BMS median ratio across 12 SoC and consecutive-dwell gates. The original day-level HTS formula is not used in this grid; NHTS SoC remains synthetic.

SoC cutoff	30 min	60 min	120 min
30%	2.11	2.25	2.14
40%	2.11	2.25	2.14
50%	2.11	2.25	2.50
60%	2.38	2.57	2.50

Table VII shows that the taxi ratio spans 2.11–2.57 across the 12-cell SoC/dwell grid; the 95% cluster-bootstrap lower bound exceeds one in every tested cell (2,000 paired replicates). At the baseline 40%/60 min gates, restricting service to 06–22 h gives ratio 2.75 (95% CI [1.83, 3.67]). For the 17–21 h window, the Korean taxi median is zero in 25.9% of bootstrap draws, so an unconditional ratio interval is undefined. The always-defined difference of medians is 2.5 h (95% CI [1.0, 4.0]).

For the within-BMS aggregation check in Eq. 2, collapsing the same taxi trips to first departure, last arrival, and total distance produces a median of 7.44 h, versus 8 h under measured-endpoint hourly reconstruction. The within-BMS contrast is -0.56 h (95% CI [-3.25, 1.29]), whose interval includes zero. On the HTS side, switching from day-level to hourly reconstruction changes its rideshare median by 0.67 h; the remaining same-formula cross-source gap is 11.23 h.

E. HTS reconstruction-parameter robustness

We test whether the taxi UC-C ratio is sensitive to the HTS-side constants (start SoC = 100%, 70 kWh, 0.18 kWh/km) by recomputing the taxi and freight ratios—whose HTS baselines are US-only (VEHCOM_RS, VEHCOM_DEL) and exactly reproducible—over a 27-cell grid (start SoC $\in [60, 100]\%$, pack $\in [40, 70]$ kWh, consumption $\in [0.15, 0.25]$ kWh/km). Because UC-C is dwell-driven and the 40 % SoC gate rarely binds at commercial daily distances, the original-estimator taxi ratio ranges from 2.24 to 2.33 and freight from 1.50 to 1.70. A US-only private baseline gives 1.228 versus the UK+US-pooled 1.230.

F. Commercial-proxy and linkage robustness

The primary VEHCOM_RS and VEHCOM_DEL assignments identify person-days in households reporting a corresponding vehicle. We therefore also require at least one trip whose vehicle ID matches the reported subtype and compare a pooled commercial category. Table VIII

gives taxi ratios of 2.33 for the household-rideshare proxy, 2.42 for the vehicle-linked subset, and 2.21 for the broad commercial pool; delivery comparisons shift less. These intervals use 2,000 NHTS-household/BMS-vehicle cluster resamples and retain all days within each cluster. For the household-rideshare comparison, changing the

HTS resampling unit from person-days (Table VI, $B=1,000$) to households (Table VIII, $B=2,000$) widens the 95% interval around the same 2.33 point estimate from [1.92, 2.67] to [1.89, 2.82], while its lower bound remains above one.

TABLE VIII. UC-C commercial-proxy sensitivity. Ratios compare the indicated HTS proxy with the Korean BMS tier median. Confidence intervals use household-cluster HTS and vehicle-cluster BMS resampling.

HTS proxy	BMS comparator	Person-days	Households	HTS median (h)	Ratio	95% CI
Household rideshare	Taxi	96	55	18.67	2.33	[1.89, 2.82]
Vehicle-linked rideshare	Taxi	53	41	19.33	2.42	[1.89, 2.88]
All commercial	Taxi	1,588	878	17.67	2.21	[1.91, 2.55]
Household delivery	Freight	203	113	18.75	1.70	[1.51, 1.97]
Vehicle-linked delivery, no rideshare	Freight	132	94	18.53	1.68	[1.48, 1.98]

Under the original all-or-zero UC-A rule, household-rideshare, vehicle-linked-rideshare, and pooled-commercial samples (96/53/1,588 days) each have a 4-h HTS median (95% household-cluster interval [0, 4] h) versus 2 h for BMS taxis; vehicle-linked all-commercial falls to 0 h. Within household delivery, linkage reduces 203 to 129 days and the median from 4 to 0 h (95% interval [0, 4] h). This 129-day subset is restricted to the original household-delivery branch; Table VIII’s 132-day row additionally includes three person-days from rideshare-labeled households with an observed linked delivery trip but no observed linked rideshare trip. Because 1.05% of BMS-taxi bootstrap medians are zero, the unconditional ratio interval is undefined.

G. Climate-conditioned derating

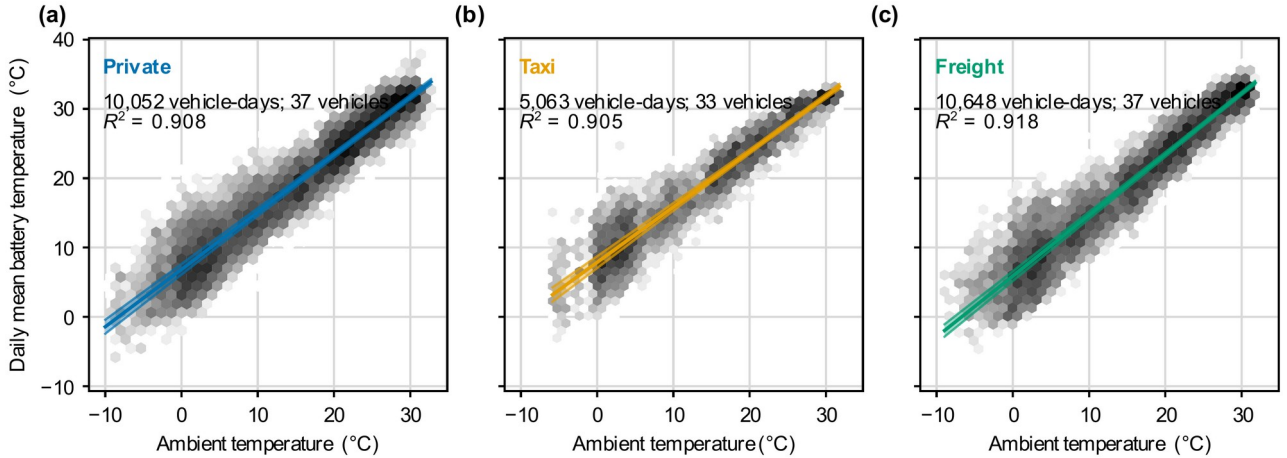


Fig. 5. Observed Korean ambient-to-battery temperature relationships for (a) private, (b) taxi, and (c) light-freight vehicle-days. Hexagons show observed vehicle-day density in the T_{air} - T_{bat} plane, colored lines show per-tier ordinary least-squares fits, and shaded bands show 95% confidence intervals for the fitted mean from 5,000 vehicle-cluster bootstrap resamples. Panel-specific sample counts and descriptive R^2 values are printed in the figure.

Fig. 5 shows the observed vehicle-day densities underlying the per-tier fits. These regressions use an independently filtered subset of 25,763 vehicle-days from 107 vehicles, rather than the 23,756 trip-reconstructable vehicle-days used for mobility analysis. KR ASOS + KR BMS daily aggregates yield $T_{bat}^{private} = 6.84 + 0.827 T_{air}$ ($R^2 = 0.908$), $T_{bat}^{taxi} = 7.87 + 0.798 T_{air}$ ($R^2 = 0.905$), and $T_{bat}^{freight} = 5.89 + 0.878 T_{air}$ ($R^2 = 0.918$). Resampling vehicles with all their days gives slope 95% intervals of [0.800, 0.854] for private, [0.764, 0.830] for taxi, and [0.854, 0.901] for freight ($B=5,000$). These intervals reflect repeated days within the sampled vehicles; all 33 taxis in the thermal fit are mapped

to Daegu. The raw-channel sensitivity compares all 18 channels with ordinal channels 1, 5, 9, 14, and 18 on the same 1,089 vehicle-day rows (7,499,242 timestamps) from 11 nominally exact-18 passenger vehicles with overlapping raw data (8 private and 3 taxi). The pooled slope changes from 0.8030 to 0.8216 (difference 0.0185, vehicle-cluster 95% CI [0.0123, 0.0255]); descriptive R^2 changes from 0.8885 to 0.8984. This raw-channel sensitivity lacks physical positions and does not reproduce the freight layout.

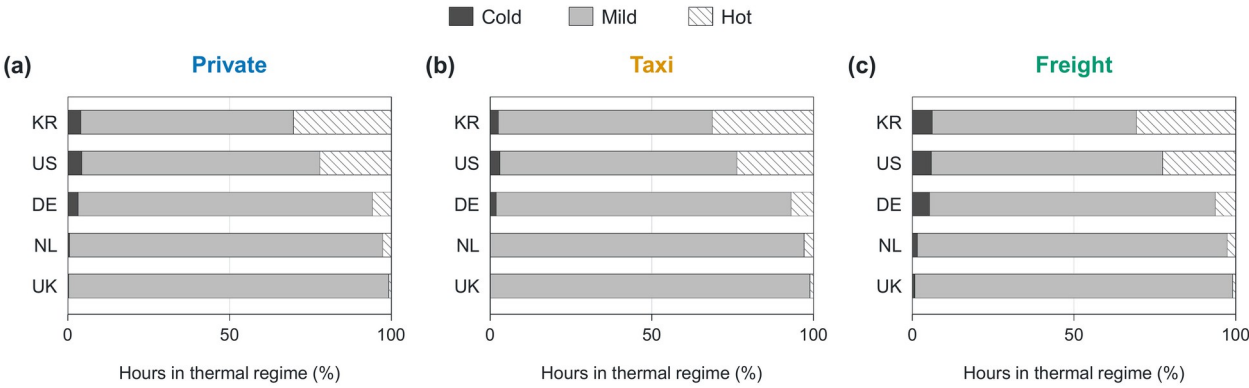


Fig. 6. ERA5-projected thermal-regime occupancy for (a) private, (b) taxi, and (c) light-freight tiers across sampled KR, US, DE, NL, and UK locations. Each country bar partitions projected hours into cold, mild, and hot battery-temperature regimes; the horizontal scale is 0–100%.

Applying the regressions to ERA5 reanalysis over sampled regions in KR/UK/US/DE/NL yields the country-by-tier occupancy in Fig. 6. The UC-A discharge-power derating scenario in Table IX reaches 7.99% for KR freight and 0.43% for UK freight.

TABLE IX. Scenario-projected UC-A discharge-power derating by sampled country locations and tier (%). The per-tier temperature models are fitted to Korean BMS data only.

Country	Private	Taxi	Freight
KR	7.26	7.02	7.99
US	5.70	5.63	6.29
DE	2.11	1.95	2.86
NL	0.68	0.57	0.97
UK	0.22	0.24	0.43

With the freight intercept fixed, perturbing its slope by $\pm 0.0185 \frac{^\circ\text{C}}{^\circ\text{C}}$ changes Table IX derating by at most 0.32 percentage points (US: 6.29% to 5.97/6.60%; KR: 7.99% to 7.73/8.23%). This is a slope stress test, not a freight sensor-layout refit.

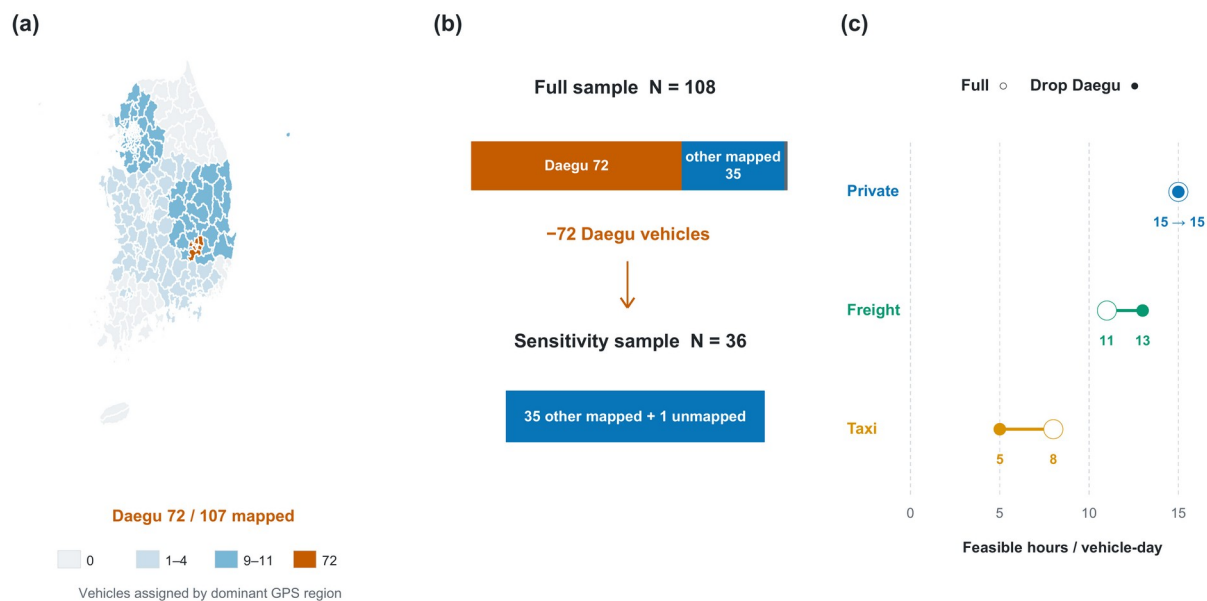


Fig. 7. Regional sensitivity of UC-C mobility opportunity. (a) Korean administrative-boundary choropleth shows the distribution of 107 region-mapped main vehicles, including 72 in Daegu. (b) Removing Daegu leaves 35 other-mapped vehicles plus 1 unmapped vehicle (36 of 108 total). (c) Tier-specific dumbbells connect full-sample and drop-Daegu medians; the private, freight, taxi order is preserved.

H. BMS sample sensitivity

The main mobility-analysis subset contains 108 vehicles: 107 are region-mapped and 1 is unmapped. Removing Daegu retains 35 other-mapped vehicles plus the unmapped vehicle (36 total). Fig. 7(c) shows the tier medians directly: private 15 → 15 h, freight 11 → 13 h, and taxi 8 → 5 h. Leave-one-region-out sensitivity yields freight UC-C in [11, 13] h and taxi UC-C in [5, 8] h; subsamples of $n = 10, 20, 30$ preserve the private↗freight↘taxi order.

VI. Discussion

A. Interpretation

HTS can supply a mobility baseline for survey-representative fleets; commercial inference requires matched operational roles. The sampled 2024–2025 UK/NL locations have lower annual-average projected derating than KR/US, but this Korean-fit scenario depends on selected grid cells, regime cutoffs, and assumed power losses. It establishes neither national averages nor immunity to heat extremes (Sec. VII).

B. Climate cutoff sensitivity

The KR/UK freight contrast is about $18\times$ at the default 5°C cold cutoff, but about $3\times$ at 10°C because UK bias rises to 4.16%. Sensitivity over $0/5/10/15^\circ\text{C}$ and mild/default/severe derating preserves the sampled-period contrast, while its magnitude changes with the scenario definition.

C. From mobility opportunity to delivered service

Under the same service-window and SoC rules, delivered service cannot exceed connected availability, which cannot exceed modeled mobility opportunity. Charger access, bidirectional capability, connection behavior, dispatch, scheduling, grid constraints, degradation, and state of health further reduce service or value. Eq. 7 is gross-price context, not measured dispatch or net revenue. External validation requires independent BMS fleets with matched roles, broader regions and seasons, and recorded connection and charger capability.

VII. Limitations

- **Climate transportability.** Korean BMS+ASOS fits (all 33 thermal-regression taxis in Daegu) are transferred to selected 2024–2025 ERA5 grid

cells using daily means. Vehicle-market transfer, national spatial coverage, short extremes, and future climates remain unvalidated; the hot-regime derate is assumed, with cutoff/derate sensitivity in Sec. VI-B.

- **Thermal sensing.** Every fit uses T_{mean} ; center/edge summaries are unused. The passenger raw-channel sensitivity and fixed-intercept freight stress test (≤ 0.32 percentage points) do not reconstruct freight sensor positions; between-tier comparisons may still reflect architecture.
- **Cross-source validity.** NHTS commercial labels are noncontemporaneous household proxies, not Korean taxi/freight analogues; private pooling also mixes UK+US while commercial proxies are US-only. Country, role, source, and assignment therefore remain inseparable, so no ratio identifies survey-design bias (Sec. V-F).
- **Estimator sensitivity.** The common-hourly UC-C check aligns timing but retains synthetic NHTS SoC and proxy roles; the evening ratio is undefined in 25.9% of bootstrap draws (Sec. V-D).
- **Connection and service translation.** The estimator omits a connection gate and therefore measures mobility-feasible dwell rather than connected availability (Sec. IV-A); downstream hardware, dispatch, degradation, grid, and economic filters are summarized in Sec. VI-C.
- **Regional representativeness.** Daegu contributes 72 of 107 region-mapped vehicles; the region/subsample checks in Sec. V-H support within-sample ordering but not magnitudes or ordering in independent fleets.
- **UC-B resolution.** The day-level HTS rule yields zero for UC-B, so this contrast is not identifiable without trip-level reconstruction.

VIII. Conclusion

Under the stated proxy mappings and rules, HTS medians do not stably distinguish UC-C hours, whereas Korean BMS regional and subsample checks retain private↗freight↘taxi. The US rideshare-equivalent/Korean-taxi ratio remains above unity across tested proxies, battery assumptions, and hourly gates; within-BMS aggregation does not explain the contrast. Korean thermal scenarios give lower annual-average derating in sampled UK/NL

locations than KR/US. Fleet planning should combine calibrated duty cycles and thermal, connection, dispatch, and grid limits.

Data Availability and Ethics

Revision scripts and aggregate outputs are retained by the authors but are not publicly deposited. Raw BMS traces are governed by a data-provider agreement and cannot be redistributed; raw reproduction requires provider authorization. UK NTS is available under UK Data Service terms; US NHTS, ERA5, and KMA ASOS are available from the cited providers. The BMS study is a secondary analysis of previously collected pseudonymous telemetry; no personally identifying driver information was used. The authors determined that this use and the survey analyses were outside institutional human-participants review; no IRB application was submitted or formal exemption issued.

Acknowledgment

OpenAI GPT-5 assisted with English editing, drafting the common-hourly and commercial-proxy sensitivity methods and analysis code (Secs. IV-D and V-D–V-F), and preparing and revising editable figures (Figs. 1–7). Anthropic Claude was used for English editing. The authors are responsible for verifying the methods, data analysis, figures, and final text.

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