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Charge Retention Exceeds Energy Retention on Average in Four Battery Histories

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Abstract

Using ampere-hour retention to describe retained electrical energy presumes a stable voltage contribution. Four NASA laboratory cell histories allow this presumption to be measured on matched observation windows. We integrated current and voltage–current products from each record's start to its first 2.7 V downward crossing, then normalized 636 discharges to each cell's first record. Energy retention minus charge retention averaged −0.810 percentage points with equal cell weights; the corresponding mean absolute gap was 1.008 points. Final-record gaps ranged from −1.233 to −2.841 points. Fixed endpoint alternatives gave mean gaps from −0.815 to −0.790 points. These finite records show that charge retention can overstate energy retention even after window alignment. Four laboratory histories supply neither population uncertainty nor evidence of lunar hardware performance.

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Charge and energy answer different questions

An ampere-hour quantity accumulates electric current through time. A watt-hour quantity additionally weights that current by terminal voltage. The two can decline together as a cell's recorded performance changes, while their normalized histories still differ. Electrochemical-system analysis distinguishes charge transfer, electrical potential and energy (Newman and Thomas-Alyea, 2004). Dividing each quantity by its own initial value removes its unit, but does not remove the voltage term that separates the underlying measurements.

We examine that distinction using four existing NASA battery histories (Saha and Goebel, 2007). The empirical question is whether charge retention approximates energy retention when both quantities are reconstructed from identical measured samples and the same discharge endpoint. We do not multiply ampere-hours by an assumed nominal voltage. Instead, each record provides its own voltage history, allowing the retained-energy comparison to be calculated directly.

Capacity estimation is an established battery-monitoring task. Farmann and colleagues review methods for estimating capacity on board vehicles (Farmann et al., 2015). Our analysis addresses a preceding measurement choice: which reported quantity is being retained? A technically valid estimate of charge capacity would not automatically estimate a different energy quantity. This follows the general requirement that a measurement's numerical representation remain connected to its defined property (Stevens, 1946).

The term state of health covers a range of monitoring requirements and estimation approaches (Berecibar et al., 2016). Likewise, reviews of lithium-ion monitoring distinguish several states and functions that an application may need (Waag et al., 2014). We therefore use narrowly defined retention variables. They compare complete observed discharge windows across a history, rather than estimating an unobserved electrochemical state or assigning a universal health score.

Two propositions guide the comparison. P1 is that normalized charge and energy need not coincide even with a common endpoint, because their relationship contains a voltage-history contribution. This is a definition-based expectation; its observed magnitude and direction require data. P2 is that a useful report should distinguish that discrepancy from choices about the recorded endpoint and from differences among the four cell histories. We evaluate both with fixed processing rules and finite descriptive summaries.

Reconstructing the discharge measurement

The source is the first group in NASA's officially linked Battery Data Set: BatteryAgingARC-FY08Q4.zip, containing B0005, B0006, B0007 and B0018. We retrieved that group on 16 November 2026 from the repository's PHM-hosted archive. The selected group contains 56,517,371 bytes and has a retained SHA256. HTTP byte ranges obtained the group without downloading the other groups in the larger archive. Original MATLAB files, their checksums, the README and the two official source pages remain in the local source record.

The repository requests the Saha and Goebel 2007 dataset citation. That requested citation year does not date every measurement: original date vectors and file headers are preserved separately from the archive's later packaging. NASA's Open Data catalog describes public access but gives no specified license. The repository offers the data for research and asks acknowledgment. We retain that qualified usage information rather than asserting an unrestricted redistribution license or a public-domain designation.

The four files contain 636 discharge records: 168 each for B0005, B0006 and B0007, and 132 for B0018. Charge and impedance operations are also present, but are not treated as additional discharge observations. Actual discharge fields include measured terminal voltage in volts, measured current in amperes, measured temperature in degrees Celsius, elapsed time in seconds and a provider-derived Capacity field in ampere-hours. The SI distinction between physical quantities and their units remains relevant after normalization (BIPM, 2019).

Every included voltage, current and time vector is finite and has matching length. Time increases strictly in all records. Each first voltage exceeds 2.7 V, and each record contains an adjacent downward crossing of that level. These checks leave all 636 discharges eligible. The metadata ambient-temperature label is 24°C throughout; it does not state that the measured cell temperature stayed constant.

The stored records are substantially less frequent than the generic catalog's approximate 10 Hz acquisition description. Record-level median intervals span 9.360-18.718 s for the first three cells and 9.391-13.985 s for B0018. The maximum observed interval is 20.5 s. All integrals therefore use actual time differences. Treating the export as uniformly sampled at the catalog's acquisition rate would produce a different and unjustified numerical measurement.

The README gives different nominal termination voltages across cells. Recorded voltage minima can undershoot those values, and many records continue through voltage recovery after current interruption. A file's final timestamp is consequently not an interchangeable discharge endpoint. We retain complete source arrays while limiting the primary calculation to the first recorded crossing of a common 2.7 V criterion. That criterion defines the comparison; it is not proposed as an operating limit.

For a crossing bracket with the preceding voltage above 2.7 V and the next voltage at or below it, we interpolate voltage and current linearly to the 2.7 V endpoint. The calculation starts at the first logged point, without selecting an initial current threshold. Small positive current values are retained alongside the mainly negative discharge currents. No absolute-value transformation or zero clipping changes their contribution. Source points after the primary endpoint, including reverse-current and recovery information, remain in the audit but do not enter the primary integrals.

Within an interval of duration dt, the selected representation makes current and voltage separately linear. Charge is minus dt times the mean endpoint current, divided by 3,600. Energy is minus dt times (2V0I0 + V0I1 + V1I0 + 2V1I1)/6, also divided by 3,600. The second expression integrates the quadratic product of the two linear functions. Numerical integration depends on the interpolant being integrated (Atkinson,

1989); exact integration of this representation is not exact knowledge of the unmeasured continuous signal.

Normalization and the empirical contrast

For record j in a cell, Q retention is Qj/Q1 and E retention is Ej/E1, using that cell's first eligible record. All four baselines are the first discharge in their files. The primary gap is 100 times E retention minus Q retention, in percentage points. A negative gap means that charge retention overstates energy retention for this specific comparison. Neither trajectory is forced to be monotone or restricted to a nominal zero-to-one range.

The quantity E/Q defines a net current-weighted mean terminal voltage under the chosen integration. Hence E retention divided by Q retention equals the ratio of effective voltages in the current and baseline records. This identity explains how the two retention variables can separate. It is not a discovered battery law or evidence of a particular degradation mechanism. Studies connecting degradation modes to measured voltage behavior use additional diagnostic information (Birkl et al., 2017). The gap calculated here does not identify those modes.

Detailed work on capacity-fading mechanisms likewise shows that mechanism identification is a separate research task (Dubarry and Liaw, 2009). A wider review describes the many physical and chemical mechanisms involved in lithium-ion degradation (Edge et al., 2021). We estimate none of their separate contributions. Our measurements retain a change in the voltage contribution without deciding whether it arose from one electrode process, resistance, temperature history, rest or another feature of the experiment.

The primary summary first averages gaps over a cell's observed records and then gives the four cell means equal weight. Thus B0018's shorter observed history does not receive less cell weight. We also average the four within-cell mean absolute gaps. Weighting must specify the quantity being summarized (Solon et al., 2015); these are descriptions of four named histories, not a cycle-pooled population effect.

For each cell we retain signed and absolute gaps, their observed range and median, and the final-record comparison. The median follows the ordinary ordered-value convention, averaging the middle two values when needed. Statistical software can use different quantile definitions, so the chosen convention matters for reproducibility (Hyndman and Fan, 1996). A distribution of serially related records describes variation along a history; it is not a collection of independent cell replications.

Numerical agreement requires a specified quantity

The common-window measurement is relevant to scenarios whose resource inputs are explicitly in watt-hours. Lunar-Bench's Table 11 supplies a 200 Wh auxiliary battery in a power-allocation example (Xiao et al., 2026). That input motivates distinguishing retained charge from retained energy. The NASA cells are laboratory specimens, not that scenario's battery. We neither scale their measurements into a 200 Wh pack nor test the benchmark's scheduling, models or evaluation indicators.

Diagnostic and prognostic battery models can relate observed changes to proposed degradation modes (Dubarry et al., 2012). Our finite integration comparison supplies a narrower result that precedes such modeling. It also differs from estimating instantaneous state of charge with a state-space estimator, as in battery-management work using extended Kalman filtering (Plett, 2004). A record's retained discharge quantity relative to its first recorded counterpart is not an estimate of its moment-to-moment state of charge.

Uncertainty statements must match the evidence supporting them. The measurement-uncertainty guide distinguishes the defined measurement model and its uncertain inputs (JCGM, 2008). This archive does not provide a complete calibration uncertainty budget for our derived integrals. We therefore do not attach standard errors, confidence intervals or probability coverage to them. The available checks concern reproducible calculations, fixed endpoint choices and the composition of the four-case summary.

The agreement literature also distinguishes a paired value difference from a high association between two measurements (Bland and Altman, 1986). Both retention histories can track a broad decline while differing systematically. Concordance concepts make the same distinction between correspondence and equality of values (Lin, 1989). The international metrology vocabulary defines the measurand as the quantity intended to be measured (JCGM, 2012). Here, retained charge and retained energy specify different quantities, so a shared normalization does not make them identical. We report paired percentage-point gaps, rather than treating a correlation as evidence that an Ah-based description preserves Wh retention. Figure 1 connects the measured channels to the two retained quantities and the fixed sensitivity comparisons.

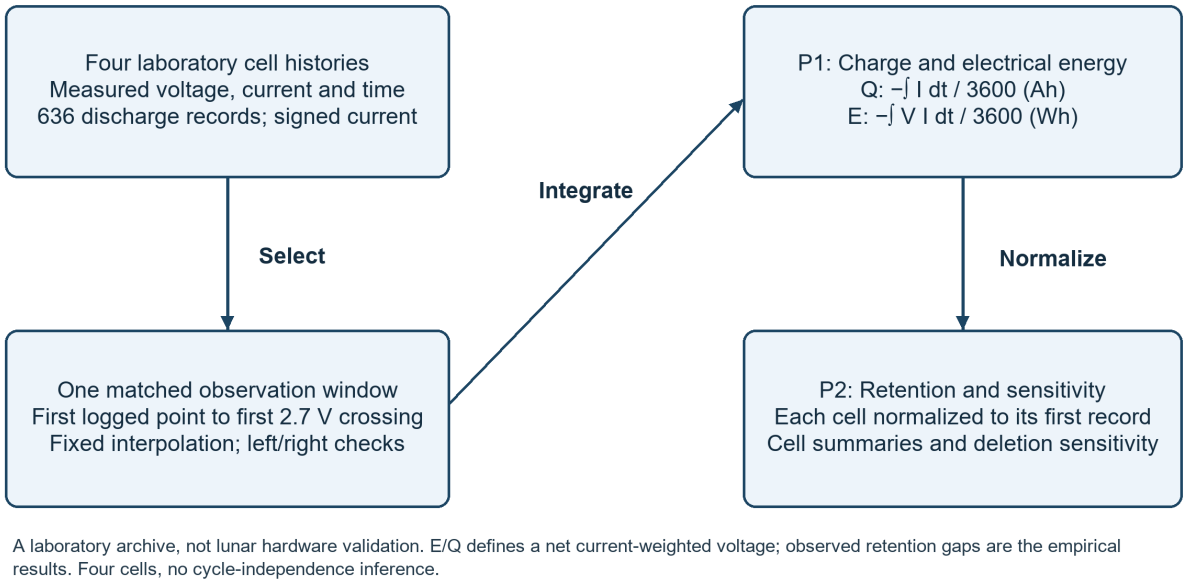


Figure 1. Measured voltage, current and time define a common window and two integrals. P1 concerns their observed normalized difference; P2 concerns cell composition and fixed endpoint processing. The arrows represent data operations, with no model of a causal degradation mechanism.

Energy retention is lower on average in every history

The equal-cell signed gap is -0.810 percentage points, and the corresponding mean absolute gap is 1.008 points. All four cell means are negative, ranging from -1.678 to -0.436 points. However, 193 of the 636 individual record comparisons have positive gaps. The mean direction therefore does not describe every step of each history. Table 1 preserves those histories as separate cases. Figure 2 shows every record's signed gap in its original within-cell order, including reversals and positive values.

Table 1. Main interpolated-endpoint results. Gap is energy retention minus charge retention. All quantities use each cell's first eligible record as baseline; final records are discharge 168 for B0005-B0007 and discharge 132 for B0018. Scope is four finite cell histories and 636 serial records. The equal-cell mean's delete-one-cell range is -0.935 to -0.521 pp, a deterministic composition sensitivity rather than a confidence interval.

Cell	Records	Mean gap (pp)	MAE gap (pp)	Final Q retention (%)	Final E retention (%)	Final gap (pp)
B0005	168	-0.599	0.869	71.438	69.854	-1.584
B0006	168	-1.678	1.772	58.140	55.299	-2.841
B0007	168	-0.436	0.657	76.107	74.875	-1.233
B0018	132	-0.528	0.733	72.359	70.834	-1.526

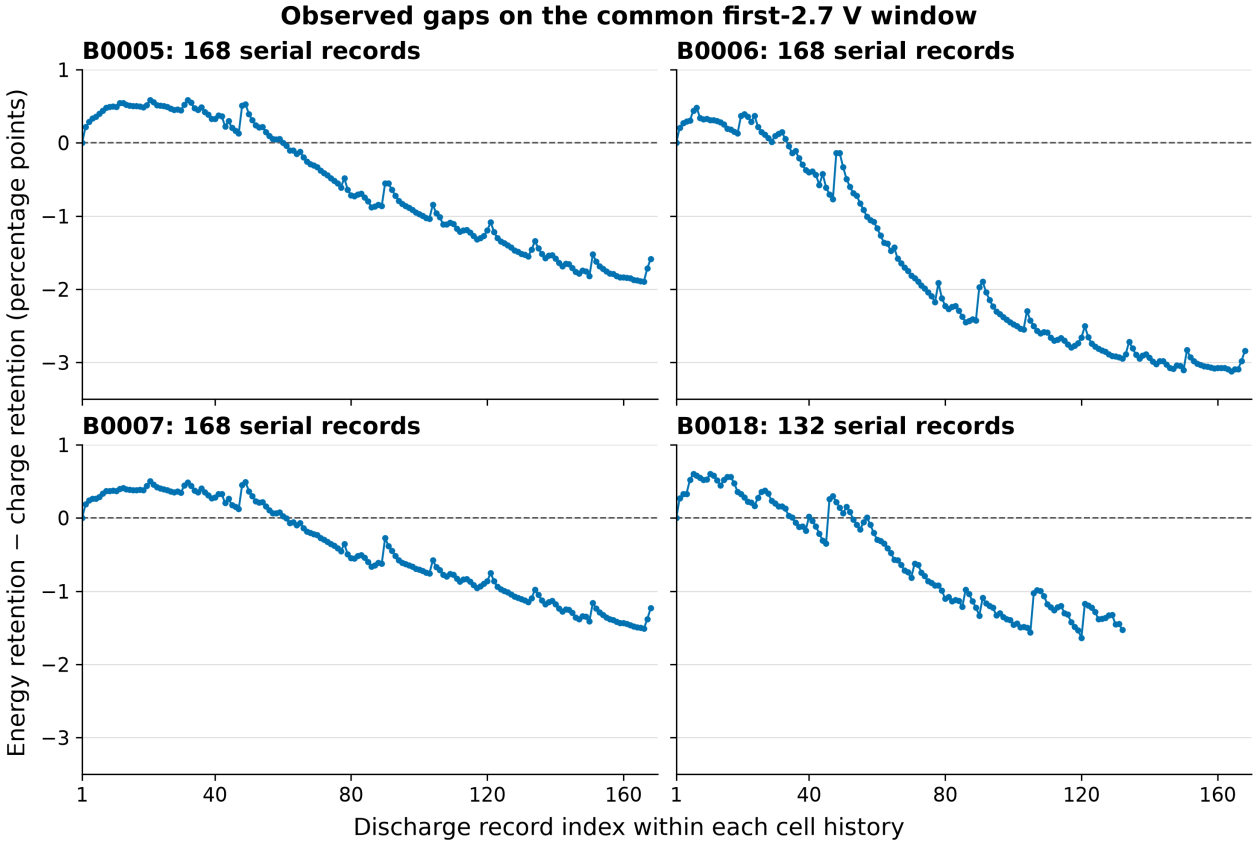


Figure 2. Main-window energy-minus-charge retention gaps for all 636 records, normalized to each cell's first discharge. Dots mark individual records; connecting segments show their order, without smoothing or an elapsed-time interpretation. The dashed reference is zero. Shared axes retain the shorter B0018 history without extrapolating it. Four cases supply no population confidence band.

For B0006, integrated charge changes from 2.032 to 1.181 Ah between its first and final records; integrated energy changes from 7.221 to 3.993 Wh. The respective final retentions are 58.140% and 55.299%, giving a -2.841-point gap. The other three final gaps are also negative. These are observed endpoint comparisons, not estimates that the cells share an identical state of life at matching discharge indices.

Prior multi-year cycling work reports capacity and discharge energy as distinct battery outputs under varied chemistry and cycling conditions (Preger et al., 2020). Our result does not introduce that distinction. It measures its consequences in this four-cell archive after aligning the observation window

and defining the baseline. Manufacturer and exact chemistry are not established in the acquired NASA files, so no chemistry-specific explanation is assigned to the differences.

The effective voltage ranges within these histories are approximately 3.36-3.58 V. Their role in the retention identity is mathematical: relative energy depends jointly on relative charge and the effective-voltage ratio. The numerical histories establish the size of the observed separation. They do not establish which microscopic process changed the voltage contribution. Measurement-error analysis also cautions that constructed variables can share uncertain inputs (Carroll et al., 2006); Q and E here both depend on the same current and endpoint data.

Endpoint choice and the provider capacity field

We fixed two endpoint alternatives before integration: stop at the last sample above 2.7 V, or include the first sample at or below it. Each policy uses the same integration formula and its own first-record baseline. Their equal-cell mean gaps are -0.815 and -0.790 points, compared with -0.810 for interpolation. Table 2 reports all three policies. The observed processing span is narrow relative to the mean gap in this collection, but it is not a bound on continuous physical energy between samples.

Table 2. Fixed endpoint-processing sensitivity. Each row includes all 636 records in the same four cells. MAE is computed within cells and then averaged equally. Deletion ranges remove one whole cell and average the remaining three; no row or range is a confidence interval.

Endpoint rule	Equal-cell mean gap (pp)	Equal-cell MAE (pp)	Delete-one-cell range for mean gap (pp)
Interpolated 2.7 V	-0.810	1.008	-0.935 to -0.521
Last sample above	-0.815	1.014	-0.947 to -0.514
First sample at/below	-0.790	0.999	-0.931 to -0.491

Whole-cell deletion changes the main mean from -0.935 to -0.521 points. This wider range describes the different contributions of these four observed histories. It cannot be interpreted as the probability distribution of another cell's discrepancy. Numerical-processing sensitivity, finite-case composition and measurement uncertainty are different considerations (Smith, 2013). Changing the last-sample convention addresses only the first of them.

The original Capacity field is documented as discharged ampere-hours to 2.7 V. We preserve it as C and compare it with our integrated Q, without forcing agreement. Across the records, C is slightly larger than Q; the maximum relative difference is 0.601%. Table 3 shows the cell-level comparisons. Their normalized-history mean absolute differences span 0.090-0.257 percentage points. This diagnostic supports a close numerical relationship under the stated processing, while leaving the provider's original integration details unresolved.

Table 3. Provider Capacity versus independently integrated common-window charge. The comparison is an algorithm/window agreement diagnostic, not an error estimate relative to a true capacity. Each row retains its full cell history and first-record normalization.

Cell	Mean provider C-Q (Ah)	Maximum (C-Q)/Q (%)	Normalized C versus Q MAE (pp)
B0005	0.003301	0.601	0.151
B0006	0.003464	0.593	0.090
B0007	0.003496	0.581	0.257
B0018	0.003476	0.552	0.101

Documentation quality matters to this interpretation. The actual discharge structures name Current_load and Voltage_load, whereas the generic description uses charge-channel names for the load fields. We use the measured terminal channels directly and retain the naming difference. Data quality for reuse includes whether field definitions and processing support the intended question (Wang and Strong, 1996). The slight C-Q discrepancies do not identify one channel or calculation as wrong.

Four histories do not identify a general aging law

The discharge index is an ordering variable. It does not separate elapsed time, rest, charging exposure and cycling effects. Calendar-aging studies explicitly investigate changes associated with storage conditions and elapsed time (Keil et al., 2016). This archive's four histories cannot identify those effects through the retention gap alone. Their common ambient-temperature label and differing nominal termination programs are not randomized interventions.

Cycle-life prediction is also another task. For example, data-driven work predicts future battery life before substantial capacity loss is observed (Severson et al., 2019). We make no held-out life prediction and infer no remaining useful life from the four final records. The observations are a finite measurement comparison over the recorded histories. Sampling theory does not turn their 636 repeated records into a probability sample of 636 cells (Neyman, 1934).

The NASA-related prognostics literature uses explicit statistical and electrochemical models to infer remaining life and uncertainty (Saha et al., 2009). Our deletion and endpoint ranges are not substitutes for those model-based quantities. They answer how the reported descriptive result changes when a named case or a fixed processing convention changes. They provide no population coverage, causal aging attribution, charge-control proposal or safety recommendation.

Retaining the distinction in reusable energy inputs

Within this source, relative Ah is an imperfect numerical proxy for relative Wh even when both use the same 2.7 V window. Its average overstatement is below one percentage point across the four cell means, while the mean absolute discrepancy and final-record gaps are larger. An application using these histories can retain both quantities instead of silently treating unit-free retention values as interchangeable. Whether a particular discrepancy is acceptable requires an application criterion not supplied by these data.

The secondary-analysis protocol was frozen after source/schema inspection and before integrals were computed. The archive retains all original records after the crossing as source evidence, with crossing indices, interpolated endpoints and tail counts in the processed table. An independent scalar implementation recomputes every primary and alternative integral directly from the original MATLAB values, using Simpson's rule for the quadratic power representation. All 1,908 charge-energy pairs and the

retention summaries agree to numerical precision. Computational reproducibility depends on such links between inputs, definitions and reported values (Peng, 2011).

The retained source identities, usage conditions, units, window definitions and output checksums support reuse under FAIR principles (Wilkinson et al., 2016). No MATLAB or author code was executed, and no new laboratory experiment or language-model evaluation was performed. Accountable human source verification and final approval remain pending. The result concerns how two explicitly defined electrical quantities separate within four acquired laboratory histories, with their common window and finite scope attached.

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