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Equal Meter Coverage Can Yield Unequal Errors in Daily Energy and Peak-Hour Indicators

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Abstract

At 90% daily meter coverage, does the accuracy of a household summary depend on where the missing minutes fell? We imposed gaps on 1,358 complete one-minute household records and recomputed daily energy and the largest clock-hour mean. With dispersed gaps, the mean absolute relative errors were 0.19% for energy and 0.60% for the peak-hour mean. A single gap starting at a random minute raised them to 5.44% and 1.92%, respectively, at the same coverage. When a separate stress test deliberately suppressed the reference peak hour, peak error reached 19.12%. A coverage report based solely on the proportion of retained minutes would miss the different consequences of gaps for daily energy and peak demand.

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A question about data completeness

A daily completeness field can say how many meter readings arrived, while offering little detail about their distribution across the day. Suppose a service records 1,296 of the 1,440 expected minutes. The available observations could cover every clock hour at nearly the same rate, or the omissions could include consecutive hours that contain information about an important part of the recorded demand. An estimator based on the daily mean and an estimator that searches for the largest hourly mean respond to those cases differently. A well-documented comparison can quantify the resulting disparity with the underlying load and data volume held fixed.

Kan et al. (2024) place the selection of evaluation indicators at the centre of assessing low-carbon microgrids. A local load indicator used in such an assessment needs a definition for both the target quantity and the observations on which it is calculated. This study asks how much the daily energy total and maximum hourly mean of a household load record change when the same fraction of a day is absent under contrasting gap patterns. The estimands are measured-demand indicators at one household boundary. They can serve as inputs to broader performance assessments, where generation, network conditions and emissions would be documented separately. Li et al. (2023) connect the choice of flexibility indicators with the datasets that support them. Tang and Wang (2021) formulate an energy-flexibility index for grid-responsive buildings. Flexibility in those studies concerns the ability to change energy use. The two quantities examined here describe the quality of information available from a historical electricity record.

Time aggregation is already recognised as an important part of interpreting demand. Wright and Firth (2007) examine how time averaging changes domestic load statistics and estimates related to onsite generation. Torriti (2020) considers methods for aggregating information on residential electricity demand. Sandmeier et al. (2025) use a living-lab experiment to compare power peaks at different sampling intervals. Our analysis holds the target resolution constant and changes the positions of absent readings. The reference peak always refers to the highest of the 24 fixed one-hour averages from a complete day. The experiment thus measures what is lost when reporting coverage changes, using the same underlying time scale for estimating the target on every trial.

Why a total and a maximum can respond differently

Daily energy reflects the sum across a fixed recording period. If omitted minutes have approximately the same mean power as retained minutes, scaling the retained average to the day may recover a similar total. Evenly dispersed omissions make such similarity more plausible in a record with gradually varying power. A contiguous gap leaves entire segments poorly represented. Its position relative to the household's higher and lower consumption periods determines the direction of the error. Richardson et al. (2010) represent detailed residential load variation in a high-resolution demand model. Anvari et al. (2022) examine fluctuations in measured residential consumption, and Sanabria-Villamizar et al. (2022) characterise household demand profiles in both time and frequency domains. Stegner et al. (2019) study differences between measured household profiles and standardised load profiles. Together these studies motivate treating a day as a structured series rather than as an unordered pool of minutes.

The daily ratio also has a useful algebraic interpretation. Let the mean power of the complete day be A, the mean of the omitted readings be M, the number omitted be m, and the full number be N. When the estimator scales the observed mean to the full day, its signed relative energy error equals m / (N − m) multiplied by 1 − M / A. The omission budget determines only the first term. Two gap patterns at the same budget can still yield different errors because they remove values from different parts of the series. The peak-hour mean has an additional sensitivity. Removing much of one hour can disqualify it under a within-hour coverage rule. When that hour is the highest reference hour, the peak estimate comes from another part of the day. If the reference hour remains eligible, averaging its retained readings can still shift its value.

The first proposition, P1, is that a randomly placed contiguous gap yields greater mean absolute relative error than evenly dispersed omissions at the same coverage, with a potentially different increase for each indicator. The second proposition, P2, concerns a deliberately adverse case. Removing the complete reference peak hour within a contiguous block should increase the peak error compared with dispersed omissions. That condition uses the complete record to place the gap, which makes it a stress test of indicator sensitivity. Rubin (1976), Little and Rubin (2002), and Schafer and Graham (2002) distinguish missing-data mechanisms and their implications for inference. The benchmark treatments assign their missingness mechanically and allow comparisons under known rules. Actual metering failures in the archive can have other causes and positions.

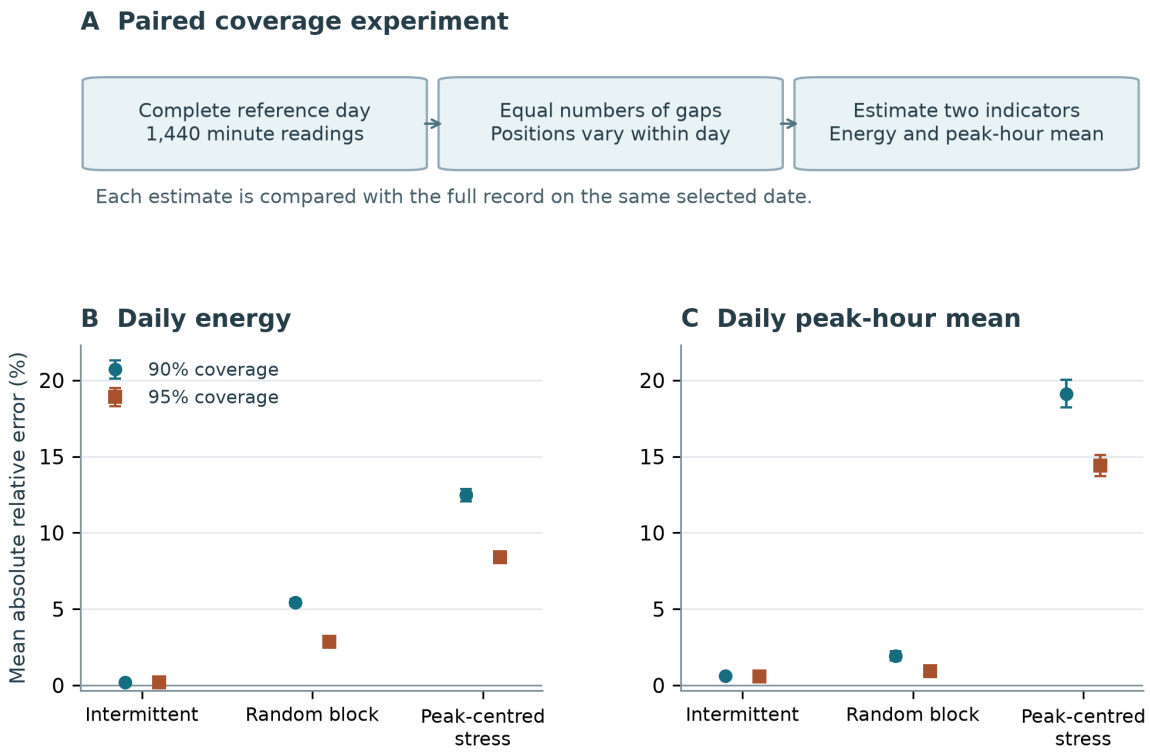


Figure 1. *Panel A shows the common reference and the two outcomes. Panels B and C show mean absolute relative errors with 95% intervals from calendar-week block resampling. The peak-centred condition is a stress test placed using the complete day.*

Reference series and designed omissions

Hebrail and Berard (2006) deposited the Individual Household Electric Power Consumption dataset in the UCI Machine Learning Repository. We read the archive date and time labels and the whole-house Global_active_power field. Values are one-minute active power in kilowatts. The archive contains 2,075,259 timestamp rows, with 25,979 missing active-power values. Timestamp labels are unique, chronologically ordered and continuous within the span. We preserve the dates and clock labels as published. The analysis uses only dates with all 1,440 minute readings available. This drops 84 candidate days, including partial days at the archive boundaries, and gives 1,358 eligible dates from 17 December 2006 to 25 November 2010. The complete-day median energy is 25.58 kWh and the median daily peak-hour mean is 2.80 kW.

The use of one recorded site is deliberate. It permits a controlled comparison with real complete-day observations while leaving population heterogeneity open. Kelly and Knottenbelt (2015) describe UK-DALE, which records domestic energy at detailed resolution across several homes. Murray et al. (2017) provide another multi-household longitudinal measurement resource. Zapata-Webborn et al. (2021) document a substantially larger smart-meter observatory with survey and dwelling information, and Thomson and Jenkins (2023) compare the scales and uses of the available household data resources. These examples show that a larger follow-up could compare the gap sensitivity of different households and recording systems. Our experiment contains no additional dwelling or appliance measurements. Wiese et al. (2019) emphasise the role of documented data processing in open electricity system modelling. Accordingly, the checksum, recorded units, and masking procedure are retained alongside the summary to make the single-site comparison reproducible.

Daily reference energy is the sum of the minute power readings divided by 60. The reference peak is the largest of the 24 one-hour means from fixed clock hours. The incomplete-record energy estimate is 24 times mean retained power. Incomplete hourly means are computed when the hour retains at least 30 of its 60 readings, and the largest eligible mean gives the measured peak estimate. These deliberately simple estimators establish a transparent baseline. The half-hour availability criterion is an analysis convention, with no claim about an instrument's operating specification. All means use the observed values assigned to the corresponding timestamp labels. No gap is filled with a reading from another day.

We examine two coverage levels. The 90% condition removes 144 minutes per day, and the 95% condition removes 72. In the intermittent treatment each hour receives a random phase. One of every ten minutes is omitted at 90% coverage and one of every twenty at 95%. This yields exactly six or three omissions in every hour. In the random-block treatment a single gap starts at a uniformly drawn feasible position that fits inside the day. The peak-centred stress treatment uses a contiguous gap of the same length, centred at the midpoint of the highest complete clock hour. When clipping is necessary at a day boundary, the gap shifts just enough to stay inside the day and still covers that full clock hour. The eligible days are the same for every condition. The two coverage experiments use the same seeded generator with separate draws, so the gaps at 95% coverage are not subsets of the 90% draws.

Relative error expresses the estimate minus the complete-day reference divided by the reference. We report the mean absolute relative error as the primary measure because errors of opposite sign can cancel in a signed average. Hyndman and Koehler (2006) review the effect that the choice of accuracy measure can have on time-series comparisons. In this sample the reference values for both indicators are positive for all retained dates. Each condition is first estimated at the date level. The paired increment in error compares the magnitudes for the same date under one assigned contiguous gap and under its intermittent counterpart. The 95% intervals resample from the 207 represented Monday–Sunday calendar weeks 5,000 times. Künsch (1989) motivates resampling blocks to retain local dependence. Here each draw retains the assigned masks and the set of available dates within each sampled week. The intervals describe the variation associated with the selected dates and fixed mask assignments, leaving uncertainty about other households and simulated assignments outside their scope.

Results on matched days

At 90% coverage, the mean absolute relative error in daily energy is 0.19% with dispersed omissions and 5.44% with a randomly placed block. The paired increase is 5.26 percentage points, with a 95% interval from 5.03 to 5.48. For the peak-hour outcome, the corresponding errors are 0.60% and 1.92%, with a paired increase of 1.32 points (1.03 to 1.64). The mean signed energy error under the random block is −0.27%, much smaller in magnitude than the mean absolute error. Gaps placed in lower- and higher-load parts of the day can offset each other in a signed average. They still create meaningful distortions when the daily indicator is used to compare individual dates.

Table 1. *Errors after controlled removal of minute readings from complete days.*

Coverage	Gap pattern	Daily energy mean absolute error, % [95% interval]	Peak-hour mean absolute error, % [95% interval]	Reference peak hour remains eligible (%)
90%	Intermittent	0.19 [0.18, 0.20]	0.60 [0.57, 0.64]	100.00
90%	Random block	5.44 [5.22, 5.67]	1.92 [1.63, 2.24]	89.84
90%	Peak-centred stress	12.47 [12.07, 12.88]	19.12 [18.22, 20.02]	0.00
95%	Intermittent	0.18 [0.17, 0.19]	0.59 [0.56, 0.62]	100.00
95%	Random block	2.87 [2.75, 2.99]	0.92 [0.72, 1.15]	95.73
95%	Peak-centred stress	8.41 [8.14, 8.67]	14.42 [13.73, 15.10]	0.00

Table 1 note. *Each condition uses 1,358 matched dates. An hour is eligible with 30 or more recorded minutes. Intervals are percentile intervals from resampling 207 calendar-week blocks. The reference peak hour comes from the complete record and is unavailable to a user inspecting an incomplete day.*

The maximum-hour result has a concentrated failure pattern. At 90% coverage the reference peak hour remains eligible on 1,220 of the 1,358 dates under a randomly placed block. On those dates the mean absolute peak error is 0.42%. On the 138 dates when the reference peak hour is ineligible, it is 15.19%. Eligibility is defined by the observed minute count within the reference clock hour. Matching that clock hour still allows deviations in the hourly mean, and the largest retained mean can come from a different hour. The conditional decomposition helps explain why the overall peak error is smaller than the overall energy error with random blocks. For the maximum-hour outcome the error is clustered on days whose reference peak is obscured. The energy estimator, by contrast, averages across the whole day and responds even to a retained sample that misses only lower-consumption periods.

Both indicators respond more strongly to the peak-centred stress test. At 90% coverage it produces mean absolute errors of 12.47% for energy and 19.12% for the peak-hour mean. The signed peak error averages −19.07%, consistent with removing the highest complete hour and estimating a maximum among those left. Increasing coverage to 95% reduces the random-block errors, but an outcome-targeted block still yields a mean absolute peak error of 14.42%. This case deliberately removes the reference peak hour on every date. Its result concerns the consequences of a specified loss of information, and the experiment supplies no estimate of the probability that a real monitor would fail in this way.

What to carry into a local indicator report

A daily reading count is useful for describing acquisition. On its own it leaves out the distribution of coverage within the day. Reporting the number of eligible hours or the longest consecutive gap would describe a different property of the observation design. A daily energy indicator can also retain its convention for extending the observed mean over missing minutes. For a peak indicator a separate clock-hour minimum makes the eligible comparison set explicit. An energy assessment can therefore expose the particular missingness summary that matters for each quantity while keeping the engineering definition of the quantity intact. This follows from the measurement distinction in the index-design problem raised by Kan et al. (2024).

Sophisticated gap filling may recover some structurally missing information by borrowing from nearby hours, days, or sites. Moritz and Bartz-Beielstein (2017) compare methods designed for univariate time series. Peppanen et al. (2016) consider smart-meter gap filling, and Weber et al. (2021) use similar

observed segments to impute energy series. Duarte et al. (2024) examine reconstruction of missing daily shapes, while Sartipi et al. (2025) benchmark a variety of statistical and learning methods for smart-meter imputation. Their results motivate evaluating whether an imputation method reconstructs the target feature as well as the individual values. This study supplies a baseline for that distinction. It leaves replacement model comparisons, forecasts, and new control policies outside the executed analyses.

Site-level electricity totals and peaks can be used in wider evaluations, but their implications depend on the setting. Völker et al. (2021) discuss the kinds of information obtainable from smart-meter data, and Newing et al. (2016) examine collection and interpretation of digital trace information for population statistics. The present data provide neither a representative population sample nor information about appliance capacity or household activity. Carbon implications would also require information on supplying generation and electricity exchanges. Hawkes (2010) distinguishes marginal emissions associated with demand changes, and de Chalendar et al. (2019) show why emissions tracking can depend on the location and timing of electricity generation and transfers. The errors in this experiment concern the reported active-power indicators. Their useful comparative result is that the same coverage fraction can leave very different evidence about the day.

Data and code availability

The public UCI archive is available under CC BY 4.0. The reproducibility record identifies the source URL, checksum, member CRC and full-day screen. The scripts save daily relative errors, indicator estimates, and fixed random seeds. The derived table excludes minute traces and the clock time of the household's peak. The figure reads the same estimate record used to report the results in Table 1.

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