

Article

Operational Diagnosis and Data Suitability Assessment Using BMS and Smart-Meter Data in a Multi-Zone University Building

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Abstract

Aggregate building indicators can obscure substantial differences in electrical demand and thermal operation among monitored spaces. This case study examined 89 days of one-minute building management system (BMS) and smart-meter records from a multi-zone university building. Routine data-quality screening was combined with physical interpretation and task requirements to determine how the available channels could be used in the exploratory analyses. The resulting map specifies each channel's permitted use and any associated monitoring priority. Meter TR1 was selected as the primary monitored-load proxy, whereas Meter G was retained for comparative diagnosis. Primary energy analysis used 59 fully observed TR1 days without imputation or scaling. Sensitivity analyses used all 61 days meeting the 90% and 95% completeness thresholds and reported their energy values as available-minute energy aggregates. Across the 59 fully observed days, weekday energy exceeded weekend energy, and complete 24 h TR1 energy was strongly inversely associated with daily mean outdoor temperature (Spearman $\rho_s = -0.889$). Of the 21 monitored spaces, five were warm-biased, four were cold-biased, and 12 were near setpoint. Within the observed winter-to-shoulder-season period, the data supported exploratory load and zone-temperature modeling. The combined assessment established record eligibility and channel use in this incomplete real-world export, and it identified priorities for later monitoring.

Keywords: building management system; operational diagnosis; multi-zone building; high-resolution monitoring data; energy–thermal coupling



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1. Introduction

Buildings remain a major source of energy demand and carbon emissions. Improving their operational performance requires effective monitoring as well as efficient technologies [1,2]. Yet, operational data are often incomplete or difficult to interpret physically. Before predictive or control-oriented analysis begins, the available channels must be evaluated for completeness, physical meaning, and relevance to the intended analysis.

Building management systems and smart meters can provide minute-level records of electrical demand, indoor temperature, setpoints, weather conditions, and binary equipment states. Smart-meter analytics has been widely used for load analysis, forecasting, and energy-management applications [3]. Large-scale building energy datasets further show that meter data, weather data, and metadata can support benchmarking, forecasting,

anomaly detection, and energy analysis [4]. Error analyses of large-scale building energy prediction tasks show that machine-learning models can remain constrained by data quality, metadata availability, feature definition, and unobserved operating factors that can all limit predictive performance [5,6].

Data-driven building-energy prediction is a mature research area, with statistical and machine learning models widely used for load forecasting and operational analysis [7,8]. For a site-specific BMS export, however, model selection is preceded by a practical interpretive question: whether the available channels are sufficiently complete, physically interpretable, and temporally appropriate for the proposed task. Existing work has established the importance of data-quality reporting and BMS metadata standardization for reusable analytics [9,10].

Model predictive control and related data-driven approaches are widely studied for building energy management, flexibility provision, and indoor-climate regulation [11]. Their performance depends not only on model structure but also on whether the available measurements identify the relevant states, disturbances, references, and manipulated inputs [12,13]. Here, these requirements are used only to assess how completely the export represents the building's thermal and operational conditions. The available data describe monitored states, external conditions, electrical load, and binary operating states. Occupancy, schedules, and continuous actuation are priorities for later monitoring.

Routine BMS preprocessing, missing-data screening, and performance indicators are established components of building operational analytics and fault diagnosis [14]. Digital-twin research further emphasizes that data interpretation depends on semantic structure and documented relationships among monitored variables [15]. Operational energy-flexibility studies likewise show that measurement and operating assumptions affect the interpretation of building-load indicators [16]. Real monitoring exports may combine complete timestamps with incomplete channel values, uncertain meter hierarchies, or operating-state records with limited context.

Existing studies have established how to quantify data quality, standardize BMS semantics, and support building analytics. However, they less often show how these assessments should change the permissible use of a specific incomplete monitoring export. The practical question is not only whether data quality can be measured, but whether a channel can support a stated task after its completeness and physical meaning have been examined.

This study addresses that practical decision problem in a multi-zone university building. Its scientific contribution is empirical rather than methodological: it documents how completeness, physical interpretability, task relevance, and contextual dependence jointly changed the permitted use of the available records and channels. In the present export, combined evidence placed 59 fully observed TR1 days in the primary complete-day analysis and assigned the remaining channels to their permitted analytical uses. The resulting task-specific evidence-to-use map applies to the studied building, operating period, and exploratory tasks.

Multi-zone university buildings add spatial variation to these data problems. Such buildings contain classrooms, offices, laboratories, corridors, and service spaces with different schedules, internal gains, setpoint settings, and control behavior. Occupant-centric control studies have shown that occupancy-related uncertainty and occupant behavior can strongly influence HVAC operation and indoor thermal conditions [17]. Thermal-comfort research shows that air temperature alone does not fully describe occupant comfort because environmental, physiological, and behavioral factors also influence thermal perception [18,19]. Room temperature remains a useful operational indicator when considered alongside setpoints and control states. Building-simulation studies have also identified occupant

behavior, operational assumptions, and model uncertainty as persistent challenges for reliable building-performance assessment [20]. Consequently, a single aggregate electrical series may conceal substantial differences in thermal conditions across monitored spaces in a multi-zone building.

This case study evaluates the operational interpretability and modeling suitability of one-minute BMS and smart-meter records from a multi-zone university building. It identifies eligible load records, characterizes exploratory load profiles and zone-level setpoint tracking, and assigns the available channels to task-specific analytical roles.

2. Materials and Methods

2.1. Case-Study Building and Monitoring Dataset

The case-study building is a university teaching and laboratory facility in Debrecen, Hungary. It contains classrooms, laboratories, offices, workshops, circulation areas, and technical spaces with different schedules, internal gains, and thermal operating conditions. Available documentation indicates that the HVAC system includes heat-recovery air-handling units, variable-refrigerant-flow systems, chillers, and associated building-services equipment. The monitoring system records outdoor conditions, zone-level thermal operation, equipment states, and electrical loads.

The dataset comprised 89 daily CSV exports collected between 1 February and 30 April 2026 at one-minute resolution, yielding 128,160 timestamped records. It therefore represents winter-to-shoulder-season conditions only. Weather variables included outdoor air temperature, relative humidity, and atmospheric pressure. Zone-level variables included room temperature, temperature setpoint, ON/OFF status, and error codes. Equipment channels included outdoor-unit states and two Hydrobox units. Smart-meter variables included active, reactive, and apparent power, phase-level active power, power factor, and cumulative active energy. The thermal analysis included 21 monitored spaces. Hydrobox 1 and Hydrobox 2 were treated as equipment-side channels because their temperatures represented system operation rather than occupied-space thermal conditions.

2.2. Data Preprocessing and Quality Assessment

The 89 files were integrated chronologically. A secondary row containing measurement units was removed before numerical processing and retained in the variable dictionary. The date encoded in each filename was combined with the recorded time of day to reconstruct the timestamp. Repeated raw column names were assigned unique identifiers, and weather, space-level, equipment, and meter channels were converted to numeric form. Date, hour, day of week, and weekday/weekend status were derived from the reconstructed index. Data processing was conducted using Python 3.13.5, and figures were generated in Microsoft Excel. The procedures below follow established practices for timestamp reconstruction, range screening, gap treatment, and completeness assessment.

Data quality was evaluated before energy and thermal-performance indicators were calculated. For each channel, data availability was characterized by the missing-data rate and the longest continuous gap, which distinguish isolated interruptions from prolonged outages that may affect prediction, diagnosis, and operational interpretation. The reconstructed timestamp index was checked against the expected one-minute sequence and screened for duplicate timestamps. The missing-data rate was calculated as

$$R_{\text{miss},j} = \left(1 - \frac{N_{\text{valid},j}}{N_{\text{expected}}} \right) \times 100\%, \quad (1)$$

where $N_{\text{valid},j}$ is the number of valid observations for channel j , and N_{expected} is the expected number of one-minute observations. Weather variables, room temperatures, setpoints, and electrical power were screened against physically plausible ranges. Negative active-power values were excluded from positive-consumption calculations unless bidirectional flow could be independently verified. Extreme values were identified using the robust median absolute deviation criterion:

$$|x_t - \tilde{x}| > 10 \text{ MAD}, \quad (2)$$

where $\tilde{x}$ is the median of the corresponding variable, and MAD is its median absolute deviation. Nonzero equipment and zone error codes were retained as quality flags rather than interpreted directly as confirmed equipment faults.

Short missing intervals of no more than 5 min in continuous non-meter variables were linearly interpolated only when valid observations bounded both sides of the gap. Longer gaps were retained as missing to avoid reconstructing unobserved building operations. Binary ON/OFF states were not interpolated across long gaps, and switching events were counted only between consecutive valid observations.

Meter TR1 active-power values used to determine daily completeness and to calculate daily energy were not interpolated or scaled. For these analyses, an observation was considered valid only when a raw, plausibility-screened TR1 value was available; therefore, a fully observed day contained 1440 observed one-minute TR1 values. If interpolation was used for any ancillary visualization, those interpolated values were flagged and excluded from the completeness and energy calculations. Daily meter completeness was calculated separately for Meter G, Meter T1, and Meter TR1:

$$C_{m,d} = \frac{N_{\text{valid},m,d}}{1440} \times 100\%, \quad (3)$$

where $N_{\text{valid},m,d}$ is the number of valid one-minute active-power observations for meter m on day d . The primary complete 24 h TR1 energy analysis retained only days satisfying $C_{\text{TR1},d} = 100\%$, corresponding to 1440 valid one-minute TR1 observations. No additional imputation or scaling was used to create complete 24 h TR1 energy totals.

Sensitivity analyses were conducted using the 90% and 95% completeness thresholds. For these thresholds, energy was calculated as the unscaled aggregate of the retained one-minute observations and was explicitly interpreted as an available-minute energy aggregate rather than a complete 24 h energy total. The sensitivity analysis compared eligible-day counts, weekday/weekend distributions, and associations with outdoor temperature.

To assess whether lower-frequency acquisition would preserve the main analytical results, a retrospective temporal-resolution sensitivity analysis was conducted using the original one-minute TR1 series. The series was sampled at fixed 10 min and 15 min intervals. All possible sampling phases were evaluated, corresponding to ten phases for 10 min sampling and fifteen phases for 15 min sampling, to avoid dependence on an arbitrarily selected starting minute. No retained observation was interpolated, imputed, or otherwise adjusted; the corresponding 10 or 15 min interval was used solely to integrate active-power observations into daily energy.

For each sampling phase, daily energy was calculated by integrating the retained active-power samples over the corresponding interval, and daily peak load was defined as the maximum retained sample. Hourly profiles were constructed from the retained observations within each hour, and ON/OFF transitions were counted only between consecutive retained binary observations. Results were compared with the one-minute baseline using the same 59 complete TR1 days in terms of daily energy, weekday-weekend

contrast, energy–temperature association, exploratory daily-profile clustering, daily peak load, and observed ON/OFF transitions (Figure 1).

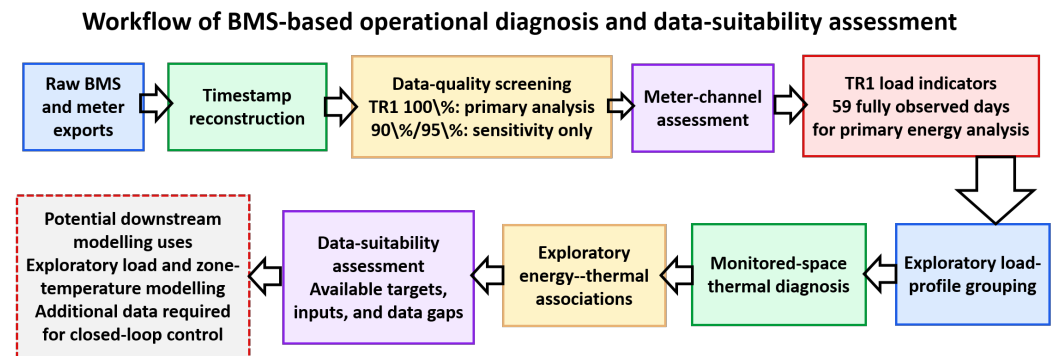


Figure 1. Workflow for BMS data-quality screening, operational diagnosis, and channel-use assessment. Primary complete 24 h TR1 energy, load-profile, and energy–thermal analyses used 59 fully observed TR1 days. The 90% and 95% thresholds were applied only in the sensitivity analyses.

Table 1 summarizes the predefined quality-control rules used before indicator calculation. These criteria covered timestamp integrity, missing-data treatment, anomaly screening, and daily meter completeness. More detailed channel-level quality statistics are reported in the Results section.

Table 1. Key data-quality criteria and treatment rules.

Quality-Control Item	Criterion	Treatment
Timestamp integrity	Missing or duplicate one-minute timestamps	Identify, verify, and report.
Short missing gap	Continuous non-meter-variable gap ≤ 5 min	Linearly interpolate only bracketed non-meter gaps; exclude interpolated TR1 values from completeness and energy calculations.
Long missing gap	Gap > 5 min	Retain as missing and exclude from affected calculations.
Anomaly screening	Physical-range violation, negative active power, or nonzero error code	Flag for review and exclude where technically justified.
Daily meter completeness	$C_{TR1,d} = 100\%$ for primary complete 24 h TR1 energy analysis; 90% and 95% thresholds for separately reported sensitivity analyses.	Use fully observed TR1 days for primary daily-energy, load-profile, and energy–thermal analyses. Report sensitivity results as unscaled available-minute energy aggregates.
Main monitored load	Meter TR1 has 1440 valid, raw, plausibility-screened one-minute active-power observations	Retain the day for complete 24 h TR1 energy analysis.
Supporting meter channels	Valid paired observations are available for comparative minute-level diagnosis.	Retain for paired secondary-channel diagnosis; do not use these channels to construct the primary complete 24 h TR1 energy total.

The rules in Table 1 preserved the one-minute structure while excluding long unobserved periods from reconstruction. Days failing the 100% TR1 completeness criterion were retained for data-quality reporting but excluded from the primary complete 24 h TR1 energy comparison, exploratory load-profile grouping, and energy–thermal coupling analysis. The 90% and 95% eligibility rules were applied only in the explicitly labeled sensitivity analyses.

2.3. Energy Characterization and Exploratory Load-Profile Grouping

The three smart-meter channels were compared to identify the primary monitored-load indicator within the available export. The comparison considered sustained load magnitude, coverage of observed operating periods, paired minute-level temporal synchronization, relative magnitude across paired observations, and anomalous-load behavior. Daily completeness was subsequently used to determine which TR1 records were eligible for complete 24 h energy analysis.

The primary monitored-load proxy at time t was defined as:

$$P_{\text{load}}(t) = P_{\text{TR1}}(t) \quad (4)$$

This definition was applied only when the Meter TR1 active-power measurement was valid. For the primary daily-energy analysis, a day was retained only when all 1440 one-minute TR1 observations were valid. Complete 24 h TR1 energy was then calculated as:

$$E_d = \sum_{t=1}^{1440} P_{\text{load}}(t) \Delta t, \quad \Delta t = \frac{1}{60} \text{ h}, \quad (5)$$

where E_d is the complete 24 h TR1 energy total for day d . Daily mean power and peak power were calculated from the same 1440 observations:

$$\bar{P}_d = \frac{1}{1440} \sum_{t=1}^{1440} P_{\text{load}}(t), \quad (6)$$

$$P_{\text{peak},d} = \max_{t=1,\dots,1440} P_{\text{load}}(t). \quad (7)$$

The primary daily-load analysis used 59 fully observed TR1 days. Sensitivity analyses used 61 threshold-qualified days and reported their energy values as available-minute aggregates. Weekday–weekend comparison served as the calendar-based baseline analysis.

For exploratory load-profile grouping, one-minute TR1 data from the 59 fully observed days were aggregated to hourly means. Each day contributed 24 complete hourly values, indexed from 0 to 23. The clustering was used as a descriptive diagnostic tool and not as evidence of discrete operating states [21,22].

$$\mathbf{x}_d = [\bar{P}_{d,0}, \bar{P}_{d,1}, \dots, \bar{P}_{d,23}], \quad (8)$$

where $\bar{P}_{d,h}$ is the mean TR1 load during hour h of day d . Each hourly feature was standardized across the 59 fully observed days before clustering. This prevented hours with greater numerical variability from dominating the distance calculation.

K-means clustering with Euclidean distance was applied to the standardized daily load profiles. Candidate cluster numbers from $k = 2$ to $k = 6$ were evaluated. For each candidate value, the algorithm was initialized 50 times using a fixed random seed of 42, with a maximum of 300 iterations per initialization. The solution with the lowest within-cluster sum of squares was retained. The final number of clusters was selected according to the highest mean silhouette coefficient.

After model selection, the two profile groups were summarized by their hourly centroid profiles, complete 24 h TR1 energy totals, daily peak load, weekday/weekend composition, and mean outdoor temperature. Profile Group 1 and Profile Group 2 were numbered in descending order of mean complete 24 h TR1 energy. The comparison was descriptive and assessed whether the grouped profiles differed beyond calendar classification.

The energy and exploratory load-profile grouping indicators derived from quality-screened active-power measurements are summarized in Table 2. Different temporal resolutions were used according to the analytical objective.

Table 2. Energy and exploratory load-profile grouping.

Indicator	Definition	Resolution	Purpose
Primary monitored-load proxy	$P_{\text{load}}(t) = P_{\text{TR1}}(t)$	1 min	Represent the primary monitored-load proxy.
Daily energy	$E_d = \sum_{t=1}^{1440} P_{\text{load}}(t) \Delta t$, where $\Delta t = 1/60$ h and all 1440 observations are valid	Daily	Quantify complete 24 h TR1-based electrical energy use.
Daily mean load	$\bar{P}_d = \frac{1}{1440} \sum_{t=1}^{1440} P_{\text{load}}(t)$	Daily	Characterize the average daily load level.
Daily peak load	$P_{\text{peak},d} = \max_{t=1,\dots,1440} P_{\text{load}}(t)$	Daily	Characterize the maximum daily power demand.
Hourly load profile	Hourly mean values of $P_{\text{load}}(t)$	Hourly	Represent the 24 h daily load shape.
Calendar day type	Weekday or weekend classification	Daily	Provide the calendar-based operating baseline.
Exploratory load-profile group	K-means cluster of the standardized 24-dimensional hourly profile	Daily	Describe exploratory daily load-profile patterns.

2.4. Setpoint-Based Thermal and Coupled Operational Diagnosis

Thermal operation was evaluated for the 21 monitored spaces. A zone-specific assessment was adopted because spatially distinct thermal states and operating conditions are relevant to multi-zone predictive-control formulations [23]. Hydrobox 1 and Hydrobox 2 were excluded because their temperature channels represented equipment operating conditions rather than occupied-space thermal conditions. All thermal indicators were calculated from valid observations. For daily energy–thermal associations, temperature- and setpoint-based metrics required at least 1296 paired observations per space-day, whereas ON-state metrics required at least 1296 valid binary observations. Daily building-level values were calculated as equal-weight averages across eligible monitored spaces and were retained only when at least 17 of the 21 spaces contributed.

For monitored space i at time t , the setpoint deviation was defined as

$$D_i(t) = T_{\text{room},i}(t) - T_{\text{set},i}(t), \quad (9)$$

where $T_{\text{room},i}(t)$ and $T_{\text{set},i}(t)$ denote the measured room temperature and corresponding setpoint, respectively. Positive values indicate operation above the setpoint, whereas negative values indicate operation below it.

The mean setpoint deviation and mean absolute deviation were calculated as:

$$\bar{D}_i = \frac{1}{N_i} \sum_{t \in \mathcal{V}_i} D_i(t), \quad (10)$$

$$\text{MAE}_i = \frac{1}{N_i} \sum_{t \in \mathcal{V}_i} |D_i(t)|, \quad (11)$$

where $\mathcal{V}_i$ is the set of valid observations for zone i , and N_i is the number of valid paired room-temperature and setpoint observations.

Setpoint-tracking compliance within a tolerance δ was calculated as

$$C_{i,\delta} = \frac{1}{N_i} \sum_{t \in \mathcal{V}_i} \mathbb{I}(|D_i(t)| \leq \delta) \times 100\%, \quad (12)$$

where $\mathbb{I}(\cdot)$ is the indicator function. Compliance was evaluated at $\delta = 1^\circ\text{C}$ and $\delta = 2^\circ\text{C}$. The $\pm 2^\circ\text{C}$ criterion was the principal setpoint-tracking measure, and the $\pm 1^\circ\text{C}$ criterion provided a stricter sensitivity measure. The diagnosis matrix used the fixed 20–24 °C temperature-band compliance as a secondary indicator.

Warm and cold exceedance fractions were defined as

$$W_i = \frac{1}{N_i} \sum_{t \in \mathcal{V}_i} \mathbb{I}(D_i(t) > 2^\circ\text{C}) \times 100\%, \quad (13)$$

$$K_i = \frac{1}{N_i} \sum_{t \in \mathcal{V}_i} \mathbb{I}(D_i(t) < -2^\circ\text{C}) \times 100\%. \quad (14)$$

The zone ON fraction was calculated as

$$F_{\text{ON},i} = \frac{1}{N_{\text{ON},i}} \sum_{t \in \mathcal{O}_i} u_i(t) \times 100\%, \quad (15)$$

where $u_i(t) \in \{0, 1\}$ is the recorded operating state, $\mathcal{O}_i$ is the set of valid ON/OFF observations, and $N_{\text{ON},i}$ is the number of valid state observations. Switch count was determined from transitions between consecutive valid states:

$$S_i = \sum_{t=2}^{N_{\text{ON},i}} \mathbb{I}[u_i(t) \neq u_i(t-1)]. \quad (16)$$

Transitions across missing intervals were excluded to avoid interpreting unobserved state changes as actual switching events.

The fraction of valid room-temperature observations within 20–24 °C was calculated as a secondary indicator for the zone diagnosis matrix. Zone-specific setpoint deviation remained the principal measure of tracking performance. Neither measure was treated as a complete occupant-comfort metric because the available air-temperature records lacked the wider building and occupant context required for comfort assessment [24].

Table 3 summarizes the thermal and operational indicators. Setpoint deviation describes tracking relative to the recorded reference. Temperature-band prevalence describes an absolute room-temperature condition, and ON fraction describes the observed prevalence of the binary state. Their joint interpretation can reveal operational mismatches that would remain obscured when any indicator is considered in isolation; however, these patterns provide diagnostic hypotheses for further investigation rather than verified fault causes.

Zones were classified according to their mean setpoint deviation. Zones with $\bar{D}_i > +1^\circ\text{C}$ were classified as warm-biased, whereas zones with $\bar{D}_i < -1^\circ\text{C}$ were classified as cold-biased. Zones satisfying $|\bar{D}_i| \leq 1^\circ\text{C}$ were classified as near-setpoint.

A zone diagnosis matrix was then constructed to jointly interpret temperature-band compliance and observed ON-state prevalence. The x-axis represents the zone ON fraction, and the y-axis represents the fraction of valid room-temperature observations within the fixed 20–24 °C band. Marker colors represented the diagnosis classes, and marker labels identified the monitored spaces.

The diagnosis matrix used a 70% threshold for 20–24 °C temperature-band compliance and a 50% threshold for zone ON fraction. Spaces were classified as high-ON/high-compliance, low-ON/high-compliance, high-ON/low-compliance, or low-ON/low-compliance according to whether their values met the respective thresholds. These labels describe the observed prevalence of the binary ON state and temperature-band compliance; they do not indicate control effort, delivered capacity, or occupant comfort. The thresholds were predefined for comparative interpretation within this case study.

Setpoint deviation was used to characterize the magnitude and direction of observed room-temperature tracking relative to the recorded temperature reference.

Table 3. Definitions of thermal and coupled operational indicators.

Indicator	Definition	Interpretation
Mean deviation	$\bar{D}_i = \frac{1}{N_i} \sum_{t \in \mathcal{V}_i} D_i(t)$	Direction and magnitude of the mean thermal bias relative to the setpoint.
Mean absolute deviation	$MAE_i = \frac{1}{N_i} \sum_{t \in \mathcal{V}_i} D_i(t) $	Overall setpoint-tracking error independent of direction.
$\pm 1^\circ\text{C}$ compliance	$C_{i,1} = \frac{1}{N_i} \sum_{t \in \mathcal{V}_i} \mathbb{I}(D_i(t) \leq 1) \times 100\%$	Strict setpoint-tracking performance.
$\pm 2^\circ\text{C}$ compliance	$C_{i,2} = \frac{1}{N_i} \sum_{t \in \mathcal{V}_i} \mathbb{I}(D_i(t) \leq 2) \times 100\%$	Principal setpoint-tracking compliance metric.
Warm exceedance	$W_i = \frac{1}{N_i} \sum_{t \in \mathcal{V}_i} \mathbb{I}(D_i(t) > 2) \times 100\%$	Frequency of deviations more than 2°C above the setpoint.
Cold exceedance	$K_i = \frac{1}{N_i} \sum_{t \in \mathcal{V}_i} \mathbb{I}(D_i(t) < -2) \times 100\%$	Frequency of deviations more than 2°C below the setpoint.
ON fraction	$F_{\text{ON},i} = \frac{1}{N_{\text{ON},i}} \sum_{t \in \mathcal{O}_i} u_i(t) \times 100\%$	Fraction of valid observations for which the monitored zone state was ON.
Switch count	$S_i = \sum_{t=2}^{N_{\text{ON},i}} \mathbb{I}[u_i(t) \neq u_i(t-1)]$	Frequency of transitions between consecutive valid operating states.
$20\text{--}24^\circ\text{C}$ compliance	$B_i = \frac{1}{N_i} \sum_{t \in \mathcal{V}_i} \mathbb{I}(20 \leq T_{\text{room},i}(t) \leq 24) \times 100\%$	Secondary temperature-band proxy, not a complete occupant-comfort metric.

Associations among daily outdoor temperature, TR1-based daily electrical energy use, zone ON fraction, and thermal indicators were evaluated using Spearman rank correlation:

$$\rho_s = \text{corr}[\text{rank}(X), \text{rank}(Y)]. \quad (17)$$

Spearman rank correlations were calculated for the daily series. Confidence intervals were estimated from 10,000 stationary-block bootstrap resamples (seed 42; mean block length, 6 days) restricted to contiguous eligible-day runs.

For the energy–thermal analysis, the daily energy outcome was restricted to the same 59 fully observed TR1 days. Zone-level daily metrics retained their predefined coverage criteria, and only date-matched daily observations were included in each association.

2.5. Data-Suitability Assessment

The case-specific data-suitability assessment applied four criteria to each channel group: completeness, physical interpretability, task relevance, and contextual dependence. It considered their joint implications for exploratory load modeling, zone-temperature modeling, comparative diagnosis, and the measurement requirements of later control-oriented work. For each channel group, the task-specific evidence-to-use map records a suitability class, an assigned analytical role, a use restriction, and any monitoring implication.

Completeness was high when at least 90% of expected observations were valid, moderate from 70% to below 90%, and low below 70% or when the variable was unavailable. Physical interpretability was high when the physical meaning, unit, and monitored object were documented; moderate when the general meaning was known but the end-use allocation or equipment relationship remained uncertain; and low when no reliable physical linkage could be established.

Task relevance was determined by the role of a variable in the stated analysis. Roles included prediction target, observed state, reference, candidate explanatory variable, operational proxy, and secondary diagnostic record. A binary ON/OFF status was not treated as a continuous manipulated input. Contextual dependence captured whether a variable could be interpreted without essential unavailable information. For example,

room temperature and setpoint describe observed thermal states and references, whereas ON/OFF status may also depend on unobserved occupancy, timetable rules, controller logic, and actuation magnitude.

Based on the documented evidence, each variable group was assigned one of three within-case labels:

- Suitable for the stated exploratory task: high completeness, clear physical interpretation, and a direct analytical use;
- Usable with stated limitations: potentially informative, but affected by moderate incompleteness, uncertain end-use interpretation, proxy-based meaning, or contextual limitations;
- Unavailable for the stated task: insufficient completeness, unclear physical meaning, no defined role in the stated task, or dependence on essential information that was unavailable.

These labels link the screening evidence to the permitted use of each channel. Their interpretation is limited to the building, monitoring export, operating period, and analyses examined here.

The assessment criteria are summarized in Table 4. Channel-specific within-case suitability results are reported in Section 3.5.

Table 4. Criteria used in the data-suitability assessment.

Criterion	High/Favorable	Moderate	Low/Limiting
Completeness	Valid observations $\geq 90\%$	Valid observations from 70% to $<90\%$	Valid observations $< 70\%$ or variable unavailable
Physical interpretability	Physical meaning, unit, and monitored object are clearly documented	General meaning is known, but end-use or equipment allocation remains uncertain	Signal cannot be reliably associated with a physical building process
Task relevance	Defined role as a prediction target, observed state, reference, candidate explanatory variable, or diagnostic record in the stated task	Indirect operational-state proxy or secondary diagnostic record	No defined role in the stated exploratory task
Contextual dependence	Usable without critical unavailable information	Interpretation is affected by missing contextual information	Meaningful use requires essential information that is unavailable

3. Results

3.1. Data Quality and Meter Eligibility

The merged dataset contained 128,160 one-minute records across 89 consecutive days. No missing or duplicate timestamps were detected; the timestamp index was structurally complete. Channel-level availability differed substantially among the monitored variable groups.

Weather variables had a missing rate of approximately 1.45%, and the mean missing rate across occupied-zone temperature, setpoint, and ON/OFF channels was approximately 1.42%. The longest continuous gaps were 25.95 h for weather variables and 25.85 h for one occupied-zone temperature channel. Thus, the timestamp sequence was complete even though individual channels contained missing observations.

The active-power channels of Meter G and Meter T1 each had a missing rate of 5.39%, with a longest continuous missing period of 50.40 h. Extended channel-level missing periods reduced the number of fully observed TR1 days from 89 calendar days to 59 complete days for primary analysis. Meter TR1 had a missing-data rate of 25.42% and a maximum continuous missing period of 157.77 h. Sixty-one days met both the 90% and 95% completeness thresholds. The 59 complete days were used for primary complete 24 h

energy analysis, whereas the two partial days were used only in sensitivity summaries as available-minute energy aggregates (Figure 2).

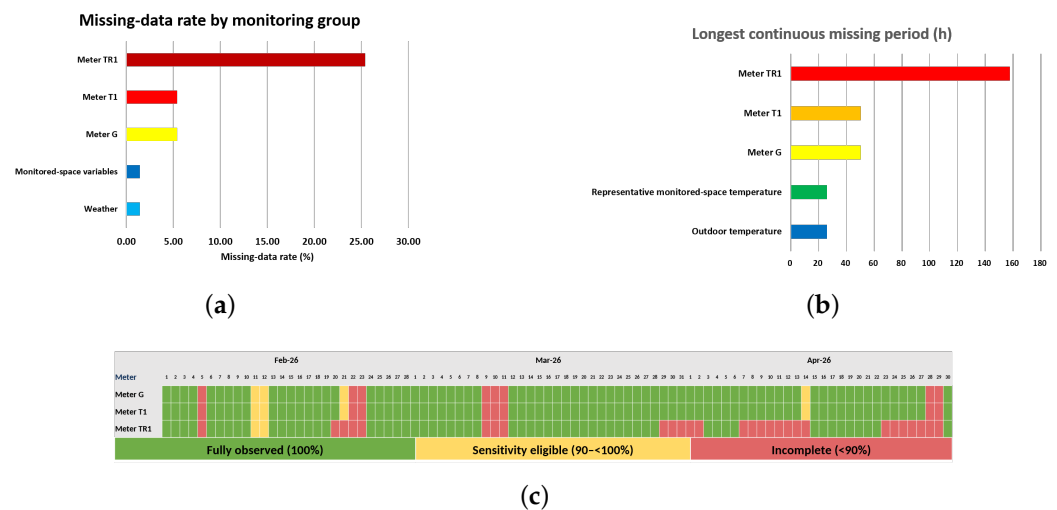


Figure 2. Data-quality assessment of the building monitoring system: (a) missing-data rates across monitoring groups; (b) longest continuous missing-data periods; and (c) daily active-power completeness by meter. In (c), green denotes fully observed days with 100% completeness (1440 valid raw, plausibility-screened one-minute TR1 observations), yellow denotes days with 90% to below 100% completeness, and red denotes days below 90%. Primary complete 24 h energy analyses used the 59 green TR1 days. The two yellow days were retained only for the separately reported 90% and 95% sensitivity analyses.

The selection of TR1 as the primary monitored-load indicator was based on cross-meter evidence rather than completeness alone. Among the three active-power channels, TR1 captured the largest sustained load range and showed strong minute-level synchronization with Meter G across paired valid observations (Pearson $r = 0.967$; Spearman $\rho_s = 0.970$). TR1 exceeded Meter G in 99.88% of paired observations, indicating that the two channels followed closely aligned operating patterns while TR1 represented the broader monitored load signal.

Meter T1 did not provide a comparably stable primary load signal. Its median active power was 0.143 kW, its 95th percentile was 0.475 kW, and an isolated maximum of 150.27 kW indicated intermittent spikes. Meter T1 also showed weak correlations with Meter G and Meter TR1, with coefficients of 0.180 and 0.229, respectively. Taken together, sustained magnitude, temporal synchrony, relative magnitude, and anomaly behavior supported the selection of TR1 as the primary monitored-load proxy. Meter G was retained for comparative diagnosis, whereas Meter T1 was used for secondary diagnostic inspection (Table 5).

Table 5. Data availability and completeness of the principal monitoring groups.

Monitoring Group	Missing Rate (%)	Longest Missing Period (h)	Valid Days at 90% Threshold
Timestamp	0.00	0.00	89
Weather variables	1.45	25.95	—
Monitored-space variables	1.42	25.85	—
Meter G active power	5.39	50.40	81
Meter T1 active power	5.39	50.40	81
Meter TR1 active power	25.42	157.77	61

Across sampling phases, 10 min and 15 min subsampling preserved the daily-energy summaries, weekday–weekend contrast, energy–temperature association, and broad daily-

profile grouping (Table 6). Lower-frequency sampling produced larger daily-peak errors and missed a median of 29.7% of observed ON/OFF transitions. Daily-energy summaries were therefore less sensitive to subsampling than peak and switching diagnostics.

Table 6. Sensitivity of selected analytical results to 10 min and 15 min fixed-interval subsampling of the original one-minute TR1 series across all sampling phases.

Metric	1 min Baseline	10 min Sampling	15 min Sampling
Median absolute complete 24 h TR1 energy error (%)	–	0.79 (0.59–1.00)	1.23 (0.97–1.60)
Weekday energy higher than weekend energy (%)	24.5	24.5 (23.4–25.3)	24.3 (23.4–25.8)
Spearman ρ_s : complete 24 h TR1 energy vs. outdoor temperature	–0.889	–0.887 (–0.891 to –0.882)	–0.885 (–0.889 to –0.879)
Daily-profile clustering consistency, ARI	–	0.929 (0.929–1.000)	0.930 (0.863–1.000)
Median absolute daily-peak error (%)	–	12.1 (10.0–14.7)	16.1 (12.1–21.6)
Observed ON/OFF transitions missed (%)	–	29.7 (2.7–29.7)	29.7 (2.7–29.7)

Notes: All analyses used the same 59 complete TR1 days. For each sampling interval, values are medians across all fixed sampling phases; ranges in parentheses are phase-specific minima and maxima. Daily energy was integrated using the corresponding sampling interval. “Transitions missed” denotes the percentage of transitions detected in the one-minute baseline that were not detected after subsampling. ARI, adjusted Rand index.

3.2. Energy Operation and Exploratory Load-Profile Groups

After applying the 100% daily-completeness criterion to Meter TR1, 59 of the 89 monitoring days were retained for the primary complete 24 h TR1 energy analysis, including 41 weekdays and 18 weekend days. Complete 24 h TR1 energy ranged from 168.3 to 1161.1 kWh, with a mean of 615.8 kWh, a median of 574.5 kWh, and an interquartile range of 423.7–752.0 kWh. The temporal distribution, weekday/weekend comparison, and mean hourly load profiles are summarized in Figure 3.

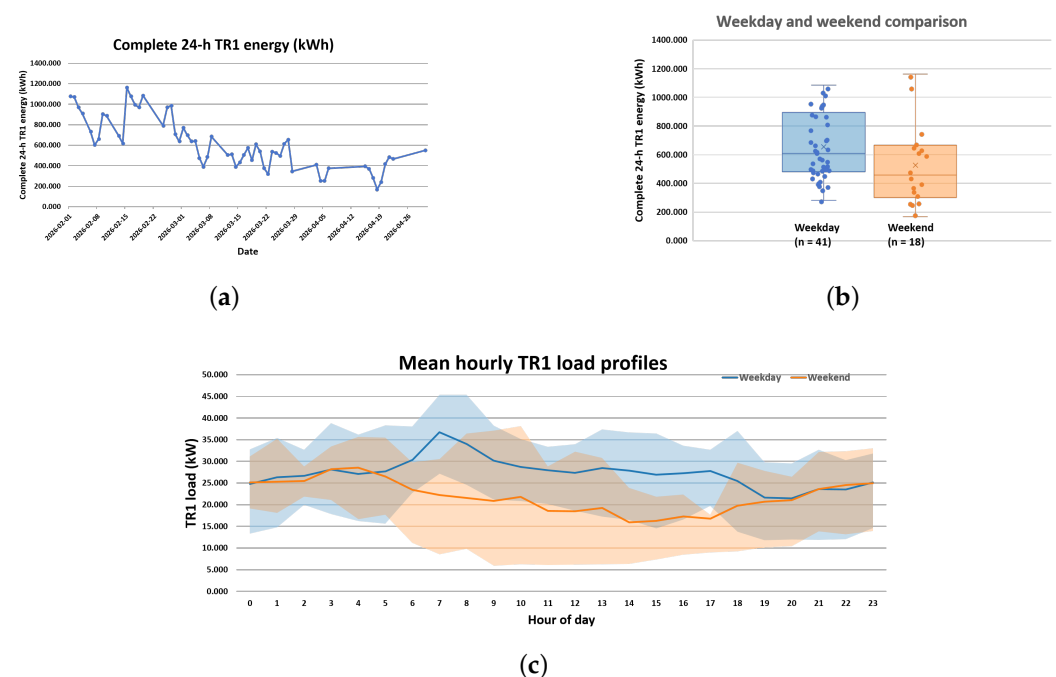


Figure 3. Calendar-related variation in the Meter TR1 monitored electrical load for the 59 fully observed days: (a) complete 24 h TR1 energy; (b) distribution of complete 24 h TR1 energy by day type; and (c) mean hourly TR1 load profiles by day type, indexed by hour of day (0–23). Shaded bands in (c) indicate interquartile ranges.

Mean energy was 655.2 kWh on weekdays and 526.1 kWh on weekends. Weekday energy was therefore 24.5% higher. The corresponding median values were 609.1 and 458.3 kWh. Figure 3c shows higher daytime weekday loads and substantial variation within both day types. This comparison provides a descriptive calendar-based baseline; the available records do not separate the contributions of weather, occupancy, schedules, and end uses.

Supplementary Table S1 reports eligible-day counts, weekday and weekend counts, energy summaries, and associations with daily mean outdoor temperature across the three completeness thresholds. The 100% values are complete 24 h TR1 energy totals. The 90% and 95% values are unscaled available-minute energy aggregates. The table reports medians and interquartile ranges, whereas the main text reports means for the weekday–weekend comparison.

The 59 fully observed days each provided a complete 24 h TR1 profile for clustering. Among the candidate solutions, $k = 2$ was retained as an exploratory grouping that captures load variation not fully described by the weekday/weekend label alone. Figure 4 shows the model-selection evidence, the group profiles, and their observed weather and calendar compositions.

Profile Group 1 represented a high-load pattern associated with colder outdoor conditions. It contained 16 days, accounting for 27.1% of the valid days. Its mean complete 24 h TR1 energy was 959.5 kWh, its mean daily peak load was 94.8 kW, and its mean outdoor temperature was 2.7 °C. The mean hourly load remained comparatively high throughout the day and reached approximately 46.3 kW at 07:00.

Profile Group 2 contained the remaining 43 complete 24 h TR1 days. Its mean complete 24 h TR1 energy was 487.9 kWh, its mean daily peak load was 66.5 kW, and its mean outdoor temperature was 10.0 °C. Its hourly profile also peaked near 07:00, at approximately 28 kW. Profile Group 1 included 13 weekdays and 3 weekend days, whereas Profile Group 2 included 28 weekdays and 15 weekend days (Figure 4b). Both day types occurred in both groups, so calendar classification alone did not account for the observed profile differences. The groups provide descriptive patterns for representative-day selection and stratified exploratory modeling.

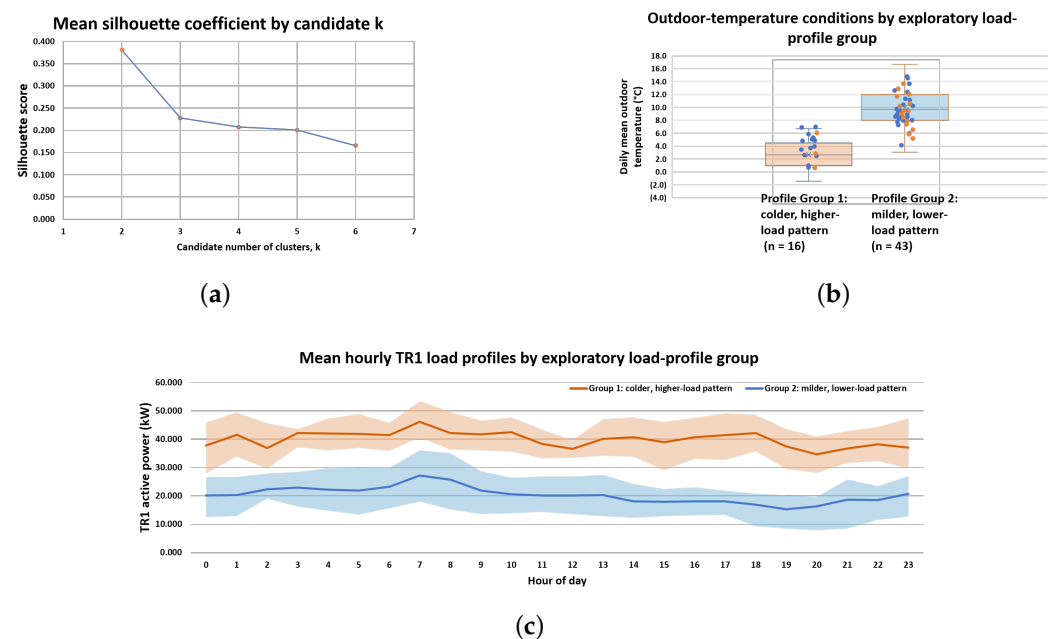


Figure 4. Exploratory load-profile grouping of the Meter TR1 monitored electrical load: (a) silhouette scores for candidate cluster numbers; (b) outdoor-temperature conditions by exploratory load-profile group; and (c) mean hourly TR1 load profiles by exploratory load-profile group. Shaded bands in (c) indicate interquartile ranges.

3.3. Zone-Level Thermal Heterogeneity and Diagnosis Matrix

The zone-level analysis included 21 monitored spaces. Hydrobox 1 and Hydrobox 2 were excluded because their temperature and setpoint channels represented equipment-side operating conditions rather than occupied-space thermal conditions. Figure 5 summarizes zone-level thermal heterogeneity and operational diagnosis. Figure 5a reports the mean setpoint deviation for each monitored space, while Figure 5b uses the fixed 20–24 °C temperature-band compliance and the ON fraction to identify operational diagnosis classes.

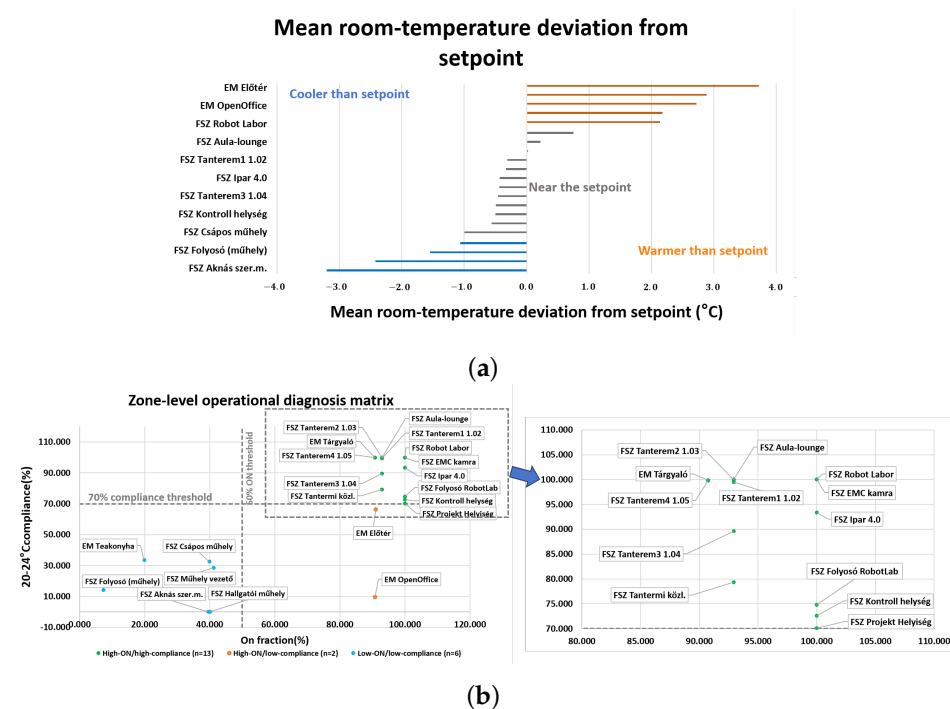


Figure 5. Zone-level thermal heterogeneity and operational diagnosis across 21 monitored spaces: (a) mean room-temperature deviation from the corresponding setpoint; (b) diagnosis matrix relating 20–24 °C temperature-band compliance to ON fraction. The vertical and horizontal dashed lines indicate the predefined 70% temperature-band-compliance and 50% ON-fraction thresholds, respectively. The inset enlarges the high-compliance region.

Among the 21 monitored spaces, five were classified as warm-biased, four as cold-biased, and 12 as near-setpoint. Mean setpoint deviation differed substantially in both direction and magnitude (Figure 5a). EM Előter exhibited the largest positive mean deviation at +3.72 °C, followed by FSZ Tantermi közl. at +2.88 °C and EM OpenOffice at +2.72 °C. The largest negative deviation occurred in FSZ Aknás szer.m. at −3.21 °C, followed by FSZ Hallgatói műhely at −2.42 °C. These results indicate substantial spatial heterogeneity that was not apparent from whole-building averages.

The diagnosis matrix combined the 20–24 °C temperature-band compliance with the ON fraction (Figure 5b). Thirteen monitored spaces were classified as high-ON/high-compliance, two as high-ON/low-compliance, and six as low-ON/low-compliance. No monitored space was classified as low-ON/high-compliance. EM Előter and EM OpenOffice formed the high-ON/low-compliance group. The low-ON/low-compliance group comprised EM Teakonyha, FSZ Aknás szer.m., FSZ Csápos műhely, FSZ Folyosó (műhely), FSZ Hallgatói műhely, and FSZ Műhely vezető.

Temperature-band compliance and setpoint tracking captured different aspects of the monitored thermal state. FSZ Robot Labor was within the 20–24 °C band for 98.6% of valid observations, but no observation was within ± 1 °C of its setpoint; its mean deviation was +2.14 °C. In contrast, FSZ Projekt Helyiség was within ± 1 °C of its setpoint for 93.8% of

observations, although its temperature-band compliance was 69.1%. Together with ON fraction, these measures identify zones for targeted operational follow-up.

3.4. Coupled Energy–Thermal Diagnosis

Associations between outdoor temperature, complete 24 h TR1 energy, zone operation, and thermal indicators were evaluated using the 59 fully observed TR1 days. The results are summarized in Figure 6 and Table 7.

Table 7. Associations between complete 24 h TR1 energy and operational indicators ($n = 59$).

Predictor	n	Spearman ρ_s	Stationary-Block 95% CI
Daily mean outdoor temperature	59	−0.889	[−0.944, −0.608]
Mean monitored-space ON fraction	59	0.737	[0.170, 0.848]
Mean absolute setpoint deviation	59	−0.470	[−0.766, 0.065]
Warm-biased space fraction	59	0.068	[−0.643, 0.677]
Cold-biased space fraction	59	−0.323	[−0.689, 0.336]
Mean 20–24 °C compliance	59	0.484	[−0.071, 0.814]

Notes: All associations use the 59 days with complete 1440-min TR1 records. Confidence intervals were estimated using 10,000 stationary-block bootstrap resamples (seed 42), with blocks sampled only within contiguous eligible-day runs. All relationships represent statistical associations rather than causal effects.

After complete-day screening and meter comparison, complete 24 h TR1 energy showed a strong negative monotonic association with daily mean outdoor temperature (Spearman $\rho_s = -0.889$, $n = 59$, stationary-block-bootstrap 95% CI: −0.944 to −0.608; Figure 6a). Lower outdoor temperatures were associated with higher TR1 energy during the monitoring period, supporting its use as a monitored-load proxy for exploratory analysis.

The temperature-bin analysis showed lower complete 24 h TR1 energy at higher outdoor temperatures (Figure 6b). Mean complete 24 h TR1 energy values were 1075.0, 931.4, 576.6, 390.4, and 321.8 kWh for the <0 °C, 0–5 °C, 5–10 °C, 10–15 °C, and >15 °C bins, respectively. These bins contained 3, 12, 27, 13, and 4 days. The binned values are descriptive because the number of days differed across temperature ranges.

Complete 24 h TR1 energy was positively associated with the mean monitored-space ON fraction ($\rho_s = 0.737$, $n = 59$, stationary-block-bootstrap 95% CI: 0.170 to 0.848). Days with a greater aggregate ON fraction tended to have higher TR1 energy. This association supports the use of aggregate ON fraction as a candidate explanatory variable in exploratory modeling (Figure 6c).

Relationships between complete 24 h TR1 energy and thermal-deviation indicators were less consistent. The point estimate for mean absolute setpoint deviation was negative ($\rho_s = -0.470$), but its 95% CI crossed zero (−0.766 to 0.065). The point estimate for mean 20–24 °C compliance was positive ($\rho_s = 0.484$), but its 95% CI also crossed zero (−0.071 to 0.814). Likewise, the point estimates for the warm-biased and cold-biased space fractions were 0.068 and −0.323, respectively, and both corresponding 95% CIs crossed zero. Outdoor temperature and mean monitored-space ON fraction showed the largest raw associations with complete 24 h TR1 energy.

3.5. Task-Specific Data-Suitability Results

Table 8 summarizes the permitted use of each monitoring channel. The combined assessment distinguished 59 fully observed TR1 days for primary complete 24 h energy analysis from two partial days used only in sensitivity reporting. It also identified the appropriate use of the supporting meter and operational-state records.

For the stated exploratory analyses, TR1 was retained as the primary load target and room temperature as the zone-level target. The remaining channels supplied supporting, comparison, or diagnostic information under the qualifications reported in Table 8.

For zone-temperature modeling, setpoint, weather, historical temperature, and ON/OFF status can serve as candidate explanatory variables. The ON/OFF record is an operational-state proxy. It does not provide the continuous input or actuator-constraint information required for MPC formulation or feasibility assessment. Accordingly, the retained channels support bounded exploratory load and zone-temperature modeling, together with comparative diagnosis. Priority measurements for a later monitoring campaign are occupancy, timetable, and continuous-actuation signals.

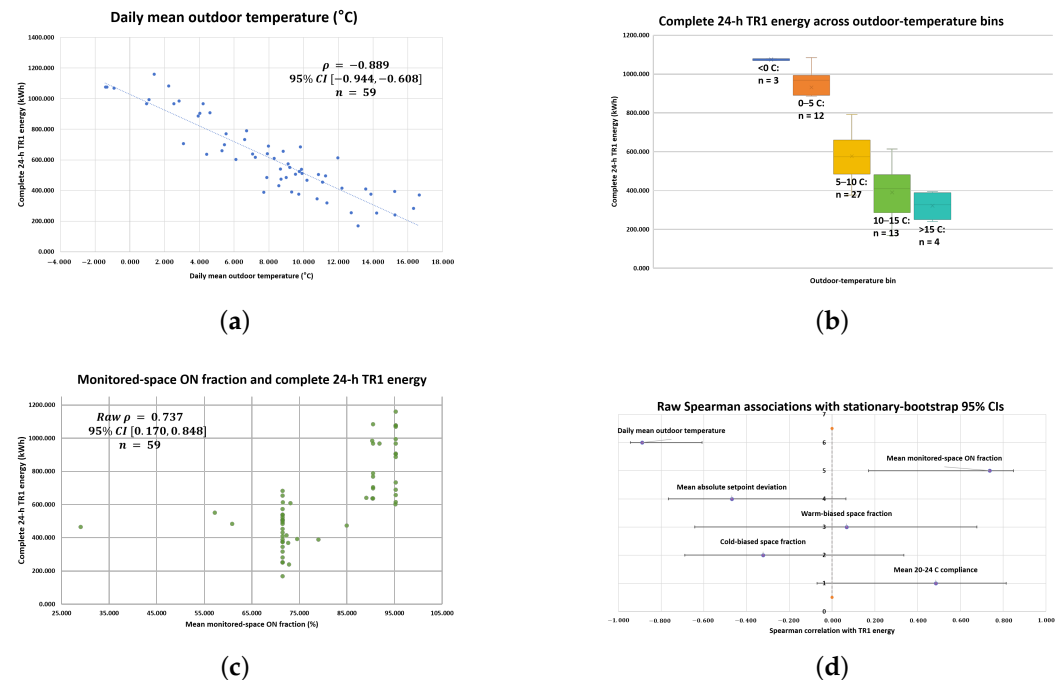


Figure 6. Exploratory energy–thermal associations for the 59 fully observed TR1 days: (a) complete 24 h TR1 energy versus daily mean outdoor temperature; (b) complete 24 h TR1 energy across outdoor-temperature bins; (c) complete 24 h TR1 energy versus mean monitored-space ON fraction; and (d) raw Spearman associations with stationary-block-bootstrap 95% confidence intervals.

Table 8. Task-specific evidence-to-use map for the available monitoring channels.

Channel Group	Task-Suitability Class	Assigned Role	Use Restriction
Meter G active power	Usable with stated limitations	Comparative monitoring	Secondary series not combined with TR1
Meter TR1 active power	Usable with stated limitations	Primary monitored-load proxy for exploratory load modeling and complete 24 h TR1 energy analysis	59 fully observed TR1 days for primary analysis; 61 days meeting the 90% and 95% thresholds for sensitivity reporting
Meter T1 active power	Usable with stated limitations	Secondary diagnostic channel	Unverified end use, low base load, and intermittent spikes
Outdoor weather	Suitable for stated exploratory task	Exogenous prediction input	Possible local microclimate uncertainty
Room temperature	Suitable for stated exploratory task	Zone thermal state and prediction target	No radiant-temperature or occupant-feedback measurements
Zone setpoint	Suitable for stated exploratory task	Control reference and deviation calculation	Occupancy and operating schedules are unavailable in the monitoring export.
Zone ON/OFF status	Usable with stated limitations	Binary operational-state proxy	Does not represent continuous actuation magnitude
Error codes	Usable with stated limitations	Data-quality flag	Code definitions and physical meanings require verification
Occupancy and timetable	Unavailable for stated task	Potential disturbance and schedule inputs	Not included in the monitoring export
Continuous actuation	Unavailable for stated task	Required control-input variables	No valve position, flow rate, fan speed, or command signals

Table 9 summarizes the analytical consequences of the combined assessment. It contrasts the initial screening result with the final permitted use of each record or channel. The TR1 decision is the clearest example: 61 days met the completeness thresholds, but only 59 fully observed days entered the complete 24 h energy analysis.

Table 9. Analytical consequences of the combined assessment.

Channel or Record	Screening Result	Permitted Use	Analytical Consequence
TR1 daily records	61 days met the 90% and 95% thresholds	59 complete days retained for primary analysis; two partial days retained only for sensitivity reporting	Separates complete daily-energy evidence from available-minute sensitivity evidence
Meter G	Valid paired observations available	Retained as a comparison channel	Supports comparative diagnosis, not construction of the primary TR1 energy series
Meter T1	Active-power data available	Assigned a secondary diagnostic role	Low baseline load, unverified end use, and intermittent spikes qualify its use
ON/OFF status	Binary state observations available	Retained as an operational-state proxy	Does not represent actuation magnitude or operating constraints
Continuous actuation	No channel available	Assigned a monitoring-priority role	Identifies measurements needed for later control-oriented work

4. Discussion

4.1. Diagnostic and Operational Insights

In this export, numerical availability alone did not establish analytical eligibility. The combined assessment separated complete-day TR1 records from sensitivity-only records and assigned different uses to the remaining channels. These decisions define the analytical scope of the exploratory results.

Established approaches address complementary questions. Data-recovery methods determine whether faulty or incomplete records can be detected and reconstructed [25]. Semantic schemas document the identity and relationships of BMS points [26]. Fault-detection and diagnosis methods identify abnormal operation from building automation data [27]. Rather than reconstructing data or detecting faults, the present case study determines the permitted analytical use of each monitored channel by combining screening evidence, physical interpretation, and task requirements.

Control-oriented modeling requires a selected set of disturbance inputs and system states [28]. MPC formulations further require defined manipulated inputs and operating constraints [29]. The present assessment identifies which of these prerequisites are available in the export and which measurements should be prioritized before a subsequent control study.

The observed association between outdoor temperature and TR1 energy, together with the weekday–weekend contrast, supports representative-day selection and stratified exploratory modeling. Its interpretation remains conditional on the observed period because weather, occupancy, schedules, and end uses were not separately resolved. Table 6 shows that fixed-phase 10 and 15 min subsampling preserved the daily-energy summaries and energy–temperature associations, whereas one-minute data retained more information about daily peaks and ON/OFF transitions.

Substantial thermal heterogeneity was observed across the monitored spaces. High-ON/low-compliance and low-ON/low-compliance patterns identify locations for follow-up inspection of setpoints, schedules, sensing, capacity, and control response. After completeness screening, TR1 was retained as a provisional target for exploratory building-level load modeling, while individual room temperatures were retained as zone-level prediction targets. Weather, calendar descriptors, setpoints, and historical temperatures provide candidate explanatory variables; ON/OFF status is used only as an operational-state proxy.

The qualifications of these variables are summarized in Table 8. Any subsequent predictive model should use chronological holdout or rolling evaluation. Occupancy and timetable data would improve disturbance representation, and continuous actuator measurements would support identification of input–state effects.

4.2. Scope of the Findings

This study examined one university building during a winter-to-shoulder-season period. The findings describe the observed conditions and monitoring export.

A cooling-season dataset would require a new assessment because cooling demand, solar gains, humidity, cooling setpoints, and equipment staging may change both the load profiles and the evidence needed for interpretation. The thresholds, cluster descriptions, and channel uses should therefore be reassessed for the target building, climate, season, HVAC configuration, and intended analysis.

5. Conclusions

This case study assessed the analytical suitability of an incomplete BMS and smart-meter export by combining channel completeness with physical interpretation and task requirements. Primary complete-day energy and energy–thermal analyses used 59 fully observed TR1 days. Sensitivity analyses used 61 threshold-qualified days and reported their energy values as available-minute aggregates.

For the studied building, the combined evidence determined which records entered the primary analysis and how the monitored channels were used. Within the observed winter-to-shoulder-season period, the data supported exploratory analysis of load variation and zone-temperature patterns. The findings apply to the studied building, monitoring export, season, and stated analyses.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/buildings16163231/s1>, Table S1: Sensitivity of day-type energy summaries and the association with daily mean outdoor temperature across TR1 completeness thresholds.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BMS	Building Management System
HVAC	Heating, Ventilation, and Air Conditioning
MPC	Model Predictive Control
MAD	Median Absolute Deviation

CI	Confidence Interval
TR1	Smart-Meter Channel TR1
T1	Smart-Meter Channel T1

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