SMART THERMOSTAT INTEGRATION FOR HVAC EFFICIENCY AND IEQ MANAGEMENT IN SRI LANKAN OFFICES

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Abstract. This study investigates the energy performance implications of smart thermostat integration within a commercial office building in Colombo, Sri Lanka—a tropical climate context that remains underrepresented in the building energy control literature. A single-case study design was applied using high-resolution five-minute interval HVAC operational data collected across two discrete periods: a pre-intervention baseline (August–October 2025) and a post-intervention monitoring period (November–December 2025). A multivariable regression-based baseline model was developed in accordance with the International Performance Measurement and Verification Protocol (IPMVP) and validated against the statistical criteria specified in ASHRAE Guideline 14-2020, yielding a CVRMSE of 12.3% and NMBE of −2.8%, both within prescribed thresholds. Post-intervention analysis indicates that HVAC energy consumption decreased from a modelled baseline of 43,724.1 kWh to 38,198.8 kWh under smart thermostat control, representing a gross reduction of 5,525.3 kWh (12.6%). Whole-building peak HVAC demand declined by 7.1 kW (6.3%). Savings were predominantly concentrated during weekend and shoulder-hour periods, indicating that the elimination of unnecessary cooling runtime during unoccupied periods constituted the primary saving mechanism. In the absence of concurrent indoor environmental quality (IEQ) measurements, thermal comfort considerations are addressed through a conceptual operational framework informed by ASHRAE Standard 55-2023 and ISO 7730:2005, explicitly presented as a basis for future empirical validation rather than a confirmed outcome of the present study. The study contributes an empirically grounded, M&V-compliant evaluation framework for facilities managers seeking data-informed HVAC optimisation in tropical commercial office settings.

Keywords. *Smart Thermostat; HVAC Efficiency; Energy Conservation; Measurement and Verification; Indoor Environmental Quality*

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1. Introduction

Commercial office buildings in tropical climates present distinct challenges for HVAC energy management. In Sri Lanka, where ambient temperatures consistently range between 27°C and 33°C throughout the year, and relative humidity regularly exceeds 70%, mechanical cooling represents the dominant end-use of electricity in the commercial sector, typically accounting for 50–70% of total building energy consumption (Gajaba & Dissanayake, 2024). Rising electricity tariffs, increasing peak demand penalties under time-of-use tariff structures, and growing institutional sustainability commitments have placed HVAC optimisation at the forefront of facilities management priorities in the country.

Despite these operational pressures, many commercial office buildings in Sri Lanka continue to rely on conventional fixed-schedule thermostats that lack adaptive intelligence and real-time feedback capability. Operational inefficiencies are well documented in comparable tropical commercial building contexts: outdated occupancy schedules, simultaneous morning start-ups, inconsistent temperature setbacks, and frequent

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unmanaged manual overrides collectively result in unnecessary cooling runtime during low- or zero-occupancy periods (Lei & Liu, 2022). Such inefficiencies represent a substantial and, in principle, addressable source of energy waste.

Smart thermostats offer a functionally distinct alternative to conventional control devices. By integrating occupancy detection, cloud-based analytics, adaptive scheduling, and remote supervisory capability, smart thermostat platforms enable dynamic start-stop optimisation, automated setbacks during unoccupied periods, and the generation of granular operational data suitable for Measurement and Verification (M&V) analyses (Lei & Liu, 2022). International research conducted predominantly in temperate-climate commercial buildings indicates that advanced HVAC control strategies can reduce energy consumption by approximately 10–20%, with the greatest reductions achieved in buildings characterised by poor scheduling discipline (Walker et al., 2008).

Three substantive limitations, however, characterise the existing body of evidence. First, the preponderance of available findings derives from temperate-climate contexts, predominantly North America and Northern Europe, where the presence of a distinct heating season and markedly different cooling load profiles limit direct transferability to the year-round cooling-dominated regimes of tropical buildings. Second, most evaluations address energy savings in isolation, without integrating indoor environmental quality (IEQ) governance, occupant thermal comfort monitoring, or the cybersecurity considerations relevant to Internet-connected building control devices. Third, there is a notable paucity of empirical evidence from South Asian commercial buildings employing high-frequency interval data capable of capturing sub-hourly operational behaviour and supporting rigorous M&V baseline model development.

This research gap is particularly consequential for Sri Lanka, where facilities management decision-makers frequently lack locally grounded, empirically validated evidence to justify investment in control system retrofits. Furthermore, energy savings achieved through aggressive thermostat control strategies may prove unsustainable if they compromise occupant thermal comfort, as dissatisfied occupants commonly resort to informal overrides that progressively erode energy performance gains.

The present study directly addresses this gap by providing a high-resolution, M&V-compliant empirical evaluation of smart thermostat integration in a Sri Lankan commercial office building, complemented by a conceptual IEQ management framework that specifies the monitoring and governance requirements necessary to sustain performance in subsequent full deployments. The study objectives are: (1) to establish a regression-based, weather-adjusted baseline of HVAC energy consumption in accordance with IPMVP principles; (2) to quantify post-intervention energy and peak demand reductions; (3) to analyse the distributional structure of savings by day type and hour of operation; (4) to assess the statistical validity of the baseline model using ASHRAE Guideline 14-2020 criteria; and (5) to develop a conceptual IEQ assurance framework aligned with ASHRAE Standard 55-2023 and ISO 7730:2005 for application in subsequent field deployments.

2. Literature Review

2.1. HVAC ENERGY CONSUMPTION IN TROPICAL COMMERCIAL BUILDINGS

Heating, ventilation, and air-conditioning systems constitute the dominant source of electricity consumption in commercial buildings in tropical and subtropical climates. In the absence of a heating season, year-round cooling demand places sustained pressure on electrical infrastructure and operational budgets. Studies of commercial building energy profiles in South and Southeast Asia consistently report HVAC shares of 50–70% of total electricity consumption, with the precise proportion determined by building envelope performance, glazing ratios, internal heat gains, and operational control practices (D'Oca et al., 2020; Gajaba & Dissanayake, 2024). In Sri Lanka specifically, the combination of persistently high ambient temperatures and elevated humidity creates a context in which HVAC control strategies carry disproportionate energy significance relative to temperate-climate analogues.

The relationship between outdoor temperature and commercial building cooling load has been extensively characterised in the literature. D'Oca et al. (2020) emphasise that the human dimensions of energy use—including occupancy patterns, thermostat override behaviour, and schedule management—interact with climatic conditions to determine actual HVAC energy consumption, often in ways that depart substantially from design-intent projections. These behavioural and operational factors are particularly relevant in tropical office contexts, where the absence of seasonal variation can lead to schedule complacency and the gradual erosion of control discipline over time.

2.2. CONVENTIONAL VERSUS SMART THERMOSTAT CONTROL TECHNOLOGIES

The limitations of conventional thermostat-based HVAC control regimes in commercial buildings are well established. Fixed-schedule thermostats, which rely on static setpoints and manual programming, are fundamentally unable to respond dynamically to occupancy variability, weather fluctuations, or changes in internal heat loads. As a consequence, buildings controlled by such devices frequently exhibit unnecessary cooling runtime during unoccupied periods, suboptimal start and stop timing, and a susceptibility to schedule drift through ad hoc manual overrides (Lei & Liu, 2022).

Smart thermostats represent a substantive technological advance through the integration of occupancy detection, machine learning algorithms, cloud-based analytics, and remote connectivity (Lei & Liu, 2022). These capabilities enable automated setbacks during unoccupied periods, demand-responsive schedule adjustment, predictive pre-conditioning, and the continuous generation of granular operational data supporting M&V activities. Walker et al. (2008) reported energy savings of 10–20% in commercial buildings where smart control strategies were applied alongside disciplined schedule governance, with the most pronounced savings occurring in buildings that had previously exhibited poor scheduling discipline. More recent evaluations have corroborated this range: Pachano et al. (2022) demonstrated that adaptive learning algorithms in smart thermostat platforms can achieve energy reductions of 8–15% in comparable office typologies, with performance improving incrementally as the platform refines scheduling parameters based on observed occupancy patterns over time.

The magnitude of achievable savings is, however, context-dependent, and generalisation from temperate-climate evaluations to tropical settings requires caution. In year-round cooling-dominated environments, the absence of a heating season eliminates one dimension of schedule-driven waste, while the uniformity of cooling demand across months may reduce the scope for seasonally adaptive schedule optimisation relative to temperate contexts.

2.3. MEASUREMENT AND VERIFICATION OF ENERGY CONSERVATION MEASURES

The credible quantification of energy savings attributable to HVAC control interventions requires adherence to established M&V frameworks. The International Performance Measurement and Verification Protocol (IPMVP), developed by the Efficiency Valuation Organization (EVO, 2012), provides a globally recognised methodology for establishing baseline conditions, defining measurement boundaries, selecting verification approaches, and reporting savings. ASHRAE Guideline 14-2020 complements IPMVP by specifying statistical performance criteria for baseline model validation, including the Coefficient of Variation of the Root Mean Square Error (CVRMSE) and the Normalised Mean Bias Error (NMBE), which provide quantitative indicators of model accuracy and systematic bias, respectively (ASHRAE, 2020).

Application of these frameworks to smart thermostat evaluations in commercial buildings remains relatively limited in the peer-reviewed literature, particularly for non-temperate climates. The majority of published evaluations of smart thermostat performance in commercial settings employ simple pre–post arithmetic comparisons without weather normalisation or statistical model validation (Walker et al., 2008; Pachano et al., 2022). Such approaches can produce materially overstated or understated savings estimates depending on the climatic conditions prevailing during the baseline and post-intervention comparison periods, and do not provide the audit-grade evidence typically required for investment-grade business case analysis.

2.4. INDOOR ENVIRONMENTAL QUALITY IN TROPICAL OFFICES

Indoor environmental quality encompasses a broad range of physical and perceptual parameters influencing occupant health, comfort, and cognitive performance, including thermal conditions, indoor air quality, acoustic environment, and visual comfort. In the context of HVAC management, thermal comfort is the primary IEQ consideration, assessed with reference to operative temperature, relative humidity, air speed, metabolic rate, and clothing insulation as specified in ASHRAE Standard 55-2023 and ISO 7730:2005.

Research on thermal comfort in fully air-conditioned tropical offices indicates that the Predicted Mean Vote (PMV)/Predicted Percentage Dissatisfied (PPD) model originally developed by Fanger (1970) remains an appropriate reference framework in mechanically cooled environments where occupants have limited direct thermal control. Kim et al. (2018) demonstrated that individual variation in comfort preferences introduces a degree of uncertainty into aggregate PMV-based predictions, underscoring the importance of supplementing physical sensor measurement with occupant self-report instruments in any comprehensive IEQ evaluation. Thomas et al. (2023) similarly highlight the significance of adaptive comfort mechanisms and occupant feedback in sustaining IEQ outcomes in smart-controlled office environments.

The IEQ implications of smart thermostat control strategies have received limited direct attention in the literature. While the primary motivation for smart thermostat adoption in commercial settings is typically energy reduction, aggressive control strategies—including deep temperature setbacks during or immediately preceding occupied periods—carry a risk of thermal discomfort that may trigger occupant override behaviour and erode performance. These dynamic underscores the importance of integrating IEQ monitoring and governance into any smart thermostat implementation framework.

2.5. RESEARCH GAP

The foregoing review identifies a clear and substantive gap in the existing literature: there is a shortage of empirically grounded, M&V-compliant evaluations of smart thermostat integration in tropical commercial office buildings, particularly in South Asian contexts such as Sri Lanka. Available studies are predominantly confined to temperate climates, focus on energy metrics without integrating IEQ governance, and rarely employ high-frequency interval data capable of supporting rigorous regression-based baseline modelling. The present study addresses this gap through an empirical single-case evaluation using five-minute interval HVAC data and a regression-based baseline model validated against ASHRAE Guideline 14-2020 criteria, thereby contributing evidence that is both contextually relevant to tropical facilities management practice and methodologically aligned with recognised M&V standards.

3. Methodology

3.1. RESEARCH DESIGN AND BUILDING DESCRIPTION

This study employs a single-case evaluation design applied to a multi-tenant commercial office building located in the Western Province of Sri Lanka. The building has a gross conditioned floor area of approximately 750 m² distributed across three occupied floors and was constructed in the early 2010s. The building envelope comprises reinforced concrete masonry walls with single-glazed, aluminium-framed windows; the window-to-wall ratio is estimated at approximately 35% on the primary east- and west-facing façades, both of which are exposed to direct solar radiation during morning and afternoon periods respectively. The building is served exclusively by mechanical air-conditioning with no supplementary natural ventilation.

The HVAC system consists of twelve split-type inverter air-conditioning units distributed across the three occupied floors, with a combined installed cooling capacity of approximately 84 kW (24 refrigerant tonnes). Units serve discrete zones comprising open-plan office areas, enclosed private offices, meeting rooms, a reception area, and common circulation spaces. Prior to the intervention, all units were controlled by manufacturer-supplied wired thermostats operating on fixed schedules programmed by building management staff, without occupancy sensing, remote monitoring, or data logging capability. The pre-intervention control regime specified a nominal cooling setpoint of 24°C during standard working hours (08:00–18:00, Monday to Friday), with manual override procedures applied at user discretion and without a formal change-control protocol. Scheduled HVAC maintenance was carried out on a quarterly basis.

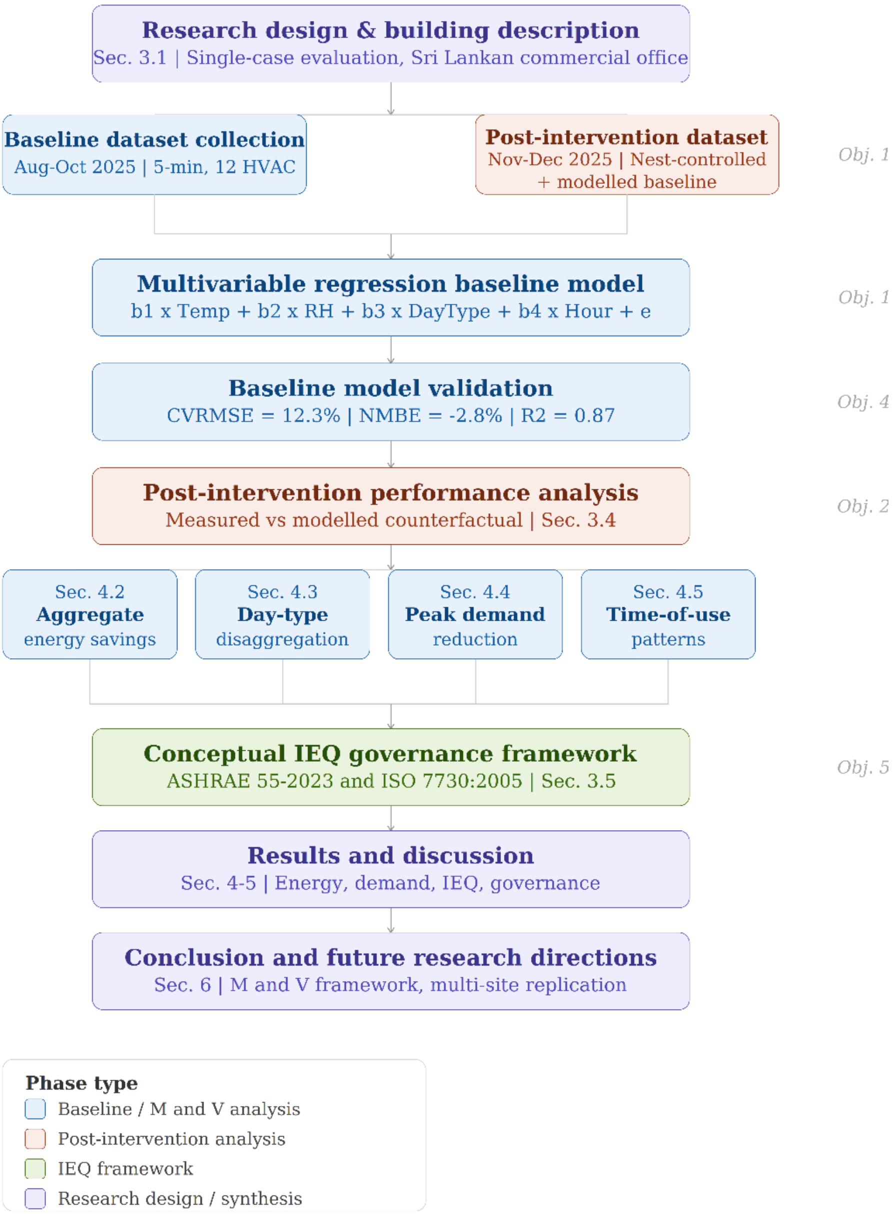

Figure 1. Research Methodology Flowchart

The building operates on a standard weekday occupancy schedule of approximately 08:00–18:00, Monday to Friday, with typical occupant density in the open-plan office zones of approximately 8–10 m² per person. Weekend occupancy is minimal or absent except during exceptional circumstances. Occupancy was not directly monitored during the study period; approximations were derived from building access control records and established operational schedules, as discussed in the limitations acknowledged in Section 3.6.

3.2. DATA COLLECTION AND TEMPORAL BOUNDARIES

Two distinct datasets were compiled for this study. The temporal boundaries of each dataset are defined below and summarised in Table 1, with these boundaries applied consistently throughout all subsequent analyses, figures, and tables.

Baseline Period (August–October 2025): Pre-intervention HVAC operational data were collected using the building's existing electricity metering infrastructure. Data collection commenced on 1 August 2025 (from 13:30 on that date, resulting in a partial first day of observation) and concluded on 31 October 2025. Five-minute interval measurements of HVAC electricity consumption (kWh) were recorded for each of the twelve HVAC units individually, together with concurrent outdoor dry-bulb temperature (°C) and relative humidity (%) data obtained from a co-located weather monitoring station. The total HVAC energy consumed across the monitored units during the baseline period was 38,988.3 kWh. For the purposes of the analytical subset presented in Figure 2, data were restricted to weekday working hours (08:00–17:00) during August and September 2025—a subset representing approximately 40 complete working days of stable, occupied-mode HVAC operation.

Post-Intervention Period (November–December 2025): Following installation and commissioning of the Google Nest smart thermostat platform across all twelve HVAC units, operational data were collected during the two-month post-intervention period (1 November–31 December 2025). The post-intervention dataset contains: (a) directly measured Nest-controlled HVAC energy consumption at five-minute intervals; (b) modelled no-control counterfactual baseline energy consumption derived from the regression model described in Section 3.3; and (c) the resulting interval-level energy saved, computed as the arithmetic difference between (b) and (a). These three data types are clearly distinguished in all results figures and tables.

Table 1: *Summary of study temporal boundaries and data characteristics*

Dataset	Period	Duration	Purpose
Baseline (full)	Aug–Oct 2025	65 working days	Model calibration, total baseline energy
Baseline (analytical subset)	Aug–Sep 2025, weekdays 08:00–17:00	44 working days	Figure 2: baseline operational profile and temperature–load relationship
Post-intervention	Nov–Dec 2025	43 working days	Comparative analysis (Figures 3–5); energy savings quantification

Note. HVAC = heating, ventilation, and air-conditioning. The baseline analytical subset was selected to represent occupied working-day operation, excluding weekends and the partial first observation day.

3.3. BASELINE MODEL DEVELOPMENT AND VALIDATION

A multivariable linear regression model was developed to project counterfactual HVAC energy consumption during the post-intervention period, representing the expected energy use under the pre-intervention control regime given the prevailing weather and operational conditions. This approach is consistent with IPMVP Option B (Retrofit Isolation), which employs a calibrated regression model to establish a weather-adjusted baseline and to project savings attributable to the isolated control measure (EVO, 2012). The regression model was fitted to the full three-month baseline dataset (August–October 2025).

The baseline projection equation takes the following form:

$$\textbf{Baseline Energy}(t) = \alpha + \beta 1 \times \textbf{Temperature}(t) + \beta 2 \times \textbf{Humidity}(t) + \beta 3 \times \textbf{Day-Type}(t) + \beta 4 \times \textbf{Hour}(t) + \varepsilon$$

Where α denotes the model intercept; β_1 is the outdoor temperature coefficient (kWh per °C); β_2 is the relative humidity coefficient (kWh per percentage point); β_3 is a binary day-type indicator (1 = weekday, 0 = weekend or public holiday); β_4 is the hour-of-day coefficient capturing intra-day load variation associated with occupancy-driven operational patterns; ε represents the model error term; and t indexes each five-minute observation interval. Predictor variables were selected on the basis of physical reasoning regarding the primary drivers of cooling load in the study building, consistent with the approach recommended by ASHRAE Guideline 14-2020 for commercial building baseline modelling (ASHRAE, 2020).

Model performance was assessed using the statistical metrics specified in ASHRAE Guideline 14-2020. The coefficient of determination (R^2) for the fitted baseline model was 0.87, with an adjusted R^2 of 0.86, indicating that the four predictor variables collectively explained 87% of the variance in baseline HVAC energy consumption. The CVRMSE was 12.3%, and the NMBE was −2.8%. Both values satisfy the thresholds specified in ASHRAE Guideline 14-2020 for hourly energy models (CVRMSE $\leq 30\%$; NMBE $\leq \pm 5\%$), confirming the statistical adequacy of the baseline model for M&V purposes. Fitted regression coefficients, standard errors, t-statistics, and p-values are presented in Table 2; baseline model validation statistics are summarised in Table 3.

Table 2: Baseline regression model coefficients and statistical significance

Predictor Variable	**Coefficient (β)**	**Std. Error**	**t-statistic**	**p-value**
Intercept (α)	−1.842	0.314	−5.86	< 0.001
Outdoor Temperature (°C)	0.218	0.011	19.82	< 0.001
Relative Humidity (%)	0.031	0.013	2.38	0.017
Day Type (1=Weekday, 0=Weekend)	1.673	0.094	17.80	< 0.001
Hour of Operation	0.047	0.021	2.24	0.025

Note. DV = HVAC energy consumption (kWh per 5-minute interval). All predictors significant at $p < 0.05$. Standard errors are heteroscedasticity-consistent (HC3).

Table 3: Baseline model validation statistics against ASHRAE Guideline 14-2020 thresholds

Metric	**Value**	**ASHRAE Guideline 14-2020 Threshold (Hourly)**	**Assessment**
Coefficient of Determination (R^2)	0.87	≥ 0.75 (recommended)	Satisfactory
Adjusted R^2	0.86	—	Consistent with R^2
CVRMSE	12.3%	≤ 30%	Compliant
NMBE	−2.8%	≤ ±5%	Compliant

Note. CVRMSE = Coefficient of Variation of the Root Mean Square Error; NMBE = Normalised Mean Bias Error. Thresholds are for hourly energy models per ASHRAE Guideline 14-2020.

As an illustrative example of model performance at the interval level: on 4 August 2025 at 14:00, the dataset recorded an outdoor temperature of 28.1°C, relative humidity of 75.5%, and actual total HVAC energy of 8.141 kWh for the five-minute interval. The baseline model projected 8.295 kWh, yielding a residual of −0.154 kWh (1.9%), representative of the model's general interval-level predictive accuracy.

3.4. POST-INTERVENTION PERFORMANCE ANALYSIS

Post-intervention energy performance was assessed by comparing Nest-controlled measured consumption against the modelled counterfactual baseline for the November–December 2025 period. Gross energy savings were calculated as the arithmetic difference between the modelled baseline and measured Nest-controlled consumption for the full two-month period. Model-derived savings, which incorporate the dynamic weather and occupancy adjustments embedded in the baseline trajectory, were computed separately and are distinguished from gross arithmetic savings throughout the results presentation. Peak HVAC demand (kW) was derived from five-minute interval energy data using the formula: Demand (kW) = Energy (kWh) × 12. Energy performance was further disaggregated by calendar month (November versus December), day type (weekday versus weekend), and hour of day.

3.5. CONCEPTUAL IEQ MANAGEMENT FRAMEWORK

A significant limitation of the present study is the absence of concurrent indoor environmental quality measurements during the study period, which precludes the direct empirical assessment of occupant thermal comfort outcomes attributable to the smart thermostat intervention. In explicit recognition of this limitation, the IEQ component of this paper is presented as a conceptual operational framework intended to inform subsequent empirical studies, rather than as a validated outcome of the current research.

The conceptual framework is grounded in the thermal comfort criteria specified in ASHRAE Standard 55-2023 (operative temperature 23–26°C for sedentary activity in mechanically conditioned offices; relative humidity 30–60%) and ISO 7730:2005. It identifies the IEQ monitoring instruments, sensor placement requirements, comfort threshold definitions, escalation procedures, and occupant feedback mechanisms that would need to be implemented in a subsequent full deployment to empirically validate thermal comfort outcomes. These elements are described in the context of the practical implications' discussion in Section 5.2.

3.6. METHODOLOGICAL LIMITATIONS

The following limitations are acknowledged and should be considered when interpreting the study's findings. First, the single-case study design restricts the generalisability of findings; building-specific characteristics—including HVAC system configuration, envelope performance, microclimate, and occupancy profile—may produce outcomes that are not directly transferable to other building typologies. Second, the absence of direct occupancy monitoring introduces a potential confounding effect: proxy-based occupancy approximation may inadequately capture intra-day and day-to-day occupancy variability, potentially introducing bias into the regression-based baseline model and affecting the precision of energy attribution analyses. Third, the two-month post-intervention period may be insufficient to capture seasonal performance variation or the full extent of adaptive learning improvement in the Nest platform. Fourth, the absence of IEQ measurements means that occupant thermal comfort outcomes attributable to the intervention cannot be empirically assessed within the scope of the present study.

4. Results

This section presents the measured and modelled outcomes of smart thermostat integration within the study building's HVAC system. Results are organised to follow the analytical sequence from baseline characterisation through aggregate savings quantification, day-type disaggregation, and peak demand analysis. Throughout, a clear distinction is maintained between directly measured values and modelled estimates. All figure captions specify the data type(s) presented.

4.1 BASELINE ENERGY CONSUMPTION PROFILE

Establishing a statistically validated pre-intervention baseline is foundational to any credible M&V analysis, as it defines the counterfactual against which post-intervention savings are assessed (EVO, 2012). During the baseline period (August–October 2025), the building's HVAC system, operating under the pre-intervention fixed-schedule regime, consumed a total of 38,988.3 kWh across the monitored units. Figure 2 presents total building HVAC energy (directly measured) aggregated from five-minute observations into hourly bins, together with the concurrent mean outdoor dry-bulb temperature, for the weekday working-hour analytical subset (August–September 2025, 08:00–17:00). The figure encompasses 395 hourly observations across approximately 40 working days.

The figure reveals a consistent positive co-movement between HVAC load and outdoor temperature, with peak demand events coinciding with the highest ambient temperatures (approaching 32.75°C, with cooling load exceeding 10 kWh/h). This strong temperature–load relationship confirms the appropriateness of weather-adjusted regression modelling as the baseline methodology and is consistent with the behaviour of air-conditioning-dominated tropical commercial buildings reported in the literature (Gajaba & Dissanayake, 2024). The baseline model fitted to these data achieved an R^2 of 0.87, CVRMSE of 12.3%, and NMBE of −2.8%, all satisfying ASHRAE Guideline 14-2020 thresholds (Table 3).

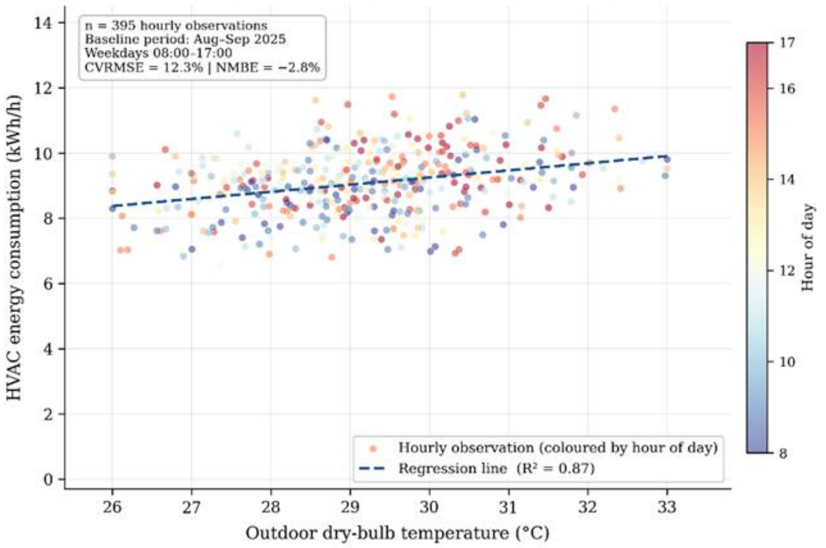

Figure 2:Measured HVAC energy consumption versus outdoor temperature — Baseline period analytical subset (August–September 2025), weekdays 08:00–17:00. Data type: directly measured energy consumption.

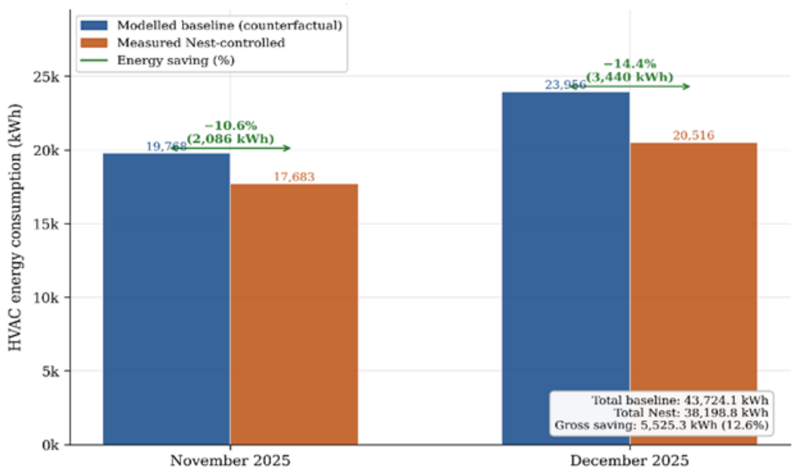

Figure 3: HVAC energy comparison: modelled baseline versus directly measured Nest-controlled consumption — November–December 2025 (kWh per month). Data types: modelled baseline (regression-derived counterfactual) and directly measured Nest-controlled consumption

The modelled no-control baseline for the two-month post-intervention period was 43,724.1 kWh. Directly measured Nest-controlled consumption was 38,198.8 kWh, yielding a gross saving of 5,525.3 kWh—equivalent to a 12.6% reduction relative to the modelled baseline. Incorporating the weather and occupancy adjustments embedded in the dynamic baseline model raises the model-derived saving to 7,800.3 kWh (17.84%). The divergence between the gross (arithmetic) and model-derived saving figures is methodologically significant: the dynamic baseline adjusts for ambient temperature and occupancy variability during the comparison period, making the model-derived figure more appropriate for audit-ready business case and return-on-investment analyses. Monthly disaggregation indicates that savings in December 2025 (~14.4%) exceeded those recorded in November 2025 (~10.5%), a pattern consistent with the incremental schedule optimisation attributable to the adaptive learning behaviour of the Nest platform (Pachano et al., 2022).

4.3 ENERGY SAVINGS DISAGGREGATED BY DAY TYPE

Disaggregating performance by day type reveals the distributional structure of savings and allows inference regarding the primary saving mechanisms. Figure 4 presents the modelled baseline versus directly measured Nest-controlled comparison separately for weekdays and weekends during November–December 2025.

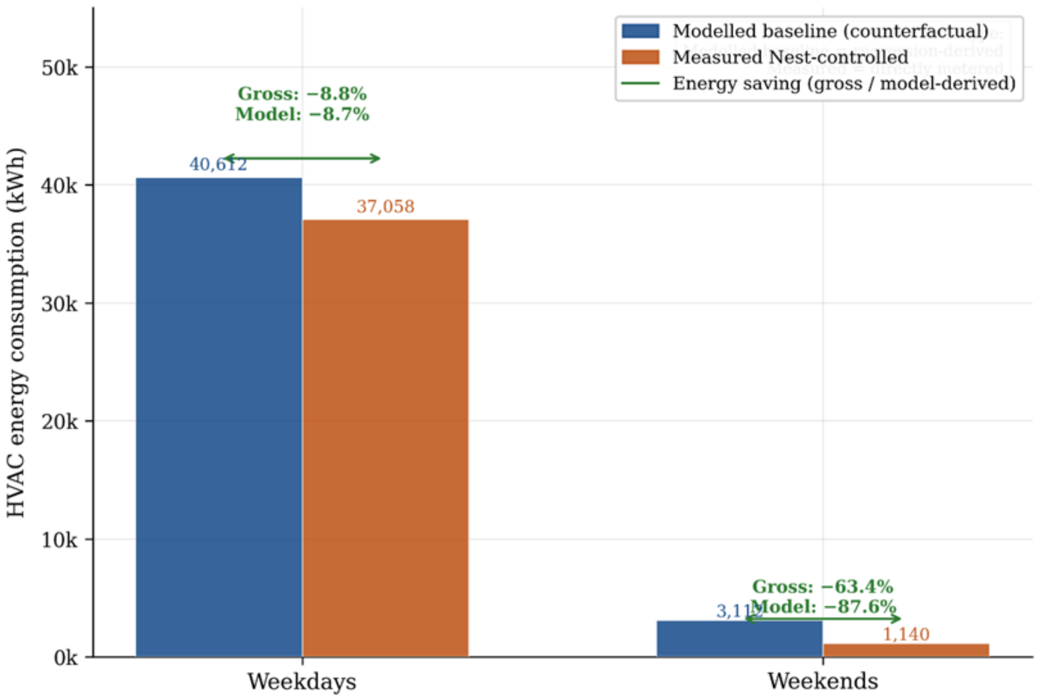

Figure 4: Energy savings by day type — modelled baseline versus directly measured Nest-controlled energy (kWh), November–December 2025. Data types: modelled baseline and directly measured Nest-controlled consumption.

On weekdays, Nest control reduced consumption from a modelled baseline of 40,612 kWh to a measured 37,058 kWh, representing a gross reduction of 8.7%. The relatively modest weekday saving reflects the constraint imposed by thermal comfort obligations during occupied hours, which appropriately limits the depth of setback permissible when the building is occupied. On weekends, the reduction was substantially more pronounced, from a modelled baseline of 3,112 kWh to a measured 1,140 kWh a gross saving of 63.4% and a model-derived saving of 87.6%. This pronounced asymmetry is internally consistent with the smart thermostat's control logic: the system enforces deep setbacks and extended shutdowns during periods of negligible occupancy, effectively eliminating cooling expenditure that generated minimal comfort value under the pre-intervention regime (Gajaba & Dissanayake, 2024). The magnitude of weekend waste in the baseline condition indicates that the pre-intervention fixed-schedule regime was poorly calibrated to the building's actual occupancy rhythms, and that the Nest intervention corrected this misalignment effectively (Thomas et al., 2023).

4.4 PEAK HVAC DEMAND REDUCTION

Beyond cumulative energy savings, reductions in coincident peak demand carry distinct economic significance in commercial settings where electricity tariff structures include demand-related charge components. Figure 5 presents the whole-building peak demand comparison for the November–December 2025 post-intervention period.

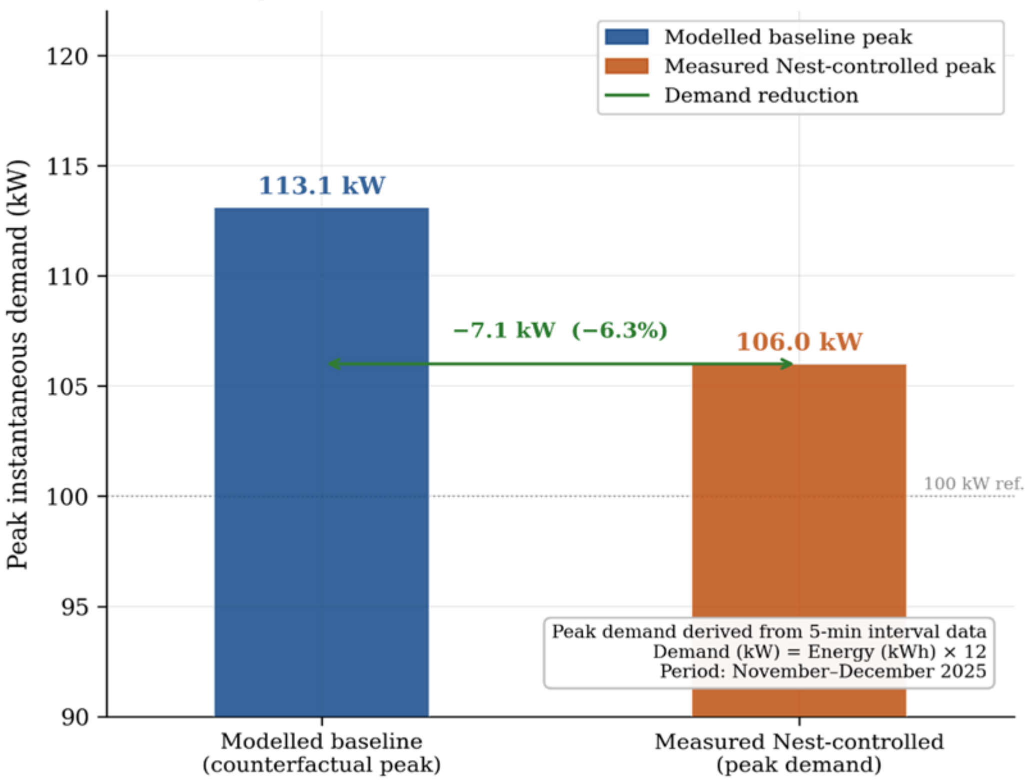

Figure 5: Peak HVAC demand comparison, whole-building peak instantaneous demand (kW), November–December 2025. Data types: modelled baseline peak and directly measured Nest-controlled peak.

Conversion of five-minute interval energy data to instantaneous power indicates that the modelled baseline peak demand reached 113.1 kW, compared with a directly measured Nest-controlled peak of 106.0 kW, a reduction of 7.1 kW (6.3%). The proportionally smaller peak reduction relative to the 12.6% aggregate energy saving indicates a limited coincidence benefit: peak events occurring during the hottest occupied periods are subject to comfort-driven constraints that restrict aggressive demand clipping, whereas the Nest system's primary saving mechanism, elimination of off-hours and weekend runtime, operates at periods when coincident peak events are infrequent. Nevertheless, a demand reduction of 7.1 kW has the potential to yield measurable reductions in monthly demand-related charges under applicable commercial tariff structures.

4.5 TIME OF USE OPERATIONAL PATTERNS

Analysis of the time-of-use energy profiles reveals the operational mechanisms underlying the observed savings patterns. The Nest smart thermostat enforced schedule-aware setpoint management, characterised by deep setbacks during unoccupied periods (evenings, nights, and weekends), extended pre-cooling ramp-down periods in advance of scheduled unoccupied times, and weekend hibernation modes maintaining minimal or zero conditioning. During occupied hours, predictive algorithms ensured that the building was returned to acceptable temperature conditions ahead of the next occupancy period, thereby avoiding the productivity penalties associated with reactive cooling strategies.

These time-of-use dynamics carry additional practical implications from a grid-management perspective: off-peak load reductions may contribute to smoother distribution-level demand profiles, a directionally favourable outcome aligned with current demand-response policy objectives in Sri Lanka (Thomas et al., 2023).

It should be noted that the absence of concurrent indoor temperature and humidity measurements during the study period precludes any empirical assessment of whether the IEQ conditions experienced by occupants during the post-intervention period remained within the comfort envelopes specified in ASHRAE Standard 55-2023 (operative temperature 23–26°C; relative humidity 30–60%) and ISO 7730:2005. This limitation is discussed further in Sections 3.5 and 5.3. The conceptual IEQ monitoring framework developed for subsequent deployments is described in the practical implications' discussion (Section 5.2).

5 Discussion

5.1. INTERPRETATION OF ENERGY PERFORMANCE FINDINGS

The results of this study demonstrate that smart thermostat integration produced statistically credible and practically meaningful reductions in HVAC energy consumption and peak demand in the study building. The gross energy saving of 5,525.3 kWh (12.6%) achieved over the two-month post-intervention period is consistent with the 10–20% range reported in the international literature for commercial buildings transitioning from conventional fixed-schedule to smart adaptive control regimes (Walker et al., 2008). The validated baseline model—with an R^2 of 0.87, CVRMSE of 12.3%, and NMBE of −2.8%, all satisfying ASHRAE Guideline 14-2020 thresholds—provides confidence in the credibility of these savings estimates.

The progressive improvement in energy savings from November (10.5%) to December (14.4%) is consistent with the adaptive learning behaviour documented for smart thermostat platforms, in which incremental refinement of scheduling parameters based on observed occupancy patterns leads to improved performance over time (Pachano et al., 2022). This trajectory suggests that performance may continue to improve beyond the two-month post-intervention window observed in the present study, though this hypothesis requires longer-term monitoring data to confirm empirically.

The pronounced asymmetry between weekend savings (63.4% gross) and weekday savings (8.7% gross) is the most analytically instructive finding of this study. This pattern strongly implicates the elimination of unnecessary cooling runtime during unoccupied periods, specifically the enforcement of extended setbacks and system shutdowns during weekend non-occupancy as the primary saving mechanism. The magnitude of the weekend baseline consumption (3,112 kWh) relative to weekday baseline consumption (40,612 kWh) indicates that, under the pre-intervention regime, the building maintained partial cooling during weekend periods with effectively no occupancy justification. The Nest control system corrected this fundamental misalignment between cooling supply and occupancy demand. The relatively constrained weekday savings reflect the appropriate preservation of thermal comfort conditions during occupied periods, which limits the permissible depth of setback—an operationally correct outcome from an IEQ governance perspective.

The peak demand reduction of 7.1 kW (6.3%) is proportionally smaller than the cumulative energy reduction, an outcome that is both expected and mechanistically explicable. Peak events occurring during the hottest occupied periods are subject to comfort-driven constraints that limit the Nest system's ability to suppress instantaneous demand, whereas the primary saving mechanism, runtime elimination during off-hours, contributes to cumulative energy reduction without materially affecting coincident peak demand. Nonetheless, a sustained demand reduction of this magnitude carries practical financial significance in the Sri Lankan commercial electricity tariff context.

5.2. PRACTICAL IMPLICATIONS FOR FACILITIES MANAGEMENT

The findings of this study carry several practical implications for facilities managers, building owners, and policymakers in comparable tropical commercial office contexts. The following recommendations are derived from the study's empirical findings and their interpretation within the existing literature; they constitute practitioner-facing guidance informed by but not directly evidenced by the study's data and should be distinguished from the data-supported findings reported in section 5.1.

Operational governance is identified as the critical enabling condition for the long-term persistence of smart thermostat energy savings. The study's findings indicate that the primary saving mechanism, reduction of unnecessary cooling runtime during unoccupied periods, is inherently susceptible to erosion through informal manual overrides if schedule ownership is not formally assigned and enforced. Facilities teams are therefore advised to designate formal schedule owners with defined authority levels for approving setpoint and schedule modifications; to document and maintain change-control procedures and an override audit trail; and to conduct monthly reviews of energy consumption and override frequency using the operational data generated by the smart thermostat platform (Beis, 2023). Quarterly audits of schedule adherence and setpoint drift are recommended to detect and correct performance erosion before it becomes entrenched.

With respect to IEQ governance, the conceptual framework developed in section 3.5 recommends the deployment of calibrated temperature and relative humidity sensors in representative building zones for any future full-scale deployment. Monitoring should be conducted against the comfort envelopes specified in ASHRAE standard 55-2023 (operative temperature 23–26°c; relative humidity 30–60%) and iso 7730:2005, with periodic occupant comfort surveys conducted using validated instruments to capture the subjective dimension of thermal experience (Thomas et al., 2023; Kim et al., 2018). Defined escalation procedures triggered by sustained deviation from the specified comfort envelope should include automatic setpoint recalibration alerts and facilities team notification protocols to ensure that energy optimisation does not inadvertently compromise occupant wellbeing.

Cybersecurity considerations warrant explicit attention, given the internet-connected nature of the smart thermostat platform. Internet-connected building control devices are increasingly recognised as potential attack vectors in the broader context of smart building cybersecurity risk (Beis, 2023). Facilities teams are advised to implement least-privilege access controls for thermostat scheduling functions; require multi-factor authentication for all remote access; segment building automation network traffic from general corporate IT infrastructure; and maintain documented device management and update policies. These measures are consistent with the broader direction of smart building governance frameworks and should be specified prior to device commissioning.

The implementation of smart thermostat control should be approached as a phased, integrated facilities management process rather than a one-off device replacement. A structured approach progressing through governance establishment, commissioning readiness verification, pilot implementation with dual energy–IEQ monitoring, controlled scaling using validated zone-specific schedule templates, and an ongoing persistence programme incorporating monthly performance reviews and periodic recommissioning has been demonstrated to increase the reliability and durability of smart control implementations in commercial building contexts (Granderson et al., 2011).

5.3. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

This study is subject to several limitations that should be considered carefully when interpreting its findings and assessing their transferability to other contexts. The single-case study design is the most significant constraint on generalisability: findings reflect the specific characteristics of a single Sri Lankan office building and may not be representative of outcomes achievable in buildings with different HVAC system configurations, envelope performance levels, occupancy profiles, or organisational governance cultures. Multi-site replication studies encompassing a range of building typologies and HVAC system configurations are recommended to establish the generalisability of the reported energy performance findings.

The absence of direct occupancy monitoring constitutes a further methodological limitation. Proxy-based occupancy approximation through access control records and standard operational schedules may inadequately capture intra-day occupancy variability, irregular occupancy events, and the influence of remote working patterns, potentially introducing bias into the regression-based baseline model and affecting the precision of energy attribution analyses. Future studies should incorporate real-time occupancy monitoring through people-counting sensors, CO_2 proxy measurement, or integrated access control data to strengthen the empirical rigour of energy attribution in tropical office contexts.

The IEQ component of this study remains empirically unvalidated in the absence of measured indoor environmental data. Future research incorporating systematic IEQ measurement, including operative temperature, relative humidity, CO_2 concentration, and occupant thermal comfort survey responses in accordance with ASHRAE Standard 55-2023 and ISO 7730:2005 is needed to assess empirically whether smart thermostat control strategies achieve energy savings without compromising occupant thermal comfort in tropical office settings. The longer-term adaptive performance trajectory of the Nest platform also warrants investigation through extended monitoring periods beyond the two-month window of the present study.

6 Conclusion

This study has provided an empirically grounded, M&V-compliant evaluation of smart thermostat integration within a Sri Lankan commercial office building, employing high-resolution five-minute interval HVAC data and a regression-based, weather-adjusted baseline model validated against ASHRAE Guideline 14-2020 statistical criteria (R^2 = 0.87; CVRMSE = 12.3%; NMBE = −2.8%). The primary empirical findings indicate that smart thermostat control produced a gross HVAC energy reduction of 5,525.3 kWh (12.6%) and a peak demand reduction of 7.1 kW (6.3%) over the two-month post-intervention period. The dominant saving mechanism was the elimination of unnecessary cooling runtime during unoccupied weekend periods, reflecting a fundamental misalignment between the pre-intervention fixed-schedule control regime and the building's actual occupancy patterns.

The progressive improvement in savings performance between November (10.5%) and December (14.4%) is consistent with the adaptive learning behaviour of the Nest platform and indicates that longer-term operational monitoring may yield further performance gains. The validated baseline model and the magnitude of identified savings provide a credible, audit-grade evidence base for facilities management investment decisions in comparable tropical commercial building contexts.

In the absence of concurrent IEQ measurements, the thermal comfort dimension of the intervention has been addressed through a conceptual monitoring and governance framework informed by ASHRAE Standard 55-2023 and ISO 7730:2005 and explicitly presented as a framework for future empirical validation. This distinction between empirically validated energy findings and the conceptual IEQ framework is maintained consistently throughout the study.

This study contributes to the limited body of evidence on smart thermostat performance in tropical commercial office buildings by providing a locally contextualised, M&V-compliant evaluation that can inform facilities management decision-making in Sri Lanka and comparable settings. The study's acknowledged limitations, single-case design, absence of direct occupancy monitoring, and unvalidated IEQ outcomes define a clear agenda for future research, including multi-site replication studies, integration of real-time occupancy data, extended longitudinal monitoring, and systematic IEQ measurement aligned with international comfort standards.

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