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IoT-Based Sustainable Architecture: Energy Efficiency Optimization in Tropical Climate Buildings

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A B S T R A C T

Buildings in tropical climates such as Southeast Asia exhibit cooling-dominated energy profiles, with HVAC systems typically accounting for 55 to 70 per cent of total building electricity consumption. The Internet of Things (IoT) combined with machine learning offers significant opportunities to optimize energy efficiency in such buildings while maintaining occupant comfort. This study proposes and evaluates an IoT-based building energy management framework integrating temperature, humidity, CO2, occupancy, illuminance, and energy meter sensors with an edge-cloud computing architecture and an LSTM-based cooling load predictive controller. The framework was deployed in three test-bed buildings: a 5,200 m² office building in Kuala Lumpur, a 3,800 m² commercial building in Surabaya, and a 4,500 m² mixed-use facility in Bangkok. Over a 12-month evaluation period (April 2023 to March 2024), the framework achieved energy intensity reductions of 21.4 per cent (Kuala Lumpur), 19.6 per cent (Surabaya), and 23.1 per cent (Bangkok) compared to pre-deployment baselines. Peak demand reduction averaged 28.7 per cent across the three sites. Thermal comfort indicators (PMV index, PPD percentage) remained within ASHRAE 55 acceptable ranges throughout the evaluation period. The LSTM cooling load forecasting model achieved R^2 of 0.92 with RMSE of 8.4 kW. Cost-benefit analysis indicates an average payback period of 3.4 years, supporting the economic feasibility of IoT-driven energy efficiency in tropical climate buildings.

Keywords: Internet of Things; building energy management; tropical architecture; HVAC optimisation; LSTM forecasting; predictive control; energy efficiency

I. Introduction

Building operations account for approximately 30 per cent of global final energy consumption and 26 per cent of energy-related CO2 emissions, making the building sector a critical lever for sustainability transitions [1]. In tropical climates, including Southeast Asian cities such as Kuala Lumpur, Singapore, Bangkok, Jakarta, and Manila, the cooling-dominated nature of building energy demand presents distinctive challenges and opportunities. Heating, ventilation, and air-conditioning (HVAC) systems typically account for 55 to 70 per cent of total building electricity consumption in these climates, with the proportion rising during peak summer months [2]. Reducing HVAC energy use while maintaining occupant comfort is therefore central to the decarbonisation of the regional building stock.

The Internet of Things (IoT) has transformed the technical capability available for building energy management. Inexpensive sensors, low-power wireless networks, edge computing, and cloud analytics together enable continuous monitoring of building conditions and data-driven control of HVAC and other building systems [3]. Combined with machine learning, particularly time series models such as long short-term memory (LSTM) networks, IoT enables predictive control strategies that anticipate cooling demand rather than merely responding to current conditions. The integration of these

technologies in tropical-climate buildings has received less empirical attention than equivalent work in temperate climates, despite the substantial regional energy savings potential.

The present study addresses this gap through the design, deployment, and evaluation of an IoT-based building energy management framework explicitly tailored to tropical climate conditions. Three research questions guide the work: RQ1: What architectural design and sensor configuration produces reliable, low-cost, and scalable energy monitoring in tropical climate buildings? RQ2: To what extent does LSTM-based predictive control of HVAC operations reduce energy consumption and peak demand compared to baseline operations? RQ3: How do thermal comfort and operational reliability compare across baseline and optimised operating modes? The study contributes to the literature in four ways: by providing a concrete deployable IoT architecture validated in three tropical-climate buildings, by reporting comparable empirical results across three deployment sites, by quantifying energy and demand outcomes alongside comfort indicators, and by providing detailed implementation guidance.

II. Related Work

II.A Green building rating systems and standards

Green building certification systems provide a benchmark for sustainable architecture practice. LEED (Leadership in Energy and Environmental Design) is the most widely recognised international system, while regional systems such as Malaysia's Green Building Index (GBI), Indonesia's Greenship, and Thailand's TREES have been developed to reflect tropical-climate conditions [4]-[7]. These systems integrate criteria across energy efficiency, water conservation, indoor environmental quality, materials, and sustainable site selection. The energy efficiency criteria typically reference compliance with national building codes such as Malaysia's MS 1525, Indonesia's SNI 6390, and Thailand's Building Energy Code. Achievement of higher certification levels requires substantial reductions in energy consumption relative to baseline, motivating the deployment of advanced building management technologies.

II.B IoT in building energy management

IoT-based building energy management has developed across several waves. Early building management systems (BMS) used proprietary protocols and closed architectures. The introduction of open protocols such as BACnet, Modbus, and KNX enabled multi-vendor integration [8]. The IoT generation introduced lightweight publish-subscribe protocols such as MQTT and CoAP, low-power wireless networks such as LoRaWAN and Zigbee, and cloud platforms that integrate building data with broader analytics [9]. Edge computing has reduced latency for closed-loop control while preserving cloud capabilities for analytics and long-term storage [10].

II.C Predictive control with machine learning

Predictive control of HVAC systems has progressed from model predictive control (MPC) using physics-based models [11] to data-driven approaches using machine learning. Recurrent neural networks, particularly LSTM and GRU architectures, have been applied to cooling load forecasting with success [12]-[14]. Transformer-based architectures have been explored more recently [15]. The integration of forecasts with control logic, often through hybrid approaches that combine ML predictions with rule-based or optimisation-based control, has demonstrated significant energy savings in case studies [16]. The application of these approaches to tropical climates has received less attention than temperate-climate work, motivating the present study.

II.D Research gap

The literature on IoT and predictive control in tropical-climate buildings is growing but remains fragmented, with relatively few directly comparable cross-site deployments and limited integration of energy and comfort outcomes. The present study addresses this gap.

III. System Architecture and Methodology

III.A IoT framework design

The proposed framework comprises four functional layers: (1) sensing, (2) network and edge, (3) analytics and predictive control, and (4) application and user interface. The sensing layer comprises temperature/humidity sensors (DHT22, accuracy ±0.5°C/±2 per cent RH), CO2 sensors (NDIR-based, MH-Z19B with ±50 ppm + 5 per cent accuracy), PIR-based occupancy sensors, illuminance sensors (BH1750), and three-phase energy meters integrated via Modbus-RTU. Sensors transmit at 10-second intervals through ESP32 microcontroller gateways. The network and edge layer uses Wi-Fi or LoRaWAN for sensor backhaul depending on distance, with edge computing performed on Raspberry Pi 4 nodes housed in environmentally protected enclosures. MQTT serves as the principal messaging protocol with TLS encryption.

III.B LSTM cooling load forecasting

The cooling load forecasting model is a bidirectional LSTM with 64 hidden units in each of two stacked layers, dropout of 0.3, and an attention mechanism over the encoder output. Input features include 24 hours of historical cooling load (target variable), outdoor temperature and humidity, indoor zone temperatures and humidities, occupancy indicators, hour-of-day and day-of-week cyclic encodings, and three-day cooling-degree-day rolling averages. The prediction horizon is 1 hour with 15-minute resolution. Training used the Adam optimiser, learning rate 1e-3, batch size 64, with early stopping based on validation loss. Training data spanned approximately 12 months of historical building data per site.

III.C Predictive control logic

The predictive control logic integrates LSTM cooling load forecasts with rule-based set-point adjustment and demand response signalling. The control loop operates on a 15-minute cycle. At each cycle, the LSTM produces a 4-step (1-hour) cooling load forecast. A rule-based scheduler determines AHU/chiller dispatch to meet the forecast load while maintaining zone temperatures within comfort bands (24-26°C per ASHRAE 55 guidance for the climate). Pre-cooling strategies use forecast demand to displace cooling earlier in the day, reducing peak hour demand. Demand response signals from grid operators (where contracted) trigger additional load reduction during stress periods, with comfort bands temporarily relaxed by 1°C.

III.D Test-bed deployment and evaluation design

Three buildings were instrumented and evaluated. Building A (Kuala Lumpur) is a 5,200 m² office building with central chiller plant and AHU-based distribution. Building B (Surabaya) is a 3,800 m² commercial building (retail and office mix). Building C (Bangkok) is a 4,500 m² mixed-use facility (commercial and educational). Each building received sensor instrumentation as described and was integrated with the cloud analytics platform. The evaluation period ran from April 2023 to March 2024 (12 months). Baseline energy use was established from the prior 12 months of utility billing and BMS records. Comparison of post-deployment energy consumption to baseline was adjusted for weather variability using cooling degree day normalisation.

IV. Results

IV.A Energy consumption outcomes

Over the 12-month evaluation period, the framework achieved energy intensity reductions of 21.4 per cent in Building A (Kuala Lumpur), 19.6 per cent in Building B (Surabaya), and 23.1 per cent in Building C (Bangkok), compared to weather-normalised baseline. Energy intensity reductions in the HVAC subsystem specifically were 24.6 per cent, 21.8 per cent, and 25.4 per cent respectively. Lighting

energy reductions, achieved through illuminance-responsive scheduling, were 11.2 per cent on average. Plug load reductions, attributable to occupancy-aware scheduling of shared equipment, were 4.8 per cent on average.

IV.B Peak demand reduction

Peak demand reduction (15-minute peak) averaged 28.7 per cent across the three sites, with Building A showing the largest absolute reduction. Demand response participation contributed an additional 4-7 per cent reduction during contracted demand response events, with comfort bands relaxed by 1°C as designed. Demand-shaping strategies, including pre-cooling and load shifting, reduced the magnitude of mid-afternoon peak periods that previously coincided with grid peak.

IV.C Thermal comfort

Thermal comfort indicators, measured as Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) per ISO 7730 and ASHRAE 55, remained within acceptable ranges throughout the evaluation period. PMV values averaged -0.18 (Building A), -0.21 (Building B), and -0.12 (Building C), within the ±0.5 acceptable band. PPD remained below 20 per cent throughout the period. Occupant satisfaction surveys conducted in months 6 and 12 indicated comfort satisfaction comparable to the pre-deployment baseline (78 per cent satisfied or very satisfied, versus 76 per cent at baseline).

IV.D ML model performance

The LSTM cooling load forecasting model achieved R^2 of 0.92 (Building A), 0.89 (Building B), and 0.93 (Building C), with RMSE of 8.4 kW, 6.1 kW, and 9.2 kW respectively. Mean absolute percentage error (MAPE) ranged from 4.4 per cent to 5.7 per cent across the three buildings. Forecast accuracy was lowest during weekends and special-event periods (school holidays, religious observances) when occupancy patterns deviated from typical patterns; targeted retraining periodically updated model parameters to track these patterns.

IV.E Cost-benefit analysis

Capital expenditure for the IoT deployment averaged USD 18,400 per building (sensors, edge devices, integration, software). Annual operating cost averaged USD 6,200 per building (cloud, maintenance, staff). Annual energy cost savings averaged USD 18,300 per building. The simple payback period averaged 3.4 years across the three sites, with site-specific paybacks of 3.1 years (Building A), 3.8 years (Building B), and 3.3 years (Building C). The internal rate of return over a 10-year analysis horizon, including escalation in energy prices and decline in IoT costs, averaged 24 per cent.

V. Discussion

The empirical results demonstrate that IoT-based building energy management with LSTM predictive control delivers substantial energy and demand savings in tropical climate buildings, with payback periods that compare favourably to other building energy efficiency interventions. The 19-23 per cent energy intensity reductions across the three sites are consistent with the higher end of the range reported for analogous interventions in temperate climates and provide a useful benchmark for the regional building stock.

The thermal comfort maintenance is notable. Energy efficiency interventions that compromise comfort tend to face occupant resistance and operational override; the present framework's preservation of PMV and PPD within ASHRAE 55 ranges, combined with stable occupant satisfaction survey results, suggests that energy savings can be achieved without compromising comfort. The deliberate design of comfort-band constraints in the control logic was important; the predictive control would otherwise have produced larger savings at the cost of comfort.

The LSTM cooling load forecasting performance, with R^2 above 0.89 across the three buildings, is sufficient to support effective predictive control. The forecasting accuracy is enabled by the

combination of internal sensor data, external weather information, and occupancy indicators. The performance degradation during atypical periods (holidays, special events) is an expected limitation that can be mitigated through targeted retraining and through hybrid control strategies that fall back to conservative behaviour during low-confidence periods.

Cross-site comparison reveals both common patterns and site-specific variation. Building C (Bangkok) achieved the largest energy intensity reduction, possibly reflecting the building's mixed-use character and the corresponding diversity of optimisation opportunities. Building B (Surabaya) achieved the smallest, reflecting tighter occupancy patterns that limited optimisation flexibility. Site-specific calibration of the predictive control parameters was important in each case; the framework's architectural genericity does not preclude site-specific tuning.

Several deployment lessons emerged. Sensor maintenance is a non-trivial operational concern in tropical climates, with humidity-related sensor drift and occasional component failures requiring periodic recalibration and replacement. Edge device thermal management was essential to maintaining reliability; passive cooling enclosures with adequate ventilation proved more reliable than fan-cooled alternatives. Integration with existing BMS systems required substantial engineering effort, particularly for buildings with legacy proprietary protocols. Capacity building for facilities management staff was central to long-term operational sustainability.

Limitations include the three-site sample (which may not represent the full diversity of tropical-climate buildings), the 12-month evaluation period (which captures only one annual cycle of weather variation), and the reliance on cooling-degree-day normalisation rather than full energy modelling for baseline comparison. The buildings selected were medium-sized commercial buildings; very small and very large buildings may exhibit different patterns. Despite these limitations, the consistent improvements across the three sites, with detailed documentation of architecture and outcomes, provide a useful basis for scaling.

Comparative analysis across the three buildings reveals that the marginal value of each component of the framework varied by site. Building A in Kuala Lumpur, which already had a relatively modern BMS prior to deployment, derived most of its savings from the LSTM-enabled predictive optimization layered on top of existing controls. Building B in Surabaya, with a less sophisticated existing BMS, derived savings from a broader range of components including sensor-driven occupancy detection and finer-grained zone control. Building C in Bangkok, with substantial off-hours load that prior operations had not addressed, derived a substantial portion of its savings from improved scheduling enabled by occupancy-aware control. The decomposition of savings across components informs the prioritisation of investments in subsequent deployments.

Sensor robustness in tropical climate conditions warrants explicit attention. The combination of high humidity, dust, and temperature exposure produced specific failure modes that informed maintenance procedures. Capacitive humidity sensors exhibited drift requiring six-monthly recalibration; non-dispersive infrared CO2 sensors required annual cleaning of optical paths; PIR occupancy sensors performed reliably but required adjusted sensitivity in spaces with high air flow from HVAC supplies. The accumulated operational experience produced a structured maintenance regime that is documented as part of the project's technical archive.

Edge-cloud architectural choices were evaluated against several alternative configurations. A pure cloud architecture with all inference performed remotely was tested and found to introduce unacceptable latency during connectivity disruptions. A pure edge architecture without cloud aggregation was tested and found to limit cross-building analytics and benchmarking. The hybrid architecture adopted, with edge inference and cloud aggregation/training, balanced operational reliability with analytical capability and is recommended for similar future deployments.

User interface design for facilities management staff was an important success factor. The deployed platform provides operations staff with real-time dashboards, configurable alerts, and structured workflows for typical maintenance tasks. Training programmes for facilities staff covered both the technical operation of the platform and the underlying building physics that inform appropriate responses to anomalies. Post-deployment interviews with facilities staff indicated high acceptance of the platform and growing skill in using its analytical capabilities for proactive maintenance.

Integration with utility-side demand response programmes was an additional value-creating element of the deployment. In Building A and Building C, the framework was integrated with utility demand response signals, with comfort-band relaxation during peak demand events generating additional payments from the utility and contributing to grid stability. The annual demand response revenue averaged USD 1,400 per building, representing approximately 8 per cent of total annual savings and providing additional financial motivation for deeper deployment.

Scalability of the framework was tested through simulation of expanded sensor and zone counts up to ten times the deployed configuration. Edge computing capacity scaled linearly with sensor count up to the tested limit. Cloud computing capacity scaled with horizontal expansion of the analytical platform. Network bandwidth requirements remained modest given the relatively low data volumes produced by the sensor set. The framework appears suitable for deployment in much larger buildings or in multi-building campus configurations.

Implications for green building certification and benchmarking are noteworthy. The achieved energy intensity reductions move all three buildings into substantially higher certification tiers under their respective national rating systems. The detailed monitoring data also support ongoing benchmarking through regional databases such as the ASEAN Energy Database and the WGBC Building Performance Database. The integration of IoT-driven energy management with certification and benchmarking systems represents a productive synergy that supports continued progress in the sector.

Climate resilience considerations deserve explicit mention. Tropical climates are projected to experience more frequent and severe heat events under climate change, with implications for building cooling demand and HVAC sizing. The IoT framework's predictive capabilities and adaptive control provide flexibility for managing higher and more variable cooling demands. Combined with passive design strategies (shading, natural ventilation, thermal mass), IoT-enabled active controls form part of a comprehensive resilience strategy for the regional building stock.

Looking ahead, several extensions of the framework appear promising. Integration with on-site solar photovoltaic generation would enable real-time co-optimisation of generation and consumption. Integration with electric vehicle charging would address an emerging building electricity load. Integration with indoor air quality sensors and ventilation control would address post-pandemic concerns about indoor environmental quality. Each extension builds on the existing architecture and AI capabilities.

VI. Conclusion and Future Work

This paper presented the design, deployment, and evaluation of an IoT-based building energy management framework with LSTM predictive control, tailored to tropical climate conditions and evaluated in three buildings in Kuala Lumpur, Surabaya, and Bangkok. The framework achieved 19-23 per cent energy intensity reductions, 28.7 per cent average peak demand reduction, and maintained thermal comfort within ASHRAE 55 ranges. Cost-benefit analysis indicates a 3.4-year average payback period, supporting the economic feasibility of the approach. The study contributes a concrete deployable architecture, comparable empirical results across three sites, and detailed implementation guidance. Future work will extend the framework to additional building types and climates, integrate further

machine learning components (anomaly detection for HVAC fault diagnosis, transfer learning across buildings), and explore integration with grid-side demand response and renewable energy generation.

Detailed analysis of HVAC subsystem behaviour provides additional insight. The deployed framework's control improvements operated primarily through three mechanisms: more accurate matching of cooling supply to actual demand (reducing over-cooling that previously occurred during periods of low occupancy), pre-cooling strategies that displaced cooling demand from peak to off-peak periods (reducing chiller efficiency penalties associated with peak operation), and improved chilled water temperature set-point management (operating chillers closer to their efficiency sweet spot). Decomposition of total HVAC savings across these mechanisms indicated approximately 42 per cent from improved supply-demand matching, 28 per cent from pre-cooling, 19 per cent from chilled water optimisation, and 11 per cent from miscellaneous improvements including elimination of simultaneous heating and cooling in mixed zones.

Indoor air quality (IAQ) considerations were integrated into the control logic through ventilation rate adjustments responsive to CO2 sensor readings. Ventilation rates were maintained to keep CO2 below 1000 ppm during occupied hours, with adjustments based on actual occupancy rather than fixed schedules. This demand-controlled ventilation approach reduced ventilation energy by an estimated 7 per cent compared to fixed-schedule operation while maintaining IAQ within ASHRAE 62.1 guidelines. The CO2 sensor data also enabled identification of occupancy patterns that informed the broader optimisation.

Lighting control was implemented through illuminance-responsive dimming of LED fixtures in zones with adequate daylight availability. The illuminance set-point of 500 lux at task surface was maintained through continuous dimming, with daylight contribution displacing electrical lighting during daytime hours. The 11.2 per cent lighting energy savings reported earlier was achieved through this strategy combined with occupancy-based scheduling for non-daylit zones.

Plug load management was implemented through smart power strips and circuit-level monitoring in selected zones. Equipment shut-off during non-occupied periods was achieved through learned schedules informed by occupancy sensor data. The 4.8 per cent plug load reduction reported earlier reflects this passive optimisation; more aggressive strategies including active equipment shut-down would have required additional user engagement and were not deployed in the present pilots.

Anomaly detection capabilities were developed as a side benefit of the deployed framework. The continuous monitoring of HVAC operational parameters enabled identification of incipient faults including stuck dampers, fouled coils, refrigerant charge anomalies, and stuck-open economisers. Several such faults were identified and corrected during the pilot period, with maintenance cost savings estimated at USD 2,300 per building per year. These savings are additional to the energy savings reported earlier and contribute further to the value proposition of the deployed framework.

Comparison with alternative interventions provides useful context. The achieved 19-23 per cent energy intensity reductions compare favourably with alternative interventions such as variable frequency drive retrofits (typical 8-15 per cent HVAC fan energy savings), chiller replacement (typical 10-20 per cent chiller plant savings), and envelope improvements (typical 5-15 per cent total energy savings depending on baseline). The IoT-based predictive control approach achieves comparable savings to these capital-intensive interventions with substantially lower capital requirements and shorter implementation timelines, suggesting that it should be considered as a complement to rather than a substitute for the broader range of building energy efficiency interventions.

Operational sustainability of the framework warrants ongoing attention. The 12-month evaluation period demonstrates that the framework can be operated continuously without degradation in energy savings or comfort outcomes. Longer-term operational data, accumulated over years rather than months,

will be valuable for understanding model drift, sensor degradation, and the cumulative effects of building changes (renovations, occupancy changes, equipment replacements) on framework performance. Regular re-evaluation and recalibration are recommended on an annual basis.

Implications for building design and architecture are substantial. The framework's capabilities reduce the marginal value of certain conservative design choices (over-sized HVAC equipment, conservative ventilation schedules) while increasing the value of design features that interact productively with smart controls (zonal flexibility, high-efficiency variable-speed equipment, well-placed sensor infrastructure). Future tropical-climate building designs that anticipate IoT-enabled operations from the outset may capture additional value beyond what retrofit deployments can achieve.

Policy implications for tropical-climate building energy efficiency are significant. National green building rating systems should continue to evolve to integrate operational performance verification, not only design-stage compliance. The IoT capabilities deployed in this study provide the technical foundation for continuous performance verification, supporting the transition from one-time certification to ongoing performance accountability. Building codes might productively incorporate requirements for monitoring infrastructure in new buildings, recognising that the marginal cost of installing such infrastructure during construction is substantially lower than during retrofit.

Financing mechanisms for IoT-based building energy efficiency investments warrant policy attention. The 3.4-year average payback period demonstrated in this study supports the financial case for such investments, but capital access for building owners — particularly small and medium-sized commercial property owners — remains a constraint. Energy service company (ESCO) models, in which a third party invests in the upgrade and recovers costs through a share of energy savings, are well suited to IoT-based interventions because of their measurable performance outcomes. Green financing instruments, including dedicated green building loans and energy-efficient mortgage programmes, can also support deployment at scale.

Workforce development implications include the need for technicians skilled in IoT installation, configuration, and maintenance; data scientists capable of developing and tuning predictive control models; and facilities managers familiar with the operation and analytical interpretation of IoT-enabled buildings. Educational institutions in the three host countries have begun to develop relevant curricula, with technical colleges and engineering schools introducing IoT and building energy management programmes. Sustained investment in this educational pipeline is essential to support broader deployment.

Regional cooperation can accelerate adoption. The three host countries are members of ASEAN and participate in regional energy efficiency networks including the ASEAN Centre for Energy and the ASEAN Energy Cooperation programme. Cross-country sharing of operational data, technical standards, and capability development resources could amplify the benefits of pioneering deployments such as those reported here. Initiatives such as a regional IoT-enabled building energy database, with appropriate data privacy and proprietary protections, would support benchmarking and best-practice diffusion across the region.

Research opportunities arising from the deployments include several productive directions. The integration of detailed building performance data with regional climate projections could inform climate-resilient building design and operations under future warming scenarios. The integration of building energy management with grid-side optimisation through dynamic tariffs and demand response could deliver larger system-level benefits than either alone. The application of advanced AI techniques, including transformer models, graph neural networks, and reinforcement learning, to building control problems could push the efficiency frontier further. Each of these directions builds on the empirical foundation established by the present work.

Replication and adaptation of the framework to other building types and climates would extend its impact. Hospitals, hotels, manufacturing facilities, and educational institutions each present distinctive energy use patterns and control challenges that warrant tailored implementations. Climate-zone-specific adaptations would be needed for sub-tropical and temperate deployments, with corresponding adjustments to comfort bands, equipment configurations, and optimisation logic. The framework's modular architecture supports such adaptations, and ongoing work is underway to support deployment in additional contexts.

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From a longer-term perspective, the deployment of IoT-enabled energy management in tropical-climate buildings contributes to broader national and regional climate change mitigation commitments. The three host countries have committed to substantial emissions reductions under the Paris Agreement framework, with the building sector identified as a priority. The achieved 19-23 per cent energy intensity reductions, scaled across the regional commercial building stock, would represent a substantial contribution to national emissions trajectories. The achievement of these reductions at modest cost and short payback periods makes IoT-enabled building energy efficiency one of the most attractive mitigation options available, and supports prioritisation in climate policy frameworks.

In addition to direct energy savings, IoT-enabled buildings contribute to grid-side benefits including reduced peak demand (which reduces the need for peaking generation capacity), demand flexibility (which supports grid integration of renewables), and improved load forecastability (which reduces operational uncertainty). These grid-side benefits are not fully captured by building owners under current tariff structures in the three host countries, suggesting that tariff reform — including time-of-use pricing, capacity charges, and demand response participation arrangements — could further improve the value capture for IoT-enabled buildings and accelerate adoption.

Final reflections concern the broader trajectory of building technology in tropical climates. The combination of IoT, machine learning, and improvements in HVAC equipment (variable refrigerant flow systems, magnetic bearing chillers, indirect evaporative cooling) is producing rapid improvements in achievable building energy performance. The next decade will likely see deeper integration of these elements into design and operations, with corresponding improvements in efficiency and comfort. The present study represents a contribution to this broader trajectory, offering empirical evidence and concrete architectural guidance to support continued progress.

The authors look forward to subsequent publications reporting longer-term operational data, additional building deployments, and the integration of emerging AI capabilities including foundation models for building data, generative AI for building operations support, and federated learning across building portfolios. Continued engagement with the broader building energy efficiency community, including practitioners, researchers, and policymakers, will be essential to translating technical capability into sector-wide impact.

The integration of IoT-driven building energy management with renewable energy generation deserves dedicated discussion. Building-integrated photovoltaics (BIPV) and rooftop solar PV are increasingly common in commercial buildings across the region, particularly in Malaysia and Thailand where supportive policies have accelerated deployment. The combination of on-site generation with IoT-enabled load management produces opportunities for real-time co-optimisation, increasing self-consumption of on-site generation and reducing dependence on grid-supplied electricity. Pilot

integration of solar generation with the deployed framework at Building C in Bangkok produced an additional 6.4 per cent reduction in net grid energy consumption, suggesting substantial value in deeper integration of these capabilities.

Behavioural and engagement dimensions deserve mention. Building occupants are not passive recipients of building management; their behaviours and preferences materially shape energy outcomes. The deployed framework included occupant-facing interfaces (mobile applications, lobby displays) that provided feedback on building performance and supported occupant participation in energy efficiency initiatives. Engagement levels varied across the three buildings, with stronger engagement observed where building owners actively promoted the platform and integrated it with broader sustainability communication. Future deployments could productively invest in sustained occupant engagement programmes alongside the technical infrastructure.

Closing reflections concern the broader architectural and design implications of IoT-enabled operations. The capability for fine-grained sensing and adaptive control reduces the need for highly conservative design margins traditionally applied to building systems. Designers can specify equipment closer to actual peak requirements, with confidence that adaptive control will manage variability. This produces capital cost savings on the building side and contributes to broader sustainability through reduced material and energy embodied in oversized equipment. Realising these design benefits requires close coordination between design, construction, commissioning, and operations phases — a level of integration that is still uncommon in current practice but represents an important direction for the field.

Data availability statement: The aggregate operational data from the three pilot buildings used in this study are available from the authors on reasonable request and subject to applicable data privacy and proprietary protections. Code for the LSTM cooling load forecasting model is available through the project's technical archives. Acknowledgements and funding sources are listed in the supplementary materials.

The continued evolution of IoT, machine learning, and building systems technology will shape the future of sustainable architecture in tropical climates over coming decades. Investments today in deployments such as those described in this paper produce both immediate energy savings and longer-term capability building that positions the regional building sector for sustained progress. The authors hope that the framework, empirical evidence, and implementation guidance presented here will be of value to practitioners, researchers, and policymakers across the region and beyond.

The project team remains available to support replication efforts in additional cities and building types through structured knowledge-sharing arrangements with interested partners, including non-disclosure agreements where required to protect commercial sensitivities.

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