Operational Optimization of HVAC Performance in Hot–Humid Climate: Minute-Level Case Study of an Institutional Building in Bangkok, Thailand

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Operational efficiency is one of the fundamental factors that determine the energy performance of buildings in terms of their ability to maintain thermal comfort. This research aims to evaluate operational HVAC characteristics such as cooling loads, energy intensity, and thermal comfort in an institutional building in Bangkok, Thailand. The building has seven floors with 33 zones. This study utilizes minute-level electricity consumption and indoor environmental conditions to determine operational efficiency. The study found significant underutilization of operational HVAC systems in buildings. The load factor of the building is 26.0%, indicating that some parts of the building consume 4.5 times more energy than the zone with the lowest consumption. The thermal comfort of the building is only 60.6%, indicating that there is significant overcooling in buildings. The research has also found that there is no significant relationship between outside temperatures and energy consumption in buildings ($R^2 = 0.023$). The research has proposed several strategies that could potentially reduce peak demand by 12.8% while improving thermal comfort by 15%, without requiring any upgrades to HVAC equipment.

Keywords: HVAC Operational Performance, Cooling Load Profiling, High-Granularity Data, Data-driven optimization

Introduction:

The building sector accounts for approximately 20–40% of global energy consumption, with commercial buildings representing a significant portion of this footprint [1][2]. It is projected that energy demand in buildings will continue to rise at an estimated annual growth rate of about 1.5% [3]. Implementing energy efficiency measures in buildings can yield substantial and economically viable effects, potentially slowing or offsetting increases in worldwide energy consumption [4]. As energy demand continues to grow alongside environmental concerns, optimizing building operation has become increasingly critical [5][6].

HVAC optimization research has evolved from component-level improvements to whole-system, data-driven methodologies [7]. While traditional approaches to energy management have relied on physics-based models and aggregated data, the proliferation of smart meters and building automation systems has enabled data-driven methodologies capable of revealing optimization opportunities that remain invisible to conventional analysis [8][9]. While previous studies have established fundamental knowledge in several key areas, significant limitations remain in current approaches, particularly with respect to data granularity, climatic context, and analytical scope [10]

To date, most research has focused on aggregated energy analysis at the building level with hourly or daily resolution [11]. Such studies have successfully characterized large-scale consumption patterns and seasonal trends, supporting basic load forecasting and benchmarking against industry standards [12]. Past analyses relying on hourly or coarser whole building data effectively identify long-term consumption trends, seasonal patterns, and benchmarking metrics such as Energy Use Intensity (EUI). However, such approaches inherently conceal short-duration dynamics and spatial heterogeneity in buildings [13].

Consequently, significant gaps remain in the field of HVAC and building energy research. Most studies rely on aggregated or hourly data, which obscures transient behaviors and rapid load changes in building operations [14][15]. An overreliance on coarse temporal resolution fails to capture rapid load fluctuations, short-duration anomalies, and precise temporal relationships among environmental conditions and equipment operation [16]. As a result, phenomena such as rapid load ramping, short cycling of HVAC equipment, zone-level control conflicts, and transient comfort violations are often unobservable at hourly scales. Previous research has highlighted that conventional whole building performance evaluations often overlook the distinct thermal behavior and occupancy patterns of individual zones, potentially neglecting important differences in energy use and occupant comfort across these zones [17].

Beyond data granularity, analytical depth presents another limitation. Many studies have collected extensive datasets from commercial buildings, but have not fully exploited them. Generally, these works restricted analytics to simple visualizations, such as power consumption histograms of selected AC units or indoor temperature and humidity histograms [18]. These approaches cannot capture the complex interactions among multiple air conditioning units or between lighting systems and plug loads in individual zones. Furthermore, most studies lack detailed analytics, state-of-the-art machine learning-based forecasting, anomaly detection, and other data-driven strategies that enable detailed operational optimization and zone-specific control. Recent developments have focused on increased temporal resolution and zone-level monitoring. However, most studies pursue discrete objectives such as load forecasting, benchmarking, or comfort assessment individually rather than within an integrated analytical context [19]. This fragmented approach limits the translation of analytical findings into actionable operational decisions. Moreover, inconsistencies exist regarding the interaction between energy efficiency and occupant comfort: EUI-focused studies often report localized comfort losses, while comfort-centric studies frequently overlook energy penalties from overcooling [20]. These discrepancies largely stem from inadequate temporal and spatial resolution.

Furthermore, the geographical and climatic context of this research addresses another critical gap in the literature. Despite the challenges of hot, humid climates, such as those in Bangkok, studies on HVAC performance in these environments are limited. Buildings in these regions face unique thermal loads, humidity control requirements, and occupant comfort expectations that differ significantly from those in temperate climates [21][22]. Comparative research typically focuses on temperate regions or generalized hot climates, without explicitly addressing the persistent humidity and its interaction with cooling demand [22]. Latent loads, continuous cooling operation, and limited economizer potential in such environments fundamentally alter HVAC system behavior [23]. Hourly aggregation masks humidity-driven inefficiencies, delayed system responses, and short-term control mismatches that may accumulate substantial energy waste over time. Bangkok's consistently hot and humid climate provides an ideal case study for understanding HVAC performance under these conditions.

To address these interconnected gaps, high-resolution data fundamentally reshape conclusions about building performance [24]. Fine temporal scale data provides insight into short-term inefficiencies, enhances load forecasting accuracy, and enables real-time anomaly detection that is unattainable with coarser measurements [25]. Zone-specific analysis also allows a deeper understanding of how particular locations respond to environmental conditions and occupancy profiles, facilitating targeted and bespoke optimization strategies.

This research utilizes the CU-BEMS dataset—a uniquely detailed collection of building operation data from the seven-story Chamchuri 5 office building, which has a floor area of 11,700 m^2 and is located in Bangkok, Thailand [26].

Figure 1. 3D visualization of Chamchuri 5, illustrating the overall building layout.

Unlike typical datasets that aggregate overall consumption, the CU-BEMS dataset provides a granular breakdown of electricity use by individual air-conditioning units, lighting, and plug loads across 33 zones, while simultaneously recording corresponding indoor environmental conditions and outdoor weather at one-minute intervals throughout 2019.

By leveraging one-minute, zone-specific operational data, this study identifies inefficiencies that hourly data fail to capture. Minute-scale analysis exposes transient peak amplification from synchronized zone start-ups, sustained part-load inefficiencies from oversized systems operating far below design capacity, and systematic overcooling in selected zones, simultaneously creating energy waste and comfort inequities [27]. These findings have direct implications for operational decision-making: instead of uniform scheduling and static set points, the results support staggered equipment start-up, zone-prioritized control, adaptive set point adjustments, and targeted retro commissioning of high-impact zones.

File name	Zone No.	AC	Light	Plug	Sensor
Floor1	Zone 1	0	1	0	0
	Zone 2	4	1	1	0
	Zone 3	0	1	1	0
	Zone 4	0	1	1	0
Floor2	Zone 1	1	1	1	3
	Zone 2	14	1	1	3
	Zone 3	0	1	1	3
	Zone 4	1	1	1	3
Floor3	Zone 1	4	1	1	3
	Zone 2	1	1	1	3
	Zone 3	0	1	1	0
	Zone 4	1	1	1	3
	Zone 5	1	1	1	3
Floor4	Zone 1	4	1	1	3
	Zone 2	1	1	1	3
	Zone 3	0	1	1	0
	Zone 4	1	1	1	3
	Zone 5	1	1	1	3
Floor5	Zone 1	4	1	1	3
	Zone 2	1	1	1	3
	Zone 3	0	1	1	0
	Zone 4	1	1	1	3
	Zone 5	1	1	1	3
Floor6	Zone 1	1	1	1	3
	Zone 2	1	1	1	3
	Zone 3	0	1	1	0
	Zone 4	4	1	1	3
	Zone 5	1	1	1	3
Floor7	Zone 1	4	1	1	3
	Zone 2	1	1	1	3
	Zone 3	0	1	1	0
	Zone 4	1	1	1	3
	Zone 5	1	1	1	3
Total	All zones	55	33	32	72

Figure 2. Zone-wise HVAC and electrical asset distribution, highlighting the granularity.

Several critical questions remain unaddressed in the current literature:

How much operational inefficiency arises from transient, sub-hourly HVAC behavior hidden in hourly data?

How can energy efficiency and thermal comfort be jointly evaluated without compromising either objective?

Which control and scheduling strategies are most effective under persistent hot–humid climatic conditions, where conventional economizer logic is less effective?

This study addresses these questions using minute-level, zone-resolved data and an integrated analytical methodology, providing new empirical knowledge and practical guidance for HVAC operation and control in hot–humid climates.

Methodology:

Data Collection and Preprocessing:

The indoor environmental and energy consumption data for the Chamchuri 5 building were obtained from the publicly available CU-BEMS dataset, which provides measurements at one-minute intervals throughout 2019. To establish a complete environmental context, outdoor weather conditions were collected using the Meteostat Python library, providing outdoor temperature, humidity, and solar radiation at one-hour intervals, which were subsequently interpolated to one-minute resolution to align with indoor measurements [28].

Data preprocessing involved several critical steps: missing value imputation using linear interpolation for gaps shorter than 30 minutes, and outlier detection using the interquartile range (IQR) method with a threshold of 1.5 ×IQR [29].

Analytical Framework:

The analysis was implemented using Python 3.8, leveraging key libraries including:

Pandas for data manipulation.

NumPy for numerical computations.

Matplotlib and Seaborn for 2D visualizations.

Plotly for interactive 3D plotting.
Scikit-learn for statistical analyses.

The analytical framework integrates high-resolution, zone-level energy and environmental data to evaluate HVAC performance, detect anomalies, assess comfort compliance, and inform actionable operational strategies.

Load Calculation Using Heat Balance Method:

A simplified heat balance method was employed to estimate zone-level cooling loads. The governing equation for the cooling load of each zone is expressed as [30]:

$$Q_{cooling} = Q_{external} + Q_{internal} - Q_{storage}$$

where:
$Q_{external}$ represents external heat gains through the building envelope.
$Q_{internal}$ includes internal gains from occupants, lighting, and equipment.
$Q_{storage}$ accounts for thermal storage in the building mass.

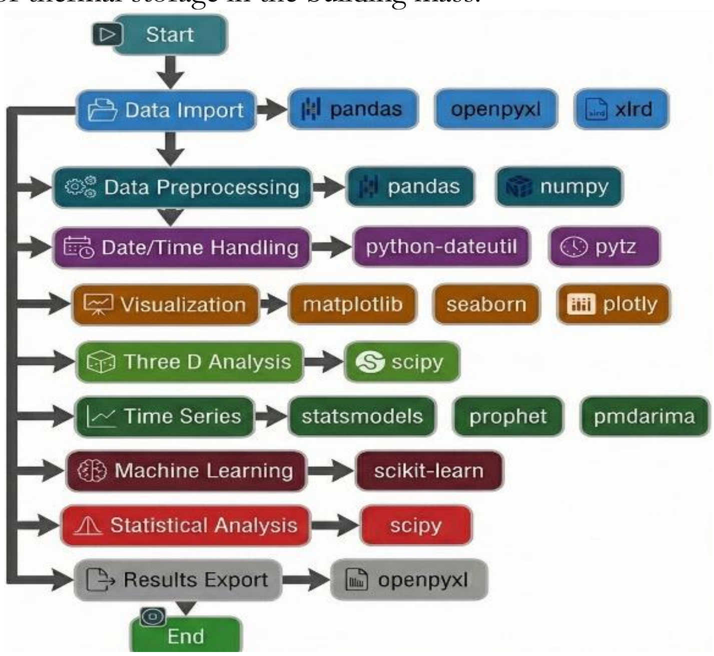

Figure 3. Analytical workflow for operational optimization.

Key Assumptions Included:
Steady-state conditions are assumed for each one-minute interval.
Air distribution is uniform within each zone.
Constant specific heat capacity of air (1.006 kJ/kg·K).
Negligible infiltration due to building pressurization.
Simplified solar heat gain coefficients based on window orientation.

Time Series Analysis:

Temporal patterns were analyzed using Seasonal-Trend decomposition using Loess (STL). Autocorrelation functions were examined to identify temporal dependencies. Anomaly detection employed both statistical ($\pm 3\sigma$) and decomposition-based methods [31].

Energy Performance and Efficiency Analysis:
Key performance indicators included:
Energy Use Intensity (EUI):

$$\text{EUI} = \frac{E_{Annual}}{A_{Floor}}$$

Load Factor:

$$\text{Load Factor} = \frac{P_{Avg} \times 100\%}{P_{Peak}}$$

Diversity Factor:

$$\text{Diversity Factor} = \frac{\sum_{i=1}^{n} P_{Peak,i}}{P_{Coincident\ peak}}$$

Comparative Zone Analysis:

Analysis of Variance (ANOVA) was used to evaluate differences in HVAC performance across building zones. ANOVA is appropriate for this analysis, as it enables comparison of mean performance metrics among multiple independent zones [32].

The assumptions underlying ANOVA were examined before analysis. Data normality within each zone was assessed using the Shapiro–Wilk test [33]. Independence of observations was ensured through the study design, as zone-level measurements were collected independently. Homogeneity of variances across zones was verified using Levene's test [34].

Multidimensional Visualization:

Multidimensional visualization techniques were employed to better understand how different HVAC variables interact. Three-dimensional surface plots illustrated how system performance changes when multiple parameters vary simultaneously, facilitating observation of trends and interaction effects [35]. Heat maps were also used to highlight spatial and temporal patterns across zones, enabling rapid identification of performance differences and emerging trends [36].

Statistical Validation:

Statistical validation was performed to ensure that the observed results were not attributable to random variation. Parametric t-tests [37] were used to compare mean values where appropriate, while chi-square tests [38] were applied to examine associations between categorical variables. Additionally, regression analysis was conducted to quantify relationships between key HVAC parameters and performance indicators. All statistical tests were evaluated at a significance level of $a = 0.05$, providing a consistent framework for assessing statistical significance [39].

Temporal Resolution and Data Aggregation:

Considering the one-minute resolution of the CU-BEMS dataset, a differentiated temporal resolution strategy was adopted in accordance with analytical requirements. Most of the analysis has retained this original resolution to better understand sub-hourly dynamics, inefficiencies, and zone-specific variations, which might be lost in aggregated data. However, in order to fulfill the requirements of time series forecasting and related temporal pattern recognition, data aggregation has been performed to a resolution of hourly intervals through mean resampling. This is because these types of forecasting algorithms, such as ARIMA, SARIMA, and Prophet, are generally optimized to operate on hourly resolution.

Results and Discussion:

Building Load Analysis:

The annual cooling and electrical load assessment indicates that the building operates with a high energy intensity, characteristic of large, centrally air-conditioned institutional buildings in hot–humid climates. The total annual electricity consumption was estimated at approximately 2,092,294 kWh (2.092 GWh), corresponding to an EUI of 178.8 kWh/m²·year when normalized by floor area. This value lies at the upper end of reported EUI ranges for office and institutional buildings in Southeast Asia, where typical benchmarks range from approximately 140 to 180 kWh/m²·year [40]. It also exceeds ASHRAE-referenced targets for high-performance office buildings [41]. The elevated energy consumption can be primarily attributed to year-round cooling demand, high internal heat gains from occupants and equipment, and the limited applicability of economizer-based operation under Bangkok's persistently hot and humid climatic conditions [42].

The peak cooling demand of 917.45 kW, occurring in April, coincides with the region's highest ambient temperatures and humidity levels. Although such a peak is expected in hot–humid climates, its magnitude relative to the annual average load of 238.85 kW highlights a pronounced disparity between peak and typical operating conditions. From a system design and operation perspective, this suggests that capacity is sized primarily for infrequent extreme conditions rather than sustained demand, resulting in system oversizing and part-load inefficiency for much of the year. This is further reflected in the low annual load factor of 26.0%, indicating that installed capacity remains underutilized for a substantial proportion of operating hours.

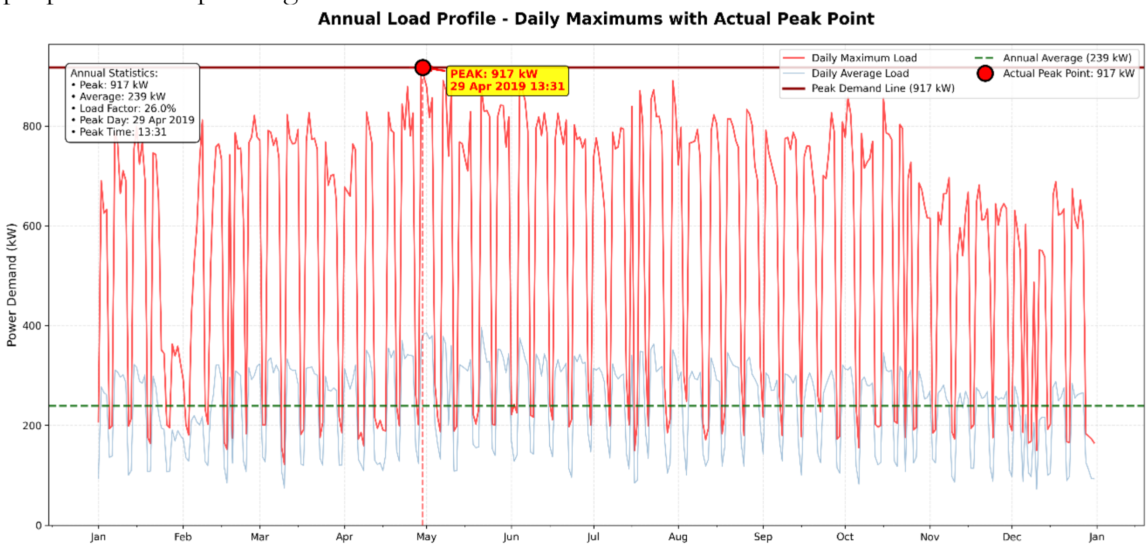

Figure 4. Daily cooling load profile demonstrating peak requirements and baseline load.

Analysis of the load duration curve and the calculated diversity factor of 1.81 confirms that peak loads across different floors and zones are largely non-coincident, illustrating significant spatial variance in cooling requirements throughout the operational day.

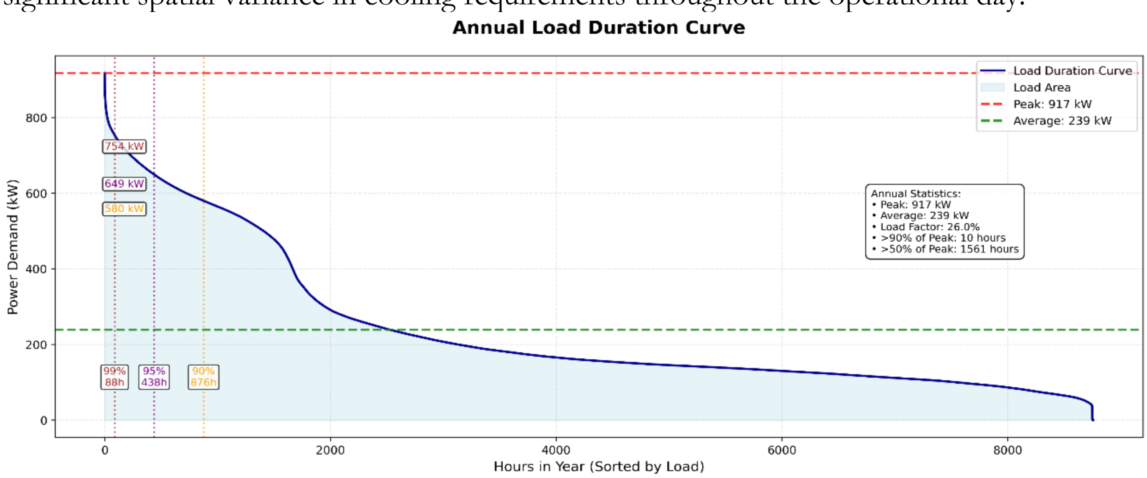

Figure 5. Annual load duration curve confirming non-simultaneous peak loads.

The Energy Use Intensity (EUI) was 178.8 kWh/m²·year, influenced by occupancy density, operating hours, and system configuration. The observed level of consumption reflects the combined effects of year-round cooling demand, high internal heat gains, and limited seasonal relief from the prevailing outdoor climatic conditions.

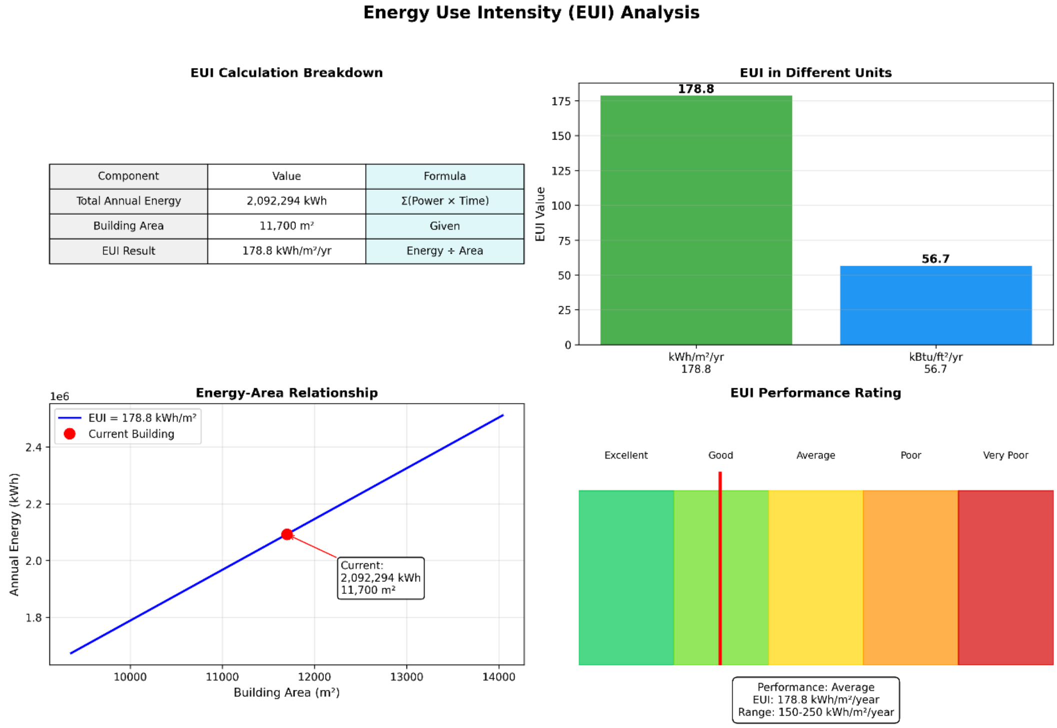

Figure 6. Energy Use Intensity (EUI) benchmarking.

The daily and hourly load profiles indicate that demand variability is influenced more by operational schedules and occupancy patterns than by short-term weather fluctuations. Peak loads occur predominantly around 08:00, with average demand reaching approximately 443.63 kW, whereas minimum loads of roughly 120.73 kW are observed near 06:00. The pronounced morning ramp-up suggests that building systems respond reactively to occupancy rather than following a controlled pre-conditioning strategy.

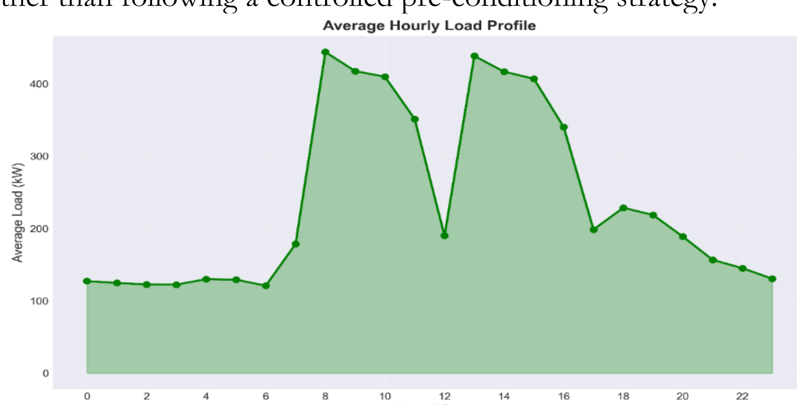

Figure 7. Average hourly load profile revealing occupancy-driven morning ramp-ups.

At the zone level, Floor 1, Zone 2 was identified as the most energy-intensive, exhibiting an average demand of 55.77 kW. The concentration of energy consumption within a limited number of zones highlights significant disparities in spatial energy distribution.

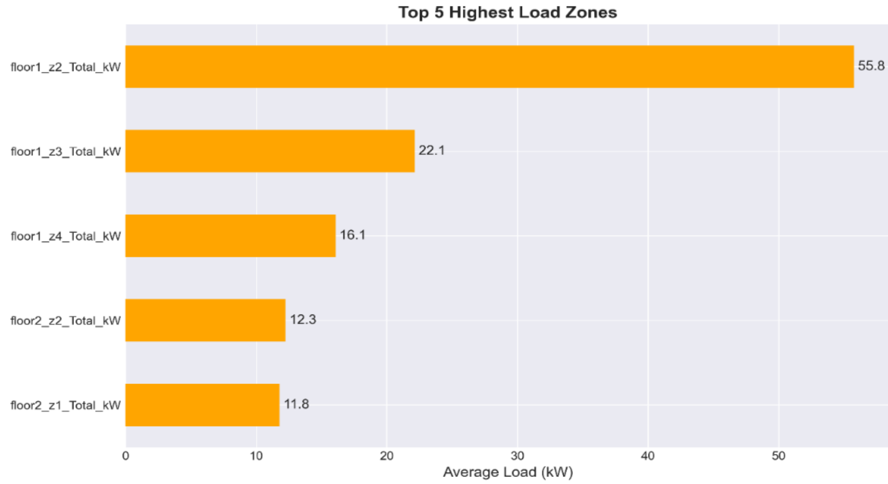

Figure 8. Comparative load analysis of the top five zones, demonstrating spatial demand.

Directly addressing the research question regarding which control and scheduling strategies are most effective under persistent hot–humid conditions, these operational load profiles inform three key, evidence-based interventions:

Load Shifting: The reactive morning peak demand patterns suggest that early-morning pre-cooling and staggered equipment start-up can be implemented to reduce peak electrical demand and improve overall load factor without compromising occupant comfort.

Zonal Control Optimization: Significant spatial variability in energy use across floors and zones underscores the need for localized scheduling, adaptive temperature set points, and zone-level airflow control, rather than relying solely on uniform centralized strategies.

Maintenance and Retro-Commissioning Prioritization: The concentration of high loads in specific floors and zones indicates that maintenance and performance monitoring should be prioritized in these areas to mitigate part-load inefficiencies, reduce equipment stress, and enhance long-term system reliability.

Comparative Zone Analysis:

Before analyzing variance (ANOVA), the assumption of normality was assessed using the Shapiro–Wilk test for all 24 zones. In each case, the null hypothesis of normality was rejected ($W < 1.0$, $p < 0.05$), indicating that normality was rejected for all zones ($p < 0.05$), demonstrating that none of the zone-level datasets satisfied the normality assumption.

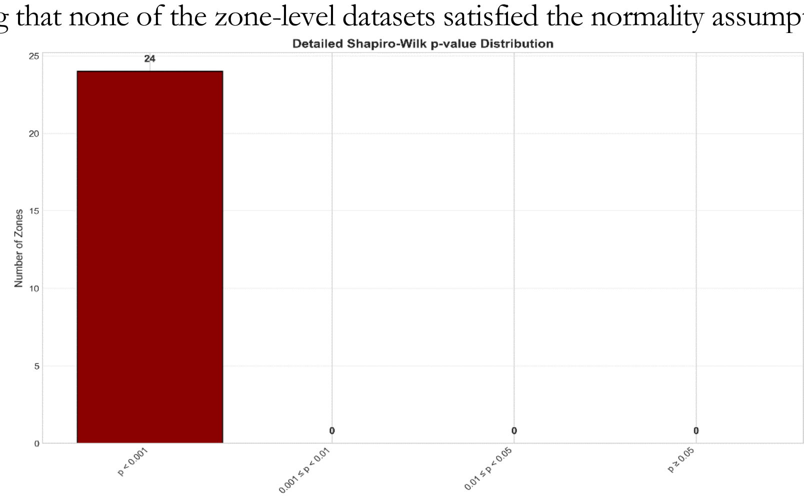

Figure 9. Shapiro–Wilk *p*-value distribution confirming non-normal data structures.

Despite the violation of the normality assumption, the one-way ANOVA was deemed appropriate and robust for this dataset. According to the Central Limit Theorem, the sampling distribution of the mean approximates normality with a sufficiently large sample size. With a total of N = 8,760 observations (averaging approximately 365 observations per zone), this study satisfies the conditions for reliable parametric analysis, thereby reducing the likelihood of Type I errors associated with non-normal distributions.

The one-way ANOVA was conducted to determine whether statistically significant differences exist in performance measures across the 24 zones. The analysis revealed a statistically significant difference between groups:

$$F(23,8736) = 799.05,\ p < 0.001 \quad (1)$$

The effect size was calculated as $\eta^2 = 0.6778$, indicating a large effect. This suggests that approximately 67.8% of the total variance in the dependent variable can be attributed to the specific Zone ID. These results highlight that zone location and configuration are the primary contributors to performance variability, rather than random variation or measurement noise.

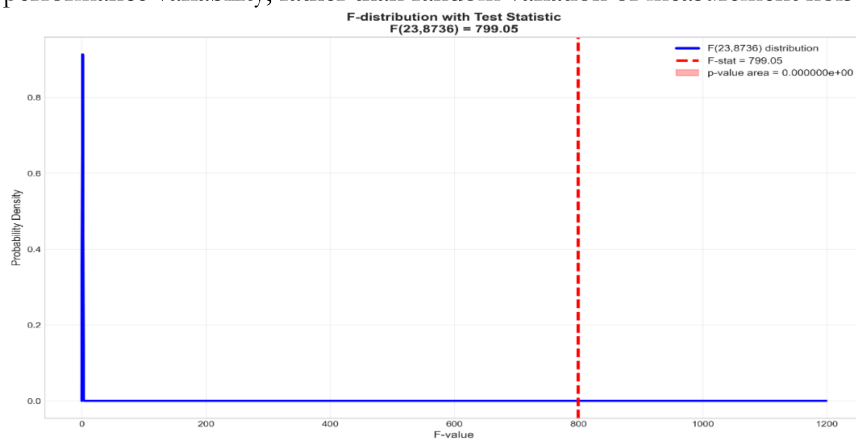

Figure 10. ANOVA *F*-value distribution ($\eta^2 = 0.6778$) verifying the zone configuration.

With this in mind, a post-hoc Tukey Honestly Significant Difference (HSD) test was also conducted across all possible pairs (k = 276) to identify which specific zones differed significantly. While the omnibus ANOVA indicated overall differences among zones, the Tukey HSD provided detailed insight into the pairwise divergences:

Significant Comparisons: 92 pairs (33.3%) exhibited statistically significant differences ($p < 0.05$).

Non-Significant Comparisons: 184 pairs (66.7%) showed no statistically significant differences.

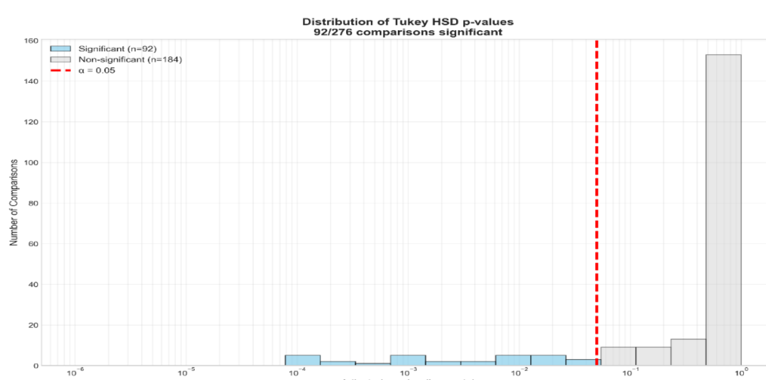

Figure 11. Tukey HSD post-hoc results showing significant pairwise differences.

These statistical findings directly address the research question regarding the inefficiencies hidden in aggregated data. The 92 significant pairwise differences quantitatively demonstrate that relying on whole-building, hourly data inherently masks profound spatial heterogeneity. Zones cluster into distinct performance "tiers," indicating that whole-building averages fail to capture the operational reality of individual spaces, thereby validating the necessity of high-granularity sensing.

Energy–Temperature Regression:

The Energy–Temperature Regression analysis assesses the dependence of building energy consumption on outdoor ambient temperature. The regression results indicate a very low coefficient of determination ($R^2 = 0.023$) and a root mean square error (RMSE) of 177.81 kW, demonstrating that outdoor temperature alone is a weak predictor of energy use in this building.

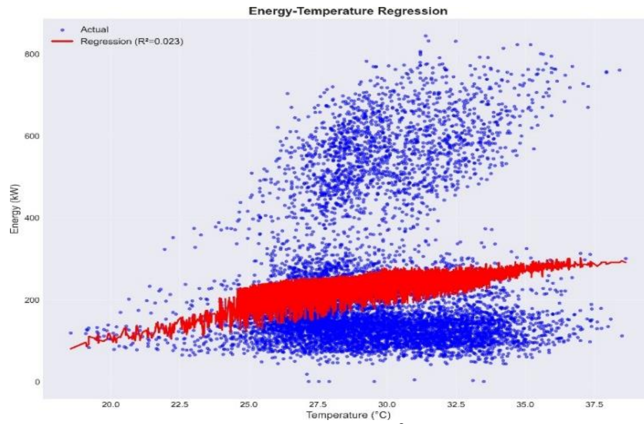

Figure 12. Energy–Temperature regression ($R^2 = 0.023$), confirming internal gains.

Thermal Comfort Analysis:

Thermal comfort performance was evaluated using the ASHRAE 55 fixed comfort temperature range of 20–26°C [43]. This standardized criterion allows direct comparison with international benchmarks and prior studies of large commercial buildings. Although Bangkok is characterized by a hot–humid climate, applying a fixed comfort range is justified in this context because the building relies on centralized mechanical air-conditioning, where occupant adaptation to outdoor conditions is minimal and indoor thermal conditions are primarily dictated by system operation rather than natural ventilation [44].

However, the fixed comfort band has inherent limitations in hot–humid climates. It does not fully account for occupants' adaptive behaviors, seasonal acclimatization, or tolerance to higher indoor temperatures [45]. Consequently, conservative upper limits may encourage overcooling, whereas adaptive comfort models suggest acceptable indoor temperatures could exceed 26°C without compromising occupant satisfaction.

The mean indoor temperature across all zones was 24.7°C, with a standard deviation of 2.8°C, indicating substantial spatial and temporal variability. Only 60.6% of recorded temperatures fell within the ASHRAE 55 comfort band, suggesting both widespread thermal discomfort and significant inter-zonal inequality. Notably, the best-performing zone (Floor 4, Zone 5) achieved 69% compliance, whereas the worst-performing zone (Floor 2, Zone 3) achieved only 17.1% compliance, highlighting inter-zonal disparity as a primary performance deficiency rather than a random anomaly.

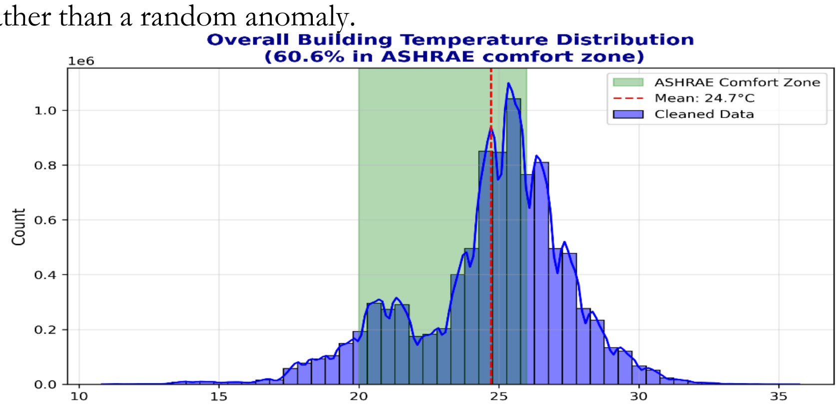

Figure 13. Thermal comfort compliance against ASHRAE 55 limits.

To address how energy efficiency and thermal comfort can be jointly evaluated without compromising either objective, the analysis must move beyond fixed criteria. Augmenting the evaluation using Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD) indices provides a dynamic solution. These indices integrate multiple factors, including air temperature, humidity, metabolic rate, clothing insulation, and air velocity, to yield a comprehensive representation of occupant thermal sensation.

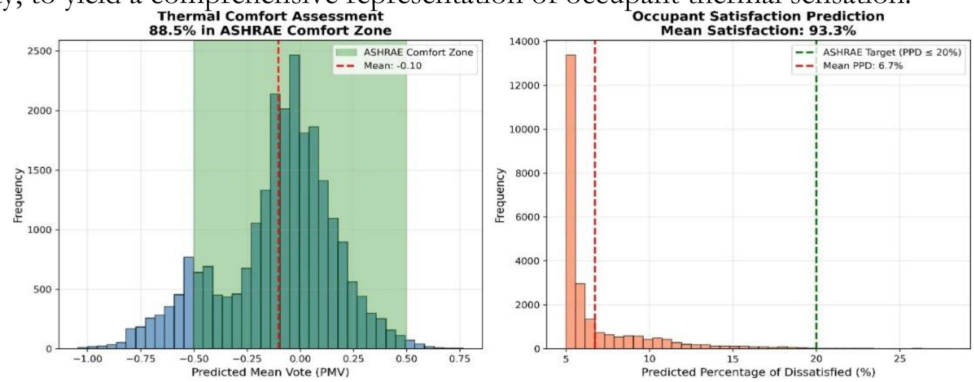

Figure 14. Statistical overview of PMV-PPD indices, providing a dynamic baseline.

By incorporating PMV and PPD, operational boundaries can be shifted from temperature adherence to holistic comfort compliance. This shift enables targeted, zone-specific set point recalibrations that simultaneously reduce unnecessary overcooling (improving energy efficiency) while maintaining or enhancing the actual thermal satisfaction of occupants [46].

Time Series, Forecasting, and Anomaly Detection:

The dataset comprises 8,760 hourly observations over one year. Forecast models were trained on 80% of the data and tested on the remaining 20%, with a one-week forecast horizon to support operational decision-making. All analyses were conducted at an hourly temporal resolution. Initially, the original timestamped data were resampled to hourly intervals using mean aggregation (resample('H'). mean to establish a consistent baseline dataset. A multi-level aggregation strategy was subsequently applied to align different analytical objectives with appropriate temporal scales.

The choice of aggregation was guided by both practical and analytical considerations. From a practical perspective, temporal aggregation significantly reduces data volume, improving computational efficiency and enhancing the interpretability of visualizations. From an analytical standpoint, aggregation mitigates high-frequency noise that can obscure meaningful patterns in building energy consumption. Furthermore, commonly used time series forecasting models, such as ARIMA, SARIMA, and Prophet, are designed to perform optimally with hourly or daily data.

Four anomalies were identified using a rolling mean approach with a $\pm 3\sigma$ confidence band. These anomalies, representing approximately 0.05% of total observations, primarily manifested as transient spikes or short-lived deviations from the local mean. Positive excursions are indicative of short-term equipment irregularities, such as simultaneous startup currents or sensor-related glitches, where brief failures in data transmission produced artificially elevated readings. The isolated and non-recurring nature of these anomalies suggests that they are attributable to discrete sensor or data-quality events rather than persistent system-level faults.

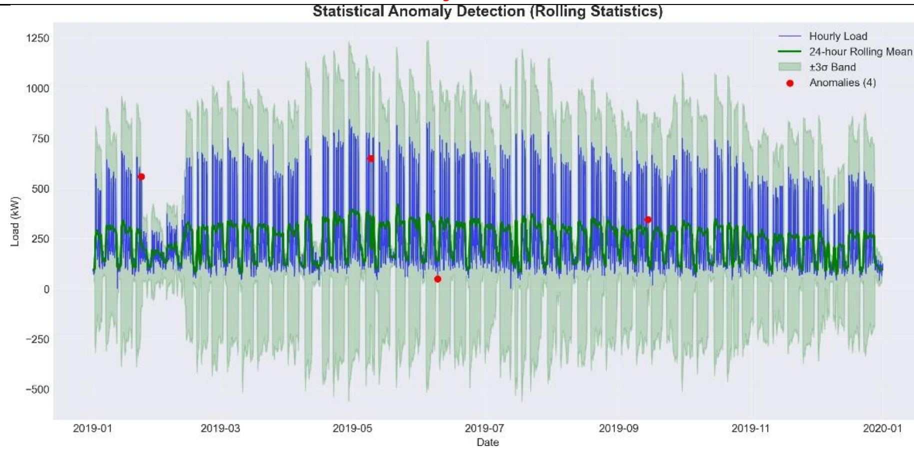

Figure 15. Identification of transient statistical anomalies ($\pm 3\sigma$), isolating equipment glitches.

In contrast, sixteen negative anomalies were identified through residual-based decomposition analysis. Unlike typical statistical outliers, these events are characterized by deep and sustained drops in residual values, often falling below −100 kWh. Such systematic negative deviations indicate periods during which actual energy consumption was substantially lower than model expectations. These intervals likely correspond to unrecorded non-operational days or prolonged sensor outages, during which the measured signal remained near zero. Accurate identification of these anomalous periods is critical for data cleansing, as their inclusion could bias the forecasting model toward learning spurious low-load patterns.

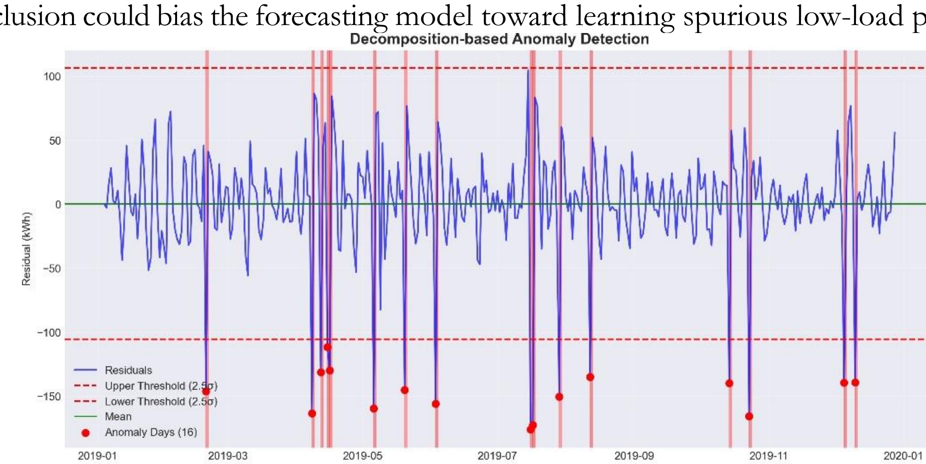

Figure 16. Residual-based anomaly detection captures sustained negative deviations.

A comparative performance evaluation was conducted between deterministic statistical forecasting techniques, including ARIMA and Naive models, and the regression framework implemented by Prophet. The Naive persistence model and a seven-day moving average (MA (7)) were established as baseline benchmarks. The Naive model produced the highest prediction error (MAE: 135,514.1 kWh), confirming that the dataset exhibits complex temporal structures and seasonality beyond the representational capacity of simple persistence. The standard ARIMA model demonstrated limited performance (MAE: 94,036.4 kWh), producing an overly smoothed trend that failed to capture high-frequency diurnal variations. While the SARIMA formulation improved predictive accuracy (MAE: 64,126.3 kWh) by modeling seasonal components, it remained challenged by the stochastic volatility associated with peak demand periods. Model hyperparameters were optimized using a grid search procedure guided by Akaike Information Criterion (AIC) minimization. Among all tested approaches, the Prophet model achieved the lowest forecasting error (MAE: 58,519.5 kWh), corresponding to a 56% reduction relative to the Naive baseline.

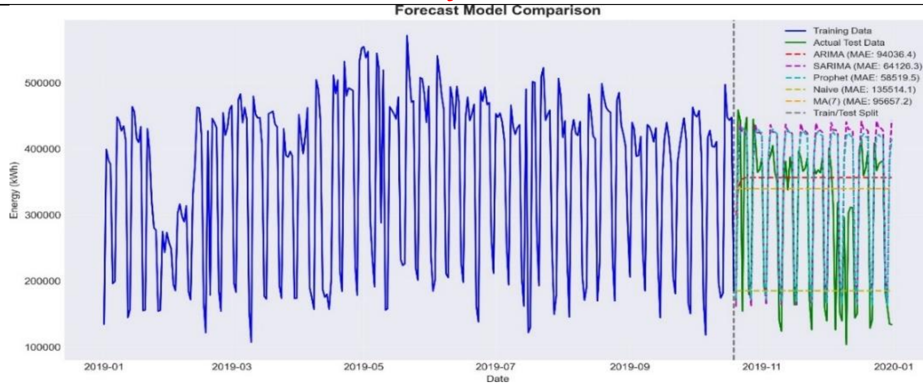

Figure 17. Forecasting model comparison demonstrating Prophet's superior accuracy.

The superior performance of the Prophet model is primarily attributed to its decomposable additive structure, which explicitly models trend, seasonality, and holiday effects as independent components. Consequently, the Prophet forecast closely tracks the observed test data, accurately capturing both daytime operational peaks and nocturnal base-load behavior. In comparison, ARIMA-based methods rely heavily on fixed lag relationships, limiting their adaptability to the rapid, nonlinear demand fluctuations commonly observed in building energy consumption profiles.

Multidimensional Visualization:

Three-dimensional surface plots were employed to better understand how power consumption varies throughout the day. The results reveal a clear daily cycle, with consistently higher demand between 10:00 and 16:00, corresponding to the building's primary operating period. Short-lived, localized reductions during the mid-day period appear to reflect internal adjustments in load distribution or management, rather than a decline in overall system performance.

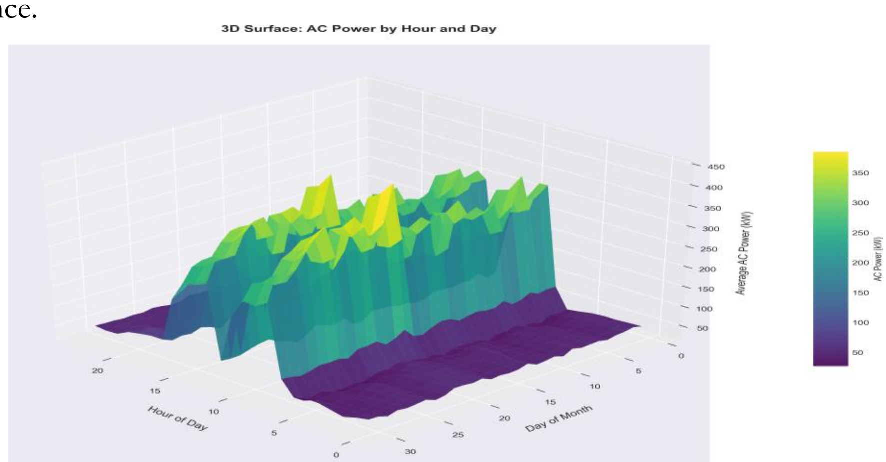

Figure 18. 3D surface plot of AC power consumption, visualizing consistent diurnal cycles.

Heat maps provided a complementary perspective by illustrating the temporal and spatial distribution of performance variations throughout the day. These visualizations indicate that the localized midday reductions are both brief and spatially limited, reinforcing that these variations stem from internal load management rather than systemic performance decline.

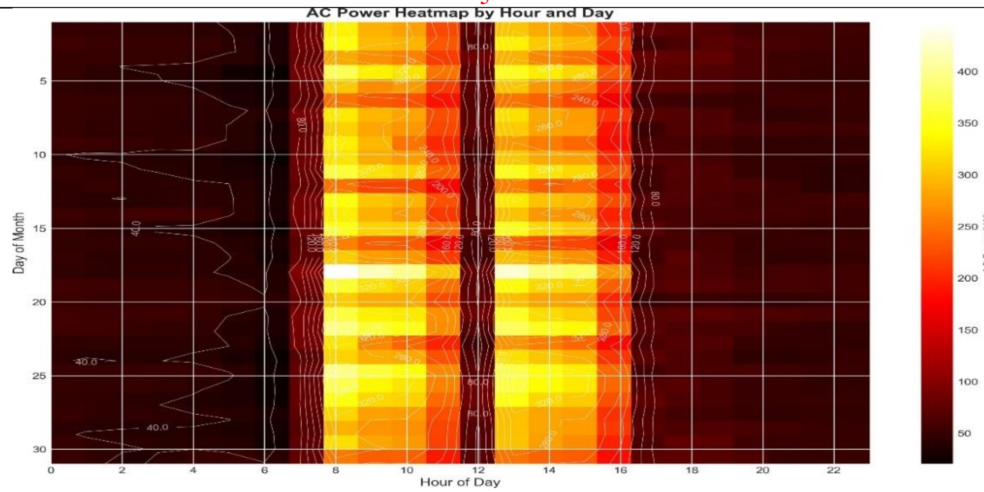

Figure 19. Temporal AC power Heat map verifying that midday demand reductions are localized and transient.

These visualizations support load-shifting strategies, identify high-consumption periods for targeted interventions, and enable cross-zone comparisons to prioritize high-impact control adjustments.

Conclusion:

This study identifies the primary limitation of conventional HVAC performance assessment as stemming not from analytical capability, but from the scale of data examination. By integrating minute-level, zone-resolved data across multiple domains, it demonstrates that major inefficiencies in hot–humid buildings are operational rather than climate-driven. Considered holistically, the analyses underscore a critical insight: building-level averages and hourly aggregation are insufficient to guide meaningful HVAC optimization.

Synthesizing these analyses highlights spatial heterogeneity in building performance. Because energy consumption, operational behavior, and comfort outcomes vary significantly across zones, HVAC optimization must be reframed from a problem of system sizing to one of localized control. Uniform scheduling, static set points, and centralized control logic emerge as primary contributors to both wasted energy and inconsistent occupant experience.

A second key insight is that energy efficiency and thermal comfort are not inherently in conflict. The analysis demonstrates that areas of poor comfort often coincide with operational inefficiencies, reflecting system misalignment rather than a necessary trade-off. This challenges the common assumption that improving comfort increases energy consumption; instead, targeted control refinement and airflow management can simultaneously improve both outcomes.

Operationally, these findings suggest that differentiation rather than uniformity should guide HVAC improvements in hot–humid climates. Zone-prioritized interventions and staggered scheduling are likely to yield higher returns than capacity expansion or blanket retrofits. Furthermore, because aggregate performance indicators alone can obscure critical deficiencies, zone-aware metrics are essential for future policy and benchmarking.

Future research should focus on translating these analytical insights into closed-loop operational control. Rather than simply expanding analytical toolkits, studies should implement adaptive, zone-level controls and assess real-world outcomes. Incorporating adaptive comfort models, occupancy sensing, and feedback logic will help realize data-driven HVAC optimization in tropical climates. Extending this approach to building portfolios could ultimately establish climate-specific benchmarks based on actual rather than design system behavior.

In summary, the value of high-resolution building data lies in enabling better decision-making. By analyzing HVAC systems closer to their actual operation minute by minute and zone by zone, inefficiencies become actionable, comfort disparities become visible, and optimization becomes technically feasible and operationally realistic.

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Author's Contribution Statements:

Muhammad Fawad Saleem: Developed the core data-driven framework and implemented the Python-based analytical pipeline for the study.

Majid Baseer: Provided overall project supervision.

Sardar Ahmed Imtiaz: Conducted time series forecasting and anomaly detection.

Fawaz: Performed thermal comfort assessment across all building zones.

Sheryar Shoukat: Executed statistical validation to identify performance variances between zones.

Nauman Fayaz: Conducted a comprehensive literature review and benchmarked the building's Energy Use Intensity (EUI).

Code Availability:

The code and dataset used in this study are publicly available at:
https://github.com/22jzmec0460-cmd/HVAC-Building-Analytics-Platform

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