

ENHANCING THE ACCURACY OF BUILDING PERFORMANCE SIMULATION THROUGH POST-OCCUPANCY CALIBRATION

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Abstract: The performance gap between predicted and actual energy consumption in buildings remains a significant challenge in sustainable construction. This study investigates the role of post-occupancy evaluation (PoE) in refining Building Performance Simulation (BPS) models to enhance accuracy and reliability. A case study approach was employed to analyse a five-storey office building in Sri Lanka, where discrepancies between simulated and actual energy performance were assessed. The study identified HVAC inefficiencies, lighting usage variations, and unpredictable occupant schedules as key contributors to the energy performance gap. A structured calibration process was implemented using empirical PoE data to iteratively refine the simulation model. A Sensitivity analysis was conducted to determine the most influential parameters affecting performance discrepancies. Under this, HVAC inefficiencies were identified as the dominant factor, followed by lighting and daily occupant patterns. The calibration process reduced the energy performance gap from an initial 22.11% to 8.88%, demonstrating a significant improvement in predictive accuracy. Findings underscore the need for a paradigm shift from static, assumption-driven modelling to dynamic, data-informed simulation practices. The study proposes a replicable methodological framework for integrating PoE into BPS workflows, emphasizing real-time monitoring and adaptive controls as essential for performance-driven design. The implications reach design professionals, facility managers, and policymakers who aim to enhance building energy performance and meet long-term sustainability goals.

Keywords: *Building Performance Simulation (BPS), Energy Performance Gap, Post-Occupancy Evaluation (PoE), Sustainable Building Design*

1. Introduction

The building sector accounts for 20.1% of global delivered energy, with consumption projected to grow annually by 1.5% through 2040 (U.S. Energy Information Administration, 2016). In response, improving energy performance through sustainable design and innovation has become a global imperative to mitigate environmental impacts and reduce carbon emissions (Al Mughairi et al., 2023). A key component of sustainable construction, building performance enables substantial reductions in energy use and CO₂ emissions during occupancy by integrating technological solutions with social and behavioural considerations (Gram-Hanssen & Georg, 2018). It encompasses environmental, eco-nomic, and social dimensions throughout a building's lifecycle (Kamali & Hewage, 2015). However, evidence suggests that buildings often underperform in practice compared to initial design expectations (Alhindawi & Jimenez-Bescos, 2020). This discrepancy arises from unpredictable occupant behaviour, microclimatic variation, and discrepancies between design and as-built conditions (Negendahl, 2015). The resulting "performance gap" refers to the divergence between predicted performance during the design phase and actual performance measured after occupancy (Yang et al., 2022). A key contributor to this gap is the lack of systematic feedback to designers after handover, which limits opportunities for improving both current buildings and future designs. Bridging this performance gap requires coordinated efforts among all stakeholders in the design, construction, and operation phases (Imam et al., 2017). One promising approach is Post-Occupancy Evaluation, which assesses how buildings perform in real-world conditions and provides designers with actionable feedback (Menezes et al., 2012).

PoE is a structured and comprehensive approach used to assess how buildings perform in real-world conditions after occupancy (Elsayed et al., 2023). By analysing energy use patterns, user interactions, and system operations under real conditions, PoE offers actionable insights to develop more reliable simulation models, refine building codes, and enhance user satisfaction (van Dronkelaar et al., 2019). It extends beyond traditional performance assessments by emphasizing user-centered metrics including energy efficiency, indoor environmental quality (IEQ), occupant satisfaction, health, safety, psychological comfort, and productivity (Li et al., 2018). Unlike conventional simulations and compliance-based evaluations, PoE prioritizes the lived experiences of occupants and the functional quality of the built environment. Serving as a feedback mechanism, PoE allows stakeholders to evaluate how effectively a building meets its intended design objectives after construction and a defined occupancy period (Li et al., 2018; Mustafa, 2017). Data collection for PoE typically includes both objective methods, such as energy monitoring and system performance data, and subjective methods including resident questionnaires, walkthrough assessments, and user interviews (Elsayed et al., 2023). The use of standardized guidelines during these assessments enables the identification of performance shortfalls, user dissatisfaction, or operational inefficiencies that might otherwise remain unnoticed (Mustafa, 2017).

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Previous studies have extensively examined PoE in the construction sector, encompassing diverse building types such as educational, residential, public, govern-mental, and mixed-use developments across various geographic contexts (Elsayed et al., 2023; Li et al., 2018; Menezes et al., 2012). However, office buildings, despite their prevalence in urban settings, pose distinct challenges for PoE. These include complex building systems, irregular operational schedules, diverse user groups, and the integration of advanced building management systems (Elsayed et al., 2023). Additionally, frequent spatial and organizational changes complicate long-term performance assessments (Duarte et al., 2013), while institutional and cultural differences limit the generalizability of findings (Boissonneault & Peters, 2025). Consequently, the absence of consistent and transferable post-occupancy data limits the development of robust, evidence-based strategies for office building design and operation.

To mitigate these limitations, de Wilde (2014) advocated for single-building case studies employing one to one comparison between predicted and measured performance. This approach, grounded in post-construction calibration, enables the identification of discrepancies between simulation assumptions and real-world out-comes, offering valuable insights for refining future predictive models. Despite significant advancements in building performance assessment, the field continues to lack a universally accepted and methodologically robust Post-Occupancy Evaluation (PoE) framework that is adaptable across various building typologies. This study addresses this critical gap by proposing actionable in-sights and methodological innovations to enhance the effectiveness of post-occupancy assessments and to inform future design, operational, and policy decisions across diverse building types.

2. Literature Review

2.1 BUILDING PERFORMANCE SIMULATION (BPS)

Building energy use accounts for nearly 30% of global energy consumption, underscoring the urgent need for improvements in energy efficiency (Yoshino et al., 2017). In response, Building Performance Simulation (BPS) has emerged as a critical and cost-effective tool for supporting energy-efficient building design and operation by enabling predictive analysis of energy consumption and performance (Alhindawi & Jimenez-Bescos, 2020). BPS employs computational models to simulate the thermal, mechanical, and operational behaviours of buildings, enabling performance predictions under various scenarios (Hensen & Lamberts, 2010). Over the past few decades, BPS has evolved into an indispensable tool for addressing the complexities of modern building systems (Nguyen et al., 2014).

The International Energy Agency (IEA) pointed out six factors that influence building energy usage including climate, building envelope, service systems, indoor environmental criteria, operation and maintenance, and occupant behaviour (Alhindawi & Jimenez-Bescos, 2020). Among these factors, occupant behaviour is recognized as a major cause for the simulation uncertainty. This has led to growing interest in using BPS to analyse behavioural impacts, evaluate energy conservation measures (ECMs), and improve the accuracy of performance assessments (Chong et al., 2021).

However, pre-occupancy simulations typically rely on assumed inputs, such as standardized occupancy profiles and fixed equipment loads, that rarely reflect actual conditions (de Wilde, 2014). Consequently, a persistent "performance gap" exists between predicted and measured building performance, as highlighted in post-occupancy studies (Menezes et al., 2012; van Dronkelaar et al., 2019). This gap highlights the need for model calibration, whereby simulation inputs are aligned with real-world data to improve prediction accuracy and decision-making reliability. PoE plays a critical role in this process by providing empirical data that corrects assumptions, captures dynamic building behaviours, and ultimately refines BPS outputs.

2.2 POST OCCUPANCY EVALUATION AND BPS CALIBRATION

PoE provides a robust empirical foundation for recalibrating BPS models (Menezes et al., 2012). By incorporating performance data, such as indoor climate conditions, energy use patterns, and control system operations, alongside user feedback, PoE enables the refinement of key assumptions, particularly those related to occupant behaviour and operational schedules (Li et al., 2018).

As emphasized by van Dronkelaar et al (2019), embracing PoE as an integral part of the building lifecycle is essential to bridge the performance gap and improve the environmental sustainability of the built environment. To illustrate how PoE has been utilized to investigate and mitigate the energy performance gap, scholars have conducted key empirical studies across various building types and regions. These case studies span commercial, residential, educational, and institutional sectors and adopt diverse methodologies to explore the discrepancies between design intentions and operational realities. The PROBE studies in between 1995-2002 were carried out across 23 commercial buildings in UK, revealed that actual energy usage is twice than the design predictions (Bordass et al., 2001). PoE with energy data and interviews was conducted under a low carbon buildings programme in year 2000s. It Identified issues in system commissioning and controls and contributed to better post occupancy and design stages (Energy Saving Trust, 2009). However, the Building Performance Evaluation (BPE) Program conducted in between 2010-2014 was revealed that there is a persistent gap even in "low carbon" buildings (Innovate UK, 2016). A study on energy performance gap in educational buildings discussed the significant gaps in performance due to schedules and equipment uses and proposed dynamic modelling updates based on PoE results (Menezes et al., 2012). The LEED certified office buildings in North America were evaluated for energy performance and found out that there is 18–39% energy savings in those buildings. However, high variation in design and actual energy consumption were identified (Newsham et al., 2009). Australian NABERS Post-Occupancy Studies on office buildings stated

that buildings with high ratings do not always perform well (National Australian Built Environment Rating System (NABERS), 2013). These case studies consistently highlight the persistent gap between predicted and actual outcomes as a critical issue in building performance.

The discrepancy underscores the limitations of conventional design-stage simulations, which often fail to capture the dynamic and variable nature of actual building use. However, the early implementation of Building Energy Performance Simulation (BEPS) tools remains limited (Mahmoud et al., 2020). Thus, future trends in Building Performance Simulation (BPS) include integrating occupant behaviour and weather models to better align simulated results with real-world conditions, as well as developing statistical and machine learning-based tools for predicting building behaviour in early design stages (Casini, 2022).

This integrated approach of combining PoE and BPS enhances calibration accuracy, informs performance-driven design, and helps align actual building operations with sustainability goals (Di Stefano et al., 2023). Despite these advancements, performance discrepancies persist across the building lifecycle. The following section explores the underlying causes of this gap, focusing on the design, construction, and operational phases.

2.3 ORIGINS AND DIMENSIONS OF THE PERFORMANCE GAP

The Post-Occupancy Review of Buildings and their Engineering (PROBE) studies exposed a significant absence of post-occupancy feedback, highlighting the well-documented 'performance gap' which refers to the divergence between predicted and actual energy performance (Yang et al., 2022). In many cases, actual energy consumption was found to be as much as twice the initial design predictions. The literature suggested that discrepancies between simulated and actual building performance can arise at any of the design, construction, and operation phases (Carbon Trust, 2007).

2.3.1 The Design gap

Numerous studies identify the design phase as a major contributor to the performance gap (de Wilde, 2014). A common issue is misalignment of performance expectations, either between clients and design teams or within the design team itself (Imam et al., 2017). For example, it showed that inconsistent interpretations of EUI targets among architects and engineers led to incompatible decisions and underperforming schools.

Even well-intended designs can falter when buildability and construction tolerances are overlooked. O'Brien et al. (2017) demonstrated that façade systems designed with unrealistic airtightness assumptions performed significantly worse once installed. Challenges also emerge when specifying advanced technologies; Barone et al. (2022) found that poorly integrated control strategies for hybrid ventilation systems caused higher-than-predicted energy use, while Santos and Leal (2012) reported that mis-specified heat pumps increased auxiliary energy demand.

A lack of understanding of how design assumptions influence real performance further contributes to the gap (Zero Carbon Hub, 2014). Designers rarely undertake uncertainty analyses, despite evidence that envelopes and occupancy assumptions significantly affect predictions (Yan et al., 2015). Misuse of simulation tools also remains widespread, with default settings and inaccurate input data leading to optimistic predictions (Banerjee & Roy, 2024; de Wilde, 2014).

2.3.2 The construction gap

Another factor contributing to the performance gap is the construction phase (Imam et al., 2017). Numerous studies and industry reports analyzed diverse case studies, which highlight that on-site construction quality often fails to meet design specifications. There has often been insufficient attention on proper insulation and airtightness (Carbon Trust, 2007; de Wilde, 2014; Menezes et al., 2012). Additionally, late-stage design alterations often lead to performance shortfalls and yet these changes are rarely reflected in updated simulation models (van Dronkelaar et al., 2019). While both builders and engineers contribute to discrepancies in building performance, identifying, and quantifying the precise sources of these gaps remain challenging.

2.3.3 The Operational Gap

The operational phase of a building is frequently cited as a major contributor to the discrepancy between predicted and actual performance, with occupant behavior identified as a key influencing factor (de Wilde, 2014; Menezes et al., 2012). Occupant behavior further complicates predictions, as users interact with building systems in unpredictable ways, such as by opening windows, adjusting thermostats, or introducing plug loads that are not modeled in compliance tools (Heydarian et al., 2020). It has been suggested that incorporating data from PoEs could enable more informed assumptions during the design stage, thereby reducing this aspect of the performance gap (Menezes et al., 2012). However, such data are seldom collected in practice.

To address the persistent gap between predicted and actual building performance, the Royal Institute of British Architects (RIBA) and the Chartered Institution of Building Services Engineers (CIBSE) launched Carbon Buzz in 2008 (CIBSE, 2020; Royal Institute of British Architects, 2016). This open-access platform allows design professionals to anonymously benchmark projected and measured energy use across building types. Findings reveal substantial discrepancies, with electricity use in schools and offices exceeding predictions by 60–70%, and university buildings showing deviations of over 85% (Menezes et al., 2012). These outcomes highlight the need for systematic PoE to align design intent with operational realities. Despite progress in calibration and data acquisition, PoE integration into design workflows

remains limited, underscoring the demand for scalable frameworks that embed real-use insights into simulation models and design-stage decision-making.

3. Methodology

This study adopted a mixed-method case study approach to evaluate the energy performance of a representative office building in Sri Lanka. Quantitative simulation outputs were integrated with qualitative insights derived from walkthrough assessments and stakeholder interviews to examine the underlying factors contributing to the building's energy performance gap. As illustrated in Figure 1, the research process commenced with a comprehensive literature review to establish the theoretical foundation and identify key variables influencing performance discrepancies. Subsequently, a case study strategy was applied, incorporating semi-structured interviews with occupants and facility managers, alongside walkthrough surveys to collect behavioural and operational data. Finally, a sensitivity analysis was conducted to assess the influence of occupancy patterns, lighting usage, HVAC efficiency, and weather conditions on the performance gap. This multi-layered methodological framework enabled a robust evaluation of the building's performance and supported the development of targeted recommendations to enhance energy efficiency and occupant comfort.

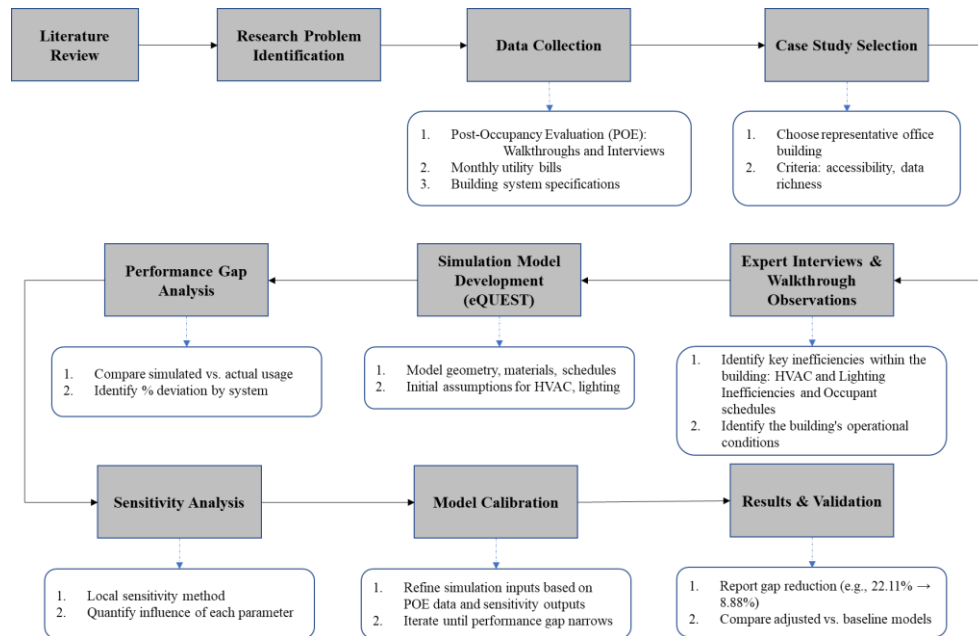


Figure 1: Research Process

3.1 DATA COLLECTION

3.1.1 Case Study Selection

The selected case study is an office building located in Sri Lanka, with a total gross floor area of 2,757 m² distributed across five typical floors. The building comprises general office spaces, executive areas, conference rooms, restrooms, MEP (Mechanical, Electrical, and Plumbing) rooms, as well as lobby and corridor areas. On average, it accommodates approximately 360 occupants. Figure 2 illustrates the typical floor plan layout, providing an overview of the building's spatial organization and functional zones.

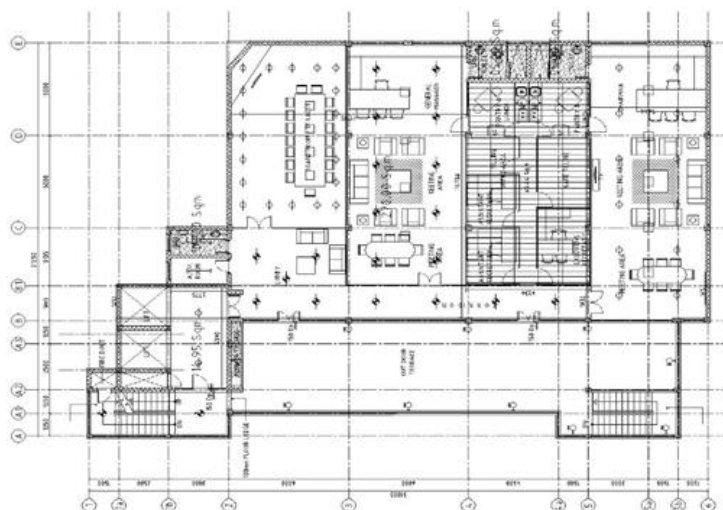


Figure 2: Plan view of the typical floors

Figure 3 presents the power supply installation for the typical floors, highlighting the distribution of electrical systems and the placement of key components on each level.

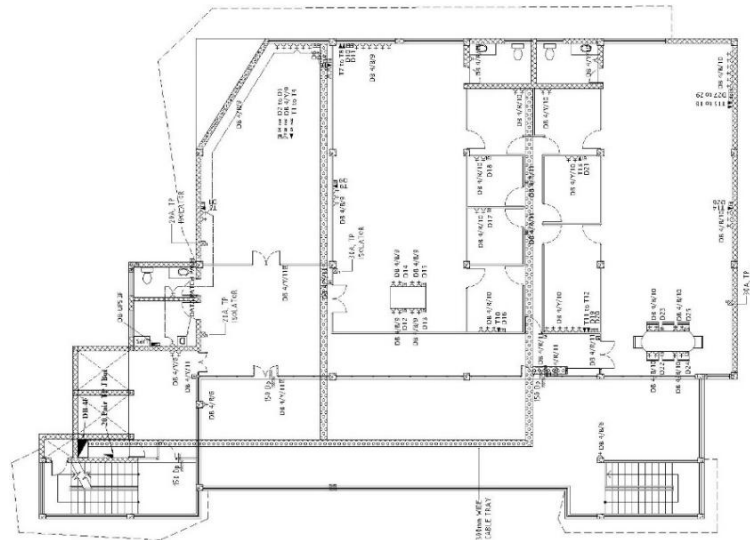


Figure 3: Power supply layout of the building

Two principal factors influenced the selection of this building for the study. Firstly, as noted by Mostafavi et al (2021), commercial buildings, such as office buildings, tend to exhibit significantly higher energy consumption per unit area compared to residential buildings. This increased consumption is primarily due to their extended operational hours and greater dependence on HVAC systems. Secondly, the decision to focus on a building located in Sri Lanka was driven by the practicality of data collection, particularly the ease of conducting site visits and accessing relevant building information.

By integrating both research-driven and practical considerations, this commercial building provided a highly suitable context for examining energy performance. Its five-storey scale and straightforward architectural layout supported continuous monitoring and facilitated reliable model calibration. Additionally, the building's accessibility enabled consistent data collection, ensuring the acquisition of accurate operational and environmental information.

3.1.2 PoE data collection

To collect the PoE data expert interviews, walkthrough observations and manual data logs were used. Occupancy data and building system data were obtained from the interviews with facilities managers and the data were validated by cross checking with the building hand-over documents and recommissioning reports. The capacities of the HVAC systems, lighting systems were obtained from the facilities manager. The monthly energy consumptions were obtained using electrical sub meters for HVAC and lighting.

3.1.3 Walkthrough Observations

A walkthrough assessment was conducted to understand the building's operational conditions, including AC systems, lighting, occupancy patterns, and maintenance practices. Supporting documents, such as AC schedules, manuals, energy bills and maintenance records, were reviewed to complement visual observations. This provided practical insights into building services and user behaviour, helping identify potential inefficiencies.

3.1.4. Expert Interviews

Semi-structured interviews were conducted with ten professionals occupying diverse roles within the case study building. Consistent with established qualitative research practices, the sample size was guided by the point of theoretical saturation; no new themes or insights emerged beyond the tenth interview, indicating that additional participants were unlikely to yield further meaningful information (Andarz et al., 2025). The expertise of the experts is characterized by deep immersion in specialist habits and practices, and their ability to provide reliable and trustworthy information (Hardoš, 2018). Therefore, participants were selected based on their involvement in the design, operation, or daily use of the facility, ensuring a broad spectrum of perspectives. The interviews aimed to explore perceived inefficiencies, occupant comfort, operational practices, and the alignment between design expectations and actual building performance.

Semi-structured interviews were chosen for their ability to balance structure with adaptability, enabling the researcher to follow a predefined framework while also probing emerging themes through responsive questioning (Ahlin 2019). This approach is particularly well-suited for post-occupancy evaluation, where nuanced insights into occupant behaviour, perceptions, and system usage are critical for understanding actual energy outcomes.

A purposive sampling strategy was employed to recruit participants with specific knowledge of building systems and operations. This targeted approach enhanced the relevance and richness of the qualitative data by engaging individuals most likely to offer meaningful contributions to the research objectives.

3.1.4. Interview respondents

A brief overview of the ten experts interviewed, including their designation, stage involved and the key discussion topics, is presented in Table 1.

Table 1: Respondents and Interview Topics

Respondent	Current Designation	Stage Involved	Questions Asked During Interview
E1	Office worker	Operational Phase	Are lighting and thermal comfort levels adequate for occupants throughout the building?
E2	Office worker	Operational Phase	
E3	Office worker	Operational Phase	
E4	Electrical Engineer	Construction Phase	Based on your experience, what design or system-level improvements could enhance both energy performance and occupant satisfaction? In your experience, what are the most common assumptions or inputs in energy models that lead to discrepancies between simulated and actual building performance?
E5	Mechanical Engineer	Construction Phase	
E6	Assistant Facilities manager	Operational Phase	How would you evaluate the building's overall energy performance compared to expectations? What is the most common comfort or system-related complaints received from occupants? Which operational practices or systems do you believe most significantly affect energy efficiency?
E7	Facilities manager	Operational Phase	
E8	Interior Designer	Operational Phase	What post-occupancy adjustments or interventions have been implemented to improve performance? From your perspective, how well do the initial design assumptions align with the actual operational performance of the building?
E9	Architect	Design Phase	
E10	Operations Manager	Operational Phase	

All interviews were audio-recorded with participant consent and transcribed for analysis. Where recording was not possible, detailed notes were taken and verified immediately. The data were analysed using content analysis, which identifies patterns and themes within textual data (Renz, Carrington & Badger 2018). This method enabled the coding of responses to extract recurring themes related to occupant behaviour, system control, perceived comfort, and discrepancies between design intent and actual use, highlighting key contributors to the energy performance gap.

3.2 DATA ANALYSIS

3.2.1 Model Development

eQUEST is one of the most widely used programs in the building simulation community (Yu et al., 2016; Zerroug & Dzelzitis, 2015). In this study, eQUEST was employed as a reliable platform to simulate the energy performance of the selected case study building. Figure 4 shows the model developed using the eQUEST software.

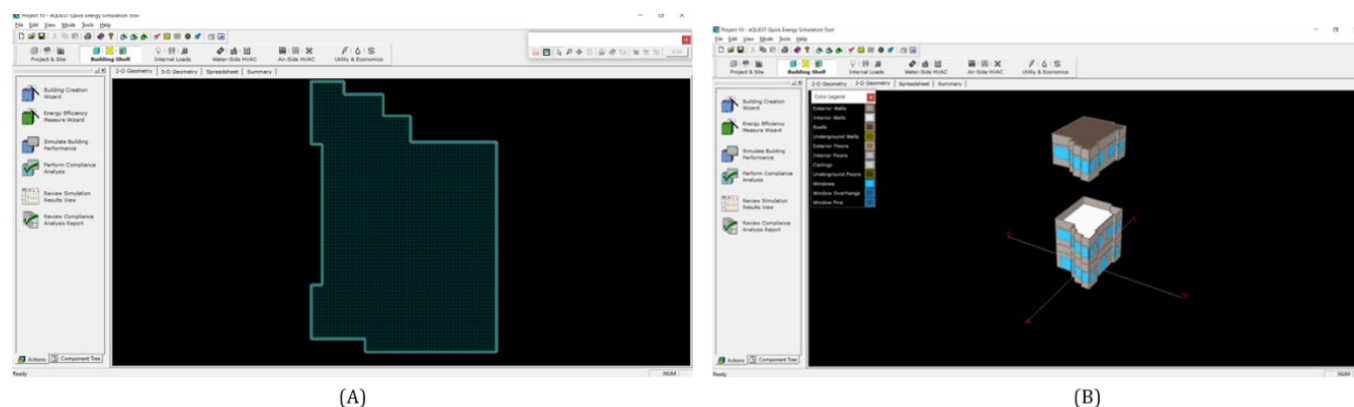


Figure 4: (A) 2D building geometry representation in eQUEST and (B) 3D building geometry representation in eQUEST

3.2.2 Structural parameters

The simulation model was developed using the building's architectural drawings, with material specifications obtained from the drawings and the Bill of Quantities (BoQ), in consultation with the building's facilities manager. After modelling the external envelope, the internal zones were categorized into air-conditioned and non-air-conditioned areas. Air-conditioned

spaces included static work zones such as general office areas and conference rooms. The remaining areas, including restrooms and corridors, were modelled as non-air conditioned.

Key envelope parameters included a north-facing orientation, concrete external walls, and fenestration consisting of both general and double clear glazing. Aligning with the architectural drawings, the window distribution was modelled with 15% of openings-oriented east and west and 35% oriented north and south, accurately reflecting the actual façade configuration while supporting effective passive solar control strategies.

3.2.3 Air-conditioning system parameters

The local climate was a key consideration in system specification. As illustrated in Figure 5, the region exhibits a consistently warm temperature profile with minimal monthly variation from January to December 2024. Daily maximum and minimum temperatures typically range between 74°F and 90°F, indicative of a stable tropical climate.

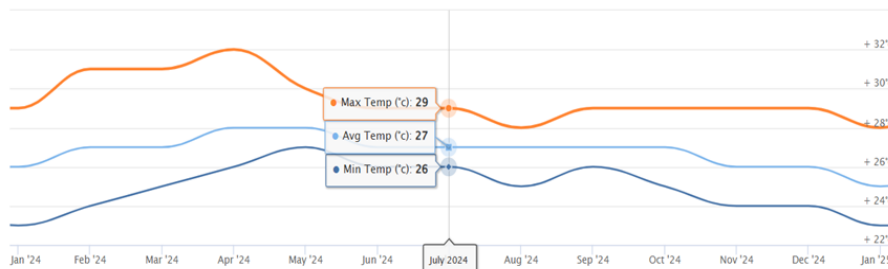


Figure 5: Diurnal temperature variation around the building location;

(a) Orange curve – Maximum temperature; (b) Light blue curve – Average temperature (c); Dark blue curve – Minimum temperature

Source: World Weather Online

Figure 6 illustrates annual humidity levels, which remain persistently high throughout the year. These environmental conditions necessitate an HVAC design that emphasizes cooling and dehumidification, as there is no requirement for space heating.

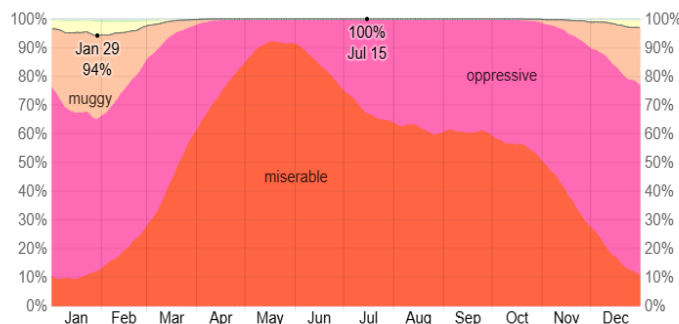


Figure 6: Annual humidity levels around the building

To address these environmental demands, the building utilizes a range of air-conditioning units with varied capacities and distributions. Figure 7 presents the breakdown of air-conditioning units by model, floor, and cooling capacity, offering insight into the system's spatial and functional deployment across the building.

Model	Location	BTU	TON
MWCP 18A	G floor	54600	4.55
MWCP 55A	1st floor	158000	13.16
MWCP 35A	1st floor	110920	9.24
MWH 70C	2nd floor	68303	5.69
MWH 70C	2nd floor	68303	5.69
MWW 60C	2nd floor	51159	4.26
MWCP 30A	3rd floor	81900	6.82
MWCP 30A	3rd floor	81900	6.82
MWCP 55A	3rd floor	158000	13.16
MWCP 70A	4th floor	226960	18.91
MWCP 35A	4th floor	110920	9.24
MWH 40C	C floor	42348	3.52
MWH 70C	C floor	68303	5.69
MWH 40C	C floor	42348	3.52
MWH 70C	C floor	68303	5.69

Figure 7: Air-conditioning unit distribution by model, floor, and cooling capacity

3.2.4 Calibration Workflow

To enhance the accuracy of the Building Performance Simulation (BPS) model, a structured post-occupancy calibration workflow was implemented (see Figure 8), integrating empirical data obtained from PoE activities with iterative simulation refinements.

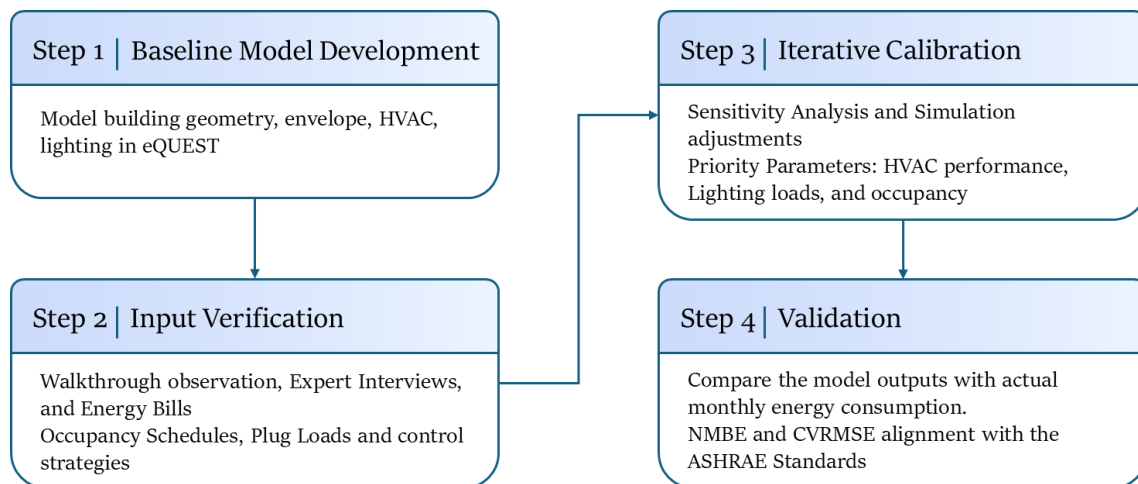


Figure 8: Implemented post-occupancy calibration workflow

The calibration process followed four sequential stages: (1) Baseline Model Development, where the building geometry, envelope characteristics, HVAC system configurations, and lighting layouts were modelled in eQUEST (v3.65); (2) Input Verification, which compared design-stage assumptions, including occupancy schedules, plug-load densities, equipment efficiencies, and control strategies, with measured operational data from walkthrough observations, energy bills, and expert interviews; (3) Iterative Calibration, where priority parameters identified through sensitivity analysis (HVAC performance, lighting loads, and occupancy schedules) were systematically adjusted in the simulation environment until convergence criteria were met; and (4) Validation, in which the calibrated model outputs were assessed against measured monthly energy consumption.

3.2.5 Performance Metrics

Calibration accuracy was evaluated using industry-accepted performance metrics, including the Normalized Mean Bias Error (NMBE) and Coefficient of Variation of the Root Mean Square Error (CV(RMSE)), in accordance with ASHRAE Guideline 14. The iterative adjustments continued until calibration criteria were satisfied and the divergence between measured and modelled energy consumption was reduced from 22.11% to 8.88%, indicating substantial improvement in model fidelity. This structured calibration workflow not only ensured reproducibility but also strengthened the reliability of the final simulation outputs used for subsequent analysis and recommendations.

3.2.6 Simulation Assumptions

Simulation assumptions were developed using architectural and MEP drawings, default ASHRAE 90.1 parameters, and locally applicable climatic data. Baseline inputs, such as fixed occupancy profiles, equipment efficiencies, and idealized HVAC control sequences, were subsequently replaced with measured operational characteristics, including actual AC runtimes, zoning behaviour, and observed lighting usage patterns. Weather inputs were derived from the nearest Typical Meteorological Year (TMY2) dataset, obtained from the NREL/DOE-2 weather library embedded within eQUEST. This DOE-2 BIN-format file provides hourly typical climatic data for temperature, humidity, solar radiation, and wind based on the closest Sri Lankan meteorological station. Measured monthly utility data from January–December 2024 was used as calibration targets to address deviations between TMY-based assumptions and real-year weather conditions.

3.2.7 Sensitivity Analysis

This study employed sensitivity analysis to examine how HVAC and lighting inefficiencies, occupant schedules, and weather conditions influence building energy performance, with the objective of reducing the discrepancy between modelled and actual consumption. As emphasized by Elhadad & Orban (2021), sensitivity analysis enhances model reliability by clarifying how variations in input parameters affect simulation outputs, while Attia et al. (2012) highlight its value in identifying critical design and operational factors shaping thermal and energy outcomes. Among the available methods, local, global, and screening (Hu, 2024; Tian et al., 2016), the local sensitivity analysis approach was selected due to its capacity to isolate the direct effects of individual variables, aligning with the study's aim of identifying key contributors to the performance gap. Following established practice in building simulation research, each input parameter (HVAC efficiency, lighting power density, occupancy schedules, and weather conditions) was systematically varied by $\pm 10\%$ to compute sensitivity coefficients (Hopfe & Hensen, 2011). This controlled perturbation enabled a clear quantification of each parameter's isolated influence on total energy consumption.

3.3 ETHICAL CONSIDERATIONS

The study did not involve collecting data from vulnerable individuals or handling sensitive information. However, informed consent was obtained from all participants prior to data collection. Participants were also informed that they could withdraw from the study at any time without any consequences.

4. Results

This section outlines the results of the expert interviews, observations, and sensitivity analysis.

4.1 RESULTS OF THE EXPERT INTERVIEWS

The expert insights collectively highlighted that the building's performance gap arises from a complex interplay of design-phase assumptions, technical limitations, operational inefficiencies, and occupant related factors.

E5 and E8 identified a critical issue originating in the early design and simulation stages, where overly optimistic assumptions lead to distorted predictions of performance. E8 also emphasized that simulation models often incorporate inputs, such as insulation, fixed occupancy schedules, and optimal system efficiency, that fail to account for the variable nature of actual building operations. This mismatch significantly contributes to the gap between modelled and measured energy consumption.

E7 and E10 pointed out that operational inefficiencies stem from inadequate control strategies and insufficient user training. Occupants frequently override present HVAC controls or misuse equipment, leading to higher energy use. Additionally, E8 stated that, some automated systems have not been recalibrated since initial commissioning. Therefore, E8 explained that “there are limitations in responding to the changing occupancy patterns or seasonal conditions”.

E10 identified a critical design flaw in the air distribution network, stating: “this building utilizes a package cooling unit; but the ductwork design is inadequate. So that this leads to uneven air distribution and inconsistent cooling across the workspace.” This inconsistency has directly impacted thermal comfort and overall workplace satisfaction. Supporting this observation, E3 remarked: “inadequate air conditioning is among frequent complaints in office areas, significantly affecting employee comfort and productivity.” Further reinforcing these concerns, E8 highlighted the continuous operation of the HVAC system even during non-occupied periods, due to the absence of zoning controls. This inefficiency leads to increase the energy consumption without any corresponding benefit. Further E8 explained that the absence of a Building Management System in the building causes less centralized control over the systems. E1 supported this observation, stating that, “the air conditioning system operates from 8:30 AM to 5:30 PM continuously, and if there is overtime work, it continues until 10:00 PM.”

Lighting inefficiencies emerged as another recurring theme among the experts. E10 reported frequent complaints related to inadequate task lighting and poor fixture placement. E6 elaborated, “LED lights do not provide sufficient illumination for employees because of the poor positioning. As employees are working on screens for extended periods this leads to eye strain and discomfort.” Additionally, E2, E4, and E6 highlighted the use of fluorescent lights in certain areas, despite the organization's broader transition to LED technology. E9 explained, “even though our initial design intent was to install LEDs across the facility to enhance energy performance, fluorescent fixtures were ultimately implemented in some areas, due to cost considerations.”

Most notably, several experts attributed a significant portion of the performance gap to daily occupant attendance and behaviour. E7 emphasized the unpredictability of occupant actions, noting that users often leave lights and equipment running overnight. These behaviours contrast with the rational energy-consumption patterns typically assumed in simulation models. E10 reinforced this observation by stating that, “occupants often misuse HVAC systems or override controls, which significantly affects energy use.”

The expert findings indicated that the energy performance gap of the building results due to unrealistic design-phase assumptions, HVAC and lighting inefficiencies, operational inefficiencies, and occupant related factors. Simulation models failed to reflect actual conditions, while poor system maintenance and limited zoning controls further increased energy use. Addressing this gap requires a holistic approach that integrates realistic modelling, continuous system calibration, and active occupant engagement.

4.2 ENERGY PERFORMANCE GAP BETWEEN THE MEASURED AND MODELED ENERGY CONSUMPTION VALUES BASED ON THE INITIAL BUILDING DESIGN

Measured energy consumption data for the building were obtained from monthly utility bills from January to December 2024. Additionally, detailed information on lighting systems, HVAC usage, and occupant schedules, including monthly attendance, was gathered through consultations with the building's facilities manager. Figure 9 presents a comparison between the monthly measured and modelled energy consumption of the case study building.

The results showed a 22.11% discrepancy between measured and modelled energy consumption, indicating a substantial performance gap. This highlights that the simulation outputs from the design phase significantly underestimated actual energy use, revealing a clear misalignment between projected and operational performance.

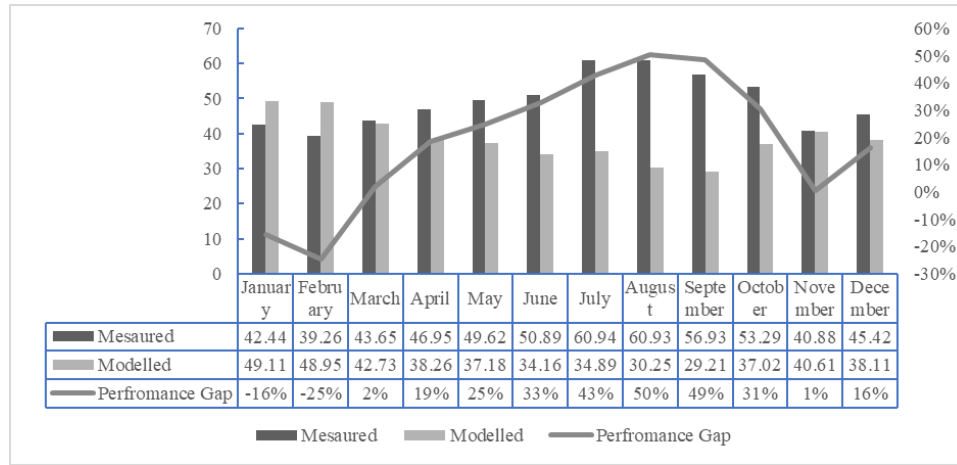


Figure 9: Comparison of measured vs. modelled energy consumption of the case study building from January to December 2024.

4.3 RESULTS OF WALKTHROUGH OBSERVATIONS

4.3.1 Inefficiencies in the lighting system

Figures 10 and 11 show the current lighting layout and the initially designed lighting layout of the building, respectively.

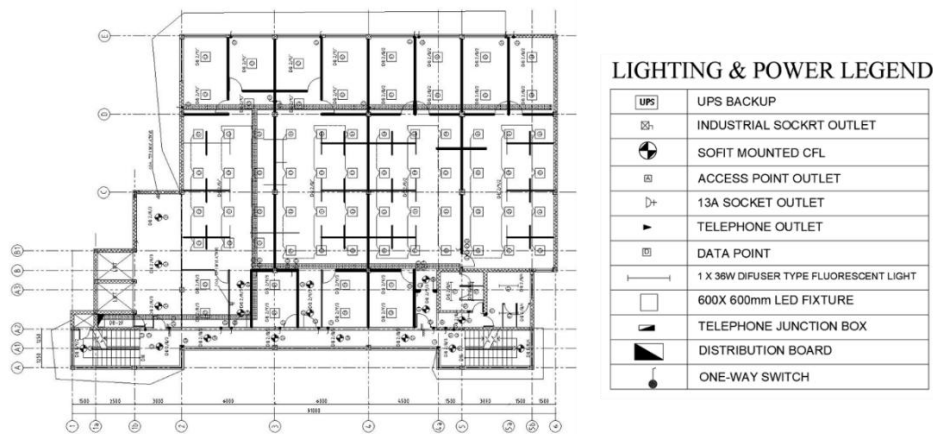


Figure 10: Current lighting arrangement

As shown in Figure 10 and reinforced by expert interviews, fluorescent lamps remain in use in several areas of the building. Figure 11 illustrates the initial lighting layout and highlights modifications made during the operational phase, specifically the replacement of LED fixtures with fluorescent lights in certain zones. The current arrangement (Figure 10) shows that identical fixture types are being used in various spaces with vastly different functions, such as open-plan offices, enclosed rooms, corridors, and service areas. This uniform approach neglects task-specific lighting requirements, resulting in unnecessary energy consumption in low-use or low-illumination-demand areas.



Figure 11: Current lighting arrangement

Additionally, the observations highlighted the high number of ceiling-mounted fixtures, which can complicate maintenance access, particularly in high-ceilinged or obstructed zones. Limited access often leads to dirty, malfunctioning, or mismatched lamps, further diminishing lighting quality and energy efficiency.

4.3.2 Inefficiencies in the occupancy schedule

Figure 12 illustrates the monthly measured and expected occupancy schedule of the building for the year 2024, as obtained from the facility manager.

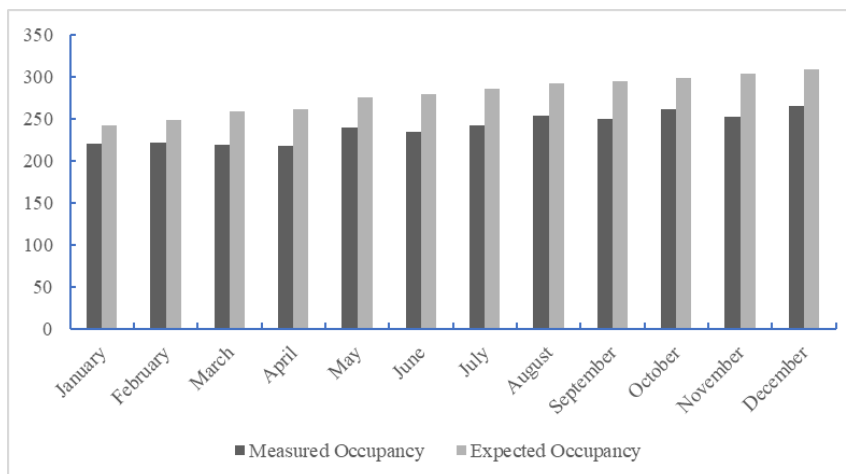


Figure 12: The actual and planned occupancy schedule for the building

Figure 12 reveals a clear gap between estimated and actual occupancy levels. Throughout the year, measured occupancy consistently falls below projected values, indicating a significant deviation from initial assumptions. Although both trends indicate a gradual increase from January to December, the disparity is more pronounced in the early months and narrows toward the year-end. The highest measured occupancy occurs in December, closely aligning with the expected peak, suggesting improved accuracy in forecasts or increased space utilization in later months.

4.3.3 Inefficiencies in the air conditioning system

Figure 13 illustrates the air conditioning distribution across a single floor of the building.

The zones represented in blue and dark blue indicate the coolest areas, reflecting strong and consistent air-conditioning coverage. These regions likely benefit from optimal supply vent placement and effective HVAC zoning. In contrast, zones shaded in yellow to orange represent moderate temperatures, suggesting partial cooling, potentially due to extended duct lengths and thermal gains from external walls and windows. The warmest areas, highlighted in red and bright orange, lack sufficient cooling, likely resulting from poor duct coverage and inadequate insulation, as noted by E10. The gradient transitions between these zones also reveal airflow drift and cooling inefficiencies. Overall, the thermal distribution suggests a need to rebalance the HVAC system, optimize duct placement, and consider implementing zoning controls to achieve more uniform thermal comfort across interior spaces.

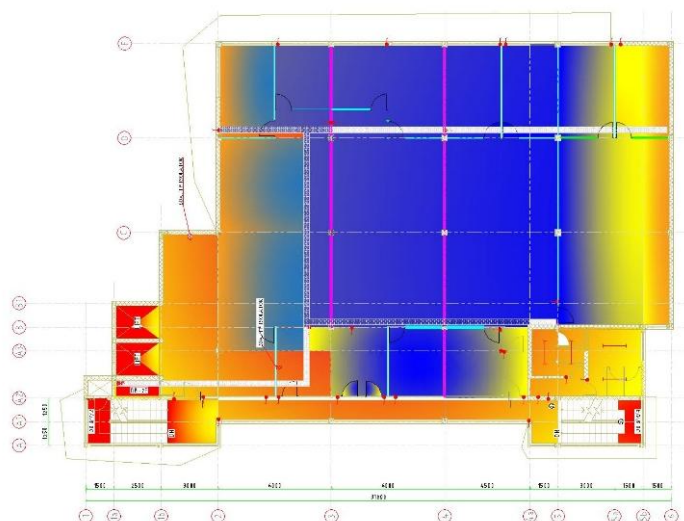


Figure 13: Thermal map illustrating the air conditioning distribution across the building floor plan. Cooler zones (in blue) indicate areas with effective air conditioning coverage, while warmer zones (in red and orange) highlight regions with insufficient cooling

4.4 RESULTS OF THE SENSITIVITY ANALYSIS

The objective of this research was to evaluate the influence of key input parameters on reducing the performance gap between modelled and measured building performance, thereby improving the reliability and accuracy of early-stage energy simulations. Findings from expert interviews identified lighting inefficiencies, HVAC inefficiencies, and occupant schedule patterns as the most impactful contributors. Additionally, based on the literature review, weather conditions were also considered for the analysis. As illustrated in Figure 14, the mean sensitivity coefficients quantify the relative influence of these parameters on performance deviation.

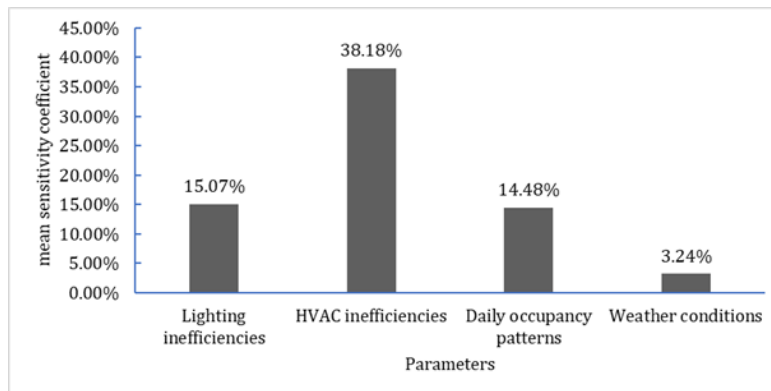


Figure 14: Mean sensitivity coefficients for each change in the lighting inefficiencies, HVAC inefficiencies, daily occupancy patterns and weather conditions

Figure 14 shows that HVAC inefficiencies have the greatest impact on the performance gap (38.18%), followed by lighting inefficiencies (15.07%) and occupant schedule patterns (14.48%). Weather conditions have the least influence (3.24%). These findings underscore the critical importance of accurately modelling HVAC systems, lighting loads, and occupancy patterns to minimize the divergence between modelled and measured energy performance.

4.5 CALIBRATION THE SIMULATION MODEL

The final step involved calibrating the simulation model using actual data to assess the reduction in the performance gap. Figure 15 illustrates the discrepancy between modelled and measured energy values after calibration.

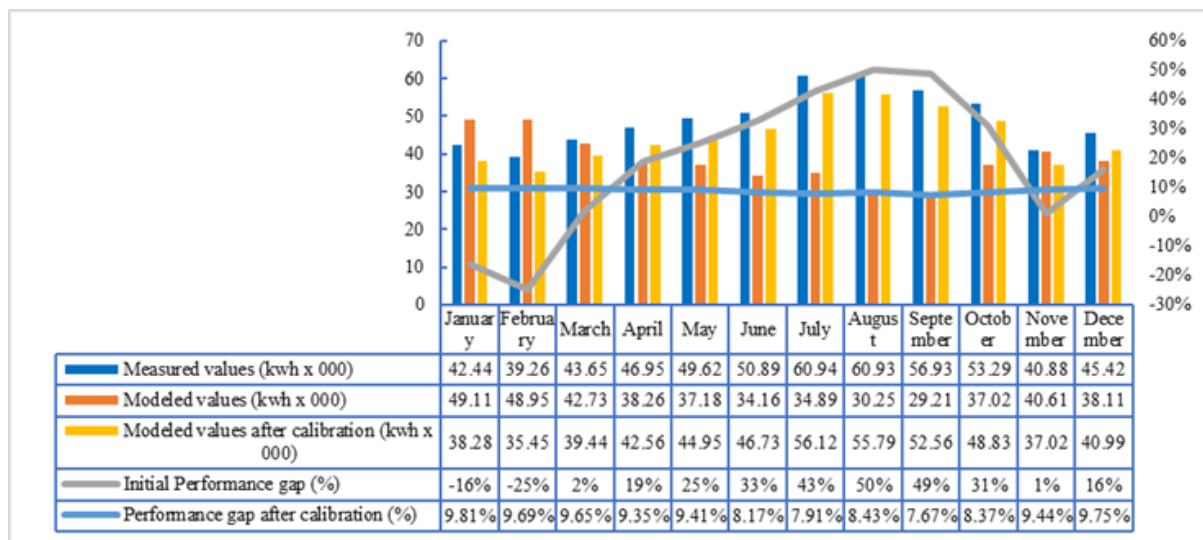


Figure 15: Performance gap between the measured and modelled energy values after calibration

Figure 15 shows a clear reduction in the performance gap following model calibration using actual data. After calibration, the adjusted modelled values closely align with actual data across all months, reducing the overall performance gap to 8.88%. This improvement highlights the effectiveness of post-occupancy calibration in enhancing the accuracy and reliability of energy simulations.

4.6 RESULTS OF NMBE AND CV(RMSE) CALCULATIONS

Using monthly measured energy data from January–December 2024, calibration accuracy was evaluated according to ASHRAE Guideline 14 using the Normalized Mean Bias Error (NMBE) and the Coefficient of Variation of the Root Mean Square Error (CV(RMSE)). The initial model exhibited an NMBE of 24.12% and a CV(RMSE) of 35.29%, indicating substantial underestimation of actual energy use. Following the integration of post-occupancy measurement data and iterative parameter adjustments, the calibrated model achieved an NMBE of 9.77% and a CV(RMSE) of 13.43%. While the CV(RMSE) satisfies ASHRAE monthly calibration criteria ($\leq 15\%$), the NMBE remains slightly above the recommended threshold of 5%. Nonetheless, the results demonstrate a significant enhancement in model fidelity and a substantial reduction in prediction error.

5. Discussion

Bridging the energy performance gap is critical for aligning design and engineering decisions with actual building outcomes. This study presents a detailed case study demonstrating effective strategies to reduce the gap and enhance the accuracy of performance predictions.

5.1 IDENTIFIED CAUSES OF THE ENERGY PERFORMANCE GAP

Expert interview findings identified several key contributors to the energy performance gap in the case study building. These contributors include inefficiencies in HVAC and lighting systems, unpredictable occupancy patterns and behavior, shortcomings in maintenance and commissioning, and overly idealized design assumptions. In addition to that, experts highlighted that due to the lack of involvement of facilities managers during the design stage is also a reason to this performance gap. These findings align with existing literature, which highlights similar causes, including inaccurate modelling of occupant density, external weather conditions, construction quality, material properties, and building system inefficiencies (Cozza et al., 2021; Di Stefano et al., 2023; Negendahl, 2015).

One of the most significant challenges is predicting occupancy patterns and energy consumption during the early design phases. Cozza et al (2021) also emphasized that unpredictable occupant behavior is a primary driver of the discrepancy between modelled and measured energy performance. Additionally, variations in occupant comfort preferences can lead to frequent overrides of HVAC and lighting systems, resulting in fluctuations in heating, cooling, and ventilation demands. These behavioral variations are difficult to anticipate during the design stage, making it challenging to accurately model real-world performance. Consequently, such discrepancies contribute to the persistent gap between modelled and measured energy use in buildings.

5.2 OUTCOMES FROM MODEL RECALIBRATION

The initial energy model revealed a significant performance gap of 22.11% between the measured and modelled energy consumption of the building. Based on the insights gain from the experts and empirical data, the model was recalibrated accordingly to reflect actual operational conditions more accurately. The recalibration resulted in reducing the performance gap to 8.88% by adjusting for the current HVAC, lighting, occupancy patterns, and weather conditions. Similarly, Kim et al. (2020) reported a dynamic energy performance gap of nearly 25% between the as-designed and in-use models. Their study demonstrated that aligning building operations with appropriate schedules and implementing effective management strategies can significantly reduce energy consumption, bringing it closer to the levels predicted during the design stage. Furthermore, Pan et al. (2023) reported that 23% of studies from 2011 till date stated that the performance gap is reduced by calibration. Calibration is an iterative process of fitting the design or operational parameters of the virtual model to those of the notional or actual building.

5.3 FINDINGS OF THE SENSITIVITY ANALYSIS

The results of the sensitivity analysis revealed that HVAC inefficiencies were the highest contributing factor to the performance gap of the selected building with a contribution of 38.18%. Lighting inefficiencies hold the second place with a contribution of 15.07%. These findings align with Zhu (2006), who utilized the eQuest simulation tool to evaluate various energy-saving measures in a university library in China. Zhu's analysis revealed that the air conditioning system accounted for 49% of total energy use, followed by the lighting system at 35%. Similarly, Pan et al (2023) emphasized that HVAC systems play a direct and often dominant role in bridging the performance gap between actual and simulated energy consumption.

However, other studies offer a slightly different perspective. Barone et al. (2022) and Love (2014) concluded through simulations of multiple energy-saving strategies, that lighting systems can also play a primary role in minimizing the performance gap, particularly when inefficient lighting layouts and controls are addressed. These contrasting viewpoints suggest that while HVAC systems often have the largest impact, the influence of lighting should not be underestimated, especially in buildings with outdated or poorly designed lighting infrastructure.

As per Figure 14, daily occupancy patterns have a 14.48% of contribution, which is the third most influential factor in the energy performance gap of the building. A review of 62 non-domestic buildings by van Dronkelaar et al. (2019) found that occupant behavior and suboptimal operational practices contributed significantly to the energy performance gap, with estimated impacts ranging from 10–80% and 15–80%, respectively. Furthermore, Norouziasl et al. (2024) stated that occupant density, arrival and departure times, and occupants' stay time have a direct influence on the energy performance gap of a building. Similarly, Aftab et al. (2017) stated that occupant-related factors have been identified as a major factor contributing to the discrepancy between simulation predictions and real energy use.

Finally, the sensitivity analysis revealed that weather conditions contributed 3.24% to the performance gap. This aligns with the findings of Wang et al. (2012), who reported weather-induced deviations of up to 3-6% in building energy use for typical U.S. office buildings. Additionally, Alhindawi and Jimenez-Bescos (2020) emphasized that reliance on current weather data for thermal calculations can result in future inaccuracies, thereby contributing to a weather-related performance gap.

5.4 IMPACT OF MATERIAL VARIATIONS ON THE PERFORMANCE GAP

Discrepancies between the actual building materials and the default eQUEST library constructions can be considered a major contributor to the initial 22.11% performance gap observed in the case study. Table 2 shows the impact of material variations on the performance gap.

Table 2: impact of material variations on the performance gap

Building element	Actual construction (as built / BoQ)	eQUEST library construction used in baseline model	Nature of discrepancy
External wall	200 mm reinforced concrete wall with 12 mm internal cement plaster and external paint; no dedicated thermal insulation	Generic <i>"Heavyweight concrete wall – insulated"</i> from DOE-2 library (e.g. concrete + internal insulation layer defined to meet ASHRAE 90.1 minimum U-value for the climate zone)	Library walls assume lower U-value (better insulation) than the actual uninsulated concrete wall, leading to underestimation of conductive heat gains and cooling demand.
Roof / slab over top floor	150–200 mm reinforced concrete roof slab with waterproofing and screed; dark external finish; no thermal insulation	<i>"Insulated roof"</i> construction from eQUEST (roof deck + insulation layer + light-coloured surface, meeting ASHRAE 90.1 requirements)	Simulated roof has higher thermal resistance and higher solar reflectance than the actual roof, reducing simulated solar heat gains through the roof compared to reality.
Glazing (office façade)	Double clear glazing in aluminium frames; standard tint; limited low-E coating; external shading only on selected elevations	eQUEST default <i>"Double glazing, low-E, tinted"</i> window type with relatively low U-value and SHGC (ASHRAE 90.1 compliant)	Library glazing is more energy-efficient (lower U and SHGC) than the actual system, thus underestimating solar and conductive gains and associated cooling loads.
Internal partitions	100 mm solid block / brick partitions with plaster finish	<i>"Lightweight partition wall"</i> from library (e.g. gypsum on studs)	Library partitions have lower thermal mass than the actual masonry partitions, which affects heat storage, peak load shifting and the dynamic response of indoor temperatures.
Ground floor slab	Reinforced concrete slab-on-grade, uninsulated, tiled finish	<i>"Insulated slab-on-grade"</i> or generic <i>"Mass floor"</i> with default insulation thickness	Library floor often assumes some insulation or more favourable boundary conditions, slightly reducing conductive gains from the ground compared to the actual configuration.
Roof/ceiling of non-AC spaces (corridors, toilets)	Bare concrete soffit or suspended ceiling with limited reflective finish	Generic <i>"Ceiling – conditioned space above/below"</i> with default reflectance and insulation	Differences in reflectance and insulation change inter-zonal heat transfer and internal gains, particularly where non-AC spaces are adjacent to conditioned zones.

The use of insulated, ASHRAE-compliant library walls, roofs, and glazing to represent a building that is predominantly uninsulated introduced a systematically optimistic portrayal of envelope performance, leading to underestimation of conductive heat transfer and cooling loads in a tropical climate. Similarly, the assumption of high-performance glazing reduced simulated solar heat gains, diverging from the thermal behaviour of the installed glazing systems.

Although post-occupancy calibration significantly reduced the performance gap, aligning the model more closely with actual operating conditions, residual discrepancies remained. The remaining 8.88% gap can be attributed to persistent material differences that could not be fully replicated in the simulation environment, along with natural variations in occupant behavioural patterns such as plug-load usage, thermostat settings, and space utilisation. These findings highlight the critical importance of using accurate, as-built envelope data in early-stage energy modelling and emphasize the need for detailed post-occupancy validation to ensure model reliability and predictive credibility.

5.5 IMPLICATIONS OF THE STUDY

The findings of this study offer critical advancements in performance-driven building design by empirically demonstrating that integrating PoE data into BPS can reduce the energy performance gap from 22.11% to 8.88%. For both existing buildings and future projects, this study underscores the need to shift from static, assumption-based models to dynamic, data-informed simulations that reflect real-world operational complexity. The sensitivity analysis identified HVAC inefficiencies (38.18%), lighting inefficiencies (15.07%), and daily occupancy patterns (14.48%) as the most influential parameters affecting performance discrepancies. These findings can be leveraged to pinpoint inefficiencies within the building, enabling designers, facility managers, and energy modelers to implement targeted retrofit measures that align actual performance more closely with design-stage assumptions. By continuously updating simulation models with post-occupancy data, stakeholders can maintain an adaptive approach to performance management, facilitating the early detection of

inefficiencies and achieving long-term energy and operational benefits. Figure 16 shows the proposed framework for reducing the energy performance gap supported by post-occupancy calibration.

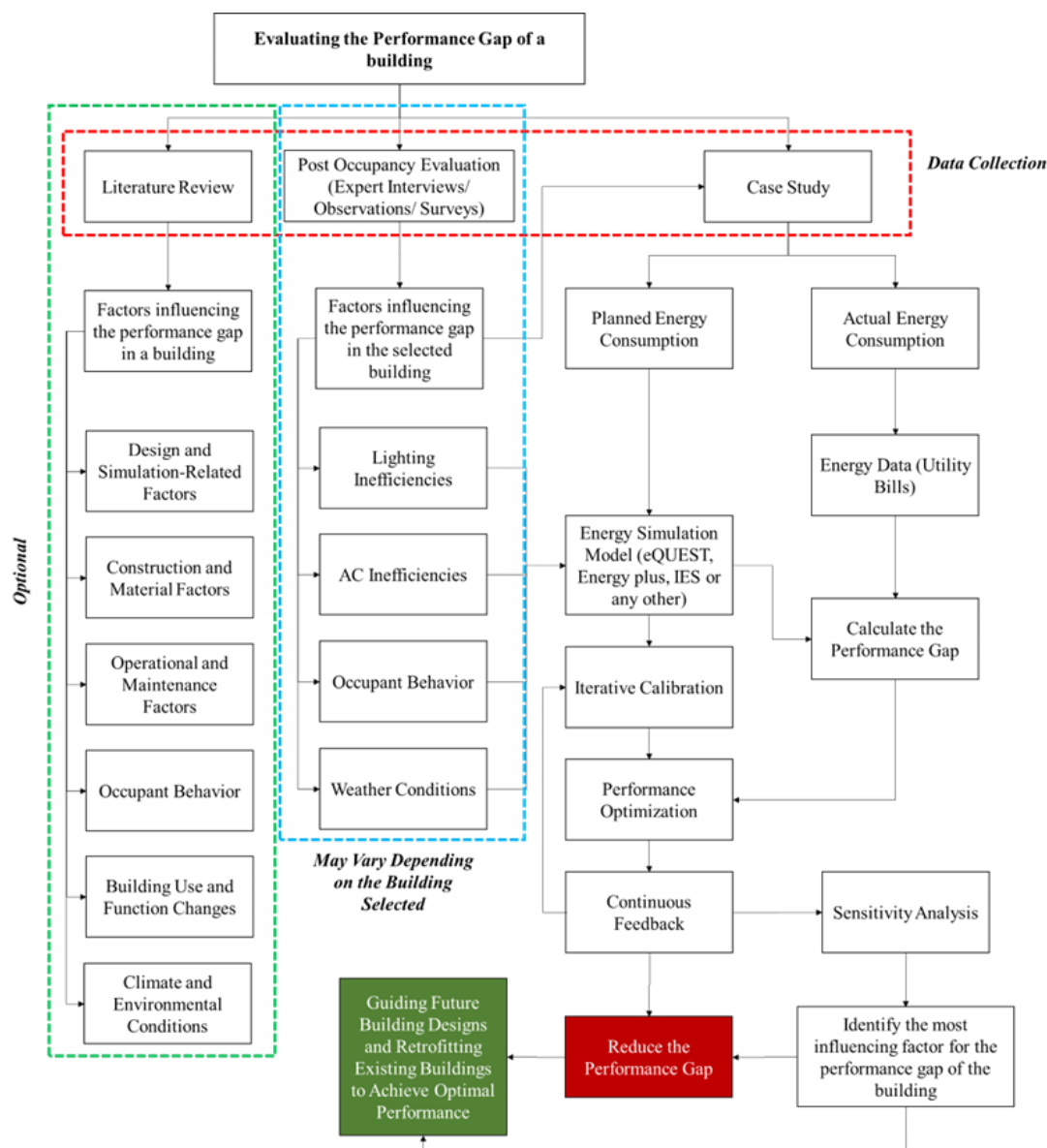


Figure 16: Proposed framework for reducing the energy performance gap supported by post-occupancy calibration

The proposed framework (Figure 16) provides a structured, replicable process for reducing the energy performance gap by integrating post-occupancy data into Building Performance Simulation. It begins with a review of design-stage assumptions, addressing the common issue that pre-occupancy models rely on idealised inputs that rarely reflect real operational conditions. The second step introduces a standardised approach to Post-Occupancy Evaluation (PoE) through walkthrough observations, expert interviews, and measured operational data. This ensures consistent and high-quality data collection, an area where existing PoE practices often vary widely, contributing to the absence of a universally accepted framework.

The third step incorporates sensitivity analysis to quantitatively identify the most influential parameters driving the performance gap. By prioritising HVAC inefficiencies, lighting loads, and occupancy patterns, the framework establishes a method for systematic parameter selection, overcoming the ad-hoc approaches commonly seen in current PoE methodologies. The fourth step operationalises these findings through iterative calibration, where model inputs are refined using empirical data until simulated results converge with measured energy use. The fifth step validates the calibrated model using industry-standard metrics such as NMBE and CV(RMSE), reinforcing methodological rigour and ensuring the reliability of outcomes.

Finally, the framework establishes a formal feedback loop, translating calibrated insights into future design decisions, facility management practices, and retrofit strategies. This lifecycle-oriented process directly addresses the gap identified in the Introduction, that the field lacks a universal, methodologically robust PoE framework capable of integrating prediction, evaluation, and operational feedback. By standardising data collection, embedding quantitative prioritisation, and formalising iterative refinement, the proposed model offers a scalable and transferable approach that can be applied

across building types. As demonstrated in this study, it provides a practical pathway to reduce the performance gap and strengthen the connection between design intent and real-world building performance.

Using this process (Figure 16), the study reduced the performance gap to 8.88%, with potential for further reduction and identification of additional inefficiencies through deeper analysis. This study introduces a site-specific, iterative calibration framework that integrates high-resolution PoE data into the simulation process, enabling more granular, context-sensitive model refinement at the building level.

The integration of advanced technologies, such as real-time sensor data and machine learning-based predictive control, can further enhance this framework by enabling buildings to adapt dynamically to changing occupancy patterns and environmental conditions. Overall, this study advocates for an occupant-aware, data-driven, and lifecycle-oriented approach to building performance management, one that aligns closely with long-term sustainability and operational efficiency objectives.

5.6 LIMITATIONS OF THE STUDY

A key limitation of this study is that, while occupancy parameters were considered, detailed occupant behaviors were not thoroughly examined. Additionally, the study assumed static building envelope characteristics, potentially overlooking performance variations resulting from material degradation or retrofitting. Future research should address these factors to enable a more comprehensive and scalable understanding of energy efficiency across diverse building contexts.

6. Conclusion and way forward

This study demonstrates the critical role of Post-Occupancy Evaluation (PoE) in enhancing the predictive accuracy of Building Performance Simulation (BPS) models and reducing the energy performance gap, using an office building as a representative case study. Using a detailed case study strategy, the integration of real-world operational data into simulation calibration reduced the performance gap from 22.11% to 8.88%, underscoring the efficacy of data-driven model refinement. The findings further identified HVAC inefficiencies, lighting system shortcomings, and unpredictable occupant schedules as the primary contributors to the performance discrepancy. Through sensitivity analysis, HVAC inefficiencies were revealed as the most influential factor, responsible for 38.18% of the deviation.

This research reinforces the importance of transitioning from static, assumption-based simulation practices to dynamic, lifecycle-oriented performance management frameworks. Conventional BPS models, which rely heavily on idealized assumptions, fall short of capturing the complex interactions between systems, occupants, and environmental conditions. By incorporating PoE insights into simulation workflows, practitioners can more accurately represent operational realities and proactively manage energy use.

To advance the integration of post-occupancy insights into predictive modelling, the next logical step is the development of a machine learning based model capable of enhancing the accuracy, adaptability, and scalability of BPS. While traditional simulation tools like eQUEST are valuable for scenario-based analysis, they remain limited by static assumptions and deterministic inputs. ML algorithms, by contrast, offer a data-driven approach that can dynamically learn complex patterns from diverse datasets, making them particularly suitable for modelling the stochastic nature of occupant behavior, system interactions, and environmental variability.

7. Data Availability

Data will be made available on request.

8. Competing Interests Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors confirm that there are no conflicts of interest associated with this publication.

9. Authors' Contributions Statement

Rahubadda R.V.A.D. (First Author, Corresponding Author): Conceptualization, methodology design, data collection, simulation modelling, formal analysis, preparation of figures and tables, and writing, original draft.

Maddakandage M.N.U. (Second Author): Conceptualization, Introduction and Literature review, data collection, writing, original draft.

Kulatunga U. (Third Author): Supervision, verification of material specifications and HVAC parameters, assistance with data interpretation, writing, review and editing.

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