Occupancy optimisation strategies for energy demand reduction – case study of an educational building

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Abstract

A methodology for operational schedules optimisation is introduced to reduce energy demand by exploiting monitored occupancy patterns for dynamic thermal model calibration. Significant periods of low occupancy were identified on a case study building to leverage with proactive operational strategies to reduce energy demand. These strategies involve the closure of specific building zones during these periods to optimise resource utilisation. Up to 6% annual energy savings was estimated, highlighting the effectiveness of zone closures.

The study's replicable data-driven framework can be scaled and extended to other buildings, with potential for widespread energy efficiency enhancements and cost reductions across similar type buildings. The research enhances the understanding of the relationship between occupancy and energy demand, while offering adaptable recommendations for more energy efficient and sustainable building operations.

Keywords
building energy simulation, occupancy analysis, building operational efficiency, purpose-led calibration

1. Introduction
Buildings serve as significant contributors to global energy consumption, specifically building operations accounting for 26% of total global energy consumption (1). Internationally, government policies and schemes have focused on amplifying energy efficiency to reduce carbon emissions of the buildings sector (1). Furthermore, operational energy consumption has been identified as the predominant contributor of a building's life cycle energy usage, accounting for 80-90% (2). All stakeholders in the built environment bear a collective responsibility to champion enhanced sustainability practices, particularly in the domain of operational energy consumption.

Building Energy Models (BEMs), particularly dynamic thermal simulation models, are tools for analysing energy flows, occupant behaviours, and environmental interactions in buildings (3). These models enable informed decision-making, supporting the development of operational strategies and addressing energy concerns in the built environment. They are essential instruments that allow stakeholders to gain a deeper understanding of energy dynamics within the built environment and to pave the way for more sustainable building practices.

Efficient building operations are pivotal in achieving energy reduction goals, and the integration of data-driven responsiveness holds promise in this endeavour. The incorporation of smart data-driven control systems into building operations has gained prominence, offering the potential to optimise operational strategies without affecting building occupants. The influence of occupancy on building energy consumption can be substantial (4), motivating a focused exploration of strategies that respond operations to occupancy patterns to achieve significant energy savings. Occupancy-based climate controls were found to save energy consumption in both simulations and field experiments (5). Accounting for occupancy patterns without architectural changes can result in energy savings with minimal financial investments (6).

This study proposes a novel approach to leverage occupancy data to enhance operational energy efficiency strategies, which is adaptable to evolving occupancy patterns. The methodology is demonstrated on a 24-hour case study university building, henceforth termed “CSUB”, primarily serving as study spaces. Objectives of the study are:

- Gain comprehensive understanding of the occupancy patterns of the building of interest;
- Construct a baseline energy model;
- Calibrate the energy model using measured electricity data;
- Propose and simulate operational strategies in response to identified occupancy patterns;
- Assess the impact of proposed strategies in social, operational, environmental and economic dimensions;
- Recommend operational strategies that are responsive to occupancy patterns.

The replicable data-driven framework is suited for scalability across different building stocks, providing a versatile energy reduction strategy without requiring significant physical retrofits. The research offers actionable recommendations for sustainable operational practices in buildings, addressing a major source of global carbon emissions.

2. Methodology

2.1. Case study building

The case study building is an eight-storey educational building in London, United Kingdom. The building is unique in its 24/7 operations as a university library space that is operational throughout the year. The 5,400 m^2 building has a range of spaces such as study spaces, café and staff offices.

The building attained an Energy Performance Certificate (EPC) rating of “A” in 2018 and adopts a “passive-first” design approach which uses efficient fabric materials, thermal mass and natural ventilation when possible (7).

The operational aspects of the building are notably complex and has some sources of uncertainties. One of the challenges lies in the mixed variety of HVAC configurations throughout. While the HVAC system is electrically powered with ground-source heat pumps, the domestic hot water (DHW) supply is separately sourced from a district heating system.

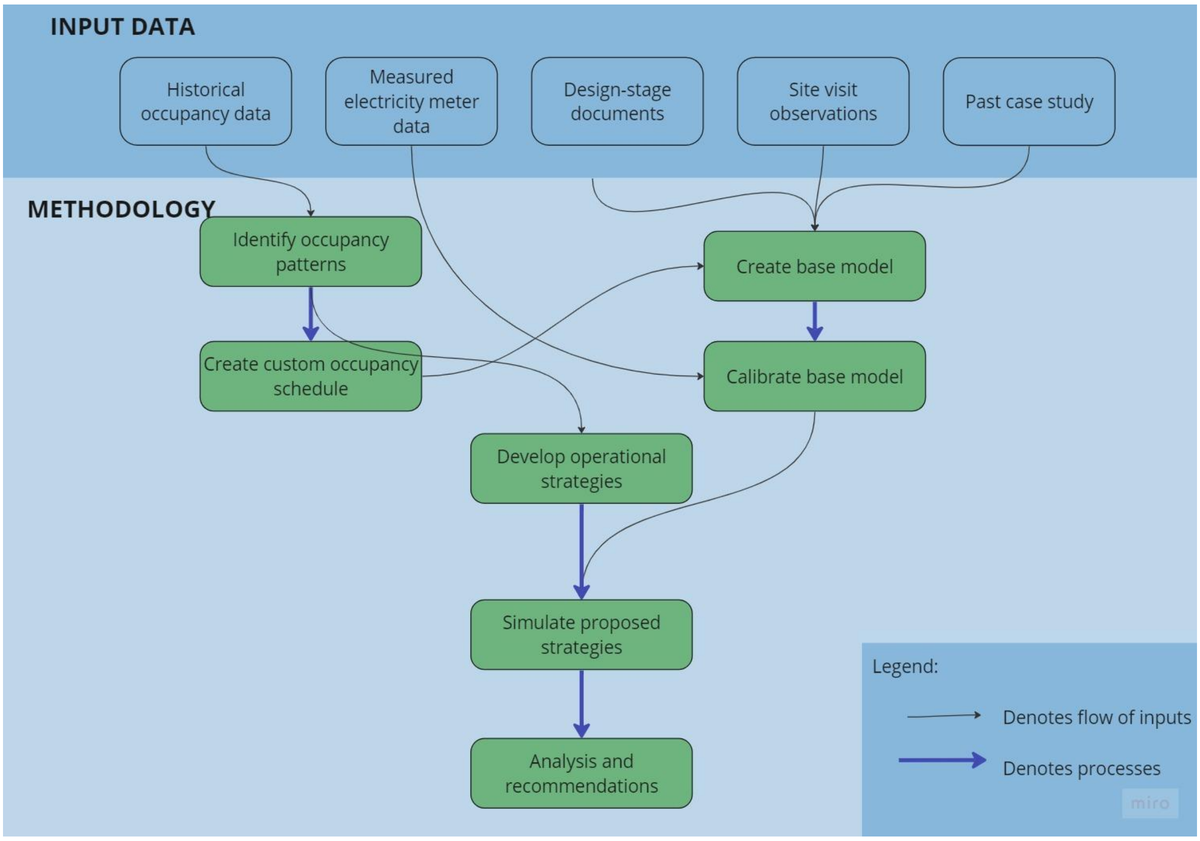
Additionally, the presence of a central atrium void spanning from the ground floor to the main roof skylight, introduces further intricacies in managing the building's HVAC requirements. There are some entire zones on levels L1 and L2 directly exposed to this atrium void. This design is likely to have significant implications on the HVAC loads that is complex and challenging to discern.

Besides the building’s design with operable window openings to utilise natural ventilation when outside temperatures allow, the COVID-19 pandemic necessitated increased air change rates during operations to address safety concerns. Perhaps one of the most significant operational variations is the use of temperature sensors for HVAC control, departing from the originally intended carbon dioxide sensor-based system.

Notably, the building's design does not include occupant controls, with the lighting, windows, and HVAC centrally controlled. Throughout the building, the only control accessible to occupants is shading control. This element of the building design has made the building an interesting case study for the methodology devised for examining how operational controls can be responsive to occupancy patterns. This distinction sets it apart from other studies in the field that tend to focus on the impact of occupants' control over system loads. The described complexities highlight the need for a detailed examination of CSUB's building operations and the relationship with energy consumption.

Figure 1 outlines the systematic approach undertaken to achieve the research objectives.

Figure 1 - Methodology overview of input data sources and workflow



2.2. Data collection/sources

The data required for this work primarily involve two types of data: occupancy and measured energy consumption data. Occupancy data serves multiple purposes: understanding occupancy patterns, informing energy model inputs for occupancy schedules, and shaping proposed operational strategies.

Both datasets are openly available for CSUB and accessible to individuals with university credentials. Data from the full calendar year of 2022 was selected due to completeness and up-to-date nature of the sources.

2.2.1 Occupancy data

Occupancy data originated from the university API platform (8) and comprise of historical readings from seat occupancy sensors located in CSUB. The historical seat occupancy readings were processed in several temporal dimensions such as academic term dates (Table 1), monthly, day of the week and hour of the day to investigate potential occupancy patterns. Utilising a k-means clustering algorithm (9), two distinct clusters of dates with notably different occupancy rates were identified and termed peak and off-peak periods. This analysis derived an evidence-based occupancy rate schedule for CSUB reported in Section 3.1 alongside further discussion.

Academic Year (AY) calendar	Dates (Calendar year 2022)
AY 21/22 Winter break	1 – 9 Jan
AY21/22 Term 2	10 Jan – 25 Mar
AY 21/22 Easter break	26 Mar – 24 Apr
AY 21/22 Term 3	25 Apr – 10 Jun
Summer break	11 Jun – 25 Sep
AY22/23 Term 1	26 Sep – 16 Dec
AY22/23 Winter break	17 Dec – 31 Dec

Table 1 - Academic calendar dates

Subsequently, occupancy data were mapped against seats location in the building to identify zones with reduced occupancy at specific time of the year; this presented the potential to optimise occupancy by closing some zones within CSUB. This process spotlighted two strategic time intervals for targeted operational strategies: off-peak dates and weekends (further discussed in Section 2.4).

2.2.2 Measured energy consumption data

Measured energy meter data are sourced from the university Carbon Dashboard (10) and daily main meter electricity consumption for CSUB. Notably, submeter and system-level data were unavailable. The data was used to calibrate the energy model, where the model's prediction was compared to the measured data to assess its performance.

2.3. Modelling

The modelling process started with the creation of a baseline model using available existing data. The building was modelled using DesignBuilder v7.0 (11) and simulated using the EnergyPlus v9.4 engine (12). Subsequently, the baseline model underwent a calibration procedure to ensure a close correspondence with actual metered data. The calibrated model was then used to simulate a variety of scenarios for the proposed operational strategies, enabling subsequent detailed analysis.

2.3.1 Baseline model inputs

Design-stage documents were used to model the building geometry, interior layouts, construction materials and their U-values (7)(13). As detailed specification for the heating, ventilation and air conditioning (HVAC) systems were absent, such characteristics were mostly auto-sized by the software. Valuable insights were also drawn from a prior case study (14).

Considering data availability constraints, only electricity-consuming segments of the building were modelled (which represent all energy demand of the building except domestic hot water). The weather file of the actual 2022 weather conditions of the area was utilised, courtesy of the DesignBuilder Climate Analytics platform (15). Table 2 summarises key inputs of the building systems:

Variable	Inputs
Occupancy	• Occupancy density of 0.2194 person/m^2, derived from 1185 occupants across 5400 m^2 • Occupancy schedule derived from historical occupancy readings (Section 3.1), except for staff zones which utilised a generic office schedule
Lighting	• 400 lux (16)
Equipment power density	• 12.01 W/m^2 (software default value)
HVAC	• Auto-sized by software due to lack of specifications available • HVAC setpoints were varied as part of the calibration process (Section 2.3.2)

Table 2 - Variable inputs for energy model

2.3.2 Calibration

Model calibration was carried out using a deterministic approach involving the utilisation of three key variables as outlined in Table 3. A series of 60 iterations were carried out using jEPLUS v2.1.0 software (17) based on the number of unique combinations of variables. The monthly energy consumption of each iteration was then compared to the measured meter data and evaluated based on the Coefficient of the Variation of the Root Mean Square Error (CV(RMSE)) and Normalised Mean Bias Error (NMBE), aligning with the standards established by ASHRAE Guideline 14 (2002) (18).

No.	Variable	Range
1	Heating setpoint	19-22 °C (1 °C increments)
2	Cooling setpoint	23-25 °C (1 °C increments)
3	Mechanical ventilation rate	15-25 litres/person (2.5 litres/person increments)

Table 3 - Key variables varied for calibration

2.3.3 Modelling of scenarios

The operational strategies to be modelled involved closing specific floors and/or zones during designated time frames of low occupancy and concentrating the users in other areas. Two periods of low occupancy were identified and used in the modelling: off-peak dates (15 May to 02 Oct 2022) and weekends throughout the year. In the proposed strategy, occupancy count is maintained but redistributed across areas of the building that is operational and not closed. Occupancy count is determined by occupancy density (person/m^2) multiplied by the occupancy rate (%) multiplied by the floor area (m^2) of the building/ zone. The concentration of occupancy in opened areas of the building was simulated in the energy model by increasing the occupancy density or rate. The increases of occupancy density and rate were calculated in proportion to the closed zones' floor area to maintain total occupancy count across the building, which simulated the redistribution of occupants across opened areas. The closure of zones was simulated by setting their occupancy, HVAC and lighting schedules to zero.

2.4. Proposal of operational strategies

Operational strategies were formulated by understanding the building usage during low occupancy periods. Two operational strategies are proposed, which entail the temporary closure of specific floors or zones within the CSUB during 1) off-peak dates and 2) weekends (elaborated in Section 3.1). This would allow both the consolidation of occupancy into smaller operational areas - potentially reducing energy demand - and a more responsive operation of the building during periods of lower occupancy - enhancing efficiency.

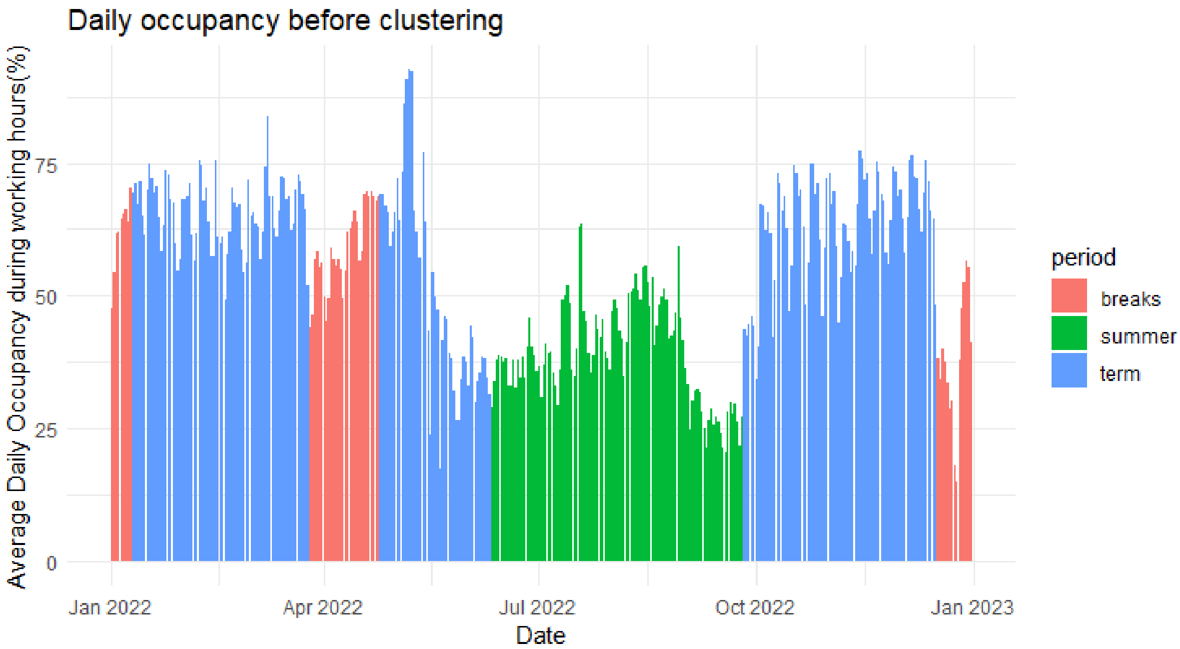
The subsequent consideration revolved around determining which specific floors or zones to close off. This was guided by whether the floors or zones contained essential functions (e.g., entrances); if it could be feasibly closed off; or if similar workspaces are available elsewhere in the building. The appendix contains a breakdown of the CSUB floors and their usage. Consequently, B2 and Ground floors were excluded from the scenario modelling as they served essential functions, while L1 was omitted from the off-peak-period scenarios as it primarily comprised staff offices that are occupied throughout the year. Formulation of scenarios involving closed zones ensured that no zones within the remaining operational areas of the building would reach maximum occupancy during the simulated period, avoiding overcrowding.

3. Results & Discussion

3.1. Insights into CSUB's occupancy patterns

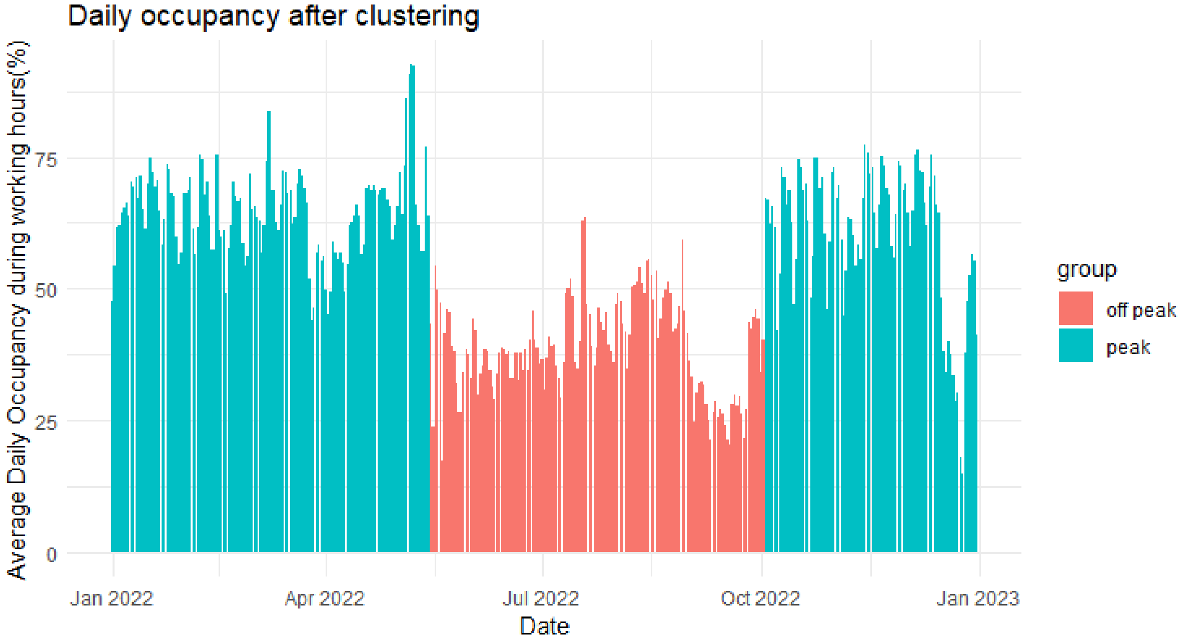
A key objective of this study was to gain a comprehensive understanding of occupancy patterns, which serves two purposes: firstly, to create a custom CSUB occupancy schedule for input into the energy model, and secondly, to explore potential avenues for energy reduction in response to occupancy dynamics. Firstly, "working hours" (WH) between 9am to 9pm were established from the average hourly occupancy data. This decision was rooted in the typical starting time of university timetables at 9 am, alongside a decline in occupancy after 9 pm. Academic term dates, term breaks, and the summer break were further integrated into the dataset. However, a clear demarcation between occupancy rates during these academic periods was not clear (Figure 2).

Figure 2 - Daily occupancy, with academic term dates, before clustering



In response, a k-means clustering algorithm (9) was used and the outcome yielded two distinct clusters of dates characterised by notably different occupancy rates (Figure 3). These clusters were subsequently referred to as "off-peak" (between 15 May to 02 October 2022) and "peak" (for the rest of the year).

Figure 3 - Daily occupancy after clustering



A custom weekly occupancy schedule (Table 4) was generated for the two periods, with average weekday and weekend rates to reflect the nuanced occupancy dynamics throughout the week.

Period	Peak (01 Jan - 14 May and 03 Oct - 31 Dec)				Off-peak (15 May - 02 Oct)			
Day of the week	Weekday		Weekend		Weekday		Weekend	
Time of the day	WH	Non-WH	WH	Non-WH	WH	Non-WH	WH	Non-WH
Average occupancy rate (%)	66.3	26.3	57.0	24.4	41.6	12.3	35.7	12.6

Table 4 - Custom occupancy schedule for CSUB

The observed working hours for CSUB extend beyond the conventional 9am-5pm working hours common in the UK. Furthermore, the occupancy rates did not adhere to the expected academic dates, with the off-peak period overlapping with term dates. Despite the absence of academic activities during the weekends and hence an expectation of a lower occupancy rate compared to weekdays, the reduction in occupancy was only around 15%.

This divergence between empirical evidence and established assumptions for default occupancy schedules highlights that field measurements may differ greatly from default values (4) and the importance of adapting model inputs to specific building attributes. The custom CSUB occupancy schedule identified two key periods of low occupancy 1) off-peak dates and 2) weekends for the exploration of operational strategies involving zone closures for possible energy savings.

3.2. CSUB model

3.2.1 Calibration results

Following the calibration process, the most effective iterations are outlined in Table 5. Evaluation based on monthly CV(RMSE) and NMBE, in alignment with ASHRAE Guideline 14 (18), revealed that Iteration 54 demonstrated the most optimal performance. It was thus selected as the model for subsequent scenario simulations, with heating and cooling setpoints of 21 and 23°C respectively, and mechanical ventilation rate of 25 litres/person.

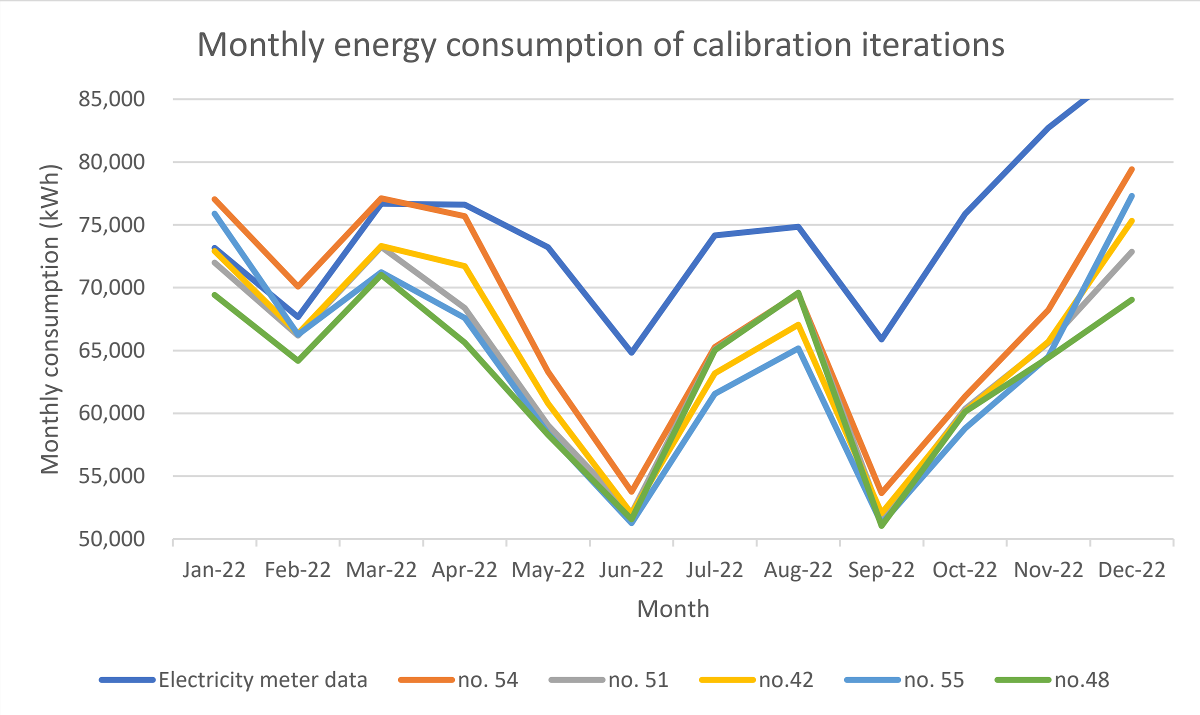
	ASHRAE Guideline 14 (2002) thresholds	no. 54	no. 51	no.42	no. 55	no.48
CV(RMSE)	15%	12.21%	15.11%	14.63%	16.12%	16.66%
NMBE	+/- 5%	-0.74%	-1.10%	-1.05%	-1.16%	-1.25%
Absolute annual deviation (kWh)	NA	- 79,095	- 117,461	- 112,966	- 124,393	- 134,190

Table 5 - Calibration results compared against ASHRAE Guideline 14 thresholds

The iterations (Figure 4) generally follow the overall trend of the metered data, closely aligning with it in the earlier months of the year while displaying a larger deviation in the later half. Although several factors were investigated to explain this discrepancy (including outdoor air temperature changes, heating/cooling seasonality, and occupancy variations) a definitive explanation was not identified. The sources of uncertainties in the building detailed in Section 2.1. may have contributed to this phenomenon. An alternative explanation may be that the energy model's operations remain fixed throughout the entire year, while in reality CSUB's operations might have undergone changes at some points during 2022; this could account for the divergence from the modelled pattern towards the end of the year.

While the calibration process yielded outputs that aligned well with ASHRAE standards, it is crucial to acknowledge that identifying parameter combinations leading to a good fit with observed data does not necessarily guarantee an accurate representation of reality (19).

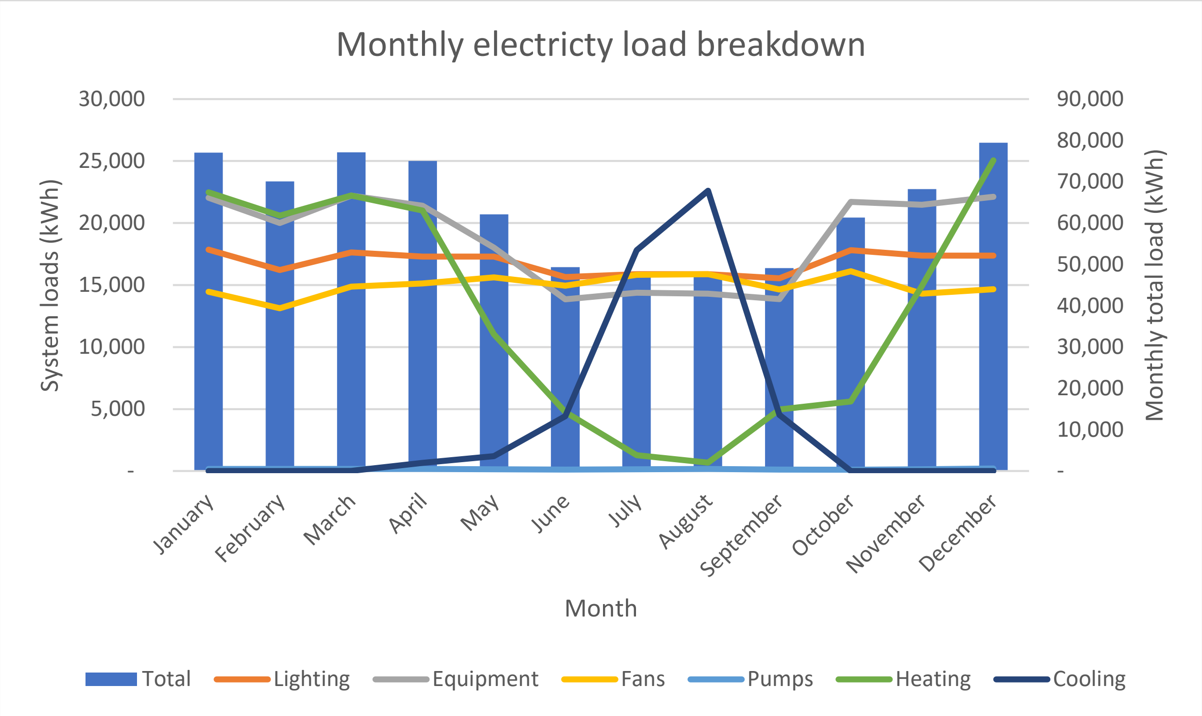
Figure 4 - Monthly energy consumption of calibration iterations



3.2.2 Model outputs

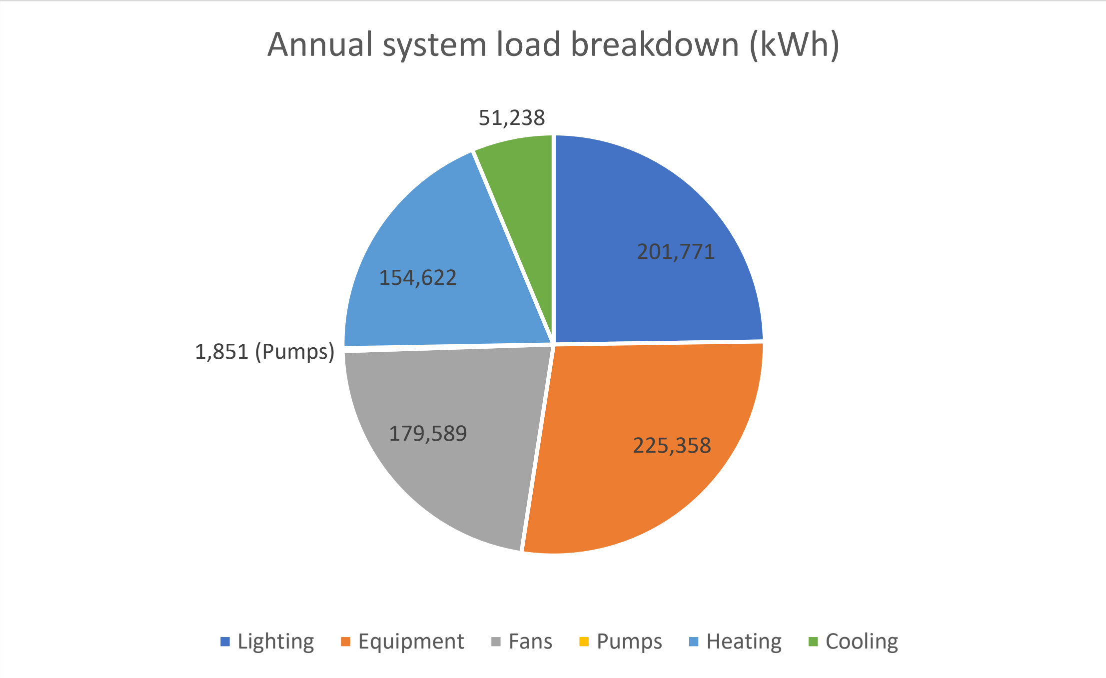
The breakdown of the model's simulated system loads and total monthly energy consumption are presented in Figure 5. The distinctive patterns of heating and cooling seasons can be observed. The equipment loads reflect a reduction during off-peak months as informed by the custom occupancy schedule, reinforcing the interplay between occupancy patterns and energy usage.

Figure 5 - Monthly electricity load breakdown of CSUB for 2022



Lighting loads represent a significant 25% share of annual energy consumption, while equipment usage contributes 28% of the overall consumption (Figure 6). The remaining portion is predominantly allocated to HVAC, particularly ventilation and heating systems. The notable prominence of lighting load can be attributed to the building's unique 24/7 operations.

Figure 6 - Annual system load breakdown



With the absence of submeter data, calibration could not be done based on individual system loads. It is possible that while the overall energy consumption totals may exhibit close correspondence with actual values, the distribution of system loads within the model may deviate from reality.

3.3. Scenarios Analysis

For each period, initial simulations involving the closure of five individual floors were carried out. Then, the best-performing floor was combined with the second and third best-performing floors individually, to create scenarios of two closed floors each. This aimed to assess the performance of simultaneously closing multiple floors. In total, seven simulation scenarios consisting of five individual floors and two combined floors were carried out for each period using the calibrated CSUB model. The simulations for the off-peak period were analysed for 140 days (15 May to 02 October 2022), whereas the weekend simulations encompassed 104 days in total (all weekends throughout the year). The findings shared between the two periods are first discussed to set the foundation, before respective results are presented in further detail.

Overall energy reductions are evident across all scenarios for both periods (although with varied magnitude), with the exception of one scenario. The energy savings are attributed to the shutdown of HVAC, lighting, and equipment loads on the closed zones, leading to the redistribution of occupancy throughout the remaining operational areas. This allows for “economies of scale” to benefit the building’s energy consumption. The incremental energy consumption per occupant becomes lesser since these areas are already occupied, with their base loads already active. A noteworthy observation is that the energy savings achieved from closing individual floors do not cumulatively add up when multiple floors are closed simultaneously. This phenomenon becomes apparent in the combination floors scenarios, where the savings are marginally incremental in comparison to the individual floor. This phenomenon can be attributed to the fact that the HVAC systems on other floors need to compensate for the higher occupancy levels, surpassing the initial “economies of scale” benefits.

3.3.1 Off peak period

The scenarios for off peak periods saw a range of energy savings from 2.22% to 6.05% of annual consumption, translating into 18,000 to 49,000 kWh (Table 6 and Figure 7). This equates to the annual electricity consumption of 6-17 medium-sized UK households (20).

Floor	Off peak months' total energy savings (excl. peak months) (kWh)	Percentage of annual
L3 and L4	- 49,248	-6.05%
Mezz (study area only)	- 48,316	-5.93%
L3 (study area only)	- 43,726	-5.37%
Mezz and L3	- 41,296	-5.07%
L4	- 28,174	-3.46%
L2 (study area only)	- 22,974	-2.82%
B1	- 18,087	-2.22%

Table 6 - Off peak period scenarios summary (in ranking order)

Figure 7 - Total energy reductions during off peak period scenarios

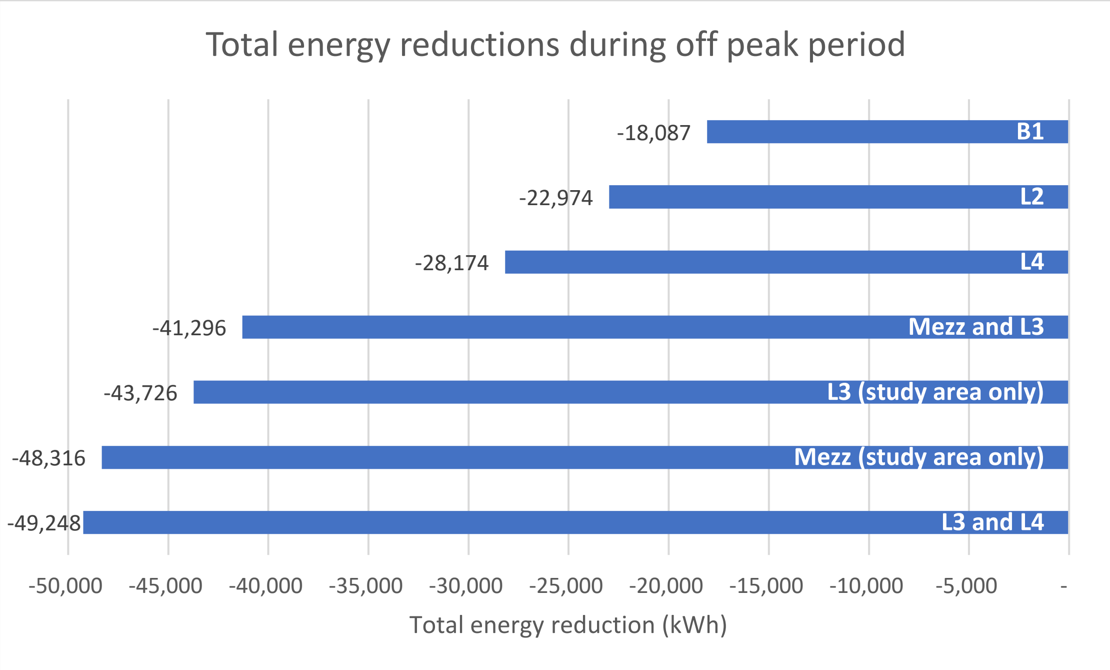
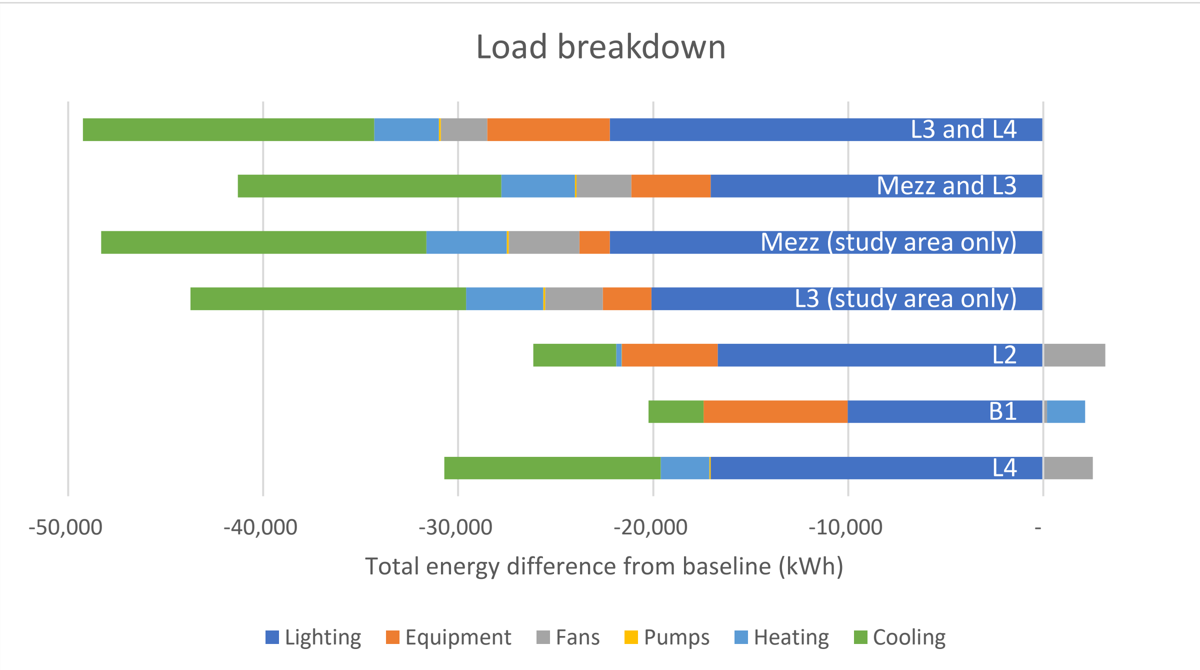


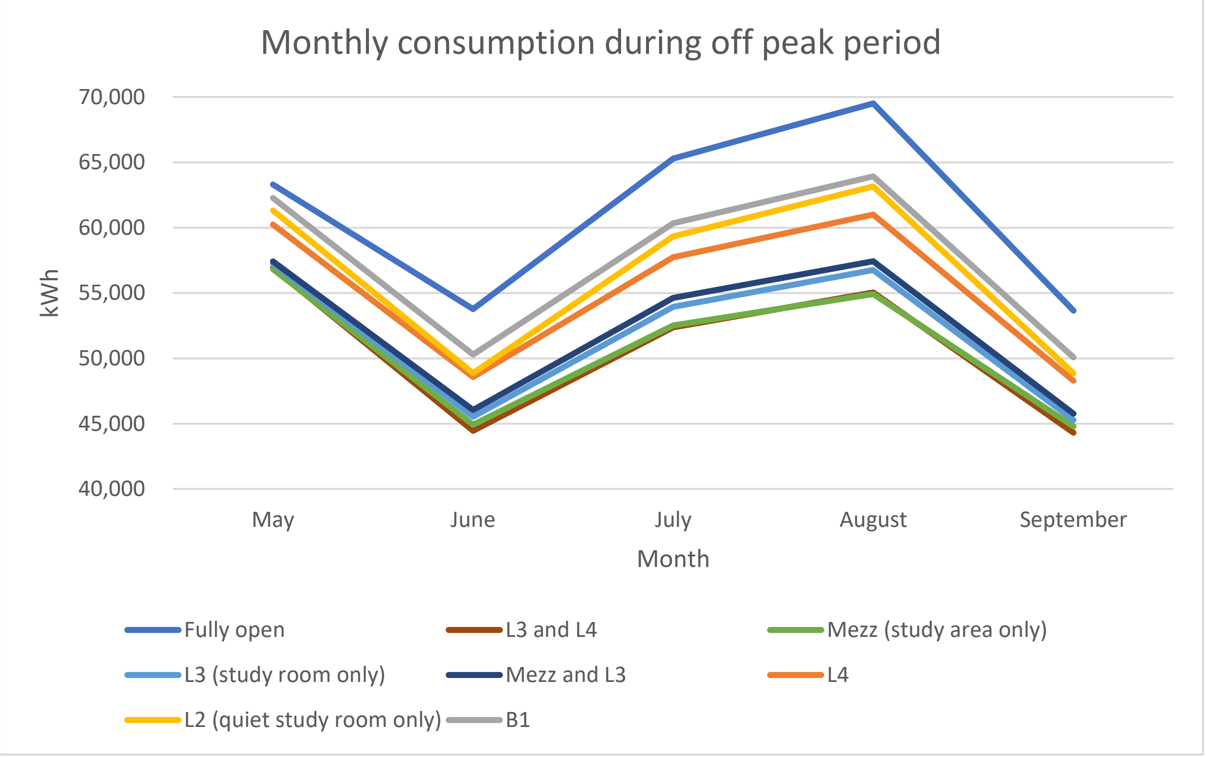
Figure 8 shows the breakdown of energy savings for each scenario, highlighting that the majority of savings are from lighting and cooling loads. Notably, the savings in lighting loads are substantial, which may be attributed to how occupancy is reassigned to spaces that are already illuminated, translating into absolute savings.

Figure 8 - Load breakdown of energy reductions during off peak period scenarios



The cooling load savings are particularly pronounced during the summer months, when cooling demands are prevalent. Monthly consumption of the fully operational building in comparison to scenarios involving closed areas (Figure 9) show that the most significant savings are evident in July and August across all scenarios, aligning with the months of peak cooling load for the building as a whole. Recalling Figure in Section 3.2.1, the model underestimates energy consumption in the months of May to October by approximately 14%. This may suggest that the energy savings of these scenarios could potentially be higher in absolute terms in reality.

Figure 9 - Monthly consumption of off peak period scenarios



Conversely, equipment savings are comparatively less significant. As occupancy was redistributed, additional equipment power was consumed in the areas where occupancy has shifted to. In addition, the elevated fans load observed in L2, B1, and L4 is likely attributable to higher fans loads in the remaining operational areas, which accommodated the additional occupancy resulting from the closed zones.

It is crucial to note that closing multiple floors in the scenarios of Mezzazine and L3, and L3 and L4, did not result in cumulative savings from two individual floors. Individually, Mezzanine, L3, and L4 demonstrated robust performance, likely due to their smaller enclosed floor areas, which facilitated easier isolation. In contrast, L2 exhibited lower energy savings, influenced by a significant portion of open-air space exposed to the main atrium. The energy savings in B1 were comparatively less, attributable to its location underground which is less influenced by outdoor air temperature variations. This is evident in its notably lower cooling energy savings, reflecting a lower demand during the cooling season compared to other floors.

3.3.2 Weekends

The scenarios for the weekend periods throughout the year saw a range of annual energy consumption changes from -2.09% to +1.26%, translating into -17,000 to +10,000 kWh (Table 7 and Figure 10). The savings equate to the electricity consumption of 3-6 medium-sized UK households (20).

Floor	Difference from baseline (kWh)	Percentage of annual
L4	- 17,025	- 2.09%
L1	-16,259	- 2.00%
Mezz (study area only)	- 14,860	- 1.82%
B1	- 12,584	- 1.55%
L1 and 4	- 12,242	- 1.50%
L2 (quiet study room only)	- 11,497	- 1.41%
L3 (study room only)	- 8,225	- 1.01%
L4 and Mezz	+ 10,278	+ 1.26%

Table 7 - Weekend period scenarios summary (in ranking order)

Figure 10 - Annual consumption of weekend period scenarios

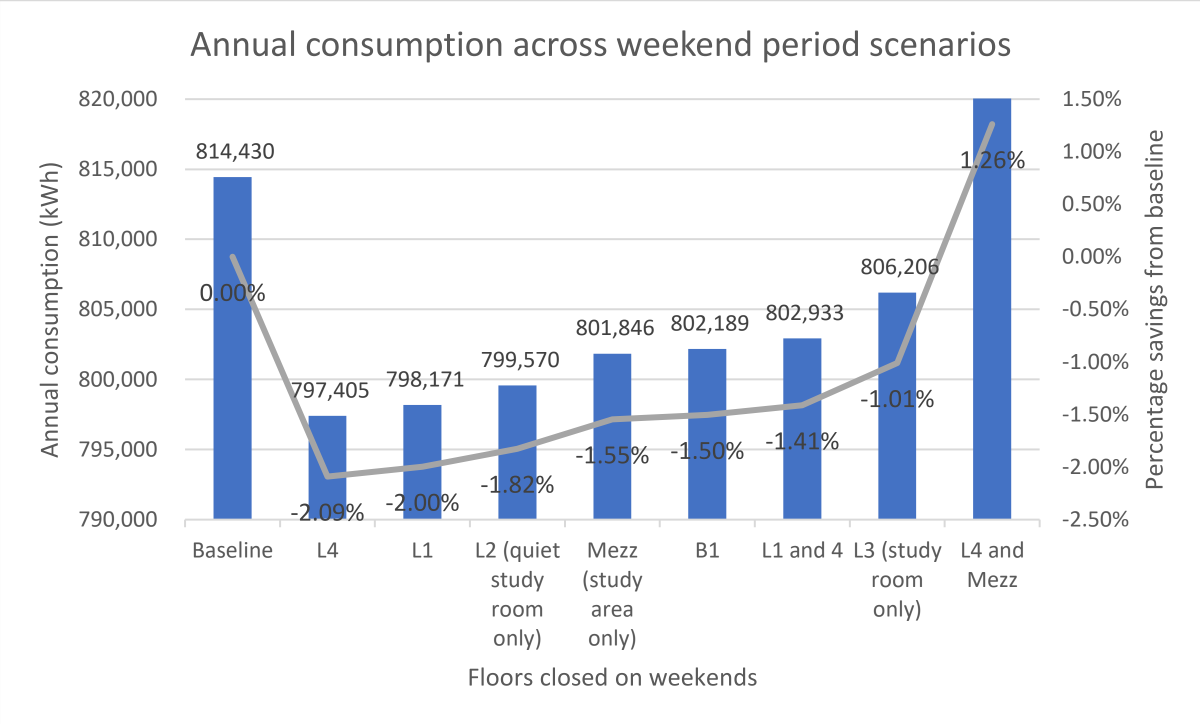
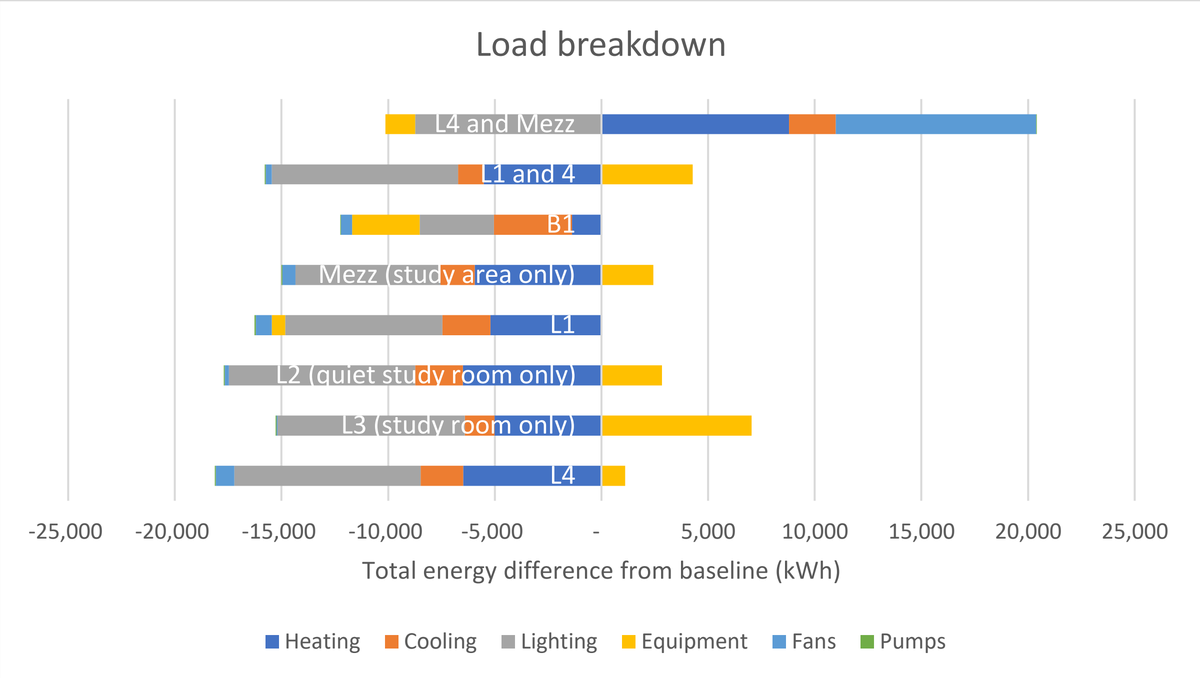


Figure 11 shows that the predominant sources of savings are lighting and heating loads, which contrasts with the off-peak period scenarios, where cooling savings are more prominent. Notably, heating savings are significant as these scenarios encompass the entire calendar year, for a building located in a heating-dominated climate.

Figure 11 - Load breakdown energy differences of weekend period scenarios



An interesting observation is the dissimilarity in the magnitude of savings between the weekend and the off-peak scenarios. The highest energy savings achieved in the weekend scenarios reach 2.09% compared to the off-peak period scenarios of 6.05%. This does not align with the proportional ratio of 104 days for weekends and 140 days for off-peak dates. It can be attributed to the short and recurrent nature of the weekend closures, where some potential savings are negated by the frequent need for space reconditioning upon reopening every Monday. In contrast, the off-peak scenarios occur within a continuous time frame, resulting in a once-off reconditioning energy consumption.

It is worth noting that variance in savings between the highest (L1) and lowest (L3) stands at approximately 8,000 kWh, amounting to 1.08% of the annual consumption. This marginal difference indicates that closing different zones does not yield significantly more savings, which aligns with the earlier-discussed recurring need for space reconditioning leading to reduced energy savings.

As discussed in Section 3.3, higher occupancy loads in the remaining operational areas potentially lead to a loss of economies of scale benefits, evident in the L4 & Mezzanine scenario. Here, HVAC loads in the form of heating, cooling, and fans exhibit overall energy increases rather than savings.

3.3.3 Comparison to existing literature

The study's findings are juxtaposed with relevant literature to contextualise them within the existing body of knowledge. Dong and Lam (2014)’s research (3) adjusting HVAC operations based on predicted occupant behaviour and weather conditions demonstrated energy savings of 30.1% for heating and 17.8% for cooling loads. These findings align with this case study, although the magnitude of energy savings differs. This divergence can likely be attributed to the scale of operational strategies employed. Dong and Lam (2014)'s study (3) was based around a much smaller university building and controlled the entire facility, while this research examined an eight-story building and investigated operational controls for only one and two floors. Wang, Mathew and Pang (2012)’s research (21) exploring the impact of operational practices on annual consumption underscored HVAC operations as the most influential system load and revealed a direct relationship between lighting and HVAC loads on energy consumption. This further corroborates the outcomes of this study, where lighting loads, combined with cooling during off-peak periods and heating during weekend periods, emerged as the predominant contributors to energy savings. The authors also highlighted a 3.9% savings in annual energy consumption from optimising operational practices of vacant spaces, such as using setback temperatures and shutting off lighting and equipment loads. This CSUB study redistributed occupancy to create vacant spaces, then optimised the operational controls of these spaces. While the energy savings figures cannot be compared directly due to the different scale of vacant spaces and time periods examined between the two studies, the results of this study is congruent with Wang, Mathew and Pang (2012) (21).

4. Recommendation

The proposed framework in this study can help identify valuable occupancy insights for optimising operations. This facilitates assessment of the strategies and quantifies environmental and economic implications for assessment of the operational strategies. This aids in evaluation against the economic, operational and user impact for decision making. Importantly, this occupancy-driven operational strategy is cost-effective, requiring no architectural retrofits, making it easily accessible for building professionals.

The recommendation for CSUB is to close off the Mezzanine floor during off-peak periods due to the potential energy savings which translate to approximately 9,300 kg of CO_2 emissions (CO_2e) (at 0.193 kg/kWh) (22) or annual cost savings of £14,500 (at 30 p/kWh) (23). Although the simultaneous closure of L3 and L4 yields the highest energy savings, it is not recommended due to marginal gains compared to the significant user and operational impact of closing an additional floor. While strategies for better thermal control for zone closures (eg glazed screens for areas exposed to the central atrium void) were considered to enhance potential energy savings; it would require physical retrofits and design changes, as opposed to the current methodology that is simple operational optimisations.

Regardless, it is crucial for buildings to conduct their own detailed and case-specific feasibility study, focusing on user receptivity and technological feasibility of the systems.

While this case study has attempted to simulate occupancy responsiveness by analysing the occupancy patterns of 2022 and retrospectively applying them to the energy model, it is important to acknowledge the inherent time lag and retroactive nature of this approach. Buildings are "artifacts with very long lifespans" (4), accommodating to changing usages and user groups over time, alongside the implications of shifting occupancy trends. The occupancy patterns of future years may not mirror those observed, potentially leading to disparities in the actual energy savings realised through the proposed operational strategies.

5. Conclusions

The methodology proposed is a replicable data-driven framework that can be scaled and extended to other buildings to similarly explore the optimisation of their operational strategies based on their occupancy patterns. This research not only enhances the understanding of the intricate relationship between occupancy and energy but also offers actionable recommendations for building operations that contribute to sustainable practices and energy efficiency.

The case study of CSUB demonstrates the framework, providing a comprehensive exploration of occupancy patterns and proposing an occupancy-based operational strategy to optimise the building operations for energy demand reduction.

By investigating historical occupancy data and creating a calibrated dynamic thermal energy model of CSUB, this research has unveiled valuable insights into the dynamics between building occupancy and energy demand. It was observed that the occupancy pattern of the CSUB diverges from conventional expectations of an educational institution, emphasising the significance of capturing nuanced occupancy patterns to enhance the accuracy of BEMs. Additionally, operational strategies were proposed to reduce energy consumption of CSUB in response to periods of low occupancy. They centred around targeted zone closures during off-peak and weekend periods. A notable observation is that the closure of multiple floors simultaneously demonstrated that the energy savings were only marginally more when compared to the individual closure of floors. This is likely attributable to the greater concentration of occupancy in remaining zones, adding HVAC loads that surpasses the initial “economies of scale” savings from a closed zones’ base loads. Based on the empirical evidence collected for 2022, the study recommends the closure of the Mezzanine study area during the off-peak period. The strategies that involved closures for a longer continuous timeframe (off-peak scenarios), rather than recurrent short closures (weekend scenarios) exhibited greater energy and carbon emissions savings as they avoided incurring energy consumption for frequent space reconditioning after the closures. The proposed strategies are also adaptable as they are based on optimising operations and not physical retrofits. This allows it to be responsive to shifts in occupancy patterns and new data over time.

Further work could explore operational strategies that respond in real-time to occupancy patterns or minimise the time lag between occupancy pattern identification and responsive action.

6. References

1. International Energy Agency, Breakthrough Agenda Report 2023, 2023.
2. Ramesh T, Prakash R, Shukla KK, Life cycle energy analysis of buildings: An overview, *Energy and Buildings,* 2010;42(10):1592–600.
3. Dong B, Lam KP, A real-time model predictive control for building heating and cooling systems based on the occupancy behavior pattern detection and local weather forecasting, *Building Simulation*. 2014;7(1):89–106.
4. Yan D, O'brien W, Hong T, Feng X, Burak Gunay H, Tahmasebi F, et al., Occupant behavior modeling for building performance simulation: Current state and future challenges, *Energy and Buildings,* 2015;107:264–78.
5. Mirakhorli A, Dong B, Occupancy behavior based model predictive control for building indoor climate-A critical review, *Energy and Buildings,* 2016;129:499–513.
6. Eguaras-Martínez M, Vidaurre-Arbizu M, Martín-Gómez C, Simulation and evaluation of Building Information Modeling in a real pilot site, *Applied Energy,* 2013;114:475-84
7. Nicholas Hare Architects, Stage 3 Report - Volume 2: Architectural Design Report, 2015.
8. UCL API, 2023 Aug 9, https://uclapi.com/
9. Maechler M, Rousseeuw P, Struyf A, Hubert M, Hornik K, Studer M, et al., Package 'cluster' : `Finding Groups in Data'': Cluster Analysis Extended. Version 2.1.4 CRAN Repository, 2022. https://cran.r-project.org/web/packages/cluster/cluster.pdf
10. UCL Carbon Dashboard, 2023 Aug 9, https://platform.fabriq.space/analytics/trends/
11. DesignBuilder v7.0, 2023 Dec 5, https://designbuilder.co.uk/software/product-overview
12. EnergyPlus v9.4, 2023 Dec 5, https://energyplus.net/documentation
13. Nicholas Hare Architects, Stage 3 Report - Volume 3: Engineering Services Report. 2015
14. Wismadi F, Jain N, Kourgiozou V. Benchmarking Buildings in the Context of Net-zero Targets: Tracking Energy Performance of a Case Study from

Design to Operation. Passive Low Energy Architecture, Santiago De Chile, PLEA Organisation, 2022.

15. DesignBuilder Climate Analytics platform, 2023 Aug 12, https://analytics.designbuilder.co.uk/#index

16. Chartered Institution of Building Services Engineers - SLL Code for Lighting 2012, 2023 Aug 21, https://www.cibse.org/knowledge/knowledge-items/detail?id=a0q20000008I6xiAAC

17. jEPlus v2.1.0, 2023 Dec 5, https://www.jeplus.org/wiki/doku.php?id=docs:manual_2_1

18. ASHRAE Guideline 14-2002 for Measurement of Energy and Demand Savings, 2002.

19. Heo Y, Choudhary R, Augenbroe GA, Calibration of building energy models for retrofit analysis under uncertainty, *Energy and Buildings,* 2012;47:550–60.

20. Ofgem. Average gas and electricity use explained, 2023 Aug 10, https://www.ofgem.gov.uk/information-consumers/energy-advice-households/average-gas-and-electricity-use-explained

21. Wang L, Mathew P, Pang X, Uncertainties in energy consumption introduced by building operations and weather for a medium-size office building, *Energy and Buildings*. 2012;53:152–8.

22. Department for Business Energy & Industrial Strategy. Greenhouse gas reporting: conversion factors 2022, 2023 Apr 21, https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2022

23. Ofgem. Energy price cap, 2023 Aug 21, https://www.ofgem.gov.uk/information-consumers/energy-advice-households/energy-price-cap

7. Appendix

CSUB floors, their usage and suitability for closure

Floor	Usage (areas unsuitable for closure marked in red)	**Comments**
B2	• Quiet contemplation rooms • Showers	• Essential function
B1	• Quiet study area	• Easily closed as access from stairs/lift lobby can be restricted
Ground	• Entrance from street	• Essential function
Mezzanine	• Entrance from UCL campus • Quiet study area	• Study area can be easily closed off due to single point of access • Rest of the floor serves essential functions
1	• Staff offices • Group study meeting rooms • Open group study area	• Less ideal to be closed due to porous nature of open study area
2	• Quiet study room • Open group study area • Group study meeting rooms	• Less ideal to be closed due to porous nature of open study area
3	• Café • Quiet study room • Group study meeting rooms	• Study areas can be easily closed off due to single point of access • Café serves essential functions
4	• Group study room	• Easily closed due to single point of access

Table 8 - CSUB floors, their usage and suitability for closure