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Analyzing energy consumption patterns of an educational building through data mining

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A R T I C L E I N F O

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A B S T R A C T

Green building standards were adopted around the world to minimize energy consumption and carbon emission from the building sector. However, designing buildings following the standards does not guarantee a low-energy building. Actual energy consumptions in buildings were reported, on average, 2.5 times higher than predictions during the design stage, which is known as the performance gap. Most building operation managers do not have the tool and knowledge to understand the reasons for such differences. Moreover, current building management systems (BMS) do not have the intelligence to identify such differences and their sources. Understanding the root causes of the performance gap is even more difficult in an educational building because of its different usage patterns and various space types. This research aims to analyze the energy consumption patterns of different spaces in a mixed-use educational buildings and identify possible sources of energy waste using an unsupervised data mining approach. A 5-star Green Star-rated educational building in Melbourne, Australia, was considered for the case study. The results showed electrical and gas energy performance gaps of 2.4 and 3.1 times, respectively, in the studied building. Further analysis revealed that energy consumption during non-working hours was 48% of total energy consumption during the one-year studied period, which is very high and was one of the possible sources of waste. During the holidays, the mechanical system and plug loads ran as per the weekday operating schedule in an empty building, resulting in energy waste. Actual hourly lighting and plug load consumption profiles differed significantly from the predicted profile during design. Based on the findings, several recommendations were made to minimize the performance gap in an educational building.

1. Introduction

In this era of technology, energy usage is essential in every sector, including transport, industry, building, agriculture, etc. In Australia, electricity consumption increased by 70% in the last three decades, resulting in a 47% increase in the total CO_2 emissions [1]. Out of the various sectors, the building sector accounts for 40% of the total energy consumption globally and 19% of Australia's total energy consumption [2,3]. Therefore, reducing energy consumption in the building sector is crucial for environmental sustainability. Smart strategies to predict building energy consumption and enhance building energy performance are being investigated continuously worldwide with different dynamic methods [4]. But the mismatch between the predicted and actual operational energy consumption is becoming a real concern and is posing a threat towards achieving carbon emission reduction goals [5]. It has been observed that the energy-efficient buildings are consuming as much as 2.5 times of predicted energy and, as a result, are costing more than the planned value [6]. This difference is often termed as the energy performance gap or simply "the performance gap" [4,7].

The building energy consumption depends upon four considerable factors i.e., building characteristics, the behavior of the occupants, the system efficiency and operation, and climatic conditions. The uncertainty and complexity of these factors make it challenging to predict building performance beforehand [8]. Underlying causes of building energy performance gap exist in all stages of a building life cycle. De Wilde [7] categorized the factors of performance gap based on their sources in a project: the discrepancies during the design stage, the construction stage, and the operational stage. During the design stage, these factors include inaccurate assumptions of building operation, plug load consumption, and occupant behavior [9]. Moreover, the complex design, absence of feedback for the designer, and uncertainties in simulation tools also contribute to the performance gap at this stage [10]. During construction, the value engineering to reduce capital costs, incomplete commissioning [11], time pressure, poor workmanship, and

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poor quality and non-standard construction materials [12] may contribute to the performance gap. Zou et al. [10] suggested strategies for better regulations to deal with issues like lack of accountability, inaccurate energy models, and stakeholder communications during the design phase to address the performance gap.

The operational stage is the most crucial of all, as it accounts for up to 90% of the total energy use of the building during its life cycle [13]. In modern energy-efficient and net-zero energy buildings (nZEBs), the percentage of operational energy consumption could be comparatively lower due to the application of energy-efficient materials and equipment and embodied energy becomes an important factor [14]. However, understanding operational energy consumption pattern in those buildings is still equally important to ensure desired energy efficiency or net-zero energy goal. Because, as mentioned above, a number of energy-efficient buildings are actually consuming more energy than predictions. The performance gap at this stage occurs due to inexperienced building managers, not-following the building operational manuals, degradation of building services and lack of a feedback system that could indicate the facility manager of the potential misuse or overuse of energy.

Many models, assessment tools, prediction methodologies, dynamic solutions and data analysis techniques were applied to quantify and minimize the energy performance gap [15]. From a review of 62 case study buildings, Dronkelaar et al. reported that, on average, actual energy use is 34% higher than the predictions with 55% standard deviations. Fokaides, Maxoulis [16] compared the actual and predicted energy consumptions for ten dwellings in Cyprus in terms of cooling, heating, hot water, lighting and equipment. Their results showed that the actual energy consumption is over 4 times of predicted energy consumption. It was suggested that occupant behavior is a key contributing factor to performance gap, and therefore the daily schedule of the equipment and HVAC needs to be reviewed. Similar conclusions were also reported by Ahn, Kim [17] when they performed different experiments in two laboratories and three library rooms in two university buildings in South Korea. They used webcams for monitoring the occupancy and behavior to get the real-time data and mapped the pattern using Markov chain and random walk models. Sun et al. [18] experimentally and numerically studied ten office rooms in Harbin, China to identify the influence of occupant behavior on the thermal performance gap. Their analysis showed 10–13% difference between actual and designed window operation patterns in winter. Occupancy schedules were studied in detail by D'Oca and Hong [19] in 16 offices in Germany and found variations up to 60% in hourly occupancy rate during office hours. However, the lighting schedule in those buildings was kept constant throughout the day which represents energy waste. Another study in an office building in Central London [20] monitored lighting, power and equipment energy consumption against the occupancy patterns. The data were analyzed with five different models, and a significant energy gap was reported.

Modern buildings are equipped with a Building Management System (BMS) that can schedule the operation of different service equipment and record energy consumption of lighting, heating, and cooling systems, mechanical and plug-in loads. However, it does not have the intelligence to analyze and identify energy waste, nor does it provide any feedback regarding consumption patterns or recognize any energy waste. Moreover, it can be very time-consuming to analyze the big data available from the BMS system manually and will not be very effective. The systematic analysis of these data sets to improve building energy performance using data mining is an emerging science in the building sector. Data mining is a powerful process to extract hidden knowledge from large data sets [21]. This process involves structuring semi-structured and unstructured data sets and apply suitable data mining techniques and algorithms to find consumption patterns and useful relationships between different variables [22]. These findings reveal systematic hidden patterns within the data set that cannot be discovered with traditional statistical methods. Various data mining techniques can be applied during the design, construction and operational phases of the building [23]. Data mining uses the knowledge of different subjects such as statistics, engineering methods, machine learning, artificial intelligence and high-performance computing [15, 24].

Several studies were carried out to improve building energy performance using data mining techniques [25]. Corten et al. used the regression analysis technique to study the energy-saving potential in HVAC system operation. It was revealed that 7–13% of heating and 41–70% of cooling energy can be saved in their case study office and nursing home buildings [26]. Kim, Stumpf [27] analyzed an emergency station facility's energy consumption during its design stage. The data mining helped to discover energy consumption patterns that were used to improve the design and energy efficiency of the building. Wei, Zhang [28] reviewed different approaches of prediction and classification of energy patterns to benchmark, profile, map and forecast the energy usage in the building industry for efficient and reliable energy management system. A study conducted on four offices in a university building in Korea revealed that automatic dimming control of lighting could reduce lighting consumption up to 43% and the change in occupancy pattern can reduce consumptions by up to 50% [29]. Similar research on occupancy patterns with eighty residential buildings in Japan showed that 21% of energy can be saved by changing the occupant's energy habits. This research used the clustering analysis on the outdoor temperature data set and association rule mining technique to find its relationship with the various end-use loads [8]. According to Masoso and Grobler [30], the occupant behavior caused more energy usage in the non-working days as compared to working days as the people do not turn off the lighting and equipment as they leave the premises. To evaluate the energy consumption, and improve building efficiency, correlation and data tree analysis were used to develop energy benchmarks in office buildings and the results were validated using analysis of variance (ANOVA) [6]. Benchmarking was also done by Singapore's hotel industry for energy and greenhouse gas emissions by regression modeling and in China to evaluate the performance of variable refrigerant flow (VRF) using decision tree and ANOVA analysis [31, 32]. Li, J., et al. [33] applied the clustering and association rule mining technique to find the relationship between occupancy and energy consumption pattern and identified energy waste patterns in the residential building. Clustering analysis was also used in Hong Kong to identify power consumption patterns in a high-rise building. The framework of this study consisted of five steps; preparation of data, clustering, association rule mining (ARM), post-mining and application [34]. A four-phase framework was proposed by Ref. [23] which included the data exploration, data partitioning, knowledge discovery, and post-mining. Similar data mining techniques were used in a residential building in Japan in an effort to identify energy waste and reduce energy consumption [35] and in Canada to monitor occupant behavior and forecasting energy consumption patterns [36].

Previous studies on building energy consumption mostly focused on residential and commercial buildings. The magnitude of the performance gap in an education building is higher than that in residential, office and retail buildings [37]. Yet, very few studies have been conducted to understand the energy consumption pattern in educational buildings to date. A Canadian educational institute used data mining association technique and identified the energy waste patterns for one full academic year in three classrooms. The results showed that 70% of the wasted energy could be saved [38]. Research to optimize the university timetable to decrease energy consumption in Xi'an, China showed the potential of 3.6% reduction in total energy consumption and 6.71% in lighting energy [39]. Another study on eleven university buildings in South Korea, calculated potential savings of 6–29% through retrofitting windows and insulations as well as changing occupant behavior [40]. Khoshbakht et al. [41] reported that energy use characteristics in an educational building depend on the type of activities and discipline of study. The buildings that are used mostly for research are more energy-intensive than the ones used for academic offices.

The challenge with educational buildings is that it does not have a fixed occupancy or operating schedule like the office or residential buildings. Offices buildings mostly operate on weekdays during the daytime and the occupancy pattern of the residential buildings is well established. In contrast, an educational building consists of mixed-use spaces (i.e, laboratory, classroom, office) occupied by students, researchers, academics and administrative staff. The occupancy patterns and energy usage patterns are different for each space type and should be considered carefully during the design stage to accurately predict the energy consumption and minimize the performance gap.

This research aims to identify and analyze the energy consumption patterns in different spaces of educational buildings and provide recommendations to improve energy efficiency and minimize the performance gap. This would be done through a detailed case study of an educational building in Melbourne, Australia. Further description of the case study building can be found in section 2.1. Section 2.2 describes the data mining process that has been adopted in this study for the identification and analysis of energy consumption patterns. Section 3 presents the results, analysis and discussions of the findings. The practical implications of this research have been outlined in section 4. Finally, the key conclusions and recommendations from this study are presented in section 5.

2. Methodology

2.1. Description of the case study building

The selected 11-storey educational building belongs to a leading university in Melbourne, Australia. The building was rated 5 star green star for design by the Green Building Council of Australia [42]. The construction of this building was completed in June 2014. This is a mixed-use building with spaces for teaching and study, laboratory and specialty learning, academic and administrative office, plant room and car park. The building has a gross floor area of 16,700 m^2 and was predicted to be occupied by 1705 people during office hours for various purposes. The spaces were predicted to be occupied from 7am to 7pm.

2.2. Data mining

A four-step approach was used to analyze the energy consumption pattern using the data mining technique as shown in Fig. 1.

2.2.1. Data collection

Data were collected from a number of sources to undertake this case study. Time series data of actual energy consumption of the building was downloaded from the building management system (BMS) for one year period (September 1, 2018 to August 31, 2019). In total, there are 64 submeters that record energy consumed by various building systems at 5 min intervals. In the BMS, the building systems were mainly divided into four categories: lighting, plug load, mechanical and baseload systems. Out of the 64 submeters, 23, 24, 7 and 10 submeters belong to lighting, plug load, mechanical and baseload systems, respectively. Each level has two lighting and two plug-load submeters to monitor energy consumed by various space types. In contrast, mechanical submeters record energy consumed by various systems associated with heating and cooling of the building (Air handling units, ventilation and exhaust fans, chillers, chilled and hot water pumps etc.). The baseload submeters record energy consumed by lifts, escalators, uninterrupted power supply (UPS), fire pumps and various water pumps at the basement. To interpret the results achieved by clustering analysis, further information related to the design and operation of the building was needed, which was obtained from the architectural drawing, operational manual, and Green Star energy efficiency report.

2.2.2. Data-preprocessing

Data pre-processing was done to prepare the input file in a format that is suitable for the data mining process and take care of any missing value. Firstly, the downloaded time-series energy consumption data from the BMS system was converted from 5 min intervals to hourly consumption data using the pivot function in excel. Then the excel file was imported into Google Collaboratory where a Python program was written to take care of the missing value using “SimpleImputer” function “mean” strategy. This strategy automatically replaces any missing

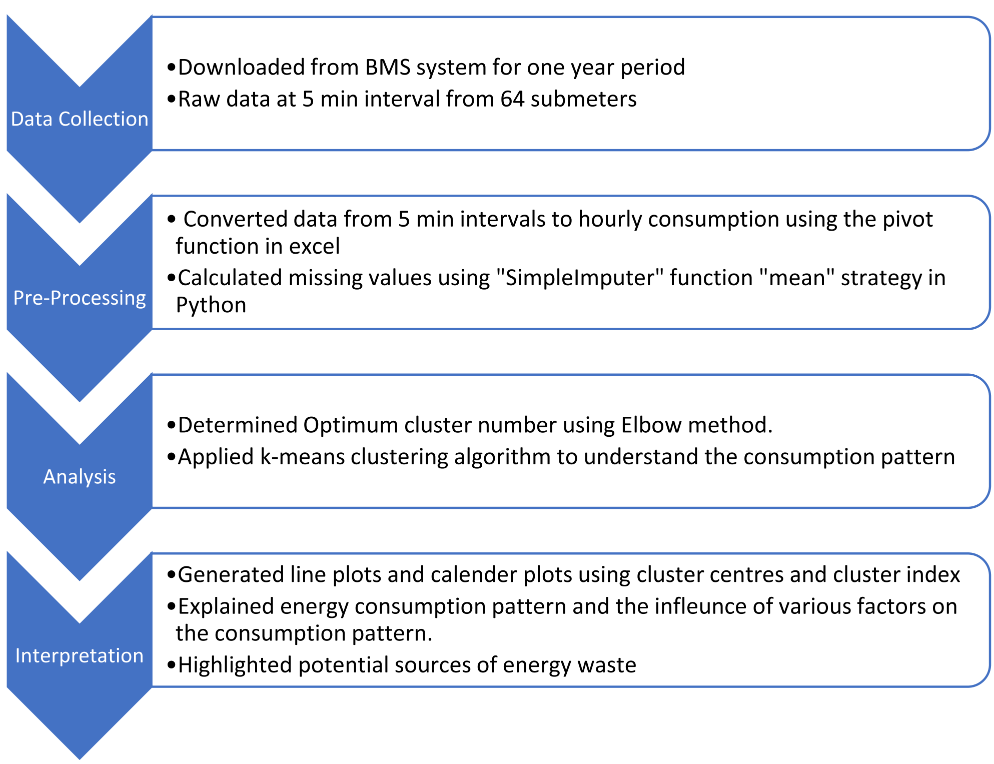

Fig. 1. Research methodology.

values in a column using the mean value in that column. However, in cases where the values were missing for a number of days, this function was not used, and those observations were excluded from the analysis.

2.2.3. Data analysis using k-means clustering

Once the input file was corrected for missing values, it was then analyzed using k-means clustering method. It is an unsupervised data mining technique that make inferences from datasets using only input vectors without referring to known or labeled outcomes. This technique groups similar data points together and discovers the underlying patterns [36,43]. k-mean clustering is suitable for a large number of data readings. This method intends to group 'n' number of data in a dataset into 'k' number of clusters in which each data belongs to a cluster with the nearest mean. However, the accuracy of the k-mean clustering algorithm in analyzing data patterns greatly depends on the k-value (cluster number), which needs to be decided before using this method. Use of wrong k-value will provide an incorrect description of the energy consumption pattern. In this study, the elbow method was used to decide the optimum number of clusters required for the clustering analysis of each data set. This method uses the Within Cluster Sum of Square (WCSS) algorithm, which calculates sum of square of the distances of each data point in a cluster from its centroid following equation (1) below:

$$WCSS = \sum_{j=1}^{k}\left(\sum_{i=1}^{d}(X_i - C_j)^2\right) \tag{1}$$

where, X is the data point in each cluster and C is the cluster centroid. The WCSS value reduces with an increase in cluster number, but the rate of decrease of WCSS value drops as seen in Fig. 2. For example, the figure shows that from cluster 1 to 2 and 2 to 3, WCSS value dropped significantly but the drop is minimum after cluster 5. Hence, 5 would be the optimal value of k for the clustering analysis of this dataset. This approach was used to determine the optimum cluster number in the clustering analysis of all sub-meter data in this study.

Once the k value is known, k-means algorithm works as below:

a. Assign k number of centroids randomly. A centroid is the imaginary or real location representing the center of the cluster.
b. Calculate the distance of each data point from each centroid according to the Euclidean distance function using equation (2) and assign to the centroid which is closest to it.
c. Re-calculate the centroid of each cluster by averaging all data points that belong to that cluster using equation (3).
d. Iteration continues between step b and c until there is no change in the position of the centroids [44].

As the k-means clustering method depends on the initial random selection of centroids, 10 different initializations were used to eliminate any impact of initialization on the accuracy. In this study, open-source platform Python was used to perform all clustering analyses using equation (1),(2) and (3).

$$J = \sum_{i=1}^{n}\sum_{j=1}^{k} w_{ij}(X_i - C_j)^2 \tag{2}$$

$$C_j = \frac{\sum_{i=1}^{n} w_{ij}X_i}{\sum_{i=1}^{n} w_{ij}} \tag{3}$$

where, J is the objective function, $w_{ij} = 1$ for data point X_i if it belongs to cluster k; otherwise, $w_{ij} = 0$. C_j is the centroid of X_i's cluster.

2.2.4. Data interpretation

Once the analysis is done in Python, the cluster center and cluster index data were imported in excel to create the hourly energy consumption pattern of different clusters. Calendar plots with cluster index were also created to understand which cluster belongs to which days in a year. The calendar plot helped to understand the impact of climates, building activities (teaching or non-teaching period), weekends and holidays on the energy consumption pattern. The cluster analysis results were compared with predictions made during the design stage (obtained from design documents mentioned in section 2.2.1) to understand the potential source of energy waste.

3. Results and discussion

3.1. Total energy consumption pattern

Fig. 3 shows the actual and predicted electricity and gas energy consumption during the studied one-year period. The actual electricity and gas energy consumptions were 2.4 and 3.1 times of predicted consumptions, respectively, which represents a significant energy performance gap. In this building, gas is used for domestic hot water and space heating. Due to technical issues, time-series data from gas sub-meters were not available during the period of study. Hence the present study focused on understanding electricity energy consumption pattern and possible sources of electrical energy waste. In the rest of this paper, the word 'energy' is used to represent electrical energy.

Fig. 4 shows the percentage of energy consumed by different building systems. Energy consumed by mechanical load was the maximum

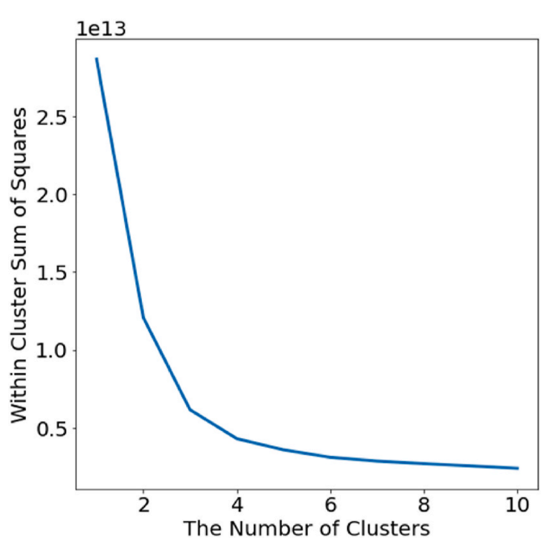

Fig. 2. Calculation of optimum cluster size using Elbow Method.

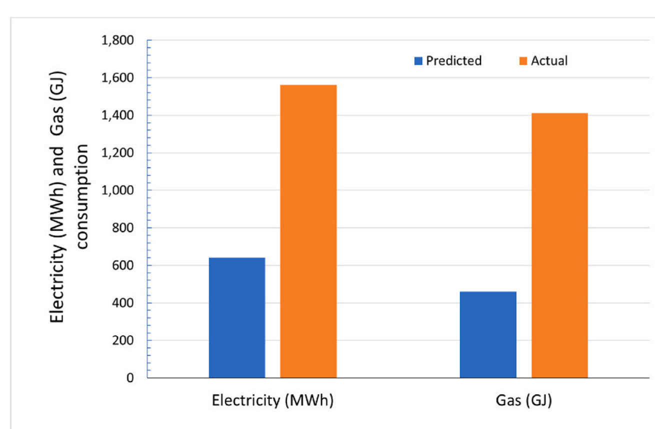

Fig. 3. Predicted vs Actual energy consumption of the studied building from September 1, 2018 to August 31, 2019.

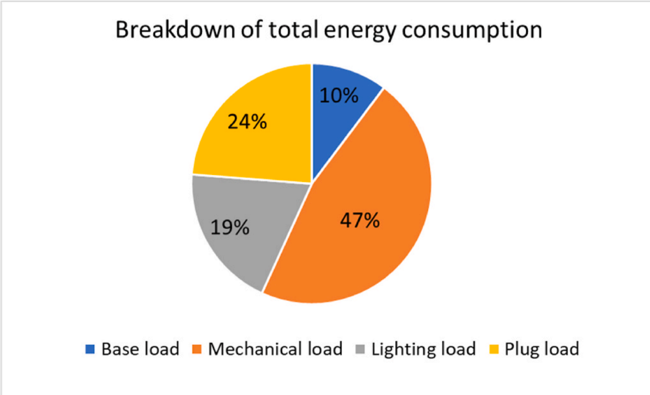

Fig. 4. Percentage of electrical energy consumed by different building systems.

(47%) amongst the four systems, followed by plug load (24%), lighting load (19%) and baseload (10%). The mechanical load includes energy consumed by heating, ventilation, and air-conditioning units (i.e. air handling units, exhaust fans, ventilation fans, pumps, chillers etc.). As the name suggests, the lighting load represents the energy consumed by the lights. Plug load refers to the energy used by any equipment (appliances, computers, laboratory equipment, printers etc.) that are plugged into a power outlet. The baseload in this building includes energy used by lifts, fire pumps, distribution boards and the uninterrupted power supply (UPS) system.

To understand the energy consumption pattern, k-means clustering method was used. The Elbow method revealed that 5 is the optimum cluster number for this data set. Hence, the number of clusters, k = 5 was used in the model to analyze the total energy consumption pattern.

Fig. 5 shows five clusters of total energy consumption with varying energy consumption rates. Cluster 2 has the highest daytime energy consumption rate, followed by clusters 3, 0 and 4. Cluster 1 has the lowest energy consumption rate. Between 8pm and 5am, the energy consumption rates are almost similar for all clusters except cluster 2. Moreover, for all clusters (except cluster 1), the energy consumption rate starts to increase from 5am and drops to the minimum level at 8pm.

To further understand the clustered data, a calendar plot has been presented in Fig. 6. Weekends are predominantly represented by cluster 1, which explains the almost flat line of this cluster because the university is closed. Cluster 0, cluster 3 and cluster 4 represent the energy consumption pattern of working days in winter (June to August), summer (December to March) and shoulder periods (March to May, September to November), respectively. Between October 16 to November 14, time-series data was mostly missing due to technical fault

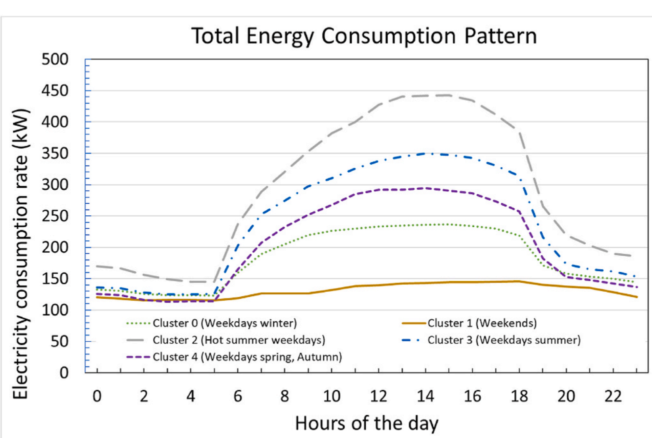

Fig. 5. Clusters of total energy consumption pattern.

(red highlighted NA) and therefore was excluded from the analysis. Cluster 2 only occurred for a few days during the summer due to higher (between 30 and 40 °C) than average summer temperature (26 °C), resulting in higher cooling demand. This is explained further in the mechanical load section.

The academic calendar of the university for the studied period (September 2018 to August 2019) is presented in Table 1. Comparison of holidays with calendar plot in Fig. 6 revealed that the energy consumption pattern during holidays was similar to a working day consumption pattern instead of a weekend. For example, the university was closed on 25th and 26th of December, but the energy consumption patterns on those days were same as cluster 4 whereas it was supposed to be cluster 1. Similarly, during Easter Friday (April 19) and Monday (April 22), the consumption pattern was 0 instead of 1. These phenomena represent significant energy waste in an unoccupied building. Therefore, there is a need to include holidays in the building operation schedule.

Fig. 5 also shows that the building had a constant energy consumption rate of 125 kW irrespective of the days of the week and time. During the design stage of the building, it was considered that the building would be occupied between 7am and 7pm on a working day. Keeping that in mind, total energy consumed during occupied and non-occupied hours is presented in Fig. 7. During the weekends, the building was mostly un-occupied, and hence, the energy consumptions were almost similar during '7am to 7pm' and '7pm to 7am' for all building systems. However, during weekdays, energy consumed during the unoccupied hours was 52% of the occupied hours consumption. Energy consumed by baseload, lighting, mechanical and plug load systems, during weekdays unoccupied hours were 63%, 62%, 62% and 41% of their corresponding occupied hours energy consumptions, respectively. Overall, 52%, 27% and 21% of the total energy were consumed during weekdays occupied hours, weekdays unoccupied hours and weekends, respectively. Including the weekends, total unoccupied hours energy consumption was 48% which is almost similar to the occupied hours consumption (52%) and, therefore, indicates a possible source of energy waste. To further understand the energy consumption pattern during unoccupied hours, clustering analysis was carried out for all building systems and discussed in the following sections. Table 2 presents a summary of the clustering analysis of different building systems in various end-use spaces. The table should be read in conjunction with Figs. 5–22 to have a detailed understanding of the consumption pattern.

3.2. Lighting consumption patterns

Fig. 8 presents the total lighting energy consumption pattern. Clusters 1 and 2 represent weekend and holiday consumption patterns, respectively. Comparison of calendar plot of lighting cluster (Figure A1 in appendix) and Table 1 revealed that clusters 0 and 3 represent the consumption pattern of weekdays non-teaching and teaching period, respectively. During weekdays (both teaching and non-teaching), the lighting energy consumption starts to increase at 5am in the morning, which is too early, and drops to the minimum level at 3am in the morning, which is too late.

The studied building has five different space types: Laboratory and special learning center, Academic and administrative office, teaching and study, plantroom, and basement. Table 3 shows that the lighting and plug load consumption intensity was highest in the laboratory and special learning spaces followed by teaching and study spaces and academic and administrative office spaces. This is in agreement with the findings of Khoshbakht et al. [41] where it was reported that research buildings have the highest energy density and academic office buildings have the lowest. Further investigation of lighting consumption patterns in these individual space types revealed that laboratory and office space consumptions do not depend on the teaching periods (Fig. 9 and Fig. 11) whereas the teaching and study spaces consumption strongly correlates with university teaching periods mentioned in Table 1. This is

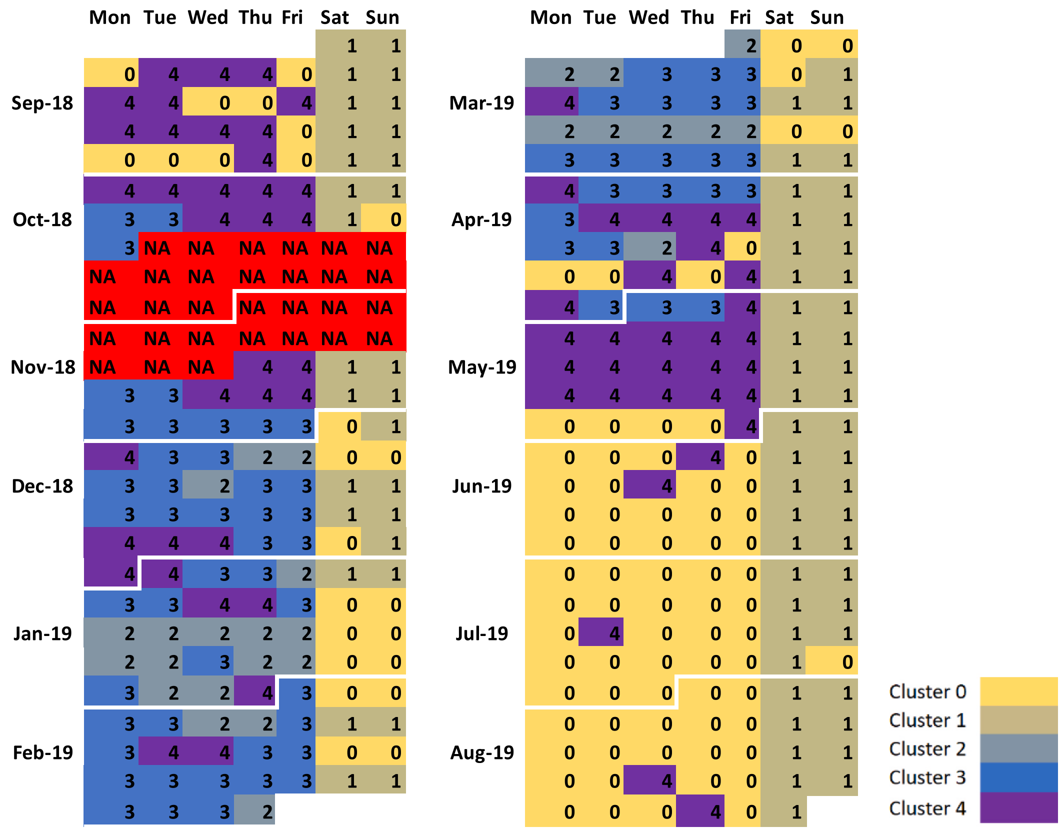

Fig. 6. Calendar plot of identified clusters for total energy consumption.

Table 1
Academic calendar of the university.

Descriptions	Dates
Public and Swinburne Holidays	September 28, 2018, November 6, 2018 25th to December 28, 2018, 1st and January 28, 2019 19th, 22nd, 23rd and April 25, 2019, June 10, 2019
Semester 2 teaching period	September 1 to October 28, 2018 (September 10 to September 14 was mid semester break) August 5 to August 31, 2019
Exam period	November 2 to November 18, 2018 June 7 to June 23, 2019
Non-teaching period	November 19, 2018 to March 3, 2019 June 24 to August 2, 2019
Semester 1 teaching period	March 4, 2019 to June 2, 2019

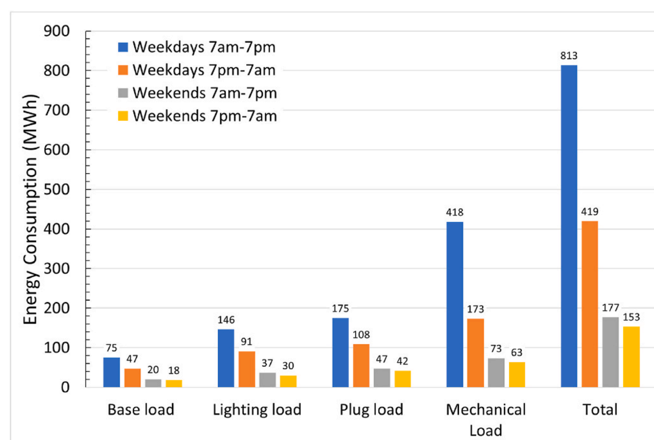

Fig. 7. Energy consumed by different building systems during occupied (7am – 7pm) and non-occupied (7pm – 7am) hours.

understandable because the laboratory and office spaces are occupied by the research students and academic and administrative staff throughout the year. In contrast, the teaching and study spaces are utilized in full capacity only during the semester 1 and 2 teaching periods, resulting in higher energy consumption.

For all three space types, measured weekdays lighting consumption profiles were very different from the predicted profiles during the design as shown in Fig. 12. For example, in laboratory and teaching spaces, the energy consumption rate drops from the peak daytime rate only at 9pm whereas it was predicted to drop to minimum at 7pm. Moreover, at 9pm weekdays, the consumption rate only drops to 72%, 70% and 53% from their peak daytime usage rate in laboratory, teaching and office spaces, respectively. These are too high compared with the predicted profile shown in Fig. 12 where the consumptions were predicted to be only 15%, 5%, and 10% of the peak daytime usage in laboratory, teaching, and office spaces, respectively. Furthermore, the consumption rates increase again at 10pm and finally drops to the minimum at 3am in the morning before increasing again at 5am. At 3am weekdays, the consumption rate only drops to 39%, 23% and 22% from their peak daytime usage rate in laboratory, teaching and office spaces, respectively, which is still too high compared to the predicted profile. The schedule of lighting control documents of this building states that lighting in each space is operated by occupancy sensors and can be controlled by manual on/off switches. The occupancy sensors have auto off function to turn off the light if no movement is detected for a predefined period. This period can be adjusted between 0 and 120 min, depending on the space.

It can be interpreted from Figs. 9–11 that these spaces are occupied between 7am and 9pm. However, it does not explain the reasons for higher afterhours lighting energy consumption rate which can be caused by the occupants, faulty sensors or large time delay settings in auto-off

Table 2
Description of energy consumption patterns of different clusters in Figs. 5–22.

	Cluster 0	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Total Energy Fig. 5	Weekdays in winter (June to August)	Weekends	Hot summer weekdays (>30 °C)	Weekdays days in summer (December to March)	Weekdays in shoulder periods (March to May, September to November)
Lighting Total Fig. 8	Weekdays non-teaching	Weekends	Holidays	Weekdays teaching	NA
Lighting: Laboratory and special learning Fig. 9	Weekdays September to mid-January	Weekends and holidays	Weekdays mid-January to March	Weekdays April to August	NA
Lighting: Teaching and study Fig. 10	Weekdays teaching	Weekdays non-teaching	Weekends and holidays	Weekdays teaching	NA
Lighting: Academic and administrative office Fig. 11	Weekdays September to February	Weekends and holidays	Weekdays March to August	NA	NA
Plug load Total Fig. 13	Weekdays non-teaching (June and July) and holidays	Weekends	Weekdays non-teaching (November to February)	Weekdays teaching	NA
Plug load: Laboratory and special learning Fig. 14	Weekdays and holidays	Weekends	Weekdays (March to May, August, November to December) and holidays	NA	NA
Plug load: Teaching and study Fig. 15	Weekdays non-teaching (June, July and November) and some weekends	Weekdays Teaching (August to October)	Weekdays non-teaching (Dec to February) and most weekends and holidays	Weekdays teaching (March to May)	NA
Plug load: Academic and administrative office Fig. 16	Weekdays (May to July)	Weekends winter	Weekdays other months	Weekends summer and holidays	NA
Mechanical Total Fig. 18	Weekdays and holidays in autumn (March–April) and spring (October–November)	Hot summer weekdays (>30 °C)	Weekdays and holidays during May to September. Weekends during October to March	Weekends (April to September)	Weekdays in summer (December to February)
Mechanical MSSB 11-04 Fig. 20	Weekdays and holidays November to March	Weekdays June to September and most weekends	Hot summer weekdays (>30 °C)	Weekdays October to November and April to May and some weekends	NA
Mechanical MSSB 11-03 Fig. 21	Weekdays April to October	Weekdays November to March	Weekends April to October	Weekends November to March and holidays	NA
Baseload Total Fig. 22	Weekdays non-teaching	Weekends and holidays	Only once in a year due to fire pump testing	Only once in a year due to fire pump testing	Weekdays teaching

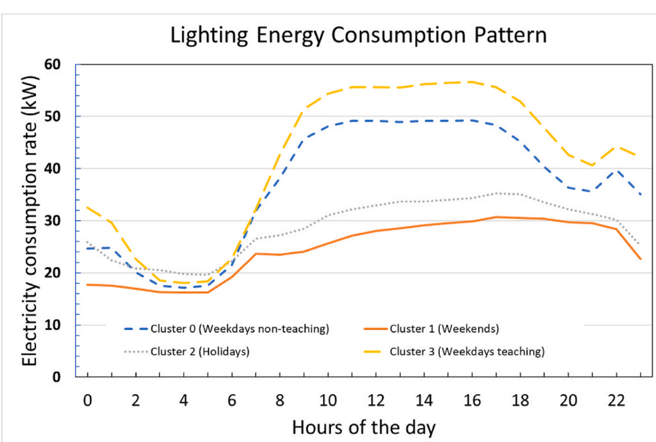

Fig. 8. Total lighting energy consumption pattern.

function. Further research is required to understand the actual occupancy pattern of various space types in an educational building. In addition, occupancy sensor settings and functionality should be reviewed.

3.3. *Plug load consumption patterns*

Fig. 8 shows the total plug load energy consumption patterns. Here the cluster 1 represents the weekend, and cluster 3 is the weekdays

Table 3
Lighting and Plug load energy intensity in different spaces of the building.

Space types	Area (m^2)	Lighting energy intensity ($kWh/m^2/yr$)	Plug load energy intensity ($kWh/m^2/yr$)	Total lighting and plug load ($kWh/m^2/yr$)
Laboratory and special learning center	4746	23	38.4	61.4
Teaching and Study	3298	20.3	11.6	31.9
Academic and administrative office	4991	17.3	14.5	31.8
Basement	1899	9.2[a]	10.9[b]	20.1
Plantroom	1228	10.4	6.7	17.4

[a] For six months only due to missing data.
[b] Energy consumed by various water pumps in the basement.

teaching period consumption pattern. Clusters 0 and 2 show the consumption pattern of non-teaching periods during winter (June–July) and summer, respectively (please refer to calendar plot of plug load in Appendix Figure A2). Cluster 0 also represents the holiday consumption pattern. It was interesting to see that although the lighting consumption pattern during holidays was the same as the weekend, this was not the case for plug load. The peak plug load consumption rates during holidays were 48–60% higher than the consumptions during the weekend, which suggests that some equipment may be running as usual during the holiday although the building was unoccupied.

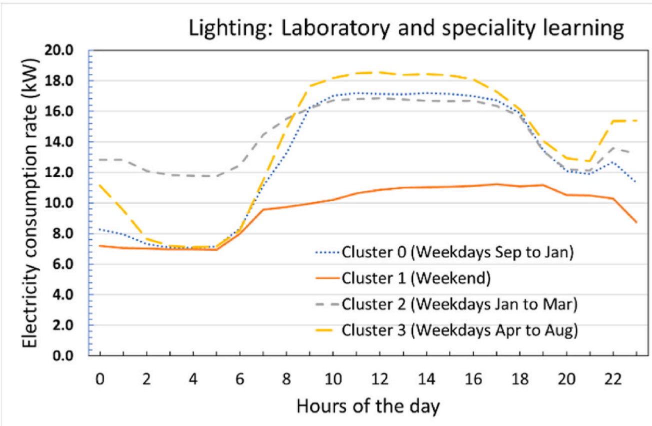

Fig. 9. Lighting consumption pattern in laboratory and specialty learning spaces.

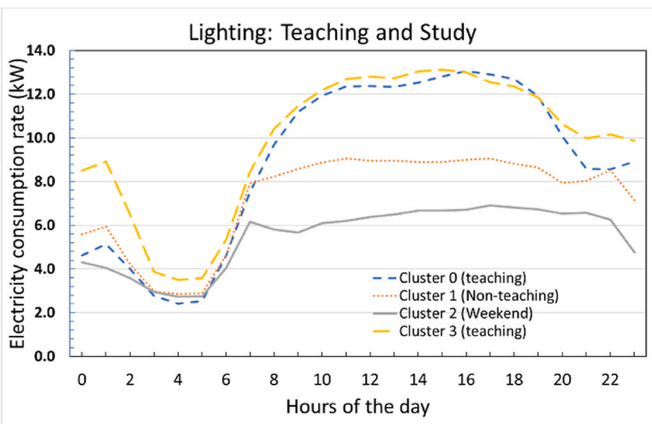

Fig. 10. Lighting consumption pattern in teaching and study spaces.

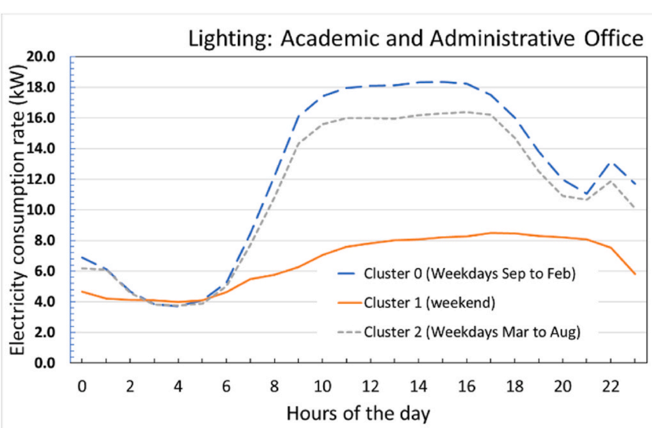

Fig. 11. Lighting consumption pattern in academic and administrative office spaces.

Clustering analysis of the plug load consumption in different spaces revealed that in laboratory spaces, the holiday consumption rate is same as weekdays consumption patterns (Fig. 14). In contrast, the holiday consumption pattern in teaching and office spaces were similar to their corresponding weekend consumption pattern shown in Fig. 15 and Fig. 16, respectively. This finding suggests the need for a schedule change for equipment in laboratory spaces to account for holidays.

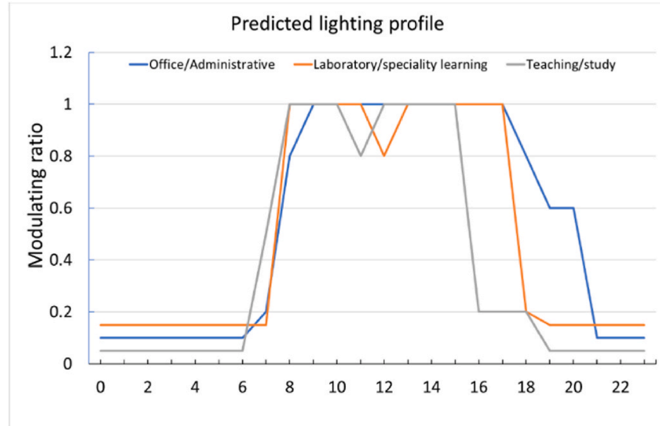

Fig. 12. Predicted lighting profile for different space types.

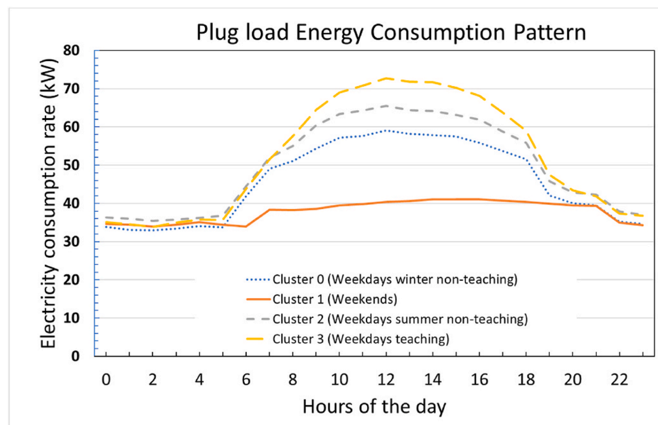

Fig. 13. Plug load energy consumption pattern.

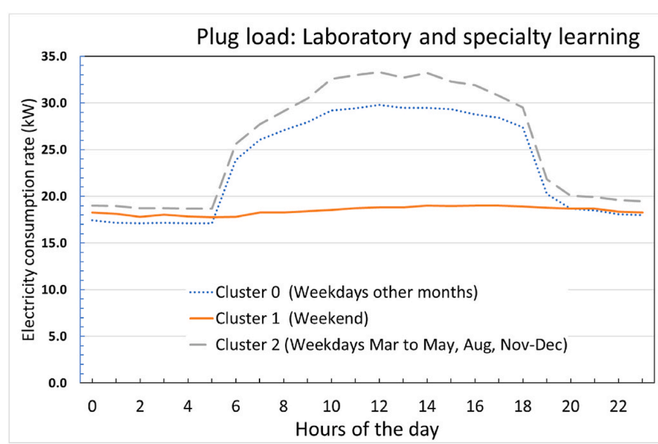

Fig. 14. Plug load consumption pattern of laboratory and specialty learning spaces.

Moreover, similar to lighting, plug load consumption rate in laboratory and office spaces do not depend on the teaching periods (Figs. 14 and 16), whereas the teaching and study spaces consumption strongly correlates with university teaching periods mentioned in Table 1. However, observed plug load consumption profiles were different from the predicted profile for these spaces during design, as shown in Fig. 17. In laboratory and office spaces, energy consumption rate started to increase after 5am whereas it was predicted to increase at 7am. The

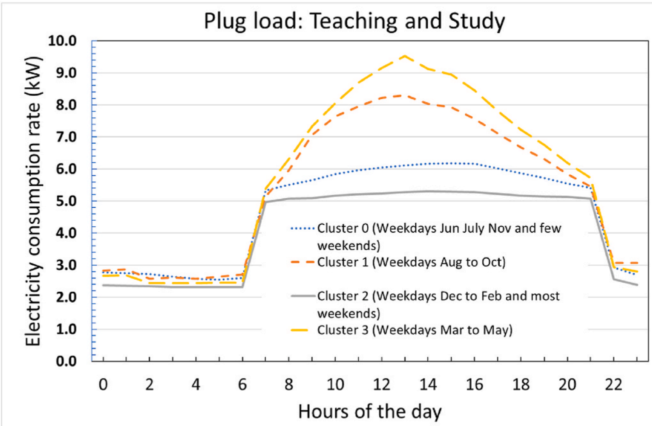

Fig. 15. Plug load consumption pattern of teaching and study spaces.

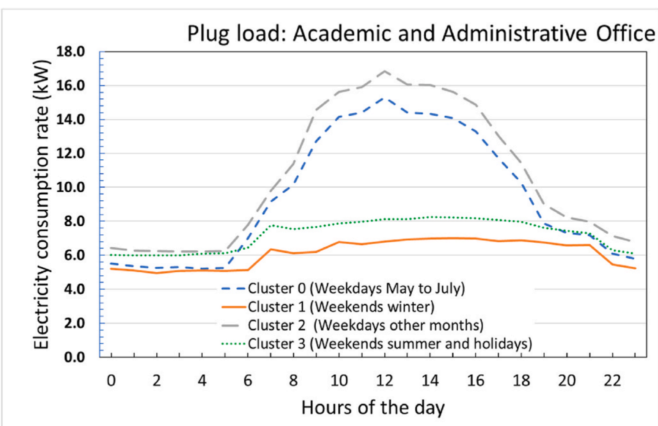

Fig. 16. Plug load consumption pattern of academic and administrative office spaces.

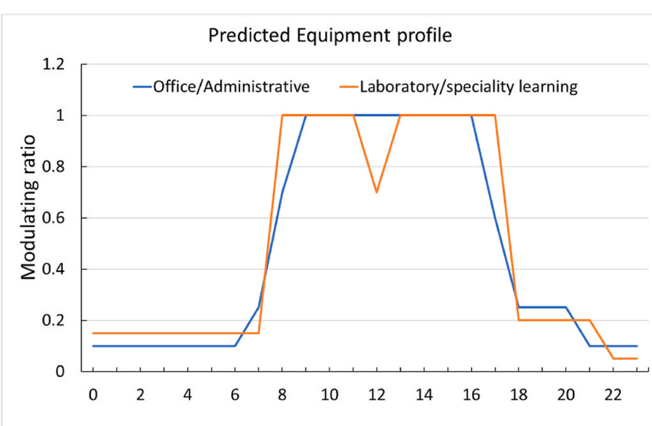

Fig. 17. Predicted equipment load profile for different space types.

consumption rate started to drop from 6pm in laboratory spaces and 4pm in office spaces which were similar to predictions. But the minimum consumption rates were significantly higher in both spaces. For example, at 10pm weekdays, the consumption rate only dropped to 60% and 40% from the peak daytime usage rate in laboratory and office spaces, respectively. These were too high compared to the predicted profile shown in Fig. 17 where the consumptions were predicted to be only 5% and 10% of the peak daytime usage at 10pm in laboratory and office spaces, respectively.

In teaching and study spaces, the consumption rates started to increase from 6am and dropped to a minimum at 10pm. The minimum consumption rate is 31% of peak daytime usage. No predicted profile for plug load in teaching and study area is available in design documents for comparison. The weekend consumption pattern is similar to non-teaching period weekdays pattern, which was not expected.

3.4. *Mechanical system consumption patterns*

Fig. 18 shows the energy consumption patterns of the mechanical load, which includes air handling units, ventilation fans, exhaust fans, chillers, chilled water pumps, hot water pumps, heat rejection loop (condenser pumps and dry coolers) and packaged air conditioners.

Cluster 3 has the lowest energy consumption pattern which represents weekends in colder months (April to September). Cluster 2 represents weekdays consumption in colder months (May to September) and most weekends in warmer months (October to March). Cluster 0 shows the weekdays consumption pattern during autumn (March–April) and spring (October–November). The summer (December to February) weekdays consumption pattern is represented by cluster 4. Cluster 1 shows the highest energy consumption pattern which occurred only 6% of the days in the whole year when the outdoor air temperatures were between 30 to 40 °C, higher than the average summer temperature of 26 °C. It was also observed that mechanical energy consumption during public holidays follows the same pattern of weekdays consumption of that season which is not ideal. (See the appendix Figure A3 for the cluster calendar plot of mechanical energy consumption).

Fig. 19 shows that the mechanical energy consumption was directly related to outdoor weather and was not influenced by the teaching and non-teaching period. Average daily energy consumption was highest, corresponding to the maximum mean monthly temperature in January. It should be noted that the mechanical energy consumption does not include the gas energy consumed during colder months for heating purpose. That is why it is showing minimum energy consumption during winter.

The clustering analysis in Fig. 18 also shows that the mechanical system energy consumption rate started to increase after 5am and reached to peak level between 2 and 4pm. Then it started to decrease from 6pm before reaching the minimum level at 8pm. The afterhours minimum energy consumption rate mostly varied between 50 and 60 kW except for cluster 1 (around 90 kW for cluster 1) which was very high. Further analysis of the seven sub-meters that monitor mechanical system energy consumption revealed that submeter MSSB 11-04 recorded the highest energy consumptions followed by MSSB 11-03. MSSB 11-04 submeter includes all the cooling systems (chillers, chilled water pumps, condenser water pumps, dry cooler) and some exhaust fans

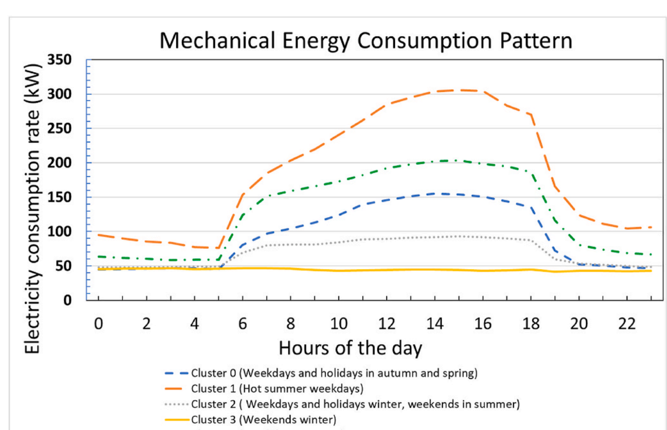

Fig. 18. Mechanical energy consumption patterns.

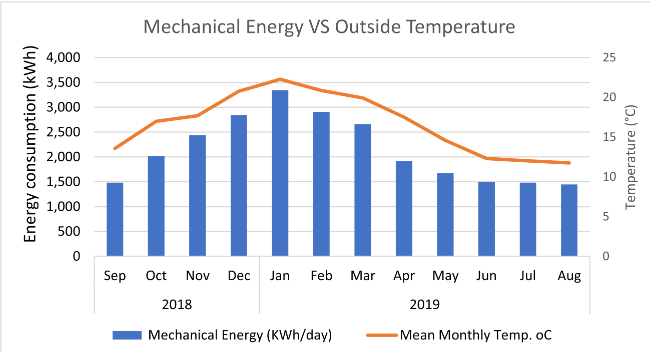

Fig. 19. Average daily mechanical energy consumption per month vs outdoor temp.

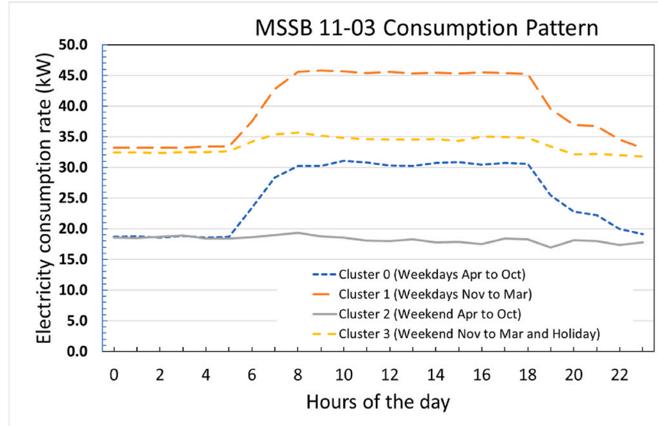

Fig. 21. Mechanical energy consumption rate in submeter MSSB 11-03.

(fume cupboard, tearoom, cleaner room, and utility room exhaust fans). As seen in Fig. 20, the minimum energy consumption rate of MSSB 11-04 was mostly between 20 and 25 kW except for cluster 2 which only occurred for 6% of the days in the whole year due to higher than average outdoor temperature. The MSSB 11-03 submeter includes hot water pumps, all kitchen and cleaner exhaust fans in level 6 to 9, and battery and water pump room exhaust fans in the basement. As seen in Fig. 21, the minimum energy consumption rate of MSSB 11-03 was around 18 and 33 kW, depending on the seasons. Together MSSB 11-03 and MSSB 11-04 represented 92% of the total after-hours energy consumption rate of the mechanical system. As there is no heating demand during the summer period and after hours, the continuous minimum energy consumption shown in MSSB11-03 may be the result of other exhaust fans attached to it. Similarly, as there is no cooling demand during winter and after hours, the continuous minimum consumption in MSSB11-04 also must be the result of the exhaust fans consumption. Due to the lack of sub-metered data, it was not possible to identify which fans are consuming more energy than others and a site investigation is recommended for that purpose. Nevertheless, the systematic clustering analysis carried out in this research revealed the possible source of energy waste and provided a lead for further investigation.

3.5. *Baseload energy consumption pattern*

The baseload includes lifts, escalators, fire pumps, distribution boards and uninterrupted power supply (UPS) system. Fig. 22 shows the energy consumption patterns of the baseload system where cluster 1, cluster 4 and cluster 0 represents weekend, weekdays teaching and weekdays non-teaching periods, respectively (Please see appendix Figure A4 for baseload cluster calendar plot). Cluster 2 and 3 occurred

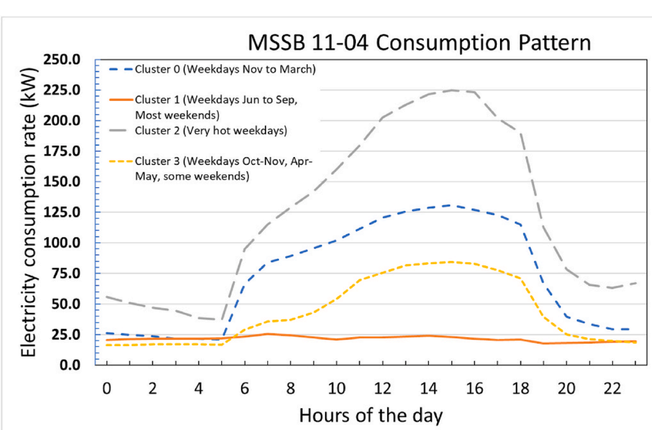

Fig. 20. Mechanical energy consumption rate in submeter MSSB 11-04.

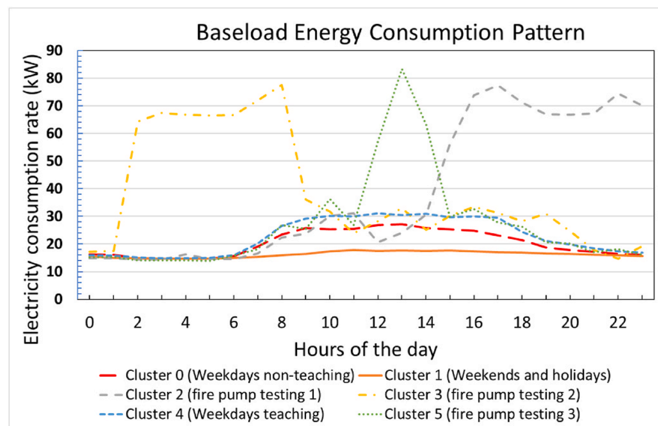

Fig. 22. Baseload energy consumption pattern.

only once in the whole year and cluster 5 occurred only twice due to the testing of fire pumps. As these are not regular activities, these clusters were not considered for further analysis. Clustering analysis of the 10 individual submeters that recorded the energy consumption of various systems under baseload revealed that energy consumed by the three lifts, escalators (level 1 to 3) and UPS system consumed over 98% of the total baseload energy consumption. The after-hours consumption was mainly from the UPS system which constantly consumed 14 kW power all year round. The UPS system ensures uninterrupted power supply in case of a power cut. However, further investigation of this system is recommended to see whether constant consumption all year round is required for this system. During the weekdays, energy consumption started to increase from 6am due to the operation of lifts and escalators and dropped at 7pm. During the teaching period, the consumption rate was higher than the non-teaching period, and the lifts were used for a longer period which is understandable due to the increased number of building users.

4. Research implication

The outcome of this research has several practical implications. Firstly, it can provide valuable real-time feedback to the building operations manager regarding the energy consumption status. Currently, a large volume of building operational data remains unused and the BMS is only used to see whether every system is functional without any focus on energy efficiency. This research can contribute to the development of an extension of the current BMS system where the proposed method can analyze the recorded data and provide feedback to the operations manager at regular intervals about the consumption pattern and possible sources of energy waste. Secondly, this study can provide feedback to the designer and energy modeler to assume more realistic lighting and plug load consumption in different spaces of an educational building and the building operational schedule. Finally, the outcome of this research can help to decide an optimum operational schedule for an educational building considering the teaching/non-teaching period, space types, and holidays.

5. Conclusions and recommendations

Energy consumption pattern in a 10-storey educational building was investigated using unsupervised data mining technique k-means clustering. Energy consumption data from 64 submeters of the building were included in the analysis, amongst which lighting, plug load, Mechanical and baseload consumptions were recorded by 23, 24, 7 and 10 submeters, respectively.

The energy performance gaps in terms of electricity and gas were found to be 2.4 and 3.1 times, respectively, for the studied period of September 2018 to August 2019. Mechanical system consumed the highest 47% of total energy, followed by plug load 24%, lighting 19% and baseload 10%. Clustering analysis of the total energy consumption data revealed that the energy consumption rate depends on the climate and days of the week (weekdays or weekend). However, the holidays were found to have a similar consumption pattern as weekdays which was due to the mechanical and plug load consumption. Although the holiday consumption pattern for lighting and baseload energy was found to be similar to the weekend consumption rates, in case of plug load and mechanical system, these were similar to weekdays consumption. These indicate the need to revisit the schedule of plug load and mechanical systems to consider holidays. Moreover, the total after-hours energy consumption (weekdays afterhours and weekends) was found to be 48% of total energy consumption. During weekdays, afterhours energy consumption was 52% of the daytime occupied hours consumption which are not ideal. These findings demonstrate potential opportunities to improve energy efficiency and minimize energy waste.

The studied building is a mixed-use building with spaces for laboratory and specialty learning, teaching and study, and academic and administrative offices. The laboratory and specialty learning center spaces were found to be most energy-intensive in terms of lighting and plug load, followed by teaching and office spaces. In laboratory and office spaces, lighting and plug-load consumption rates were independent of teaching/non-teaching periods and only varied with weekdays, weekends, and holidays whereas teaching spaces consumption also varied with teaching/non-teaching period in addition to others. However. actual lighting and plug load profiles of these spaces were very different from the predicted profile during design and demonstrated significantly higher consumption after hours.

The baseload consumptions were directly related to the weekends, holidays, weekdays teaching and weekdays non-teaching. Energy consumed by the mechanical system was directly related to the outdoor air temperature and is not influenced by teaching/non-teaching periods and holidays. Amongst the various mechanical sub-meters, the one with cooling systems (chillers, chilled water pumps, condenser water pumps, dry cooler, tearoom, and cupboard exhaust fans) consumed maximum energy and was also running during the holidays as per weekdays schedule. The submeter with heating systems (hot water pumps, and kitchen, cleaner, battery and water pumps room exhaust fans) was the second highest consumer of mechanical energy. In the absence of heating and cooling demand, energy consumptions recorded by these two submeters were still considerably higher given that the it was only due to exhaust fans consumptions. This also indicates a potential source of energy waste.

Based on the current study, the following recommendations were made to improve energy efficiency and minimize the performance gap:

1) The control schedule of plug load and mechanical systems should be revisited to accommodate holidays. Although mechanical systems consumed the highest 47% of total energy, only 7 submeters were installed (the least of all four systems) to record the consumption. More submeters in the mechanical system (Particularly, in MSSB11-03 and in MSSB11-04 which showed significant after-hours consumption) would provide more granular data and a better understanding of energy consumption patterns and energy waste.
2) Currently, the start time of the building systems is 5am which is too early and should be revisited.
3) Afterhours energy consumptions by the buildings systems are very high, has to be investigated further through site inspection.
4) The difference in the predicted and actual profile of lighting and plug load may be caused by a number of reasons, including faulty sensors, extended occupancy or auto off setting. Further study is required to understand the occupancy pattern in different spaces of this building and review the sensor settings.

In terms of limitations of this study, it was not possible to identify the magnitude of the energy performance gap at a system level because of the unavailability of predicted consumption data at a system level. Only total predicted energy consumption data was available in the energy efficiency report. Although the building is equipped with PIR sensors to detect occupancy, the data was not stored in the BMS due to storage limitations. Hence, it was not possible to determine the actual occupancy status of the building using PIR sensor data. However, as per the building operational manual, as soon as the occupancy sensor detects occupancy, the lights are turned on. Therefore, the lighting consumption pattern was used to infer the possible occupancy profile of the building.

The study provided an understanding of the energy consumption pattern in a mixed-use education building which can help the building designer/energy consultant/facilities manager to design and optimize the building operation. It provides information about how the energy consumption in different spaces of an educational building varies with parameters like teaching periods, holidays, climate, etc. The study has developed a methodology to analyze the energy consumption data of the BMS system based on k-means clustering data mining techniques which can be used to evaluate the energy consumption pattern of any educational building. Then it demonstrated how to identify possible sources of performance gap by analyzing the clustered data. The proposed method can be applied to any building with different end uses to understand energy consumption patterns and identify possible sources of energy waste as long as there are enough submeters recording energy consumptions of different systems and sub-systems. For older buildings without submeters, the recently proposed data analytics method by Samadi and Fattahi [45] can be applied to disaggregate total building energy consumption to lighting, thermal, occupancy and common building load. However, this model is not yet capable of understanding consumption patterns of different end use space types and mechanical equipment.

Author statement

Morshed Alam – Conceptualization, Software, Formal analysis, Writing - Review & Editing, Supervision, Maisum Raza Devjani – Methodology, Investigation, Writing - Original Draft.

Declaration of competing interest

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.

Appendix

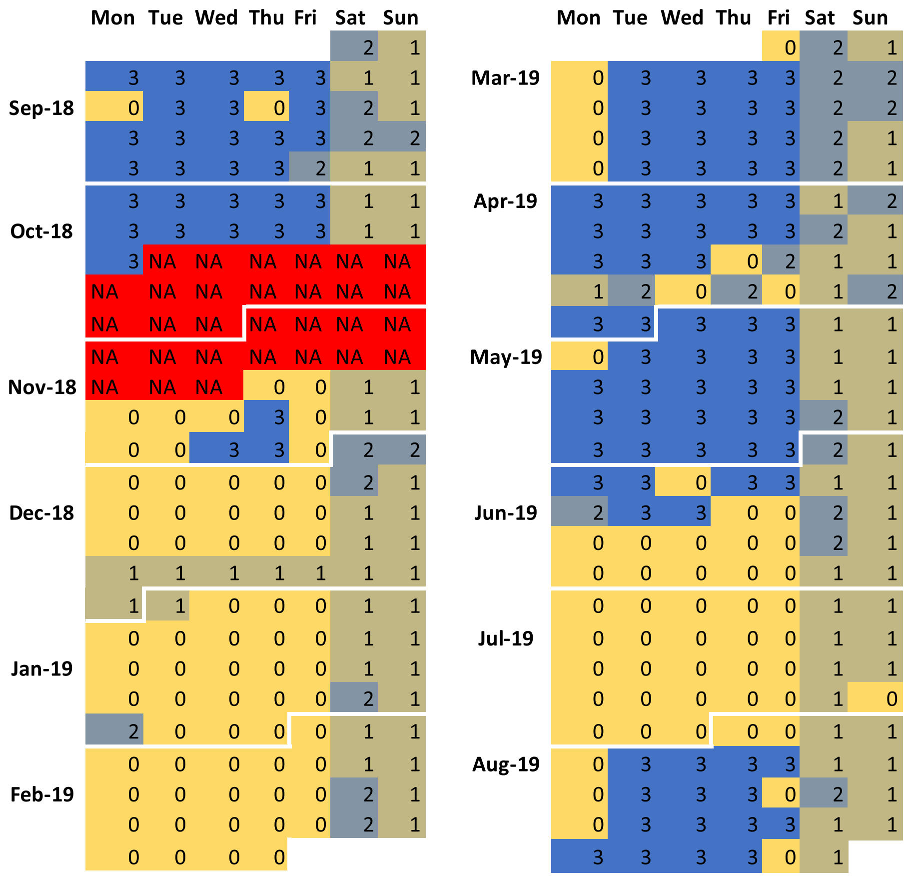

Fig. A1. Calendar Plot of Lighting cluster

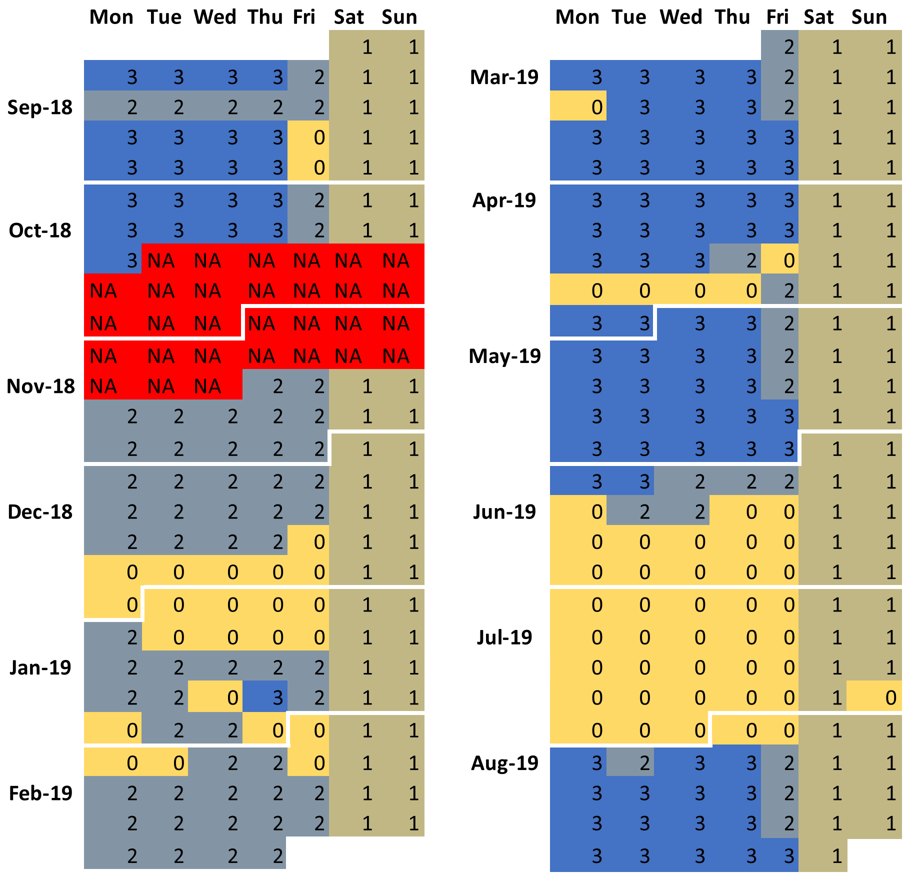

Fig. A2. Calendar plot of plug load cluster

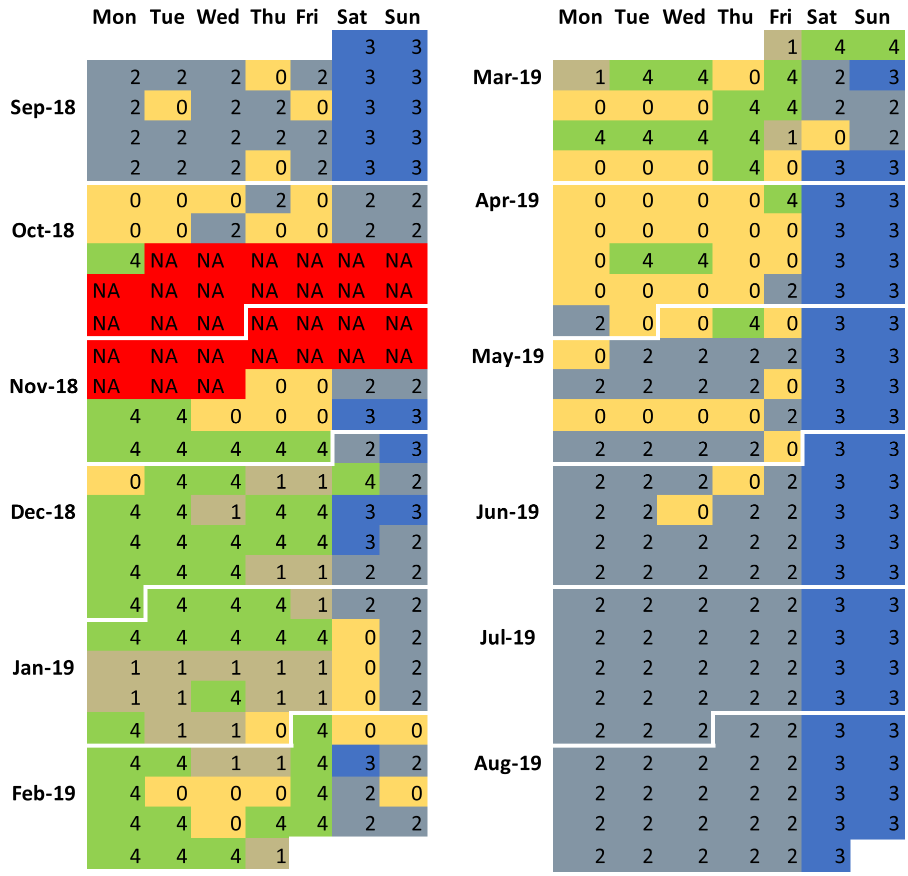

Fig. A3. Calendar plot of Mechanical cluster

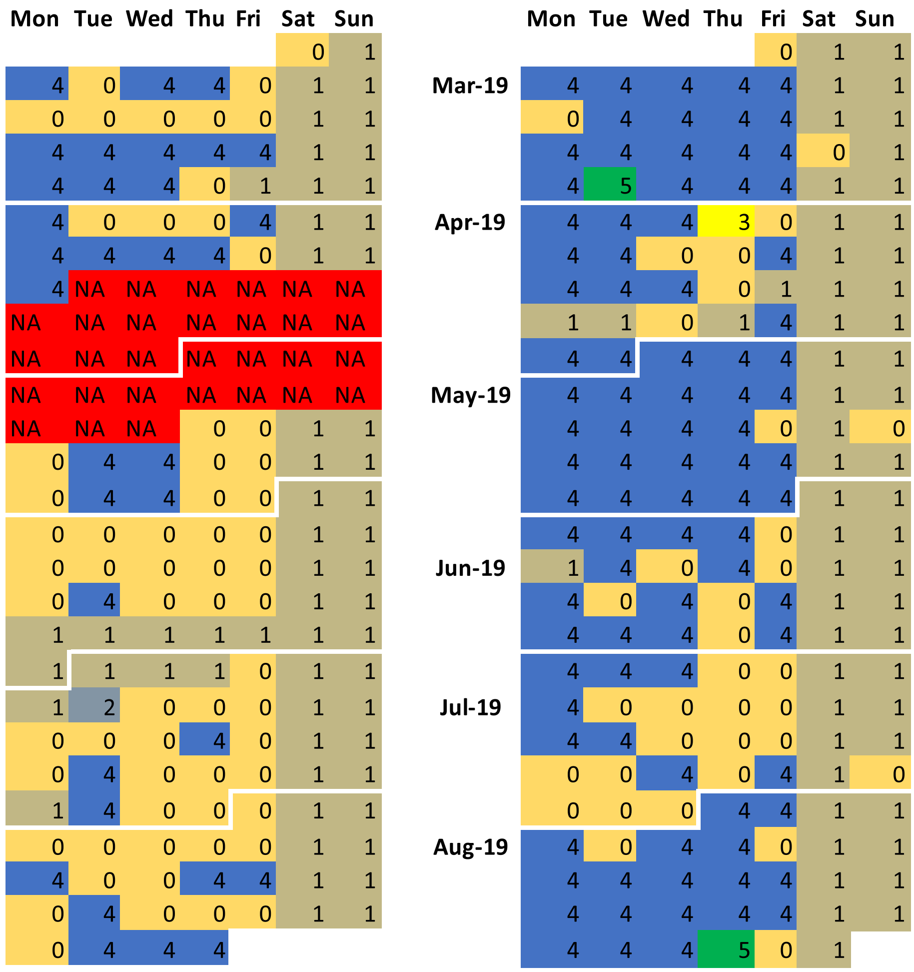

Fig. A4. Calendar plot of Base building consumption

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