Data-driven analysis of occupancy and lighting patterns in office building in Norway

FANG YUAN
M.Sc.
Tianjin University of Technology – School of Computer Science and Engineering
13821918710@163.com

YUEMIN DING
Postdoctoral fellow
Norwegian University of Science and Technology – Department of Energy and Process Engineering
yuemin.ding@ntnu.no

NATASA NORD
Associate professor
Norwegian University of Science and Technology – Department of Energy and Process Engineering
natasa.nord@ntnu.no

Energy usage in buildings

Both commercial and residential buildings are major energy users. Together, they are responsible for 36% of global final energy use and 40% of the CO_2 emission [1]. In buildings, the energy is used for a variety of purposes, including space heating/cooling, ventilation, lighting, cooking, working, entertainment etc. For better energy efficiency in buildings, it is important to understand the characteristics of energy use by different sub-sectors. This is typically conducted via building energy performance modelling.

However, the energy usage is affected by a large number of factors, including building envelope, outdoor temperature, occupant behaviour, etc. Among all them, although the impact of some factors could be expressed by physical models, it is impossible to model the impact of the other factors, like the occupant behaviour. However, it has been shown that occupant behaviour has significant affections on the energy consumption of buildings [2,3]. As a result, it is important to investigate the patterns of these factors, for which data-driven analysis is an efficient solution.

Smart building enables data-driven analysis

With the rapid development, smart building facilitates data-driven solutions to understand the characteristics of energy use patterns. Utilizing sensors and internet-of-things (IoT), a large number of factors affecting energy usage pattern could be monitored and investigated in smart buildings. As a result, huge amount of data is generated, which promotes data-driven analysis for better energy-efficient management of buildings and for better energy performance modelling.

To demonstrate the advantages of data-driven analysis in building environment, this study analysed the occupancy and lighting patterns of an office building in Trondheim, Norway, based on yearly data collected from occupancy and lighting sensors. Through analysing these data, several interesting findings are summarized. On the one hand, these findings can be used to improve the control strategy of the building system for better energy efficiency. On the other, the occupancy and lighting level could be directly used as inputs of the building energy performance model for better accuracy.

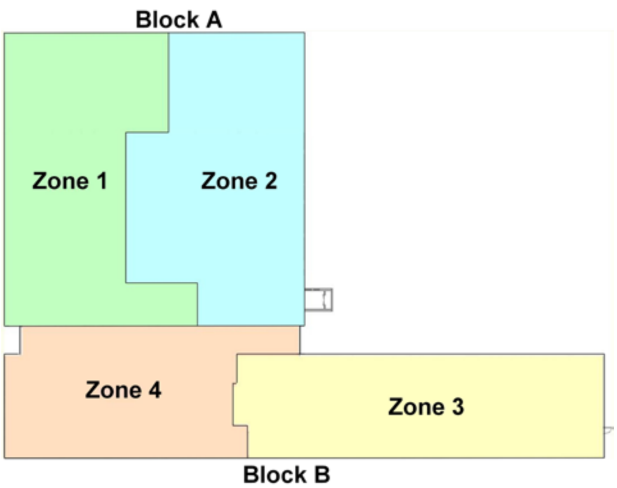
Office building in Trondheim

Figure 1 (a) shows our study object with an example floor plan given in **Figure 1 (b)**. This is an office building with five floors. The building is composed of two blocks (Block A and B), which are further divided into different zones (Zones 1 to 4), where each zone shares same utility facilities. In this building, two monitoring platforms were developed. One with a large number of sensors at each office to monitor indoor environment. The second platform was installed to monitor the building services and supply system. The second platform may be treated as building energy monitoring platform.

In each office, occupancy and lighting sensors are installed to capture the characteristics of occupants and the lighting system. The sensors are configured to sense and upload data periodically with the time interval set to 15 minutes. This leads to 4 packets/hour, 96 packets/day, and 35 040 packets/year for each sensor.

In this study, the yearly monitoring data from occupancy and lighting sensors installed in nine sample offices of three different zones were analysed to capture their characteristics and correlations. This helped us to analyse the impact of occupancy on energy usage, to understand the energy use pattern of lighting systems, and to improve the energy management strategies accordingly.

(a) Appearance



(b) Floor plan

Figure 1. The smart building at Trondheim, Norway.

Data-driven analysis of the occupancy and lighting patterns

To conduct data-driven analysis, we considered three cases to analyze the occupancy and lighting patterns for selected sample offices.

- Case 1: investigated the daily occupancy and lighting patterns. For a specific day, the occupancy and lighting data from the same sample office were analysed to find the correlations and to identify potential energy-saving opportunities.
- Case 2: studied the stochastic pattern from Monday to Sunday. With yearly data collected from sample offices, the stochastic pattern was examined to understand the occupancy and lighting characteristics of each day.
- Case 3: compared the average patterns for weekdays between summer and winter. With monthly data collected from sample offices, the stochastic pattern was studied to compare the differences of occupancy and lighting patterns between summer and winter.

Daily occupancy and lighting patterns

The results of Case 1 are shown in **Figure 2**, illustrating the data collected by occupancy and lighting sensors for two selected days, namely July 25th and August 6th, 2018. Here, the occupancy data were represented by the solid blue line and the lighting data are plotted with the red dashed line. For both occupancy and lighting sensors, the value '1' indicated that a human was detected / the lights was on in the office; the value '0' indicated that nobody is in the office and the lights are off.

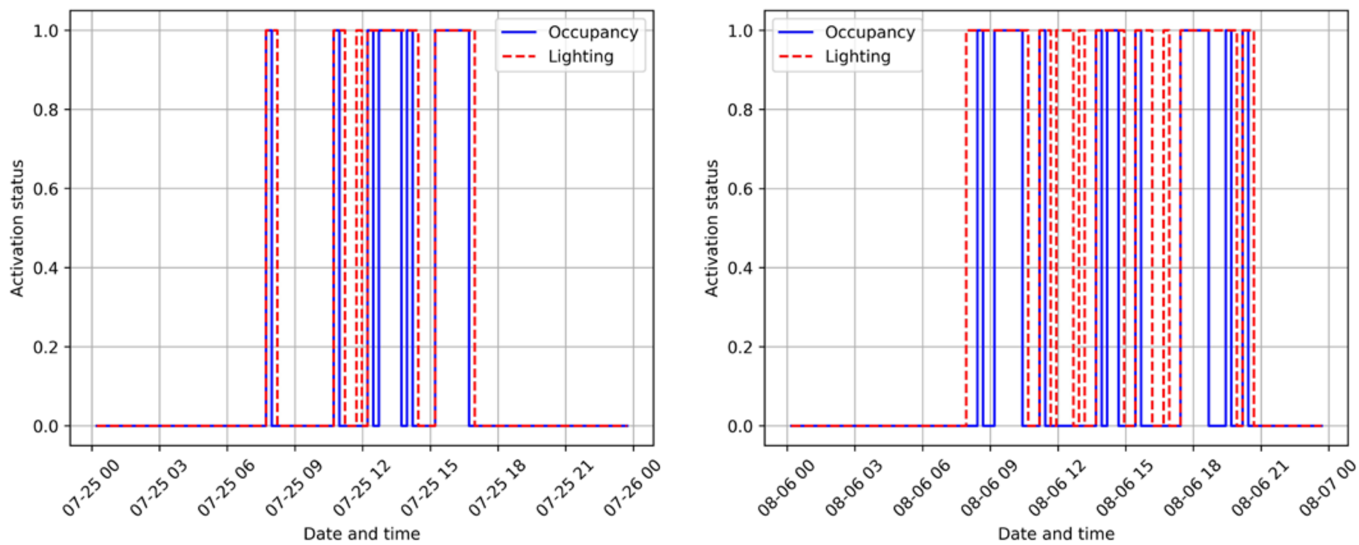
Comparing **Figure 2 (a)** and **(b)**, it was found that both the occupancy and lighting show significantly different patterns from one day to another, even for the same office. The random variations of occupancy and lighting were the main reasons why they cannot be modelled with physical models. Analysing **Figure 2 (a)** and **(b)** in detail, it was found that the occupancy and lighting were highly correlated. The presence of occupants simultaneously triggers the lights to turn on. It was even more interesting to find that the absence of occupants did not trigger the lights to turn off immediately, which was beyond our expectation. Actually, the lights turned off 15 minutes later than the occupant left the office. This unnecessary delay could be further shortened for energy-saving purpose. The third finding was that the lights occasionally turn on but the occupancy sensor did not detect any occupant. To find out what occurs during these periods, it is necessary to reduce the measuring period of the occupancy sensor for further investigation.

Comparison from Monday to Sunday

The results of Case 2 are given in **Figure 3**, showing the averaged value of each time interval from Monday to Sunday. After data cleaning process, the collected data from August 6th 2018 (Monday) to May 26th 2019 (Sunday) were used to capture the characteristics of occupancy and lighting from Monday to Sunday. Data from different zones were analyzed separately as shown in **Figure 3 (a)-(c)** for the occupancy and **Figure 3 (d)-(f)** for the lighting in Zones 1-3, respectively.

Looking into **Figure 3 (a)–(b)**, it is found that occupants could be detected stochastically from 6 a.m. on weekdays and the average occupancy rate gradually increases to the maximum value until 8 a.m. for all the three zones. After that, the occupancy rate fluctuated around the maximum value until 4 p.m. when occupants started to leave the offices. As for the decreasing of the occupancy rate, Monday and Friday are special weekdays showing different patterns than the others. On Monday, occupants tended to stay in the office longer and the decreasing speed was much slower than that of the other weekdays. Whereas, the occupants tended to leave the office early on Friday. This phenomenon implied higher energy demand on Monday and lower energy demand on Friday, which should be taken into consideration for energy management in this building. On Saturday and Sunday, the influence of the occupancy and the lighting might be neglected compared to weekdays.

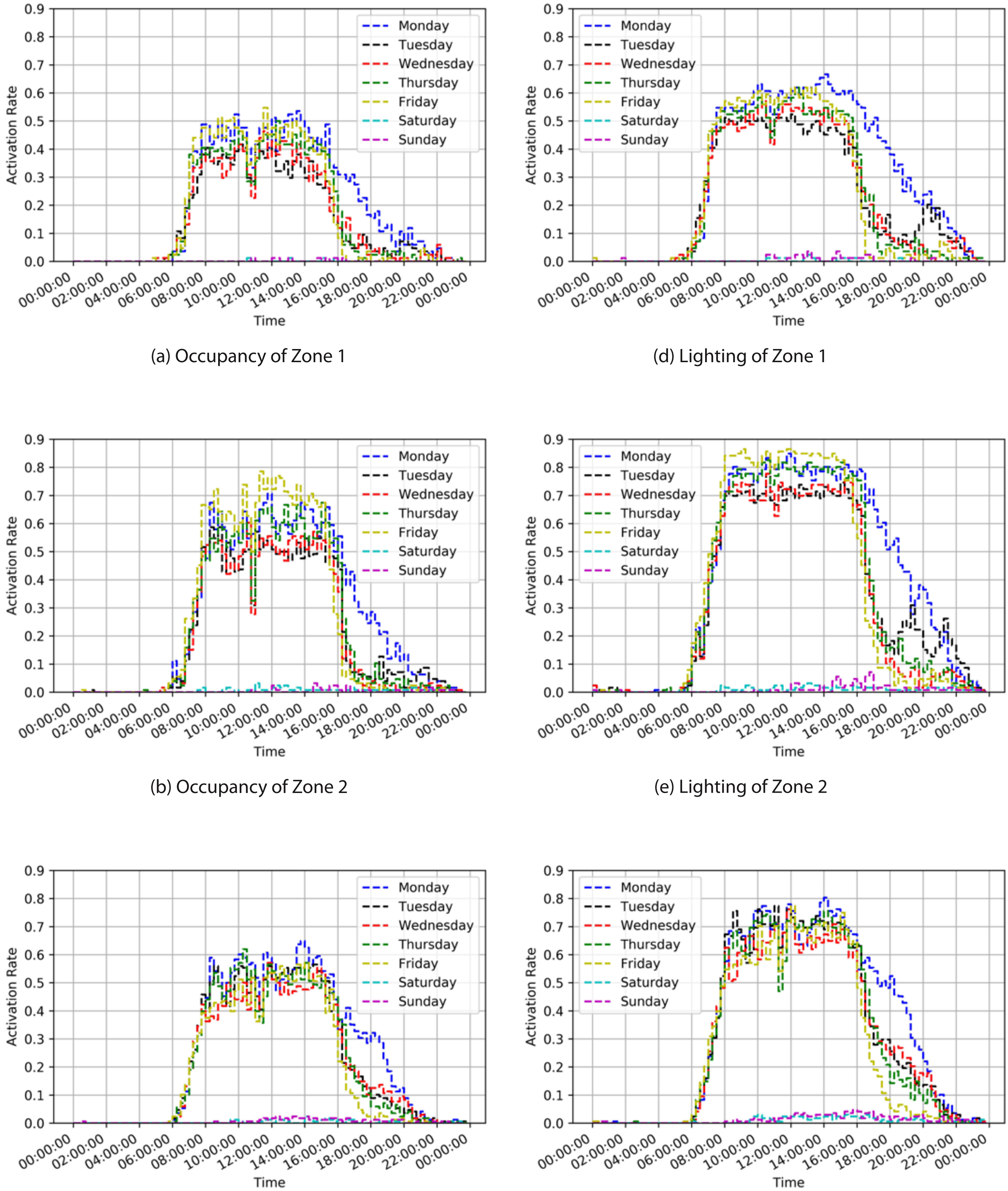
Interestingly, it is found that the lighting rate was stochastically 10% higher than that of the occupancy by comparing the graphs for each zone, e.g. **Figure 3 (a)** and **(d)**. The main reasons were that the lights remain on for an additional time interval after occupants left the office and the light occasionally turned on for unknown reasons. Due to these reasons, we could conclude that there were huge potential for energy-savings in the lighting system. This cannot be neglected when improving the energy control strategies for this building.



(a) Data for 25 July, 2018

(b) Data for 06 August, 2018

Figure 2. Daily occupancy and lighting patterns for an office in Zone 1.



(a) Occupancy of Zone 1

(d) Lighting of Zone 1

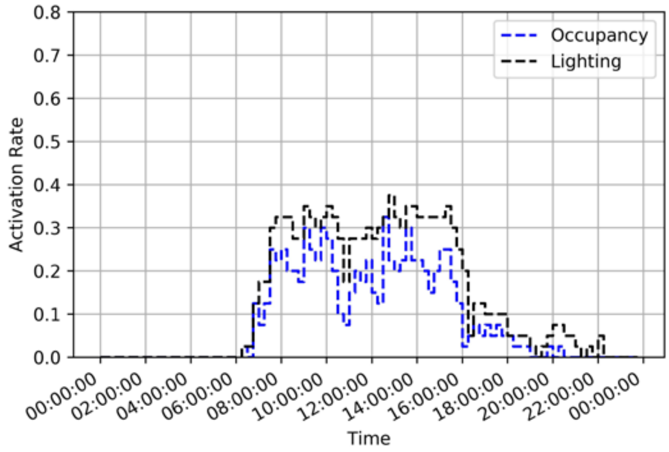
(b) Occupancy of Zone 2

(e) Lighting of Zone 2

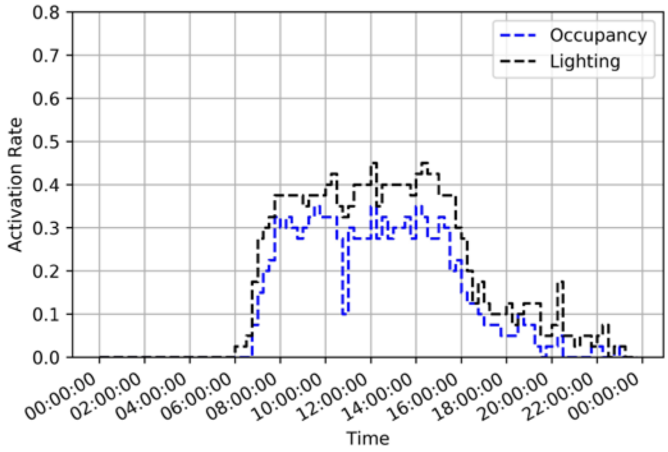
(c) Occupancy of Zone 3

(f) Lighting of Zone 3

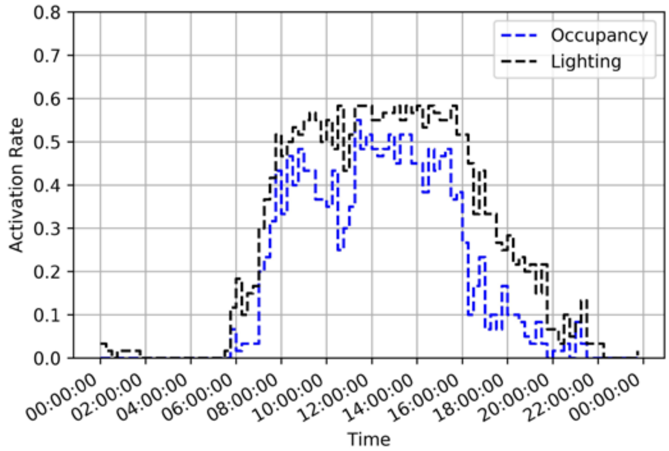
Figure 3. Comparison of patterns from Monday to Sunday..



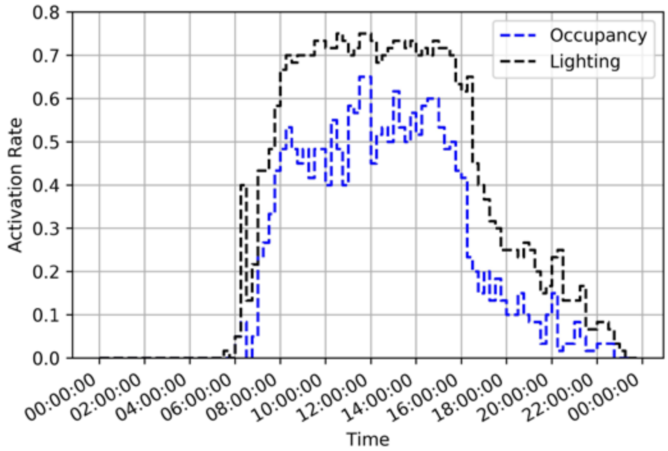
(a) Results of Zone 1 in summer



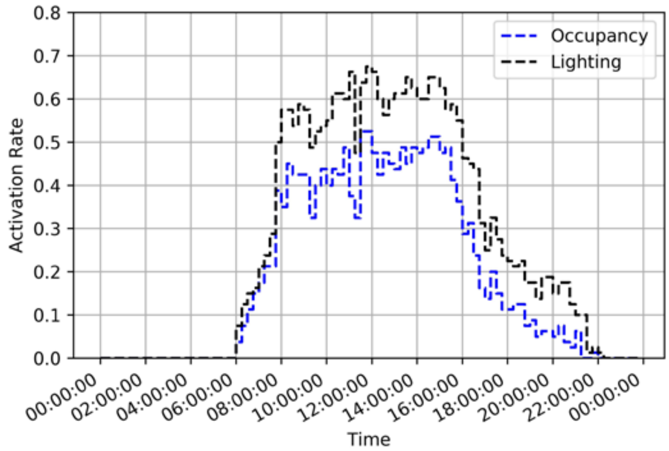
(d) Results of Zone 1 in winter



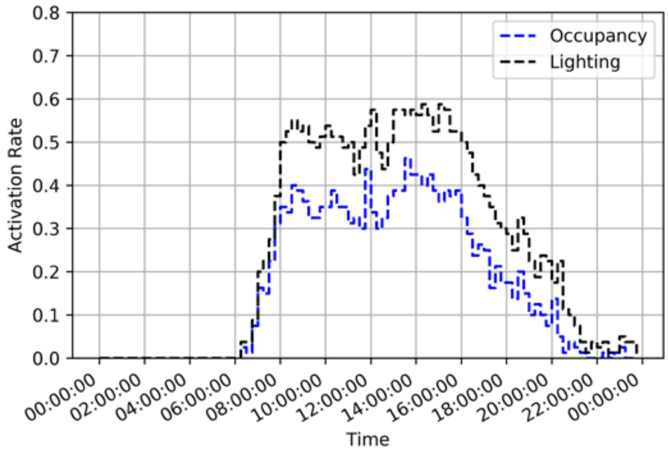
(b) Results of Zone 2 in summer



(e) Results of Zone 2 in winter



(c) Results of Zone 3 in summer



(f) Results of Zone 3 in winter

Figure 4 . Comparison of patterns between summer and winter.

Comparison between summer and winter

The results of Case 3 are illustrated in **Figure 4** showing the averaged value of weekdays in summer and winter. The data used for summer were collected from August 6th to September 2nd and those for winter were collected from November 26th to December 23rd, 2018. Similar to Case 2, the averaged value of the occupancy and the lighting rate were compared between the winter and the summer for different zones.

By investigating the data from **Figure 4 (a)-(b)** in comparison with those from **Figure 4 (d)-(f)**, it is found that the occupancy and the lighting patterns were highly correlated both in the summer and the winter. Moreover, it is surprising that no obvious difference could be identified for the lighting patterns between the summer and the winter, especially when we take the daytime length into consideration. In Trondheim, Norway, the daytime was longer than 17 hours in July and less than 5 hours in December and the light intensity was much stronger in the summer than in the winter. A possible reason that there was no difference between the summer and the winter light patterns may be due to shading devices. The shading devices are covering the windows whenever the sun irradiation was above a certain level, which may not be so high. The shading devices induce the need for automatic turning on the light. For better energy performance of this building, the control strategy for the lighting system and the operation of the shading devices in the summer should be improved to fully utilize the natural light for illumination purpose and decrease the cooling need at the same time. Please note that the observed building has no cooling devices.

Conclusions and future work

With the office building at Norway, this study conducted data-driven analysis to identify the occupancy and lighting patterns as well as the correlations between them. Through analysing the data collected by occupancy and lighting sensors, several interesting conclusions were drawn:

i) The occupancy and lighting patterns were highly correlated with each other for our study case;
ii) The occupancy and lighting showed different patterns on Monday and Friday in comparison with Tuesday to Friday;
iii) Further opportunities still exist to improve the energy efficiency of the lighting system, such as reducing the delayed time interval after occupants leave the office and utilizing nature light for illumination purpose in summer without increasing the cooling needs.

The analytical results of occupancy and lighting could also be used to build accurate building energy performance models.

For the future, it is necessary to use data-driven analysis to identify the energy usage patterns of the other sub-sectors, such as ventilation and space heating system. It is also important to investigate further energy-saving opportunities for this office building to improve the energy management strategies accordingly, and to verify the analytical results with practical experiments. ■

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