

# Data-driven analysis of electricity use for office buildings: a Norwegian case study

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**Abstract.** Buildings are major consumers of primary energy and main contributors to carbon emission. To improve energy efficiency, it is essential to understand the characteristics of energy use in buildings. This study uses an in-use office building with digital systems for monitoring and control in Trondheim, Norway, as the study case. Based on data collected from this office building, a data-driven analysis was conducted to capture the characteristics of electricity use of different parts in the office building. The approaches used in this study included statistical analysis and polynomial regression. The impact of occupancy level on the total electricity use, the electricity use in office areas, and that in corridors & meeting rooms was also studied. The hourly electricity use profiles were obtained for ventilation fans and the cantina. In the end, the electricity use characteristics and existing issues in this office building were discussed.

## 1 Introduction

In 2018, the European Commission developed a long-term strategic vision for a prosperous, modern, competitive, and climate-neutral economy by 2050 [1]. Being responsible for approximately 40% of the total primary energy use in the EU and over 30% of the greenhouse gas emission, buildings are major participants to reduce energy demands and achieving the carbon-neutral target [2]. As a result, it is essential to improve the energy efficiency of buildings.

Depending on the type of services, buildings are generally categorized into two classes, namely residential buildings and non-residential buildings. It has been reported that the energy use per square meter is averagely 40% higher in non-residential buildings than that in residential buildings [3]. For energy management in non-residential buildings, data-driven approaches have attracted significant attention due to the rapid development of Internet-of-Things (IoT), big data, artificial intelligence, etc. Among the wide adoption of data-driven approaches in office buildings, they mainly focus on building energy prediction and energy optimization/ control.

For energy prediction in office buildings, [4], [5] have evaluated the effect of input variables on the accuracy of cooling and heating load forecast for an office building with data-driven approaches, such as clustering, Artificial Neural Network, Principle Component Analysis. [6] has presented a data-driven approach to predict electricity use in an office using a feed-forward neural network and extreme learning machine. [7] has suggested a vector field-based support vector regression scheme to predict the building energy

use of a large office building. Meanwhile, regarding energy optimization, [8] has introduced a model predictive control strategy to optimize the energy use of floor heating and cooling systems based on data collected from an actual office building. [9] has proposed a cooperative energy management scheme between buildings and districts with data-driven and multistage stochastic optimization.

Besides data-driven energy prediction and optimization as mentioned above, it is also helpful to capture the basic and unique characteristics of an office building to optimize its energy use accordingly [10], [11]. However, the features of energy use can be diverse due to various energy facilities, building services, location, occupancy patterns, etc. In this study, an in-use Norwegian office building has been chosen for the study case. With statistical analysis and polynomial regression, the electricity use for office equipment, heat pump, ventilation, etc., were studied. The impacts of occupancy level on electricity use were also addressed. The hourly electricity use profiles were obtained for ventilation fans and the cantina. Finally, discussions were conducted on the characteristics of electricity use in this office building, and this study was concluded.

The rest of this paper is organized as follows: Section 2 provides insight into the office building and the data collected from the building energy management system. Section 3 introduces the methods used for data analysis, namely statistical analysis and polynomial regression. Section 4 offers the detail on electricity use characteristics in this office building. Finally, Section 5 discusses the energy use patterns and energy saving potentials, and Section 6 concludes this study.

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## 2 Insights into the study case and data set

### 2.1 Description of the office building

In this study, an office building located in Trondheim, Norway, is used as the study case. This building consists of one underground floor for parking, several rooms on the roof for building facilities, and four floors for offices, meeting rooms, and one cantina. Figure 1 shows the appeal of this office building. In this building, the office area is divided into four zones for analyzing heating, ventilation, and air conditioning (HVAC) as shown in Figure 2.

The building heat energy supply system is arranged with an air-to-water heat pump (HP) and district heating (DH) network. The HP has a nominal heating capacity of 281 kW and serves to cover baseload. DH is used for covering peak load and supplying domestic hot water.

The heating or cooling energy is distributed to each office room through the HVAC system with the ventilation air as the carrier, and an air handling unit is installed in each office zone with an airflow of 16 000 m<sup>3</sup>/h at rated conditions. The ventilation systems are variable air volume (VAV) systems controlled with a demand-based policy based on occupancy level and environmental conditions.

The lighting system is also controlled with an on-demand policy based on the output of occupant detection sensors.



Figure 1. Illustration of building body.

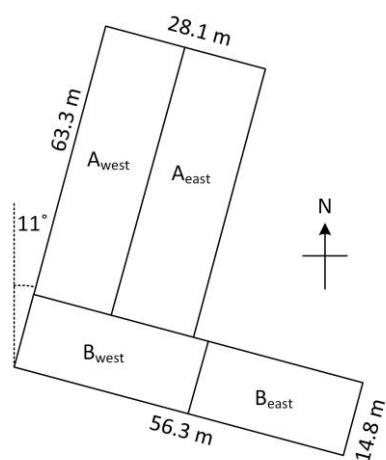


Figure 2. Building orientation and office zones.

### 2.2 Data set for analysis

In this building, many sensors and actuators have been installed at the office level to monitor the building environment, maintain comfortableness, and manage energy use. The monitored parameters include occupancy, lighting, indoor/outdoor temperature, flow rate, energy use, etc. For all parameters, the sampling rate is configured as four packets per hour, leading to 96 samples per day and nearly 3 000 samples per month for each sensor. The monitored data from sensors is used to build the data set to analyze the electricity use characteristics in this office building.

## 3 Methodology

### 3.1 Descriptive statistics

Descriptive statistics refers to the methods of summarizing data samples with indexes like mean, standard deviation, median, distribution function, etc. These methods are efficient to capture the key features of given data set and are easy to use for researchers or engineers of all levels. In this study, descriptive statistics are used to obtain electricity use profiles of different parts in the office building.

### 3.2 Polynomial regression

Polynomial regression is a method to retrieve the relationship of two or more variables based on given data set. Taking the simplest version, unary polynomial regression, as an example, it is used to find the relationship of two variables,  $x$  and  $y$ , into Eq. (1).

$$y = a_0 + a_1x + a_2x^2 + \dots + a_nx^n \quad (1)$$

where  $a_0, \dots, a_n$  are the parameters to be identified and  $n$  is the maximum degree of polynomials. In this study, polynomial regression is applied to identify the numeric relationship between electricity use and occupancy level in different parts of this office building.

## 4 Data-driven analysis and results

### 4.1 Total electricity use

The impact of occupancy on total electricity use in the office building is investigated as shown in Figure 3. Overall, the total electricity use increases linearly with the increasing occupancy level. As a result, linear regression is adopted to fit the measured data of hourly electricity use in the office building. The relationship between hourly electricity use and the occupancy level has been modelled. It is found that an average of 80 kWh electrical energy is used with a maximum of 175 kWh, even if the occupancy level is zero. Special attention should be put on this area to identify further energy-saving opportunities for improved energy efficiency in the office building.

Based on the electricity meters installed in the office building, the electricity use of subsystems in the office building has also been investigated as shown in Figure 4. Overall, main office areas account for over 42.45% of the total electricity use. Heat pump and heating plant jointly use over 18% of the total electricity. Another 7.28% of the electricity is used for ventilation purposes. The cantina, basement, and corridors & meeting rooms use 9.46%, 8.94%, and 5.23% of total electricity, respectively. It is noted that 8.56% of the electricity has been used for other purposes and has not been monitored effectively. Here-in-after, the electricity use characteristics of different parts in the office building are investigated.

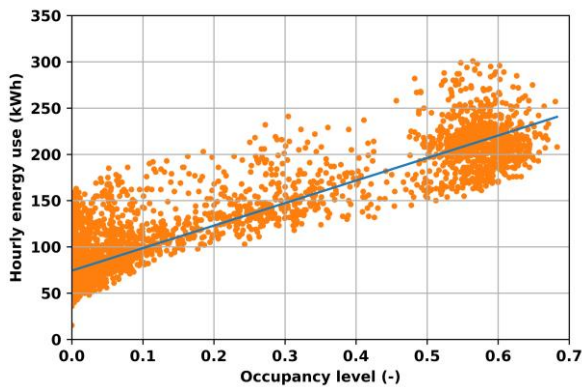


Figure 3. Total electricity use against occupancy level.

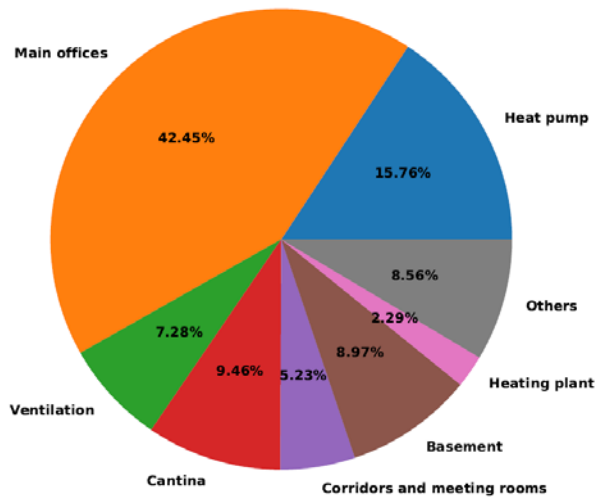
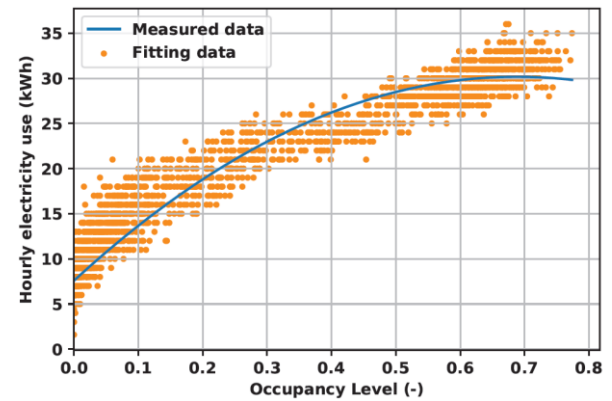


Figure 4. Electricity use of different parts in the office building.

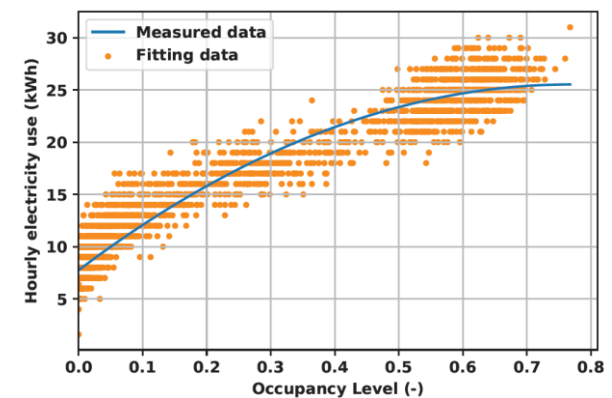
#### 4.2 Electricity use in office areas

In office areas, electricity is used to support office equipment and lighting. As a result, occupancy level is the dominant factor to impact the electricity use in offices as illustrated by Figure 5, showing hourly electricity uses of office zones against occupancy level. As the electricity uses in Zones  $B_{west}$  and  $B_{east}$  are jointly measured in this office building, the relationship of electricity use and occupancy level is revealed by Figure

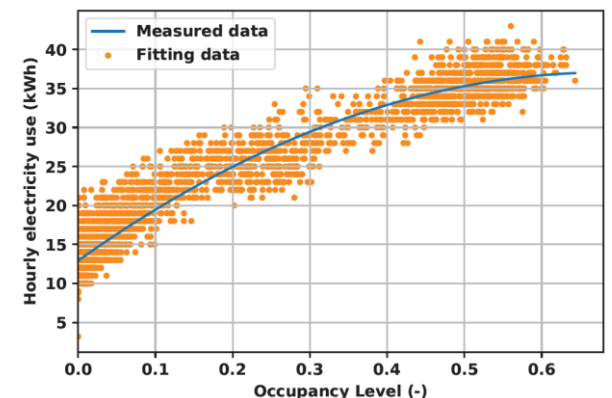
5(c). Based on the measured electricity use and occupancy level of office zones, it is found that polynomial regression with a degree of two fits the measured data quite well for all the zones as shown by Figure 5. For each office area, there is a minimum of hourly electricity use even if the occupancy level is zero or very low, namely, 7.6 kWh for Zone  $A_{west}$ , 7.75 kWh for Zone  $A_{east}$ , and 12.93 kWh for Zones  $B_{west}$  and  $B_{east}$ , leading to potential energy-saving opportunities. Besides, increasing the occupancy level of an office area indeed leads to better efficient electricity use.



(a) Zone  $A_{west}$



(b) Zone  $A_{east}$



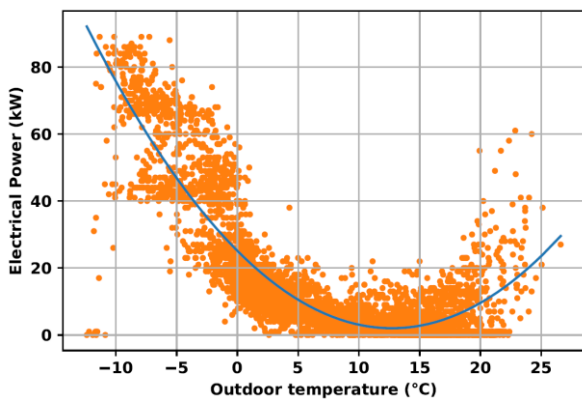
(c) Zones  $B_{west}$  and  $B_{east}$

Figure 5. Electricity use of office equipment against occupancy level.

#### 4.3 Electricity use of heat pump

The electricity use of the heat pump is shown in Figure 6. Different from that in office areas, the

occupancy level of the office building has a limited impact on the electricity use of the heat pump. Whereas, the hourly electricity use of heat pump is significantly impacted by outdoor temperature. To fit the measured electricity use and outdoor temperature, polynomial regression with a degree of two is adopted. When the outdoor temperature is lower than  $-10\text{ }^{\circ}\text{C}$ , a control policy has been implemented to stop the heat pump from operating, preventing inefficient electricity use for heating or cooling purposes. Further analysis on COP of heat pump has been conducted. It mainly falls in the range of 2 to 4 for heating purposes and is in the range of 2 to 3 for cooling purposes.



**Figure 6.** Electricity use of heat pump against outdoor temperature

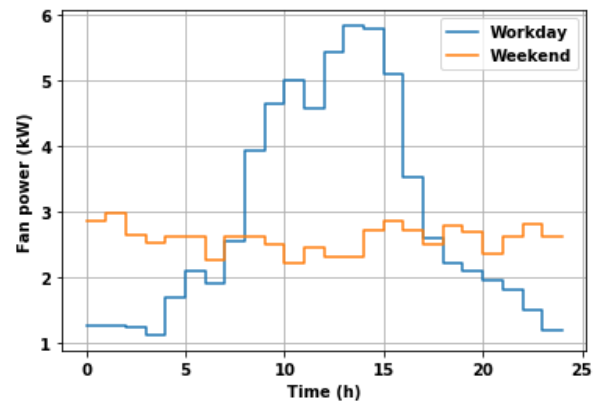
#### 4.4 Electricity use of ventilation fans

The hourly electricity use profile of ventilation fans in each zone is depicted respectively for workdays and weekends, as shown in Figure 7. The hourly electricity use profiles of ventilation fans differ significantly on workdays and weekends.

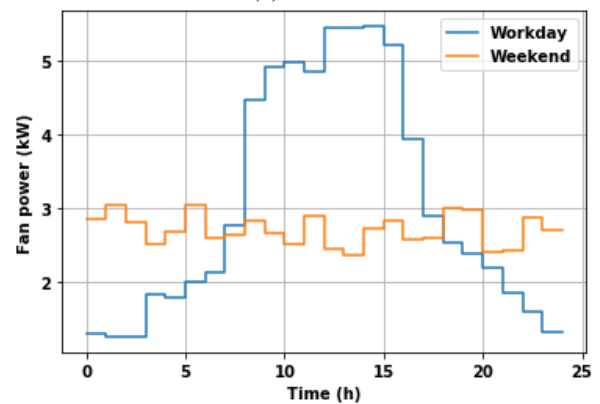
On workdays, the electricity use is high during work hours for all the four zones, namely 4-6 kW for Zone  $A_{west}$ , 4-5.5 kW for Zone  $A_{east}$ , 1.8-2.5 kW for Zone  $B_{west}$ , and 3-4.5 kW for Zone  $B_{east}$ . Whereas, for off-work hours, the electricity use in each zone is much lower than that in work hours. The reason is that the temperature setpoint in off-work hours differs from that in work hours. In winter, a lower temperature setpoint is applied in off-work hours than that in work hours, and a higher temperature setpoint is applied in off-work hours than that in work hours in summer. Therefore, less heating/cooling energy is required for off-work hours than work hours. The temperature setpoints in off-work hours are satisfied by thermal inertia. However, on weekends, the electricity use of ventilation fans is relatively stable, compared to that in work hours on workdays. Since the temperature setpoint cannot be satisfied with thermal inertia during weekends, the supply of heating/cooling energy into the office area is required from 0:00 to 5:00 and from 20:00 to 24:00.

Another observation is that the electricity use of ventilations fans in Zone  $B_{west}$  is only half of the electricity use in Zones  $A_{west}$  and  $A_{east}$ , and that in Zone  $B_{east}$  is also much less. However, these four zones are installed with the same ventilation equipment,

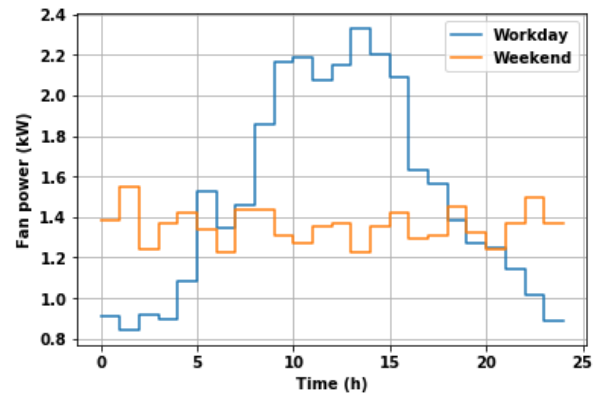
indicating improper equipment sizing, especially for Zone  $B_{west}$ .



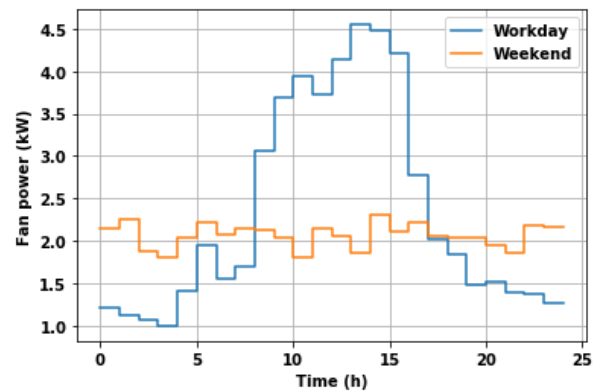
(a) Zone  $A_{west}$



(b) Zone  $A_{east}$



(c) Zone  $B_{west}$



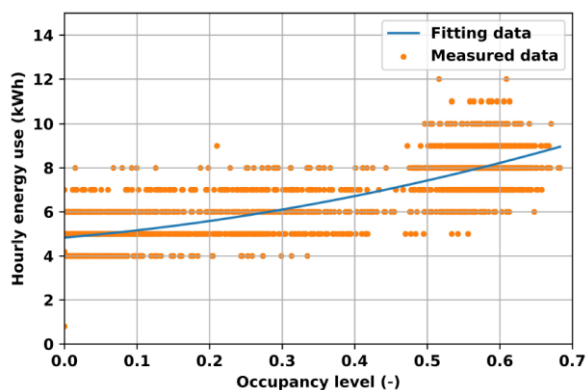
(d) Zone  $B_{east}$

**Figure 7.** Electricity use of ventilation fans against occupancy level.



#### 4.5 Electricity use of corridors and meeting rooms

Fig. 8 shows the electricity use of corridors and meeting rooms against occupancy level. Here, polynomial regression with a degree of two is used to fit the data. Overall, the electricity use in corridors and meeting rooms increases with the occupancy level of the office building. However, an average of 4.83 kWh electricity is used when the occupancy level of the office building is zero or very low. Further research needs to be conducted to analyze if potential energy-saving opportunities exist in this area. The hourly electricity use increases to 9 kWh when the overall occupancy level reaches 0.7.



**Figure 8.** Electricity use of corridors and meeting rooms against occupancy level.

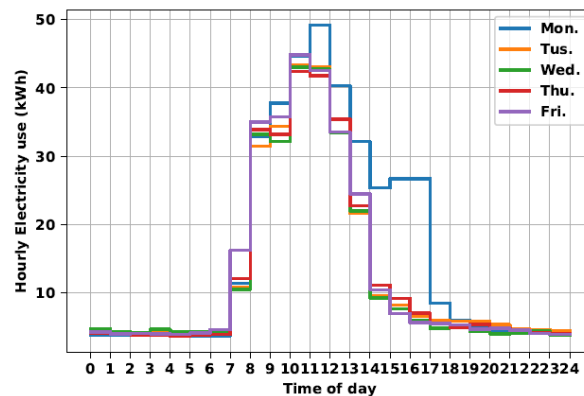
#### 4.6 Electricity use of cantina

The electricity use in the cantina is given in Fig. 9. In this study, the occupancy level is estimated with sensors deployed in offices, it cannot be used to represent the occupancy status in the cantina. Instead, the daily schedule of electricity use in cantina has been studied for regular working days. Generally, the electricity use in cantina increases from 7:00 a.m. with a considerable increase at 8:00 a.m., and reaches the peak during 10:00 a.m. - 12:00 p.m., after which it drops consecutively. One interesting finding is that the hourly electricity use of cantina on Tuesday to Friday drops to 10 kWh at 14:00, but that on Monday keeps a high electricity use around 27 kWh until 17:00. This difference between Monday and the other regular working days needs to be taken into consideration for energy planning. Besides, a minimum level of 4 kWh electricity is used hourly during the off-work time.

### 5 Discussion

This study conducts a data-driven analysis of the electricity use based on data collected from an in-use office building. Based on the analytical results, several issues need to be discussed further.

The first issue that we would like to discuss is the electricity use when the occupancy level is very low. From Figures 3, 5, and 8, it can be found that there is



**Figure 9.** Electricity use of cantina.

still considerable energy use when the occupancy level is nearly zero. For instance, the hourly total electricity use when the occupancy level is near zero is roughly one-third of that when the occupancy level reaches 0.6. This is also found for the electricity use in the office area. It is questionable if it is really necessary to use so much amount of electricity when the occupancy level is low. There is high chance that energy-saving potentials can be identified in this area. To be confident if there are any energy-saving potentials in this area, further research work is required to analyze how electricity is used when the occupancy level is low. It is also helpful to develop technical guidelines or solutions for energy management in buildings when the occupancy level is low.

The second issue that we would like to talk about is the energy monitoring data collected from the office building. In Figures 5 and 8, it can be found that the energy monitoring data collected from this office building are integer values, which are not accurate enough for deeper and accurate analysis. It is also one reason why the energy values are scattered significantly around the fitting line. However, increasing the accuracy of energy sensors certainly causes further investment. It is necessary to evaluate the potential benefit and pay-back time to update these facilities.

### 6 Conclusions

Based on the data collected from an in-use office building in Trondheim, Norway, this study conducts data-driven analysis to identify its energy use characteristics. It has been found that occupancy level has a significant impact on the total electricity use, the electricity use in the office area, the electricity use in corridors & meeting rooms. It has also been found that the electricity use of the heat pump is mainly impacted by the outdoor temperature. As for the ventilation, although a demand-based policy has been implemented to operate ventilation fans. Due to different temperature setpoints for work hours and off-work hours, a significant difference is detected for workdays and weekends. It is also questionable to install the same equipment for all the ventilation zones, especially for Zone  $B_{west}$ , in which the electricity use is only half of that in Zones  $A_{west}$  and  $A_{east}$ . In addition, the electricity use in the cantina on Monday is different from the other

workdays with much higher electricity use until 17:00, which should be considered for future energy management.

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## References

- [1] P. O. of the E. Union, "Going climate-neutral by 2050 : a strategic long-term vision for a prosperous, modern, competitive and climate-neutral EU economy.," Jul. 16, 2019.  
<http://op.europa.eu/en/publication-detail/-/publication/92f6d5bc-76bc-11e9-9f05-01aa75ed71a1> (accessed Feb. 01, 2021).
- [2] X. Cao, X. Dai, and J. Liu, "Building energy-consumption status worldwide and the state-of-the-art technologies for zero-energy buildings during the past decade," *Energy Build.*, vol. 128, pp. 198–213, Sep. 2016, doi: 10.1016/j.enbuild.2016.06.089.
- [3] P. Bertoldi, "GreenBuilding: Enhanced Energy Efficiency for Non-residential Buildings," *EU Science Hub - European Commission*, Jul. 30, 2012.  
<https://ec.europa.eu/jrc/en/publication/thematic-reports/greenbuilding-enhanced-energy-efficiency-non-residential-buildings> (accessed Feb. 01, 2021).
- [4] Y. Ding, Q. Zhang, T. Yuan, and F. Yang, "Effect of input variables on cooling load prediction accuracy of an office building," *Appl. Therm. Eng.*, vol. 128, pp. 225–234, Jan. 2018, doi: 10.1016/j.applthermaleng.2017.09.007.
- [5] Y. Ding, Q. Zhang, T. Yuan, and K. Yang, "Model input selection for building heating load prediction: A case study for an office building in Tianjin," *Energy Build.*, vol. 159, pp. 254–270, Jan. 2018, doi: 10.1016/j.enbuild.2017.11.002.
- [6] Y. Wei *et al.*, "Prediction of occupancy level and energy consumption in office building using blind system identification and neural networks," *Appl. Energy*, vol. 240, pp. 276–294, Apr. 2019, doi: 10.1016/j.apenergy.2019.02.056.
- [7] H. Zhong, J. Wang, H. Jia, Y. Mu, and S. Lv, "Vector field-based support vector regression for building energy consumption prediction," *Appl. Energy*, vol. 242, pp. 403–414, May 2019.
- [8] J. Joe and P. Karava, "A model predictive control strategy to optimize the performance of radiant floor heating and cooling systems in office buildings," *Appl. Energy*, vol. 245, pp. 65–77, Jul. 2019.
- [9] G. Darivianakis, A. Georghiou, R. S. Smith, and J. Lygeros, "The Power of Diversity: Data-Driven Robust Predictive Control for Energy Efficient Buildings and Districts," *ArXiv160705441 Cs Math*, Jul. 2016, Accessed: Feb. 01, 2021.  
[Online]. Available: <http://arxiv.org/abs/1607.05441>.
- [10] K. Sun, T. Hong, S. C. Taylor-Lange, and M. A. Piette, "A pattern-based automated approach to building energy model calibration," *Appl. Energy*, vol. 165, pp. 214–224, Mar. 2016.
- [11] Y. Zhang, X. Bai, F. P. Mills, and J. C. V. Pezzey, "Rethinking the role of occupant behavior in building energy performance: A review," *Energy Build.*, vol. 172, pp. 279–294, Aug. 2018.