Study on occupancy presence and heat use in a Norwegian office building

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Abstract. Energy management in buildings is facing a great challenge in Norway due to the COVID-19 pandemic. The largest difference between the pre-pandemic and post-pandemic period is the occupancy pattern in non-residential buildings. However, existing research only discussed the energy use change by longitudinal analysis, and no related research has been conducted based on the measured occupancy data in the post-pandemic period. Therefore, to fill this research gap, a case study with an office building in Trondheim, Norway, was conducted in our work to compare occupancy presence, heat use, and their relationship before and after the pandemic by using data-driven methods. For occupancy presence, on the one hand, occupants' presence rate was lower during the post-pandemic period compared with during the pre-pandemic period; on the other hand, occupants' absence rate in the lunchtime was decreased during the post-pandemic period compared with during the pre-pandemic period. In addition, two typical occupancy presence patterns in workdays were given in our study, the normal-working day pattern and half-working day pattern. The half-working day occupancy pattern appeared when Norway faced the second wave pandemic and the government implements more restrictive measures. In terms of heat use, the heat use increased markedly in the post-pandemic period, with the largest gap in hourly heat use between pre-pandemic and post-pandemic on workdays increasing around 21%, and increasing around 31% on holidays. The minimum daily heat demand of this building during the post-pandemic period was much higher than that in the pre-pandemic period, with increasing around 46% (on workdays and increasing around 86% on holidays. Regarding to their relationship, a more significant correlation between the daily heat use and the daily maximum occupancy rate during the post-pandemic period was observed compared with that during the pre-pandemic period. This study indicates that the operation of the heating system of the case building may be inefficient in the post-pandemic period, and findings of this study could help engineers to optimize the operation mode of the heating system according to the change of occupancy pattern and achieve better energy-efficiency management in the post-pandemic period for similar type of building.

Keywords. Occupancy, Heat use, Data-driven, COVID-19 pandemic.
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1. Introduction

At the March of 2020, the World Health Organization declared that Coronavirus disease-19 (COVID-19) became a global pandemic [1]. To prevent virus spreading, many restrictions were taken by governments from all over the world. City lockdown, keeping social distance, and working at home were basic measures to prevent people from gathering and slow down the spread of COVID-19. Occupancy pattern is one of the most significant factors that affect energy demand of buildings [2–5]. Such restrictions caused by COVID-19 had a great effect on occupants' life habits and potentially affected energy demand of buildings due to the fact that working remotely would decrease occupancy presence in non-residential buildings, while occupants spent more time at their home.

Building energy demand change related to COVID-19 is a new challenge in building energy management area and many publications discussed this issue. Some researchers focused on city-level electricity usage changes related to COVID-19. Investigation in [6] summarized the impact of pandemic on the power system all over the world and presented that power demand in many countries was reduced by around 8%~30% during the pandemic. A study that investigated electricity use among several European countries, showed that, in post-pandemic period, electricity use in countries (Spain, Italy, Belgium, and the UK) with severe restrictions was noticeably reduced, and their electricity usage pattern in weekdays presented similar profiles with weekend profiles in pre-pandemic period. However, lower decrease in electricity use was observed in countries with less restrictive measures, like Netherlands and Sweden [7]. Some researchers concentrated on the longitudinal comparison of energy use in residential buildings before and after the pandemic. For example, Rouleau and Gosselin [8] investigated the energy use difference before and after the lockdown in the Canadian social housing building, revealing that the electricity and hot water use increased obviously at the beginning of the city lockdown, and there was no evident change in space heating use during the lockdown period. Some researchers also conducted analysis only in non-residential buildings. For example, Geraldi et.al [9] conducted an analysis to explore the impact of the city lockdown on the electricity use in municipal buildings in Florianópolis, Brazil. Ivanko et.al [10] investigated how the city lockdown affected the heat use in Norwegian educational buildings. Ding et.al [11] analyzed how the city lockdown influenced the electricity use in Norwegians' educational buildings and residential buildings and discussed the energy saving potential in educational building by changing operation mode during the lockdown period.

Although the energy demand was declined in most countries during the pandemic period [12], the COVID-19 also adds many uncertainties for energy efficiency [13]. Improving the building energy efficiency in the post-pandemic period is a great challenge [14] and it varies on building type[11, 15]. However, on the one hand, the analysis of the pandemic impact on the energy use in office building is less. On the other hand, in the office building, one of the major differences between the pre-pandemic and post-pandemic period is the occupancy pattern due to the increasing trend of remote work, and as is well known that occupancy is also one of the most significant factors that affect building energy demand [2–5]. However, no related research has been conducted to investigate the difference in occupancy pattern of office building and how it influences on the energy use.

To fill the research gap, this study would focus on the impact of COVID-19 pandemic on occupancy pattern and heat use of an office building in Norway. An energy efficiency passive office building in Norway was conducted as the case study. The purposes of this study are composed of three parts:

1) Compare the occupancy pattern of this building in pre-pandemic period and post-pandemic period.

2) Compare the heat use of this building in pre-pandemic period and post-pandemic period.

3) Compare the relationship between the occupancy and heat use in pre-pandemic period and post-pandemic period.

2. Case introduction

2.1 Description of the case building

An office building located in Trondheim, Norway, was investigated in this study. Some details about this building are introduced as follows. The appearance of this building is shown in **Fig.1**. The building is composed of six floors. There are two floors underground, one of which is a parking area at the lowest floor, and another of which is used for cafeteria, office room, meeting rooms, and partially for the parking area. The other four floors above ground are composed of a mixture of meeting rooms, single-celled offices, miscellaneous rooms, and open-landscape working areas. The ventilation system in this building is a variable air volume (VAV) system. The heating ventilation system mode would adjust automatically according to the occupancy registered.

Fig. 1 - Body of this office building.

The thermal performance parameters of this building are summarized in **Tab 1**. The building was designed according to the Norwegian building code TEK17 [16]. The building code TEK17 is similar to the passive house standard. Although the parameters of the envelope of this building do not totally reach the passive house standard, it could be approximately seen as a passive building.

The heat demand of this building is caused by space heating (SH) and domestic hot water (DHW). An air-to-water heat pump with the rated heating capacity of 281 kW supplies the base heat demand for heating. The building is also connected to the district heating (DH) system, which offers the heat demand for the peak load demand. The heat pump would be turned off when the outdoor temperature is less than -10°C, and the SH heat demand in this building would be totally covered by the DH system.

Tab. 1-Parameters of building envelope.

	U-value (W/m²·K)
Outer wall	0.18
Inner wall	0.15
Ground floor	0.13
Roof	0.13
Windows	0.8

2.2 Data collection

Building management system (BMS), including the indoor environment monitoring and energy monitoring system, is used in this building. Monitoring data can be acquired from this system. There are many sensors installed in this building to sample parameters including occupancy state, indoor and outdoor air temperature, energy use, etc. The sample interval of sensors in this building was 15 minutes. Occupancy data are key parameters used for analysis in this study. Regarding the occupancy sensors in this building, only the occupancy state within an area can be obtained, meaning that 0 or 1 would be recorded to represent whether an area is occupied by occupants, while occupant counts can't be known. To define the approximate occupancy level in this building, the hourly occupancy rate was calculated by dividing the sum of the occupancy status of all sensors in one hour by the total number of records of the occupancy status of all sensors in this hour.

2.3 Dataset selection and description used for this study

In our study, due to the limitation of data storage in the BMS system, the monitoring data in the BMS system can be only saved for a limited period, resulting in that the downloaded data didn't cover the whole year, leading that the data in the pre-pandemic period and post-pandemic period was not united in date. Therefore, different time period monitoring data was applied in different research purposes. For the first purpose, the comparison of occupancy pattern, data from January 1st to October 21st in 2019, from May 21st in 2020 to March 29th in 2021, was used for pre-pandemic period and post-pandemic period, respectively. For the second and third purpose, the comparison of heat use and the relationship between occupancy and heat use, considering that the heat use is influenced by the outdoor temperature, to eliminate the effects of the outdoor temperature on heat use profiles as much as possible, those days with their daily average outdoor temperature from -10 to 6°C during the same period (January 1st to March 27th) in 2019 and 2021, was chosen for the heat use comparison analysis. Finally, the data description for different research purposes is summarized in **Tab. 2**.

Tab.2- Dataset description for different research purposes.

	Research purpose	Data recording period	Number of days recorded in database	Number of hours recorded in database
pre-pandemic period	Comparison of occupancy pattern	January 1st to October 21st in 2019	294	7056
	Comparison of heat use and the relationship between occupancy and heat use	January 1st to March 27th in 2019	85	2040
post-pandemic period	Comparison of occupancy pattern	May 21st in 2020 to March 29th in 2021	313	7512
	Comparison of heat use and the relationship between occupancy and heat use	January 1st to March 27th in 2021	66	1584

3. Methodology and results

Next, a series of data-driven methods would be applied to achieve our research aims.

3.1 Comparison analysis of occupancy pattern

In this section, firstly, basic statistical analysis would be taken to explore the occupancy presence distribution difference in the pre-pandemic period and post-pandemic period. Then, clustering would be used for identifying typical occupancy patterns in these two periods and compare the clustering results.

Fig.2 shows that the distribution of daily maximum occupancy rate of workday both in the pre-pandemic and post-pandemic period. In order to obtain the most obvious impact of the pandemic on the occupancy pattern, the occupancy data of workdays was only used for this comparison analysis. As circled in red of **Fig.2**, in the post-pandemic period, a bimodal distribution was observed for the daily maximum occupancy rate, while that in the pre-pandemic presents a unimodal distribution. The most frequent values of the daily maximum occupancy rate in the pre-pandemic period was from 0.6 to 0.7, while the most possible daily maximum occupancy rate in the post- pandemic period decreased to the range of 0.5 to 0.6, as can be noted in **Fig. 2**. Besides the most frequent daily maximum occupancy rate from 0.5 to 0.6, the daily maximum hourly occupancy rate from 0.25 to 0.30 also occurred frequently in the post- pandemic period, which indicated that there might be existed some particular occupancy scenarios in the post-pandemic period. Differences in the occurrence time point of the daily maximum hour occupancy rate could also be observed, as is shown in **Fig.3**. The most frequent time of the maximum occupancy rate of a day in the post-pandemic period was around 10 am to 11 am and 12 pm to 1 pm, while it was 1 pm to 2 pm in the pre-pandemic period. These observed differences in occupancy could give some references for the optimization of the operation mode in this building in the post-pandemic period.

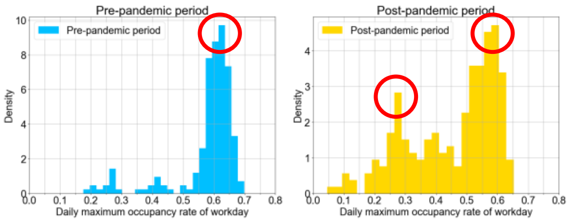


Fig. 2 - The distribution of daily maximum occupancy rate of workday in the pre-pandemic and post-pandemic period.

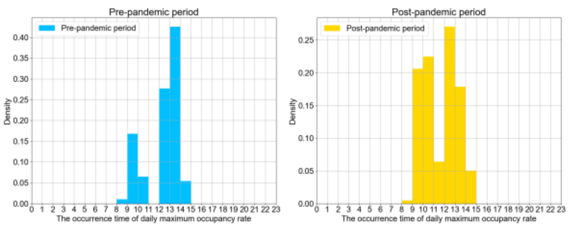


Fig. 3 - The distribution of the occurrence time point of the daily maximum occupancy rate for workday in the pre-pandemic and post-pandemic period.

To obtain the typical occupancy pattern, the fuzzy c-means was used in this study, which is considered as a best clustering method for occupancy pattern[17]. The Davies–Bouldin index (DBI) [18], a metric for evaluating clustering performance, was used to select the best cluster number for clustering. The smaller the DBI value, the better the clustering performance. From the results of DBI index, two was the best cluster number both for the pre-pandemic and the post-pandemic data set. Clustering results are shown in **Fig.4**. It can be seen that, no matter in the pre-pandemic or post-pandemic period, the two typical patterns of working days were identified. Pattern 1 was a normal-working day that accounted for the most of the days, accounting for 88% (178 of 202) in the pre-pandemic period and 64% (140 of 218) in the post-pandemic period of all investigated working days. Pattern 2 was the half-working day pattern when overall occupancy level was only about 50% of the normal-working day.

The differences of the typical occupancy patterns between the pre-pandemic and post-pandemic period could be explained from three aspects, as shown in **Fig.4**. Firstly, we could see that the occupied percentage for the half-working day pattern in the post-pandemic period was higher than that in the pre-pandemic period, from 12% increasing to 36%. Another difference was that the occupancy level was decreased in the post-pandemic period. For the normal-working day pattern, the occupancy rate decreased from 0.60 to 0.55, for the half-working day pattern, the occupancy rate decreased from 0.3 to 0.25. Lastly, occupants' absence rate in the lunch time was decreased during the post-pandemic period, no matter of the normal-working pattern or the half-working day pattern. This might be due to occupants' life habit change in the post-pandemic period, such as they did not tend to go to the common canteen to have lunch or there were rules which group of occupants could go to the common canteen to reduce the infection risk of COVID-19.

To observe the distribution of typical occupancy patterns on the timeline more clearly, we displayed the occupancy patterns distribution on the calendar, as shown in **Fig.5**. The calendar for 2019 presented the typical occupancy pattern distribution at the time axis in the pre-pandemic period. The calendar for 2020 and 2021 presented the typical occupancy pattern distribution in the post pandemic period. Due to the limitation of data access, we could not get the whole year data, so only a part of the year was presented. In this calendar, 0 presents the holiday occupancy pattern, 1 presents the normal-working day pattern, and 2 presents the half-working day pattern.

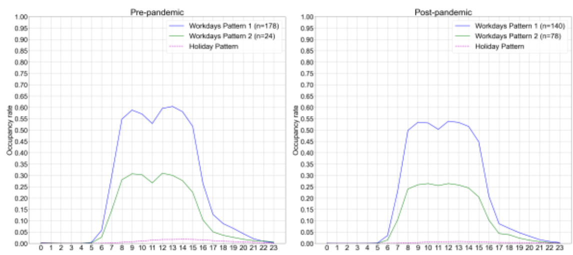
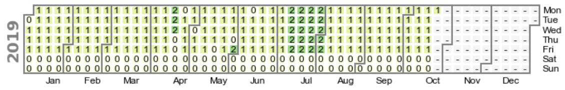
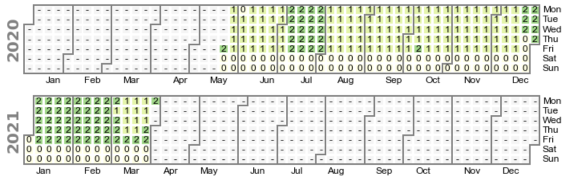


Fig. 4 - Clustering results of typical occupancy patterns in the pre-pandemic and post-pandemic period (The number in the bracket is the number of days belong to the pattern).



(a) In the pre-pandemic period



(b) In the post-pandemic period

Fig. 5 - The occupancy patterns' distribution in the pre-pandemic and post-pandemic period.

From the **Fig.4** and **Fig.5**, it can be seen that, the half-working day pattern would occur at three scenarios: 1) on Fridays; 2) on the days before a long national holiday such as the Easter; 3) in July, when many people take their annual vacation in Norway. However, in the post-pandemic period, we could see that, not only in previous mentioned scenarios, the half-working day would also occur in days at January, February, and some days on March in 2021, which might be due to the fact that Norway faced the second wave pandemic and the government implemented restrictive measures during that that days. Further, the results in **Figs. 4 and Figs. 5** could indicate that, when the pandemic rebounded, the occupancy presence pattern would show the half-working day occupancy pattern as it showed in July in the normal year.

3.2 Comparison analysis of heat use

In this section, we would take a comparison analysis of the heat use. Firstly, we would use the linear regression model to compare the relationship between the heat use and outdoor temperature in the pre-pandemic period and post-pandemic period. And then, the daily heat use profile in these two periods would be compared.

Due to the cold climate in Norway, the energy use for space heating and domestic hot water represents the main part of the total energy use. Accordingly, the outdoor temperature may be regarded as the key factor determining the heat demand. Therefore, this section would explore how the pandemic influences the relationship between heat use and outdoor temperature. To convince that our comparison analysis was conducted in a similar outdoor temperature distribution, before the comparison analysis, according to the research method in a similar analysis[19], the Kruskal-Wallis H-test [20] was used to test whether the distribution of the outdoor temperature before and after the pandemic was the same, showing that there were no statistically significant differences in the outdoor temperature distribution in these two data sets used for the comparison analysis. And then, we started to process the comparison analysis. First, the scatter plot of the daily heat use versus the daily outdoor temperature is shown in **Fig.6**. In **Fig. 6**, the daily heat use was the sum value of hourly heat use for 24 hours of a day, while the daily average outdoor temperature was the average value of hourly outdoor temperature for 24 hours of a day. The linear regression was used to describe the relationship between the daily heat use and the average outdoor temperature. In **Fig. 6**, it is possible to note that the linear relationship in the post-pandemic period was less steep than that in the pre-pandemic period, no matter on workdays or on holidays. However, the R^2 value was decreased more in holidays compared that in workdays. From this linear regression models in **Fig. 6**, it is also possible to note that when the outdoor temperature was above -4°C, the heat use in the post-pandemic period was higher than that in the pre-pandemic period.

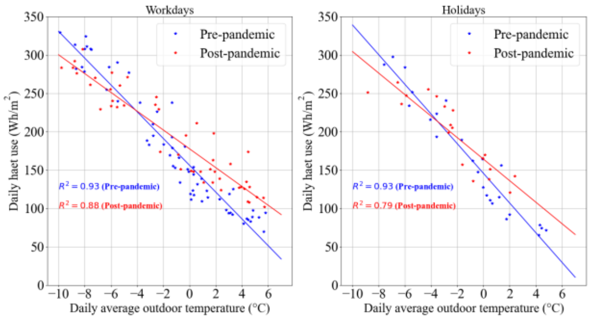


Fig. 6 - The relationship between daily heat use and daily outdoor temperature in the pre-pandemic and post-pandemic period.

The daily heat use profiles (24-dimensional curve) in the pre-pandemic and post-pandemic period are shown in **Fig.7**. Hourly heat use in the daily profile was the average value of the corresponding hourly value in all investigated days, as calculated as **Eq.(1)**, in which $HHU_{av,j}$ ($j \in [0,23]$) represents the daily average value in the daily profile, and i represents i^{th} day, and n represents the total number of investigated days.

$$HHU_{av,j} = \frac{\sum_{i=1}^{n} HHU_{i,j}}{n} \quad (1)$$

It can be observed that, on holidays, the daily heat use profile curve was higher in the post-pandemic period than that in the pre-pandemic period. On workdays, in most of hours, the hourly heat use is higher in the post-pandemic when compared with that in the pre-pandemic; however, in some particular hours, the hourly heat use is a little lower in the post-pandemic period than that in the pre-pandemic period, like the 2pm and 4am. Besides, the largest gap in the pre-pandemic and the post-pandemic on workdays occurred at 10 am (increasing around 21%, from 7.2 W/m² to 8.7 W/m²), and occurred at 2 am (increasing around 31%, from 7.0 W/m² to 9.1 W/m²) on holiday. Additionally, the peak demand time was also changed: on workdays, the peak load time was forward one hour during the post-pandemic period, shifted from 6 am to 5 am; on holidays, the two peak times could be seen in the post- pandemic period, 2 am and 7 am, while only one peak demand time, 6 am, can be observed in the pre-pandemic period.

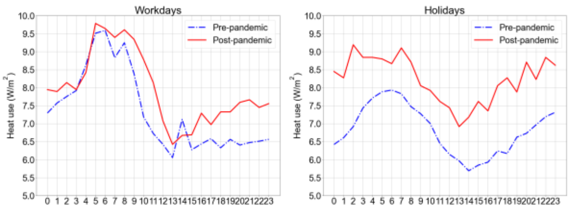


Fig. 7 - Heat use profile in the pre-pandemic and post-pandemic period.

From above analysis, we could see the heat use in the post-pandemic period seems to be higher than that in the pre-pandemic period. To explore how much the heat use increased due to the pandemic, the cumulative distribution function (CDF) curve of the daily heat use is plotted in **Fig.8**. From the curve in **Fig.8**, it can be obviously observed that the start point of the CDF curve was much higher in the post-pandemic period than in the pre-pandemic period, as summarized in **Tab.3**. The start point of the CDF could be considered as the minimum daily heat demand of this building. **Tab.3** indicates that the minimum daily heat demand was evidently increased in the post-pandemic period, especially on holidays, showing an increase of around 86%. It can be concluded from above heat use comparison analysis that, when outdoor temperature was in the similar situation, more heat use was observed in post-pandemic period than that in the pre-pandemic period, indicating that there may be inefficient operation mode in the post-pandemic period.

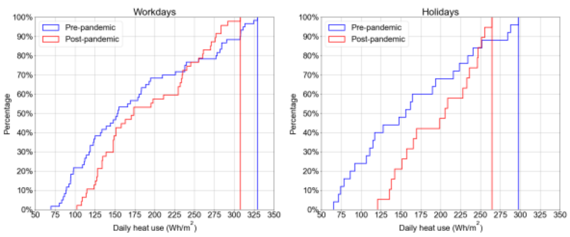


Fig. 8 - The cumulative distribution function curve of daily heat use in the pre-pandemic period and post-pandemic period.

Tab.3- Difference in the start value of CDF curve in the pre-pandemic period and the post-pandemic period.

	In the pre-pandemic (Wh/m^2)	In the post-pandemic (Wh/m^2)	Increase
Workdays	70	102	46%
Holidays	65	121	86%

3.3 Comparison of the correlation relationship of occupancy with heat use

As we addressed before, the heating ventilation system mode would adjust automatically according to the occupancy registered; also, this building is a passive building. Accordingly, the heat use may have some relevance with the occupancy rate. Therefore, in this section, we would like to explore how the pandemic has affected the relationship between the occupancy and the heat use. Firstly, the scatter plot of the daily heat use and the daily maximum occupancy rate is shown in **Fig.9**. As shown in **Fig.9**, a relatively dependence relationship between the heat use and the occupancy level could be observed (as the yellow arrow line) on workdays in the post-pandemic period. Therefore, to investigate their relationship more quantitatively, the Spearman correlation coefficient and Spearman correlation test was used to compare the relationship between the heat use and the occupancy level before and after the pandemic, as shown in **Tab.4**. The null hypothesis for the Spearman correlation test was that the two datasets were not correlated; as such, a p-value <0.05 indicated that these two datasets were correlated at a significance level of 0.05. Therefore, from the results of Spearman correlation test, a statistical significance negative correlation between the daily heat use and the daily maximum occupancy rate in the post-pandemic period was identified of the Spearman correlation coefficient of -0.63 (p-value<0.05), while their correlation relationship was not evident before the pandemic. The stronger relationship between the heat use and occupancy indicates that the inefficiency operation mode may be resulted from the occupancy pattern change in the post-pandemic period. Maybe due to the fact that the building performance is similar to the passive building, the internal heat gain of the building from the occupancy was decreased, resulting in that the increase of the heat use in the post-pandemic period was obviously, despite the outdoor temperature was similar. Above results indicate that it's an urgency to optimize the heating system operation mode to fit the occupancy pattern presented in the post-pandemic period.

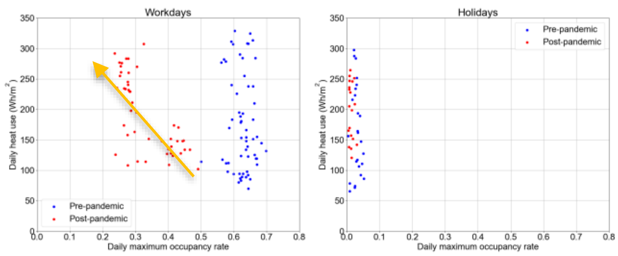


Fig. 9 - The scatter plot of daily heat use and daily maximum occupancy rate in the pre-pandemic and post-pandemic period.

Tab.4- Spearman correlation coefficient of daily heat use and daily occupancy rate on workdays in the pre-pandemic and post-pandemic period.

	Spearman correlation coefficient	p-value
In the pre-pandemic period	-0.05	0.7287
In the post-pandemic period	**-0.63**	**2.06E-06**

4. Conclusions

In this study, we applied a series of data-driven methods for the comparison analysis of the occupancy and heat use in the pre-pandemic and post-pandemic period. A passive office building located in Trondheim, Norway was taken as the case study. Firstly, the occupancy pattern in these two periods was compared. Then, the heat use in these two periods was compared. Finally, the relationship between the occupancy and heat use in these two periods was compared. The results show that, overall, due to the pandemic, some differences in these two periods can be obviously observed in this passive office building, which are summarized as follows:

1) The occupants' presence in this building in the post-pandemic period was lower than that in the pre-pandemic period. When Norway faced the second wave epidemic and the government implemented restrictive measures, the occupancy pattern in this case office building would show likes the half-working day pattern that would occur at some particular scenarios during the pre-pandemic period.

2) The heat use was increased markedly in the post-pandemic period. On the one hand, for hourly heat use, the largest gap in hourly heat use between these two periods on the workdays increased around 21% (from 7.2 W/m^2 to 8.7 W/m^2), and increased around 31% (from 7.0 W/m^2 to 9.1 W/m^2) on holidays. On the other hand, for daily heat use, the minimum daily heat use of this building during the post-pandemic period was much higher than that during the pre-pandemic period, with increasing around 46% (from 70 Wh/m^2 to 102 Wh/m^2) on workdays and increasing around 86% (from 65 Wh/m^2 to 121Wh/m^2) on holidays.

3) The relationship between occupancy rate and heat use presented a stronger negative correlation in the post-pandemic period than in the pre-pandemic period.

This study indicates that the operation of the heating system of the case building may be inefficient in the post-pandemic period, and the findings of this study could help engineers to optimize the operation mode of the heating system according to the change of occupancy pattern and achieve better energy efficiency management in the post-pandemic period for the similar type of building.

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References

[1] Coronavirus Disease (COVID-19) – events as they happen, https://www.who.int/emergencies/diseases/novel-coronavirus-2019/events-as-they-happen.

[2] Motuziene V, Vilutiene T. Modelling the Effect of the Domestic Occupancy Profiles on Predicted Energy Demand of the Energy Efficient House. *Procedia Engineering* 2013; 57: 798–807.

[3] Happle G, Fonseca JA, Schlueter A. Impacts of diversity in commercial building occupancy profiles on district energy demand and supply. *Applied Energy* 2020; 277: 115594.

[4] Gul MS, Patidar S. Understanding the energy consumption and occupancy of a multi-purpose academic building. *Energy and Buildings* 2015; 87: 155–165.

[5] Guerra Santin O, Itard L, Visscher H. The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock. *Energy and Buildings* 2009; 41: 1223–1232.

[6] Madurai Elavarasan R, Shafiullah G, Raju K, et al. COVID-19: Impact analysis and recommendations for power sector operation. *Applied Energy* 2020; 279: 115739.

[7] Bahmanyar A, Estebsari A, Ernst D. The impact of different COVID-19 containment measures on electricity consumption in Europe. *Energy Research & Social Science* 2020; 68: 101683.

[8] Rouleau J, Gosselin L. Impacts of the COVID-19 lockdown on energy consumption in a Canadian social housing building. *Applied Energy* 2021; 287: 116565.

[9] Geraldi MS, Bavaresco MV, Triana MA, et al. Addressing the impact of COVID-19 lockdown on energy use in municipal buildings: A case study in Florianópolis, Brazil. *Sustainable Cities and Society* 2021; 69: 102823.

[10] Ivanko D, Ding Y, Nord N. Analysis of heat use profiles in Norwegian educational institutions in conditions of COVID-lockdown. *Journal of Building Engineering* 2021; 102576.

[11] Ding Y, Ivanko D, Cao G, et al. Analysis of electricity use and economic impacts for buildings with electric heating under lockdown conditions: examples for educational buildings and residential buildings in Norway. *Sustainable Cities and Society* 2021; 74: 103253.

[12] Werth A, Gravino P, Prevedello G. Impact analysis of COVID-19 responses on energy grid dynamics in Europe. *Applied Energy* 2021; 281: 116045.

[13] Covid-19 and energy efficiency – Energy Efficiency 2020 – Analysis. *IEA*, https://www.iea.org/reports/energy-efficiency-2020/covid-19-and-energy-efficiency (accessed 27 May 2021).

[14] Jiang P, Fan YV, Klemeš JJ. Impacts of COVID-19 on energy demand and consumption: Challenges, lessons and emerging opportunities. *Applied Energy* 2021; 285: 116441.

[15] Kang H, An J, Kim H, et al. Changes in energy consumption according to building use type under COVID-19 pandemic in South Korea. *Renewable and Sustainable Energy Reviews* 2021; 148: 111294.

[16] Byggteknisk forskrift (TEK17).

[17] Vázquez FI, Kastner W. Clustering methods for occupancy prediction in smart home control. In: *2011 IEEE International Symposium on Industrial Electronics*. 2011, pp. 1321–1328.

[18] Davies DL, Bouldin DW. A Cluster Separation Measure. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 1979; PAMI-1: 224–227.

[19] Yan L, Li J, Liu M, et al. Heating behavior using household air-conditioners during the COVID-19 lockdown in Wuhan: An exploratory and comparative study. *Building and Environment* 2021; 195: 107731.

[20] Kruskal WH, Wallis WA. Use of Ranks in One-Criterion Variance Analysis. *Journal of the American Statistical Association* 1952; 47: 583–621.