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Analysis of electricity use and economic impacts for buildings with electric heating under lockdown conditions: examples for educational buildings and residential buildings in Norway

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ABSTRACT

The COVID-19 pandemic has caused significant impacts on energy demand in Norway and many countries. It is important to improve the existing knowledge of building operation under unforeseeable disturbances. This study aimed to identify the potential problems of electricity use patterns for four building types with electric heating: kindergartens, schools, apartments, and townhouses. By comparing the electricity profiles for the lockdown period 2020 with the normal condition in previous years, it showed that the electricity demand in the two educational institutions was almost on the same level, while there were apparent changes for the residential buildings. To estimate the energy saving potential and increase, three scenarios were developed considering different operation strategies: Scenario 1 considered operation under normal settings; Scenario 2 considered operation of educational buildings under nighttime and weekend settings; Scenario 3 considered operation of residential buildings under work-at-home conditions. Energy signature curve models were built to predict yearly demand. The results showed that the electricity demand might be reduced by one-third in educational buildings by following Scenario 2. Meanwhile, the electricity density of small apartment varied more significant than the townhouse, causing an electricity increase of 27% for the apartment and 1.3% for the townhouse under Scenario 3.

1. Introduction

Since the World Health Organization (WHO) announced COVID-19 disease as the pandemic in March 2020, many countries have undertaken restrictive measures to tackle the pandemic and slow down the spread of the coronavirus [1]. Due to the partial or full lockdown imposed on public places, commercial, and industrial schemes, building occupancy schedules have been adapted into remote work. The drastic changes have led to significant impacts on energy demand and put pressure on energy sector management and energy market.

Energy profiles are powerful tools in energy system planning and management. They reflect the requirements of total demand and energy use patterns of the customers. The COVID-19 related demand variation and corresponding energy load profiles have been analyzed on different grid levels and scales in several publications.

In the analysis of electricity use trends during the pandemic in Ontario province, Canada, it is found a 14% of electricity decline with a considerable CO_2 reduction in April 2020 [2]. The hourly-based load curve shows the weekly highest electricity demands were moved from the latter part of the week to the earlier part. Meanwhile, the morning peak loads, and the evening peak loads were avoided, which yielded a noticeable flattened curve [2]. Peak load shift is also reported in other studies [3–6]. From the analysis of electricity data covering millions of customers in Illinois, USA, the results show that weekday load profiles for dwellings became more likely to weekend profiles [3]. Through extrapolation of the findings on total load profiles, COVID-19 related profiles may change long-term workplace arrangements and further influence peak hourly loads. In a study of a Canadian social housing building during the 4-month of lockdown, it was found out that on average the daily electricity use was slightly increased by 2% while the daily hot water use was slightly decreased by 3% [4]. The biggest impacts on energy use were mostly seen during the first two months (April and May) of the lockdown period, for example, in April the electricity use increased by 46% and the hot water increased by 103% during the middle of the day [4]. An online survey to explore the impacts of

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Nomenclature

ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BAS	building automation systems
DHW	domestic hot water
ED	Euclidean distance
ES curve	energy signature curve
GESD	generalized extreme studentized deviate
MAPE	mean absolute percentage error
PCC	Pearson Correlation Coefficient
SH	space heating
TMY	typical meteorological year
WD	weekday
WE	weekend
el	electricity
n	number of observations
R^2	coefficient of determination
S	standard deviation
t_{ot}	outdoor temperature
yr	year
€	currency of Euro

California's Shelter-in-place order on energy activities in the residential buildings under the confinement measures was conducted in [5] and the responses indicate an increase of energy demand from 10 to 15 o'clock, which is also related to the characteristics of respondent and dwelling. The main findings present the relationship between such COVID-19 related changes and intention to adopt smart home technologies, which may benefit household practices in the future [5]. The Brazilian power system and its four subsystems before and after adopting the distancing measures were analyzed in [6]. The comparison results of the weekly electricity profiles and the weekly change percentages show a remarkable reduction of energy demand. And the energy use trends of the subsystems were observed with different dynamics depending on the geographic locations.

The energy use and energy profiles for certain building types were investigated in [7–10]. The impacts on energy use in residential aged care facilities were analyzed in [7]. From the comparison of electricity peak demand and profiles experiencing lockdown in four Australian climatic zones, the energy use and peak loads are shown greatly climatic related. Another study was performed on one energy-intensive laboratory building at a university campus [8]. After the lockdown, it was found that the unregulated electricity use in the laboratory reduced the power demand by half. The authors suggest a communication with the building managers about the typical building function and the actions taken during lockdown [8]. Four simulation scenarios of energy use in a typical Serbian household were analyzed in [9]: S1 – reference case, S2 – mild protection measures, S3 – semi-quarantine measures, S4 – complete quarantine, to assess the link between user behavior and energy source uses. By using the occupancy profiles in the building as input, the simulation models show that there was an increase in heating and electricity use during the pandemic due to the increased user presence. Compared with the normal conditions, the increase of heating and electricity use for the scenario-based models could be 31-32% and 54-58% respectively [9]. From the energy analysis in a southern Brazilian city, Florianópolis, during the lockdown [10], it was observed that the electricity use of administrative buildings, elementary schools, and nursery schools was reduced by 38.6%, 50.3%, and 50.4%, respectively, comparing with the same period of 2018-2019. These almost unoccupied municipal buildings do require considerable energy demand with nearly half of the energy being used regardless of the occupants' presence [10].

The extent of total energy demand influence from the various restrictive approaches was examined in [11]. The investigation contains four European countries with strict containment measures and two European countries with less restrictive ones. By comparing the total electricity demand depending on the residents' activities, it shows that there was a considerable electricity demand decline in the countries with severe lockdown measures [11]. These sudden changes of energy demand have influenced energy production and utility company's investment plans. Regarding the energy supply side, the following research has worked on the problems on energy production, economy, and security experiencing the confinement measures.

The power sector in Southeast Asia was examined in [12] and the study finds out the restrictive action has aggravated the vulnerabilities of their current power system. It highlights the significance of buildings as a resilient system in this region. A data-driven analysis was performed on the U.S. bulk power systems and electricity markets during the pandemic in [13]. The power sector was severely affected from March to May 2020. From the market-specific study, the northeast region suffered the most severe impacts on power operation and economic interests. Meanwhile, the authors believe more attention should be paid to possible shocks and disproportionate impacts between energy companies and consumers. From a thorough study of global power system operation [14], many countries have suffered considerable revenue loss due to a reduction of ca.8 to 30% of total electricity demand. The substantial decrease mainly came from the temporary halt of industrial, commercial, and public transportation activities. Power generation from the conventional nuclear power was affected, meanwhile it was noticed that the contribution from renewable energy increased by 3.5- 72% depending on the countries [14]. In addition to the economic problems of conventional utility companies, the authors in [15] underscore the challenges on load forecasting and required flexibility because of the changed balance and increased uncertainty.

The COVID-19 related indoor air quality issues have been studied as well. The indoor CO_2 concentration in residential buildings experiencing the home office regime was investigated in [16]. It shows that the adoption of a proper aeration process can minimize the increase of heating energy caused by changing the room function [16]. Another study shows that the mean daily PM2.5 concentration rose by approximately 12% and the mean volatile organic compound concentration by 37% to 559% comparing with the condition before and during the COVID-19 lockdown [17].

The literature review shows that there is a number of investigations regarding COVID-19 related energy use in non-cold climate region. However, the real data analysis and scenario-based modelling of electric heating use are missing for buildings in Norway and the similar climate zones. Therefore, the main objective of this study is to investigate the energy use behavior in Norwegian buildings with electric heating during the COVID-19 pandemic. The reason to study electric heating in buildings is that the country remains highly dependent on electricity. According to the statistics [18], nearly three quarters of Norwegian households are using electricity for heating purposes in the form of either electric radiator, electric floor heating, air source heat pump, or central electric heating. In the service sector, electricity accounts for approximately 77% of total energy use by supplying heating demand at a large extent. Moreover, within the Nordic region, although heat pumps are gradually replacing direct electric heating, the electricity demand in the residential sector has been increasing over the last decade, according to the report from the Nordic Energy Research [19].

As an important section of non-residential buildings at a municipal level, kindergartens and schools are commonly dispersedly located in cities or towns. Statistically, costs for building operation management become the second biggest expenditure of educational institutions, only beneath salaries of employees [20]. Building operators are therefore responsible for maintaining the required indoor environment in energy-efficient ways.

By complying with the Norwegian national lockdown regime

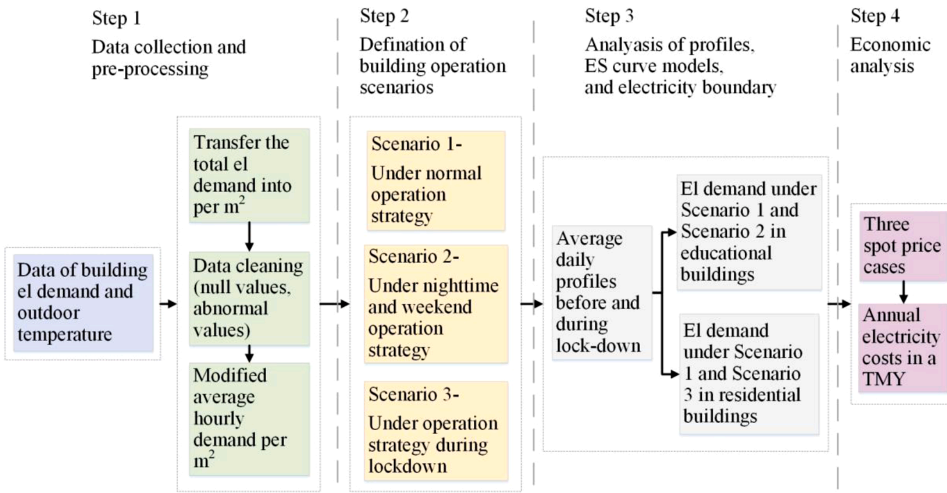


Figure 1. The workflow of the analysis of electricity use

Table 1
List of building information.

Building type	Floor area (m^2)	Data duration (Y/M/D)
Kindergarten	279- 1 143	2018.01.01- 2020.12.31
School	2 157- 5 443	2018.01.01- 2020.12.31
Apartment	40	2018.10.01- 2020.12.31
Townhouse	133	2018.10.01- 2020.12.31

initiated in March till May 2020, the teaching activities on campus were severely interrupted and transferred into remote learning, meanwhile many employees followed work-at-home rules. Therefore, this study focuses on the educational buildings and residential buildings in Norway and similar climatic regions. Concerning both for personal interests and municipality's public expenses, the secondary objective is to estimate the energy demand and economic impacts on the buildings with electric heating during the lockdown and future unforeseeable disturbances, which may also have influences on local energy planning.

To fulfill the research purposes, the three questions shall be answered: 1) whether the educational buildings were managed in an energy-efficient way during the temporary closure? 2) are there any energy and economic saving potentials in the educational buildings that might have been neglected and how much saving potentials may be reached? 3) how much electricity and economic impacts influenced the residential buildings with different household size and family members?

The novel contributions of this study may be summarized as follows. In our analysis, we utilized the measured electricity use data in real buildings during the lockdown and normal time. In such a way, the analysis was based on statistics rather than certain assumptions. It was found out that the common assumptions about energy use during COVID-lockdown in publications for public buildings were not always true and the household scale affected energy use in these buildings. Three scenario-based models were proposed, and they were used to discuss their impacts on energy management and local energy planning by varying building type ratio.

The rest of the paper is organized as the following. Section 2 introduces the study methods including the data information of the observed buildings, and the description of the three scenarios that were used to establish the energy models. The main results of the study are presented in Section 3. The electricity profiles under the three scenarios were analyzed and compared based on the measured data. The regression models' accuracies were evaluated by ASHRAE criteria. An economic analysis was further carried out to compare the annual electricity costs for the scenario-based models. Due to the different use characteristics between the educational buildings and the residential buildings, the feasible energy-saving strategies were proposed for the former ones, and the impacts on increased bill were studied for the latter ones. Lastly, the limitations, future work, and conclusions are discussed and summarized in Section 4 and Section 5.

2. Methodology

The outline of the main steps for this study is illustrated in Figure 1. Section 2.1 collects the building information. Section 2.2 – Section 2.4 explain the three scenarios regarding the different building operation strategies. In Section 2.5, the method for the economic analysis is introduced by considering the three levels of electricity spot price. Section 2.6 introduces the method for assessing the consequence on local energy planning.

2.1. Description of the observed buildings

During the lockdown, the educational buildings were supposed to be closed with minimum energy use, meanwhile the residential buildings were supposed to have higher energy demand under work-at-home conditions. To answer the above research questions, 14 kindergartens, eight schools, one apartment, and one residential house located in Trondheim, Norway, were analyzed in this study. The building areas of the kindergartens are between 279 and 1 143 m^2, while those of the schools are between 2 157 and 5 443 m^2, of which six are primary schools, one is a middle school, and one is a mixed one. All of them use electricity as their main building energy supply source, for instance, space heating (SH), domestic hot water (DHW), ventilation, and other electric appliances. About the space heating demand, there are electric panel heaters and ventilation heating in the kindergartens and schools. The maintenance and operation of these educational institutions are handled by Trondheim Municipality. The energy data were retrieved from the municipality's energy monitoring platform [21]. The historical annual demands of these observed buildings were close to the local average level. Therefore, these buildings may be representative to present the energy use changes and variations during the pandemic period. The residential house is a two-story townhouse with a floor area of 133 m^2, where accommodates a family of two adults and two pupils. The building is supplied by natural ventilation, and heated by a radiant wood stove, three electric radiators, and supplemented by an air source heat pump. In addition to the electric assistant heating, electricity is used for DHW, lighting, and other appliances. The apartment with natural ventilation has a floor area of 40 m^2, where accommodates an adult. It uses electricity for radiator (for SH), DHW, and other appliances. The electricity data of the two residential buildings were voluntarily shared

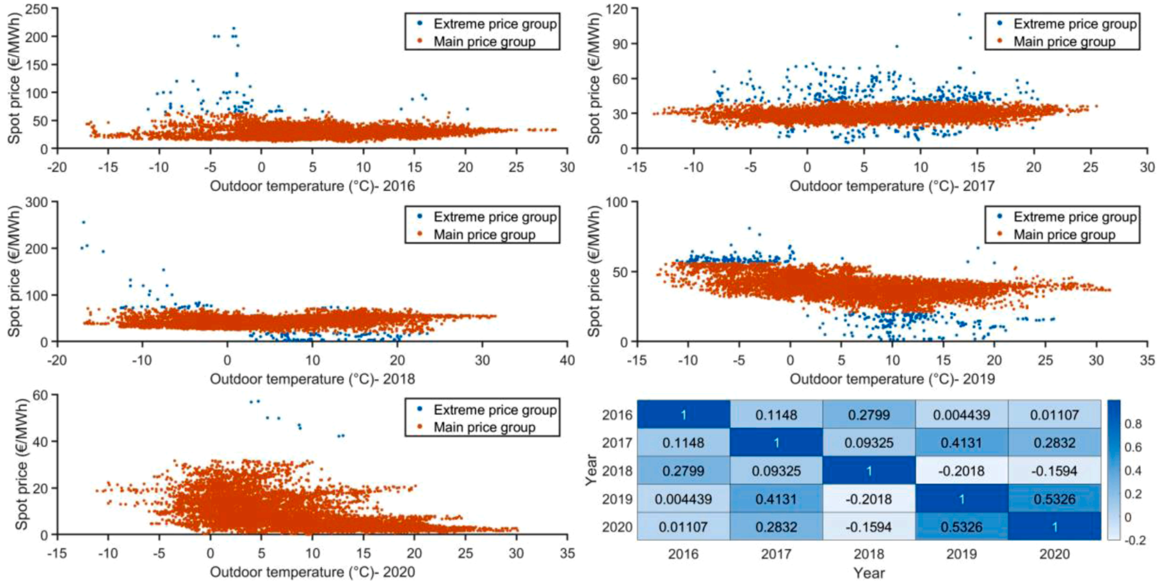


Figure 2. Electricity spot price vs Outdoor temperature, and Correlation of electricity spot price in 2016- 2020

by the dwellers who retrieved them from the local power grid supplier Tensio [22]. All these observed buildings have no submeter.

Weather conditions were considered in the energy analysis, and the historical weather data were obtained from the local meteorological station [23]. The electricity use of the educational buildings was from the beginning of 2018 to the end of 2020, while the electricity use of the two residential buildings was from October 2018 to the end of 2020 due to the upgrade into smart meter in September 2018. The data information is briefly explained in Table 1. The analysis was performed on average specific electricity use (kWh$_{el}$/ m^2), to define the representative electricity use concerning buildings with different characteristics. MATLAB was used for the data analyses.

2.2. Scenario 1 - Electricity demand based on normal operation mode

Scenario 1 considered the electricity use under normal conditions without the disturbance from lockdown or other temporary disruption from 2018 to 2020 except March - May 2020. In the educational buildings, there is a remarkable difference in electricity demand between daytime on weekdays and off-work hours, which is mainly caused by the different campus activities and attendance between the two time slots. Whereas, the electricity use pattern in residential buildings is unlike kindergartens and schools. It generally has low demand during working hours and high demand when dwellers are at home.

As addressed before, large proportion of electricity is used for heating purposes in the electric-heated buildings in the cold climate areas. Accordingly, outdoor temperature (t_{ot}) may be regarded as the key predictor to determine the related heating electricity use in buildings under different operation strategies. To find the relationship between the electricity demand and outdoor temperature, energy signature curve (ES curve) was used in the study. ES curve has been widely utilized in building energy planning by researchers and engineers at all levels [24–26]. ES curve generally consists of two parts, the temperature dependent part and temperature independent part. They are divided by changing point temperature (CPT) or heating effective temperature. The formulas for the ES curve may be expressed as:

$$\text{If } t_{ot} \leq \text{CPT}, \quad P(t_{ot}) = p_1 \cdot t_{ot} + p_2 + \varepsilon \tag{1}$$

$$\text{If } t_{ot} > \text{CPT}, \quad P(t_{ot}) = p_1 \cdot t_{ot} + p_2 + \varepsilon; \approx p_2 \tag{2}$$

In Eqs.(1) and (2), p_1 and p_2 are the coefficients of each ES curve model, and ε is the residual error. The heating demand follows the linear growth under the slope of p_1. Besides the outdoor temperature, the work schedules also decide the operation settings and affect the electricity use. In the educational buildings, the ES curves were made for weekdays and weekends, separately. Concerning the possible random operation of electric appliances, which may cause irregular electricity use, the ES curves for the residential buildings were defined based on average weekly base.

The importance of using typical meteorological year (TMY) to estimate building energy performance from one single year analysis is highlighted in [27]. The outdoor temperature is made based on the most "representative" conditions over the last decade. In this analysis, TMY data 2007- 2016 of Trondheim were retrieved from the European Union website [28]. Combining the acquired energy signature under Scenario 1, the TMY data were applied to obtain the electricity use of the typical year. This scenario was applied to both the educational buildings and the residential buildings.

2.3. Scenario 2 - Electricity demand based on night and weekend operation mode in the educational buildings

This scenario referred to the energy-saving mode for a limited operation of buildings during a temporary closure. It was assumed that building management sector switched the energy supply operation to the settings of low demands during normal weekdays' nighttime and weekend to save energy. In the educational buildings, the electricity use was usually observed at minimum levels to maintain the acceptable indoor temperatures and air quality during weekends and off-work hours on weekdays, with the almost zero attendance. Similar as the study in [11], the weekday demand profiles for educational buildings during the pandemic were assumed to be identical as the weekend profiles of the reference week in 2019. Thus, Scenario 2 was only applied to the educational buildings in this study.

The hypothesis was made by considering the guidance of building operation in epidemic situations by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE). It highlights that buildings equipped with or without a building automation systems (BAS) are not recommended to completely shut down the HVAC systems during the temporary closure or no occupancy [29]. The buildings shall be maintained "within a reasonable range of temperature and humidity" by setting the HVAC systems with relaxed temperature and humidity.

To find the electricity characteristics for Scenario 2, the ES curve was developed based on the hourly electricity use during the normal

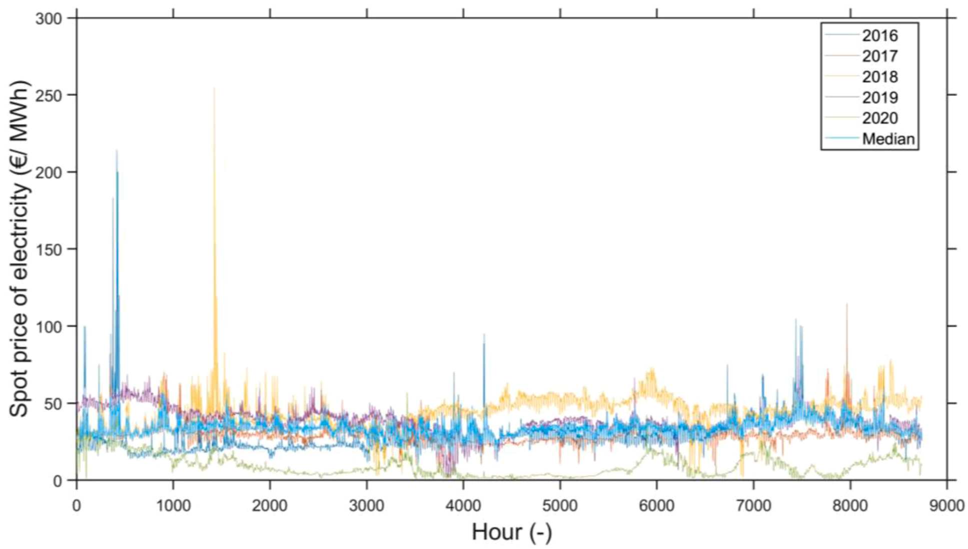


Figure 3. Annual electricity spot price profiles in 2016- 2020

weekdays' nighttime and weekends. After that, by following the similar way as Scenario 1, the electricity use of the TMY under Scenario 2 was acquired. It enables us to see the possible electricity reduction that may be achieved in the educational buildings when the building energy supply system runs at a low demand level.

2.4. Scenario 3 - Electricity demand based on lockdown operation mode in the residential buildings

When the rule of home office was in effect, the hypothesis of electricity use in the residential buildings might be higher than normal situation, especially during daytime since the work schedules of dwellers changed, similar as in the Canadian residential community [4]. Scenario 3 was to find the increased electricity use caused by the influence from lockdown in the residential buildings, and to study energy robustness by dwelling scale.

The ES curve was established based on the average weekly electricity use from March to May 2020. The electricity characteristics for this scenario were extrapolated to the whole typical year by using the coefficients acquired from this period. Then a yearly electricity use was obtained by using the similar methods for Scenario 1 and Scenario 2.

2.5. Economic impact assessment

In Norway, the specific electricity price contains two parts, the fixed grid rent price (f_i) and the variable price (v_i), see Eq.(3). This pricing mode is commonly adopted in many European countries [30, 31]. f_i refers to the fee and tax when using the grid, which is generally determined by the local authority and the value is normally constant within a certain amount of time, while v_i varies a lot based on the demand and supply in the power market.

$$p_i = f_i + v_i \tag{3}$$

Using the spot price as reference, each energy company charges with different price packages concerning their own interests. To calculate the annual electricity costs in this study, the fixed price was retrieved from Statistic Norway [18], and the variable price was considered with the spot price of Trondheim from NordPool (2016- 2020) [30].

The five-year spot price versus the outdoor temperature is plotted in Figure 2, where the orange dots represent the main price groups and the blue dots represent the extreme price groups (very high and low spot price). These extreme data points were separated from the main clouds by the method of Generalized extreme studentized deviate (GESD). The explanation and application of GESD can be found in [32, 33]. Moreover, as illustrated in the correlation heatmap at the bottom right in Figure 2, the five years had weak relation with each other. Most of the two-year correlation factors were smaller than 0.3. In Figure 3, it compares the annual spot price profile from 2016- 2020, showing the high-price level in 2018 in yellow line, the low-price level in 2020 in green line, and the others in between. Both the heat map and the annual spot price profiles were adjusted with the same starting day of the five years. As shown in Figure 2 and Figure 3, it is rather difficult to define a simple mathematical method explaining the variations of the five-year spot prices. Regarding the complex prediction of electricity prices, some examples are shown in [34–36]. Thus, in this study, three price cases were made. The spot price of 2018 was treated as the case of highest price level, that of 2020 for the case as the lowest price level, and the median values of the rest of the years as the case of moderate price level. The thick blue line is for the median values as shown in Figure 3. It was assumed that these three price levels were capable to represent the electricity market situation in recent years.

By combining the annual electricity profiles of a TMY and the three price levels, it allows us to calculate the annual electricity costs for the observed buildings regarding the three operation scenarios and further compared the costs.

2.6. Aggregation and consequence on energy planning

Local energy planning may be improved by analyzing the energy use during critical and special circumstances such as lockdown. An imaginary community could be assumed to be made up of one kindergarten, one school, and one residential area composed of 40% of apartment and 60% of townhouse. By aggregating the annual specific electricity demand for the four building types in a normal year (Scenario 1) and lockdown year (Scenario 2 and Scenario 3), the annual total electricity use for this community was calculated as

$$\begin{aligned} E_{nor\ yr} = {} & e_{nor\ yr,kind} \cdot A_{kind} + e_{nor\ yr,\ sch} \cdot A_{sch} + e_{nor\ yr,\ apm} \cdot A_{resi} \cdot 40\% \\ & + e_{nor\ yr,\ house} \cdot A_{resi} \cdot 60\% \end{aligned} \tag{4}$$

$$\begin{aligned} E_{ld\ yr} = {} & e_{ld\ yr,\ kind} \cdot A_{kind} + e_{ld\ yr,\ sch} \cdot A_{sch} + e_{ld\ yr,\ apm} \cdot A_{resi} \cdot 40\% \cdot i \\ & + e_{nor\ yr,\ apm} \cdot A_{resi} \cdot 40\% \cdot (1-i) + e_{ld\ yr,\ house} \cdot A_{resi} \cdot 60\% \cdot i \\ & + e_{nor\ yr,\ house} \cdot A_{resi} \cdot 60\% \cdot (1-i) \end{aligned} \tag{5}$$

where $e_{nor\ yr,\ kind}$, $e_{nor\ yr,\ sch}$, $e_{nor\ yr,\ apm}$, and $e_{nor\ yr,\ house}$ refer to the annual specific electricity use for kindergarten, school, the apartment, and the

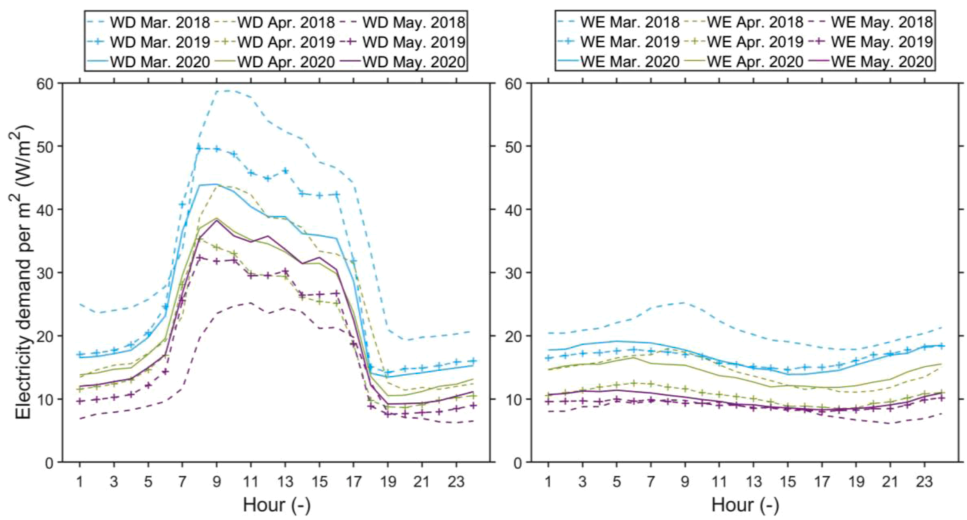
Table 2
Monthly average temperature

	March	April	May
2018	-3.1 °C	4.7 °C	12.3 °C
2019	-0.4 °C	6.7 °C	7.4 °C
2020	1.4 °C	3.5 °C	6 °C

townhouse in a normal year, respectively; $e_{ld\ yr,\ kind}$, $e_{ld\ yr,\ sch}$, $e_{ld\ yr,\ apm}$, and $e_{ld\ yr,\ house}$ refer to the annual specific electricity use for kindergarten (Scenario 2), school (Scenario 2), the apartment (Scenario 3), and the townhouse (Scenario 3) in a lockdown year, respectively; A_{kind}, A_{sch}, and A_{resi} refer to the building area of kindergarten, school, and the residential area, respectively; and i refers to the percentage of work-from-home adoption in the residential area. By varying the residential area A_{resi} and the work-from-home adoption percentage i, the electricity demand especially the peak demand and the capacity factor may be affected. Capacity factor of an energy plant is the ratio of the actual total energy production over a period to the maximum output if the plant operates at its rated capacity, and it measures the overall utilization of an energy plant [37]. These influences on local energy planning are discussed in Section 4.

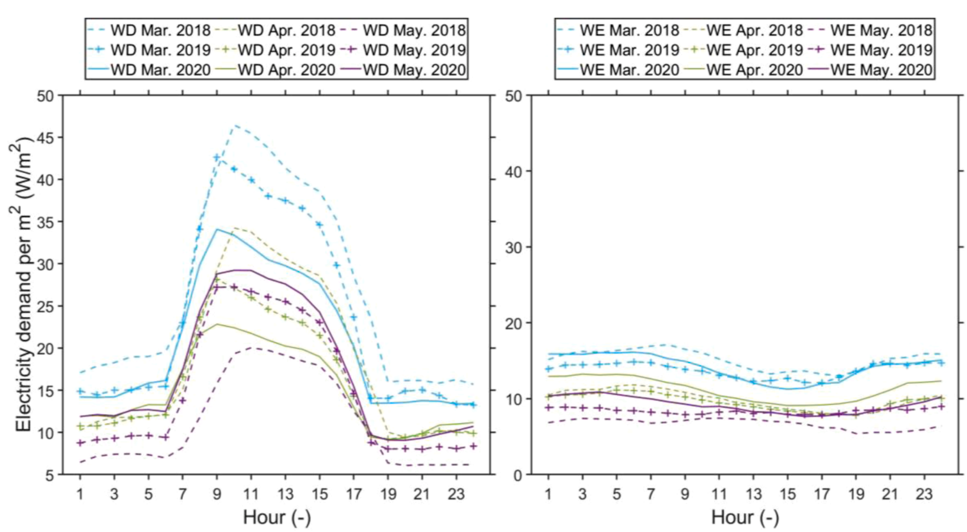
3. Results

The analysis results of electricity daily profiles before and during COVID-19 lockdown are presented in Section 3.1, the scenario-based electricity demands are illustrated in Section 3.2, Section 3.3 shows the electricity profiles in a TMY under the three scenarios, and the yearly electricity costs under different scenarios and price levels are compared in Section 3.4.



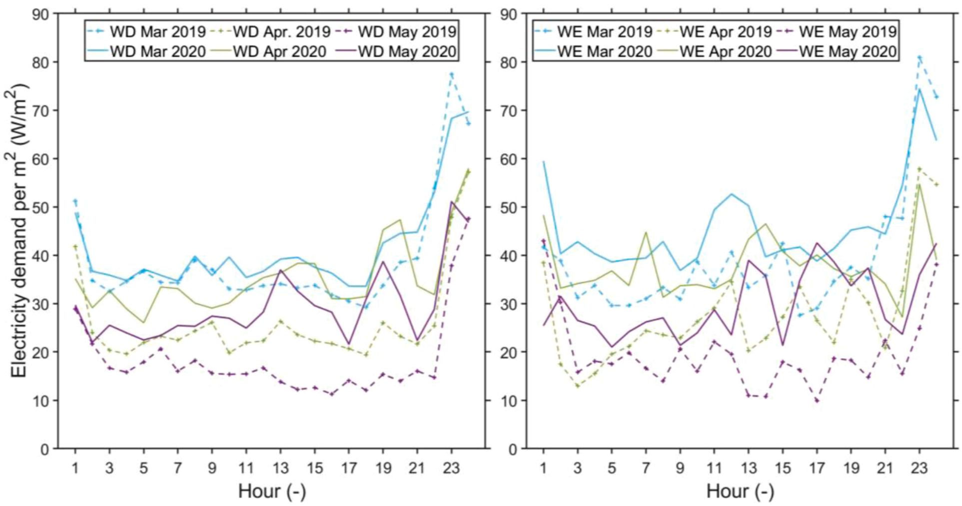
a) b)

Figure 4. The average daily electricity profiles for kindergartens from March to May in 2018- 2020, where a) profiles on weekdays, b) profiles on weekends



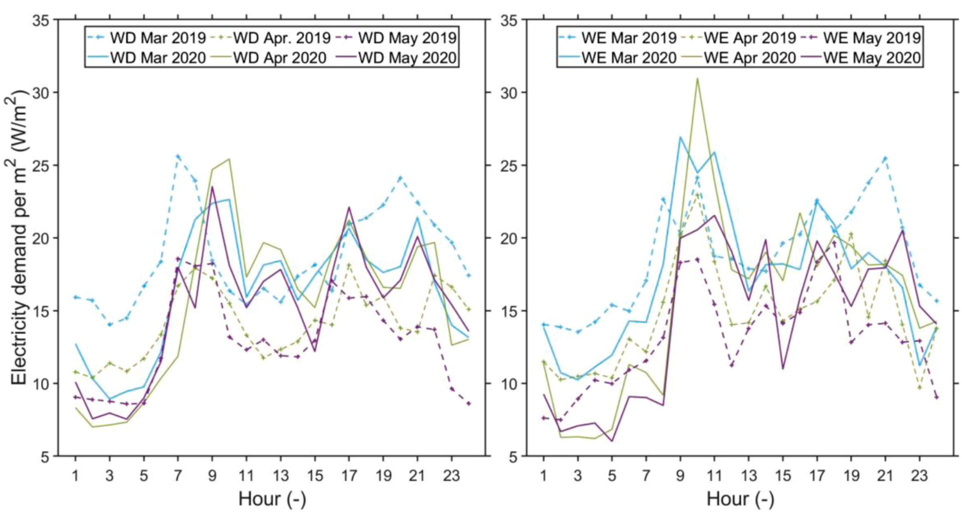
a) b)

Figure 5. The average electricity profiles for schools from March to May in 2018- 2020, where a) profiles on weekdays, b) profiles on weekends



a) b)

Figure 6. The average electricity profiles for the single apartment from March to May in 2019- 2020, where a) profiles on weekdays, b) profiles on weekends



a) b)

Figure 7. The average electricity profiles for the townhouse from March to May in 2019- 2020, where a) profiles on weekdays, b) profiles on weekends

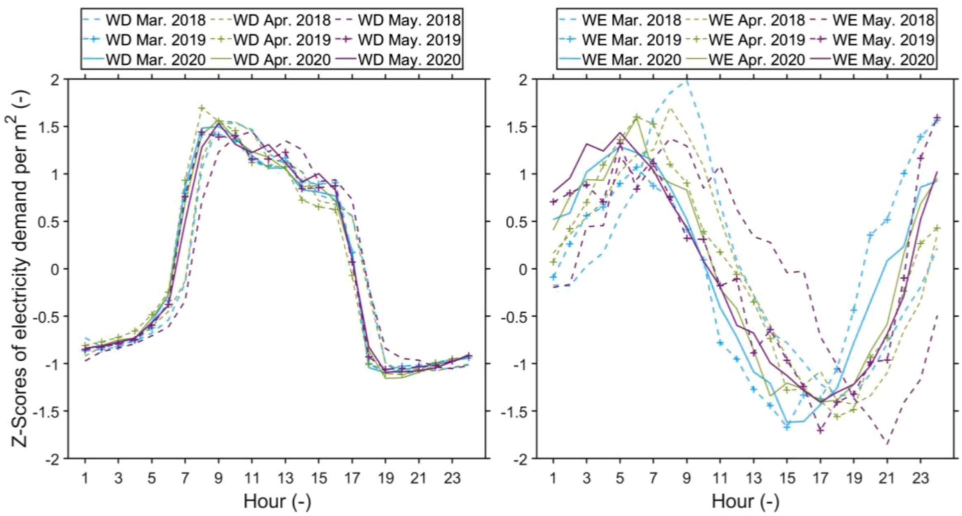
3.1. Analysis of daily electricity profiles before and during COVID-19 lockdown

According to previous research and statistics, nearly half of energy use in buildings is used for heating in the cold climate. Therefore, the outdoor temperature has large influence on the total electricity use. The average monthly outdoor temperature between March and May during the three years are listed in Table 2, where 2018 had the coldest March and the warmest May, 2019 had the warmest April, and 2020 had the warmest March and the coldest April and May.

Considering different schedules and occupancy levels on weekdays and weekends, the electricity use profiles were therefore analyzed separately. The average daily electricity demand profiles for kindergartens, schools, and two residential buildings during March to May 2018- 2020 are compared in Figure 4 - Figure 7, respectively. In these figures, WD denotes weekday and WE denotes weekend, and the dashed lines stand for 2018, the dashed lines with plus symbol for 2019, and the solid lines for 2020.

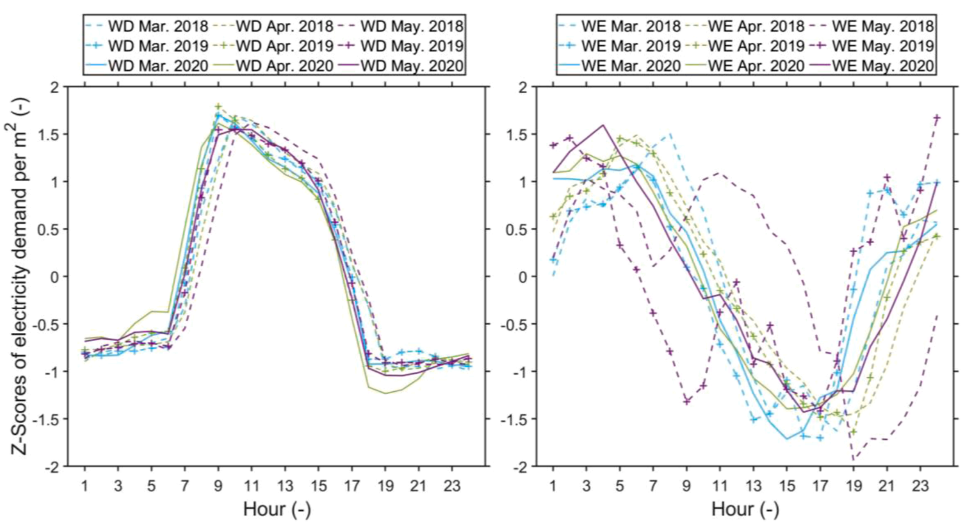
For the educational buildings shown in Figure 4 and Figure 5, the electricity use followed the opening hours and schedules. On weekdays, the demand generally arose between 6 and 17 o'clock with the peak demand at around 8 or 9 o'clock. The demand rising ahead of the teaching activities was aimed extending the thermal comfort and improve the indoor air quality. From 19 to 6 o'clock next morning, the energy supply systems maintained at a low demand. It may be observed that the shapes of the three- year electricity profiles from March to May were quite similar. The average demands were mostly in line with the average monthly outdoor temperature. Also, kindergartens generally require higher energy demand than schools, which follows the statistical data due to the higher requirement of thermal comfort and hygiene in kindergartens [38].

Regarding the residential buildings, the electricity use patterns were different. In the apartment see Figure 6, there was distinct higher demand during the daytime on weekdays in 2020 than 2019. Meanwhile



a) b)

Figure 8. Z-Scores of average daily electricity profiles for kindergartens from March to May in 2018- 2020, where a) Z-Scores for weekdays, b) Z-Scores for weekends



a) b)

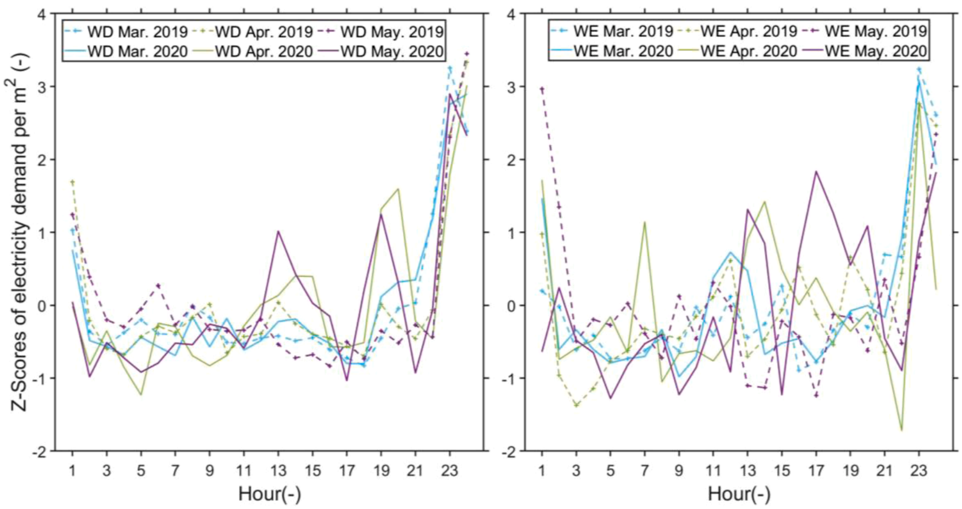
Figure 9. Z-Scores of average daily electricity profiles for schools from March to May in 2018- 2020, where a) Z-Scores for weekdays, b) Z-Scores for weekends

several local peak demands were noticed, such as 10, 13, and 14 o'clock in March, 14 and 15 o'clock in April, 9 and 13 o'clock in May. Additionally, the average higher demand in the evening was mainly due to the running of appliance, and the peak load in the midnight was used for recharging the hot water tank. The use pattern during weekends were similar with weekdays, but due to more time spent indoors there were several local peak loads both in 2019 and 2020. In the townhouse see Figure 7, March 2020 had slightly higher daytime electricity use, while April 2020 and May 2020 used more electricity during daytime than 2019. The morning peaks arising at 7 or 8 o'clock in 2019 was shifted later to 9 or 10 o'clock in 2020 due to the study- and- work- at home regime. Again, several local peak demands were also noted during the daytime on weekdays, such as around lunch period. The specific electricity demand in the single apartment was generally higher than the townhouse. The WD values were similar to the WE values in the residential buildings, which is also mentioned in [3]. This may indicate that the effect of occupants on private buildings plays a more important role than in public buildings, and the household energy demand varies based on residents' behavior, as mentioned in [39, 40].

In general, among the four building types, March claimed the highest electricity, May needed the lowest electricity, and April was in between, with an exception of the unusually cold May in 2020. To identify the effect from the outdoor temperature difference to the electricity, Euclidean Distance (ED) was calculated to prove that the larger outdoor temperature difference was supposed to yield the higher ED and vice versa. ED was calculated as:

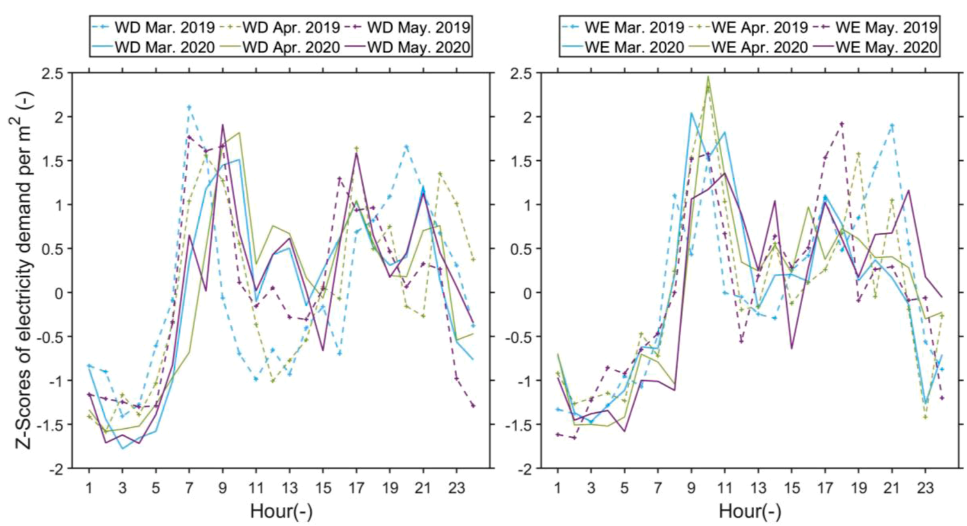
$$d_{ED}(X,\ Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{6}$$

where X and Y refer the vector of the average daily profile in each year, x_i and y_i refer to the electricity demand at *i-th* hour in each year.



a) b)

Figure 10. Z-Scores of average daily electricity profiles for the single apartment from March to May in 2019- 2020, where a) Z-Scores for weekdays, b) Z-Scores for weekends



a) b)

Figure 11. Z-Scores of average daily electricity profiles for the townhouse from March to May in 2019- 2020, where a) Z-Scores for weekdays, b) Z-Scores for weekends

Besides the difference defined by ED, the average daily profiles were further performed with Z standardization (Z-Score) and Pearson Correlation Coefficient (PCC) analysis to identify the similarities. Through the calculation of Z-Scores and PCC, the amplitudes of demand values were normalized by making the profiles of compatible scales, and the shape similarities of each two profiles can be measured by PCC. This may avoid the possible influence of the outdoor temperature to the energy profile shapes. The benefits of using the PCC measures to effectively recognize the profiles similarities were highlighted in [41].

The Z-score and PCC were calculated as Eqs.(7) and (8), respectively:

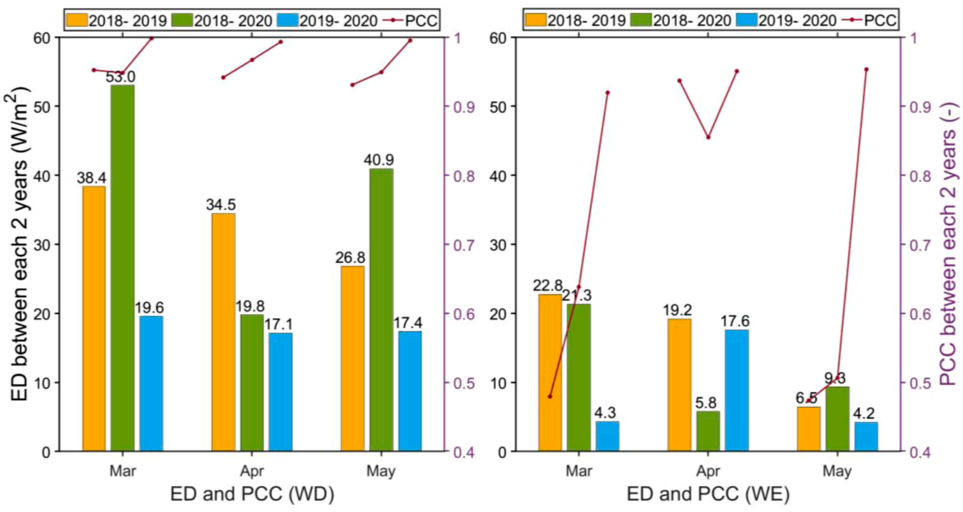
$$Z_i = \frac{x_i - \overline{x}}{S} \tag{7}$$

where x_i refers to the electricity demand at *i-th* hour, S refers to the standard deviation of the day (24 hours), $\overline{x}$ refers to the mean value of the day.

$$PCC(X,\ Y) = \frac{cov(X,\ Y)}{S_X S_Y} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{8}$$

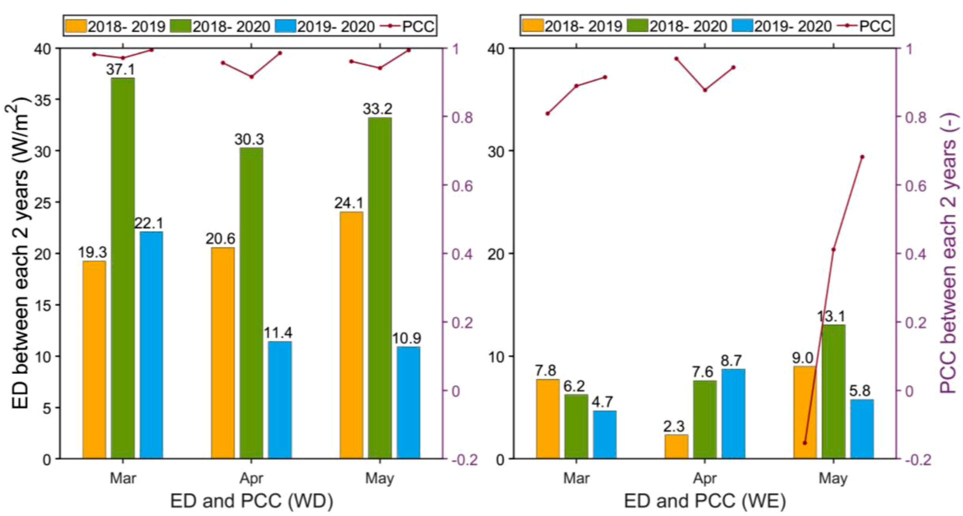
where *cov* means the covariance.

The Z-Scores of each average daily profile corresponding to Figure 4- Figure 7 are presented in Figure 8- Figure 11. When demand scales were normalized and discarded, the educational buildings reflected a highly similar pattern on weekdays during the three months from 2018 to 2020. However, the energy use on weekend varied from month to month. As for the residential buildings, the energy use patterns over the three months from 2019 to 2020 were quite different, with noticeable local peak demand during daytime on weekdays, for example from 12 to 16 o'clock in the single apartment 9 to 14 o'clock in the townhouse.



a) b)

Figure 12. The ED and PCC results of kindergartens in 2018- 2020, where a) for weekdays, b) for weekends

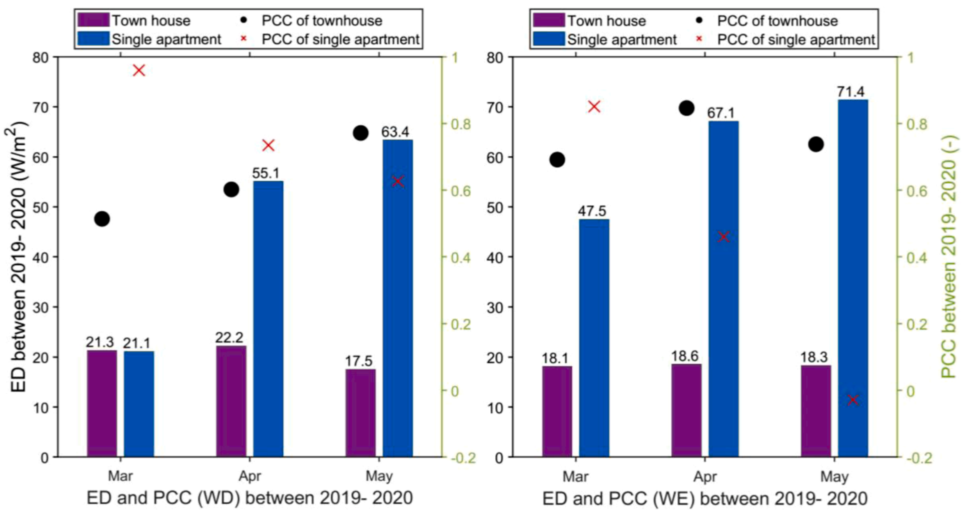


a) b)

Figure 13. The ED and PCC results of schools in 2018- 2020, where a) for weekdays, b) for weekends

The results of ED and PCC measures within every two years for kindergartens and schools are compared in Figure 12 and Figure 13, where the yellow bars stand for the EDs within 2018- 2019, the green bars for the EDs within 2018- 2020, and the light blue bars for the EDs within 2019- 2020. The PCCs are plotted by the red lines with the dots, and each dot refers to the same year of the bar where it is located. By discarding the real energy demand scales influenced by the outdoor temperature, it was observed that the PCC results from March to May during the three years were higher than 0.93 in kindergartens and 0.91 in schools on weekdays, and the highest PCCs were even found within 2019- 2020 (the red dots located at the light blue bars). Even on weekends, there were also several PCCs beyond 0.7 between 2019 and 2020. This proved again that the patterns and operation of the three-year average daily energy use were of high similarity. The higher temperature deviation from 2018 to the other two years led to larger energy demand differences, which was reflected in the ED results. The closer outdoor temperature between 2019 and 2020 led to the smaller ED on weekdays. Comparing with weekdays, both the daily profiles and the ED results of electricity presented much lower demands on weekends in kindergartens and schools. This is mainly because the educational institutions in Norway usually do not carry out teaching activities on weekends, but the buildings can be occasionally rented out to maximize the public resource usage [38]. This explained the much lower impact from the outdoor temperature difference to the energy demand on weekends than that on weekdays, and the weekend demand was alike the night mode.

About the residential buildings, the ED and PCC results of the townhouse (purple columns and black dots) and the single apartment (blue columns and red crosses) between 2019 and 2020 are compared in Figure 14. The ED values of the townhouse were lower than those of the apartment within the three months both on weekdays and weekends, only with the exception in March when the two were close. Additionally, the EDs of the townhouse on weekends were smaller than on weekdays, which was also backed by the high average PCC values. It mostly implied



a)   b)

Figure 14. The ED and PCC results of townhouse and single apartment in 2019- 2020, where a) for weekdays, b) for weekends

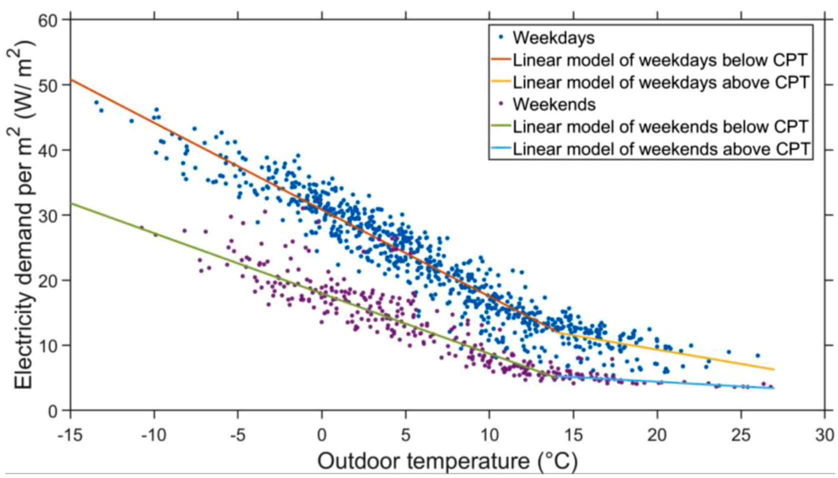


Figure 15. Energy signature curve models for kindergartens for Scenario 1

that the residents kept their usual weekend plans, for example the outdoor activities. Generally, EDs of the townhouse were rather stable. Whereas the apartment had much larger ED values and more various PCC values, which was similar with the findings in the average profiles in Figure 6 since more time was spent at home. The occupant behavior in smaller dwelling size had higher energy impacts.

Based on the findings from the weekday electricity profiles of kindergartens and schools during the lockdown period, the operation might not shift to night/weekend settings as the hypothesis. Due to the practical reasons, the schools and kindergartens were still open during the period to support the parents who were working in the critical positions such as health system, police station, transportation and so on. Both kindergartens and schools showed similar operation strategies between March and May from 2018 to 2020, by showing their similar electricity use patterns with the close average daily profiles and PCC results. This is unlike the electricity use examined in the university laboratory building [8] and the nursery school and elementary school buildings [10]. In the former building, most of the users are adults and able to take care of themselves [8]; in the latter buildings, although most of users are children same as in this study, nearly half of electricity demand was reduced [10].

Meanwhile the residential buildings showed a large variation influenced by the changes of the dweller's working schedule during the period as projected. Besides that, there was a bigger influence on specific electricity demand in the single apartment than the multi-member townhouse. Since the apartment has a smaller floor area and one dweller, it may be more sensitive with the changes. And the wood stove in the townhouse was not treated in the study.

3.2. Analysis of scenario-based electricity demands

This section studies the electricity use under the three scenarios in the observed buildings. All the ES curve models were established based on the measured data.

In the educational institutions, as shown above, the building energy systems were most likely maintained at normal level during the lockdown. Hence, the electricity use in kindergartens and schools during 2018- 2020 was treated under normal operation. In Scenario 1, the daily-based ES curve models of weekdays and weekends were built separately. The ES curve models of kindergartens are shown in Figure 15, where the weekdays (blue dots) and weekends (purple dots) have great demand differences. Since the ventilation, heating, and other

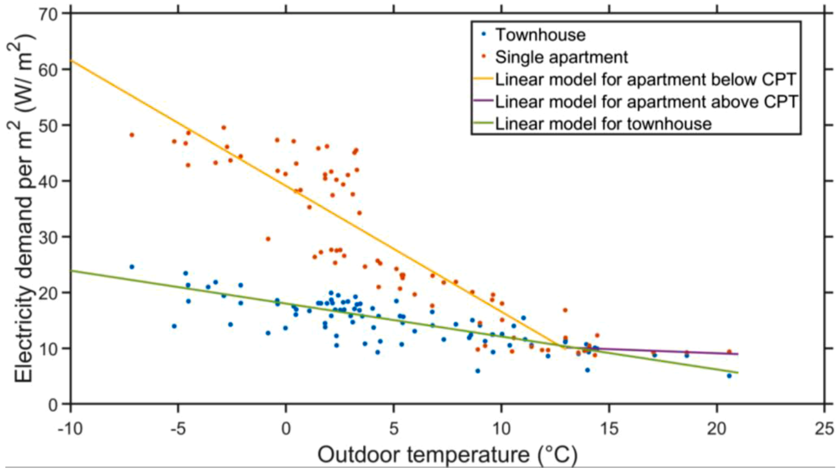


Figure 16. Energy signature curve models for the single apartment and the townhouse for Scenario 1

Table 3
Coefficients and Accuracy of the ES curve models for Scenario 1

Building type	Coefficients of model CPT (°C)	p_1	p_2	Accuracy of model R^2	MAPE (%)
Kindergarten (WD)	14	-1.3 (≤ 14°C) -0.4 (>14°C)	30.8 (≤ 14°C) 18.1 (>14°C)	0.90	11.9
Kindergarten (WE)	14	-0.9 (≤ 14°C) -0.1 (>14°C)	17.9 (≤ 14°C) 7.6 (>14°C)	0.79	
School (WD)	14	-1.2 (≤ 14°C) -0.3 (>14°C)	25.1 (≤ 14°C) 13.6 (>14°C)	0.82	18.2
School (WE)	14	-0.7 (≤ 14°C) -0.2 (>14°C)	15.1 (≤ 14°C) 7.7 (>14°C)	0.80	
Apartment	13	-2.3 (≤ 13°C) -0.2 (>13°C)	38.5 (≤ 13°C) 12.2 (>13°C)	0.80	18.2
Townhouse	/	-0.6	17.9	0.63 (↓)	14.6

appliances were much less operated on weekends, the electricity demand was lower than weekdays by around 35- 40%. The CPT was identified at 14°C both on weekdays and weekends by giving the adequate piece-wise approximation. The needs for electricity demand became less when the outdoor temperatures were above the CPT, that the regression lines had milder slopes than the ones below the CPT. This was mainly because of the reduction for electric space heating. Schools had similar electricity demand characteristics and their ES curve models are shown in Appendix Figure A1.

For the residential buildings in Scenario 1, the ES curve models for the single apartment and the townhouse were built on the weekly electricity use by excluding the lockdown period. Figure 16 presents their weekly-based ES curve models, where the orange dots are for the apartment and the blue dots for the townhouse. The CPT of 13°C gave a proper division between the temperature-dependent and temperature-independent electricity use in the apartment. Meanwhile, the relatively low electricity density in the townhouse made it follow the same linear relation over the whole outdoor temperature range without a CPT. When the outdoor temperature was below the CPT, the slope for the apartment was steeper than the townhouse. When the outdoor temperature was close and above the CPT, the slopes for the two residential buildings were close. This implied that when it was cold outside, the share of electricity used for space heating in the apartment was much higher than in the townhouse.

Table 3 gives the coefficients and the accuracy evaluation of the ES curve models for all the observed buildings for Scenario 1. Accuracy of

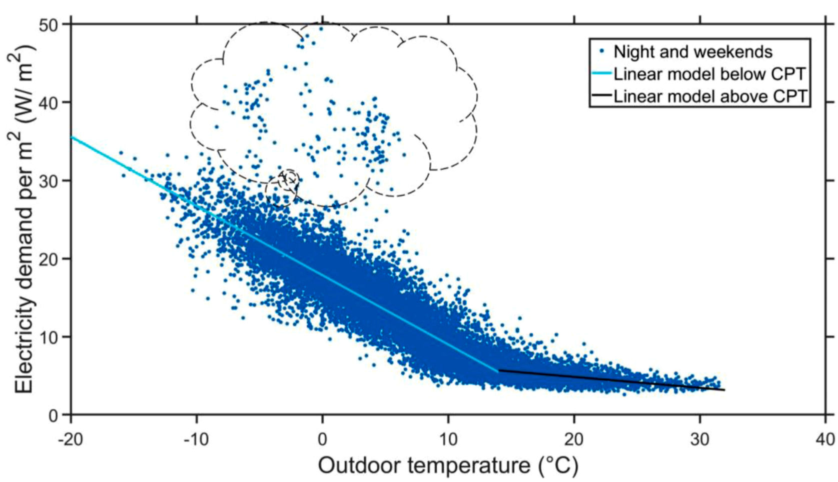


Figure 17. Energy signature curve models for kindergartens for Scenario 2

Table 4
Coefficients and accuracy of the ES curve models for Scenario 2

	Coefficients of model			Accuracy of model	
Building type	CPT (°C)	p_1	p_2	R^2	MAPE (%)
Kindergarten	14	-0.9 (≤ 14°C) -0.1 (>14°C)	17.9 (≤ 14°C) 7.6 (>14°C)	0.76	15.9
School	14	-0.7 (≤ 14°C) -0.1 (>14°C)	15.4 (≤ 14°C) 7.1 (>14°C)	0.75	19.4

the regression models were evaluated by two criteria, the coefficient of determination (R^2) and the mean absolute percentage error (MAPE). Except for the townhouse, the ES curve models for all the other building types had the R^2 higher than 0.75 and the MAPE lower than 20%, which meant they all satisfied the requirements of ASHEAE Guidelines for carrying out a satisfying model [42, 43]. The lower R^2 for the regression model in the townhouse might be explained by the relatively low share of electricity used for space heating purpose, while the other electric appliances accounted for a reasonably high share of electricity accordingly. It led to the linear relationship between the outdoor temperature and electricity not as strong as the other building types, where the space heating was only supplied by the electricity. However, according to the proposal from Henseler that R^2 with 0.5 is moderate in scholarly research as a rule thumb [44]. Also, the MAPE of the model for the townhouse was lower than 20% as required in [45] for a good forecasting. Therefore, the ES curve model for the townhouse was regarded qualified at some extent and may be utilized for a rough identification of profile in TMY in the following section.

As explained in Section 2.3, Scenario 2 considered the electricity demand level for buildings with low attendance during nighttime and weekends under normal situation. This energy-saving mode was regarded as the hypothesis of the operation mode that the kindergartens and schools should have adopted during the temporary closure.

The ES curve models for the kindergartens were carried out on hourly-based data, see Figure 17. It was noted that there were some outliers, marked within the dashed cloud. This must be caused by the occasional activities held during the weekends with high use of lighting, ventilation, and other appliances, as mentioned in Section 3.1. The ES curve models for schools were similar with kindergartens, and they are shown in Figure A2. The coefficients and the accuracy criteria of the ES curve models for kindergartens and schools under Scenario 2 are briefed in Table 4. The CPT of the two building types were still noted at 14°C with proper piecewise regression. The MAPE for the two building types were below 20%, and R^2 for the two building types are no less than 0.75. The ES curve models for the educational buildings meet the ASHRAE requirement of satisfying regression models.

Scenario 3 meant to identify the electricity use when the work-at-home regime was adopted. The weekly-based ES curve models for the two residential buildings under Scenario 3 are plotted in Figure 18. There was a noticeable higher electricity demand for the apartment under Scenario 3 than Scenario 1 (Figure 16), within the same outdoor temperature range. It indicated that there was higher electricity impact on the apartment, which was also consistent with the findings in the average daily profiles and ED results above. Because of the relatively small range of outdoor temperature during the work-at-home period, one linear model was sufficiently identified for the apartment without a CPT.

Table 5 gives the coefficients and the accuracy criteria of the ES curve models for the two residential buildings under Scenario 3. The R^2 for the two building types were higher than 0.8, and the MAPEs were below 10%, indicating these ES curve models were accurate to be used in the following work.

3.3. Scenario-based electricity profiles

A yearly electricity use profile may be predicted by combining the regression coefficients defined in Section 3.2 and the outdoor temperature in a typical weather year. Figure 19- Figure 21 illustrate the possible electricity profiles for kindergartens, schools, the single apartment, and the townhouse.

As shown by the solid red lines in Figure 19 and Figure 20, kindergartens and schools needed 172 kWh and 139 kWh electricity per m^2 in a typical year, under the normal operation settings (Scenario 1). These demand values were lower than the Norwegian Statistics, 183 kWh/(m^2•yr) for kindergartens and 167 kWh/(m^2•yr) for schools [38]. While under the energy-saving mode (Scenario 2), only 112 kWh/m^2 was needed in kindergartens and 99 kWh/m^2 in schools in a TMY, as shown by the green dashed lines. From the comparison between the two building management modes, it indicated that there was a remarkable energy saving potential during a temporary shutdown. By implementing proper settings for the building service systems and improving the arrangement of the educational institutions, the electricity use may be reduced by approximately 35% in the kindergartens and 29% in the

Table 5
Coefficients and Accuracy of the ES curve models for Scenario 3

	Coefficients of model			Accuracy of model	
Building type	CPT (°C)	p_1	p_2	R^2	MAPE (%)
Apartment	/	-1.6	41.9	0.88	8.1
Townhouse	/	-0.5	17.7	0.84	9.2

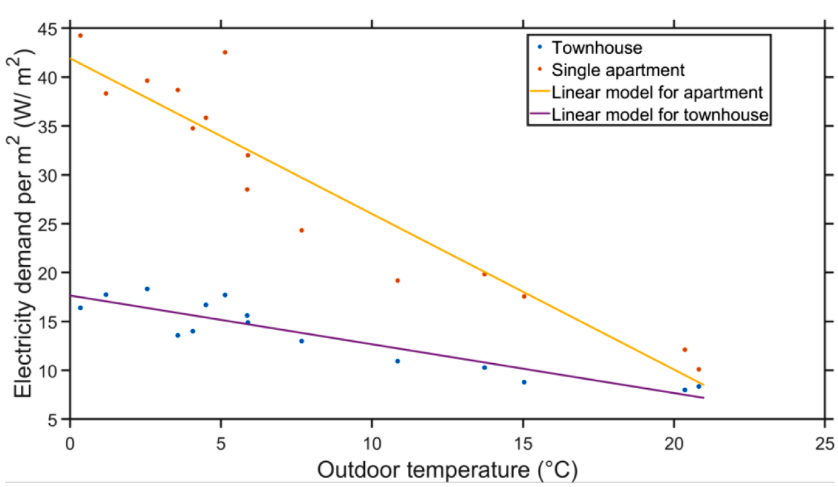


Figure 18. Energy signature curve models for the single apartment and the townhouse for Scenario 3

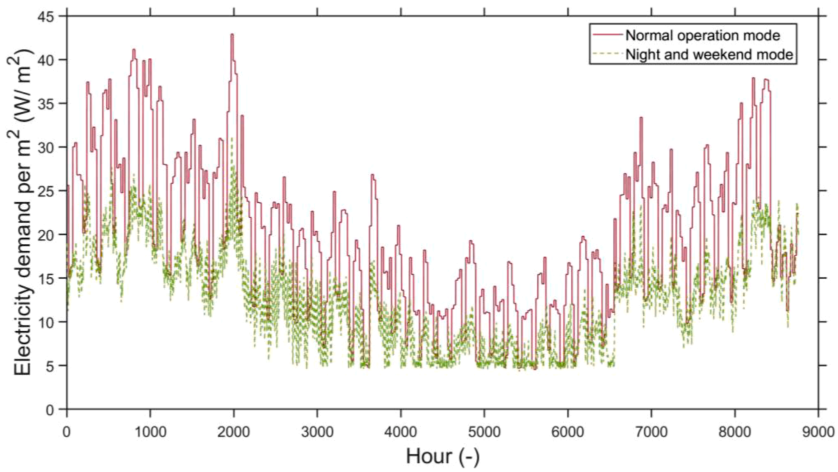


Figure 19. Annual electricity profiles for kindergartens under Scenario 1 and Scenario 2

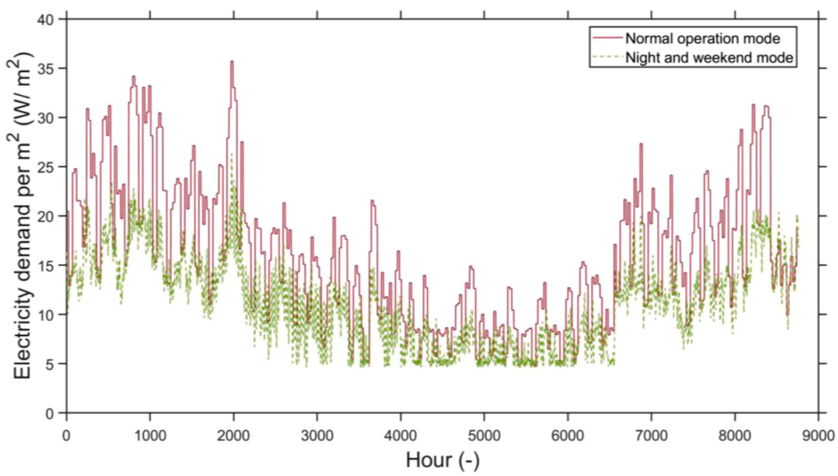


Figure 20. Annual electricity profiles for schools under Scenario 1 and Scenario 2

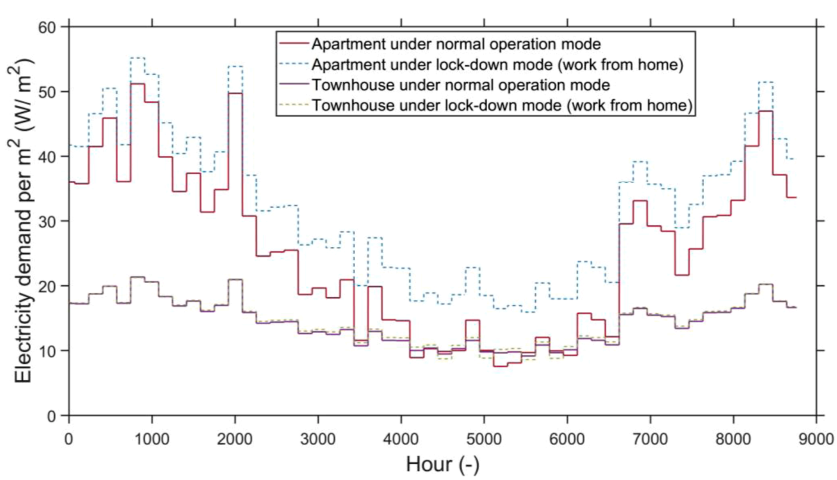


Figure 21. Annual electricity profiles for the single apartment and the townhouse under Scenario 1 and Scenario 3

schools. Since kindergartens usually have longer opening hour and higher indoor temperature requirements than schools, it explains kindergartens may have 6% more electricity reduction possibility than schools.

Regarding the scenario comparison in the residential buildings, the impact on the specific electricity demand was much higher in the single apartment than in the townhouse, as plotted in Figure 21. Under the normal situation when the daytime attendance was low, the annual electricity demand of a typical year was 222 kWh/m^2 and 126 kWh/m^2 in the apartment and townhouse, respectively, as shown in the solid

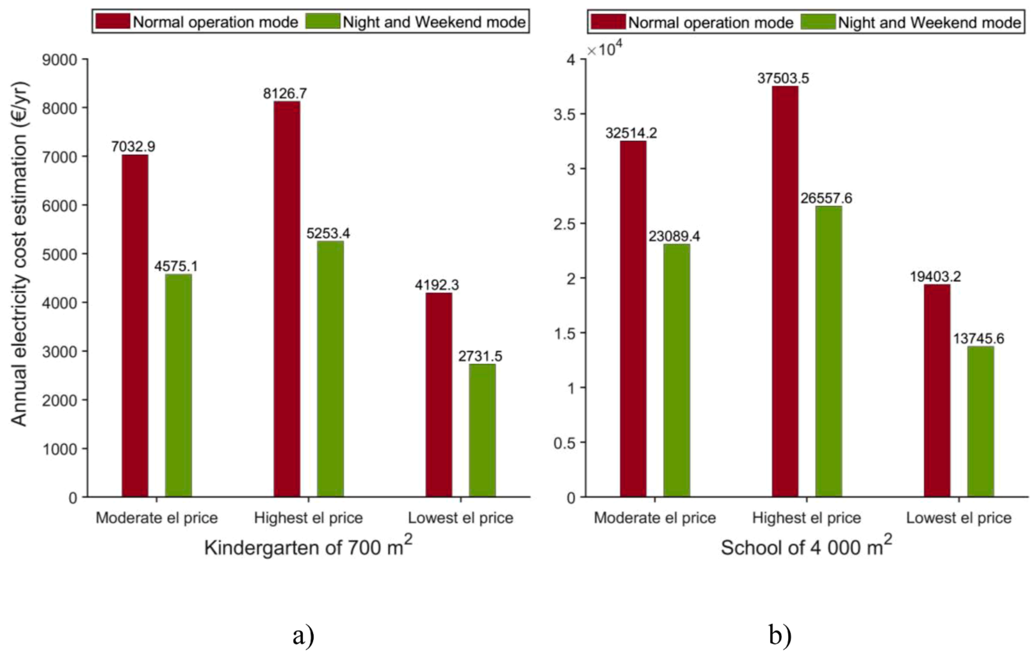


Figure 22. Annual electricity cost estimation of kindergartens and schools under two operation scenarios, where a) annual cost of kindergartens, b) annual cost of schools

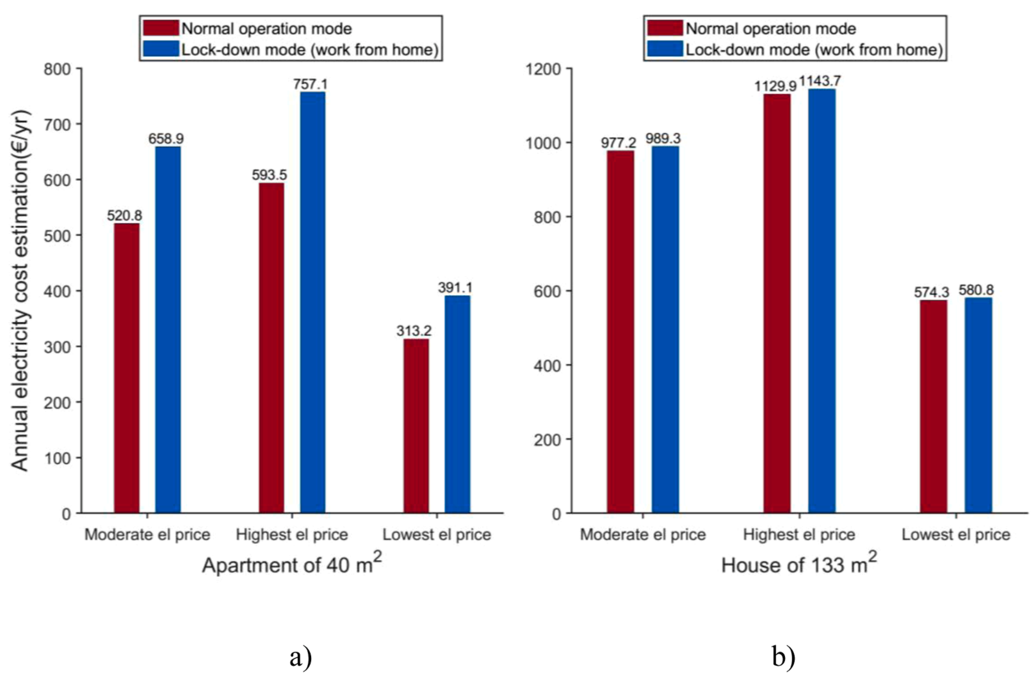


Figure 23. Annual electricity cost estimation of the single apartment and the townhouse under two operation scenarios, where a) annual cost of the apartment, b) annual cost of the townhouse

lines. Comparing with the Norwegian Statistics of the average energy use per household, this apartment used 20% more energy than the average level, and this townhouse used 14% less electricity than the average level (the fuel of wood was not considered) [18]. However, when the rule of work-at-home was in effect, 26.9% more electricity was needed in the apartment, while the townhouse only required 1.3% more electricity, as shown in the dashed lines. Again, the higher electricity density in the single apartment makes it more sensitive after the use pattern changed. Unlike the educational institutions, it may not be straightforward to point out the energy saving potential in the residential buildings. The possibilities and measures to save electricity can be realized by upgrading the building energy supply methods in the apartment building or its neighborhood community, for example, to introduce ground source heat pump, or connect to a district heating network if available [46–48].

3.4. Results of economic costs calculation

By combining the predicted electricity profiles defined in Section 3.3 and the three price levels described in Section 2.5, the annual electricity

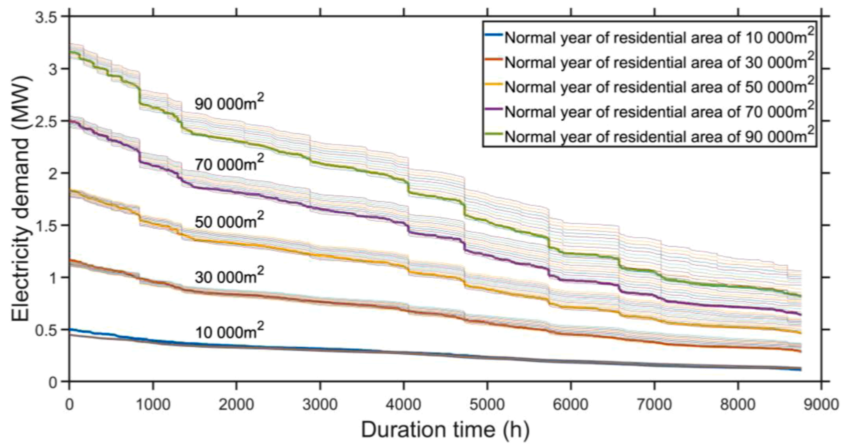


Figure 24. Electricity duration curves for different residential building areas, comparing normal year with lockdown year when varying percentages of work-from-home

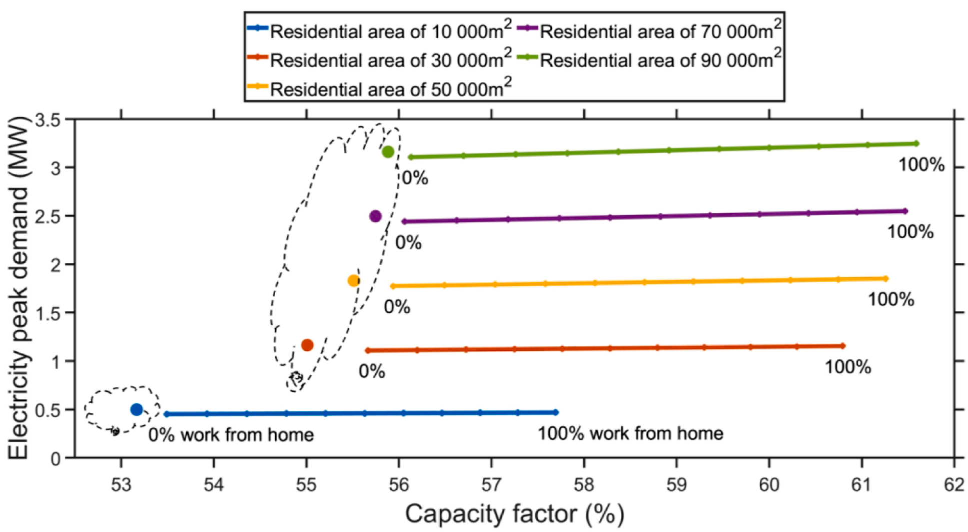


Figure 25. Capacity factor vs electricity peak demand for different residential building areas, comparing normal year with lockdown year when varying percentages of work-from-home adoption

costs for the four building types were estimated according to the three price cases.

In the educational buildings, the building area of kindergartens and schools was assigned with the Norwegian average area of 700 m^2 and 4 000 m^2, respectively [38]. Figure 22 compares the annual electricity costs of one representative kindergarten and one representative school under the normal operation mode (Scenario 1) and the night and weekend mode (Scenario 2), where moderate el price, highest el price, and lowest el price are the shortcuts of the cases of moderate, highest, and lowest electricity price. For the kindergarten, the cost reductions between the two running modes varied from 1 461 €/yr (equivalent as 2.1 €/(m^2.yr)) under the case of lowest electricity price to 2 873 €/yr (4.1 €/(m^2.yr)) under the case of highest electricity price, see Figure 22a. For the school, Figure 22b exhibits that between 5 658 €/yr (1.4 €/(m^2.yr)) and 10 946 €/yr (2.7 €/(m^2.yr)) may be saved if the building was shifted to the night and weekend settings during lockdown. It is worthy noted that the economic saving potential from switching operation mode was greater when the electricity price was higher. It further emphasized the importance of carrying out energy-efficient operation strategy during low attendance on campus.

In the residential buildings, the economic impacts were interpreted differently from the educational buildings. Due to more time spent at home by the dwellers, between 78 - 164 € (2.0 €/(m^2.yr) - 4.1 €/(m^2.yr)) more money may be needed in the apartment, see Figure 23a, while the increase would be less than 15 € (0.1 €/(m^2.yr)) in the townhouse, see Figure 23b. Although the larger dwelling of multi family members required higher total electricity expenditure than the smaller single apartment, they might act more robust in the changes of the use patterns.

To sum up, based on the findings from both energy and economic point of view, the yearly electricity costs were dependent both on the building management settings and the power market price. For example, at the lowest electricity price level, the expenses for normal operation in both kindergarten and school were still lower than the energy-efficient mode concerning the other two price cases. It was similar as in the residential buildings, the home office mode at the lowest price level might even cause less expenditures than the others.

4. Discussions and limitations of this study

In this study, there are three points worthy to be discussed.

Firstly, in these observed buildings, there are no submeters for separating the electricity used for heating purpose, lighting, and appliances. However, based on the evaluation results of the model accuracy, the R^2 and the MAPE, most of the developed ES curve models met the requirement of satisfying regression models, mainly because a large

Table A1
Peak demand and its changes regarding different residential area under normal condition and changing percentage of work-from-home adoption

Residential area (m^2)	Peak demand (MW) – normal condition	Percentage of work-from-home adoption (%)	Peak demand (MW) – work-from-home	Percentage changes of the peak demand (%)
10 000	0.498	0	0.452	-9.3
		10	0.453	-9.0
		50	0.460	-7.7
		100	0.468	-6.1
30 000	1.164	0	1.108	-4.8
		10	1.113	-4.4
		50	1.132	-2.8
		100	1.155	-0.8
50 000	1.829	0	1.774	-3.0
		10	1.782	-2.6
		50	1.813	-0.9
		100	1.851	1.2
70 000	2.495	0	2.439	-2.2
		10	2.450	-1.8
		50	2.494	-0.1
		100	2.548	2.1
90 000	3.160	0	3.105	-1.8
		10	3.119	-1.3
		50	3.175	0.5
		100	3.244	2.6

share of electricity goes to space heating. During the pandemic, the energy response of the buildings may be region and country related, which may be influenced by the building function, social aspects, and rule tightness [10, 11, 49]. Therefore, it is worthy using the ES curve models as a robust and fast method to predict the electricity demand based on different operation strategies, especially for buildings without submeters. However, the model accuracy may be weaker such as in low energy building and passive house, where space heating accounts for lower energy share.

Secondly, the COVID-19 related impacts on the buildings' annual CO_2 emissions were not included. It was considered adequate to identify the electricity demand changes and possible energy saving potential, because the change percentage of the CO_2 emissions would be the same as demand changes regardless of the CO_2 factors. However, it will still be interesting to find credible source of CO_2 factor and investigate the CO_2 emissions in response to future unforeseeable disruption.

Thirdly, the consequence on the local energy planning was discussed based on the example of the imaginary community by following Eqs.(4) and (5) in Section 2.6, where A_{kind}, A_{sch}, and A_{resi} were chosen with 700 m^2, 4000 m^2, 10 000 – 90 000 m^2 with each step of 20 000 m^2, respectively. As shown in Figure 24, the thick lines represent the electricity duration curves in the normal year, and the thin lines represent the electricity duration curves in the lockdown year by varying the percentages of work-from-home adoption from 0% to 100%. For each residential area group, the 0% of work-from-home adoption is shown with the lowest line, and the 100% is shown with the highest line. It is apparent that the duration curves in the normal year are steeper than most of the work-from-home conditions for all the residential area groups.

Figure 25 further compares the capacity factor with the electricity peak demand regarding different residential areas. The solid circles in the dashed cloud line stand for the normal year condition. The lockdown year's result for each residential area is shown with the solid line by varying work-from-home adoption from 0% to 100%. As noted in Figure 25, normal year had lower plant capacity factor and needed higher peak demand than some of work-from-home conditions for the smaller residential areas (e.g. 10 000 – 50 000 m^2). It is interesting to see the energy utilities may not be fully utilized in normal year, which may lead to uneconomic production. In the larger residential areas (e.g. 70 000 – 90 000 m^2), although the plant capacity can be better used with a higher capacity factor, it may require higher peak demand during the lockdown. For example, the percentage changes of the peak demand for the residential area of 10 000 m^2 were between -9.3% and -6.1% from 0% to 100% of work-from-home adoption, and these changes for the residential area of 90 000 m^2 were between -1.8% and 2.6% from 0% to 100% of work-from-home adoption. It may be explained as the saved electricity from the closed kindergarten and school may not be comparable with the more electricity being used when most of the residents stay at home, for a larger residential area. The detailed changes regarding each residential area are listed in Table A1.

From this example, it may be concluded that the local infrastructure sizing may be influenced by different aspects, such as the areas of residential and educational buildings, energy operation mode, and some unintended conditions. As suggested in a study of one university campus with multiple building functions [50], an appropriate building type ratio would be helpful to reduce the total load and load fluctuation of a district. Therefore, it is important to analyze the energy demand under different scenarios to discover the optimal sizing in the future planning.

Since the lockdown regime in Norway was in effect from mid-March to early May 2020, the outdoor temperature during this period (0 - 21°C on weekly base) did not cover the local historical outdoor temperature range throughout a year (such as -7 - 21°C on weekly base in 2019), especially the recorded low temperature in winter. Hence, the extrapolation of the Scenario 3 based ES curve models to the TMY might not fully represent the annual household electricity profile. The increased annual household electricity demand (especially in winter) may be higher than the estimation in this study, by extrapolating the electricity characteristics under the limited outdoor temperature range during the lockdown. Moreover, as shown in the results, the electricity use density to the outdoor temperature in the apartment was much higher than in the townhouse, making the deviation even larger for the apartment than for the townhouse. To better prepare for the future unforeseen disruptions as well as the trends of workplace and lifestyle, more data and/or seasonal correction factors are necessary for further study, for example, to take experiment of home office activities involving more dwellings. This may present a more comprehensive insight with more accurate forecasting models and better knowledge.

5. Conclusion

The COVID-19 pandemic has put heavy stress and crucial challenges around the world. Accordingly, many countries have carried out confinement regulation to hinder the infection spreading. Due to the changed work regime, the significant impacts on energy sectors have been seen in many countries. This study was focused to analyze the electricity profiles and the relevant changes in Norwegian buildings with electric heating. Two Norwegian educational building types at municipal level (kindergartens and schools) and two Norwegian residential buildings (a single apartment and a townhouse) during the lockdown were studied on the measured data.

The scenario-based analysis in this study was mainly made for identifying the possible electricity demand and corresponding electricity increase and saving potential at a macro scale if new disruption would be introduced. To achieve the aim, the article developed the three scenarios regarding the different building operation strategies. Scenario 1 modeled the electricity use under normal conditions, Scenario 2 modeled the electricity on settings during normal weekdays' nighttime and weekends for kindergartens and schools, and Scenario 3 modeled the household electricity use under the work-at-home conditions.

The work was conducted as follows. The average daily electricity profiles before and during the lockdown were identified. It was found that there were almost no changes of electricity use pattern in the two educational building types, but there was demand variation in the residential buildings. The ES curve models were then developed for describing the electricity characteristics under each scenario. Most of the models were qualified as satisfying regression models by evaluating with the accuracy criteria R^2 and MAPE. These scenario-based ES curve models were used for making annual electricity profiles in a typical weather year. Under Scenario 1, around 172 kWh_{el}/m^2 and 139 kWh_{el}/m^2 were needed in a TMY for kindergartens and schools, respectively. These electricity use could be reduced by 35% for kindergartens and by 29% for schools, with proper building operation during a temporary closure, as suggested by Scenario 2. Meanwhile, when the dwellers' schedules changed into home office regime (Scenario 3), approximately 27% and 1.3% more electricity were required for the single apartment and the townhouse, respectively. The small apartment with higher electricity density made it more electricity sensitive than the large house, especially during the lockdown period. The annual power bills were estimated in three spot price level cases, showing that more expensive electricity yielded bigger driving forces to adopt better building management. With proper settings, between 2.1 - 4.1 €/(m^2.yr) may be saved for kindergartens, and 1.4 - 2.7 €/(m^2.yr) for schools. The apartment may spend 2.0 - 4.1 €/(m^2.yr) more for electricity, while the increased bill for the townhouse may be trivial.

The analysis on the aggregated electricity demand showed that the local infrastructure sizing may be influenced by the areas of residential and educational buildings, energy operation mode, and some unintended conditions. For the residential area of 10 000 m^2, the percentage changes of the peak demand were between -9.3% and -6.1% from 0% to 100% of work-from-home adoption, and these changes for the residential area of 90 000 m^2 were between -1.8% and 2.6%. Therefore, it is important to analyze the energy demand under different scenarios to discover the optimal sizing in the future planning.

The methods and results of this article may be useful to similar or other building types in response to future unforeseeable disruption, especially the buildings in the similar climatic conditions.

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.

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Appendix A

Figure A1, A2 and Table A1

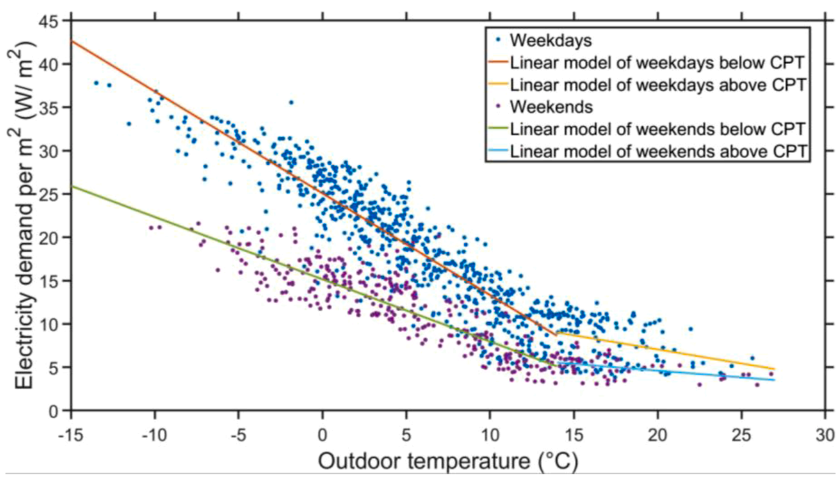

Figure A1. Energy signature curve models for schools for Scenario 1

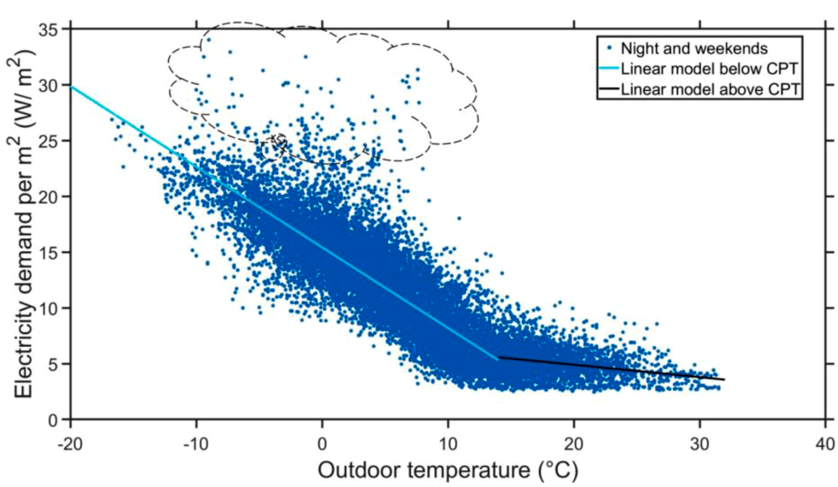

Figure A2. Energy signature curve models for schools for Scenario 2

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