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Changes in energy use profiles derived from electricity smart meter readings of residential buildings in Milan before, during and after the COVID-19 main lockdown

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ABSTRACT

The COVID-19 pandemic had a profound impact on society, causing changes in various aspects of people's lives, including their energy use habits. This has prompted a need for checking and updating standard energy use profiles, particularly for residential electricity use. To address this topic, a study was conducted on 24 multi-family buildings in Milan, using clustering to extract patterns from a database of quarter-hourly electricity use data from 2019 to 2020. This study found an increase in electricity usage during the COVID-19 lockdown period for residential buildings, likely associated with the imposed restrictions. The research also highlighted a shift in energy usage from the morning peak to the central hours of the day during the working days of the lockdown period, while a gradual increase in electricity usage throughout the day and no morning peak was observed during the Autumn (post-COVID) period. The findings can assist regulators and businesses in weighing the benefits and drawbacks of remote working and provide modellers with a complete set of daily load profiles for an Italian residential case study.

1. Introduction

In early 2020, the world faced a significant event that still persists, although, during the fifteenth meeting of the International Health Regulations Emergency Committee on the COVID-19 pandemic, the World Health Organization (WHO) Director-General determined that "COVID-19 is now an established and ongoing health issue which no longer constitutes a public health emergency of international concern" (World Health Organization, 2020). The COVID-19 virus, originally isolated in China, quickly spread across the globe, prompting the WHO to declare a global emergency (WHO, 2021). Italy was among the first countries outside China to experience a severe outbreak, putting immense pressure on its healthcare system (Gazzetta Ufficiale, 2020).

To curb the virus's spread, the Italian government imposed, in March 2020, a national lockdown, mandating people to stay home and work remotely if possible. This drastic measure significantly impacted both individuals and communities. After two months, the government sought to gradually ease restrictions, designating the reopening process as "Phase 2″ and "Phase 3″. However, a resurgence of cases in late September 2020 forced authorities to reinstate some restrictions and implement a regional alert system based on infection rates. Throughout 2020, the scientific community focused on developing COVID-19 vaccines, with the European Medicines Agency approving the first vaccines in December (European Medicines Agency, 2020). Fig. 1 provides an overview of these events. The lockdown period for Lombardy, one of the early and most affected regions in Italy, has been highlighted in blue. Since, the imposed national and local restrictions brought a change in people's lives and consequently in energy consumption patterns and uses, the data gathered during this period has been used to study the energy behavior in households during a full lockdown to understand the type and scale of changes in energy use. Four periods have been identified and used in the following analysis: "Winter" (i.e., broadly January-February) in orange, "Lockdown" (i.e., broadly March-April) in blue, "Summer" (i.e., broadly May-September) in gray, and "Autumn" (i.e., broadly October-December) in green.

In particular, the COVID-19 pandemic changed the daily occupancy of residential buildings and consequently the daily load profile. A residential daily load profile represents the electricity used by all electronic devices in a household over 24 h. Daily load profiles analyses serve several purposes, among the main ones: assisting in demand-side management for targeted cost-effective solutions (Kwac, Flora & Rajagopal, 2014); predicting daily electricity demand for transmission system

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operators (TSOs) (Terna, 2023); providing data for distribution system operators (DSOs) to improve their interface with transmission and distribution (Bosisio, Moncecchi, Morotti & Merlo, 2021); and aiding authorities and municipalities in assessing the interplay between renewable production and self-consumption (Molin, Schneider, Rohdin & Moshfegh, 2016). Daily load profiles are also employed by building and urban scale designers (Ferrando et al., 2022). Measured daily profiles are used to validate bottom-up modelled profiles from individual devices (Besagni, Premoli Vilà & Borgarello, 2020; Widén et al., 2009), data-driven segmentation of daily profiles often employs clustering (Causone, Carlucci, Ferrando, Marchenko & Erba, 2019; Ferrando, Marchenko, Erba, Causone & Carlucci, 2019) and/or advanced deep clustering techniques to classify different user groups based on their consumption pattern (Ferrando, Nozza, Hong, Causone & Milano, 2021). Besides the availability of appliances, in some cases, residential profiles are segmented based on sociodemographic behavioural analysis (Hayn, Bertsch & Fichtner, 2014). The literature emphasizes the need to update and improve residential use profiling, incorporating the growing trend of remote working (Proedrou, 2021). To this end, the Lockdown period presents an opportunity to gain a deeper understanding of remote working potential effects, not only within the context of 2020 but also in anticipation of its continued prevalence.

This research aims to examine the pandemic-induced changes in people's lives, specifically electricity consumption in the residential sector (Balest & Stawinoga, 2022), in Milan. Various studies have explored this topic, some analysing the pandemic's impact on greenhouse gas emissions (IEA, n.d.) and others using simulated data to model different scenarios (L. Li, Meinrenken, Modi & Culligan, 2021; Zhang et al., 2020). Research has also focused on the relationship between the pandemic and overall electricity use (Abu-Rayash & Dincer, 2020; Z. Li et al., 2022) and the residential sector specifically (Abdeen, Kharvari, O'Brien & Gunay, 2021). Some studies have investigated the correlation between temperature and electricity consumption during the crisis (Abdeen et al., 2021). The present study investigates the impact of COVID-19 and lockdown measures on residential energy consumption in Milan, by comparing smart meter readings from 2019 to 2020. This comparison provides insight into the behavioural changes associated with remote working, particularly in the context of the Mediterranean countries. To the best of the authors' knowledge, no studies have yet examined the effects of COVID-19 on residential energy use in Italy, making this research a novel contribution to the field. While similar studies have been conducted in other parts of the world (e.g., the United States of America (Bednar & Reames, 2023; Dai et al., 2023), Japan (Kojima & Saito, 2023), South Korea (Choi & Yoon, 2023), Indonesia (Sari & Pinassang, 2023), Colombia (Garcia-Rendon, Rey Londoño, Arango Restrepo & Bohorquez Correa, 2023)), the Mediterranean region presents unique challenges and opportunities that warrant investigation. By focusing on this understudied area, the present study aims to advance the understanding of the impacts of COVID-19 on residential energy consumption and inform future policy and decision-making. Thus, in this research, the daily load profiles, coming from a database of quarter-hourly electricity use of 24 residential buildings (for a total of around 750 apartment's load profiles) from 2019 to 2020, serve as the central element of electricity consumption analysis on an hourly basis. A clustering algorithm is applied to segment and classify the profiles, as detailed in the methodology (Section 2). The case study is described in Section 3, while Section 4 presents the results and discussions. Section 5 outlines the conclusions, limitations, and future outlooks of the study.

2. Methodology

Electricity usage in buildings is known to vary depending on the time of year, increasing during periods of extreme temperatures and decreasing during milder seasons (Alberini, Prettico, Shen & Torriti, 2019). However, it is also known that external factors can significantly impact electricity usage patterns (Fransson, Bagge & Johansson, 2019), and the implementation of COVID-19 restrictions could be identified as one of them. Therefore, to understand the effect of COVID-19 restrictions on electricity usage, the available database for the year 2020 has been divided into four periods, as shown in Fig. 1. By comparing these periods to the same periods of the previous year (2019), it is possible to infer changes in electricity usage that may be attributed to COVID-19 restrictions. The analysed periods are the Winter, the Lockdown and the Autumn, which are compared both against each other and also to the corresponding periods of 2019, to highlight pattern differences. Due to the strong lack of data, the Summer period is included only and partially in the data understanding phase, and this part of the database has not been used for clustering applications, being unsuitable for that purpose.

The methodology used in this study is divided into four main tasks, (Fig. 2) starting from the raw data (details regarding the characteristics of the data used in this study can be found in Section 3.): (1) data pre-processing, (2) data understanding, (3) data clustering and (4) distribution-based analysis. These four tasks are fundamental to gain a comprehensive understanding of the data and to identify any change in electricity usage patterns resulting from external factors, such as the implementation of COVID-19 restrictions. Python (Python Software Foundation, 2019) is used as the programming language to implement all tasks and analyses. Specifically, the scikit-learn library in Python is utilized to perform the clustering tasks and analyses.

The data pre-processing task is fundamental to ensure that the dataset is accurate, complete, and consistent. This involves cleaning the data by removing errors, missing values, or outliers and, aggregating the data spatially and/or temporally if needed. Additionally, data normalization may be necessary to ensure a consistent scale across all variables. Finally, as the literature advises [11,13,28], the daily load profiles of each building have been converted to an alternate representation consisting of an hourly load pattern and a reference power value. The hourly load pattern is calculated as the normalized profile of the original load curve, whereas the power value, in this case, is defined as the Appliance and Lighting Density Level (ALDL), which is the average of all the buildings' daily maximums. The daily maximum of each building's daily

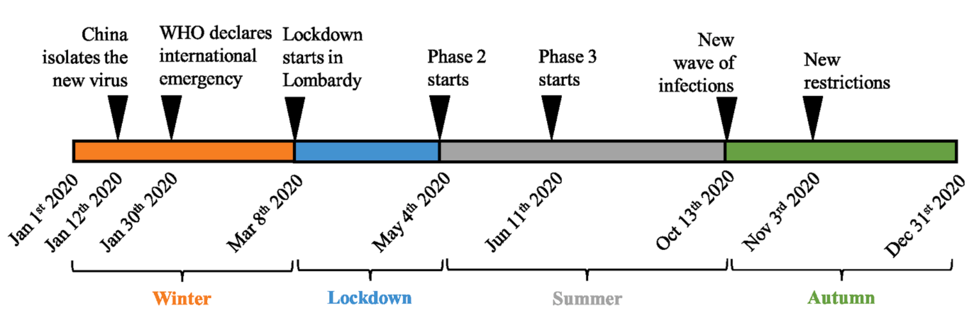

Fig. 1. Timeline of the COVID-19 development and measures during the year 2020, with a focus on Italy and the Lombardy region. The colours represent the time ranges adopted in the study.

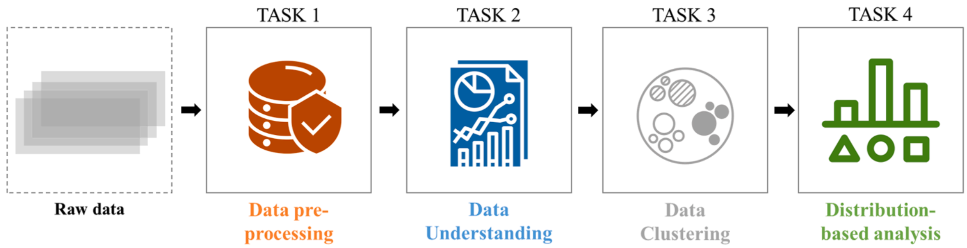

Fig. 2. Schematic of the applied methodology.

profile was used for normalization. By pre-processing the data in this way, it is possible to ensure that the subsequent analysis is based on accurate and relevant information.

The second task involves a general investigation of the data to assess trends and correlations between variables and to identify any trend, pattern, or anomaly. The data understanding task gives insights from the data, and it is important to develop knowledge of the variables and their relationships. This can be done through visualizations, such as scatter plots, histograms, or box plots, which can highlight any relationship or correlation between variables. Additionally, statistical analysis can be used to identify the strength of any relationship between variables. A first correlation analysis against weather variables is performed because they (e.g., temperature and irradiance) are known to influence electricity usage, and it is important to understand whether any observed change in usage patterns can be attributed to these variables. Pearson correlation, being a widely used statistical method for measuring the strength of the linear relationship between two variables, was employed for this task. The results of this analysis can help to identify whether the changes in electricity usage patterns can be attributed to climate variables or other external factors, such as COVID-19 restrictions.

In the third task, data are clustered into daily patterns to understand the different electricity usage patterns across different periods and years. Each cluster is characterized by a centroid (e.g., a representative daily pattern determined by averaging all the daily patterns grouped in the same cluster) and a distribution of representativeness in the original database that corresponds to the percentage of original days that are similar to one another, thus, are in the same cluster (e.g., 20% of the days fall in Cluster 1). The data clustering task is performed because the electricity usage patterns are known to exhibit recurrent daily patterns, such as peaks during certain hours of the day and dips during others (Ferrando et al., 2021). Clustering is a useful method for identifying these patterns and grouping similar usage patterns. Based on the nature of our dataset and research question, analysing the data separately for each year would best highlight potential differences in behaviours between 2019 and 2020. The intention is to focus on identifying changes rather than purely describing consumption profiles, so we used the clustering centroids primarily as an identification tool. The Davies-Bouldin index (DBI) is a measure of the similarity between clusters and provides an estimate of the optimal number of clusters. By using this method, the number of recurrent patterns can be found allowing the comparison before, during and after the implementation of COVID-19 restrictions. This analysis can help identify changes in electricity usage behavior resulting from the restrictions.

In the fourth task, clusters are analysed and compared based on their distribution of representativeness in the database between 2019 and 2020 to gain further insights into electricity usage patterns providing a detailed understanding of the recurrent trends and how they changed after the implementation of COVID-19 restrictions. Patterns of the different periods are directly compared and analysed based on their distribution in the dataset. The comparison between years aimed to investigate behavioural shifts rather than accurately quantify representation, therefore the profiles are analysed based on the raking of frequency for each year.

3. Case study

The data utilized was collected through smart meters installed in households of a selected demonstration area. A smart meter is a physical device capable of automatically detecting and transmitting information about the usage of a particular energy carrier, such as electricity, in a given perimeter, such as a flat, enabling remote monitoring (Bimenyimana, 2018). The database focuses on 24 buildings primarily used for residential purposes, divided into "zones" representing either an apartment or a common area. In this case study, a zone refers to a part of the building connected with a smart meter. Each smart meter is associated with a zone, labelled with a progressive number, and reads electric use every 15 min. Around 750 zones, and thus energy profiles, constitute the database. The available data ranges from 1st January 2019 to 31st December 2020, with localized missing data between 1st May 2020 and 31st August 2020 due to changes in the data collection system. Excluding this critical period, the energy provider filled in any missing entries using a filling algorithm based on historical electric data series. The data is anonymous, providing no information or characterization of the tenant, while limited information on the buildings is available, such as the total net area and the zones in each building. While income data for the specific households are not available, the geographic distribution from the city center to the periphery implies that the residents likely represent a range of socioeconomic characteristics. Higher incomes tend to be overrepresented in central areas, while lower incomes are more concentrated in the suburbs. Therefore, the building locations indicate that the sample covers a diversity of incomes, although public housing units are not included. The geographical distribution improves the representativeness, likely capturing a range of household incomes. The buildings in the case study are mostly multi-family, with some commercial activities on the premises, built between 1920 and 2004, with an average value for buildings constructed in 1960. The majority of flats have a gas-fired centralised building heating system and an independent split cooling system, with domestic hot water partially produced electrically through electrical boilers. The building envelopes are primarily based on hollow clay brick construction. Some buildings have an air gap between two brick layers, while others have external or internal insulation. Only a small number of buildings have prefabricated panel envelopes consisting of expanded clay blocks with internal insulation. These envelope characteristics, along with the systems and uses, are typical of residential buildings from the era commonly found in Milan. The buildings' net conditioned area ranges from 700 m^2 to 9300 m^2, with an average value of 3300 m^2, and the number of storeys varies between 4 and 12, with an average value of 6.5. All structures are well integrated into the city's residential fabric. Fig. 3 shows the location of all households in the database, positioned in the South-East area of Milan.

4. Results

4.1. Data pre-processing

The data pre-processing involves merging several databases into a single larger dataset and cleaning it to ensure a reliable comparison

Fig. 3. Location of the considered buildings in Milan, Italy.

passing through data cleaning, data reduction and data transformation. First, the data underwent a cleaning phase to remove inconsistencies. In this regard, daily string values of the smart meter readings containing missing data were deleted to reduce errors. The period with the missing values from May 1st to October 31st of 2020 was completely removed from the dataset for the clustering phase due to the massive amount of missing values. For the data reduction phase, all the readings from smart meters installed in the same building were aggregated to analyze the energy usage profile at the building level. Specifically, the study added up all the zones' electricity use for each building. While analysing electricity patterns of single flats would enable a fine-grained investigation, many systems rely on the entire building level. Isolating single flats would not capture the overall usage of shared building resources. By summarizing zones together, we assessed changes in behavior at the whole multi-family building level rather than within individual flats. Aggregating at the building scale allowed us to describe how total consumption profiles shifted between 2019 and 2020, even if behaviours in single flats did not change uniformly. Focusing on the full building usage enabled valid results to characterize changes across the multi-family dwelling as a whole. Moreover, the data reduction is performed on a time-step basis. The original database is registered every 15 min as electric power in watts. To obtain hourly values, the average within each hour is calculated. By Averaging the values also the potential eluded errors are averaged. Thus, this process reduces the impact of potential outliers on the overall results. Finally, the daily maximum of each building's daily profile was used for normalization. Additionally, data transformation involved the distinction between working days (Monday to Friday) and weekends (Saturday and Sunday and national holidays) into two different datasets since the study focused on the work-from-home phenomenon. It also followed the traditional distinction in literature between weekends and working days (Causone et al., 2019).

4.2. *Data understanding*

An analysis was conducted to compare the total monthly electricity usage given by the sum of all buildings in the case study between 2019 and 2020 and to determine whether any changes occurred during the months. Fig. 4 displays an increase in electricity usage during March and April of 2020, as compared to that of 2019. The Winter period, including data from 2019 to 2020 before the COVID pandemic, showed similarities, indicating that changes in subsequent periods may be related to COVID. During the Lockdown period, there was a noticeable increase in electricity usage, which could be attributed to the mandatory stay-at-home order. Regarding the Summer period, due to a severe lack of data, it is challenging to define a trend. Notably, a decrease in electricity usage is registered during the Autumn period. Specifically, in September and October, people had more freedom to leave their homes, and this may be reflected in the decrease in electricity usage compared to 2019. However, this trend was not followed during August and December when a low number of people went on holiday, resulting in a visible increase in electricity usage in 2020.

Table 1 presents the ALDL (average of all the buildings' daily maximums) for different periods, categorized by working days and weekends, for the years 2019 and 2020. During the Lockdown period, the

Table 1
ALDL (average of all the buildings' daily maximums) for each period.

Period label		2019	2020	Δ%
Winter	**Working days**	6.08 W/m^2	6.56 W/m^2	+7.9%
	Weekends	5.46 W/m^2	5.96 W/m^2	+9.2%
Lockdown	**Working days**	5.68 W/m^2	5.82 W/m^2	+2.5%
	Weekends	5.21 W/m^2	5.75 W/m^2	+10.4%
Autumn	**Working days**	6.83 W/m^2	6.68 W/m^2	−2.2%
	Weekends	6.92 W/m^2	6.89 W/m^2	−0.4%

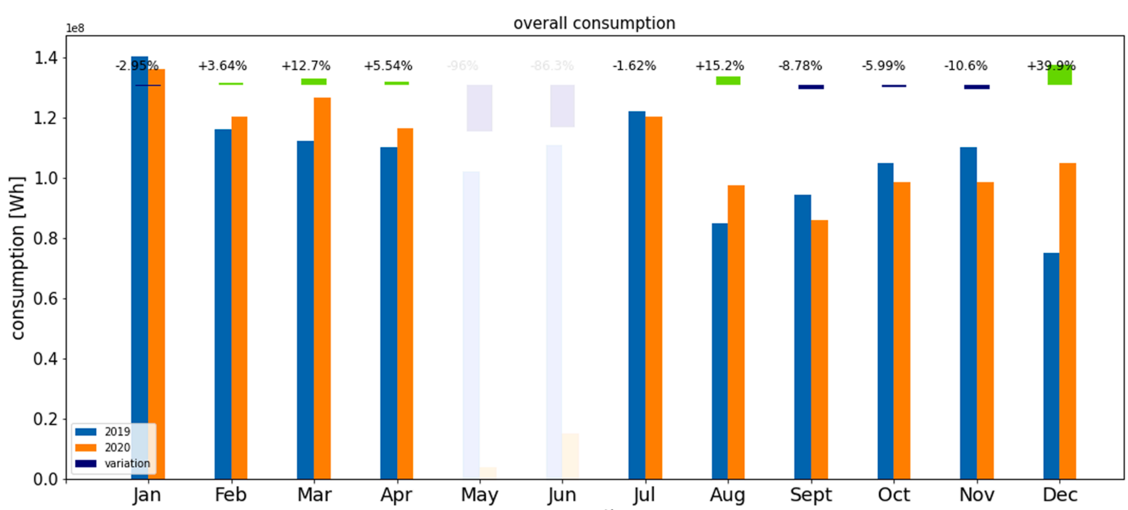

Fig. 4. Compared total monthly energy use between 2019 and 2020 of all buildings included in the study.

energy usage value was higher, especially on weekends (+10.4%). In the Autumn period, a decrease effect is registered for both working days and weekends (−0.4%) In the Winter period, the reference power level increased (i.e., +7.9% for the working days and +9.2% for the weekends). It is important to note that these power densities are based on the average of the daily maximum in the reference period, representing the peak of the power request, rather than the average power usage of all the hours in the reference period. It is thus an "average daily peak" value.

Previous studies have established a significant link between electricity consumption and climatic parameters, such as temperature and global irradiance (Lei & Hu, 2009). To investigate whether changes in usage profiles could be weather-dependent, a correlation analysis was conducted between climate data and electricity usage data. Fig. 5 illustrates the results of the Pearson correlation analysis between total electricity usage of all buildings and external air temperature and irradiance. Pearson correlation is a widely used statistical method for measuring the degree of linear relationship between two variables. It produces a coefficient, denoted as rho, which ranges between −1 and 1. When rho is close to 1 or −1, it indicates a strong positive or negative correlation between the two variables, respectively. On the other hand, when rho is close to 0, it indicates a weak or no linear correlation between the two variables. Thus, if a strong correlation had been present, the data points would form a linear or curved pattern that trend up or down in the graphs. In this study, the plots show that the Pearson rho values are on average always around 0, indicating weak correlations between the investigated variables. Based on this, it is possible to exclude weather variables as the principal cause of changes in electricity usage patterns. Since no other relevant driving force is identified during

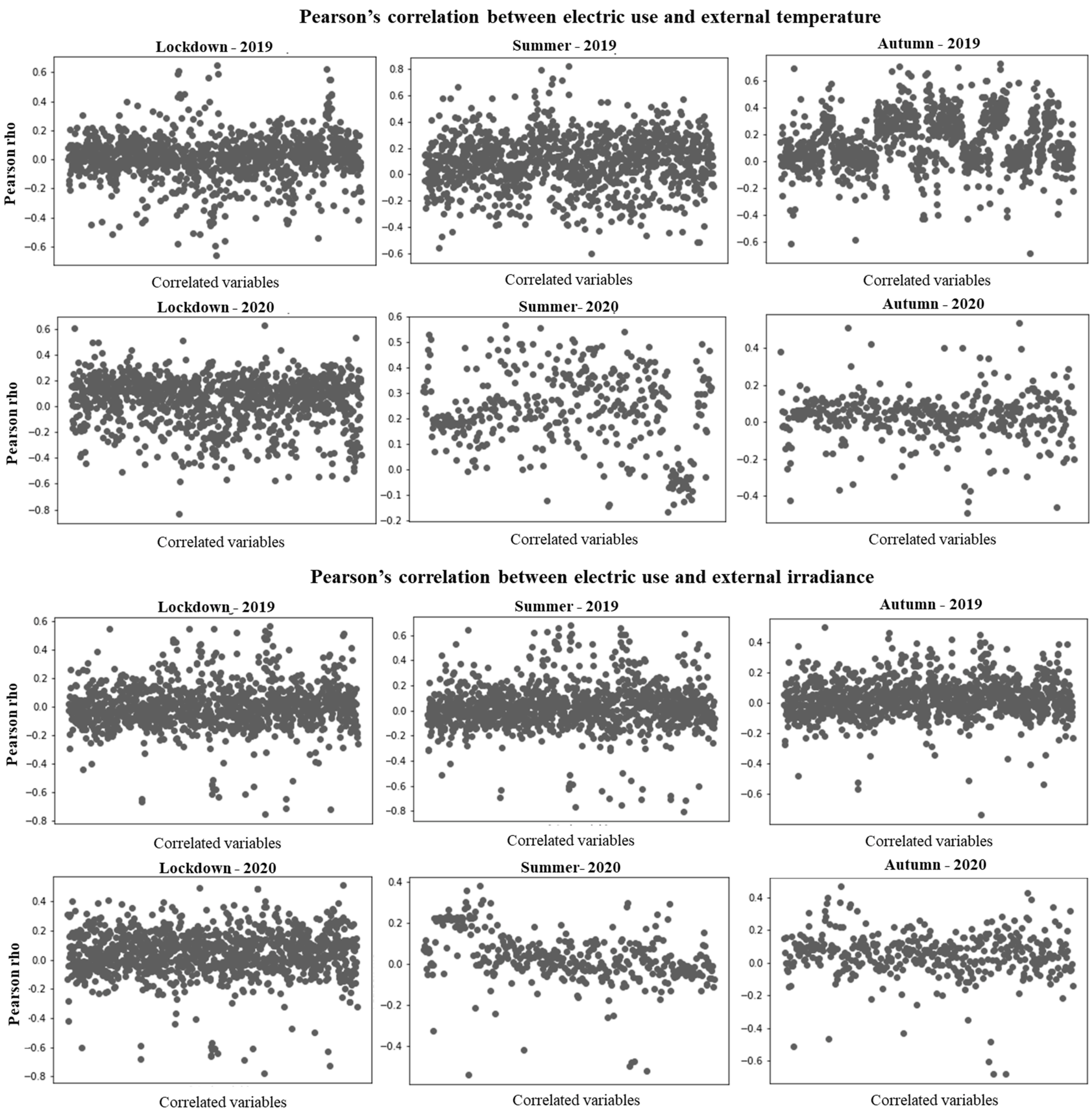

Fig. 5. Pearson's correlation between total electric use of all buildings and weather variables.

the analysed period, the assumption that the observed changes may be substantially related to the COVID-19 restrictions in 2020 is relevant. Further investigations into the impact of these restrictions on electricity usage patterns can provide valuable insights into how changes in occupants' behavior can affect energy consumption.

4.3. Data clustering

In this study, the classical K-Means algorithm is used coupled with the DBI, which allows the comparison of different cluster numbers to find the appropriate partition for the data. The data given to the algorithm is the normalized daily pattern. Normalizing data in clustering is crucial to ensure that each variable is equally important and to prevent bias towards variables with larger scales or units. This is because clustering algorithms use distance measures that are sensitive to the scale and unit of the variables. Normalizing the data by transforming it to a common scale or range can improve the accuracy and interpretability of the clustering results, as well as their generalizability to new datasets with similar variable scales and units. The K-Means method is implemented with the use of scikit-learn (``sklearn.cluster.KMeans — scikit-learn 1.2.2 documentation,'', n.d.). In particular, the chosen clustering method is the "K-Means", the chosen algorithm is "Full", the chosen initialization method is "K-Means++", the maximum iteration is set at 300, the random number generation for centroid initialization is 42. For further details refer to the literature ("sklearn.cluster.KMeans — scikit-learn 1.2.2 documentation,", n.d.). The final number of clusters was determined to be from 4 to 10, as also emerged in the literature on similar case studies (Causone et al., 2019; Chicco et al., 2005; Jang, Eom, Jae Park & Jeung Rho, 2016). Table 2 summarizes the final numbers of clusters obtained for different studied periods.

4.3.1. Winter daily patterns

The results of the data clustering for the Winter period are shown in Table 3 (i.e., clusters' distribution), Fig. 6 (i.e., daily patterns of working days) and Fig. 7 (i.e., daily patterns of weekends). The clusters are depicted in Figs. 6 and 7, which comprise "n" graphs with the hours of the day plotted on the x-axis and the normalized daily pattern for single buildings, with values ranging from 0 to 1, on the y-axis. The black profile represents the hourly electricity use of the cluster centroid, while the gray profiles represent all the objects that belong to the cluster.

For the Winter period, from Table 3 is it clear that Cluster 1, Cluster 8 and Cluster 2 are the most representative for the working days of 2019 including together almost 70% of the days. For the 2020 working days, there is less variability since only two clusters (i.e., Cluster 5 and Cluster 2) include around 78% of the daily patterns. The weekend days of both 2019 and 2020 show also low variability. The most representative cluster for weekends of 2019 is Cluster 1 including around 48% of the days and, whereas, in 2020, Cluster 3 includes 50% of them.

In terms of patterns, the results for the working days of 2019 and 2020 are, in general, similar. The most representative clusters for the working days of 2019 are Cluster 1, Cluster 8 and Cluster 2, characterized by the morning peak around 8 am and the highest peak around 8 pm. In the same period of 2020, the most representative clusters (i.e., Cluster 5 and Cluster 2) of the working days show very similar results to the patterns of 2019. Also, other less representative clusters of 2019 and 2020 are alike. For example, the shapes of Cluster 5 of 2019 and Cluster 3 of 2020 show a very high peak during the morning and a slight decrease during the day. Cluster 4 of 2019 and 2020 are very similar with a basically constant value of 0.9 from 8 am till 9 pm.

Table 2
Final number of clusters for each period.

Period label		2019	2020
Winter	Working days	8	5
	Weekends	5	4
Lockdown	Working days	10	10
	Weekends	10	10
Autumn	Working days	7	6
	Weekends	7	7

Table 3
Winter period clusters' distribution.

	Workdays		Weekend	
	2019	2020	2019	2020
Cluster 1	29.0%	8.0%	47.9%	27.1%
Cluster 2	17.6%	29.5%	4.2%	4.2%
Cluster 3	9.0%	3.8%	2.1%	50.0%
Cluster 4	5.7%	10.3%	27.1%	18.8%
Cluster 5	4.7%	48.4%	18.8%	–
Cluster 6	7.3%	–	–	–
Cluster 7	4.7%	–	–	–
Cluster 8	22.0%	–	–	–

The same is true for the weekends of the Winter periods of 2019 and 2020. The most representative clusters of 2019 are Cluster 1 and Cluster 4, showing a small peak during the morning hours and a high peak around dinner time around 8 pm. Likewise, the most representative clusters of 2020 (i.e., Cluster 1 and Cluster 3) show very similar shapes. Moreover, Cluster 2 of 2019 is similar to Cluster 2 of 2020 and the same is true for Cluster 5 of 2019 and Cluster 4 of 2020. One can concluded that in the Winter period (before the starting of the restrictions) no large differences in terms of daily patterns occur between the years 2019 and 2020. The changes noted in the most representative clusters of the other periods are due to some external factors, that, excluding the weather (Section 4.2, Fig. 5) may be identified in the restrictions due to the COVID-19 outbreak.

4.3.2. Lockdown daily patterns

The results of the data clustering for the Lockdown period are shown in Table 4 (i.e., clusters' distribution), Fig. 8 (i.e., working days) and Fig. 9 (i.e., weekends).

Looking at Table 4 it is clear that the shapes, during Lockdown, are more variable than during the Winter period. No cluster represents more than 23.5% of the days among all groups. For the workdays of 2019, the most representative clusters are Cluster 7 (i.e., 20.5%) and Cluster 2 and Cluster 6 (both around 13%). For the workdays of 2020, the most representative cluster is Cluster 2 (i.e., 23.5%) and Cluster 3 and Cluster 7 (both around 14%). The weekends show even more variability. The most representative cluster for Weekends of 2019 is Cluster 8 (i.e., 18.1%) and for 2020 is Cluster 3 (i.e., 18.6%).

The two most representative clusters for the Lockdown period of 2019 are Cluster 7 and Cluster 2, which exhibit the typical morning peak observed during the Winter periods of 2019 and 2020 for working days. However, for the Lockdown period of 2020, Cluster 2, Cluster 3 and Cluster 7 are the most representative, and they show a pattern similar to that of weekends in the Winter period with a smooth-out morning peak. This is because during this Lockdown period, people are working from home, and as a result, they wake up at different times, creating a smooth increase in the morning rather than a sharp morning peak. This smooth increase is also observed in other clusters (i.e., Cluster 3, Cluster 4 and Cluster 9) in 2020. Additionally, the Lockdown of 2020 exhibits other representative daily patterns, such as the two round peaks of Cluster 6 and Cluster 10, which are equally high. This pattern was not observed during the Winter period for working days but was typical of weekends. This type of pattern may be another typical feature of a restriction period.

The weekends of the Lockdown period, show similar results in 2019 and 2020 (Fig. 9). This means that the daily pattern of the weekends did not change drastically. However, the flatter shapes like the ones of Cluster 9 and Cluster 10 of 2019 weekends did not frequently occur in 2020 (present only in Cluster 8 which is very low representative). A relatively flat normalized shape without peaks can correspond to an all-

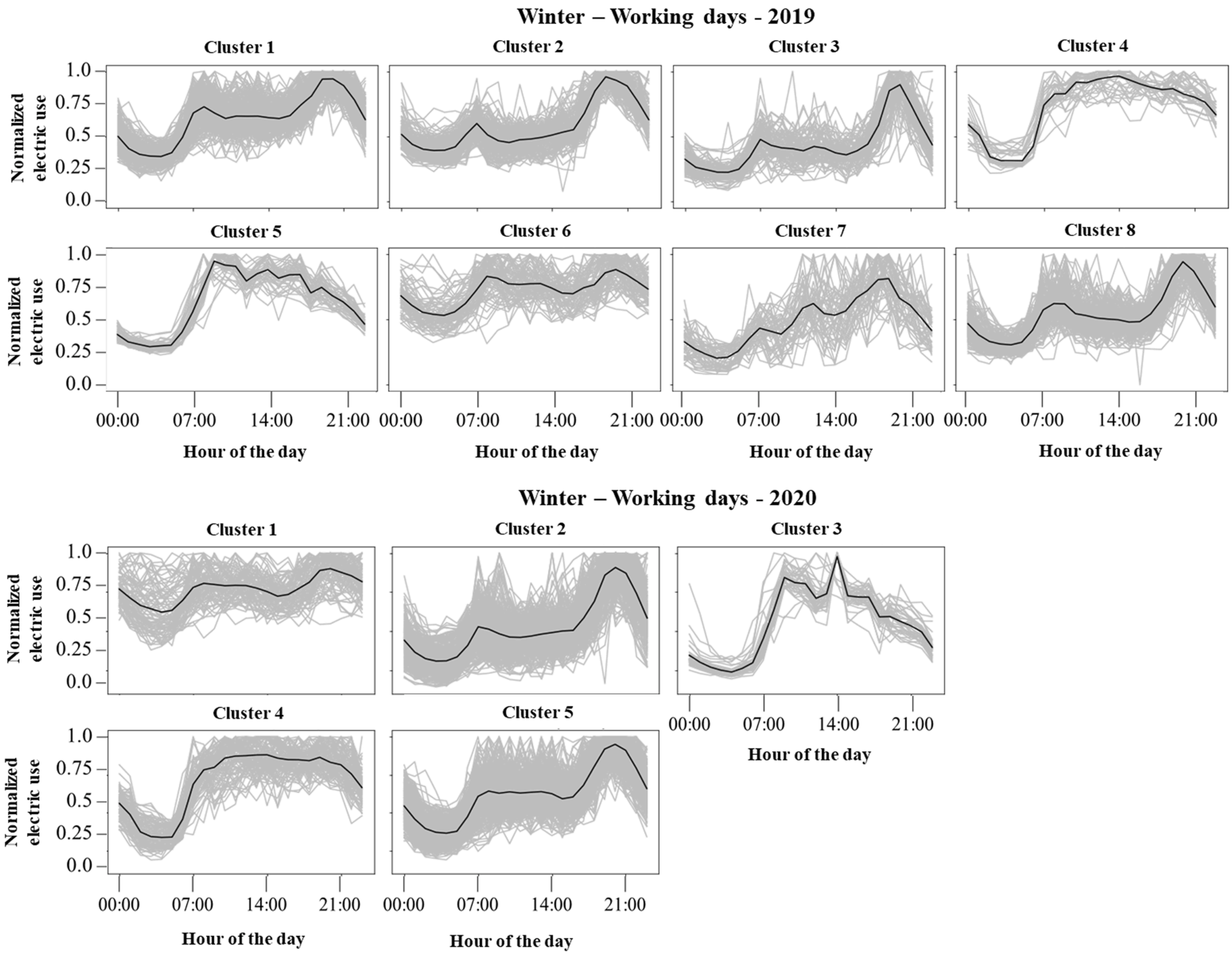

Fig. 6. Winter working days clusters' centroids.

day long strong use of electricity or an all-day long very low use of electricity. The second case can probably exist when people stay out of the house for the whole day. During the Lockdown of 2020, this possibility was hindered by restrictions, and thus it is also a less representative pattern in the results.

4.3.3. Autumn daily patterns

The results of the data clustering for the Autumn period are shown in Table 5 (i.e., clusters' distribution), Fig. 10 (i.e., working days) and Fig. 11 (i.e., weekends).

The most representative clusters of the Autumn period, for the working days of 2019 are Cluster 1 (i.e., 28.4%) and Cluster 7 (i.e., 17.6%), together including 46%. The 2020 workdays show similar variability, as a matter of fact, the two most representative clusters (i.e., Cluster 2 and Cluster 3) include basically 50% of the days. Similar percentages are registered for the weekends. In 2019, the three most representative clusters are Cluster 2 (i.e., 24.6%), Cluster 4 (i.e., 21.7%) and Cluster 5 (i.e., 19.6%). For 2020, Cluster 5 includes 26.6% of the days and Cluster 2 22.7% of the days.

During working days, the year 2019 is mostly represented by Cluster 1 and Cluster 7, which exhibit a peak in the morning and a higher peak in the late afternoon, similar to the work profile of the Winter period. In contrast, the most frequent clusters in 2020 are Cluster 2, which displays a gradual increase in electricity usage throughout the day, and Cluster 3, with high usage throughout the day. None of the 2020 clusters exhibits a sharp morning peak, except Cluster 6. This observation could indicate a potential smooth out of the morning peak in the profile pattern that is still present also with no complete restrictions, as observed during the Lockdown period. The most significant profiles for Winter weekends in 2019 are Cluster 2, Cluster 4, and Cluster 5, all of which display a significant concentration of electricity usage during the central hours of the day. The weekend profile of 2020 is similar to that of 2019 and also the other periods. In this case, the absolute ALDL (Section 4.2, Table 1) for 2020 is very similar but slightly lower than 2019.

4.4. Distribution analysis

Since the weather dependency analysis yielded weak correlations (Section 4.2, Fig. 5), the analysis and comparison proceeded without considering weather variation as a potential source of changes in electricity use. In this section, the comparison from the perspective of absolute electricity use values is expressed in terms of specific use [W/m^2]. To achieve this, the profiles are no longer treated as normalized factors but instead multiplied by their respective ALDL. As explained in the Methodology (Section 2), the objective of this study step is to evaluate changes in residential electricity use in Milan during the Lockdown period. To achieve this, the 2019 and 2020 clusters are matched according to their percentage representativeness within the period, thereby comparing the most significant and representative patterns. For example, the first most common pattern of a period of 2019 for working

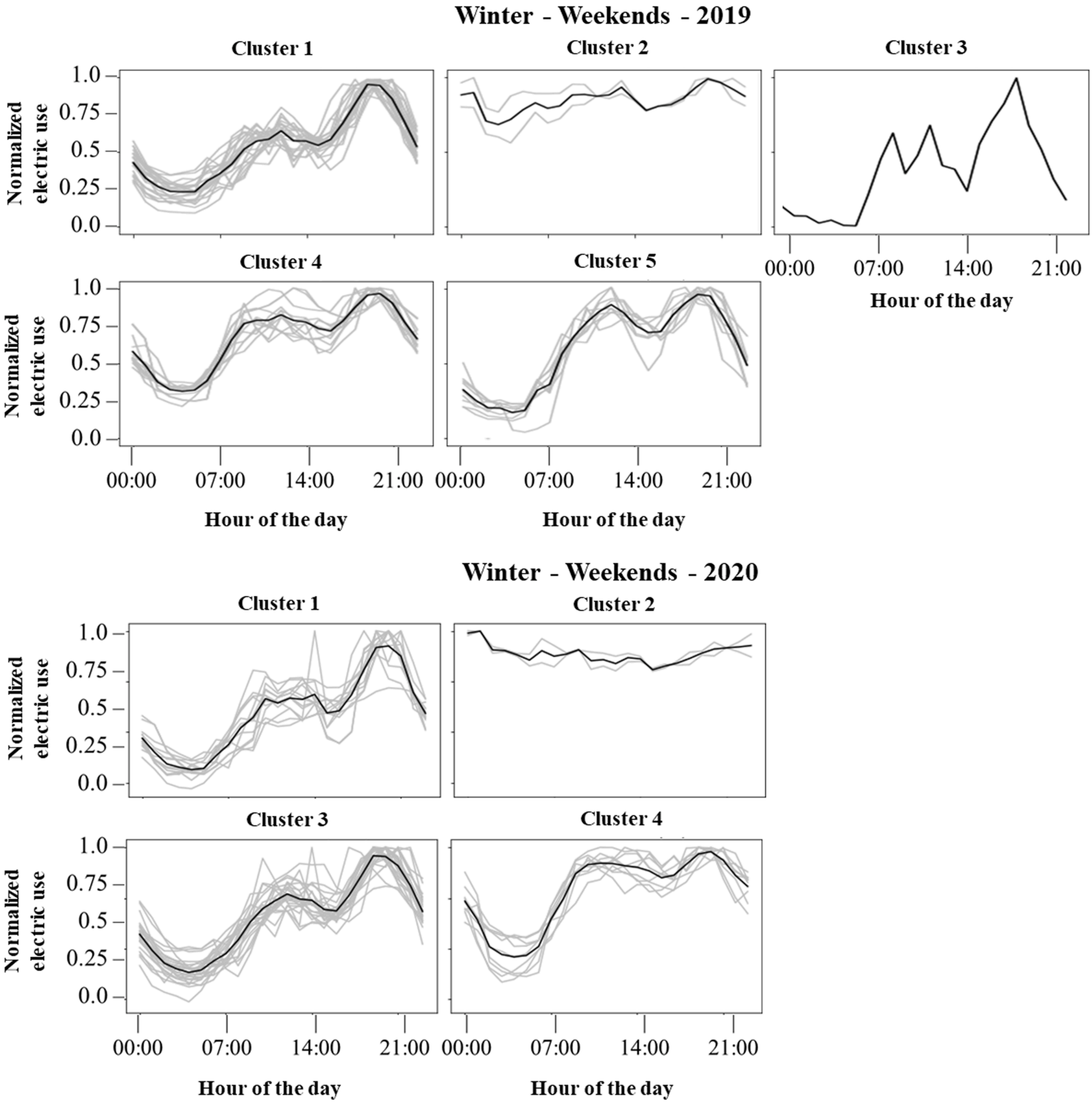

Fig. 7. Winter weekends clusters' centroids.

Table 4
Lockdown period clusters' distribution.

	Workdays		Weekend	
	2019	2020	2019	2020
Cluster 1	7.0%	2.7%	9.0%	15.7%
Cluster 2	13.3%	23.5%	11.8%	10.5%
Cluster 3	11.8%	14.1%	12.0%	18.6%
Cluster 4	7.9%	8.6%	8.3%	5.4%
Cluster 5	5.3%	4.1%	8.6%	16.9%
Cluster 6	12.7%	6.9%	10.4%	11.3%
Cluster 7	20.5%	14.0%	9.5%	6.6%
Cluster 8	6.9%	10.7%	18.1%	2.5%
Cluster 9	4.5%	7.0%	7.9%	8.6%
Cluster 10	10.1%	8.3%	4.4%	3.9%

days is directly compared with the one of 2020 multiplied by the ALDL, thus showing the pattern itself but also the absolute value of the electricity use.

4.4.1. *Winter daily patterns analysis*

Fig. 12 displays the differences between the Winter period clusters of 2020 and 2019, organized by their representativeness. In each graph, two clusters, one from 2019 (in blue) and one from 2020 (in violet), are arranged in order of their weight in the period groups, on the top part of the image the working days are plotted, in the bottom the weekends. The percentage difference with respect to 2019 is shown in gray. The shapes of the two most frequent clusters during the Winter period working days were very similar to those of 2019. With the analysis of the first representative patterns, it was determined that the difference between the

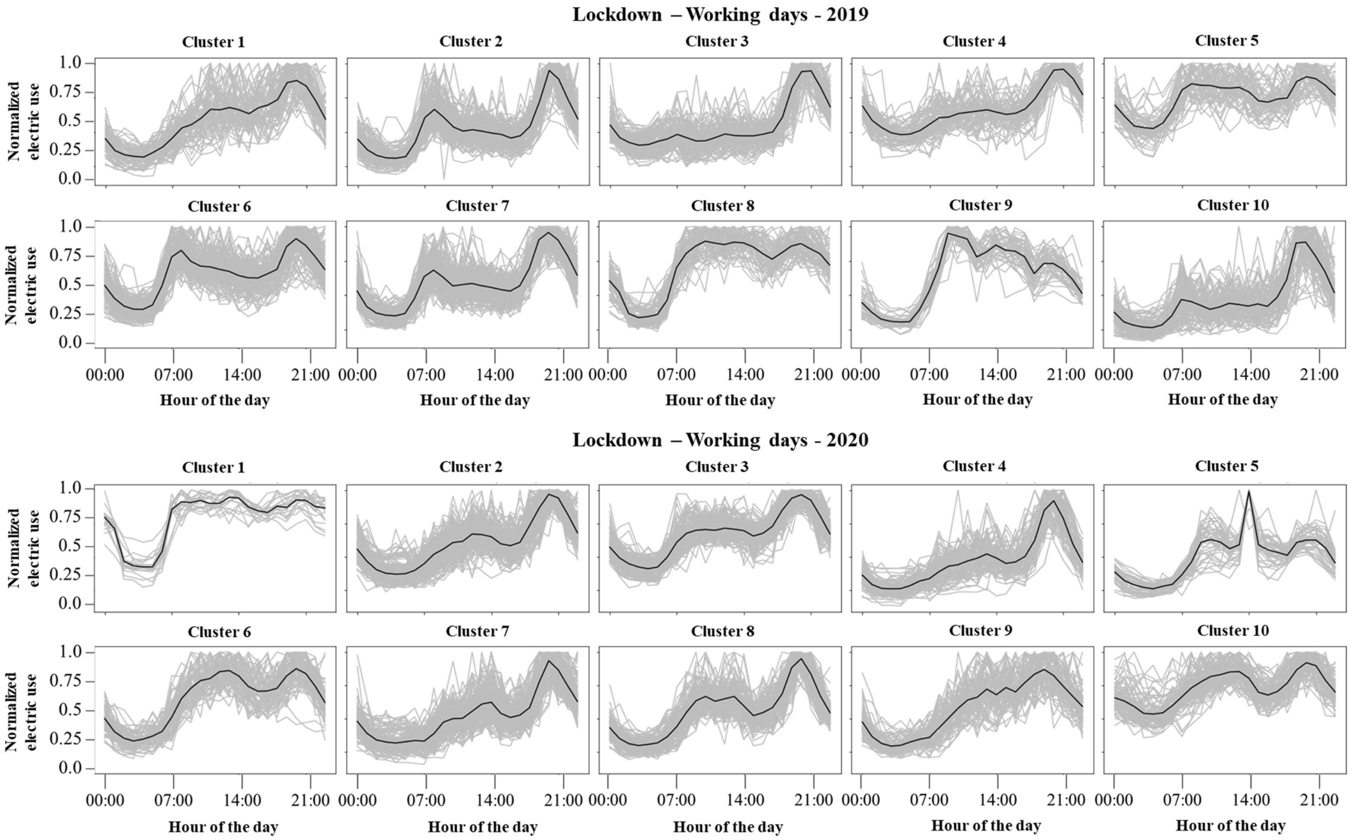

Fig. 8. Lockdown working days clusters' centroids.

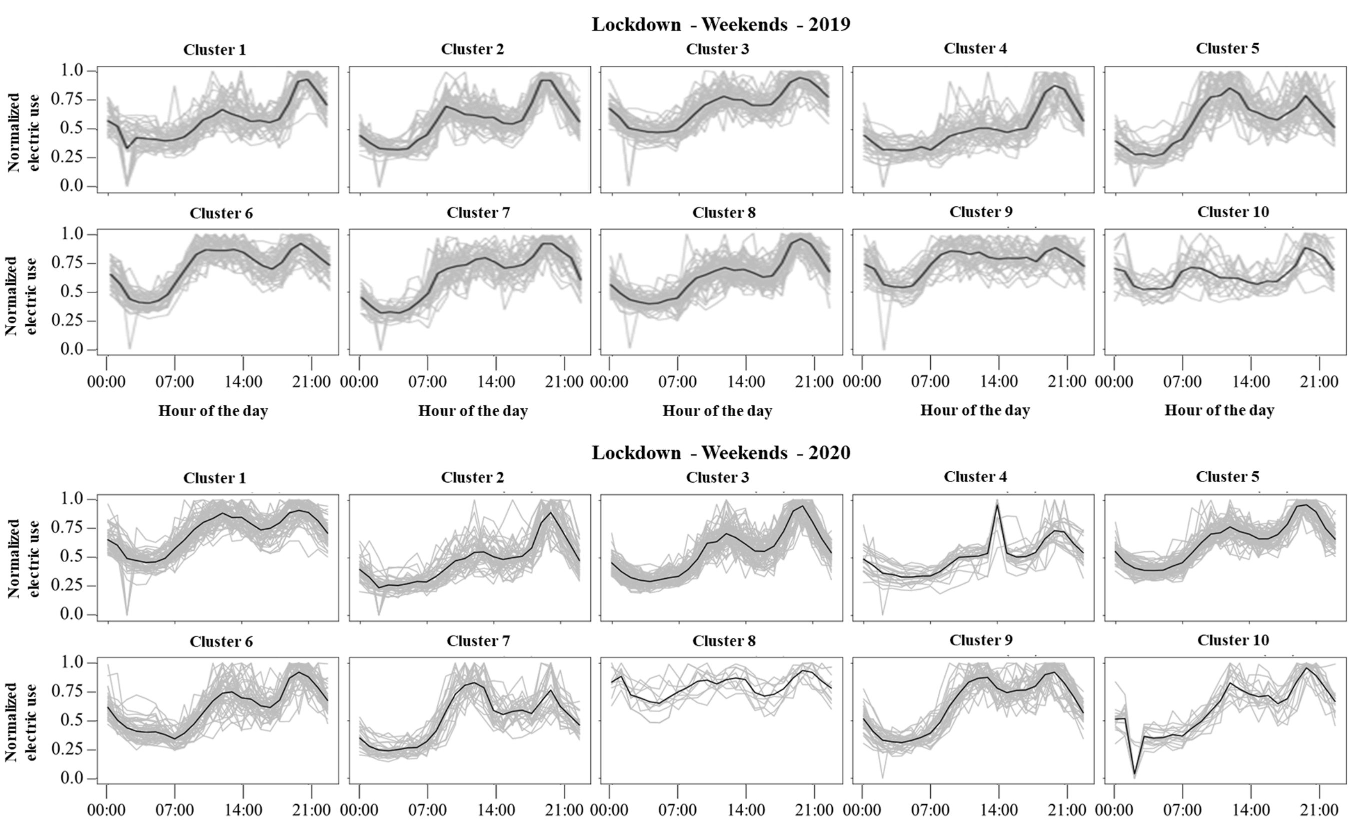

Fig. 9. Lockdown weekends clusters' centroids.

Table 5
Autumn period clusters' distribution.

	Workdays		Weekend	
	2019	2020	2019	2020
Cluster 1	28.4%	14.3%	12.3%	11.8%
Cluster 2	11.4%	29.0%	24.6%	22.7%
Cluster 3	12.1%	20.3%	10.5%	12.2%
Cluster 4	10.4%	15.2%	21.7%	16.8%
Cluster 5	14.5%	10.8%	19.6%	26.6%
Cluster 6	5.7%	10.4%	2.9%	0.3%
Cluster 7	17.6%	–	8.3%	9.5%

years 2019 and 2020 was relatively small. The changes ranged from −1.1% to 8% during the day and slightly more during the night (i.e., maximum +22%). The second representative pattern shared similarities with the 2019 cluster, but had different steepness, resulting in differences ranging from −16% to 16%. The other clusters' comparisons show higher differences both in shapes and absolute values. For the weekends the similarities are higher and permeate all clusters. The shapes are very similar for the four clusters changing mainly the absolute values, with a general increase in the electric use.

4.4.2. Lockdown daily patterns analysis

Fig. 13 provides a quantitative comparison of the profile differences between 2019 and 2020 for the Lockdown period. One notable feature is a marked change in the morning peak time, which shifted from around 7 am in 2019 to later hours in 2020, around 1–2 pm, due to increased working from home. This feature is common to almost all 2020 profiles. Another noteworthy profile is the second profile in terms of representative percentage distribution, which lacks a sharp peak throughout the day but rather exhibits a plateau that develops in the morning and continues throughout the central hours. The evening peak remains largely unchanged in almost all cases. While it is not feasible to describe and profile the users without additional data, it is possible to speculate on the most representative profiles in the analysis. Based on the first three profiles, three distinct user categories can be inferred:

- Individuals who worked from home/stayed at home and woke up later have shifted their electricity use over time, increasing it. Their morning use is decreased to a maximum of 28%, while in the afternoon it is increased by 20%.
- Individuals who worked from home/stayed at home without changing their wake-up time, producing a high and constant energy use; with respect to the equivalent percentage distribution cluster of 2019, their use in the afternoon increased by 40%.
- Individuals who stayed at home and decreased their use, by around 17% during the night and late afternoon, and by 56% in the morning; but still had a peak use at lunchtime, which equals the use of the compared 2019 cluster.

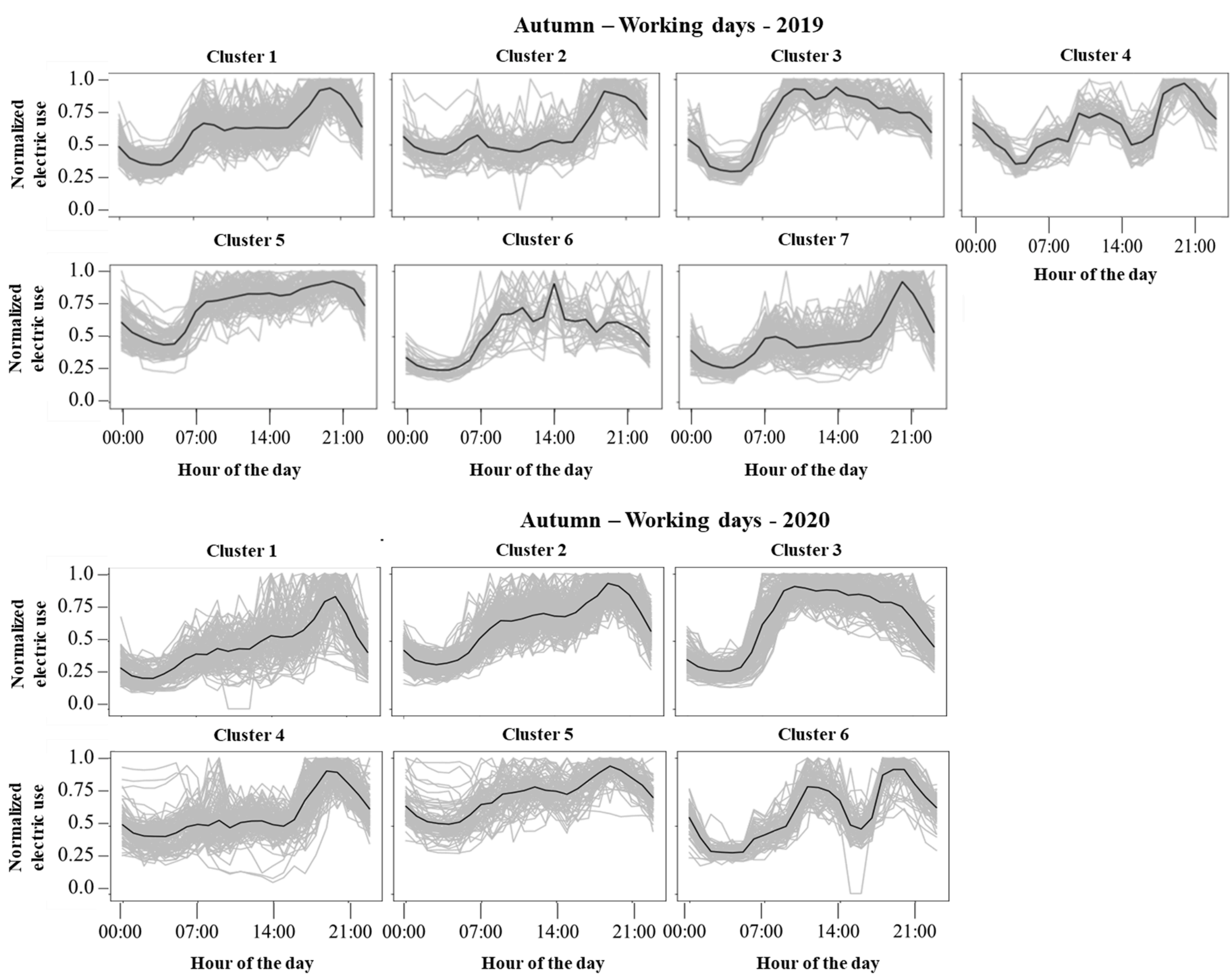

Fig. 10. Autumn working days clusters' centroids.

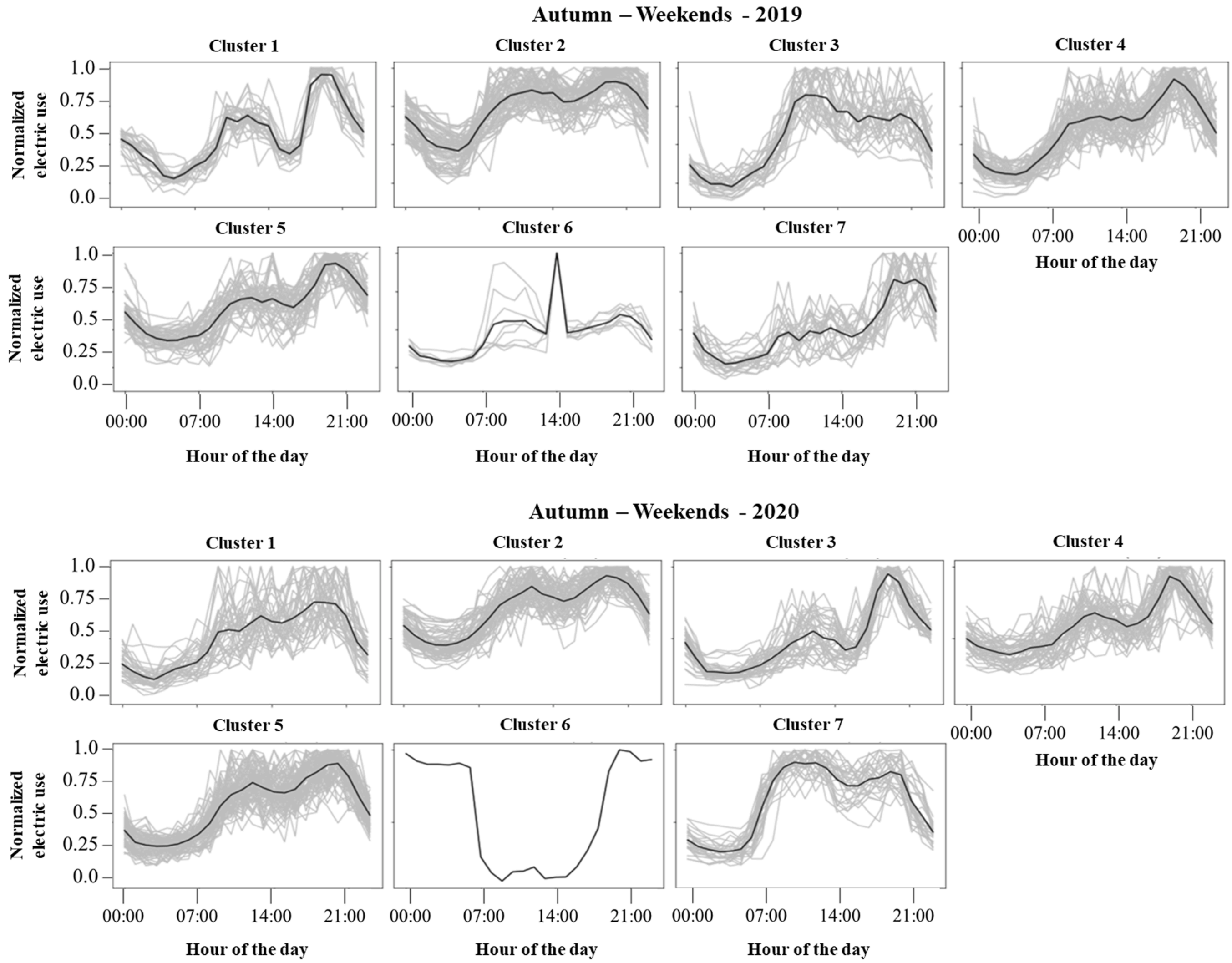

Fig. 11. Autumn weekends clusters' centroids.

For weekends during the Lockdown periods, the characteristics described above persist in the 2020 period, but the differences with 2019 are less pronounced. However, it should be noted that due to the forced stay at home, many habits such as the use of household appliances (e.g., washing machine, dishwasher) may have been diluted during the rest of the week, and others, such as receiving guests, prevented by the external situation. From this profile visualization, new information emerges, such as an increase in the evening peak in 2020 in more than one relevant case by a value ranging from 10% to 19%.

4.4.3. *Autumn daily patterns analysis*

Fig. 14 provides valuable insight into the quantitative differences observed during the Autumn period. The first cluster showed striking similarities to the 2019 cluster, with the primary difference being 16% decrease in electricity usage in the morning. However, the other clusters demonstrated significant changes in their profiles. Cluster 6 was the only one to match its most similar correlative, while the remaining clusters varied significantly between the two years, either in shape or percentage distribution. For instance, two similar clusters, such as Cluster 2 in 2019 (5th in 2020) and Cluster 4 in 2020 (3rd in 2019), had different levels of relevance in the two years.

Analysing the weekends, it becomes apparent that the differences against the 2019 clusters were more significant for the first two clusters than in the working days' case, with absolute values exceeding 16% during the central hours. The night use for the first percentage distribution cluster of 2020 was significantly lower than that of 2019. The two most common clusters from 2019 to 2020 showed mirrored similarities, with the first of one year closely resembling the second of the other year. This suggests that the same user category's weight may have changed over time. Cluster 2, the most representative cluster in 2019, may characterize people who focused their electricity usage during the weekend while at home (e.g., use of the washing machine). However, this need has been partially decreased for people working from home who can do some housework during the week while working. The 4th and 5th percentage distribution clusters were similar, except for a stronger afternoon peak in 2019. One possible interpretation is that, due to the limited social interaction allowed during those months, most people did not have visitors even on weekends, specifically during lunch hours.

5. Conclusions

This research used a sample of electricity use data from residential buildings to compare energy use profiles before, during, and after the COVID-19 pandemic main lockdown. The database was divided into periods, and clustering was used to detect recurrent patterns. In particular, the methodology involves data pre-processing, data understanding, and data clustering to gain insights into electricity usage patterns during different periods. The periods analysed are Winter, Lockdown, and Autumn, and comparisons are made between the same

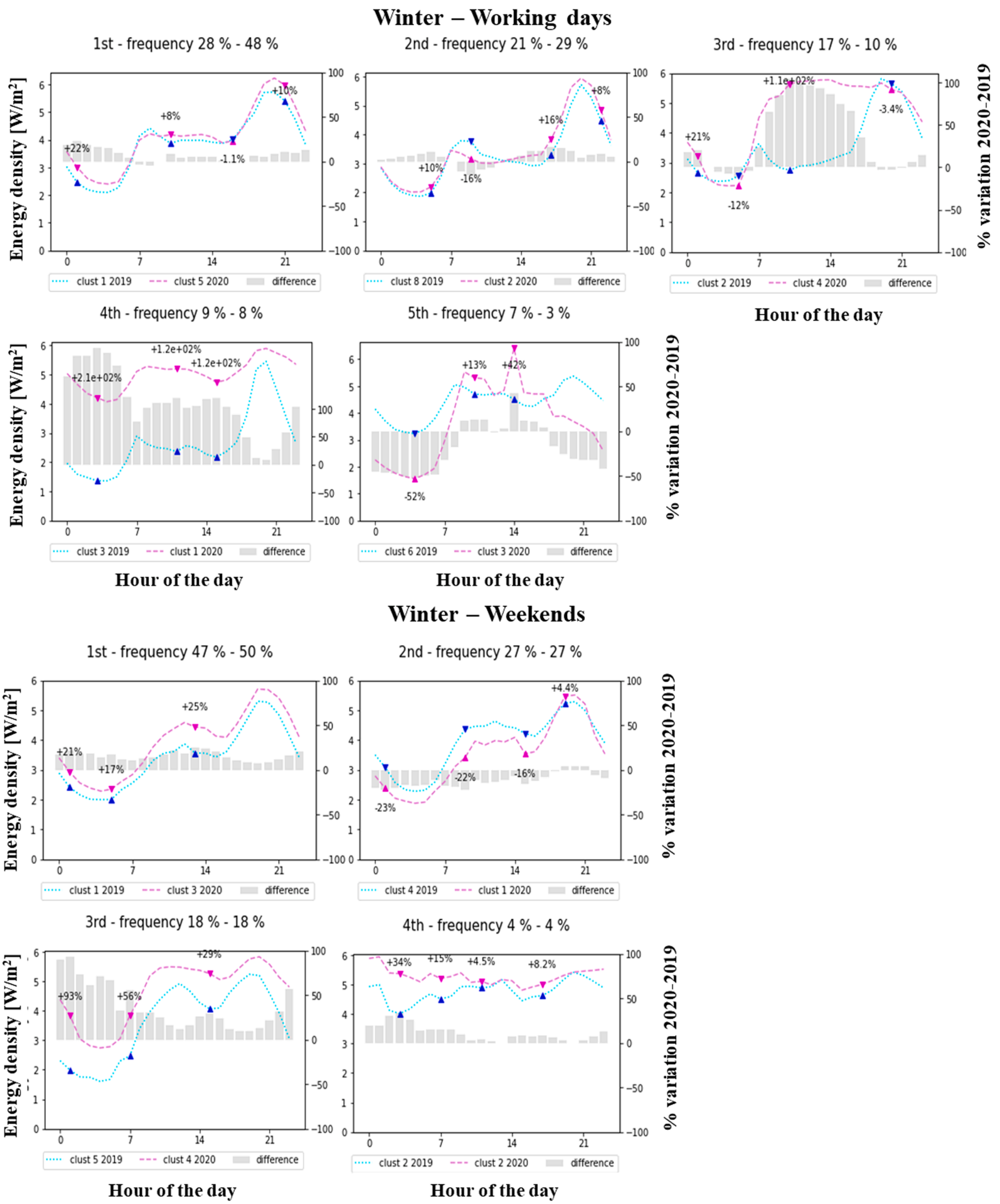

Fig. 12. Difference between 2019 and 2020 schedules for the Winter period - working days and weekends, ordered by percentage distribution.

periods in 2019 and 2020.

The analysis shows that during the COVID-19 Lockdown (March and April 2020) a significant increase in electricity usage has been registered in residential buildings; since correlation analysis showed weak correspondences between climate data and electricity usage data, the increase may be associated to the COVID-19 restrictions. The results of the clustering revealed a relevant change in the profile of working days during the Lockdown period, characterized mostly by a shift in use to the

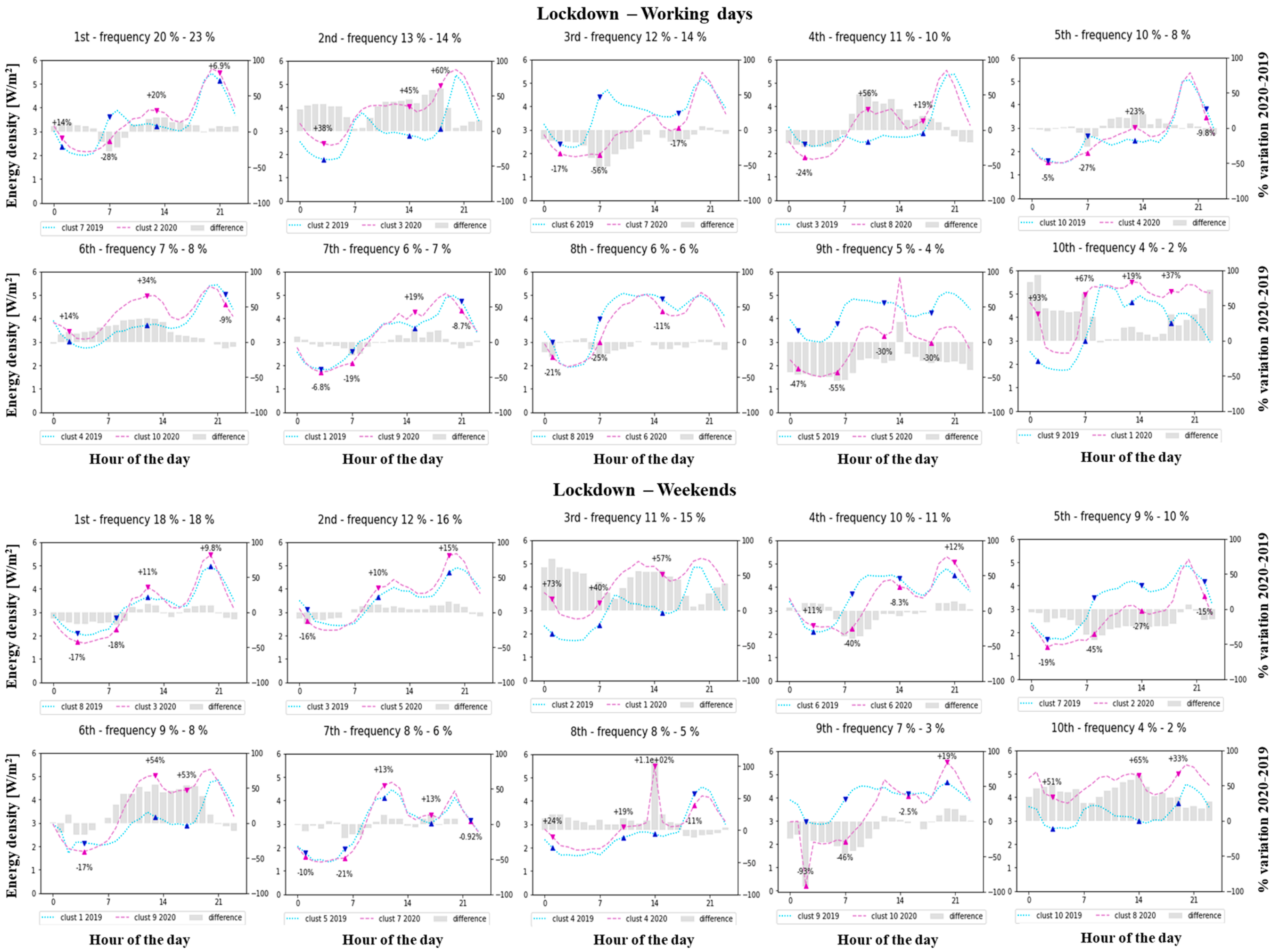

Fig. 13. Difference between 2019 and 2020 schedules for the Lockdown period - working days and weekends, ordered by percentage distribution.

central hours of the day. The lockdown period exhibited the most distinct differences respect to the other periods. Morning peaks shifted substantially from 7 am to 1–2 pm due to increased working from home. Weekday profiles varied considerably while weekend profiles still differed to a lesser extent, indicating major changes to routines and appliance usage. With regards to weekends during the same period, the difference compared to 2019 was less pronounced, which could depend on the fact that most residents do not work out of home during weekends even under normal conditions. The winter period showed the most similar daily electricity usage patterns between 2019 and 2020. Weekday profiles were almost identical while weekend profiles mainly differed in increased absolute usage. This suggests routines remained largely unchanged. However, the Autumn profiles also show a less pronounced but present shift in the pattern, with the most frequent clusters in 2020 exhibiting a gradual increase in electricity usage throughout the day and no morning peak observed. During autumn, the most frequent profiles closely resembled 2019 while others varied greatly. Weekend usage diverged more, with higher values during central hours but lower night usage in the most common 2020 profile. This indicates that while weekdays were resembling the pre-pandemic period, weekends still differed likely due to ongoing restrictions. In summary, winter saw the most similar usage, lockdown the most distinct differences, and autumn an intermediate situation especially for weekends. The degree of change appears linked to shifts in schedules, activities and social interactions imposed by circumstances during each period.

In conclusion, the main findings of this research are:

- significant increase in electricity usage during the COVID-19 lockdown period for residential buildings;
- weak correspondence between climate data and electricity usage data, suggesting the increase is associated with the COVID-19 restrictions;
- shift in energy usage from the morning peak to central hours of the day during the Lockdown period for working days and smooth out of the morning peak;
- a less pronounced shift in energy usage pattern for weekends during the Lockdown period;
- gradual increase in electricity usage throughout the day and no sharp morning peak observed still during the Autumn period (after Lockdown, with far less strict restrictions).

The results of the analysis of changes during the lockdown period in this study are consistent with the literature in several respects, in particular with regard to the increase in energy use (Abdeen et al., 2021; Krarti & Aldubyan, 2021; L. Li et al., 2021), the shift in profile patterns (Krarti & Aldubyan, 2021; Ku, Qiu, Lou, Nock & Xing, 2022; L. Li et al., 2021; Zhang et al., 2020), and the change in peak hours (Kmetty, 2021; Santiago, Moreno-Munoz, Quintero-Jiménez, Garcia-Torres & Gonzalez-Redondo, 2021). Abdeen et al. (Abdeen et al., 2021) also consider the impact of weather and find that most detected changes are weather-independent. Kang et al. (Kang et al., 2021) state that there is a strong correlation between COVID-19 factors and residential building electricity use. Ku et al. (Ku et al., 2022) predict that winter profiles will shift from two peaks to one post-COVID, a prediction that is partially

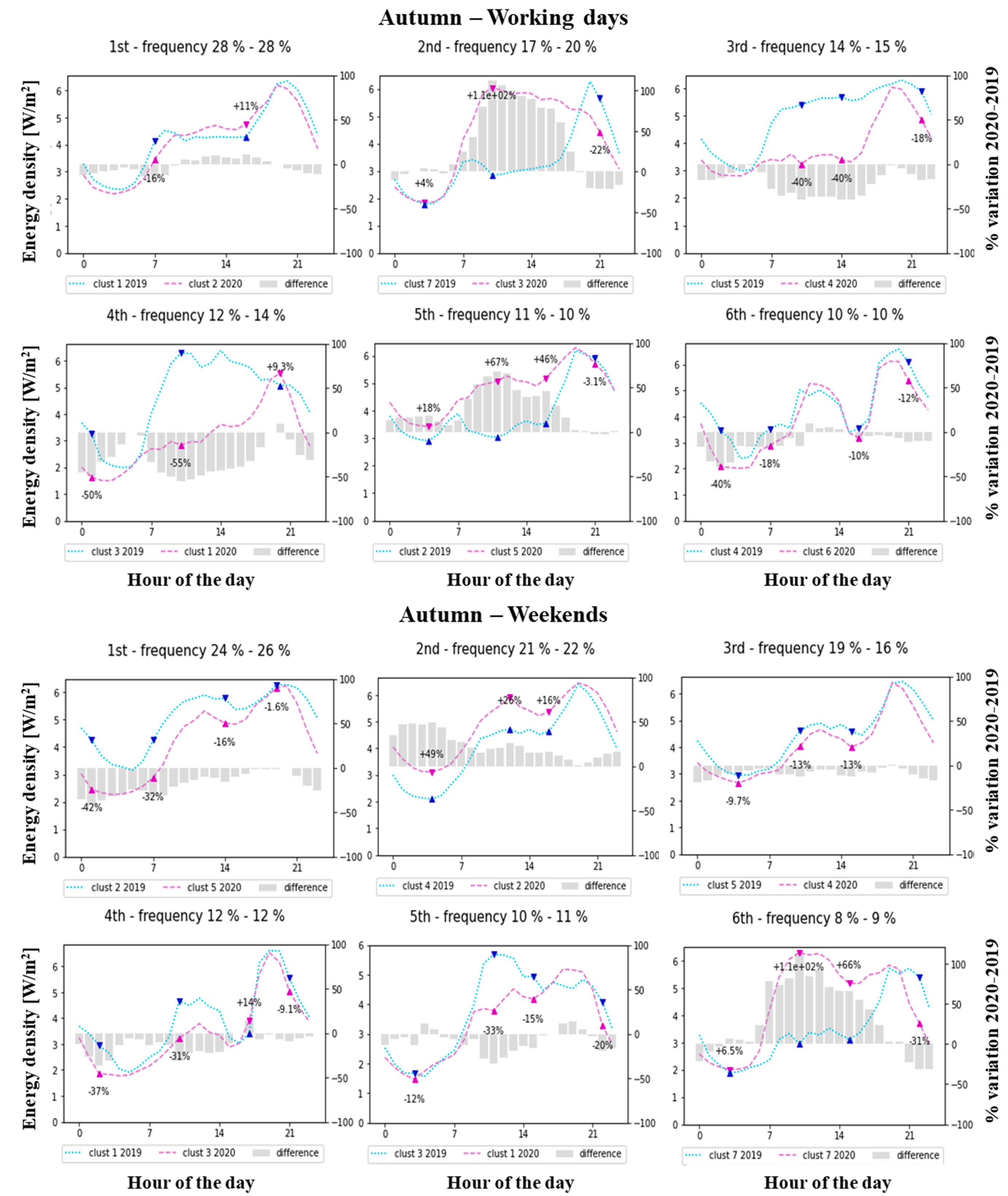

Fig. 14. Difference between 2019 and 2020 schedules for the Autumn period - working days and weekends, ordered by percentage distribution.

supported by the results of this study. However, the specific patterns and magnitudes of change observed in the present work may be particular to Milan and other large northern Italian cities due to factors like typologies, occupancy and climate. Milan's high density, mixed-use development and sustainability focus likely contribute to distinct electricity use characteristics.

Using the Lockdown period as a reference to study the remote working behavioural patterns, the findings can provide modellers with a complete set of daily load profiles for an Italian residential case study and assist cities' analysts, policy makers and businesses in evaluating the effects of remote working.

Further research is required to gain a more comprehensive understanding of the highlighted through this work. Future developments may include analysis of data collected during 2021, 2022 and following years (post-pandemic period) and correlation of businesses usage profiles against that of employees' households, to determine the private costs and benefits of remote working.

Declaration of Competing Interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), in the subject matter or materials discussed in this manuscript.

Data availability

The data that has been used is confidential.

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