Effects of COVID-19 confinement on the simulation of energy needs and uses of residential buildings in Milan

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Abstract

This paper examines the impact of COVID-19 confinement on the simulation of energy needs and uses of residential buildings in Milan. Data-driven schedules for electricity use before and during lockdown, derived from smart metering data, are applied to an urban building energy model to analyze their effects on energy needs for heating and cooling and the energy use for lighting and for other services. Electricity uses, heating and cooling needs, and total primary energy (TOE) are compared for pre-COVID and during-COVID cases. Electricity increases by 8%, while heating decreases by 10%, and cooling increases by 26%. The 5% decrease in TOE is mainly due to the decrease in heating. The study uses heat maps to display the coefficient of variation of root mean square error (CVRMSE) at different temporal and spatial aggregations, indicating significant differences between pre- and during-COVID cases. The CVRMSE for electricity consumption is highest at the hourly level for single buildings, reaching a maximum of 44, and decreases at higher levels of aggregation. The CVRMSE for TOE is highest at the hourly level for single buildings, reaching a maximum of 230. A scenario is created by combining during-COVID and pre-COVID schedules for a hybrid work model, called post-COVID. The post-COVID scenario results indicate a significant impact of remote work on energy consumption patterns.

Practical implications

The data-driven schedules derived from electric metering data in Milan can be directly used in energy models for pre-COVID, during-COVID, and post-COVID case studies in locations with similar characteristics. This study compares energy consumption before and during the COVID-19 pandemic. Electricity increased by 8%, heating decreased by 10%, and cooling increased by 26%. Heat maps show significant differences in energy consumption between the two periods, with higher discrepancies at lower temporal and spatial levels. The post-COVID scenario shows a significant impact of remote work on energy consumption patterns. The scenario created in the study provides a useful tool for policymakers and energy planners to develop targeted energy management strategies to reduce energy consumption and manage the impacts of remote working.

Highlights

- Generation of data-driven occupants-related schedules for the lockdown period with k-means clustering for UBEM applications
- Assessment of the impact of these schedules on UBEM results in a neighborhood in Milan
- Effects observed on hourly and daily energy consumption patterns
- Creation and analysis of scenarios featuring a mix of remote working and normal office work

Introduction

Building simulation is being used to optimize energy consumption in buildings. In particular, urban building energy modelling (UBEM) allows for the modelling of numerous buildings at once using multizone dynamic thermal simulation models (Ferrando et al., 2020). Among the different options (Wang et al., 2022), UBEMs typically use archetypes to define buildings, which include fixed schedules to describe Occupant Behaviour (OB), leading to unrealistic energy outcomes (Carnieletto et al., 2021). Modelling OB in UBEMs is an open topic due to the lack of data regarding occupants at the urban scale (Ferrando et al., 2022). In this scenario, smart meter readings are being used to improve large-scale building models, including schedule creation. In particular, clustering analysis of smart meter registrations is a widely used methodology to derive schedules for both electricity and occupancy(Ferrando et al., 2022). In this paper electricity use schedules are exctracted from a smart meter dataset and used in the running of energy simulations.

The COVID-19 pandemic has led to profound changes, including shifts in consumption habits. Lockdown and remote working arrangements have caused an alteration in energy consumption patterns in households, with increased use of electronic devices, appliances, and lighting during the day. Even after the lockdown phase, many people continue to work from home, thus, there is a need to update standard profiles to be used by simulation tools, to reflect new trends and behaviours. The impacts of these changes must also be assessed. So far, only a limited number of studies have analyzed the impact of the COVID-19 pandemic on energy consumption in buildings, with most of them highlighting an overall increase in residential energy use (Abdeen et al., 2021). These studies have also looked at changes in usage patterns and peak hours (Ku et al., 2022). However, there is a lack of studies on the topic, especially those that are integrated with urban building energy models (UBEM).

This study aims to address this gap in research by conducting a two-step comparison. Firstly, it compares the data-driven schedules derived by a pre-COVID and a during-COVID smart meter database. Secondly, it integrates the schedules into an energy model to analyze their effects on energy consumption simulation. An innovative method using heat maps based on coefficients of variation of the root mean square error (CVRMSE), as defined in the ASHRAE Guideline 14 (ASHRAE, 2014), is used to compare the energy results (Ferrando et al., 2022). The heat maps provide a clear visualization of the differences in the energy needs for heating and cooling and the energy use for lighting and for other services between the pre-COVID and during-COVID schedules and the schedules, based on temporal and spatial aggregation. Finally, a scenario that combines remote working and normal office work is created by mixing the during-COVID schedules with the pre-COVID schedules.

The novelty of this study lies in the structure of the methodology, sincethe creation of schedules from smart meter data for UBEM applications is not yet standardized. This methodology is a proposal for researchers working on UBEM. The paper is meant to understand its potential, limitations, and possible developments and integration in simulation tools.

Methodology

Workflow

The objective of this research is to evaluate the effects of various OB schedules derived from smart meter databases registered before and during the COVID-19 pandemic. These schedules are implemented in the urban model of Chiaravalle, a residential neighbourhood in Milan, Italy. The study consists of three phases: (I) the construction of an urban building energy model utilizing standard archetypes (Carnieletto et al., 2021), (II) the generation of schedules scenarios based on smart meter data collected before and during the pandemic (Ferrando et al., 2022), and (III) a comparison of the UBEM cases with different schedules' scenarios. Figure 1 illustrates the workflow of the research process.

The first phase of this research involves the creation of a model using one of the UBEM tools available in the literature (Ferrando et al., 2020). In the present study, the geographic information system (GIS) data provided by the Municipality of Milan was combined with the archetypes created for the Northern region of Italy (Carnieletto et al., 2021) using version 3.0 of umi, one of the main bottom-up physics base UBEM tool based on EnergyPlus™ (Reinhart et al., 2013). It also gives the possibility to change the schedules for each building in a relatively simple way compared to other similar tools. A detailed description of the model is presented in "The case study" Section.

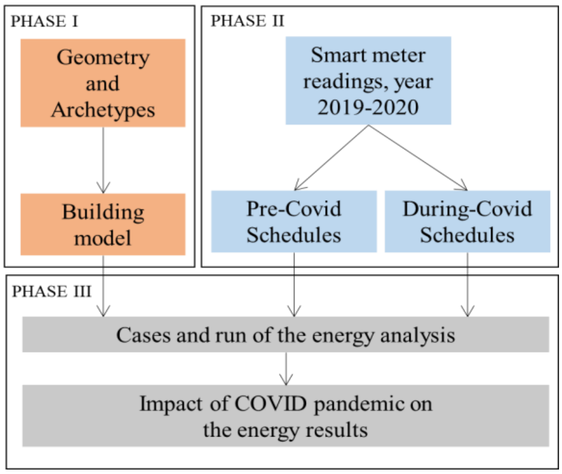

Figure 1: Workflow of the research process.

The second phase of the research aims at generating electric load schedules that accurately reflect the energy use of the buildings, for whom the first step is to obtain a series of smart meter readings from energy operators. These readings comprise a yearly dataset of electric energy use and are typically provided in anonymized form, with a 15-minute registration time step and no gaps or errors. If any errors are detected, data processing should be performed to enhance the accuracy of the results (Liguori et al., 2021). The process followed to generate the schedules is described in detail in the "The schedules' development" Section, while the smart meter dataset used in the study is detailed in "The case study" Section. In this study, daily patterns in the dataset are clustered to generate profiles according to the approach proposed in previous works (Ferrando et al., 2022). The dataset was normalized and divided into two groups: "workdays" (Monday to Friday) and "weekends" (Saturday, Sunday, and national holidays). To provide variability to the schedules, a minimum of three clusters was intended to be significant, but the final number was chosen based on the Davies-Bouldin Index (DBI). The k-means method is used for the actual clustering step (Piech Chris, 2013), being one of the main algorithm used for similar purposes and one of the fastest (Gianniou et al., 2018; Viegas et al., 2015; Yilmaz et al., 2019). The resulting cluster centroid is used as a normalized schedule in the energy model. In particular, the registrations of 2019 are used to generate schedules for the before-COVID case, a typical year in which people went regularly to work out of the house and spent time also outdoors during weekends. Smart meters from the lockdown period of 2020 (March and April) are used to generate schedules regarding the during-COVID case, in which remote working was implemented for almost all workers, consequently, people stayed at home for work and also during their free time. Lastly, a combination of the resulting schedules of these two periods is used to generate the post-COVID case, half of the buildings in the model are characterized with the pre-COVID schedules (simulating the normal office work) and half with the during-COVID schedules (simulating the remote working still left as an option for several workers till nowadays). The weekend schedules are left to be the ones related to the pre-COVID case, simulating the fact that the free time is now spent normally as before COVID.

The final phase is the creation of the cases and runs of them that are then compared against one another. The smart meter readings are not used to validate or calibrate the energy results, but they are integrated in the process in the creation of the schedules by clustering. The pre-COVID case is the hourly run with the assignment for workdays and weekends of the pre-COVID schedules. The during-COVID case is the hourly run with all during-COVID schedules assigned. Lastly, the post-COVID case is the one in which the two previous scenarios are mixed. The simulation run is for an entire year, assuming that these behaviours are ideally maintained for 12 months. To perform the comparisons, the study considers the Total Operational Energy (TOE), cooling energy needs, heating energy needs, and electric energy use as determined by the umi energy results (in kWh). TOE is the sum of energy needs for cooling, heating, domestic hot water, and electric energy use (including lighting and appliances). The results are further analysed using the CVRMSE, as defined by ASHRAE Guideline 14 (ASHRAE, 2014). In this paper, the CVRMSE is used to compare the energy outputs of pre-COVID to the scenario characterized by during-COVID schedules. The analyses are conducted at various temporal scales (hourly, daily, weekly, monthly, and yearly) and spatial scales (single buildings, groups of 5, 10, 20 buildings, and the entire neighbourhood). The cases are compared in terms of energy needs for heating and cooling and the energy use for lighting and for other services, as defined by ISO 52000-1:2017 (European commitee for standardization, 2017).

The case study

The neighbourhood

Chiaravalle is a residential district located in the south-eastern part of Milan, Italy, and comprises 49 multi-family residential buildings. For this study, a UBEM was constructed to include these 49 buildings, with a total gross floor area of 56787 m^2. The heights of the buildings range from 3.5 to 16 m, with a minimum of one and a maximum of five floors. The model assumed a fixed average window-to-wall ratio of 10% for vertical surfaces, while the floor-to-floor height was fixed at 3 m, based on building descriptions and on-site visits (Breda, 2016). The model also takes into account the shading effects of surrounding buildings that are no longer in use, abandoned, or under renovation. All buildings in the district are residential and were constructed between 1960 and 2010, according to the land registries of Milan.

The archetypes

After the creation of the geometry (in this case, solved by extruding the building footprints from the GIS provided by the Municipality), the second step is characterizing the buildings to create the energy model via archetypes. They include construction materials and thicknesses of walls, floors, and roofs, the glazing properties, the HVAC system, the lighting system, the ventilation properties, and the occupant-related schedule, fixed by default but modified with data-driven ones in this case study. Thus, the geometry of the buildings, created in Rhinoceros©, is imported into umi (Reinhart et al., 2013), and then the building properties are defined with archetypes developed for the North of Italy (Carnieletto et al., 2021).

Of the 16 existing residential archetypes (Carnieletto et al., 2021), 6 are used for this study (Figure 2). Based on visual inspections and available documentation from the Municipality of Milan, an archetype is assigned to each building based on its construction year and type (i.e., traditional or prefabricated). The archetypes already include schedules for electric appliances, lighting, and occupancy, which are derived from standards like EN 16798-1 (European Committee for Standardization-CEN, 2019) and ISO 18523-1 (International Standard Organisation - ISO, 2016) but, in this case study, the electric loads' schedules are modified based on real smart metering data and their analysis. The same is done for average density values for lighting and appliances per square meter, originally based on standards (European Committee for Standardization-CEN, 2019, 2017).

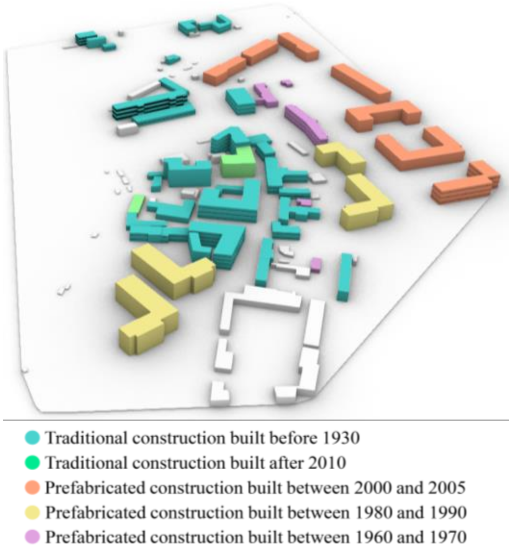

Figure 2: Chiaravalle neighbourhood coloured based on the assigned archetype.

To analyse the energy needs for heating and cooling of the buildings, we assume that the efficiency of the systems is 100%, and their capacities are infinite (European Committee for Standardization-CEN, 2017). We use a natural gas-based heating system with a setpoint of 20°C for each building, which is activated from mid-October to mid-April. Cooling is activated from mid-April to mid-October with a setpoint of 26 °C (Carnieletto et al., 2021). The lighting density levels (in Wh/m^2) are set based on the smart meter database knowing the floor area of the buildings for which the registration was available. By assuming infinite system capacities, the simulation results correspond to the energy needs required to maintain setpoint conditions.

The weather dataset

The Milano-Linate weather file, provided by the U.S. Department of Energy's (DOE) Building Technologies Office (BTO), is utilized in this study. This weather file is based on 20 years of recording (1951-1970) and represents the weather conditions for the location with latitude 45°26', longitude 9°17', and an elevation of 103 m. The weather station is located less than 4 km away from the neighbourhood. The average annual temperature in this location is 11.6 °C, with the highest monthly average occurring in July at 23 °C, and the lowest average in January at 0 °C. The maximum hourly global horizontal irradiation varies from 194 Wh/m^2 in December to 965 Wh/m^2 in June.

Although the weather conditions used in this study are based on old registrations, they are still widely used as weather files in building modelling. It is important to note that the main objective of the study is to compare the energy results rather than to analyse the accuracy of the weather data used or climate change effects.

The smart meter database

The electric energy metering data used for the study was obtained from a dataset that comprised 21 multi-family residential buildings located in southeast Milan. The dataset covers the period of the year 2019 and a few months of 2020 (from January to April), with data being registered at a frequency of 15 minutes. In addition, the electric data captured a wide range of electric uses within each apartment, including lighting, electric appliances, small space cooling or heating devices, and plug loads.

To generate the clustering for the pre-COVID period, the entire database of 2019 registrations was utilized, whereas the clustering for the during-COVID period was obtained using only the data for March and April 2020. These two months corresponded to the period when a full lockdown was implemented in Milan, resulting in most of the population staying at home. As such, the results obtained during the during-COVID period were expected to be highly representative of the changes in electric energy consumption resulting from the lockdown.

The schedules' development

The dataset provides valuable information for energy modellers who want to study energy consumption patterns in multi-family residential buildings in Milan. It includes electric energy metering for 21 buildings for the year 2019 and a few months of 2020, with a registration time step of 15 minutes with no gaps. The dataset is completely anonymous, so no information is available on the tenants' behaviour or characteristics. The average building gross area is around 3500 m^2, but there is a wide range of building sizes, with the maximum being 9322 m^2 and the minimum being 702 m^2. The mean registered value of electric energy use in the database is around 5 Wh/m^2 during the pre-COVID period, and around 5.6 Wh/m^2 during the COVID lockdown, but some buildings show relatively high electric load per square meter, especially during summertime, possibly due to the use of fans and small cooling devices.

The dataset also includes buildings situated up to a maximum distance of 10 km from Chiaravalle, all residential multi-family buildings located in Milan as the ones in the modelled area. The data in this study was categorized into workdays and weekends and were normalized and clustered using the k-means algorithm and the DBI to determine the optimal number of clusters.

For the pre-COVID data, four clusters were identified as optimal for both workdays and weekends (Figure 3), and the centroids of these clusters were used as normalized schedules in the pre-COVID model. The k-means clustering also provided the percentage distribution of each cluster in the database, which was used to randomly assign schedules to the buildings in the model. The distributions of the weekend clusters were as follows: Cluster 1 (19%), Cluster 2 (38%), Cluster 3 (22%), and Cluster 4 (21%). For workdays, the distributions were Cluster 1 (22%), Cluster 2 (20%), Cluster 3 (44%), and Cluster 4 (15%). The combination of these clusters developed 15 different schedule scenarios among the 49 buildings of the model.

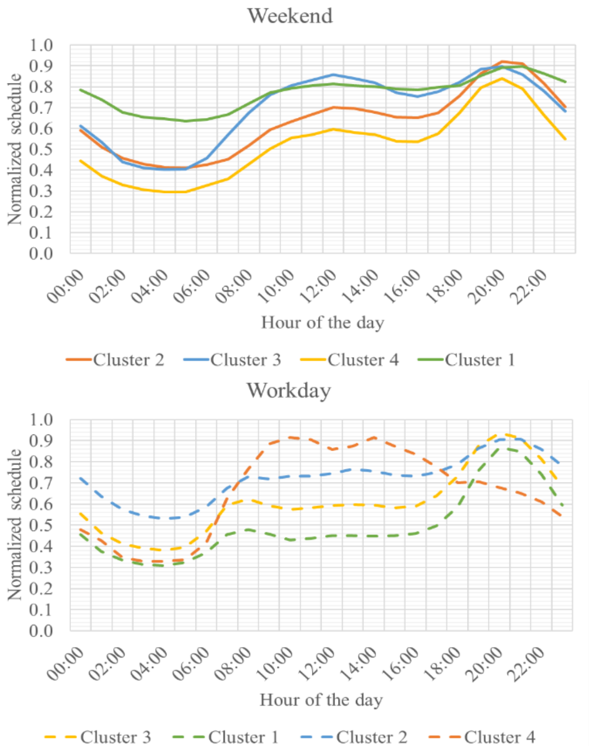

Figure 3: Clusters of centroids that can be used as normalized schedules for the pre-COVID period for the electric usage in the buildings

For the during-COVID data, ten clusters were identified as optimal using the DBI, and the centroids of these clusters are shown in Figure 4. The distributions of the clusters for weekends were Cluster 1 (16%), Cluster 2 (10%), Cluster 3 (19%), Cluster 4 (5%), Cluster 5 (17%), Cluster 6 (11%), Cluster 7 (6%), Cluster 8 (3%), Cluster 9 (9%), and Cluster 10 (4%). For workdays, the distributions were Cluster 1 (3%), Cluster 2 (23%), Cluster 3 (14%), Cluster 4 (9%), Cluster 5 (4%), Cluster 6 (7%), Cluster 7 (14%), Cluster 8 (11%), Cluster 9 (7%), and Cluster 10 (8%). The combination of these clusters developed 39 different schedule scenarios among the 49 buildings of the model.

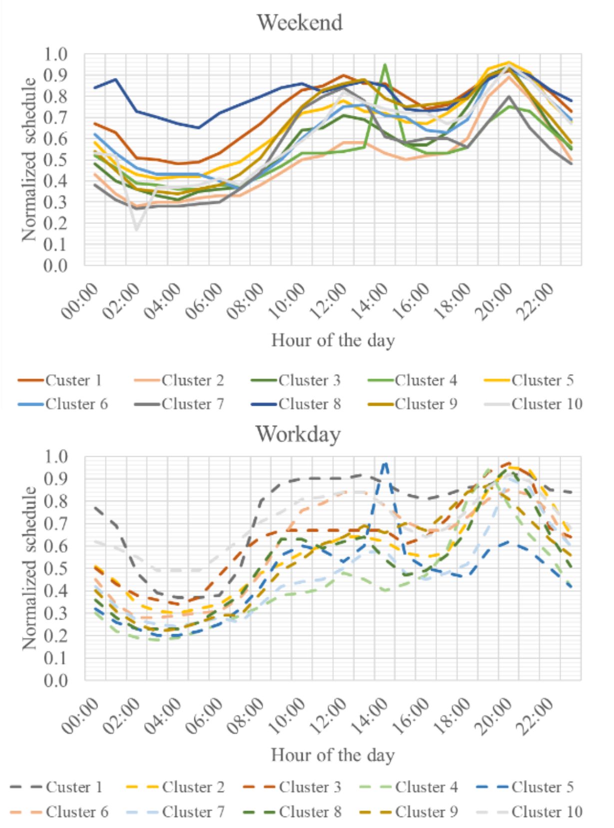

Figure 4: Clusters centroids that can be used as normalized schedules for the during-COVID period or in general as "remote working" days

The findings of the study demonstrate that during the COVID-19 pandemic, there was a noticeable shift in the morning peak and a significant increase in the usage of electricity during the central hours of the day, as indicated by the patterns of the centroids shown in Figure 5.

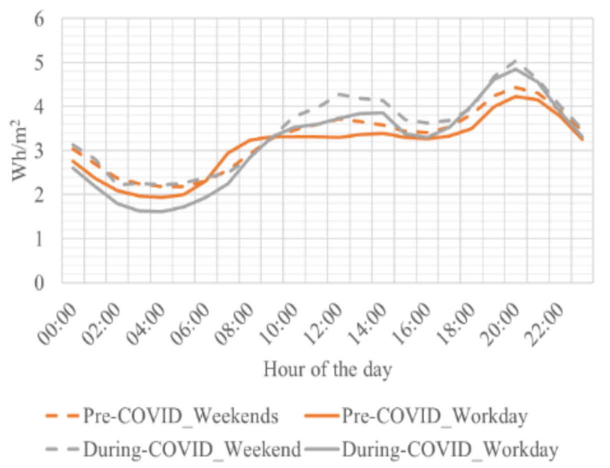

Figure 5: Average schedules multiplied by the density level (i.e., 5 for pre-COVID and 5.6 for during-COVID)

Moreover, electric use during the workdays was higher throughout the day in the during-COVID period, and the evening peak was increased but still aligned with the pre-COVID time (around 20:00). Similarly, the higher electricity usage during the weekend as compared to the pre-COVID period, can be attributed to the fact that a larger number of people stayed at home during the pandemic. These findings reveal the impact of the COVID-19 pandemic on electricity usage patterns and emphasize the importance of studying such changes to understand their implications for the energy sector.

The shift in electric consumption observed in the data analysis will be reflected in the Chiaravalle neighbourhood. However, to fully understand the impact of these changes on the neighbourhood's energy consumption, it will be necessary to further investigate the effects on heating, cooling, and TOE with the energy model.

Results and discussions

To provide a comprehensive overview of the changes in energy consumption during the COVID-19 pandemic, the study first plots the annual total electricity, heating and cooling needs, and TOE for both the pre-COVID and during-COVID cases. The resulting graph, depicted in Figure 6, serves as a useful visual aid in highlighting the significant differences between the two periods.

It is possible to observe how the electric usage patterns of occupants can have such a significant impact on the overall energy needs for heating and cooling and the energy use for lighting and for other services of a neighbourhood. The total electricity use increases by 8% due to the change in schedules and electricity density levels. On the other hand, the heating decreases by 10% due to occupants increasing the internal loads of the building by using more electric devices. As a result, the demand for heating was reduced, leading to a subsequent increase in cooling by 26% to maintain a comfortable indoor temperature. The 5% decrease in TOE is mainly due to the decrease in heating, although it is important to note that the analysis does not take into account the possible increase in temperature setpoint due to occupants spending more time at home.

This study highlights the importance of finding sustainable solutions for energy production and consumption, particularly given the significant impact of occupant behaviour on neighbourhood energy consumptions. It is crucial to promote energy-efficient building designs, as well as educate occupants on energy-saving practices to reduce the overall energy demand and promote sustainable energy consumption.

To provide a comprehensive understanding of the differences between the two cases, the study utilizes heat maps to display the CVRMSE at different temporal and spatial aggregations. This approach offers both visual and numerical insights into the degree of discrepancy between the cases. It is worth noting that a threshold of 30% and 15% is used for hourly and monthly values, respectively, to classify a single building model as "calibrated" in ASHRAE 14 (ASHRAE, 2014). In this specific case study, the CVRMSE is not utilized as a calibration criterion for the model, but rather to compare between the different cases. The CVRMSE values are computed at various temporal scales, including hourly, daily, weekly, monthly, and yearly, as well as different spatial scales, ranging from single buildings to groups of five, ten, twenty, and the entire neighbourhood. The results for electricity and TOE are presented in a heat map (Figure 7) that enables the visualization and quantification of the maximum CVRMSE that is observed across the different scales for the cases of pre-COVID and during-COVID.

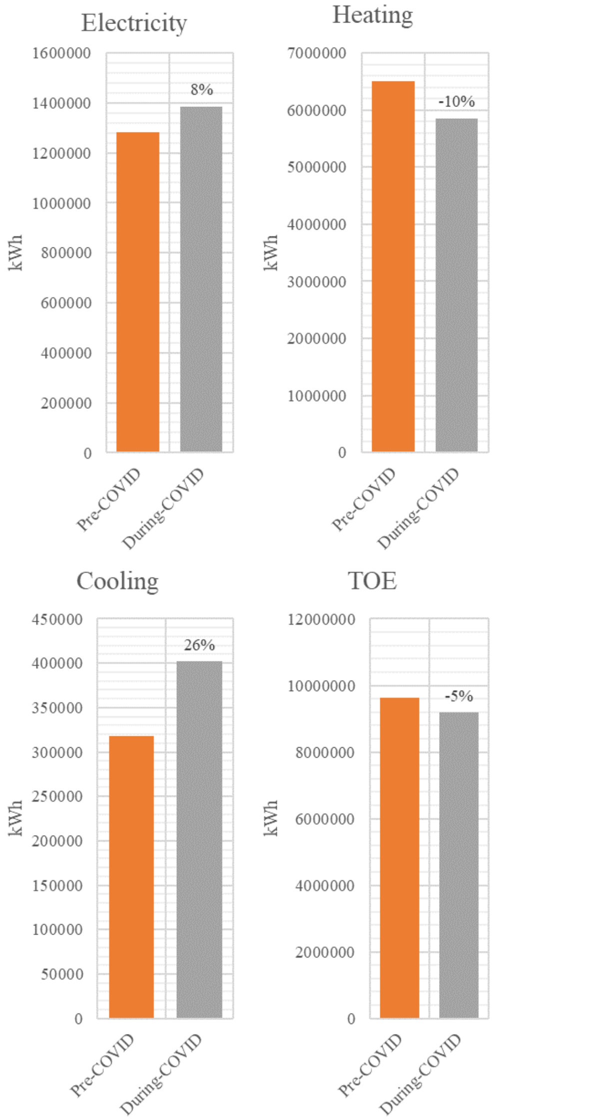

Figure 6: Annual total electricity, heating and cooling needs, and TOE for both the pre-COVID and during-COVID cases.

The analysis of the CVRMSE for electricity consumption in this case study reveals interesting insights. While the minimum CVRMSE value of 7.4 for the overall neighbourhood on a yearly basis suggests small differences between the two cases, there are variations in the CVRMSE at different temporal and spatial aggregations.

At the lowest level of aggregation, i.e., considering electricity consumption for a single building on an hourly basis, the CVRMSE value reaches a maximum of 44, indicating significant discrepancies. However, as we move to higher levels of aggregation in terms of time and space, such as daily, weekly, monthly, and yearly, the CVRMSE values tend to decrease. This suggests that the differences in consumption at lower levels of aggregation are smoothed out at higher levels. It is worth noting that the high CVRMSE values at low levels of aggregation are in this case indicative of the model performance. They reflect the inherent variability in occupant behaviour and electricity consumption patterns, which can vary significantly at shorter temporal and spatial scales.

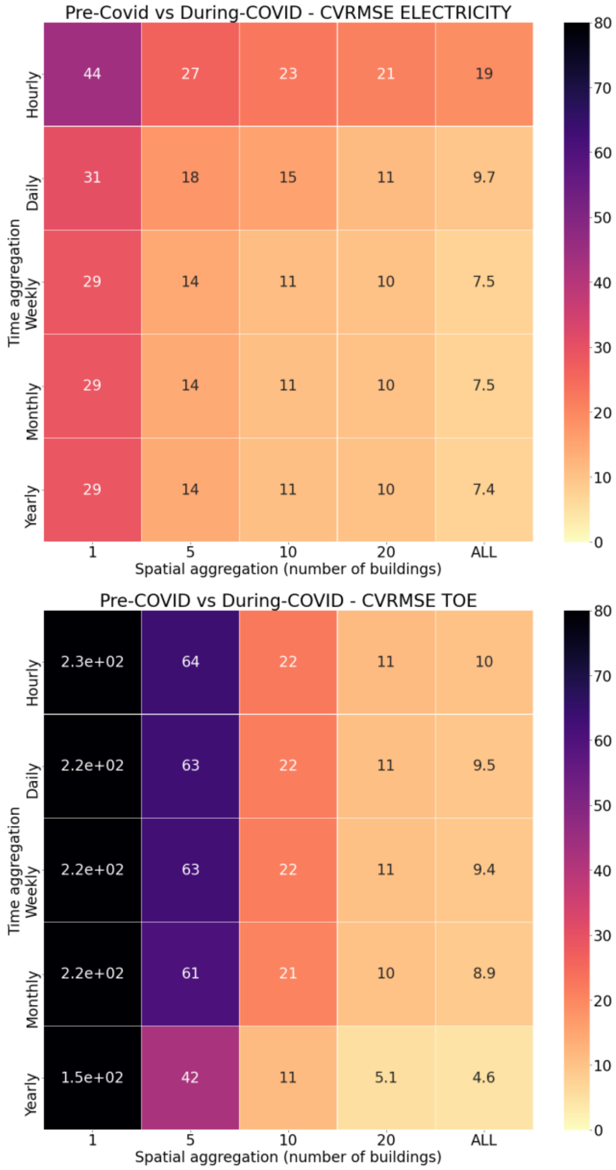

Figure 7: CVRMSE values related to the electrical energy use and TOE difference between pre-COVID and during-COVID cases, with the different spatial (horizontally) and temporal (vertically) aggregations.

Although the overall minimum CVRMSE for the TOE needs is 4.6 at the yearly scale for the entire neighbourhood, the values increase significantly for smaller temporal and spatial aggregations. The highest CVRMSE is recorded at the hourly scale for single buildings, with a value of 230. The discrepancy for TOE needs is higher than for electricity, which highlights the complexity of a dynamic energy model like UBEM. The results indicate that spatial aggregations have a greater impact on reducing pre- and during-COVID discrepancies compared to temporal aggregations. This is because spatial aggregation considers the varying schedules across different buildings, which helps to mitigate errors. In contrast, temporal aggregation considers the same schedules across the same buildings. Although the leverage of errors is present, the impact is less prominent due to the consistency in the schedules considered. These results show the importance of considering different temporal and spatial scales when analysing energy consumption data and using appropriate statistical metrics to evaluate the accuracy of the model.

Overall, the analysis of the CVRMSE for electricity and TOE needs highlights the importance of understanding the spatial and temporal variability of energy consumption patterns and the need at an urban scale.

Post-COVID scenario

The COVID-19 pandemic has caused significant changes to work patterns, with remote work becoming more common even after the pandemic has subsided. To model this shift, the post-COVID scenario was created by combining the pre-COVID and during-COVID data-driven schedules in the model. In particular, for workdays, the during-COVID schedules were assigned to 50% of the buildings chosen randomly, effectively modelling the remote working scenario.

The post-COVID scenario yielded interesting results regarding the hourly average daily patterns for both electricity and TOE, as shown in Figure 8.

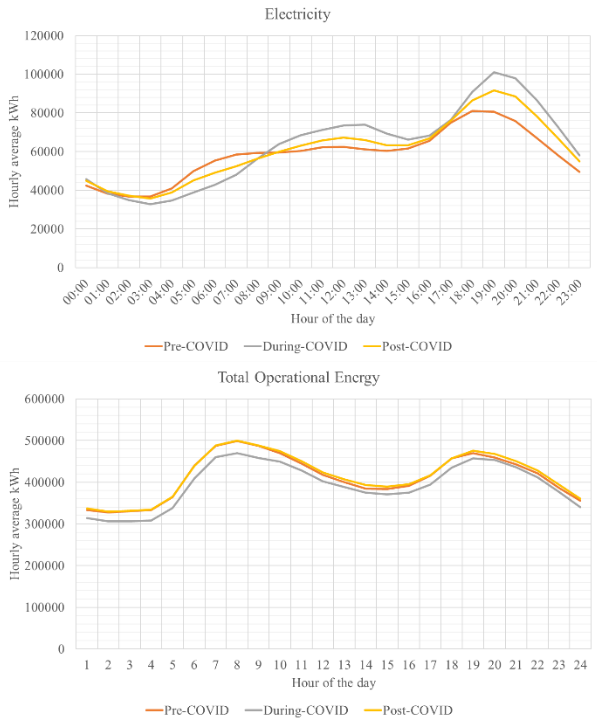

Figure 8: Hourly average daily pattern of electricity and TOE uses for the entire neighbourhood of Chiaravalle.

As expected, the post-COVID scenario is a combination of the pre-COVID and during-COVID cases for electricity usage. For electricity, the morning peak is reached around noon and gradually increases since 6:00. During the day, there is a slight decrease in consumption, followed by another peak at 19:00, likely due to dinner time. On the other hand, for the TOE, the maximum occurs at around 8:00 and a second peak is registered around 19:00. It is worth noting that the post-COVID TOE pattern is more similar to the pre-COVID pattern than an average between the pre- and during-COVID cases as for the electricity, since it is influenced by several other variables (e.g., domestic hot water, heating, and cooling patterns). However, the post-COVID electricity pattern exhibits a more evident peak at noon than the pre-COVID pattern and a general increase in electricity use.

These findings suggest that the shift towards remote work has a significant impact on energy consumption patterns and that modelling the post-COVID scenario is essential for accurately predicting future energy demands. As remote work becomes more prevalent, it will be important to continue monitoring and analysing energy consumption patterns to ensure that energy management strategies remain effective and targeted.

Conclusions

This study addresses a gap in research by conducting a two-step comparison of data-driven schedules and integrating them into an energy model to analyze the effects of the pandemic on energy consumption. The schedules derived from electric smart metering data in Milan can be directly used in energy models for pre-COVID and during-COVID case studies in locations with similar characteristics to Milan, such as climate and building typologies. However, it is important to note that the schedules may not be directly applicable to different contexts without appropriate adjustments, such as differences in climate or building characteristics.

The innovative method of heat maps based on CVRMSE, as defined in the ASHRAE Guideline 14 (ASHRAE, 2014), is used to compare the energy results. The heat maps provide a clear visualization of the differences in energy needs for heating and cooling and the energy use for lighting and for other services between the pre-COVID-19 schedules and the schedules during the confinement period, based on temporal and spatial aggregation. The analysis of the CVRMSE highlights the importance of understanding the spatial and temporal variability of energy consumption patterns, which has been overlooked in previous studies. The results show that at low temporal and spatial aggregations, there can be high differences in energy consumption patterns. However, these differences are smoothed out at higher temporal and spatial aggregations, demonstrating the need for comprehensive and accurate energy models that can capture the spatial and temporal variability of energy consumption patterns at an urban scale. Finally, the study creates a scenario that combines remote working and normal office work by mixing the during-COVID schedules with the pre-COVID schedules. The study highlights the significant impact of remote work on energy consumption patterns, emphasizing the importance of modelling post-COVID scenarios to predict future energy demands accurately. Ongoing monitoring and analysis of energy consumption patterns are necessary to ensure the effectiveness and targeting of energy management strategies in response to the increasing prevalence of remote work. The study is limited to residential buildings located in a specific area of Milan, and the assumption is made that the available dataset is representative of the simulated buildings in the same area of the city. However, the update of an Italian Time Use Survey could enable a more generalized approach in the future. Furthermore, Time Use Surveys can be utilized to validate or expand the occupants' model by including other activities besides electricity usage.

In conclusion, the study provides valuable insights into the complexity of energy consumption patterns at different spatial and temporal scales and highlights the need for comprehensive and accurate energy models to capture these patterns. The schedules derived from smart meter data in Milan can be directly used in energy models for pre-COVID and during-COVID case studies in locations with similar characteristics, but caution should be exercised when using them in different contexts. The scenario created in the study provides a useful tool for policymakers and energy planners to develop targeted energy management strategies to reduce energy consumption and manage the impacts of remote working.

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