# Application of energy signature method to analyze the energy consumption patterns before and during the COVID-19 pandemic in two public office buildings in Thessaloniki, Greece

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**Abstract.** The global COVID-19 pandemic had a significant impact on building energy use as a result of local emergency policies such as lockdowns, remote working and increased building ventilation being applied for an extended time. In this study we apply the energy signature method to two public office buildings in Thessaloniki, Greece to compare their energy performance before (2018-2019) and during (2020-2021) the pandemic. The energy signature method normalizes electricity and natural gas consumptions to the average climate, eliminating the influence of annual weather patterns on energy use and differentiates between heating, cooling and base energy. This allows us to compare the two periods using data from monthly utility bills. Results show a reduction (ranging from 16% to 26%) in both heating and cooling energy consumptions during the pandemic period for both buildings which is not related to differences in annual weather patterns. Although this old method is quick and straightforward to use it has its own limitations which are discussed along with potential ways it can improve.

**Keywords:** Building Energy, Energy signature, COVID-19, Consumption, Pandemic

## 1 Introduction

Building energy performance is affected by several parameters, such as the local climate, the thermophysical properties of its envelope, HVAC and lighting equipment and occupant behavior. The COVID-19 Pandemic disrupted normal building use globally, as lockdowns, travel restrictions and remote workingmeasures were implemented to reduce transmission of the SARS-COV 2 virus. Additionally, local governing bodies issued special guidelines for increased natural and mechanical ventilation to lower indoor viral concentration levels.

In Greece, the Ministry of Health, following REVHA and GHI-net recommendations, issued technical guidance for the operation and maintenance of HVAC systems [13] mainly suggesting prolonged operation of ventilation systems, use of air filters, use of natural ventilation and prevention of air recirculation. These changes in building operation and occupancy were widely applied in tertiary sector and especially public buildings, altering the “conventional” energy use patterns.
The aim of our study is to contribute to the increasing body of literature that studies the impact of the COVID-19 pandemic on building energy use. We compare the energy consumption of two public buildings in Thessaloniki, Greece between a pre-COVID-19 period (2018-2019) and a COVID-19 period (2020 – 2021). To perform such comparison, we utilize the energy signature method which allows us to adjust monthly energy consumptions to the local climate, thus removing the influence of annual weather patterns. Findings indicate a decrease (ranging from 16% to 26%) in annual heating and cooling demand during the pandemic in both buildings which is not attributed to changes in annual weather.

## 2 Background

The COVID-19 pandemic had a complex influence on building energy use [16]. While some operational changes, such as reduced occupancy, have led to a decrease in energy consumption for heating, cooling and lighting, others, such as increased need for natural or mechanical ventilation have led to an increase. Kang et al.[10] studied the impact of COVID-19 on energy consumption by building use type in South Korea by relating electricity and natural gas energy data with regional COVID-19 big data. The study showed average electricity usage decrease in office buildings up to 5% and monthly gas decrease up to 8.37% in various regions in comparison with electricity consumption increase in residential buildings. A similar studyby Madurai Elavarasan et al. [12] highlighted the decrease in electricity demand during the pandemic in the commercial and industrial sector in comparison to the increase in the residential sector due to new lifestyle of staying and working from home.
Additionally, various studies have shown the huge impact of HVAC irregular operation on the energy consumption of buildings. Extended HVAC operation schedules, while being crucial for a healthy indoor environment, significantly increase the energy consumption. Similarly, introducing higher air flow rates in the space results in much higher energy consumption as the systems operate constantly on their full capacity. A study by Mokhtari and Jahangir [14]showed that when HVAC operation hours were almost doubled, the energy consumption increased by up to 39.2%.
Another study by Escrivà-Escrivà et al.[6]showed that even one extra hour of HVAC operation after occupancy could lead up to 4,48% increase in energy consumption. Zheng et al[22] investigated the impact of applying the HVAC operational recommendations during the pandemic (such as introducing 100% air volume and no recirculation) on the energy consumption. By using Chinese public building energy consumption historical data,they estimated an increase of up to 128%. These findings indicate

that there is no simple answer regarding the influence of the COVID-19 pandemic on tertiary building energy use.

In our study we study this influence by applying the energy signature method to two tertiary sector public buildings.Energy consumption in buildings can be estimated by either analytical simulation models using thermodynamic equations or data-driven static or dynamic models based on data collection [2, 19, 21]. The energy signature method belongs to the latter.

Static models, such as Ordinary Least Squares (OLS) linear regression method used in this study, are suitable for energy prediction demand over long time intervals such as months [20].These methods are usually applied when accuracy is not a high priority, as they do not analyzeenergy use patterns at finer temporal scales. They are commonly applied in Measurement and Verification processes together with on-site inspections for proposing energy retrofit measures as described in IPMVP protocols [8].

The past years there is a rise in dynamic models which are made possible through smart metering and recent advances in Machine Learning (ML) [17].These modelscan be trainedon weekly, daily, or hourly weather profiles and are constantly updated on newly available data. Hence, they are suited for both long-term and short-term forecasting of energy use with good accuracy. However, a limitation of such models is the requirement for real time big data which is only possible with the use of smart meters [18].

The energy signature method has been used extensively for decades with its roots found in the 1950's [9]. Despite its relative simplicity it is used even today in several building and urban energy studies[1, 4, 5, 15].The method relies on establishing a correlation function (linear, polynomial etc.) between energy consumption and one or more parameters that significantly influence the consumption patterns, such as outdoor air temperature, building operating conditions, etc.The method is suitable for application in tertiary sector buildings. This is because parameters such lighting and HVAC equipment, as well as occupant behavior is considered stable and can be directly related to energy signatures [11].

## 3 Methodology

Our goal is to compare the energy consumption patterns two years before the COVID-19 pandemic (2018-2019) and during the pandemic (2020-2021) in two case-study public buildings in Thessaloniki, Greece. Weather has a significant influence on energy consumption for heating, cooling and ventilation. Comparing consumption patterns to detect possible differences due to changes in building use we need to eliminate the influence of weather on energy use data. This is achieved with the energy signature method that normalizes energy consumption to the "average" conditions of the local climate.

Normalized energy consumptions can then be directly compared to detect any changes between the pre-pandemic and pandemic periods that could be attributed to changes in building use, due to emergency policies such as lockdowns. An additional advantage

of the method is that it also allows us to differentiate between heating, cooling and base loads by relating energy use with air temperatures.
The energy signature method we employed in this study is described in the BS EN 15603:2008 standard [7]. ASHRAE calls this method “base model” in the Guideline on “Measurement of Energy and Demand Savings” [3]. Since energy use is recorded for any building in monthly utility bills, it can be easily related with outdoor air temperature data, as long as the building:

1. maintains a constant internal temperature through appropriate devices (thermostats, etc.),
2. has stable internal gains and
3. has low or zero solar gains from passive systems.

We applied the energy signature method to two buildings in Thessaloniki, Greece (Fig.1): The first (Building A) is the ex-town hall of the Municipality of Triandria, a four-story building erected in 1977 with a total floorspace of 1018m², of which 826m² are conditioned. It has a poor energy performance, (“E” class energy certificate) with no insulation and single-pane windows. It is heated with a central gas boiler and cooled with old air conditioning split units. The ground floor is a Citizen Service Center, the first and second floors are offices and the third is a conference hall. The building has operable windows for natural ventilation.
The second (Building B) is a six-story building erected in 2006, with a total floorspace of 1998m², of which 1574m² are conditioned. It has mediocre energy performance (“C” class energy certificate) as its envelope construction characteristics comply with the Greek Insulation Code that preceded the current Building Energy Code (KEnAK). It is heated and cooled with a central VRF unit, although some auxiliary spaces that were later converted to office space are independently heated and cooled with split units and electric radiators. Apart from offices it houses a “social pharmacy” and medical examination services. The building has operable windows for natural ventilation. Personal communication with the building’s manager revealed that HVAC operation program was not changed during the pandemic.

**Fig. 1.** The two case-study buildings. Left: Building A. Right: Building B.

We acquired utility bills for the 2018 – 2021 period from the Municipality of Thessaloniki and monthly air temperatures for the 2011 – 2021 period from the National

Meteorological Service. We then applied the energy signature method using Ordinary Least Squares (OLS) linear regression, relating mean energy consumption (electricity and/or natural gas) to mean outdoor air temperature. Each examined year was divided into a heating and a cooling period and regressions were performed for each building, fuel, year and cooling / heating period (Figs. 2 – 4) Afterwards we verified their goodness of fit by calculating $R^2$ (Figs. 2 – 4) and the Coefficient of Variation of the Root Mean Square Error CV(RMSE) (Tables 2 and 3).
Using the OLS regression parameters, we then estimate the normalized monthly energy consumptions for the climate of Thessaloniki, as it is described by the mean monthly air temperatures (2011 – 2021) of the last decade (Table 1). From the regressions we can calculate a balance temperature where the heating and cooling regression lines intersect. This is the theoretical outdoor air temperature where the building is "free running" and is useful in identifying the month with the least energy use for heating and cooling. We assume that the electricity consumption of this month corresponds to the minimum "base" consumption for the year (i.e. lighting, equipment, appliances, elevators etc).

**Table 1.** Monthly mean average temperatures for the four examined years (2018 – 2021) and the last decade (2011 – 2021). The Mean Absolute Percentage Error (MAPE) is also given for each year, calculated against the 2011 – 2021 period. Lines indicate the distinction between heating and cooling periods.

| month | 2018 | 2019 | 2020 | 2021 | 2011-2021 |
|---|---|---|---|---|---|
| Jan | 7.6 | 4.9 | 7.0 | 8.5 | 6.8 |
| Feb | 8.9 | 8.0 | 9.3 | 8.9 | 9.1 |
| Mar | 11.8 | 11.9 | 10.8 | 9.7 | 11.2 |
| Apr | 17.4 | 14.5 | 13.1 | 13.0 | 14.9 |
| May | 21.6 | 19.3 | 19.1 | 20.0 | 20.2 |
| Jun | 24.2 | 25.8 | 23.5 | 23.9 | 24.5 |
| Jul | 26.4 | 26.9 | 26.6 | 28.1 | 27.0 |
| Aug | 26.8 | 27.8 | 26.4 | 28.4 | 27.3 |
| Sep | 23.3 | 23.7 | 24.5 | 22.5 | 23.1 |
| Oct | 18.1 | 19.0 | 19.1 | 15.4 | 17.4 |
| Nov | 13.1 | 16.0 | 13.1 | 13.3 | 13.4 |
| Dec | 7.1 | 9.8 | 11.1 | 8.2 | 8.6 |
| **MAPE** | 6% | 9% | 6% | 7% | - |

For the present climate of Thessaloniki there is a clear separation between a heating and a cooling period, since months with neutral temperatures, such as May and October exist (mean air temperature around 19 – 20°C). Using the balance temperature, we then differentiated between monthly heating and cooling energy, after subtracting the base consumption from the estimated total. Finally, we calculated the average base, heating and cooling consumptions for the pre-pandemic and pandemic periods for each of the two buildings and compared results.

# 4 Results

Results from the application of the energy signature method in the two buildings are presented in Figs. 2 – 6 and Tables 2 – 3. Regarding the goodness of fit we observe that $R^2$ can vary significantly from very low (0.04) to very high (0.97). Some of the lowest $R^2$ values are observed in electric energy use for building A (all years) and only for year 2021 for building B. Gas consumptions for building A have relatively good $R^2$ values, ranging from 0.64 to 0.81. It is interesting to note that except for 2021 electricity consumption for building B has a very strong linear trend, with $R^2$ ranging from 0.87 to 0.97. However, calculated CV(RMSE)s (Tables 2 and 3) show that the linear models have a low percentage error for electricity use (6% - 22%) and a mid to high percentage error for heating use (2% - 41%).

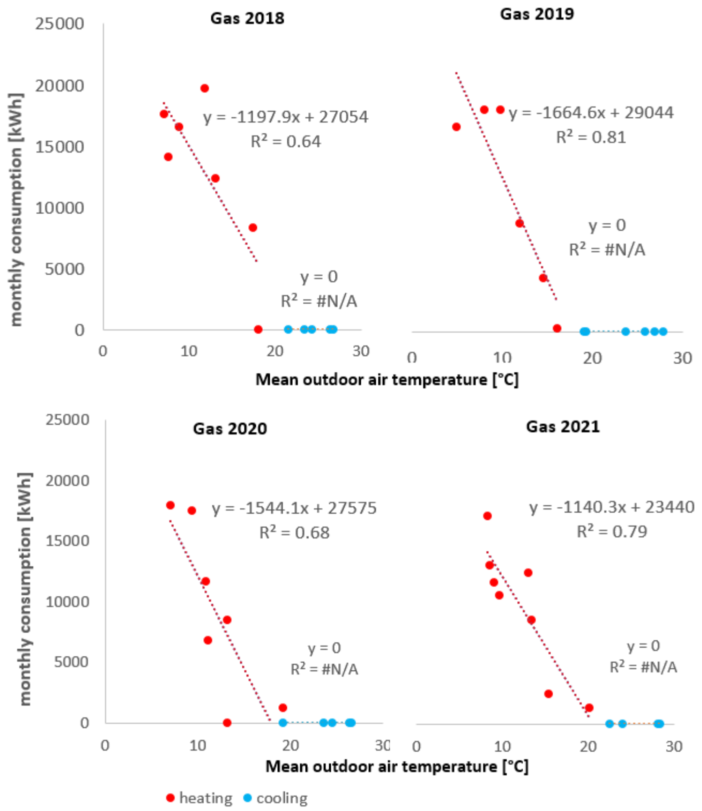

**Fig. 2.** OLS regressions for Building A (Natural gas energy consumption)

These metrics can be explained as follows: The combination of high $R^2$ and low CV(RMSE) in some cases of electricity use reveals that the linear model is introducing a large bias which in these cases fails to capture sufficiently the variability of the underlying data. However, it is still able to make reasonably accurate predictions, as indicated by the good CV (RMSE). The combination of relatively high $R^2$ values with mediocre CV(RMSE) in the case of natural gas use shows that the model is explaining a good proportion of data variance, but it is less accurate.

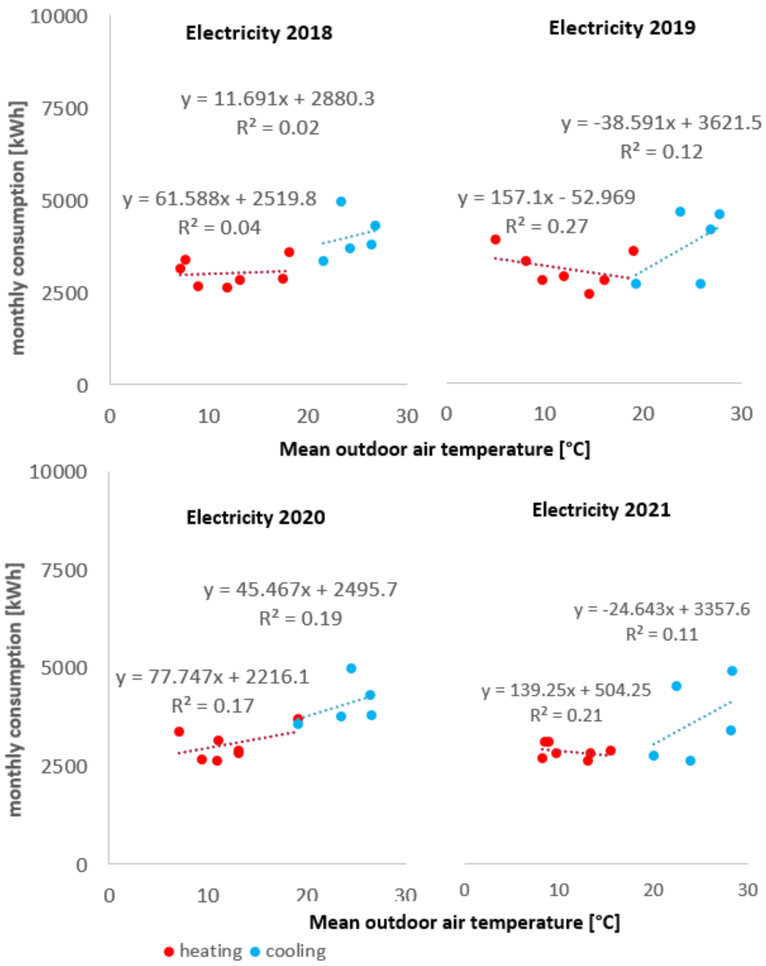


**Fig. 3.** OLS regressions for Building A (electricity energy consumption).

We also observe that there are differences between actual and normalized energy consumptions in both buildings, but values tend to be close (Tables 2 and 3). This can be attributed to the fact that the monthly air temperatures of the four examined years are – more or less– similar to the 10-year averages, with 2019 being the year with the highest declination (9%) from the climatic norm (Table 1).

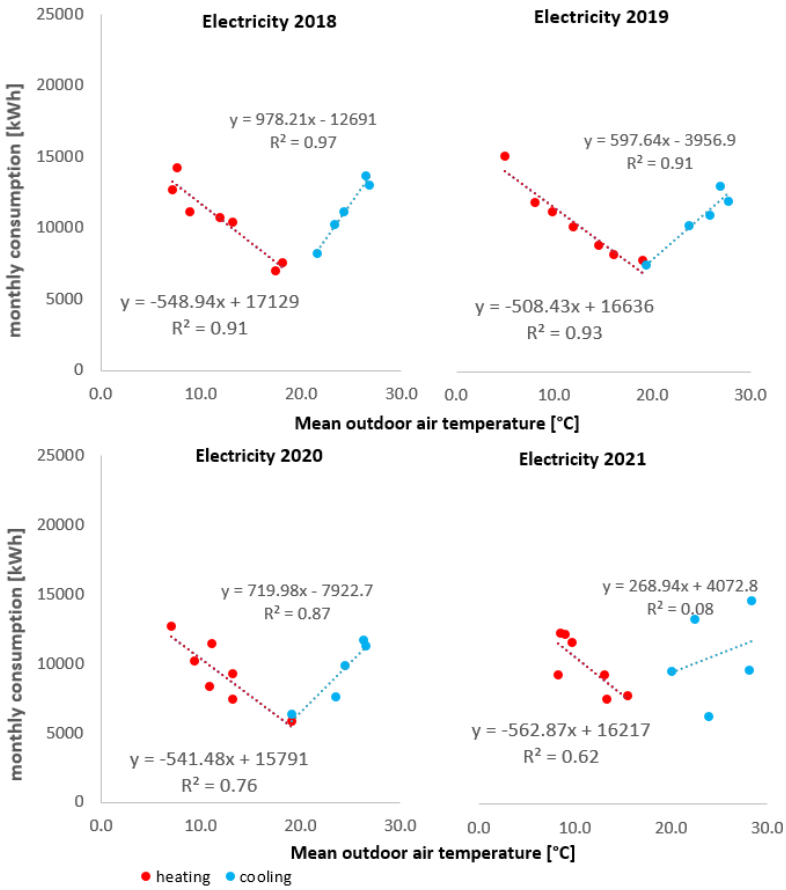


**Fig. 4.** OLS regressions for Building B (electricity energy consumption).

Figs. 5 and 6 demonstrate the observed differences in normalized monthly energy consumptions for the pre-COVID-19 and COVID-19 period and for the two buildings. Building A, having a poorly insulated envelope and an outdated gas boiler consumes a lot of energy for heating. During the COVID-19 period we observe a reduction of 16% and 22% for heating and cooling respectively that is not attributed to annual differences in weather. Base loads remain unchanged between the two periods. Building B has more than twice the base loads of Building A, as it is a much larger building with more equipment, including some medical devices. For Building B energy consumptions for heating and cooling are roughly equal. As with Building A, Building B demonstrates a reduction in energy consumption during the COVID-19 period for both heating and cooling by 26% and 22% respectively, while a negligible reduction of 1% in base consumption is also observed.

**Table 2.** Regression results for building A.

| | actual consumption [MWh] | | normalized consumption [MWh] | | CV (RMSE) [%] | |
|---|---|---|---|---|---|---|
| | n.gas | elec. | n.gas | elec. | n.gas | elec. |
| 2018 | 90.0 | 41.3 | 94.5 | 41.0 | 31% | 12% |
| 2019 | 66.0 | 41.2 | 67.6 | 41.3 | 35% | 17% |
| 2020 | 66.0 | 41.7 | 68.8 | 43.1 | 41% | 11% |
| 2021 | 77.8 | 41.2 | 72.9 | 41.3 | 28% | 12% |

**Table 3.** Regression results for building B.

| | actual consumption [MWh] | | normalized consumption [MWh] | | CV (RMSE) [%] | |
|---|---|---|---|---|---|---|
| | n.gas | elec. | n.gas | elec. | n.gas | elec. |
| 2018 | - | 130.0 | - | 131.2 | - | 6% |
| 2019 | - | 128.1 | - | 128.2 | - | 5% |
| 2020 | - | 112.1 | - | 114.7 | - | 11% |
| 2021 | - | 117.4 | - | 123.5 | - | 22% |

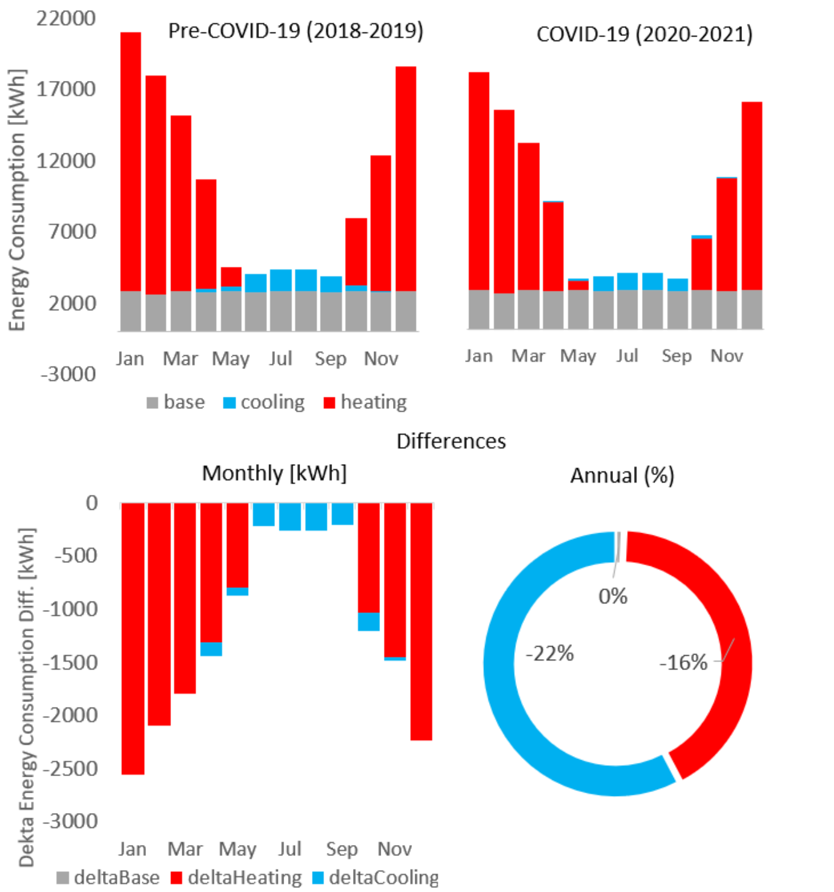


**Fig. 5.** Normalized average monthly energy consumptions in the pre-COVID-19 (2018-2019) and COVID-19 (2020-2021) periods.

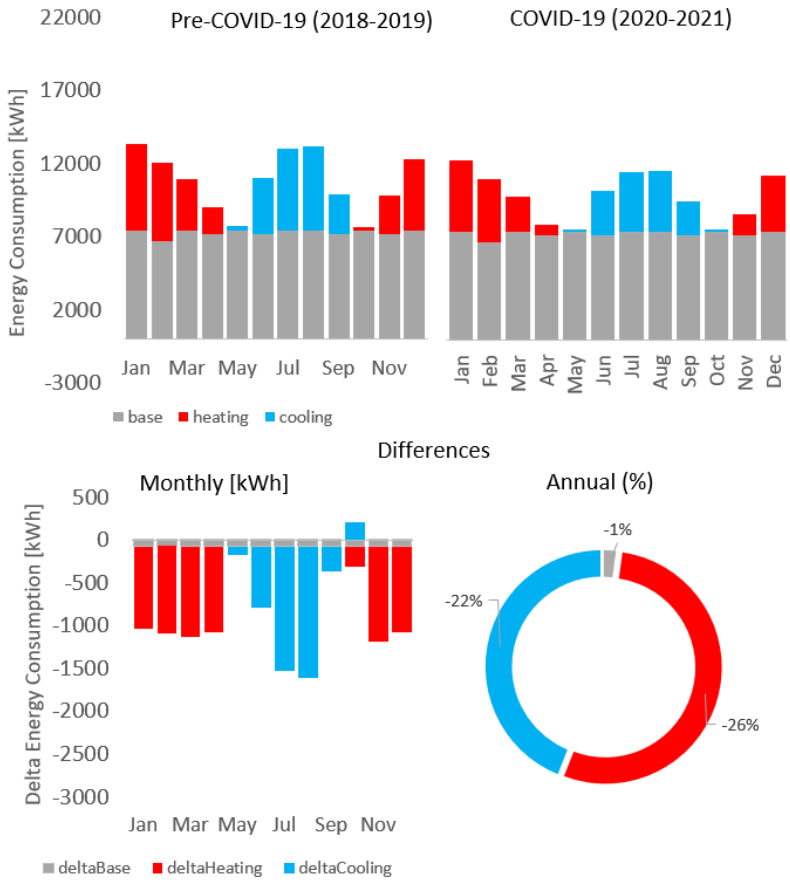


**Fig. 6.** Normalized average monthly energy consumptions in the pre-COVID-19 (2018-2019) and COVID-19 (2020-2021) periods.

## 5 Discussion

The application of the energy signature methods for two-year periods before and during the COVID-19 pandemic revealed a significant reduction in energy consumption for both heating and cooling, ranging from 16% to 26% that is not attributed to changes in annual weather patterns. Base energy use for lighting and other equipment and appliances remained virtually unchanged in both buildings. Theoretically, base consumptions should be lower too, as building occupancy is reduced. The method presented here, is not able to differentiate base consumption between its components (e.g. lighting, equipment, elevators etc.) without on-site building inspections or without making several assumptions about building use.

While we demonstrated that the energy signature method is a valuable tool for interpreting and comparing building energy consumption using nothing else but utility bills, we also acknowledge its limitations. We apply the simplest method, the OLS linear regression, which can explain only a fraction of energy use variance, especially regarding electricity. Our main data source is utility bills which allows for a monthly step of calculations. This keeps the method simple but fails to provide interpretations of building energy use in finer temporal scales (e.g. a typical winter or summer day). Another limitation is that we can only assume that the observed reductions in energy consumption are attributed to COVID-19 pandemic and not to some other factor (e.g.unrelated changes to occupant behavior and/or building use). These limitations can be improved by:

Applying more sophisticated regression methods such as polynomial regression or ML algorithms such as Random Forests, Gradient Boosting and Neural Networks. ML, however, requires big data which cannot be extracted from simple utility bills.

Measuring energy consumption at finer temporal scales, using IoT smart meters and indoor climate sensors. Constant real-time monitoring of energy use and indoorenvironmental conditions requires a significant investment in IoT equipment and adds an additional layer of complexity to all calculations.

Conducting an on-site building inspection to record heating/cooling setpoints and create an energy inventory, from where base consumptions can be broken down to specifics (e.g. lighting, equipment, appliances etc). Inspections could also diagnose problems with HVAC equipment and operation.

Using daily energy use and occupant behavior profiles. Big data gathered from buildings of similar type and in the same climate could be used to infer energy consumption at finer temporal scales from monthly utility bills.

The relevant literature (see Background section) mentions both increases and decreases of energy consumptions during COVID-19 pandemic. The significant decrease in energy consumption observed in both buildings can be attributed to their sparser use during the pandemic, but we cannot verify to what extend the recommendations for increased mechanical and natural ventilation were followed or not using the energy signature method alone.

## 6 Conclusions

We utilized the energy signature method to compare energy consumptions of two public office buildings before and during the COVID-19 pandemic. We found that the energy consumption during the pandemic period was reduced in both case studies. In building A, which utilizes natural gas for central heating and electricity for local cooling, the total energy consumption for heating was reduced by 22%, while for cooling by 16%. Similar energy decrease of 22% for heating and of 26% for cooling was found in Building B which utilizes only electricity. The energy signature method is quick and easy to use, hailing back to a pre-digital era. Despite its limitations we believe that it can still be a useful analysis tool when combined with on-site inspections and more rigorous methods of data collection.

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