The impact of the COVID-19 on households' hourly electricity consumption in Canada

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ABSTRACT

The spread of the COVID-19 pandemic caused a tremendous impact on our societies, including changes in household energy consumption. Using measured electricity use data from 500 homes in Ottawa, Canada, this study applies changepoint analysis, descriptive statistics, k-means clustering, and the corresponding change of electricity utility bills before and after COVID-19. Our analysis indicates that the average household daily electricity consumption increased by about 12% in 2020 relative to 2019, about one-third was due to warmer temperatures, with much of the rest due to the temperature-independent loads (e.g., lighting and appliances). Additionally, the highest five peak loads corresponding to post-COVID are significantly higher (15–20%) than peaks that occurred pre-COVID. The lockdown's impact on household electricity use is not consistent, and there are noticeable differences among different months, seasons, and day types. Two clusters of household electricity use patterns emerged, with about one-third showing significant increases during the pandemic and the remainder showing only minor changes. On the other hand, in the summer, all customers' electricity use profile patterns after the pandemic resemble the pattern before the pandemic. Yet, there is a significant increase (from 16.3 to 29.1%) in daily demand after COVID-19. Finally, the average increase in the utility bill post-COVID would be 9.71% if TOU rates were used instead of the flat rate that was implemented as a subsidy to consumers.

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1. Introduction

In March 2020, the World Health Organization declared COVID-19, a disease caused by SARS-CoV-2 coronavirus, to be a global pandemic [1]. Since the pandemic onset, researchers have increasingly begun to investigate the impact of the COVID-19 outbreak on health [2–4], economy [5,6], social well-being [7]. To contain the pandemic, world governments mandated stringent measures regarding building occupancy. The measures were ramped up from social distancing to the ban of mass gatherings, mandatory closure of non-essential business and even full curfew. Such measures have led the global economy into one of its most severe recessions since 1900 [8–10] as major financial and industrial markets witness a significant decline, international supply chains drop, borders have closed, and tourism has paused. For example, the gross domestic product (GDP) of the United States and the European Union dropped by 34.3% and 12.1%, respectively, in the second quarter of 2020 [11], while China's GDP decreased 6.8% in the first quarter of 2020, compared with the same period in the previous year [12].

Notably, the imposed measures affect production activities and people's lifestyles and lead to substantial energy consumption changes; over 80% of all global workplaces partly or fully closed [13]. Global energy demand fell by 3.8% in the first quarter of 2020, compared with the previous year [14], even though there was an increase in residential electricity demand [15]. Although overall energy demand declined, countries across the world varied in the degree to which they imposed policies to contain the virus. Some imposed a full lockdown, while others set either a partial curfew or requested their citizens to stay at home. This variance in measures is reflected in the electricity systems, particularly in electricity consumption profiles [16]. For example, France, India, Spain, and the UK saw their consumption fall by nearly 15% during lockdown periods. In China, energy usage dropped 6.5% in the first quarter. At the height of its outbreak, Italy saw electricity demand drop as much as 37% at times [17]. Unlike many other countries, Sweden imposed far fewer restrictions on people with the recommendation (but not enforcement) for people to physically distance themselves [18]. In this regard, its energy consumption during the pandemic was very similar to the pre-pandemic period.

Since the pandemic onset, several studies have investigated the impact of imposed lockdown measures on overall electricity con-

sumption loads in different nations [19–22]. Zhong et al., [23] reviewed the implications and challenges of COVID-19 for the electricity sector. They stated that increased uncertainty of electricity demand posed more significant pressure on system operators. Most recently, Ruan et al., [24] assessed the early impact of COVID-19 on electricity consumption in the United States. While the aggregate impact on electricity use has been quantified from different views, the impact of the lockdowns on the household level electricity consumption has yet to be studied extensively. Segregating residential electricity profiles from overall electricity demand is necessary to improve hourly load forecasts at scales relevant to the operation and planning of energy utilities and governments.

Mandatory stay-at-home lockdowns have caused residential building residents to use more energy for their daily routine activities [22]. Many homes have been transformed into an office setting for workers and into a classroom environment for students. In other words, people use computers, laptops, lighting, and other appliances at home that would typically have been used in their offices and schools. Additionally, the limited availability and closure of outdoor entertainment activities have caused people to look for alternatives within their households' boundaries – often leading to a significant increase in energy consumption.

Few studies have discussed the impact of lockdown measures on the increase of household electricity consumption. For example, UK statistics showed that midday residential energy consumption increased by about 30% [25]. Previously, such spikes were present in the mornings when people were usually preparing for work. In the US, household electricity use increased by up to 8% during lockdowns [26]. Austin Energy reported a 12% increase in residential energy consumption in the second week after lockdown began [27]. Aruga et al., [28] investigated how COVID-19 cases affected Indian energy consumption in different regions. Edomah and Ndulue [29] showed how a forced lockdown in Lagos, Nigeria lead to a momentary transition in energy use and changes in electricity demand patterns. Qarnain et al., [30] explored the most influential energy consumption factors amid the COVID-19 pandemic in Indian households. Using a survey-based analysis of 352 homes in China, Cheshmehzangi [31] evaluated the impact of the COVID-19 pandemic on household energy use. In Australia, comparing the energy consumption of 350,000 homes using two weeks' data (one before and one week after the lockdown) in north-western Melbourne, the electricity consumption was 14% higher during the lockdown's first week [32]. Moreover, using high-frequency electricity monitoring from 491 houses and interviews with 17 households in Queensland, Snow et al., [33] compared changes in energy use before and during COVID-19 lockdown, quantifying the key drivers of changes in energy use experienced by households during the lockdown. They found that overall energy use among the majority of households monitored decreased during lockdown versus prior, driven primarily by a reduction in air conditioner use during lockdown due to the cold weather. In Ireland, electricity used by households was found to be 11%–20% higher during the lockdown [34]. A recent review study by Krarti and Aldubyan [35] highlighted that the imposed lockdown to address the COVID-19 pandemic during March-May 2020 period in three countries (Australia, UK, and USA) resulted in a 11%–32% increase in the residential electricity demand. More recently, in Canada, Rouleau and Gosselin [36] compared the electricity consumption data pre-and post- COVID-19 in a 40-dwelling social housing building located in Quebec City. Their findings reveal that electricity use in the middle of the day (9:00 to 17:00) increased by 46%, relative to the same month pre-COVID. They observed that such an increase only occurred in the first month of lockdown, which was not observed for the following months (May, June, and July). Regarding space heating use,

they reported that no major change was observed during the lockdown.

Although previous studies have provided several contributions to the impact of lockdown measures on the increase of household electricity consumption, most of those studies took top-down approaches for entire regions or focused on single buildings. Higher resolution data is needed to understand the behaviour change of households. Such high-resolution data allows us better to isolate the effect of COVID-19 on energy use relative to changes caused by seasonal variation. Identifying and forecasting daily electricity demands are vital for planning efficient electricity grid operations, designing rates, and evaluating policies. Grid operators rely on load forecasts that are highly dependent on the day of the week and time of year, and weather forecasts. While most of the load forecast uncertainty at these time scales is typically driven by uncertainty in weather forecasting, behavioural changes resulting from the COVID-19 and their potential to continue beyond the current pandemic are introducing new uncertainties.

In the future, several waves of SARS-CoV-2 outbreaks are predicted potentially to last until 2024 [37], and thus prolonged or intermittent remote working is likely to be continued. Even with the end of the COVID-19 outbreak, some COVID-19-induced electricity changes might continue their current energy consumption patterns (or close to their current) as several companies have announced plans to allow for widespread permanent teleworking even as they begin to allow employees back into the office (e.g., Twitter and Square employees will have the option to permanently work from home [38]).

Additionally, results from the Global Work-from-Home Experience Survey reports that 77% of the workforce say they want to continue to work from home, at least weekly, when the pandemic is over [39]. However, a recent literature review by O'Brien and Aliabadi 2020 [40] stated that quantifying household energy impact of teleworking using detailed power metering has not been studied. In short, the impact of telework on household energy use still appears uncertain. Taking this lens, the impact of the COVID-19 pandemic on electricity transitions presents a unique opportunity to analyze in real-time the potential impact of teleworking on household electricity consumption.

The remainder of this paper is structured as follows. In the next section, a brief overview of the major events since the outbreak started in Ontario is presented, providing earlier insight into the impacts of COVID-19 on electricity demand and system operations. It then goes on to the proposed research questions. The following section describes in more detail the data used in our study and our applied methodology to demonstrate the pre- and post-COVID-19 differences of households' electricity consumption. Section 4 presents the results that answer the proposed research questions. A comparison with the current literature along with the study's limitations are discussed in section 5, and finally the paper is concluded.

2. The positioning of the study

In this research, we aim to quantify the impacts of the COVID-19 lockdown on the household's electricity consumption taking an Ontario perspective as a case study. Studying changes in energy consumption patterns under lockdown lays the groundwork to forecast how energy could be consumed in buildings if telework becomes popular in the future. Like several nations worldwide, the COVID-19 pandemic has had widespread economic and societal impacts across Ontario, Canada. Fig. 1 shows a timeline of major events since the outbreak started in Ontario.

The Independent Electricity System Operator (IESO), which operates the electricity market in all of Ontario (including Ottawa),
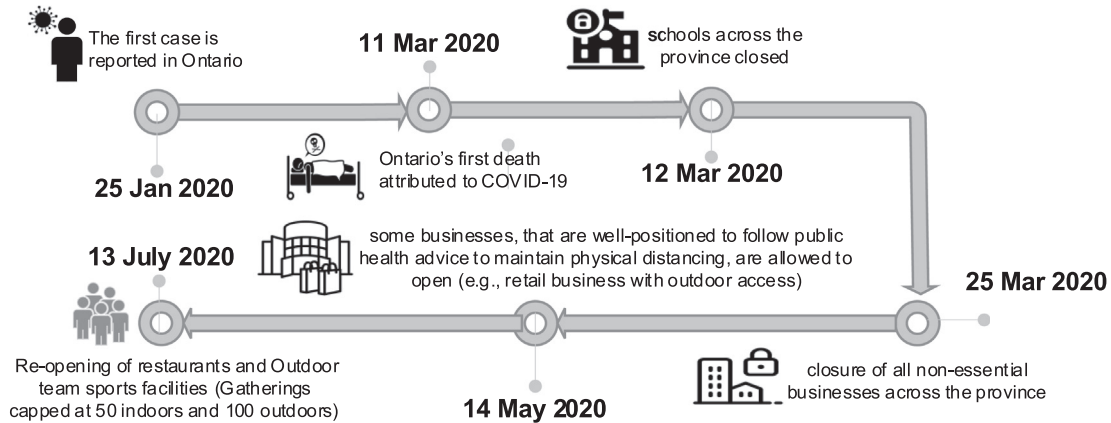
Fig. 1. Timeline of major events since the outbreak started in Ontario.

provided earlier insight into the impacts of COVID-19 on electricity demand and system operations. As shown in Fig. 2, there were notable declines in consumption patterns relative to previous years (6% to 18% decline of typical demand across all hours). On the other hand, residential electricity use has increased as people spend much more time at home since the virus-induced restrictions that have shut down schools and non-essential businesses, and work-from-home measures began (Fig. 3).

It is worth mentioning that the Government of Ontario has provided immediate electricity rate relief in terms of the time-of-use (TOU) rates to support families and relieve the financial burdens of homeowners. Starting from 24 March, utilities suspended TOU electricity rates till the end of October, holding electricity prices to the off-peak rate of 10.1 ₵/kWh [41] (compared to 14.4 ₵/kWh for mid-day peak; 11:00 to 17:00, and 20.8 ₵/kWh for on-peak; 7:00 to 11:00 on weekdays and 17:00 to 19:00 on weekends [42]). With such subsidies, customers may lose the economic incentive to shift the energy use timing associated with cooking, laundry, heating, etc.

Rather than only reporting the changes to energy use that have occurred, as per existing published data from the energy sector, our research aims to additionally quantify the impacts of the COVID-19 outbreak on the household's electricity consumption profiles at different temporal scales. The paper provides insight into how customers have responded to and managed life under lockdown by answering the following research questions:

Q1: How sensitive are the daily electricity consumption values after COVID-19 to outdoor temperature?

Q2: How did peak electrical loads change after COVID-19?

Q3: How did the households' electricity profiles change after COVID-19?

Q3 seeks to determine how households' electricity demand patterns changed during COVID-19 compared to before. It is important to determine such a change during different time periods. Thus, this question has been broken down into four sub-questions:

Q3-a: How did the monthly electricity profiles change after the pandemic?

Q3-b: How did the seasonal electricity profiles change after the pandemic?

Q3-c: How did the weekday and weekend electricity profiles change in each season?

Q3-d: What are the intra-daily (i.e., day of the week) variations in electricity demand pre-and post-COVID-19?
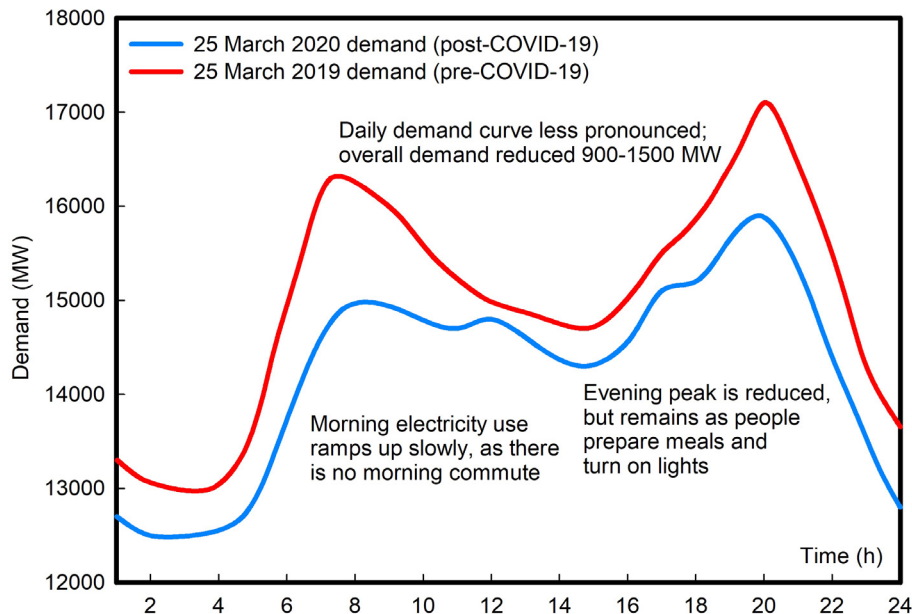

Fig. 2. Impacts of COVID-19 on Ontario's electricity demand, reported by IESO.
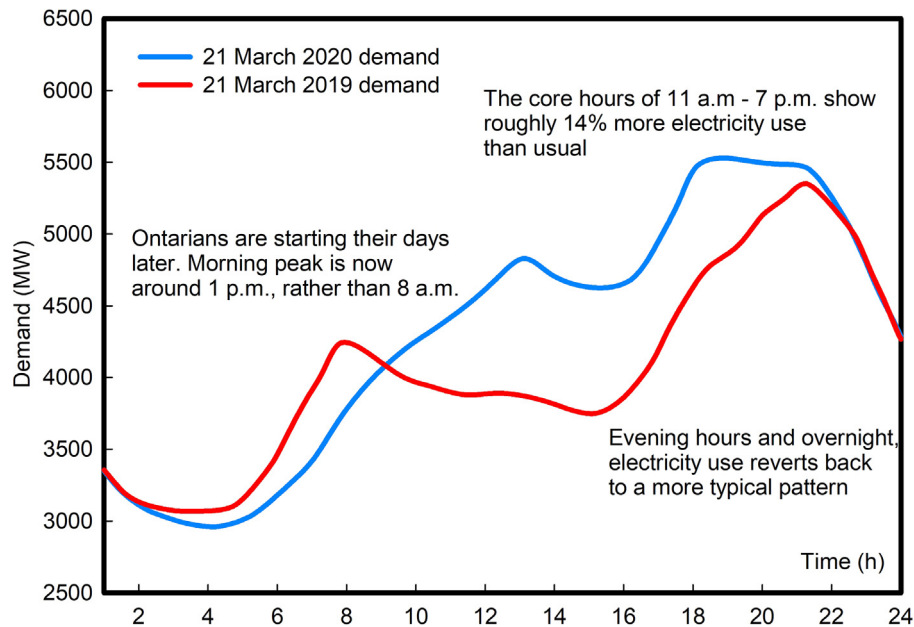
Fig. 3. Impact of COVID-19 on Ontario's electricity demand from the residential sector, reported by IESO.

Q4: Do all households/customers have a similar profile, or are there discrete groups? And how did these customers' profile patterns change post-COVID-19?

Q5: How would household energy bills be affected by the TOU vs. flat rate?

Q5 seeks to quantify the impact of applying the flat rates on electricity usage instead of TOU rates. Accordingly, this question has been broken down into three sub-questions:

Q5-a: What would the average electricity bill have been if the Government of Ontario kept the time of use pricing versus flat rate?

Q5-b: What fraction of homes' bills would increase vs. decrease if TOU pricing was kept?

Q5-c: What fraction of energy use occurs during each period (low, medium, high) before and after the COVID-19 pandemic?

To address our research questions, we captured the impact of seasonal variability and outdoor air temperature by calculating the heating and cooling degree days. Heating and cooling degree days provide a powerful yet simple way of analyzing weather-related energy consumption [43]. Thus, many researchers commonly use these to estimate the impact of outdoor conditions on building energy use [44–46]. In order to isolate the effect of outdoor air temperature effects between periods (pre-and post-COVID-19), we applied changepoint model. While changepoint analysis is a common building energy modelling approach in practice [47], it neglects solar radiation and latent loads, both of which affect cooling loads for air conditioners. We then calculated the total hourly electrical during the pre-COVID and the same period in post-COVID time to capture how peak electrical loads changed after COVID-19.

Throughout the literature, most of the scientific knowledge on reporting what changes to energy use have occurred owing to the pandemic is based on aggregated data for entire regions [48] or focused on single buildings [24,33,36] through short periods after the pandemic has started when many people were not ready enough for large-scale remote work implementation. Accurately tracking the energy consumption at building levels demands considering temporal factors; in short, analyzing energy use at different periods is essential. In this regard, a comparison between average electricity daily profile pre-and post-COVID-19 was conducted for different temporal level (e.g., season, month, day type) to identify how did the households' electricity profiles change after COVID-19. In this paper, we supplement understandings of COVID-19 related changes to electricity demand with detailed high-frequency household level contributes to filling the research gap and isolate the effect of COVID-19 on energy use relative to changes caused by seasonal and day type variations.

One of the key contributions of this study, compared to the literature, is detecting customers' energy-related behavioral changes due to the COVID-19 measures. There is no research literature available that discusses the individual customers' energy-related behavior due to the COVID-19 measures. In our paper, we applied the k-means clustering to segment household's load profiles into clusters/groups by pattern and consequently detecting customers' energy-related behavioral changes. The k-means algorithm is one of the most popular partitional clustering methods for its efficiency and simplicity [49]. Throughout the literature, there are numerous different clustering methods for handling time series data; however, usually, they can be grouped under the hierarchical and partitional methods [50]. A hierarchical clustering method works by grouping data objects into a tree of clusters. However, such a method is more susceptible to outliers within the data and has difficulty dealing with clusters of different sizes [51]. In contrast, partitional clustering (e.g., as the k-means, k-medoid and self-organizing maps) divides the data into a predefined number of non-overlapping clusters [52]. Finally, to quantify how would household energy bills be changed due to the COVID-19 measures under different electricity rates (time-of-use rates vs. flat rate), the average electricity usage was calculated for each home using those rates during the COVID-19 pandemic. More details about each method to answer the aforementioned research questions are discussed in the following sections.

3. Material and methods

Data used for this study was obtained from Hydro Ottawa Holding Inc., a regulated electricity local distribution company operat-

ing in Ottawa [53]. The original data included two years of hourly measured electricity use data (1 August 2018 to 30 August 2020) for 500 residential customers located in Ottawa, Ontario. In this regard, each customer was represented within the dataset with 25 months of hourly electrical energy use values, i.e., 17,520 distinct time points. Note that a limitation of the data is the hourly resolution, which means peak loads may be slightly different than these results due to sub-hourly fluctuations. Moreover, being limited to Ottawa, makes these findings less generalizable to other Canadian regions. In particular, Ottawa's economy significantly centers on two major sectors - high technology and the federal government [54]. Thus, the population tends to be knowledge-based workers (e.g., government bureaucrats, engineers, educators, researchers, software developers) whose work can be performed from home. Additionally, while the homes were anonymized, they are all paying customers. Thus, the dataset will tend to be biassed towards wealthier and larger households (e.g., it does not include those for which electricity is subsidized due to social housing or for which the metering is at the building level, rather than home level). However, the limited geography of the sample provides some control over weather and climate and is dominated by a particular building typology (i.e., mostly wood-framed low-rise detached or townhomes with natural gas heating and a possibility of air-conditioning).

Before starting our analysis, the data were preprocessed (e.g., cleaning, transformation, normalization). First, data cleaning was performed by detecting and removing homes if: the data have consecutive missing hourly values, missing value, or the stagnant/frozen values (the repetition of the same value for consecutive observations). The time-series data did not indicate any missing and frozen values, after passing through a data quality check. However, two meters had more than 200 consecutive missing hourly values. As such, the dataset was reduced from the initial 500 sub-meters to 498 m. Given that the electricity meter data used in our study are used for billing, they required by law to meet stringent requirements to ensure they measure accurately [55]. Prior to the clustering step (section 3.4), the data is normalized to improve the data integrity and emphasize the load shape patterns rather than the absolute amplitude value.

For the sake of comparison, the procedures followed to start from separating the whole data into two groups (pre-and post-COVID). Thus, we have defined 25 March 2020 as the beginning of the "COVID-19 period" for this study, meaning that we have compared electricity use before and after that date. Using these two sets of data, we gradually applied more conducive analysis, described in the following section, to answer the aforementioned research question. Fig. 4 provides a flowchart of the analysis progression.

3.1. Seasonal variability and the influence of temperature

To answer Q1, an essential factor that needs to be considered while analyzing household electricity consumption is the impact of seasonal variability and the influence of outdoor air temperature. In this regard, the heating and cooling degree days (base temperature 18 °C) were calculated for Ottawa from a local weather station (see Fig. 5). They indicate that summer 2020 was somewhat warmer than 2019, though note that the absolute differences are not very significant. These results should be interpreted in the context that Ottawa's annual number of cooling degree days has spanned 165 to 394 in the past 25 years [56].

Changepoint analysis was applied to each home's electricity data to better understand the impact of outdoor temperature on electricity. The electricity dataset does not include metadata about the HVAC equipment, though this can be somewhat inferred from the data. Most homes in Ottawa are heated using natural gas, thus

the changepoint analysis is primarily relevant to the cooling season (since air conditioners use electricity). However, given that the dataset only includes spring and summer post-COVID, this is not a major shortcoming. The changepoint analysis allowed the effect of outdoor air temperature effects between years to be isolated.

3.2. Peak load analysis

To answer Q2, we investigated the sum of the electrical loads for the 498 houses. Given that Ottawa and Ontario peak electrical loads on the grid occur in the summer as a result of high cooling loads [57], the impact of COVID-19 related behaviors on electrical loads is of particular interest. Thus, initially, the total hourly electrical loads for the period April 1 to August 31 in 2019 (pre-COVID) and the same period in 2020 (post-COVID) were calculated. Additionally, five peak loads for each year and the corresponding temperature and time were identified.

3.3. Electricity load profiles change

To answer Q3, we created the average daily profile for each household/customer. Then, all households were averaged over each hour to create hourly profiles at two different periods (pre- and post-COVID-19) and gradually moving towards a more detailed data analysis by segmenting each data group for different detail levels: i) monthly and seasonal profiles, ii) differentiate the weekdays and weekends load profile, and iii) intra-daily variations in electricity demand (i.e., day of the week). A comparison between average electricity daily profile pre-and post-COVID-19 was conducted for each generated level (e.g., season, month, day type).

3.4. Cluster analysis

Herein, the goal of clustering is to identify and categorize the customers with similar consumption patterns and to compare how the electricity profile pattern of each group/cluster changed post-COVID-19 relative to pre-COVID time (to answer Q4). To that end, we applied the k-means clustering, an unsupervised machine learning algorithm [34], to segment each seasonal household's load profiles (spring and summer seasons post-COVID-19) into clusters/groups by pattern (profile shape). In this analysis, we used the silhouette coefficient to determine the optimal number of clusters. The main advantage of silhouette is that its calculation starts from each data point, and average it out for all the data implicated to get the silhouette score [49]. This metric is one of the most efficient and popular measures to determine the optimal number of clusters in several problems [58–61]. After obtaining the cluster profiles for each season, we compared the same customers/cluster's average load profile against their usual load pattern pre-COVID-19 to detect customers' behaviour change.

3.5. Analysis of time-of-use (TOU) and flat rates

Prior to the pandemic, Hydro Ottawa charged its electricity consumers based on the time-of-use (TOU) rates which varied based on off-, mid-, and on-peak hour of usage [42]. However, a flat rate of 10.1 cents per kWh was applied after March 25, 2020, for all consumers during all hours of the day [41]. The purpose of TOU analysis is to quantify the impact of applying the flat rates on electricity usage instead of TOU rates.

Fig. 6 shows the TOU prices for off-, mid-, and on-peak hours of usage and weekends in the summer and winter seasons. It should be noted that Hydro Ottawa charges the off-peak rate on entire weekend. To answer Q5-a, the average electricity usage was calculated from the hourly electricity usage of 498 households and it was multiplied by the corresponding TOU time using the data from
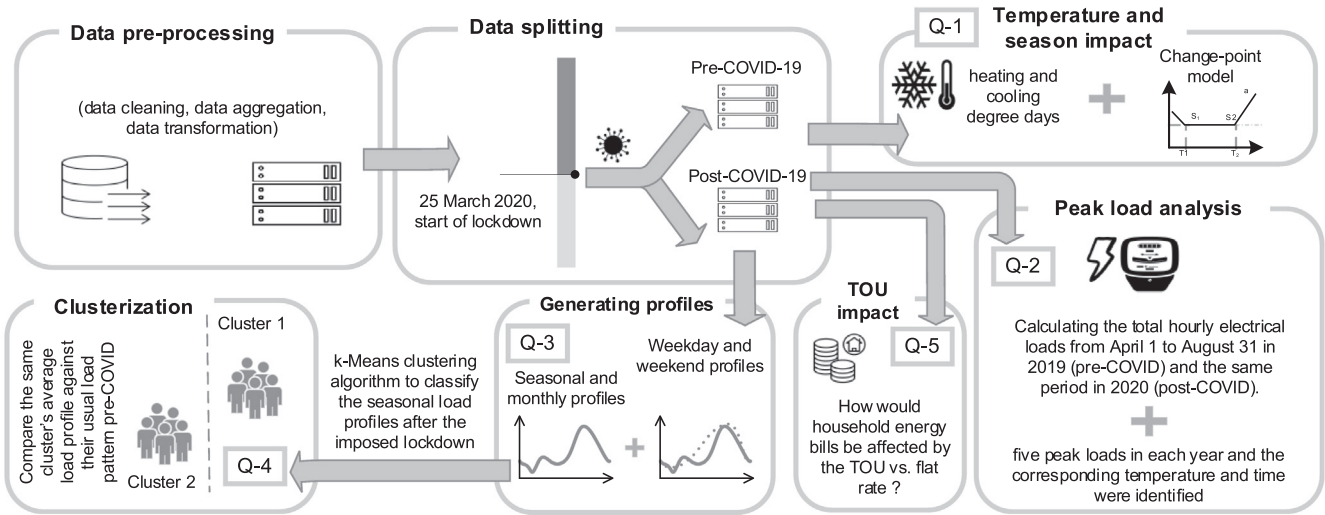
Fig. 4. Flowchart of the method to analyze the behaviour and the impact of COVID-19 restrictions on household electricity data.
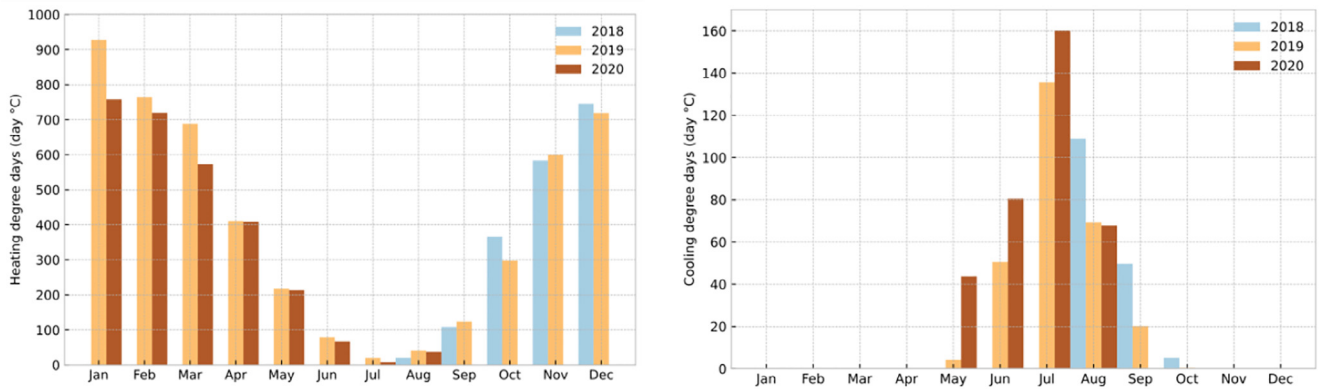

Fig. 5. The heating (left) and cooling (right) degree days between 2018, 2019, and 2020.
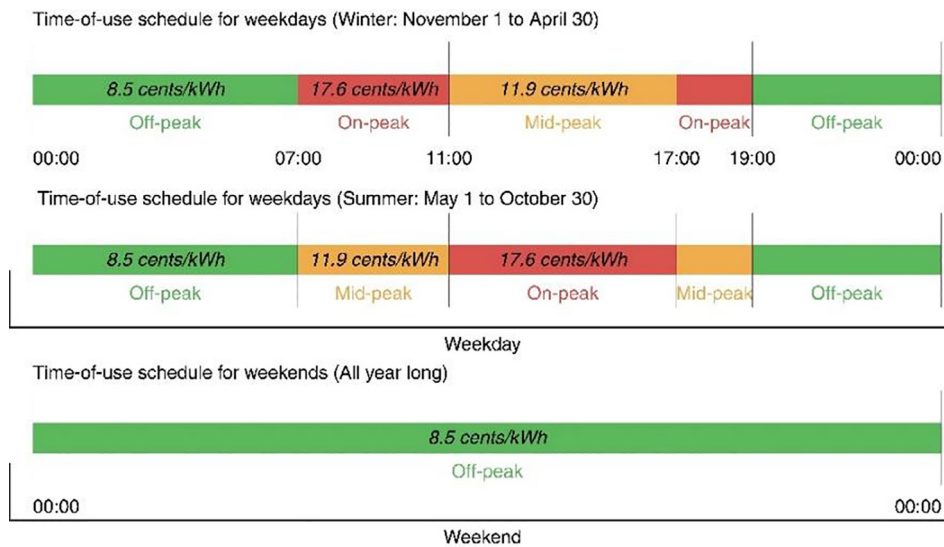

Fig. 6. Time-of-use (TOU) structure for weekdays and weekends.

April 1 to August 31, 2020. Note that the analysis excludes fixed fees for delivery and other minor charges. For Q5-b, the electricity usage was calculated for each home based on TOU and flat rates during the COVID-19 pandemic using the same dataset. Then, the numbers of homes that would have higher bills with TOU rates were counted by comparing TOU and flat rates for their bills. For

Q5-c, the fraction of electricity usage for TOU periods was calculated for pre- and post-COVID-19 pandemic based on the average electricity usage of 498 households using data from April 1 to August 31 for 2019 and 2020.

4. Results

4.1. Change-point model results

Given this research's main aim (quantifying the impacts of the COVID-19 lockdown on the household's electricity consumption), hourly electricity demand data was analyzed at two different periods (pre-and post-COVID-19). Initially, we provide an overview of the average daily energy use changes, divided between pre-and post-lockdown periods. Fig. 7 compares the distribution of average daily consumption for the dataset after the lockdown to that preceded the lockdown, giving an initial sense of the extent of change/increase in the electricity demand at the household level. Before the lockdown, the average household daily electricity consumption is 19.70 kWh, relative to 22.1 kWh after the lockdown (12.1% increase). Table 1 summarizes the results of the previous studies that quantified the impact of COVID-19-related lockdowns on electricity demand for the residential building. The trends presented in the cited papers are qualitatively consistent with the observations obtained from the research presented in this article. The quantitative differences attribute to local conditions (e.g., climatic conditions and average living standards, degree of lockdown measures, household size, etc.), which impact the way energy is used by occupants.

The data were fit to a piecewise linear equation as shown in Fig. 8. Two main parameters of interest were extracted: the magnitude of the horizontal segment and the slope as the outdoor temperature rises. The former is indicative of the electricity used by the homes when there is little heating or cooling demand. The latter indicates the sensitivity of the electricity use to warmer temperatures. In general, a steeper slope suggests that the home uses more electricity for air conditioning as outdoor temperatures increase. The slope may also be affected by other behaviours, such as avoiding using the oven when conditions are warm. Moreover,

we were interested to see how these parameters change between before and after COVID. We hypothesized that both values would increase in value for a given home since base loads and sensitivity to warm temperatures would likely increase due to increased occupancy and electricity-consuming activities.

Given that Ottawa is temperate enough that air-conditioning in homes is not necessarily the norm, we hypothesized that two distinct groups would emerge: homes with air-conditioning and homes without. Those without would be expected to have a near-zero slope. Based on the 2015 Survey of Household Energy Use (SHEU) [63], over 85% of households in Ontario had an air-conditioning system.

First, we checked if there are two distinct groups of houses: those with central air-conditioners and those without. Fig. 9 shows the distribution of S_2 values (the slope of the fit above temperature T_2). The figure shows a continuous distribution for the variable, thus suggesting that it is difficult to distinguish homes with air-conditioning from those without. This may be due to sporadic use of central or window air-conditioners and the use of fans. There are other pieces of equipment that are seasonally affected, such as swimming pool pumps and refrigerators. Moreover, the summer break for students coincides with the warmest months. Thus, the presence of more occupants can increase overall electricity for plug-in equipment and large appliances. About 5% of S_2 values in both years are negative, which could be a result of occupants taking vacation in the summer or avoiding high-power electric equipment for the sake of reducing internal heat gains that could lead to discomfort.

Though Fig. 9 suggests a similar distribution for S_2 values for the sample of 498 homes between years, we performed a paired sample T-test which similarly indicates no significant difference (p greater than 0.1). This suggests that few, if any homes installed and used air-conditioners for the first time in 2020 (whether or not because of COVID-related factors). In an analysis of occupant-related behaviour in Canadian households, Abdeen et al., [64] found that the cooling setpoints are typically varied by less than 1.5 °C during a day, thus suggesting that most occupants do not actively engage with their thermostat regularly. Thus, it is entirely
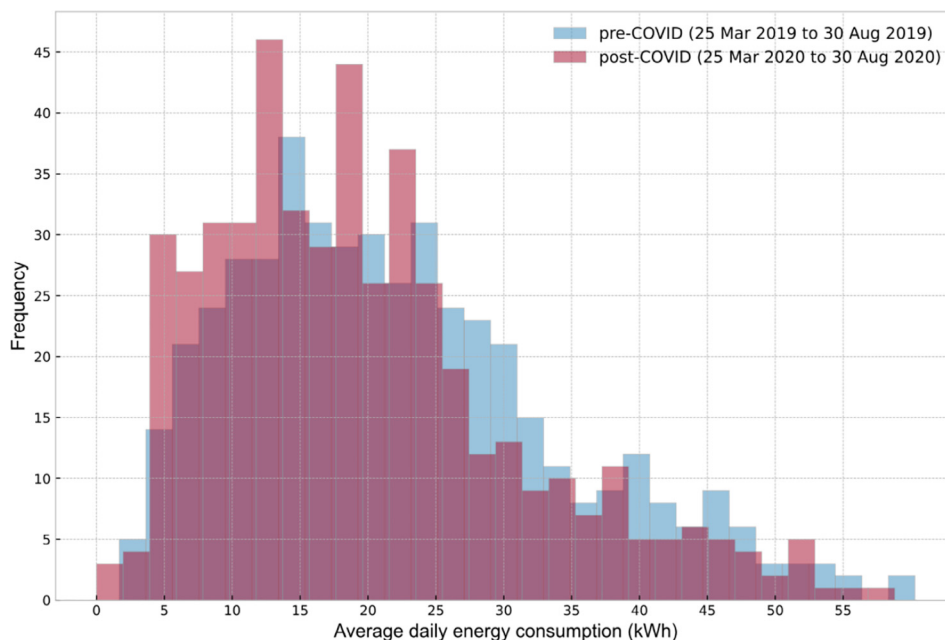

Fig. 7. Distribution of average daily consumption for the dataset after the lockdown to that preceded the lockdown.

Table 1
Summary of the previous studies that quantified the impact of COVID-19-related lockdowns on electricity demand for the residential building.

| Study	Location	Study sample	Impact on residential electricity demand	Period of analysis
Austin Energy [27]	Austin, USA	NA	12% increase in residential electricity demand in the second week of lockdown	One week before and after lockdown
Bulb Energy Ltd. [25]	UK	more than 2000 customer smart meters	Households are using 17% more electricity since the UK went into lockdown.	NA
Burleyson et al., [62]	Texas, USA	113 homes	The average daily residential demand during lockdown was ∼ 20% higher than in pre-lockdown.	Three weeks after staying home order vs same periods of 2017–2019
Jemena, a distribution network service provider in Melbourne [32]	Australia	NA	the electricity consumption was 14% higher during the lockdown's week	One week before (1–7 March 2020) and after (22–28 March) lockdown
Savills-Pinergy Energy Monitor [34]	Ireland	NA	Overall consumption in family homes is up approximately 11%, with some up by over 20%	two weeks before (1–14 March 2020) and after (25–29 March) lockdown
Snow et al., [33]	Australia	491 houses	Overall energy use among most households decreased during lockdown versus prior, driven primarily by a reduction in air conditioner use during the lockdown as the weather cooled.	The dataset includes data from February to May 2020.
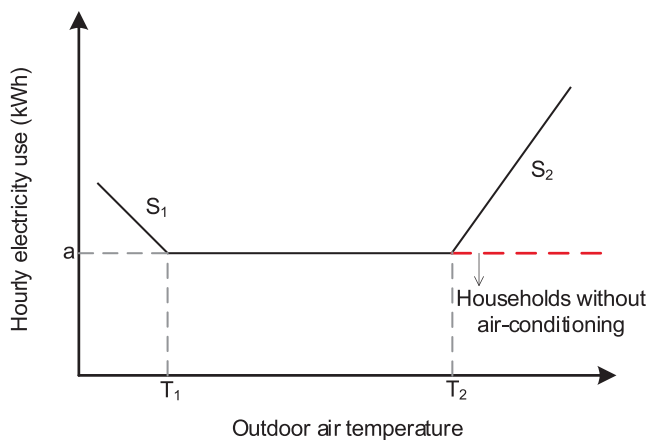
Fig. 8. General change point model, showing five parameters (a, T_1, T_2, S_1, and S_2) and hypothesized profile for homes without air-conditioning.
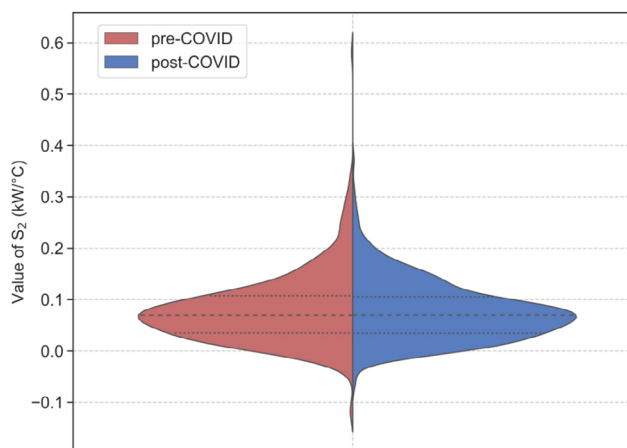

Fig. 9. Distribution of change point analysis parameter S_2 pre- and post-COVID.

isolate plug-in equipment, water heating (for electric water heaters), lighting, and major appliances.

We hypothesized that the values of a would increase post-COVID because people are more likely to be present, use work and entertainment-related equipment, and cook more. Similar to above, we plotted the distribution of the a values. Fig. 10 shows a small but perceptible increase in the values post-COVID. In this case, the mean value of a increased from 0.77 kW to 0.85 kW. 71% of homes had an increase in value post COVID, with the remainder having a decrease. Moreover, the paired sample T-test indicates a significant difference between years (p less than 0.001).

During the April 1 to August 31 analysis period, total electricity for the homes increased from 1,637 MWh in 2019 to 1,888 MWh in 2020. According to the changepoint model, approximately 153 MWh of the 251 MWh increase in electricity use post COVID is a result of this increase in base load. Thus, we conclude that the most significant cause for the increase in electricity use from COVID is from increased use of plug-in equipment, lighting, and major appliances. Application of the post-COVID outdoor air temperature data to the change-point model from the pre-COVID year indicates that the warmer weather can account for 84 MWh. Thus, we conclude that the two main causes for an increase in household electricity post COVID are an increase in base load (parameter a) and warmer weather in the cooling season.

We note that the value of the two studied parameters cannot entirely explain the increase in electricity use (14 of 251 MWh)

possible that many households maintained similar setpoints and setpoint schedules between the years.

The other parameter of interest for this analysis is the base load, parameter a, which is designed to be independent of temperature (i.e., the average electricity use of the home when the outdoor temperature is high enough to not require heating and cold enough not to require air conditioning). Thus, this parameter can be used to
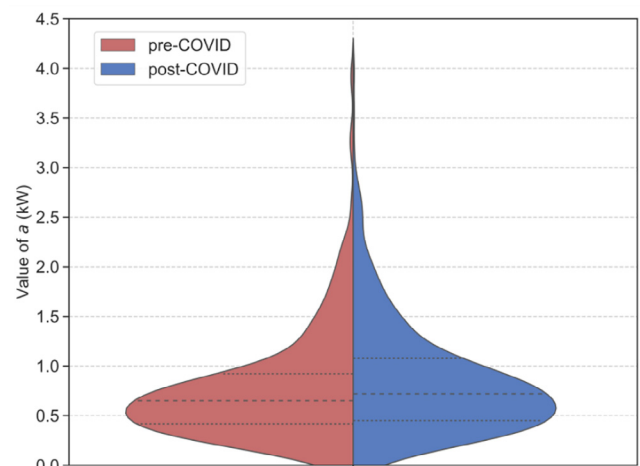

Fig. 10. Distribution of change point analysis parameter a pre- and post-COVID.

between years. Changepoint analysis has numerous limitations, such as neglecting solar radiation and relative humidity – both of which can affect conditioning loads. Moreover, time of day, length of day (which may affect lighting), and seasonable occupant behaviors are largely neglected. Finally, water supply temperature into the homes changes seasonally and some homes likely have electric water heaters. However, the analysis yields new insights that would not be apparent from the other analysis and it accounts for year-to-year climate differences.

4.2. Peak load results

Fig. 11 shows the ranked total hourly electrical loads from April 1 to August 31 in 2019 (pre-COVID) and the same period in 2020 (post-COVID). As shown in the figure, the difference between post-COVID loads at the higher end is approximately 15 to 20% higher than pre-COVID.

Table 2 shows the five peak loads each year (2019 for pre-COVID and 2020 for post-COVID) and the corresponding temperature and time. As expected, the peak load across the homes occurs late afternoon on very warm days. While the post-COVID peaks occur during slightly warmer temperatures, the peaks are significantly (15–20%) higher.

4.3. Electricity load profiles visualization

Each month of the post-COVID electricity use profiles is compared with its corresponding month before the lockdown (e.g., April 2020 with the average of April 2019 and 2018). Fig. 12 displays the average daily electricity consumption profile of 498 customers for five months (from April to August), without distinguishing between weekdays and weekends, for the pre-and-post COVID-19 periods.

In terms of temporal patterns and magnitude, varying consumption levels can be seen among different months of a year. These variations highlight the difference in residential seasonal electricity use caused by weather-driven space conditioning loads,

Table 2
The five peak loads that occurred in pre-and post-COVID period.

Pre-COVID (2019)			
Load (kW)	Date	Time	Outdoor temperature (°C)
1046	Monday, July 20	15:00	28.3
1045	Monday, July 20	16:00	28.9
1019	Monday, July 20	14:00	24.2
1001	Sunday, July 4	18:00	30.7
997	Monday, July 20	18:00	30.6
Post-COVID (2020)			
Load (kW)	Date	Time	Outdoor temperature (°C)
1183	Friday, July 10	16:00	31.0
1181	Friday, July 10	17:00	31.6
1174	Friday, July 10	18:00	33.7
1169	Sunday, July 26	17:00	29.3
1158	Thursday, July 9	17:00	29.9

daylight hours influenced by sunrise and sunset times, and customer behaviour change.

The average daily electrical consumption reached a value of 20.4 kWh in the first month of the lockdown (April) compared to 19.1 kWh of the same month before the lockdown, with a 6.8% increase. It appears that the first month of the lockdown led to a slight increase in the average daily electrical consumption as many organizations were not ready enough for large-scale remote work implementation (e.g., lack of technology infrastructure). In May, the second month of lockdown, the average daily electrical consumption was 21.4 kWh, compared to 17.2 kWh before the lockdown (22.6% increase). In June and July, the average daily electrical consumption reached 25.0 kWh (26.3% increase) and 32.2 kWh (13.7% increase). However, in August, when the adults and kids started their summer break, the average daily electrical consumption reached 25.1 kWh, compared to 24.2 kWh before the lockdown, with a 3.7% increase.

The daily electricity demand had an overall increasing trend across different months after the statewide stay-at-home order. However, there is temporal and spatial variability in the consumption patterns. Generally, the daily profiles' flattening is noticeable during the lockdown, with an evening peak around 18:00 which
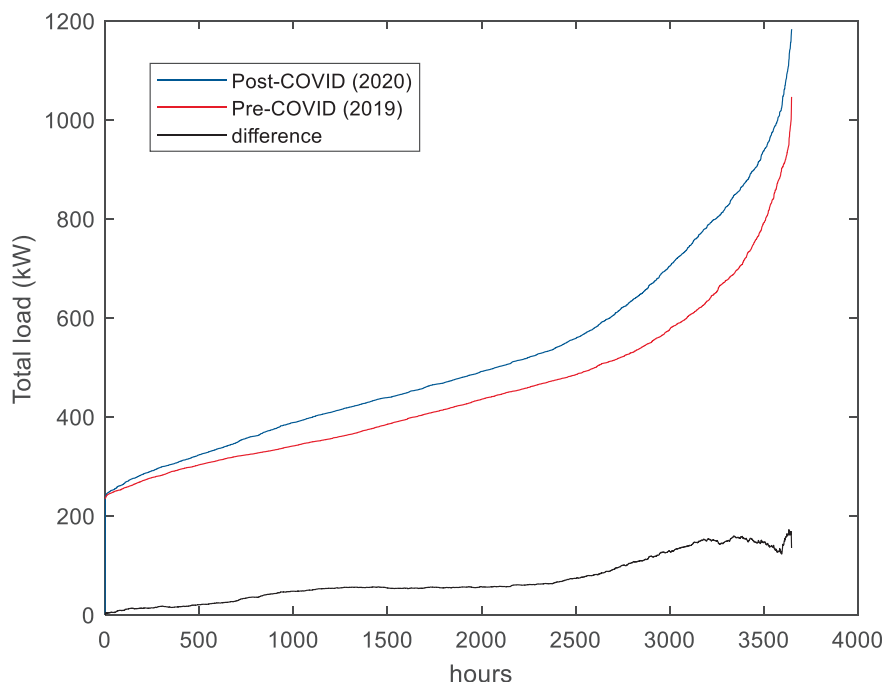

Fig. 11. Total hourly electrical loads for the period April 1 to August 31 in 2019 (pre-COVID) and the same period in 2020 (post-COVID), ranked from lowest to highest. The difference between the curves is provided for reference.
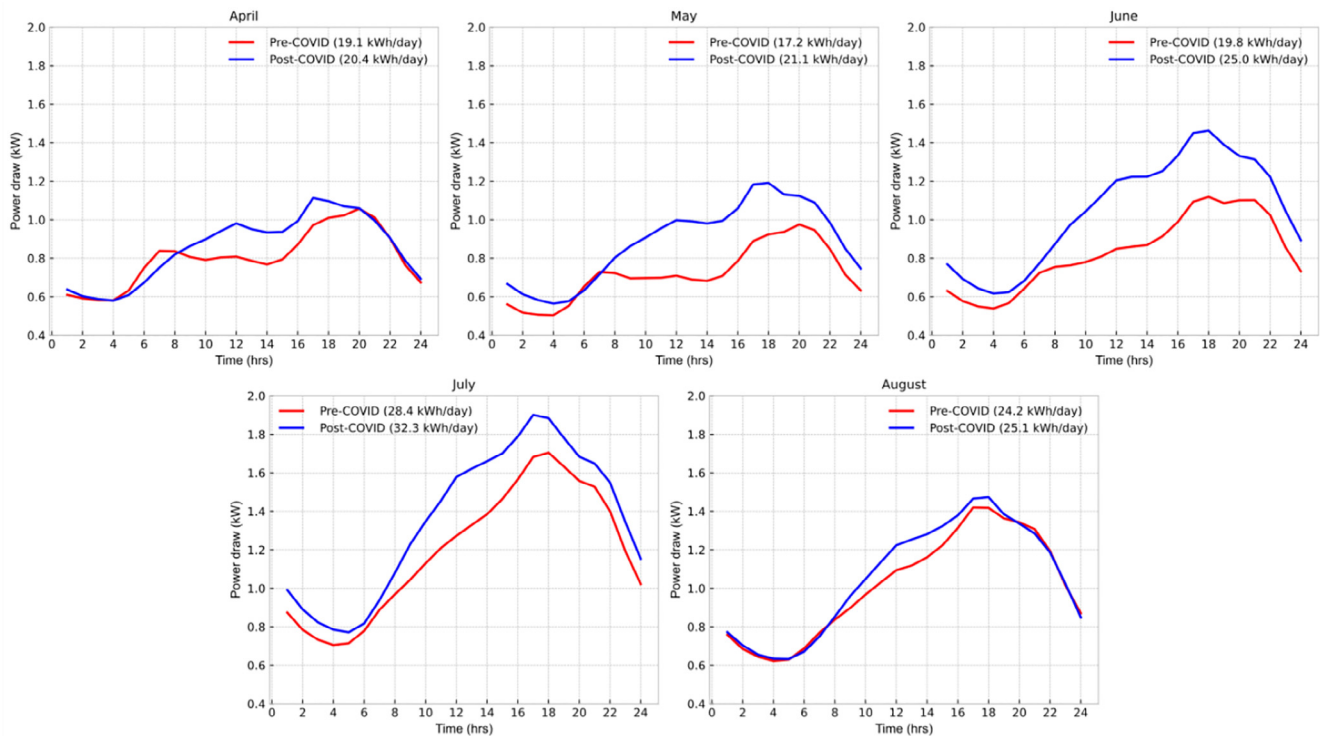
Fig. 12. Monthly average load profiles curves, (red) for pre-COVID time and (blue) for post-COVID. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

contrasts with April and May's average daily pattern before the lockdown, where two sharp peaks occur. One is in the morning as household occupants awaken and start to use electrical appliances, and a second is in the evening when occupants return home, reflecting domestic routines and mealtimes. On the other hand, the lockdown did not significantly change the household profile shape throughout July and August. This might be due to the air-conditioning loads during the warmer summer season and the presence of more occupants when the adults and kids started their summer break.

After creating average profiles for each five months, we developed average load profiles split by seasons (spring: 21st March to 20th June, summer: 21st June to 20th August), where the weekdays and weekends load profiles per each month are separated to detect behaviour changes between summer and spring seasons (see Fig. 13). Overall, the seasonal impact on the electricity load profile indicates more electricity being consumed over the late morning and early afternoon periods during the summer. Such an increase is most likely related to increased occupancy over the daytime period during the summer months and the increased cycling of cold appliances.

For the daily profiles before the lockdown, the weekday profile of spring season has a pronounced morning peak around 7:00 with a relative decrease in mid-day demand followed by a high evening peak around 20:00 before falling back down during late evening hours. Contrary to the weekend profile, which lacks the morning peak (as occupants get up at different times due to lower work or schooling commitment) and a relative decrease in mid-day demand until a prolonged peak of consumption is reached in the evening. Given the summer season, a change in profile pattern during early morning and mid-day is apparent, which could correspond to occupancy changes (e.g., children being at home during school holidays). The main difference between weekday and weekend profiles in the summer season is the small morning peak's absence with a steeper increase in the latter's mid-day demand.

Overall, after the lockdown, it can be seen that the weekday demand was not dissimilar from the weekend profile, with a much smaller peak at lunchtime in the spring season.

After creating the average daily profile on a monthly and seasonal basis, a more detailed look at the data is done by disaggregating the load patterns per day of the week for different seasons (see Fig. 14). On a daily basis, the profile pattern can change significantly from one day to the next in terms of magnitudes of electricity demand and the time at which it is used. By separating the demand profile by days of the week, the following observations can be made:

- Before the lockdown, a clear distinction can be shown between weekend and weekday profiles during the spring season. From Monday to Friday, occupants tend to use electricity earlier in the morning (from 5:00 to 7:00), most likely due to employment and schooling commitments. A pronounced increase is also observed during the evening after occupants return home or school. Friday profile observed a relatively smaller peak in the evening than the other weekdays, suggesting that most occupants are out of the home during the Friday night. There is an absence of morning peak in the weekend profiles with a relative increase in mid-day demand until a prolonged peak of consumption is reached in the evening. Monday and Sunday show the highest demand throughout the weekdays and weekends, respectively.
- During the spring season after the lockdown, overall, weekday profile patterns were not dissimilar from the weekend profiles. All weekdays lack the morning peak where occupants tend to start their remote work at 8:00 with a gradual increase in mid-day demand followed by a typical prolonged evening peak around evening as usual. Monday observed lower electricity demand than the rest of the weekdays. However, before the lockdown, the same day shows the highest demand throughout the weekdays.
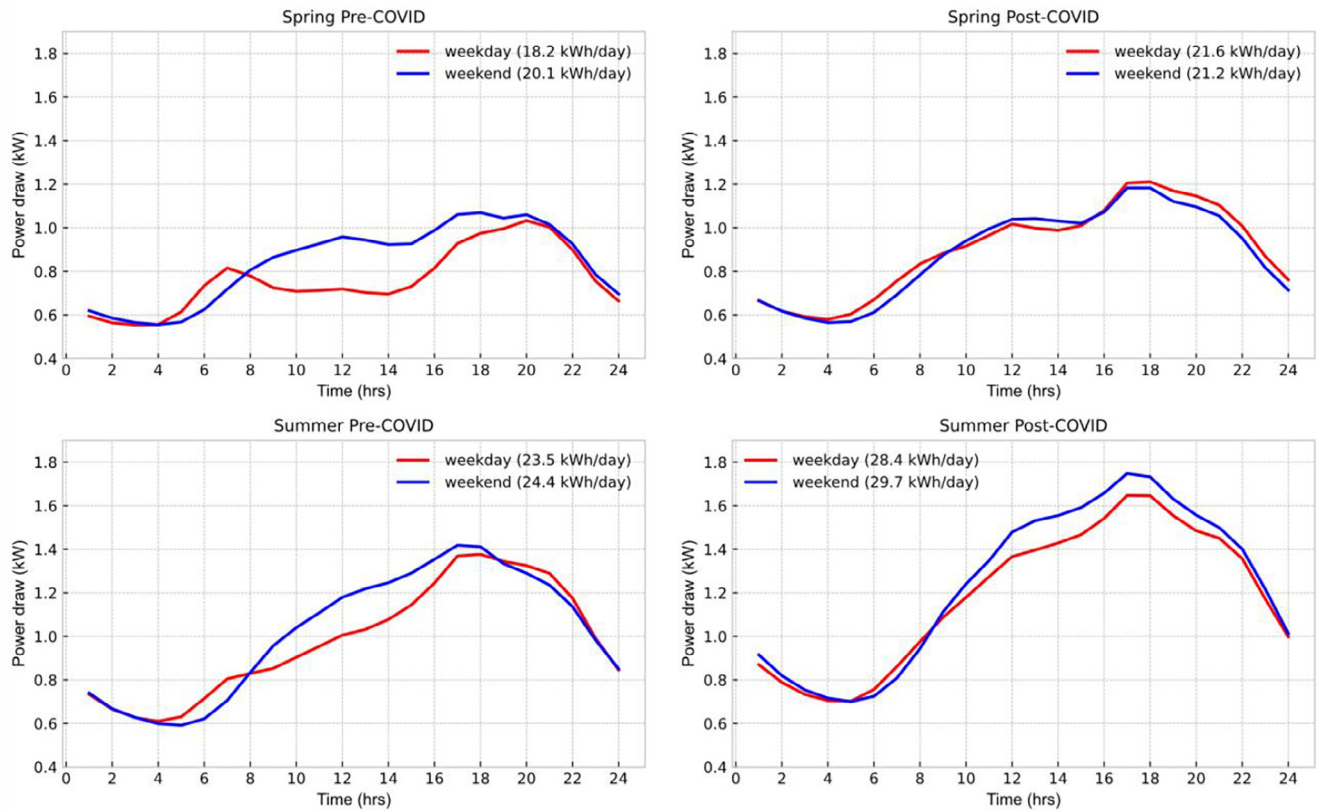
Fig. 13. Seasonal average load profiles pre-COVID time (left) and post-COVID (right).
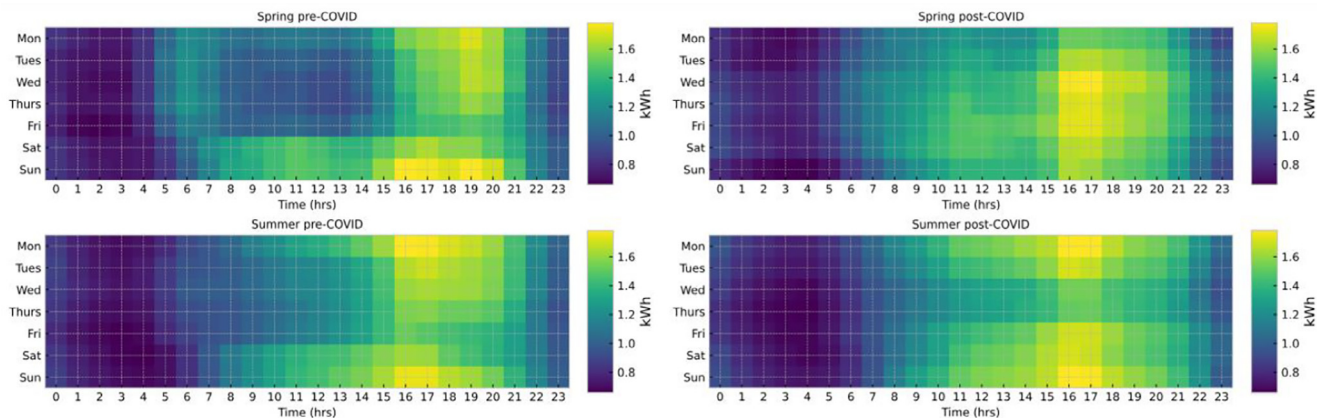

Fig. 14. Averaged hourly electricity profiles of seven days within the summer season (left) and spring season (right).

- During the summer season before the lockdown, the weekday (Mon-Fri) profile patterns were similar to the weekend. The main difference is that the weekend (Sat-Sun) profiles show more electricity demand during the mid-day. Like the spring season before the lockdown, Monday and Sunday had the highest demand throughout the weekdays and weekends, respectively.
- During the summer season after the lockdown, the observed mid-day demand of the weekend profiles is no longer characteristic. Additionally, since occupants began working from home and schools shut, the typical morning electricity peak flattened out during the weekdays. In this regard, it can be seen that the weekday profile patterns were not dissimilar from the weekends, with the lowest demand observed on Wednesdays and Thursdays.

4.4. Determining distinctive clusters within seasons

We applied the silhouette method to determine the optimal number of clusters k in each post-COVID season. Each season has two clusters that represent seasonal household electricity demand. That is, every home in each season falls in one of two groups. As an example, Fig. 15 shows the relationship between the silhouette with and number of clusters representing the households' electricity profile during the spring season post-COVID-19.

This section's central focus is temporal variation in electricity use (i.e., profile pattern) rather than magnitude. Therefore, we normalized the average daily profile shape by rescaling the data from its original range to the maximum and minimum for the time range (24 hourly values) for each meter/customer data set so that all home profiles would be on a fractional 0 to 1 scale. In this

regard, the k-means clustering algorithm was applied to the normalized seasonal profiles to extract each group's consumption behaviours. Note that we applied the clustering algorithm to each season (spring and summer) post-COVID-19 independently. Coincidentally, the percentage of customers belongs to each cluster is similar between seasons. Fig. 16 shows the normalized profiles clustered into groups as well as the cluster mean.

Spring cluster 1 represents 36.3% of the total examined customers that have an overall increasing trend followed by a pronounced evening peak at 21:00, somewhat later than pre-COVID time. Cluster 2 (63.7% of the households), on the other hand, tends to start their daily routine earlier than cluster 1 with an absence of morning peak. However, cluster 2 exhibits two peaks, one in the afternoon followed by a relative decrease in demand until the second peak in the evening at 17:00.

Summer cluster 1 (63.7% of the households) has a sharp increasing trend starting from 5:00 till afternoon followed by a slight increase during the mid-day demand. This cluster starts its evening peak at 17:00. Given to cluster 2 (36.4% of the households), customers of this cluster tend on average to start their day later than cluster 1 with an absence of morning peak. Then, there is an overall increasing trend within the day till reaching the evening peak at 21:00.

To detect customers' behaviour change due to the pandemic, we compared the average daily profiles of each cluster (using the same customers) after the lockdown against the ones before the lockdown. For example, a possible finding is that two clusters emerge post-COVID: a group who continues working out of their homes (e.g., front-line workers) and uses a similar amount of electricity, and a second group start working from home and use more electricity – particularly during the day. In our analysis, we used the same customers of each group and compared their average daily profiles after the lockdown against the ones before the lockdown. Figs. 17-18 compare the daily profile of the two clusters between pre-and post-COVID −19 within different seasons.

In the spring season, cluster 1 (36.3%) profile changed significantly from pre- to post-COVID-19. Before the lockdown, this cluster has an apparent morning peak at 7:00 due to employment and schooling commitments. After the morning peak, the homes maintained a relatively fixed level of power draw till 14:00, suggesting that there is little or no activity within the household at these times than other times of the day. Starting from 14:00, the demand

starts to increase sharply till the evening peak at 20:00 when occupants return home, reflecting domestic routines and mealtimes. After the lockdown, the observed morning peak no longer exists as occupants working from home and schools shut. In this sense, there is a gradual increase in mid-day demand followed by a typical prolonged evening peak around evening as usual.

On the other hand, the profile pattern of cluster 2 (63.7%) exhibited a slight change from pre- to post-COVID-19. The usual morning electricity peak has flattened out during the day till a weak peak afternoon. The main difference between the pre- and post-COVID-19 patterns is that the former has a prolonged evening peak from 17:00 to 20:00 before falling back down during late evening hours.

Given to the summer season, the profile pattern of cluster 1 (36.3%) before the pandemic closely matches the pattern after the pandemic. Nevertheless, there is a 16.3% increase of daily demand relative to the pre-COVID-19 time in terms of consumption magnitude. There are several causes behind such an increase. For example, several households had to adapt additional computers and other office equipment such as printers and monitors for teleworking or home-schooling. Also, additional time spent indoors because of imposed restrictions leads to changing comfort requirements (e.g., decreasing cooling setpoint temperature).

On the other hand, there is a slight difference in the profile pattern of customers belongs to cluster 2. Before the lockdown, this cluster has a small morning peak at 7:00 followed by a gradual increase till reaching a pronounced evening peak at 20:00. Like cluster 1, there is a 29.1% increase in daily demand relative to pre-COVID-19 time. Table 3 summarizes the characteristics of each cluster pre-and post- COVID-19.

4.5. TOU and flat rates results

As shown in Fig. 19, if TOU rates were applied to the post-COVID period for the 498 studied homes, the minimum increase in the average bill would be in August (8.23%) while the maximum would be in July (11.53%). Meanwhile, the average increase would be 9.71% by implementing the TOU rates instead of the flat rate. According to Fig. 19, the maximum increase in bills for an individual if TOU pricing was used is slightly less than 20%. All but two of the 498 homes' electricity bills would increase TOU pricing had been in place. Note that monthly bills include some fixed charges
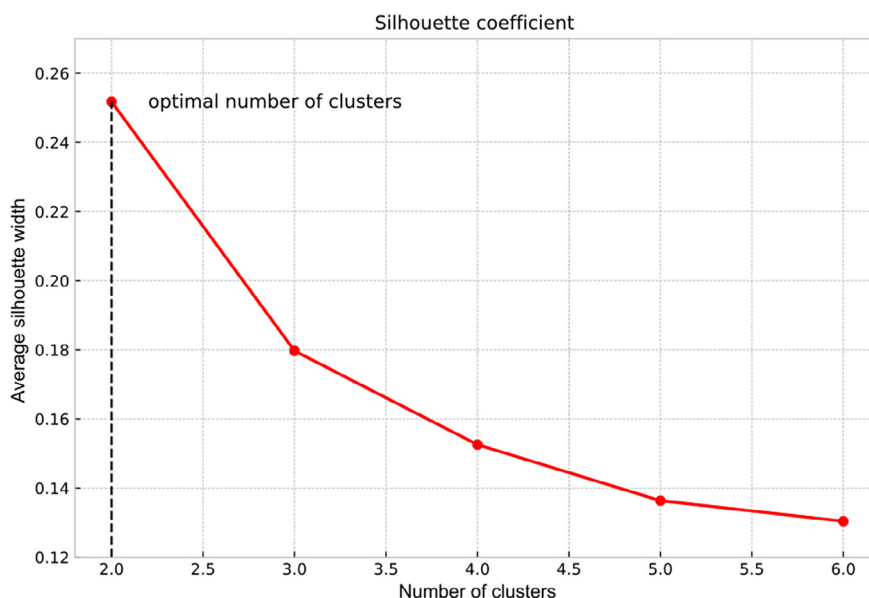

Fig. 15. Determining the optimum number of clusters for spring season post-COVID time.
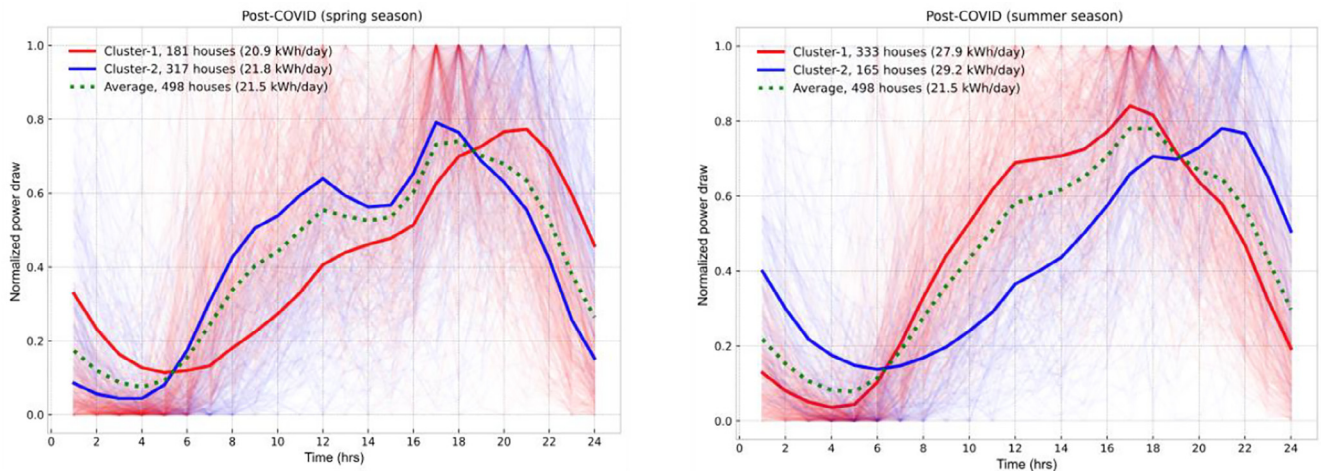
Fig. 16. Normalized load profile curve of each of the 2 clusters, (left) spring season and (right) summer season.
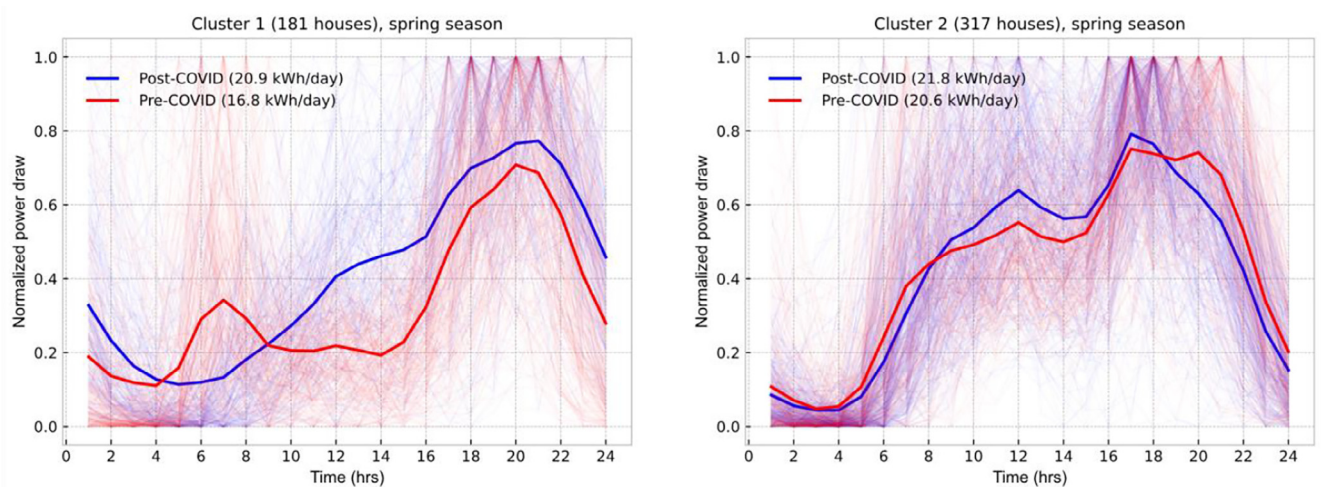

Fig. 17. Load profile comparison for the 2 clusters between pre-and-post COVID-19 within spring season.
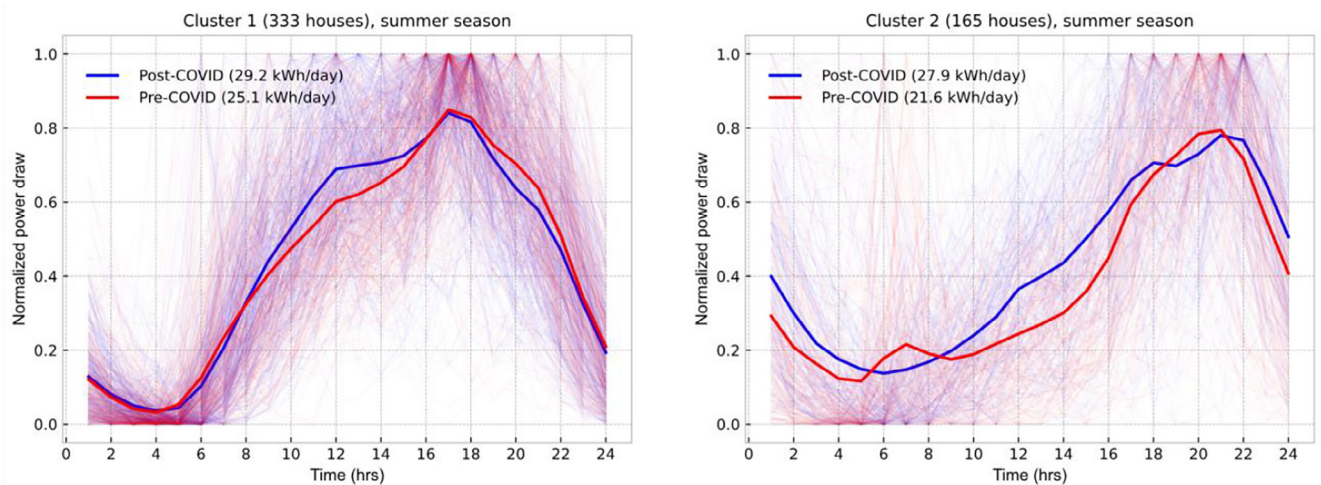

Fig. 18. Load profile comparison for the 2 clusters between pre-and-post COVID-19 within summer season.

that are independent of usage. These are not included in the analysis.

Fig. 20 demonstrates only a slight change is observed in the average fraction of electricity usage during TOU hours, with the fraction of hours for the on-peak electricity usage increasing slightly after the pandemic. While daily habits clearly changed profoundly for many people, this result may give some indication of the extent to which the relaxation of TOU pricing would affect peo-

Table 3
Clustering analysis results showing the behaviour changes within different times.

| cluster	peak type	spring season		summer season	
		pre-COVID	post-COVID	pre-COVID	post-COVID
cluster 1	morning	apparent morning peak at 7:00	flatten morning peak	flatten morning peak	flatten morning peak
	mid-day	maintained a relatively fixed level of power draw	gradual increase in mid-day demand	gradual increase in mid-day demand	gradual increase in mid-day demand
	evening	evening peak at 20:00	evening peak at 20:00	evening peak at 17:00	evening peak at 17:00
cluster 2	morning	lacks morning peak	flatten morning peak	small morning peak at 7:00	flatten morning peak
	mid-day	small afternoon peak	small afternoon peak	gradual increase in mid-day demand	gradual increase in mid-day demand
	evening	evening peak at 17:00	prolonged evening peak from 17:00 to 20:00	evening peak at 20:00	evening peak at 20:00
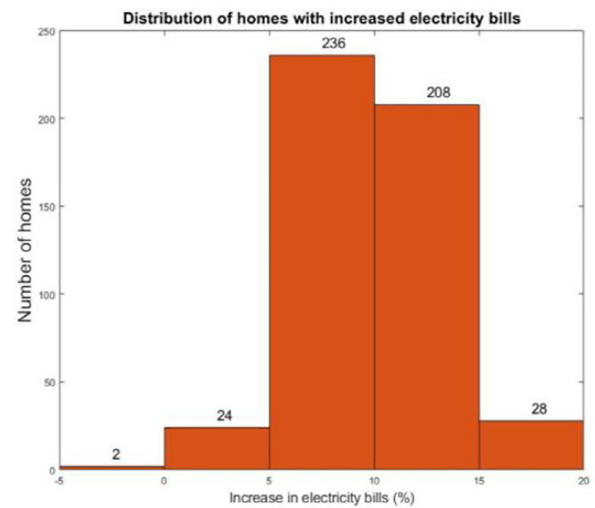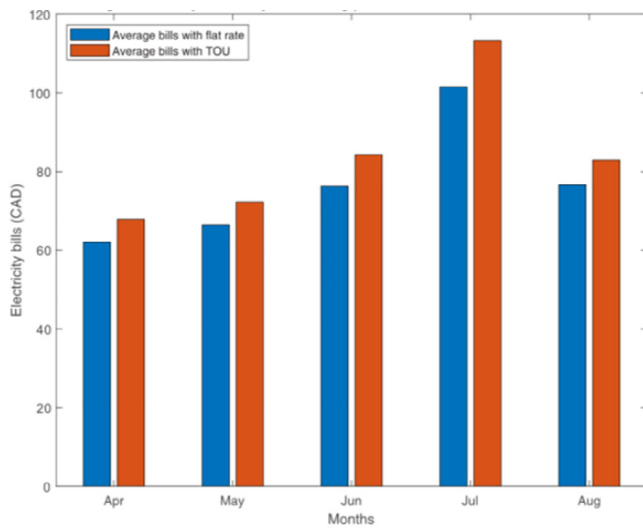
Fig. 19. Monthly electricity bills during the pandemic with the flat and TOU rates based on the average of 498 homes (left) and the distribution of each house based on the difference in their electricity bills with the TOU and flat rates during the pandemic (right).
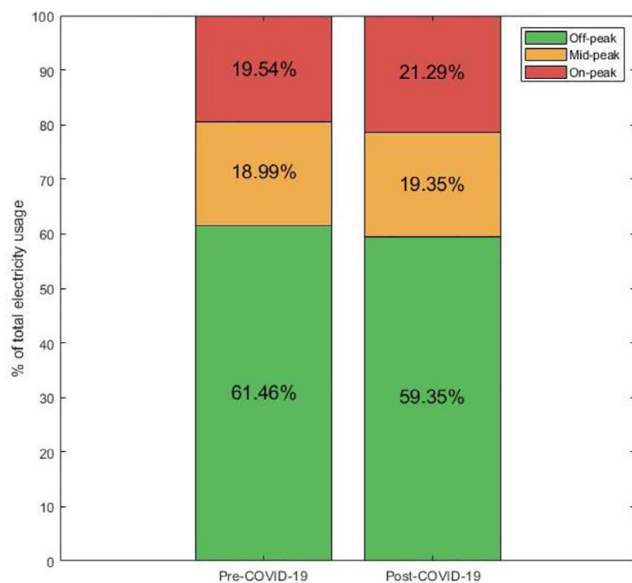

Fig. 20. Comparison of the average fraction of electricity usage in off-, mid-, and on-peak hours before and after the pandemic.

ples' behaviours. This is in accordance with previous studies and reports that showed compelling evidence that TOU rates would shift the electricity consumption to off-peak hours [65–67]. More-over, Rowlands and Furst [68] showed that the average impact of changing electricity rates from a flat two-tier system to TOU was less than 0.25%. The present study suggests shifting from TOU to flat rates favoured the consumers substantially.

5. Discussion

Generally, the imposed measures in response to the COVID-19 pandemic led to household electricity use changes as stated by several researchers. However, most of the scientific knowledge on this topic so far is based on aggregated data, without measured data at the household level. For example, using the aggregated data of about 7000 dwellings/flats in Warsaw, Bielecki et al., [48] demonstrated how the average daily energy demand profiles changed during early morning and mid-day amid the COVID-19 pandemic compared to the analogous period of the year before the pandemic. Other studies reported the impact of the imposed lockdown measures on overall electricity consumption loads in different nations [19–21]. Rather than only reporting what changes to energy use have occurred, as per existing in the literature, our study sought to quantify the impacts of the COVID-19 lockdown on the household's electricity consumption (at the household level), using the actual electricity meter data (hourly resolution) of 500 households located in Ottawa, Canada. Using high-resolution electricity use data in our study contributes to filling the research gap and allows us to isolate the effect of COVID-19 on energy use relative to changes caused by seasonal variation.

Our detailed analysis indicates that the pandemic's effect on household electricity use is not consistent, and there are noticeable differences among different months, seasons, and day types caused by weather-driven space conditioning loads, daylight hours, and customer behaviour change. For example, in the first month of lockdown (April), there was a significant temporal variation in the daily profile pattern relative to the same month pre-COVID, but with a small magnitude difference. In May, on the other hand, there were significant temporal and magnitude differences compared to the same month pre-COVID. In short, different temporal and magnitude variations were observed among different months post-COVID-19 relative to pre-COVID-19. Understanding such household demand changes is essential to system operators and utilities that are in charge of maintaining the power grid's reliable operation. In this regard, our results could serve as a starting point for utilities to design new policies that target load shifting, time-of-use structure, and demand-side management. Additionally, knowledge of such changes in energy consumption patterns under lockdown lays the groundwork to forecast how energy could be consumed in buildings if telework becomes popular in the future.

One of the key outcomes of this study, compared to the literature, was detecting customers' energy-related behaviour due to the COVID-19 measures. In the spring season, we observed that the profile pattern of 36.3% of customers changed significantly from pre- to post-COVID-19. On the contrary, the profile pattern of 63.7% of customers exhibited a slight change after the pandemic. On the other hand, in the summer season, all customers' profile pattern after the pandemic approximately matches the usual pattern before the pandemic. Yet, there is a significant increase (from 16.3 to 29.1%) in daily demand after the COVID-19.

Comparing our findings with Rouleau and Gosselin's [36], which has a similar climate, confirms the impact of lockdown that has led building residents to use more energy for their daily routine activities. However, the changes observed in their investigation differ from those observed in our study. For example, Rouleau and Gosselin observed that the average daily electricity consumption significantly increased by 17.5% in the first month of lockdown (April) compared to the pre-COVID, which was not observed for the following months. This differs from our findings presented here, as we found that at the first month of the lockdown, there was a slight increase (6.8%) in the average daily electrical consumption as many organizations were not ready enough for large-scale remote work implementation. Such an increase reached 22.6 % in May and 26.3% in June and July, which contrasts with the slight change reported by Rouleau and Gosselin for the same months.

Given to the peak load, Rouleau and Gosselin reported that peak values during the lockdown were approximately the same as those observed pre-COVID; they just occurred at different times of the day. However, our findings observed a 15–20% increase in peak load post-COVID-19. Several factors could explain this difference/inconsistency. For example, our study sample is a mix of private dwellings, whereas Rouleau and Gosselin focused on social housing dwellings; thus, our dataset will tend to be biased towards wealthier customers who may prioritize comfort over energy costs and their home lifestyle and occupants' number might differ. Other reasons explaining such change are weather conditions and the different utility costs between the two cities (10.1 ¢/kWh in Ontario compared to 7.3 ¢/kWh in Quebec). In this regard, there is clearly a need to disseminate more energy data analysis related to the COVID impact from different regions of the world and different contexts. In Snow et al.,'s study [33], the peak demand for all analyzed households (491 homes) during the lockdown approximately reached the same values as during the pre-lockdown. In Bielecki et al.,'s study [48], the peak demand in the 7000 apart-

ments on average increased by about 9% during the lockdown compared to the same period of the year before the lockdown.

The generalisability of our results is subject to certain limitations:

- Our findings are focused on a specific geographic and climatic area (Ottawa). The sample is primarily from urban areas, so regional and rural areas are not represented). Different geographical, climatic, socio-political, and cultural norms might affect residents' routines and, hence, their energy-related behaviour.
- These findings cannot be extrapolated to all Canadian households due to the small sample size investigated (500 households). Additionally, household size, demographics, and heating system characteristics are not available for this dataset.
- Our investigated dataset lacks post-COVID data in the winter and autumn seasons, though this is not necessarily a major limitation since most homes in Ottawa do not use electricity for heating.

5.1. Conclusions

The recent technology of smart meter and smart grid developments vastly increases the amount of energy use information being created and analyzed. In particular, such data open up the possibility for temporal assessment of electricity use, with the potential to reveal non-obvious insights about electricity consumption and the behavioural drivers of that consumptions. Unlike previous investigations conducted after the pandemic started, our analysis benefits from examining smart meter data at the customer level over a long period. Moreover, the main contribution of this study, compared to the literature, lies in studying individual customers' energy-related behaviour due to the COVID-19 measures. In this paper, we compared the energy consumption patterns observed in 500 Canadian households after the pandemic with the ones that were measured before the pandemic. The key conclusions from this study which lie in answering the raised research questions are listed below:

- How sensitive are the daily electricity consumption values to outdoor temperature?

Contrary to the authors' hypothesis, the electricity use of the homes for cooling (and other warm temperature effects) does not appear to be significantly affected by the COVID-induced behaviours. However, the homes' electricity use is generally sensitive to outdoor air temperatures, with an average increase of 0.08 kW/°C above an average of 18 °C. The changepoint analysis showed that of the 15% increase in electricity for April to August between 2019 and 2020, about one-third was due to warmer temperatures, with much of the rest due to the temperature-independent loads (e.g., lighting and appliances).

- How did peak electrical loads change after COVID-19?

By calculating the total hourly electrical loads for April 1 to August 31 in 2019 (pre-COVID) and the same period in 2020 (post-COVID), our analysis indicated the difference between post-COVID loads at the higher end are approximately 15 to 20% higher than pre-COVID. Additionally, identifying the highest five peak loads in each year (2019 for pre-COVID and 2020 for post-COVID) showed that the peaks corresponding to post-COVID are significantly higher (15–20%) than peaks that occurred pre-COVID. These results agree with those obtained by Bielecki et al., [6] that found a 9% increase in peak load during the lockdown compared to the same period of the year before the lockdown. How-

ever, this does not appear to be the case in previous observations (Snow et al., [33] and Rouleau and Gosselin [36]) that reported no change within peak load values during the after the pandemic compared to the pre-pandemic.

- How did household electricity profiles change after COVID-19?

Before the lockdown, the average household daily electricity consumption is 19.70 kWh, relative to 22.1 kWh after the lockdown (12.1% increase). This finding accords with earlier observations by several studies [25,27,32,34,62], which showed that the imposed lockdown resulted in increasing the residential energy demand by 11%–20%. Additionally, our detailed comparison between average electricity daily profile pre-and post- COVID-19 revealed that the lockdown's impact on household electricity use is not consistent, and there are noticeable differences among different months, seasons, and day types. For example, at the monthly level, temporal and magnitude differences in May post-COVID were significant relative to May pre-COVID. In April post-COVID, a similar temporal difference was observed, but with a small magnitude difference relative to the same month pre-COVID. On the other hand, June, July, and August exhibit similar profile patterns relative to the pre-COVID time, with an increasing demand on average over the day. Differentiation between weekday and weekend profiles showed that weekday demand post-COVID was not dissimilar from the pre-COVID weekend profile. Interestingly, a similar trend was observed before the pandemic within the summer season – there is only a slight change in profile pattern during the early morning.

- Do all households/customers have a similar profile, or are there discrete groups? And how these customers' profile pattern changes post-COVID-19?

Our analysis indicated that each season post-COVID (spring and summer) has two clusters representing seasonal household electricity demand. In the spring season, we observed that the profile pattern of 36.3% of customers changed significantly from pre- to post-COVID-19. On the contrary, the profile pattern of 63.7% of customers exhibited a slight change after the pandemic. On the other hand, in the summer season, the profile pattern of all customers after the pandemic approximately matches the usual pattern before the pandemic. Yet, there is a significant increase (from 16.3 to 29.1%) in daily demand after the COVID-19.

- How would household energy bills be affected by the TOU vs. flat rate?

Our analysis indicates that the average increase in the utility bill post-COVID would be 9.71% if TOU rates had been used instead of the flat rate. We found that the usage pattern post-COVID-19 slightly shifted from off-peak hours to mid-, and on-peak hours, relative to pre-COVID-19.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

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