Implications of COVID-19 for Electricity Use in Commercial Smart Buildings in Canada – A Case Study

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Abstract

When the country-wide lockdown for public employees in Canada took place because of the COVID-19 pandemic, all non-essential commercial activities were shut down and the majority of office workers began working from home. As a result, a considerable change in occupancy-driven electricity use was observed in commercial buildings. In this study, two years of hourly electricity use data for 27 government buildings equipped with smart energy management systems are analysed to quantify those changes, and to understand the economic and environmental impacts. Multi-linear regression and time-series decomposition methods are applied to metered electricity data in order to isolate characteristics such as base load, peak load, weather, and estimated occupancy. Results indicate a reduction of 10% in electricity use and 1,000 tons of CO_2 emissions in the year following the pandemic. However, the pattern was not uniform in all buildings, and some showed increased baseloads and weekend usage. The reasons behind such differences are further investigated.

Introduction

The International Energy Agency (IEA, 2021) reported an overall drop in energy demand by 20% following the global pandemic lockdown order in March 2020 (Soava et al., 2021). In Canada, actual country-wide lockdown for federal employees took place on March 16th, 2020 where all non-essential commercial activities were shut down and the majority of office workers worked from home. Up to the time of writing, a series of different restriction levels have been introduced since the summer of 2020. The restriction levels were imposed by each provincial government based on its reported cases. The global pandemic is one of many forms of sudden curtailment that could happen in buildings. Even smart buildings, pre-COVID, were not programmed to adapt to sudden long-term lockdown events. We take the COVID-19 pandemic as an example to study how the various building archetypes responded in both the short- and long-term. An example of short-term response to an event analogous to a lockdown is how buildings perform during public holidays that do not occur during weekends. Some buildings do not have their schedules changed during public holidays and some employees leave plug loads and lights on, or even windows unsealed. Buechler et al. (2022) found a correlation between a building's holiday energy performance and its corresponding COVID-19 lockdown performance. For that, we aim to study the behaviour of various commercial building archetypes, specifically during the COVID-19 lockdown order.

Background

Previous studies on the impact of the COVID-19 pandemic used baselining, coefficients of regression, and clustering analysis of electricity consumption changes (Buechler et al., 2022). Agdas & Barooah (2020) used a baselining method to investigate the impacts of the COVID-19 pandemic on the U.S. electricity demand. Buechler et al. (2022) studied the effect of the COVID-19 pandemic on global electricity consumption in 58 countries during the early pandemic duration in April-October 2020. A heterogenic effect in electricity consumption in response to the pandemic was concluded. The severity of response and rate of recovery depended on each country's government-imposed restriction, mobility, daily death rate, and reaction to holiday closures. Soava et al. (2021) studied the impact of the COVID-19 pandemic on electricity consumption and economic growth in Romania. Hamad M et al. (2020) used a genetic algorithm to predict the energy demand in Kuwait during the COVID-19 pandemic at its early stages. Time-series decomposition method was deployed by Alasali et al. (2021) to quantify the implications of the COVID-19 pandemic and to utilize these implications to improve the electricity demand forecast during and post-pandemic in three major cities in Jordan. Bahmanyar et al. (2020) studied the change in electricity demand in multiple European countries, some of which had strict lockdown measures, such as Spain and Italy, while others had less restrictive measures, such as Sweden and The Netherlands. These studies found that the change in energy demand was defined by the restriction level for such countries.

Research objectives

This research aims to systematically quantify the impacts of the COVID-19 pandemic lockdown on energy usage patterns in Canadian government commercial buildings, while accounting for the impacts of other possible metrics such as weather conditions, occupancy, peak loads and base loads. A time-series decomposition method is deployed on two years-worth of historical smart-meter electricity data for four selected buildings where energy usage data is disaggregated into three main components: trend, seasonality, and residual. The trend, in this case, represents the magnitude of change in electricity usage following the COVID-19 pandemic lockdown.

Methods

Baselining

The first part of this paper focuses on the statistical analysis and baselining of historical electricity usage data. This study utilizes metered electricity usage hourly data from 27 commercial buildings (as presented in Table 1) for two full years: one year immediately before the National lockdown declaration in Canada in March 16, 2020, and another year immediately after, with particular attention to systematic changes that occurred from March 2020 onwards. The analysis in this section includes time-series data analytics at several temporal resolutions, peak load and base load analysis, and rates of change in electricity usage patterns. In this study, we focus on electricity usage. While seasonal weather patterns have been shown to have minimal effect on electricity use in most buildings connected to central heating and cooling plants, other changes in operations may affect electricity use. Consideration of the most recent comparison year helps to control for such effects.

Multi-linear regression

In this model, time-series electricity data is predicted by a number of relevant independent parameters such as month of year (MoY), hour of day (HoD), hours of operation (*oh*), day type (*dt*), Covid-19 clustering period (*cvd*), province-wide Covid-19 reported daily deaths (*D*), outdoor temperature (*T*), and sun's altitude (*ALT*).

Time-series decomposition

The third approach focuses on applying the time-series decomposition method (Zaeri et al., 2022) on four selected buildings (Building Ids 2, 5, 7, 25) to observe the systematic change in electricity usage trends while accounting for the effects of seasonality, weather, and potential noise (variability) due to occupant behaviour. The selection of the buildings is based on the range of building archetypes and data completeness during the pandemic lockdown occurrence, especially directly after the national lockdown order. Zaeri et al. (2022) used an end-use disaggregation approach to predict electricity and heating consumption in commercial buildings using smart meter data. This study suggests that the load disaggregation approach can disseminate the metered electricity data into four categories: occupant-controlled loads, air distribution loads, and heating loads: AHU demand for heating coils and perimeter heating devices.

For this approach, one year worth of data collected in 2020 is used for four buildings to observe the immediate changes in response to the government-imposed lockdown order.

Table 1: List of studied buildings (NA entries indicate no data available).

ID	Gross floor area (m^2)	Archetype	Year built
1	20,466	office	1916
2	48,660	office	1976
3	26,868	office	1995
4	45,265	office	1952
5	14,071	education	1847
6	20,955	NA	1987
7	14,163	office/retail	1913
8	8,413	bank	1930
9	27,934	parliamentary	1932
10	37,140	NA	1956
11	12,520	conference	1912
12	16,425	NA	1938
13	47,691	library	1967
14	102,524	government / cafeteria	1973
15	30,825	court	1938
16	8,913	parliamentary	1928
17	43,752	parliamentary	1927
18	36,144	government	1960
19	67,740	office	1969
20	9,713	lab	1990
21	NA	lab	1978
22	7,912	office	1952
23	70,970	government	1979
24	NA	lab	1954
25	NA	lab	1955
26	21,119	office	1965
27	NA	museum	1875

Results

Baselining

In Figure 1, the annual electrical energy use intensity (EUI) is plotted for both years 2019 and 2020. 2019 data is shown in blue, whereas 2020 pandemic data is shown in red, and the annual averages per unit area (of all 27 buildings) for both 2019 and 2020 are represented in the horizontal lines. It is found that a change in EUI in response to the COVID-19 lockdown took place which ranged between −33% and +25%; there was a reduction for a large majority of buildings, and an overall average of −12%.

The average electricity EUI has changed from 460 to 410 $MJ/m^2/yr$ (12% reduction on the average EUI) for the years 2019 and 2020, respectively. The largest reductions by building type were 33% (office), 30% (education), and 28% (government), as shown in Figure 2. It should be noted that the clustering by building type is based on a small sample size and may not represent all buildings of the same archetype. The boxplot in Figure 2 shows the minimum (red cross), 1st quartile (bottom error bar), median (grey bar), 3rd quartile (pink bar), and maximum (top error bar), change percentages for the sample population per building archetype. Some archetypes, such as education, court, bank, etc., are represented by only one building, and hence, these archetypes lack variability in the current study.

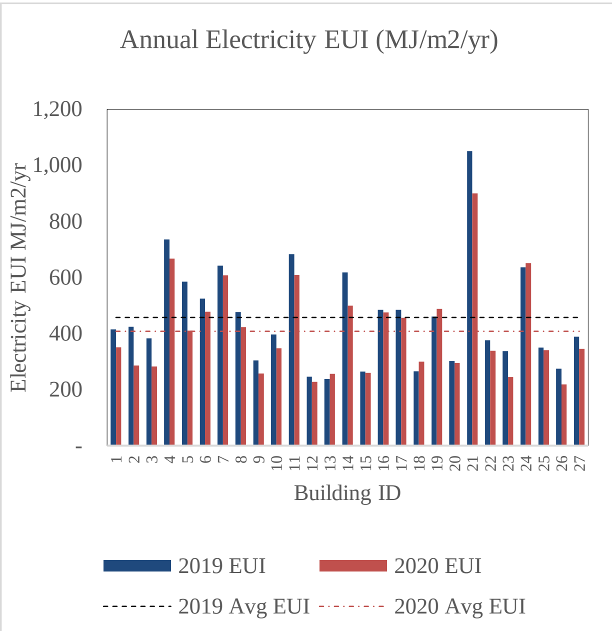


Figure 1: Annual electricity usage intensity for 2019 and 2020.

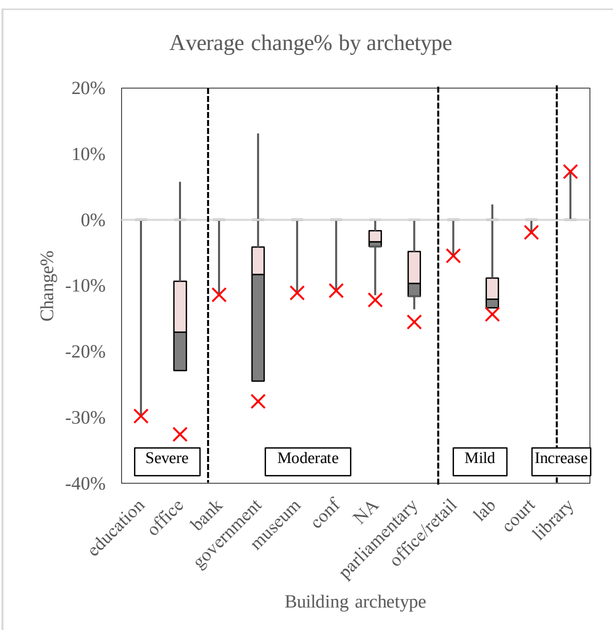


Figure 2: Change in annual electricity consumption due to the COVID-19 pandemic, averaged by building archetype.

The classification of the severity level of COVID-19 response (i.e, severe, moderate, mild, and increase) in Figure 2 is based on the classifications defined by Buechler et al. (2022). Other facilities with minimal occupancy such as banks, government, parliamentary, museum, and conference halls had moderate reductions.

On the other hand, a mild reduction is observed in buildings that operated with partial occupancy during the lockdown order such as mixed office/retail, laboratory, and courthouse. Finally, the library category had a mild increase in the annual electricity usage. At time of writing, no detailed information on how those buildings were operated during the COVID-19 pandemic was available.

Figure 3 presents the average weekday peak load and base load for the year pre- and the year during pandemic for each building. For all buildings, the peak load dropped by 13% on average; however, for the base load there was an inhomogeneity of both increase (up to 31%) and decrease (up to 24%) from the pre-pandemic year. We hypothesize that the increase in base load, which typically occurs during non-operating hours, is caused by the enhancement measures of sanitization and disinfection such as increased ventilation rates and fan operations, additional sanitization pre- and post- operating hours and such.

The annual average daily profile was also calculated to identify the change in electricity usage profile pre- and during pandemic. Four clusters of behavioural changes are found: (a) electricity usage reduction throughout the entire day, (b) electricity usage reduction during operating hours only, (c) electricity usage reduction during operating hours and increased usage during non-operating hours, and (d) electricity usage increase throughout the entire day.

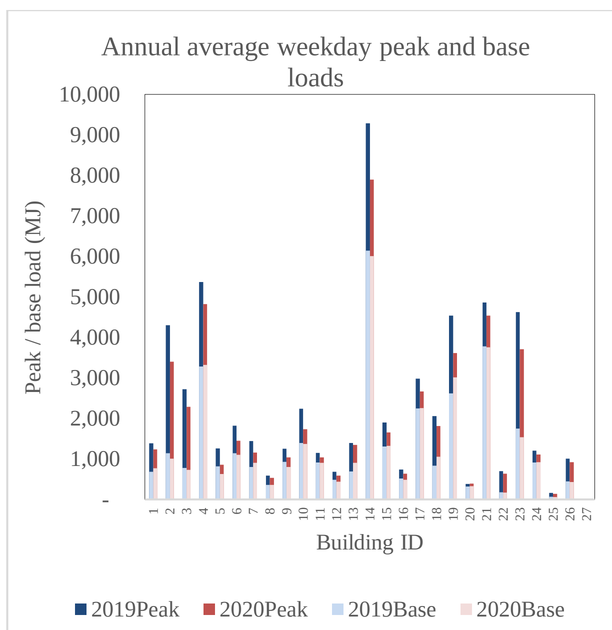


Figure 3: Annual average weekday peak and base loads pre- and during pandemic.

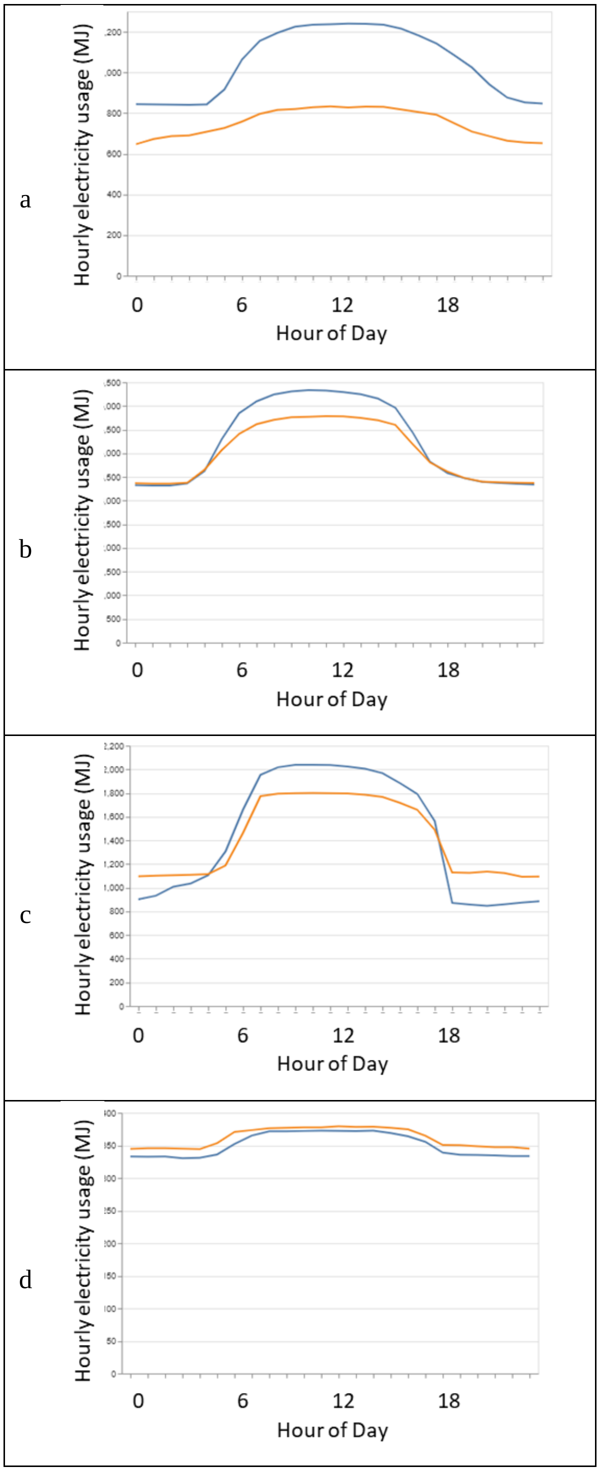


Figure 4: Annual average daily profile showing the weekday electricity usage patterns for 2020 (orange) and 2019 (blue) for 4 sample buildings representing the four clusters a-d.

The majority (52%) of buildings are classified under category (a) “overall reduction”, followed by category (b) (26%), category (c) (18%), and finally, only one building representing category (d) (<4%) which happens to function as a laboratory.

Multi-linear regression

The purpose of the Multiple Linear Regression (MLR) model is to determine the coefficients of regression associated with each independent parameter. There are two types of independent parameters used; categorical and numerical parameters. Examples of categorical parameters are HoD. On the other hand, the numerical parameters used in this model are the daily COVID-19-related deaths (Ontario Agency for Health Protection and Promotion (Public Health Ontario), 2022), outside temperature, solar irradiance, and the sun’s altitude. It is observed from the data that weekend load profiles are different than weekday profiles. Therefore, a single coefficient (oh) for hours of operation cannot represent both weekday and weekend clusters, since the model tends to over-predict the weekday non-operating hours. On that note, we separate weekdays from weekends and holidays to accurately determine the coefficients of regression, especially *cvd*. As per Buechler et al. (2022) the reported daily COVID-19-related deaths may be correlated to the depth of energy usage reductions. Similarly, the province-wide reported cases, hospitalizations, and deaths (Ontario Agency for Health Protection and Promotion (Public Health Ontario), 2022) were collected since January 15th, 2020. It is worth mentioning that the reporting of cases may lag (and under-report) actual infection within the community, and that weekend reporting may be supressed or delayed until the next working day. However the publicly available data can be considered as a proxy to indicate the severity of the infection rates and hence the restrictive measures in response to those rates. Table 2 is a summary of correlation analysis between hourly electricity usage and the candidate independent parameters. It is found that the daily reported deaths parameter had a higher correlation to electricity usage than cases and hospitalizations. Up to this moment, it is not clear whether the reported deaths are caused by partial opening of buildings, especially those buildings which are open to the public.

Table 2: Correlation coefficients for relevant independent parameters.

Parameter	Hourly electricity usage (MJ)
T	0.008
T^2	0.040
Daily reported COVID-19 Cases (Case)	-0.049
Daily reported COVID-19-related hospitalizations (Hospitalization)	-0.086
Daily reported COVID-19-related deaths (*D*)	-0.118
Sun's altitude (*ALT*)	0.201
COVID-19 clustering period (*cvd*)	-0.211
Operating hours clustering period (*oh*)	0.695

The Scikit-learn package for Python was used to train the MLR model (Pedregosa et al., 2011). Since *MoY, Season of Year (SoY), HoD, cvd*, and *oh* are all considered categorical parameters, 42 groupings of models are run independently and then the regression results are compared to the actual electricity usage for all groupings. Table 3 summarizes the MLR results for the weekday model. An R^2 of 0.781, 0.736, 0.646 and 0.827 are achieved for building Ids 2, 5, 7, and 25, respectively. Table 3 also shows the constant value (intercept) as well as the coefficients of regression for each independent parameter. For instance, the temperature (*T*) is inversely proportional to electricity consumption, which means the building consumes more electricity at lower temperatures, especially in winter and shoulder seasons. This can be true for high-latitude jurisdictions which are heating-driven. The constants, as well as the coefficients of the MLR model, are summarized in Table 3.

$$e_{id} = C + \alpha \cdot m + \beta \cdot h + \theta \cdot cvd + \gamma \cdot oh + \delta \cdot T + \varepsilon \cdot T^2 + \mu \cdot ALT + \partial \cdot D \qquad (1)$$

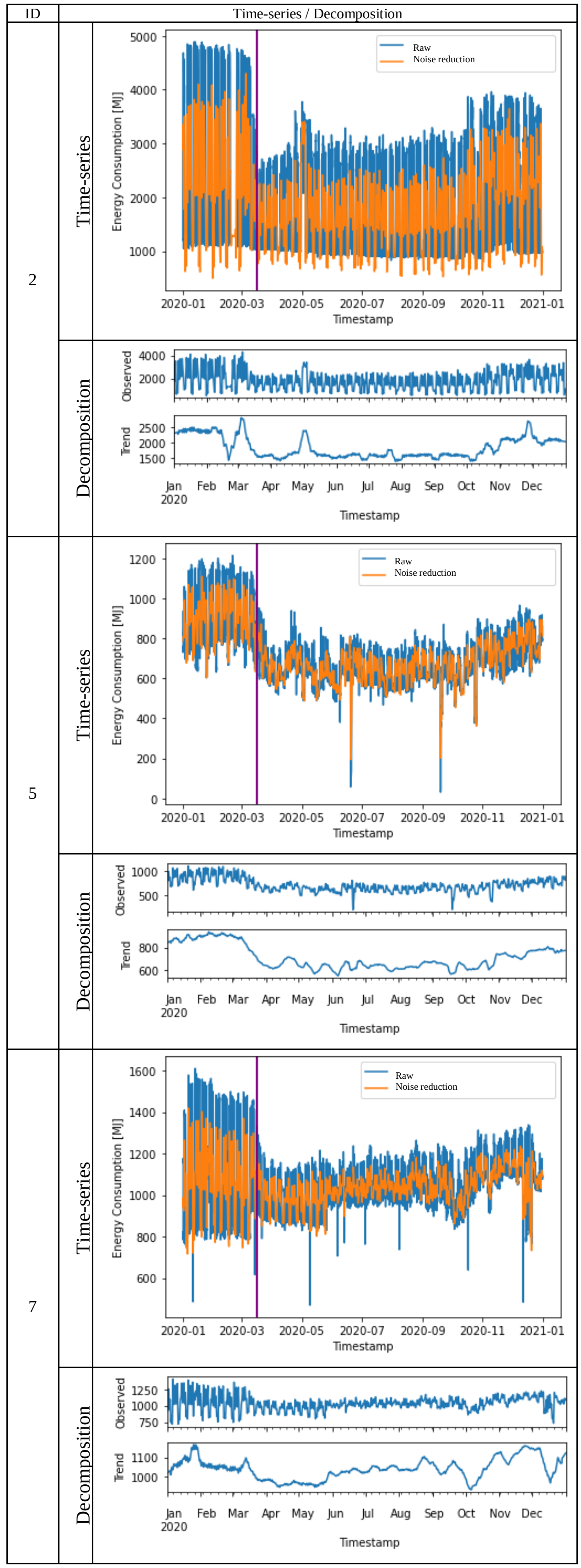
where *e* stands for predicted hourly electricity consumption, *id* for building ID , *h* for hour of day (0,1,…23), *m* for month of year (1,2, …12), *cvd* for COVID clustering period (1 for COVID period, 0 for pre-COVID), *Oh* for operating hours (1 for operation, 0 for non-operation), *C* for constant, *T* for temperature (°C), *ALT* for sun's altitude, *D* for daily reported COVID-19-related deaths, α for month coefficient, β for hour coefficient, θ for COVID coefficient, γ for operating hour coefficient, δ for temperature, ε for squared value of temperature, ∂ for daily deaths. Table 3 shows the concluded coefficients of regression for each variable for weekdays.

Table 3: Coefficients of regression for weekdays for selected buildings

ID		2	5	7	25
C		1467.11	749.60	861.42	63.87
θ	COVID cluster	-665.77	-319.34	-83.61	-7.16
	Pre-COVID	0.0			
γ	Operating hours cluster	2,131.96	198.38	276.95	65.72
	Pre-operation	0.0			
T		-17.11	-4.51	-0.27	-0.65
T^2		0.16	0.07	0.02	-0.01
ALT		-15.67	-1.43	-2.31	0.02
∂		4.67	1.83	-0.10	-0.22
Groupings		42			

Time-series decomposition

Figure 5 shows the time-series hourly electricity usage data, where the blue line and orange line indicate the actual and "de-noised" data, respectively. The plots on the right show (from top to bottom) the observed de-noised data and trend. Each row represents one of the selected buildings.



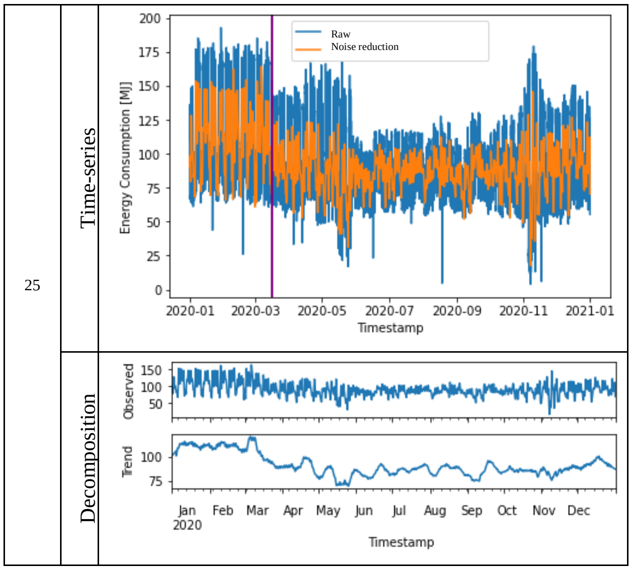


Figure 5: Time-series decomposition for selected buildings: observed data, de-noised data, and trend.

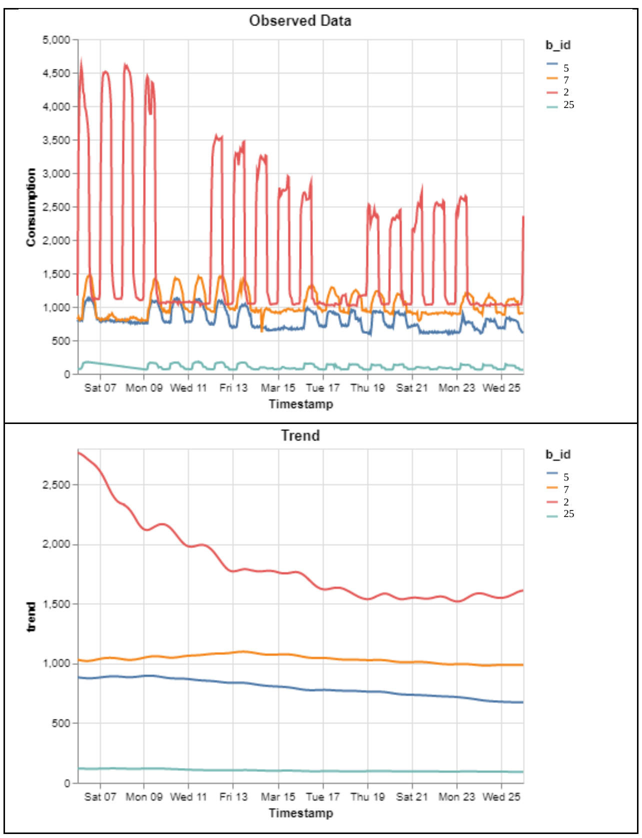


Figure 6: decomposition results for 10 days immediately before and after the National lockdown order on March 16, 2020: observed data and trend.

By extracting the data noise and seasonal variation on the weekly basis, the trend in electricity usage can be derived. Hence, the direct implications from the COVID-19 lockdown order, while controlling for seasonal variation, are quantified. For a better understanding of the short-term impacts, we take a closer look at the 10 days preceding and following the National lockdown order, as seen in Figure 6.

For the initial response period, 1 week immediately following the National lockdown order, three discrete response groupings are found, 'severe', 'moderate', and 'mild' which indicate the steepness of response of electricity consumption, in terms of trend, in the selected buildings as presented in Figure 7. The initial response indicators were determined by calculating the change percentage in trend between the first week of the national lockdown order and one week immediately preceding it, while comparing the same DoW and HoD. Similarly, future work will focus on the recovery indicators for each building and the ability of each building to bounce back to its pre-COVID-19 electricity usage levels.

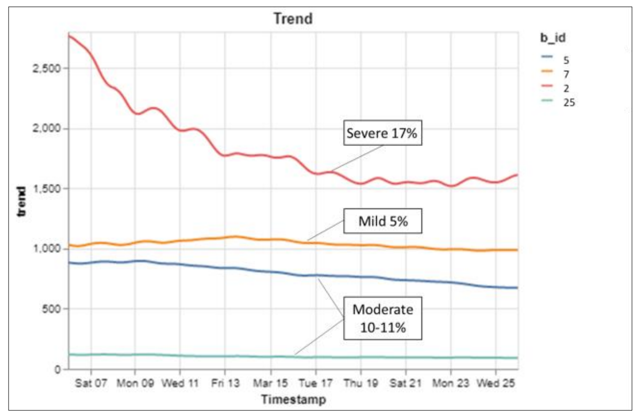


Figure 7: Severity of response to National lockdown.

Discussion

Three approaches were used to quantify the impact of the COVID-19 pandemic on electricity usage patterns in commercial buildings: baselining, coefficients of regression, and time-series decomposition. Each approach has its advantages and disadvantages. The baselining method can quantify the absolute changes in usage, where the reference for baselining is the year 2019 which happens to be immediately before the pandemic year 2020. However, this method does not control for other features which might contribute to changes in electricity usage patterns such as outdoor temperature, changes in hours of operation, or seasonal variations.

The coefficients of regression method (MLR) accounts for other independent parameters which may be impactful on electricity usage. The more metadata available on building characteristics and operation, the more accurate the model may become. In this study, we focus on parameters that can be publicly obtained, such as temporal parameters (MoY, HoD, SoY, daytype) combined with weather data (outdoor temperature, sun's azimuth angle), and reported COVID-19-related data, in addition to a single data-driven parameter (oh), which can be sufficient for a relatively reasonable model. Improving the model may require a large set of parameters, which can be computationally challenging.

Time-series decomposition can be used to quickly determine trends in electricity usage while easily accounting for the effects of seasonality and data noise. This method is found to be effective in tracking trends of electricity usage at the weekly level, and thus, can be used efficiently to track the changes due to lockdown, ability to bounce back, and also for unforeseen shocks or events irrelevant to COVID-19 that could happen in the near- or far future.

Also, some of the studied buildings might have undergone major renovations or functional alterations simultaneously during the pandemic period, some others have implemented energy efficiency measures directly before the pandemic event, and some buildings might have shut down in an *ad hoc* manner. At this time of writing the paper, there is no ground truth information on these possible scenarios, and thus further investigations need to be pursued.

Correlation but not causation

As discussed earlier, we found a correlation between the electricity usage trend during the COVID-19 pandemic and the province-wide reported daily deaths as seen in building ID 5 in Figure 8. However, this relationship may not imply a direct causation between both features. In other words, one may not conclude that the death rate has contributed to the increase in electricity usage directly. A better possible explanation is that the loosened restrictions in building occupancy both increased the likelihood COVID-19 spread, and an increase in occupancy-related energy consumption.

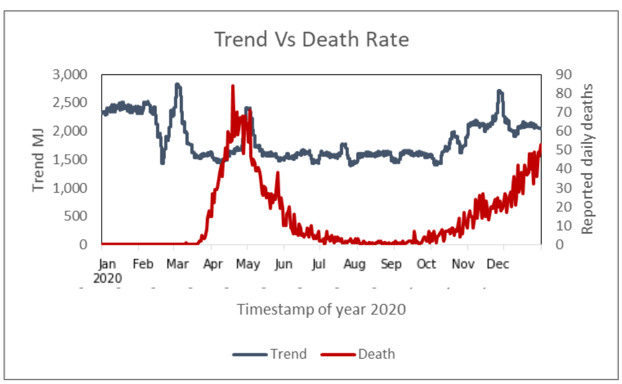


Figure 8: Correlation between daily death rate and electricity usage for building ID 5.

Conclusion

The electrical energy performance from a portfolio of Smart Buildings before and after the COVID pandemic was studied. For the electricity analysis, 27 qualified buildings were selected for detailed statistical analysis. Overall, the total gross area of all buildings combined is approximately 796,499 m^2. Out of 27, four buildings were selected for time-series decomposition analysis in order to observe the trend in electricity usage before and after the National lockdown order. As a result of the COVID-19 lockdown, a total electrical energy reduction of 44,174 GJ was observed (12%). It is also concluded that in 2020, a total of 1,070 metric tons of CO_2 equivalent ($MTCO_2e$) were saved as compared to the corresponding 2019 usage levels. This change was heterogeneous for the studied buildings where the change in annual energy use varied between −33% and +25%. Average daily electricity use was reduced by 9% and 1% for weekdays and weekends, respectively, for all studied buildings. Peak loads and base loads were affected differently: average peak loads have been reduced for almost all qualified government buildings while more than 43% of buildings had their average base loads increased. This finding aligns well with the hypothesis that buildings might have increased their ventilation rates up to 100% at all times of day as a measure of eliminating COVID-19 contamination.

Four categories of daily usage profile change due to the pandemic lockdown have been observed: (a) overall daily reduction, (b) reduction during operating hours only, (c) reduction during operating hours and increase during non-operating hours, and (d) overall daily increase. More analysis is needed to be performed to better understand the implications of these four categories. More than 50% of qualified government buildings can be categorized under category (a), followed by category (b) (26%), category (c) (18%) and finally only one building under category (d) (<4%).

It is expected that this situation will remain in flux for some time, and will continue to affect energy use patterns. More efforts could be done to serve buildings that are poorly suited to partial occupancy. Upgraded building controls and additional occupancy sensing could result in substantial energy savings. Hence, future work will focus on a detailed understanding of variations in electricity use patterns over time in accordance to the changes in pandemic response implemented by governments at all levels, employers, school boards, transit authorities, etc.

The coefficients of the regression method have shown effectiveness in defining the change in electricity usage due to the COVID-19 event. It is found that all studied buildings had a negative coefficient for the *cvd* cluster, indicating a decline in energy usage during the pandemic, while controlling for other parameters such as outdoor temperature, sun's altitude, hour of day, hours of operation, and month and season of year. However, this model is hard-wired to the COVID-19 setting: if any unforeseen non-COVID-19 related shocks or events occurred in the future, this model will require major customization in order to respond to such events.

The time-series decomposition method has proven to be effective in removing the seasonal variations so that the resulting trend could represent the major changes over longer periods of time. In this paper, we used the trend to determine the depth of initial response to the government-imposed lockdown in March 16, 2020, by comparing the change in trend for one week immediately before and one week immediately after the lockdown. Three levels of severity are concluded: severe (>15%), moderate (10-15%), and mild (<10%).

Future work will expand this work to estimate the rate of recovery in energy use in each building as pandemic restrictions are lifted. Also, building resilience KPIs with a special focus on response to lockdowns will be defined and scorecards will be given to the buildings under the current study.

Acknowledgments

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