Energy performance of commercial buildings in partial-to-no-occupancy: lessons learned from the COVID-19 pandemic lockdown in Canadian government buildings

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Canada

Energy performance of commercial buildings in partial-to-no- occupancy: Lessons learned from the COVID-19 pandemic lockdown in Canadian government buildings

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Abstract

Following the global lockown as a measure to contain the spread of the COVID-19 pandemic, the world has witnessed a temporary decline in energy usage, especially in the commercial building sector. However, the magnitude of decline in that sector was not as large as the expected decline for unoccupied spaces. Energy performance of low-/unoccupied commercial buildings coupled with the new minimum requirement for outdoor air intake is an intriguing research question. However, occupancy data is expensive to obtain and is challenging from a privacy standpoint. Instead, by comparing the business-as-usual electricity usage with that of the known unoccupied period during the early stage of the lockdown, a wide spectrum of hybrid work electricity usage can be estimated. In this study, two years of hourly energy (thermal load-free electricity) use data for 49 commercial buildings equipped with smart energy management systems are analyzed to quantify those changes. A linear regression predictive model to estimate low-occupancy electricity loads is conducted. Results indicate that the proposed model is promising and can be further improved for better repeatabilitiy.

Highlights

- Annual electricity usage was reduced by 5% and 6% in the first and second years following the pandemic lockdown order in studied government commercial buildings in Canada.
- The proposed predictive model is developed to estimate partial occupancy electricity loads in case of absence of occupancy data, by using at least two distinctive cases where the occupancy fraction is known.
- Linear regression predictive model was created to estimate partial and low-occupancy electricity usage.
- The model identifies the baseload, typical occupancy loads, and the loads at any given occupancy fraction.

Introduction

Following the global lockdown and work-from-home order for non-essential businesses and employees as a measure to contain the spread of the COVID-19 pandemic, the world has witnessed a substantial decline in energy usage, especially in the commercial building sector (Beyer et al., 2021). The COVID-19 pandemic had disrupted economies worldwide (Beyer et al., 2021) due to several reasons, including imposed lockdown orders, forcing employees and businesses to either shutdown or work remotely from home. In order to contain the spread of the COVID-19 virus, various measures were taken, some of which are partial or complete lockdowns, some others include curfews, restrictions on public gatherings, and shutdown of unnecessary businesses (Santiago et al., 2021). In 2020, right after COVID-19 was declared by the WHO as a global pandemic, researchers were motivated to use the trends in electricity usage right after the stringent containment measures to predict future demand given limited information on the long-term socio-economic impacts of the pandemic and the duration of those impacts. Agdas & Barooah (2020) shed light on the heterogeneity of the variation in electric power demand during the COVID-19 pandemic, referring to the responses of the various states in the U.S. to the initial pandemic lockdown order. The variation is not only on the aggregate level, but also on the grid stress level, for example, peak demand, where some states indicated increased stress, others less stress, and still others no significant change. Leach et al. (2020) found that during the initial stage of the COVID-19 pandemic (i.e., March 2020-June 2020), electricity demand in Canada dropped by 10% in Ontario, and about 5% in Alberta, British Columbia, and New Brunswick. In April 2020 alone, the electricity demand in the Province of Ontario dropped by 14%, and particularly by 16% in Ottawa (the National capital of Canada) (Abu-Rayash & Dincer, 2020). Awad et al. (2022) studied the electricity performance of 27 commercial smart buildings in the National Capital Region in Canada during the two years following the COVID-19 pandemic lockdown. Their study concluded an average reduction of 10% in commercial smart buildings during the first year following the COVID-19 pandemic lockdown order, where the change rate was non-uniform across the different building archetypes. It is worth mentioning that in Ontario, the share of annual electricity demand for the building sector is 36%, 29%, and 31% for commercial, industrial, and residential buildings (Leach et al., 2020). Immediately after COVID-19 had been declared as a global pandemic by the WHO, stay-at-home orders were set in place worldwide at different restrictive levels. Understanding the deviation in electricity demand during the initial response to the COVID-19 pandemic at the national level caught researchers' attention, especially due to the shift of energy usage patterns and load profiles. In conclusion, the

electricity demand at the building sector, municipal, national and international levels had been clearly affected by the socio-economic implications of the COVID-19 pandemic. However, the extent and duration of disruption showed heterogeneity, depending on the building sector (e.g. housing, commercial, educational), degree of lockdown strictness, spread of the virus, as well as behavioral aspects and protective measures in buildings (e.g. increased outdoor air intake, limited capacity, mobility). It is critical that while we prioritize health and safety in buildings by, for example, maximizing outdoor air intake, we also ensure that actions against climate change are supported (Halbrügge et al., 2021). Energy demand is directly linked to people's activities, in particular, work activities (Santiago et al., 2014). Existing commercial buildings have been traditionally designed and scheduled to accommodate full capacity "business as usual" operations, while considering weekday and weekend scheduling modes only. Other *ad hoc* and unplanned events, such as statutory holidays, maintenance, new organizational missions, natural disasters, and, as seen recently, pandemic response have not been considered in the past. By proposing new energy efficiency measures during low-to-no occupancy, further energy, as well as GHG emissions, savings could be achieved immediately. Since the COVID-19 pandemic spread globally in early 2020 up to the present date, and due to the government-imposed lockdowns and other operating restrictions, it was found that buildings have reacted with inhomogeneity to these restrictions. Reasons for differences could be behavioural, operational changes, the capability of legacy control systems, or energy efficiency measures in place. It is also noted that some older buildings may lack zoning, which results in full HVAC (and, in some cases, lighting) operation during partial occupancy. Previous studies aimed at undestanding occupancy and occupancy-driven operations and the associated energy demand in commercial buildings. Zou et al. (2017) investigated the use of Wi-Fi infrastructure to detect Wi-Fi-enabled mobile devices to count building occupants. Hobson et al. (2019) studied occupancy sensing via sensor fusion where available data included Wi-Fi, CO_2 concentration, PIR motion detctors, and plug and light electricity load meters. They found that Wi-Fi-enabled device counts had high relevance for occupancy-count estimations compared to ground truth counts. However, due to the scarcity of occupancy data, especially in buildings that are highly secure (and access to WiFi data would violate privacy), and/or where the occupancy detection technologies required infrastructure that is expensive to implement (Zou et al., 2017), novel non-intrusive, blackbox methods are required to understand the correlation between user behaviour and electricity demand. This mandate has become even more critical post the COVID-19 pandemic due to the proposed flexible work environment, allowing employees to choose to work on-site, hybrid, or off-site. This "new normal" mode requires a thorough understanding of the sensitivity of occupancy ratios to electricity demands, so that the established relationship

can be used in predicting electricity demand based on estimated occupancy ratio as a proxy. The aim of this study is to perform a black-box sensitivity analysis on the effects of occupancy levels on electricity usage, where occupancy data is unavailable, taking the COVID-19 stay-home period as a reference for unoccupied electricity performance, and the pre-COVID period as a reference for business-as-usual electricity performance. By comparing these performance points, a wide spectrum of hybrid work energy proportion can be estimated.

Methods

Building Automation System (BAS) data from 49 commercial Smart Buildings located in Ontario, Canada is collected at 1-hour interval granularity for the periods before, during, and post the COVID-19 pandemic. The study utilizes metered electricity (lighting, plug loads, and fans), usage data for the full years of the pandemic from April 2019 – March 2022 with particular attention to systemic changes that occurred from March 2020 onwards. The analysis includes time-series data analytics at several temporal resolutions, peak load and base load analysis, and rates of change in usage patterns. For annual energy aggregation accounting, since the national imposed lockdown in Canada took place on March 16th, 2020, we simplify the comparison by counting the pandemic years from April 1st, 2020until March 31st 2021, and same for the following pandemic year 2021-22. Similarly, the pre-pandemic year starts on April 1st, 2019 until March 31st, 2020. Since this set-up aligns with the Canadian Federal Government Fiscal Year (FY), we use FY instead as follows: FY 2019-20, FY 2020-21, FY 2021-22 to reflect the pre-pandemic (during which COVID-19 had not been observed), post-pandemic, and recovery years. For hourly data analysis, e.g. peak and base load accounting, the COVID labelling reflected the actual lockdown start date (March 16th and thereafter is labelled as COVID, otherwise is labelled as pre-COVID). Data from FY 2019-20 is considered as the control period to compare the pandemic energy performance in FYs 2020-21 and 2021-22 to the pre-pandemic energy performance. The terms "post-pandemic" and "recovery" do not imply or indicate the end of the pandemic as a public health matter. 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. For more accurate results on pre- and post- lockdown energy usage, we focus on comparing the 2-year period of the pandemic onset in FY 2020-21 and FY 2021-22 against the corresponding period from FY 2019-20 as a non-pandemic control year.

Changes in electricity usage due to the COVID-19 pandemic lockdown

In a previous study, multiple comparative methods were addressed to quantify the impacts of the COVID-19 pandemic on energy usage in commercial buildings with focus on electricity only (Awad et al., 2021, 2022), where methods included baselining, multilinear regression, and time-series decomposition. In this article, an expansion of

the previous analysis includes electricity loads for a different, larger set of the building stock (49 buildings). To determine the deviation in electricity usage in FYs 2020-21 and 2021-22 with respect to the reference FY 2019-20, Eq.1 is used to calculate the deviations for each building.

$$deviation_{e,FY}(\%) = [E_{e,FY} - E_{e,ref}] * 100/E_{e,ref} \qquad (1)$$

where e represents the energy type (electricity, steam, chilled water, gas), E is the annual aggregate of the given energy type, FY represents the fiscal year under investigation, and ref indicates the reference year. Here, since we focus on electricity only, e and E denote electric energy. While considering the pre-pandemic reference year as the benchmark, an average drop of 5% and 6% in electricity usage in FYs 2020-21 and 2021-22, respectively, was observed. The mild reduction can be due to aggressive ventilation and other protective measures suggested by building operators, which may have offset larger reductions elsewhere.
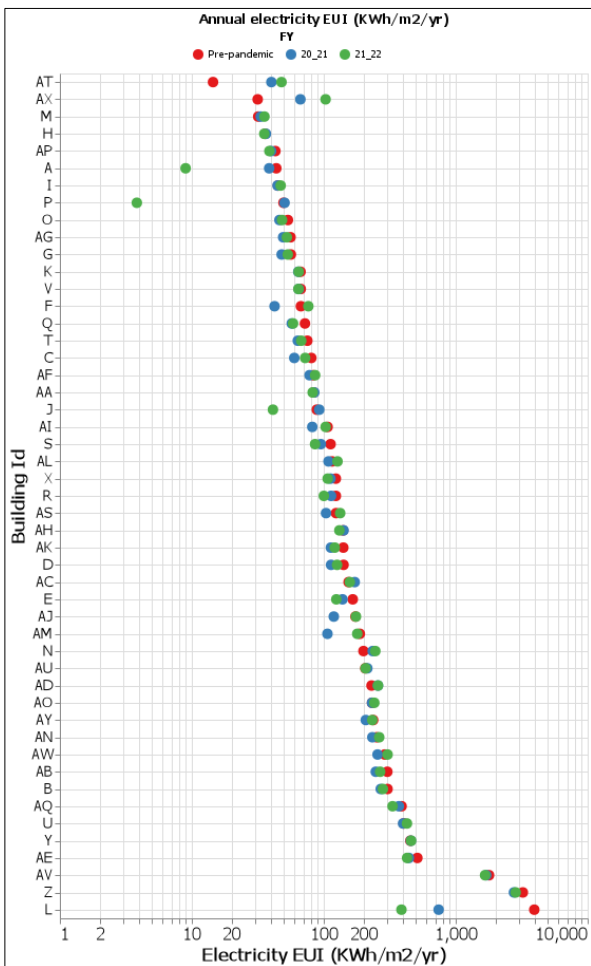
Figure 1 compares the pre-pandemic electricity usage intensity (EUI) levels for each of the study buildings against their corresponding electricity EUI levels during the two years following the pandemic lockdown order. The red marker represents the pre-pandemic levels, and, the blue and green markers represent the post-pandemic levels. Blue and/or green markers exceeding the red marker's value, simply means that this building's pandemic electricity EUI exceeded its pre-pandemic levels, and the opposite is also true. Table I summarizes the deviation in electricity EUI during both pandemic years as compared to the reference pre-pandemic year. The variance in response to the complete and/or partial lockdown is found to be large spanning between a minimum of -92% in building P and maximum of +230% in building AT, both in FY 2021-22. The Coefficients of Variance (CV) for the $deviation_e(\%)$ are calculated as -8% and -137% for FYs 2020-21 and 2021-22, respectively. Future studies will address in detail the building performance behaviour during the pandemic.

Figure 1. Annual electricity usage intensity during the two years following the pandemic lockdown order with reference to pre-pandemic levels.

Table I. Building-level deviation in annual electricity usage in FYs 2020-21 and 2021-22 as compared to pre-pandemic FY 2019-20.

Name	Deviation$_e$(%)		Name	Deviation$_e$(%)	
	20_21	21_22		20_21	21_22
A	-11.68	-79.46	AA	1.0286	-1.764
B	-11.14	-7.726	AB	-18.26	-11.8
C	-25.75	-10.22	AC	11.231	2.1653
D	-19.58	-10.67	AD	11.9	11.947
E	-16.39	-24.9	AE	-13.74	-16.35
F	-36.87	13.808	AF	-6.454	3.1328
G	-14.84	-5.26	AG	-12.11	-6.26
H	1.2815	-1.558	AH	0.9017	-6.232
I	-0.822	4.7256	AI	-23.47	-3.415
J	4.2982	-53.5	AJ	-31.53	0.8112
K	-3.806	-3.178	AK	-19.48	-13.82
L	-81.15	-90.16	AL	-6.115	9.8291
M	4.496	11.428	AM	-43.18	-4.407
N	17.544	22.947	AN	-7.262	4.5003
O	-13.72	-9.674	AO	-0.101	3.965
P	1.881	-92.26	AP	-7.231	-9.92
Q	-20.58	-18.73	AQ	-4.654	-14.58
R	-7.963	-18.91	AS	-16.07	7.4246
S	-15.68	-23.71	AT	176.91	230.31
T	-15.32	-10.11	AU	3.53	0.3325
U	-1.117	5.7985	AV	-4.756	-6.637
V	-3.534	-3.97	AW	-11.75	5.1035
X	-8.957	-13.27	AX	110.77	227.18
Y	0.9336	1.3097	AY	-12.02	-1.528
Z	-14.37	-11.73			

Estimating electricity EUI during partial occupancy

Since the initial COVID-19 pandemic lockdown order in March 16th, 2020 had resulted in *ad hoc* shutdown in commercial buildings, followed by a series of step-wise ease of restrictions based on the spread of the virus, we took advantage of the confirmed lockdown period (i.e., within 2 weeks following the initial lockdown order) to represent the no-occupancy operation period (we assume the building was unoccupied during all hours due to immediate pandemic restrictions). On the other hand, the typical full occupancy "business-as-usual" operation was extracted from the pre-pandemic reference year. Here, "full" occupancy does not mean occupancy at maximum design capacity, or every seat occupied, but rather means typical pre-pandemic daytime occupancy. In order to control for other possible parameters that may affect electricity usage we applied data filters to exclude possible electric thermal loads, weekends, holidays, and pre- and post-occupancy conditioning periods (typically 2 hours directly before and after normal operation). Therefore, we selected weekday peak operation loads (i.e., 8:00 am to 4:00 pm) during shoulder seasons (i.e., spring and fall). Similarly, base loads were selected between 10:00 pm and 4:00 am. Linear regression was then used to establish the relationship between no-occupancy (pandemic lockdown) and typical full occupancy (pre-pandemic) electricity usage intensity.
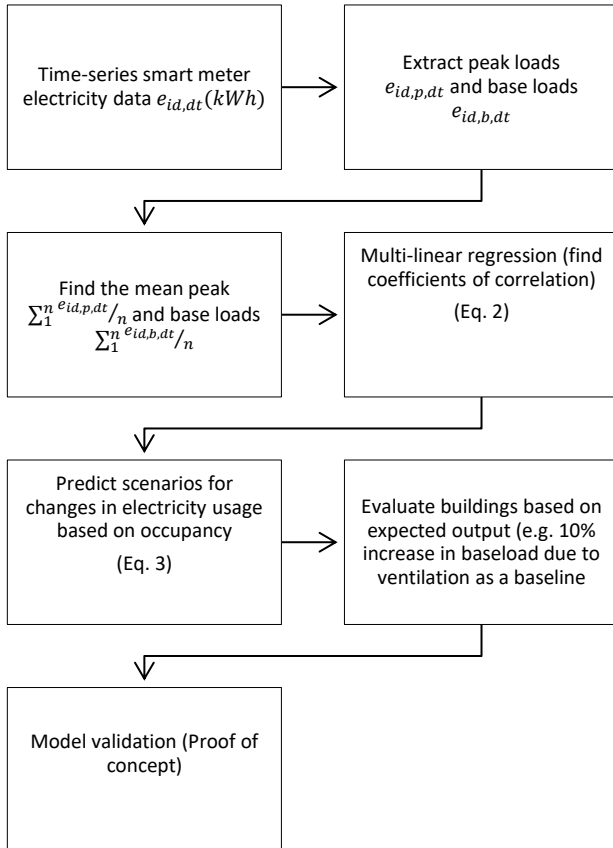
Extrapolation from the linear regression equation was then deployed to predict partial occupancy electricity usage intensity. Figure 2 presents the methodology in detail. Eq. 2 denotes the multilinear regression (MLR) equation that was developed to quantify the impacts of the lockdown order on electricity use while controlling for other parameters such as the daytype (weekday, weekend, holiday) dt, month of year m, hour of day h, hours of operation h, outdoor temperature T, direct normal irradiance DNI, daylight hours ALT, and reported provincial death statistics (Ontario Agency for Health Protection and Promotion (Public Health Ontario), 2022) linked to the Covid-19 pandemic D. Eq. 3 was deployed to estimate the electricity EUI $e_{id,f,dt}$ for any given fraction of occupancy $f_{id,dt}$ (0-1) where $e_{id,b,dt}$ denotes the base load b for building id and daytype dt, K is the intercept, s is the slope that indicates the electricity load intensity due to occupancy, and $f_{id,dt}$ is the fraction of occupancy (in this study, 0 for the occupancy shortly after the pandemic lockdown order and 1 for the typical pre-pandemic full occupancy).

$$e_{id,dt} = C + \alpha.m + \beta.h + \theta.cvd + \gamma.oh + \delta.T + \varepsilon.T^2 + \mu.ALT + \omega.DNI + \partial.D \quad (2)$$

$$e_{id,f,dt} = e_{id,b,dt} + K + s.f_{id,dt} \quad (3)$$

Results and Validation

In order to validate the proposed model, additional information, such as occupancy count during at least two distinct periods (i.e., during full occupancy and during no occupancy), as well as major changes in ventilation protocols was critical. Instead, the model was tested on two case studies of other buildings with occupancy information. Case study #1 is an office building in Ottawa, Canada where hourly electricity usage and occupancy count were both available between January and June 2020. Case study #2 is an office building in Ottawa, Canada with hourly electricity and access badge swipe-in data were available.

Case Study #1 – with Actual Occupancy Count

Building 1 (B1 thereafter) is an 8,250 m^2 post-secondary institution's office building in Ottawa, Canada. Occupancy counts ranged between 4 (minimum) and 265 (peak occupancy) (Hobson & Gunay, 2022). Occupancy count was normalized to fractions between 0 and 1 where the pre-pandemic occupancy (January 1st – March 16th, 2020) was defined as the typical full occupancy period, and the post-pandemic occupancy (April 1st – June 30th, 2020) as the 0% occupancy. Later on, the model was calibrated, since the lowest occupancy record during operating hours was 4 individuals (not 0). Filters were applied to exclude weekends and holidays, as well as durations where thermal loads existed (i.e., cooling loads). First, the linear regression model was deployed using only electricity usage data (without occupancy input), then, occupancy data was used to compare the calculated slope with the actual slope. Figure 3 presents

Figure 2. Methodology for predicting occupancy-driven electricity usage intensity during partial occupancy.

both calculated and actual occupancy fractions based on electricity EUI above baseload. The value of interest here is the slope s, since it defines the electricity EUI. The calculated and actual slopes for building B1 are 0.119 and 0.127, respectively. At this point of model development, since electricity usage is known and occupancy fraction is unknown (except for the initial estimators 0 and 1), the electricity EUI is considered the predictor (x-axis) and the occupancy fraction is considered the response (y-axis).
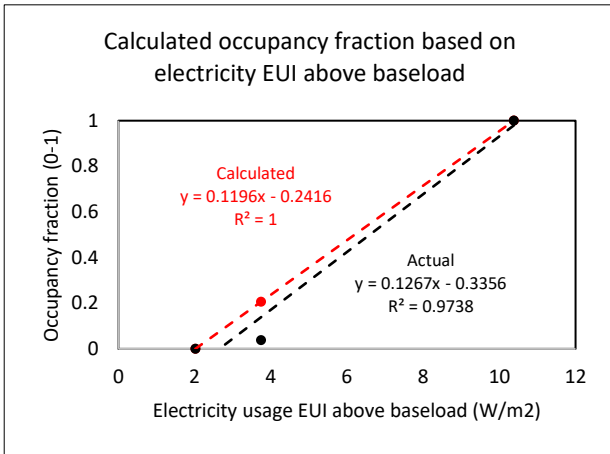

Figure 3. Calculated and actual occupancy fraction based on electricity usage intensity (EUI). Here, the slope determines the EUI.

Later on (e.g. Figure 7), once the regression equation is determined and validated, the predictor and response variables will be switched, since the value of interest is the electricity EUI given a specific occupancy fraction. The third point on the plot is the occupancy/electricity usage during the second year of the pandemic where partial occupancy is expected. The deviation between the actual and calculated occupancy fraction is considerably large and more data points and calibration are required to testify the method.

Case Study #2 – with Badge-in Data

The model was also tested at one other commercial building (B2) in Ottawa, Canada, where only electricity and access badge swipe-in data was available, while actual occupancy count was not. Data for this building was available for the timeframe between October 2014 and October 2015. In such case, the COVID-19 pandemic lockdown period, which was previously used to represent the no-occupancy electricity EUI had not yet occurred. Instead, confirmed unoccupied (no badge swipes) weekdays were selected, for example, statutory holidays occurring on a typical weekday (to avoid planned weekend operating schedules). Like the many secure commercial buildings, only personnel with valid badge Ids are allowed to access the building. On the other hand, they may not be required to badge-out upon exiting the building. Several assumptions were made to extract meaningful information from the badge-in data. The badge-in data was completely anonymized, to access only timestamp and the condition to access "permitted or

denied". First, as mentioned earlier, holidays occurring on weekdays were selected to represent the no-occupancy electric loads, while typical occupancy weekdays were selected to represent typical electric loads. Hours of operation, as confirmed by the building operators, are typically between 8:00 am to 4:00 pm; however, occupants may show up as early as 6:00 am (also confirmed by badge-in data). That said, occupancy count start time was set at 6:00 and stopped at 11:00 am. It is assumed that at 11:00 am peak occupancy is reached, while later at noon, a portion of the employees may leave for lunch and therefore it becomes difficult to keep track of occupancy counts.
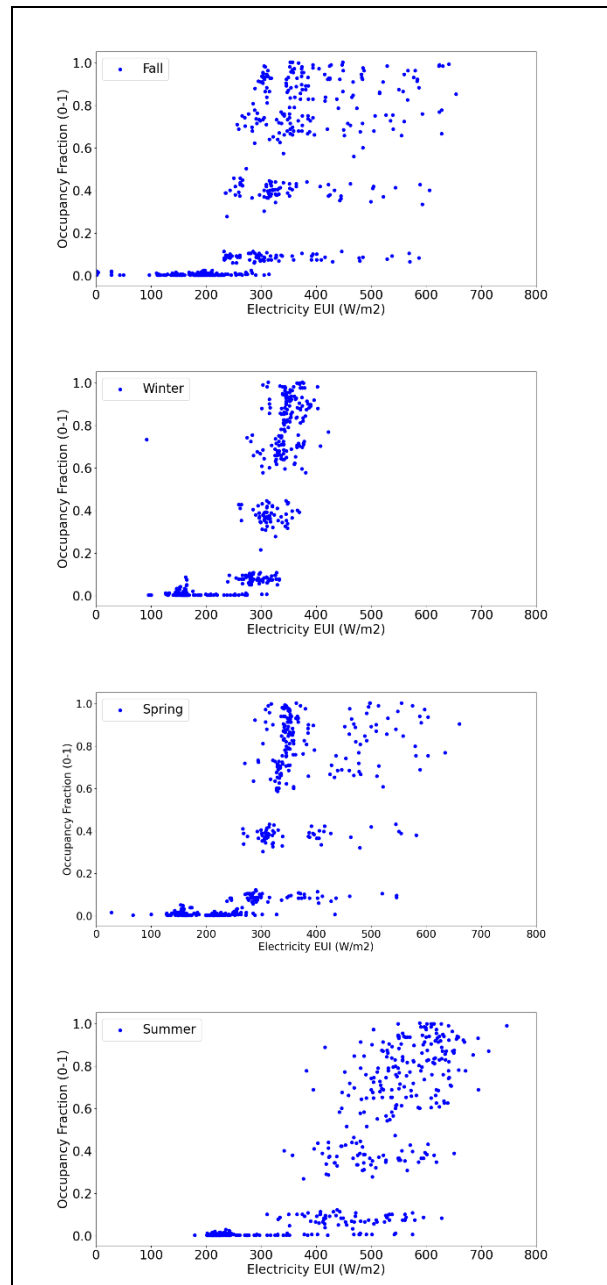

Figure 4. Scatter plots showing the correlation between badge-in data and electricity usage intensity during each season.

Second, like in the previous example (B1), durations when weather-dependent trends are observed, were excluded. Figure 4 shows scatter plots of calculated occupancy fraction (y-axis) and electricity EUI (x-axis) in each season. Cooling loads appear to have a major contribution to the summer electricity EUI and a minor contribution to that of shoulder seasons. To avoid weather-driven electricity loads, the winter season was selected for the model development.

The plots in Figure 4, especially during the winter season, do suggest a linear relationship between occupancy fraction and electricity EUI. Finally, cumulative sum of badge-in signals between 6:00 am and 11:00 am is calculated and peak operating electricity usage intensity is determined at exactly 11:00 am. Since we are interested in occupancy fraction, occupancy count is normalized to values between 0 and 1, where 0 represents no-occupancy and 1 represents the peak measured occupancy. Figure 5 (left) shows the cumulative sum of occupancy fraction between midnight (12:00 am) and 11:00 am. It is clear that occupants started entering the building at 6:00 am and occupancy count continued to rise until 11:00 am. On the other hand, electricity usage started to rise at nearly 2:00 am and stabilized at 10:00 am. Therefore, baseload value was extracted at the duration between 8:00 pm and 12:00 am to avoid pre- and post-occupancy conditioning periods, whereas typical full occupancy period is captured at exactly 11:00 am.

Figure 6 presents calculated (linear regression model), actual (from badge-in data), and calibrated (corrected badge-in data) occupancy fractions based on electricity EUI above the baseload. Calibration was carried out by re-normalizing the occupancy fractions during typical full occupancy period (i.e., from 0.85 to 1.00).
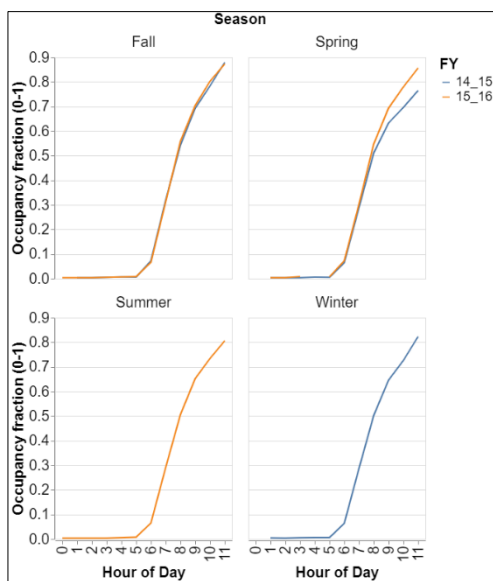

Figure 5. Top: cumulative sum of occupancy fraction extracted from badge-in data. Bottom: corresponding weekday electricity EUI, grouped by season. Winter season is most preferred due to weather independence.

While calculating the average of the peak-hour electricity EUI, the corresponding average occupancy fraction was 0.85 (versus the absolute peak occupancy electricity EUI), hence, the average peak occupancy fraction value was corrected to 1.00 instead of 0.85, and the linear equation function was calibrated accordingly. With calibration, we see that the linear regression fit is promising since it clearly aligns with the calculated occupancy fractions.
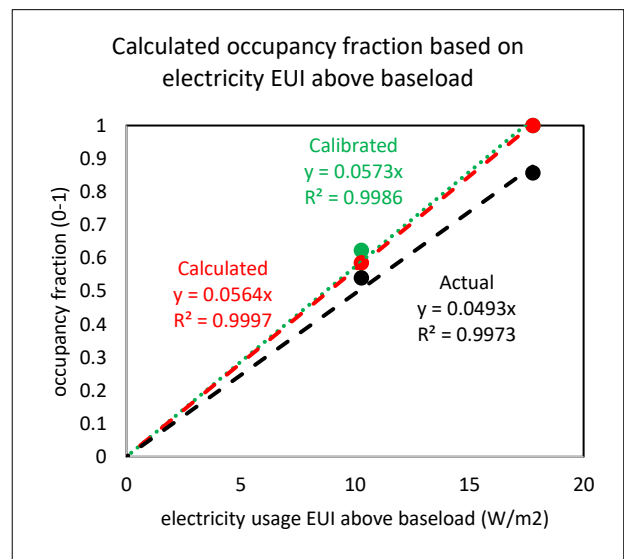

Figure 6. Calculated and actual occupancy fraction based on electricity usage intensity (EUI) where actual occupancy is calculated from badge-in data.

The badge-in occupancy estimation method, with calibration, indicated promising results and can be easily adapted to different buildings at scale, and applied to

buildings that require occupants to tap/swipe their badges upon entry. It should be noted that there are possibilities of over- and under-estimation associated with this method for a number of reasons (1) occupants do not badge-out, hence, we cannot estimate the time when each individual had left the building, (2) one occupant could enter the building multiple times for shipping/delivery, this will count as multiple occupants, (3) multiple occupants may enter the building with one swipe, this will count as one occupant, and (4) temporary visitors may not be counted as well. In the future, with proper proof of concept data, confidence intervals associated with the abovementioned uncertainties will be calculated and added to the model.

Conclusions & Future Work

After validation, the electricity demand sensitivity to occupancy model was finally deployed on all 49 demonstration buildings without occupancy data. By knowing the base (night-time), no-occupancy and typical full-occupancy electricity EUIs, and slope (calculated), we were able to establish a relationship between the electricity EUI and occupancy fraction, given that occupancy count data is not available. That said, electricity demand can be estimated at any given fraction of occupancy using the generic methodology summarized in Figure 2.
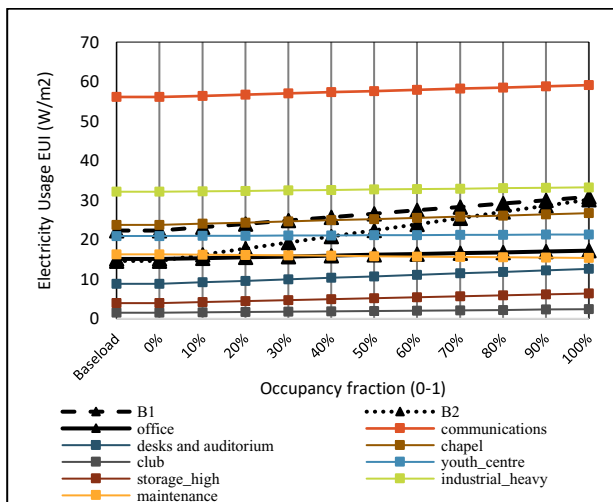

Figure 7. Estimated electricity EUI based on occupancy fraction.

This methodology will allow building operators to apply occupancy fraction (i.e., hybrid work environment, shutdowns, over-occupancy) as a proxy to predict and keep track of electricity demand. Figure 7 summarizes the average (per building archetype) estimated electricity EUI (y-axis) based on occupancy fraction (x-axis) at 10% increments of occupancy fraction. Highlighted in dashed black are the case studies of the two office buildings (B1 and B2) that we used as proof-of-concept. For the purpose of comparing the case studies to the demonstration buildings of similar functionality, the calculated average office building performances from the demonstration buildings are highlighted in solid black line for easy comparison of the case studies (B1 and B2). It is clear that base load varies widely across the different building archetypes, depending on their lighting, plug loads, and HVAC requirements. Office buildings with large server rooms can be highly load intensive compared to typical office buildings. Dining facilities may have fairly low base loads outside of the hours of operation, but substantially high electricity loads prior to and during service hours. However, certain outliers may require the building operator's attention, such as (1) buildings with base loads exceeding the statistically acceptable boundary range (i.e., mean ± std), such as those with base loads above 40 W/m^2, and (2) Also, flat horizontal lines in Figure 7 indicating lack of zoning, especially for lighting and HVAC electric loads. In other words, seeing the same occupancy-driven electricity loads at both 10% and 100% occupancy.

For the demonstration buildings, since no information on the actual number of occupants (we only assumed fractions based on typical pre-pandemic occupancy), there could be multiple explanations for the slope defining electricity usage intensity: (1) typical occupancy could be originally quite low and less effective compared to plug loads (e.g. maintenance buildings could be electric load intensive and hence, electric loads are less sensitive to occupant behaviour), (2) lack of zoning for lighting and electric HVAC components may result in a full operation regardless of the number of occupants, (3) some buildings may have been fully or partially operated remotely (e.g. data centres, departments with large server rooms). This may validate the reason why only a 5% reduction during the first year following the COVID-19 pandemic lockdown order was observed.

The model was developed using nearly black box methods, shedding light on the impacts of occupancy on electricity usage intensity and allowing us to estimate future partial occupancy scenarios, while using very limited information. It also allows us to identify buildings that may need smart sensor retrofits for improved zoning moving forward, for example, motion sensors for lighting, demand-controlled ventilation, etc.

The strength of the proposed method is that it is applicable and repeatable widely given accessible information. In our study, we took advantage of the COVID-19 pandemic lockdown period to measure the electricity usage at durations when buildings are clearly unoccupied, and compared it with the typical full occupancy electricity loads while subtracting baseloads from both scenarios. An alternative could be a holiday occurring on a weekday (non-weekend) when buildings are unoccupied, but also scheduled for normal weekday operation.

Future work will include the following:

- application of time-series decomposition method to filter out noise, seasonality and residuals, and only compare the highest and lowest points on the trend (Awad et al., 2021). It is critical to isolate weather and other possible parameters that may affect the electricity usage trends.

- it is critical to disaggregate the electricity loads to user dependent (e.g., kitchen appliances, personal devices, lighting intensity) and user-independent (e.g., security systems, lab equipment, servers, baseloads for minimum HVAC operation, especially in winter months), in order to fully capture the effects of occupancy on electricity usage intensity. The method we proposed was able to capture user-independent baseloads during the COVID-19 pandemic *ad hoc* lockdown period. In the future, we aim to cross validate those findings by conducting either field visits, questionnaires, or, if possible, submetering for major plug loads.
- cross validate the proposed method with occupancy data from one or more demonstration buildings. Proxies for occupancy such as badge-in (combined with badge-out) or CO_2 concentration have proven to be useful at varying degrees of accuracy.
- expand the model to include all-season data, not only shoulder seasons

Acknowledgement

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