



Impacts of COVID-19 related stay-at-home restrictions on residential electricity use and implications for future grid stability



Lechen Li^a, Christoph J. Meinrenken^{b,d}, Vijay Modi^{c,d,*}, Patricia J. Culligan^{d,e}

^a Department of Civil Engineering and Engineering Mechanics, Columbia University, New York, USA

^b Earth Institute, Columbia University, New York, USA

^c Department of Mechanical Engineering, Columbia University, New York, USA

^d Data Science Institute, Columbia University, New York, USA

^e College of Engineering, Notre Dame, IN, USA

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ABSTRACT

“Stay-at-home” orders and other health precautions enacted during the COVID-19 pandemic have led to substantial changes in residential electricity usage. We conduct a case study to analyze data from 390 apartments in New York City (NYC) to examine the impacts of two key drivers of residential electricity usage: COVID-19 case-loads and the outdoor temperature. We develop a series of regression models to predict two characteristics of residential electricity usage on weekdays: The average occupied apartment’s consumption (kWh) over a 9am–5pm window and the hourly peak demand (Watt) over a 12pm–5pm window. Via a Monte Carlo simulation, we forecast the two usage characteristics under a possible scenario in which stay-at-home orders in NYC, or a similar metropolitan region, coincide with warm summer weather. Under the scenario, the 9am–5pm residential electricity usage on weekdays is predicted to be 15% – 24% higher than under prior, pre-pandemic conditions. This could lead to substantially higher utility costs for residents. Additionally, we predict that the residential hourly peak demand between 12pm and 5pm on weekdays could be 35% – 53% higher than that under pre-pandemic conditions. We conclude that the projected increase in peak demand - which might arise if stay-at-home guidelines coincided with hot weather conditions - could pose grid management challenges, especially for residential feeders. We also note that, if there is a longer lasting shift towards work and study-from-home, utilities will have to rethink load profile considerations. The applications of our predictive models to managing future smart-grid technology are also highlighted.

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1. Introduction

1.1. Background and prior work

Since early 2020, the COVID-19 pandemic has caused a global catastrophe, impacting almost every aspect of daily life in most countries [1]. In early 2020, approximately one third of the world’s population was in “lockdown” via various types of “stay-at-home” orders or similar guidelines [2]. This severe situation saw more than 80% of workplaces worldwide partially or fully closed, resulting in significant economic impacts, including a global recession that might rival the Great Depression [3].

Generally, how to effectively respond to global disasters is a crucial issue for local governments and decision-making personnel

[4]. Energy and electricity infrastructures (from energy supply to demand) have faced disruptions due to the COVID-19 pandemic and related shelter-in-place orders that are believed to be the most severe in seven decades [5]. Specifically, the partial or complete shutdown of many commercial and social activities has substantially reduced energy demand in 2020 [6]. Worldwide, a significant decrease in energy consumption was observed during the lockdown period of March–April 2020. Mousazadeh et al. [7] report an electricity demand decrease as high as 30% in Italy and 12–20% in France, Germany, Spain, India, and the UK [7]. Other studies of Europe have shown changes in electricity profiles due to the pandemic. An investigation by Werth et al. [8] demonstrated that a significant load drop occurred in most of the 16 countries investigated in Europe during the period of COVID-19 restrictions (except for Scandinavia and Switzerland, whose consumption was relatively stable, probably because of their less prohibitive restrictions and consistent industrial activities throughout the

* Corresponding author at: Department of Mechanical Engineering, Columbia University, New York, USA.

E-mail address: modi@columbia.edu (V. Modi).

Nomenclature

PTAC	Packaged terminal air conditioner	$\hat{y}_{peakinc}^{(i)or(ii)}$	Predicted increase of weekday 9am–5pm peak demand from 2019 to 2020
NYISO	New York Independent System Operator	$y_{use2020}^{(i)or(ii)}$	Observed weekday 9am–5pm electricity use in 2020
NOAA	National Ocean and Atmospheric Association	$\hat{y}_{use2020}^{(i)or(ii)}$	Predicted weekday 9am–5pm electricity use in 2020
B_{April}	Baseline electricity use in April	$y_{peak2020}^{(i)or(ii)}$	Observed weekday 9am–5pm peak demand in 2020
B_{month}	Baseline electricity use in targeted month	$\hat{y}_{peak2020}^{(i)or(ii)}$	Predicted weekday 9am–5pm peak demand in 2020
T_{April}	Electricity-use threshold of April	WBT_{thresh}	Wet-bulb-temperature threshold
T_{month}	Electricity-use threshold of targeted month	$WBT_{9am-5pm}$	Average wet-bulb temperature during 9am–5pm
$y_{use2019}^{(i)or(ii)}$	Observed weekday 9am–5pm electricity use in 2019	$WBT_{9am-5pm}^{exp}$	Exponential-transformed average wet-bulb temperature during 9am–5pm
$\hat{y}_{use2019}^{(i)or(ii)}$	Modeled weekday 9am–5pm electricity use in 2019	$WBT_{12pm-5pm}$	Average wet-bulb temperature during 9am–5pm
$y_{peak2019}^{(i)or(ii)}$	Observed weekday 12pm–5pm peak demand in 2019	$WBT_{12pm-5pm}^{exp}$	Exponential-transformed average wet-bulb temperature during 12pm–5pm
$\hat{y}_{peak2019}^{(i)or(ii)}$	Modeled weekday 12pm–5pm peak demand in 2019	$DCC_{Avg7Day}$	7-day moving-average of daily confirmed Covid-19 cases
$y_{useinc}^{(i)or(ii)}$	Observed increase of weekday 9am–5pm electricity use from 2019 to 2020	$DCC_{Avg7Day}^{log}$	Natural logarithm of $DCC_{Avg7Day}$
$\hat{y}_{useinc}^{(i)or(ii)}$	Predicted increase of weekday 9am–5pm electricity use from 2019 to 2020	R^2	Coefficient of determination
$y_{peakinc}^{(i)or(ii)}$	Observed increase of weekday 9am–5pm peak demand from 2019 to 2020		

pandemic). Bahmanyar et al. [9] compared the effect of different containment policies carried out by six European countries (Spain, Italy, Belgium, the Netherlands, Sweden, and the UK) on their electricity consumption during the COVID-19 pandemic. They found that the weekday consumption in most of these countries considerably decreased and that the consumption profiles were close to pre-pandemic weekend profiles when compared to the same period in 2019.

National-level energy system disruptions caused by severe hazards or disasters have occurred before. For example, between the 10th of January and 2nd of February 2008, southern China experienced 5 continuous storms, as snow and low-temperature sleet hit the region. The storms compromised 35,710 power lines and 2007 substations [10]. As another example, in March 2011, an Earthquake in East Japan destroyed multiple power stations, resulting in severe power shortages. In both cases, energy supply rather than energy demand was curtailed. To deal with reduced supply capacity after the earthquake in Japan, one important policy implementation sought to reduce summer peak loads in the affected areas by limiting the use of air-conditioning [11].

Although the overall energy consumption during the pandemic decreased, the decrease was driven by reduced commercial loads in large metropolitan areas such as New York City (NYC), London, or Paris, whereas residential electricity consumption increased as many residents switched to working or undertaking educational or other activities from home [12,13]. In addition, the shape of the residential energy demand profile shifted, with weekday diurnal profiles resembling pre-COVID-19 weekend diurnals [12]. Some studies showed electricity peaks disappearing during morning periods, with these peaks instead shifting to noon. For example, one study reported an approximate 30% increase in electricity use around midday in the UK during early April 2020, compared to pre-pandemic times [14]. In the NYC metropolitan area, also in early April 2020, a 23% increase during typical working hours (9:00 am to 5:00 pm) was observed [15].

Significant changes in household day-time use would lead to new load profiles that might produce new challenges for the consumers and for the grid. In many settings, utilities and governments have allowed customers to defer payments, leading to large past-due electricity bills [16]. The bills, especially in summer months, have also been higher than pre-pandemic bills [17]. Even

in heating dominated-geographies such as New York City, one experiences hot weather, and during those periods the cooling demand can dominate residential energy consumption. This need is met through the use of electricity, unlike much of the heating. Hence one would expect that if residents spend more time at home between 9am and 5pm on weekdays than they would have otherwise, the energy use during that period will be higher. Generally, households contribute major portions to peak electricity demand during the summer. For example, on hot days, US and European residential customers comprise a significant portion of electricity consumption [18,19] and an even larger portion of peak demand [19,20]. One way to reduce residential summer peak load is to incentivize behavioral modification, e.g., encouraging residents to curb on-peak electricity-usage, such as for laundry, by shifting respective activities to other times of the day [21,22]. For managing summer peaks during global crises, such as the COVID-19 pandemic – or even national-level crises, such as the 2011 Japan Earthquake – more factors need to be taken into account, including how hot it gets over the summer months, and whether more residents are allowed, willing or even encouraged to return to the usual place of work/school during the aftermath of a crisis [17].

1.2. Focus and objective of present study

A case study is conducted to investigate Covid-19-related increases in residential electricity usage from 2019 to 2020 in NYC multi-family residential buildings, using a sample of 390 apartments. The apartments are, in size and vintage, representative of NYC multi-family building stock, and their electricity consumption is consistent with other multi-family settings in the same climate region [23]. We focus on two characteristics of the electricity usage of an average apartment, (i) the electricity consumption (kWh) on weekdays during the 8 h from 9am to 5pm (in order to gauge how much electricity use and commensurate financial burden shifts from commercial buildings and schools to the residential sector); and (ii) the hourly peak demand (Watt) on weekdays during the 5 h between 12pm and 5pm (in order to gauge possible stress on the electricity grid when increased residential peak demand either coincides with system-wide loads or becomes larger than the substations and/ or distribution lines in residential areas were designed to handle). We develop a series of robust pre-

dictive models and identify two key drivers of residential electricity usage, namely the severity of the pandemic – as measured by the Covid-19 case load – and the outdoor wet-bulb temperature. We then use these models to predict electricity usage characteristics for conditions when there is a confluence of high outdoor temperatures during the summer with medium to high portions of residents working or studying from home. Such conditions might occur if COVID-19 stay-at-home orders in urban areas like NYC persist into the summer months – or if there is widespread adoption of a work and study from home lifestyle that is non-pandemic related but part of a future, “new normal”. The predictions are used to understand how much residential summer electricity peaks might increase financial burdens for residents and the risks of grid stress or failure.

2. Data and methods

An overview of the electricity consumption dataset and the approaches to collection, data cleaning and adjustments are introduced in section 2.1. Preliminary analysis of key factors affecting residential electricity patterns, and the relevant time windows of the residential consumption are given in section 2.2. The selection of predictors, model setup and calibration are introduced in section 2.3. The mechanism of the Monte Carlo simulation, employed for the forecast of a future possible risky scenario (described in section 1.2), is introduced in section 2.4. Finally, the evaluation metric used in the study is introduced in section 2.5. A flowchart of all the data processing and methodologies is given by Fig. 1.

2.1. Dataset for apartment-level electricity usage

2.1.1. Overview

We used MFRED, a database of electricity use in over a dozen residential buildings in NYC, covering 390 apartments ranging in size from studios to 4-bedroom units [23]. The apartments are representative of NYC multi-family building stock in both size and vintage, and their annual electricity consumption matches that of comparable residences in the U.S. units in similar climate zones [23]. The heating in 89% of the apartments is supplied centrally

(burning natural gas and distributed within buildings, using steam or hot water), whereas the air conditioning is supplied by personal appliances (commonly window-mounted electric air conditioners). Therefore, heating in most apartments does not contribute to the apartments’ own electricity usage (except for heating blankets or space heaters) but air conditioning does. The other 11% of apartments are equipped with different forms of packaged terminal air conditioners (PTACs), with the majority of the cooling and heating supplied centrally, such that the PTACs’ electric load does not materially contribute to an apartment’s electricity usage [23]. Therefore, the vast majority of apartments in our dataset exhibit higher electricity use during the summer, depending on weather conditions, especially temperature. In contrast, the electricity usage during the winter and shoulder seasons depends much less on the weather.

Electricity usage for every apartment was metered by a Siemens® SEM3 micro-meter system with 50-amp split core current transformers and $\pm 1\%$ accuracy [24]. In this study, we used the incremental electricity consumption (kWh) from one hour to the next from January 1st to August 31st of both 2019 and 2020. The 2019 and 2020 data were compared to reveal modified diurnal shapes and increases in both consumption (kWh) and peak demand (Watt) due to the effects of stay-at-home conditions during the pandemic in 2020.

2.1.2. Removing vacant apartments from dataset

Before analyzing the overall daily electricity use of apartments, we sought to eliminate the impact of uninhabited apartments on average electricity consumption. Therefore, apartments that were not occupied for a long period of time (henceforth “vacant apartments”) were removed from the dataset.

In order to robustly identify vacant apartments, a threshold T for the 1-month average load of an individual apartment was set at 1.067 Watts per square meter (W/m^2). The value was determined for the average size of studios and one-bedroom apartments of our dataset, which usually have a minimum consumption of 70 Watt that consists of a refrigerator (~ 50 Watt) plus ~ 20 Watt for a router/Wi-Fi and other electronics in standby mode. It should be noted that for heating, some apartments have supplementary electrical fans that are centrally equipped and controlled. For cooling, most apartments are equipped with window air conditioners that residents usually turn off when they leave their apartments. However, a small subset of apartments are supplied by central air conditioning controlled by the building. In addition, the electrical consumption of refrigerators in the vacant apartments can vary considerably with the changes of climate conditions. Therefore, the $1.067 W/m^2$ definition of the threshold does not yet consider any additional loads caused by weather changes, but instead is only applicable in the shoulder seasons (and thus, in this study, was used for April only). To determine the thresholds suitable for identifying vacant apartments in other months, the April value was scaled in proportion to the average electricity consumption of all 390 apartments in the respective month, as follows:

$$T_{month} = T_{April} \times \frac{B_{month}}{B_{April}} \quad (1)$$

where T_{April} is the April threshold ($1.067 W/m^2$), T_{month} is the threshold of any month, and B_{April} and B_{month} are the baseline consumptions, defined as the time-averaged apartment electricity load during April and the targeted month, respectively.

By the defined threshold, the numbers of identified temporarily vacant apartments from Jan. to Aug. in 2019 and 2020 are computed and shown separately in Fig. 2. One can easily observe that an increase in the number occurs after February 2020, probably due to the outbreak of the pandemic in NYC, which prompted some

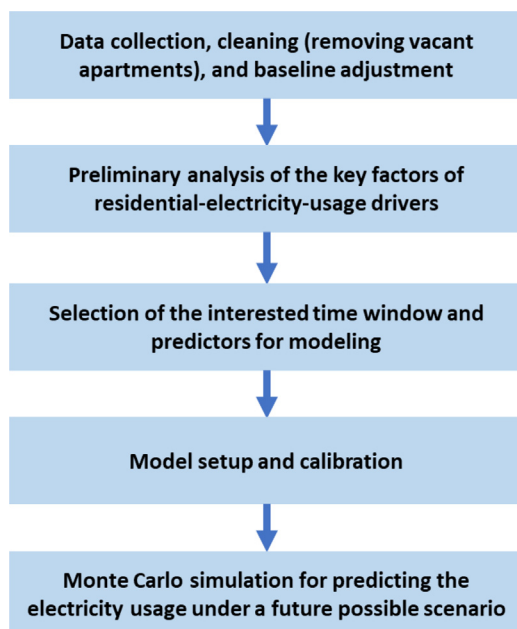


Fig. 1. Flowchart of all the data processing and methodologies.

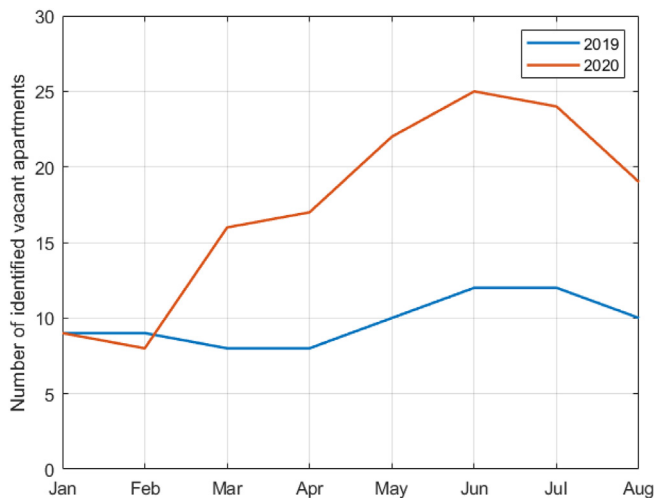


Fig. 2. Numbers of identified vacant apartments of each month from Jan to Aug in 2019 and 2020.

residents to move out of their apartments temporarily. In this study, to maximize consistency between the 2019 and 2020 datasets (i.e., same apartments in both years), an apartment was removed from both datasets whether it was deemed vacant in 2019, in 2020, or both. Based on this approach, 84 vacant apartments were removed from the 2019 and 2020 data, leaving 306 apartments for all subsequent analyses.

2.1.3. Electricity consumption baseline adjustment for 2020 data

Electricity consumption in the 306 apartments might have changed from 2019 to 2020 for reasons other than the pandemic. This effect was accounted for via a baseline adjustment. Since the residents' work and study patterns started changing in NYC only from March 2020 onwards, the electricity data from Jan. 1 – Feb. 29, 2020 was not yet impacted by the pandemic. Therefore, this period was chosen as a benchmark to reveal any difference in electricity-use baselines between 2019 and 2020. The average usage in Jan. – Feb. 2020 was 2.0% lower than during Jan. – Feb. 2019. One possible reason could be the adoption of more energy-efficient devices such as LED light bulbs or electronics with lower stand-by power consumption [25]. In order to further confirm that the difference of the electricity-use baseline between 2019 and 2020 is not due to weather conditions instead, especially to the temperature which is the key factor impacting electricity demand [29], we investigated the average monthly electricity consumption and the average daily wet-bulb temperature (discussed in section 2.3.1) in Jan. and Feb. of 2018, 2019 and 2020. These are shown in Table 1 for each year. One can observe that although the average temperature in Jan. – Feb. of 2019 is 0.2 °C and 2.4 °C lower than the respective ones in 2018 and 2020, it is the monthly electricity consumption in Jan. – Feb. of 2018 that is the highest (2.2% larger than the one in 2019). This indicates that the weather condition is probably not the key factor leading to the decrease of the electricity-consumption baseline from Jan. and Feb. 2019 to Jan.

Table 1

Monthly electricity consumption (average per apartment) and average daily wet-bulb temperature in Jan. and Feb. of 2018, 2019, and 2020.

Years	January		February	
	Monthly electricity consumption (kWh)	Average daily temperature (°C)	Monthly electricity consumption (kWh)	Average daily temperature (°C)
2018	260.91	-2.1	231.21	3.5
2019	254.30	-2.3	226.92	-0.1
2020	249.65	0.1	221.89	2.5

and Feb. 2020. Therefore, to isolate the difference in electricity use as a result of the pandemic from concurrent efficiency measures, the hour-to-hour electricity consumption data for 2020 (see above) was increased by 2.0%. All subsequent analyses, results, and figures reflect the 2020 data after this adjustment.

2.2. Choice of relevant factors and time-windows of interest

2.2.1. Preliminary analysis of factors driving residential electricity usage patterns

In order to analyze in what time-windows the residential electricity usage has changed most significantly due to the pandemic in 2020, an electricity-diurnal analysis was carried out. For brevity, we henceforth refer to the times before March 21st 2020 as the “pre-stay-at-home” period, and the times after that as the “stay-at-home” period.

First, it can be noted from Fig. 3 (a) that there are shifts in demand during the morning hours on weekdays, as previously described by Meinrenken et al. [15]: Pre-stay-at-home, the early-morning load ramp-up started at about 6.00am and peaked at 8.30am, followed by a decline, with no second ramp-up until the early evening. In contrast, stay-at-home usage exhibited a smoother ramp-up that started between 6.00am and 6.30am, reached the height of the pre-stay-at-home morning demand peak only at 9am, and then continued to increase through the morning and early afternoon [15].

Regarding electricity use, Fig. 3 (a) shows that, overall, 2020 weekday electricity usage of apartments (24 h) shows a more significant increase (7% increase) versus 2019 use than on weekends (4% increase). These increases became more pronounced once advancing into warmer weather in July, where the increase in 24 h weekday-use above 2019 reached 13%, probably due to higher loads from air-conditioners (Fig. 3 (b)).

Studies for commercial buildings in the U.S. have shown that their principal electricity use is mostly concentrated in the work-time period (usually 9am – 5 pm) on weekdays [26]. Focusing on the same time window in the residential sector, when many residents would usually be at work/school or otherwise outside of their homes, the stay-at-home usage increases are even larger than over the 24 h period: Comparing 2020 to 2019 usage during 9am to 5 pm, one can see a 22% increase in average electricity use in early April and an even larger increase of 27% in early July.

Fig. 4 shows the overall trends in the 24-hour-electricity-use and 8-hour-electricity-use (9am–5pm) as percentage increases from 2019 to 2020, over the same period of Jan 1st – Aug 31st. Percentage increases in the hourly peak demand on weekdays between 12 pm and 5 pm are also shown (see rationale in section 2.2.3). It can be observed that the three characteristics, especially the hourly peak demand between 12 pm and 5 pm and the 8-hour electricity use, are correlated with two metrics, i.e., the outdoor wet-bulb temperature and the number of new confirmed Covid-19 cases in every month: During the stay-at-home period, the pandemic led to significant increases in residential electricity use, even when temperatures had not yet reached levels where air conditioning was required. These increases were therefore most likely due to an increased use of

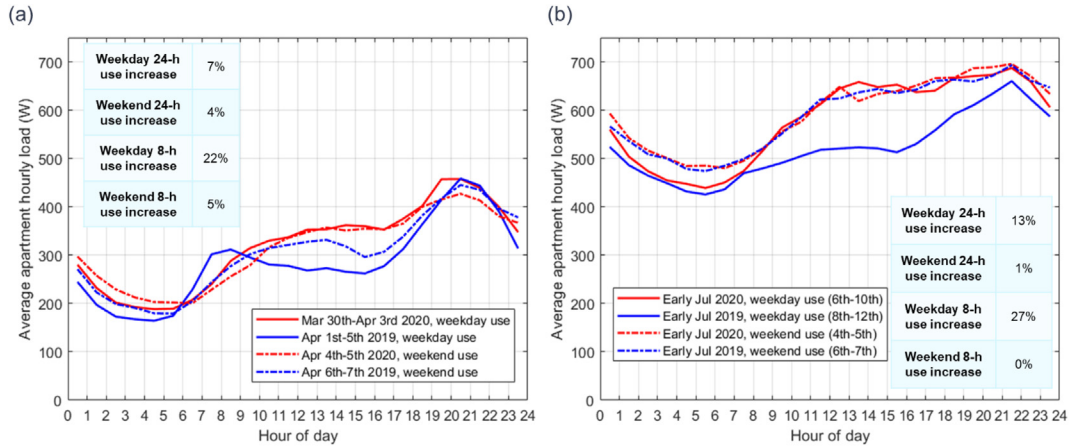


Fig. 3. (a) Stay-at-home and pre-stay-at-home electricity diurnals of one week in early April of 2019 and 2020, respectively. (b) Same for one week in July. Diurnals are shown separately for weekdays and weekends. Data tables provide the comparisons of electricity usage in 2020 versus 2019, namely: 24-hour electricity-use increase of weekdays and weekend, and 8-hour electricity-use increase (9am-5pm) of weekdays and weekend.

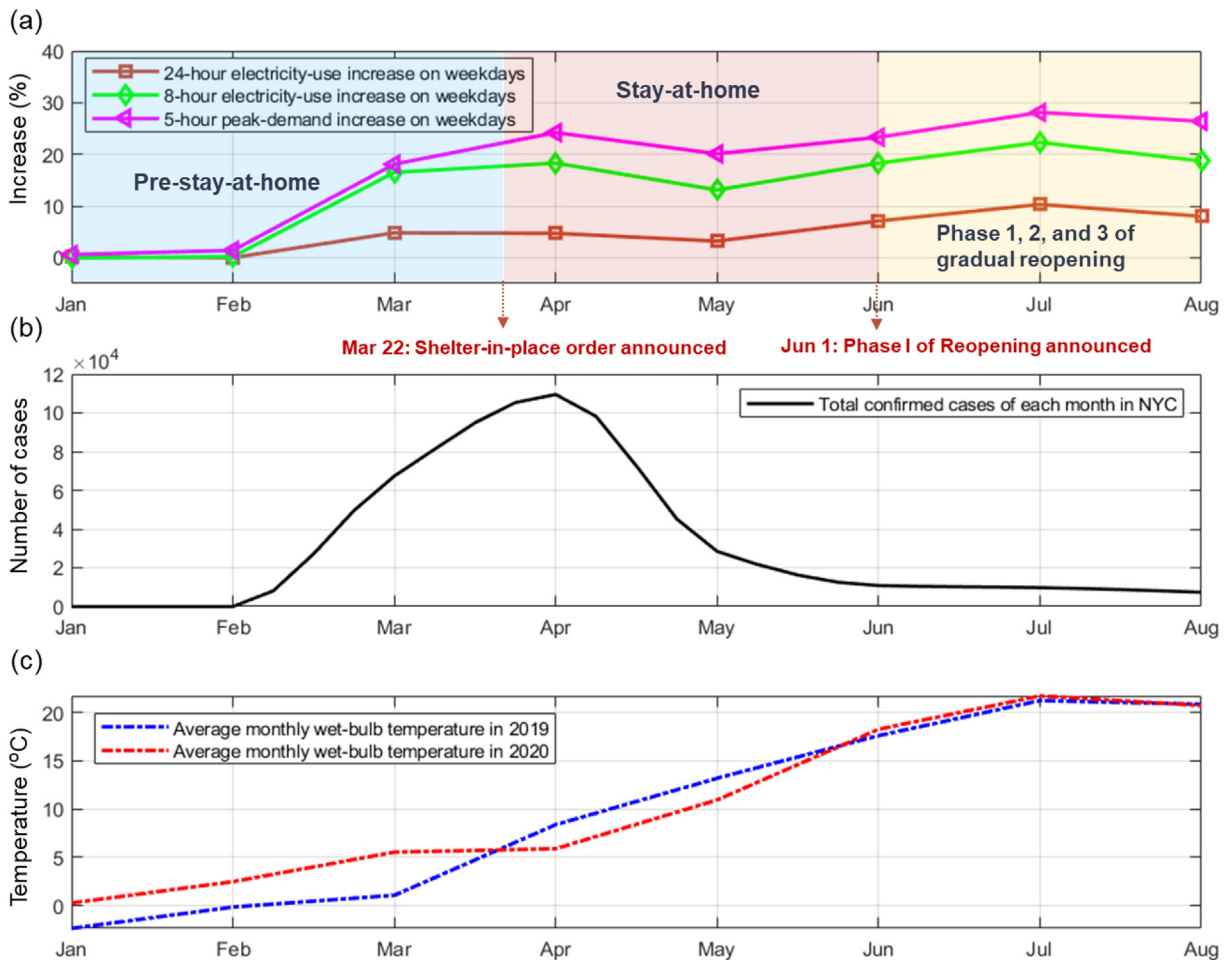


Fig. 4. (a) Increases in 24-hour-use, 8-hour-use, and 5-hour peak-demand (weekdays) between 2019 and 2020, by month. (b) Total monthly new confirmed Covid-19 cases in NYC in 2020, by month. (c) Average monthly wet-bulb temperature in 2019 and 2020, by month. The three areas in (a), denoted by blue, red, and yellow shading, represent the three degrees of government shelter-in-place orders in NYC due to the varying pandemic severity in NYC. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

lights, appliances for food preparation, computers, and entertainment systems because more residents worked/studied from home. Once entering Phase 1 of the gradual reopening, new daily

Covid-19 cases in NYC were declining, and the portion of residents remaining in their homes during the day was likely declining as well [27]. However, due to the higher outdoor

temperatures now requiring increased cooling loads, the 8-hour electricity usage exhibits a notable further increase during the summertime in 2020.

In summary, both the outdoor temperature and Covid-19 cases should be considered when explaining differences in electricity usage between 2019 and 2020.

2.2.2. Context of system-wide electricity use

According to the average weekday load profiles in NYC (NYISO [28], Fig. 5), system-wide demand in Jan. – Aug., 2019 and 2020 (i.e., residential, commercial, and industrial electricity usage combined) ramped up during the morning hours and reached 98% or higher of daily peak levels from 12 pm onwards until well into the afternoon. System-wide demand went down from 2019 to 2020, with the largest reduction (about 700 megawatts or 10%) around 4 pm to 5 pm. In contrast, based on our NYC residential electricity dataset (Fig. 3), there were substantial increases in hourly demand peaks from 2019 to 2020 during the time window of 12 pm – 5 pm (up to 50% on some days; not shown) as well as substantial increases in residential electricity consumption from 2019 to 2020 during the time window of 9am – 5 pm (up to 55%).

2.2.3. Choice and rationale for time windows and electricity metrics of interest

Based on the observations in sections 2.2.1 and 2.2.2, for the remaining analyses, we therefore focus on the following two characteristics of electricity usage, which capture different time windows and different electricity metrics:

(i) Average per-apartment electricity consumption (kWh) cumulatively from 9am to 5 pm on a given weekday, for brevity also referred to in this study as “8-hour-electricity-use”. This was analyzed in order to gauge the electricity usage (and associated costs) that can shift from the commercial sector (such as office buildings and schools) to the residential sector because of “stay-at-home” and/or “work-from-home” guidelines.

(ii) Hourly peak demand (Watt) for an average apartment at any time between 12 pm and 5 pm on a given weekday, defined at 1-hour resolution, for brevity also referred to in this study as “5-hour-peak-demand”. “Peak demand” was defined as the highest of the hourly average load (in Watts) between any two consecutive full hours in the time window of interest. To establish these, first, the hourly average Watts between 12 and 1 pm, 1–2 pm, . . . and 4–5 pm on a given day were determined, and then the “5-hour-peak-

demand” on that day was taken to be the maximum of these five, hourly values. The peak demand was analyzed in order to gauge potential stress on local or region-wide grid infrastructure when increased residential demand coincides with (still) high system-wide demand. The peak demand during full or partial stay-at-home orders was further compared to the highest ever hourly residential peak in a no-pandemic condition in 2019. This peak typically occurs in the evenings of hot/humid days. The comparison was carried out in order to gauge whether the increased afternoon peak demand during widespread stay-at-home conditions could lead to black-outs or brown-outs of the local substations and distribution system in predominantly residential regions of a city (because the demand is larger than what the system was designed to handle), even if other areas of the city with higher commercial and industrial usage experience reduced system-wide electricity use (see *Conclusions and Discussion*).

2.3. Model components and calibration

2.3.1. Model inputs and outputs

2.3.1.1. Wet-bulb temperature. Previous work on electricity usage forecasting for households has shown that outside temperature is the strongest factor driving electricity demand in the residential sector, if the cooling systems of the targeted households, as in our case study, comprise electrical air conditioners [29]. Regarding the specific type of temperature, previous work has shown that wet-bulb temperature is a better predictor for residential cooling loads than dry-bulb temperature, as the former captures both temperature and humidity [30]. Therefore, we chose wet-bulb temperature (henceforth *WBT*) as our first independent factor for modeling. *WBT* was available at approximately hourly time resolution, typically with a data point available near the full hour (National Oceanic and Atmospheric Association (NOAA); Central Part weather station in NYC) [31]). For simplicity, the temperature reported at e.g., 8.51 am was subsequently used as the temperature for 9.00 am, 2.51 pm for 3.00 pm, and so forth. In the models, as the predictor for the 9am–5 pm electricity use, the 9am–5 pm average *WBT* ($WBT_{9am-5pm}$) was then determined by averaging the 9 *WBT*s from 9 am to 5 pm. Similarly, the predictor for the 12 pm–5 pm peak demand is the average of the 6 temperatures from 12 pm to 5 pm ($WBT_{12pm-5pm}$).

2.3.1.2. Daily new confirmed Covid-19 cases. Next, a 7-day moving-average of daily new confirmed Covid-19 cases (henceforth $DCC_{Avg7Day}$) in NYC was used as another independent factor in the regression models. Specifically, for any day for which the electricity consumption was modeled, the factor was the average of the $DCC_{Avg7Day}$ of the previous 7 days, which was obtained from the NYC Department of Health and Mental Hygiene [32]. The factor, which in NYC was commonly reported in the news, can be interpreted as a proxy for the severity of the pandemic, and the daily confirmed cases are important references for government agencies to propose specific policies including banning of mass gatherings, quarantines, and population-wide stay-at-home orders [33]. A study conducted by Gao et al. [34] showed that due to the implementation of the stay-at-home orders after the pandemic, increased rates of the Covid-19 confirmed cases and time spent at home show a positive correlation of 0.526 (95% confidence interval: 0.293–0.700). Their data was collected from 45 million anonymous mobile phones in 50 states of the U.S. between Mar. 11 and Apr. 10, 2020. In addition, a study by Sen et al. [35] assessed the association between the statewide “stay-at-home” orders and Covid-19 hospitalizations in four states in the U.S. Their results show that the cumulative hospitalizations up to and including the median effective date of a stay-at-home order closely fit an exponential function (0.97–0.99 R^2) better than a linear one

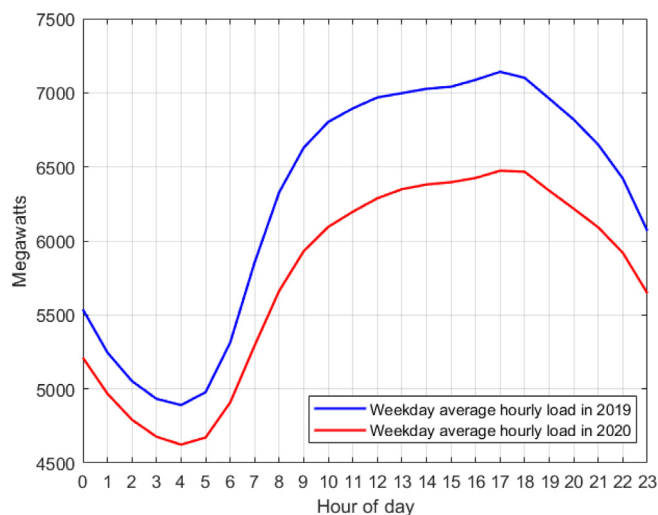


Fig. 5. Weekday average hourly load (residential, commercial, and industrial; MW) in NYC from Jan. to Aug. in 2019 and 2020 (NYISO).

(0.69–0.80 R²). Shelter-in-place restrictions can result in increased electricity demand at home, due to more cooking (e.g., microwave) working (computers, lights, air-conditioners, etc.), and entertainment (electronics) by residents. Therefore, the daily confirmed cases can be another key factor impacting electricity demand, as it reflects the probability that residents stay at home vs. not (whether out of caution, in response to city-wide guidelines of the “stay-at-home” orders, or both).

2.3.1.3. Separation of parameter space into high and low temperatures. As described in Section 2.1.1, most apartments in our dataset consume more electricity in the summer when air conditioners are used, whereas consumption during winter depends only marginally on the weather. Therefore, we developed separate models for times when cooling is not required and times when cooling is required. The threshold temperature (dry-bulb) for requiring cooling versus not in NYC is commonly 18.3 °C [36,37]. Since *WBT* was chosen as the predictor in this study, we converted 18.3 °C_{dry-bulb} into its approximate respective *WBT* by using the average of all hourly NOAA-reported *WBT*s measured at times of 18.25–18.34 °C_{dry-bulb} in 2019 and 2020. The thus obtained *WBT* threshold (*WBT_{thresh}*) is 13.8 °C.

2.3.2. Model structure and rationale

Separate models were devised to forecast the 8-hour-electricity-use on one hand and the 5-hour-peak-demand on the other. Each model was further differentiated into 2 sub-models, one for cooling times and one for non-cooling times, thus yielding a total of 4 separate models.

Inputs, logical flow, and outputs of the 4 models are summarized in Fig. 6. Each of the four models follows two basic steps to predict the electricity usage characteristics during stay-at-home behavior. In step one, the electricity usage data observed in 2019 is used in order to model the two usage characteristics as a function of *WBT* only. This reflects the usage characteristics under a non stay-at-home scenario. In step two, the difference between the observed 2020 usage (observed at a certain *WBT* and *DCC_{Avg7Day}*) and the non-pandemic 2019 usage (modeled for the

same *WBT*) is used to devise models to predict the stay-at-home-related increase in electricity usage. As will be shown in sections 2.3.2 and 2.3.3, this increase is a function of *DCC_{Avg7Day}*, and, for outdoor temperatures where cooling is required, also a function of the average *WBT* observed in the daily particular time window for which the electricity usage is predicted. The reason for the separate step 1, i.e., for modeling the 2019 data separately rather than simply using the observed 2019 data, is to maximize the use of the available 2020 data to calibrate the models: By using a model for the 2019 electricity usage characteristics, each observed 2020 usage can be compared to the usage that would be expected without stay-at-home conditions but at the exact same average *WBT* in the respective time window (9am-5 pm or 12 pm-5 pm).

It should be noted that in this study, instead of more complex methods such as neural networks, we opted for traditional multi-factor regression models in order to retain transparency of the mathematical relationships. This approach was chosen in particular to retain robustness of the models when predicting electricity usage for parameter ranges of *DCC_{Avg7Day}* and *WBT* that had not been observed (see section 2.4). Similar to e.g., the method implemented by Bianco et al. [38], the optimization of coefficients was carried out stepwise: The coefficients for modeling 2019 data and for the single factor transformations were optimized first, and these coefficients were then held constant in the subsequent 2-factor linear regressions. The step-wise optimization of coefficients minimizes the degrees of freedom in each modeling step and thus further reduces any risk of overfitting. Coefficients in all regression models were chosen to minimize the mean squared errors between the observed and the modeled electricity data.

In keeping with this 2-step process, the sections below are therefore organized as follows: Section 2.3.3 illustrates the broad relationship between *WBT* and the 8-hour-electricity-use, including the impact of stay-at-home conditions from 2019 to 2020. Section 2.3.4 illustrates the same for the 5-hour-peak-demand. Based on these impacts, sections 2.3.5 and 2.3.6 then illustrate the details of the modeling process for the 8-hour-electricity-use and 5-hour-peak-demand, by employing single-factor analysis, log and exponential factor transformations, and multi-factor linear regression.

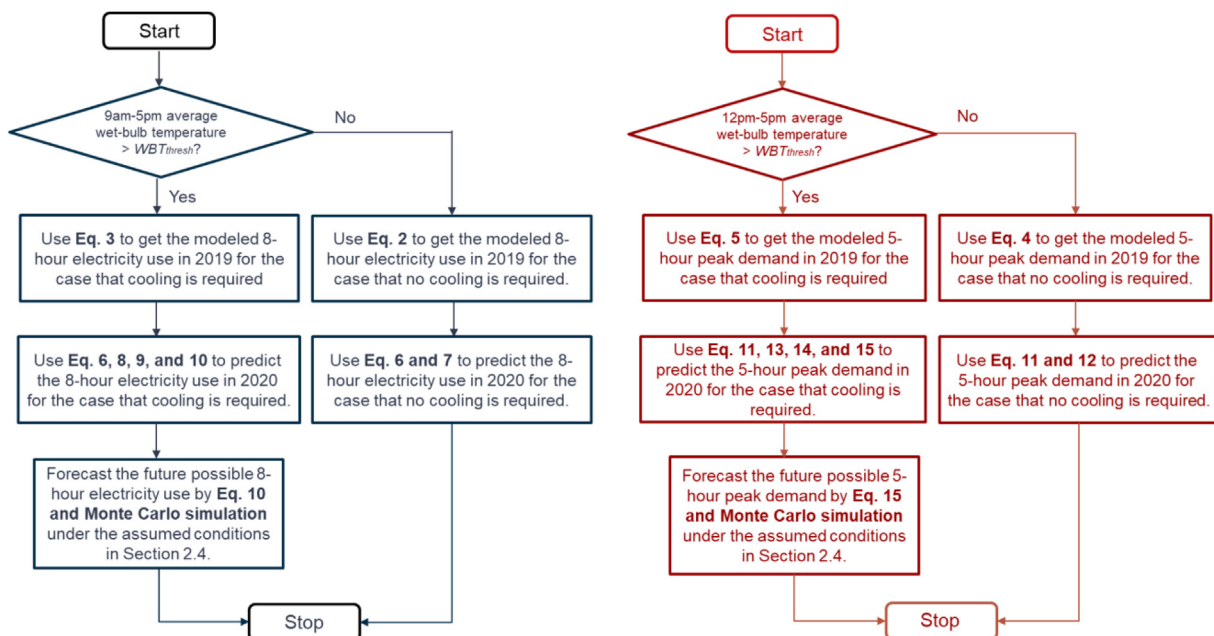


Fig. 6. Flowcharts of the forecast models for weekday 8-hour-electricity-use (in kWh per average, occupied apartment; left) and 5-hour-peak-demand (in Watt per average, occupied apartment; right).

Section 2.4 provides the equations for combining these models to forecast the 8-hour-electricity-use and 5-hour-peak-demand under a potential future scenario of widespread stay-at-home conditions that also coincide with warm weather. Section 5 provides the evaluation metric for the models' prediction accuracy.

2.3.3. Modeling 2019 usage: 9am-5 pm (8-hour) weekday electricity-use

As seen in Fig. 7 (a), when cooling is not required, WBT only marginally impacts the 8-hour-electricity-use, and a straight line with a negative slope thus provides a robust fit. This simple linear regression follows the approach by Shin et al. [38], except that a downward slope was added to account for the observed, weak downward trend, which is expected because of the occasional use of personal electric space heaters or heating blankets at colder temperatures:

$$\hat{y}_{use2019}^{(i)} = m_1 WBT_{9am-5pm} + m_2 \tag{2}$$

where $\hat{y}_{use2019}^{(i)}$ is the modeled 8-hour-electricity-use in 2019, and $WBT_{9am-5pm}$ is as above. m_1 and m_2 are the two coefficients of the linear regression. The superscript "(i)" represents the case where cooling is not required (i.e., $WBT_{9am-5pm}$ smaller than WBT_{thresh} (13.8 °C)).

For times when cooling is required, as shown in Fig. 7 (b), one choice is to model the 8-hour-electricity-use variation with WBT

to be approximately exponential. There are other choices as well, for example one could model the behavior between 13.8 °C and ~17 °C as nearly constant followed by a linear increase as WBT increases. We chose an exponential relationship as it provided the best R² (compared to using constants and linear regressions, or their combinations) in the temperature range of interest. As introduced in the dataset overview (Section 2.1.1), heating in most apartments does not contribute to the apartments' electricity usage (except for heating blankets or space heaters) but air conditioning does. Therefore, the electricity consumption does not vary significantly with the increase of temperature at a lower temperature range (no cooling required) and, for higher temperatures, implementing an exponential relationship provided a good fit. This fit is defined as follows:

$$\hat{y}_{use2019}^{(ii)} = m_3 e^{m_4 WBT_{9am-5pm}} \tag{3}$$

where $\hat{y}_{use2019}^{(ii)}$ is the predicted 8-hour-electricity-use in 2019, and $WBT_{9am-5pm}$ is as above. m_3 and m_4 are the two coefficients of the exponential regression. The superscript "(ii)" represents the case where cooling is required (i.e., $WBT_{9am-5pm}$ larger than WBT_{thresh} (13.8 °C)).

As seen in Fig. 7 (c) and (d), the 8-hour-electricity-use in 2020, both for when cooling is required and not, shows considerable increases vs. 2019, consistent with the diurnal analysis discussed in Section 2.2. Specifically, we can find from Fig. 7 (c) that during

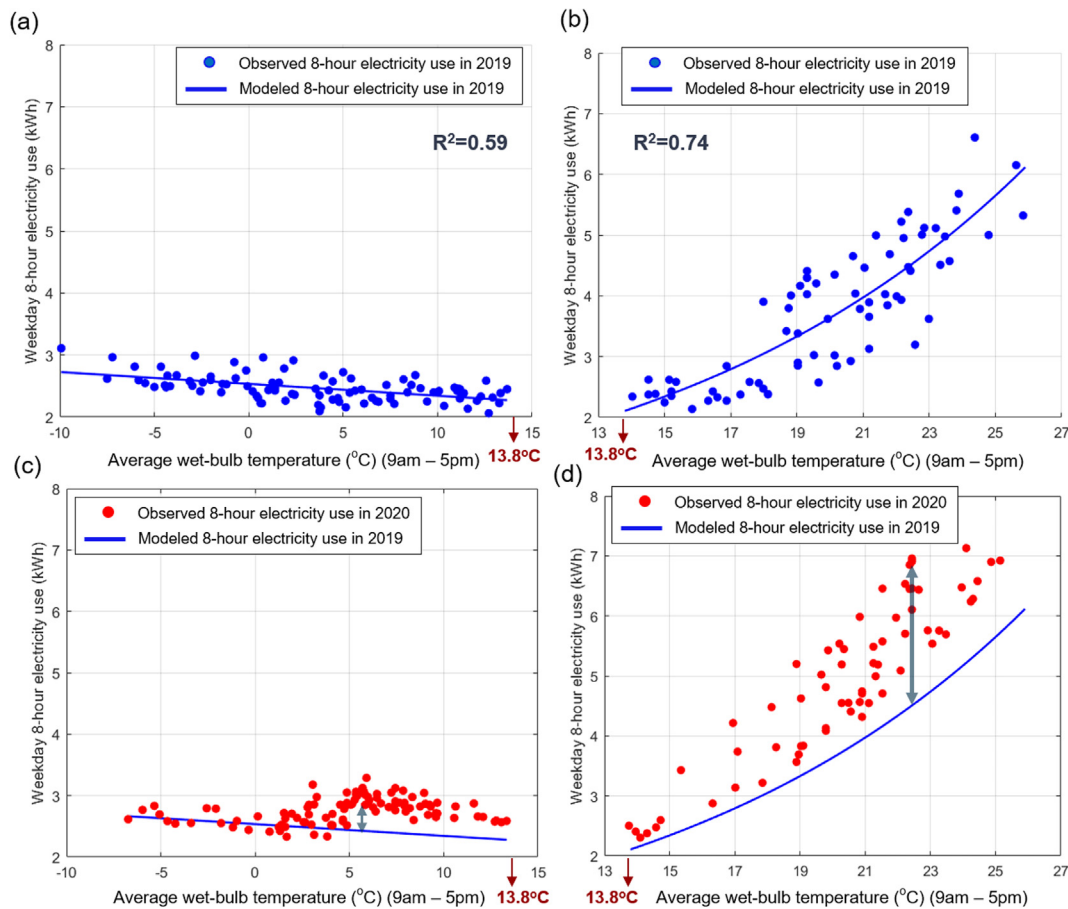


Fig. 7. Weekday 8-hour apartment electricity usage vs. WBT. (a) Observed 2019 data vs. $WBT_{9am-5pm}$ when $WBT_{9am-5pm}$ smaller than WBT_{thresh} (i.e., without cooling). (b) Same as (a), but for $WBT_{9am-5pm}$ larger than WBT_{thresh} (i.e., with cooling). (c) Observed 2020 data ($WBT_{9am-5pm}$ smaller than WBT_{thresh} , i.e., no cooling). (d) Same as (c), but for $WBT_{9am-5pm}$ larger than WBT_{thresh} (i.e., with cooling). The R² in (a) and (b) represent the modeling performance of the intermediate regressions in Eq. (2) and (3), respectively, not however the prediction accuracy of the final model. Black arrows in (c) and (d) represent two examples of the usage increase between the usages observed in 2020 (red markers) and the usages modeled for 2019 at same WBT (blue lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

low-temperature periods (below $\sim 5^\circ\text{C}$), there is no material difference between the 8-hour-electricity-use of the two years. That is consistent with the fact that, in NYC, the COVID-19 pandemic, and thus the associated stay-at-home conditions, only started at the end of winter. In contrast, in warmer weather (above $\sim 5^\circ\text{C}$), there is a difference in the 8-hour-electricity-use of the two years (indicated by black arrows), and this difference rises exponentially for temperatures above WBT_{thresh} (13.8°C). This indicates that, during the summertime, stay-at-home conditions led to more pronounced increases in the 8-hour-electricity-use in 2020 due to the dominant impact of the higher temperature, even though $DCC_{Avg7Day}$ had decreased at that time and, following gradual relaxing of stay-at-home guidelines, presumably fewer residents were “sheltering-in-place”. Again, this is consistent with the result shown in Section 2.2 (Fig. 4).

2.3.4. Modeling 2019 usage: 12 pm–5 pm (5-hour) weekday demand peaks

A linear regression and an exponential regression, both based on WBT , were set up to model the 5-hour-peak-demand in 2019 (Fig. 8), as follows:

$$\hat{y}_{peak2019}^{(i)} = k_1 WBT_{12pm-5pm} + k_2 \quad (4)$$

$$\hat{y}_{peak2019}^{(ii)} = k_3 e^{k_4 WBT_{12pm-5pm}} \quad (5)$$

where $WBT_{12pm-5pm}$ is as defined above. $\hat{y}_{peak2019}^{(i)or(ii)}$ is the modeled 5-hour-peak-demand. k_1 , k_2 , k_3 and k_4 are the coefficients of the regression. Again, the superscripts “(i)” and “(ii)” denote the two cases of no cooling required and cooling required, respectively. As seen in Fig. 8(d), the 5-hour-peak-demand is even more sensitive

to temperature fluctuations in warmer weather than the 8-hour-electricity-use (Fig. 7(d)), with implications for grid stability (see Conclusions and Discussion).

2.3.5. Predicting increases in usage: 9am–5 pm (8-hour) weekday electricity-use

Next, we carried out a series of single-factor analyses to identify a robust model for the increase in weekday 8-hour-electricity-use (9am – 5 pm) from 2019 to 2020 as a function of $WBT_{9am-5pm}$ and $DCC_{Avg7Day}$. As motivated in section 2.3.2, the increase was defined as follows:

$$y_{useinc}^{(i)} = y_{use2020}^{(i)} - \hat{y}_{use2019}^{(i)}$$

$$y_{useinc}^{(ii)} = y_{use2020}^{(ii)} - \hat{y}_{use2019}^{(ii)} \quad (6)$$

where $y_{useinc}^{(i)or(ii)}$ denotes the increases of the 8-hour-electricity-use from 2019 to 2020, each determined as the difference between the observed use in 2020 $y_{use2020}^{(i)or(ii)}$ and the modeled use in 2019 $\hat{y}_{use2019}^{(i)or(ii)}$ (modeled for $WBT_{9am-5pm}$ observed in 2020; see section 2.3.2). The superscripts “(i)” or “(ii)” denote the two cases of no cooling required ($N = 107$ observations) or cooling required ($N = 67$ observations), respectively.

2.3.5.1. Use-increase when cooling is not required. Through the single-factor analysis shown in Fig. 9 (a), one can find that the increase in 8-hour-electricity-use is logarithmically impacted by $DCC_{Avg7Day}$. As seen in Fig. 8. (b), the increase resembles a step function as WBT rises. However, the step is most likely not principally caused by the WBT change but rather by stay-at-home conditions: Fig. 7 (c) shows that the average increase that corresponds to lower

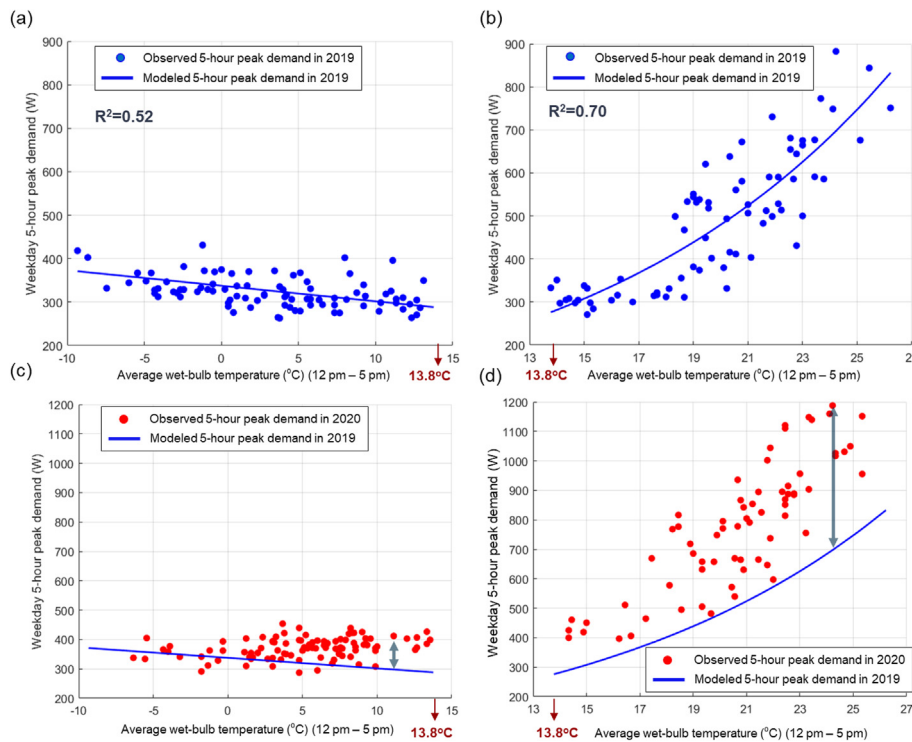


Fig. 8. Weekday 5-hour apartment peak demand vs. WBT . (a) Observed 2019 data vs. $WBT_{12pm-5pm}$ when $WBT_{12pm-5pm}$ smaller than WBT_{thresh} (i.e., without cooling). (b) Same as (a), but for $WBT_{12pm-5pm}$ larger than WBT_{thresh} (i.e., with cooling). (c) Observed 2020 data ($WBT_{12pm-5pm}$ smaller than WBT_{thresh} , i.e., no cooling). (d) Same as (c), but for $WBT_{12pm-5pm}$ larger than WBT_{thresh} (i.e., with cooling). The R^2 in (a) and (b) represent the modeling performance of the intermediate regressions in Eq. (4) and (5), respectively, not however the prediction accuracy of the final model. Black arrows in (c) and (d) represent two examples of the increase between usage observed in 2020 (red markers) and the usage modeled for 2019 at same WBT (blue lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

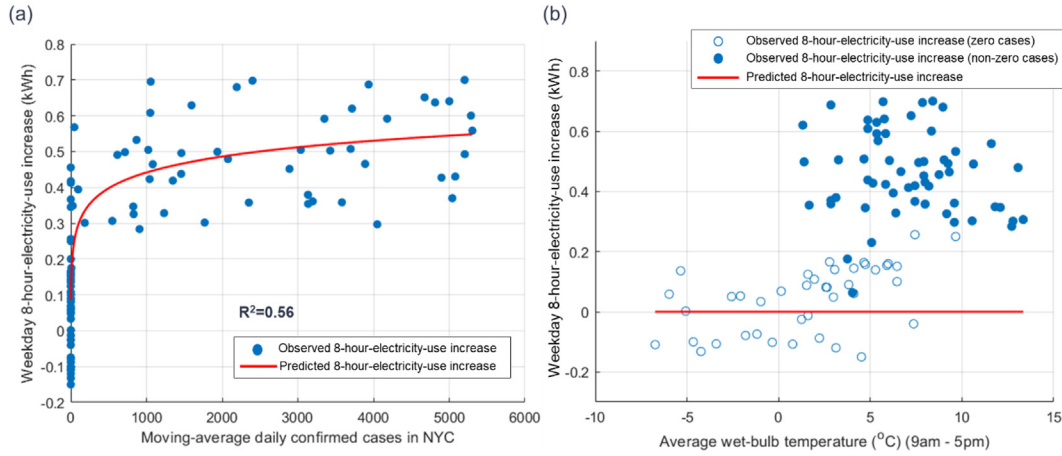


Fig. 9. (a) Increase in weekday 8-hour-electricity-use (9 am – 5 pm) vs. $DCC_{Avg7Day}$ in NYC. (b) Same vs. $WBT_{9am-5pm}$. All data points in (a) and (b) are for times when cooling is not required. The red line in (a) shows the increase in weekday 8-hour-electricity-use as predicted by the regression in Eq. (7a) and the R^2 in (a) represents the evaluation result of the intermediate regression in Eq. (7a), not however the prediction accuracy of the final model 1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$WBTs$ (around $-6.7\text{ }^\circ\text{C} - 4.5\text{ }^\circ\text{C}$) is zero (open blue circles in Fig. 9 (b)). These lower $WBTs$ correspond to the period pre-stay-at-home (before the pandemic) from January to February 2020. When the WBT reaches about $5\text{ }^\circ\text{C}$, the increase in 8-hour-electricity-use is higher (solid blue circles in Fig. 9 (b)), but there are no additional noticeable trends as a function of further increasing WBT . Therefore, we set the dependence of the increase in 8-hour-electricity-use on WBT to zero. For temperatures when cooling was not required, the final regression model was thus defined as follows:

Model 1:

$$\text{Model 1 : } \begin{cases} \hat{y}_{useinc}^{(i)} = \beta_{1.1} \ln(DCC_{Avg7Day} + \beta_{1.2}) & (7a) \\ \hat{y}_{use2020}^{(i)} = \hat{y}_{use2019}^{(i)} + \hat{y}_{useinc}^{(i)} & (7b) \end{cases}$$

where $\hat{y}_{useinc}^{(i)}$ denotes the predicted increase in the 8-hour-electricity-use, and $\hat{y}_{use2020}^{(i)}$ denotes the predicted 8-hour-electricity-use in 2020. $\beta_{1.1}$ and $\beta_{1.2}$ are the two coefficients of the regression. The corresponding statistical metrics and modeling performance are shown in Table 2 and 6, respectively.

2.3.5.2. Use-increase when cooling is required. We first analyzed the relationship between the 8-hour-electricity-use-increase and $DCC_{Avg7Day}$. As shown in Fig. 10 (a), the data again shows a roughly logarithmic trend. Therefore, to maximize the forecasting accuracy of the subsequent regression model, a logarithmic transformation for the $DCC_{Avg7Day}$ was implemented, as follows:

$$DCC_{Avg7Day}^{log} = \max(a_1 \ln(DCC_{Avg7Day}) + a_2, 0) \quad (8)$$

where $DCC_{Avg7Day}$ as above and $DCC_{Avg7Day}^{log}$ denotes its transformation to be used in the subsequent regression model. a_1 and a_2 are the two coefficients. The maximum operator in Eq. (8) sets a zero floor to avoid negative predicted values for electricity usage.

Table 2

Coefficients for Model 1 (prediction of the 8-hour-electricity-use when cooling is not required). 95% confidence intervals of the coefficients are reported in parentheses. N denotes the number of data points in the regressions.

	m_1	m_2	$\beta_{1.1}$	$\beta_{1.2}$
Results	-0.019 (-0.022, -0.016)	2.535 (2.513, 2.557)	0.0641 (0.059, 0.069)	3.828 (1.409, 6.248)
P	4.15e-08	2.36e-10	2.21e-4	7.56e-8
N	107			
Used in Eq.	(2), (6), (7)			

As seen in Fig. 10 (a), the employed logarithmic transformation does not match data observations ideally, for the following reason: By summer time 2020, $DCC_{Avg7Day}$ in NYC had decreased substantially. This led to the fact that at high-temperatures, when the 8-hour-electricity-use is largely affected by cooling as displayed by the data highlighted by the black dashed circle in Fig. 10 (a), the observations at high temperatures are not actually at times of high $DCC_{Avg7Day}$. However, when $DCC_{Avg7Day}$ were higher earlier that year, as represented by the data points highlighted by the black solid circle in Fig. 10 (a), temperatures were not yet that hot and the corresponding 8-hour-electricity-use thus had not reached its maximum possible values. This re-confirms our observation in section 2.2 that the final regression model for increases in electricity use during widespread stay-at-home conditions must consider both $DCC_{Avg7Day}$ and WBT .

As for the relationship between increases in electricity usage and WBT , Fig. 9 (b) shows an approximately exponential relationship. We therefore devised an exponential transformation for WBT , as follows:

$$WBT_{9am-5pm}^{exp} = b_1 e^{b_2 WBT_{9am-5pm}} \quad (9)$$

where $WBT_{9am-5pm}$ in 2020 is as above, and $WBT_{9am-5pm}^{exp}$ is its exponential transformation to be used in the subsequent linear regression. b_1 and b_2 are the two coefficients. The two transformed variables $DCC_{Avg7Day}^{log}$ and $WBT_{9am-5pm}^{exp}$ were then used as the two independent variables in a two-factor linear regression model for predicting the 8-hour-use-increase when cooling is required, as follows:

Model 2:

$$\text{Model 2 : } \begin{cases} \hat{y}_{useinc}^{(ii)} = \beta_{2.1} + \beta_{2.2} DCC_{Avg7Day}^{log} + \beta_{2.3} WBT_{9am-5pm}^{exp} & (10a) \\ \hat{y}_{use2020}^{(ii)} = \hat{y}_{use2019}^{(ii)} + \hat{y}_{useinc}^{(ii)} & (10b) \end{cases}$$

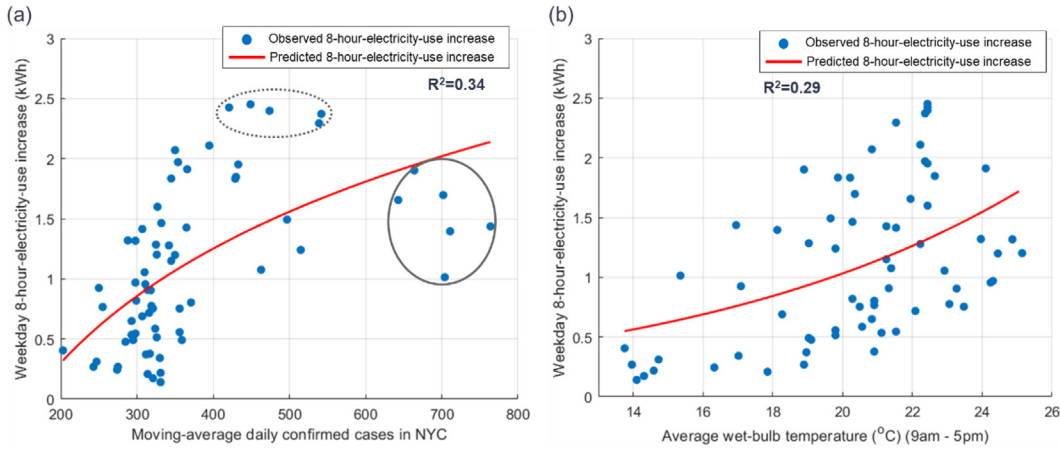


Fig. 10. (a) Increase in weekday 8-hour-electricity-use (9am – 5 pm) vs. $DCC_{Avg7Day}$. (b) Same vs. $WBT_{9am-5pm}$. All data points are for times when cooling is required during Jan – Aug. The data points in the dashed black circle represent the weekdays with relatively high WBT (about 24 °C) but relatively low daily Covid-19 case numbers. The data points in the solid black circle represent weekdays with relatively low WBT (about 20 °C) but relatively high daily case numbers. The red line in (a) [(b)] shows the prediction of a single factor model using the transformed $DCC_{Avg7Day}$ [$WBT_{9am-5pm}$]. The R^2 in (a) [(b)] corresponds to the evaluation result of the intermediate single-factor regression using the transformed $DCC_{Avg7Day}$ [$WBT_{9am-5pm}$], not however the prediction accuracy of the final model 2. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

where $\hat{y}_{useinc}^{(ii)}$ denotes the predicted increase in 8-hour-electricity-use, and $\hat{y}_{use2020}^{(ii)}$ denotes the predicted 8-hour-electricity-use in 2020. $DCC_{Avg7Day}^{log}$ and $WBT_{9am-5pm}^{exp}$ are as defined above, and $\beta_{2,1}$, $\beta_{2,2}$, and $\beta_{2,3}$ are the three coefficients of the 2-factor linear regression model, whose statistical metrics and modeling performance are shown in Table 3 and 6, respectively.

2.3.6. Predicting increases in usage: 12 pm-5 pm (5-hour) weekday peak demands

Next, we used similar methods to analyze and forecast the weekday 5-hour-peak-demand (12 pm – 5 pm) as a function of the two factors ($WBT_{12pm-5pm}$ and $DCC_{Avg7Day}$). The increase was defined as follows:

$$y_{peakinc}^{(i)} = y_{peak2020}^{(i)} - \hat{y}_{peak2019}^{(i)}$$

$$y_{peakinc}^{(ii)} = y_{peak2020}^{(ii)} - \hat{y}_{peak2019}^{(ii)} \tag{11}$$

where $y_{peakinc}^{(i)or(ii)}$ denotes the increases of the 5-hour-peak-demand from 2019 to 2020, each determined as the difference between the observed peak demand in 2020 $y_{peak2020}^{(i)or(ii)}$ and the modeled peak demand in 2019 $\hat{y}_{peak2019}^{(i)or(ii)}$ (modeled for the respective $WBT_{12pm-5pm}$ observed in 2020; see section 2.3.2). Again, the superscripts “(i)” or “(ii)” represent the two cases of no cooling required (N = 105 observations) and cooling required (N = 69 observations), respectively.

2.3.6.1. Peak-demand-increase when no cooling is required. For $DCC_{Avg7Day}$, Fig. 11 (a) reveals an approximately logarithmic trend,

similar to the one for increases in 8-hour-electricity-use in Fig. 9 (a). The relationship with $WBT_{12pm-5pm}$ shown in Fig. 11 (b) is similar to a step function, as above. Therefore, we chose again to set the dependence of the increases in 5-hour-peak-demand on $WBT_{12pm-5pm}$ to zero. The final model is as follows:

Model 3:

$$\text{Model 3 : } \begin{cases} \hat{y}_{peakinc}^{(i)} = \beta_{3,1} \ln(DCC_{Avg7Day} + \beta_{3,2}) & (12a) \\ \hat{y}_{peak2020}^{(i)} = y_{peak2019}^{(i)} + \hat{y}_{peakinc}^{(i)} & (12b) \end{cases}$$

where $\hat{y}_{peakinc}^{(i)}$ denotes the predicted increase in the 5-hour-peak-demand, and $\hat{y}_{peak2020}^{(i)}$ denotes the predicted 5-hour-peak-demand in 2020. $\beta_{3,1}$ and $\beta_{3,2}$ are the two coefficients of the logarithmic regression model, and $DCC_{Avg7Day}$ is as above. The corresponding statistical metrics and modeling performance are shown in Table 4 and 6, respectively.

2.3.6.2. Peak-demand-increase when cooling is required. The relationships for increases in 5-hour-peak-demand in Fig. 12 are similar to what we described for the increases in 8-hour-electricity-use: (i) When cooling is required, only considering $DCC_{Avg7Day}$ is not sufficient to predict the increases. Instead, the impact of $WBT_{12pm-5pm}$ must be considered as well; (ii) a logarithmic and exponential transformation can be used to maximize the forecasting accuracy of the subsequent linear regression model. The factor transformations were as follows:

$$DCC_{Avg7Day}^{log} = \max(c_1 \ln(DCC_{Avg7Day}) + c_2, 0) \tag{13}$$

$$WBT_{12pm-5pm}^{exp} = d_1 e^{d_2 WBT_{12pm-5pm}} \tag{14}$$

Table 3

Coefficients for Model 2 (prediction of the 8-hour-electricity-use when cooling is required.). 95% confidence intervals of the coefficients are reported in parentheses. N denotes the number of data points in the regressions.

	m_3	m_4	a_1	a_2	b_1	b_2	$\beta_{2,1}$	$\beta_{2,2}$	$\beta_{2,3}$
Results	0.625 (0.447, 0.803)	0.088 (0.075, 0.101)	1.377 (0.911, 1.843)	-6.998 (-9.744, -4.255)	0.137 (0.023, 0.297)	0.101 (0.047, 0.154)	-1.151 (-1.408, -0.883)	0.978 (0.839, 1.117)	1.058 (0.875, 1.241)
P	3.12e-5	4.11e-13	7.26e-5	1.12e-4	8.55e-4	3.24e-8	3.99e-8	8.25e-9	6.14e-9
N	67 (3), (6),								
Used in Eq.	(8), (9), (10)								

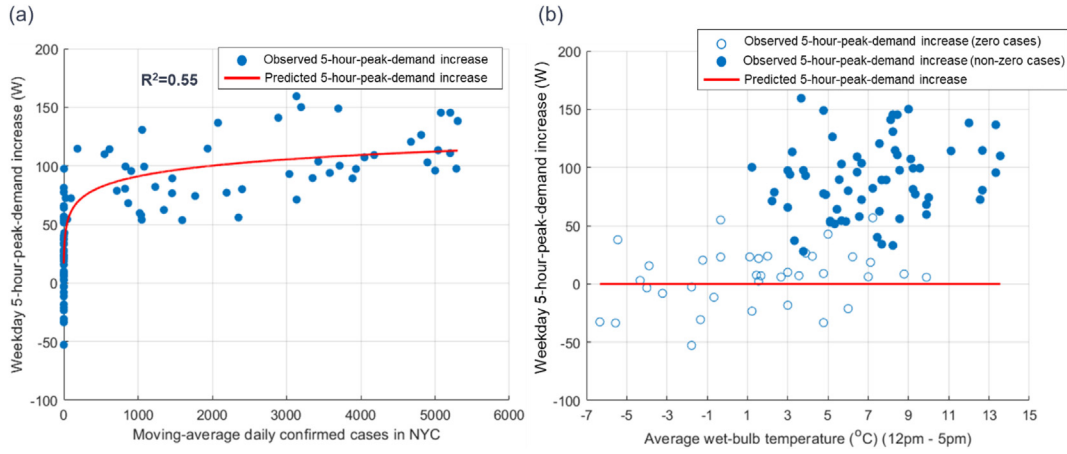


Fig. 11. (a) Increase in weekday 5-hour-peak-demand (12 pm – 5 pm) vs. $CDD_{Avg7Day}$. (b) Same vs. $WBT_{12pm-5pm}$. Data points are for times when cooling is not required. The red line in (a) shows the increase in weekday 5-hour-peak-demand as predicted by the regression in Eq. (12a), and the R^2 in (a) represents the evaluation result of the intermediate regression in Eq. (12a), not however the prediction accuracy of the final model 3. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4

Coefficients for Model 3 (prediction of the 5-hour-peak-demand when cooling is not required.). 95% confidence intervals of the coefficients are reported in parentheses. N denotes the number of data points in the regressions.

	k_1	k_2	$\beta_{3.1}$	$\beta_{3.2}$
Results	-3.578 (-4.168, -2.988)	337.6 (333.5, 341.6)	13.17 (12.11, 14.24)	3.556 (1.282, 5.830)
P	4.88e-6	2.71e-7	3.12e-3	4.11e-7
N	105			
Used in Eq.	(4), (11), (12)			

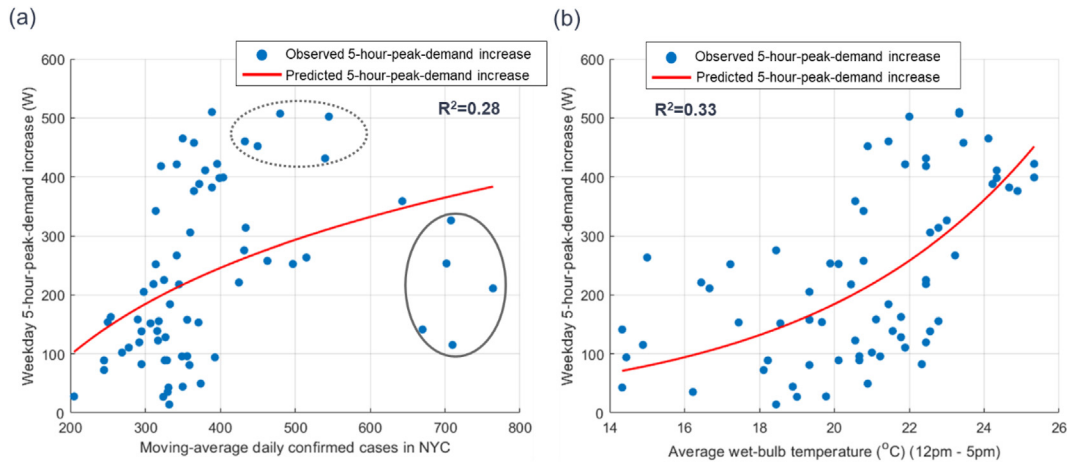


Fig. 12. (a) Increase in weekday 5-hour-peak-demand (12 pm – 5 pm) vs. $CDD_{Avg7Day}$. (b) Same vs. $WBT_{12pm-5pm}$. Data points are for times when cooling is required. The data points in the black dashed circle represent weekdays with relatively high WBT (approximately 24 °C) and relatively low daily case numbers. The datapoints in the black solid circle represent weekdays with relatively low WBT (about 20 °C) but relatively high daily case numbers. The red line in (a) [(b)] shows the prediction of a single factor model using the transformed $DCC_{Avg7Day} [WBT_{12pm-5pm}]$. The R^2 in (a) [(b)] represents the evaluation result of the intermediate regression using the transformed $DCC_{Avg7Day} [WBT_{9am-5pm}]$, not however the prediction accuracy of the final model 4. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

where $DCC_{Avg7Day}$, $DCC_{Avg7Day}^{log}$, $WBT_{12pm-5pm}$ and $WBT_{12pm-5pm}^{exp}$ are as defined above. c_1 , c_2 , d_1 , and d_2 are the coefficients of the log and exponential transformations. The maximum operator in Eq. (13) sets a zero floor for the transformation so that the subsequent regression model does not yield negative predicted values.

Next, the two transformed variables $DCC_{Avg7Day}^{log}$ and $WBT_{12pm-5pm}^{exp}$ were used as independent variables in a two-factor linear regres-

sion model to forecast the increase in 5-hour-peak-demand, as follows:

Model 4:

$$\text{Model 4: } \begin{cases} \hat{y}_{peakinc}^{(ii)} = \beta_{4.1} + \beta_{4.2} DCC_{Avg7Day}^{log} + \beta_{4.3} WBT_{12pm-5pm}^{exp} & (15a) \\ \hat{y}_{peak2020}^{(ii)} = y_{peak2019}^{(ii)} + \hat{y}_{peakinc}^{(ii)} & (15b) \end{cases}$$

Table 5

Coefficients for Model 4 (prediction of the 5-hour-peak-demand when cooling is required.). 95% confidence intervals of the coefficients are reported in parentheses. N denotes the number of data points in the regressions.

	k_3	k_4	c_1	c_2	d_1	d_2	$\beta_{4,1}$	$\beta_{4,2}$	$\beta_{4,3}$
Results	81.38 (57.86, 104.9)	0.088 (0.075, 0.102)	212.9 (93.94, 331.8)	-1030 (-1743, -325.6)	6.426 (9.711, 3.451)	0.1678 (0.1123, 0.2233)	-248.9 (-305.1, -192.7)	1.0963 (0.8973, 1.2953)	0.9969 (1.1196, 0.8742)
P	6.72e-5	1.19e-12	9.61e-4	4.47e-5	3.75e-3	7.22e-4	3.58e-5	6.64e-7	1.77e-11
N	69								
Used in Eq.	(5), (11), (13), (14), (15)								

Table 6

Model accuracy determined from the observed and predicted 8-hour-electricity-use and 5-hour-peak-demand in 2020, as shown in Eq. (16). N denotes the number of data points for each R^2 statistic.

	Model 1: 8-hour-electricity-use without cooling	Model 2: 8-hour-electricity-use with cooling	Model 3: 5-hour-peak-demand without cooling	Model 4: 5-hour-peak-demand with cooling
R²	0.57	0.84	0.56	0.80
N	107	67	105	69

where, $\hat{y}_{peakinc}^{(ii)}$ denotes the predicted increase in the 5-hour-peak-demand, and $\hat{y}_{peak2020}^{(ii)}$ denotes the predicted 5-hour-peak-demand in 2020. $\beta_{4,1}$, $\beta_{4,2}$, and $\beta_{4,3}$ are the three coefficients of the 2-factor linear regression model, whose statistical metrics and modeling performance are shown in Table 5 and 6, respectively.

2.4. Monte Carlo simulation for possible future scenario of Covid-19 lockdown during warm weather

Our ultimate objective is to predict the possible values of 8-hour-electricity-use and 5-hour-peak-demand in the future, if widespread stay-at-home behavior (due to a worsening pandemic or other reasons) and warm weather were to coincide in NYC. We chose a simulation for this rather than the directly observed data itself, for the following reason: In 2020, NYC did not experience a scenario when high $DCC_{Avg7Day}$ coincided with high WBT . Rather, in April, when the daily case numbers were at their highest, the WBT in NYC was still below the value of WBT_{thresh} , and air conditioning did not yet take place at any material rate. When WBT rose in June and July, the impacts of the pandemic in NYC had eased, and people were no longer required to comply with the stay-at-home guidelines (known as phase one and phase two reopening). There is therefore no directly observable electricity usage data for the putative “worst case” scenario of high $DCC_{Avg7Day}$ (and thus a high portion of residents working/studying from home) combined with high temperatures.

For such a prediction, we extracted those observed values of the two predictors ($DCC_{Avg7Day}$ and WBT) that met the assumed conditions separately and recombined them to create a new dataset via simulation, as follows: We selected only the subset of observed $DCC_{Avg7Day}$ that were greater than half of its Jan.-Dec. 2020 maximum (i.e., greater than 2,651) and only the WBT that were greater than WBT_{thresh} . Then, in a Monte Carlo simulation [39], we randomly sampled 1,000 times from the two extracted subsets to generate a new set of predictive factors consisting of 1,000 pairs of data (each pair with one value for $DCC_{Avg7Day}$ and one value for WBT). The simulated factors were then used in Eq. (10) and Eq. (15) to predict the corresponding 1,000 predictions for 8-hour-electricity-usage (kWh) and the 1,000 predictions for 5-hour-peak-demand (Watt).

2.5. Evaluation metric for prediction accuracy

In order to assess the prediction accuracy of the four models (Model 1 – 4), we compared the predicted values of the 8-hour-

electricity-use and 5-hour-peak-demand to the respective values observed in 2020 using the common R^2 metric (coefficient of determination):

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (16)$$

where y_i is the observed 8-hour-electricity-use or 5-hour-peak-demand in 2020, and \hat{y}_i is the corresponding predicted value, and the corresponding evaluation results of the four models are shown in Table 6. It should be noted that the R^2 results in Figs. 7–12 are the intermediary evaluation results of the single-factor regressions needed in the stepwise modeling process, which do not reflect the accuracies of the four models as evaluated by Eq. (16).

3. Results

3.1. Model calibration and prediction accuracy

As outlined in the section *Data and Methods*, we used a set of four models to predict the two electricity usage characteristics we focused on in this study: (i) The cumulative 9am–5 pm electricity usage (in kWh) for the average apartment on weekdays (henceforth “8-hour-electricity-use”); and (ii) the highest hourly peak demand (in Watt) for the average apartment in the hours of 12 pm–5 pm (henceforth “5-hour-peak-demand”). The two independent variables used in each prediction are (i) the 7-day rolling average of daily confirmed Covid-19 case numbers in NYC prior to the day of observed electricity use ($DCC_{Avg7Day}$); and (ii) the outdoor WBT averaged over the respective time window on the day of observed electricity use, $WBT_{9am-5pm}$ or $WBT_{12pm-5pm}$.

Specifically, Model 2 and Model 1 predict the 8-hour-electricity-use, separately for the two cases when cooling is required or not, respectively. Model 4 and Model 3 predict the 5-hour-peak-demand for the same two cases. The regression coefficients and their 95% confidence intervals for all models are provided in Tables 2–5. Fig. 13 displays the predicted and observed 8-hour-electricity-use and 5-hour-peak-demand in 2020. The prediction accuracies, assessed as R^2 separately for each of the four models, are shown in Table 6.

Overall, the models enable robust predictions of the two electricity usage characteristics in 2020, with R^2 from 0.56 to 0.84 (Table 6). However, differences in accuracy between the 4 models exist. The prediction accuracy is higher at higher temperatures of WBT greater than 13.8 °C (R^2 of 0.84 and 0.80 for Models 2 and

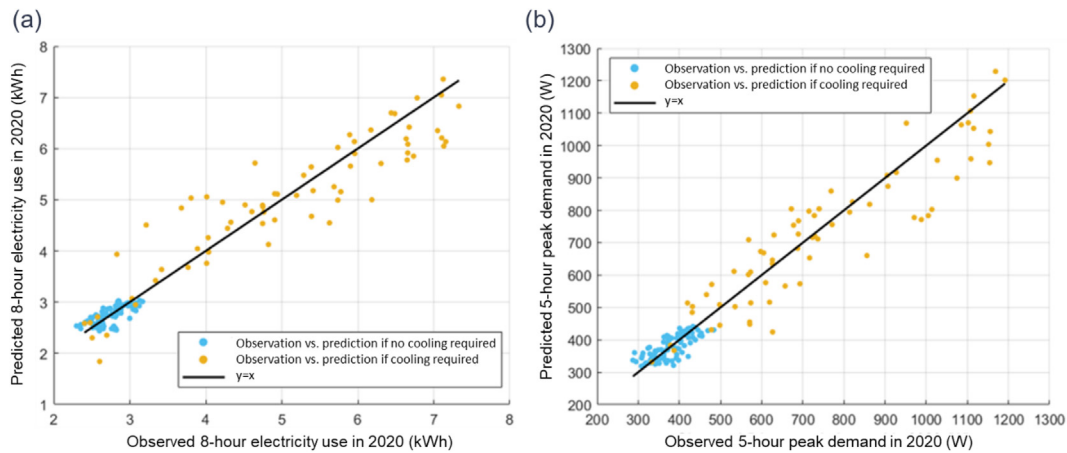


Fig. 13. Model performance. (a) Observed vs. predicted 8-hour-electricity-usage in 2020. (b) Same for 5-hour-peak-demand.

4) than the accuracy at smaller temperatures when no air conditioning is required (R^2 of 0.57 and 0.56 for Models 1 and 3). The more accurate regime is key to determining whether there are potential challenges and risks for electricity grids (see *Conclusions and Discussion*). Another, but less pronounced difference is that, within the high temperature regime, the model to predict the 8-hour-electricity-use ($R^2 = 0.84$ for Model 2) is moderately more accurate than the model for the 5-hour-peak-demand ($R^2 = 0.80$ for Model 4). This is also reflected in the narrower 95% confidence intervals of the respective model coefficients. It is possibly due to more volatile/idiosyncratic cooling loads during the summertime. The main conclusions of this paper (section 3) are reached by Model 2 and Model 4 (i.e., the high-temperature cases where cooling is required), which have promising accuracies with the R^2 of 0.84 and 0.80, respectively.

3.2. Forecasting the two usage characteristics in a hypothetical future scenario

Finally, the models were applied to predict the possible 8-hour-electricity-use and 5-hour-peak-demand in a scenario in which both warm weather and widespread stay-at-home behavior – due to (for example) a renewed, severe level of the pandemic – might coincide in NYC or similar metropolitan areas in the future. As shown in the preliminary analyses in section 2, there are no observed data points for the combined condition, where WBT is larger than WBT_{thresh} (13.8 °C) and $DCC_{Avg7Day}$ is larger than 2,651 (half of the maximum $DCC_{Avg7Day}$ observed in Jan.-Aug. 2020). For such a scenario, a Monte Carlo simulation (section 2.4) was employed to generate new data satisfying the respective conditions. The Monte Carlo simulation provided the following advantage: In the range of interest, neither WBT nor $DCC_{Avg7Day}$ followed a normal distribution (Kolmogorov-Smirnov (K-S) test [40] yields $p < 0.05$). Therefore, a Monte Carlo simulation is likely to generate more realistic electricity data for the two predictors, instead of simply using the averages

and plus/minus ranges of the two predictors in the non-linear regression models.

The corresponding predicted future-possible 8-hour-electricity-use and 5-hour-peak-demands are shown in Table 7. The Monte Carlo simulations show that, for the average, occupied apartment, the 8-hour-electricity-use and 5-hour-peak-demand are likely to be 7.63–8.21 kWh and 1211–1369 Watts, respectively. Note that this is an estimate spanning a range of conditions where WBT is larger than 13.8 °C and $DCC_{Avg7Day}$ is larger than 2,651. As seen in Fig. 8, the highest observed 8-hour-electricity-use and 5-hour-peak-demand in 2019 were 6.61 kWh and 894 Watts respectively. Compared to these observed values, we therefore predict that the 8-hour-electricity-use could be 15%–24% higher than the one under normal circumstances (pre-stay-at-home period), and the 5-hour-peak-demand could be 35% – 53% higher.

Large WBT values could lead to a potential rapid rise of the 5-hour-peak-demand, and we thus further explored the observed and predicted 5-hour-peak-demand under the various $DCC_{Avg7Day}$ scenarios and $WBT_{12pm-5pm}$ observed in Jul.-Aug., the warmest summer months [31] (Fig. 14). One observes that when $WBT_{12pm-5pm}$ is constant, the 5-hour-peak-demand increases logarithmically with the increase in the number of $DCC_{Avg7Day}$, as stated in the established Model 4 (section 2.3.6). Observe that the maximum 5-hour-peak-demand in 2019 was 894 Watts at $WBT_{12pm-5pm}$ of 24.2 °C and 0 cases, and the maximum observed value in 2020 was 1,188 Watts at $WBT_{12pm-5pm}$ of 24.4 °C and $DCC_{Avg7Day}$ of 396. The green band illustrated in Fig. 14 corresponds to the projected peak for the highest-case load band of between 2,651 and 5,301 of $DCC_{Avg7Day}$, if these cases were to occur during the hotter temperatures shown here that require cooling. The projected 5-hour-peak-demand could certainly exceed the maximum observed one in 2019 (894 Watts), and at hotter temperatures could be twice as high as the corresponding 2019 peak, potentially leading to new risks for electrical grids in the future (see *Conclusions and Discussion*). The peak demand for any hour in 2019 was observed to be up to 983 Watts, which, without stay-at-home orders, commonly

Table 7

Predicted results (per average, occupied apartment) of the 8-hour-electricity use and 5-hour-peak-demand, generated using Monte Carlo simulations (section 2.4) with Model 2 and Model 4 respectively, under the hypothetical scenarios covering a range of WBT greater than 13.8 °C and $DCC_{Avg7Day}$ from 2,651 to 5,302. The predicted results show the mean values, with values for ± 1 standard deviation in parentheses.

	Predicted results in 2020	Maximum observed in 2019	Estimated percentage increase ranges
8-hour electricity use (kWh)	7.92 (8.21, 7.63)	6.61	15%–24%
5-hour peak demand (W)	1289 (1369, 1211)	894	35%–53%

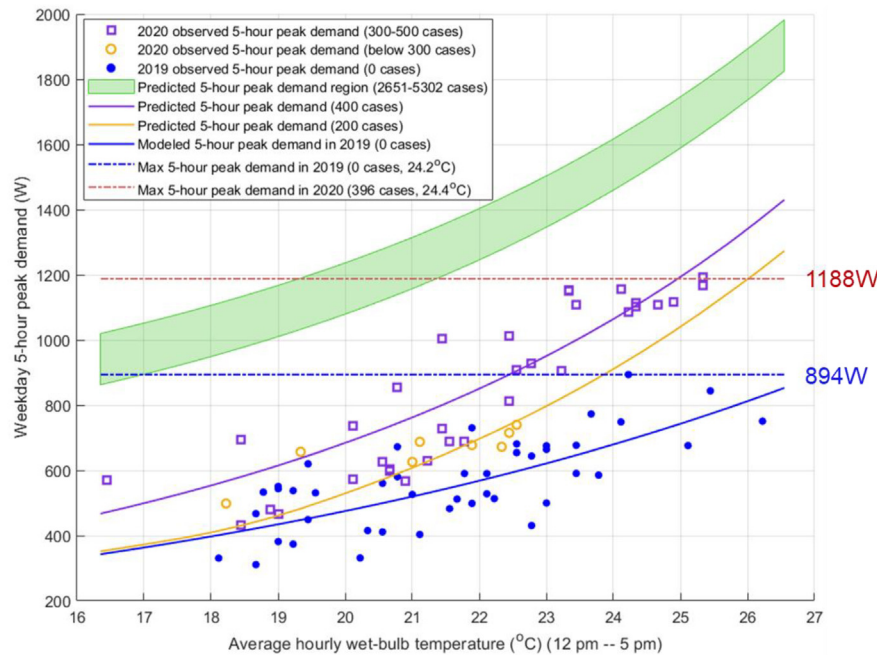


Fig. 14. Observed and predicted weekday 5-hour-peak-demand (12 pm-5 pm, per apartment) in Jul.-Aug. 2019 and 2020 under the scenarios of various $DCC_{Avg7Day}$. The green region represents the prediction under a hypothetical future scenario, in which $DCC_{Avg7Day}$ is larger than 2,651 (larger than half of the Jan.-Aug. 2020 maximum). For comparison, respective 2019 values, as well as the highest-ever observed 5-hour-peak-demand in 2019 and 2020 (894 Watt and 1,188 Watt, respectively) are also shown. All temperatures shown in the figure are *WBTs*, and all the values of COVID-19 cases represent $DCC_{Avg7Day}$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

occurs only in the late evenings over the summer [31]. The projected green band also exceeds this peak by a wide margin.

4. Conclusions and Discussion

Comparing 2020 with 2019 residential electricity consumption data, a case study was conducted to investigate and forecast Covid-19-related increases in residential electricity usage of occupied apartments in NYC, based on a sample of 390 apartments. The apartments are, in size and vintage, representative of NYC residential building stock, and their electricity consumption is consistent with other multi-family settings in the same climate region. We focused on two characteristics of residential electricity usage, (i) the electricity consumption (kWh) of an average apartment on weekdays in the 8 h from 9am to 5 pm (in order to gauge shifts in energy use and commensurate financial burdens from commercial buildings and schools to the residential sector); and (ii) the hourly peak demand (Watt) of an average apartment in the 5 h between 12 pm and 5 pm (in order to gauge possible stress on the electricity grid when this peak either coincides with system-wide loads or becomes larger than what feeders and distribution lines in residential areas were designed to handle).

We identified two factors and built a series of regression models which can predict the above two characteristics with an R^2 of 0.56–0.57 for days when no cooling is required and 0.80–0.84 for warmer days. The two factors are the severity of the pandemic (measured as a 7-day rolling average of daily confirmed Covid-19 cases in NYC) and the outdoor *WBT* (measured as the average *WBT* during the respective 8-hour or 5-hour window). The models indicate that increases in residential electricity usage between 2019 and 2020 were the higher, the more severe the pandemic (which we interpret as a proxy for the portion of residents working and studying from home). And for times when cooling was required, these increases were further modulated by the outdoor temperature. Therefore, in NYC in 2020, usage increases versus

2019 continued to grow more pronounced during the summer months even while lockdown measures were being partially lifted.

In a Monte Carlo simulation, we then used the models to forecast the two usage characteristics for conditions which, fortunately, did not actually occur in 2020, but which could occur in the future in NYC, in similar regions, or indeed in future pandemics or natural catastrophes with comparable stay-at-home guidelines. These conditions were the combination of high outdoor wet bulb temperatures (such that cooling in the apartments is required) coupled with medium to high pandemic severity (and with it a high presumed portion of residents working or studying from home).

We found that under such assumed future conditions, the weekday 8-hour-electricity-use (9am-5 pm) could be 15%–24% higher than the one under normal circumstances (i.e., no stay-at-home behavior), implying a corresponding substantial increase in electricity costs for residents.

We further found that the weekday 5-hour-peak-demand (12 pm-5 pm) could be 35%–53% higher than otherwise. This suggests possible grid stress especially if substantial increases in residential demand coincide with recovery in commercial demand. At high daily case numbers (100% of Jan.-Aug. 2020 maximum) and $WBT_{12pm-5pm}$ above 25 °C, the 5-hour hourly peak demand would be nearly twice that of the maximum 5-hour-peak-demand in 2019 (894 Watts). It would also be much higher than the largest-ever observed peak demand in 2019 (983 Watts). In predominantly residential network areas and feeders with no commensurate load reduction in commercial buildings to offset this increase, such high peaks – nearly twice as high as the prior year peak – could lead to loads that exceed the designed feeder capacity, possibly leading to failure risks of the local substation and distribution infrastructure.

Note that the model predictions are for occupied apartments for the specific climatic settings of NYC. For certain times of the year and/or for geographies where a large fraction of apartments is

unoccupied (because residents choose to temporarily move away from urban areas), the prediction for such specific neighborhoods would have to be reduced accordingly. Residential consumption in aggregate is impacted by what fraction of residents move away and where they move, changes in occupancy patterns of an occupied apartment, and climatic conditions.

It should be noted that the impacts of the pandemic on the way people work may be somewhat irreversible, and could have long-term permanent effects on some members of the workforce in the future [41]. Based on the results of the US remote work survey of PricewaterhouseCoopers, about 72% of workers expressed that they would like to work from home for two days or more even though the pandemic is no longer a concern [42]. Therefore, our results can be instructive for the future of the residential electricity sector if the current work/study from home behavior becomes a permanent “new-normal” lifestyle.

This study can also provide a meaningful reference point for building managers and utilities to improve the balance of supply and demand in future grids, for example through market mechanisms-based demand response [47,48,55], electrical storage (whether onsite [49], distributed [44], or in electric vehicles [46]), combined thermal and electrical storage [50], proactively pairing residents with apartments that match their personal climate preference [51], or, finally, modifying electricity consumption patterns via sending personalized feedback messages to residents [22]. In such contexts, the models introduced in this study could be integrated with emerging smart-grid management techniques, in order to improve the residential electricity forecasting accuracy [48] under stay-at-home guidelines due to a pandemic or other natural catastrophes – or to account for the potential of a “new-normal” lifestyle, even in the absence of a catastrophe. A further extended study could be focused on employing advanced forecasting techniques by applying a more comprehensive dataset to overcome the data limitation discussed in this study, especially once additional electricity data will be available for analysis as the pandemic evolves.

CRediT authorship contribution statement

Lechen Li: Methodology, Visualization. **Christoph J. Meinrenken:** Supervision, Data curation, Investigation. **Vijay Modi:** Supervision, Formal analysis, Methodology. **Patricia J. Culligan:** Funding acquisition, Project administration.

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.

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