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The impact of COVID-19 pandemic on electricity consumption and electricity demand forecasting accuracy: Empirical evidence from the state of Qatar

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ABSTRACT

The goal of this study is to use machine-learning (ML) techniques and empirical big data to examine the influence of the COVID-19 pandemic on electricity usage and electricity demand forecasting accuracy in buildings in Qatar over time and across sectors. Furthermore, this study statistically investigates the relationship between building electricity consumption and the number of daily infected cases in the State of Qatar. The effect of the pandemic on electricity usage was quantified during various periods of the pandemic years. Around 1 million electricity meter readings per year were considered for six different types of building usage between the years 2010 and 2021. The findings indicate that there was a gap between the actual and simulated electricity consumption during the pandemic years. Furthermore, the results show that the fluctuation in electricity consumption was correlated with the number of daily infected cases in some socioeconomic sectors. The changes in the pattern of electricity consumption during the pandemic years (2020–2021) affected the accuracy of the ML models in predicting electricity consumption in 2022.

1. Introduction

Since the global prevalence of the COVID-19 pandemic, societies around the world have witnessed multiple waves of highly infected cases of the disease in different periods. To contain the spread of the disease, governments imposed a variety of measures, such as strict lockdowns, limited travel, social distancing, and limited capacity in workplaces, among others [1–4]. These measures forced societies to change their normal life patterns, and consequently, they have had a direct impact on how, when, and where electricity is consumed, and they have increased/decreased electricity demand and supply [5–9]. Understanding the impact of the pandemic on electricity demand and consumption can therefore provide additional insights into how governments and consumers will respond to future unexpected extreme events.

Although the propagation of the COVID-19 pandemic and the associated societal, governmental, and individual responses have been unprecedented in nature in modern history, the possibility of different natural or human disruptive events, such as extreme weather events fuelled by climate change, recessions, and other pandemics, may greatly affect the electricity sector at the national, regional, and international scales. In addition, understanding the impact of the pandemic on the electricity sector can indicate the significance of governments and policy-making to alter long-standing consumption patterns. The imposed policies and restrictions and individuals' choices around mobility have been suggested to be potential drivers underlying changes in electricity consumption; however, the stringency of these restrictions varied over time between and within countries [2,7,9–11]. At the local scale, other elements, such as the features of the national electricity system and the severity of the propagation of the pandemic, have also been identified as potential contributors to changes in electricity demand and consumption [11,12]. Finally, understanding the impact of different factors and policies on electricity demand and consumption during the course of the pandemic can highlight its relevance and significance as a key economic metric moving forward [13–15].

The State of Qatar is one of the countries that imposed very strict policies to slow the pandemic in the country [6,16]. The national lockdown in the country started on March 9, 2020 and continued for almost three months. During this time, industrial and commercial

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operations and services were reduced to the bare minimum. Employees in the industrial and commercial sectors, as well as government employees and students in schools and higher education institutions, were instructed to remain at home. Mobility was restricted; public transportation operations stopped completely, and restrictions were imposed on international flights [16–18]. These restrictions affected the country's electricity demand and usage. Very few studies have been conducted to analyse the effect of the COVID-19 pandemic and associated measures on the power generation sector within the State of Qatar [6,16,19]. Abulibdeh [6] examined the effect of the pandemic on electricity usage across commercial, residential, industrial, governmental, and productive farm sectors using Geographic Information System (GIS) techniques and spatial statistical modelling. The study compared electricity usage prior to and during the pandemic between 2017 and 2020. The results reveal variations in electricity use over space and time and across sectors. Implementation of the lockdown contributed to a reduction in electricity usage in the commercial and industrial sectors, while an increase was observed in the residential, governmental and productive farm sectors. Another study [16] examined the spatiotemporal electricity and water usage in Doha city across six socioeconomic sectors. The study utilized five geospatial methodologies in a GIS context to examine the variation in consumption on the block level as well as the association between water and electricity consumption across governmental, commercial, residential, hotel, and industrial sectors. The study found spatial changes in water and electricity consumption during the lockdown and a direct correlation between electricity and water consumption. Al-Awadhi et al. [19] also examined the effect of the COVID-19 pandemic on electricity consumption in Doha city. They compared electricity consumption across the residential, commercial, industrial, governmental, and hotel sectors using a GIS and statistical analysis. They reached the same conclusion as the two previous studies and mapped the hot/cold spots that emerged over the course of the pandemic in the city. However, these studies tended to analyse the influence of the pandemic on Qatar's electricity and the changes in electricity consumption in the pandemic years relative to previous years.

2. Literature review

During the past few years, the effect of the COVID-19 pandemic on the electricity sector has been investigated worldwide. In the United States, studies examining the influence of containment measures on electricity usage discovered a substantial association between reduced electricity consumption and the number of virus-infected cases, level of commercial activity, stringency of lockdown measures, and degree of social distancing [11,20,21]. Ruan et al. [11] examined the impact of the pandemic during the lockdown period on the US electricity sector. In their study, they used different explanatory variables such as weather data, satellite imagery data, mobile device location information, and COVID-19 public health data. They formulated a statistical model that calibrated electricity use by using mobility and public health data. They found that the policies imposed by the federal or state authorities associated with the positive individual behavioural change response had a pronounced effect on electricity usage. They observed a decrease in electricity usage across all US markets of between 6.36 and 10.24% in April 2020 and of between 4.44 and 10.71% in May 2020. This decline is connected with the number of infected individuals, the stay-at-home policy, social distancing, and mobility to commercial areas. Burleyson et al. [22] investigated the effect of the COVID-19 pandemic on electricity demand in the US. They compared the effect of the pandemic on electricity usage by utilizing three datasets across different spatiotemporal and customer scales. The study found that due to lockdown measures, residential electricity usage during weekdays shifted to resemble weekend profiles before the pandemic. Furthermore, electricity usage in the commercial sector declined. In general, the change was smaller during summer 2020 due to re-opening and the spatial variability in re-opening. At the state level, the study found an increase in electricity consumption at the residential level and a decline at the commercial level. In Ontario, Canada, the highest overall daily reduction in energy consumption was 25% [23].

Several studies have been undertaken in Europe to investigate the influence of the COVID-19 pandemic on electricity usage [22–26]. Bahmanyar et al. [24], for example, compared the impact of the pandemic on electricity systems in countries that implemented strict lockdown (i.e., Spain, Italy, Belgium and the UK) with that in countries that were less restricted in implementing a lockdown policy (i.e., the Netherlands and Sweden). They concluded that nations with stringent restrictions saw a decline in commercial and industrial electricity usage and an increase in residential electricity consumption. For the Netherlands, daily electricity usage decreased due to the imposition of some measures, such as the ban on major public events and gatherings. Conversely, electricity usage in Sweden had a different pattern than that in the other countries. The morning peak demand was reduced between Monday and Thursday. The evening electricity consumption peak remained, while the electricity consumption during Thursday evening and the weekend was greater than for the reference week of 2019. Halbrügge et al. [5] stated that the reliance on electricity decreased and that the reliance on renewable energy sources increased during the first wave of the pandemic. They noticed changes in electricity consumption, prices, generation, and imports/exports. In Italy, electricity consumption declined by 37% in 2020 compared with 2019 [30]. In Turkey, energy consumption in March, April, and May 2020 decreased by 5%, 20%, and 22%, respectively, compared with 2019 [25,26]. The electricity consumption pattern in China followed the same pattern as that in the US and Europe. During the lockdown period, residential and agricultural electricity consumption rose by 5.3% and 4%, respectively [27–29]. In contrast, electricity usage in the service and industrial sectors was reduced by 19.8% and 3.1%, respectively [28,30].

In the Middle East, few studies have been conducted to investigate the impact of COVID-19 pandemic on the electricity sector. Samara et al. [31] assessed the impact of the pandemic and the pandemic lockdown mitigation measures on the local energy sector in the UAE taking Sharjah City as a case study. They found that the pandemic lockdown measures reduced the electricity demand in the industrial, commercial, and agricultural sectors and increased the electricity demand in residential and governmental sectors. Overall, the electricity consumption in the first year of the pandemic was reduced by 1.04% compared with electricity consumption rate between 2016 and 2019. Ashkanani et al. [32] investigate the impact of the pandemic lockdown measures on electricity production in Kuwait. They compared electricity production under various post-pandemic lockdown scenarios with that pre-pandemic using longitudinal archival data from 2015 to 2020. They found that the pandemic affected the hourly electricity load, where the load during the various post-pandemic scenarios has declined between 9.0% and 14.0% compared to pre-lockdown period. This decline varied across the type of lockdown measure and the hourly load but increased during imposing lockdown measures leading to a net reduction of up to 16.4%.

Forecasting electricity consumption across various socioeconomic sectors in times of crisis is important for establishing related policies and developing and planning electricity demand and supply to these sectors in the future. During the past few decades, several studies have attempted to forecast electricity consumption. Different traditional statistical models, econometric models, and machine-learning techniques have been used in these studies. Hussain et al. [33] and Jamil [34] used an autoregressive integrated moving average (ARIMA) model to forecast the total electricity consumption in Pakistan. Fumo and Biswas [35] used a multivariate regression model to predict residential energy consumption. These models are classified under time series forecasting. Recently, many studies have used ML techniques for power consumption forecasting [36–39]. ML techniques have many advantages, such as their robustness, ability to deal with nonlinear problems, ability to process small samples, and statistical accuracy, and they offer strong generalizability [36,40–43]. Sahin et al. [36] utilized ML approaches and fractional grey prediction models to investigate and forecast European nations' electricity production during a COVID-19-induced shutdown. Khan et al. [37] formulated a hybrid energy forecasting system based on machine learning for imputation and accurate energy demand forecasting. They used different techniques, including random forest, extreme gradient boosting, and categorical boosting models. Kaytez [38] used a hybrid approach to forecast the long-term net electricity consumption in Turkey. This hybrid model was based on an autoregressive integrated moving average model and a least squares support vector machine. The study concluded that this hybrid model produced more realistic and accurate forecasts and performed better than other models, such as a single autoregressive integrated moving average model. Graf et al. [44] used a deep-learning approach to predict electricity market performance during the lockdown period in Italy. They found that the predicted re-dispatch costs during this period in the pandemic were 26% higher than those in the same period in previous years. Pham et al. [45] utilized ML models to forecast electricity usage in the short term in buildings at an hourly resolution. Luís et al. [46] used ML techniques to forecast electricity demand and PV power production in Portugal. Solyali [47] used ML models to predict electricity demand in Cyprus. The study used adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN), support vector machine (SVM), and multiple linear regression (MLR) models for this purpose and proposed criteria for power generation.

The current challenges to the electricity sector induced by the propagation of the pandemic require an accurate assessment to understand the current and future impact for better planning to meet the required supply and demand. Existing studies on the effect of the pandemic on electricity consumption in Qatar were based on year-over-year calculations. Therefore, this paper adopts a different approach, comparing the actual and simulated (business as usual, no pandemic scenario) electricity consumption across six socioeconomic sectors in Qatar during the 2020 and 2021 pandemic years based on the electricity consumption trend from 2010 to 2019. Three machine-learning techniques covering time series were used to ensure the accuracy and credibility of the simulation results and to reduce the simulation error. By analysing the difference between the actual and simulated electricity usage in Qatar during the COVID-19 pandemic years, we can determine the effect of the pandemic on the power generation sector in the country. Therefore, the goal of this study is to re-quantify the effect of the pandemic on electricity consumption across six socioeconomic sectors in Qatar. This study adds to the body of literature in the following ways:

(1) The studies conducted in Qatar and many other countries focus on comparing electricity usage in the pandemic years and electricity usage prior to the pandemic (year-over-year calculation) to determine the effect of the pandemic on electricity usage. This study compares actual electricity usage and simulated electricity usage based on machine-learning prediction models. The difference should indicate the effect on electricity usage during the pandemic.
(2) The purpose of this study is to examine the influence of the pandemic on power usage by six socioeconomic sectors: residential villas, residential flats, industrial buildings, governmental buildings, commercial buildings, and hotels. Since the pandemic affected these sectors differently, it is imperative to analyse the pandemic's influence on power consumption in these sectors to gain a general outlook of the pandemic's impact on electricity usage.
(3) The temporal dimension of this study consists of two levels. First, the study uses monthly electricity consumption data between 2010 and 2019 to simulate the pandemic-free scenario in 2020 and 2021. Second, the study classifies the first year of the pandemic into four stages: pre-lockdown, lockdown, easing the lockdown, and post-lockdown. These stages illustrate the evolving phases of the pandemic in Qatar and the associated containment strategies. The second year of the pandemic (2021) was marked by two devastating pandemic waves; hence, this study focuses on these two periods.
(4) This study incorporates three forms of ML models, including support vector machine (SVM), extreme gradient boosting (XGBoost), and random forest (RF) models, to simulate electricity usage across the above-mentioned six socioeconomic sectors in Qatar under the pandemic-free scenario. ML techniques are robust techniques in time series analysis since they evaluate multivariate data, as opposed to other traditional methods that consider the data as a single variable.
(5) The correlation between the daily number of infected cases and electricity usage in buildings is another indicator of the effect of the pandemic on electricity usage. Therefore, this study takes into account this relationship over four periods during the first year of the pandemic and during the major propagation (waves) of the pandemic in the second year across the six socioeconomic sectors.
(6) According to the literature, electricity usage was impacted by the propagation of COVID-19; therefore, this study investigates the effect of the changes in electricity usage on the forecast accuracy of the ML models by comparing the simulated electricity consumption with the actual consumption.

3. COVID-19 in Qatar

The first verified case of COVID-19 in Qatar occurred on February 27, 2020 [47]. Since then, the transmission of the COVID-19 virus in the country has increased, prompting the government to impose various measures and regulations to halt the spread of the disease. On March 9, 2020, the country announced the start of a countrywide lockdown [48]. The industrial and commercial activities were closed, as were many non-essential services, such as retail stores, parks and green areas, and restaurants. The lockdown also had an impact on the government sector, as the authorities asked many employees to work from home and pupils at public and private schools to study online. In general, residents' mobility in the country was restricted since people were encouraged to stay at their homes. Therefore, public transportation services and international flights were suspended. These policies and measures were imposed for different periods and resulted in a decrease in the number of daily infected cases and the mortality rate in the country.

According to Google's COVID-19 Community Mobility Reports [48], the mobility patterns for retail and recreational areas (i.e., cafes, theme parks, restaurants, shopping centres, cinemas, libraries, and museums) in Qatar witnessed a decline at an average of 45% during March and April 2020 compared to the baseline (the five-week period of 3 January 2020–6 February 2020). For grocery and pharmacy supplies (i.e., grocery markets, farmers markets, food warehouses, drug stores, pharmacies, and specialty food shops), mobility declined by an average of 19%. For parks, transit stations, and workplaces, mobility declined by 42%, 43%, and 25%, respectively, compared with the baseline. Conversely, the mobility trends for places of residence increased by 18% compared to the baseline. These changes in mobility to these places induced by the COVID-19 lockdown affected electricity consumption in each sector by increasing or decreasing their consumption.

A month after the first case was confirmed, the number of confirmed infected cases increased rapidly in the country until the end of May, while at the end of April, it reached a climax at a rapid rate. Fig. 1 shows the number of new daily infected cases and the cumulative number of infected cases in Qatar in 2020 and 2021. The curve of the daily number of newly infected cases shows a consistent range of change, while the curve of the cumulative number of cases shows the slope of an increase/decrease in the number of infected cases in the country. As indicated in Fig. 1a, the number of cases in the country decreased after three months of lockdown and reached a phase of stabilization at the beginning of August 2020. The authorities announced a four-phase plan that aimed to

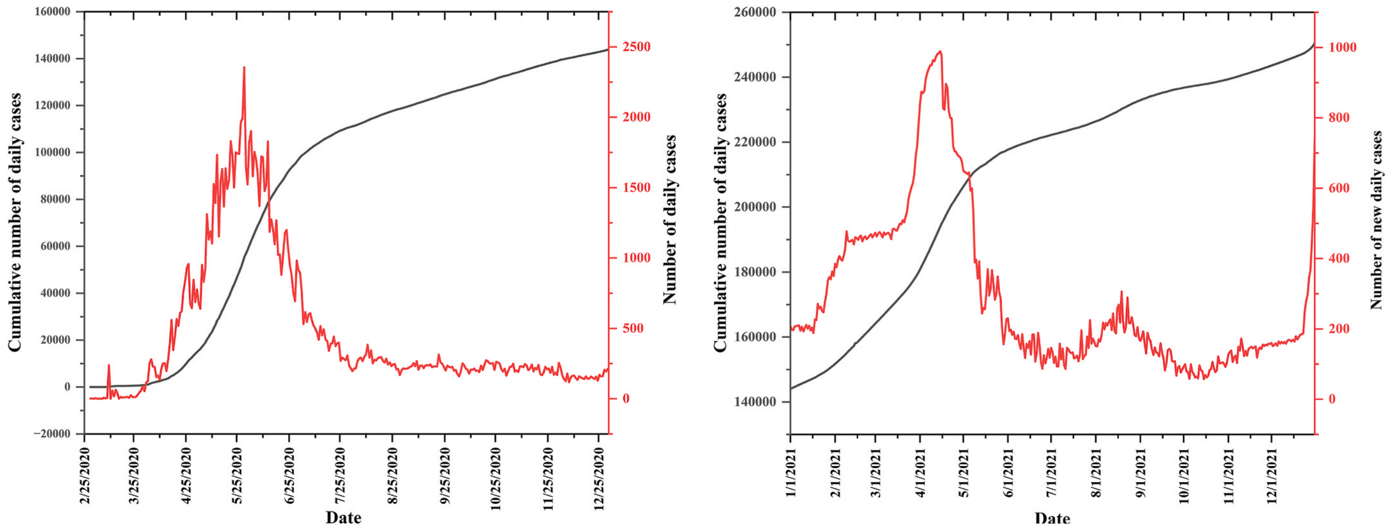

Fig. 1. The number of daily COVID-19 cases and cumulative cases in pandemic years (a) 2020 and (b) 2021.

re-open all activities that were impacted by the lockdown policy and return to normal operational capacity. On June 15, 2020, the first phase started by easing some restrictions on the commercial and industrial sectors, while the fourth phase went into effect on September 1, 2020, allowing the commercial, industrial, and governmental sectors to operate at full capacity.

Accordingly, various temporal scales were utilized in this study. First, electricity consumption in the socioeconomic sectors was compared annually over time since 2017 to determine the electricity usage trend over time and across sectors. Second, during the pandemic years and prior to the pandemic year, a monthly comparison was carried out to determine the difference in electricity usage on a monthly basis by socioeconomic sector. Finally, analysis was conducted on a finer time scale, focusing on four stages during the pandemic years while taking into account variations in disease propagation and the accompanying steps that the country took to restrict the spread of the virus. On this basis, this study considers four phases in investigating the impact of the propagation of the COVID-19 pandemic on energy usage during the first year of the pandemic (2020) [49]. The phases are as follows.

1) Pre-lockdown: This phase extended from January 2020 to February 2020, when the disease was not officially announced as a pandemic. There were no or very few infected cases in the country, no special measures were taken, and people lived normally.
2) Lockdown: This phase extended from March 2020 to the end of May 2020. During this phase, the government imposed many restrictions to mitigate the spread of the disease, including closing non-essential services. This phase may have had a direct effect on electricity usage across the six socioeconomic sectors.
3) Easing the lockdown: This phase extended from June 2020 until the end of September 2020. During this phase, the government tended to ease lockdown measures while reaching a stage of partial opening of all socioeconomic sectors due to people's panic. However, people at this stage maintained social distancing and took other precautionary measures.
4) Post-lockdown: This phase extended from October 2020 to the end of January 2021. During this phase, the country underwent full opening, except for schools and universities, with most students being engaged in online learning. During this stage, people's panic gradually subsided. The authorities focused on restoring the economy while maintaining precautionary measures.

The second year of the pandemic (2021) witnessed two waves of the spread of the disease. The first wave started mid-January and lasted until the end of May, with a peak in April, as shown in Fig. 1b. The second wave was less severe and lasted for approximately one month between August and September, as shown in Fig. 1b. The measures taken by the authorities were less stringent than those in 2020, with most businesses in the industrial and commercial sectors operating at full capacity. Students returned to school, and online teaching and learning were minimized. In this pandemic year, the COVID-19 vaccine was developed by different companies globally, and people from different countries, including Qatar, were vaccinated against the virus. However, the first doses of the vaccine were allocated to elderly people, as they were the most vulnerable to severe health problems and death if they were infected. Furthermore, the country developed a phone application called "EHTERAZ" showing the health condition related to COVID-19 infection of the phone holder. The application consists of different colours, and each colour indicates a specific health condition of that person. For example, the colour red means that this person is infected by the disease, while the colour green indicates no infection, and the colour yellow indicates that this person is in quarantine. This application was made mandatory for all people who live in and visit Qatar, and they are required to have the green colour to enter their workplace, shopping centres, factories, or any other places. The aim was to reduce the number of infected cases by eliminating the transmission of the disease between people. Those who have the colour red or yellow should stay at their houses and quarantine for 14 days.

4. Materials and methods

4.1. Dataset description

This study utilizes big data, and use monthly electricity consumption (KWh) data for six socioeconomic building sectors in Doha city (i.e., residential villas, residential flats, commercial buildings, governmental buildings, industrial buildings, and hotels) between 2010 and 2021 as well as the number of daily infected cases of COVID-19 in Qatar in 2020 and 2021. Two sets of data were used. The first set of data consists of the electricity monthly reading at the metre level for each building in the six sectors spanning between January 1, 2017 and December 31, 2020. The rational of selecting these types of buildings is shown in Table 1, and the total number of buildings in each sector is shown in Table 2. The second set of data consists of the total monthly electricity consumption of the buildings in each sector starting from January 1, 2010 and ending on December 31, 2021. KAHRAMAA (the Qatar General Electricity and Water Corporation) generously shared the raw monthly electricity usage data based on the building use type. However, these data are not suitable

Table 1
The rational of selecting the six socioeconomic building sectors.

Socioeconomic sector	Description	Rational
Residential	Villas (townhouses or standalone houses), flats (all types of apartments)	Residential sector is important to determine if the electricity consumption has been affected by the propagation of the disease, particularly during the lockdown stage. We assume that the residential sector witnessed high consumption rate due to the implementation of the mitigation measures to curb the spread of the disease such as stay-at-home policy. This policy forced hundreds of thousands of people to perform their duties from their homes. Villas denote.
Commercial	Banks, SMEs, retail, private organizations, services institutions, groceries and pharmacies, etc.	Many of the commercial services were asked to shut down during the lockdown period, particularly at the first wave of the propagation of the disease. This affect the electricity consumption in this sector. This sector is one of the pillars of the Qatari economy and hence electricity consumption can be considered as an indicator of the productivity of this sector.
Industrial	Liquefied natural gas, petrochemicals, crude oil production and refining, steel reinforcing bars, fertilisers, cement, commercial ships, ammonia, and repairs	Although Qatar is not an industrial country, it is consider one of the major countries in oil and gas production. Furthermore, many of the major production in the country is related to the petrochemical sector. This sector was affected by the lockdown policies and this was reflected on electricity consumption.
Government	Ministries, offices, public schools, hospitals, and universities, etc.	The public sector is an important sector in the State of Qatar as it employs a numerus number of people and is responsible for issuing and implementing policies to slow down the spread of the disease particularly to protect children at schools. Therefore, many public entities were closed and the employees and students were asked to work and learn from home.
Hotels	Hotels and service apartments	The tourism industry was affected globally by the spread of the pandemic. Countries, including Qatar, closed its borders not allowing international travellers to enter the country. However, many hotels in Qatar were used for quarantine purposes for residents of the country who were traveling to the country.

for conducting an analysis of electricity usage in buildings in the context of the pandemic. Therefore, preparation, organization, arrangement, and processing of the data into a format suitable for analysis are required and hence were performed.

Data filtering was conducted to improve database quality and to ensure the reliability of the analysis and the results. The data were subjected to intensive quality control checks and filtering to exclude any metre with zero or missing values throughout any given month of the study period to ensure the reliability of the analysis results. Furthermore, buildings of any use type that were constructed recently or whose use type changed between 2010 and 2021 were excluded from the analysis to eliminate any negative impact of these data on the results. Finally, the upper and lower 5% of the data were also excluded to avoid any effect of outliers. As a result, a total of 1,090,185 building data points were collected. Furthermore, this study utilized time-variant COVID-19 pandemic variables, mainly the number of daily infected cases, number of fatalities, and cumulative number of infected cases in both years of the pandemic obtained from the Qatar Open Data Portal (https://qatar.opendatasoft.com/explore/dataset/covid-19-cases-in-qatar/table/?sort=date). These data are associated with different measures taken by the authorities nationally and internationally to curb the transmission of the disease.

Table 2
Database 1 number of readings for each sector between 2017 and 2020.

Type	2017	2018	2019	2020	Number of Records
Villas	103,230	104,832	106,972	111,873	426,907
Government	12,644	13,410	15,283	15,181	56,518
Hotels	353	394	406	605	1758
Industrial	379	475	552	314	1720
Flats	103,229	104,831	106,971	116,057	431,088
Commercial	39,653	42,286	46,415	43,840	172,194
Total number of records					1,090,185

4.2. Methodology

Over the past two decades, the State of Qatar has witnessed a leap in economic development and population growth, which have accelerated over the past decade, driven by winning the right to host the 2022 FIFA World Cup [50–55]. This growth affected the electricity sector, as both the annual electricity generation and the country's peak electricity demand have increased more than twofold [6,43,56,57]. To detect deviations in this trend, it is critical to examine the pattern of energy usage before and during the pandemic years. Doing so will allow us to determine if there is a change in electricity consumption during the pandemic years and hence investigate whether this change is related to the spread of the pandemic.

The first step in assessing the effect of the pandemic on Qatar's electricity usage is to simulate the electricity consumption pattern using data from 2010 to 2019. Such simulation enable us to calculate the electricity consumption gap between the actual and simulated values. Under the pandemic-free scenario, we employ high-precision predictive machine-learning models to simulate and forecast electricity consumption across six socioeconomic sectors in the State of Qatar. Then, we calculate the models' fit r2_score, mean squared log error, and mean absolute percentage error values for each model to determine the prediction performance of each of these models. Afterwards, we select the results of the model with the highest r2_score value to calculate the electricity consumption gap between the actual and simulated electricity usage to determine the effect of the pandemic on electricity usage.

The second step is to determine the relationship between the number of COVID-19 infected cases and electricity consumption in different socioeconomic building usages. The Pearson correlation, a parametric statistical method, is used to statistically verify the relationship between the propagation of the COVID-19 pandemic and monthly electricity usage in buildings of different socioeconomic utilization. Among parametric statistical methods, Pearson correlation analysis can be performed since the data used in this study approach a normal distribution pattern (bell-shaped distribution) when using log transformation. The third step is to convert the number of infected cases by log transformation to prevent anomalies due to the large difference in the number of infected cases in some months, particularly the first few months of the spread of the pandemic. This step is necessary to transform the distribution of the variables into a bell-shaped distribution and to maintain high accuracy of the results when performing the correlation analysis [7,58]. Conversely, the electricity usage rate of change variable is considered the main variable to use to investigate the relationship between the pandemic and electricity usage on a monthly basis. The target variables are those related to the rate of change (ROC) (%) in electricity consumption based on the building type and those related to COVID-19 variables, i.e., the number of new infected cases, the cumulative number of cases, and the number of mortality cases. The ROC in electricity consumption is calculated based on the difference between the consumption in 2020 and that in previous years, mainly 2017, 2018, and 2019, based on Equation (1).

$$\mathrm{ROC}(\%) = \left| \frac{Y_{ijk}^{2020} - Y_{ijk}^{2019}}{Y_{ijk}^{2019}} \right| \times 100 \tag{1}$$

ROC(%) denotes the rate of change in energy consumption in 2020 compared to previous years

Y_{ijk}^{2020} denotes the total energy consumption for district i and building use type j at month k, 2020

Y_{ijk}^{2019} denotes the total energy consumption for district i and building use type j at month k in previous years

4.2.1. Machine-learning models

The next step is to perform prediction analysis using machine-learning models to determine the values of electricity that should be consumed during the pandemic years and hence determine how and to what extent the pandemic affected electricity consumption across the different socioeconomic sectors. Three machine-learning models (XGBoost, RF, SVM) were employed to determine building electricity consumption patterns during the 2020 COVID-19 pandemic year and to extend the prediction to the years 2021 and 2022. Conducting prediction analysis using three models gives more precise and accurate results for electricity consumption. Data on electricity consumption in the different types of building use spanning between 2010 and 2019 were utilized in the prediction process. In addition, we used several evaluation metrics to perform a quantitative analysis of each algorithm's performance.

4.2.1.1. Extreme gradient boosting (XGBoost). XGBoost [59] is an effective and widely used tree-based algorithm in ML applications. It has an outstanding capacity to solve numerous challenging problems in the data science area [60]. The following is a general unregularized XGBoost algorithm.

Input: training-set $\{(x_i, y_{i,})_{i=1}^{N}\}$, which represents the samples of 70% of the participants, differentiable loss function $L(y, F(x))$, a number of weak learners (trees) M, and a learning rate α.

Input: training set $\{(x_i, y_i)\}_{i=1}^{N}$, a differentiable loss function $L(y, F(x))$, a number of weak learners M, and a learning rate α. Algorithm:

Establish a model with a constant value:

$$f_{(0)}(x) = \underset{\theta}{\mathrm{argm}} \sum_{i=1}^{N} L(y_i, \theta) \tag{2}$$

where arg min denotes the argument of the minimum θ value and $f_{(0)}(x)$ is the initial output.

For $m = 1$ to M:

Compute the 'gradients' and 'Hessians':

$$g_m(x_i) = \left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)} \right]_{f(x) = f_{(n-1)}(x)} \tag{3}$$

$$h_m(x_i) = \left[\frac{\partial^2 L(y_i, f(x_i))}{\partial f(x_i)^2} \right]_{f(x) = f_{(m-1)}(x)} \tag{4}$$

Fit a base learner (or weak learner, e.g., tree) employing the training set $\left\{ x_i, -\frac{g_m(x_i)}{h_m(x_i)} \right\}_{i=1}^{N}$ by resolving the optimization problem below:

$$\varphi_m = \underset{\varphi \in \Phi}{\mathrm{argm}} \sum_{i=1}^{N} \frac{1}{2} h_m(x_i) \left[-\frac{g_m(x_i)}{h_m(x_i)} - \varphi(x_i) \right]^2 \tag{5}$$

$$f_m(x) = \alpha \varphi_m(x)$$

$f_m(x)$ is the model corresponding to the current base learner m; α denotes the learning rate.

Update the model:

$$f_{(m)}(x) = f_{(m-1)}(x) + f_m(x) \tag{6}$$

Output

$$f(x) = f_{(M)}(x) = \sum_{m=0}^{M} f_m(x) \tag{7}$$

4.2.1.2. Support vector machine (SVM). The SVM algorithm [61] is a widely used traditional machine-learning algorithm owing to its simplicity and flexibility in resolving various prediction problems. Kernel approaches that aid the SVM as kernel functions are utilized to address optimization issues in high-dimensional domains. In the new feature space, the SVM generates a high-margin separation between training samples. Given labelled sequences $(x_1, y_1), \ldots, (x_m, y_m)$, where x denotes the covariates and $y \in \{-1, 1\}$ is the response, kernel function k is utilized by the SVM in Equation (5):

$$f(x) = \sum_{i=1}^{m} a_i k(x_i, x) + b, \tag{8}$$

where coefficients a_i and b are estimated by minimizing the following function:

$$\sum_{i,j=1}^{m} a_i a_j k(x_i, x_j) + C \sum_{i=1}^{m} \zeta_i \tag{9}$$

$$y_i f(x_i) \geq 1 - \zeta_i \tag{10}$$

where ζ_i measures the degree of misclassification of x_i and C denotes the penalty parameter of misclassification. In addition, function $f(x)$ translates training vectors x into a higher-dimensional or even infinite space. Based on $f(x)$, the SVM identifies a linear hyperplane separating training samples with the greatest margin in the higher-dimensional space. Please refer to Cortes and Vapnik [62] for more information.

4.2.1.3. Random forest (RF). The RF [63] has attracted considerable attention because of its reliability and outstanding classification results [64]. Commonly, RF classifiers have been employed to rank and select variables and consequently make the best decision. Random forest classifiers are ensemble techniques. The RF uses bootstrap aggregating (bagging) to construct a set of decision tree estimators [56] by sampling the training dataset. The bagging approach seeks to generate an ensemble of predictors for random subsets of the primary training dataset to improve the ensemble's generalizability. Decision trees can fit sophisticated patterns in both regression and classification tasks. Overall, several decision tree learning algorithms aim to recursively divide samples into homogenous subsets (nodes) on the basis of an attribute. The trained classifier makes it possible to perform feature importance analysis. We used Gini impurity to achieve this goal. Gini impurity represents the basis of the measure of the quality of split, and it is defined as follows:

$$G_i = 1 - \sum_{k=1}^{n} p_{i,k}^2 \tag{11}$$

where Gi denotes the Gini impurity of node I and pi represents the ratio of class k among all cases in node i. We defined the cost function to train a decision tree based on Gini impurity and the CART algorithm to determine the optimum split as follows [65]:

$$J(k, t_k) = \frac{m_{\text{left}}}{m} G_{\text{left}} + \frac{m_{\text{right}}}{m} G_{\text{right}} \tag{12}$$

where $J(k, t_k)$ represents the cost function based on feature k and threshold tk, $G_{\text{left/right}}$ denotes the impurity of the left or right subset, and $m_{\text{left/right}}$ denotes the number of instances on the left or right. Random sampling is employed in both the training dataset and the feature set in a random forest classifier. Random forest classifiers possess an inherent feature. More specifically, they have the capacity to measure the relative importance of features. Based on Equation (12), the feature importance is identified considering the extent to which a feature, on average, decreases the impurity measure.

$$NI_i = w_i G_i - w_{\text{right},i} G_{\text{right},i} - w_{\text{left},i} G_{left,i} \tag{13}$$

$$FI_i = \frac{\sum_{j:\ \text{node } j \text{ splits on feature } i} NI_j}{\sum_{j \in \text{all nodes}} NI_j} \tag{14}$$

where NI_i denotes the importance of node i, w denotes the weighted number of instances, and FI_i represents the importance of feature I.

5. Results and discussion

5.1. Descriptive analysis

Fig. 2 compares the average electricity consumption between 2010 and 2019 with the monthly electricity consumption in pandemic years 2020 and 2021 in different socioeconomic groups in Qatar. The goal is to compare the pattern of electricity use during the pandemic years to that of the pre-pandemic years. Prior to the pandemic years, the highest electricity consumption occurred in summer for all sectors. This finding is due to the high demand for cooling during the extremely hot summer months. Furthermore, the figure evidently indicates that electricity usage is low during the beginning of the year during the winter season and starts to gradually increase until it reaches its peak during the summer and then starts to decrease at the end of the year. The residential sector's electricity usage followed the same pattern during the pandemic years. This pattern changed dramatically in the other sectors, particularly the industrial sector. In the pandemic years, the monthly electricity usage in the industrial sector was much less than the average electricity usage prior to the pandemic, demonstrating the effect of the pandemic on electricity usage in this sector.

In the other sectors (commercial buildings, hotels, and governmental buildings), electricity usage deviates slightly from the pre-pandemic pattern. This deviation illustrates the effect of the measures taken to slow the propagation of the disease. For example, electricity consumption in the hotel sector decreased in the first few months in the first pandemic year following the spread of the disease in 2020 and the imposition of the first lockdown. However, electricity usage in 2021 decreased due to the spread of the fourth wave of the disease and the imposition of measures in many countries around the world to reduce the spread of the disease; consequently, the number of tourists declined during these months. In contrast, the hotel sector's electricity consumption climbed during the summer of 2020 because a significant number of hotel rooms were designated obligatory quarantine premises upon entry into the country. A noticeable surge in electricity usage occurred during December 2021 because Qatar hosted the 2021 FIFA Arab Cup, which is a major tournament that took place at the time and attracted thousands of visitors to the country. In the commercial and government sectors, electricity consumption in 2021 was less than that in the same period in 2020. The main reason behind this deviation from the normal pattern is the spread of a new wave of the pandemic where the daily number of infected cases exceeded 4000 people. Consequently, the authorities imposed strict measures to slow the spread of the disease, including closing down many commercial activities and asking government employees to work online from their homes.

The heat map of the electricity monthly ROC by sector shown in Fig. 3 illustrates the ROC between consecutive years to determine the pattern of increase or decrease in electricity consumption over time and across sectors on a monthly basis. In the case of commercial buildings, monthly electricity consumption witnessed a steep decline during the lockdown period, particularly during April and May 2020. This drop continued in June but started to increase beyond that and encountered some fluctuation in energy consumption post-lockdown period. In general, there is no clear pattern in monthly electricity consumption in the commercial sector; however, it is clear that the enormous drop in electricity consumption between April and June is associated with the measures taken by the authorities to slow the propagation of the pandemic. The same is true for the other sectors except for the residential sector, where electricity consumption increased during the lockdown period for almost the three months during the lockdown period, excluding in May for the villa building type. In general, the entries in the figure indicate that there was no specific pattern of electricity consumption in all sectors prior to the pandemic to conclude that there was a significant effect of the propagation of the disease on electricity usage. However, the large drop in electricity usage in some sectors during the lockdown period, where the number of infected cases was high, may be attributed to the pandemic.

5.2. Predicting electricity consumption in the first pandemic year (2020)

The analysis conducted above clearly shows that there is no identified pattern of electricity consumption over time. Although the enormous drop in electricity consumption, particularly in the lockdown period, is an indication that the pandemic increased/decreased electricity use in different sectors, the effect of the pandemic does not clearly show that prices follow this approach. To better understand this impact, this section compares actual electricity consumption data with pandemic-free scenarios in 2020 and 2021 and predicts the electricity consumption in 2022. Three machine-learning models were used not only to predict electricity consumption under the pandemic-free scenarios but also to determine which of these models is more accurate.

In this study, three performance metrics are used to evaluate the effectiveness of the developed machine-learning models: the coefficient of determination (R^2) [66], mean squared log error (MSLE) [67] and mean absolute error (MAE) [68], as shown in Table 3. The results show that the model created by the XGBoost algorithm has the best coefficients of determination and the fewest errors ($R^2 = 0.838$, MSLE = 0.185). The other two models, however, have good coefficients of determination, as shown in the table.

Fig. 4 quantitatively analyses the difference between actual electricity consumption during the 2020 pandemic year and the business-*as*-usual scenario (pandemic-free scenario) based on the simulation performed using the three machine-learning models. The results represent the electricity consumption gap caused by COVID-19 in the 2020 pandemic year. The figure demonstrates that the gap in electricity consumption varies between sectors and over time. In the residential sector, the gap increased rapidly as the lockdown was being eased and during the post-lockdown period. Although residents were instructed to remain at home during the lockdown, the gap was less pronounced in this time compared to the summer period. During the summer, residents stayed in the country, and hence, due to the hot weather, they

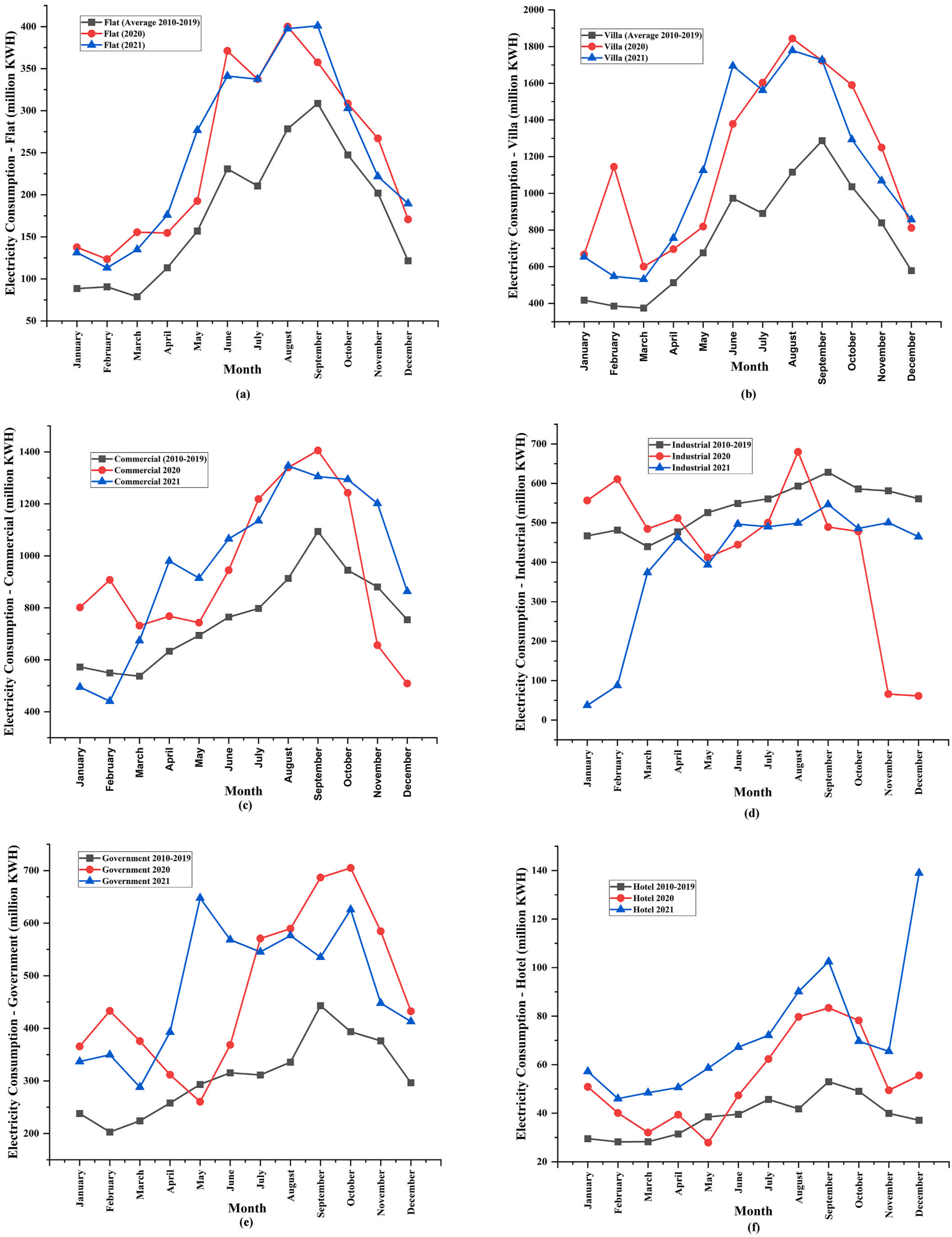

Fig. 2. The average actual monthly electricity consumption between 2010 and 2019 compared to the pandemic years 2020 and 2021.

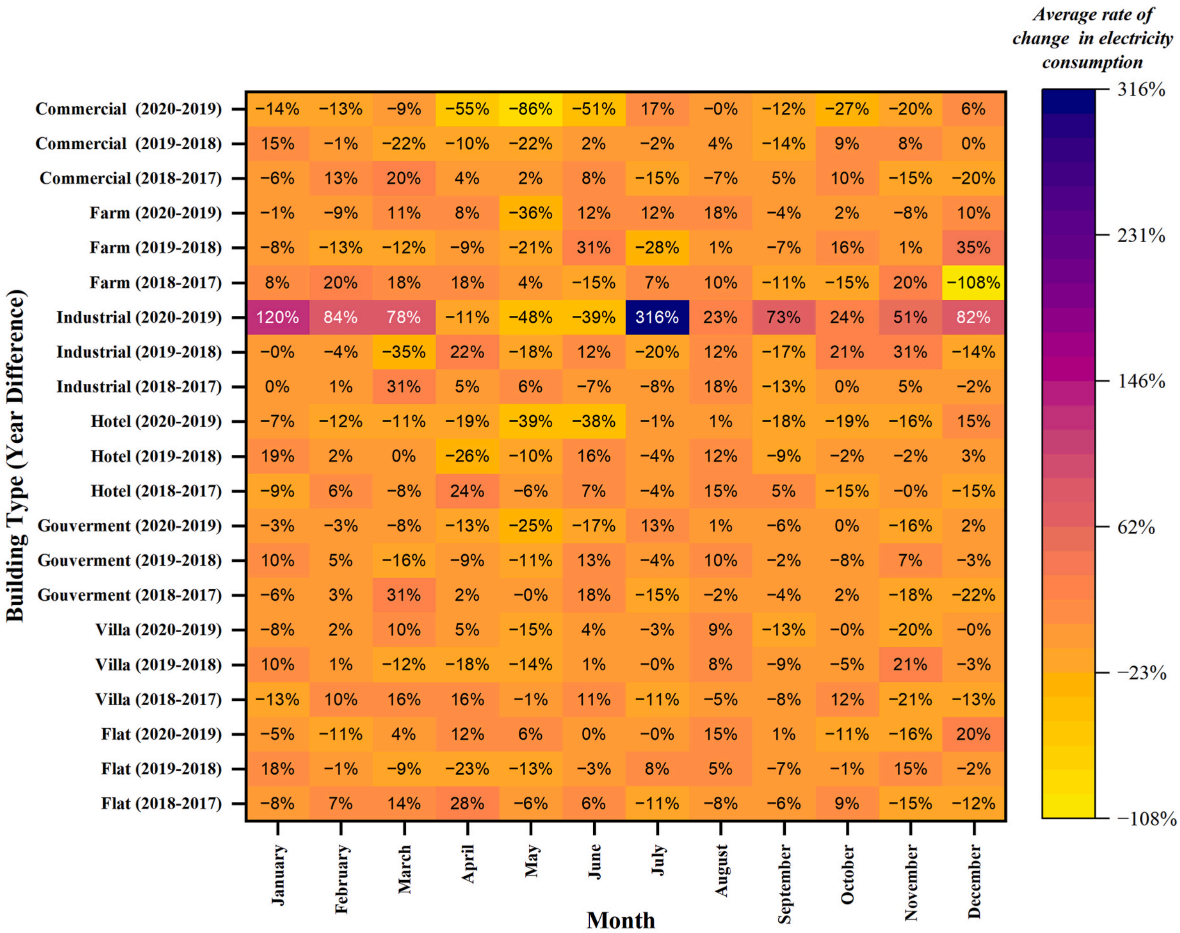

Fig. 3. The percentage difference in electricity consumption between 2017 and 2020.

Table 3
Machine-learning model evaluation.

	XGBoost	RF	SVM
Coefficient of determination (R^2)	0.838	0.814	0.746
Mean squared log error (MSLE)	0.186	0.260	0.198
Mean absolute percentage error (MAPE)	0.219	0.198	0.310

extensively used cooling systems, which consume a considerable amount of electricity. In the commercial and hotel sectors, there was under-consumption of electricity during the lockdown period and over-consumption during the summer. The reason is that people were asked to partially or fully shut down these activities to slow the propagation of the disease. During the summer, hotels were used as quarantine places during the post-lockdown period, while commercial activities returned to operate for longer hours due to the limited capacity restrictions during this period.

The industrial sector's electricity consumption decreased throughout the majority of the 2020 pandemic year. Electricity consumption was high during the lockdown period, narrowed during the summer and increased during the months of November and December 2020. The electricity consumption gap in the government sector was high during the lockdown period and the period of easing the lockdown, and it was narrowed in the summer. In the months of September and October, the actual electricity consumption in this sector increased due to school openings and because work was performed in person in governmental institutions, and the gap increased afterwards because students went back to online schooling and the number of workers at government institutions was limited due to the higher number of infected cases. In general, the actual electricity consumption and the simulated consumption using the three machine-learning models show irregularly shaped gaps based on the socioeconomic sector and over time during the pandemic years. This finding is related to the severity of the pandemic and to the corresponding measures enforced by the authorities as well as how each sector reacted to these issues. This represents the impact of the pandemic on electricity consumption over time and across sectors in this pandemic year. It can be concluded from the figure that the propagation of the pandemic and the associated measures that were taken by the authorities broke the balance and pattern of electricity consumption and demand in many socioeconomic sectors.

5.3. Gap in electricity consumption in the first pandemic year between actual consumption and the pandemic-free scenario

By comparing the actual electricity consumption and simulated (business as usual scenario (free-pandemic year)) electricity consumption in the 2020 pandemic year, we can obtain a general outlook into the effect of the pandemic on electricity consumption. In addition, this outlook will enable us to calculate the discrepancy in electricity consumption in terms of the difference between the actual electricity consumption and the simulated values. Fig. 5 shows the former point numerically and expresses it as the percentage of the actual electricity consumption that should be consumed under the pandemic-free scenario based on the three machine-learning models. Monthly electricity consumption data between 2010 and 2019 were used to predict the expected trajectory of electricity usage in a pandemic-free situation. The values of the three models vary but have similar values. However, there is a variation between the simulated and actual values over time and

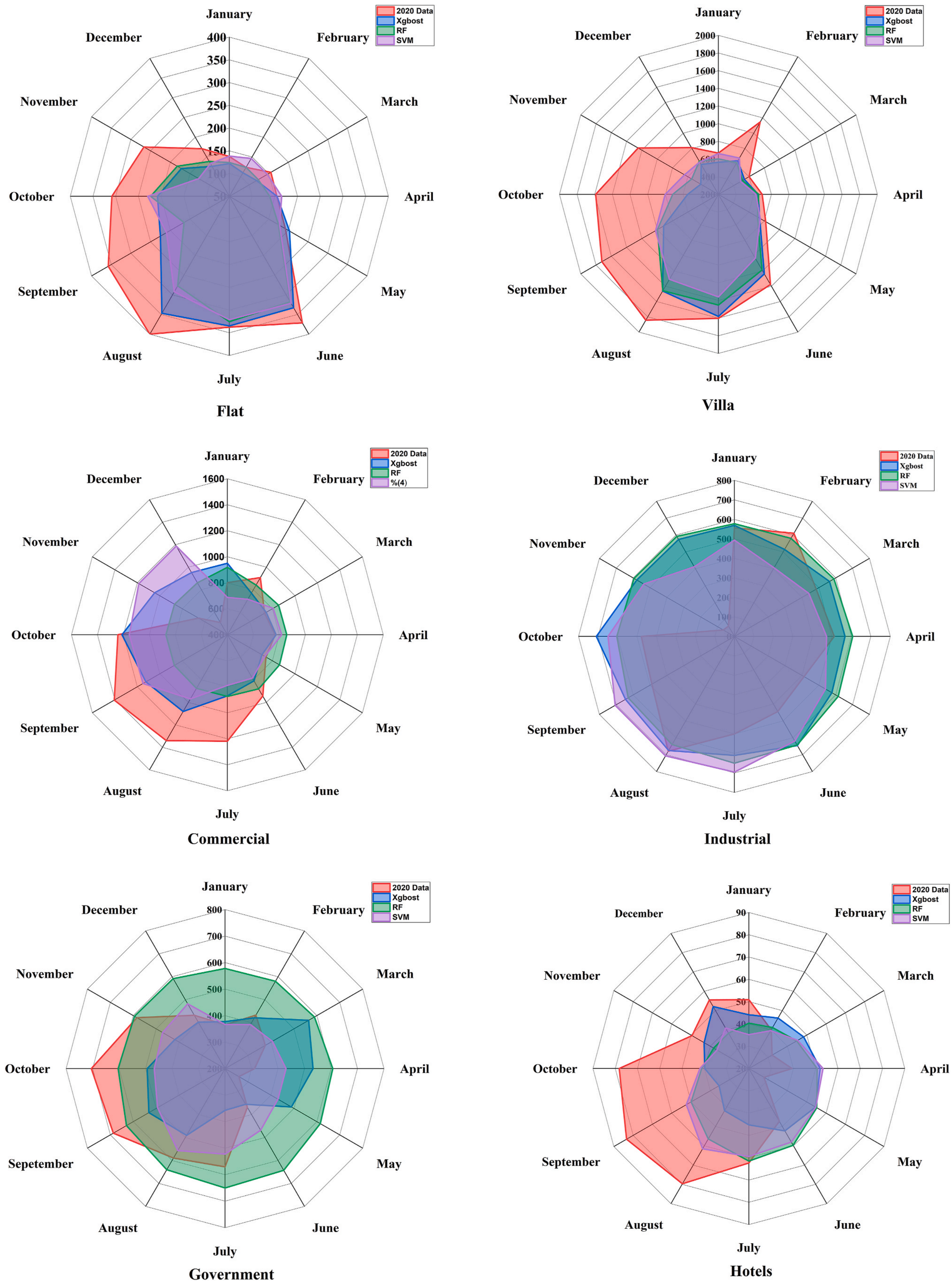

Fig. 4. Actual electricity consumption compared to the pandemic-free estimation in 2020.

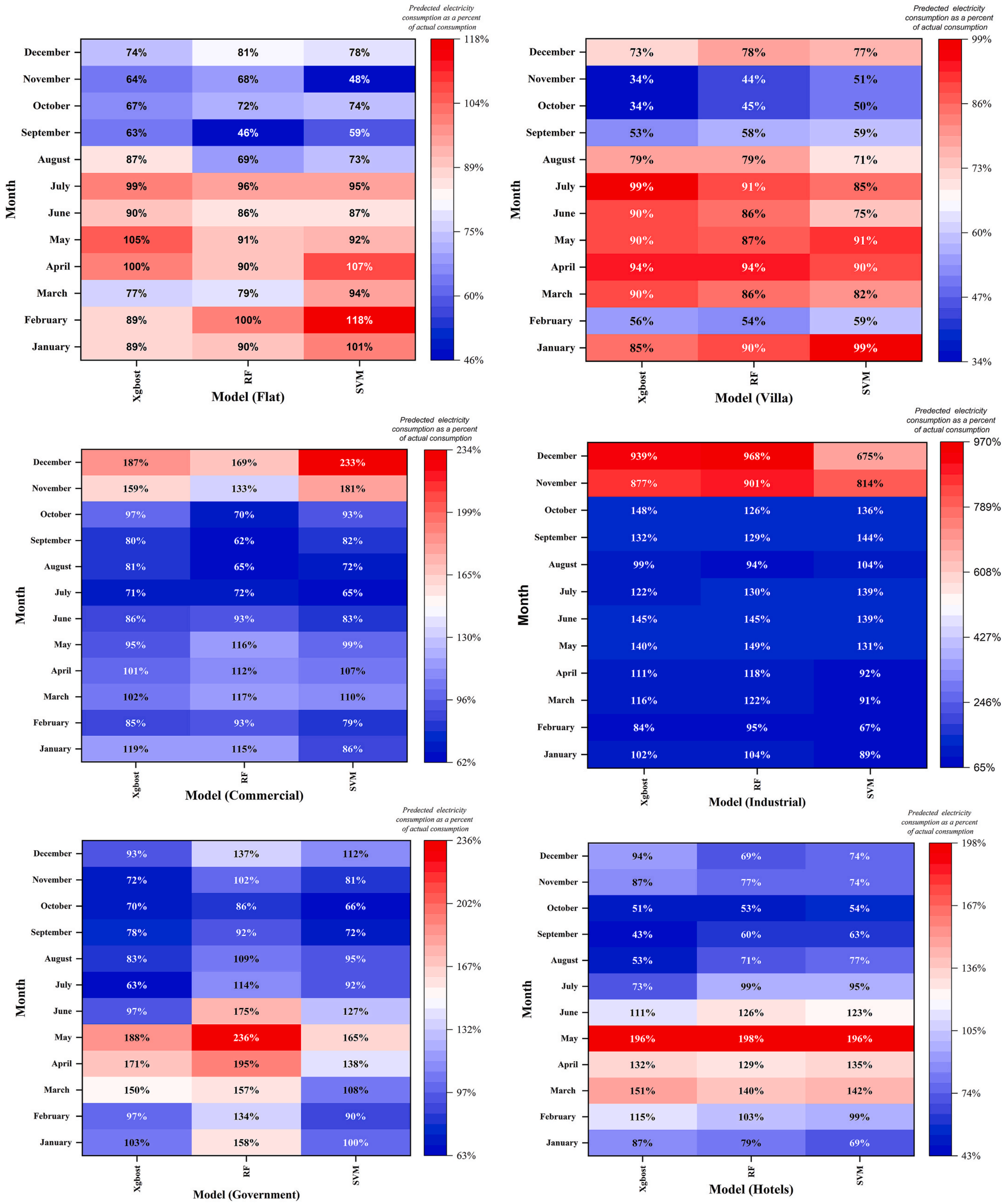

Fig. 5. The simulatedd electricity consumption as a percentage of the actual value based on the machine-learning prediction models.

hence irregularly shaped gaps over the pandemic year. Based on the data in the figure, the models demonstrate that electricity consumption in the residential sector should be less than the recorded electricity consumption in almost all months during the 2020 pandemic year. The most noticeable difference between the actual and simulated electricity consumption in the residential sector is in October and November. The models estimated that this sector should consume between 34% and 50% of the recorded consumption. This gap demonstrates the effect of the pandemic on residential electricity use. This gap increased in the industrial sector, as the figure shows that since the beginning of March, electricity consumption dropped considerably. This gap fluctuated in the remaining sectors. For example, in the commercial sector, the models predict higher electricity consumption than the actual values in the lockdown months March and April, and they reach a state of equilibrium in May. Actual consumption exceeded the simulated value in the consecutive months until November. To a certain extent, this result is due to the severity of the pandemic and the stringency of the associated measures to slow the spread of the disease. It can be seen from this analysis that these socioeconomic sectors in Qatar showed dynamic and fundamental changes during the first pandemic year. Therefore, it is important to investigate the correlation between the number of daily confirmed infected cases and electricity consumption across these sectors. Doing so will give us a better understanding of the reasons behind the gap in actual and simulated electricity consumption values.

5.4. Correlation between electricity consumption and COVID-19 in different socioeconomic sectors

The next step in the analysis is to determine if there is a correlation between the COVID-19 variables and the electricity consumption of buildings belonging to different sectors. Pearson correlation analysis was performed for 2020 compared to 2019 based on the building types. A correlation coefficient (r) and significant value (p) were calculated between electricity consumption and the COVID-19 variables, as shown in Table 4. The entries in the table show that the rate of change in electricity consumption in some socioeconomic sectors had a significant positive correlation with some of the COVID-19 variables. Regarding electricity consumption, hotels are the only sector that is not correlated with any of the COVID-19 variables. The pandemic had a detrimental impact on the hotel industry, but the fall in electricity consumption is attributable to the decline in the number of visitors to the country as a result of the lockdown measures, not the number of infected cases within the country.

Electricity consumption in the residential (villas and flats) and commercial sectors is significantly (at the 5% level) and positively correlated with the cumulative number of infected cases and the number of mortality cases. In the residential sectors, it is clear that the increase in the number of infected and mortality cases forces residents to stay at their homes, and hence, electricity consumption increases. The opposite happens in the commercial sector as the increase in the number of infected and mortality cases forces most commercial services to close, and hence, electricity consumption decreases. While electricity usage in the industrial sector is significantly positively correlated with the three variables, electricity consumption in the government sector is correlated with the number of infected cases only. During the spread of the pandemic in the industrial area during the onset of the pandemic, industrial activities in the country were halted, resulting in a significant decrease in electricity consumption. This effect was also associated with oil and gas production in Qatar, as the country is one of the main producers and exporters of these resources in the world. The production of these resources almost came to a complete stope due to the surplus of these resources in the global market and the restrictions imposed on the movement of people and goods.

Table 4
Results of the Pearson correlation coefficient (r) based on COVID-19 and building use variables.

Building Type		New infected cases (n)	Cumulative number of infected cases (n)	No. of mortality cases
Villas	***r***	0.206	**0.289**	**0.381**
	p	0.569	0.042*	0.028*
Government	***r***	**0.335**	0.206	0.008
	p	0.034*	0.569	0.982
Industrial	***r***	**0.344**	**0.331**	**0.297**
	p	0.033*	0.035*	0.041*
Flats	***r***	0.260	**0.298**	**0.382**
	p	0.469	0.040*	0.028*
Commercial	*r*	0.245	**0.386**	**0.535**
	p	0.494	0.027*	0.011*
Hotels	***r***	0.065	0.177	0.328
	p	0.858	0.624	0.355

Note: * denotes a significance level of 5%.

5.5. Correlation between the electricity consumption gap and COVID-19 infected cases in different socioeconomic sectors

To investigate the correlation between the dynamic evolution of the pandemic and the gap in electricity consumption, the electricity consumption simulated by XGBoost was considered as a baseline since the r2-score of this model was the highest compared to the other machine-learning models used in this study. Therefore, the correlation is investigated based on the curve of the electricity consumption gap resulting from XGBoost and the number of daily infected cases. Fig. 6 shows the electricity consumption gap based on the difference between the simulated electricity consumption by XGBoost and the actual electricity consumption throughout the 2020 pandemic year and by sector. The figure indicates that the actual electricity consumption in the residential sector (flats and villas) exceeded the simulated value. The same is true for the governmental sector in the months of July until December. The actual electricity consumption in the commercial and industrial sectors is less than the simulated consumption.

To elaborate more on the correlation between the COVID-19 variables and the electricity consumption gap, we plot the gap in electricity consumption based on the simulated values using XGBoost and the number of daily infected cases, as shown in Fig. 7. The black line represents the electricity consumption gap, and the red line represents the number of daily infected cases in Qatar. If the value of the line is negative, then the electricity consumption in the ideal situation (simulated) value is less than the actual consumed value and vice versa when the value is positive. The figure shows a variety of correlations based on sector and over time, and it clearly shows the impact of the number of daily infected cases on electricity consumption. It can be seen from the figure that electricity consumption increased in the residential sector when the number of confirmed infected cases increased during the first few months of the pandemic. This result is mainly due to the lockdown measures that forced people to stay at home, where these months correspond to the most severe period of the pandemic in the initial year of the pandemic in Qatar.

Electricity consumption was still high in the consecutive months, the period during which the lockdown was eased, even though the number of infected cases started falling. This result is due to many reasons, such as the tense atmosphere of the people that was dominant at this time because of the pandemic. Furthermore, many measures were imposed nationally and internationally to curb the spread of the virus. Among these measures was the ban on international travel for the majority of people. Residents of Qatar usually travel during the summer months due to the high temperature and humidity, visiting families (especially expat workers) and for entertainment purposes. Therefore, the majority of people did not travel during these months, which resulted in an extensive utilization of cooling systems; hence, the electricity consumption gap was still high. In the other sectors, especially the industrial and commercial sectors, it is clear that with the increase in the number of confirmed infected cases, the electricity consumption gap decreased,

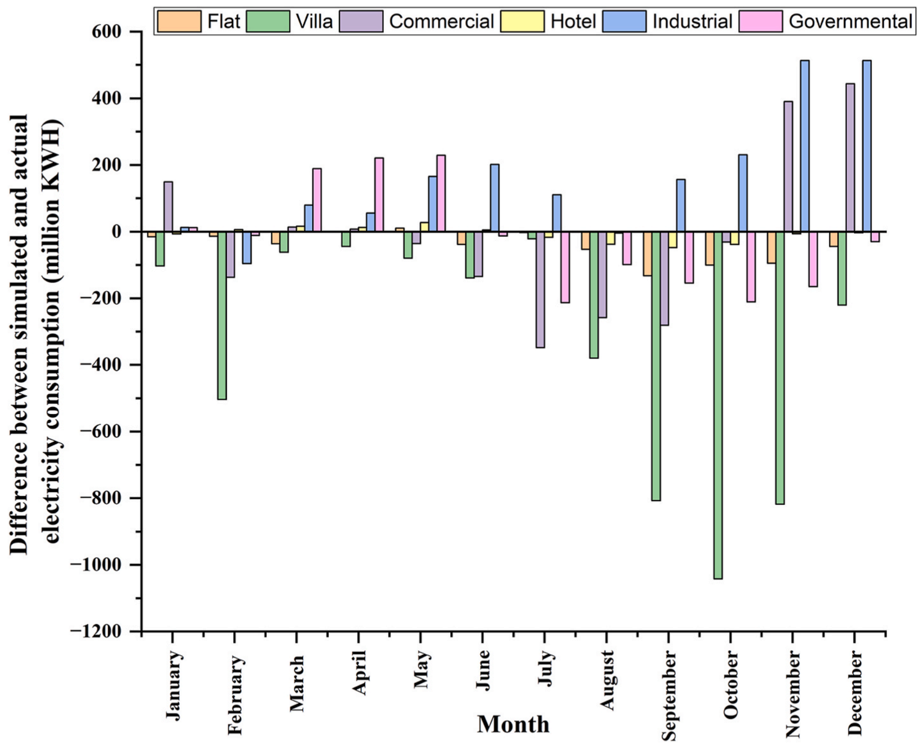

Fig. 6. Electricity consumption gap between the electricity consumption simulated using XGBoost and the actual electricity consumption.

and when the number of infected cases started falling in the consecutive months, the electricity consumption gap started increasing. In general, the figure shows different correlations between the numbers of confirmed daily infected cases and the electricity consumption gap over time and across sectors.

From February to May, the number of confirmed daily infected cases showed a rising trend. On the other hand, the gap in electricity use showed the same pattern in the residential sector and opposite patterns in the other sectors. During these months, the pandemic began to swiftly spread throughout the country, compelling the authorities to implement rigorous measures to halt the spread of the disease. These restrictive measures included imposing stay-at-home orders for residents, the suspension of work and production in many sectors and activities, online schooling, and the ban on international travel [6]. These measures resulted in a growing electricity consumption gap between the simulated and actual values in the residential sector. This result indicates that there is a positive correlation between the electricity consumption gap and the number of daily infected cases in the lockdown period.

In the period of easing the lockdown, June–September, the number of daily infected cases dropped significantly, with many measures still in effect. The electricity consumption gap followed the same pattern and dropped in all of the socioeconomic sectors. This finding means that although the spread of the disease was slowed, the electricity consumption of the whole society had not recovered and returned to the normal pattern as in previous years. There are different reasons that can explain this phenomenon. First, many services and production activities were not functioning at full capacity, particularly in the commercial and industrial sectors, which reduced electricity consumption in these sectors. Second, people were still psychologically panicked by the disease, and they experienced a prolonged immersion in anxiety from the pandemic, particularly due to the absence of any vaccine. This played an important role in making people hesitate to return to normal life, and hence, the whole society had not yet recovered to perform their activities at the same level as that prior to the pandemic. Looking at the electricity consumption gap in this period, we see the decline in the gap corresponding to the decline in the number of infected cases. Therefore, there was a positive correlation between the two despite the delayed impact of the pandemic during this period.

In the post-lockdown period, October–December, the daily confirmed cases were stabilized at a low level ranging between 150 and 250 daily cases. The authorities lifted all restrictions, and life almost returned to where it was prior to the pandemic. The electricity consumption gap declined in the residential (villas and flats), hotel, and government sectors. On the other hand, the gap increased in the industrial and commercial sectors, where the actual electricity consumption values were higher than the simulated values. This result indicates that the electricity consumption of Qatari society rebounded sharply, especially in the industrial and commercial sectors, as the values exceed the ideal values in a pandemic-free situation. This finding shows signs of economic recovery and the resumption of work and production at full capacity in the country.

5.6. Predicting electricity consumption in the second year of the pandemic (2021)

To understand the impact of the pandemic on electricity consumption in the second year of the pandemic (2021), we compared the actual electricity consumption values with the simulated values resulting from using the three machine-learning models, as shown in Fig. 8. In predicting electricity consumption in 2021, monthly electricity consumption data between 2010 and 2020 were used. The figure shows a different pattern in this year compared to the first pandemic year. During the first wave in 2021, the three models estimated that electricity consumption would exceed the actual electricity consumption in the residential sector, which is very different from the first year of the pandemic. The same is true for the months of November and December in the residential villa sector, while the models estimated the electricity consumption values to be less than the actual values between the onset of July and the end of October in the residential villa sector and the end of December in the residential flat sector.

In the commercial sector, the models estimated electricity consumption values higher than the actual values between the months of

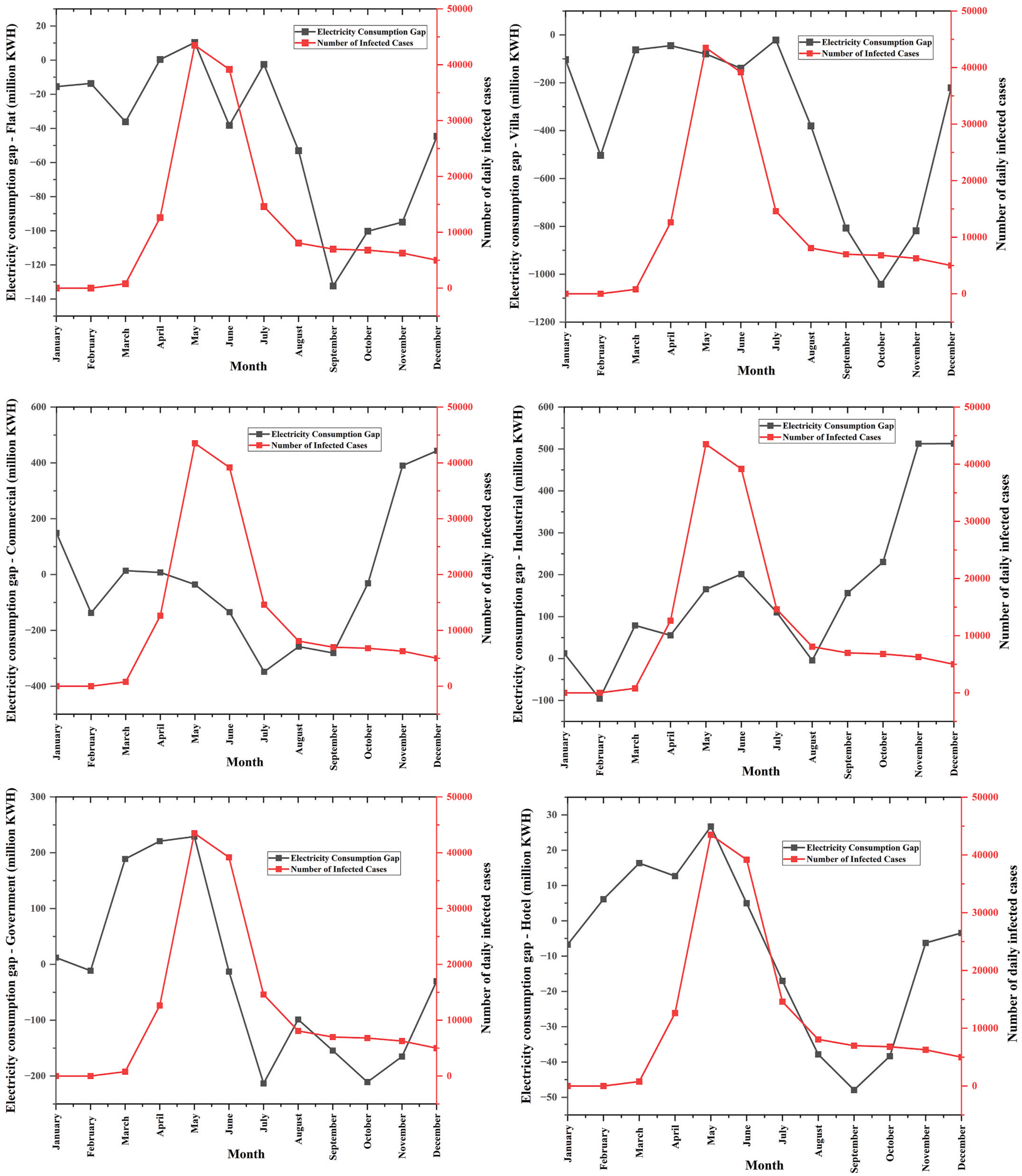

Fig. 7. Curve of the relationship between daily confirmed cases and the electricity consumption gap across sectors and over time in the 2020 pandemic year.

January and July, except for April, which is also a different pattern compared to the same period in 2020. The actual electricity consumption values exceeded the estimated values between August and the end of November 2021 and between June and the end of September 2020. In the hotel sector, the gap between the estimated and actual values of electricity consumption was very small during the two waves of the propagation of the disease during this pandemic year. However, a noticeable increase in this gap occurred during December because Qatar hosted the FIFA Arab Cup. The estimated electricity consumption in the industrial sector in 2021 had the same pattern as that in 2020 throughout the year; however, the actual consumption was different over time. The actual electricity consumption increased during the first

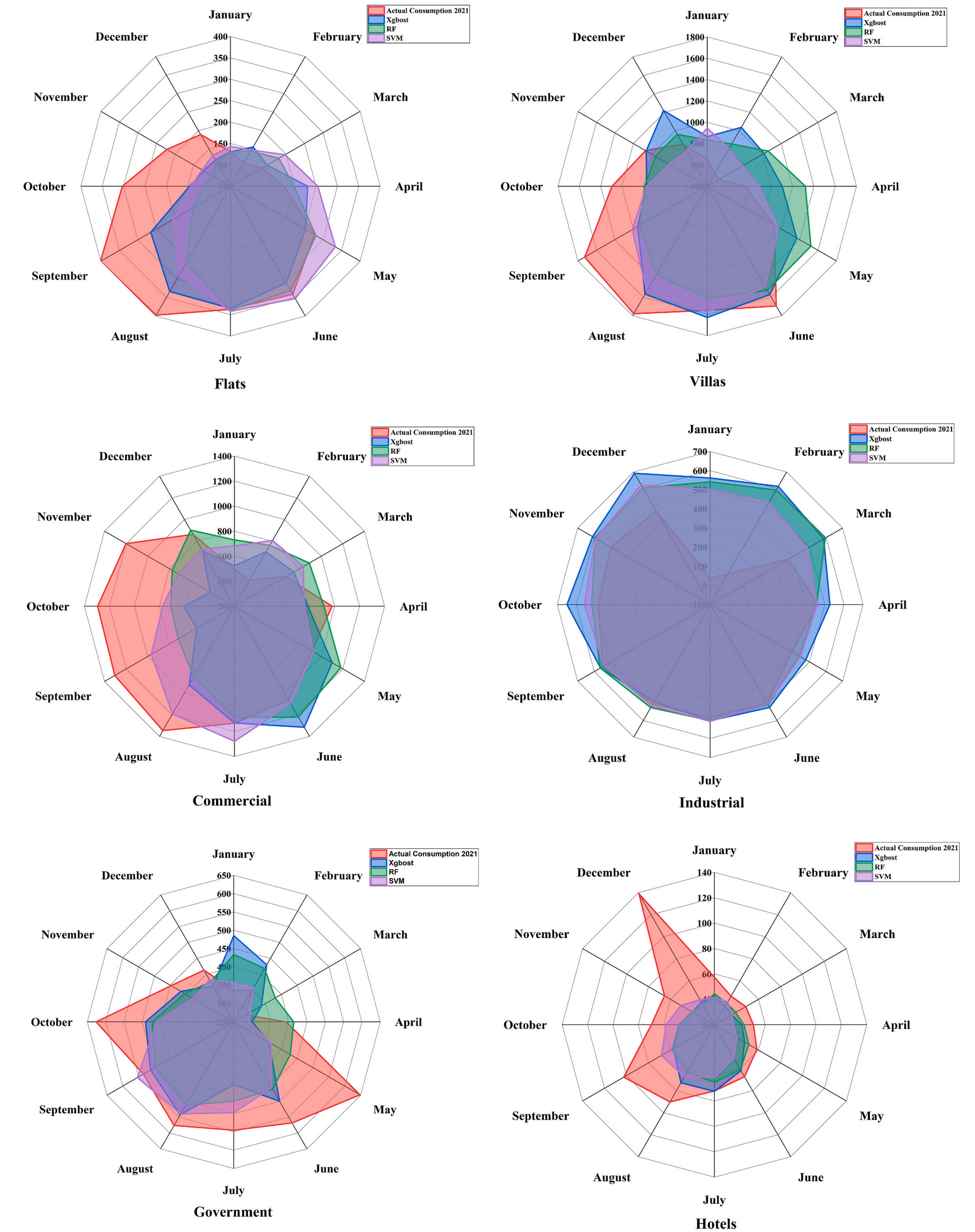

Fig. 8. Actual electricity consumption compared to the pandemic-free estimation in 2021.

wave period in 2021 compared to the same period in 2020. This finding shows that the industrial sector was not affected by the propagation of the pandemic at this time because workers performed their duties normally and no stringent measures were taken as the authorities started the vaccination process. Furthermore, people have to show the colour green on the EHTERAZ application before they are allowed to enter any place. In addition, masks were mandatory outside and inside places other than home. In the government sector, the actual electricity consumption was lower than the predicted values. One reason is online schooling since the vaccine was not approved for children, and during the first wave, the authorities preferred to switch to online teaching and learning to protect children from the disease.

One important observation in estimating electricity usage in the second year of the pandemic is the impact of the pandemic on electricity usage in the first year, which affected the accuracy of electricity consumption prediction; hence, the pattern in this year is different from what it was during the years prior to the pandemic. The analysis in Section 5.5 showed that the pandemic affected electricity consumption in the lockdown, easing the lockdown, and post-lockdown periods in all socioeconomic sectors in the first year of the pandemic. Consumption increased or decreased significantly in these three stages, as in the residential, commercial, and industrial sectors. Therefore, this unusual pattern of electricity consumption has an effect on estimating the values of electricity consumption under a pandemic-free scenario in the second year of the pandemic.

5.7. Predicting electricity consumption in 2022

The aim of this section is to predict the electricity consumption in 2022 using the three machine-learning models based on the electricity consumption data between 2010 and 2021. Furthermore, this section investigates how electricity consumption during the pandemic will affect the accuracy of the model predictions in consecutive years. Fig. 9 shows the results of the three models in predicting electricity consumption during 2022. Comparing these results with those obtained in Fig. 2, we see a significant difference in the pattern of electricity consumption in all socioeconomic sectors. In the residential sector, the figure shows a rapid increase in electricity consumption in the period between the beginning of January and the end of May, which corresponds to the lockdown period in 2020 and the new wave of the propagation of the disease in 2021. Therefore, the effect of the higher consumption during this period over the two years of the pandemic affects the pattern of electricity consumption in the consecutive year. The peak of electricity consumption occurs in April and May, while in Fig. 2, the pattern is very different, where the peak of electricity consumption occurred during the months of August and September. On the other hand, the lowest electricity consumption values were predicted to occur from August to October 2022, which is the opposite of the electricity consumption pattern prior to the pandemic. The same is true for the other sectors except the industrial sector. The figure shows that the predicted lowest electricity consumption should take place during the first few months in 2022, which corresponds to the months of lockdown in 2020 where electricity consumption was low or during the wave that took place in the early months of 2022. In general, the patterns of electricity consumption that resulted from the propagation of the pandemic affected the accuracy of predicting electricity consumption for 2022 and may also affect the accuracy of the prediction models in the short and long terms.

6. Conclusion and policy implications

The goal of this study is to assess the effect of the COVID-19 pandemic on electricity consumption across six socioeconomic building types. Furthermore, the study aims to investigate the relationship between the number of daily infected cases and electricity consumption across these building types. The study also investigates the effect of electricity consumption patterns on the accuracy of forecasting future electricity consumption using three machine-learning techniques. This study follows the historical development trajectory of electricity consumption between 2010 and 2019 to predict the pandemic-free scenario during the 2020 and 2021 pandemic years and to compare it with the actual electricity consumption as well as the correlation with the number of daily infected cases. This measurement can enhance our understanding of the effect of the pandemic on electricity usage during these two years.

This study use big data and machine learning techniques to investigate the impact of imposing the restriction policies on the real electricity consumption, which has important practical implications. The findings of this study clearly show that the impact of the COVID-19 pandemic on electricity consumption was highly heterogeneous when considering different socioeconomic sectors. The study shows that the spread of the disease created unusual changes in the electricity consumption across different socioeconomic sectors in Qatar. This creates challenges to electricity generation, distribution, transmission, and planning. These challenges are dynamic following the severity of the propagation of the pandemic and the restriction policies imposed to mitigate and slow down the spread of the disease. This impact was critically disclosed in this study by comparing the actual electricity consumption with the simulated one.

Based on the results of this research, the COVID-19 pandemic has had a negative effect on monthly electricity consumption in some socioeconomic sectors, mainly the residential sector. The actual monthly electricity consumption increased in the pandemic years due to the stay-at-home policy and the public's subsequent concerns over the disease, particularly during the first year of the pandemic, when there was no vaccination or cure for this disease. The stay-at-home policy resulted in an increase in the indoor activities of residents and the use of more electronic devices in residential buildings. On the other hand, the decrease in monthly electricity consumption in the other sectors, mainly the industrial and commercial sectors, indicates that economic activities declined during the first year of the pandemic. These factors resulted in changes in the building electricity consumption pattern. These differences in monthly electricity consumption between socioeconomic sectors can gradually maximize energy demand since the residential sector is the dominant sector in terms of electricity consumption in the country when COVID-19 is prolonged or in any future prolonged crises. This finding suggests that the authorities have to take different measures to reduce electricity consumption during crises. In Qatar, electricity prices are subsidized for expats, and electricity is free for citizens; therefore, increasing electricity prices, considering the economic consequences of the pandemic, can encourage residents to reduce their electricity consumption. Alternatively, the authorities can introduce new electricity tariff zones, where the tariff will be highest during the peak hours and lowest at night or on weekends.

The analysis clearly shows that impact of the government policies on electricity consumption over time and sector, which indicates that the imposed restrictions affecting individual behavior are considered powerful tools to affect electricity consumption. In addition, the number of COVID-19 infected cases mirrored the electricity consumption at the beginning of the pandemic, particularly during the lockdown period, confirming the importance of mitigation policies. However, the number of COVID-19 cases were no longer affect electricity consumption in the post-lockdown periods.

This analysis is important for policymakers in the country for several reasons. First, it helps them in planning and forecasting electricity consumption in times of crises and hence electricity demand and supply. Second, it enables them to detect changes in electricity consumption patterns and accurately predict electricity consumption over time and sector in the context of crises such as the pandemic. Third, policymakers can plan for sustainable management of resources to avoid weakening the country's economic development. Fourth, it helps them to formulate more realistic electricity demand management policies based on

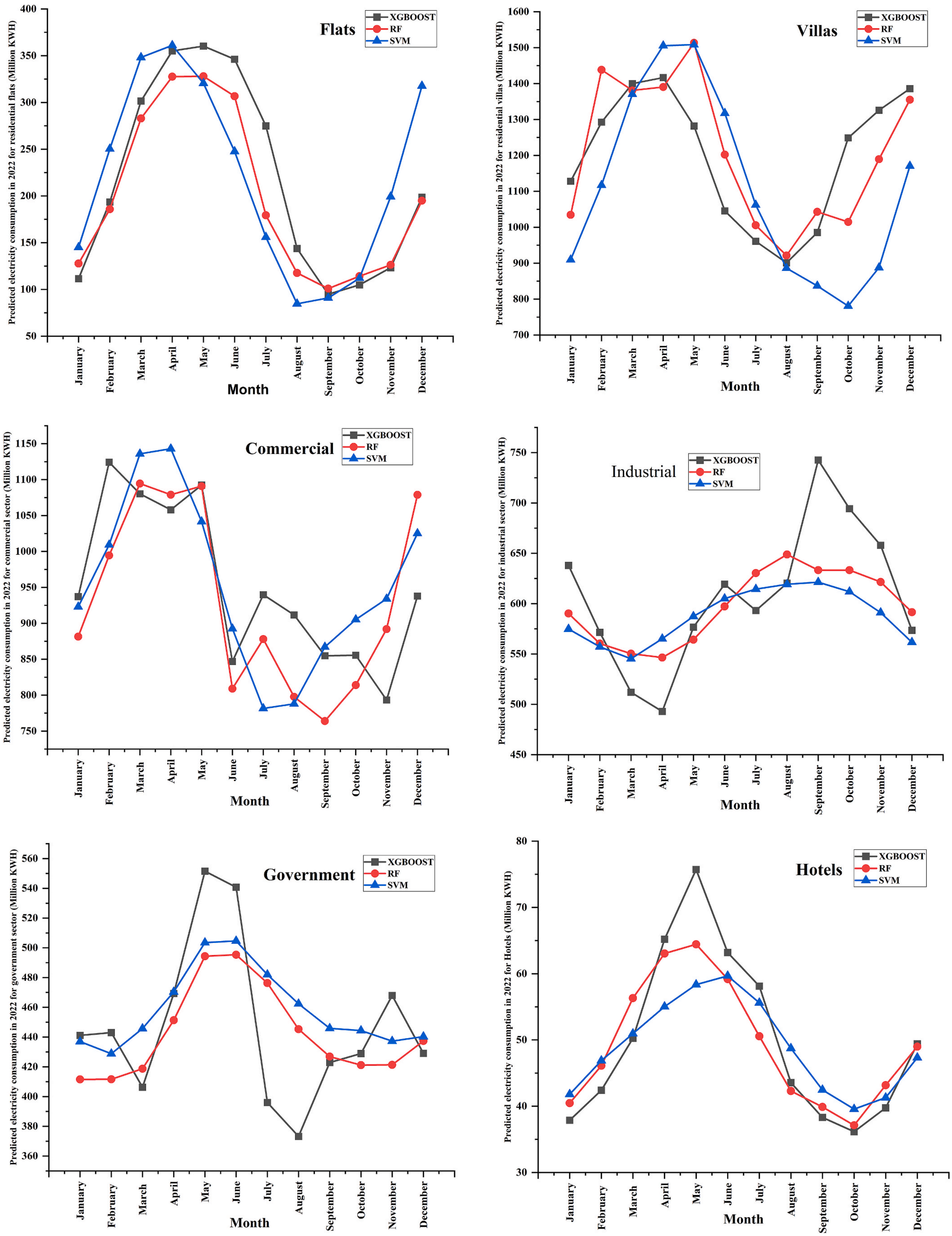

Fig. 9. The predicted values of electricity consumption during 2022.

socioeconomic sector during future crises and optimize electricity supply loads and energy profile. Fifth, the study can guide policymakers to adopt fiscal and non-fiscal tools to plan for industrial development and sustainable production in the time of crises, such as adjusting the pandemic mitigation policies and prevention strategies based on the expectation of negative effects. Sixth, the authorities may transform electricity consumption in other socioeconomic sectors of intensive electricity demand, such as the residential sector, by encouraging the use of high-energy-efficient appliances and improve the emergency response capabilities of the electricity sector in times of such crises. Finally, Although the country has abundant fossil fuel resources (oil and gas), the renewable energy system is another source of electricity generation that needs to be established and implemented in the country. This alternative can be implemented first as solar PV with a battery energy storage system on the roofs of residential buildings to reduce the reliance on the main conventional sources of electricity. The presence of this alternative is important in unexpected circumstances, such as this pandemic, where electricity usage changes rapidly.

Forecasting energy consumption in the midst of unprecedented crises such as pandemics is imperative for Qatar to determine load demand fluctuations and maintain a smooth process of supply to residents and commercial organizations. Industrial and commercial electricity consumption is highly correlated with the economic performance of the industrial and commercial sectors. Forecasting electricity usage therefore enables the authorities to plan for the future well-being of citizens and the economic growth represented by the performance of the industrial and commercial sectors.

Credit author statement

Ammar Abulibdeh: Conceptualization, Resources, Formal analysis, Methodology, Writing - Original Draft, Funding acquisition; Project administration. Esmat Zaidan: Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Resources; Writing - Original Draft. Rateb Jabbar: Formal analysis; Investigation; Methodology; Software; Validation.

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.

Data availability

The authors do not have permission to share data.

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