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Understanding Energy Behavioral Changes Due to COVID-19 in the Residents of Dubai Using Electricity Consumption Data and Their Impacts

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Abstract: The building sector consumes as much as 80% of generated electricity in the UAE; during the COVID-19 pandemic, the energy consumption of two sub-sectors, i.e., commercial (50%) and residential (30%), was significantly impacted. The residential sector was impacted the most due to an increase in the average occupancy during the lockdown period. This increment continued even after the lockdown due to the fear of infection. The COVID-19 pandemic and its lockdown measures can be considered experimental setups, allowing for a better understanding of how users shift their consumption under new conditions. The emergency health measures and new social dynamics shaped the residential sector's energy behavior and its increase in electricity consumption. This article presents and analyzes the identified issues concerning residential electricity consumers and how their behaviors change based on the electricity consumption data during the COVID-19 period. The Dubai Electricity and Water Authority conducted a voluntary survey to define the profiles of its residential customers. A sample of 439 consumers participated in this survey and four years of smart meter records. The analysis focused on understanding behavioral changes in consumers during the COVID-19 period. At this time, the dwellings were occupied for longer than usual, increasing their domestic energy consumption and altering the daily peak hours for the comparable period before, during, and after the lockdown. This work addressed COVID-19 and the lockdown as an atypical case. The authors used a machine learning model and the consumption data for 2018 to predict the consumption for each year afterward, observing the COVID-19 years (2020 and 2021), and compared them with the so-called typical 2019 predictions. Four years of fifteen-minute resolution data and the detailed profiles of the customers led to a better understanding of the impacts of COVID-19 on residential energy use, irrespective of changes caused by seasonal variations. The findings include the reasons for the changes in consumption and the effects of the pandemic. There was a 12% increase in the annual consumption for the sample residents considered in 2020 (the COVID-19-affected year) as compared to 2019, and the total consumption remained similar with only a 0.2% decrease in 2021. The article also reports that machine learning models created in only one year, 2018, performed better by 10% in prediction compared with the deep learning models due to the limited training data available. The article implies the need for exploring approaches/features that could model the previously unseen COVID-19-like scenarios to improve the performance in case of such an event in the future.

Keywords: COVID-19; lockdown; electricity consumption; behavioral analysis; machine learning

Citation: Manandhar, P.; Rafiq, H.; Rodriguez-Ubinas, E.; Barbosa, J.D.; Qureshi, O.A.; Tarek, M.; Sgouridis, S. Understanding Energy Behavioral Changes Due to COVID-19 in the Residents of Dubai Using Electricity Consumption Data and Their Impacts. *Energies* **2023**, *16*, 285. https://doi.org/10.3390/en16010285

Academic Editor: Yuji Yamada

Received: 16 November 2022
Revised: 6 December 2022
Accepted: 20 December 2022
Published: 27 December 2022

1. Introduction

COVID-19 has challenged the traditional ways of living and interacting worldwide since the World Health Organization (WHO) declared a COVID-19 pandemic on 11 March 2020. COVID-19 has become a global health concern and has changed how people live and work, affecting their lifestyles. The 21st-century pandemic condition has introduced many changes in people's lives. Since the virus emerged in late 2019, it has resulted in more than half a billion recorded cases and over 6.3 million deaths as of June 2022 [1]. Apart from the health crisis, where many people were hospitalized due to the effects of the novel coronavirus, the pandemic has affected the global economy, electricity, water consumption, and CO_2 emissions [2]. The movements of people were restricted both locally and internationally to contain the virus's spread. Several campaigns and lockdown measures, such as curfews, transport restrictions, and the suspension of civic and commercial activities, were implemented worldwide, ultimately affecting human behaviors and lifestyles. These changes can also be reflected by analyzing residential energy consumption, which is the main aim of this article.

Global energy consumption was reduced in 2020 by 4% due to the various imposed lockdown measures [3]. A lockdown is a restriction measure that forces individuals to isolate themselves from others and prevents them from forming crowds, such as gathering at parks and dine-in restaurants, working at offices, and operating educational institutes. Each government dealt with the pandemic differently, imposing lockdowns in several phases and modes, such as partial and complete (or full) lockdowns, which inevitably altered their general energy consumption. The pandemic has brought previously unseen scenarios affecting everyday needs. Besides COVID-19 front-liners, most individuals were urged to work remotely. These scenarios have abruptly altered the demands for water and energy in the commercial and, more importantly, residential sectors. As a result, the electricity and energy consumption in the commercial and industrial sectors experienced a steady decline, while an increase in consumption was observed in the residential sector [4]. The restricted measures have disrupted everyday activities for businesses and people, forcing them to adapt to new social dynamics and, consequently, shifting their energy demand patterns. With reduced mobility, working from home, distance learning, individual fitness, and online shopping transformed many daily urban activities to take place indoors. Bahmanyar et al. [5] compared the severity of COVID-19 restrictions with the effects on electricity consumption in different European countries. Countries with more severe restrictions, such as Spain, Italy, Belgium, and the UK, experienced relatively higher declines in electricity demand than countries with fewer or no restrictions, such as the Netherlands and Sweden.

During the earlier stages of the pandemic, an average drop of about 25% in the energy demand was reported in countries that implemented full lockdowns compared to an 18% drop for the countries that enforced partial lockdowns [6–8]. The electricity consumption of developed countries decreased drastically during the pandemic's earlier stages between February and April 2020. When considering February alone in 2019 and 2020, consumption in China dropped by more than 10% in 2020 because of the enforcement of a full lockdown [9,10]. Moreover, electricity consumption increased by about 5% in August 2020 compared to 2019 when the full lockdown was lifted. On the other hand, the French and Italian governments implemented lockdowns that lasted longer than the other countries, impacting the commercial and industrial sectors and the residential sectors [11]. With the lockdown enforcement and restrictions on other non-essential services, energy consumption has significantly reduced.

In contrast, domestic electricity and water consumption have increased, with people mainly being inside their homes. Some countries, such as Poland and Australia, experienced increases of 16% and 15%, respectively, in household energy demand due to the COVID-19 pandemic [12,13]. Since the response to COVID-19 transformed the modern lifestyle, researchers have attempted to model this impact by observing how people transformed their behaviors by analyzing the electricity consumption data [13,14]. The different sources of information and data characteristics have shaped the approaches of the different analyses. Some have studied the problem from a broad perspective, compiling reports from multiple countries to observe the effects on the national and regional levels [15]. Others have had access to national intra-day generation/consumption data and used simple metrics to compare the post-COVID-19 periods with the previous year's equivalent period [12].

Recently, Li et al. [16] quantified the impacts of COVID-19 on electricity consumption and emphasized a data-driven approach to predict electricity consumption in the non-COVID-19 scenario.

Figure 1 shows that ever since the lockdown in Dubai in April 2020 was imposed, consumption for sample residential users in Dubai has increased compared to other years. Although the surface-level assessment of COVID-19's impact was conducted in Sharjah [17], Dubai's neighbor emirate in the UAE, this work investigates the effects of these measures on electricity consumption patterns regarding Dubai residents using smart meter data at higher hourly resolutions. Thus, this article presents the work in two parts: the behavioral analysis of consumers and COVID-19's impacts on consumption demand. Therefore, the first objective of this work included analyzing the results of electricity consumption considering residents of Dubai in 2020 and comparing the results before and after the full lockdown period to understand the behavioral changes brought by COVID-19. In addition, Figure 1 also shows how the consumption patterns for sample residents across 2018 and 2019 are somewhat closer to each other and, hence, are considered normal or pre-COVID consumption. Moreover, the varying consumption patterns for 2020 and 2021 can also be observed as COVID-19 and post-COVID, respectively. Thus, the impacts of COVID-19 on electricity demand forecasting are explored in the second part. The rest of the manuscript is organized as follows. 'Background' is provided in Section 2, which is followed by 'Methodology' in Section 3, while Section 4 presents the 'Observation and Results' before the 'Conclusion', which is provided in Section 5. In the article where it specifically mentions 'total consumption', the 'consumption' mentioned elsewhere in the manuscript represents the mean hourly energy consumption for the sample users considered in the study.

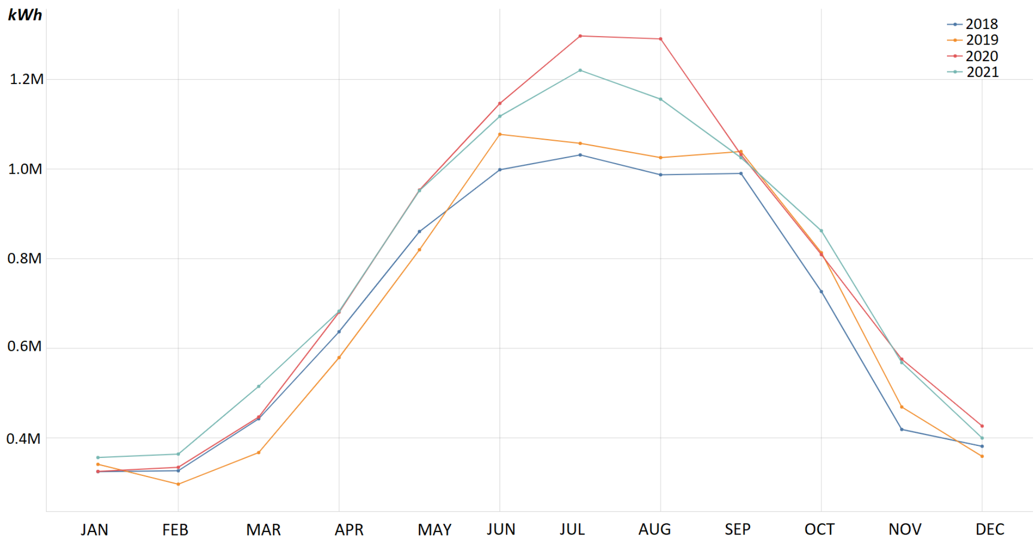

Figure 1. Total consumption for sample users in Dubai since 2018.

2. Background

2.1. COVID-19 in the United Arab Emirates (UAE)

The United Arab Emirates (UAE) imposed its first lockdown during the COVID-19 pandemic in April 2020. As a result, the UAE's electricity consumption in different sectors followed the global trend, and the CO_2 emission decreased to 203.14 Mt in 2020 as compared to 212.83 Mt in 2019 [18]. During the pandemic, the UAE emphasized the importance of protecting its residents against the possible consequences of the COVID-19 virus. As a result, many governmental and private sectors were directed to work from home, which led to an increase in electricity consumption in residential sectors [19].

Dubai, as part of the United Arab Emirates (UAE), took swift action to contain the crisis and reduce its impacts on the general public and economy. The city's main initiatives [20] were:

- Strengthening economic and business continuations;
- The National Disinfection Program and social distancing rules

Such a plan resulted in measures that changed how Dubai's economic activities were driven. For example, the social distancing program and the National Disinfection Program meant that Dubai closed all international borders on 23 March 2020, had a curfew enforced between 30 March 2020 and 24 June 2020, and had a full lockdown between 4 April 2020 and 26 April 2020. Additionally, on 25 March 2020 [21,22], most non-essential business operations and public events were instructed to shut down, and only after 26 April 2020 were businesses, such as dine-in cafes, allowed to resume but were limited to only 30% of their capacity. The authorities also defined several protocols to promote remote work and the digital transformation of businesses via virtual platforms [23]. Consequently, changes in the habits of Dubai's population were reflected in Google's COVID-19 Community Mobility Reports. It is estimated that during the lockdown period, there were significant reductions in several activities, such as retail and recreation, groceries and pharmacies, parks, transit stations, and workplace areas, as the overall time people spent indoors increased significantly. The main steps taken by the local authorities are presented below in the timeline and shown in Figure 2.

Figure 2. Timeline for COVID-19 containment actions in Dubai in 2020 [24].

- 25 February 2020: Authorities at Dubai International Airport (DBX) suspended many flights to/from Iran.
- 23 March 2020: The government suspended all inbound and outbound passenger flights and the transit of airline passengers in the UAE.
- 25 March 2020: Closing orders were issued for commercial centers, malls, and open markets.
- 30 March 2020: Stay-at-home orders were designed to curb the COVID-19 spread implemented through a curfew between 20:00 and 06:00.
- 4 April 2020: Authorities locked down Dubai as of 4 April due to the COVID-19 outbreak; a 24-h curfew was in effect.
- 26 April 2020: The full lockdown ended while maintaining a night curfew. Cafes and dine-ins resumed activity (limited to 30% capacity).
- 27 May 2020: Other business activities resumed and free movement was allowed in Dubai.

- 3 June 2020: All shopping malls and private sector businesses in Dubai were permitted to resume operations at full capacity, provided social distancing measures and other controls were met.
- 24 June 2020: Authorities in the UAE lifted the nightly curfew while permitting free movement day and night. However, social distancing measures were to be observed. Many businesses and restaurants have since reopened nationwide.
- 7 July 2020: The Dubai government announced that foreign visitors would be permitted to enter.
- 2 February 2021: Dubai reimposed one month of operations in public spaces at 70% capacity due to new COVID-19 outbreaks

2.2. Understanding Load Profiles during the COVID-19 Lockdown

The UAE is a country that is highly dominated by expatriates. Moreover, due to travel restrictions in the UAE in the summer of 2020, many stayed back and could not take travel vacations. The load profiles from the COVID-19 period are considered atypical compared to the standard consumption profiles before COVID-19, as observed in Figure 1. However, unlike other calamities, such as earthquakes, excessive rainfall, sand storms, and cyclones (where parts of the energy grid are required to repair or restart), this previously unseen COVID-19 pandemic scenario affected energy grids differently [25]. To avoid extended power losses in such calamitous scenarios, they typically relate to the need for an incremental grid restart to avoid over-voltage [26]. Instead, COVID-19 hardly affected Dubai's electricity demands [27], as shown in Figure 3, and there was no need for the extra purchase of electricity from other external grids. The statistics of total electrical power demands in Dubai (including industrial and commercial sector loads) as shown in Figure 3 show a decrease in the overall electricity demands during the COVID-19 lockdown period in March, April, and May. Yet, a substantial increase in residential energy demand was observed, up to 2.5% in the UAE [27,28]. Given the substantial residential demand increases reported elsewhere [4,13], it can be said that households whose occupancies increased due to working from home would have increased energy consumption.

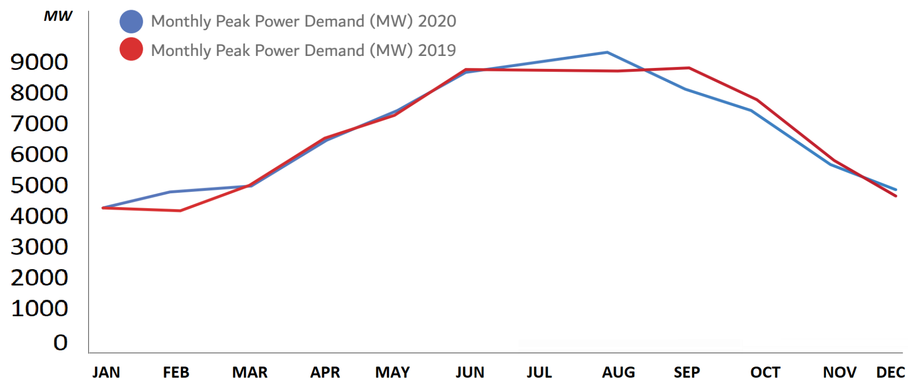

Figure 3. Monthly peak electric power demand for Dubai in 2020 compared to 2019 [27].

2.3. Profile Data of Residential User Surveys

"My sustainable living" is a Dubai Electricity and Water Authority (DEWA) program that encourages residential users to fill out surveys about the characteristics of their households and for residents to better benchmark their consumption against similar homes in the area. Thus, participating in this survey allows consumers to check their consumption and compare and monitor their electricity and water consumption with similar efficient homes in the area. One of the survey questionnaires is about the household's cooling service, which allows the categorization of consumers (based on cooling that is included in the billing or excluded because of the district cooling). Of the 439 residential consumers, 297 accounts were from the AC-included category, while the remaining 142 were from the AC-excluded category.

2.4. Regional Mobility Data for Dubai during COVID-19 Lockdown

When the pandemic became a global issue, Google and Apple made efforts to provide mobility data by collecting "anonymized sets of data from consumers who had turned on the Location History setting". Such data have proved to be useful for various studies, including mobility analyses before and during the pandemic [29–31], COVID-19 cases predictions [32,33], and economic responses during the pandemic [34,35].

In this study, Google's mobility report [36] was preferred compared to Apple's mobility trend data due to the representation of activity levels, the availability of data for Dubai, and the similarities with the utility bill categorization. Google's community mobility report demonstrates the changes in activity levels at the regional level within countries from the start of the pandemic in March 2020. The data are categorized into various economic activity sectors, namely retail and recreation, grocery and pharmacy, parks, workplaces, and residential, which can be seen in Figure 4. The activity levels were calculated by changing visitor numbers concerning the median value from the baseline period, 3 January–6 February 2020. Seven median values for each day of the week for different sectors allowed for a more accurate comparison without the day-of-the-week effects. Notably, for the residential sector, the activity levels were calculated utilizing the changes in the times that people spent at their residences. For instance, if a person initially spent 16 h at home, and this increased to 20 h during the pandemic, the mobility change value calculated in the mobility data would be 0.25 according to the mobility change equation provided in Equation (1).

$$Mobility_{change} = \frac{time_{COVID} - time_{baseline}}{time_{baseline}} \tag{1}$$

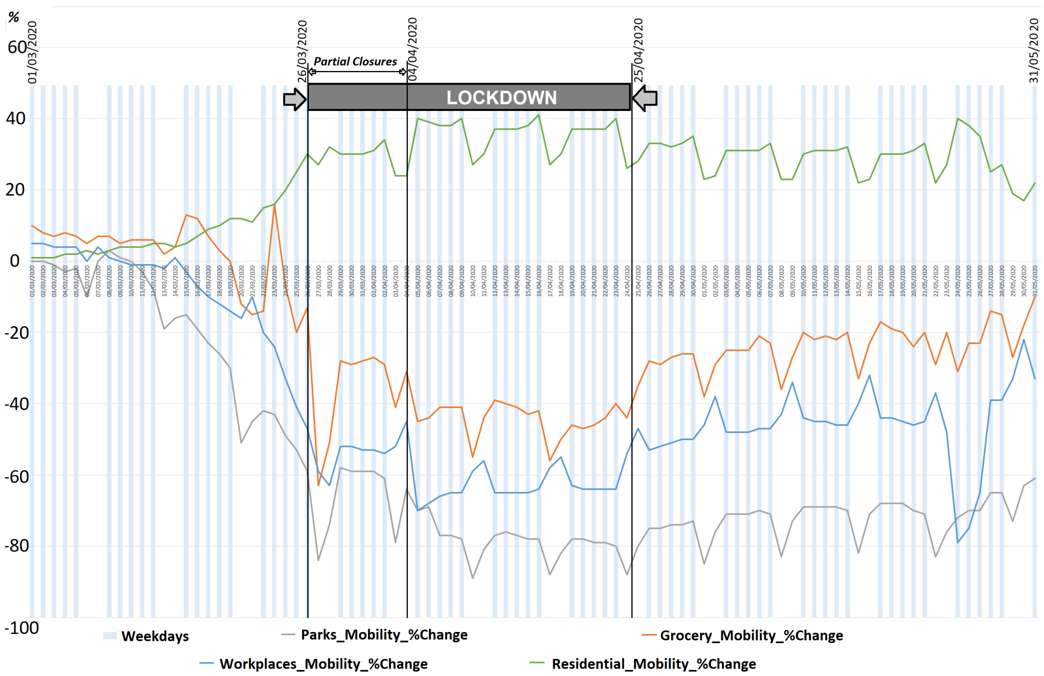

Figure 4. Google mobility chart for Dubai's residents during the lockdown period [36].

Since a typical working day is 8 h, the variations in the residential sectors are relatively small compared to other sectors. Another important factor is that mobility data do not specify seasonality and holidays. A sharp reduction in the residential mobility data should not necessarily be attributed to the influence of COVID-19. It can be attributed to the end of a window when the weather permits people to visit outdoor areas comfortably. The mobility chart for Dubai around the lockdown period (as shown in Figure 4) provides insightful information regarding the distribution of residents residing at home during weekdays and weekends as compared to going outside, such as parks, groceries, and workplaces. Figure 4 shows how the mobility percentage of residents residing at home increased when COVID-19 started to make inroads and when the full lockdown was imposed, the percentage of the residents living at home reached a maximum, and the mobilities of groceries, parks, and workplaces decreased. However, it can be observed that as their relative outdoor movements increased during the weekend, as indicated by significant dips at regular intervals, it consequently decreased residential mobility. Hence, a correlation was observed between residing at home and going outside for other activities.

3. Methodology

The overview of the approach carried out in this work is provided in Figure 5.

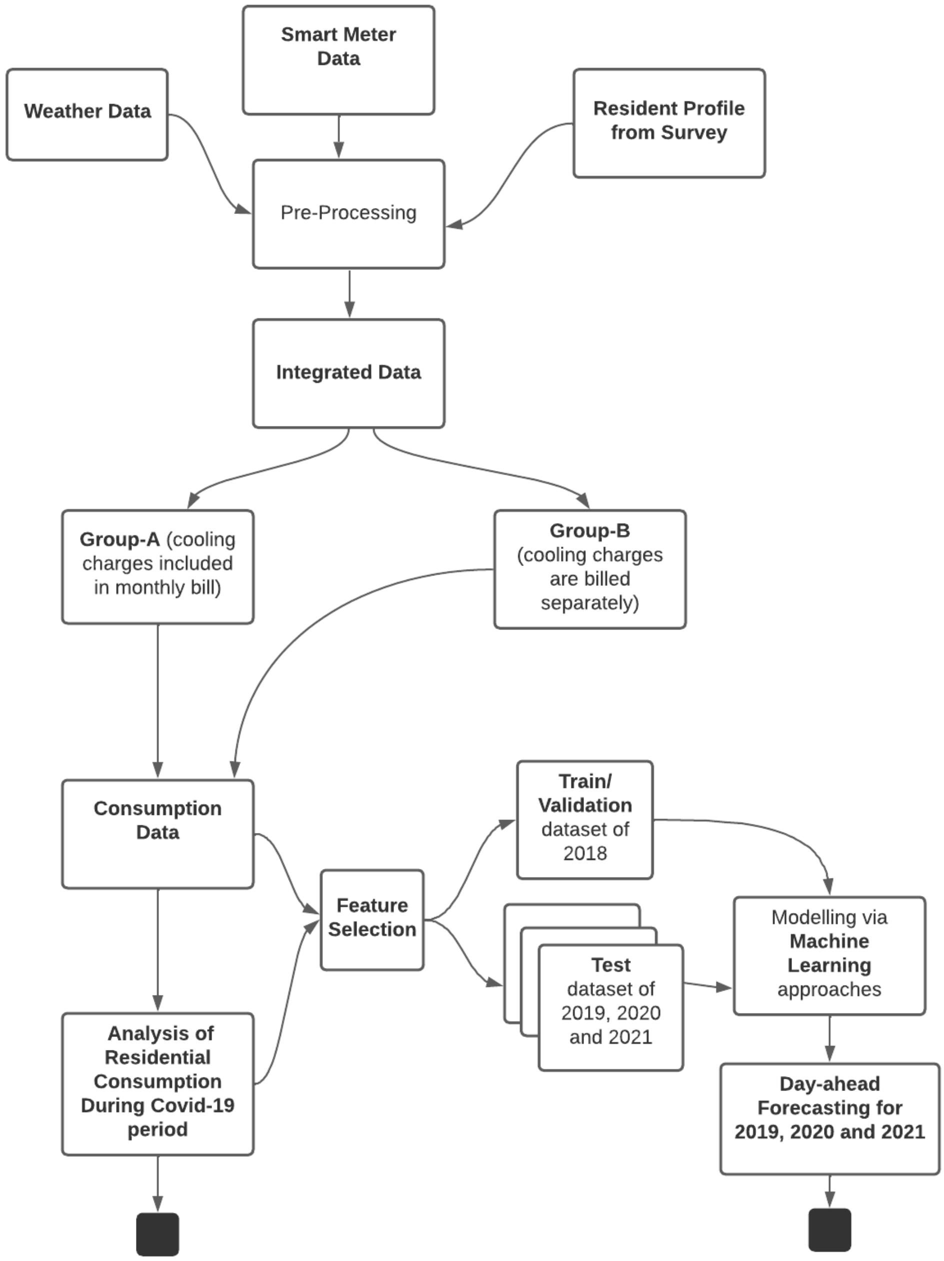

Figure 5. Flowchart of the approach used.

3.1. About Data

The three different data sources, such as smart meters, weather, and survey data, were considered for the analysis. The smart meters and weather data were pre-processed at an hourly resolution to consider the data for analysis after filtering out only those residents whose continuous data were available throughout the study period. Then, the consumption data for residents were segregated based on survey data into two cooling categories, namely 'AC-included' and 'AC-excluded', which represent residents whose cooling charges are included in their electricity bills, and those who use district cooling and, hence, cooling charges are excluded from their electricity bills. Thus, this work particularly focuses on the 'AC-included' category consumers as these consumers are the ones whose consumption would likely be able to capture seasonal weather characteristics and, hence, the varying consumption profile would hint toward their occupancy level.

A sample of 297 'AC-included' residential consumers with continuous smart meter records throughout the four years was used for analysis and modeling. Since 2018 and 2019, data belonged to the pre-COVID era, the data from these years are considered normal consumption data. Thus, for the behavioral analysis part, three years of data have been used since 2019, aggregating at an hourly level. Moreover, the consumption data are analyzed considering the full lockdown period in Dubai, which started in April 2020. When the full lockdown was imposed in April, all residents/occupants were expected to stay at home and work from home during that period. However, even after the full lockdown was lifted in Dubai, many people worked from home, and some still do. For simplicity, the three months of data for 2020 discussed in this article are:

- Pre-lockdown: March 2020;
- Full-lockdown: April 2020;
- Post-lockdown: May 2020.

Moreover, for the data modeling part, considering 2020 as an atypical period, the machine learning model was used for day-ahead forecasting trained on a typical period from 2018. The forecasting results for 2019, 2020, and 2021 data are compared.

3.2. Behavioral Data Analysis

The behavioral analyses of the residential consumers were carried out by understanding their mobilities and restrictions during the lockdown and COVID-19 era. At first, smart meter data for 'AC-included' cooling category consumers were analyzed to understand the behavioral analyses of consumption during the lockdown and the COVID-19 period compared to the analogous periods. The data were analyzed considering the temperature effect since Dubai has a hot and humid climate most of the year. The data were also examined from the perspective of working weekdays to weekends. Before 2022, the UAE observed weekends on Friday and Saturday; hence, residents used to enjoy weekends starting from Thursday evenings. Therefore, the weekdays referred to in this article represent Sunday to Thursday. Moreover, the time frame reflected in the analysis for 'day' is from 6 a.m. to 6 p.m., while 'night' refers to the other remaining hours.

3.3. Data Modeling

Machine learning approaches have been extensively used in recent times for forecasting and prediction compared to time-series analyses [37]. In this work, the findings of feature selection based on available data are presented, and the significance of the selected features in the various applied machine-learning approach is also reported.

3.3.1. Machine Learning Methods

Machine learning is a branch of artificial intelligence (AI) that deals with learning from data, identifying patterns, and making decisions with or without less human interventions. This section describes three machine learning approaches used in our study.

Support Vector Regression

Support vector regression (SVR) [38] is a supervised learning algorithm that attempts to find the best fit line representing a hyperplane with the maximum number of points. It works in a similar principle to a support vector machine (SVM). The SVM method involves projecting non-linear data onto a higher dimension space so that it can be linearly divided by a plane known as a "support vector". The kernel used in the SVR represents the function to approximate the data. Among the various available kernel options, such as the polynomial, sigmoid, and radial basis function (RBF). In our study, the RBF kernel is preferred for modeling as it performs mostly well with normal distribution data.

Random Forest

Random forest (RF) [39] is also a supervised learning method that combines the results from various forms of bagged decision trees (DTs) or with varying subsets of sample training data. The decision in a random forest is obtained using the majority voting of individual trees. It helps to improve the performance of the overall performance as the ensemble approach uses the output from multiple learning approaches to obtain a better predictive performance than that obtained from any of its constituents underlying a DT. The random forest output in the classification task case represents the class selected by the most trees. In contrast, the mean or average predicted values of individual trees are used for the regression task. In this study, about 200 DTs are trained, consisting of varying subsets of not only training data but also of varying subsets of features that help to make the final robust decision.

Deep Learning

Long short-term memory (LSTM) is a type of recurrent neural network with feedback connections and is a widely used technique of deep learning in many applications. LSTM networks can capture the sequence pattern information in time series data. LSTMs are designed to work with temporal correlations, utilizing only the attributes provided in the training set. LSTM refers to the analogy that a standard RNN has both 'long-term memory' and 'short-term memory'. The network's connection weights and biases change once per training episode, analogous to how physiological changes in synaptic strengths store long-term memories; the activation patterns in the network change once per time-step, analogous to how the moment-to-moment changes in the electric firing patterns in the brain store short-term memories.

3.3.2. Feature Selection vs. Importance of Features in the Model

Feature Selection

The feature selection [40] process allows for identifying significant features from the available list of features in the data that affect the target variable. The feature selection also reduces the dimensionality of available data, making mining tasks much more straightforward while ensuring quality in the underlying information for processing the data. Moreover, desirable features can be identified to create a subset by using a method such as the Ranker-based feature selection algorithms that first evaluate the features and then generate a rank list based on the score (distance, correlation, information gain, consistency measures).

The linear correlation coefficient measure [41] is one of the most recognized methods of classical linear correlation. The linear correlation coefficient 'r' for a pair of variables (X; Y) is defined by the formula r' described in the equation below.

$$r = \frac{\sum_i (x_i - x_i')(y_i - y_i')}{\sqrt{\sum_i (x_i - x_i')^2}\sqrt{\sum_i (y_i - y_i')^2}}$$

where x_i and y_i represent the values of the 'X' and 'Y' variables while x_i' and y_i' represent the mean of values of these 'X' and 'Y' variables, respectively.

Importance of Features in the Model

The Shapley additives [42] are used to understand the influence of each feature in the trained model. Apart from knowing the important features of the data, it would also be beneficiary to know how the so-called black-box machine learning model interprets the features. Thus, the feature importance allows for estimating how much each feature of the data contributed to the model's prediction.

3.3.3. Evaluation Metrics

To validate the effectiveness of the forecasting model, metrics, such as RMSE, MAE, and MAPE, are used to determine the model's fit.

Root Mean Square Error

The RMSE is calculated as follows, where (x_i) is the actual value while (x_i') is the modeled or predicted value for 'n' number of observations:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - x_i')^2}$$

Mean Absolute Error

The MAE is calculated as follows, where (x_i) is the actual value while (x_i') is the modeled or predicted value for 'n' number of observations:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - x_i'|$$

Mean Absolute Percentage Error

The MAPE is calculated as follows, where (x_i) is the actual value while (x_i') is the modeled or predicted value for 'n' number of observations:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{x_i - x_i'}{x_i}|$$

4. Observations and Results

4.1. Behavioral Analysis

The consumer behaviors are compared before and after the event to understand the behavioral changes. Even though COVID-19 has not disappeared, due to the vaccination campaign, COVID-19 is contained to a certain extent. Hence, the analogous period during the lockdown of April, the month before, and the month after were mainly considered across three years for the analysis.

4.1.1. The Need for High-Resolution Data

COVID-19-related modeling and analyses have been performed with monthly resolution data [17,43]. However, while considering monthly data (as shown in Figure 6), the impacts of the COVID-19 periods on the monthly level consumption data are not entirely evident. The graph of both AC categories (i.e., AC-excluded/included in billing) does not shed light on the effects of COVID-19 on the consumption data. The plots for 2020 for both AC categories started to rise after the third month, but it is unclear whether it was due to COVID-19, weather, or other factors. Thus, it is necessary to have higher-resolution data (of at least hourly resolution data) to analyze the behavioral changes due to the impacts of COVID-19 and the lockdown.

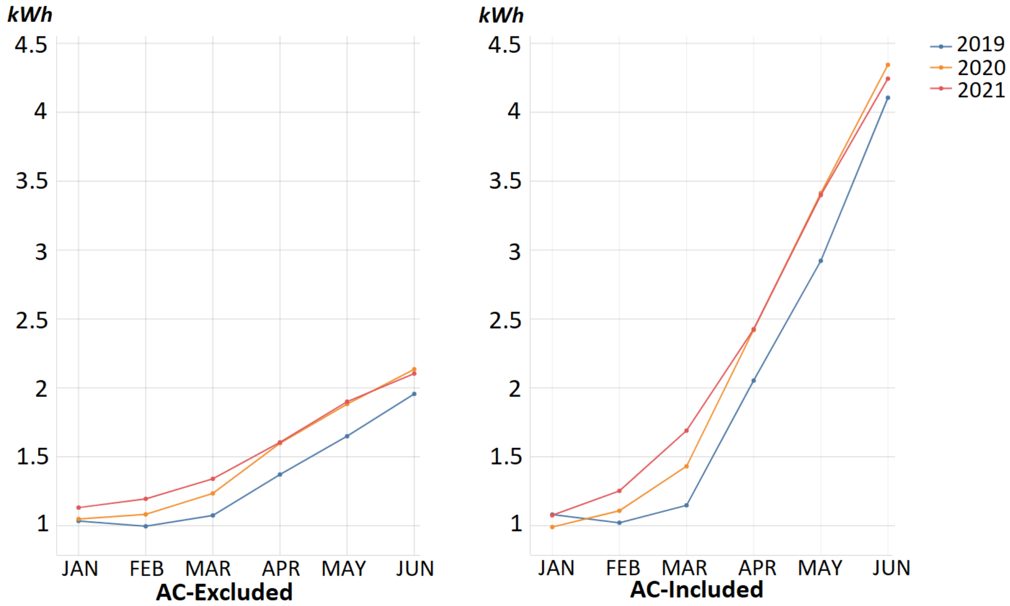

Figure 6. Consumption per user on monthly billing cycle for two AC categories.

4.1.2. The Effect of Mobility Restriction

Figure 7 shows the variation in the mean consumption across two AC categories compared to the residential mobility changes. Here, with the help of a mobility chart, the impact of COVID-19 on consumption is explored. Before the full lockdown was imposed, outdoor mobility started to decrease, and the residential mobility change reached a maximum during the lockdown period. During the same time, as the season changed from spring to summer, the AC-included category's consumption increased sharply as compared to the consumption of the AC-excluded category. As seen in Figure 7, during the full lockdown in the early days of April, the mean consumption reached its maximum for both categories on the weekends compared to weekdays despite a slight increase in outdoor mobility. It can be attributed to consumers settling down to remote settings, initially allocating most of their household tasks over the weekends. The consumption peaked later toward weekdays as the full lockdown was lifted, indicating that consumers were distributing their household tasks throughout the week. Despite the full lockdown being lifted on 26 April in Dubai, it did not necessarily take us back to pre-COVID conditions but alleviated some of the measures that forced most consumption at home.

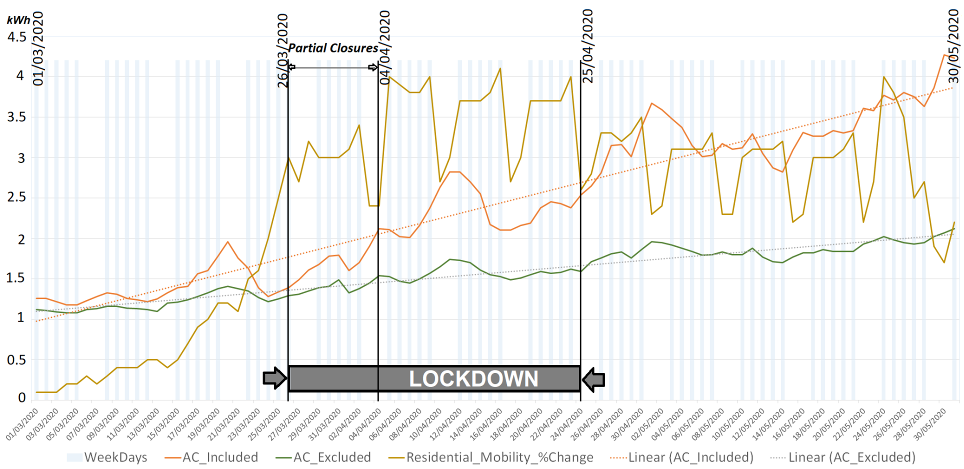

Figure 7. Google mobility chart [36] vs. consumption for AC-included/excluded categories during the lockdown period.

4.1.3. The Temperature Effect

Temperature is the dominant factor in Dubai that drives the consumption of electricity. As shown in Figure 8, moving from January onward to March, the mean temperature increased by 2–3 °C each month and by 4–5 °C from March to May. The electricity consumption increased with the temperature increase as more cooling was required to maintain thermal comfort.

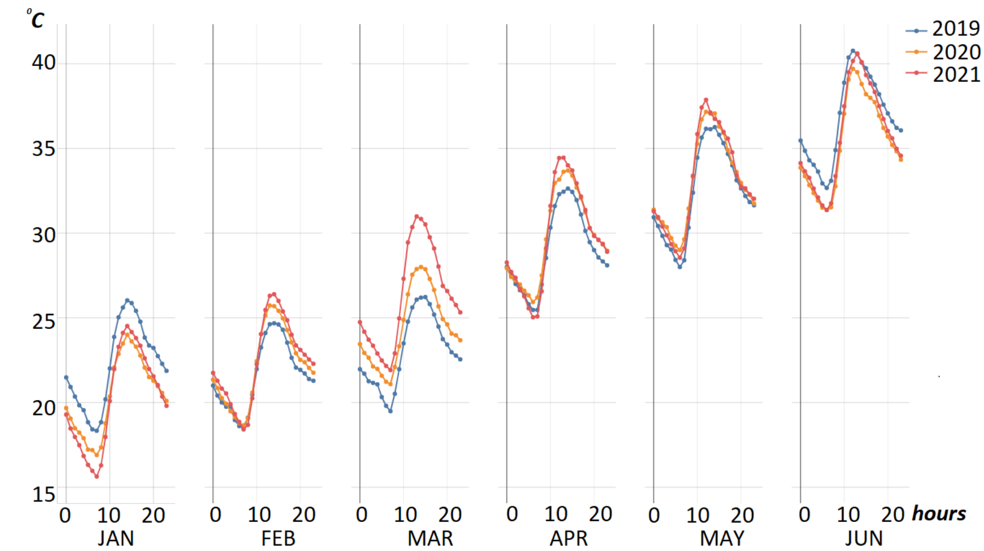

Figure 8. Mean hourly temperature for the first 6 months over 3 Years.

In Figure 9, the consumption for AC-included category consumers increased by an average of 10% each month from January until March, switching from the winter to the summer season. Even though the full lockdown was imposed on 4 April 2020, the pre-lockdown effect was observed for the first three months as the COVID-19 'line' of 2020 was well between the other two-year plots. After the full lockdown was enforced, consumption increased by almost 40% during the daytime. A similar pattern was also observed after the full lockdown period, with an average increase of 30% from April to June. It indicates that apart from weather influences, other factors are involved, leading to the rise in consumption associated with consumer occupancy at home.

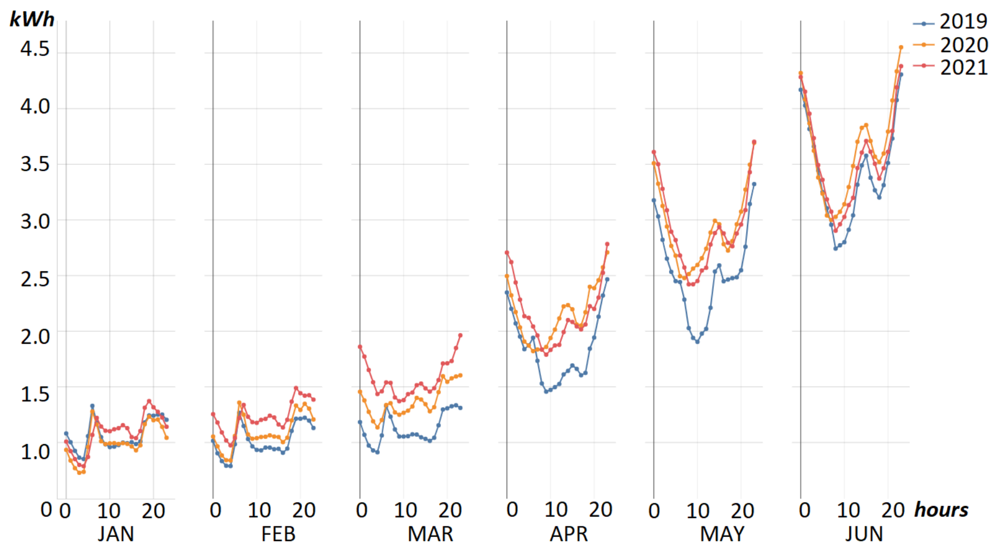

Figure 9. Mean hourly consumption profiles for AC-included category consumers for the first 6 months over 3 years.

In Figure 10, AC-included category consumers for the three months (March, April, and May) were analyzed across analogous months from three years to de-emphasize the effect of temperature. It can be observed that at the same temperature, consumption in 2020 and 2021 increased compared to 2019. This was especially noticed in the daytime during the full lockdown in 2020 when occupancy was at its maximum. It indicates that occupancy is dominant, leading to higher consumption. Thus, the behavioral changes in the consumers are explored to identify the cause.

4.1.4. The Behavioral Traits during and after the Lockdown Period in 2020

Habits and lifestyles are represented by various behavioral means. For example, when COVID-19 and the lockdown were in full swing, people changed their work lifestyles and settled in remote settings, which would have decreased commercial consumption and increased residential consumption. In Figure 11, the three months of 2020, from March to May, are referred to as pre-lockdown, full-lockdown, and post-lockdown, respectively. Figure 11 shows the ratchet effect of the increased consumption progression since the lockdown period. The trend did not revert after the lockdown as the temperature significantly contributed to the higher consumption.

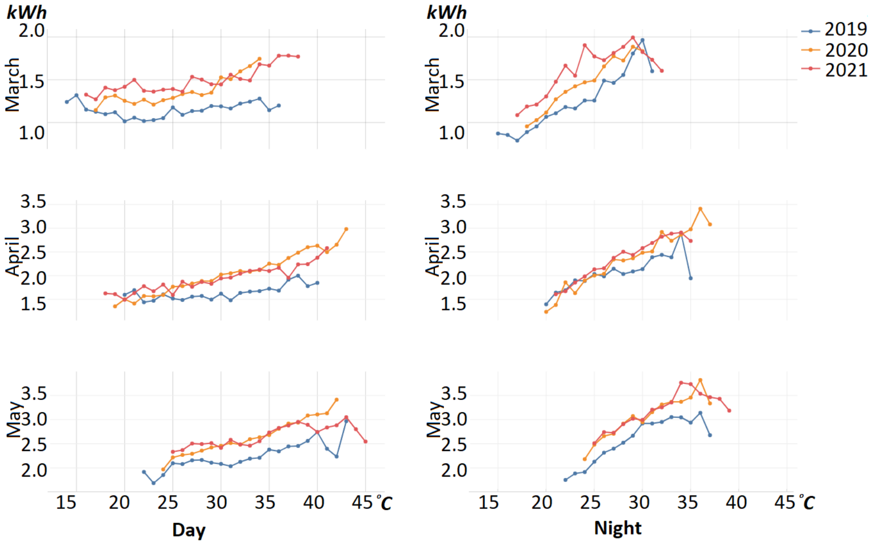

Figure 10. Consumption vs. temperature comparison for 3 analogous months (March, April, and May) over 3 years.

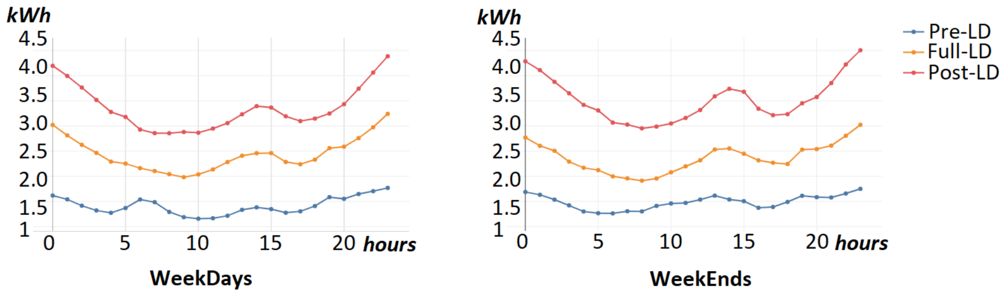

Figure 11. Mean hourly consumption profiles for weekdays/weekends during the lockdown period in 2020.

In addition, the profile patterns changed for these consumers over the week. In the pre-lockdown period, the weekday consumption rose at 5 a.m., but during the full lockdown period, the trend seemed to follow until 9 a.m. before it rose. However, during the full lockdown period, the weekday consumption patterns matched the weekend consumption patterns with the only difference in magnitude, with the consumption being higher on the weekdays. Moreover, the same trend was noticed for the post-lockdown period in 2020 as most of the consumers were still working from home during that time, and the higher consumption could be linked to a higher temperature.

When Figure 11 is observed from another angle, as shown in Figure 12, the weekday and weekend profiles of AC-included consumers match the daytime during the full lockdown and post-full-lockdown period. Moreover, the trend is similar but has a slight variation in magnitude throughout the day. However, before the lockdown, the trend between the weekday and weekend profiles used to differ.

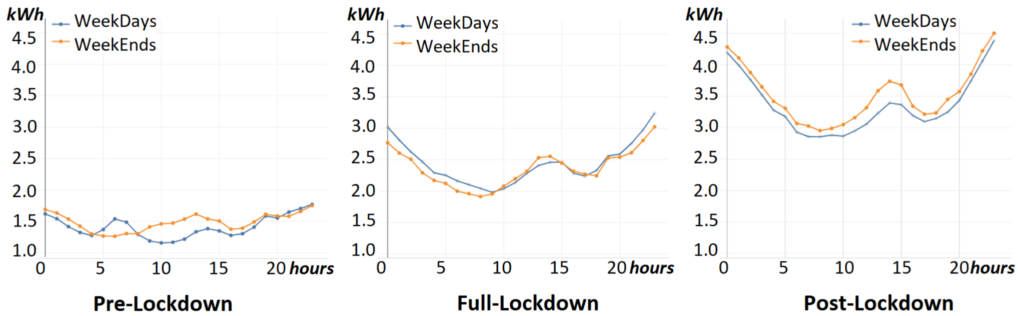

Figure 12. Comparison of weekends vs. weekdays mean hourly consumption profile before/during/and after the lockdown in 2020.

4.1.5. Comparison of the Consumption Profile across Analogous Periods

The data (at hourly levels for three years) were analyzed for the 'AC-included' category throughout April when the full lockdown was imposed in 2020, as shown in Figure 13. Consumption in 2020 was higher during most of the 'sun-hour' period from 8 a.m. to 9 p.m. for the weekdays, illustrating the maximum occupancy during this time. Moreover, the peak observed in 2019 in the morning at around 6 a.m. during weekdays disappeared in 2020, showing that the residents woke up late as they did not need to be outdoors for work or school. Therefore, the profile of 2021 captures the mixture of both 2019 and 2020 profiles. The trend of the 2021 profile was more toward attempting to regain the 2019 profile and heading toward normalcy, which shows that consumers started spending time outdoors, which resulted in less consumption.

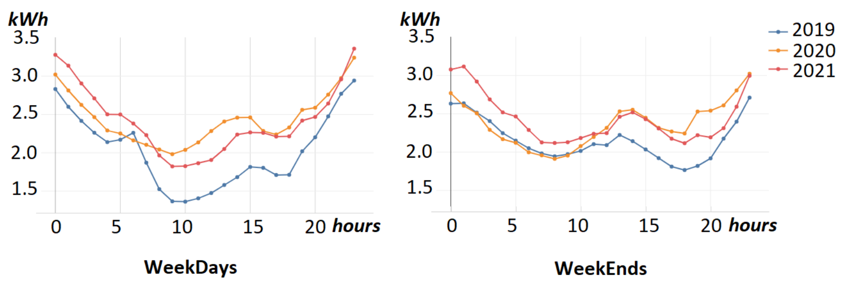

Figure 13. Mean hourly consumption profile for weekdays/weekends for April across 3 years.

Comparison between Weekdays

A weekday usually represents a working day where people rise early in the morning, get ready for work, and return from work in the evening. However, COVID-19 resulted in people working from home, and the electricity consumption profile changed, reflecting the changes in behavioral traits. Figure 14 (top) shows how the behaviors of residents have changed on weekdays. Consumption has generally increased, especially during the daytime during the COVID-19 period in 2020. Sunday is observed as the busiest working day, with consumption rising throughout the day and night. The profiles of consumers seem to have similar trends on working days. The most significant difference that can be inferred from observing the consumer profiles in 2019 comes from those who enjoyed

Thursday evenings with lesser consumption compared to those who were out. These scenarios changed drastically in 2020 as the Thursday evening plot clustered more closely with other working days (as consumers stayed home). In contrast, consumers in 2021 started regaining their pre-COVID trends as they noticeably recovered their Thursday evening moods by being outdoors; the gap widened with lesser consumption.

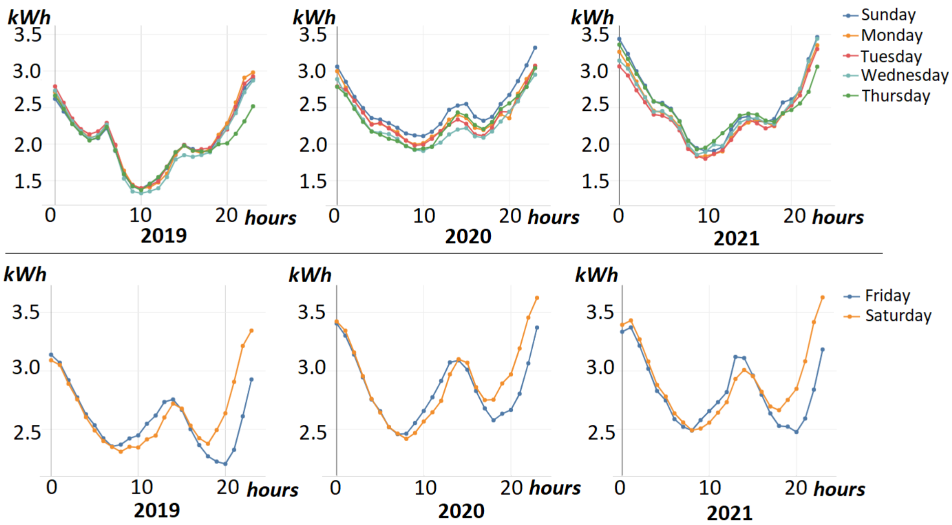

Figure 14. Mean hourly consumption profile for weekdays (**top**) and weekends (**bottom**) for 3 months over 3 years.

Comparison between Weekends

The weekend is a time for leisure purposes. However, COVID-19 and the lockdown changed the habits of people as they stayed home throughout the week. Thus, the weekend profiles of consumers were explored to understand the variations during the study period. From Figure 14 (bottom), Friday seems to be the most celebrated day of the weekend, as the overall consumption is lower (by 2.5% as compared to Saturday). In 2019, the consumption until noon seemed similar, but Saturday showed higher consumption, indicating consumers were going out on Friday or conducting minimum activities while staying home. Moreover, consumption relatively increased in 2020 and 2021 over the weekends, indicating more indoor usage. In 2020, the consumption patterns for Friday and Saturday were similar. Hence, the percentage difference was minimal across three years, with 2.1% for the AC-included category. In addition, we observed that the impacts on peak load hours due to COVID-19 and the lockdown did not affect the overall peak hour load as it remained the same at 11 p.m. for the three months (pre-lockdown, full-lockdown, and post-lockdown). The overall peak hour was 11 p.m. and most of the consumers were at home irrespective of the lockdown; thus, this was expected to have no impact on the overall load shifting. However, when looking at the AC-included category for the daylight hours during weekdays, the peak hour changed for consumers from 6 a.m. in the pre-lockdown period to 3 p.m. in the full lockdown and then to 2 p.m. in the post-lockdown period. For the weekends, the peak hour changed from 1 p.m. to 2 p.m. during the full lockdown and afterward.

Consumption vs. Occupancy in Bedrooms

Considering sample residents, it is evident that the consumption across most types of bedrooms for the AC-included category increased during the April lockdown period compared to the previous year and the following year, as observed in Figure 15. The consumption seemed to be lower during the lockdown in 2020 in cases where the number of bedrooms to occupant size ratio was lower than 0.33. When exploring the profiles of the above-mentioned specific cases, these profiles appeared to belong to residents having three or more children.

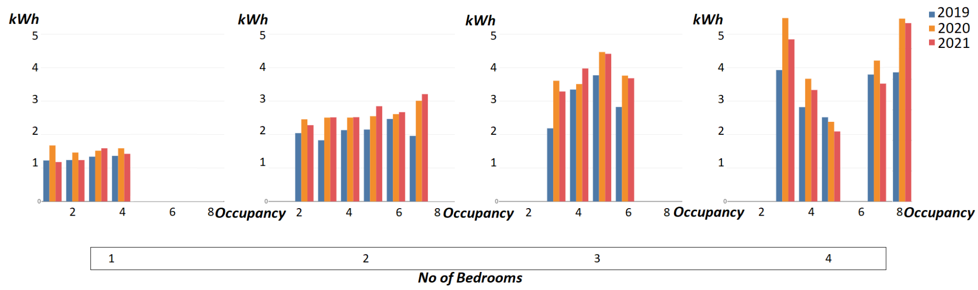

Figure 15. Mean consumption vs. occupancy in bedrooms in April over 3 years for the 'AC-included' category.

4.1.6. Discussion and Summary of the Analysis

After analyzing the hourly electricity consumption of 439 consumers in Dubai in the pre-lockdown, full-lockdown, and post-lockdown periods of 2020 and comparing them with the analogous periods in 2019 and 2021, a direct effect of temperature was observed. The consumption and analyzed plots show that COVID-19 has changed consumption patterns. An up-shift in consumption was observed since the COVID-19 inception, which has continued to date. Various factors could have contributed to the rise in consumption. One of the main reasons is the maximum indoor occupancy during the lockdown. Since consumers were mostly locked up in one place, one can relate this to the higher usage of electrical appliances. Moreover, many people used electrical appliances during COVID-19 for their engagements, such as for cooking experimentations and fitness purposes (usage continues to the present today). A 12% increase in annual consumption was observed for residents in 2020 compared to 2019, with the mean consumption increasing from 2.49 kWh to 2.80 kWh for the 'AC-included' category. The total consumption demand remained almost constant in 2021, with 2.79 kWh (i.e., only a 0.2% decrease from 2020 as opposed to a huge surge observed since 2019). A similar distribution was observed in the 'AC-excluded' category of consumers for 2020, while 2021 showed a 0.6% decrease in consumption.

The following points summarize the behavioral analysis:

- Residential energy consumption during and after 2020 has increased, especially during the day, compared to previous years (i.e., 2018 and 2019).
- There has been an up-shift in consumption by 12% since the COVID-19 era.
- Seasonality effects of temperature were observed in consumption data for AC-included consumers.
- The mean electricity consumption increased with the temperature increase as more cooling is required to maintain thermal comfort.
- The mean electricity consumption among Dubai residents/households increased despite the temperature effects and considering the full occupancy during the full lockdown period compared to the pre-lockdown period.
- The mean consumption profiles of consumers during Weekdays and Weekends were similar throughout the full lockdown period.
- The mean consumption profiles of consumers across all working days had similar profiles in the full lockdown period.

4.2. Electricity Demand Modeling

4.2.1. Feature Selection and Modeling

Machine learning approaches, such as SVR and RF models, are used for modeling day-ahead forecasting with hourly mean consumption data. The metrics, such as RMSE, MAE, and MAPE are used for the evaluation purposes of the above two models.

To demonstrate the impacts of COVID-19 and the lockdown on electricity demand, mean hourly consumption data for 2018 were used for forecasting day-ahead via machine learning approaches. The developed model has been used for prediction each year since 2019. The primary focus was on the prediction for April when a full lockdown was imposed in 2020. The features used in the model included a 5-day historical consumption lag at the hourly level, day of the week, weekday/weekend, temperature, and relative humidity. The 5-day historical consumption lag at the hourly level is vital because it helps to model the hourly consumption for the day-head consumption and it represents the consumption of previous days, which are likely to be similar for the forecasted hours in the majority of cases. Apart from weather data, such as temperature and relative humidity, as well as smart meter data with hourly lags, the behavioral analysis in the earlier section shows that the day of the week and weekday/weekend data are vital in the study. These two attributes ('Day of the Week' and 'Weekday/Weekend') helped to increase the R-squared values of the machine learning models, which are reported in the results section, compared to the features without these two.

4.2.2. Feature Analysis

Despite the feature selection process, the selected features that played roles in the trained model were also analyzed. Among the two machine learning methods used, the SVR model was considered based on its ability to observe features that influenced the black-box model. By using the Ranker-based correlation feature selection, the critical features observed are in the respective order: 'Lag Hour 24', 'Lag Hour 48', 'Lag Hour 72', 'Lag Hour 96', 'Lag Hour 120', 'Temperature', 'Weekday/Weekend', 'Day of the Week', and 'Relative Humidity'.

Based on Shapley Additives, as shown in Figure 16, 'Lag Hour 24' is the most important feature that influenced the random forest model followed by other essential features, such as 'Temperature', 'Weekday/Weekend', 'Day of the Week', 'Lag Hour 48', 'Lag Hour 72', 'Lag Hour 96', 'Lag Hour 120', and 'Relative Humidity'.

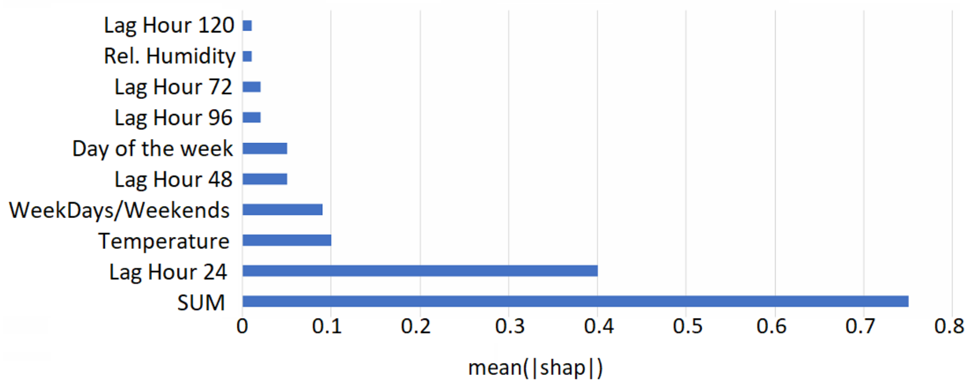

Figure 16. Influence of features in the support vector regression model.

4.2.3. Results and Discussion

After performing the behavioral analysis of the consumers' data before, during, and after the lockdown, the features were determined. To understand the impacts on the consumption demand due to the pandemic, we analyzed the electricity consumption results, considering residents of Dubai in 2020, and compared the results before and after the full lockdown period to determine the deterministic features for modeling the consumption demand. The trained models (based on machine learning for the 'AC-included' category) have certain model performance observations, as provided in Table 1. Two features ('Day of the Week' and 'Weekday/Weekend') helped to increase the R-squared values of both machine learning models (from 0.92 to 0.95 for the AC-included category). Figure 17 shows the actual observed and modeled values for day-ahead forecasting. SVR models had better modeling and predictive performances with the provided features and lags. Thus, Figure 18 shows the performance for each of the three years and focuses on April for the 'AC-included' category. Fewer 2019 forecasted values fall across the 10% error line compared to 2020 and 2021 as well as their respective April months, where the data lying across 10% were much higher, showing the disruption caused by COVID-19 and the lockdown, respectively.

Table 1. Trained model performance for the 'AC-included' Category.

Models	Random Forest	SVR
RMSE (kWh)	0.17	0.15
MAE	0.18	0.16
R-Squared	0.95	0.95

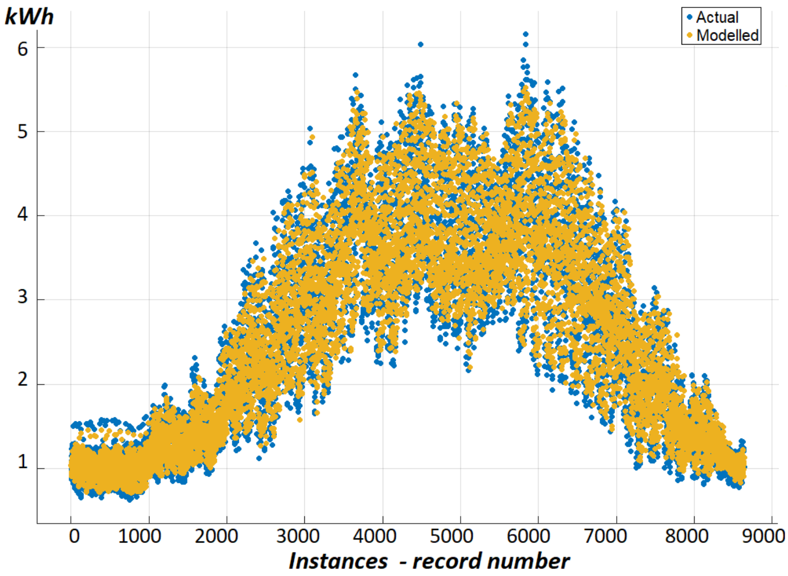

Figure 17. Day-ahead SVR-based forecast models for the 'AC-included' category.

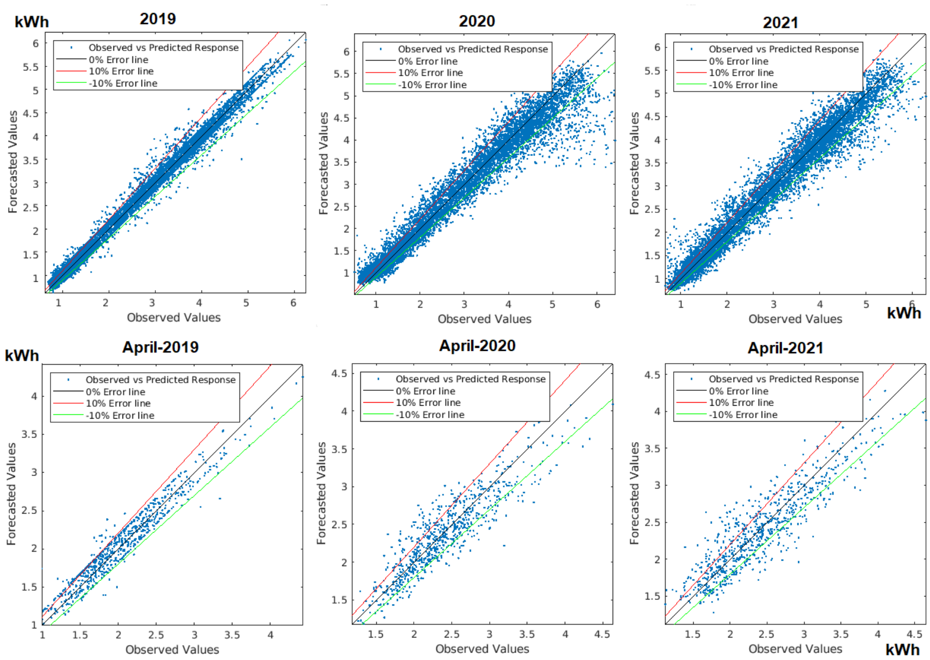

Figure 18. Observed vs. predicted values for day-ahead forecasting using the SVR approach for the AC-included cooling category.

Figure 19 shows that the energy consumption a week before the lockdown was relatively poor as consumers were already in a partial-lockdown mode. As a result, the model undermined their consumption. The modeling performance improved slightly toward the middle of the lockdown period by modeling the peaks and troughs using 5-day lag information and eventually maintaining a similar performance a week after the lockdown.

The performances of the models are provided in Table 2. The table shows that the machine learning model predicted data for 2019 with much better performances observing RMSE, MAE, and MAPE compared to 2020 and 2021. The table also shows that there was a performance degradation for April 2020 because of the full lockdown. It is evident from Figure 20 that when the full lockdown was imposed on April 4, the predicted model underestimated the consumption after the lockdown in 2020 as compared to the year before, which had a comparatively better prediction. Therefore, for these results, it can be inferred that in dealing with atypical periods such as COVID-19, a generic model is required to be updated regularly to address unseen scenarios with additional features and to achieve better forecasting performances.

Table 2. Day-ahead prediction performance comparison for the AC-included category.

Model	**RF**			**SVR**		
Time Period	**RMSE (kWh)**	**MAE**	**MAPE**	**RMSE (kWh)**	**MAE**	**MAPE**
2019	0.17	0.11	5.06	0.15	0.12	5.77
2020	0.24	0.17	6.92	0.36	0.23	9.00
2021	0.23	0.17	6.54	0.29	0.20	8.24
April 2019	0.21	0.15	7.43	0.14	0.12	6.10
April 2020	0.27	0.20	8.69	0.28	0.21	8.91
April 2021	0.26	0.20	8.61	0.27	0.21	9.05

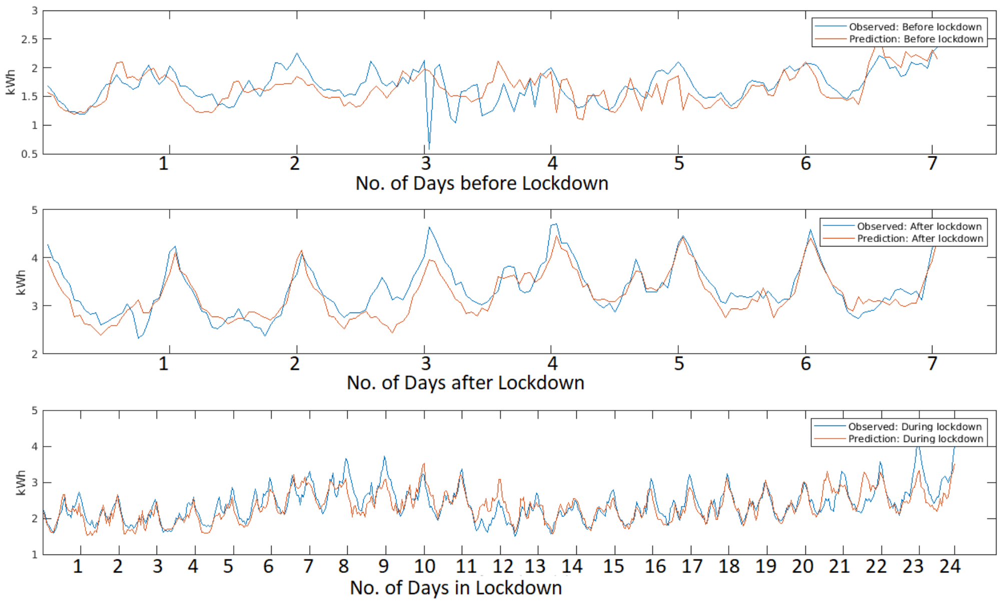

Figure 19. Day-ahead prediction for the week before, after, and during the lockdown.

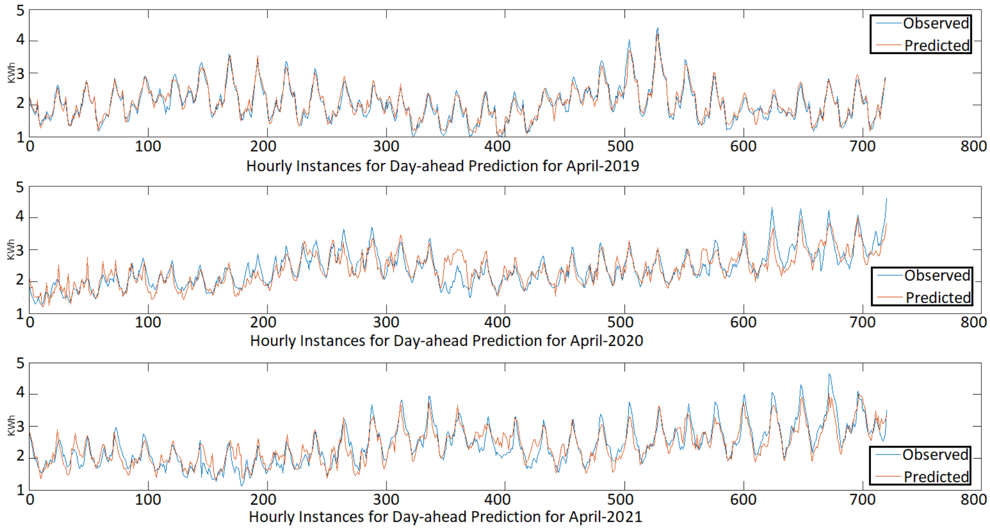

Figure 20. SVR-based forecast models for April's day-ahead prediction for the AC-included category over 3 years.

4.2.4. Comparison of Machine Learning vs. Deep Learning Results

In addition to machine learning approaches, several configurations of long short-term memory (LSTM)-based deep learning approaches were also used to model the typical consumption of data from 2018. However, due to the limited training data available, the performances of the best LSTM-based deep learning approaches were observed to be worse than SVR approaches, outperforming by almost 10%. However, even the LSTM-based models showcase the same machine learning trend by predicting better metrics for 2019 than the 2020 and 2021 periods.

4.2.5. Limitations

One of the strengths of this study involves the four years (2018–2021) of 15 min resolutions of smart meter data and household characteristics (through a voluntary survey) of 439 residential customers in Dubai. This sample provides a comprehensive picture of residential consumption in Dubai, including all building typologies and covering 22 communities in 10 of its regions. Additionally, the survey allowed separately analyzing the dwellings with cooling consumption included and excluded from smart meter measurements.

However, the main limitation of the present study comes from the fact that—prior to 2018—smart meters in Dubai were in the deployment stage, and many of the installed meters were in the testing phase. Therefore, the authors only had the 2018 data of the sampled households to create a forecasting model. The use of only one year of data affects the robustness of the model since various types of data can vary from one year to another, such as weather, seasonality, and holiday times. Additionally, if there had been more historical information available, the MAPE for 2019 could have been smaller.

5. Conclusions and Future Works

This article analyzes consumer behaviors related to COVID-19 and highlights the impact on the performance of data modeling caused by such unseen circumstances. The main implication of this research involves dealing with unknown or unseen situations by analyzing the underlying features. For this purpose, to understand the impact on consumption demand, this work focuses on understanding behavioral changes due to COVID-19 with the help of electricity consumption data. Moreover, machine learning models are used to understand the impact of COVID-19 on the demand side. In addition, other features that could have contributed to the consumption during the COVID-19 era were also explored.

After analyzing the hourly electricity consumption of 439 consumers in Dubai during the lockdown period of 2020 and comparing it with the analogous periods in 2019 and 2021, consumption has been observed to be directly affected by temperature. There was an up-shift in consumption by almost 12% since COVID-19's inception, and the demand remained constant in 2021. The consumption patterns of consumers changed significantly during the COVID-19 period, associated mostly with consumers staying at home throughout the day during the full lockdown, changing their behavioral traits, such as waking up, sleeping, and relaxing. A similar pattern is observed to persist after the full lockdown in fear of COVID-19, evident with 2021 data as many consumers continue working from home even though there were no real restrictions in 2021. The consumption patterns were almost similar for both weekdays and weekends during the lockdown period, indicating no differences between working and non-working days. In addition, the extra electrical appliances bought by consumers during the lockdown could have contributed to the up-shift in consumption since the COVID-19 era, as they are still being used. The features (such as weekdays/weekends, day of the week, and hourly lags) were considered in the behavioral analysis and effective while training the machine learning model using 2018 data compared to the model without these features. However, despite the improved results, the model had relatively poor predictive performances for 2020 and 2021 compared to the prior year (2019); the same statement holds for April when Dubai had a full lockdown imposed. The modeling result indicates that COVID-19 and the lockdown, in particular, disrupted the typical consumption pattern, and there has been an up-shift in consumption since the COVID-19 era. The article also explored machine learning models and deep learning approaches for forecasting. It is quite evident from the results that machine learning models perform better by 10% compared to deep learning models due to the limited training data available.

The limitation of the proposed work involves the use of only one year of data for modeling, which could have hindered the creation of a robust model. This scenario could have improved if typical data from the previous year were available for creating a more reliable and robust model or with an additional sample size of residents. A possible future research direction (to increase training data) may consist of an approach that integrates real and simulated data in the absence of historical data, which can be explored to increase the robustness of the forecasting model. The next step would be to explore additional features that could model the previously unseen COVID-19-like scenarios to improve the performances in such events. In addition, a study can be performed on electricity consumption (considering non-COVID-19 scenarios) to undermine the COVID-19 effect. It would then allow for comparing and analyzing the impact of COVID-19, helping to model the COVID-19 scenarios and unfold the underlying features.

Author Contributions: Conceptualization, P.M., H.R., and E.R.-U.; methodology, P.M. and H.R.; formal analysis, P.M.; investigation, P.M., H.R., and O.A.Q.; resources, P.M. and H.R.; data curation, P.M.; writing—original draft preparation, P.M.; writing—review and editing, E.R.-U., O.A.Q., M.T., J.D.B., and S.S.; visualization, H.R.; supervision, E.R.-U.; project administration, E.R.-U.; funding acquisition, E.R.-U. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The monthly resolution electricity consumption data can be found in the following link: https://www.dubaipulse.gov.ae/organisation/dewa/service/dewa-consumption.

Acknowledgments: This work was financed by the Dubai Electricity & Water Authority (DEWA) under the project "Decision Support Tool for Developing Energy Strategies Based on Data-Driven Models".

Conflicts of Interest: The authors declare no conflict of interest.

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