Applied Energy 287 (2021) 116547

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

A retrospective analysis of the impact of the COVID-19 restrictions on energy consumption at a disaggregated level

Sebastián García *, Antonio Parejo, Enrique Personal, Juan Ignacio Guerrero, Félix Biscarri, Carlos León

Department of Electronic Technology, Escuela Politécnica Superior, University of Seville, Spain

HIGHLIGHTS

- The analysis splits customers into clusters based on the consumption behavior.
- The disaggregated analysis shows the behavior and resilience of various sectors.
- The impact of the COVID-19 measures is evaluated at short and mid terms.
- The proposed approach is able to show which sub-sectors have been the vulnerable.

ARTICLE INFO

Keywords:
COVID-19
Demand analysis
Data mining
Segmentation
Smart meter

ABSTRACT

Since the emergence of the virus that causes COVID-19 (the SARS-CoV-2) in Wuhan in December 2019, societies all around the world have had to change their normal life patterns due to the restrictions and lockdowns imposed by governments. These changes in life patterns have a direct reflection on energy consumption. Thanks to Smart Grid technologies, specifically to the Advance Metering Infrastructure at secondary distribution network, this impact can be evaluated even at the customer level. Thus, this paper analyzes the consumption behavior and the impact that this crisis has had using Smart Meter data. The proposed approach includes the selection and normalization of features, automatic clustering, the obtaining of the estimated consumption without considering the crisis (at short and mid-terms) and the impact evaluation. The proposed approach has been tested on a case with a real Smart Meter infrastructure from Manzanilla (Huelva, Spain). The results of this use case showed that residential customers have increased their consumption around 15% during full lockdown and 7.5% during the reopening period. In contrast, globally, non-residential customers have decreased their consumption 38% during full lockdown and 14.5% during the reopening period. However, referring to non-residential customers, five different consumption profiles were found with different short-term and mid-term behaviors during the COVID crisis. The different behavior found shows customers who have maintained their normal consumption during the lockdown, others who have reduced it (to a greater or lesser extent) and have not recovered it after the removal of the restrictions, and others who have reduced the consumption but then they recovered it when the restrictions were removed. The metadata of the customers in each behavior cluster found are highly correlated to the restrictions imposed to control the spread of the virus. This study shows evidence about the proposed approach usefulness to analyze the behavior and the impact at customer level during the COVID-19 crisis.

1. Introduction

In December 2019, China reported 27 cases of a pneumonia of an unknown character related to the city of Wuhan [1]. On January 7th, the pathogen that causes these pneumonias was discovered: SARS-CoV-2. The illness caused by SARS-CoV-2 has been named COVID-19. Since the emergence of this virus in late 2019, governments from all around the world have been taking action that have changed the behavior of societies, firstly in Asia and later in Europe and continental America.

Many countries have established lockdowns to control the spread of the virus. On January 24th, 2020, China was the first country to lockdown, specifically at the Hubei province, limiting 40 million people to

* Corresponding author.
E-mail address: sgarcia15@us.es (S. García).

https://doi.org/10.1016/j.apenergy.2021.116547
Received 30 October 2020; Received in revised form 17 January 2021; Accepted 20 January 2021
Available online 28 January 2021
0306-2619/

their homes. With the arrival of the virus in Europe, there were also limitations on mobility, business closures and confinements of people in their homes. On March 7th, Italy limited movement in the northern region of the country by putting into lockdown 16 million people. Subsequently, on March 9, Italy closed the entire country, becoming the first European country to lockdown its entire population. On March 11th, the World Health Organization (WHO) declared COVID-19 a global pandemic [2].

In Spain, where the spread of the virus had a similar pattern to Italy, the "State of Alarm" was decreed on March 14th lockdown the entire country. From that date, Spain went through different levels of lockdowns, with strict levels of confinement (one of the toughest in Europe) at the beginning and gradually releasing the restrictions throughout the country until the lifting of limitations on June 21st.

As a consequence of these limitations, changes have been taken place in societies, businesses and the economy of the countries. In particular, in Spain, the closure of businesses and prohibition of non-essential services during lockdowns has had a tremendously serious impact on the economic and social environment. This impact has been reflected on supply consumption and transport services. In this sense, focusing on how COVID-19 has been reflected on the consumption of supplies and, in particular, in the electric sector. This paper shows the impact on energy consumption at secondary distribution level.

In contrast with other related papers that have evaluated the impact of the COVID-19 at aggregated levels (country or region), the proposed approach at secondary distribution level is able to get more detailed results of the impact of the containment measures to control the spread of the virus at specific economic activities or even at customer level. The main contribution of the paper is to propose and evaluate this approach as a possible tool that reflects various aspects about the economic structure of the analyzed dataset and how their respective recuperation was with regarding to the COVID-19 restrictions.

Thus, this analysis is based on data from Smart Meters collected through the Advance Metering Infrastructure (AMI) Systems at secondary distribution (at low-voltage) level. With this analysis, customers are split into residential and non-residential customers. Non-residential customers are clustered, depending on their economic activity and on their consumption profile, taking into account the restrictions imposed due to the COVID-19 lockdowns. Once this clustering is obtained, the forecasted consumption of these groups of clients is obtained (assuming that lockdowns had not taken place). Thus, the impact of the COVID-19 pandemic from the point of view of the energy consumption on different activities is presented.

Additionally, as a use case, the impact of the COVID-19 lockdowns from the energy point of view in Manzanilla (Huelva, Spain) has been evaluated. However, the proposed approach can be applied with any dataset coming from the AMI system of the secondary distribution network.

The paper is organized as follows. Section 2 gives an overview of what was being done in the bibliography related to the impact of the pandemic from the data point of view. The context of the study performed in this paper is given in Section 3. In Section 4, the approach is presented. The results of applying the proposed approach on a use case (the town of Manzanilla) is provided in Section 5. The discussion of the results is presented in Section 6. Finally, the conclusions are presented in Section 7.

2. Related work

Since the emergence of the virus, some contributions have studied the impact of it on non-medical sectors.

In this sense, analyzing environmental data, some authors have conducted research in order to study the COVID-19 impact. In [3], the impact of lockdowns in China are studied from CO_2 emission data obtaining that CO_2 emissions decreased by 18.7% according to the authors estimations. Similarly, [4] estimates a reduction of 15% in the CO_2 emissions in the United States. And [5], where their authors contribute with a global study in which a 17% reduction in the CO_2 emissions, is obtained. In addition to the CO_2 reduction studies, [6] analyzes the relation between the decrease of air pollution during lockdowns in India and the increase of photovoltaic generation thanks to the increase of solar radiance because of clear skies.

Thanks to these contributions, it is clear that lockdowns have had an impact that is reflected in pollution data. In addition to these environmental studies, other authors have made contributions based on the changes on the energy consumption profiles as result of the COVID-19 crisis. Some of the studies related to the impact on energy consumption are presented below.

How the energy consumption profiles changed in European countries during lockdowns are studied in [7,8]. In [9], an open-access data hub to track the impact of the COVID-19 on the energy consumption on some states of the US is proposed. Additionally, in this last study, the authors evaluate the reduction in the energy consumption on the different states. The impact of the COVID-19 restrictions on the electric sector is analyzed in [10], in which the authors evaluated the energy consumption drop in several countries, the changes in both electricity prices and the generation mix and the challenges for the power system operation. The changes in electric energy prices in Spain have also been studied in [11]. How the generation mix has changed in three Transmission System Operators in the United States due to the COVID-19 is also assessed in [12]. In [13], a deeper analysis of the electric energy demand in the states of California, Florida and New York has been conducted. An energy consumption analysis over the whole country of Italy during the COVID-19 crisis is performed in [14]. In this last study, the authors state that the energy consumption has been reduced 25% during the full lockdown period in Italy. A similar study has been performed in Spain, in which authors obtained a 13.5% reduction in the global energy consumption of the country [15]. In [16], the authors affirm that the state of Ontario (Canada) has had a reduction of 14% in the energy consumption during lockdowns. A study of the energy consumption profile during lockdowns in the state of Kuwait is presented in [17], where their authors estimate that the energy consumption has been reduced in a 17.6% during the full lockdowns. In [18], the impact in the electric energy consumption in different regions of Brazil has been estimated, obtaining reductions between 20% and 7% depending on the region. The work presented in [19] studies the impact on energy consumption in Indian utilities and the challenge that it has supposed. Additionally, in this last study, the authors proposed a list of recommendations for a smooth operation of the power grids during the pandemic. [20] analyzes the impact on energy generation primary sources (coil, gas, renewable, etc.) and how the lessons learnt during the pandemic could help obtain a more reliable, flexible, and sustainable energy grid. Artificial Intelligence and data analytics were also used in the literature to study the COVID-19 impact. As an example [21] uses Artificial Neural Networks to model the impact of lockdowns in China at the beginning of the crisis.

Besides to the global analysis of the COVID-19 impact on energy consumption in countries or regions, other authors are focusing on other more specific events related to the COVID-19. As an example, in [22] the impact on the energy consumption and grid stability of the public solidarity gesture with frontline healthcare workers in India (in which public lights were turned off during 9 min) is analyzed. Other authors have taken advantage of the energy consumption patterns during lockdown periods to estimates the decrease in the Gross Domestic Product (GDP) due to the COVID-19 lockdowns in Italy [23].

As a conclusion, several papers have been published evaluating the impact that the COVID-19 has had on societies using non-medical data (mainly environmental and energy consumption data). The proposed analyses in the literature are performed with aggregated data at country or regional level not focusing on specific activities. To the best of the authors knowledge, only the work presented in [24] attempted to evaluate the impact of the COVID-19 at a disaggregated level in energy demand. However, the authors carried out an exploratory pilot in which the consumption of a virtual neighborhood with 166 buildings was simulated, obtaining the behavior in energy consumption due to the COVID-19, based on different containment levels. Even though the study is interesting, the results are limited because of the lack of real data measurement as the authors of the mentioned study state.

Thus, our proposal is to use the real information from the Smart Meters deployed for the AMI infrastructure at the secondary distribution network and the metadata associated to each one, to perform a retrospective analysis in order to obtain the different consumption profiles of low-voltage customers. Thus, using this kind of analysis, not only could the big picture of the impact on the energy consumption because of the COVID-19 restrictions be obtained, but also the impact on smaller groups at customer level depending on their consumption profiles during the COVID-19 lockdown. This approach based on disaggregated information has the advantage of allowing one to discover behavior that is normally hidden when using aggregated data. Moreover, with the proposed approach, the impact on the consumption profile of different economic activities, which is difficult to quantify at aggregated levels [17], can also be obtained and analyzed. To the best of our knowledge, no analysis of this kind has been done using data at customer level using Smart Meters.

3. Context overview

As described above, this paper studies how the COVID-19 crisis has been reflected over low-voltage customers. In order to do that, Smart Grid technologies will be used [25,26]. These technologies have taken a great step forward during the last few years for the management of electric grids [27]. In this sense, the AMI is one of the keystones of a Smart Grid [28,29]. Specifically, AMI philosophy has been exploited by Distribution System Operators (DSOs) for the secondary distribution network (at low-voltage) management [30]. The AMI is a system that makes it possible to gather and analyze data coming from the grid in an automatic way. Mainly, at the secondary distribution network, the AMI is made up by two types of devices which are deployed along the network: Smart Meters and Concentrators. On the one hand, the Smart Meters are deployed along the network, one at each customer supply point, making it possible to monitor their consumption, communicating it using Power Line Communications (PLC) over the distribution lines. On the other hand, the Concentrators, which are located at the secondary distribution substations, make it possible to manage the Smart Meters and gather their measurements.

With this AMI deployment, DSOs can perform Automatic Metering Reading (AMR) and Automatic Metering Management (AMM) tasks. AMR provides the DSOs to get measurements in an automatic and remote way while AMM allows them to remotely manage the Smart Meter devices and perform customer management operations (e.g. tariff change, power limit settings, etc.).

This level of digitalization is allowing a new era in the low-voltage distribution that has also opened up to data analytics applications using the AMI data. In this context, the BALANCE Project (Spanish acronym of "Big Data Analytics and Cyber-Physical Instrumentation for Distribution Grid Support Operations") is applying artificial intelligence techniques to obtain information from the data coming from the AMI. The BALANCE Project is supported by the Spanish Government and it is being done in collaboration with the Medina Garvey Company, which is a DSO from the west part of Andalusia (Spain).

4. Methods

In the BALANCE project framework, this paper studies how the COVID-19 has affected energy consumption at a customer-level point of view using data from the low-voltage AMI systems. This subsection provides a methodology approach which can be applied over different datasets in several geographical locations. This allows one to analyze the impact of the COVID-19 from different point of views, not only at aggregated levels (countries or regions). The aggregated approach is widely described in the references from the related work subsection. In this case, this paper is centered on the analysis of mid and short-term impact at disaggregated level.

As a summary, the proposed approach for the analysis is shown in Fig. 1. First of all, data acquisition from the DSO systems is performed. In the second stage (period selection), the consumption during relevant periods of the pandemic will be extracted from the system (see periods in Table 1). Thirdly, the whole sample is split into two parts: residential and non-residential customers. Later, an automatic clustering is performed on non-residential customers according to their consumption profiles during the COVID crisis obtaining the different behaviors. In addition, some relevant groups of customers are obtained based on their economic activity codes. Observing the characteristics of the obtained clusters, the evolution of the consumption during the lockdown can be analyzed. The expected consumption profile without considering lockdowns is also obtained for each cluster. Finally, based on the expected consumption and on the behavior during lockdowns impact metrics for every group of clusters, are obtained. This approach provides tools to analyze the evolution of consumption during a certain time period, evaluating the mid and short-term impact, based on real data from a real DSO. A detailed description of each phase is provided during the following subsections.

4.1. Dataset acquisition

The data set collected from the DSO systems is made up of heterogeneous information about the consumers: economic activity, contracted power, Smart Meter data, etc. The criterion basis to select a population to perform the study should be related to the economic activity, the population, and the location. In Spain, as well as in other places, locations are usually related to specific economic activities. With this approach, several scenarios could be analyzed but it is important to dismiss the cases in which the economic activity is focused on a single sector (as the results will be biased). Additionally, other criterion is the population density of municipality: when the population density is increased, the services and infrastructures are increased to support the population needs. Thus, it is important to consider this fact when selecting a population to perform the study.

4.2. Period selection

To analyze the impact on energy consumption, it is necessary to firstly take into account how the restrictions and their subsequent removal during the COVID-19 crisis have been temporarily happening. Particularly, in Spain, which will be the focus of the use case, from March 14 to May 11 the Spanish government established that all the population must stay at home. From May 11 until June 21, the limitations in Spain gradually disappeared, allowing the opening of non-essential businesses, restaurants, etc.

In addition to these two timeframes, the interval between February 1 and March 14 is also used to establish the reference consumption previous to the COVID-19 lockdown. Therefore, the analysis is split into three main time frames as can be seen in Table 1.

Furthermore, in order to establish a comparison with the forecasted consumption at mid-term without considering the COVID-19 crisis, the consumption on the same intervals in the previous years is also used.

4.3. Sample split

To correctly evaluate the impact that the measures imposed due to the COVID crisis have had on energy consumption, it is necessary to separate customers according to their consumption profiles.

In this sense, the economic activity has a direct relationship with consumption [31]. Specifically, in Europe, the NACE (French acronym

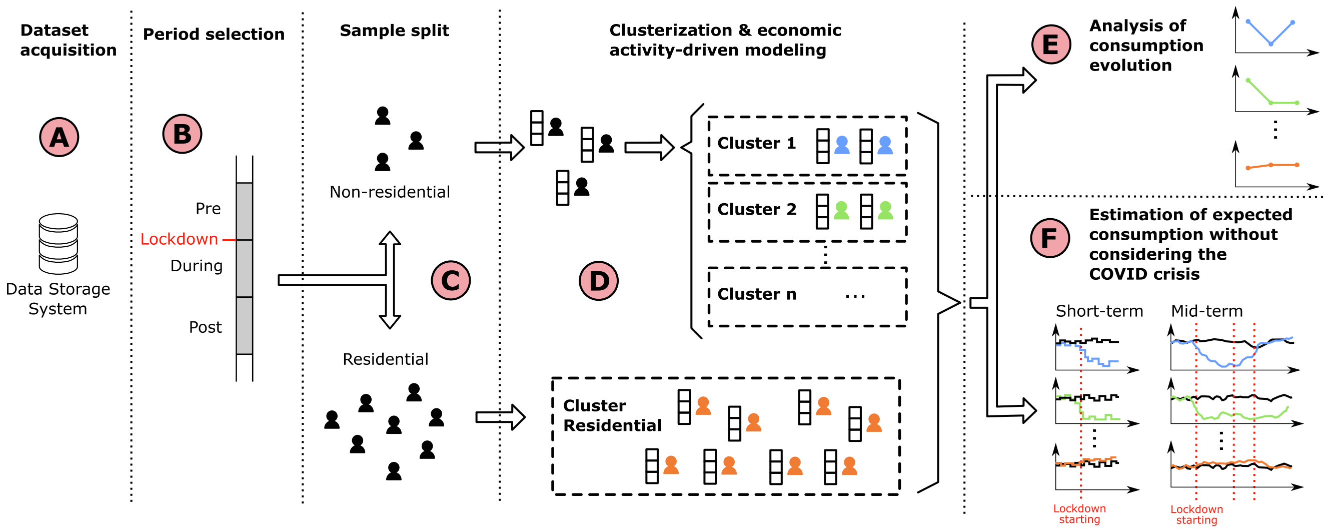

Fig. 1. From left to right: steps of the proposed method to analyze the behavior and the impact of COVID-19 restrictions on Smart Meter data.

Table 1
Data intervals for each phase of the analysis.

Description	Start	End
Previous to the COVID-19 lockdown	01/02/2020	13/03/2020
Strict lockdown	14/03/2020	10/05/2020
Reopening	11/05/2020	21/06/2020

of “Statistical Classification of Economic Activities in the European Community”) code is a categorization in behavioral groups [32]. Therefore, using this code, customers can be split into residential and non-residential activities. In general, residential customers should have a similar pattern of consumption during lockdown. Conversely, non-residential customers behave differently depending if they are essential or not according with the restrictions decreed by the government.

Thus, non-residential customers could behave differently depending on the government restrictions (e.g. some of them were considered as essentials and were able to open, some others not, some others were able to open with restrictions, etc.). In order to analyze the impact on the electric consumption during lockdowns, non-residentials need to be grouped depending on their behavior. Using the NACE code of these non-residentials customers, these customers can be split again according to their economic activity but, even having the same economic activity, customers could be considered as essential or not. For example, two small size businesses may have the same economic activity code (4700–4799 according to the NACE code in Europe) but one could be a small grocery store and the other a computer store. Additionally, this code, sometimes, may not be very specific.

Therefore, there is no direct way to cluster non-residential customers depending on their behavior during lockdowns. In this context, one way to group customers depending on the impact of the COVID-19 restrictions is to use an unsupervised segmentation based on their energy consumption over the different phases of the imposed restrictions.

4.4. Clustering and economic activity-driven modeling

In order to cluster the non-residential customers according to their consumption profiles over the COVID-19 restrictions, the mean energy consumption per day is obtained as features for the chosen periods.

There is a great variety of segmentation algorithms available, one of the most used ones is the K-Means algorithm [33], which has been widely proposed for automatic customer load clustering [34,35]. The K-Means algorithm has been widely used for customer segmentation using Smart Meter data [36,37] and is especially useful for domestic loads characterization [38,39]. K-Means is a centroid-based algorithm which choose centroids that minimize the within-cluster distances to them, as can be seen from the cost function shown in Eq. (1) (k is the number of clusters, d the dimension of the features, x the features of a sample with $x \in k$, and μ the cluster centroid).

$$argmin = \sum_{j=1}^{k} \sum_{i=1}^{d} \|x_i - \mu_j\|^2 \tag{1}$$

As this algorithm tries to minimize the distances of the features to the cluster’s centroids, all the features must be normalized in order to enable the comparison between consumers, regardless of the absolute energy consumption of each one of them. Therefore, the features are normalized using L2 Ridge Regression [40] before using them to feed the algorithm.

One important question when a segmentation is done is the selection of the number of clusters: the value of k. For unsupervised clustering, several methods are available for this task. The most common ones are:

- **“Elbow”:** This criterion is one of the simplest, it consists of plotting the sum of squared distances error (SSE) for every value of k. The value of k when the SSE starts to decrease slowly, it is the selected value of k. This method is quite simple, but it has some limitations: it does not take in to account the cohesion of the points nor the overlapping of the clusters.
- **Silhouette:** The silhouette method is a graphic representation based on the silhouette coefficient which is calculated based on the mean distance between data points in the same cluster and the mean distance between samples and the nearest clusters [41]. Unlike the elbow method, this analysis gives a measure of the cohesion of the points with their own cluster and the separation with the rest of clusters.
- **Davies-Bouldin Index (DBI):** This index measures the separation between clusters [42]. It is obtained using the distances between clusters and the size of them. Thus, this index gives a measure of the overlapping between clusters (the lower the better).

As can be seen, each metric evaluates a different parameter: proximity to the centroid (elbow), cohesion of the cluster (silhouette) and overlapping of the clusters (silhouette and DBI). Therefore, with joint evaluation of all these metrics, the optimum number of clusters can be obtained.

Using the described tools in this subsection, non-residentials customers will be clustered based on their impact on consumption due to the COVID-19 restrictions.

4.5. Analysis of consumption evolution

Once the k-means segmentation algorithm has been applied using the optimum number of clusters obtained from the above metrics, the consumption behaviors can be extracted. As the segmentation algorithm has been fed with the normalized mean energy consumption profiles of the customers as features, each cluster will represent a different consumption profile during the COVID-19 pandemic. A simple way to observe the evolution in the consumption profiles is to represent the features in each period of the lockdown of the customers of each cluster in a box plot. This is clearly seen in the case of the proposed used below.

4.6. Estimated consumption without considering the COVID crisis

To evaluate the impact of the COVID-19 crisis it is necessary to estimate the consumption that would have happened without this singular situation.

To evaluate the estimated consumption of a cluster (considering that the COVID-19 crisis had not happened), the aggregated energy consumption profile of the cluster must be obtained. In order to do that, the consumption cannot be obtained just adding the individual raw consumptions of the customers associated to each cluster because of the possible differences that individual raw consumptions may have. For example, if there is a customer with an average consumption much higher than the rest of the customers in a cluster, the total consumption will be biased by this customer. Therefore, prior to getting the aggregated consumption of the cluster, the consumption profile of every customer is normalized. This normalization is done using the proposed method by Reem Al-Otaibi et al. in [36]. In the cited paper, the authors normalize the consumption profile of Smart Meter data between the interval [0,1].

After getting the normalized consumption profile of the individual customers, the mean normalized consumption of the cluster is obtained.

Once the normalized aggregated consumption profile of the cluster is obtained, it is necessary to establish a methodology to get the expected consumption without considering this abnormal situation. In this sense, the exceptional situation is relatively long (a few months). Therefore, it is important not to use any of the affected days for the estimation of the consumption. Two possible approaches can be followed to perform the estimation, short-term (a few days during the start of the quarantine) and mid-term (a few months, including all the quarantine period). The criteria of short-term and mid-term is the same that other authors apply, as can be seen in [43]. In this paper, C. Kuster *et al.* states that short-term refers to forecasting from one hour to several days, while mid-term is applicable for predictions from one month to a season.

These two approaches are applied to each cluster obtained in the clustering analysis previously exposed, which pretends to group customers of the same typology according to their observed behavior during the lockdown. Another subset has been considered as especially interesting, deserving its own analysis. Additionally, the estimation of consumption has also been applied on the “economic groups”, which are groups of customers in the same type of economic activity according to the registers of the distribution company. Not all the existing groups are exposed, but only those that were considered as especially interesting from the point of view of their number of customers, or their magnitude of consumption. The chosen economic groups are: small stores, restaurants, and food and drink services, residential and all of those different from residential activities (non-residential).

The applied methods to get the estimations are as described in the next sections.

4.6.1. Short-term impact

The change in tendency during the first days of the quarantine is analyzed comparing the registered consumption and the forecasting. This forecasting is obtained using the average value of similar days during a previous week while maintaining a gap of two weeks before the day to be predicted. The reason for this gap is to be sure of keeping the abnormal days out of the dataset used to make the forecasting. Specifically, three groups of similar days are considered: days from Monday to Friday as the first group, Saturdays as the second group (half-working days in some cases) and Sundays as the third group (non-workable days generally).

To clarify how the short-term forecasting under these considerations is obtained, some examples of forecasted days using the described method are given:

– The forecasted consumption for the 2nd of March is the average value of the days 10th to 14th February.
– The forecasted consumption for the 5th of March is the average value of the days 13th February, 14th February, and 17th to 19th February.
– For the day 7th of March, the forecast is equal to the consumption on the 15th of February (which was Saturday).

4.6.2. Mid-term impact

A mid-term impact includes the whole exception period, i.e., about four months (from March to June). Of course, the previously exposed method of day averaging is not valid for this new analysis, as it would require a huge gap between the day to predict and the input days (to avoid using the abnormal days affected by the COVID-19), which would introduce errors due to the difference of season, temperature, etc.

Therefore, the methodology for this mid-term impact study is the direct comparison of historical data of the year 2020 with the average consumption of the two previous years. This is the most common way to evaluate the impact, many authors who have studied the variation of energy consumption due to the COVID have assessed the impact evaluation using the energy consumption in previous years [7–10,14–17,19,20,23].

4.6.3. Measuring the impact.

Once the expected consumption has been obtained for the different periods studied (assuming that the COVID crisis has not happened), a Variation Rate (VR) with respect to the expected consumption will be obtained. This rate will be obtained from Eq. (2).

$$Variation\ \ Rate(\%) = \frac{100}{n}\sum_{i=1}^{n}\frac{P_i^{real} - P_i^{exc}}{P_i^{exc}} \tag{2}$$

where n is the number of samples in the evaluated interval, P_i^{exc} the expected consumption and P_i^{real} the current consumption at sample *i*. As can be seen, this Variation Rate is based on the MPE (Mean Percentage Error) as our approach is meant to measure the deviation on energy consumption.

5. Use case

The proposed approach is implemented in a use case using data from a real AMI network throughout this section.

5.1. Data set acquisition

Thanks to the collaboration within the BALANCE project with the Medina Garvey Company, the data from Manzanilla, which is a town from Huelva (Spain), are available. In this sense, the AMI systems of the DSO have been integrated into the management systems of the BALANCE project, allowing the same AMR functions that the DSO has. The AMM has not been implemented due to security reasons. The general architecture of the system is shown in Fig. 2 in which the different elements of secondary distribution network and their relationship with the AMI systems are depicted.

Using the described data acquisition system, data from all Smart Meters of the Manzanilla town can be easily gathered. The collected dataset includes hourly energy consumption and metadata associated

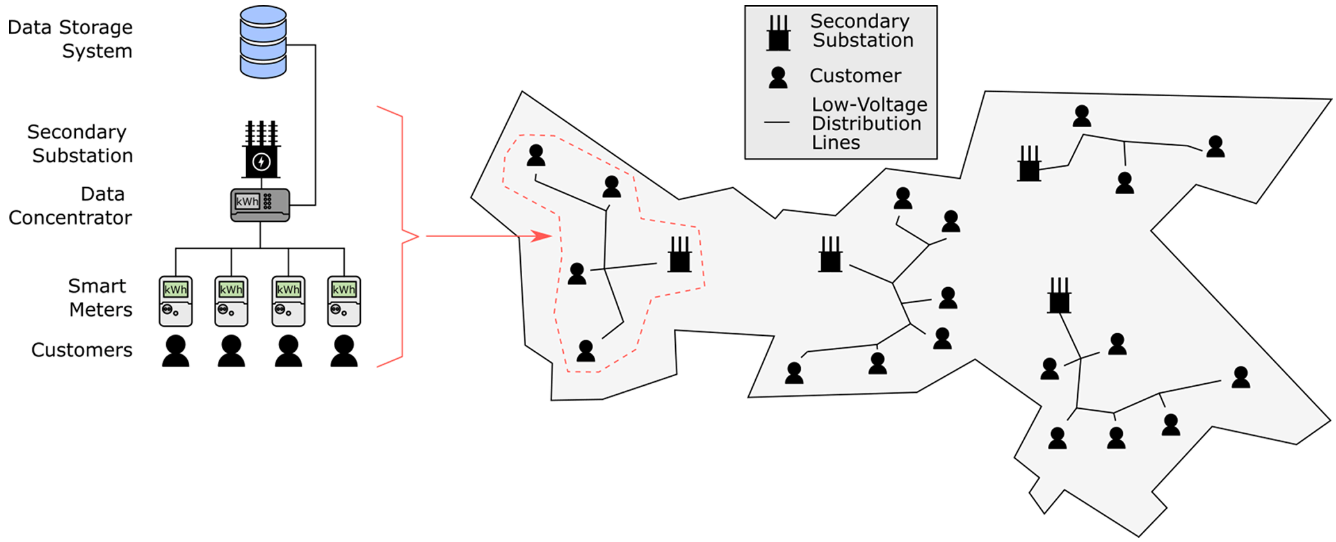

Fig. 2. AMI structure and its relationship with the secondary distribution network.

for every client (economic activity, contract information, etc.). This phase corresponds to the stage A of the Fig. 1.

The town of Manzanilla has 14 secondary distribution substations with a mean of 102 Smart Meters per secondary substation having a total of 1426 customers. The mean power consumption of the town is around 550 kW with important differences depending on the seasonality.

5.2. Customer clustering

Firstly, customers will be split into residential Fig. 1and non-residential (stage C of Fig. 1) Fig. 1. Additionally, non-residential customers will be clustered based on their behavior during the COVID-19 crisis, which corresponds with the stage D of the Fig. 1.

5.2.1. Residential clients

As described in the previous sections, using the NACE code the residential customers can be obtained. A total of 1348 Smart Meters are labeled as residential customers. In Fig. 3 a), the total energy consumption of residential customers is shown. In this figure, four timeframe intervals can be seen: previous to the COVID lockdowns, during full lockdown in Spain, the reopening period (with restrictions) and the full reopening. From this figure, an increase in the consumption can be seen just after the start of the lockdowns and during the full reopening but, only with this figure, no conclusions can be extracted as this increase may be the normal consumption pattern of the town of Manzanilla or it may be due to the seasonal nature of the data. However, as it will be seen later from the analysis done in this paper, the increase just after lockdown is clearly because of the COVID restrictions removal.

5.2.2. Non-residential client clustering

A total of 78 customers with non-residential economic codes were found in the dataset. The total energy consumption of these clients is shown in Fig. 3 b). As can be seen in this figure, unlike residential customers, non-residential customers have decreased their consumption after lockdown but, again, this decrease may be the normal consumption of these customers or it may be due to the seasonal nature of the data. Nevertheless, as it will be analyzed later, this decrease has been mainly because of the COVID-19 lockdowns ending.

Of these clients, 19 were found to have an unusual low consumption (previous to the lockdowns) so they were discarded. Most of these clients were labeled as storage locations or garages. Thus, 59 non-residential customers were used. With the normalized mean energy consumption computed per day on the timeframes described in Section 4.2 used as features, the best selection for the number of clusters were obtained using he described methods: the “elbow” method, Silhouette analysis and Davies-Bouldin index (Figs. 4 and 5).

From the elbow method, the optimum number of clusters is between five and six.

According to the silhouette analysis, from five (included) onwards, the mean silhouette value (red line) starts to decrease. Although all

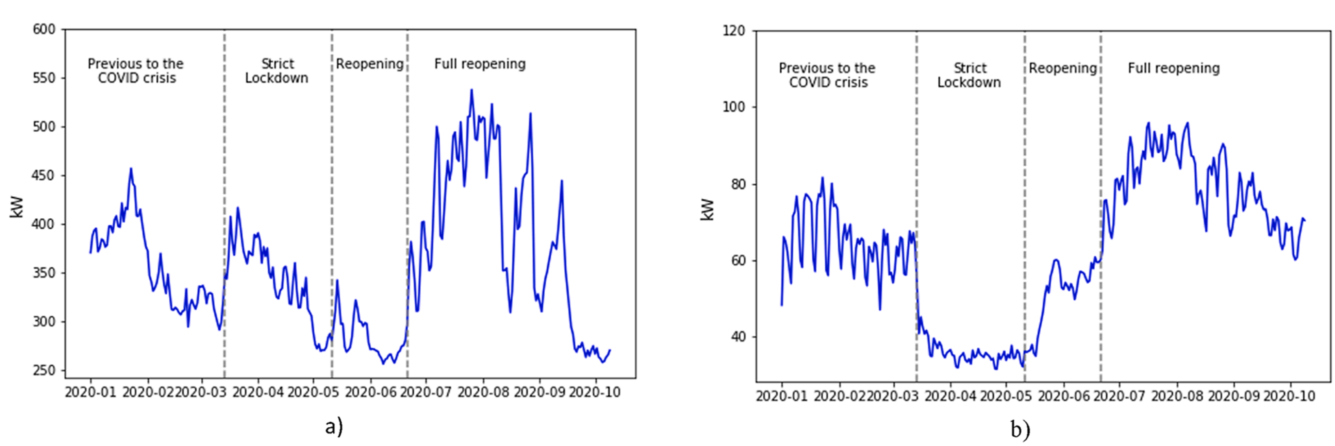

Fig. 3. Aggregated consumption profile of residential and non-residential customers during the COVID-19 crisis; a) residential; b) non-residential.

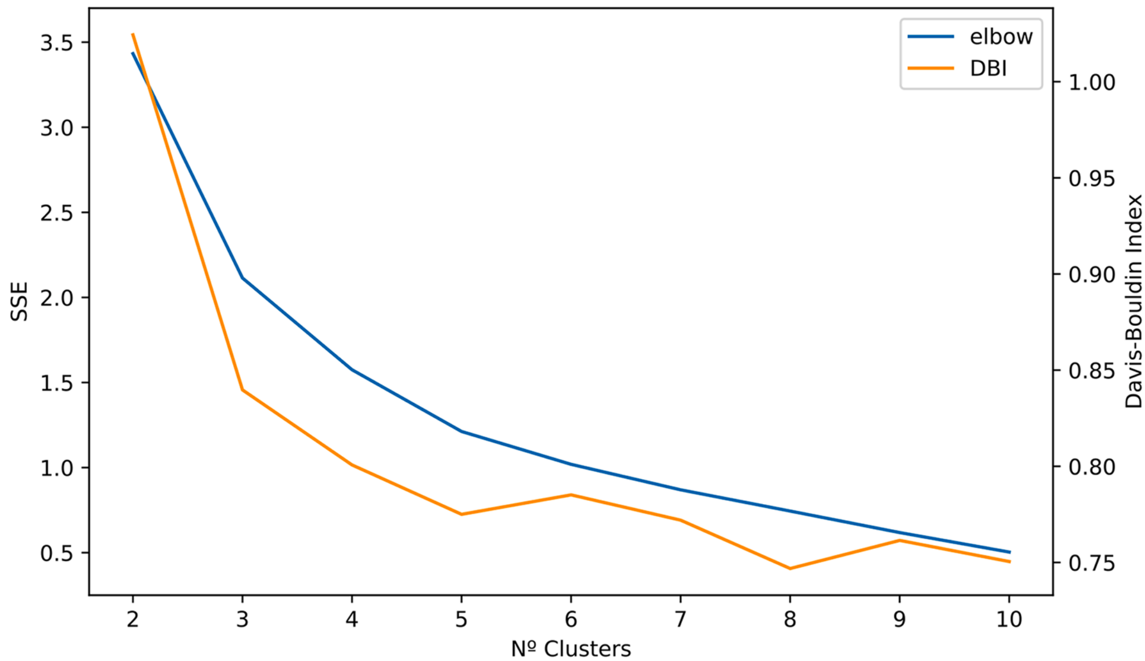

Fig. 4. Sum of Squares distances Error (SEE) and Davies-Bouldin Index (DBI) for different values of k.

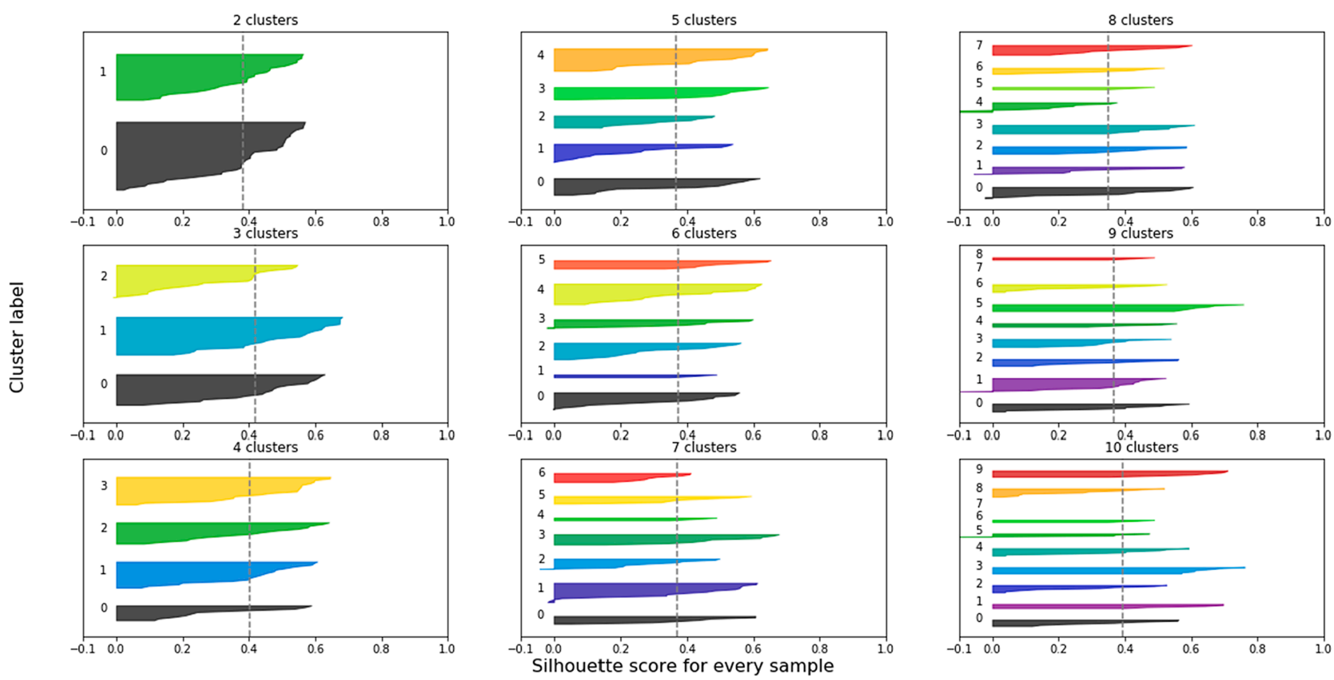

Fig. 5. Silhouette score analysis for different values of k.

clusters from five onwards remain samples above the average Silhouette value, some groups begin to over-split, becoming very thin, indicating possible over-segmentation.

If we look at Davies-Bouldin index, it starts to stay from five at the same values, with lower indexes in 8 and 10 clusters but very insignificant differences with the rest.

Taking this analysis into account, and according to these metrics, the selected number of clusters for the study was five.

In this sense, using five clusters, a K-Means model was obtained. A box plot of every cluster is shown in Fig. 6. Every subfigure shows one of the clusters, the boxes are the features of the customers that have been assigned to the depicted cluster (normalized consumptions during the periods described in Section 4.2). From left to right: previous to the COVID-19 crisis, during strict lockdowns and during the openings after the strict lockdowns.

Some conclusions can be extracted from Fig. 6. Customers from Cluster 0 have maintained their consumption during all the COVID crisis. Clusters 1 and 2 have reduced their consumption during full lockdown and the reopening having a more notable drop in consumption in cluster 1 than cluster 2. Clusters 3 and 4 have reduced their consumption during full lockdown but have recovered after it. Cluster 3 has had a much smaller drop in consumption than cluster 4 and it has had a higher consumption during the re-opening than it has previously to the lockdown.

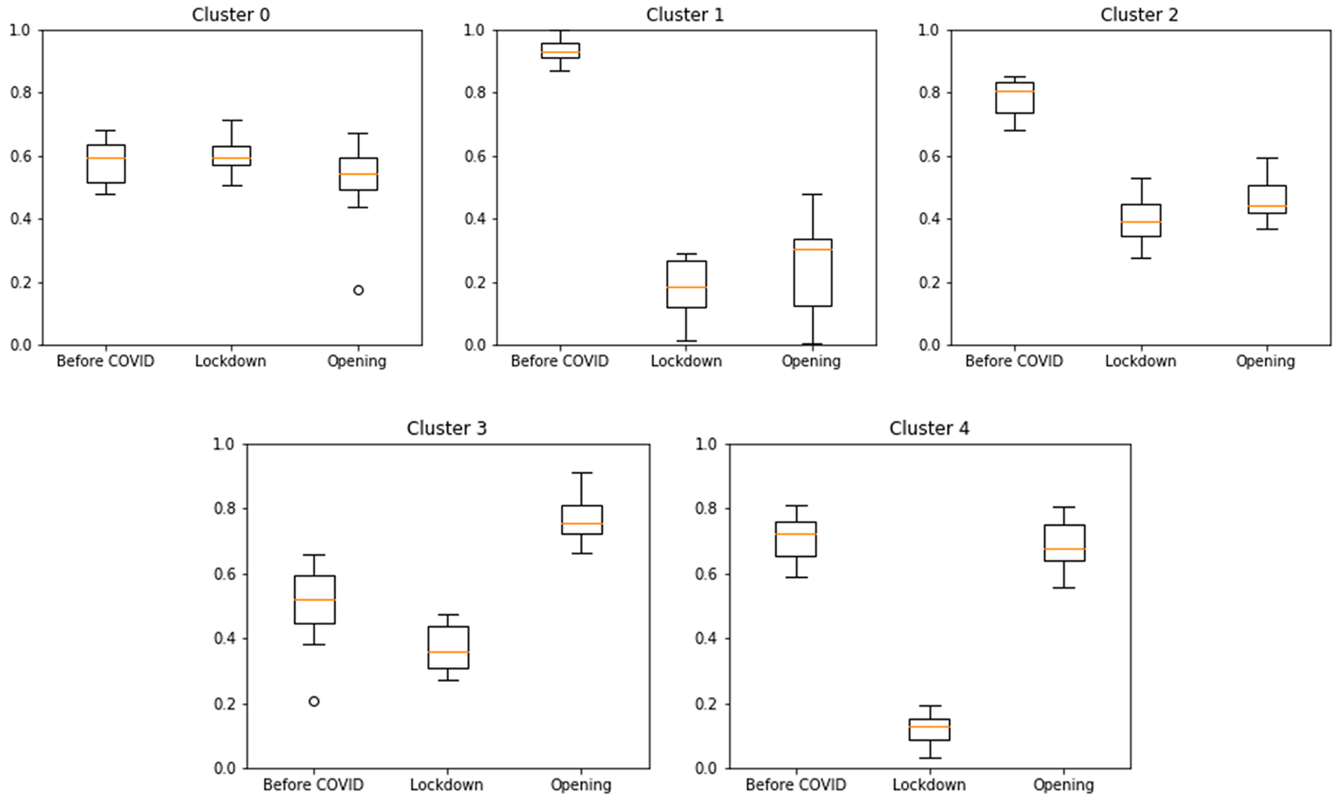

Fig. 6. Box plot of the selected features during the different containment periods for each of the obtained clusters.

This behavior extracted from the features is clearly seen if the normalized mean consumption of the clusters is represented (Fig. 7).

Additionally, Table 2 shows a summary of the economic activities of the customers of every cluster.

5.3. *Expected consumption without considering the COVID crisis*

Once the clients are split into this subsection, the expected consumption is obtained considering that the pandemic has not occurred both in short and mid-terms (stage F of Fig. 1).

5.3.1. *Impact analysis validation*

The short-term and mid-term impact analysis have been validated first using time intervals not affected by the deviation in the consumption profiles due to the COVID-19. Specifically, the short-term analysis has been performed and evaluated for the whole year of 2019 while the mid-term analysis has been performed using the average consumption of 2017 and 2018 and evaluated using 2019. The comparison between the

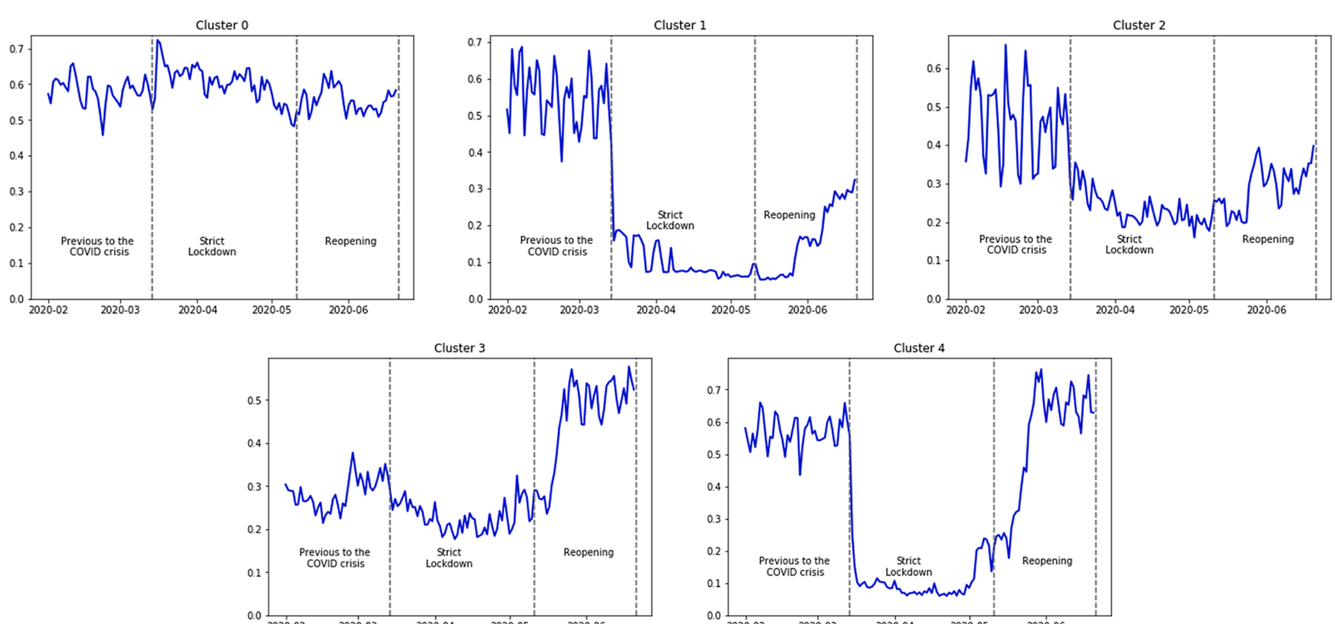

Fig. 7. Normalized consumption profile during the selected periods for each cluster.

Table 2
Summary of economic activities found in the customers of each cluster.

Cluster	No. Customers	Summary of economic activities found in the cluster (NACE code)
0	16	Businesses (mainly for grocery activities), public services (public lights and water distribution), health services (pharmacies and health centers)
1	10	Restaurants, pubs and public institutions.
2	13	Public institutions and industrial services.
3	11	Small businesses.
4	9	Restaurants and small businesses

expected consumption and the real consumption of 2019 for the aggregated consumption of the town of Manzanilla for both approaches is shown in Fig. 8.

As can be seen, the short-term approach has higher precision (lower dispersion around the error) than the mid-term. The variation rate (see Section 4.5.3) between the expected and real consumption has been obtained for both approaches, with a result of a 0.57% and a −1.03% for the short and mid-terms respectively. Taking into account the level of disaggregation (the consumption of a town with 1426 Smart Meters), the results are in the range of what is expected.

The short-term approach seems to be a little bit better but, as it was explained in Section 4.5.3, the short-term approach is only valid to predict the impact of an abnormal situation two weeks from the start of it, as predicting further than that would require introducing in the prediction some of the abnormal days (biasing the forecast by these days). Thus, the short-term is a great and relatively easy way to obtain the impact of a certain event but it is only valid for the next two weeks after the start of the event.

In contrast, the mid-term approach is more appropriate to obtain an estimation of the expected consumption for longer intervals, but it has lower accuracy than the short-term approach. However, as the objective is to measure the impact on energy consumption, the mid-term approach is a good estimation, as the variation rate shows (−1.03% of error). This is because in longer intervals, although there are some errors in some days, the global compute of energy consumption for the interval, which is what the variation rate measures (and the objective of the study), is able to obtain good results.

As a conclusion, each impact evaluation approach has its advantages and disadvantages, both being complimentary approaches to each other.

5.3.2. Short-term impact analysis

Using the described methodology in Section 4.5.1, the short-term impact of the first weeks of lockdown has been obtained.

Firstly, the short-term impact has been obtained for all the customers in Manzanilla. Fig. 9 represents the normalized expected and real consumptions for the first weeks after lockdowns. As can be seen, the consumption during the first weeks of the lockdown is slightly higher than the expected. This is explained because the vast majority of customers in the town of Manzanilla have a residential profile that, because of the restrictions, had to remain at home during lockdown.

Additionally, the same analysis has been separately done for the aggregated consumption of residential customers and non-residential customers. In Fig. 10, the forecasted consumption for the first weeks of lockdown is depicted. As can be seen, residential customers have increased their consumption during the first weeks of lockdown in contrast to non-residential customers who have dramatically decreased their consumption compared with the expected forecasted consumption.

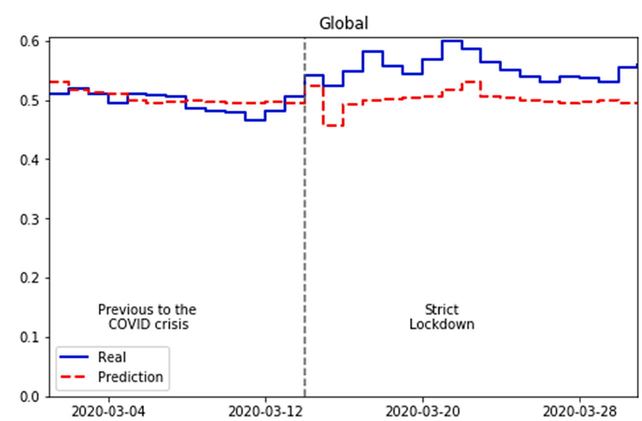

Fig. 9. Normalized real consumption and the expected consumption for the whole town of Manzanilla during the first weeks of lockdown.

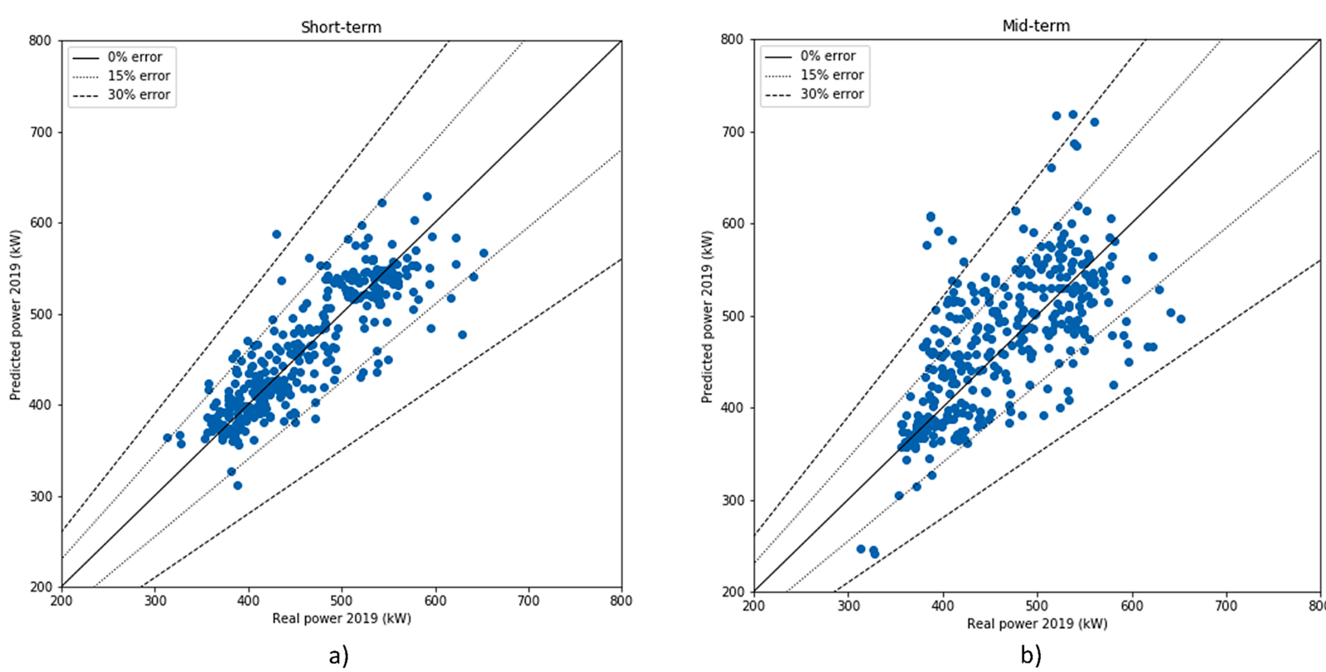

Fig. 8. Short-term (a) and Mid-term (b) validation against 2019 for the aggregated consumption of Manzanilla (each point represents the consumption of a day).

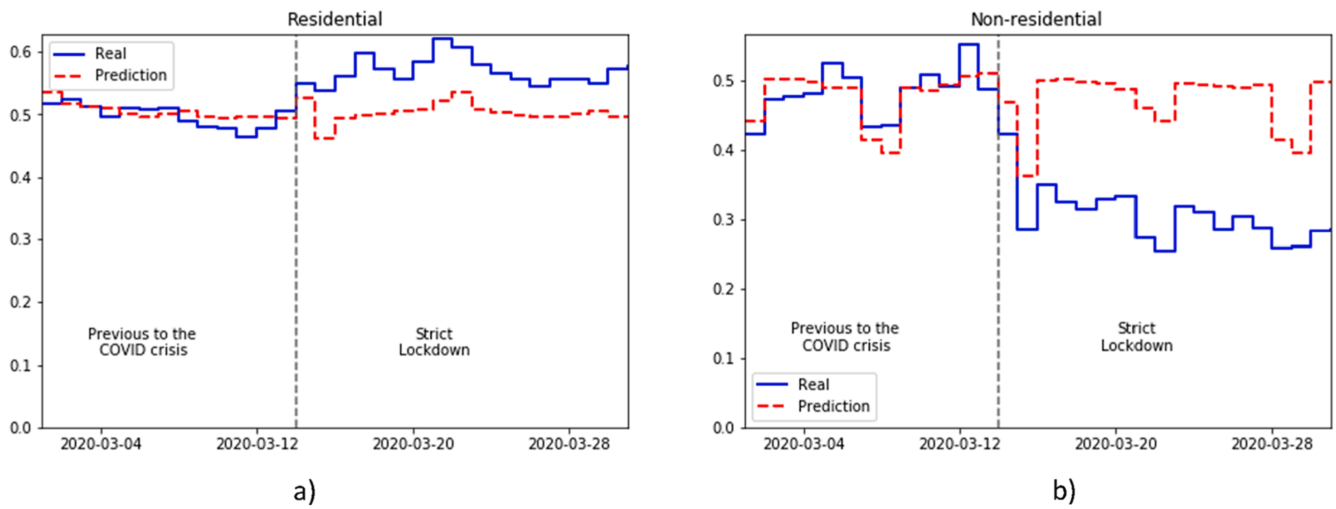

Fig. 10. Normalized real consumption and the expected consumption for residential (a) and non-residential (b) customers during the first weeks of lockdown.

Additionally, the results of the short-term forecasting against the aggregated consumption of each cluster obtained in Section 5.2.2 are as shown in Fig. 11:

As expected from the cluster's representation depicted in Fig. 6, clusters 1 and 3 have almost maintained their normal consumption just after lockdowns (slightly increasing it in the case of cluster 0 and slightly decreasing it in the case of cluster 1) while clusters 1, 2 and 3 have decreased their consumption.

Furthermore, some representative non-residential economic groups have been analyzed thanks to the NACE economic code. Specifically, small businesses (NACE codes from 4700 to 4799) and food and drinks business (NACE codes 5600 to 5699 which corresponds to restaurants, pubs, take away foods, etc.). Fig. 12 shows the expected consumption and the real consumption during the first weeks of lockdown. As can be seen, small businesses have maintained their expected consumption after the first weeks of lockdown. On the contrary, food and drink services have drastically decreased their consumption.

A summary of the variation rate of the expected consumption and the real consumption of the described grouping of customers during the first weeks of lockdown is shown in Table 3. Positive values mean an increase in energy consumption while negative values mean a decrease.

5.3.3. *Mid-term impact analysis*

A mid-term comparison has also been done using the consumption during the same periods in the two previous years. Firstly, the global consumption of the town of Manzanilla compared to the average consumption of the previous years is shown in Fig. 13.

Following the same structure as in the previous subsection, the same mid-term comparison has been done in Fig. 14 for residential customers and non-residential customers. From these figures, it is also clear that residential customers have increased their consumption while non-residential customers have decreased it.

Fig. 15 shows the same mid-term real and expected behavior analysis during all of the COVID-19 crisis for the obtained clusters of customers.

Also, the same comparison has been done for the small businesses and food and drinks economic codes. Fig. 16 represents this comparison.

The impact of lockdowns can be clearly observed in the groups of customers with the same economic category (NACE codes). One of these

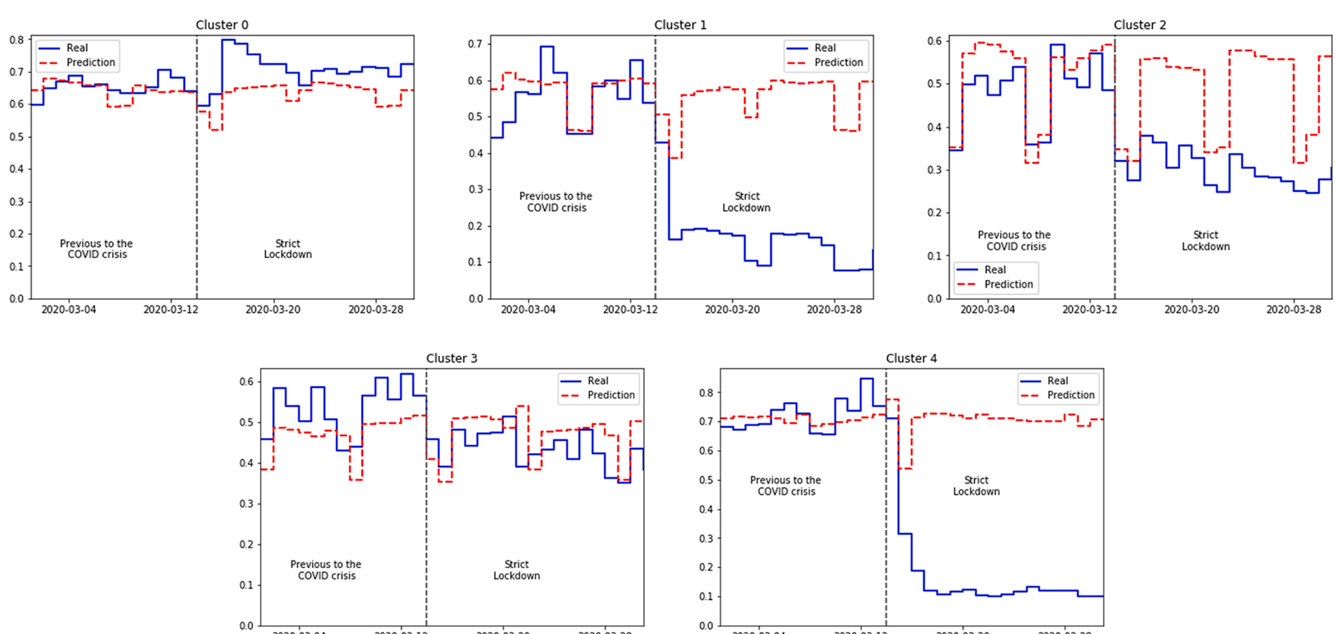

Fig. 11. Normalized real consumption and the expected consumption for each of the obtained clusters during the first weeks of lockdown.

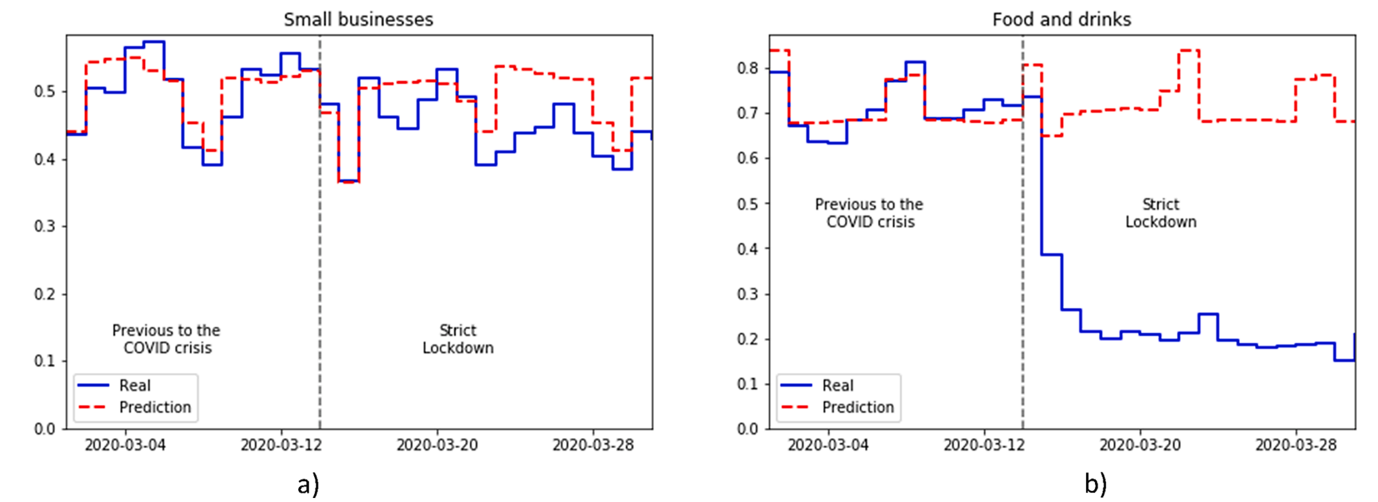

Fig. 12. Normalized real consumption and the expected consumption for small businesses (a) and food and drink services (b) during the first weeks of lockdown.

Table 3
Variation rate on the real and the expected consumption during the first weeks of lockdown different groups of customers.

Description	VR (%)
All customers	10.4
Residential	13.1
Non-residential	−35.2
Cluster 0	12.2
Cluster 1	−70.3
Cluster 2	−36.0
Cluster 3	−7.1
Cluster 4	−77.0
Economic Activity: Small businesses	−8.8
Economic Activity: Food and drinks	−66.4

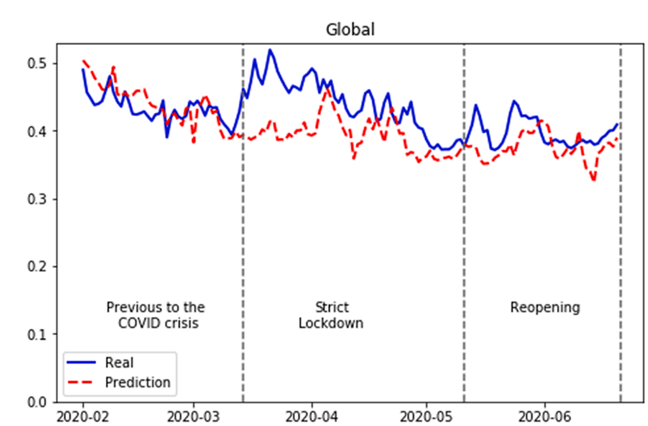

Fig. 13. Normalized real consumption and the expected consumption for the whole town of Manzanilla during all the COVID-19 crisis.

groups includes shops and minor selling in general, with a predominance of grocery stores in the group of customers under study. The evolution of this group shows stable behavior during which the food and essential products stores were open until the final period of the quarantine, in which the opening of all types of shops (not only food and essential products) was permitted again. One of the most affected economic sectors are also analyzed: drink and food services, such as bars, restaurants and caterings. Their evolution performs an asymmetric V-shape, suffering a big drop on their consumption during the quarantine with a slow recuperation during the end of the period.

In the same way, the variation rate with the consumption of the same period of the previous year has been obtained in Table 4.

6. Discussion of the impact on energy consumption

It is clear that the lockdowns imposed due to the COVID-19 have had an impact on energy consumption. Specifically, an increase on the global consumption for the analyzed customers of a 10.4% during the first weeks of the lockdown, a 12.1% during all the lockdown period and a 6.0% during the reopening have been obtained. This result contrasts the 15% to 25% decrease that has been obtained in the already published papers. This is mainly due because the already published papers are a global analysis in which aggregated data at country or regional level is used. However, as our results are based on low-voltage customers, the vast majority of the customers used are residential which, during lockdown, are forced to stay home and, therefore, have increased their consumption.

This is clearly seen if residential and non-residential customers are analyzed separately, as it has been done along this paper. In this sense, residential customers have increased their consumption in a 13.1% during the first weeks of lockdown in contrast to the 35.2% of decrease of non-residential customers. This result is consistent, based on the restrictions of the Spanish government during the second half of March 2020 in which all the population had to stay home and non-essential business had to close. The increase in the residential sector is also consistent with the results found by other authors. For example, Zhang et al. [24] found an increase of a 14.3% for a level 4 containment level (full lockdown) of a residential neighborhood while Madurai Elavarasan et al. [19] found an increase of a 14% in residential consumption in North-Western Melbourne (Australia).

In addition, an automatic clustering based on the behavior of non-residential customers has been performed. The results showed that five different consumption profiles can be found in low-voltage customers. If the result of the clustering is analyzed, they are also consistent with the restrictions imposed by the government and with the behavior of the Spanish society. In this sense, if the clusters are analyzed:

- Cluster 0 has almost maintained the same consumption as it would have normally had as the mid-term impact shows (2.7% increase during full lockdown and 1.8% increase during the reopening). Even though it has maintained their consumption during all the COVID crisis, during the first week of lockdown the customers associated to this cluster have increased in a 12.2% their consumption. Additionally, the metadata of the customers associated to this cluster show that are mainly grocery stores and essential public services

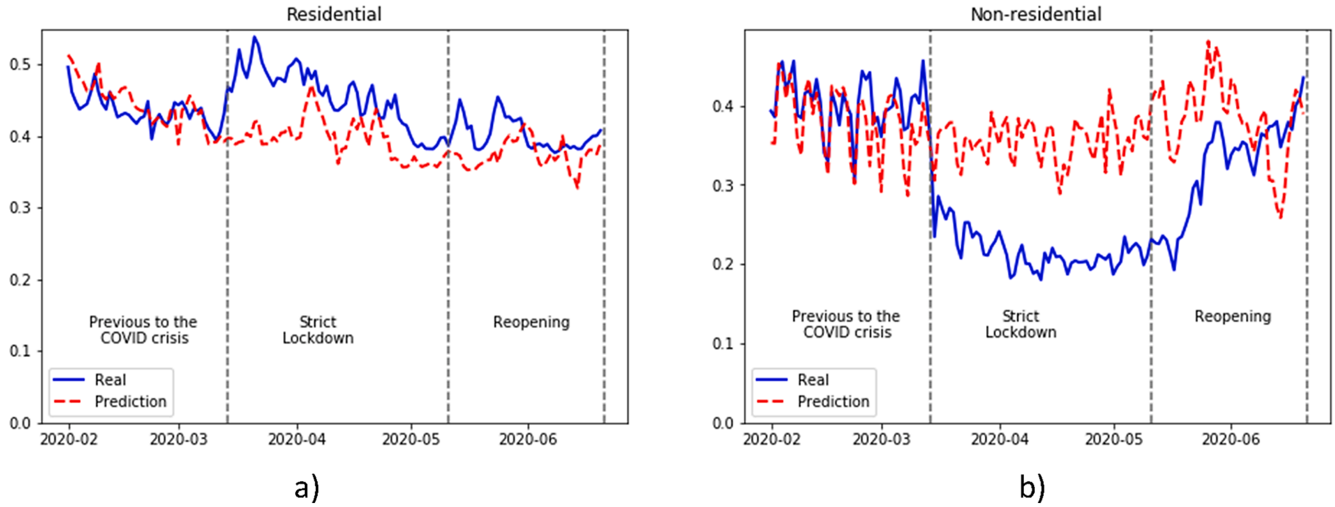

Fig. 14. Normalized real consumption and the expected consumption for residential (a) and non-residential (b) customers during all the COVID-19 crisis.

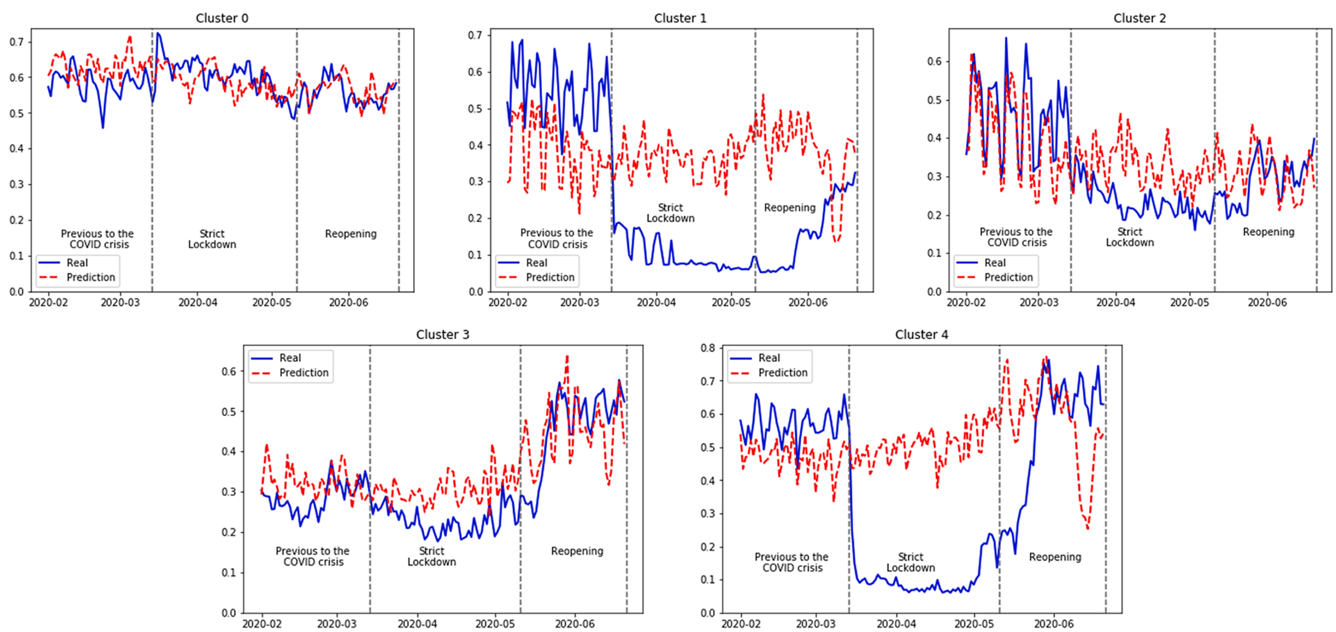

Fig. 15. Normalized real consumption and the expected consumption for the obtained clusters during all the COVID-19 crisis.

(health and supplies). This result can be associated to essential businesses based on the lockdown restrictions.

- Cluster 1 has drastically reduced their consumption as the short-term (−70.3%) and the mid-term (−71.2% during full lockdown and −47.9% during the reopening). Based on this behavior it is expected that these customers would be fully non-essential customers that have not recovered after the restrictions. The metadata of the customers of this cluster show that they are mainly restaurants, bars and some public institutions.
- Cluster 2 reduced their consumption but much lower than cluster 1 as the variation rates indicates: −36% for the short-term (first weeks of lockdown), a −27.4% during the full lockdown period and a −3.7% during the reopening. Seeing this data, these customers are expected to be non-essential businesses that have recovered their normal consumption. This is partially supported by the metadata of the clients under this cluster: industrial services and some public institutions.
- Cluster 3 have decreased their consumption during lockdowns: there seems to be an increase during the first weeks of lockdown (−7.1% according with the short-term analysis) but during the whole lockdown period the consumption has decreased much more (−24.2% according to the mid-term). In addition, this group of customers have recovered their consumption during reopening (1.3% of increase compared with previous years).
- Cluster 4 have drastically reduced the consumption both during the first weeks of lockdown (−77%) and during all the lockdown period (−78.5%) but have recovered almost their normal consumption during the reopening (1.9%). These customers are expected to be non-essential businesses that were allowed during the reopening and they have effectively reopened.

Thanks to this segmentation of customers' behavior, it can be said that some of them have maintained their normal consumption (Cluster 0), others have decreased their consumption with higher or lower rates but then have recovered (Clusters 1, 2 and 3) while others have decreased their consumption not recovering it during the reopening after lockdown (Cluster 4).

Additionally, some information can also be extracted from certain

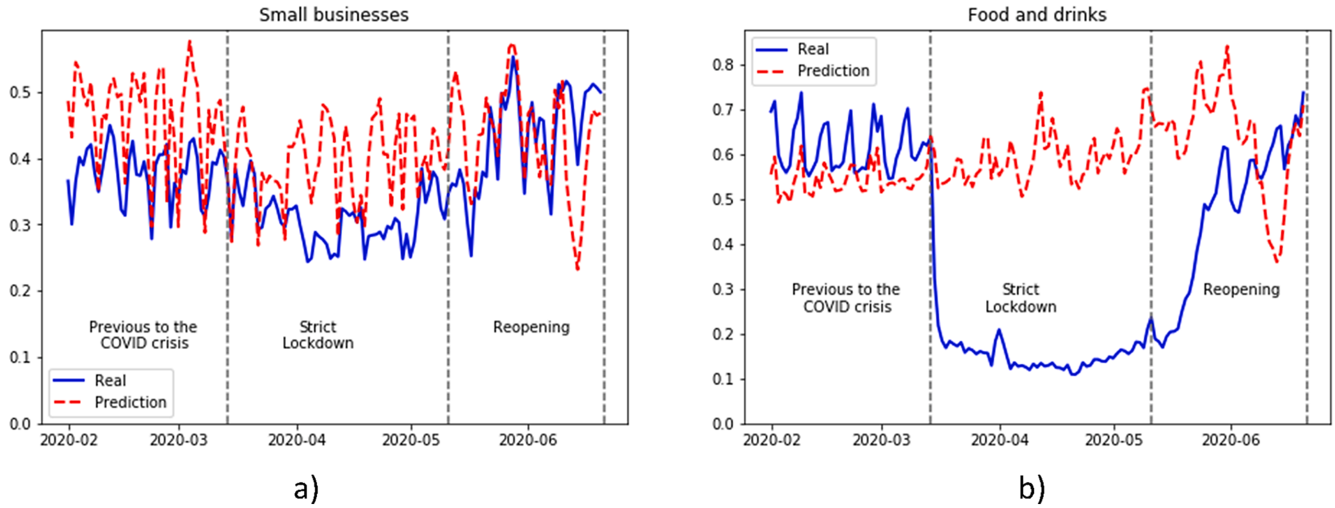

Fig. 16. Normalized real consumption and the expected consumption for small businesses (a) and food and drink services (b) during all the COVID-19 crisis.

Table 4
Variation rate on the real and the expected consumption during the full lockdowns and the reopening periods for the different groups of customers.

Description	VR during lockdown (%)	VR during the reopening (%)
All customers	12.1	6.0
Residential	15.0	7.5
Non-residential	−38.0	−14.5
Cluster 0	2.7	1.8
Cluster 1	−71.2	−47.9
Cluster 2	−27.4	−3.7
Cluster 3	−24.2	1.3
Cluster 4	−78.5	1.9
Economic Activity: Small businesses	−20.2	2.9
Economic Activity: Food and drinks	−72.5	−21.7

economic activities. As an example, bars and restaurants that have been studied showed that they have decreased their consumption –72.5% during lockdown and with a –21.7%. These results show that the COVID-19 restrictions have had a serious impact on this specific economic activity.

Other economic groups that have been analyzed is the related to small businesses which, due to the location (a town), are mainly local shops. This economic group shows a decrease in the consumption of an 8.8% during the first weeks of lockdown, a 20.2% of decrease during the full lockdown period and a 2.9% of increase in the reopening. These results show that small businesses have had an impact during lockdown but then they have recovered.

7. Conclusions

The COVID-19 has had a tremendous impact on societies and on the economies of countries and regions all over the world. This impact is clearly reflected on energy consumption. In this paper, an approach to evaluate the behavior and the impact on energy consumption at the secondary distribution network over Smart Meter data is proposed. Thus, not only the impact at aggregated levels of the COVID-19 restrictions can be extracted but also the impact on smaller groups at customer level.

Using this approach, automatic customer clustering can be performed based on the consumption profile behavior during the COVID-19 crisis. This has the advantage that the behavior of small groups that they may not affect at aggregated levels can be discovered. As an example, in the presented use case, the global consumption of Manzanilla has increased its consumption during lockdown but, if the data is analyzed, it can be seen that this increase is biased towards residential customers. Moreover, it is also possible to analyze the impact on customers of specific economic categories, showing interesting results regarding the response and resilience of some of them, and showing which have been the most vulnerable ones (those which had to be closed, temporally or permanently).

In the study case of Manzanilla, a total of five types of behavior (clusters) were identified for non-residential customers, showing different impacts and differences both in short and mid-term. These five clusters are consistent with the expected consumption profile based on the restrictions in Spain. Regarding of the economic groups, the most affected areas were those related to food and drink services, while the area of small businesses (mainly little local shops) showed a lesser impact in their electric consumption. The behavior of the residential consumption was characterized by a remarkable increase during the quarantine.

Additionally, some future research lines can be established. With larger data sets, more accurate and comparable results of the energy consumption behavior of secondary power distribution customers could be addressed, obtaining not only the behavior between relevant date intervals but also, hourly behavior (since more features could be used to segment the behavior) obtaining how the pandemic has changed the consumption slots during the day. Moreover, as the clusters can be associated to specific groups of customers, the obtained models can be used to reclassify customers who do not have their economic activity correctly labeled. Thus, all customers could be classified using these models and determine which of them might be mislabeled.

As a final conclusion, the proposed approach got results that reflect various aspects about the economic structure of the analyzed town, and how their respective recuperation was. Its application over other type of towns or even regions in the future could grant a detailed analysis including other types of activities.

CRediT authorship contribution statement

Sebastián García: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft. **Antonio Parejo:** Methodology, Software, Formal analysis, Investigation, Writing - original draft. **Enrique Personal:** Validation, Investigation, Resources, Supervision, Writing - original draft. **Juan Ignacio Guerrero:** Validation, Investigation, Writing - review & editing. **Félix Biscarri:** Validation, Supervision, Project administration, Writing - review & editing. **Carlos León:** Supervision, Project administration, Funding acquisition, Writing

- review & editing.

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.

Acknowledgements

Authors would like to thank the Medina Garvey Company for their collaboration and support providing access to their Advanced Metering Infrastructure. This work was supported by the "*Ministerio de Ciencia, Innovación y Universi*dades", Government of Spain under the project "*Bigdata Analitycs e Instrumentación Cyberfísica para Soporte de Operaciones de Distribución en la Smart Grid*", number RTI2018-094917-B-I00. Sebastián García is also supported by this project. Moreover, Antonio Parejo is supported by the scholarship "*Formación de Profesorado Universitario (FPU)*", Grant Number FPU16/03522 from the "*Ministerio de Educación y Formación Profesional*", Government of Spain.

References

[1] Lu H, Stratton CW, Tang Y-W. Outbreak of pneumonia of unknown etiology in Wuhan, China: The mystery and the miracle. J Med Virol 2020;92:401–2. https://doi.org/10.1002/jmv.25678.

[2] WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020 n.d. https://www.who.int/dg/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020 (accessed October 12, 2020).

[3] Wang Q, Lu M, Bai Z, Wang K. Coronavirus pandemic reduced China's CO2 emissions in short-term, while stimulus packages may lead to emissions growth in medium- and long-term. Appl Energy 2020;278. https://doi.org/10.1016/j.apenergy.2020.115735.

[4] Gillingham KT, Knittel CR, Li J, Ovaere M, Reguant M. The short-run and long-run effects of Covid-19 on energy and the environment. Joule 2020;4:1337–41. https://doi.org/10.1016/j.joule.2020.06.010.

[5] Le Quéré C, Jackson RB, Jones MW, Smith AJP, Abernethy S, Andrew RM, et al. Temporary reduction in daily global CO 2 emissions during the COVID-19 forced confinement. Nat Clim Change 2020;10:647–53. https://doi.org/10.1038/s41558-020-0797-x.

[6] Peters IM, Brabec C, Buonassisi T, Hauch J, Nobre AM. The impact of COVID-19-related measures on the solar resource in areas with high levels of air pollution. Joule 2020;4:1681–7. https://doi.org/10.1016/j.joule.2020.06.009.

[7] Bahmanyar A, Estebsari A, Ernst D. The impact of different COVID-19 containment measures on electricity consumption in Europe. Energy Res Social Sci 2020;68:101683. https://doi.org/10.1016/j.erss.2020.101683.

[8] Werth A, Gravino P, Prevedello G. Impact analysis of COVID-19 responses on energy grid dynamics in Europe. Appl Energy 2021;281:116045. https://doi.org/10.1016/j.apenergy.2020.116045.

[9] Ruan G, Wu D, Zheng X, Zhong H, Kang C, Dahleh MA, et al. A cross-domain approach to analyzing the short-run impact of COVID-19 on the US electricity sector. Joule 2020;4:2322–37. https://doi.org/10.1016/j.joule.2020.08.017.

[10] Zhong H, Tan Z, He Y, Xie L, Kang C. Implications of COVID-19 for the electricity industry: a comprehensive review. CSEE J Power Energy Syst 2020;6:489–95. https://doi.org/10.17775/CSEEJPES.2020.02500.

[11] Norouzi N, Rubens GZZ de, Enevoldsen P, Forough AB. The impact of COVID-19 on the electricity sector in Spain: An econometric approach based on prices. International Journal of Energy Research n.d.;n/a. Doi: 10.1002/er.6259.

[12] Eryilmaz D, Patria M, Heilbrun C. Assessment of the COVID-19 pandemic effect on regional electricity generation mix in NYISO, MISO, and PJM markets. Electricity J 2020;33:106829. https://doi.org/10.1016/j.tej.2020.106829.

[13] Agdas D, Barooah P. Impact of the COVID-19 pandemic on the U.S. electricity demand and supply: an early view from data. IEEE Access 2020;8. https://doi.org/10.1109/ACCESS.2020.3016912.

[14] Ghiani E, Galici M, Mureddu M, Pilo F. Impact on electricity consumption and market pricing of energy and ancillary services during pandemic of COVID-19 in Italy. Energies 2020;13. https://doi.org/10.3390/en13133357.

[15] Santiago I, Moreno-Munoz A, Quintero-Jiménez P, Garcia-Torres F, Gonzalez-Redondo MJ. Electricity demand during pandemic times: the case of the COVID-19 in Spain. Energy Pol 2021;148:111964. https://doi.org/10.1016/j.enpol.2020.111964.

[16] Abu-Rayash A, Dincer I. Analysis of the electricity demand trends amidst the COVID-19 coronavirus pandemic. Energy Res Social Sci 2020;68. https://doi.org/10.1016/j.erss.2020.101682.

[17] Alhajeri HM, Almutairi A, Alenezi A, Alshammari F. Energy demand in the state of Kuwait during the Covid-19 pandemic: technical, economic, and environmental perspectives. Energies 2020;13. https://doi.org/10.3390/en13174370.

[18] Carvalho M, Delgado DB de M, Lima KM de, Cancela M de C, Siqueira CA dos, Souza DLB de. Effects of the COVID-19 pandemic on the Brazilian electricity consumption patterns. International Journal of Energy Research n.d.;n/a:e5877. Doi: 10.1002/er.5877.

[19] Madurai Elavarasan R, Shafiullah G, Raju K, Mudgal V, Arif MT, Jamal T, et al. COVID-19: Impact analysis and recommendations for power sector operation. Appl Energy 2020;279:115739. https://doi.org/10.1016/j.apenergy.2020.115739.

[20] Chiaramonti D, Maniatis K. Security of supply, strategic storage and Covid19: Which lessons learnt for renewable and recycled carbon fuels, and their future role in decarbonizing transport? Appl Energy 2020;271:115216. https://doi.org/10.1016/j.apenergy.2020.115216.

[21] Norouzi N, Zarazua de Rubens G, Choubanpishehzafar S, Enevoldsen P. When pandemics impact economies and climate change: exploring the impacts of COVID-19 on oil and electricity demand in China. Energy Res Social Sci 2020;68. https://doi.org/10.1016/j.erss.2020.101654.

[22] Boddapati V, Nandikatti ASR. Salient features of the national power grid and its management during an emergency: a case study in India. Energy Sustain Dev 2020;59:170–9. https://doi.org/10.1016/j.esd.2020.10.010.

[23] Fezzi C, Fanghella V. Real-time estimation of the short-run impact of COVID-19 on economic activity using electricity market data. Environ Resource Econ 2020;76:885–900. https://doi.org/10.1007/s10640-020-00467-4.

[24] Zhang X, Pellegrino F, Shen J, Copertaro B, Huang P, Kumar Saini P, et al. A preliminary simulation study about the impact of COVID-19 crisis on energy demand of a building mix at a district in Sweden. Appl Energy 2020;280:115954. https://doi.org/10.1016/j.apenergy.2020.115954.

[25] Farhangi H. The path of the smart grid. IEEE Power Energ Mag 2010;8:18–28. https://doi.org/10.1109/MPE.2009.934876.

[26] Personal E, Guerrero JI, Garcia A, Peña M, Leon C. Key performance indicators: a useful tool to assess smart grid goals. Energy 2014;76:976–88. https://doi.org/10.1016/j.energy.2014.09.015.

[27] Karimulla S, Ravi K. A Review on Importance of Smart Grid in Electrical Power System. 2019 International Conference on Computation of Power, Energy, Information and Communication (ICCPEIC), 2019, p. 022–7. Doi: 10.1109/ICCPEIC45300.2019.9082355.

[28] Rashed Mohassel R, Fung A, Mohammadi F, Raahemifar K. A survey on advanced metering infrastructure. Int J Electr Power Energy Syst 2014;63:473–84. https://doi.org/10.1016/j.ijepes.2014.06.025.

[29] Kabalci Y. A survey on smart metering and smart grid communication. Renew Sustain Energy Rev 2016;57:302–18. https://doi.org/10.1016/j.rser.2015.12.114.

[30] England BS, Alouani AT. Multiple loads-single smart meter for measurement and control of smart grid. IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia) 2019;2019:2440–4. https://doi.org/10.1109/ISGT-Asia.2019.8881529.

[31] Guerrero JI, Monedero I, Biscarri F, Biscarri J, Millán R, León C. Non-technical losses reduction by improving the inspections accuracy in a power utility. IEEE Trans Power Syst 2018;33:1209–18. https://doi.org/10.1109/TPWRS.2017.2721435.

[32] Regulation (EC) No 1893/2006 of the European Parliament and of the Council of 20 December 2006 establishing the statistical classification of economic activities NACE Revision 2 and amending Council Regulation (EEC) No 3037/90 as well as certain EC Regulations on specific statistical domains Text with EEA relevance. vol. 393. 2006.

[33] MacQueen J. Some methods for classification and analysis of multivariate observations. The Regents of the University of California; 1967.

[34] López JJ, Aguado JA, Martín F, Muñoz F, Rodríguez A, Ruiz JE. Hopfield–K-Means clustering algorithm: a proposal for the segmentation of electricity customers. Electr Power Syst Res 2011;81:716–24. https://doi.org/10.1016/j.epsr.2010.10.036.

[35] Biscarri F, Monedero I, García A, Guerrero JI, León C. Electricity clustering framework for automatic classification of customer loads. Expert Syst Appl 2017;86:54–63. https://doi.org/10.1016/j.eswa.2017.05.049.

[36] Al-Otaibi R, Jin N, Wilcox T, Flach P. Feature construction and calibration for clustering daily load curves from smart-meter data. IEEE Trans Ind Inf 2016;12:645–54. https://doi.org/10.1109/TII.2016.2528819.

[37] Tureczek A, Nielsen PS, Madsen H. Electricity consumption clustering using smart meter data. Energies 2018;11:859. https://doi.org/10.3390/en11040859.

[38] Rhodes JD, Cole WJ, Upshaw CR, Edgar TF, Webber ME. Clustering analysis of residential electricity demand profiles. Appl Energy 2014;135:461–71. https://doi.org/10.1016/j.apenergy.2014.08.111.

[39] McLoughlin F, Duffy A, Conlon M. A clustering approach to domestic electricity load profile characterisation using smart metering data. Appl Energy 2015;141:190–9. https://doi.org/10.1016/j.apenergy.2014.12.039.

[40] Hoerl AE, Kennard RW. Ridge regression: biased estimation for nonorthogonal problems. Technometrics 1970;12:55–67. https://doi.org/10.1080/00401706.1970.10488634.

[41] Rousseeuw PJ. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. J Comput Appl Math 1987;20:53–65. https://doi.org/10.1016/0377-0427(87)90125-7.

[42] Davies DL, Bouldin DW. A Cluster Separation Measure. IEEE Transactions on Pattern Analysis and Machine Intelligence 1979;PAMI-1:224–7. Doi: 10.1109/TPAMI.1979.4766909.

[43] Kuster C, Rezgui Y, Mourshed M. Electrical load forecasting models: a critical systematic review. Sustain. Cities Soc. 2017;35:257–70. https://doi.org/10.1016/j.scs.2017.08.009.