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Impact of COVID-19 on electricity demand of Latin America and the Caribbean countries

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ABSTRACT

Governments worldwide have adopted different public health measures in order to slow down the spread of COVID-19. As a result, the electricity demand has been impacted by the changes in human activity. Many of the Latin America and the Caribbean (LAC) countries have adopted different approaches to control the COVID-19 pandemic, including severe shutdown of most social and economic activities. This paper analyzes how this pandemic has influenced, from its appearance until the fall of 2020, the demand of ten LAC countries (Peru, Bolivia, Costa Rica, Brazil, Guatemala, Mexico, Dominican Republic, Argentina, Chile and Uruguay). The approach is based on the concepts of size and shape impacts, which have been proposed in order to decompose the problem for a better understanding of the impact. The size impact accounts for the observed variations on the daily demand, whereas the shape impact focuses on the variations observed on the standardized hourly demand profiles for each day. To calculate both impacts, the observed demand is compared to the expected one if the COVID-19 crisis had not happened. To obtain reliable estimations in the scenario without COVID-19, machine learning techniques have been used. Peru and Bolivia are the two countries where the pandemic has had the greatest impact during 2020, with a size impact in April 2020 of around -30%. At the opposite extreme would be Chile and Uruguay, with a maximum monthly size impact of -6%. The other considered countries have maximum monthly impacts in the range of -11% to -17%.

1. Introduction

In December 2019 the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) was detected in Wuhan (China). Just a few months later, it was spread to create the COVID-19 pandemic, the worst global public health crisis since the 1918 flu pandemic [1]. In June 2021, the total number of COVID-19 cases in the world is counted in the hundreds of millions, with direct deaths attributable to COVID-19 in over three million cases [2].

With the arrival of SARS-CoV-2, governments worldwide have adopted different public health measures in order to slow down the spread of the virus. These measures range from social distancing recommendations to stay-at-home orders by means of enforced partial or complete lockdowns, non-essential business closures, etc. Under this unusual situation, the electricity demand has been significantly impacted by the changes in human activity brought on by the COVID-19 pandemic.

The impact of COVID-19 pandemic on the electricity demand has been previously reported in academic literature, where numerous studies can be found analyzing a wide range of countries applying different methodologies. This literature has been growing since the pandemic arrived, hence, an in-depth comparison of the available references has been performed with focus on several factors: regions of study, type of electricity demand analyzed, methodology used and observed impact of demand measured.

The methodology followed to evaluate the impact of COVID-19 pandemic on the demand is diverse, however, it can be classified into two main approaches: On the one hand, Table 1 shows the articles that perform a direct comparison of the actual demand during the year 2020 with the consumption of year 2019 or with an average consumption of previous years. On the other hand, Table 2 shows the papers that follow a model-based approach, where the actual demand during the year 2020 is compared with an estimate of the demand in the event that COVID-19 would not have arrived. For this approach an statistical model is trained with pre-COVID-19 data to model factors such as trend, seasonality, holidays and the effect of temperature in the demand.

Regarding the type of demand analyzed, most papers analyze daily or hourly electricity demand, except some analyzing weekly consumptions. Depending on the study, aggregated demand at a National level is analyzed whereas others dive into the differences between residential and industrial consumptions. In general, the

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Table 1
Summary of literature review for approaches mainly based on direct comparison.

Ref.	Regions	Type of demand	Methodology	Observed impact on demand
[3]	Spain, Italy, Belgium, UK, Netherlands, Sweden	Hourly electricity consumption. Daily load profiles.	Comparison against reference week (the one with similar daily average temperature) form 2019. Analyzed the second week in April 2020.	Hourly demand: Reduction in Spain (-25%), Italy (−17.7%), Belgium (−15.6%), United Kingdom (−14.2%), Netherlands (−11.6%). Increased in Sweden (2.1%). Load profiles: working days of 2020 similar to weekends of 2019.
[4]	Spain	Daily electricity demand.	Comparison against average of 2015–2019 in same period. Analyzed from March 14th to April 30th 2020.	Percentage of reduction in electricity demand. 13% reduction on average. 25% maximum reduction.
[5]	Italy, France, Spain, Germany, Sweden, Switzerland	Hourly demand time series. Daily load profiles.	Comparison to same period in 2019. Analyzed beginning of March 2020 until June 2020.	Hourly demand: demand reduced in Italy (−20.9%), in France (−18.9%), Spain (−16.9%), UK (−15.2%), Belgium (−13.3%), The Netherlands (−12.0%). Load profiles: working days of 2020 similar to weekends of 2019. Working day profiles shifted in time.
[6]	Romania	Monthly electricity consumption. Differences in domestic, household and non-household consumption.	Comparison with same period in 2019 for analyzing impact. Analyzed March to December 2020. *Model-Based for Relation between GDP and demand by statistical model. Time series and multi-linear regression models for GDP vs Demand.	Domestic: Average demand reduction in March (−2.75%) and −14.25% reduction in April. Household: Demand increase to a total maximum of 8.33% in December 2020. Non-household: Average demand reduction of -4% in March and −21.3% reduction in April.
[7]	Spain	Smart Meter data Differences in residential and non-residential.	Comparison with same period in 2019 for analyzing impact. *Model-based for first days. Short-term forecasting model for first days.	Residential sector: 13% increase for residential sector. Non-residential sector: -35% demand reduction.
[8]	Warsaw (Poland)	Hourly consumption for residential users Daily load profiles.	Direct comparison with same period in 2018 for analyzing impact. Analyzed 5 week from March 16th to April 18th 2020.	Hourly demand: 16% increase compared to analogous period in 2018. Load profiles: Changes in the shape of the daily profile Increase in energy consumption during the daytime.
[9]	Italy	Hourly consumption data.	Direct comparison with same period in 2018 and 2019. Analyzed 5 week from March to April.	Reduction of consumption up to -37%.
[10]	Canada (Ontario)	Hourly consumption data.	Direct comparison with same period in 2019. Analyzed April 2020.	−14% reduction in the monthly electricity demand, with the highest daily reduction of -25%.

impact is measured as the difference between the observed demand and the reference demand in percentage with respect to the reference demand. The results show a wide variety of impacts, mainly ranging from 2% to 25% average demand reduction. However, not all impacts show reductions in consumption. Studies such as [6,7,16], which analyze demand on different sectors, show that significant increases up to 13% have been observed on residential areas. In addition, studies such as [5,19] have analyzed daily load profiles, identifying time shifts in the morning consumption during weekdays. Moreover, weekday profiles during confinement resembled weekend profiles.

Regarding the regions analyzed, while most studies have been performed for countries in Europe, North America, and Asia, very few studies address the impact on Latin American countries.

The Latin America and the Caribbean countries (LAC) have adopted different approaches to control the COVID-19 pandemic, but many of them have imposed the severe shutdown of most social and economic activities during the first months of the pandemic. A sample of ten countries has been selected to carry out the study, based on the availability of the required data for the application of the proposed methodology. The existence of historical demand with hourly detail with a sufficient depth and quality has been a critical factor to adjust the proposed explanatory models used to estimate the reference demand. The LAC sample consists of the following countries: Peru, Bolivia, Costa Rica, Brazil, Guatemala, Mexico, Dominican Republic, Argentina, Chile and Uruguay. To the best of our knowledge, this is the first study that quantifies the impact of COVID-19 pandemic on electricity demand for a representative set of Latin American countries.

This paper analyzes how the COVID-19 pandemic has influenced the selected LAC countries, from its appearance until the fall of 2020. A model-based approach for estimating the impact is used, instead of a straightforward comparison with the average of previous years. Furthermore, our methodology is based on the computation of the size and the shape impacts, which decompose the problem for a better understanding of the impact. The size impact accounts for the observed variations on the daily demand time series, whereas the shape impact focuses on the variations observed on the standardized hourly demand profiles for each day.

The paper is organized as follows. Section 2 describes the proposed methodology to carry out the study. In Section 3 the data preparation is described. Additional details about the proposed size and shape impacts are described in Sections 4 and 5, respectively. The results are shown in Section 6, further discussed in Section 7. Finally, conclusions are summarized in Section 8.

Table 2
Summary of literature review for approaches based on models for comparison.

Ref.	Regions	Type of demand	Methodology	Observed impact on demand
[11]	UK	Daily electricity demand. All 2020 analyzed.	Linear regression with temperatures: population weighted Heating Degree Days (HDD) and Cooling Degree Days (CDD). Separate regressions for weekdays, weekends and holidays. Model trained with years 2017–2019. Use of temperature scenarios for uncertainty.	Percentage of reduction during restrictions: −11.7 ± 1.2%.
[12]	India (5 different regions)	Log series of energy consumption data.	Obtain relationship between indian energy consumption and number of cumulative confirmed COVID-19 cases. Auto-regressive time series models.	As lockdown measures are relaxed, energy consumption in India is inclined to increase to levels before the lockdown. Regions with higher income levels are quicker to recover their energy consumption to levels before the lockdown.
[13]	Brazil (4 regions)	Weekly consumption data.	Identify significant trend changes in weekly data using joinpoint Regression	Percentage change between time interval (Weekly Percentage Change) Between -7% and -20% consumption drop depending on the zone.
[14]	Jordan (3 main areas)	Half-hourly, daily and monthly consumption of commercial, household, demand and factories.	Comparison with same period in years 2016 to 2019 for analyzing impact. Trend removal of monthly demand.	Average demand reduced by -40% with respect to 2019 in city center.
[15]	Poland	Hourly data demand data.	Difference between energy consumed in subsequent weeks and the expected values of consumption. Linear regression based on weekly values of consumption in the 4 weeks before lockdown.	Energy consumption drop between -15% to 23% during the first lockdown.
[16]	US (California, Florida, New York)	Hourly electricity demand.	Weather correction method with Cooling Degree Days (CDD) and Heating Degree Days(HDD).	10% increase in electricity demand is likely to have occurred due to COVID-19 for the city of Grainesville.
[17]	Kuwait	Daily electricity demand.	Linear regression model with temperatures, weekdays and holidays. Train with last 4 years. Test with 2020. Analyze 3 months from March to May 2020.	The stay at home phase (13–21 March) recorded a −2.2% reduction. The partial curfew (March 22nd –10 May) and full lockdown (11–30 May) phases showed −13.7% and −17.6% respectively.
[18]	China	Daily electricity demand.	Auto-regressive time series and Artificial Neurlal Networks with explanatory variables such as GDP and population increase and epidemic variables.	Identified effects of different variables on demand: A 1% increase in population infected induces a −0.58% demand reduction.
[19]	Germany, France, Italy, Spain and Poland	Hourly electricity demand. Daily load profiles.	High dimensional time series change-point models to the electricity log-load of each country. Analyzed 2 months from March to April 2020.	Hourly demand: Significant demand reduction (not specified). Load profiles: Identifies shifts in the morning load peak on the daily demand profiles.
[20]	Austria, Germany, Spain France, Italy UK, USA (Florida & New York)	Daily electricity demand.	Dynamic harmonic regression with Fourier terms for complex seasonality, quadratic temperature, and calendar effects. Analyzed 5 months from March to August 2020.	Most countries experienced a reduction between -3% and -12%, except Florida, which showed no significant impact.
[21]	Canada	Hourly electricity demand.	Linear regression with weekdays, holidays, Heating Degree Days (HDD) and Cooling Degree Days (CDD). Analyzed March 2020 until June 2020.	Demand variation form -4% to -10%.
[22]	US	Weekly averaged electricity demand.	Polynomial regression and a two-step augmented regression prediction model were used for forecasting energy demand during the test period. Analyze late March to June 7th.	Overall reduction in electricity demand around -7%.

2. Methodological approach

In this section the proposed methodology to analyze the main impacts of COVID-19 pandemic on the electricity demand of a specific country is described. Two different impacts are considered. The *size impact*, that accounts for the observed variations on the daily demand time series, and the *shape impact*, that focuses on the variations observed on the hourly demand profiles for each

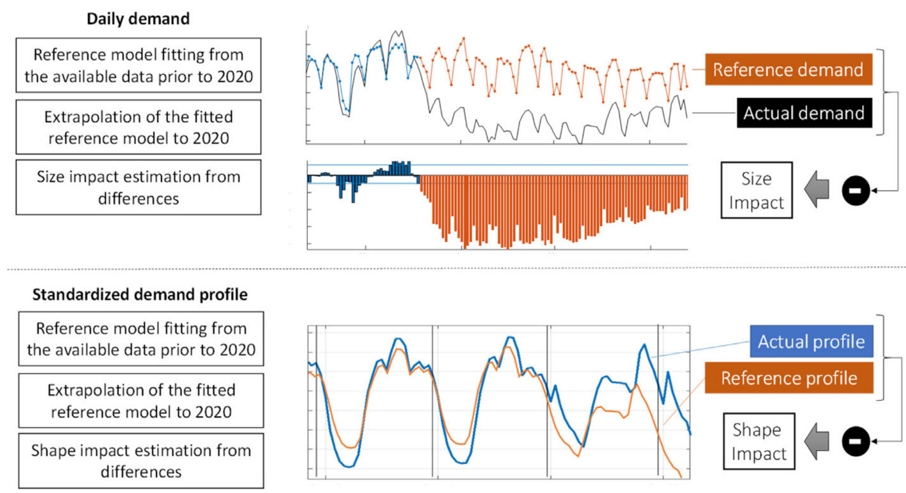

Fig. 1. Proposed methodology to calculate the size and shape impacts of COVID-19 on demand.

day. The use of these two impact components is based on the fact that the hourly demand can be decomposed using a simple multiplicative decomposition:

$$D_{d,h} = w_{d,h} D_d, \tag{1}$$

where $D_d = \sum_h D_{d,h}$ is the daily demand at day d and $w_{d,h}$ is the proportion of D_d observed at hour h. Thus, the vector $\mathbf{w}_d = \left(w_{d,1}, \ldots, w_{d,h}, \ldots, w_{d,24}\right)^T$ represents the standardized hourly demand profile for day d. Note that the profile's coefficients are calculated straightforward as the ratio of the hourly demand $D_{d,h}$ divided by the daily demand D_d.

Therefore, instead of analyzing directly the impact of COVID-19 on hourly demand, the proposed approach is based on decoupling the effect in two factors. The first factor, the size impact, focuses on quantifying how the daily demand D_d has changed due to the alterations in human activity brought on by the COVID-19 pandemic. On the other hand, the shape impact accounts for the pandemic-induced changes in the standardized hourly demand profile $\mathbf{w}_d$ for each day. Thus, both the size and the shape impacts will show different aspects of the same issue, allowing a better understanding by decoupling the problem.

The proposed methodology to calculate both impacts relies on a simple idea: compare the observed demand to the expected one if the COVID-19 crisis had not happened. In this way, size and shape impact indicators can be defined from the differences between the observed demand and the reference one. The key point of this approach is how to obtain a reliable estimation of the daily demand D_d and the standardized demand profile $\mathbf{w}_d$ in the scenario without COVID-19. In this paper these estimations are obtained applying well-known machine learning techniques. In particular, the proposed methodology consists of the following main steps (see Fig. 1):

- Step 1: Data preparation for implementing the approach.
- Step 2: Creation of the reference models from the available data prior to 2020 (before COVID-19 crisis).
- Step 3: Extrapolation of the fitted reference models to 2020 to obtain the references for the daily demand and the standardized demand profile.
- Step 4: Comparison of the real data to the references and calculation of impact indicators.

3. Data preparation

To implement the methodology proposed for estimating the impact of COVID-19 pandemic on the LAC's electricity demand, a complete dataset of different variables has been collected. In addition to the hourly demand data, daily temperatures as well as holidays and special events have been collected. Note that the temperature is the main weather driver of the demand, whereas including public holidays as inputs in the forecasting demand models is especially useful in order to improve their accuracy (see e.g. [23]). Therefore, a special effort has been undertaken to obtain a valuable dataset of input variables for explaining the demand.

3.1. Demands

Hourly demand data has been obtained from the web sites of the system operators of each country. This hourly demand is used to calculate the daily demand and the standardized demand profiles using Eq. (1), required to estimate the proposed size and shape impacts.

Fig. 2 shows the daily demand time series collected for the LAC countries. Note that the number of recovered years is different for each country, according to the availability of data. A simple visual inspection allows detecting the high impact of the COVID-19 pandemic in some countries such as Peru, Bolivia or Costa Rica. On the other hand, Fig. 3 shows the standardized demand profiles for the two first consecutive weeks of February 2020. Note that the profiles are quite stable for each country, with visible differences in shape during the weekends. It is also easy to see the clear differences between the country profiles. For example, in Guatemala the standardized demand spreads out in a larger range of values that in Peru, with a significant peak at 6:00 p.m.

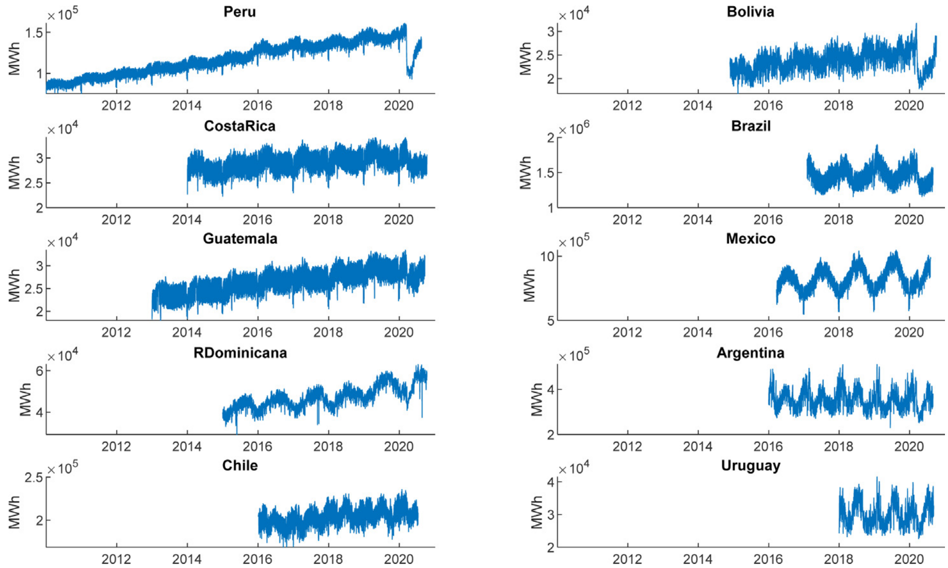

Fig. 2. Daily demand for the LAC countries.

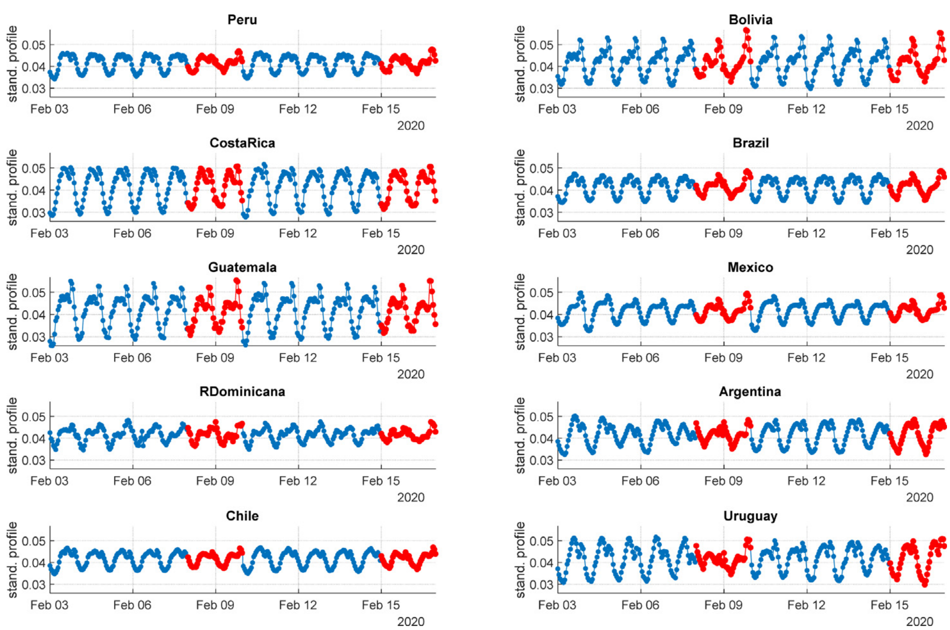

Fig. 3. Standardized demand profiles for the LAC countries (weeks from 3/2/2020 to 16/2/2020). The Saturdays and Sundays hours are marked in red. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2. Temperatures

As aforementioned, it is well known that the temperature is one of the main drivers of electricity demand (see e.g. [25–27]). For example, Fig. 4 shows how the daily demand of Mexico changes with the average daily temperature. During summer the electricity demand reaches its maximum values due to high temperatures. In particular, during summer 2018, two heat waves (early June and late July) were responsible of several weeks with very high electricity demand due to the use of air conditioning for cooling.

For each country, the average daily temperature (TAVG), measured in different weather stations distributed throughout the country, has been collected from NOAA (National Oceanic and Atmospheric Administration, www.noaa.gov). For example, Fig. 5 shows the 37 weather stations in Argentina for which there is quality data for TAVG since 2004 (with less than 250 days without measurement).

The proposed model to estimate the reference demand for each country requires a unique temperature, representative of those temperatures in the region that have larger influence in the demand. Thus, in order to create this reference temperature for each country, we first clustered similar weather stations using hierarchical clustering. Then, the reference temperature is obtained as a weighted average of the TAVG of a subset of weather stations, selected by hand taking into account both the information provided by the dendrogram and the spatial distribution of the main cities and the stations. It should be noted that in order to better select the reference temperature, methods such as those described in [26] would provide better results in terms of error. However, in this study we have decided to exploit the spatial information available about the location of the weather stations

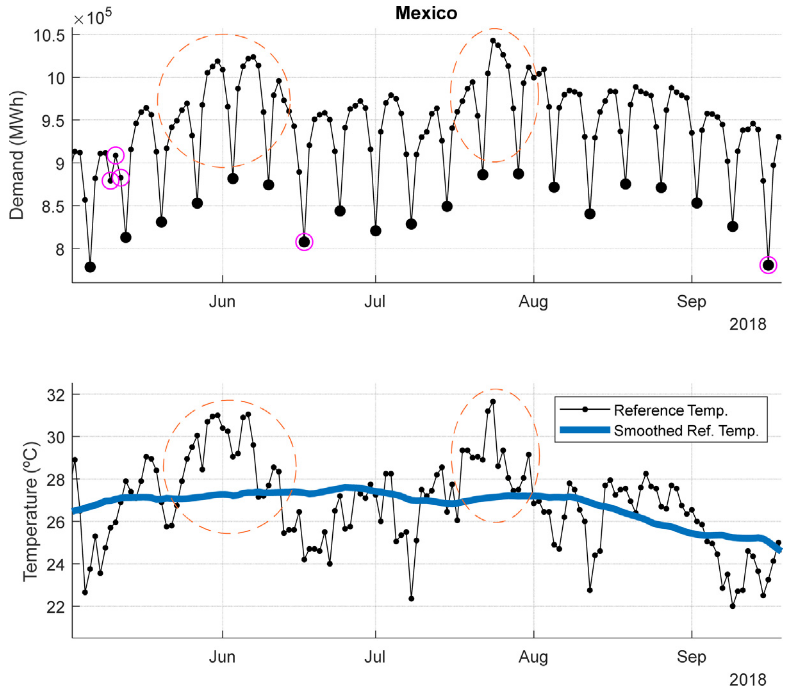

Fig. 4. Example of variations in the daily demand of Mexico due to temperature. Top: real demand, the magenta circles mark holidays. Bottom: Reference temperature (black) and smoothed reference temperature (blue).. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

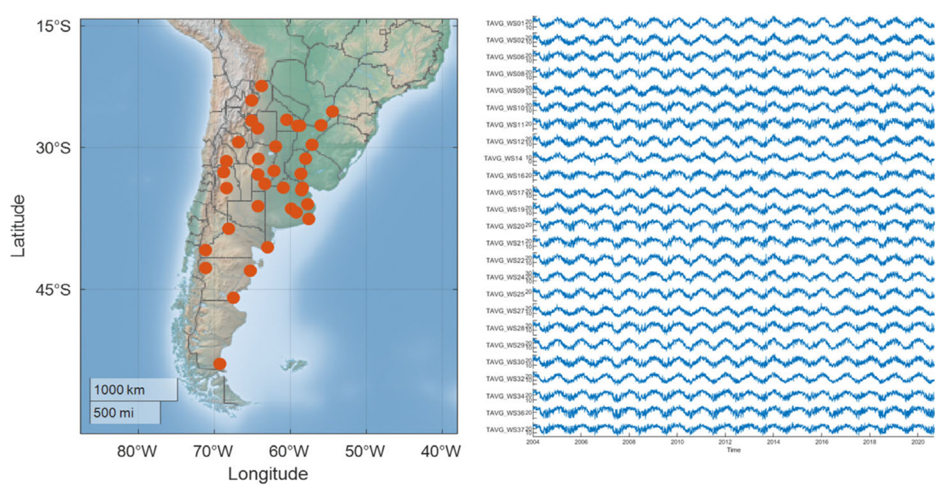

Fig. 5. Selected 37 weather stations for Argentina. Left: Location (longitude and latitude). Right: average daily temperature for each weather station.
Source: Extracted from [24] (Fig. 5, p. 11).

and the relevant cities of the country to select a reasonable set of TAVG to be averaged.

Fig. 6 shows the dendrogram obtained for the candidate 37 weather stations of Argentina. Taking into account the location of the three main cities where most of the population is concentrated (Buenos Aires, Córdoba and Rosario), the high correlation between weather stations and their spatial location, we finally decided to calculate the reference temperature for Argentina as the mean of TAVG_WS01 and TAVG_WS30. Table 3 shows, for each country, the selected stations and the weights used in the average to obtain the final reference temperature. Fig. 7 shows the relationship between the daily demand and the reference temperature for each country. As it can be seen, depending on the range of temperature values, this relationship is very different. For example, it is clearly non-linear for Argentina, Chile and Uruguay.

Finally, note that in our pre-processing step of temperatures, missing values have been filled by using a hierarchical regression imputation process, based on the approach presented in [28]. First, single missing values are filled by linear interpolation with the days before and after of the same TAVG time series. Second, the remaining missing values are filled by means of a multiple linear regression using as inputs the temperatures of other weather stations where there are values for the days to be filled.

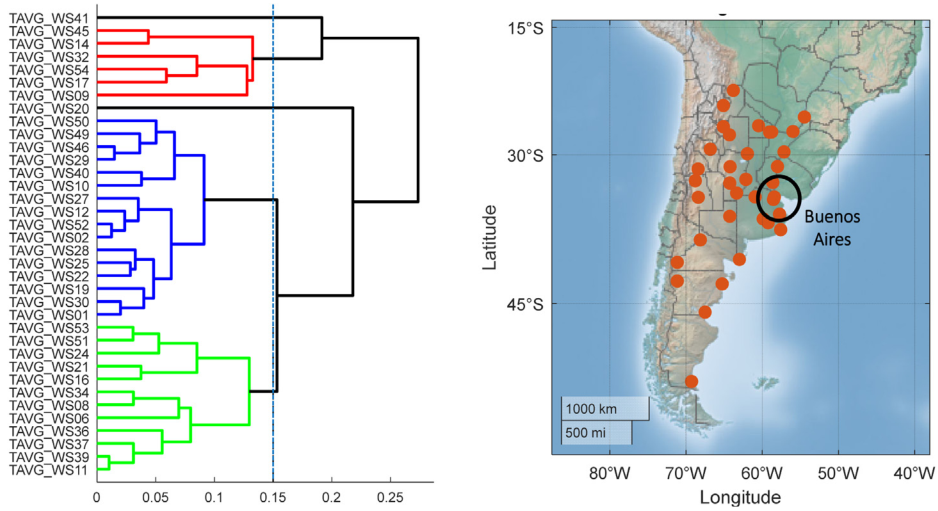

Fig. 6. Selection of the reference temperature for Argentina. Left: Dendrogram of the 37 weather stations of Fig. 5. The dissimilarity threshold has been set to 0.15, resulting five clusters (colored). Right: Main weather stations for Argentina (TAVG_WS01 *y* TAVG_WS30).
Source: Extracted from [24] (Fig. 7, p. 13).

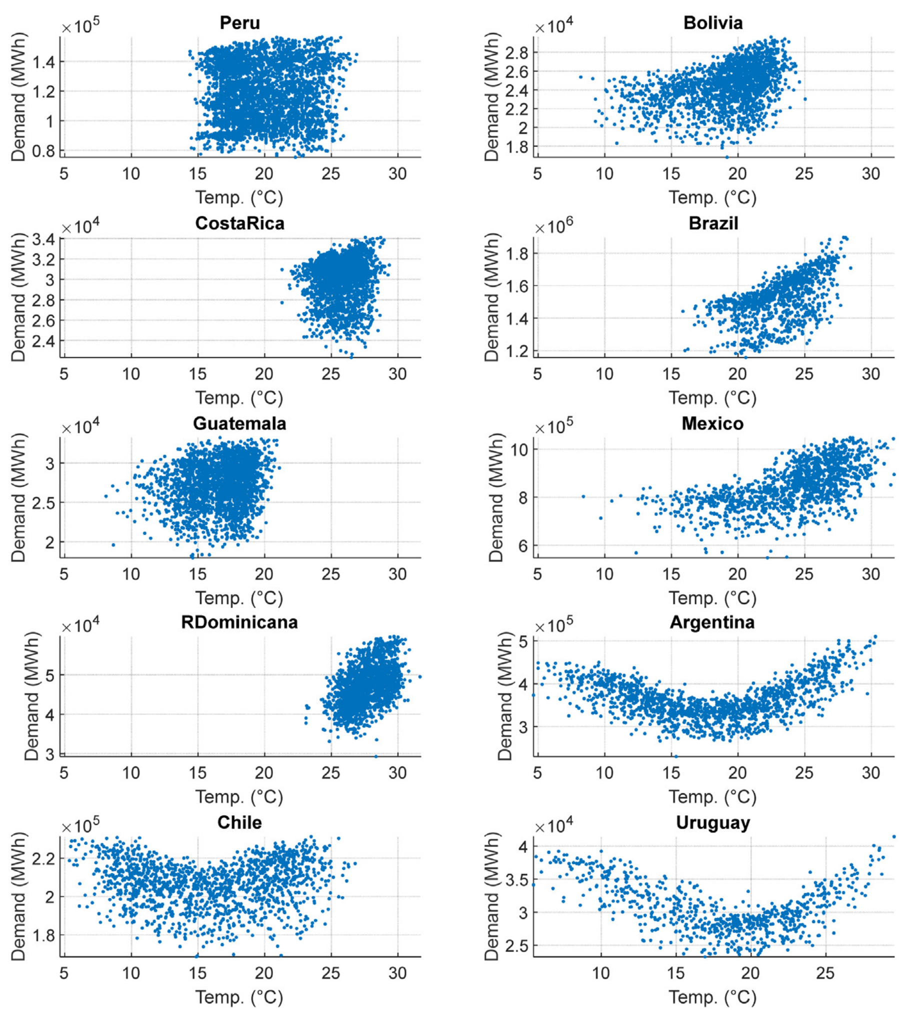

Fig. 7. Relationship, for each country, between the daily reference temperature and the real electricity demand. Data from 2020 has been removed to avoid the COVID-19 period.

Table 3
Selected weather stations for each country. The STATION_NAME is the name of the weather station according to NOAA.

COUNTRY	ID	WEIGHT	STATION_NAME
RDominicana	TAVG_WS01	0.5	MARIA MONTEZ INTERNATIONAL DR
RDominicana	TAVG_WS03	0.5	PUNTA CANA INTERNATIONAL DR
CostaRica	TAVG_WS01	0.5	JUAN SANTAMARIA INTERNATIONAL CS
CostaRica	TAVG_WS02	0.5	LIBERIA CS
Bolivia	TAVG_WS06	0.33	EL ALTO INTERNATIONAL BL
Bolivia	TAVG_WS07	0.33	EL TROMPILLO BL
Bolivia	TAVG_WS24	0.33	VIRU VIRU INTERNATIONAL BL
Guatemala	TAVG_WS01	1	SN._CRISTOBAL_LAS_CASAS_CHIS_MX
Argentina	TAVG_WS01	0.5	AEROPARQUE JORGE NEWBERY AR
Argentina	TAVG_WS30	0.5	MINISTRO PISTARINI AR
Brazil	TAVG_WS05	0.24	CAMPINAS AEROPORTO BR
Brazil	TAVG_WS12	0.24	GALEAO ANTONIO CARLOS JOBIM BR
Brazil	TAVG_WS18	0.23	MACEIO AEROPORTO BR
Brazil	TAVG_WS28	0.29	SAO PAULO AEROPORT BR
Uruguay	TAVG_WS01	0.25	CARRASCO INTERNATIONAL UY
Uruguay	TAVG_WS08	0.25	PRESIDENTE GENERAL DON OSCAR UY
Uruguay	TAVG_WS09	0.25	ROCHA UY
Uruguay	TAVG_WS10	0.25	SALTO UY
Peru	TAVG_WS21	1	PISCO INTERNATIONAL PE
Mexico	TAVG_WS10	0.5	CUERNAVACA MX
Mexico	TAVG_WS25	0.5	MONCLOVA MX
Chile	TAVG_WS01	0.83	ANTOFAGASTA CI
Chile	TAVG_WS03	0.17	ARTURO MERINO BENITEZ INTERNATIONAL CI

3.3. Holidays and special events

It is well-known that electricity demand time series show regular weekly patterns, usually modified when a public holiday or a special event occurs (see e.g., public holidays marked in Fig. 4). Therefore, it is of utmost importance to correctly model the calendar effects to obtain an accurate reference model [23].

Special events that have been considered in this study are those rare events that make the demand lower than what could be expected according to temperature, public holidays, and calendar. In particular, four types of special days have been considered and specific dummy variables have been created and labeled for each realization:

1. Significant national and regional holidays.
2. Relevant natural disasters that have influenced the demand, such as catastrophes associated with tropical storms, hurricanes, floods, earthquakes, etc.
3. Important atypical social events that have influenced the demand, such as strikes, protests, riots, etc.
4. Other fortuitous events with a clear impact on demand, such as power outages.

This information has been obtained from different sources. For public holidays, the holiday calendars for each country have been consulted. The approach for obtaining the information has been different for natural disasters or atypical social events, based on the fitted regression model. For each country, the residuals from the daily demand model were analyzed, identifying those days where the residual was negative and significatively large. Once these atypical periods were detected, a web search was carried out to determine the occurrence of a significant event on those dates that could have affected the electricity consumption of the particular country. Fig. 8 shows two examples, a power outage affecting one day and a strike impacting the electricity demand during two weeks.

4. Proposed methodology for size impact

The size impact accounts for the observed variations on the daily demand due to COVID-19. As aforementioned, to calculate this impact during 2020, a good estimate of the daily demand that should have existed without COVID-19 is required. In this section, the models designed to obtain this daily reference demand are described, as well as the particular size impact indicators proposed to quantify the observed variations.

4.1. Reference models

The reference model for each country has been created from the available data described in Section 3. In particular, a multiple regression model has been used to estimate the daily demand from the available exogenous variables (temperature, calendar, holidays, and special events). This model cannot capture the COVID-19 effects because it is fitted using data before the pandemic, providing the required reference to determine the COVID-19 effect.

The proposed reference model has the same main terms for all the LAC countries. It has been designed to capture the most relevant features of the demand time series properly:

$$D_d = \widehat{D_d} + \varepsilon_d = T_d + S_d + H_d + R_d + \varepsilon_d, \tag{2}$$

where D_d is the actual demand at day d, $\widehat{D_d}$ is the reference demand and ε_d is the error term. The reference demand is obtained as a sum of four terms: T_d is the trend component, S_d is the annual seasonal component, H_d is the term related to regular weekdays, holidays and special events effects, and R_d is the component related to the reference temperature effect. These model components are built using a set of basic variables that can be grouped according to their nature (see Table 4):

- TIME, a continuous variable used to model the linear trend. This variable interacts, when required, with a categorical variable PIECE specifying different ranges of years in the training set to model non-linear trends. To obtain the reference demand for 2020, the last linear section of the trend component of the regression model has been extrapolated.
- MONTH, month of the year, included as a categorical variable.

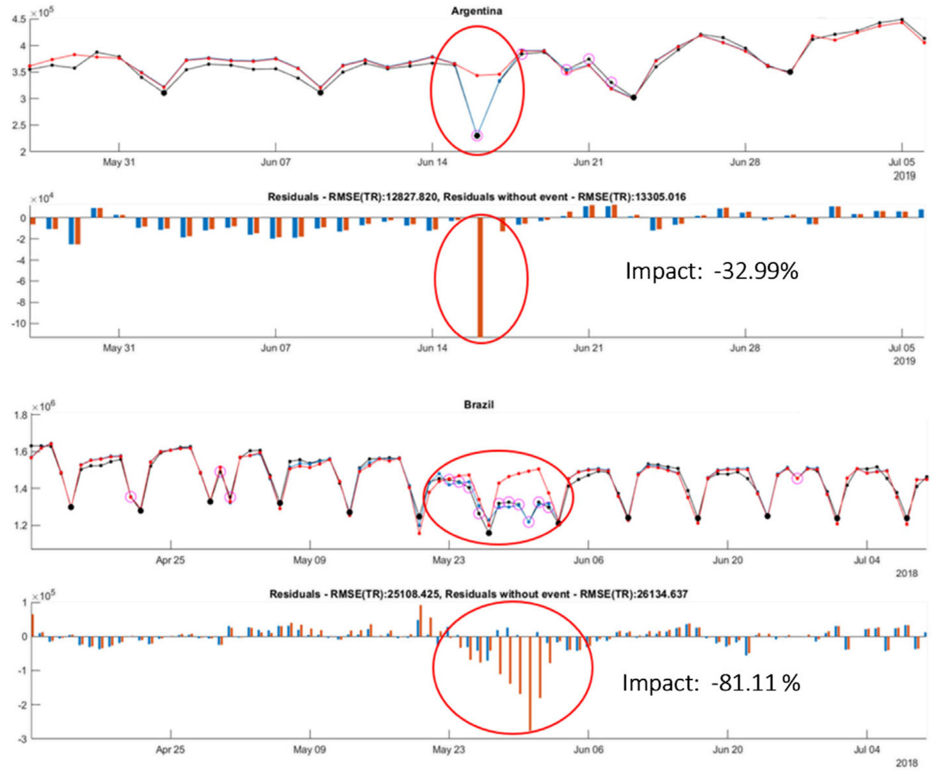

Fig. 8. Examples of unusual demands, identified by analyzing the residuals of the fitted model. Top: In Argentina, an electricity blackout that lasted several hours meant a 33% decrease in the demand expected for June 19th, 2019. Bottom: In Brazil, a truckers' strike severely altered the demand for electricity between May 23rd and June 2nd, 2018, with a decrease of 81% over expected.
Source: Extracted from [24] (Fig. 13, p. 20).

Table 4
Specification, using Wilkinson notation, and number of coefficients estimated for the proposed reference models for quantifying the size impact of COVID-19.

Country	Model specification (Wilkinson notation)	Number of Coeffs.
Peru	DEMAND ∼1 + TIME*PIECE + RTAVG^2 *MONTH + DAYTYPE	88
Bolivia	DEMAND ∼1 + TIME + RTAVG^2 *MONTH + DAYTYPE	106
CostaRica	DEMAND ∼1 + TIME*PIECE + RTAVG^2 *MONTH + DAYTYPE	78
Brazil	DEMAND ∼1 + TIME + RTAVG^2 *MONTH + DAYTYPE	89
Guatemala	DEMAND ∼1 + TIME*PIECE + RTAVG^2 *MONTH + DAYTYPE	83
Mexico	DEMAND ∼1 + TIME + RTAVG^2 *MONTH + DAYTYPE	77
RDominicana	DEMAND ∼1 + TIME*PIECE + RTAVG^2 *MONTH + DAYTYPE	132
Argentina	DEMAND ∼1 + TIME*PIECE + RTAVG^2 *MONTH + DAYTYPE	92
Chile	DEMAND ∼1 + TIME + RTAVG^2 *MONTH + DAYTYPE	82
Uruguay	DEMAND ∼1 + TIME + RTAVG^2 *MONTH + DAYTYPE	78

- RTAVG, the average reference temperature for that country. All models use the interaction between MONTH and the quadratic RTAVG to properly model the response of the demand to the temperature.
- DAYTYPE, a categorical variable used to label each day with a particular type. Most of the days are considered regular and labeled with the day of the week. However, the significant national and regional holidays have been labeled with the name of the holiday. Furthermore, we have used this variable also to label relevant natural disasters such as storms, hurricanes, floods, earthquakes, important atypical social events such as strikes or riots, and other fortuitous events with a clear impact on demand, such as power outages, observed from time to time in one of the demand series studied.

Once the reference model has been fitted using ordinary least squares, it can be extrapolated to 2020 to obtain the reference demand for each day. Fig. 9 shows the estimated demand for Peru, both during the training period and the extrapolation to 2020. The analysis of this figure allows us to determine that the effect of the COVID-19 pandemic on electricity demand in Peru started on March 16th, 2020, with a very significant decrease in consumption.

4.2. Impact indicators

Once the reference daily demand for each country has been estimated using the proposed reference model, it is possible to compare the observed daily demand with the reference daily demand to quantify the impact of the COVID-19 pandemic on the electricity demand.

A set of simple impact indicators have been defined to facilitate the interpretation of the effect observed daily and to be able to have a robust measure of what happened. In particular, the size impact indicators are based on the daily residuals, i.e., the differences between the observed demand and the estimated

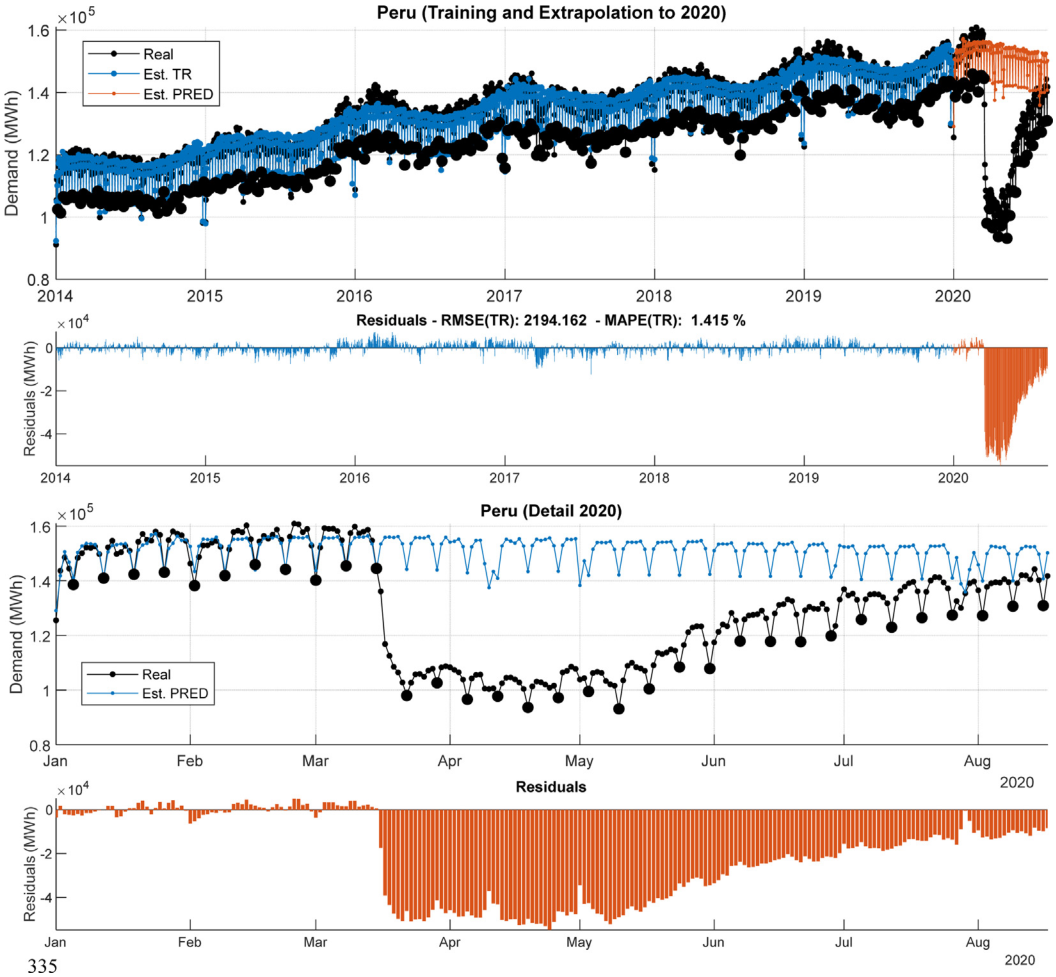

Fig. 9. Daily electricity demand for Peru.

one. These indicators are expressed as a percentage of variation with respect to the reference demand estimated by means of the regression model. Specifically, three size impact indicators have been defined:

- Daily size impact index:

$$DI_d(\%) = \frac{100\left(D_d - \widehat{D_d}\right)}{\hat{D}_d}. \tag{3}$$

- Weekly size impact index:

$$WI_w(\%) = \frac{100\sum_{d\in w}\left(D_d - \widehat{D_d}\right)}{\sum_{d\in w}\hat{D}_d}. \tag{4}$$

- Monthly size impact index:

$$MI_m(\%) = \frac{100\sum_{d\in m}\left(D_d - \widehat{D_d}\right)}{\sum_{d\in m}\hat{D}_d}. \tag{5}$$

In the previous expressions D_d is the daily demand on day d, and $\widehat{D_d}$ is the reference daily demand, estimated by the model. The subscripts w and m indicate the week and the month, respectively.

These indicators allow not only to quantify the impact observed in a given country but also to compare the impact in different countries as they are expressed as percentage values referred to demand. In addition, they also allow, for example, to determine in which month or months the impact has been more significant.

Fig. 10 shows the impact indicators estimated for Peru, the country with the most impacted electricity demand of the ten countries analyzed. The daily size impact index provides highly detailed information, complemented by the actual and estimated weekly and monthly demands, as well as the monthly and weekly impact indicators calculated in the period considered. As can be seen, April 2020 is the most affected month, with a 32% decrease in demand. On a weekly basis, the most significant impact is observed in the fourth week of April, with an impact of -34%. From that moment on, a gradual recovery in demand is observed, but even so, in August 2020 the demand still had not recovered the levels it would have had if the pandemic had not existed.

5. Proposed methodology for shape impact

The shape impact accounts for the observed variations on the demand profile due to COVID-19. Following a similar approach to the size impact, a good estimate of the hourly demand profile that should have existed without COVID-19 is required to calculate the impact during 2020. In this section, the models designed to obtain this hourly reference are described, as well as the particular shape impact indicators proposed.

5.1. Reference models

In order to study the impact on the shape of the consumption, the normalized hourly demand time series for each country is segmented into daily demand profiles, where each profile is

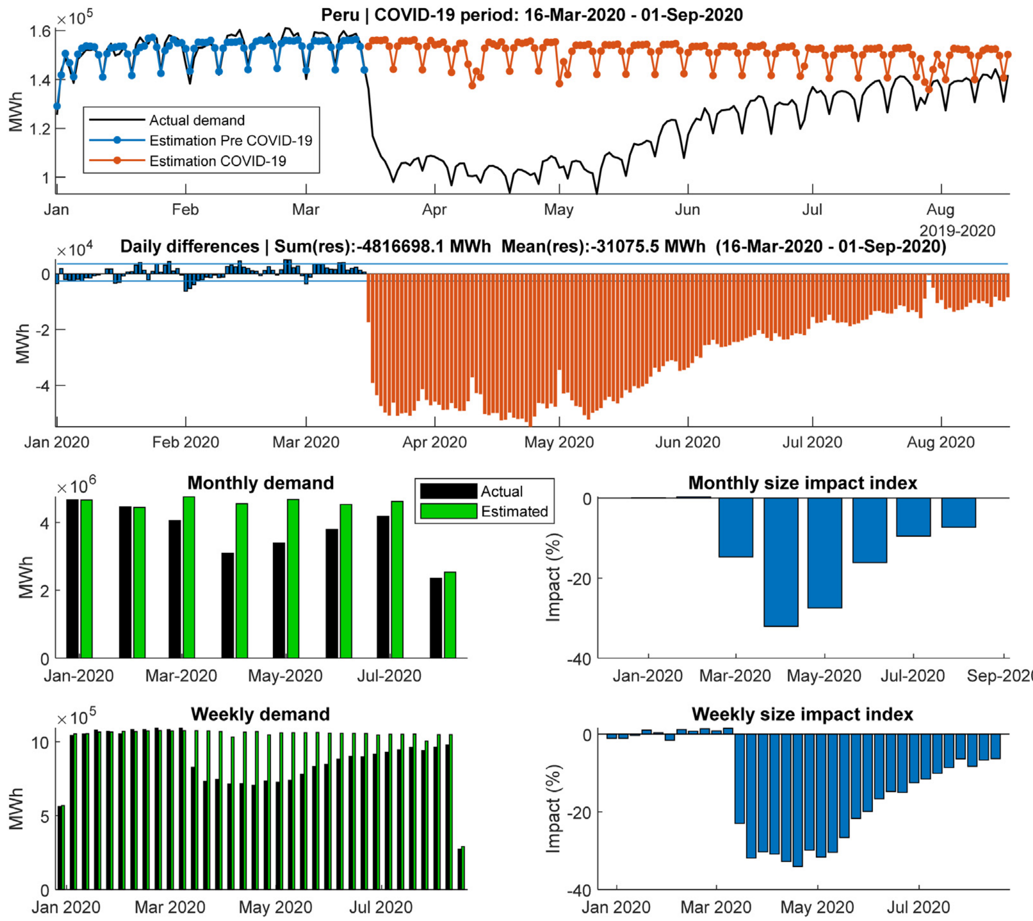

Fig. 10. Impact of COVID-19 on the demand in Peru during 2020. Thanks to the estimated reference demand, it can be stated that the demand suffered a very sharp decrease as of March 16th, 2020, reaching the maximum impact in the month of April, with an impact of -32%, the highest of all the countries studied. In August 2020, the demand had not yet recovered the expected values according to the reference demand.
Source: Extracted from [24] (Fig. 15, p. 23).

composed of the 24 coefficients given by the percentage of the demand of the day consumed in each hour. Therefore, a multivariate dataset is obtained with one sample per day and 24 demand variables, one for each hour. The objective is, therefore, to analyze the time evolution of the 24 hourly demands simultaneously.

In order to analyze the daily demand profiles it is common in the literature to represent the set of historical profiles reliably with a small number of reference profiles that need to be identified [27]. Therefore, the first step in the proposed methodology consists in applying a *kmeans* clustering algorithm to all historical daily profiles up to 2020 to obtain representative profiles of pre-COVID consumption. For each country, the number of clusters is selected by accounting for the quantization error.

Fig. 11 shows the representative profiles of normalized demand obtained with the clustering model for each country. It can be observed that the number of clusters needed to model the demand profiles in each country is different. A common behavior stands out: a low demand in the early morning hours that increases throughout the morning. Then, a slight decrease in the late afternoon to then have a peak consumption at night and finally go back down at the end of the day. Nevertheless, the representative profiles obtained can vary significantly from one country to another. For example, comparing Guatemala with Chile, it can be seen that the difference between the maximum and minimum consumption of the day is much more pronounced in Guatemala.

Table 5
Number of representative profiles obtained and the Cross-Validation accuracy of the tree for each country.

Country	Number of clusters	Tree k-fold CV - Accuracy
RDominicana	4	0.59
Costa Rica	5	0.82
Bolivia	4	0.85
Guatemala	6	0.87
Argentina	6	0.70
Brazil	7	0.84
Uruguay	6	0.63
Peru	6	0.87
Mexico	8	0.90
Chile	6	0.84

The next step is to develop a prediction model that estimates the representative profile that should be activated each day of 2020. A decision tree is trained for estimating the historical representative profiles associated to each day of the training period (before 2020) using the weekday, the month and a holiday variable as explanatory variables.

For training the different decision trees, it is critical the selection of the length of the tree to avoid overfitting. 10-fold Cross-Validation has been used to select the optimum length for each country. Table 5 shows the number of representative profiles obtained and the Cross-Validation accuracy of the tree.

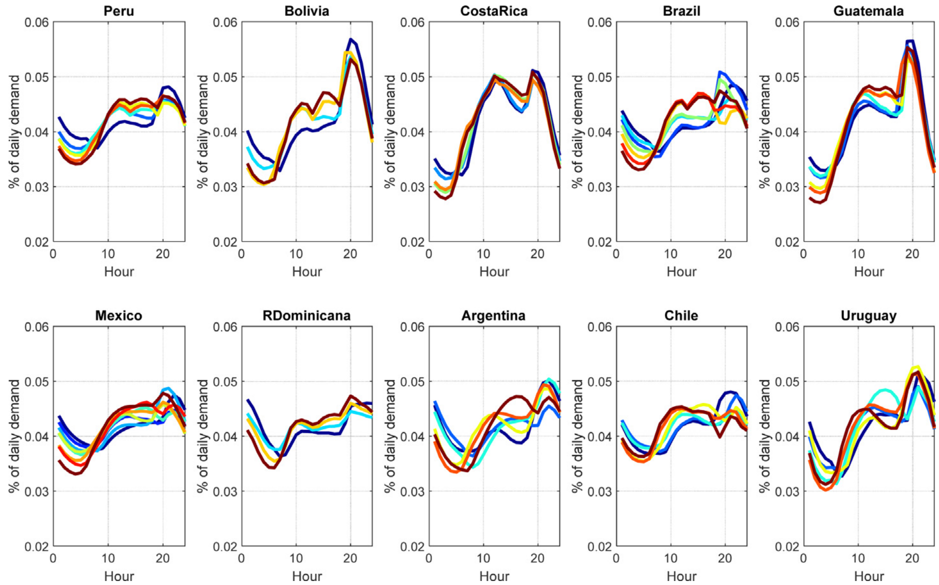

Fig. 11. Representative profiles of normalized demand obtained with the *kmeans* clustering model for each country.

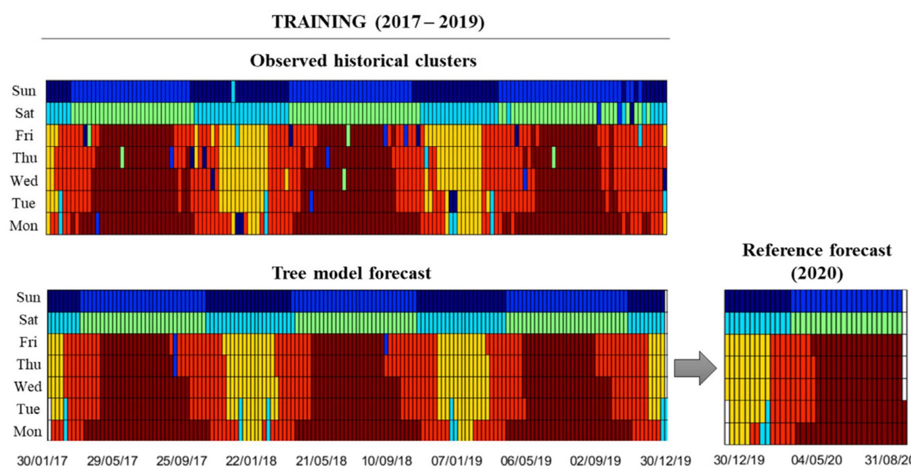

Fig. 12. Illustration of the performance of the decision tree used to model the activation of the representative daily demand profiles for Brazil. The heatmaps represent in each cell the cluster activated for each day. Rows are days of the week and columns represent weeks.

Fig. 12 shows an illustrative example of the methodology for Brazil. On top, the representative profile associated to each day in the training period is represented. Below, the tree estimated representative profile is shown. As can be seen, the tree's predictions reflect the seasonal dynamics in the activation of the patterns and the estimate for 2020 can be used as a reference to compare it with the actual observed profiles.

5.2. Impact indicators

The representative profile forecasted by the decision tree for 2020 is an estimate of the profile that would be expected in a situation where COVID-19 had not existed and, therefore, can be used as a reference to compare it with the actual profiles observed in 2020.

Therefore, the profile estimated by the model can be compared with the actual profile observed. First, the differences between the two profiles are calculated, which allows to measure how the shape of demand has changed on that day.

Fig. 13 shows the calculation of the profile differences and the two main proposed indicators that allows to visualize the impact: the heat map of the differences and the shape impact index.

The heatmap of the differences illustrates how differences between the estimated and the real profiles evolves over time. It is a matrix where each column is a day and each row is an hour. The color of each cell in the array depends on the value of the observed hourly difference. Hours whose observed normalized demand is less than the expected value are shown in blue. In yellow–red, the hours whose observed normalized demand is greater than the expected value. It is observed that, in the first months, there are no major differences between the observed and expected profile. However, since the beginning of confinements, the differences change significantly. In the case of Brazil, there is a reduction in demand during the central hours of the day and an increase in the early morning and at night, starting at 7 p.m. It is also observed that the impact is much more pronounced during the beginning of confinement and is lessened as the months go by.

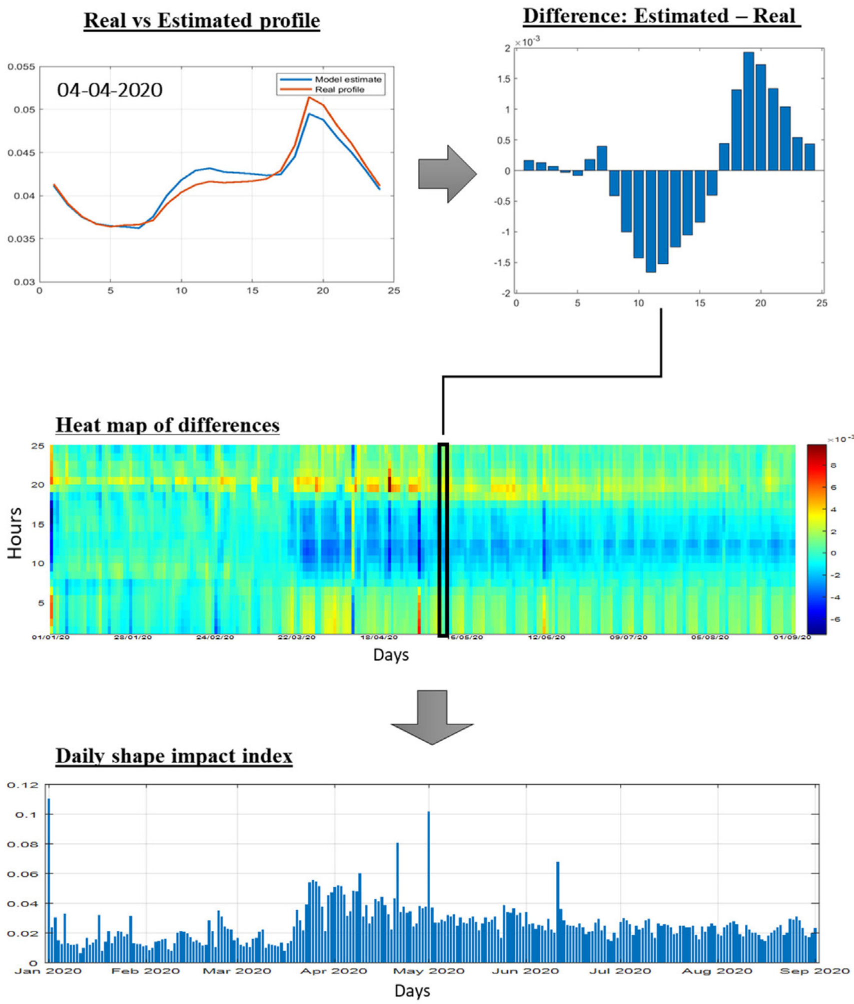

Fig. 13. Illustration of the calculation of the differences between the actual and estimated profile and calculation of the impact for Brazil. In the top-left figure, the estimated profile (blue) and the actual profile (orange) are shown for one day. The top-right bar chart is displayed with the difference between the estimated and the actual value. The middle figure represents the heat map of the differences in time. At the bottom, the daily shape impact index calculated. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Finally, to quantify the impact for a specific day, the proposed shape impact index is defined as follows

- Daily shape impact index:

$$DIw_d\,(\%) = \sum_{h\in d} |\widehat{w_{d,h}} - w_{d,h}|. \tag{6}$$

Therefore, for each day, its impact index is the average of the differences in absolute value of that day. Conceptually, this can be interpreted as the average percentage change in an hour from daily demand.

In addition, a weekly index is obtained that helps visualizing the time evolution.

- Weekly shape impact index:

$$WIw_w(\%) = \sum_{d,h\in w} |\widehat{w_{d,h}} - w_{d,h}|. \tag{7}$$

Analyzing the temporal evolution of the impact index allows us to quantify how relevant the impact was during confinement and whether the differences have been reduced over the months.

6. Results

Following the proposed decomposition approach, in this section the main results on the impact of the COVID-19 pandemic on the demand for the ten LAC countries studied are described.

6.1. Size impact results

This section contains the main results on the impact of the COVID-19 pandemic on the daily demand for the ten LAC countries studied. During 2020, according to the methodology used, COVID-19 has impacted on the daily demand of all the countries considered, but in a very different way. In the vast majority of countries the impact on daily demand begins to be observed in mid-March 2020, less in the case of Mexico, where the effect begins to be significant on April 1st, 2020.

Fig. 14 shows the temporary evolution of daily demand in 2020 for each country. For the LAC countries analyzed, a general decrease in daily demand is observed in 2020 with respect to the reference demand. The months most affected were April and May, with an average decrease in demand of approximately 10%. The difference between the real demand and the estimated one, i.e. the daily size impact index, is shown in Fig. 15. It can be observed that the greatest differences occurred in the first months of the onset of the pandemic, with Peru and Bolivia being the most affected.

Table 6 summarizes the impact obtained for each LAC country. Important differences are observed in the maximum impacts, with Peru and Bolivia being the two countries where the reduction in demand during the onset of the COVID-19 pandemic has

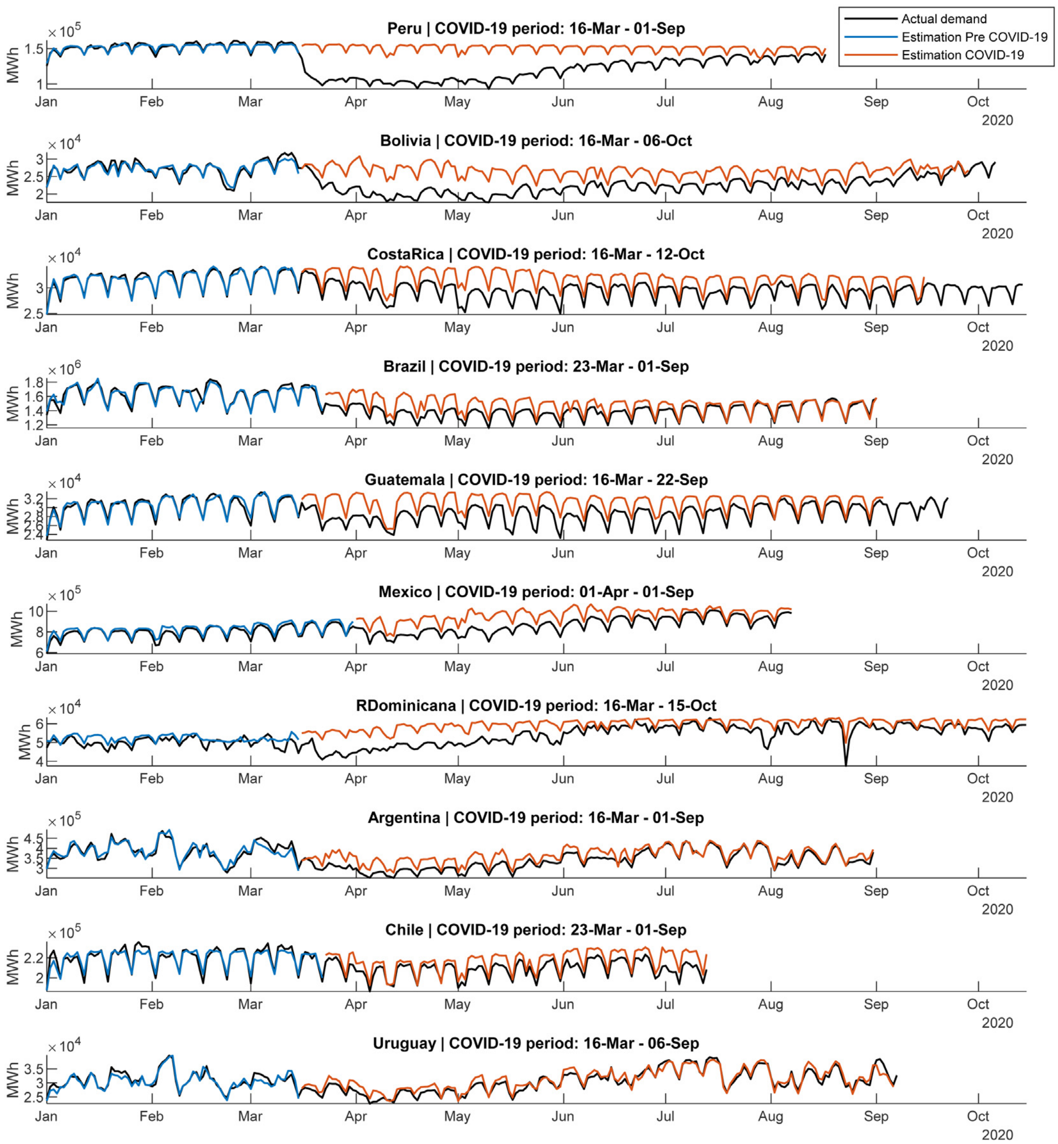

Fig. 14. Daily comparison for 2020 between the real demand (in black) and the reference demand estimated by the model. The reference demand is shown before the start of the effect of the pandemic (in blue) and during the pandemic (in orange). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

been greater, in contrast to Chile and Uruguay, countries with a lower size impact. According to the maximum monthly impact in Table 6, the LAC countries can be grouped into three main groups. The countries clearly most affected are Peru and Bolivia, with an impact in April 2020 of around −30%. At the opposite extreme would be Chile and Uruguay, with an approximate maximum impact of −6%. The rest of the countries have maximum impacts between −11% and -17%. Table 7 shows the monthly detail of the impact of COVID-19 during the first months of 2020.

6.2. Shape impact results

This section shows the results of the methodology for estimating shape impact for each country. Firstly, a comparison is done similar to other studies and is followed by a comparison of the proposed shape impact methods.

Following the methodology in [3] or [5], the demand profiles observed in 2020 are compared with the demand profiles observed in former years. In this study, the first four weeks from the start of confinement measures in each country are analyzed. Fig. 16 shows for each type of day (Working days, Saturdays, and Sundays), the average of the actual 2020 profiles in the four weeks from the beginning of the confinements (orange curve) and compared with the average of the real profiles in those same four weeks in previous years (blue curve).

It is observed that, in general, the greatest changes are observed on working days, while on weekends, especially Sundays, no great differences are observed worth noting that confinement has produced, in general, a horizontal shift of the consumption profile in the early hours of the morning. That is, the beginning of the rise in demand has been displaced a few hours during the confinement. It is also interesting to highlight the case of the Dominican Republic, where the consumption profile is very different compared to the expected one.

In addition, Fig. 17 shows the detail of the differences between the average profiles in the first 4 weeks of COVID-19 and those same weeks in past years for the working days of each country. These graphs reflect the essence of the impact that containment measures have had in each country on the standardized demand profile.

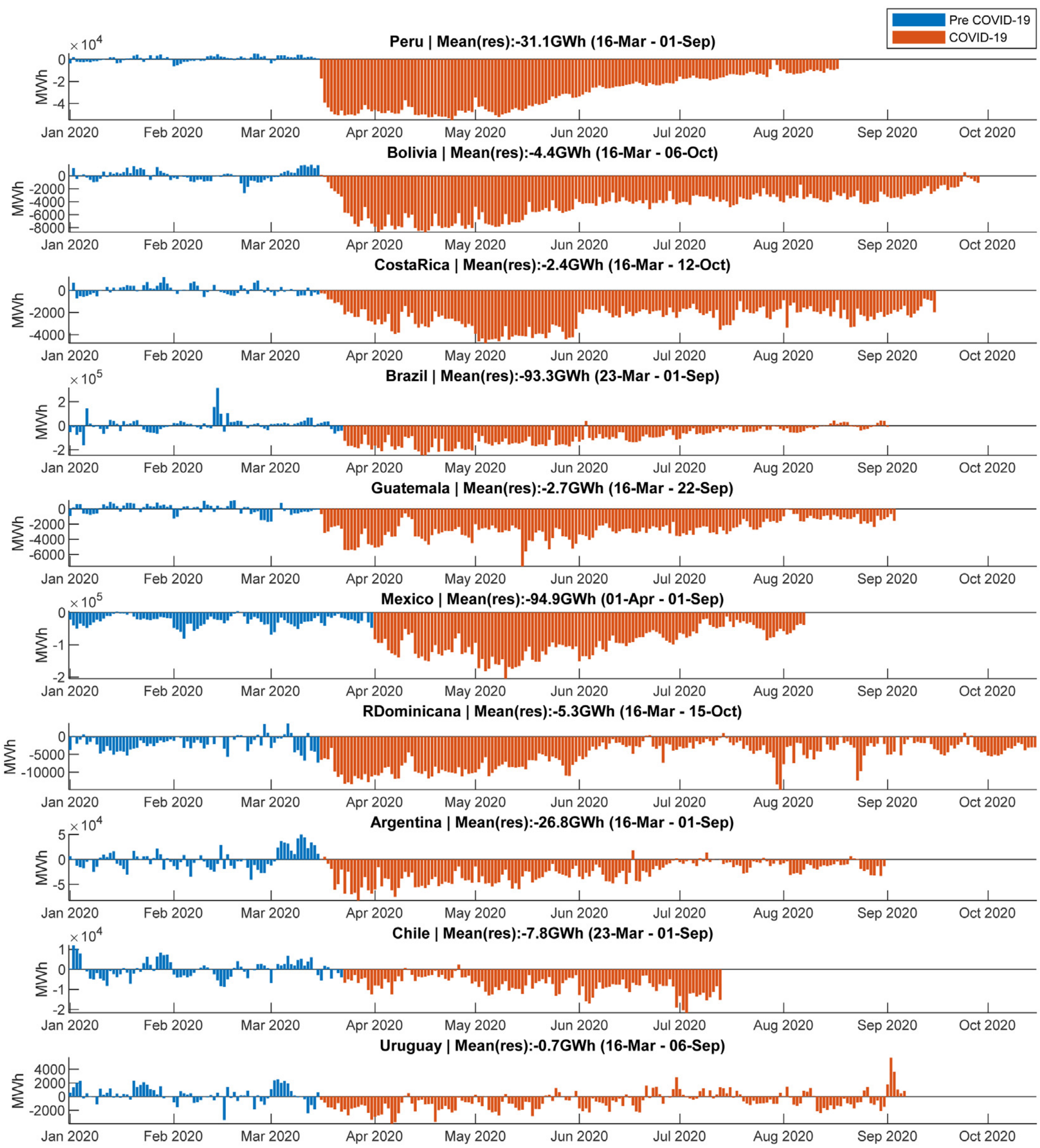

Fig. 15. Differences between the reference demand estimated by the model and the real daily demand (see Fig. 14). Two periods are shown, before the start of the effect of the pandemic (in blue) and during the pandemic (in orange). The mean of the daily residuals during the COVID-19 period are shown. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 6
Summary of the impact of COVID-19 during 2020 on the daily demand for each LAC country.

Country	Start of COVID-19 impact	Month of maximum size impact	Maximum monthly size impact	Week of maximum size impact	Maximum weekly size impact
Peru	16-Ma r-20	Apr-2020	−32.00%	4th Apr	−34.00%
Bolivia	16-Mar-20	Apr-2020	−27.60%	3th Apr	−29.40%
RDominicana	16-Mar-20	Apr-2020	−16.80%	4th Mar	−21.90%
Mexico	01-Apr-20	May-20	−14.30%	3rd May	−17.00%
Argentina	16-Mar-20	Apr-2020	−13.30%	4th Mar	−15.20%
Costa Rica	16-Ma r-20	May-20	−12.50%	2nd May	−13.50%
Brazil	23-Ma r-20	Apr-2020	−11.40%	3rd Apr	−12.80%
Guatemala	16-Mar-20	May-20	−10.90%	4th Mar	−14.70%
Chile	23-Mar-20	July-20	−6.30%	5th Jun	−6.50%
Uruguay	16-Mar-20	Apr-2020	−5.80%	5th Mar	−8.10%

While the former comparison is easy to interpret, it does not show the temporal dynamics of the changes in the shape of the demand. Therefore, the proposed shape impact methods are compared ahead.

Fig. 18 shows the heatmap of the differences obtained for each country. The following conclusions can be drawn.

Before the start of confinements due to COVID-19, it is seen that, in general, the heatmap has a greenish color, indicating that

Table 7
Monthly summary of the impact of COVID-19 during the first months of 2020. For each country, the observed monthly demand, the reference demand estimated with the regression model and the monthly size impact are shown.

Month	Real demand (GWh)									
	Peru	Bolivia	CostaRica	Brazil	Guatemala	Mexico	RDomincana	Argentina	Chile	Uruguay
mar-20	4054.4	814.4	984.0	49049.4	913.1	25854.3	1462.9	11139.4	6766.9	909.2
Apr-20	3089.2	598.2	887.5	40939.2	836.9	23496.7	1430.1	8534.1	6186.6	772.0
may-20	3393.5	618.6	877.5	41338.5	871.1	25459.7	1596.3	9613.8	6413.4	878.2
jun-20	3798.6	663.7	890.2	41165.8	842.5	27205.3	1728.8	10776.7	6418.6	971.4
jul −20	4181.9	698.2	901.1	43882.9	896.3	29320.9	1794.8	12179.5	2698.2	1088.8
Aug-20	2351.1	710.8	901.4	44989.9	926.7	6632.5	1776.6	10725.5		970.4
sep-20		708.2	438.8	1571.4	93.5		1684.3			207.8
oct-20							861.6			
Month	Estimated demand (GWh)									
	Peru	Bolivia	CostaRica	Brazil	Guatemala	Mexico	RDomincana	Argentina	Chile	Uruguay
mar-20	4752.3	872.4	1012.0	50189.5	976.3	26724.2	1660.6	11454.2	6807.7	928.9
Apr-20	4546.2	826.1	971.5	46204.8	933.4	26813.8	1719.6	9849.4	6314.3	819.6
may-20	4676.6	805.0	1002.4	45548.6	977.7	29722.5	1839.5	10688.8	6659.6	905.1
jun-20	4528.0	782.2	948.9	43933.2	927.3	30046.8	1817.7	11527.4	6689.6	987.9
jul −20	4621.1	807.2	964.8	45164.6	973.1	30791.0	1894.9	12394.9	2879.5	1089.8
Aug-20	2535.2	815.0	965.0	45259.2	963.9	6988.5	1890.0	11203.9		993.6
sep-20		765.9	464.3	1580.6	96.8		1764.4			194.4
oct-20							917.8			
Month	Monthly size impact index (%)									
	Peru	Bolivia	CostaRica	Brazil	Guatemala	Mexico	RDomincana	Argentina	Chile	Uruguay
mar-20	−14.7	−6.6	−2.8	−2.3	−6.5	−3.3	−11.9	−2.7	−0.6	−2.1
Apr-20	**−32.0**	**−27.6**	−8.6	**−11.4**	−10.3	−12.4	**−16.8**	**−13.4**	−2.0	−5.8
may-20	−27.4	−23.1	**−12.5**	−9.2	**−10.9**	**−14.3**	−13.2	−10.1	−3.7	−3.0
jun-20	−16.1	−15.2	−6.2	−6.3	−9.1	−9.5	−4.9	−6.5	−4.1	−1.7
jul −20	−9.5	−13.5	−6.6	−2.8	−7.9	−4.8	−5.3	−1.7	**−6.3**	−0.1
Aug-20	−7.3	−12.8	−6.6	−0.6	−3.9	−5.1	−6.0	−4.3		−2.3
sep-20		−7.5	−5.5	−0.6	−3.4		−4.5			**6.9**
oct-20							−6.1			

the differences between the expected pattern and the actual profile are not very large. However, when COVID-19 begins, areas in dark blue (indicating a significant decrease in actual normalized demand versus expected at those times) and areas with yellows (indicating a significant increase in actual normalized demand versus expected at those times) begin to appear.

In addition, it can be seen how each country's reaction to COVID-19 has had a very different impact on demand. In countries such as Brazil, the Dominican Republic, Bolivia, Mexico or Chile, significant decreases in demand were detected in the central hours of the day, and increases in the early morning and afternoon hours from 7 p.m. However, countries such as Guatemala and Bolivia had an evolution with more dynamic changes over the months. Guatemala, for example, had a significant decrease in hours 4 p.m. to 7 p.m. at the beginning, but the decline in the latter can be seen gradually changing over the months ending in a decrease in demand in hours 9 p.m. to 11 p.m.

Fig. 19 shows the shape impact index on the daily profiles aggregated on a weekly basis. In this way, it is possible to quantify the weeks that had greater differences with respect to what was expected, and, in addition, it allows to see if a stability has been achieved in the way of consuming electricity. It is observed that the first weeks since the start of the measures are the ones that have had the highest impact rate. In countries like Peru, Brazil and Bolivia the impact was very significant in the first few months, however, it has returned to pre-COVID levels. On the other hand, other countries, such as Chile, have not recovered.

7. Discussion

COVID-19 has significantly affected electricity consumption under lockdown all over the world. For example, in the United States, average load reductions in the range of 8% to 10% have been reported by the New York Independent System Operator [29] and up to 5% by the California Independent System Operator [30]. The International Energy Agency (see [31]) reported an electricity demand drop to Sunday levels under lockdown across Europe and India and a reduction in China that reached 11% in February 2020. In Europe, most of the countries have experienced a negative cumulative impact of between 4% and 13% within the four months following the start of the crisis (see [20]). In Spain, from March 14th to April 30th, there has been a 13.49% reduction in electricity consumption compared to the previous five years (2019–2015), see [4].

The monthly size impacts estimated in this research for the LAC countries are coherent with the previously reported effects in different regions over the world, except for Peru and Bolivia, where the impact during the onset of the COVID-19 pandemic was notably more significant.

Countries declared quarantine measures at different times and with varying levels of enforcement. The Peruvian government announced a general quarantine on March 16th, the effects of which were visible a week later (see Fig. 15). In Bolivia, a quarantine was declared on March 22th, with a significant impact vis-à-vis the baseline scenario once the measures were taken and enforced. In Chile, measures were taken locally, affecting only some regions of the country and increasing in intensity over time as the pandemic expanded. In that case, we can observe a progressive increase of electricity demand shifting on the Shape Impact Index. Conversely, in Uruguay, where no measures were imposed in the period analyzed in this study, there are no significant changes in the Shape Impact Index compared to the estimated counterfactual demand, both before and after the pandemic's start.

Countries with large electro-intensive industries were affected more significantly by the adopted sanitary measures, as shown in Figs. 15 and 19. This is the case of Peru and Bolivia, where the mining sector accounts for 67.9% and 78.2% respectively of their exports. However, even though Chile has similar mining exports (54.4% in 2019), the change in electricity consumption was not as abrupt as in Bolivia or Peru, according to the Economic Complexity Observatory [32]. This is probably a consequence of

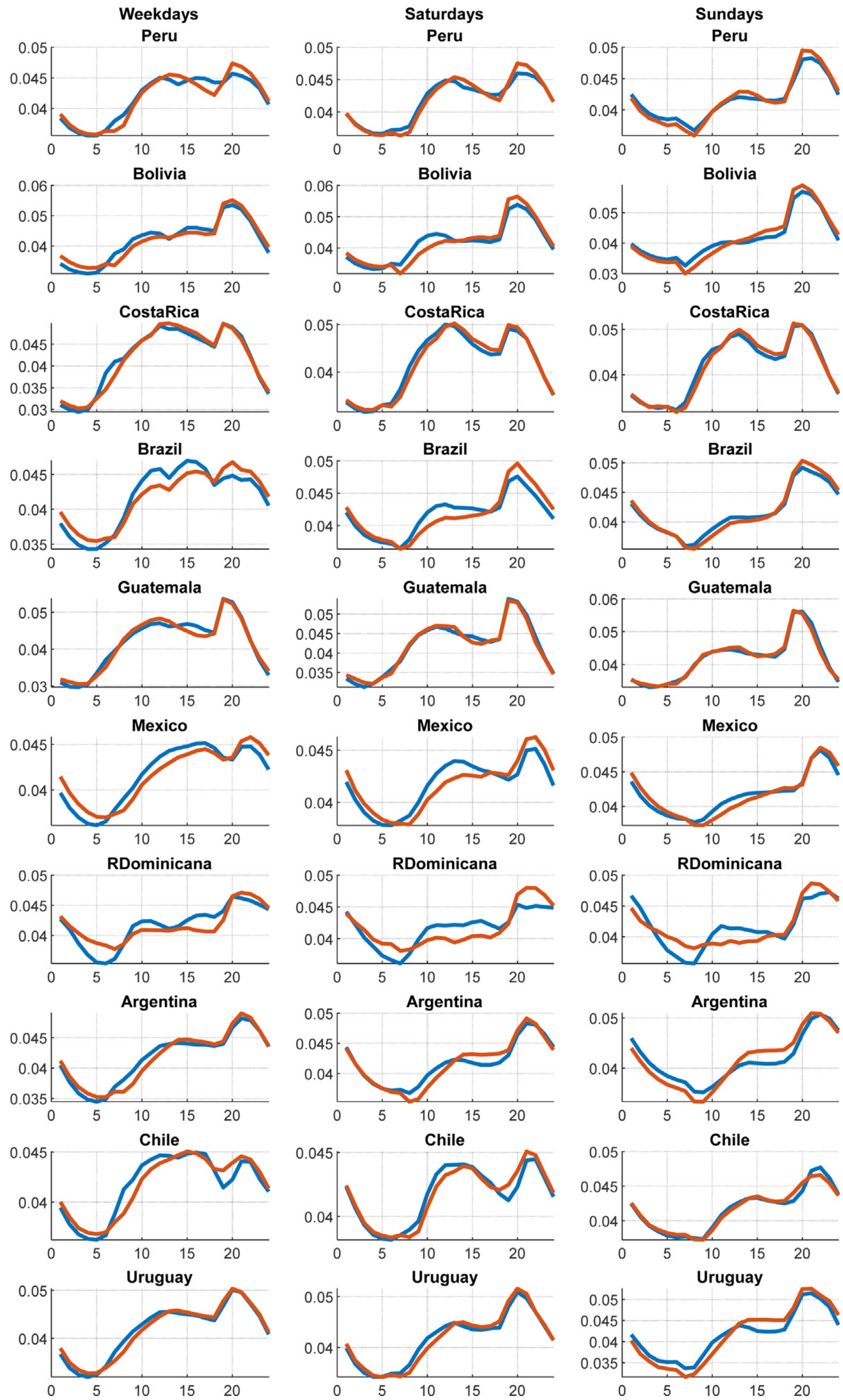

Fig. 16. Analysis of profiles during the first four weeks from the start of confinement measures in each country. The average of the actual profiles in those 4 weeks of 2020 by type of day (orange curve) is compared with the average of the actual profiles in those 4 weeks of previous years by type of day (blue curve). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

its gradual adoption of sanitary measures. When focusing on Costa Rica, with a service sector covering 76% of its GDP according to the Central bank of Costa Rica [33], a much more modest impact is seen in comparison to the baseline scenario (see Fig. 15).

Consequently, a general trend is distinguished in all these countries that links the composition of the country's economy and the rhythm in which the measures were imposed to the size and shape of the impact on electricity demand.

8. Conclusions

The objective of this study has been the quantitative analysis of the impact of the COVID-19 pandemic on the demand for electricity in a group of ten countries in Latin America and the Caribbean. In particular, it has analyzed how the pandemic has influenced from its appearance until the fall of 2020.

To carry out this study, a particular methodology has been used. The proposed approach, instead of analyzing directly the

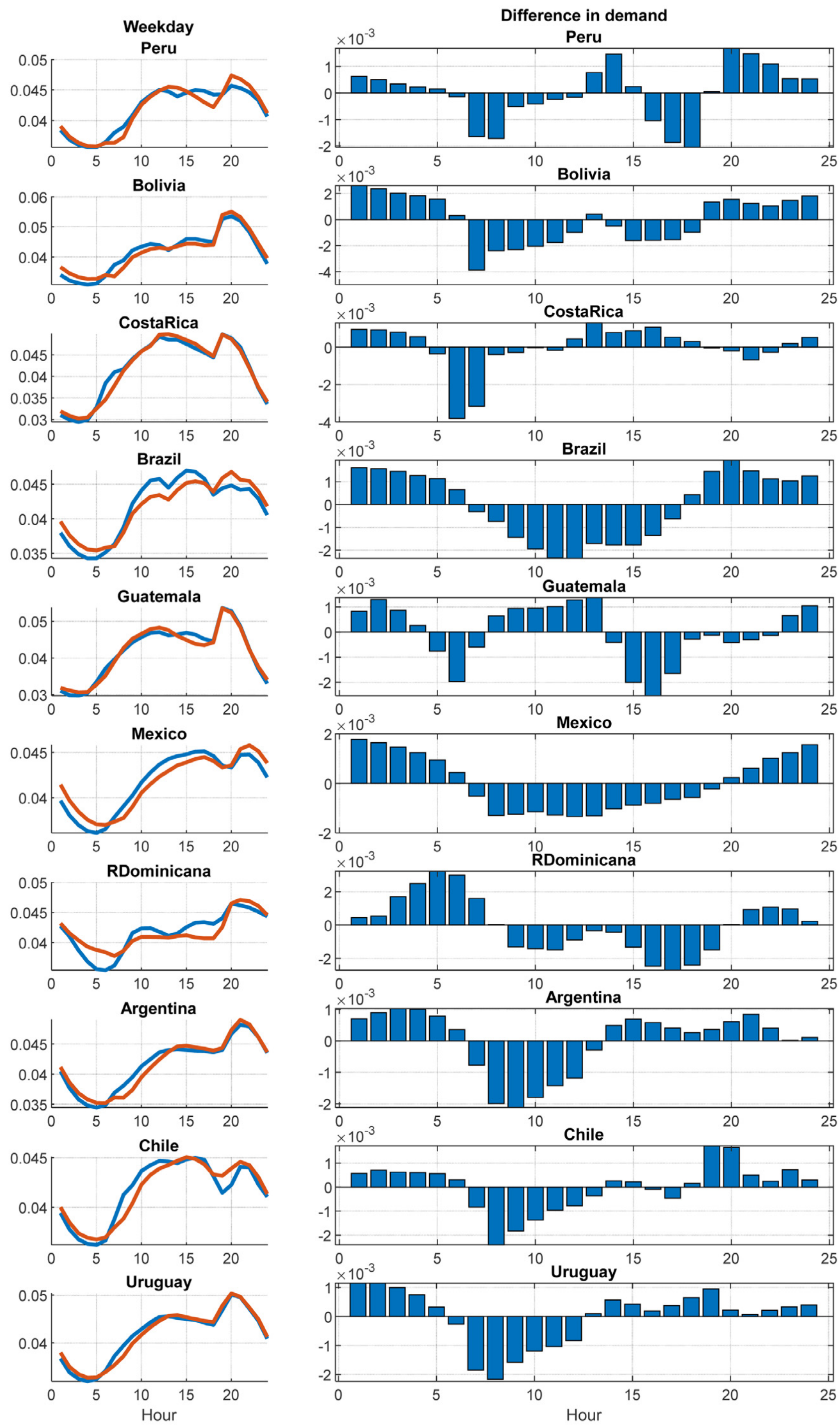

Fig. 17. Differences between the average profiles in the first 4 weeks of COVID-19 and those same weeks in past years for each country's weekdays.

impact of COVID-19 on hourly demand, considers decoupling the effect in two terms. The size impact accounts for the observed variations on the daily demand time series, quantifying the changes due to the alterations in human activity brought on by the COVID-19 pandemic. The shape impact accounts for the pandemic-induced changes in the standardized daily demand profile, i.e. on the variations observed on the demand profiles for each day. Thus, both the size and the shape impacts show different aspects of the same concern, allowing a better understanding by decoupling the problem. To calculate both impacts, the observed demand is compared to the expected one if the COVID-19 crisis had not happened. In this way, size and shape impact indicators have be defined from the differences between the observed demand and the reference one. To obtain a reliable estimation of the daily demand as well as the standardized demand profile in the scenario without COVID-19, well-known machine learning techniques have been used.

In all the countries studied, the daily demand for electricity has experienced a reduction to a greater or lesser extent during 2020 compared to the values that would be reasonable to expect if the COVID-19 pandemic had not occurred. To quantify the observed impact for each LAC country, a multivariate regression

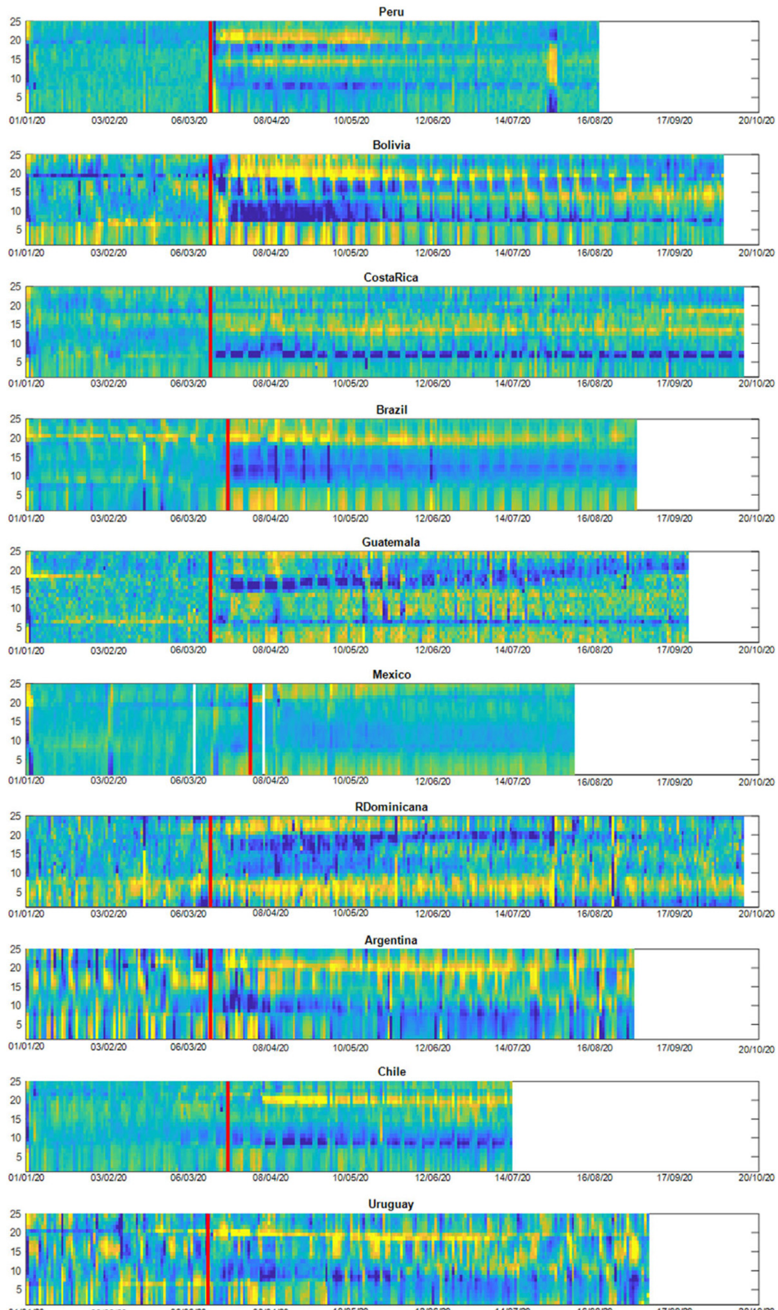

Fig. 18. Heat maps of the differences for each country during 2020. The vertical red line marks the start of confinement in each country. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

model has been created to explain the daily behavior of the demand based on input variables such as temperature or festivity. This model, adjusted with data prior to the onset of the pandemic, has allowed to generate an estimate of the expected daily demand for 2020, used as a reference to measure the decrease in observed demand. Peru and Bolivia are the two countries where the pandemic has had the greatest impact during 2020, with an impact in April 2020 of around −30%. At the opposite extreme would be Chile and Uruguay, with a maximum monthly impact of approximately −6%. The rest of the countries have maximum monthly impacts between −11% and −17%.

On the other hand, the results of the analysis of the daily demand profiles have allowed to study the impact of COVID-19 on electricity consumption habits. To this end, an explanatory model has been created for each country that allows obtaining an estimate of the expected demand profile for the whole of 2020 if there had been no COVID-19. Comparing the expected profiles with the actual profiles, significant changes have been observed in the way electricity is consumed. Mainly, a shift in the profile has been observed in the morning hours, between 7 and 12, indicating that the start of electricity consumption in the countries has been delayed. In addition, this reduction in demand in the morning produces an increase in demand in the afternoon or evening hours.

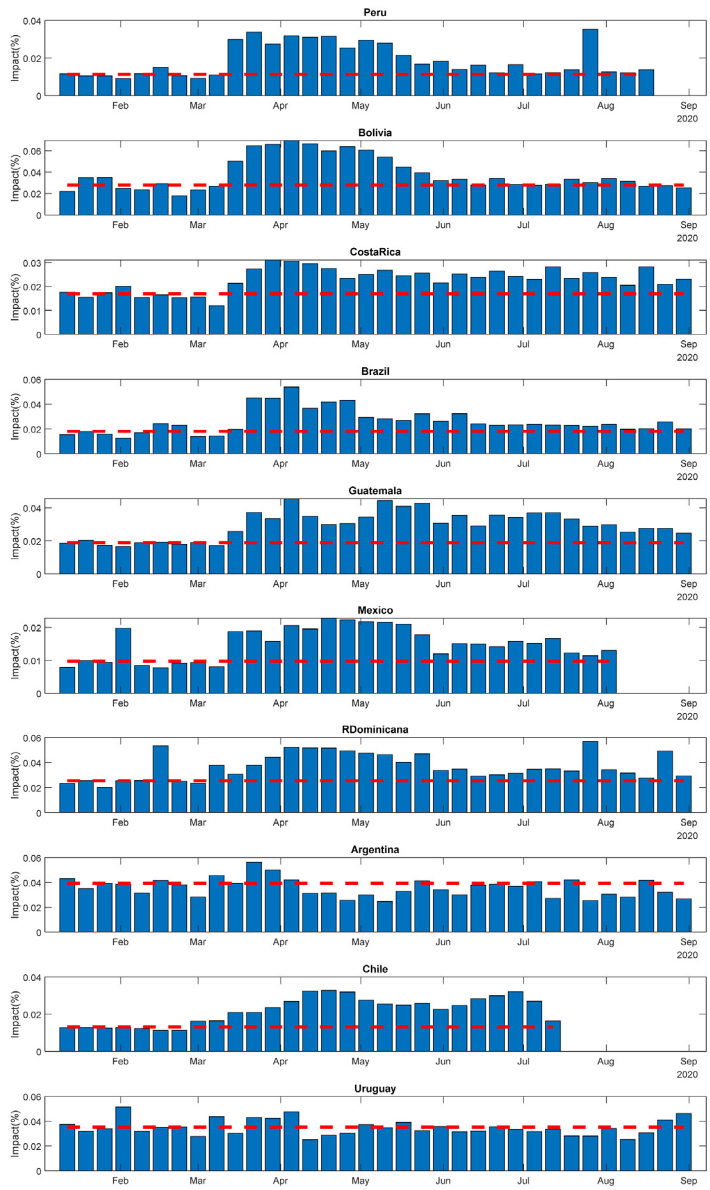

Fig. 19. Evolution of the weekly Shape Impact Index for each country.

CRediT authorship contribution statement

E.F. Sánchez-Úbeda: Conceptualization, Methodology, Data curation, Software, Visualization, Writing – original draft, Supervision. **J. Portela:** Conceptualization, Methodology, Software, Visualization, Writing – original draft. **A. Muñoz:** Conceptualization, Methodology, Writing – review & editing. **E. Chueca Montuenga:** Conceptualization, Data curation, Writing – review & editing. **M. Hallack:** Conceptualization, 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.

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