The impact of the COVID-19 pandemic and behavioral restrictions on electricity consumption and the daily demand curve in Turkey

E. Yukseltan, A. Kok, A. Yucekaya [*], A. Bilge, E. Agca Aktunc, M. Hekimoglu

Department of Industrial Engineering, Kadir Has University, Istanbul, Turkey

ABSTRACT

The rapid spread of COVID-19 has severely impacted many sectors, including the electricity sector. The reliability of the electricity sector is critical to the economy, health, and welfare of society; therefore, supply and demand need to be balanced in real-time, and the impact of unexpected factors should be analyzed. During the pandemic, behavioral restrictions such as lockdowns, closure of factories, schools, and shopping malls, and changing habits, such as shifted work and leisure hours at home, significantly affected the demand structure. In this research, the restrictions and their corresponding timing are classified and mapped with the Turkish electricity demand data to analyze the estimated impact of the restrictions on total demand and daily demand profile. A modulated Fourier Series Expansion evaluates deviations from normal conditions in the aggregate demand and the daily consumption profile. The aggregate demand shows a significant decrease in the early phase of the pandemic, during the period March–June 2020. The shape of the daily demand curve is analyzed to estimate how much demand shifted from daytime to night-time. A population-based restriction index is proposed to analyze the relationship between the strength and coverage of the restrictions and the total demand. The persistency of the changes in the daily demand curve in the post-contingency period is analyzed. These findings imply that new scheduling approaches for daily and weekly loads are required to avoid supply-demand mismatches in the future. The long-term policy implications for the energy transition and lessons learned from the COVID-19 pandemic experience are also presented.

1. Introduction

After starting as a regional epidemic in China in December 2019, COVID-19, caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARSCOV-2), rapidly spread to at least 185 countries worldwide and was declared as a pandemic by the World Health Organization on March 11, 2020. As of January 13, 2021, according to the Johns Hopkins University database, nearly 93 million people have been infected, and almost 2 million people have died due to COVID-19 (JHU, 2021). The US, India, and European countries have been the most affected regions from COVID-19. Various measures are taken to limit the spread of the virus and flatten the curve of the number of patients so that healthcare systems are not overwhelmed. These measures include social distancing, quarantine, self-isolation, closure of schools, workplaces, and shopping centers, full lockdowns, and constrained air, sea, and road transportation. As a result of these measures, almost all industrial facilities and sectors were affected, demand plunged significantly, and remote working and education became common practices (Nicola et al., 2020).

Although some countries announced mandatory full lockdowns against this global challenge, their duration, as well as the strategies and policies proposed by decision-makers, changed considerably. Short- or long-term restrictions and regional or country-wide restrictions were adopted in different countries. These extraordinary precautions changed the daily industrial and household electricity consumption routine; however, the impact on the electricity demand is expected to be different depending on the size and duration of the restrictions. A time log of these restrictions is presented in the University of Oxford's COVID-19 Government Response Tracker, where a Government Response Stringency Index (GRSI) is proposed to monitor and compare the restriction policies around the world (University of Oxford, 2020).

As the impact of complete lockdowns on the economy is dramatic, complete long-term lockdowns are not preferred unless they are required. Turkey has followed a different strategy than many other countries and implemented age-specific restrictions (ages above 65 and

below 20), closure of schools, lockdown in certain cities for limited times, and travel limitations between cities. The majority of the industrial facilities stopped operations, and people stayed at home between March and June 2020, at the beginning of the pandemic. Pandemic conditions have significantly impacted the electricity sector as it is a supply chain in which resources are planned, delivered, and used to generate electricity to be transmitted to end consumers. The total electricity demand has decreased considerably and, as expected, the impact of each restriction on the aggregate electricity demand is different and needs to be analyzed respectively.

The substantial revenue loss is an obvious effect of the fall in electricity demand on electricity producers. For Turkey, resources such as natural gas and imported coal are purchased with long-term contracts, and physically delivered resources must be consumed. Besides, the cost of these resources is calculated based on the assumption that electricity demand, and therefore prices, will continue in their ordinary course. According to the Turkish Electricity Transmission Corporation (TEIAS) reports, the share of installed capacity of natural gas and imported coal in the Turkish electricity system are 28% and 10%, whereas their contributions to annual generation in 2019 were 19% and 21%, respectively (Turkish Electricity Transmission Corporation, 2020). The liberated Turkish power market has a merit-based system, and the typical scheduling order in the supply stack is as follows: state-owned thermal plants, wind, solar, biomass, hydroelectric resources with dams, lignite, imported coal, hydroelectric (peak hours) resources, natural gas, and fuel oil-based generation resources (SHURA Energy Transition Center, 2020). The order is determined based on the net cost that depends on the offer prices. The market mechanism had worked as expected such that when the demand decreased, the electricity was supplied from cheaper resources, and hence, the electricity price decreased.

The total demand needs to be met with the available resources; however, the level of demand needs to be known for resource planning, maintenance, transmission, market operation, and investment planning. Given that there might be a risk of supply issues for imported coal and natural gas, the resources in the supply stack need to be used carefully, such as hydro resources that are considered base units in the Turkish power market. As it is still uncertain how the pandemic will continue and end, a possible solution might be using the available water wisely for more crucial times and prioritizing the use of resources that are easily accessible. Another possible issue is that long-term resource procurement may be interrupted, and the impact of each restriction on demand should be estimated to revise resource planning.

The daily demand curve in a typical week has an expected pattern shaped by work hours and daily habits. The formation of this cyclic curve is based on typical conditions where people work in their offices, the schools are open, and people travel without any restrictions. The weekly cycle can be classified as weekdays and weekends, classified as Saturday and Sunday. Although demand changes in this weekly cycle, the pattern is determined based on the habits and routines and hence is similar. However, the pandemic measures have changed almost every manner and routine, and the daily variation curve was affected by this change. The demand shifted from daytime to night-time, and the peak hours were altered. The scheduling and resource planning decisions need re-planning based on this new paradigm, and the characteristics of the new curve need to be analyzed.

Since the COVID-19 pandemic is an entirely new experience, there is relatively limited research in the literature addressing the effects of COVID-19 on the energy sector, especially for electrical energy, yet the number of studies is growing every day. Those works investigate the impacts of COVID-19 on the energy sector from various perspectives such as emissions, clean energy transitions, operational reliability, and market prices. However, studies considering the effects of the pandemic on electricity demand forecasting are limited. Ghiani et al. (2020) study the effects of restrictions on electricity demand, load shapes, and market prices in Italy during the COVID-19 outbreak. Their analysis shows that the demand plunged up to 37% compared to the year before.

Abu-Rayash and Dincer (2020) investigate the trend changes in electricity demand in the province of Ontario, Canada. They handle the subject from the perspective of smart cities and report that the average monthly demand decrease is 14% for April, and the highest daily demand reductions were observed on weekends, with an average daily reduction of 18% and a maximum reduction of 25%. Another study from Canada uses hourly electricity data and finds that demand declined by about 10% in Ontario and about 5% in Alberta, British Columbia, and New Brunswick (Leach et al., 2020). This study also reports that supply from some natural gas plants is reduced in Alberta, and net electricity exports increased in Ontario. Carvalho et al. (2020) analyze how electricity consumption has changed due to the mobility restrictions in Brazil, and their findings show that the decline in consumption varies from 7% to 20% between regions because of the different electricity consumption profiles. The most affected regions are those with high industrial density, and the least affected ones are those with high residential density.

Similarly, Delgado et al. (2021) show that electricity loads decreased by 3%–19% for different regions in Brazil between January and September 2020. Snow et al. (2020) attempt to reveal drivers of household consumption shifts by monitoring the electricity use of 491 residents and interviewing 17 households in the state of Queensland, Australia. The results identify substantial changes such as greater use of cooking and digital equipment, but a decrease in aggregate electricity consumption of most of the monitored households during the lockdown period, possibly as a result of reduced use of air conditioning due to the cold weather compared to the same period of last year. Aruga et al. (2020) investigate two hypotheses for India; the first one is that energy consumption rebounds after the ease of the lockdown measures, and the second one is that the energy consumption of economically developed regions is affected more positively. The results showed that both hypotheses are accepted, and the result of the first hypothesis is parallel to our findings. In our study, the main focus is not only on the rebound effect, and regional analysis is not held.

Several models are suggested in the literature to investigate the relationship between various factors and electricity demand during the pandemic. Norouzi et al. (2020) try to reveal the links between the pandemic and main economic parameters such as GDP growth, manufacturing PMI, and exports income, and impacts of these parameters on oil and electricity demand in China using two different methods: regression and artificial neural networks. In this paper, we also use a regression model but without any economic indicators. Liu and Lin (2021) introduce a deep-learning-based multivariate time series forecasting model to investigate the correlations among containment measures, weather conditions, renewable energy supplies, and electricity demand in the UK. They show that renewable energy supplies significantly affect the accuracy of this predictive model besides the number of new COVID-19 tests.

Lu et al. (2021) developed a hybrid electricity consumption prediction model that can be applied in the pandemic using daily infections, daily deaths, and GRSI data. They use a multi-objective optimizer to ensure accuracy and stability and a support vector machine as the prediction model. Using the daily electricity demand of the US, the model considering the daily infections is reported to have the highest prediction accuracy and stability, although the number of daily infections is not the most correlated factor with the electricity demand. Eryilmaz et al. (2020) show that peak load and peak-to-base ratio decreased for all three major regional transmission organizations (RTOs) in the US during the stay-at-home advisory due to COVID-19, and electricity generation mixes were affected such that coal use decreased while the use of natural gas and renewables increased. In a more comprehensive study, Ruan et al. (2020) develop a cross-domain open-access data hub (COVID-EMDA[+]) that integrates data across all seven existing US RTOs with COVID-19 public health data, weather, mobile device location, and satellite imaging data, including night-time light brightness. A significant reduction in electricity consumption is found to be strongly

correlated with the number of COVID-19 cases, degree of social distancing, and level of commercial activity.

From a broader viewpoint, Zhong et al. (2020) discuss the implications of COVID-19 on the electricity market by analyzing supply and demand, describing difficulties in the operation of the power system, suggesting solutions, assessing market prices, and explaining emission and environmental influences as external impacts of the pandemic. Werth et al. (2021) investigate the impact of governmental restrictions on electrical load, generation, and transmission in 16 European countries using a subset of indices provided by the Oxford COVID-19 Government Response Tracker. They identified "stay at home, school closing, restriction on internal movements, and workplace closing" as the limitation types that correlate significantly with the load reduction during the pandemic. They also note that generation from nuclear, fossil coal, and gas sources was reduced in favor of renewables, and European countries balanced these changes by increasing energy exports and imports. Buechler et al. (2020) use clustering to analyze the electricity consumption of 58 countries for January–May 2020 and find out that there is a 2%–26% decline in the demand due to the pandemic situation. López Prol and O (2020) forecast baseline daily electricity consumption in the nine most impacted European countries and USA states between March and July 2020, using country-specific ARIMA dynamic harmonic regressions with Fourier terms for complex seasonality, quadratic temperature, and calendar effects. They show that COVID-19 measures decreased electricity consumption by 3%–12% in 5 months; still, most countries have recovered baseline levels by the end of July, and stringency measures and consumption decline are non-linearly related.

There are many studies in the literature about short- and long-term electricity demand forecasting. The electricity demand data is structured as time series due to its nature, and hence linear models and time series methods are commonly used for forecasting. Authors present literature on forecasting methods in which the usage of Artificial Neural Networks (ANN), Genetic Algorithms (GA), Support Vector Machines (SVM), and Particle Swarm Optimization (PSO) and other numerical methods are discussed (Suganthi and Samuel, 2012). ARMA and ARIMA models are also used to include stochastic effects in demand forecasting (Andersen et al., 2013; Lo and Wu, 2003; López Prol and O, 2020; Niu et al., 2010). The impact of temperature on electricity demand depends on the infrastructure and heating resources, and the temperature is used to increase the forecast accuracy. The different aspects of the influence of the temperature on the electricity demand have been analyzed in (Bašta and Helman, 2013; De Felice et al., 2013, 2015; Hor et al., 2005; Islam et al., 1995; Lusis et al., 2017; Momani, 2013; Taylor, 2012). The methods used for long-term forecasting differ from time series methods (Torrini et al., 2016). However, such forecasting approaches are used to forecast and analyze the demand assuming normal circumstances and expectations, i.e., no COVID-19 effects.

The impact of COVID-19 should be considered multidimensional as it will also affect producers, customers, and the economy in general. Due to its criticality, the electricity sector should be prepared for generation and transmission problems. The impacts of the crisis caused by the current COVID-19 outbreak should be examined, and they are mostly related to the restrictions taken by authorities. Hence, the impact of each restriction on total demand and the daily demand curve should be analyzed compared to pre-pandemic periods to extract useful information for upcoming periods.

This study aims to analyze the impact of the global pandemic on the electricity demand and daily demand profile using the Turkish Power Market as a case study. The novelty of this study revolves around the sensitivities of electricity demand to restrictions, how the system responds to changes, the change in the daily demand profile and how much of the demand is shifted to night-time. The proposed restriction index is based on the restricted population, and how much more demand loss should be expected if the restricted population increases are also worth mentioning. This paper contributes to the discussions on electricity in relation to the pandemic conditions by forecasting electricity

demand, identifying the level of decrease in the demand due to each restriction and affected population, determining the level of shift in daily demand, and discussing the potential impact of these changes on the electricity sector. The possible policy implications for energy transitions deduced from the pandemic process are also presented in the discussion section. The specific objectives of this work can be further described as:

- To determine the estimated impact of each restriction on the total demand within the context of the Turkish power market and COVID-19 restrictions in Turkey,
- To analyze the change in the daily demand profile and determine the estimated level of shifted demand to other hours, especially from daytime to night-time,
- To develop a population-based restriction index and determine the relationship between the restricted population and the total demand,
- To extract useful information for policymakers from this unexpected situation to address the energy transition and future crises.

The remainder of the paper is organized as follows. In Section 2, an overview of the restrictions and their effects on electricity demand in terms of changes in total demand and the daily demand curve is presented. Section 3 presents the methods used to estimate the impact of each restriction on total demand. A modulated Fourier Series Expansion method is used to forecast the demand based on past data, estimating the changes in consumption caused by the pandemic. The impact of restrictions on total demand and daily demand profile is presented in Section 4. In Sections 5 and 6, discussions for future directions and conclusions are provided, respectively.

2. Data processing and overview of the COVID-19 effects

The electricity sector is unique as it is related to all sectors, and an interruption can lead to catastrophic consequences. The hourly demand and hourly generation data, as well as the breakdown of generation resources, are released by Energy Exchange Istanbul (EPIAS), the electricity system operator of Turkey. The released data include total generation from each resource, historical hourly demand data, reserve rates, scheduling data, maintenance information, and other parameters to analyze the market. The total hourly demand data for the 2016–2020 period is obtained from EPIAS (EPIAS, 2020). Although the restrictions and the progression of the pandemic were similar to other countries, the timing of the restrictions was different. The first case was observed on March 11, 2020, and the first fatality was reported on March 18th, 2020. On March 21st, the first restriction, an age-based mobility restriction imposing a stay-at-home requirement for people of ages above 65 and below 20, was announced. Then, other restrictions follow as the spread of the pandemic progresses. The restrictions can be classified as age-based restrictions, travel-based restrictions and closure of the noncritical facilities, and lockdowns. Their order is determined almost in parallel to the spread rate of COVID-19, and they are classified into three levels as listed below. It should be noted that Level 2 restrictions include the shutdown of mostly service industry while Level 3 restrictions include the shutdown of the production industry.

Level 1 (Age-specific restrictions): Turkey started to apply restrictions based on risky age groups, and the people above 65 are required to stay at home because of greater vulnerability to disease. The restriction was expanded to include people below the age of 20 to slow down the spread of the epidemic.

Level 2 (Social restrictions and business shutdown): In April, Turkey started to apply social restrictions to decrease contact between people in daily life. Travel restrictions between cities, closing social places like restaurants or cafés, and suspension of sports events were applied. Schools and universities started online learning, and remote working became common to prevent mobility.
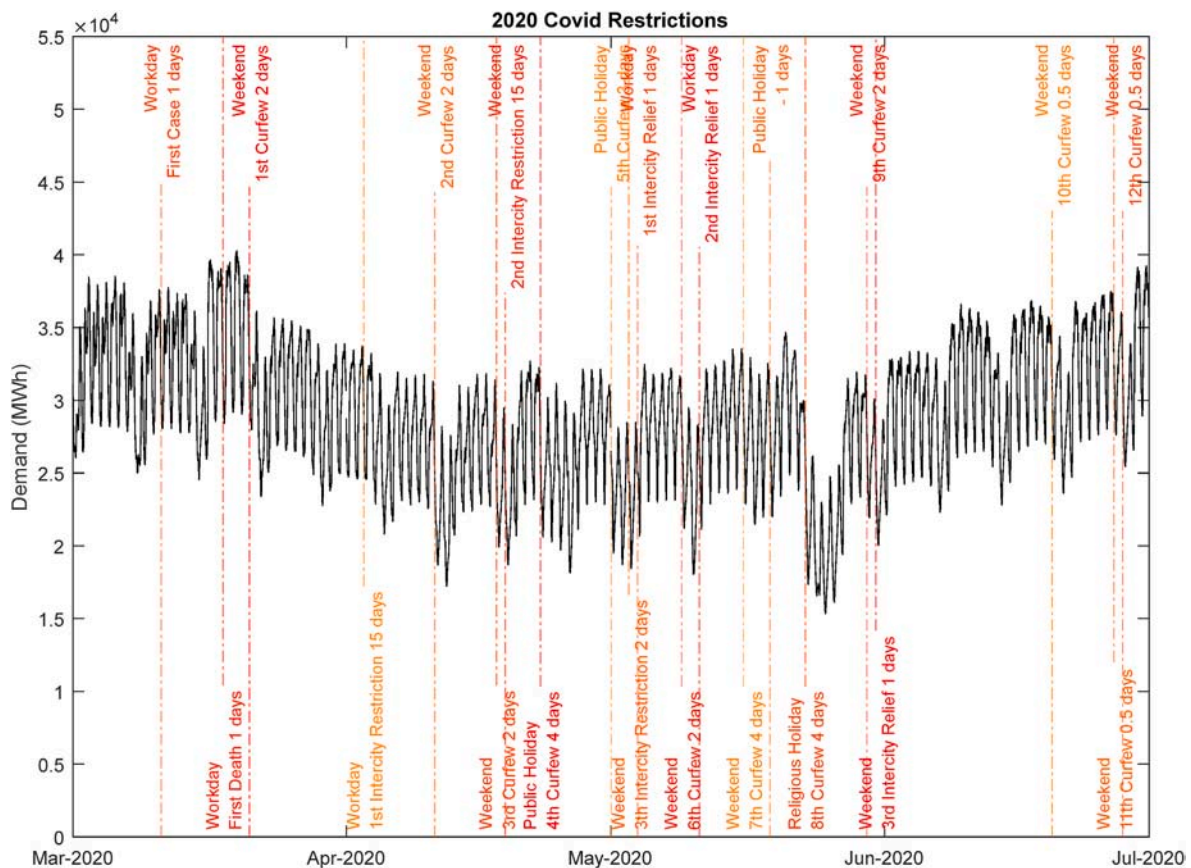
Fig. 1. COVID-19 restrictions and total hourly electricity demand in Turkey (March–June 2020).

Level 3 (Lockdowns and industrial shutdown): Complete lockdowns were applied during weekends and public holidays in April and May. On these days, all industry was shut down except for only critical industrial factories, and people were banned from leaving their homes.

Such classifications are determined to analyze the impact of each restriction on the demand profile. Fig. 1 presents the timing of restrictions and the total demand change. The restrictions started in March, applied in April and May, and a transition to normal life was made at the beginning of June. After a summer period with relatively lower risk, the cases started to increase in fall, but no restrictions were applied until December 2020. Hence, the March–June period is selected as the analysis period. The figure shows that as the level of restrictions increases, so does the decline in total demand. The level of demand loss is observed clearly when a new restriction is imposed. Also, the sudden decline in total demand due to the religious holiday is observed at the end of May.

2.1. COVID-19 and the total electricity demand

The sudden fall in demand is expected to impact the revenue for electricity producers significantly, and the consequences might be devastating if the pandemic is prolonged. Decreasing demand lowers market prices due to the merit-based market system. A lower-than-expected demand will also impact investment plans and market operation. The total electricity demand in Turkey during the years 2016 through 2020 is shown in Fig. 2. One can see the significant fall in March–June 2020 compared to the same period of the previous year.

Possible reasons for the decreasing demand include production interruption in plants, shortened work hours due to restrictions, and lockdowns in cities. Total electricity demand typically depends on climatic conditions and industrial activities, but fluctuations under normal conditions cannot explain the observed decrease. This sudden fall is due to a crisis and a clear result of the pandemic conditions. In Fig. 2, sharp decreases in the demand both in 2019 and 2020 are due to religious holidays on which most industrial facilities are closed. The consumption in such periods is representative of the base household consumption (EPIAS, 2020). The timing of these religious holidays is based on the lunar calendar, and they move back by 11 days each year. Thus, the low demand period of 2020 lags the same holiday period in 2019.

In Fig. 2, total demand over the March–June period is presented separately for 2016–2020. When the demand in March for the last four years is compared with that of 2020, it is observed that the first reaction is higher electricity consumption in the following week compared with weekly averages of March. This finding can be explained by increasing industrial use due to restriction expectations in the following weeks. The main reason for these expectations was that the first COVID-19 case was observed very late in Turkey compared to the other European countries. Therefore, companies and the public were aware of the possible restrictions and took action rapidly. The sudden fall in 2017–2020 is due to national holidays, as explained above.

2.2. COVID-19 and the daily demand profile

The primary motivation behind the restrictions is to maintain social distance due to the pandemic. The figures above show a significant decrease in demand between March and May 2020 due to restrictions. All public places such as restaurants, shopping malls, schools, and universities were locked down during the same period. People intended to stay at home as much as possible, most companies allowed working from home, and universities switched to online education.

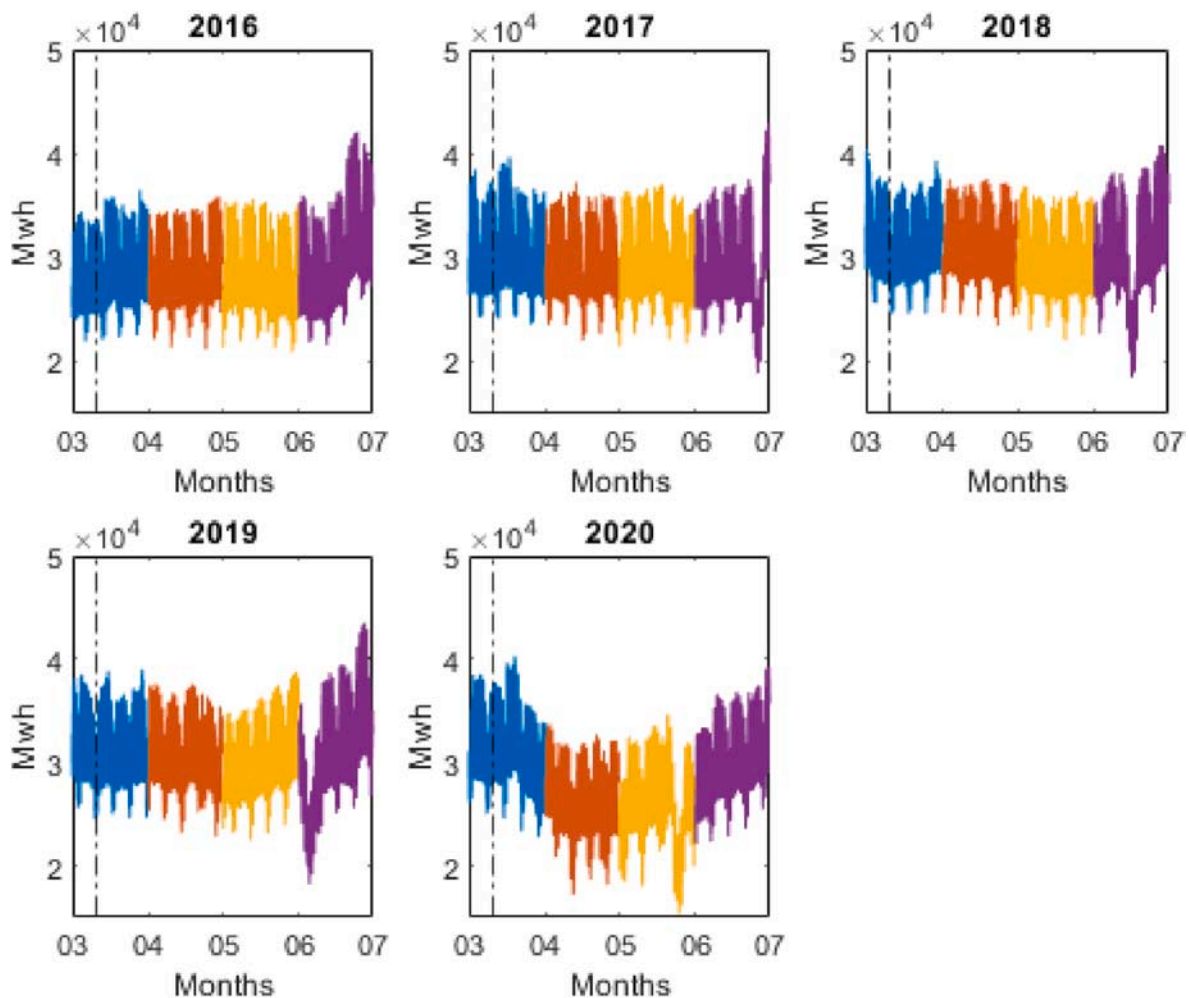As people stayed at home more, they moved away from the

Fig. 2. Total electricity demand in Turkey in 2016–2020 (March–June) (EPIAS, 2020).

environments where they regularly work or spend time. The change in sleeping habits and other daily activities followed. The cyclic consumption profile, known as the weekly electricity demand profile, where the demand started to increase in the morning hours on working days, peaked in the afternoon, and dropped to its lowest level at night and weekends, is affected by this situation. Fig. 3 shows the total and normalized demand for 13–20 April 2019 and 15–22 April 2020. The demand data is normalized by dividing each hour's consumption by the total consumption in the day to identify the level of pattern change.

When the electricity demand curve is examined, it is seen that the demand increases when people are active and during working hours and decreases at the end of working hours when people return to their homes under normal conditions. Industrial demand and household demand portray an expected profile under typical conditions in the electricity demand curve; nevertheless, due to people spending a significant amount of time at home, both the shape of the demand curve and the amount of demand change.

3. Methodology and model development

Electricity demand has an increasing trend component, climatic effects, and stochastic characteristics. The restrictions on electricity demand are superimposed on this stochastic behavior. Thus, a direct comparison with the previous year may be misleading; hence it is necessary to compare actual demand with a forecast by a model. In order to measure the impacts, a modulated Fourier Series Expansion (FSE) is used to forecast the demand, as presented in Section 3.1. Section 3.2

proposes two contingency indices, a 3-level contingency index, Index 1, and a population-based restriction index, Index 2. The percentage decrease in the demand is evaluated as a function of these indices. Finally, Section 3.3 discusses changes in the daily variation curves.

3.1. Estimating the demand loss using Fourier Series Expansion

A linear model of a modulated Fourier series expansion was used to forecast hourly electricity demand over a 1-year horizon (Yukseltan et al., 2020). This method is especially useful in cases where periodic variations are dominant, and electricity is used predominantly for illumination, i.e., heating and cooling-related demand is negligible. The model's effectiveness is shown by Yukseltan et al. (2017) and Yukseltan et al. (2020).

The model based on modulated FSE can be summarized as follows. A periodic function f(t) with period T can be represented as an infinite sum of cosine and sine functions with periods T/n. Those sinusoidal functions with periods T/n are called the "harmonics" of the main variation. In the time series for the hourly electricity demand, the daily variation with a 24-h period is the dominant component of the hourly electricity demand. The harmonics of this variation have periods of 12, 8, 6, 24/5, and so on, hours. In addition to these "fast" variations, there are weekly and seasonal variations. The weekly variation reflects the weekend effect, i.e., industrial and office consumption shutdown. Seasonal variations have components arising from illumination, heating, and cooling needs. The change in the demand due to the changes in the daylight hours can be incorporated into the FSE by adding the "modulation" of
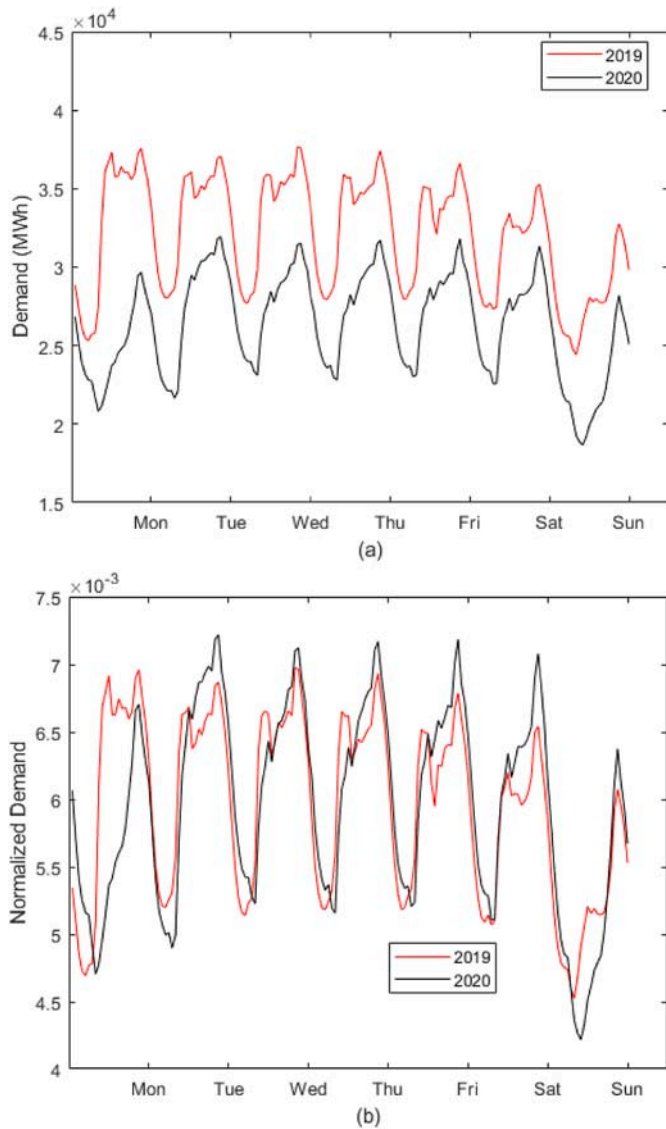
Fig. 3. Hourly electricity demand for the weeks of 13–20 April 2019 and 15–22 April 2020, (a) total demand, (b) normalized demand.

the high-frequency variations (i.e., sinusoids with periods of 24/n hours, n = 1,2, …) and the low-frequency variations (i.e., the harmonics of the seasonal variation with periods of 365/n days, n = 1,2, …). This "modulation" takes into account the variations in the amplitude of the 24-h variation throughout a year, and it is achieved by adding the products of high- and low-frequency harmonics as regressors. The demand arising from heating and cooling needs is modeled by adding the deviations from comfortable temperatures as a regressor to the linear model. In addition to these periodic components, overall trends arise from demographics and economic growth. Finally, it should be noted that electricity demand on special days, such as holidays, has to be treated separately. Time-series methods, such as AR or ARMA, focus on short-term electricity consumption forecast, while the modulated FSE provides hourly forecasts over a long-term horizon such as a year, within acceptable modeling and forecast errors, in particular in cases where illumination and industrial usage are dominant (Yukseltan et al., 2017).

The number of regressors to be included in the modulated FSE is limited theoretically by the "Sampling Theorem", stating that the shortest period that can be included in the expansion is twice the sampling interval, in this case, 2 h. Accordingly, the number of regressors should be large enough to capture the essence of the data but should be moderate to avoid the inversion of matrices with high condition numbers.

In the model, the hourly electricity demand is denoted by S. A constant vector (denoted by 1) and a linear term (denoted by t) are used for the linear trend in the data. Periodic variations consist of X_n (the nth harmonics of sinusoidal functions with a period of one year, i.e., 364/n days, n = 1,..,N), Z_m (the mth harmonics of one week, i.e., 7/m days, m = 1, …,M) and of Y_k (the kth harmonics of sinusoidal functions with a period of 24 h, i.e., 24/k hours, k = 1,..,K). The regressors that represent the modulation of the high-frequency variations (Z_m and Y_k) by the low-frequency variations (X_n) is included by the component-wise product of the corresponding vectors, denoted as $X_n Z_m$ and $X_n Y_k$. The number of this last group of regressors should be moderate to avoid over-learning. The effect of climatic conditions is represented by $T_\delta = \text{abs}(T_c - T)$, which measures the deviation from a threshold temperature T_C, that people start to use electricity for cooling or heating. By taking these considerations into account, a model is built that uses 47 time-based regressors to represent sinusoidal variations and 80 regressors to implement modulation effects as follows.

$$F = \left[1, t, X_1 X_2 \ldots X_N, Z_1 Z_2 \ldots Z_m, Y_1 Y_2 \ldots Y_K, X_1 Z_1 ..X_i Z_j ..X_1 Y_1 ..X_k Y_l T_\delta\right] \quad (1)$$

Then, the coefficient vector a and model vector y can be calculated as below.

$$a = (F^t F)^{-1} F^t S \quad (2)$$

$$y = Fa \quad (3)$$

The model is adopted to the prediction as follows. Data is split into "training" and "test" periods. Recall that the regression coefficients are obtained from the equation a=(F^{t}F)$^{-1}$ F^t S, where S is the data and F is the matrix whose columns are the model functions and the best fit to the data in the mean square sense is given by y = Fa. Splitting the data into training and test periods corresponds to splitting the matrix F and the vector S as, F^t = [F$_1$^{t} F$_2$^{t}], S^t = [S$_1$^{t} S$_2$^{t}], where F$_1$ and S$_1$ cover the training period. The model coefficients are computed in terms of F$_1$ and S$_1$ as

$$a_1 = \left(F_1^t F_1\right)^{-1} F_1^t S_1 \quad (4)$$

and the prediction for the test period is obtained from the equation

$$y_2 = F_2 a_1 \quad y_2 = F_2 \times a_1 \quad (5)$$

The prediction error is the norm of the difference between the prediction for the test period, y$_2$, and the data for the test period, S$_1$, i.e., | F$_2$a$_1$-S$_2$|. In the present case, the training period covers 2018–2019 and the test period is 2020. Forecast errors and their relation to COVID-19 restrictions are discussed in detail below.

3.2. Restriction indices

In the pandemic period, different types of restrictions were imposed by governments to prevent the spread of the virus and decrease the load of healthcare services. After the outbreak of COVID-19, the University of Oxford proposed a Government Response Stringency Index (GRSI) as an indicator of the degree of lockdown and separated restrictions into three groups: "Containment and closure", "Economic response", and "Health systems" (University of Oxford, 2020). Then the average restriction index, GRSI, is calculated for each country. This index that aims to relate stringency measures to the spread of the epidemic consists of economic support and health system response together with closures. Thus, it is not adequate for explaining changes in electricity demand since economic supports or policy changes in the health system do not impact consumption directly. For this purpose, we designed two contingency indices, Index 1 (I_1) and Index 2 (I_2), described below, to figure out the level of restriction applied in Turkey.

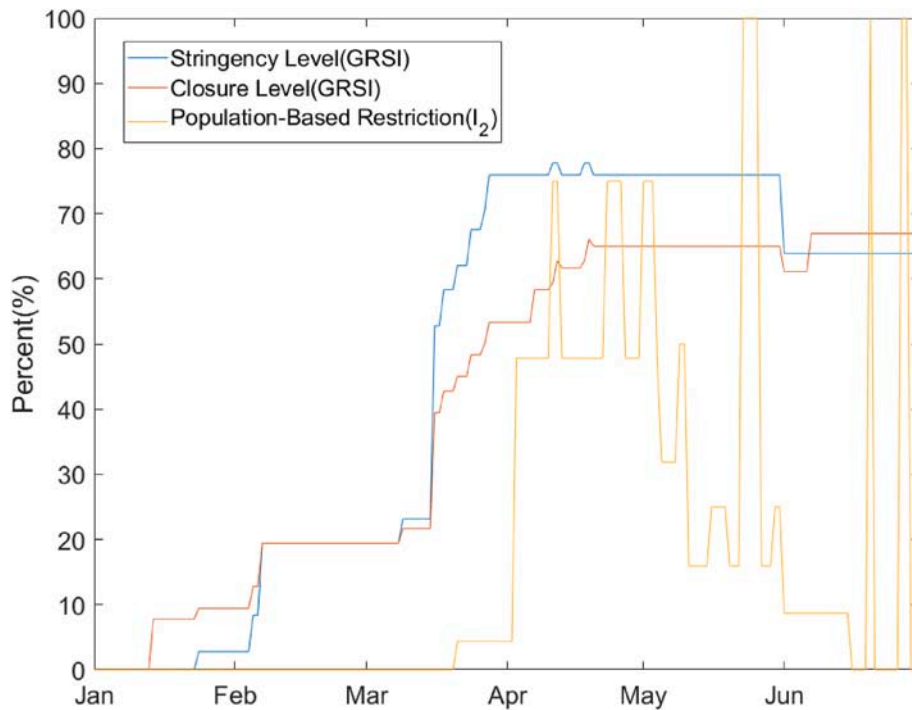In order to determine the relationship between the contingency

Fig. 4. Comparison of the population-based index (I_2) with Oxford stringency and closure index (GRSI).
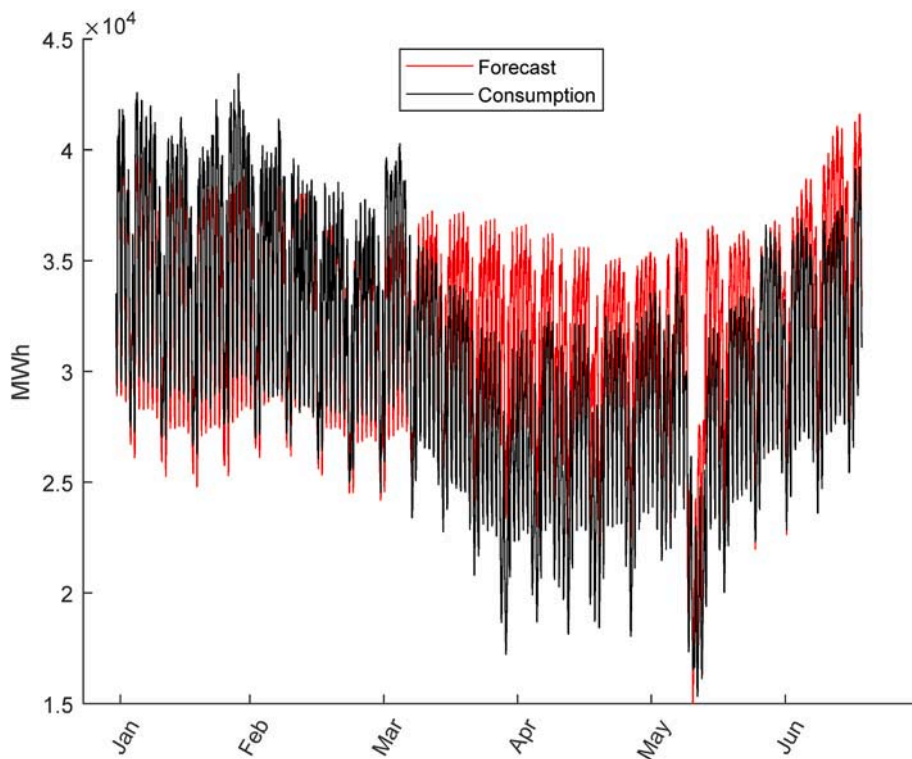

Fig. 5. Actual and forecasted demand for January–June 2020.

measures and the electricity demand, the Level 1, 2, and 3 restriction classifications are used for I_1 to analyze the total electricity demand when these restrictions are in place. As mentioned, the total electricity demand is forecasted based on the past demand, and the expected demand is determined to be compared with the actual demand. For a more accurate representation of the coverage of restrictions, we consider regional aspects of Level 1, 2, and 3 restrictions, some restrictions in

terms of the affected population. The affected population of each restriction is calculated based on affected regions/cities and used as I_2. In Fig. 4, the components of the GRSI (stringency level) for Turkey and population-based index, I_2, for the period January–June 2020 are compared. I_2 is rising after March 2020 and, except for peaks arising from weekend restrictions, falls in May and June 2020, consistent with the gradual return to normal conditions. Although the I_2 index is quite
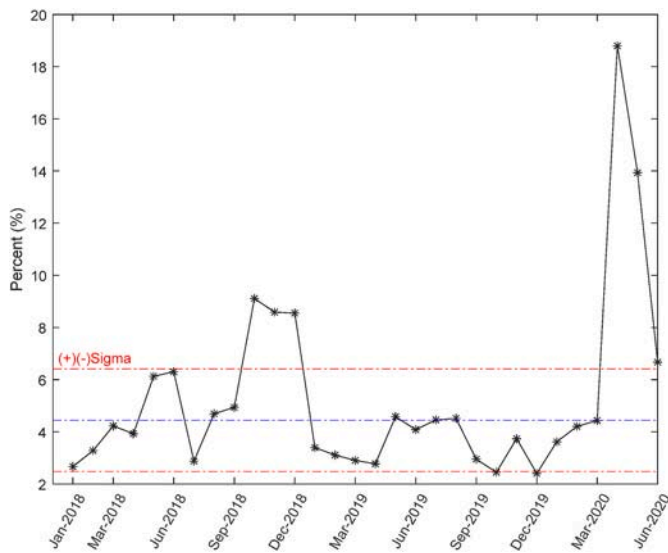
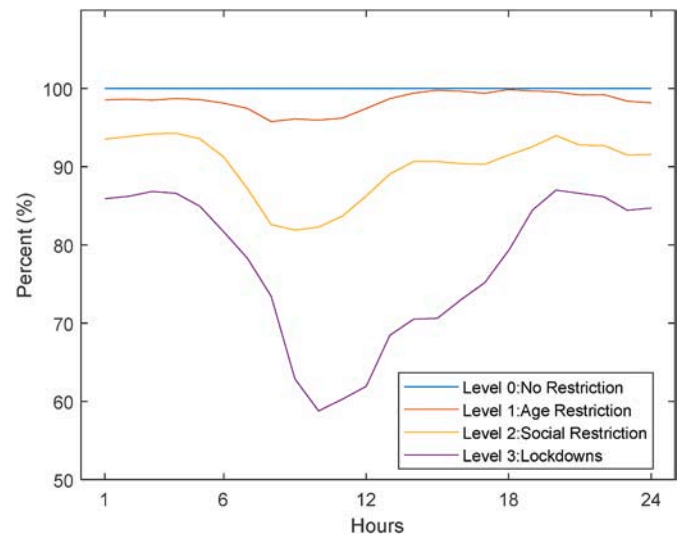**Fig. 6.** Forecast errors (MAPE) for 2018–2020.

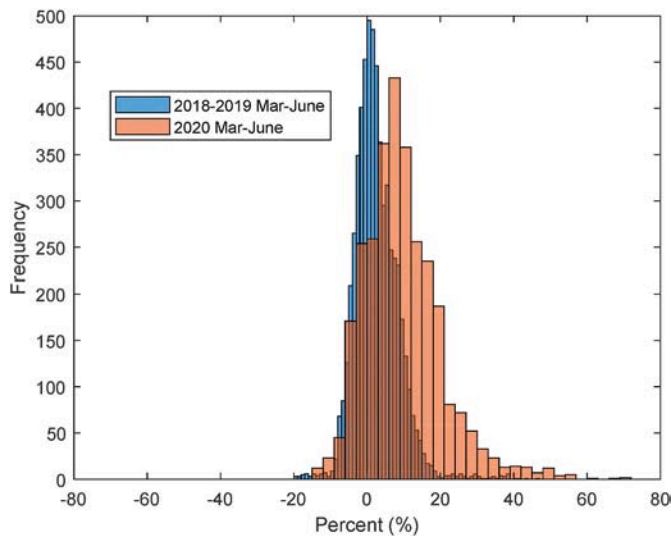**Fig. 8.** The effect of restrictions on demand for each hour.

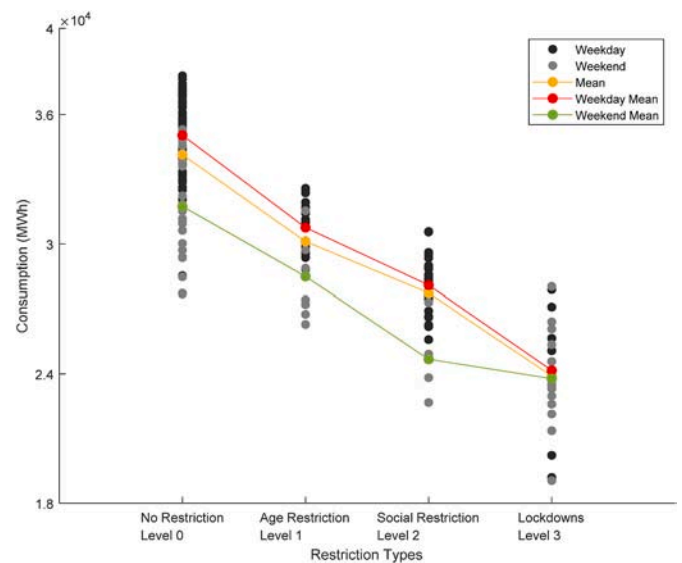**Fig. 7.** Histogram of hourly forecast errors.

Fig. 9. Electricity demand as a function of restrictions.

Table 1
Reductions of consumption for weekdays, weekends, and all days of the week.

Restrictions	Weekdays	Weekends	All Days
Level 1	2%	2%	2%
Level 2	9%	8%	9%
Level 3	21%	10%	12%
Total loss	31%	19%	23%
R^2			89.92%

similar to GSRI, there are differences, especially in the peak levels. It is observed that no other restriction affects electricity demand more than complete lockdowns.

4. The impacts of COVID-19 and market analysis

COVID-19 is an obvious threat and unexpected challenge which impacts many sectors profoundly, including the electricity market. As explained above, the restrictions and their duration varied across the countries, and the restrictions applied in Turkey are classified into three

categories. I_1 and I_2 are proposed to assess the restriction level imposed in Turkey to compare it with other countries. A modulated FSE is proposed to forecast the expected demand based on the past data as if the pandemic was ineffective. The estimated impact of each restriction is determined based on the comparison of expected and actual demand. The estimated level of demand that is shifted in the daily demand curve and the impact of restricted population on demand are also analyzed in this section.

4.1. The impact of COVID-19 on total demand

The modulated FSE is applied to the data set for 2018–2019, the demand is forecasted for each year based on the previous two years, and monthly errors are calculated to make comparisons. In this computation, hourly demand over a year horizon is obtained from data for the previous two years; that is, data for 2016–2017 is used to forecast hourly demand for 2018. Similarly, data for 2017–2018 is used to forecast hourly demand for 2019, and finally, data for 2018–2019 is used to predict hourly consumption during 2020.

Fig. 5 shows the forecasted demand and the actual demand for

Table 2
Description of eleven pairs of restrictions and affected populations.

Age Group	City Group*	Population Type	Affected Population	Percentage of Affected Population	Details of the Contingency Measures	Population Types and Contingency Levels (I₂)	Percentage of Demand
All ages	All cities	A	0	0	No restriction	A.0	100.00%
>65	All cities	B	7,550,727	0.0908	Age restrictions (>65)	B.1	87.90%
>65 and < 20	All cities	C	33,094,666	0.3979	Age restrictions (>65, <20)	C.1	87.95%
All ages	15 Metropoles	D	60,424,294	0.7266	Age restrictions (>65, <20) + Social restrictions for 15 metropoles	C.1, D.2	84.04%
All ages	15 Metropoles	D	60,424,294	0.7266	Age restrictions (>65, <20) + Social restrictions for 15 metropoles + Lockdowns for 15 metropoles	C.1, D.2, D.3	83.51%
All ages	24 Metropoles	E	66,931,982	0.8049	Age restrictions (>65, <20) + Social restrictions for 24 metropoles	C.1, E.2	79.09%
All ages	24 Metropoles	E	66,931,982	0.8049	Age restrictions (>65, <20) + Social restrictions for 24 metropoles + Lockdowns for 24 metropoles	C.1, E.2, E.3	77.64%
All ages	31 Metropoles	F	72,742,762	0.8747	Age restrictions (>65, <20) + Social restrictions for 31 metropoles	C.1, F.2	70.57%
All ages	31 Metropoles	F	72,742,762	0.8747	Age restrictions (>65, <20) + Social restrictions for 31 metropoles + Lockdowns for 31 metropoles	C.1, F.2, F.3	69.29%
All ages	All cities	G	83,154,997	1.0000	Half-day lockdown (08:30–18:30) for all cities, no industrial shutdown	C.1 G.3	89.76%
All ages	All cities	G	83,154,997	1.0000	Age restrictions (>65, <20) + Social restrictions for all cities	C.1 G.2	58.85%

* 15 Metropoles: Ankara, Balikesir, Bursa, Eskisehir, Gaziantep, Istanbul, Izmir, Kayseri, Kocaeli, Konya, Manisa, Sakarya, Samsun, Van, Zonguldak.
24 Metropoles: Adana, Ankara, Balikesir, Bursa, Denizli, Diyarbakir, Eskisehir, Gaziantep, Istanbul, Izmir, K.Maraş, Kayseri, Kocaeli, Konya, Manisa, Mardin, Ordu, Sakarya, Samsun, Şanliurfa, Tekirdag, Trabzon, Van, Zonguldak.
31 Metropoles: Adana, Ankara, Antalya, Aydin, Balikesir, Bursa, Denizli, Diyarbakir, Erzurum, Eskisehir, Gaziantep, Hatay, Istanbul, Izmir, K.Maraş, Kayseri, Kocaeli, Konya, Malatya, Manisa, Mardin, Mersin, Mugla, Ordu, Sakarya, Samsun, Sanliurfa, Tekirdag, Trabzon, Van, Zonguldak.
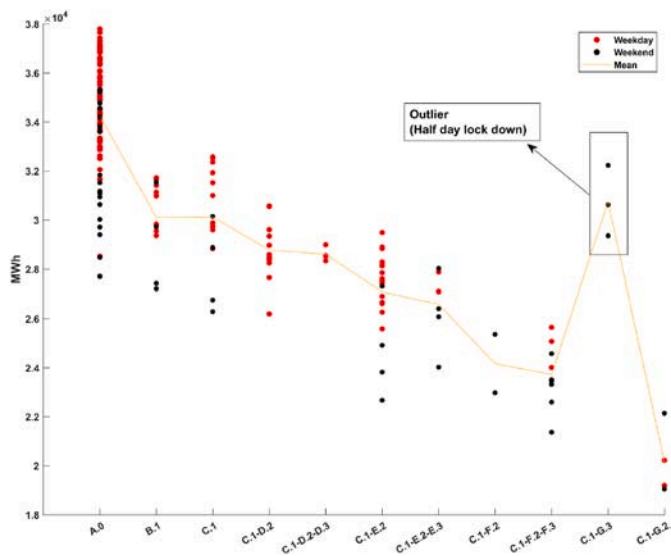

Fig. 10. Electricity demand with respect to I_2.

January–June 2020. As seen in Fig. 5, there is a considerable difference between the model forecast and actual consumption during the period March–June 2020.

In order to assess the discrepancy between the forecasted and the actual demand, Mean Absolute Percentage Errors (MAPE) are computed as presented in Fig. 6. The mean MAPE is 4.4% for January 2018 to March 2020, but it rises to 13.13% for April–June 2020, much beyond previous statistical variability. Forecast errors rise above the 1-σ band during fall 2018 also. This relatively high error level is still within statistical variability due to unusual climatic conditions in that period. In June 2020, with the "return to the normal", forecast errors fell back to the 1-σ band. We recall that the errors displayed in Fig. 6 are monthly errors of the hourly forecast over a year horizon. This prediction method is tailored to long-term forecasts and overlooks short-term variations in the demand, such as variations in the demand due to climactic effects as in 2018, or the drastic change in the demand such as in 2020, due to unusual events. We also note that temperature effects would be included in the model by updating the FSE model by more sophisticated models, but as the errors during 2018 are within statistically acceptable limits, while the errors during 2020 are substantially beyond, we omit this analysis.

The histogram of forecast errors for hourly demand is given in Fig. 7. It is observed that the forecast errors are within the 20% band under normal conditions. The histogram is skewed to the right, reaching the 60% band, and since the demand is reduced, the errors are positive and high. The error rates indicate a parallel structure with the restriction indices, they increase as more restrictions are imposed, and they can be used to estimate the impact of restrictions on demand.

The error rates are mapped with the demand and timing of the restrictions, and they are used to calculate the impact of each restriction on total demand. For this, each day is labeled by the level of the relevant restriction, as given by the index I_1, and forecast errors, as representatives of the deviations from the expected demand, are tabulated. In Table 1, we present their averages to represent the decrease in the demand caused by the corresponding type of restriction, i.e., the impact of each restriction on total demand. Note that the decrease rates are marginal, and the cumulative impact should be considered at each level. The restrictions range from low to high levels; hence, the incremental impacts explain decreasing demand when a new restriction is imposed. The coefficient of determination, R^2, of the model for all days of the week is almost 90%, as provided in Table 1.

The results in Table 1 show that the age-specific restrictions result in a 2% decrease in demand. If the social distancing restrictions are added, the total decrease becomes 11%; finally, total lockdown leads to a 23% decrease in total demand. The forecasting model's predictive power is extensively tested using two types of k-fold cross-validation tests, details of which are given in the Appendix. Validation tests show that the proposed model generates demand forecasts with a prediction error of 3–5% for 2018 and 2019. For 2020, forecast deviation larger than this
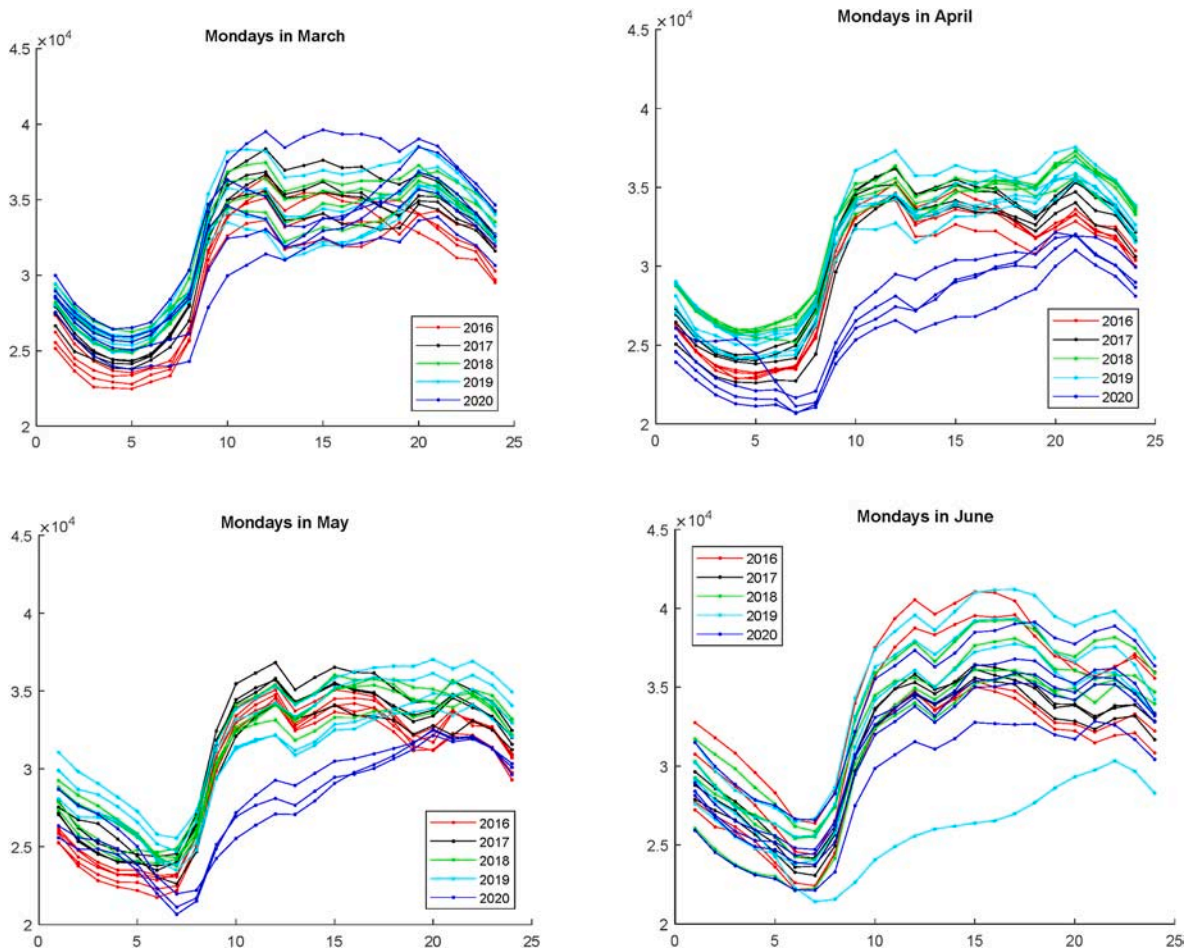
Fig. 11. Daily consumption pattern on Mondays of March–June in 2016–2020.

base-level error is attributed to the impact of curfews and COVID-19.

The percentage decrease in the demand for each restriction and hour in a day is computed similarly to examine changes in the hourly demand, with the results are presented in Fig. 8. From Fig. 8, one can see that the impact of all restrictions on daytime demand is higher than the impact on night-time demand. It is also worth mentioning that Level 1 restrictions have almost no impact on night-time demand, whereas other restrictions have gradual impacts.

The restriction levels forming the index I_1 increase in severity and the percentage of the affected population. They are also inclusive because Level 2 includes Level 1, and Level 3 includes level 2. It is thus expected that the plot of total demand with respect to I_1 will be monotone decreasing. In Fig. 9, we present the plot of total demand for weekdays, weekends, and all days of the week for days corresponding to Level 1, 2, and 3 restrictions and for days without restriction. The impact of each restriction is observed. Even though demand is usually higher on weekdays than on weekends, weekday demand gets closer to weekend demand with each applied restriction. Weekday and weekend means are approximately the same for Level 3 restrictions. Level 1, i.e., the "Age restriction" effect, seems higher than expected since all ordinary days in 2020 are in the Winter, and the restrictions started at the beginning of the Spring. The consequence is a higher mean for days with "No restrictions" due to the already high consumption in Winter.

During March–June 2020, the age restrictions classified as Level 1 were applied nationwide. The coverage of Level 2 and Level 3 restrictions increased gradually; they were put in force in 3 groups of major metropolitan areas, consisting of nested sets of 15, 24, and 31 cities. In order to refine the dependency of the electricity both on the severity of the restrictions and on their coverage, we use a two-variable

index I_2, consisting of a pair of labels, such as A.0, where the first label represents the coverage as "the affected population" and the second label represents the "Level" of restrictions applied. Population groups are labeled by capital letters, A-G, denoting nested sets of cities, as described in Table 2 below. Different restrictions may be applied to different groups of people at a given period, as indicated in Table 2.

Fig. 10 shows the relationship between the demand and the population affected by each restriction, i.e., the index I_2. Restrictions are grouped based on types and number of affected people, and eleven different restriction and population pairs are obtained as described in Table 2. It is observed that electricity demand decreases with the contingency level, with the only exception for the type G.3 contingency measure. This restriction is a half-day lockdown for the whole country because of the country-wide university entrance exam. It seems that it had little effect on electricity consumption. The restrictions on this specific day had little effect on electricity consumption, mainly because it was not accompanied by the shutdown of industrial plants, as opposed to previous lockdowns.

4.2. The impact of COVID-19 on the daily demand curve

In order to observe the changes in daily habits and response to restrictions, daily demand curves are plotted for each day. We analyzed pattern changes in March–June in Fig. 11 by plotting the data for Mondays in each month. The figures show that the daily curves of the weekday (Monday) demand pattern changed in April and May in 2020. On typical weekdays, the consumption starts to increase at 7:00 a.m. On the contrary, in the pandemic period, the starting time for the rise in consumption shifted approximately 1 h and became 8:00 a.m.
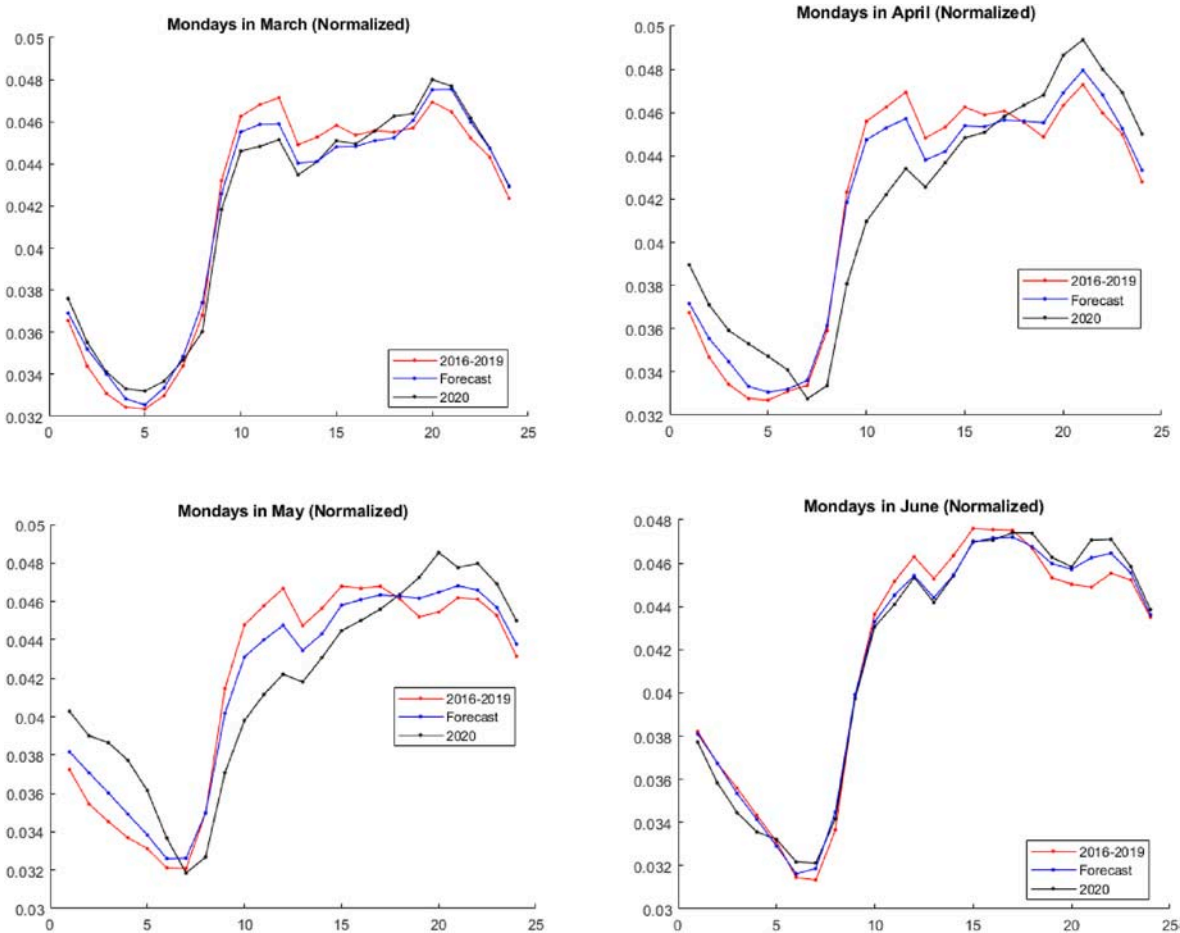
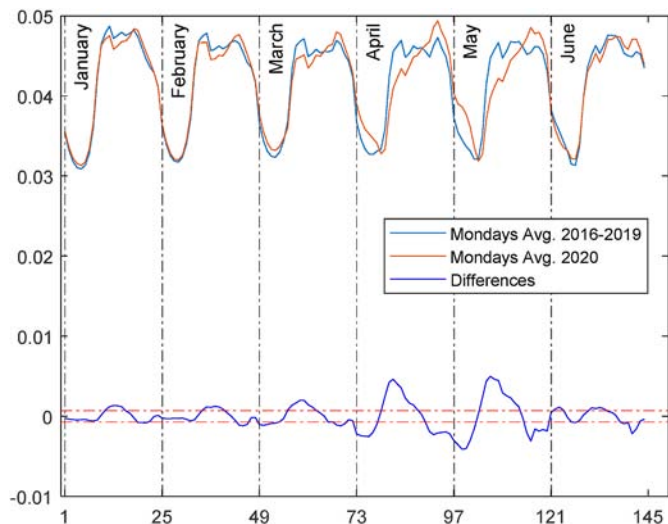Fig. 12. Normalized daily electricity demand for the months March–June.

Fig. 13. Comparison of normalized consumption profiles for the months March–June.

Moreover, the shape of the curve changes in that weekend and weekday consumption patterns are similar, and differences observed between typical weekend and weekday consumptions are not observed here. In addition to this, intra-day consumptions have an increasing trend between 08:00 a.m. and 09:00 p.m.; this is also different from the typical weekday pattern. Normally, consumption reaches a higher level at noon and continues at this level until 07:00 p.m. We can clearly say that stopping industrial use and closing residential buildings/areas cause a lower consumption profile and represent household habits more clearly. People working from home during the pandemic start and finish daily active life later than before. Their routine daily activities are shifted, and consumption patterns resemble those of national holidays. There are no differences between the years in June because of reduced restrictions that allowed industrial operations and residential activities to return to normal. Starting on the 1st of June, public places like shopping malls and restaurants were allowed to open, and many industrial companies started operating again.

The estimated ratio of shifted demand to other hours is helpful information for the market operator and electricity system players. In order to measure the estimated level of demand shifted to other hours, the hourly demand of the day is normalized over 24 h of demand, and the ratio of demand allocated to each hour is calculated. The same process is followed for 2016–2019, and their average values are calculated for each hour. Then, the normalized curves of 2020 and 2016–2019 are compared. Fig. 12 shows the total normalized demand for Mondays of March–June 2020, and the average normalized demand for Mondays of 2016–2019. In the pandemic period, a change in the demand pattern is observed, such that the ratio of night-time demand increases and the peak demand in daytime decreases and shifts. The demand shift to other hours starts in March, increases in April and May, and approaches normal expectations with the transition to normal life in June. The daily peaks change and sometimes flatten, the peak demand at night increases. It is also observed that more demand is shifted to night hours, where the demand used to be the lowest.

The same approach is applied to all Mondays in the March–June

Table 3
Comparison of hourly demand shift ratios in January–June 2020.
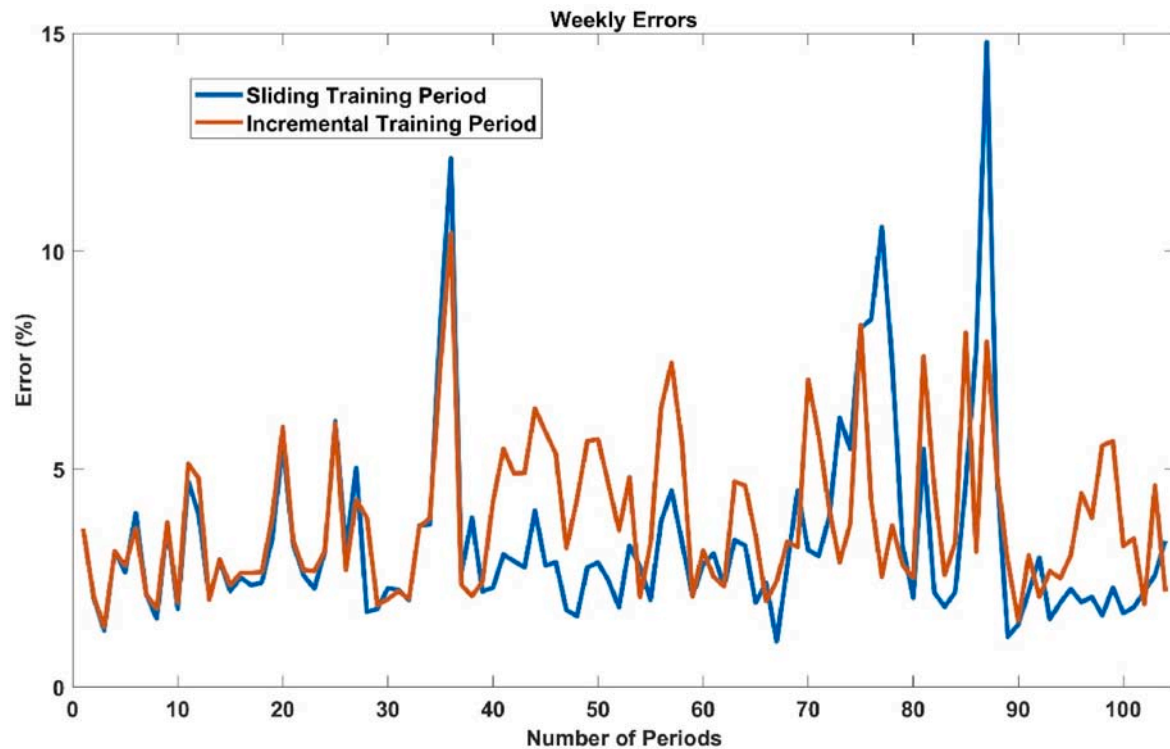
period, and the ratio of the shifted demand to other hours is calculated. Fig. 13 shows both normalized data and their difference. It is observed that the demand profile in the daily curve changed significantly in April and May.

The ratio of the difference from the 2016–2019 averages for each hour is calculated to estimate further the percentage of demand that is shifted. Table 3 provides the percentage change in the consumption for each hour and each month. The provided data shows the value of the line labeled "Differences" in Fig. 13. In this table, changes below ±1% are considered as horizontal behavior. It can be seen that there is no significant change in January and February; there is an increase in the consumption at night, starting from March with the onset of restrictions. This consumption shift to night-time increased in April and reached a maximum in May. Such a result might show that the level of risk and threat was understood well, and people behaved accordingly. In June, electricity consumption returns to normal levels as activities transition to normal. The standard deviations also confirm this argument.

4.3. An overview of the change in sectoral demand

The dynamics of electricity demand have changed along with other sectors. The demand for this unique commodity comes from industrial, residential, commercial, and other areas. Generation, transmission, and maintenance schedules are planned long before the actual generation day, and the demand forecasts are critical inputs to this process, even if they are not perfect. Although the total hourly demand data is released by the system operator EPIAS, the demand is not classified at this phase. The demand is classified as residential, industrial, business, and agricultural by Energy Market Regulatory Authority (EMRA), and the data is released as monthly sector reports in which the total monthly demand is released. In Fig. 14, electricity consumption is plotted for residential, industrial, business, and agricultural use in 2020 compared to the average consumption in the years 2016–2019. The latest sectoral data available for 2020 is published in October (EMRA, 2020).

In 2020, there is a persistent increase in residential consumption, whereas business consumption decreased significantly until September due to the measures taken to reduce mobility. As there have been recent business shutdowns in November and December 2020, business consumption is expected to decline further. Although a sharp decline in industrial consumption can be observed in April and May, there is a steep increase starting in June with over-consumption due to delayed production. However, there is no significant change in agricultural consumption, other than a slight increase that becomes more apparent starting in August, since food supply never ceased to be essential and agricultural production had to be maintained during the pandemic. These trends in electricity consumption by various sectors highlight the importance of reliable power supply, and the impact of disruptions in the electricity supply chains based on generation types can be investigated as a future research direction. Understanding the impact of the pandemic and behavioral restrictions on demand requires further work as the future of COVID-19 is still uncertain.

5. Discussion and lessons learned

Electrical energy is an essential resource for the well-being of humanity and has become even more crucial in 2020 with the outbreak of the COVID-19 pandemic that profoundly affected lives globally. There are several uncertainties about the duration and extent of the pandemic, as well as the development, delivery, and effectiveness of the drugs and vaccines against the disease. Due to these uncertainties, the duration and characteristics of the restrictions such as social distancing, the closing of borders, and limiting transportation are also uncertain. The electricity market strives to use the most proper resources to meet the total demand at the most affordable prices. The measures taken due to the spread of COVID-19 were unexpected and had unforeseen effects.

It is an obligation to carry out informative studies on the level of effects such emergency events may have on the electricity demand to inform decision-makers and relevant stakeholders by examining the
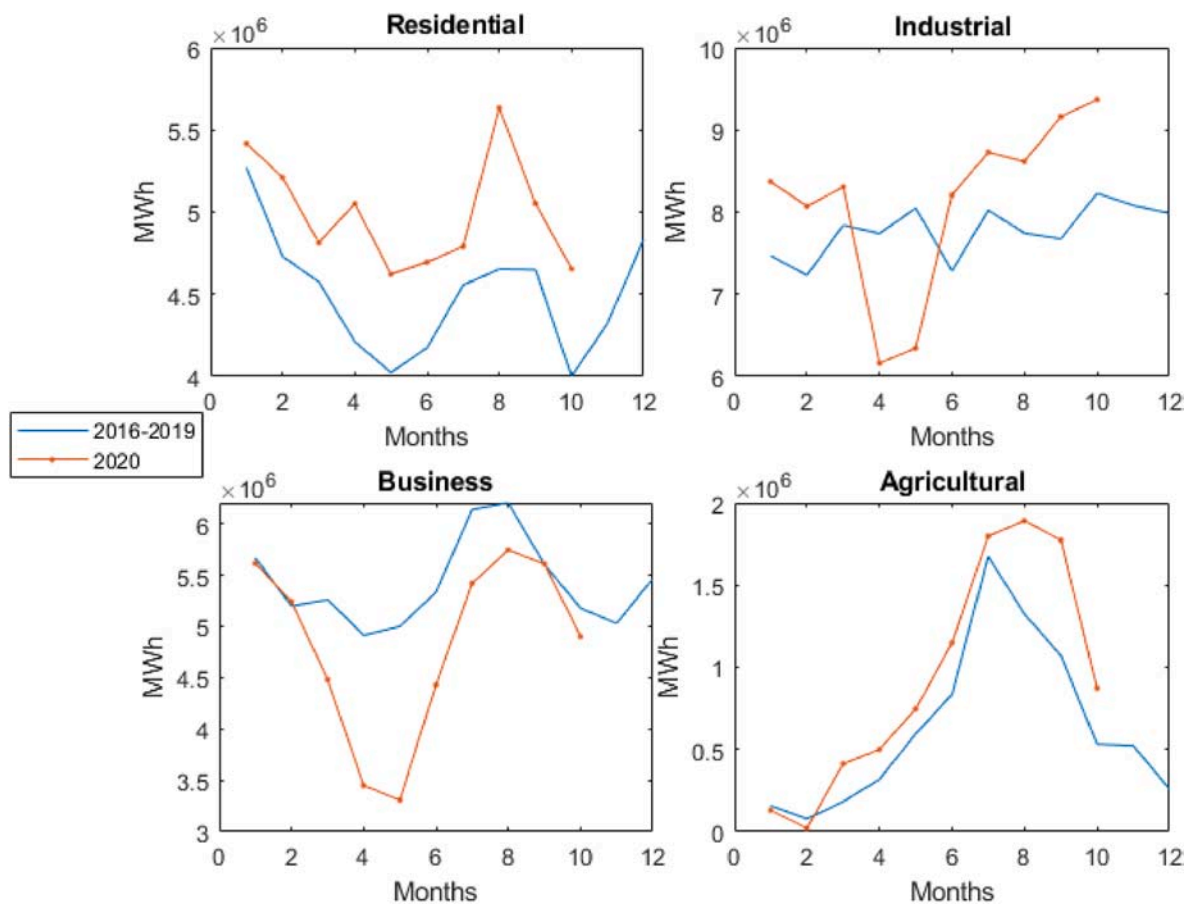
Fig. 14. Electricity consumption by area.

data with uncertainty assumptions. When the pandemic is examined, the duration of the outbreak, the levels of restrictions, and the availability of international supply/transportation stand out as the three most important aspects. Although it is known that drug and vaccine studies are continuing, a short-term solution is not envisaged, the epidemic may come in new waves, and the virus may mutate. The restrictions imposed by the governments varied depending on the size of the spread, and in Turkey, the restrictions are imposed gradually. The proposed indices I_1 and I_2 and comparison with the Oxford stringency index (GRSI) show that the contingency measure level in Turkey is quite close to GRSI.

The pandemic experience recalls national holidays on which industrial facilities are closed, and demand behaves differently than under normal circumstances but raises unique estimation issues. In previous work, the effect of industrial demand has been calculated in terms of the decrease in electricity demand during holidays, and it was also shown that the role temperature is limited in increasing forecast accuracy (Yukseltan et al., 2017). It was observed that adding the temperature information of past years gives little improvement to predicting hourly demand for a one-year horizon, just for the fact that the modulation of diurnal variation by the seasonal variation is good enough to predict the demand under "normal" climate conditions, provided that, electricity is not used excessively for heating and cooling. However, climate conditions that are way above the expected limits can still lead to an increase in the forecast error; but this situation can be remedied only in forecasts over shorter horizons. The proposed Modulated Fourier Series Expansion methodology applied to the electricity consumption in Turkey is shown to forecast demand quite successfully as it captures daily and seasonal variations as well as temperature effects, in such a way that no additional explicit climatic information is needed. The forecasted and actual demand comparison produced the rate of demand loss in each restriction type that provides interesting results. Although the total

impact of a lockdown is estimated as 23%, Level 1, 2, and 3 have 2%, 9%, and 12% expected marginal impacts on demand. The most significant demand loss is apparently due to reduced industrial demand rather than the reduced mobility of social groups. These rates can be used for demand forecasting, given that the expected demand can be estimated.

The daily demand profile in a typical week is also relevant to system sustainability, considering the availability of renewable and nonrenewable generation resources and the transmission system. The analysis shows that the demand is shifted, especially to night-time. The peaks in the daytime shifted and sometimes flattened, while the peaks at nights increased and shifted to hours where normally lower demands are expected. The estimated impact of restrictions on hourly demand confirms this argument. The system operator, as well as market participants, can adjust their plans based on the restrictions if the pandemic is prolonged.

Turkey is a net energy importing country, and a significant amount of electricity is provided from imported resources. Natural gas and imported coal comprise a significant portion (28% and 10%) of installed capacity in the Turkish electricity system, and each contributes around 20% to the annual generation (TEIAS, 2020). The pandemic process severely impacted the supply chains, and the supply of natural gas and coal can be a problem if the epidemic lasts longer in the region, in which case the available capacity should be able to meet the demand. However, demand has declined, and the rate of decline depends on restrictions.

6. Conclusion

The impacts of restrictions on the total demand and daily demand profile are apparent and need to be carefully analyzed for each country. The impacts are expected to differ based on industrial, residential, and commercial use. The total demand declined more as the restrictions

were imposed incrementally in Turkey, and the daily demand profile significantly changed. A comparison with the Oxford stringency index (GRSI) shows that Turkey is restricted almost like other countries. This analysis of demand pattern changes due to the pandemic helps us observe significant changes in habits and routines in terms of electricity. The main findings can be summarized as follows:

- Demand decreased by 2%, 9%, and 12% when Level 1, 2, and 3 restrictions were in place, respectively, while the cumulative decline in Level 3 reached 23%.
- The proposed population-based index (I_2) provides analysis for restricted population and the demand loss, and it is shown that the demand will decline more if more of the population is restricted.
- There is a significant demand shift to nights. Especially the demand between 7:00–14:00 is shifted to evening and night hours while the ratios of shifted demand can be seen for each hour. The peak demand and the total demand at night increased as people stayed home more.
- The change in demand pattern and supply can provide vital feedback to assess the system flexibility and sustainability and a roadmap for the energy transition. The main findings and lessons learned are also discussed for the policymakers.

The first case in Turkey was observed on March 11, 2020, and the restrictions are imposed until the beginning of June. The transition to normal life started, and after a relatively stable summer in terms of the number of new COVID-19 cases, the spread increased again, and the restrictions were imposed beginning in December. However, the restrictions are not imposed after May, and hence it is not safe to use the data after May to analyze the impact on the demand. Remote working,

home offices, online meetings and education, and social distancing rules became common practices. It is expected that a significant amount of the demand will be lost due to the shifted demand structure compared to the pre-pandemic period.

Pandemics have significant impacts on almost all sectors and can be considered global crises. As the crises challenge the resilience of humanity and the systems built to provide the needs of humanity, they also teach lessons for the future and provide opportunities for change. The decision-makers should take action for the future and development of the energy system. The importance of the flexibility of the electricity system both on the supply and demand side to overcome unexpected issues is reconfirmed with the results of this study. The availability of national resources to meet the demand by replacing a missing capacity with other resources without significantly increasing the cost should be considered for a future vision. An increased resource mix, efficient responses to crises, and meeting the demand under uncertainty can help increase the flexibility and resilience of electricity systems.

Declaration of competing interest

Acknowledgment

Appendix

Our study uses the Fourier series to model hourly electricity demand in Turkey between 2016 and 2019 and then forecast electricity demand for 2020. Deviations from our forecasts are attributed to the effect of restrictions on electricity consumption.

In this part of the study, we conduct k-fold cross-validation to measure the predictive power of our model. We start our tests by dividing the data into two parts: the years 2016 and 2017 are set as the training set, and data from the 2018–2019 period is kept as the test set. The test set is divided into eight parts, each of which is a 3-month interval. After re-calibrating the model and measuring the forecast deviation, the training set is updated in two ways: a) Tested data is added to the training set, whereas the same amount of old data is removed from the training set. In this option, the training set is considered a sliding window of constant length; b) Tested data is added to the training set without removing old data. In this application, the size of the training set increases incrementally after every test until it includes the entire demand dataset for the 2016–2019 period. Results show that the model's predictive performance is satisfactory, with a maximum 4.4% MAPE value, whereas the predictions are more accurate when the training set size is held constant. As the length of the training set increases, the model slightly underestimates the actual value, observed at peak errors that occur before or after holiday periods. Table A presents the MAPE values for different time slices, and Figures A, B, and C present the ranges for weekly, monthly, and quarterly time slices, respectively.

Table A
MAPE values for different time horizons

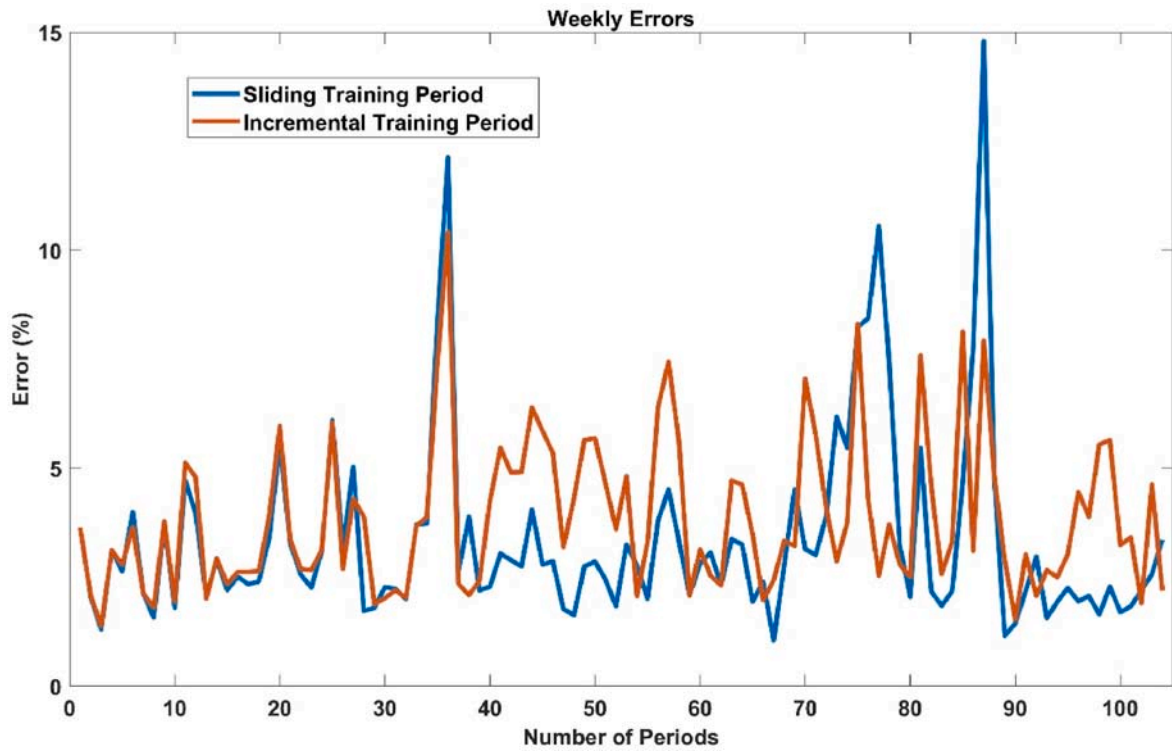| Error Period	Weekly		Monthly		Quarterly	
Training Period Type	Sliding Window	Incremental	Sliding Window	Incremental	Sliding Window	Incremental
Set 1	2.82%	2.94%	3.14%	3.20%	3.46%	3.47%
Set 2	3.22%	3.36%	3.85%	3.95%	3.27%	3.52%
Set 3	3.98%	3.73%	3.85%	3.81%	4.26%	4.22%
Set 4	2.61%	4.94%	2.87%	5.55%	4.91%	4.98%
Set 5	2.95%	4.04%	2.90%	3.80%	3.25%	5.30%
Set 6	5.16%	4.10%	5.68%	4.35%	3.04%	4.11%
Set 7	4.13%	4.22%	4.73%	4.40%	5.41%	4.07%
Set 8	2.17%	3.47%	2.27%	3.85%	4.58%	3.91%

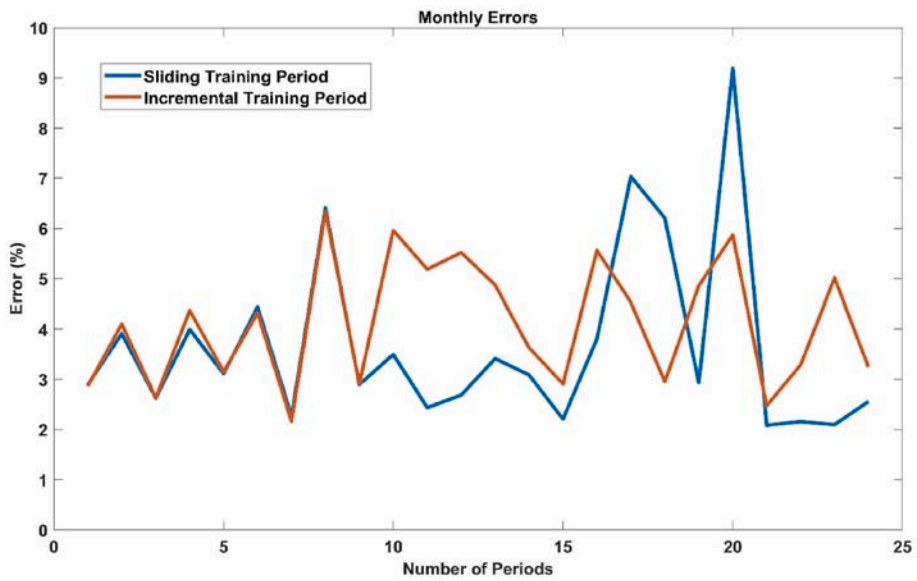**Fig. A.** Error ranges for weekly time slices

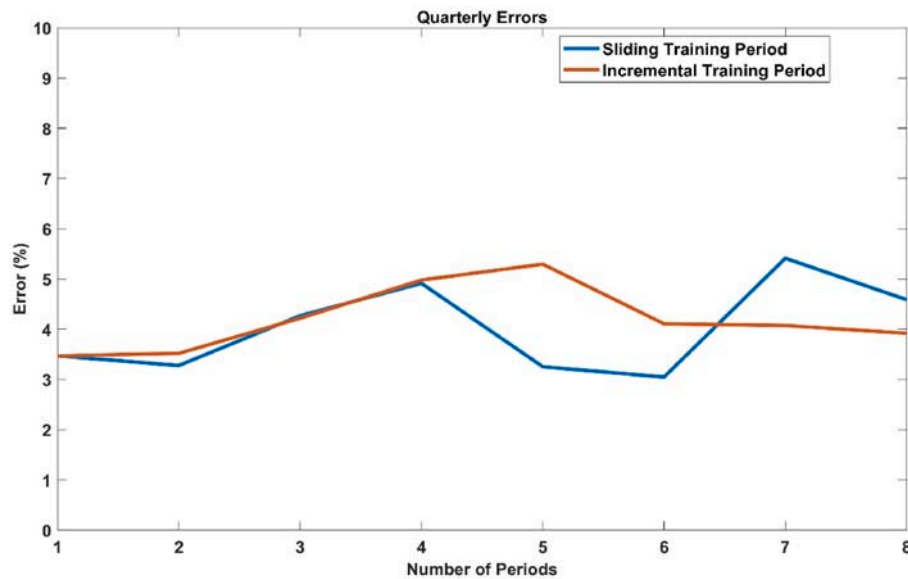**Fig. B.** Error ranges for monthly time slices

Fig. C. Error ranges for quarterly time slices

References

Abu-Rayash, A., Dincer, I., 2020. Analysis of the electricity demand trends amidst the COVID-19 coronavirus pandemic. Energy Res. Soc. Sci. 68, 101682. https://doi.org/10.1016/j.erss.2020.101682.

Andersen, F.M., Larsen, H.V., Gaardestrup, R.B., 2013. Long term forecasting of hourly electricity consumption in local areas in Denmark. Appl. Energy 110, 147–162. https://doi.org/10.1016/j.apenergy.2013.04.046.

Aruga, K., Islam, M.M., Jannat, A., 2020. Effects of COVID-19 on Indian energy consumption. Sustain. Times 12, 5616. https://doi.org/10.3390/su12145616.

Bašta, M., Helman, K., 2013. Scale-specific importance of weather variables for explanation of variations of electricity consumption: the case of Prague, Czech Republic. Energy Econ. 40, 503–514. https://doi.org/10.1016/j.eneco.2013.07.023.

Buechler, E., Powell, S., Sun, T., Zanocco, C., Astier, N., Bolorinos, J., Flora, J., Boudet, H., Rajagopal, R., 2020. Power and the Pandemic: Exploring Global Changes in Electricity Demand during COVID-19 (arXiv).

Carvalho, M., de Delgado, D.B., de Lima, K.M., de Cancela, M., dos Siqueira, C.A., de Souza, D.L.B., 2020. Effects of the COVID-19 pandemic on the Brazilian electricity consumption patterns. Int. J. Energy Res. https://doi.org/10.1002/er.5877.

De Felice, M., Alessandri, A., Catalano, F., 2015. Seasonal climate forecasts for medium-term electricity demand forecasting. Appl. Energy 137, 435–444. https://doi.org/10.1016/j.apenergy.2014.10.030.

De Felice, M., Alessandri, A., Ruti, P.M., 2013. Electricity demand forecasting over Italy: potential benefits using numerical weather prediction models. Elec. Power Syst. Res. 104, 71–79. https://doi.org/10.1016/j.epsr.2013.06.004.

Delgado, D.B. de M., Lima, K.M. de, Cancela, M. de C., Siqueira, C.A. dos S., Carvalho, M., Souza, D.L.B. de, 2021. Trend analyses of electricity load changes in Brazil due to COVID-19 shutdowns. Elec. Power Syst. Res. 193, 107009. https://doi.org/10.1016/j.epsr.2020.107009.

EMRA, 2020. Electricity sector monthly reports [WWW document] (accessed 8.1.20). https://www.epdk.gov.tr/Detay/Icerik/3-0-23/elektrikaylik-sektor-raporlar.

EPIAS, 2020. Energy Exchange Istanbul (EXIST) transparency platform [WWW document] (accessed 1.12.21). https://seffaflik.epias.com.tr/transparency/.

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

Ghiani, E., Galici, M., Mureddu, M., Pilo, F., 2020. Impact on electricity consumption and market pricing of energy and ancillary services during pandemic of COVID-19 in Italy. Energies 13, 3357. https://doi.org/10.3390/en13133357.

Hor, C.L., Watson, S.J., Majithia, S., 2005. Analyzing the impact of weather variables on monthly electricity demand. IEEE Trans. Power Syst. 20, 2078–2085. https://doi.org/10.1109/TPWRS.2005.857397.

Islam, S.M., Al-Alawi, S.M., Ellithy, K.A., 1995. Forecasting monthly electric load and energy for a fast growing utility using an artificial neural network. Elec. Power Syst. Res. 34, 1–9. https://doi.org/10.1016/0378-7796(95)00950-M.

JHU, 2021. COVID-19 dashboard by the center for systems science and engineering (CSSE) at Johns Hopkins university [WWW document] (accessed 1.13.21). https://gisanddata.maps.arcgis.com/apps/opsdashboard/index.html#/bda7594740fd40299423467b48e9ecf6.

Leach, A., Rivers, N., Shaffer, B., 2020. Canadian electricity markets during the COVID-19 pandemic:an initial assessment. Can. Publ. Pol. 46, S145–S159. https://doi.org/10.3138/CPP.2020-060.

Liu, X., Lin, Z., 2021. Impact of Covid-19 pandemic on electricity demand in the UK based on multivariate time series forecasting with Bidirectional Long Short Term Memory. Energy 227, 120455. https://doi.org/10.1016/j.energy.2021.120455.

Lo, K.L., Wu, Y.K., 2003. Risk assessment due to local demand forecast uncertainty in the competitive supply industry. IEE Proc. Generat. Transm. Distrib. 150, 573–581. https://doi.org/10.1049/ip-gtd:20030641.

López Prol, J., O, S., 2020. Impact of COVID-19 Measures on Short-Term Electricity Consumption in the Most Affected EU Countries and USA States. iScience. https://doi.org/10.1016/j.isci.2020.101639.

Lu, H., Ma, X., Ma, M., 2021. A hybrid multi-objective optimizer-based model for daily electricity demand prediction considering COVID-19. Energy 219, 119568. https://doi.org/10.1016/j.energy.2020.119568.

Lusis, P., Khalilpour, K.R., Andrew, L., Liebman, A., 2017. Short-term residential load forecasting: impact of calendar effects and forecast granularity. Appl. Energy 205, 654–669. https://doi.org/10.1016/j.apenergy.2017.07.114.

Momani, M.A., 2013. Factors affecting electricity demand in Jordan. Energy Power Eng. 5, 50–58. https://doi.org/10.4236/epe.2013.51007.

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabir, A., Iosifidis, C., Agha, M., Agha, R., 2020. The socio-economic implications of the coronavirus pandemic (COVID-19): a review. Int. J. Surg. 78, 185–193. https://doi.org/10.1016/j.ijsu.2020.04.018.

Niu, J., Xu, Z.H., Zhao, J., Shao, Z.J., Qian, J.X., 2010. Model predictive control with an on-line identification model of a supply chain unit. J. Zhejiang Univ. - Sci. C 11, 394–400. https://doi.org/10.1631/jzus.C0910270.

Norouzi, N., Zarazua de Rubens, G., Choubanpishehzafar, S., Enevoldsen, P., 2020. When pandemics impact economies and climate change: exploring the impacts of COVID-19 on oil and electricity demand in China. Energy Res. Soc. Sci. 68, 101654. https://doi.org/10.1016/j.erss.2020.101654.

Ruan, G., Wu, D., Zheng, X., Zhong, H., Kang, C., Dahleh, M.A., Sivaranjani, S., Xie, L., 2020. A cross-domain approach to analyzing the short-run impact of COVID-19 on the US electricity sector. Joule 4, 2322–2337. https://doi.org/10.1016/j.joule.2020.08.017.

SHURA Energy Transition Center, 2020. 2030 yılına doğru Türkiye'nin optimum elektrik üretim kapasitesi [WWW Document]. URL. https://www.shura.org.tr/wp-content/uploads/2020/09/rapor_TR_web_.pdf.

Snow, S., Bean, R., Glencross, M., Horrocks, N., 2020. Drivers behind residential electricity demand fluctuations due to COVID-19 restrictions. Energies 13, 5738. https://doi.org/10.3390/en13215738.

Suganthi, L., Samuel, A.A., 2012. Energy models for demand forecasting - a review. Renew. Energy Rev. 16, 1223–1240. https://doi.org/10.1016/j.rser.2011.08.014.

Taylor, J.W., 2012. Short-term load forecasting with exponentially weighted methods. IEEE Trans. Power Syst. 27, 458–464. https://doi.org/10.1109/TPWRS.2011.2161780.

Torrini, F.C., Souza, R.C., Cyrino Oliveira, F.L., Moreira Pessanha, J.F., 2016. Long term electricity consumption forecast in Brazil: a fuzzy logic approach. Socioecon. Plann. Sci. 54, 18–27. https://doi.org/10.1016/j.seps.2015.12.002.

Turkish Electricity Transmission Corporation (TEIAS), 2020. Electricity report [WWW document] (accessed 1.12.21). https://www.teias.gov.tr/.

University of Oxford, 2020. Coronavirus government response tracker [WWW document] (accessed 1.12.21). https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.

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

Yukseltan, E., Yucekaya, A., Bilge, A.H., 2020. Hourly electricity demand forecasting using Fourier analysis with feedback. Energy Strateg. Rev. 31, 100524. https://doi.org/10.1016/j.esr.2020.100524.

Yukseltan, E., Yucekaya, A., Bilge, A.H., 2017. Forecasting electricity demand for Turkey: modeling periodic variations and demand segregation. Appl. Energy 193, 287–296. https://doi.org/10.1016/j.apenergy.2017.02.054.

Zhong, H., Tan, Z., He, Y., Xie, L., Kang, C., 2020. Implications of COVID-19 for the electricity industry: a comprehensive review. CSEE J. Power Energy Syst. 6, 489–495. https://doi.org/10.17775/CSEEJPES.2020.02500.