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Disaggregation of Hourly Electricity Consumption into Subconsumptions

Ahmet Yucekaya*, Ayse H. Bilge, Ergun Yukseltan, Şenda Yıldırım, İrem Kalafat

Department of Industrial Engineering, Kadir Has University, Istanbul, Turkiye. *Email: ahmety@khas.edu.tr

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ABSTRACT

Electricity consumption in a country, region, or city comprises demand from residential, industrial, commercial, and other specific consumptions such as street lighting, and agricultural related consumptions, along with losses from leakage and transmission and unauthorized usage. However, tracking the specific consumption components in real time is challenging, as detailed consumption data for each category is typically determined only after billing periods. Understanding the electricity demand of each subcategory and its proportion within total consumption is crucial for effective system planning and operation. This study develops a framework to disaggregate total electricity consumption into subcategories—residential, industrial/commercial, irrigation, and lighting—at an hourly resolution. The methodology depends crucially on a special day detection approach that identifies consumption patterns on days at which where electricity usage is at its lowest, without any a priori information of the holidays in each country or a region. Based on this, baseline consumption levels for different periods are determined, indices for subcategories are developed, and time series models are generated to analyze consumption trends. For validation, the methodology is applied to Turkish electricity data, where the structure of consumption is analyzed in relation to holidays and special occasions, accounting for the reduction in demand during these periods. The proportions of residential, industrial/commercial, and lighting consumption are derived from total consumption, and the remaining categories are estimated accordingly. Finally, the accuracy and convergence of the results are evaluated, and the findings are presented with their implications for energy planning and grid management.

Keywords: Electricity Consumption Analysis; Electricity Demand Forecasting, Special Day Detection, Consumption Category Analysis; Consumption Disaggregation
JEL Classifications: Q47, E17, Q40

1. INTRODUCTION

Electricity is a fundamental energy source, essential for daily life, industrial operations, transportation, healthcare, and other critical sectors. The reliability of electricity supply is crucial, as power outages can lead to significant financial losses. Therefore, extensive efforts are made to ensure a continuous, cost-effective, and secure energy supply. Electricity consumption patterns vary based on consumers' work and lifestyle habits.

Residential electricity consumption follows cyclical trends, influenced by work and school schedules, homecoming times, sleep-wake cycles, and holidays. Industrial consumption, on the other hand, is shaped by working hours, shift schedules, and holiday closures, resulting in lower weekend demand. In contrast, commercial electricity demand depends highly on the social structure of a country, and it may remain relatively stable, often extending beyond traditional working hours. Additional consumption types, such as lighting and agricultural use, further contribute to overall demand.

Across different countries, electricity consumption patterns reflect the habits and lifestyles of their populations. However, existing electricity data reporting methods are limited; most regions only publish total hourly electricity consumption. In Türkiye, monthly consumption data for all sectors is provided in the Energy Market

Regulatory Authority (EPDK) reports (EPDK, 2024), while real-time hourly total electricity consumption is published by the Energy Markets Operation Company (EPİAŞ) (EPİAŞ, 2024). However, this data is not categorized by consumer groups, making it difficult to determine the specific electricity usage for lighting, heating, or cooling across different sectors. We will use monthly sectoral billing information for Turkiye to illustrate the demand segregation methodology.

Understanding sector-specific electricity demand is critical for system operators, distribution companies, and producers. As noted above, various components of the total electricity consumption have strongly distinctive features on hourly basis. While modern smart meters enable better classification of consumption types, older meters remain widely used. Furthermore, different meter types may record multiple consumption classes, complicating the classification process. Regional factors such as heating requirements and weather conditions significantly influence residential electricity demand. Additionally, in many distribution regions, not all meter types are systematically recorded, and meter readings occur on a monthly or periodic basis, limiting the ability to track real-time consumption trends.

In Turkiye, metered electricity consumption data is categorized as household, industrial, commercial, lighting and agricultural consumption and published monthly as sector reports (EPDK, 2024). However, hourly breakdowns of consumption and demand remain difficult to obtain, leading to reliance on transmission line capacity estimates, which may lack precision. Given the structure of electricity markets, all day-ahead, intra-day, and real-time planning must be conducted on an hourly basis, with day-ahead forecasts made in advance.

Disaggregating total electricity consumption into residential, industrial, and commercial categories on an hourly basis would offer significant advantages:

- It would enable more accurate pricing policies and timing of discounts.
- In cases of supply shortages, understanding sectoral usage patterns would allow for better scheduling of planned outages.
- Consumer prioritization could be optimized during times of energy scarcity.
- With the increasing share of renewable energy sources, improved understanding of consumption patterns would help in better planning for energy storage.
- Overall, data-driven energy planning would benefit all stakeholders, including generation, transmission, and distribution companies.

This study aims to develop a quantitative methodology for disaggregating total electricity consumption into subcategories such as residential, lighting, and commercial/industrial consumption at an hourly resolution. The proposed approach provides a framework for identifying consumption patterns, assisting decision-makers in market analysis and grid planning. Although this study focuses on Turkiye, the methodology is adaptable for operational planning in other regions and countries.

The novelty of this research lies in its comprehensive analysis of total electricity consumption, considering variations in population size, industrialization, cultural factors, and consumption behaviors across different regions. The specific objectives include:

- Analyzing country-specific electricity consumption and developing indices for different usage types.
- Identifying special days (e.g., national and religious holidays) from total electricity consumption to determine baseline electricity demand.
- Developing a methodology to assess the proportional share of industrial/commercial, residential, irrigation, and lighting consumption within total hourly electricity demand.

This study presents a literature review, an analysis of the effects of electricity markets, and a detailed description of the developed models and methodologies, outlining step-by-step problem-solving approaches. The results are analyzed and explained through visual representations, providing insights into electricity consumption segmentation. The findings are then discussed in detail, leading to conclusions and recommendations.

The remainder of this research is structured as follows. Section 2 presents the problem background and literature review. Section 3 discusses consumption analysis and subcategories. Section 4 introduces the proposed methodologies and consumption classification. Section 5 provides the application of the methodologies and their results. Finally, Section 6 discusses insights derived from the computational results in the conclusion.

2. PROBLEM BACKGROUND AND LITERATURE REVIEW

Research on electricity demand and consumption has primarily focused on forecasting methodologies, with an extensive body of literature on the subject. Traditional forecasting approaches widely employ linear models and time series techniques. Anand and Suganti (2012) provide an overview of forecasting methods, including Artificial Neural Networks (ANNs), Genetic Algorithms (GA), Support Vector Machines (SVM), Particle Swarm Optimization (PSO), and other numerical techniques. Additionally, ARMA and ARIMA models are frequently used to incorporate stochastic effects into demand forecasting. Studies by Andersen et al. (2013), Niu et al. (2010), and Lo and Wu (2003) indicate that ARIMA models effectively capture long-term trends and short-term fluctuations, such as weekly demand variations and economic growth trends.

Time series models have also been enhanced with heuristic and hybrid approaches. Taylor and Buizza (2003) analyzed electricity demand data from England and Wales, applying an AR model alongside the Holt-Winters method for improved forecasting accuracy. Wang et al. (2012) introduced the PSO-optimal Fourier method, which refines seasonal ARIMA forecasts, demonstrating superior accuracy when applied to the Northwest China electricity grid. Similar research by Ren et al. (2016), Vilar et al. (2012), Filik et al. (2011), and Chakhchoukh et al. (2010) further supports the effectiveness of ARIMA-based forecasting models.

The impact of temperature on electricity demand varies depending on infrastructure, heating sources, and climate conditions, but it is widely integrated into forecasting models to enhance accuracy. Several studies, including Taylor (2003), De Felice et al. (2013; 2015), Lusis et al. (2017), Islam et al. (1995), Hor et al. (2005), Momani (2013), and Bašta and Helman (2013), explore different aspects of temperature's effect on electricity consumption. Seasonal cycles, especially those driven by heating and cooling needs, significantly influence total electricity demand, particularly in residential and commercial sectors. Forecasting methodologies incorporating time series analysis, statistical techniques, surveys, artificial neural networks, simulations, heuristic algorithms, and temperature-based models have been developed to address these variations. However, most existing studies focus on predicting total electricity demand rather than disaggregating consumption into finer subcategories.

Despite advances in forecasting, research on segmentation, classification, and disaggregation of electricity consumption remains limited. Gajowniczek and Ząbkowski (2016; 2017; 2018) proposed a segmentation approach for forecasting individual household electricity load using smart meter data. Similarly, Ghofrani et al. (2011) applied Kalman filtering to predict short-term residential demand based on real-time smart meter data. Arora and Taylor (2016) introduced a probabilistic approach using conditional kernel density estimation for smart meter consumption forecasting. Additional studies by Wijaya et al. (2015), Hsiao (2014), and Taieb et al. (2016) further explore consumption prediction methods based on smart meter analytics. However, these studies do not provide the detailed disaggregation analyses presented in this research.

The lack of real-time hourly consumption data has also been noted in the literature. Valdes and Camargo (2021) proposed a segmentation method for Chile to generate synthetic electricity data for the paper and food industries, compensating for the absence of real-time hourly consumption records. Similarly, Han et al. (2022) introduced a time-series-based approach to generate synthetic hourly electricity consumption data for residential usage.

Recent research has focused on classifying electricity consumption patterns across 38 European countries, analyzing hourly demand variations and identifying special days such as holidays where consumption deviates from normal trends (Yukseltan et al., 2017; 2020; 2022; 2024). Using hourly total electricity consumption data, researchers examined holiday consumption patterns, national holiday effects, and weekend-weekday variations, quantifying their impacts on residential, industrial, and commercial electricity demand. Additionally, Fourier series expansion techniques have been employed to analyze seasonal variations, particularly the summer-winter consumption trends in different sectors (Yukseltan et al., 2022).

This study aims to analyze the structure of total electricity consumption at an hourly resolution, tracking the dynamics of sub-consumption groups to quantify their respective shares within total demand. To achieve this, we propose:

- A methodology to identify special days, such as holidays, based on consumption data, which will serve as a reference for estimating baseline electricity consumption.
- Consumption indices for different subcategories, including residential, industrial, commercial, lighting, and irrigation.
- Time series models to determine sectoral consumption patterns and proportions.

By offering a novel approach to electricity consumption disaggregation, this study provides valuable insights for energy policymakers, system operators, and market analysts, enabling more effective electricity demand management and planning.

3. ANALYSIS OF ELECTRICITY CONSUMPTION

Researchers have previously used total electricity consumption data at an hourly resolution, developed methods for total demand forecasting, and applied them to data from Turkey (Yukseltan et al., 2017; Yukseltan et al., 2020) and various European countries (Yukseltan et al., 2024). Additionally, qualitative results regarding the distribution of electricity consumption among consumer groups were obtained based on seasonality in total demand, weekday-weekend consumption, and consumption profiles on special days. The impact of restrictions due to Covid-19 on daily consumption profiles was also qualitatively examined.

In the mentioned studies, electricity consumption was modeled using a modulated Fourier Series expansion. Furthermore, meteorological data was necessary in cases where the use of electricity for heating and cooling was predominant. This allowed for precise forecasts of total consumption. In Turkey, proportional values for consumer groups were obtained for special days and holidays, where electricity consumption is predominantly residential (Yukseltan et al., 2022). Additionally, in the study examining total consumption in European countries, qualitative results were obtained regarding the distribution among consumer groups and the use of electricity for heating and cooling purposes (Yukseltan et al., 2024).

3.1. Data Analysis for Electricity Consumption

In the Turkish electricity market, hourly demand and hourly production data, as well as production data distributed by resources, are published by EPİAŞ. This data is aggregated total consumption without any specific consumption details. On the other hand, electricity consumption is generally classified as residential, industrial, and commercial consumption for invoicing purposes. Other areas of consumption, such as rail transport, street lighting, agricultural needs, electric vehicles, unless separately billed, are included in the above basic types. Monthly data collected from meters of each class in distribution regions are published as monthly electricity sector reports (EPDK, 2024). Türkiye's total electricity consumption published in hourly resolution on the EPİAŞ transparency platform (EPİAŞ, 2024) includes electricity sent to all distribution regions and it is not possible to separate it according to consumption classes. Figure 1 shows the real-time consumption of Turkiye taken from EPİAŞ Transparency platform.

Subconsumptions are generally calculated from monthly meter information and are reported from distribution regions. Table 1

Figure 1: Hourly electricity generation, price and consumption in Turkiye (EPİAŞ, 2024)

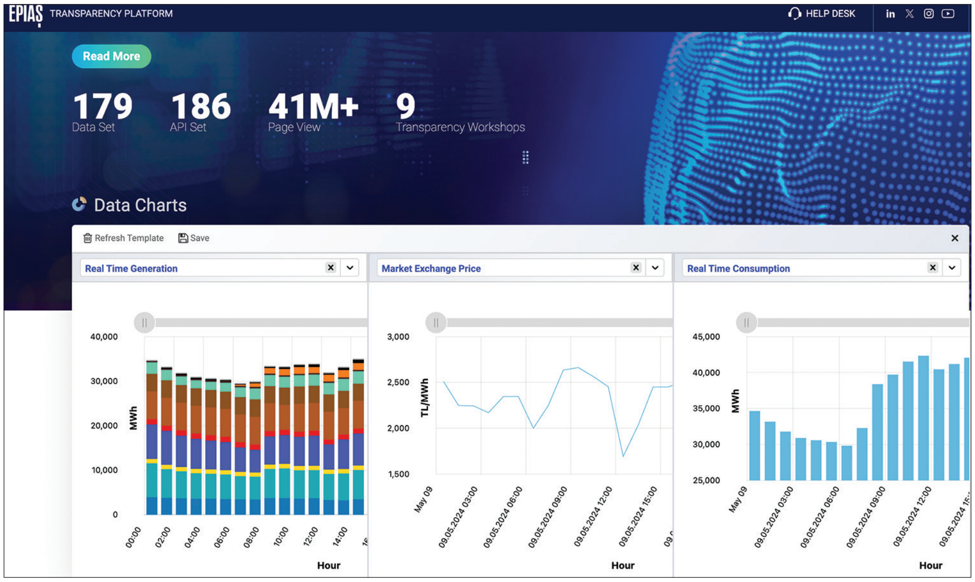


Table 1: EPİAŞ hourly electricity consumption data for 2022 (EPDK, 2024)

Sector	Electricity consumption (MWh)	Ratio (%)
Industry	111,572,993	33.9
Loss	76,600,098	23.2
Commercial	61,360,984	18.6
Residential	61,337,914	18.6
Agricultural watering	13,359,192	4.1
Lighting	5,402,816	1.6
TOTAL	329,634,000	100

shows the annual sum of total electricity consumption data of each class for 2022. Monthly distributions of these data are provided in EPDK sector reports (EPDK, 2024). The consumption values that are classified for each month for the years 2017-2022 are given in Appendix.

The residential component consists of consumption arising from household appliances, lighting, heating, and cooling needs. Appliances generally operate continuously, but lighting needs are determined by the daylight cycle, which is dependent on latitude. Consumption for heating or cooling needs is much more complex; it depends on weather conditions and social habits that determine comfortable temperatures and even show memory effects from the heating of buildings.

Commercial use of electricity is mostly limited to daytime hours, but weekend effects can vary. On the other hand, offices are generally closed on weekends. Industrial use of electricity is a significant component of non-residential consumption and can be difficult to predict as some factories may operate continuously. However, in some countries, there may be holidays or holiday periods when all (non-essential) facilities are closed. In such cases, it is possible to estimate the share of purely household consumption from the data. The relative ratios of weekday and weekend consumption are also indicators of industrial activity.

A qualitative approach to demand segregation from aggregate data has been explored in previous work where the authors examined the electricity consumption data of European Union countries and identified different consumption patterns (Yukseltan et al., 2024). For example, Sweden's consumption is seen to be high and irregular in winter, indicating the use of electricity for heating, while increased summer consumption in Croatia indicates a need for cooling. In Germany and Poland, the seasonality of electricity consumption is less pronounced, indicating that electricity is not heavily used for heating or cooling. Consumption patterns for Germany and Poland are on different scales but follow a similar structure throughout the year, characterized by strong weekly variations, as of industrialization. Within the scope of the present work, using the experiences gained, we extend the previous approaches to the quantification of the contributions of subconsumptions to be determined from total hourly electricity consumption and monthly sector reports.

The data used in the study consists of hourly total consumption data provided by the EPİAŞ transparency platform, hourly total consumption data of European countries provided by the European Network of Transmission System Operators (ENTSOE, 2024), and monthly and annual sectoral usage data provided by EPDK. Additionally, hourly consumption data of European countries provided by the European Network of Transmission System Operators (ENTSOE, 2024) was used as test data for the study (Yukseltan et al., 2024). A sectoral comparison of EPİAŞ and EPDK data is presented for the years 2017-2021 is given in Figure 2 whereas data comparison through ratio is given in Figure 3.

3.2. Analysis of Monthly Sectoral Consumption

EPDK data is classified into industrial, residential, commercial, agricultural irrigation, and lighting categories, with shares to the total consumption as given in Table 1. Figure 4 illustrates the monthly consumption patterns for each category, and their changes over the period 2017-2022. Although the shares of agricultural irrigation and street lighting are minor compared to the consumption types above, they are non-negligible. As seen in

Figure 2: Overview of the data for the years (2017-2021)

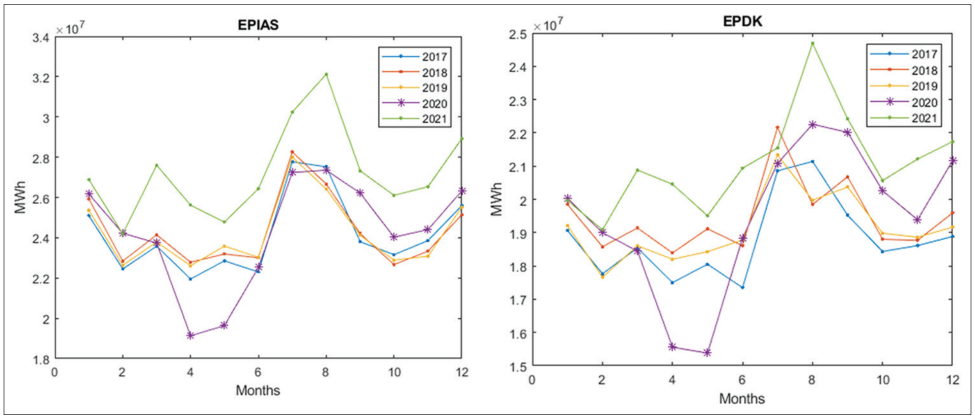


Figure 3: Monthly consumption ratios of EPIAS/EPDK, i.e, actual over billed consumption

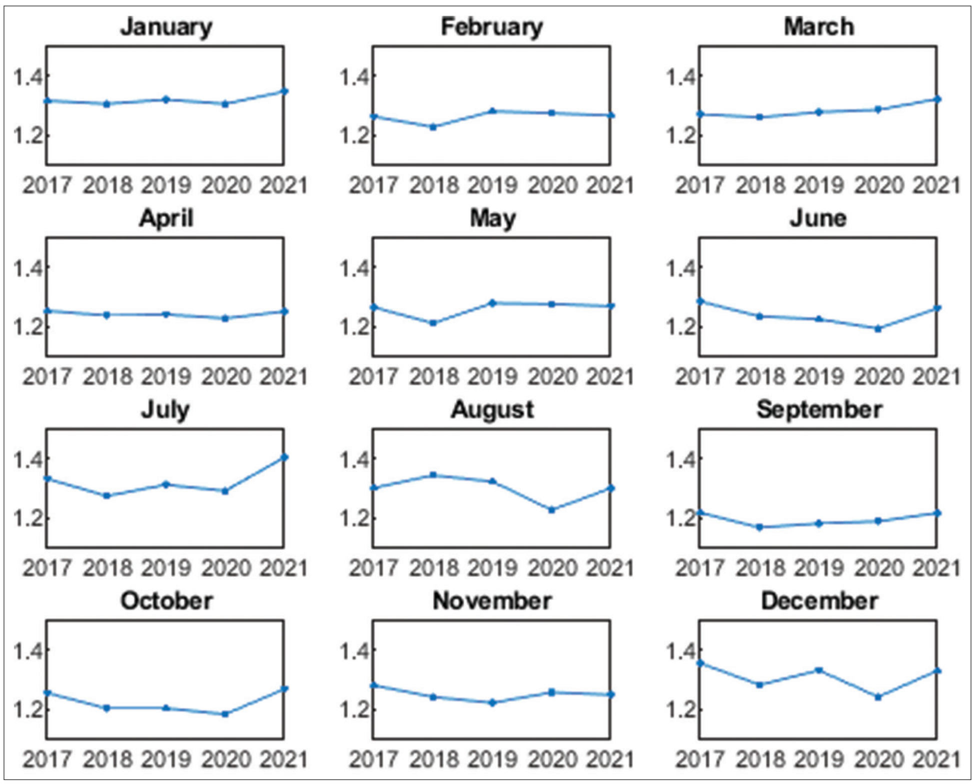


Table 1, losses constitute a sizable proportion of the total electricity production. The difference between actual electricity and billed consumption on a monthly basis for the years 2017-2021 are displayed in Figure 5.

From these figures one can see that during the period March-May 2020, where Covid-19 restrictions were applied, the household consumption was unaltered, industrial consumption decreased but commercial consumption increased.

When analyzing the sub-components, the impact of the pandemic is clearly visible. Until 2020, the residential component followed a relatively stable trend each month, but it showed a significant increase in 2021 and the second half of 2020. This is reflected as a decrease in the industrial component. For commercial establishments, the effect is more limited since many remained partially open even during full lockdowns. Similarly, the agriculture component exhibits different behavior due to seasonal effects. However, it is observed that monthly variations are parallel, follow a consistent trend, and are statistically distributed around an average ratio.

EPDK data categorized into Industrial, Commercial, Residential, Agricultural Irrigation, and Lighting based on billed consumption does not include loss/theft and other unbilled consumption categories. Therefore, the sum of sectoral consumption from EPDK is lower than the actual consumption values provided by EPİAŞ. A comparison of the total consumption values calculated from EPİAŞ and EPDK data is shown in the Figure 5 below.

As seen in the graphs in Figure 5, although some deviations exist, the overall trends remain parallel. In quantitative calculations we

Figure 4: Annual demand ratios for sub-consumptions (2017-2022)

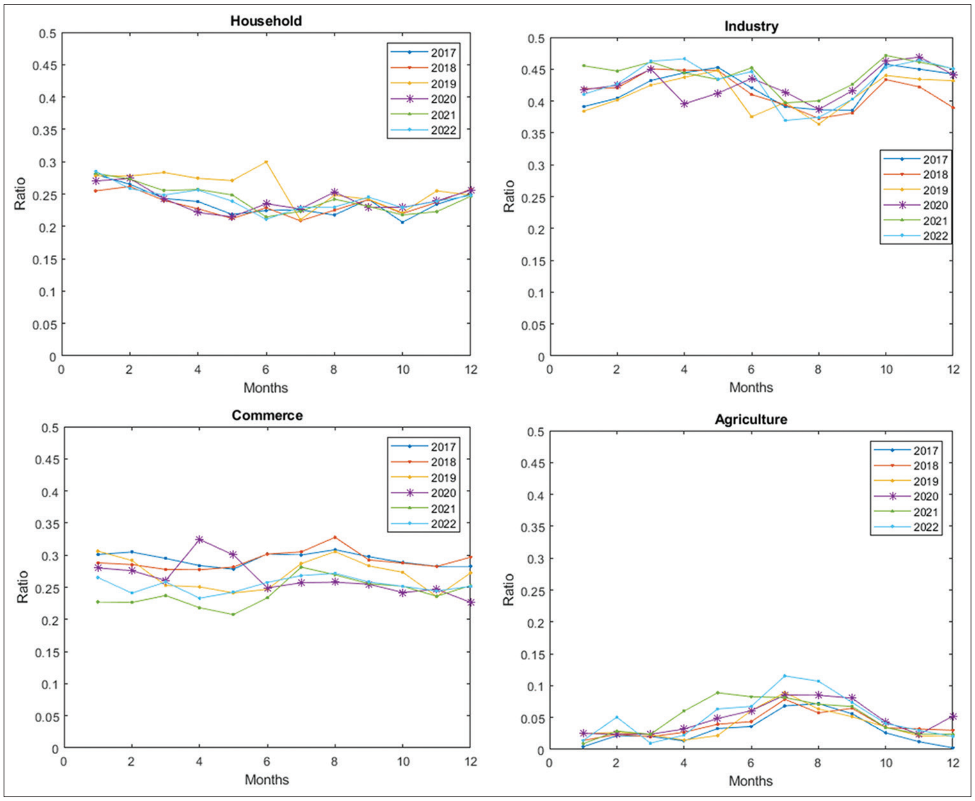
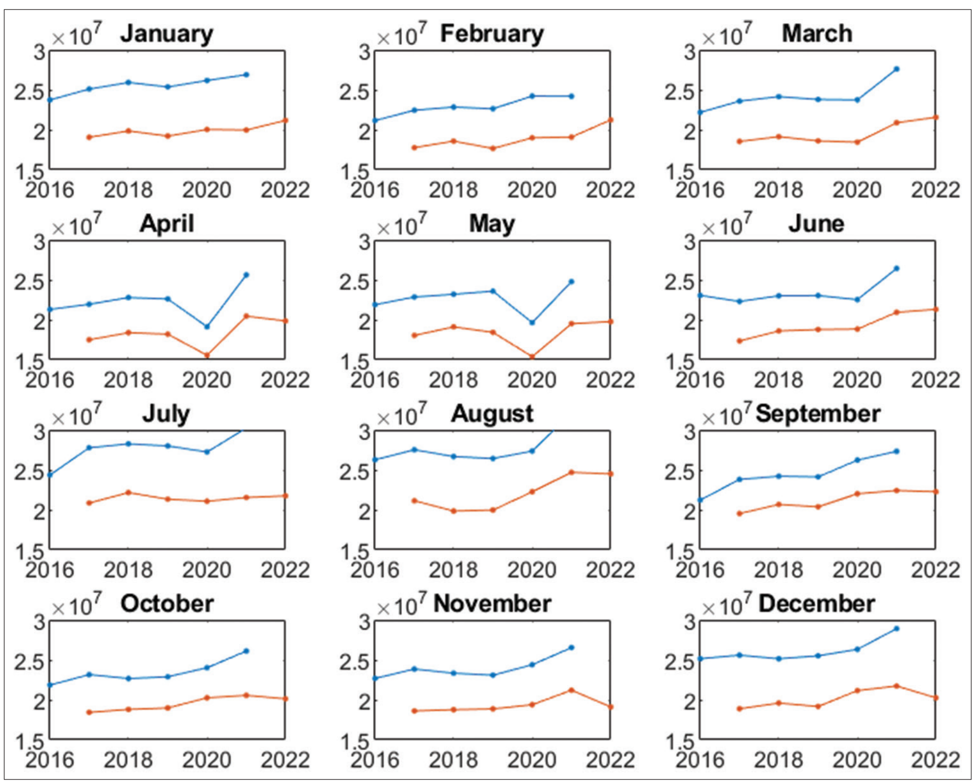


Figure 5: Monthly consumption trends of EPDK (2017-2022, Red) and EPİAŞ (2016-2021, Blue)



will scale the sectoral components of the EPDK data to match the total with the corresponding values obtained by averaging the hourly values published by EPİAŞ.

A sectoral comparison of EPİAŞ and EPDK data, along with corresponding ratios, is presented for January 2017 as an example below. To construct this table, the EPİAŞ/EPDK consumption ratio for total consumption was calculated, and sectoral consumption values from EPDK data were scaled using this ratio. Table 2 presents comparison ratios.

In Section 4.2, we describe the segregation of average household and non-household consumption together with the shares of heating and cooling, while in Section 4.3, we describe the construction of hourly time series based on certain time series of indices. Both methods described above depend crucially on the determination of the "base consumption" which in turn is calculated from the aggregate electricity consumption during "special days", as described in Section 4.1.

4. MODELLING FOR CONSUMPTION CLASSIFICATION

The methodology proposed in this paper relies crucially on the determination of a "base consumption", consisting of electricity used 7 days/24 h, needed in a sense to maintain the infrastructure of the country or of the region under investigation. In Section 4.1, we propose a data-driven methodology for the determination of special hours and special days applicable even to situations where there are no clues to the social structure of the region.

Once special days are determined either using the methods given in Section 4.1, or based on the knowledge of the social structure of the region, the base consumption denoted as B_0 can be determined, as indicated at the end of section 4.2, that is devoted to the segregation of household (H) and non-household (I) electricity consumption, and the break-down of their shares in heating (H_h, I_h), cooling (H_c, I_c) needs and their intrinsic activities (H_I, I_I). These subconsumptions are to be determined in terms of average consumptions during specific periods, by solving a linear system, with some redundancy to account for model validation. The methodology proposed in Section 4.2 aims to provide average values for each of the consumption types above, as discernable from hourly time series. In cases where average values are available, for example via sectoral monthly invoices, such as the EPDK data for Turkiye, they can used alternatively.

The main result of the present work is the methodology for reconstructing hourly sectoral consumption from hourly aggregate consumption and monthly average or total sectoral consumption, as presented in Section 4.3. In this section we define hourly time series as indices of the existence/nonexistence of sector or specific needs related activities, such as the holiday index *h(t)* to identify special days, the day of the week index *d(t)*, to identify week days and weekends, the daylight index *g(t)* to account for illumination needs, the hour of the day *s(t)* and the phase of the day index *p(t)* to discriminate electricity consumption during nighttime, daytime and evenings, a distinction that is relevant for household consumption. The contribution of these indices to the construction of hourly consumption profiles requires insight on the social habits and work principles of the given region. Finally, in Section 4.4, we present the algorithm for the construction of hourly sectoral consumptions.

4.1. Detection of Special Days, Events, and Base Consumption

Special days and events are crucial for determining the daily base consumption profiles residences, hence estimating the share of commercial and industrial consumption. National or religious holidays or annual industrial shutdowns can be considered as an anomaly in data, and time-series methods can also be used for the special day and event detection (Zhang et al., 2019). Most of the existing studies for detecting events focus on the end-user level consumption to explain different load profiles, energy efficiency for household appliances, and energy management (Eibl et al., 2018; Gajowniczek et al., 2017; Goia et al., 2010; Goodwin and Summeridi, 2014). There are different approaches and applied methods to detect special events, but they mostly use smart meter data gathered from specialized devices for specific conditions or users, and they aim to detect occupancy (Akbar et al., 2015; Becker and Kleiminger, 2018). In this work, we adopt the approach of detecting special days as data anomalies.

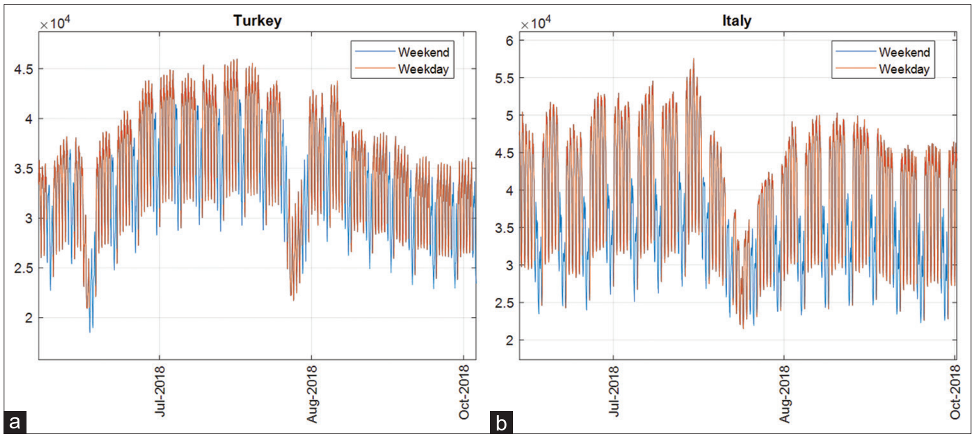
Holidays and special events can be country-specific or regional, like New Year's Eve, Christmas holidays, or changes to daylight savings time throughout Europe. In Muslim countries, the dates of the religious holidays are based on the lunar calendar and they shift back by around 11 days each year relative to the Gregorian calendar. Also, countries with higher industrial activities have industrial shutdown periods in summer. Figure 6 shows a close-up of the data for Turkiye and Italy as typical examples. In Figure 6a, we display the low consumption period in Turkiye, corresponding to religious holidays. The decrease in consumption in Figure 6b corresponds to an industrial shutdown period in Italy.

In a supervised learning scheme, one works with data from a country for which information on special days and events is available. On the other hand, if such information is unavailable, one needs to decide whether the consumption at a given hour or during a given day is unusual. In the present work an unsupervised model to distinguish special/exceptional events from data is proposed to determine whether a specific day is special/exceptional or not.

Table 2: Comparison of EPDK and EPİAŞ consumption data by sector, January 2017

Sector	Consumption share	EPDK (MWh)	EPİAŞ (MWh)
Industrial	0.3914	7 463 646	9 825 980
Commercial	0.3012	5 743 154	7 560 930
Residential	0.2803	5 345 308	7 037 163
Agricultural Irrigation	0.0044	84 358	111 059
Lighting	0.0226	430 995	567 410
Total	1	19 067 464	25 102 545

Figure 6: Holiday consumption changes. (a) Turkiye, low consumption periods coincide with religious holidays; (b) Italy, low consumption period corresponds to the shutdown of industrial facilities in mid-summer



The method is based on the observation that during the day, night hours are characterized by low and steady consumption, and there are days of off-time, i.e., Saturdays and Sundays.

For each country, the period of the data is arranged as starting at hour 00 of the Monday of the 1st year until ending at hour 24 of the Sunday of the last year under consideration. If the data covers N weeks, this time series is arranged in the form of a matrix S_{total} with 24 rows and $7\times N$ columns. With this rearrangement, the columns with index $6+7k$, $k = 0,1,\ldots,N$, correspond to Saturdays, and the columns with index $7k$, $k = 1,2,\ldots,N$ correspond to Sundays, and the remaining columns correspond to weekdays. Then, matrices corresponding to weekdays, Saturdays, and Sundays are denoted by S_w,S_{sat}, S_{sun}, respectively. With this setup, each row of S_{total} is a time series for a given hour.

Let $t_{h,d}$ be the consumption at the hour h of the day d. To decide whether $t_{h,d}$ is an outlier or not, we compare it to the mean of five hours, covering two hours before and two hours after the current hour h. The consumption ratio, $O_{h,d}$, is defined as

$$O_{h,d} = \frac{t_{h,d}}{(t_{h-2,d} + t_{h-1,d} + t_{h,d} + t_{h+1,d} + t_{h+2,d})/5} \quad (1)$$

We choose a threshold value $T_{h,d} = 0.95$ to decide whether the hour h of day d is an exceptional hour or not. That is, we define the index $E_{h,d} = 1$ if $O_{h,d} < T_{h,d}$, otherwise $E_{h,d} = 0$. Thus, depending on the threshold, each hour is classified as an "exceptional hour" ($E_{h,d} = 1$) or an "ordinary hour" ($E_{h,d} = 0$).

To decide whether a day is an ordinary or an exceptional day, we count the number of exceptional hours on that day, as

$$O_d = \sum_{h=1}^{24} E_{h,d} \quad (2)$$

The classification of a day as an "ordinary day" or an "exceptional day" is based on a choice of a threshold T_d. If $O_d > T_d$, then the day d is classified as an "exceptional day"; otherwise, it is classified as an "ordinary day". The number of exceptional hours in a day can be as high as 24, but in general, night hours tend to be ordinary hours, even if a day is an extraordinary day. Based on this observation and preliminary analysis, we have chosen $T_d = 10$. Finally, we define the index $E_d = 1$ if $O_d > T_d$, otherwise $E_d = 0$.

With his method, we were able to identify several exceptional days from data, including Christmas, Easter Monday, and All Saints and some specific holidays such as "Epiphany" (the sixth of every January) in Germany or "All Saints' Day" (first of every November) in certain countries. Also, it is found from the data that there is no holiday on May 1 as a "Labour Holiday" in the United Kingdom, but the "May Bank Holiday" is celebrated on the first Monday of May each year.

When evaluated in terms of electricity consumption, extraordinary days are characterized by low consumption rather than excessive consumption, due to the closure of industrial facilities. For Turkiye's data, special days appear to be most prominently January 1 and the 1st days of religious holidays. A holiday index was created by identifying unusual days for Turkiye and integrated into the models for further data processing. Similarly, extraordinary days were identified and listed for Germany, England, and France but they were not integrated into the models. As an example, we illustrate the application of the method to the detection of unusual days in Germany. Figure 7 below displays the number of exceptional hours in a day. Days with the number of exceptional hours above the threshold are indicated by dots. In Figure 7, a red dot corresponds to holidays, i.e., indicates true positive detection while black dots correspond to ordinary days classified as exceptional, corresponding to false positive detection.

We note that the true positive and false positive detection rates depend on the threshold, which has been set up as 10, i.e., a day is labeled as exceptional if there are more than 10 exceptional hours on that day.

The method for the detection of exceptional days has been applied to aggregate hourly electricity consumption data of Germany, the UK, and France from 2013 to 2018. The success rates for true positive detection are presented in Table 3 while the cases of false detection, i.e., missed holidays are presented in Table 4. There are significant variations in success rates and missed days, underscoring both strengths and areas for improvement. As

Figure 7: Exceptional days with respect to the electricity consumption in Germany

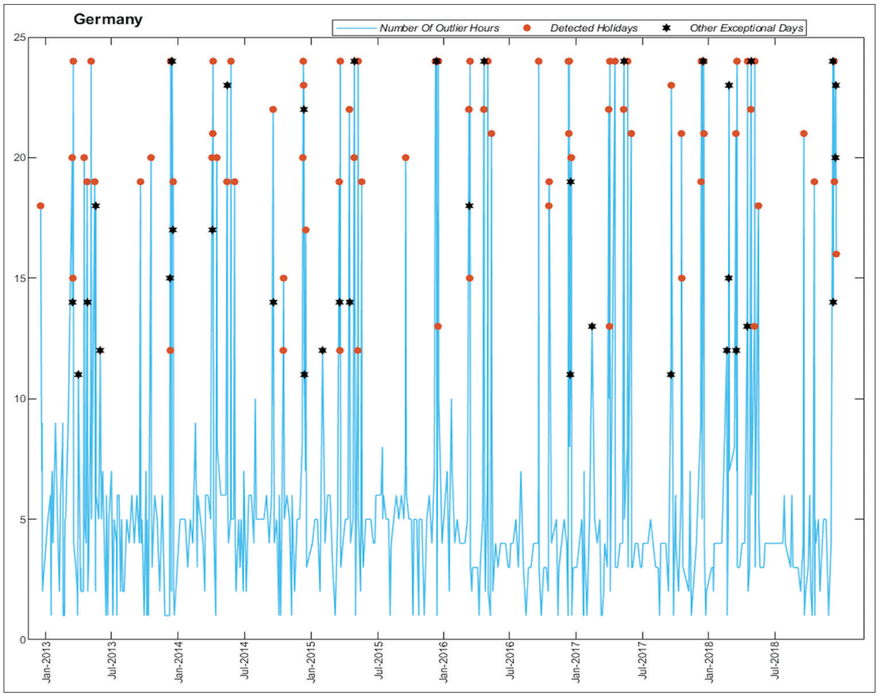


Table 3: Success rates and number of detected special days for Germany, the UK, and France

Country	# of Detected Days	# Total Holidays	# of Detected Holiday	Success Rate
Germany	120	119	84	71%
UK	235	99	52	53%
France	239	84	64	76%

Table 4: Missed special days and reasons by country, numbers in parentheses denote the ratio of missed days to the total number of special days for each country

Germany	Comments	France	Comments	UK	Comments
Epiphany (BW, BY, ST)	Local holiday (6/119)	Good Friday (Bas-Rhin, Haut-Rhin, Moselle)	Local holiday (6/84)	St Patrick's Day (Northern Ireland)	Local holiday (6/99)
Peace Festival in Augsburg (Bavaria)	Local holiday (6/119)	St. Stephen's day (Bas-Rhin, Haut-Rhin, Moselle)	Local holiday (3/84)	Battle of the Boyne (Northern Ireland)	Local holiday (6/99)
Assumption of Mary (Bavaria, Saarland)	Local holiday (6/119)	Bastille day	Weekend missed (2/84)	Summer bank holiday (Scotland)	Local holiday (6/99)
Repentance Day (Saxony)	Local holiday (6/119)	All Saints' day	Sunday missed (1/84)	St. George's day	No holiday (5/99)
Whit Sunday (Brandenburg)	Local holiday (4/119)	Labor day/May day	Sunday missed (1/84)	St Andrew's day (Scotland)	No holiday (5/99)
Reformation Day (BB, MVP, SN, ST, TH)	Local holiday (2/119)	New Year's day	Sunday missed (1/84)	St. David's day (Wales)	No holiday (4/99)
New Year's Eve	No Holiday (1/119)	Armistice day	Saturday missed (1/84)	2nd January (Scotland)	Local holiday (3/99)
All Saints' Day (BW, BY, NRW, RLP, SL)	Sunday missed (1/119)	Easter Sunday	Sunday missed (1/84)	"St Patrick's Day" day off (Northern Ireland)	Local holiday (2/99)
May Day	Sunday missed (1/119 day)	Whit Sunday	Sunday missed (1/84)	"St Andrew's Day" observed (Scotland)	Local holiday (2/99)
Easter Sunday (Brandenburg)	Sunday missed (1/119)	Mother's day	No holiday (1/84)	"Battle of the Boyne" observed (Northern Ireland)	Local holiday (2/99)
Reformation day (Most regions)	Sunday missed (1/119)	Father's day	No holiday (1/84)	Good Friday	Below Threshold (2/99)
		New Year's Eve	No holiday (1/84)	2nd January (substitute day) (Scotland)	Local Holiday (2/99)
				New Year's Day	Sunday Missed (1/99)
				Bank Holiday	No Holiday (1/99)

detailed in Table 4, France exhibits the highest success rate at 76%, with Germany at 71%, and the UK trailing at 53%. The data in Table 4 highlights that the missed days reflect the challenges in detecting holidays accurately within the observed period. For instance, Germany's missed days, such as the Peace Festival in Augsburg and the Assumption of Mary, indicate difficulties in capturing localized and less prominent holidays. Similarly, in the UK, missed holidays like St Patrick's Day and Battle of the Boyne suggest that the algorithm struggles with less uniformly observed days. France's missed days, including Bastille Day and All Saints' Day, often fall on weekends or Sundays, which aligns with typical weekend consumption patterns, making these holidays harder to distinguish from regular weekend consumption. This pattern illustrates the algorithm's challenge in identifying holidays with similar consumption profiles to weekends. The analysis underscores the need for enhanced integration of localized holiday data and further refinement of detection algorithms to improve accuracy across different regions.

Erroneous outcomes of the algorithm as given below in Table 4 shows that special days that have not been detected by the algorithm or are mostly local holidays that may have a limited effect on the aggregate demand.

The determination of special days constitutes a crucial step in the algorithm for segregation of the hourly demand, either with or without any information on the sectoral breakdown of the monthly demand.

In Section 4.2, we discuss a general scheme for the segregation of the hourly demand into the base demand, and heating, cooling and operational consumptions for household and industrial usages. This approach is applicable to cases where no sectoral information is available but requires some a priory information on the social habits of the households and work habits of industrial and commercial institutions.

4.2. Segregation of Household and Industrial Heating and Cooling Demands

In this section, we aim to segregate hourly demand into various sub-consumptions, based on a priori assumptions on the shares of the sub-consumption types at each hour, by solving systems of linear equations. As mentioned above, the determination of special days during which all nonessential industrial, commercial and official activities are halted. The consumption during these days is practically restricted to the "base consumption", that consists of all types of electrical usage by appliances 7/24 all days during a year. A reliable estimation of this base consumption is crucial for the reliability of the estimation of the remaining components.

The method is based on a partitioning of the set hours during a year into subsets on which the hourly consumption is practically constant. For example, during the 24-hour cycle, consumption is nearly constant during night hours but rises sharply during the night to morning transition. The nighttime average may be different during weekdays and weekends and can be interpreted as industrial night shift consumption. In addition, the differences between weekday/weekend consumptions at different seasons are indications of the amount of electricity used for heating or cooling.

The electricity consumption for heating and cooling has a strong dependency on the deviations from comfortable temperatures. In cases where detailed climactic information is available, it can be included as a regressor to the modulated Fourier series expansion, and time series for heating or cooling consumption can be reconstructed. In the present work will not pursue this approach, instead, we split days of the year into 3 categories, as "Spring and Fall", "Winter" and "Summer". In this methodology, it is not necessary to use the whole data, for example, transitional periods can be omitted. This grouping of the days is represented as the rows of Table 5 below and represents the contribution of the heating and cooling to the consumption.

The splitting of the sectoral consumption is based on the differences between the consumption during special days, weekdays, weekends, daytime and nighttime hours. For this purpose, similar consumption periods should be identified, and at this stage differences between social and professional practices between countries become decisive. As an example, we note that for north European countries the consumption profile of Saturdays is closer Sunday's profile, while for southern European countries it is closer to the profile of weekdays. In Table 5, we present a simple model, consisting of the splitting of the aggregate consumption into 3 components, as the "base consumption", "household consumption", H and "industrial/commercial consumption", represented by the grouping of the hours of a year as indicated. Considering the heating and cooling components, the model includes 7 variables, as displayed in Table 5. Here we note that, in this section, the "industrial" component includes commercial electricity usage, because their distinction is not observable from the time series data, i.e., in the time series, the consumption of a factory that works only weekdays/work hours is indistinguishable from the consumption of an institution that is works during the same hours. Thus, although the monthly billing data segregates non-household consumers as commercial and industrial, these groups cannot be distinguished at the hourly resolution. In Table 5, each cell represents a linear equation for the consumption types, hence there are 9 equations for 7 unknowns. The redundancy in the system is intentional and serves as check points for consistency. Detailed description of the groupings is given below.

Consumption patterns during special days occurring in different seasons provide information about heating and cooling demand. During special days occurring in spring or autumn, heating and

Table 5: Electricity components based on the seasons, type of days and hours

Season	Holiday Nighttime (Hours 00:00-05:00)	Holiday and Sunday daytime	Weekday, daytime
Spring and Fall	B_0	$B_{0+}H_1$	$B_0+H_1+I_1$
Winter	B_0+H_h	$B_0+H_1+H_h$	$B_0+H_1+I_1+I_h+H_h$
Summer	B_0+H_c	$B_0+H_1+H_c$	$B_0+H_1+I_{1+}I_c+H_c$

cooling needs are minimal, and electricity consumption consists of basic household usage. For holidays occurring in winter or summer, the consumption would be the sum of basic household usage and household heating and cooling. The base consumption, B_0, that will be precisely defined in Section 4.3, is determined by the consumption specific to night hours of special days, during spring and fall.

Heating and cooling needs depend on the differences between actual temperature and comfortable temperatures, but in cases where climactic information is unavailable, average deviations from spring and fall consumptions can be considered as a reasonable alternative to provide a measure of the heating and cooling demands. Assuming that heating and cooling consumptions are uniform during the day, night hours of special days in Winter and in summer provide information on heating and cooling needs. spring and fall are used to determine average base consumption, that we denote as B_0.

Demand we apply the determination of special days to the segregation of industrial and household demand, further subdivided into sub-consumptions for heating and cooling. Electricity consumption differs on holidays from typical consumption patterns as the closure of industrial facilities is common for such nationwide events. Public and industrial routines change during these periods, and these changes can be used to estimate the portion of industrial and household consumption on total demand.

The consumption components are classified by the type of a day, and by season. Electricity consumption of industrial plants and offices is combined, and sectoral consumption is grouped as "household" (H) and "industrial" (I). Days of the year are grouped as "Holiday", "Sunday" and "Weekday". Holidays correspond to special days during which all non-critical industrial plants are shut down. Sundays are characterized by the closure of all non-essential industrial plants and offices. As most industrial plants work at least half a day on Saturdays, at a first approximation, Saturdays are included in the Weekday category. The classification concerning seasons aims to reflect consumption for heating and cooling, hence seasons are grouped as "Spring-Autumn", "Winter" and "Summer". Consumption types are denoted as B_0, for the base consumption, H_1, H_h, H_c, for household consumption, and I_1, I_h, I_c, for industrial consumption, as described below.

To summarize, the method is based on the fact that electricity consumption during holidays in spring and fall, at night hours is the base consumption B_0, that consists of electricity used by non-stop working industrial plants, household appliances, and security devices. Daytime, exclusively household consumption H_1 consists of the additional load during holidays and Sundays. During weekdays, industrial consumption I_1 is added. Finally, consumptions for household and industrial heating and cooling needs are added during winter and summer, as displayed in Table 3.

- Base consumption including industrial non-stop production (B_0): This component consists of the consumption for the industrial sectors that never stop their production, even on holidays. The lowest consumption periods in the consumption profile of a country are represented by B_0.
- Household usage (H_1): This component consists of the electricity used in residential units on a 24-h basis, such as refrigerators, computers, and other home appliances, and the consumption for illumination purposes. This component of electricity consumption is quite deterministic, and it consists of a constant term superimposed by variations with a 24-h period. The shape of the daily variation curves reflects illumination needs during shorter daylight hours in winter and gives clues about the work habits in society.
- Household heating-cooling (H_h, H_c): This component is the consumption due to household heating, and it appears as high and irregular consumption in winter and summer. It has a strong dependence on deviations from comfortable temperatures. The heating-cooling requirement in social areas is the same throughout the week, i.e., for both weekdays and weekends, and they are considered as part of household heating-cooling.
- Industrial and commercial consumption (I_1): This component consists of electricity used by industrial plants and commercial facilities that work during weekdays. Office consumption is considered part of industrial consumption. This component can be estimated from the difference between weekday and weekend consumption.
- Industrial and Commercial heating-cooling (I_h, I_c): This component consists of heating and cooling consumption in the industry; seasonal differences on holidays and weekends can be used to estimate a portion of this consumption.

The relation between these components are based on the season and of the type of the day, as shown in Table 5, where we divide electricity consumption into its components according to season and type of day. The consumption at a given hour is categorized as follows:

As seen in Table 3, we take average consumption at nighttime in spring and autumn as a reference base consumption because we assumed that there is no or very little consumption for heating-cooling in this period. Also, household consumption is negligible at night-time due to consumers' daily routines. The exact period of winter and summer differs because of cooling and heating. Therefore, if we denote the hourly consumption on holidays as P_{ni}, where i represents the hour of day n, and k represents the total number of holidays in a given period, base consumption I_0 will be calculated as follows.

$$B_0 = \frac{\sum_{n=1}^{k}\sum_{i=1}^{5} P_{ni}}{5 * k} \quad (3)$$

The average consumptions in each category can be evaluated similarly.

As an example of this methodology, we present the special day detection methodology and segregation for industrial and household consumption methodology are applied to Turkiye and Germany. The weights of other variables can be calculated after determining the average base consumption and setting it as 100%. Each component's weights are shown in Table 6 for

Table 6: Weights of electricity consumption components for Turkiye and Germany (2006-2018)

Country	H_0(%)	H_h(%)	H_c(%)	I_0(%)	I_1(%)	I_h(%)	I_c(%)
Turkiye	12.21	6.84	13.71	100	23.32	1.69	9.02
Germany	20.62	~0	1.05	100	31.35	7.08	~0

Turkiye and Germany for the periods 2016-2018 and 2006-2018, respectively. Cooling consumption in summer is more than heating consumption in winter because Turkiye mostly depends on natural gas for heating in winter. Moreover, the cooling requirement is higher for social areas and households than for commercial and industrial areas. On the other hand, Germany's household heating and cooling consumption are minimal because the primary resource for heating is natural gas, and the cooling requirement is relatively less.

4.3. Hourly Time Series for Sectoral Electricity Consumption

In this section we develop time series of indices to generate hourly time series for sectoral consumption. To disaggregate hourly consumption by sector, hourly data has been marked using the following indices:

- Day of the Week Index, d(t):
  - d = 1 → Weekdays (full-time workdays)
  - d = 6 → Saturday (part-time workdays)
  - d = 7 → Sunday (off days)
- Holiday Index, h(t):
  - h = 0 → Normal days (All days except as specified as h = 1 or h = 2)
  - h = 1 → Public holidays (Officially declared special days, where non-essential industries still work)
  - h = 2 → Religious holidays (Officially declared special days, where all non-essential industries are off)
- Daylight Index, g(t):
  - g = 1 → Dark hours
  - g = 0 → Daylight hours
- Hour of the Day, s(t): The hours of the day
  - s(t) varies between 0 and 23, where s(i) represents electricity consumption between hour i and i+1.

Combining the information on the hour of the day and the daylight index, we define a "Phase of the Day" index, to reflect social activities and illumination purposes as follows. Using s(t), the day is divided into 3 time periods: Night, Day, and Evening. To define this classification, an hour that is consistently daylight in all months (e.g., 9 AM) was chosen as the threshold, and "night", "evening" and "day" periods are defined accordingly:

- Phase of the Day, p(t): The phase of the day, as daytime, evening and night
  - Night: s(t) < 9 and g(t) = 1
  - Evening: s(t) > 9 and g(t) = 1
  - Day: g(t) = 0

The day of the week index d(t) is used to segregate industrial, commercial, and household consumption. It should be noted that the specification given above reflects the grouping of the days of the week as workdays, part-time workdays, and off-days. The share of industrial and commercial consumptions in each category depends on the social structure of each country. For example, the hourly consumption profile for the days of the week reveals that in north European countries, the profile of Saturdays is closer to the profile of Sundays, while for south European countries it is closer to the profile of weekdays.

The holiday index h(t) plays a crucial role in the determination of the base consumption, as in most countries there are some special days during which, almost the whole nation celebrates a holiday or takes a common vacation, as discussed in detail in Section 4.1.

The daylight index g(t) is used to segregate the billed consumptions for street illuminations (referred as lighting) and agricultural irrigation. On the other hand, the determination of the consumption for illumination purposes is instead based on the work hours and social habits.

The indices developed can be used to generate hourly sectoral consumption series over monthly or yearly horizons. In either case, the method described in Section 4.1 allows us to single out special days, from which the base consumption B_0, is deduced as a constant. Then, average values of the shares of heating, (H_h, I_h) cooling (H_c, I_c) and sector specific consumptions (H_1, I_1) are obtained as described in Section 4.2.

The time series of indices as described above can be used are used to generate hourly time series for sectoral consumptions H_1 and I_1. On the other hand, hourly time series, even daily averages for (H_h, I_h) and (H_c, I_c) require temperature information at a finer resolution. In cases where this information is not available, it is still possible to work with estimates over a monthly horizon, using the average values obtained as described in Section 4.2.

4.4. Algorithm for the Estimation of Sectoral Subconsumptions at Hourly Resolution

In this section we describe the algorithm for the estimation of sectoral or purpose specific consumptions at the hourly resolution, based on hourly aggregate consumption and average sectoral or purpose specific consumptions.

The methodology is based on the following assumptions.

- Aggregate hourly consumption is available at hourly resolution over a timespan T.
- Special days for the evaluation of the base consumption B_0 are either known or they are obtained by using the algorithm given in Section 4.1.
- Average values for heating, cooling and sector specific consumptions (H_h, I_h, H_c, I_c, H_1, I_1) are either given as external data or they are evaluated for household or non-household consumptions using the algorithm of Section 4.2.
- If temperature information is available at hourly resolution, H_h, I_h, H_c, I_c, are obtained at hourly resolution by linear regression. Otherwise, time horizon T is chosen in such a way that H_h, I_h, H_c, I_c are nearly constants.

- Time series of indices for sector specific consumptions are evaluated as described in Section 4.3.
- Sector specific consumptions H_1 and I_1 (and other available specific subconsumptions) are estimated over the time horizon T at hourly resolution using the time series of indices as developed in Section 4.3.

A pseudo code for the implementation of the algorithm described above, without using temperature information is given below in Figure 8.

In the next section we illustrate the application of the algorithm to the estimation of hourly sectoral consumptions from hourly aggregate data and monthly sectoral billed consumption.

5. ELECTRICITY CONSUMPTION CLASSIFICATION FOR TURKISH MARKET

The description of the aggregate hourly data provided by EPİAŞ and monthly billed sectoral data provided by EPDK have been given in Section 3. As part of preprocessing, the EPDK data is scaled to eliminate the effect of losses and time series indices are evaluated as described in Section 4.3. We will work with a time horizon T of 1-month, to avoid the need for temperature information.

We recall that the EPDK sectoral data includes information on monthly consumptions for street lightings and agricultural irrigation. Although the shares of these billed consumptions are small, they provide good examples on how to use time series of indices to generate hourly consumption. In the following the EPİAŞ hourly data is denoted as $X_0(t)$.

5.1. Step 1: Disaggregation of Lighting L(t) and Agricultural Irrigation A(t) Consumption

The segregation lighting and agricultural irrigation consumptions assume that they are evenly distributed over dark and daylight hours respectively. Note that the daylight index g(t) is in the form of a square wave function that is 1 during dark hours and 0 during daylight hours. Thus, multiplying g(t) and 1-g(t) by average hourly consumptions, we generate hourly time series for lighting agricultural irrigation. Based on this assumption,

1. The total number of dark hours and daylight hours each month are calculated using the daylight index.
2. Total monthly consumptions for lighting and agricultural irrigation consumptions are divided respectively by the total number of dark hours and daylight hours respectively to obtain average hourly consumptions k_1 and k_2 for each category.
3. Estimated hourly lighting and agricultural irrigation consumptions obtained by multiplying these constants by $g(t)$ and 1-$g(t)$, to obtain time series $L(t)$ and $A(t)$, and these are subtracted the hourly total consumption data $X_0(t)$ to obtain the hourly time series $X_1(t)$ as the sum of household, commercial and industrial consumptions. The representation is given below.

$$L(t) = k_1 g(t),\ A(t) = k_2[1-g(t)],\ X_1\ (t) = X_0(t)-k_1 g(t) -k_2[1-g(t)] \quad (4)$$

At this stage, $X_1\ (t)$ represents the total hourly consumption of the industrial, commercial, and residential groups.

5.2. Step 2: Defining Base Consumption for Households and Commercial and Industrial Facilities

We recall that the base consumption in each sector is the electricity consumption required to maintain the infrastructure in that sector. For example, continuous use of refrigerators and other appliances constitute the household base consumption, while for commercial and industrial facilities, the base consumption consists of electricity used for computers, security systems and other essential equipment. In Step 2.1 and Step 2.2, we describe the methodology for determining aggregate base consumption and its sectoral splitting, respectively.

The determination of the base consumption requires information on the operational principles of industrial and commercial facilities that work on various shift systems, for example, some operate only on weekdays, while others operate at least half-day on Saturdays. There are also industrial facilities that operate continuously (24/7), except on holidays. For example, past research shows that, in Türkiye, electricity consumption drops significantly on January 1st and religious holidays due to

Figure 8: Pseudo code for the data processing and analysis of consumption

```
1. Start
2. Load country specific hourly total electricity consumption
  a. Determine indices for the "Day of the week", "Special day", "Daylight" and "Phase of the day" for each hour
3. Load monthly sectoral consumptions for the given month
  a. Scale if necessary, with monthly averages of aggregate actual consumption to account for losses
4. Identify any sectoral consumption that can be directly related to the indices
  a. Generate time series for the given subconsumption and remove from the hourly time series
5. Apply special days detection methodology to the data for the whole year and determine special days
  a. Determine the aggregate base consumption using the consumption at the night hours of special days.
  b. Adjust for heating and cooling corrections, in case special days occur in a different month
  c. Evaluate base consumptions for each sector by scaling with the share of each sector in the total consumption
  d. Subtract the total base consumption from hourly consumption
6. Generate time series for the household consumption as the sum of base household consumption, and the consumptions during daytime and
   evening phases of the day
7. Obtain the non-household (industrial and commercial) consumption as the remaining consumption, as a time series
8. End
```

industrial shutdowns (Yukseltan, 2024), leading to an estimation of the base consumption.

The days to be considered as reference for the base consumption are normally determined from the lowest consumption periods in the hourly time series, further refined by the methods presented in Section 4.1. In the study of demand segregation for the Turkish electricity market, initially, it was assumed that all industrial facilities were closed during holidays, leading to a residential consumption estimation error of 9%. However, using data from 2020, when all industries were shut down due to COVID-19 restrictions, industrial nighttime consumption was considered in the determination of base consumption and as a result, the residential consumption error was reduced to 2%. This result highlights the importance of accurately determining base consumption and points to possible uses of the data from the period of the unfortunate COVID-19 pandemic in scientific work.

5.2.1. Step 2.1: Determination of aggregate base consumption

In our study, holiday night-time consumption data from 2016 to 2021 was analyzed. Holiday nights were filtered, and the consumption values were ranked in ascending order based on their minimum recorded consumption. The minimum electricity consumption recorded during night hours on holiday days for each year is provided in Table 7 below.

In Spring 2020, it is known that industrial facilities were closed due to Covid-19 restrictions. The variations observed in 2016 and 2021 compared to 2017-2018 may indicate a linear trend in consumption behavior. By subtracting the 2020 minimum consumption from the 2017 to 2019 average minimum consumption, we can estimate the electricity consumption of industries operating 24/7, including during holidays. As noted earlier, the Covid-19 restrictions provided valuable insights into residential electricity consumption disaggregation.

- The average minimum consumption for 2017-2019 is 19,867.16 MWh.
- The minimum consumption in 2020 was 2,611.67 MWh lower than this average.
- This difference corresponds to a 13.14% reduction, suggesting that approximately 13% of base consumption comes from industrial production (this percentage includes street lighting, as it is calculated using total values).

In our study, the 2,611.67 MWh difference identified above represents the electricity consumption of industries operating 24/7, including holidays.

Additionally, the minimum consumption levels recorded on holiday nights generally coincide with religious holidays and New Year's Day (January 1st). The data also suggests a seasonal pattern, with the lowest consumption values typically occurring in spring or autumn. Details are provided in Table 8.

The average values for 2017-2019, which are assumed to have a homogeneous distribution of electricity consumption characteristics, are given below for the seasonal distribution of

Table 7: Minimum electricity consumption on holiday nights (MWh)

Year	Month	Day	Hour	Consumption (MWh)	Holiday
2016	9	13	5	18,142.37	Eid al-Adha, 2nd day
2017	6	26	4	20,048.60	Eid al-Fitr, 2nd day
2018	6	16	4	19,921.34	Eid al-Fitr, 2nd day
2019	6	5	4	19,631.53	Eid al-Fitr, 1st day
2020	5	25	4	17,255.50	Eid al-Fitr, 2nd day
2021	5	14	4	22,222.19	Eid al-Fitr, 2nd day

Table 8: Distribution of holiday nighttime minimum consumption by year and season

Year	Month	Day	Hour	Consumption (MWh)	Season
2016	9	13	1	18,142.37	Spring-Fall
2016	7	6	1	19,157.48	Summer
2016	1	1	7	21,844.16	Winter
2017	6	26	1	20,048.60	Spring-Fall
2017	9	2	6	21,089.31	Spring-Fall
2017	1	1	7	22,274.49	Winter
2018	6	16	6	19,921.34	Spring-Fall
2018	8	22	1	22,796.91	Summer
2018	1	1	7	23,071.96	Winter
2019	6	5	1	19,631.53	Spring-Fall
2019	1	1	7	22,714.09	Winter
2019	8	12	1	23,901.76	Summer
2020	5	25	1	17,255.50	Spring-Fall
2020	1	1	7	23,535.52	Winter
2020	8	1	6	25,206.50	Summer
2021	5	14	1	22,222.19	Spring-Fall
2021	1	1	7	24,627.81	Winter
2021	7	22	1	27,992.14	Summer

nighttime minimum consumption on holidays. Although in some years, June has been considered part of spring, seasons have been defined according to standard rules. The results are given in Table 9.

By interpolating between these values, monthly values for baseline consumption have been determined. Figure 9 shows the distribution of minimum consumption on holidays by month.

The interpolated values above can be used to determine baseline consumption levels for months without holidays. However, if the analyzed month contains a holiday, it is more accurate to take the nighttime minimum consumption of the holiday as the baseline consumption value. Also note that the interpolation results indicate that baseline consumption is lowest in spring and autumn, while in summer and winter, consumption increases due to heating and cooling demands.

5.2.2. Step 2.2: Sectoral segregation of the base consumption

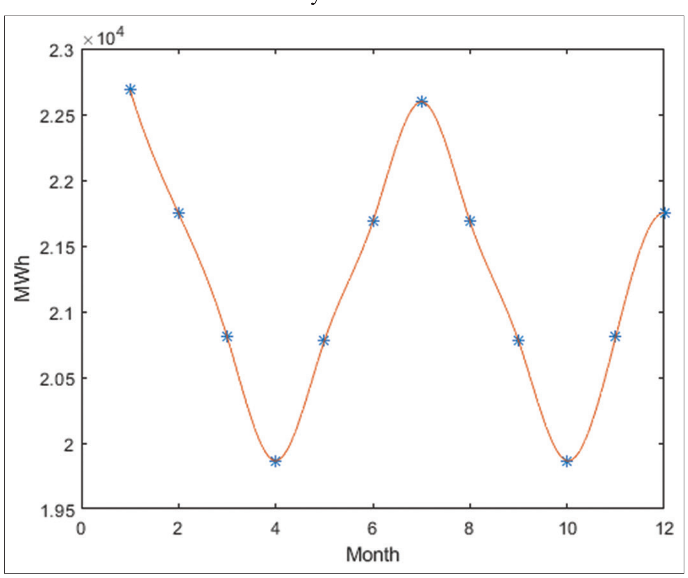
The base consumption breakdown by sector is as follows. We recall that street illumination (lighting) L(t) and agricultural irrigation A(t) have already been segregated and removed from aggregate consumption, leading to total hourly consumption time series $X_1(t)$. Note that industrial electricity consumption of the plants that run on 7-day/24-h basis cannot be distinguished from the data. Thus, the base consumption consists of the following.

- Residential Base Consumption, $B_r(t)$: Continuous use of refrigerators and other appliances.

Table 9: Seasonal distribution of baseline consumption estimates

Season	Months	Hourly consumption (MWh)
Summer:	June, Jully, August	22,595.99
Spring:	March, April, May	19,867.16
Fall:	September, October, November	19,867.16
Winter:	December, January, February	22,686.85

Figure 9: Distribution of nighttime minimum consumption on holidays by month



- Industrial Base Consumption $B_i(t)$: Electricity needed to maintain factory operations and electricity consumption for facilities that operate continuously.
- Commercial Base Consumption $B_c(t)$: Electricity needed for essential infrastructure (computers, refrigerators, etc.).

As these sectoral base consumptions are not directly observable from the hourly aggregate data, we estimate their total $B(t)$ from the consumption at night hours of days with holiday index $h = 2$, preferably in spring or fall, to exclude possible usage of electricity for heating or cooling. Then sectoral base consumptions are obtained by scaling with the share of the corresponding sector in that month, yielding the values

$$B_r(t) = \lambda_r B(t), \quad B_i(t) = \lambda_i B(t), \quad B_c(t) = \lambda_c B(t), \tag{5}$$

Where the scaling coefficients λ_r, λ_i and λ_c are the ratios of the sectoral consumptions to the total consumption for a given month, and they are computed from the EPDK data presented in the Appendix.

As an example, we present below in Figure 10 the total consumption and the consumption after removal of lighting, agricultural consumption and aggregate base consumption for January 2017. The nighttime minimum consumption value of January 1, 2017, is used to determine the aggregate base consumption.

Since the share of lighting and agricultural irrigation is relatively small, no significant qualitative difference is observed in the graph but correctly isolating the nighttime minimum consumption on holidays is crucial for determining household consumption.

5.3. Step 3: Segregation of Household Consumption

The segregation of household consumption is based on assumption that during holidays, daytime and evening consumption originate from residential sources. Then, average hourly consumption during daytime and evening on holidays is calculated as R_d and R_e, respectively and residential consumption is then determined as their sum as follows:

$$R(t) = B_r + R_d + R_e \tag{6}$$

As an example, we illustrate the procedure for January 2017. The following definitions are made for this purpose:

- x: Minimum nighttime consumption on January 1, 2020
- y: Minimum nighttime consumption on January 1, 2017
- y - x: Electricity consumption of continuously operating industries, including holidays

After isolating lighting, agricultural irrigation, and continuously operating industries, the baseline consumption is determined. For January 2017, the coefficients in Eq.(5) are found as follows.

$\lambda_r = 0.2881,\qquad \lambda_i = 0.4023,\qquad \lambda_c = 0.3096$

After removing the household base consumption, an hourly time series for household consumption is reconstructed using the time series for indices as described in Section 4.3, as presented in Figure 11.

Figure 10: Total consumption, and the consumption after removal of lighting, agricultural irrigation, and aggregate base consumption as evaluated from the holiday minimum on January 1, 2017

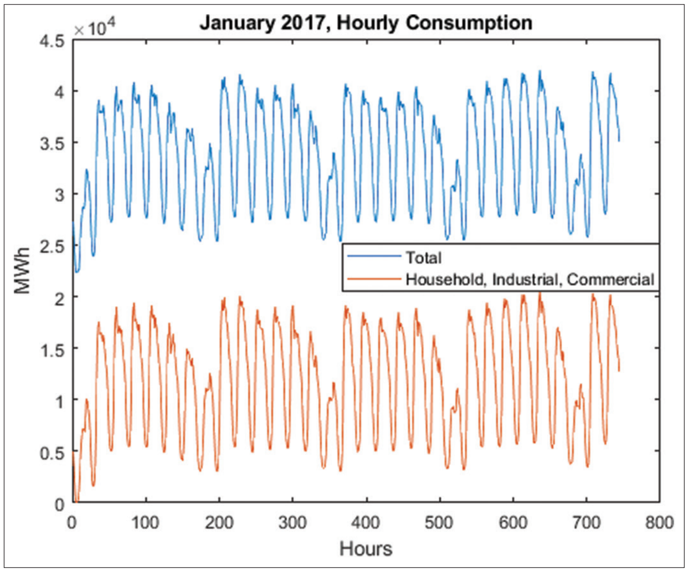
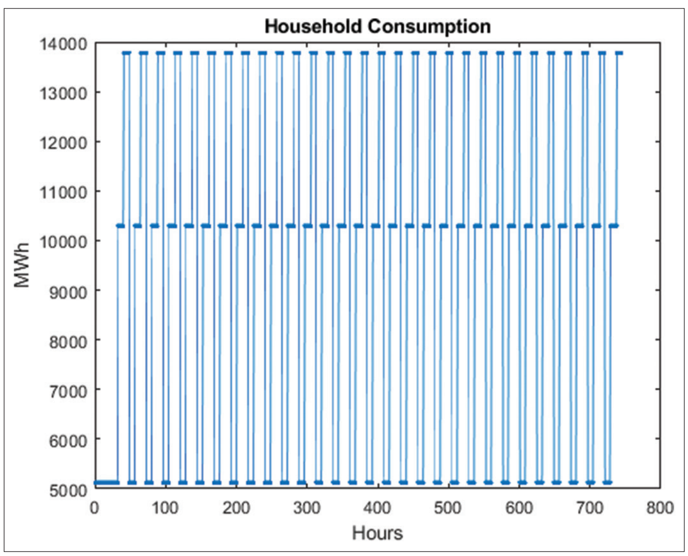


Figure 11: Household consumption model for January 2017

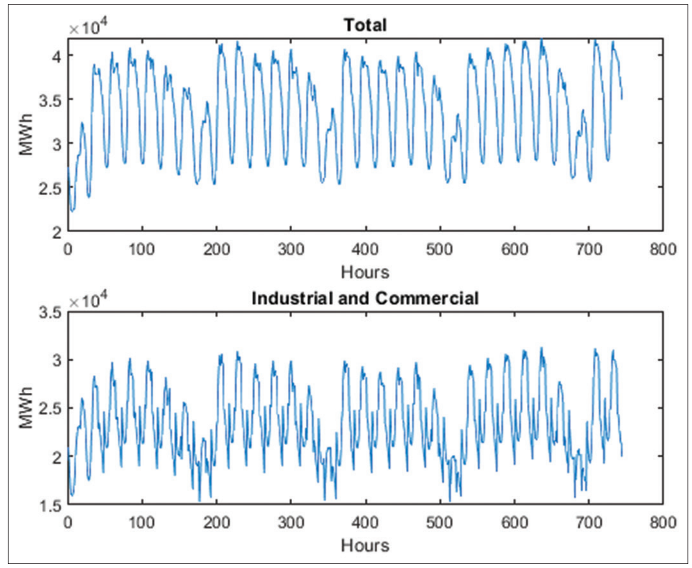


Total consumption evaluated from the piecewise-constant model presented above differs from the scaled official values published by the Energy Market Regulatory Authority (EPDK) by only about 2%. The success of this estimation depends crucially on the determination of the aggregate baseline consumption using April-May 2020, data, corresponding to period of COVID-19 restrictions. Because in previous attempts, estimations of the aggregate base consumption on the given year's special days data resulted in estimation errors as high as 9%.

5.4. Step 4: Segregation of Industrial and Commercial Consumption

After removal of the consumptions for lighting, agricultural irrigation and household consumption the remaining time series consists of the sum of industrial and commercial consumption, as shown in Figure 12, below and clearly illustrates that the share

Figure 12: January 2017 total consumption with industry and commercial consumption only



of industrial and commercial electricity consumption decreases on weekends.

6. CONCLUSION

Electricity has become an indispensable yet often unnoticed part of daily life, with consumers contributing to electricity demand at all times, either directly or indirectly. Understanding the purpose behind electricity consumption and its distribution across various subcategories is crucial for policymakers and industry stakeholders. This information plays a key role in decision-making related to power restrictions, outages, infrastructure investments, and pricing strategies. While European countries and Türkiye publish total electricity consumption on an hourly basis, the detailed breakdown into heating, cooling, lighting, residential, and industrial usage is only available through data collected at the end of billing cycles.

This study aimed to estimate subcategory consumption rates from total electricity demand using data from extraordinary low-consumption days such as holidays and vacation periods. By analyzing electricity demand when it is at its minimum, essential insights into different consumer classes were obtained, and consumption indices were developed. Previous studies, particularly those focusing on electricity demand during the COVID-19 pandemic, provided valuable insights into changes in residential, industrial, and commercial consumption patterns. Leveraging this knowledge, the study played a crucial role in determining baseline consumption levels. Furthermore, through time-series analysis, electricity consumption was disaggregated into subcomponents, identifying shares of lighting, irrigation, and residential consumption.

When applied to Türkiye and various European countries, the proposed methodology yielded meaningful results. Industrial consumption patterns were found to be closely related to heating and cooling demand. In Germany, for instance, the significant difference between weekday and weekend electricity consumption suggests that industrial usage dominates total electricity demand. Additionally, in Türkiye, loss and theft rates in total electricity consumption are reported to be around 15%, further complicating demand estimation.

A growing number of self-generating organizations are injecting surplus electricity back into the grid, adding another layer of complexity to demand calculations. Consumption data for different sectors is available through EPDK and EPİAŞ, yet discrepancies between these sources pose challenges in accurately determining subcategory proportions. Despite this data uncertainty, the study successfully analyzed consumption behaviors by examining trends during extraordinary days and pandemic-related closures.

The methodology proposed in this study has the potential to deliver even more precise results if more granular and detailed data becomes available. Replacing country-wide consumption data with regional or city-based datasets would allow for more insightful interpretations. Furthermore, access to hourly electricity consumption data would significantly enhance the accuracy and reliability of the model's predictions. Future work will focus on refining these methodologies and transforming research findings into international academic publications, further advancing the field of electricity demand analysis.

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APPENDIX

Table A1: Monthly sectoral consumption values for the years 2017-2021 published by EPDK

Consumption	2017	2018	2019	2020	2021	2022
January						
Industrial	7,463,646.87	8,324,549.57	7,387,067.23	8,369,686.04	9,092,379.45	8,693,393.18
Commercial	5,743,154.07	5,718,355.96	5,886,862.70	5,613,450.41	4,540,155.39	5,617,326.68
Residential	5,345,308.96	5,061,472.78	5,351,389.51	5,416,529.94	5,630,563.90	6,035,243.91
Irrigation	84,358.98	281,569.01	480,256.60	507,451.12	181,006.80	302,621.61
Lighting	430,995.70	465,582.23	110,907.57	129,329.10	525,708.12	521,965.50
Total	19,067,464.57	19,851,529.54	19,216,483.62	20,036,446.61	19,969,813.67	21,170,550.87
February						
Industrial	7,185,138.95	7,817,524.91	7,095,179.75	8,072,318.38	8,534,372.61	9,070,253.89
Commercial	5,417,626.30	5,303,288.41	5,152,603.44	5,242,639.28	4,323,621.04	5,118,512.63
Residential	4,711,341.34	4,864,125.20	4,906,505.24	5,209,139.49	5,216,398.53	5,493,935.17
Irrigation	387,365.09	441,908.32	472,044.15	454,408.94	551,906.42	1,075,376.93
Lighting	64,358.45	153,233.60	33,057.30	19,208.40	461,876.37	480,653.99
Total	17,765,830.13	18,580,080.45	17,659,389.88	18,997,714.49	19,088,174.97	21,238,732.61
March						
Industrial	8,019,393.63	8,621,776.44	7,910,065.74	8,305,848.79	9,631,365.74	9,973,407.57
Commercial	5,470,873.10	5,318,922.33	4,705,900.51	4,811,516.18	4,956,638.46	5,569,260.06
Residential	4,512,256.88	4,598,217.46	5,273,307.30	4,480,734.58	5,332,520.96	5,360,497.54
Irrigation	381,293.76	382,691.96	431,502.49	442,425.56	499,648.18	216,173.76
Lighting	161,109.46	218,837.74	289,191.51	412,162.39	462,413.60	446,212.48
Total	18,544,926.83	19,140,445.94	18,609,967.56	18,452,687.51	20,882,586.94	21,565,551.41
April						
Industrial	7,778,898.91	8,250,458.89	7,960,764.96	6,159,708.05	9,088,603.36	9,260,104.53
Commercial	4,966,727.73	5,100,825.99	4,562,882.30	5,050,217.67	4,465,876.62	4,628,265.83
Residential	4,173,044.34	4,182,662.17	4,994,388.36	3,447,834.62	5,262,582.79	5,091,280.02
Irrigation	236,667.70	497,549.80	266,452.64	499,414.13	1,233,500.70	445,704.81
Lighting	345,492.02	362,138.26	418,424.91	402,837.40	406,985.25	429,627.97
Total	17,500,830.69	18,393,635.11	18,202,913.17	15,560,011.87	20,457,548.71	19,854,983.16
May						
Industrial	8,173,867.58	8,562,582.97	8,255,022.94	6,343,361.15	8,466,615.33	8,588,792.31
Commercial	5,024,599.21	5,383,825.32	4,447,394.58	4,620,042.56	4,048,415.70	4,793,667.07
Residential	3,947,168.04	4,056,897.03	4,991,930.53	3,304,672.22	4,852,304.83	4,725,553.76
Irrigation	595,313.28	756,035.64	404,551.25	746,453.96	1,734,907.79	1,258,898.20
Lighting	311,131.31	356,703.44	330,488.33	367,193.33	408,880.08	403,776.42
Total	18,052,079.43	19,116,044.39	18,429,387.63	15,381,723.21	19,511,123.72	19,770,687.76
June						
Industrial	7,299,599.64	7,634,065.58	7,050,070.52	8,208,321.02	9,466,048.35	9,510,252.78
Commercial	5,239,588.62	5,616,259.91	4,635,621.71	4,693,175.89	4,892,995.21	5,490,738.35
Residential	3,899,828.17	4,259,483.79	5,627,737.37	4,429,252.87	4,498,186.83	4,495,279.85
Irrigation	624,012.98	813,579.27	1,147,642.84	1,148,059.24	1,730,456.91	1,441,156.94
Lighting	287,733.91	289,088.40	320,876.64	358,603.73	349,118.77	373,875.86
Total	17,350,763.32	18,612,476.96	18,781,949.09	18,837,412.75	20,936,806.06	21,311,303.77
July						
Industrial	8,160,268.97	8,737,466.10	8,494,251.36	8,727,089.96	8,561,875.05	8,036,776.85
Commercial	6,264,614.63	6,763,831.29	6,123,338.12	5,419,024.46	6,063,961.05	5,836,121.82
Residential	4,708,252.94	4,628,142.92	4,486,989.22	4,788,033.61	4,813,222.78	4,996,573.21
Irrigation	1,427,034.29	1,745,282.22	1,903,937.82	1,798,177.99	1,756,244.26	2,510,917.83
Lighting	299,183.30	291,246.14	329,638.88	349,260.23	353,246.81	373,568.60
Total	20,859,354.12	22,165,968.67	21,338,155.40	21,081,586.25	21,548,549.95	21,753,958.31
August						
Industrial	8,168,102.98	7,397,142.20	7,267,019.77	8,615,813.64	9,884,637.68	9,175,353.87
Commercial	6,524,704.02	6,507,388.08	6,105,321.70	5,744,116.34	6,658,852.32	6,661,322.31
Residential	4,600,466.00	4,468,924.00	4,956,729.91	5,633,203.45	5,978,600.68	5,635,508.13
Irrigation	1,522,792.18	1,141,471.85	1,272,490.65	1,892,314.04	1,753,173.32	2,626,524.15
Lighting	325,485.73	332,250.51	373,151.61	374,014.18	420,001.57	403,638.85
Total	21,141,550.91	19,847,176.65	19,974,713.64	22,259,461.64	24,695,265.57	24,502,347.31
September						
Industrial	7,531,007.94	7,888,329.53	8,212,221.07	9,162,314.98	9,559,252.95	8,967,700.34
Commercial	5,811,369.47	6,051,058.46	5,772,166.05	5,609,661.12	5,730,308.24	5,749,984.65
Residential	4,725,284.04	4,993,246.41	4,930,839.40	5,051,178.08	5,181,188.48	5,458,718.54
Irrigation	1,092,517.84	1,337,050.66	1,047,395.16	1,773,919.58	1,512,983.74	1,642,197.98
Lighting	366,055.44	410,389.66	411,369.21	419,970.00	438,559.18	445,330.36
Total	19,526,234.72	20,680,074.71	20,373,990.89	22,017,043.77	22,422,292.59	22,263,931.86

(Contd...)

Table A1: *(Continued)*

Consumption	2017	2018	2019	2020	2021	2022
October						
Industrial	8,437,106.52	8,157,623.13	8,357,097.31	9,368,984.00	9,701,650.27	9,116,898.48
Commercial	5,322,293.49	5,409,265.65	5,189,547.96	4,902,068.50	5,174,072.92	5,063,369.00
Residential	3,806,829.21	4,137,203.86	4,197,725.13	4,651,823.82	4,481,162.46	4,611,311.08
Irrigation	482,482.65	641,407.39	671,208.55	873,220.77	706,909.37	822,140.47
Lighting	387,086.35	458,593.46	566,644.28	463,717.13	502,078.71	515,638.08
Total	18,435,798.23	18,804,093.49	18,982,223.23	20,259,814.21	20,565,873.73	20,129,357.10
November						
Industrial	8,376,442.63	7,925,137.85	8,193,812.01	9,097,941.06	9,780,662.29	8,870,978.01
Commercial	5,259,318.50	5,300,419.71	4,445,199.12	4,787,937.06	5,009,870.85	4,666,959.44
Residential	4,361,498.00	4,455,315.97	4,809,677.08	4,637,618.00	4,729,715.04	4,565,281.21
Irrigation	224,575.80	605,014.39	402,870.65	460,078.85	518,657.78	571,963.48
Lighting	392,118.12	483,046.67	1,011,800.43	406,518.95	1,177,470.65	431,369.28
Total	18,613,953.06	18,768,934.59	18,863,359.30	19,390,093.92	21,216,376.61	19,106,551.43
December						
Industrial	8,357,019.84	7,640,799.68	8,280,126.13	9,338,796.51	9,805,530.69	9,129,622.03
Commercial	5,340,702.55	5,818,823.48	5,223,508.65	4,797,528.88	5,496,216.66	5,095,444.55
Residential	4,718,798.73	5,046,676.92	4,762,598.59	5,423,531.91	5,361,467.45	5,022,812.81
Irrigation	47,970.84	591,301.58	394,731.71	1,107,318.32	520,984.59	416,497.44
Lighting	421,615.23	498,436.35	504,415.18	495,875.35	555,289.98	599,149.83
Total	18,886,107.20	19,596,038.01	19,165,380.26	21,163,050.97	21,739,489.36	20,263,526.66