

The impact of social and weather drivers on the historical electricity demand in Europe



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HIGHLIGHTS

- Very diverse country-specific daily activity profiles emerged from national electricity hourly loads.
- Temperature sensitivity was modelled to find the optimal temperature range for heating and cooling states.
- Fourier analysis of residual demand suggests long-term (seasonal and annual) storage is needed.
- Perfect interconnection between European countries could reduce storage size by up to 61 TWh/year.

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ABSTRACT

Climate change, technological innovation, as well as electrification of energy services to meet carbon targets, have a significant impact on electricity demand magnitude and patterns. Increasing generation from renewable energy sources is already changing supply variability at the hourly and seasonal timescales. Our aim is to conduct a rigorous study of European historical demand, to understand its relationship with social and weather drivers and, therefore, to gain insights into appropriate storage needs.

Daily activity profiles exhibit notable differences across European countries, with some of them reporting a consistent demand reduction, up to 25%, during school closures and Christmas festivities. In addition, temperature sensitivity differentiates demand by countries' latitude (north vs. south), and by technologies (electric heating vs. other fuel based heating). Assuming a 100% renewables scenario, European countries would display quite distinct periodicities and amplitudes of their residual electricity demands.

Annual load curves and temperature sensitivities of nations with high electric heating or cooling demand can assist in the prediction of future electricity and other fuel consumption under increased electrification and climate change scenarios. Fourier periodicity and residual demand analysis suggest that, in addition to grid storage, European countries with mutual energy needs – in terms of seasonal demand and generation surplus – might benefit from international trade to balance unmet demand. Our study of consumption variability in response to social and weather drivers constitutes a valuable resource to formulate country-specific demand scenarios, as well as to improve the design of energy system models.

1. Introduction

The analysis of the historical electricity demand for the European region (EU35) is crucial to understand the relationship between demand and its drivers at the national resolution, as well as to model the future demand of the continent. A country's energy demand is driven by many factors: population, households (i.e. one or more people living in the same dwelling), social and economic activities, wealth, culture, climate, the proportions of services met with different energy types (electricity, fossil etc.) and the technologies used. All of these factors

determine both the annual electricity consumption and the hourly profiles of electricity demands.

Social behaviours in particular, which are increasingly recognised as a fundamental driver in energy models [1], can show recurring patterns in time (e.g. weekly, or summer vacation periods) and are affected by the weather, and by cultural customs, technology and policies. Diurnal patterns are predominantly determined by human activities at home, at work and elsewhere for leisure, shopping, et cetera, whereas holidays generally cause decreased activity in non-domestic sectors such as schools and factories, and increased activity in dwellings or in non-

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domestic sectors serving holidaying people, such as hotels. Since daily social activities represent the shortest cycle of those recurring patterns, energy models with various scopes (e.g. energy systems, cities or individual buildings) often include them to predict energy service demands [2], although some models may consider even longer time slices (like months or seasons). These activity patterns, or profiles, are generally expressed as a percentage of a given demand (for example, the electricity for lighting or the gas demand for hot water). Depending on the model aims, activity profiles can be estimated by different means, for example by time use surveys [3] or by metering data [4], with a time resolution ranging from hours to seconds. Moreover, energy models focussed on the Residential (or Domestic) sector can estimate social activities also by integrating the information on building occupancy [5].

Some demands are also strongly affected by environmental conditions. Most notably, space heating increases as ambient temperature decreases, and the opposite trend is shown by air conditioning. Similarly, artificial lighting increases as sunlight decreases, and hot water demand increases as water supply temperature – which varies with seasonal ground temperature – decreases.

The relationship between weather conditions and electricity consumption has been studied at the national (e.g. [7]), city (e.g. [8]), or individual households scale (e.g. [9]), as well as on specific sectors (mostly residential, e.g. [10]). The main limitation of these studies, however, is that, although analysed in detail, they focus on a limited geographic area. A few studies cover the wider European region, but at a monthly [11] or daily resolution [12]. Other studies use Heating/Cooling Degree Days (e.g. [13]), although this approach has been criticised, as the temperature threshold is arbitrary and should be adapted to each country [11].

Our study overcomes these limitations by analysing the demand temperature sensitivity of each European country at an hourly resolution, with the aim of estimating the specific heat loss coefficients for electric space heating and air conditioning. A deep understanding of how weather conditions impact electricity consumption, will make it possible to project how service demands might change in a future when electricity will provide a greater fraction of heating, or how climate changes could increase the use of air conditioning.

Regarding the future energy system at the European scale, these demands might be met by increasing renewable sources. Assuming a 100% renewable generation scenario by extrapolating historical data, we could calculate the residual demand, and therefore, gain insights into the future storage and transmission requirements in Europe. Very few studies considered the synergy between storage and interconnection within a 100% renewable scenario, focussed either on the EUMENA region (Europe, Middle East and North Africa) [14], or on the United Kingdom [15,16]. The only work regarding Europe [17] estimated the renewable backup energy demand starting from a range of storage choices and grid capacities, rather than calculating them.

Our aim was to find the theoretical boundaries of the storage size required at the European scale between two extreme cases (non-existent and perfect interconnection) to quantify the reduction of storage that can be achieved by transmission. Moreover, calculating the frequencies of the residual demand would provide a measure of the periods when storage would be necessary, and of the appropriate storage size in each period [18,19].

2. Methods

2.1. Data sources

Data on energy consumption were collected from international databases freely available for academics. In particular, the electricity hourly demand and monthly generation of the EU35 countries (see Appendix) from 2010 to 2015 was taken from the European Network of Transmission System Operators for Electricity (ENTSO-E) [20], whereas

the annual energy consumption from 1990 to 2014 for the same subset of countries was extracted from the “World energy balances” database by the International Energy Agency (IEA) [21]. The final consumption by end use was taken from the Odyssee database [22], which includes values for the EU28 countries, Norway, and Switzerland from 1990 to 2015. Data on hourly temperature, net downward solar irradiation at the surface, and wind speed by approximately 0.5 degree latitude/longitude was taken from the NASA MERRA re-analysis database [23] as detailed below:

- Temperature (K): MERRA T2M variable at 2 m above the displacement height was used as an estimate of ambient temperature;
- Solar irradiation (W/m^2): Hourly net downward solar irradiation at the surface;
- Wind speed (m/s): Hourly wind speed values at 2 m, 10 m and 50 m above the displacement height.

2.2. Data processing for energy consumption

The hourly electricity demand data time zone was converted from Central European Time/Central European Summer Time (CET/CEST) to Coordinated Universal Time (UTC). The values for Northern Ireland, reported separately by ENTSO-E until 2015 inclusive, were added to the hourly electricity demand of the United Kingdom. The hourly loads were calculated by the national Transmission System Operators (TSO) as “gross consumption” (including export, imports, distributed auto-generation, and transmission losses, but excluding plant auxiliaries, plant losses, and pumped storage); however, they seem to exclude transmission losses, despite what is stated in the ENTSO-E documentation, as the annual sums of the national loads are very similar to the final consumption of electricity in the IEA and Odyssee database. Data from the IEA database was extracted for coal and peat products (indicated as “Sol”), primary and secondary oils (“Liq”), natural Gas (“Gas”), heat (“Hea”), electricity (“Ele”), as well as biofuels and waste (“Ren”); in particular, to get an overview of the historical energy demand and fuels used in Europe the following flows were used: “Total final consumption”, “Industry”, “Transport”, “Residential”, and “Commercial and public services” (as “Services”). National energy consumption was also grouped by end use (i.e. service demand) and carrier from Odyssee.

2.3. Activity profiles from hourly national electricity load

To estimate the national social activity of a given time period, hourly electricity demand from ENTSO-E were averaged for each hour and each day of the week, to obtain the hourly demand for an average week. Then, these hourly values were divided by their sum to get the fraction of the weekly demand, and normalised by the hourly mean of the selected period to obtain an activity profile $a_{h,d}$ for each hour and day of the week:

$$a_{h,d} = \frac{x_{h,d}}{\sum_{h=0}^{23} \sum_{d=1}^7 x_{h,d}} \bar{x}_{h,d} \quad (1)$$

where $x_{h,d}$ is the electricity demand at hour h and on day d .

2.4. Population weighting of weather time series

Population weighting a gridded weather dataset is a way to get a single value for each time step that represents the weather experienced by a subset of people, for example in a country. To population weight NASA MERRA data by country, gridded population data from *The Global Rural-Urban Mapping Project (GRUMP) version 4* were used, whereas the MERRA grid was recreated in a GIS by creating Voronoi polygons around each grid point. Each grid cell’s population geographically belonging to a given country was multiplied by the weather

variable in the corresponding cell from the MERRA grid. Then, the population-weighted weather variable (e.g. temperature) was obtained by summing over all grid cells and dividing the resulting value by the total population of the country, as previously described in [12].

2.5. Modelling temperature sensitivity of electricity demand

As demand changes progressively with increasing or decreasing temperatures, the transition from heating to cooling can be approximated with two threshold temperatures rather than using only one. Therefore, it is possible to estimate the temperature sensitivity of hourly national electricity demand by fitting a simple linear regression model (using the Ordinary Least Square method), to each of the three regimes delimited by the thresholds, i.e. a two-threshold regression model [24]. The optimal temperature range for each country was found by selecting the maximum sum of the R-squared for heat and comfort regimes. The cooling state cannot be modelled for the northern countries as they do not have a substantial air conditioning consumption. Holiday periods were removed to exclude demand outliers in the data. The temperature range was restricted during the optimisation in order to prevent high R-squared values calculated for very few extreme points.

2.6. Cumulative residual demand

Assuming a scenario of 100% uncontrollable renewable sources to calculate the national cumulative residual demand, monthly time series of wind generation (w_m), solar generation (s_m), and electricity demands (d_m) were extracted from the ENTSO-E database. For each European country, the yearly scaled cumulative generation g was calculated by summing each month's (m) wind and solar values and scaling the cumulative vector up to roughly match the total electricity demand by a factor a :

$$g[i] = a \sum_{m=1}^i (w_m + s_m) \quad \text{for } i = 1, 2, \dots, 12 \quad (2)$$

where a is defined as the total demand divided by the total generation:

$$a = \frac{\sum_{m=1}^i d_m}{\sum_{m=1}^i (w_m + s_m)} \quad (3)$$

The national cumulative residual demand was calculated as the difference between the cumulative demand d and the scaled cumulative generation g .

2.7. Storage estimation

For any given year, in a scenario without interconnections the theoretical storage required at the European level can be estimated as the sum of the maximum residual demand (RD_c) over all countries:

$$S_{max} = \sum_c \max(RD_c), \quad \text{for } c \in EU35 \quad (4)$$

In case of perfect interconnection, instead, the storage needed would be the maximum sum of the national residual demand (RD_c) over all countries at each time point:

$$S_{min} = \max(RD_{EU35}) \quad (5)$$

where RD_{EU35} is a vector of the monthly sum over all EU35 countries' residual demands.

2.8. Fourier analysis of the residual electricity demand

The Fourier analysis of the residual electricity demand in 2015, both for the whole Europe and for individual countries, was performed by first transforming the residual demand into a periodic signal with a

Hanning window function, and then applying a Discrete Fourier Transform to this signal. To reveal the time patterns in the hourly residual demand time series, the frequencies returned by the Fourier transform were converted into periods. The energy consumed between these periods was estimated by multiplying them by the associated amplitude of the transformed demand. Whenever generation data was available for multiple years in a given country, the long term trend was removed - through a simple linear regression model - and the Fourier analysis was extended to include the additional years.

2.9. Software implementation

All the code required to process the data and produce the plots was written in Python 3.7, using the Pandas [25], Numpy [26], Statsmodels (<https://www.statsmodels.org/stable/index.html>), Bokeh [27], and Holoviews [28] packages.

3. Results

3.1. Energy annual consumption by energy carrier and end use

Energy final annual consumption in the EU35 region from 1990 to 2014 amounted to 14.2 PWh on average, with a standard deviation of 0.56 PWh. Electricity net consumption during the same time interval was 2758 TWh on average. Fig. 1 shows that energy consumption constantly increased until 2007–2008 and decreased thereafter, most probably due to the financial crisis – together with a number of other factors – which had a destabilising impact on the following years. Although an in depth analysis of the macroeconomic drivers influencing demand is beyond the scope of this work, it might provide useful insights into the hidden links among productive sectors in different countries, as well as into the correlation between demand and monetary measures like GDP (e.g. [29,30]).

The countries with the highest average final energy consumption in EU35 from 1990 to 2014 were Germany, France, United Kingdom, Italy, and Spain. The consumption in France, United Kingdom and Italy reached a peak from 2000 to 2005 and then started decreasing, with a delay for Germany and Spain, which recorded a reduction in demand with the financial crisis in 2007–2008. At the European region level, the most consumed carriers are liquid fuels, followed by gas and electricity (Suppl. Fig. S1). Norway and Sweden have the greatest fraction of electricity, whereas Poland has a much higher fraction of solid fuel consumption compared to the other European countries (~138 TWh in 2014), followed by Germany (~100 TWh in 2014).

We then focussed on how the energy consumption is partitioned

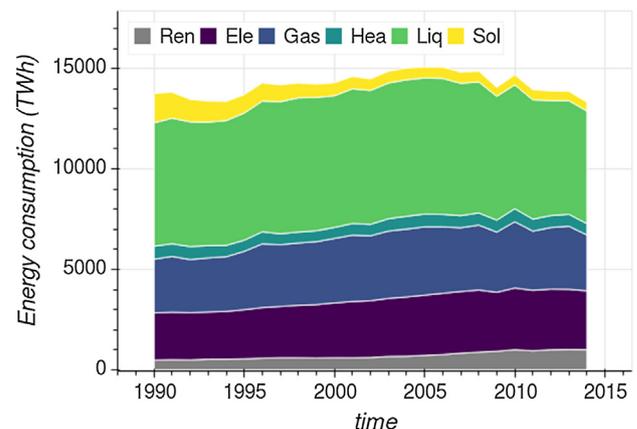


Fig. 1. Energy final consumption in EU35 as stacked areas. The maximum value was reached in 2005 with 15 PWh. Energy carriers are indicated as Sol (coal and peat products), Liq (primary and secondary oils), Gas (natural gas), Ren (biofuels and waste), Hea (heat), and Ele (electricity).

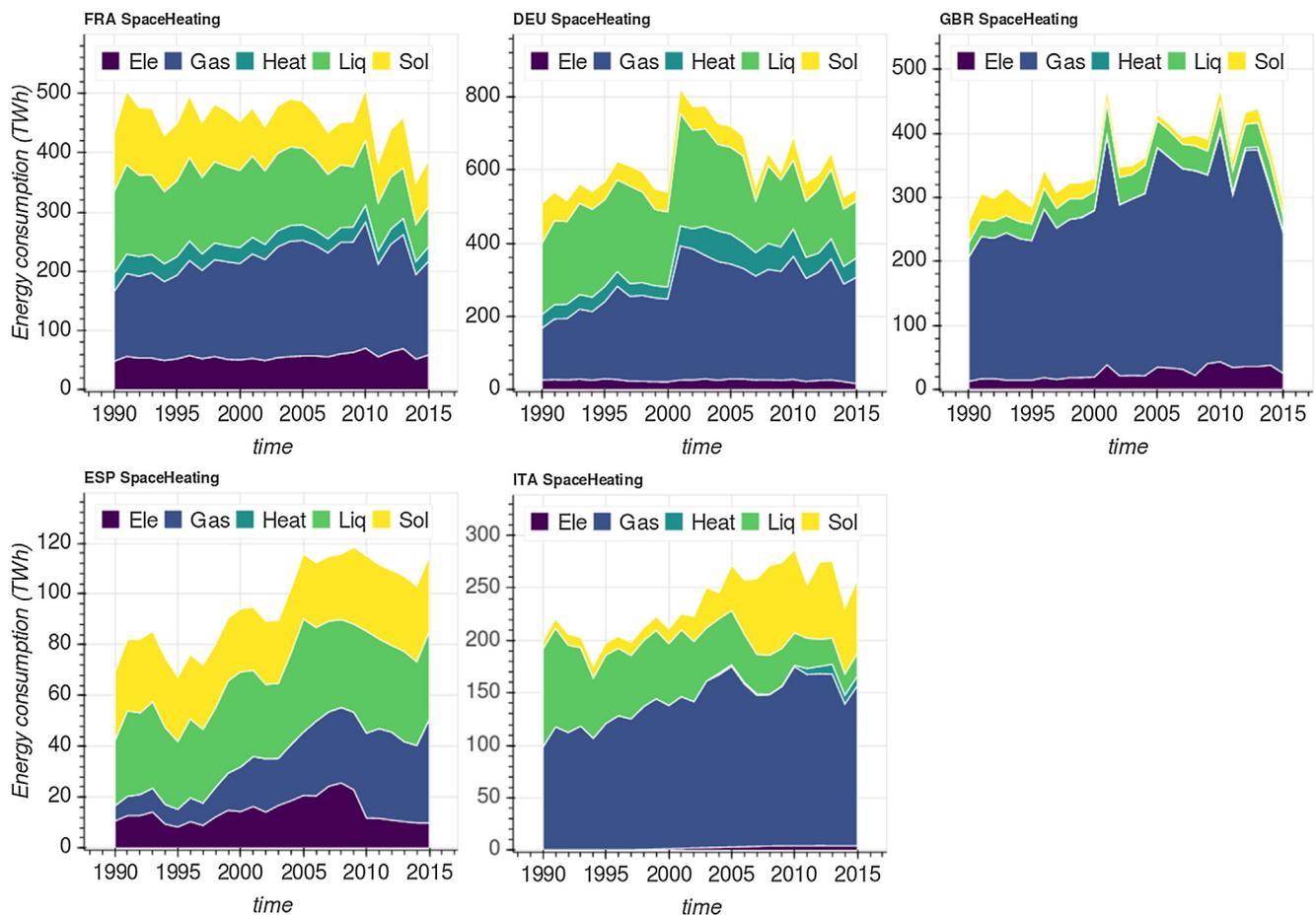


Fig. 2. Energy final annual consumption of space heating by energy carrier in France (FRA), Germany (DEU), United Kingdom (GBR), Spain (ESP), and Italy (ITA). The ISO 3-letter code is specified in the top left corner of each plot. Energy carriers are indicated as Sol (solid), Liq (liquid), Gas, Heat (heat), and Ele (electricity).

into a number of end uses (cooking, water heating, and space heating) for the Residential and Services sectors in EU28 and Norway from 1990 to 2015. At the European level, gas and solids are increasingly replacing liquid fuels; for example, gas consumption for space heating increased from 33% to 54%, whereas for water heating the consumption of solid fuel doubled from 8% to 16%, with a slight increase in heat as well (from 7% to 12%). At the national level, United Kingdom and Italy show almost constant energy consumption dominated by gas, whereas France and Germany have been replacing liquid fuels with electricity and gas. In particular, for space heating, France has the highest consumption of electricity in 2015 (~59 TWh, decreased by 15% from 2014), followed by United Kingdom with ~25 TWh (29% less than in 2014), and Germany with ~16 TWh (38% less than in 2014) (Fig. 2). However, Germany has the highest consumption of liquids, ~155 TWh, corresponding to 28% of the country’s total consumption. Noticeably, Poland’s solid consumption accounts for 60% of space heating, whereas Sweden’s main carrier for space heating is heat (60%).

3.2. Electricity annual consumption by sector and end use

The most populated five countries (DEU, FRA, GBR, ITA, and ESP) have the highest consumption of electricity summing to 60% of the total European demand, or 53% when we consider only the first four countries (Table 1).

In the EU28 and Norway, the maximum electricity consumption was ~3000 TWh in 2008, then decreasing after the financial crisis to ~2800 TWh in 2014 (Suppl. Fig. S2). The fraction of total electricity accounted by Residential consumption is stable, while Services increased by 10% from 1990 to 2015, although Industry is still the largest

Table 1

Electricity final consumption (TWh) in the countries with the highest average values in EU35 from 1990 to 2014.

Country	Mean	Std	Min	Max
DEU	492.50	30.44	440.70	527.14
FRA	390.77	44.96	297.34	449.15
GBR	316.34	22.47	274.44	348.61
ITA	271.11	31.34	214.59	309.26
ESP	197.60	46.66	125.80	255.09

consuming sector with 38%. Regarding the first five countries, the sector showing the highest consumption is Industry for Germany (~229 TWh) and Italy (~113 TWh), Residential for France (~149 TWh) and United Kingdom (~109 TWh), and a balanced mix of Industry, Residential, and Services for Spain (~60 TWh each). Transport constitutes the smallest fraction for all the countries mentioned above, and Services is usually the second sector.

We next analysed the electricity consumption by end use in the Residential and Services sectors for EU28 and Norway. As shown by Supplementary Fig. S3, the category of electrical appliances and lighting represents the main consumption (60% in 2015, although not every country reports separated data for those uses), followed by space and water heating (which decreased from 32% to 24%), cooking (stable at 8%), and air conditioning (which raised from 1% to 6%). During the time interval we considered, the total electricity consumption increased, mostly due to electrical appliances and air conditioning. However, it is important to consider that data points in Odyssee might be occasionally incomplete, leading to sharp changes as it can be seen

Table 2

Mean, Standard deviation, minimum, and maximum of the hourly demand (GW) in France, Germany, United Kingdom, Italy, Spain, and Europe from 2010 to 2015.

GW	FRA	DEU	GBR	ITA	ESP	Europe
Mean	55.02	55.41	35.40	36.23	28.60	362.89
Std	12.30	10.24	7.80	7.68	4.90	61.62
Min	29.59	29.20	18.49	18.74	17.09	226.00
Max	102.10	79.88	60.44	59.65	43.60	543.25

for space heating in Germany in Fig. 2.

At the national level, we noticed a few interesting trends (Suppl. Fig. S4). In Spain there was an increased consumption until 2010 to ~97 TWh for appliances and to ~27 TWh for air conditioning. We also observed an increase for air conditioning and appliances in France (~18 and ~60 TWh in 2015, respectively), whereas Italy showed increased space heating (~4 TWh in 2015) and air conditioning (~10 TWh in 2015). Overall, Spain, Italy, and France have the highest share of air conditioning (respectively 15%, 14%, and 12%). Finally, United Kingdom and France had the highest fraction of space heating, with a peak of ~43 TWh (9%) and ~70 TWh (34%), respectively, in 2010.

In summary, we see that electricity demand is influenced both by climate (heating vs. air conditioning) and by available generation sources (for example, the high electric heat share from high nuclear and hydro generation in France).

3.3. Electricity hourly demand

As detailed in Table 2, France and Germany shared the highest average hourly demand (55 GW) and similar minimum hourly demand (~29 GW) from 2010 to 2015, with France exhibiting the highest peak (~102 GW) and hourly standard deviation (~12 GW). Compared to the European average, France and Germany consumed 15% of average hourly demand, United Kingdom and Italy around 10%, and Spain 8%. When we calculated the sums of the hourly demands in 2015, we found that these five countries accounted for 57% of the total European demand, which was ~3190 GWh.

Looking at the mean of the weekly electricity demand in these countries over a 6-year period (Suppl. Fig. S5), France had the highest mean demand in winter (between ~70 and ~76 GW), but it was surpassed during summer by Germany (~54 GW). However, Germany showed higher standard deviation than France, suggesting a greater inter-annual variability.

Most interestingly, we found that during the period between Christmas and New Year the demand dropped by an average of 20% with respect to the national winter peak. In addition, we observed a summer local minimum, roughly from the end of July to the beginning of September, especially in Italy (–30%), France, and Norway, and to a lesser extent in Spain, United Kingdom, Sweden, and the Netherlands. The load decrease overlaps with school holidays and returns to the pre-holiday trend at the end of the school holiday term. For example, in Italy the load drops from half June to September, corresponding to school closure and reopening (although administrative regions may have slightly different start and end dates). Therefore, the change in the societal activity due to the school closure seems to reduce the national load in summer. On the contrary, during the rest of summer, only Italy and Spain exhibited peak demands, most probably due to the use of air conditioning. Particularly for Italy, this peak was higher than the winter peak load, reaching a mean of ~40 GW.

When we focussed on the second group of European nations, composed of Poland, Sweden, Norway, and the Netherlands, we found that the Scandinavian countries showed a much higher difference than Poland and the Netherlands between winter and summer average consumption (Suppl. Fig. S5). In Norway, electricity is the energy

carrier choice for 73% of household heating, mainly because almost all Norwegian generation is hydro [31]. Similarly, in Sweden “Energy use in the residential and service sector is impacted in the short-term primarily by the outdoor temperature, as a large proportion is used for heating. [...] Electricity is the most common form of energy used for heating and hot water in one-and two-dwelling buildings.” [32]. Compared to the first group of European countries, this second group had a consistently lower demand, which was on average below ~22 GW during the winter peak. Moreover, the minimum demand in Sweden and Norway was recorded in July rather than August, as seen in the other European countries. Holidays like the 1st of May and the 1st of November had a relatively greater impact on the demand in Poland than in the other European countries.

At the hourly level, each country showed a unique profile during the period between Christmas and the first week after New Year (Suppl. Fig. S6). However, the common trends we observed were a generally reduced demand compared to the average winter load profile, and a minimum on the 25th of December and on the 1st of January.

Next, we calculated the standard score of the demand for the first and second group of European countries, in order to find any similarities among their load profiles. Consistently with the previous graphs, we found that countries using electricity as the main energy carrier for heating (i.e. France, Norway and Sweden) had a very similar annual profile, with winter demand higher than 1 standard score and summer demand lower than –0.5 standard score (Fig. 3). On the contrary, southern countries like Italy and Spain exhibited a positive standard score in the summer months, with the highest peak around mid-July.

At the European level, the sum of the national demands produced the profile shown in Supplementary Fig. S7. The mean winter demand peaked at ~440 GW in February, whereas the average summer demand was ~340 GW, with a minimum in August reaching ~300 GW. The demand during the period between Christmas and New Year decreased on average by ~15%. International holidays, as for instance the 1st of May and the 1st of November, showed the same hourly load profile as an average Saturday’s load, as shown in Supplementary Fig. S8. Finally, we compared the annual summed peaks of the EU35 hourly consumption with the annual aggregated peaks. As depicted in Supplementary Fig. S9, the latter are lower than the summed peaks of ~30 GWh on average.

3.4. Activity profiles estimated from national electricity hourly demand (demand versus time)

One of the key input data for engineering energy models is human activity, which can be estimated by different means (e.g. through time use surveys or by metering energy usage) and changes across countries. This information is essential to simulate future demand upon changes in the human behaviour due to the adoption of new technologies.

Despite being consistently separated between working days and weekends until 2015, the activity profiles for France, Germany, United Kingdom, Spain and Italy showed a different trend in 2016, with a much lower difference between the two day categories (Suppl. Fig. S10).

To examine the temporal diversity of demands on diurnal and seasonal timescales, we applied the same calculation separately to winter and summer. We found that the activity during daylight hours shows similar values in both seasons for all the European countries, as shown in Fig. 4. On the contrary, for certain countries, night consumption is higher in winter, mostly due to off-peak heating which includes thermal storage (e.g. United Kingdom and France), or in summer, because of air conditioning (e.g. Italy and Spain) and country-specific life styles. In addition, during winter we noticed an evening peak similar or even higher than the morning one, most probably caused by lighting [33]. This behaviour is reversed only during summer working days, when the morning peak is the highest of the whole day. With respect to the other European countries, France has a peculiar profile, consisting of three

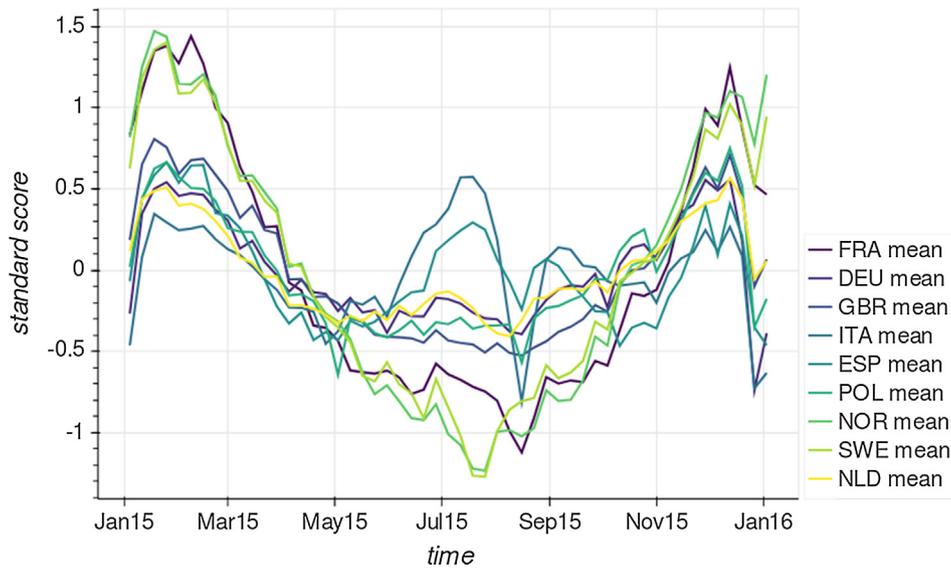


Fig. 3. Normalised mean weekly electricity demand for the top nine European countries. France (FRA), Norway (NOR), and Sweden (SWE) have the highest peaks in winter and the lowest demand in summer. Italy (ITA) and Spain (ESP) have the highest peaks in summer.

peaks, the first being around 10 AM, the second at 5 PM, and the last at 8 PM. These variations can be due to a mix of social activity patterns, technologies and energy system control strategies. To separate these accurately requires a combination of better data and exploration

assuming different models. It should also be added that changes to these factors, and demography, culture and economic structure may cause some historical patterns to change in future scenarios.

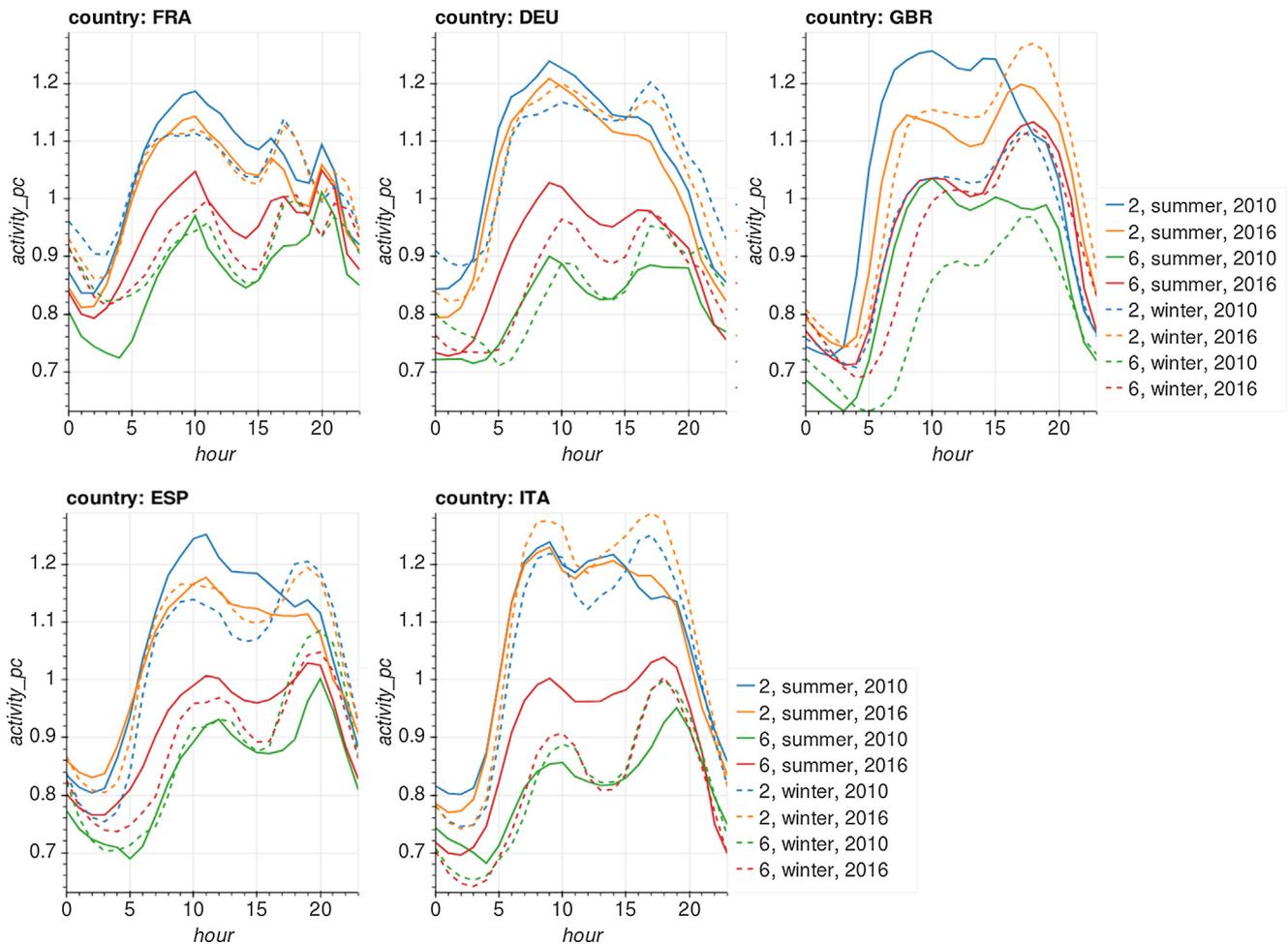


Fig. 4. Activity profiles calculated for an average working day (2, for Wednesday) and weekend (6, for Sunday), during summer (solid line) and winter (dashed line), in 2010 and 2016, for France (FRA), Germany (DEU), United Kingdom (GBR), Spain (ESP), and Italy (ITA).

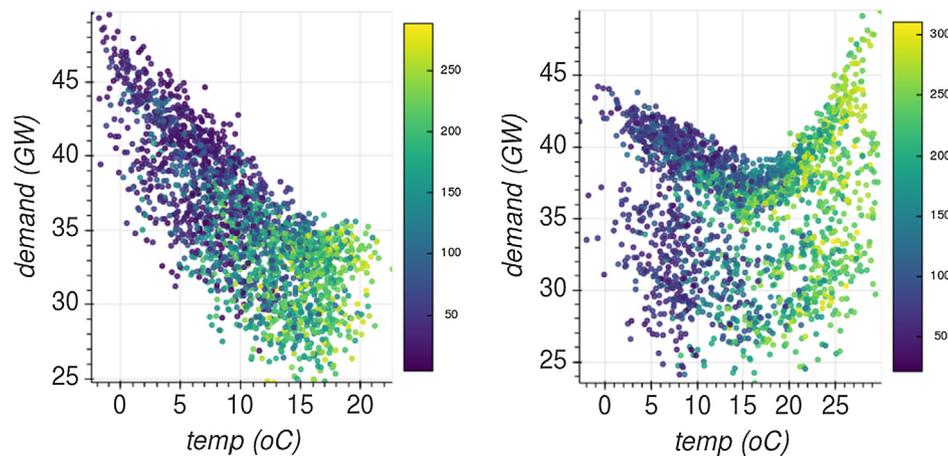


Fig. 5. Temperature ($^{\circ}\text{C}$) and electricity daily national average demand (GW) coloured by solar irradiation (W/m^2) for the period 2011–2015 in United Kingdom (left) and Italy (right). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.5. Relationship between electricity demand and weather

We then focussed on finding the relationship between national electricity demand and weather conditions, in order to identify: (i) the electricity base demand, (ii) the temperature thresholds of the weather-independent demand, and (iii) the temperature sensitivity (or “heat loss”) for air conditioning and for space heating. We analysed temperature, humidex, wind speed, and solar irradiation, weighted by population and aggregated nationally for each country in EU35, at hourly and daily resolution. We found that at the European level humidex is linearly correlated with temperature, whereas wind speed and solar irradiation alone did not show a strong relationship with demand, indicated by a Spearman correlation coefficient of 0.53 and -0.64 , respectively (Suppl. Fig. S11). The relationship between temperature and demand, however, has a different trend for each European state, with southern countries showing a parabola-like curve and northern ones generally displaying a monotonic inversely proportional trend (Fig. 5). It is worth noting that the lowest points on both types of scatterplots correspond to weekends or national holidays. As an example, in the scatterplot showing the temperature-demand relationship in Italy we noticed three clusters, corresponding to working days (top group), Saturdays (middle group), and Sundays (bottom group).

To find the optimal temperature cut-offs, we modelled hourly demand using a range of different temperatures for heating and cooling states and we selected the values that resulted in the maximum summed R-squared for the three regimes (or two, for northern countries that do not have a substantial air conditioning consumption) as thresholds. When we tried using the average or maximum temperature and demand values, instead of the hourly ones, we did not notice any significant changes in the R-squared values of the regression model. The results did not improve by adding wind speed nor taking into account solar irradiation. Since, as previously reported, temperature and humidex are well correlated, the results of the regression model did not change by substituting temperature with humidex. Finally, the hourly data allowed us to estimate also the electricity based load, which we found having the minimum median hourly demand.

3.6. Electricity residual demand

During 2015, the countries with the highest maximum residual demand were France (~ 24 TWh), Germany (~ 23 TWh), United Kingdom (~ 22 TWh), and Poland (~ 17 TWh), which showed a deficit during spring or autumn. A few exceptions – like Italy and Spain – showed instead a surplus of electricity generation during summer (Fig. 6). As an example at national level, the monthly cumulative residual demand/generation for the United Kingdom varied monthly and

across the years. The maximum value of ~ 76 TWh was reached in 2010, which corresponded to 26% of the annual demand (Fig. 7).

At the European level, assuming no interconnections among the EU35 countries, the residual demand we found ranged from 209 in 2011 to 83 TWh in 2014. When, instead, we assumed a perfect transmission among countries, the residual demand decreased substantially and in a constant manner, from 143 TWh in 2011 to 21 TWh in October 2014 (Fig. 8). The amount by which residual demand could be reduced with perfect transmission between countries during the period 2010–2015 was on average ~ 61 TWh (Fig. 8), suggesting the benefit of interconnection in terms of reduced storage requirements.

3.7. Periodicity of the residual electricity demand

A Fourier analysis of the recurring residual demand can provide useful information about the frequency of the storage needs and, potentially, valuable insights regarding the appropriate storage technologies to adopt. We performed a Fourier transform both for the whole Europe and for individual countries in 2015. In addition, we repeated the analysis across multiple years – whenever the generation data was available – by removing the long term trend through a linear regression model. At the European level, we noticed recurring residual demand of ~ 22 TWh each 9–10 months, ~ 5 TWh each 5 months, ~ 6 TWh each 3.7 months, 5.2 TWh each 2.6 months, and 3.8 TWh each 2.2 months (Suppl. Fig. S12). As an example of the results obtained at the national level, the highest peaks of residual demand for the United Kingdom, between 2010 and 2015, are ~ 9 GW for periods of 12 h, ~ 10 GW every 24 h, ~ 3 GW every 2880 h (i.e. about four months), and 5.5 GW every 8000 h (i.e. about a year). When we calculated the residual energy demand (Fig. 9), by multiplying each amplitude to the corresponding period, we found that UK would need ~ 51 TWh of energy storage for intervals of 8639 h (i.e. about a year), ~ 10 TWh every 2880 h (i.e. about four months), and ~ 4 TWh for periods ranging between 2254 and 1440 h (i.e. around a week). These results suggest that for short periods of time (from hours to a few days) it would be advantageous to dispose of a small storage with fast discharge rate; vice versa, for longer periods of time (from months to years) it might instead be beneficial to rely on large storage without a fast discharge rate.

4. Conclusions

In this study, we described the main features, in space and time, of electricity demands in Europe at the national level and examined how electricity demand is affected by social and weather drivers. Human activity has a particularly high impact over daily demand patterns, while weather conditions tend to have a stronger influence on the

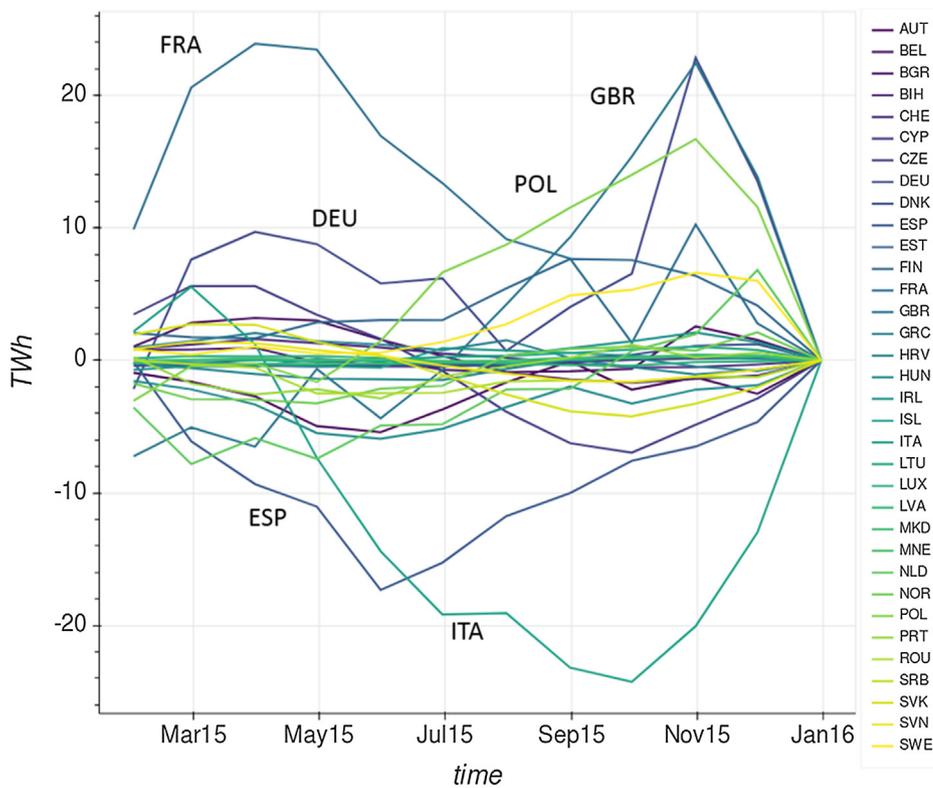


Fig. 6. National electricity residual demand scaled up to match the generation from uncontrollable renewable sources (wind and solar) for the EU35 countries in 2015. Negative values represent surplus of generation, while positive values represent residual demand. Countries with the highest residual demand or generation are labelled.

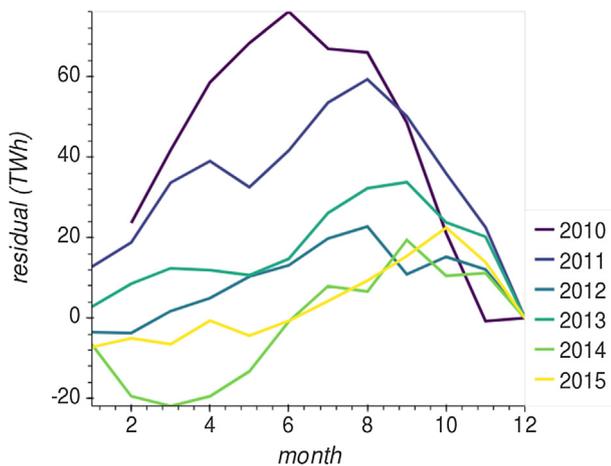


Fig. 7. Monthly cumulative residual demand/generation in UK from 2010 to 2015 assuming a 100% renewable scenario. No values for the hourly demand were reported for January 2010.

seasonal and annual scale.

Although each country has its own activity profile, most of them show a common morning and evening peak, which changes amplitude depending on the season and the day of the week. In this work, we showed that there are important differences in the activity among years, seasons, and especially days of the week. These differences cannot be captured by calculating a single profile for an average day of the year, but only by determining profiles along a whole week to take into account differences between each day type. Moreover, it is recommendable to extract activity profiles for each season, or building a single profile by combining spring and autumn, as the demand in these periods is less influenced by space heating and air conditioning than in winter and in summer. This type of profiles can be particularly useful for bottom-up models that simulate the energy demand at the national level as a function of the population activity. In addition, using a

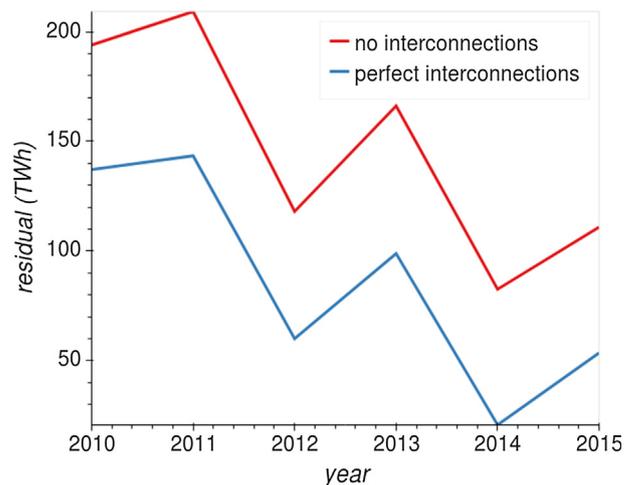


Fig. 8. Comparison between the annual sum of the residual demand peaks across the EU35 countries (assuming no trades among them, red line) and the maximum values of the aggregated peaks (assuming a perfect transmission among them, blue line), in a 100% renewable scenario from wind and solar sources. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

different profile for each day of the week makes it possible to design detailed scenarios that take into account changes in human behaviour between working days and weekends.

Among the weather variables (which include also wind, solar irradiation, humidity index), temperature shows the strongest relationship with electricity demand. The national electricity demand sensitivity to temperature depends on multiple factors, such as the fraction of service demands met by electricity, the heating technology, the building insulation, and human sensitivity. The transition between heating and cooling in demand is gradual, with the former showing an almost linear trend, whereas the latter resembles a curve. A convenient application of temperature sensitivity is to use the slopes of the linear regression

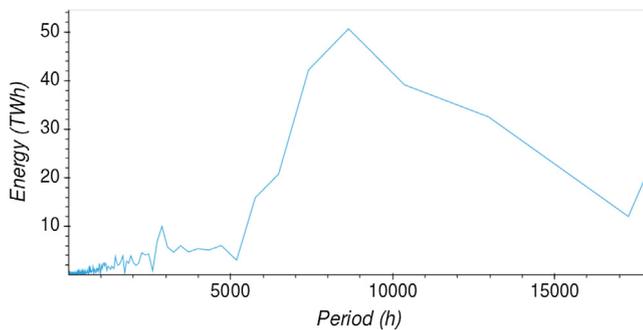


Fig. 9. Periodicity of hourly residual energy demand in 2015 for United Kingdom.

model fitting the data as an approximation of the national average specific heat loss of buildings, a crucial parameter to calculate electric space heating and air conditioning in bottom-up models. For example, when ambient temperature is above the cooling state threshold, the demand of useful energy for air conditioning can be found as a function of the specific heat loss, together with weather conditions and activity profiles. Temperature sensitivity related to the heating regime can be particularly informative about countries with a high fraction of electric space heating, like France, Norway or Sweden. The energy demands of these nations during winter can represent useful examples of the expected change in consumption in future scenarios anticipating an increasing fraction of electric heating. These demands will be probably met through a higher share of renewables, which will also add more variability to the supply side. The Fourier analysis we performed helps unveiling the hidden recurrent patterns of residual demand, which show a periodicity not only limited to the single day, but also for longer time intervals such as months or years. By assuming a 100% uncontrollable electricity generation (from wind and solar energy sources), our analysis of the periods of unmet demand can provide a crucial help to identify the optimal mix of technologies (e.g. storage and transmission) for compensating electricity supply deficits during periods of potentially high variability.

Current models for national energy systems usually approximate future demands by scaling historical profiles according to macro-economic indicators. Our research on the relationship between energy demand, human behaviour, and weather conditions helps improving the accuracy and flexibility of an energy model. For example, including data on social patterns allows to adapt the profile of the projected demands to different possible scenarios, like an increased use of electric vehicles or changes of the comfort temperature within dwellings. Similarly, energy system models can benefit from our study of the relationship between meteorology and demand to refine the estimation of space heating, air conditioning, or hot water consumption. For instance, precise information about the weather can be utilised to improve demand simulations in scenarios of increased air conditioning in northern countries, or in case of extreme weather conditions.

Our analysis provides, therefore, a valuable resource to create country-specific scenarios for the demand and to build better informed energy system models. Moreover, the residual demands we reported can be useful to evaluate the accuracy of models estimating European storage needs by providing the theoretical boundaries of the annual storage size and the storage usage frequencies at the national level.

Data availability

The national activity profiles, the residual demands, and the linear regression coefficients for the EU35 countries can be provided upon request.

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Appendix A

List of countries taken from ENTSO-E:

Albania, Austria, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Macedonia, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom.

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.apenergy.2018.07.108>.

References

- [1] Pfenninger S, Hawkes A, Keirstead J. Energy systems modeling for twenty-first century energy challenges. *Renew Sustain Energy Rev* 2014;33:74–86.
- [2] McKenna E, Thomson M. High-resolution stochastic integrated thermal–electrical domestic demand model. *Appl Energy* 2016;165:445–61.
- [3] Grandjean A, Adnot J, Binet G. A review and an analysis of the residential electric load curve models. *Renew Sustain Energy Rev* 2012;16:6539–65.
- [4] Andersen FM, Larsen HV, Boomsma TK. Long-term forecasting of hourly electricity load: Identification of consumption profiles and segmentation of customers. *Energy Convers Manage* 2013;68:244–52.
- [5] Flett G, Kelly N. A disaggregated, probabilistic, high resolution method for assessment of domestic occupancy and electrical demand. *Energy Build* 2017;140:171–87.
- [6] McKenna E, Krawczynski M, Thomson M. Four-state domestic building occupancy model for energy demand simulations. *Energy Build* 2015;96:30–9.
- [7] Thornton HE, Hoskins BJ, Scaife AA. The role of temperature in the variability and extremes of electricity and gas demand in Great Britain. *Environ Res Lett* 2016;11.
- [8] Psiloglou BE, Giannakopoulos C, Majithia S, Petrakis M. Factors affecting electricity demand in Athens, Greece and London, UK: A comparative assessment. *Energy* 2009;34:1855–63.
- [9] Sandels C, Widen J, Nordstrom L. Forecasting household consumer electricity load profiles with a combined physical and behavioral approach. *Appl Energy* 2014;131:267–78.
- [10] Blazquez L, Boogen N, Filippini M. Residential electricity demand in Spain: New empirical evidence using aggregate data. *Energy Econ* 2013;36:648–57.
- [11] Bessec M, Fouquau J. The non-linear link between electricity consumption and temperature in Europe: a threshold panel approach. *Energy Econ* 2008;30:2705–21.
- [12] Wenz L, Levermann A, Auffhammer M. North-south polarization of European electricity consumption under future warming. *P Natl Acad Sci USA* 2017;114:E7910–8.
- [13] Apadula F, Bassini A, Elli A, Scapin S. Relationships between meteorological variables and monthly electricity demand. *Appl Energy* 2012;98:346–56.
- [14] Bussar C, Moos M, Alvarez R, Wolf P, Thien T, Chen HS, et al. Optimal allocation and capacity of energy storage systems in a future European power system with 100% renewable energy generation. *Energy Proced* 2014;46:40–7.
- [15] Alexander MJ, James P, Richardson N. Energy storage against interconnection as a balancing mechanism for a 100% renewable UK electricity grid. *Iet Renew Power Gen* 2015;9:131–41.
- [16] Edmunds RK, Cockerill TT, Foxon TJ, Ingham DB, Pourkashanian M. Technical benefits of energy storage and electricity interconnections in future British power systems. *Energy* 2014;70:577–87.
- [17] Steinke F, Wolfrum P, Hoffmann C. Grid vs. storage in a 100% renewable Europe. *Renew Energy* 2013;50:826–32.
- [18] Pinnau S, Breitkopf C. Determination of thermal energy storage (TES) characteristics by Fourier analysis of heat load profiles. *Energy Convers Manage* 2015;101:343–51.

- [19] Makarov YV, Du PW, Kintner-Meyer MCW, Jin CL, Illian HF. Sizing energy storage to accommodate high penetration of variable energy resources. *Ieee T Sustain Energy* 2012;3:34–40.
- [20] European Network of Transmission System Operators for Electricity (ENTSO-E). <https://www.entsoe.eu2017>.
- [21] International Energy Agency. *World Energy Balances: World Summary Energy Balances*. UK Data Service; 2016.
- [22] Odyssee. <http://www.indicators.odyssee-mure.eu/>.
- [23] Rienecker MM, Suarez MJ, Gelaro R, Todling R, Bacmeister J, Liu E, et al. MERRA: NASA's modern-era retrospective analysis for research and applications. *J Clim* 2011;24:3624–48.
- [24] Moral-Carcedo J, Vicéns-Otero J. Modelling the non-linear response of Spanish electricity demand to temperature variations. *Energy Econ* 2005;27:477–94.
- [25] Data McKinney W. *Proceedings of the 9th Python in Science Conference*. 2010. p. 51–6.
- [26] van der Walt S, Colbert SC, Varoquaux G. The NumPy array: a structure for efficient numerical computation. *Comput Sci Eng* 2011;13:22–30.
- [27] Team BD. Bokeh: Python library for interactive visualization; 2014.
- [28] Jean-Luc R. Stevens, Philipp Rudiger, Bednar JA. HoloViews: building complex visualizations easily for reproducible science. In: *Proceedings of the 14th Python in science conference (SciPy 2015)*; 2015. p. 61.
- [29] Rocco MV, Ferrer RJF, Colombo E. Understanding the energy metabolism of World economies through the joint use of Production- and Consumption-based energy accountings. *Appl Energy* 2018;211:590–603.
- [30] Huang BN, Hwang MJ, Yang CW. Causal relationship between energy consumption and GDP growth revisited: a dynamic panel data approach. *Ecol Econ* 2008;67:41–54.
- [31] Norway S. *Energy consumption in households, 2012; 2014*.
- [32] Agency Se. *Energy use in Sweden*. 12 January 2018.
- [33] Boßmann T, Staffell I. The shape of future electricity demand: Exploring load curves in 2050s Germany and Britain. *Energy* 2015;90:1317–33.