Long term load projection in high resolution for all countries globally

Toktarova Alla, Gruber Lotta, Hlusiak Markus, Bogdanov Dmitrii, Breyer Christian

This is a Final draft version of a publication
published by Elsevier
in International Journal of Electrical Power and Energy Systems

DOI: 10.1016/j.ijepes.2019.03.055

Copyright of the original publication: © 2019 Elsevier

Please cite the publication as follows:

Toktarova, A., Gruber, L., Hlusiak, M., Bogdanov, D., Breyer, C. (2019). Long term load projection in high resolution for all countries globally. International Journal of Electrical Power and Energy Systems, vol. 111. pp. 160-181. DOI: 10.1016/j.ijepes.2019.03.055

**This is a parallel published version of an original publication.
This version can differ from the original published article.**

Long Term Load Projection in High Resolution for All Countries Globally

Alla Toktarova ^{a,*}, Lotta Gruber ^b, Markus Hlusiak ^b, Dmitrii Bogdanov ^a, Christian Breyer ^{a,b,*}

^a LUT University, Yliopistonkatu 34, 53850 Lappeenranta, Finland

^b Reiner Lemoine Institut gGmbH, Rudower Chaussee 12, 12489 Berlin, Germany

* Corresponding author. LUT University, Yliopistonkatu 34, 53850 Lappeenranta, Finland.

E-mail addresses: AllaToktarova@gmail.com (A. Toktarova), Christian.Breyer@lut.fi (C.

Breyer).

ABSTRACT: Electricity demand modelling is the central and integral issue for the planning and operation of power systems. Load projection provides important information for electricity network planning, and it is essential for the electricity system development. This work investigates the impact of specific economic, technical and climate characteristics on the shape of the electricity demand and introduces a methodology to project electricity demand in hourly resolution within a single framework for all countries. The method used is a multiple linear regression in terms of spectral analysis. 57 real load data profiles of diverse countries were decomposed into a set of sine functions to analyse the cyclical pattern of the data. Fourier coefficients contain information about frequencies and amplitudes in these sinusoids. The sum of various sine functions can be used to calibrate and project hourly electricity demand for any country with available input data for any year in the addressed period. The accuracy of proposed model function is represented in terms of R-squared error. The proposed model is flexible to be applied to different socio-economic scenarios based on alternative assumptions regarding both long-term trends as well as short-term projections.

Keywords: electricity demand, load curve, modelling, long-term load projection

Nomenclature

a^j		Amplitude
b^j		Frequency
c^j		Phase of shift
d^j		Additional ordinate offset
d_{first}		First day of year (from Monday to Sunday, 1-7)
E_{ave}^{tj}	[MWh]	Average electricity consumption over the year
E_{cap}^{tj}	[kWh/cap]	Electricity consumption per capita
E_{hng}^j	[%]	Proportion of the electricity generation share of hydro, nuclear and geothermal power plants in a country j
E_{ind}^j	[%]	Industry factor, i.e. the power consumption in the industrial sector
E_y^{tj}	[TWh]	Annual electricity consumption
GDP_{cap}^{tj}	[€/cap]	Gross Domestic Product per capita
GDP_{To}^j	[%]	Tourism and travel share in GDP
n^j		Extent of sine
Lat^j	[°]	Latitude
Lon^j	[°]	Longitude
$Peak^{tj}$	[MW]	Maximum electricity demand for the years 2017-2100
$Sunset$	[h]	Vector with the time of sunset for the specific geographical region
$T_{c\ month}^j$	[°C]	Average temperature of the coldest month

$T_{local\ hours}^j$	[°C]	Vector of temperature for each hour of year for “nearest” point to the geographical location
T_w^j	[°C]	Warmest Temperature
$T_{w\ month}^j$	[°C]	Average temperature of the warmest month
ΔT^j	[°C]	Difference of the warmest and the coldest month temperature
i		Number of sine function
j		Country index
t		Year index

1. Introduction

1.1 Motivation

The power system is one of the main subsystems of larger energy systems. It is a complex system consisting of an ever-changing infrastructure used by many actors of very different sizes. Mathematical models facilitate power system planning, operation, transmission and distribution, demonstrating problems that need to be solved over different timescales and horizons [1].

The liberalisation of power markets, an aging infrastructure and high penetration rate of renewables have increased interests in electrical load projections [2]. For these reasons, electrical load projections have been a trending topic in power research, and many new approaches have been introduced to improve projections.

1.2 Literature review

Depending on the time horizon and the operating decisions that needs to be made, electric load forecasts are categorized as short-term, medium-term and long-term [3]. Long-term demand forecasting indicating the prediction horizon from several months to several years ahead is a vital component in planning new electricity facilities and the development of transmission and distribution systems [4]. Short-term forecasting is needed for the operation of today’s power systems [5]. In current research on load, short-term demand forecasting prevails and attracts more attention than long-term demand forecasting [4, 6]. A large variety of methods and ideas has been applied to load forecasting, with varying degrees of success. In the following, a brief overview over some of the models and methods is given.

Table 1

Overview of forecasting methods and related resources.

Methods	Sources
1. Statistical methods	
Regression-based models	[4, 7-14]
Time-series approaches	[15-19],
Exponential smoothing	[20]
2. Artificial intelligence-based methods	
Artificial neural networks	[21-22]
Fuzzy logic	[23-26]
Support vector machines	[27]

Regression, as a statistical model, is a widely used technique for electric load forecasting [2]. The load is represented as a function of some descriptor variables [28]. The explanatory variables and their functional forms are key concepts for the accuracy and precision of a forecast [21].

Bianco et al. [9] suggested a linear regression model for forecasting long-term annual electricity consumption in Italy, based on gross domestic product (GDP) and population, up to 2030. Mohamed et al. [10] built a multiple linear regression model to predict electricity consumption for New Zealand, thoroughly investigating the effects of GDP, population and price of electricity on annual load. Hor et al. [8] studied the influence of weather variables and socio-economic factors on the monthly electricity demand in England and Wales by using multiple regression analysis. Kankal et al. [11] expressed energy consumption patterns for Turkey as functions of socio-economic and demographic variables using regression analysis and artificial networks. Günay [21] also used multiple linear regression and artificial networks approaches to describe the demand as a function of population, gross domestic product per capita, inflation percentage, unemployment percentage and average temperature to forecast annual electricity demand. The results were presented for Turkey to the year 2028 with an annual resolution. Hong et al. [7] proposed a probabilistic forecasting approach modernized with hourly demand data and multiple linear regression for long-term electricity forecasting. The proposed approach has been deployed across many U.S. utilities.

Similarly, in the majority of presented studies, the period of forecast is relatively short, and the described electricity load pattern has a low resolution. Recently, there has been a trend towards modeling and long-term forecasting electricity consumption in high resolution [3]. Trotter et al. [13] proposed a method to forecast the Brazilian electricity demand for the period 2016 to 2100 paying attention to weather uncertainty. Fan and Hyndman [17] introduced a short-term load forecasting model also including the impact of the weather variables. Wang et al. [29] applied a segmented regression technique to develop a short-term electricity load forecast for the United States. Temperature has been seen as the main parameter controlling electricity demand.

Another specific aspect of all studies is the focus on only one country [9-11, 21, 30-31]. Yukseltan et al. [12] proposed applying their model to any country, but quantitative results were presented only for Turkey. In [32], the hourly load curve of the Spanish power system was modelled. The model allows to combine long and short-term features by employing temporal disaggregation techniques.

Electricity demand data take the multiple pattern (classified by time, day of the week, and season), which makes it important to consider such multiple pattern in order to improve the predictability of a model. Gould et al. [18] developed models considering both additive and multiplicative seasonality. The estimation of the parameters can be done using exponential smoothing.

Borojeni et al. [19] modeled the historical load data employing time series with various cycles of seasonality in a power network. The model covers a time horizon from the short-term up to the medium-term using autoregressive and moving average components. The evaluation of data forecasting was made based on using two information criteria, namely the Akaike and the Bayesian. Quantification methods consider the complexity of a model by penalising it and the accuracy of the method by rewarding it.

1.3 Our contribution

The aim of this paper is to develop long-term projections of electricity demand of individual countries and respectively aggregated world regions until the year 2100 in hourly resolution. The model is based on a multiple linear regression considering the real demand profiles and socio-economic drivers.

The main contributions of this paper are as follows:

According to Fernández-Blanco et al. [1], regional and national scopes are the main geographical objectives of power system models, whereas local and global scopes are less used due to high complexity. The proposed model allows to project electricity demand structures in hourly resolution for all countries globally while keeping the computational complexity within acceptable limits. This includes also changing structures of countries over time, due to changing macro variables, in particular gross domestic product per capita, or a changing temperature regime due to progressing climate change. This answers a research gap, all modelers of global-local energy transition scenarios in high temporal and geographic resolution are faced to. This paper is in particularly designed to close this research gap.

The overview of the research shows that electricity demand models have become more advanced in recent years. However, it remains unclear to what extent it is possible to develop a complex modeling tool that can represent as much input information as possible (transparent linkages between input variables and demand, hourly resolved data, geographical coverage, etc.). This paper addressed in particular such issues.

1.4 Organisation of the paper

In this paper, a methodology to model and project electricity demand on a national level with an hourly time scale for every year between 2017 and 2100 is proposed. The remaining parts of the paper are organized as follows. Section 2 describes the data and construction of variables. In section 3 the linear regression model is presented using the sum of various sine functions to calibrate and project electricity demand. Applications of the model accuracy results are presented in section 4. In section 5 the main contributions of this paper are highlighted, and possible research directions are discussed. Section 6 draws conclusions. Figure 1 depicts a schematic overview of the paper.

Fig. 1. Schematic overview of the paper.

2. Data

Determination of the relevant variables affecting electricity demand and selecting the appropriate model basis are important steps in modelling and projecting electricity demand. Several applied parameters are well known and most commonly used in the literature [33], such as existing load data, economic data, annual electricity consumption, annual peak load, temperature and some country-specific economic data.

2.1 Available load data

A set of countries with available real electric load data and real peak data is presented in the Appendix (Table A1). The collected data have been used to calibrate and verify the synthetic load model. Figure 2 illustrates the collected data and how the different regions in the world are represented by load data in full hourly resolution for an entire year, or at least by the peak load.

Fig. 2. Available load data in full hourly resolution for an entire year (green) and peak load data (orange).

2.2 Economic Data

A strong relationship between electricity consumption and economic growth has been confirmed [34-36]. In this paper, the GDP per capita in purchasing power parity (PPP) data has been chosen as an economic indicator. The World Bank and International Energy Agency (IEA) provide GDP per capita values worldwide for the period 1990-2014 [37]. Long term GDP per capita projection was modelled by applying a logistic-growth function [38] based on the assumption that by the year 2100 goals set in the United Nations (UN) Resolution adopted by the General Assembly will be achieved and inequalities between countries will be declined [39]. Eq (1) is the logistic growth function in its generalized form.

$$f(t) = A + \frac{K-A}{1+10^{-B(t-M)}} \quad (1)$$

where t is time, A is the lower asymptote, K is the upper asymptote, B is the growth rate and M is the time of maximum growth.

The population weighted average value of GDP per capita of the 30 countries with highest GDP per capita in the period from 1990 to 2014 has been adopted as a reference line of convergence for all countries in the year 2100, assuming that the GDP per capita growth rate in the leading countries will be equal to the rate of growth over the past 25 years, which was 1.0% per year in real terms. The 30 countries with highest GDP per capita have been used to the UN target of high standards of living for all people and in addition for a good statistical basis for the projection. This long-term, stable economic growth of the reference wealth level leads to a unique, global GDP per capita of 88,000 € in the year 2100. A long-term average exchange rate of 1.33 USD/€ is employed, so that shorter term exchange rate variations can be avoided.

2.3 Annual Electricity Demand and Peak Load

Historical data on annual electricity demand per country is provided by IEA [40-41]. Based on the assumption that electricity consumption is closely associated with the national economy [42], a world global electricity demand trend was found as a function of GDP per capita by a two-term exponential function. Electricity per capita values were found by applying population data developed by the UN Department of Economic and Social Affairs [43].

Correlation between electricity demand per capita and GDP per capita values for the year 2012 is visualized in Figure 3. Wealthy countries have a stronger correlation between electricity demand and the value of GDP per capita than poor countries. It is also found that energy intensity decreases for higher GDP, since energy intensity per additional GDP unit shows a negative gradient (Fig. 3 right).

Fig. 3. Electricity consumption per capita as a function of GDP per capita for the year 2012 (left) and the derivation of the smoothing function (right).

Eq. (2) represents the dependence of electricity consumption per capita (E_{cap}^{tj}) on GDP per capita (GDP_{cap}^{tj}) for a certain country j and year t .

$$E_{cap}^{tj} = a \cdot \left(e^{(b \cdot GDP_{cap}^{tj})} - e^{(c \cdot GDP_{cap}^{tj})} \right) \quad (2)$$

Coefficients are:

$a = 7.721 \cdot 10^4 \text{ kWh}$, $b = -1.95 \cdot 10^{-6} \text{ 1/(€/capita)}$, $c = -5.655 \cdot 10^{-6} \text{ 1/(€/capita)}$.

Eq. (2) is used to estimate the electricity consumption per capita for the years 2013 to 2100. This equation describes the global electricity demand trend. In the model weighted average electricity demand values are used as the trend. The trend was formed by the convergence of the individual country electricity demand trend lines to the global demand trend. The convergence growth rate equals 2% per year from the year 2013. Starting from the year 2060 national electricity demand is calculated according to the global trend presented in Eq. (2). The dependence of peak demand per capita on GDP per capita is established using the linear regression method. The correlation between peak demand per capita and GDP per capita for country j and year t is shown in Figure 4.

Fig. 4. Peak demand per capita as a function of GDP per capita.

The future projection of peak demand per capita is calculated based on Eq. (3).

$$Peak^{tj} = a \cdot GDP^{tj}_{cap} + b \quad (3)$$

where a is 0.0456 W/€ and b is 14.48 W/capita.

The synthetic values of peak demand, considering the deviation of the individual peak demand of a country from the trend line in percent, are used as input variables in the model for countries with available peak demand data maintaining the relative individual peak from the trend line. For countries with unknown peak demand data, a global synthetic peak demand trend line is used.

2.4 Temperature

Mirasgedis et al. [14] illustrated the influence of temperature on electricity consumption. In this research, hourly temperature data from 1984 to 2005 are obtained from National Aeronautics and Space Administration of the United States of America (NASA) databases [44-45] and partly reprocessed by the German Aerospace Center [46]. The global temperature raw data in Kelvin units are resolved on a $0.45^\circ \times 0.45^\circ$ degree and an hourly basis. For the further calculation, these data are converted to $^\circ\text{C}$ and aggregated on a daily and monthly basis. In the model an hourly resolution is used as well as daily and monthly aggregation.

2.5 Electricity Production, Industrial Power Consumption, Contribution Tourism to GDP

The ratio of industrial electricity consumption to total electricity consumption is taken from [40-41] and defines the industrialisation of a region. If this value is not available, the corresponding ratio of industrial GDP to total GDP from [48] is used. The higher the level of industrialisation, the stronger the baseload characteristic of the entire load curve and the lower the ratio of minimum to maximum load. To consider the impact of baseload power sources with low marginal costs, the ratio of electricity sourced from hydro, nuclear and geothermal power to total generated electricity [40-41] is used in the model. This has an impact in the northern hemisphere on electricity-based heating. Other impact of specific generation technologies on the load profile could not be observed, not for solar photovoltaic and wind energy, and therefore this has been also not regarded as a factor in the model. Electricity generation of solar photovoltaic prosumers is regarded as part of electricity supply and not as a demand reduction, such as efficiency measures. This approach is also supported by separated meters in most countries which allows to trace the total load. Storage units, such as pumped hydro storage or battery systems are considered as energy system components supporting the match of generation and load without impact on the load. The contribution of travel and tourism to GDP [49] is used in the model to consider peak loads during the tourist season. Such an impact can be observed for classical tourist countries, which are quite often islands in sunny regions. Data described in this section is mainly for recent years from the 2010s, but depends on the specific dataset.

3. Methodology

The following methodology aims to describe the hourly resolved load of the power sector in its current structure. Therefore, future additional electricity demand of other energy sectors, such as for transport, is not included in the overall electricity demand nor in profiles. Such an additional demand is typically added separately to the electricity demand in the power sector for analysing energy transition trends by the means of energy system models.

Load patterns depend on the month of the year, day of the week, and hour of the day [2]. Real load profiles (see Table A1) show multilevel seasonality governed by periodic astronomical events affecting temperature, lighting and climate at a given location, but also show regular cultural and economic characteristics. As the main model-building approach, the sum of sine functions was chosen to describe various relationships between demand and underlying influencing parameters. The sine function, as a real-valued function of the complex-valued exponential function, describing mathematically periodical events, matches well different influencing factors for the load, but can be also used for linear factors. The model is represented by the following fundamental equation (4) describing the load:

$$load(x) = \sum_i y_i(x) = \sum_i a_i \sin^{n_i}(b_i x + c_i) + d_i \quad (4)$$

where x is the time in hours since the beginning of the year, running from 1 to 8760. Additional parameters are a_i the amplitude, b_i the frequency, c_i the phase shift, d_i the additional ordinate

offset, n_i the power of sine (only values 1 and 2 are used), and i denotes the number of sine functions used to describe the full load curve.

3.1 Annual consumption trend

The average consumption in MW is set to the arithmetic mean of the annual electricity consumption expressed in TWh equally distributed to all hours of the year. The average consumption ensures a constant bias of electricity consumption for all hours of the year.

$$\begin{aligned} y_1 &= a_1 \sin^{n_1} (b_1 x + c_1) + d_1 & (5) \\ a_1 &= 0 & (5a) \quad b_1 = 0 & (5b) \quad c_1 = 0 & (5c) \quad n_1 = 0 & (5d) \\ d_1 &= E_y^{tj} \frac{10^6}{8760 h} & (5e) \end{aligned}$$

Where E_y^{tj} is the electricity consumption of the regarded year and country in TWh.

3.2 Annual oscillation

3.2.1 Basic annual oscillation

Three basic patterns have been revealed for annual oscillation: (i) Temperature has a significant fundamental influence on the annual oscillation of electricity consumption for all countries, (ii) the demand is observed to be higher on cold days, (iii) on hot days the demand is also increased due to air conditioning.

$$\begin{aligned} y_2 &= a_2 \sin^{n_2} (b_2 x + c_2) + d_2 & (6) \\ d_2 &= 0 & (6a) \quad n_2 = 1 & (6b) \end{aligned}$$

The frequency of the annual cycle is b_2 . The number 8760 in the denominator stands for the number of observations in the period, here, hours in a year as an hourly sampled data set is used.

$$b_2 = \frac{2\pi}{8760} \quad (6c)$$

The time shift parameter c_2 differs for the northern and southern hemisphere. The latitude in the formula is defined as follows:

$$c_2 = 0.225 \cdot 2\pi \frac{lat}{|lat|} \quad (6d)$$

Countries where the difference between the warmest and the coldest monthly averaged temperature ΔT^j varies from 0 to 3.1 °C show a constant electricity demand without significant peaks during the year.

$$f_{a_2}^1(\Delta T^j) = \begin{cases} 1, & \Delta T^j < 3.1 \\ 0, & \Delta T^j \geq 3.1 \end{cases} \quad (6e)$$

$$a_2^1 = 0 \quad (6f)$$

A sharp increase of electricity consumption in the summer period is observed in regions where warmest temperature T_w^j can exceed 32.41 °C during the year.

$$f_{a_2}^2(T_{c\ month}^j) := \begin{cases} 1, & T_{w\ month}^j \geq 32.41 \\ 0, & T_{w\ month}^j < 32.41 \end{cases} \quad (6g)$$

$$f_{a_2}^3(lat^j) := \begin{cases} 1, & lat^j \in [-34, 35] \\ 0, & lat^j \in [-90, -34) \cup (35, 90] \end{cases} \quad (6h)$$

$$a_2^2 = E_{ave}^{tj} \left(1 - e^{-\frac{32.2 - T_{w\ month}^j}{47.9}} \right) \quad (6i)$$

where E_{ave}^{tj} is the average electricity consumption over the year and $T_{c\ month}^j$ is the average temperature of the coldest month.

For other countries the seasonal demand pattern exhibits higher consumption during winter than in summer.

$$f_{a_2}^4(T_{c\ month}^j) := \begin{cases} 1, & T_{w\ month}^j < 32.41 \\ 0, & T_{w\ month}^j \geq 32.41 \end{cases} \quad (6j)$$

$$f_{a_2}^5(lat^j) := \begin{cases} 1, & lat^j \in [-90, -34) \cup (35, 90] \\ 0, & lat^j \in [-34, 35] \end{cases} \quad (6k)$$

$$a_2^3 = 0.1335 \cdot E_{ave}^{tj} \left(1 - e^{-\frac{12.5 - T_{c\ month}^j}{15.2}} \right) \quad (6l)$$

where E_{ave}^{tj} is the average electricity consumption over the year and $T_{c\ month}^j$ is the average temperature of the coldest month. [Fig. 5 displays the combined parameter \$a_2\$ of Eq. \(6m\).](#)

Fig. 5. Dependence of coefficient a_2 on average temperature of coldest month $T_{c\ month}^j$.

$$a_2 = a_2^1 \cdot f_{a_2}^1(\Delta T^j) + a_2^2 \cdot f_{a_2}^2(T_{c\ month}^j) \cdot f_{a_2}^3(lat^j) + a_2^3 \cdot f_{a_2}^4(T_{c\ month}^j) \cdot f_{a_2}^5(lat^j) \quad (6m)$$

3.2.2 Annual oscillation driven by electric heating

The effect of increased electricity demand on cold days is substantially higher than average for countries with a high proportion of hydro, nuclear and geothermal generation of electricity in the

total annual production. Such generation is characterised by rather low marginal cost, which leads to the use of electric heating to meet heat demand during the cold season.

$$y_3 = a_3 \sin^{n_3} (b_3 x + c_3) + d_3 \quad (7)$$

$$d_3 = 0 \quad (7a) \quad n_3 = 1 \quad (7b)$$

The frequency and the time shift are equal to the basic annual oscillation (6c), (6d).

$$b_3 = b_2 = \frac{2\pi}{8760} \quad (7c) \quad c_3 = c_2 = 0.225 \cdot 2\pi \frac{lat}{|lat|} \quad (7d)$$

The amplitude value for annual oscillation driven by heating electricity is calculated for regions where $T_{w\ month}^j > 12\text{ }^\circ\text{C}$, $T_{c\ month}^j < 11\text{ }^\circ\text{C}$, $\Delta T^j > 5\text{ }^\circ\text{C}$ and E_{hng}^j varies between 80% and 100%.

$$f_{a_3}^1(T_{w\ month}^j) = \begin{cases} 1, & T_{w\ month}^j \geq 12 \\ 0, & T_{w\ month}^j < 12 \end{cases} \quad (7e)$$

$$f_{a_3}^2(T_{c\ month}^j) := \begin{cases} 1, & T_{c\ month}^j \leq 11 \\ 0, & T_{c\ month}^j > 11 \end{cases} \quad (7f)$$

$$f_{a_3}^3(\Delta T^j) = \begin{cases} 1, & \Delta T^j \geq 5 \\ 0, & \Delta T^j < 5 \end{cases} \quad (7g)$$

$$f_{a_3}^4(E_{hng}^j) := \begin{cases} 1, & E_{hng}^j \in [80, 100] \\ 0, & E_{hng}^j \in (0, 80) \end{cases} \quad (7h)$$

$$a_3^1 = \frac{(11 - T_{c\ month}^j) \cdot E_{ave}^{tj}}{100} \cdot E_{hng}^{tj} \quad (7i)$$

where $T_{c\ month}^j$ is the average temperature of the coldest month, E_{ave}^{tj} is the average electricity consumption over the year and E_{hng}^{tj} is the proportion of the electricity generation share of hydro, nuclear and geothermal power plants in a country. [Fig. 6 visualises the parameter \$a_3\$ of Eq. \(7j\).](#)

Fig. 6. Dependence of coefficient a_3 on average temperature of coldest month $T_{c\ month}^j$ and industry factor E_{ind}^j .

$$a_3 = a_3^1 \cdot f_{a_3}^1(T_{w\ month}^j) \cdot f_{a_3}^2(T_{c\ month}^j) \cdot f_{a_3}^3(\Delta T^j) \cdot f_{a_3}^4(E_{hng}^j) \quad (7j)$$

where $T^{j_w}_{month}$ is the average temperature of the warmest month, $T^{j_c}_{month}$ is the average temperature of the coldest month, ΔT^j is the temperature difference between the warmest and the coldest month, and $E^{j_{hng}}$ is the proportion of the electricity generation share of hydro, nuclear and geothermal power plants.

3.3 Diurnal oscillation

3.3.1 Basic diurnal oscillation

The electricity consumption pattern over a day shows substantial intraday variability. The demand is higher than average during noon and evening, while night demand tends to be lower than average.

$$y_4 = a_4 \sin^{n_4}(b_4 x + c_4) + d_4 \quad (8)$$

$$d_4 = 0 \quad (8a) \quad n_4 = 1 \quad (8b)$$

Periods of 24 and 12 hours are introduced to model daily oscillations.

$$b_4 = \frac{2\pi}{8760} \cdot 365 \quad (8c)$$

One hour corresponds to $2\pi/24$. The minimum point is $2/3\pi$, this corresponds to a time of 18:00. It is assumed that the lowest demand during the day corresponds to 03:00 in the morning. This implies a phase shift of 9 hours, which was fine tuned to 9.1 hours, as realised by the parameter c_4 .

$$c_4 = -9.1 \frac{2\pi}{24} \quad (8d)$$

The magnitude of the amplitude follows a decreasing exponential function.

$$a_4 = 0.12 \cdot E_{ave}^{tj} \cdot \left(1 - e^{-\frac{-GDP_{cap}^{tj}}{10}}\right) \quad (8e)$$

where E_{ave}^{tj} is average electricity consumption over the year and GDP_{cap}^{tj} is the gross domestic product per capita. [Fig. 7 displays the parameter \$a_4\$ of Eq. \(8e\).](#)

Fig. 7. Dependence of coefficient a_4 on GDP per capita, GDP^{tj}_{cap}

3.3.2 Diurnal oscillation driven by low electricity prices

A high national share of hydropower, geothermal or nuclear energy typically implies low energy prices, which in turn leads to, in general, more electricity consumption due to a lower level of efficiency.

$$y_5 = a_5 \sin^{n_5}(b_5 x + c_5) + d_5 \quad (9)$$

$$d_5 = 0 \quad (9a) \quad n_5 = 1 \quad (9b)$$

The frequency is equal to the basic diurnal oscillation (8c).

$$b_5 = b_4 = \frac{2\pi}{8760} \cdot 365 \quad (9c)$$

Sine, shifted by π , oscillation reduces the amplitude of the basic diurnal oscillation.

$$c_5 = c_4 + \pi = 2.9 \frac{2\pi}{24} \quad (9d)$$

The amplitude for daily oscillations is driven by low electricity prices induced by a high share of low marginal cost generation, which is indicated by the supply share of hydropower, nuclear and geothermal energy (E^{j}_{hng}) and applied for a respective share of higher than 80% of the total electricity supply. The function Eq. (7h) described above in section 3.2.2 is used to define the amplitude of diurnal oscillation driven by low electricity prices.

$$a_5^1 = 0.12 \cdot E_{ave}^{tj} \cdot (E_{hng}^{tj})^8 \quad (9e)$$

$$a_5 = a_5^1 \cdot f_{a_3}^4(E_{hng}^j) \quad (9f)$$

where E_{ave}^{tj} is average electricity consumption over the year.

3.3.3 Double frequency of diurnal oscillation

The available load data exhibit a double peak structure, i.e. one peak around noon and another in the later afternoon to early evening.

$$y_6 = a_6 \sin^{n_6} (b_6 x + c_6) + d_6 \quad (10)$$

$$d_6 = 0 \quad (10a) \quad n_6 = 1 \quad (10b)$$

The period 12 hours is introduced to simulate a daily double peak oscillation.

$$b_6 = \frac{2\pi}{8760} \cdot 365 \cdot 2 \quad (10c)$$

$$c_6 = 2 \cdot c_4 - \frac{3}{2} \pi = -36.2 \frac{2\pi}{24} \quad (10d)$$

$$a_6 = \frac{(a_4 - a_5)}{2.71} = 0.044 \cdot E_{ave}^{tj} \left(\left(1 - e^{-\frac{-GDP_{cap}^{tj}}{10}} \right) - (E_{hng}^{tj})^8 \cdot f_{a_3}^4(E_{hng}^j) \right) \quad (10e)$$

3.4 Optimal summer day oscillation

This oscillation is almost identical to the double peak structure of Eq. (10); however, a phase shift is chosen so that the afternoon peak disappears, and the amplitude is weaker.

$$y_7 = a_7 \sin^{n_7} (b_7 x + c_7) + d_7 \quad (11)$$

$$d_7 = 0 \quad (11a) \quad n_7 = 1 \quad (11b)$$

$$b_7 = b_6 = \frac{2\pi}{8760} \cdot 365 \cdot 2 \quad (11c)$$

$$c_7 = -2 \cdot c_6 + \pi = 84.4 \frac{2\pi}{24} \quad (11d)$$

$$a_7 = \frac{a_4}{3.7} = 0.032 \cdot E_{ave}^{tj} \cdot \left(1 - e^{-\frac{-GDP_{cap}^{tj}}{10}} \right) \quad (11e)$$

3.5 Week oscillation

3.5.1 Basic week oscillation

Electricity demand is not uniform throughout the week. It peaks during weekday working hours and is at its minimum during nights and weekends.

$$y_8 = a_8 \sin^{n_8} (b_8 x + c_8) + d_8 \quad (12)$$

$$d_8 = 0 \quad (12a) \quad n_8 = 1 \quad (12b)$$

Frequency of a weekly cycle expressed in hourly terms:

$$b_8 = \frac{2\pi}{8760} \cdot \frac{365}{7} \quad (12c)$$

It is assumed that the lowest electricity demand of the weekly oscillation occurs at 3 o'clock on Sunday morning. This hour is the 147th hour of a week. For a given length of the period of 168 hours ($24 \text{ h} \cdot 7 = 168 \text{ h}$), the lowest load of the week is equal to the 126th hour of the week ($168 \cdot 3/2 \cdot \pi$, since $3/2 \cdot \pi$ equals the minimum of the sine function). The phase shift is therefore $(126 - 147)/168 \cdot 2\pi = -0.25\pi$. The phase shift follows to:

$$c_8 = -0.25\pi + (d_{first} - 1) \cdot \frac{2\pi}{7} \quad (12d)$$

where d_{first} is the first day of the year $\in \mathbb{N}, [1,7]$ for Monday =1 and Sunday = 7.

Countries with the weekend on Friday and Saturday have the lowest demand of the weekend oscillation on Saturday morning at 3 o'clock, the 123rd hour.

$$c_8 = -0.25\pi + d_{first} \cdot \frac{2\pi}{7} \quad (12e)$$

The amplitude of the weekly oscillation has a significant dependence on the power consumption of the industrial sector, E_{ind}^j . The more a region is industrialised, the less pronounced is the difference between weekdays and weekends.

$$a_8 = 0.063263 \cdot E_{ind}^j \cdot E_{ave}^{tj} \quad (12f)$$

where E_{ind}^j is the industry factor, or the power consumption in the industrial sector, and E_{ave}^{tj} is the average electricity consumption over the year.

3.5.2 Double frequency of week oscillation

The basic week oscillation would provide too much stress on Wednesday, so the oscillation of the 3.5-day period and half of the amplitude corrects the Wednesday value and the minimum value is further emphasised.

$$y_9 = a_9 \sin^{n_9}(b_9 x + c_9) + d_9 \quad (13)$$

$$d_9 = 0 \quad (13a) \quad n_9 = 1 \quad (13b)$$

$$a_9 = \frac{a_8}{2} = 0.032 \cdot E_{ind}^j \cdot E_{ave}^{tj} \quad (13c)$$

$$b_9 = \frac{2\pi}{8760} \cdot \frac{365}{7} \cdot 2 \quad (13d)$$

$$c_9 = -2 \cdot c_8 - \frac{3}{2}\pi = -\pi - 2 \cdot d_{first} \cdot \frac{2\pi}{7} \quad (13e)$$

3.6 Weekend oscillation

3.6.1 Basic weekend oscillation

To consider the difference between weekdays and weekends, another set of oscillations is used.

With $k_l \in \mathbb{N}, [1,52]$ we get

$$\text{For } x_w^l \in \left[\frac{124 - (d_{first} - 1) \cdot 24 + (k_1 - 1) \cdot 24 \cdot 7}{172 - (d_{first} - 1) \cdot 24 + (k_1 - 1) \cdot 24 \cdot 7} \right]$$

It is assumed that weekends start at 05:00 on Saturday and end at 03:00 on Monday. For countries with the weekend on Friday and Saturday, x_w is defined as follows:

$$x_w^2 \in \left[\frac{100 - (d_{first} - 1) \cdot 24 + (k_1 - 1) \cdot 24 \cdot 7}{148 - (d_{first} - 1) \cdot 24 + (k_1 - 1) \cdot 24 \cdot 7} \right]$$

It is assumed that weekends start at 05:00 on Friday and end at 03:00 on Sunday.

$$y_{10} = a_{10} \sin^{n_{10}}(b_{10} x + c_{10}) + d_{10} \quad (14)$$

with $x \in \mathbb{N}, x_w^l, x_w^2$.

$$d_{10} = 0 \quad (14a) \quad n_{10} = 1 \quad (14b)$$

The length of the period is equivalent to the length of the period of the basic diurnal period.

$$b_{10} = b_4 = \frac{2\pi}{8760} \cdot 365 \quad (14c)$$

A sinusoidal oscillation is shifted by a half period to weaken the amplitude of the basic diurnal period.

$$c_{10} = c_4 + \pi = 2.9 \cdot \frac{2\pi}{24} \quad (14d)$$

Industrial activity has the dominating influence on the difference between weekday and weekend demand oscillations. The higher the industrial share in the total demand, the more the weekly spread is reduced.

$$a_{10} = (a_4 - a_5) \cdot E_{ind}^j = E_{ind}^j \cdot 0.12 \cdot E_{ave}^{tj} \left(\left(1 - e^{-\frac{-GDP_{cap}^{tj}}{10}} \right) - (E_{hng}^{tj})^8 \cdot f_{a_3}^4(E_{hng}^j) \right) \quad (14e)$$

where E_{ind}^j is the industry factor, i.e. the relative power consumption of the industrial sector.

3.6.2 Double frequency of weekend oscillation

To reduce the daily amplitude of the load curve over the weekend, it is also necessary to reduce the double daily frequency during that period.

$$y_{11} = a_{11} \sin^{n_{11}}(b_{11}x + c_{11}) + d_{11} \quad (15)$$

with $x \in \mathbb{N}$, x_w^1 , x_w^2 (for x_w^1 and x_w^2 see section 3.6.1)

$$d_{11} = 0 \quad (15a) \quad n_{11} = 1 \quad (15b)$$

$$b_{11} = b_6 = \frac{2\pi}{8760} \cdot 365 \cdot 2 \quad (15c)$$

$$c_{11} = c_6 + \pi = -24.2 \cdot \frac{2\pi}{24} \quad (15d)$$

$$a_{11} = a_6 \cdot E_{ind}^j = 0.044 \cdot E_{ind}^j \cdot E_{ave}^{tj} \left(\left(1 - e^{-\frac{-GDP_{cap}^{tj}}{10}} \right) - (E_{hng}^{tj})^8 \cdot f_{a_3}^4(E_{hng}^j) \right) \quad (15e)$$

where E_{ind}^j is the industry factor.

3.6.3 Decreased weekend average

The average demand on weekends is lower than on weekdays, which needs to be adjusted.

$$y_{12} = a_{12} \sin^{n_{12}}(b_{12}x + c_{12}) + d_{12} \quad (16)$$

with $x \in \mathbb{N}$, x_w^1 , x_w^2 (for x_w^1 and x_w^2 see section 3.6.1)

$$a_{12} = 0 \quad (16a) \quad b_{12} = 0 \quad (16b) \quad c_{12} = 0 \quad (16c) \quad n_{12} = 1 \quad (16d)$$

$$d_{12} = 0.136493 \cdot E_{ave}^{tj} \cdot \left(1 - e^{-\frac{-E_{ind}^j}{0.55691}} \right) \quad (16e)$$

where E_{ave}^{tj} is the average electricity consumption over the year and E_{ind}^j is the industry factor.

3.7 Afternoon and evening peak

Eq. (17) is introduced to account for lighting and other electricity demand correlating to activity in the dark hours of the day. A single sine period formulated as $\sin^2$ is used to have positive values only. This begins at sunset and ends at midnight, when it is assumed this additional demand ends.

$$y_{13} = \sum_{k_1=1}^{365} a_{k_1} \sin^{n_{k_1}}(b_{k_1}x + c_{k_1}) + d_{k_1} \quad (17)$$

$$d_{k_1} = 0 \quad (17a) \quad n_{k_1} = 2 \quad (17b)$$

As sunset occurs at various times every day, it is necessary to model 365 individual oscillations. The individual oscillations are limited to the period of the respective sunset until midnight by limiting the definition range of x (the hours of the year). The oscillations are calculated for the daily hours from 08:00 to 24:00; this time corresponds to an interval $x \in [24 * (k_1 - 1) + \text{sunset}(k_1), 24 * k_1]$, where $k_1 \in$ the 365 days of a year.

The $\sin^2$ oscillation of the afternoon / evening has the period length from the time of sunset to midnight.

$$b_{k_1} = \frac{2\pi}{2 \cdot (24 - \text{sunset}(k_1))} \quad (17c)$$

$$c_{k_1} = (24 \cdot (k_1 - 1) + \text{sunset}(k_1)) \cdot b_{k_1} \quad (17d)$$

The amplitude is dependent on the GDP per capita (GDP^{tj}_{cap}) and the time of the sunset on the specific day. In case sunset is after midnight or the sun does not set at all on a particular day, its amplitude is set to zero.

$$a_{k_1} = E_{ave}^{tj} \cdot \left(0.036 - 0.036 \cdot 0.8 \cdot (\text{sunset}(k_1) - 19.5) + 0.5 \cdot e^{\frac{\ln 0.5}{6000} GDP_{cap}^{tj}} \cdot \left(1 - \frac{\text{sunset}(k_1) - 17}{24 - 17} \right) \right) \quad (17e)$$

where E_{ave}^{tj} is the average electricity consumption over the year and GDP^{tj}_{cap} is the gross domestic product per capita.

3.8 Air conditioning

3.8.1 Day peak

If a location exhibits a temperature of more than 25°C for more than 300 hours in a year, it is assumed that air conditioning is present in a significant amount. Again, a $\sin^2$ function is used to add load.

$$y_{14} = \sum_{k_2=1}^{365} a_{k_2} \sin^{n_{k_2}}(b_{k_2}x + c_{k_2}) + d_{k_2} \quad (18)$$

$$d_{k_2} = 0 \quad (18a) \quad n_{k_2} = 2 \quad (18b)$$

$$b_{k_2} = \frac{2\pi}{2 \cdot 15} \quad (18c)$$

$$c_{k_2} = 24 * (k_2 - 1) + 8 \quad (18d)$$

The period and the phase shift are modelled to have a maximum at 15:30 provided that the maximum temperature of a day exceeds 25°C.

The oscillations are calculated for the daily hours from 08:00 to 23:00; this time corresponds to an interval $x \in [24 * (k_2 - 1) + 8, 24 * k_2 - 1]$, where $k_2 \in$ the 365 days of a year. The amplitude is described in Eq. (18i) and applied for temperatures above 25°C.

$$f_{a_{k_2}}(T_{local\ hours}^j) = \begin{cases} 1, & length(T_{local\ hours}^j > 25^\circ\ C) > 300h \\ 0, & length(T_{local\ hours}^j > 25^\circ\ C) \leq 300h \end{cases} \quad (18e)$$

Basic condition:

$$temp := T_{local\ hours}^j(x \in [24 * (k_2 - 1) + 8] : x \in [24 * k_2 - 1]), \quad (18f)$$

where $temp$ is the temperature data vector in hourly resolution. $Temp$ vector values correspond to a given hours in the interval x , $temp \in \mathbb{R}$

$$h := \max(temp) \quad (18g)$$

where h is the maximum value of the $temp$ vector.

$$f_1(h) = \begin{cases} 1, & h > 25 \\ 0, & h < 25 \end{cases} \quad (18h)$$

$$a_{k_2}^1 = \frac{E_{ave}^{tj}}{900} \cdot \left(1 - e^{-\frac{-GDP_{cap}^{tj}}{1000000}} \right) \cdot \left(1 - e^{-\frac{-(f_1(h)-26)}{7}} \right) \quad (18i)$$

$$a_{k_2}(x) = a_{k_2}^1 \cdot f_{a_{k_2}}(T_{local\ hours}^j) \quad (18j)$$

where E_{ave}^{tj} is the average electricity consumption over the year and GDP_{cap}^{tj} is the gross domestic product per capita.

3.8.2 Summer night peak

A basic assumption was made that air conditioning systems are used to a significant extent only if the temperature above 25 °C was measured for at least 300 hours per year according to Eq. (18e).

$$y_{15} = \sum_{k_3=1}^{365} a_{k_3} \sin^{n_{k_3}}(b_{k_3}x + c_{k_3}) + d_{k_3} \quad (19)$$

for $x \in [24 * (k_3 - 1) + 1, 24 * (k_3 - 1) + 48]$, two full days, before and after the summer night.

$$a_{k_3} = 0 \quad (19a) \quad b_{k_3} = 1 \quad (19b) \quad c_{k_3} = 0 \quad (19c) \quad n_{k_3} = 1 \quad (19d)$$

If summer nights have a maximum temperature exceeding 22°C between 21:00 and 08:00, additional load is set for two days adjacent to the night. Warm nights correspond to hours in the interval $x \in [24 * (k_3 - 1) + 21, 24 * (k_3 - 1) + 32]$, where $k_3 \in$ the 365 days of a year.

Basic condition:

$$temp_2 := T_{local\ hours}^j(x \in [24 * (k_3 - 1) + 21, 24 * (k_3 - 1) + 32]), \quad (19e)$$

where $temp_2$ is a temperature data vector in hourly resolution, and $temp_2$ vector values correspond to given hours in the interval x , $temp_2 \in \mathbb{R}$

$$h_2 := \max(temp_2) \quad (19f)$$

where h_2 is the maximum value of the $temp_2$ vector.

$$f_2(h_2) = \begin{cases} 1, & h_2 > 22 \\ 0, & h_2 < 22 \end{cases} \quad (19g)$$

$$d_{k_3}^1 = \frac{E_{ave}^{tj}}{1700} \cdot \left(1 - e^{-\frac{-0.038 \cdot GDP_{cap}^{tj} \cdot (f_2(h_2)-22)}{10000}} \right) \quad (19h)$$

$$d_{k_3} = d_{k_3}^1 \cdot f_{a_{k_2}}(T_{local\ hours}^j) \quad (19i)$$

where E_{ave}^{tj} is the average electricity consumption over the year and GDP^{tj}_{cap} is the gross domestic product per capita.

3.8.3 Winter peak

It is assumed that air conditioning in winter exists, based on the same conditions as defined in Eq. (18e). However, it is also assumed that no other form of heating exists if the minimum temperature does not fall below 2 °C and that air conditioning is used as heating on cold days through reverse cycling.

$$y_{16} = \sum_{k_4=1}^{365} a_{k_4} \sin^{n_{k_4}}(b_{k_4}x + c_{k_4}) + d_{k_4} \quad (20)$$

$$a_{k_4} = 0 \quad (20a) \quad b_{k_4} = 1 \quad (20b) \quad c_{k_4} = 0 \quad (20c) \quad n_{k_4} = 1 \quad (20d)$$

The oscillations are calculated for the daily hours from 06:00 to 23:00; this time corresponds to an interval $x \in [24 * (k_4 - 1) + 6, 24 * (k_4 - 1) + 23]$, where $k_4 \in$ the 365 days of a year.

$$f_{d_{k_4}}(T_{local\ hours}^j) = \begin{cases} 1, & \min(T_{local\ hours}^j) \geq 2 \\ 0, & \min(T_{local\ hours}^j) < 2 \end{cases} \quad (20e)$$

Additional restriction for this oscillation checks that daily average temperature should fall below 15 °C.

$$temp_3 := T_{local\ hours}^j(x \in [24 * (k_4 - 1) + 1, 24 * k_4]), \quad (20f)$$

where $temp$ is the temperature data vector in hourly resolution. The $Temp_3$ vector values correspond to a given hour in the interval x , $temp_3 \in \mathbb{R}$

$$h_3 := \max(temp_3) \quad (20g)$$

where h_3 is the maximum value of the $temp$ vector.

$$f_{d_{k_4}}(h_3) = \begin{cases} 1, & h_3 < 15^\circ\text{C} \\ 0, & h_3 \geq 15^\circ\text{C} \end{cases} \quad (20h)$$

$$d_{k_4}^1 = 0.1 \cdot E_{ave}^{tj} \cdot \left(1 - e^{-\frac{-GDP_{cap}^{tj}}{10000}}\right) \cdot \left(1 - e^{-\frac{-(15 - f_{d_{k_4}}(h_3))}{13}}\right) \quad (20i)$$

$$d_{k_4} = d_{k_4}^1 \cdot f_{a_{k_2}}(T_{local\ hours}^j) \cdot f_{d_{k_4}}(T_{local\ hours}^j) \quad (20j)$$

where E_{ave}^{tj} is the average electricity consumption over the year and GDP^{tj}_{cap} is the gross domestic product per capita.

3.9 Travel and tourism contribution

Real load data shows that in countries with a strongly developed tourism sector, consumption of electricity is increased during the summer period.

$$y_{17} = a_{k_5} \sin^{n_{k_5}}(b_{k_5}x + c_{k_5}) + d_{k_5} \quad (21)$$

$$a_{k_5} = 0 \quad (21a) \quad b_{k_5} = 0 \quad (21b) \quad c_{k_5} = 0 \quad (21c) \quad n_{k_5} = 1 \quad (21d)$$

The oscillations are calculated for countries where the warmest temperature T_w^j can exceed 29 °C during the year and the tourist and travel share of the $GDP^{j_{To}}$ exceeds 10.2%.

$$f_{d_{k_5}}^1(T_w^j) := \begin{cases} 1, & T_w^j \geq 29 \\ 0, & T_w^j < 29 \end{cases} \quad (21e)$$

$$f_{d_{k_5}}^2(GDP_{To}^j) := \begin{cases} 1, & GDP_{To}^j \geq 10.2 \\ 0, & GDP_{To}^j < 10.2 \end{cases} \quad (21f)$$

$$f_{d_{k_5}}^3(lat^j) := \begin{cases} 1, & lat^j \in [15, 90] \\ 0, & lat^j \in (-90, 15) \end{cases} \quad (21g)$$

The summer period corresponds to hours in the interval $x \in [24 * (k_5 - 1) + 1, 24 * k_5]$, where $k_5 \in$ the daily interval, which is equal to [152, 243].

$$f_{d_{k_5}}^4(x) := \begin{cases} 1, & x \in k_5 \\ 0, & x \notin k_5 \end{cases} \quad (21h)$$

$$d_{k_5}^1 = E_{ave}^{tj} \cdot \left(1 - e^{-\frac{-GDP_{To}^j}{80}} \right) \quad (21i)$$

$$d_{k_5} = d_{k_5}^1 \cdot f_{d_{k_5}}^1(T_w^j) \cdot f_{d_{k_5}}^2(GDP_{To}^j) \cdot f_{d_{k_5}}^3(lat^j) \cdot f_{d_{k_5}}^4(x) \quad (21j)$$

where E_{ave}^{tj} is the average electricity consumption over the year and $GDP^{j_{To}}$ is the tourism and travel share in the GDP.

3.10 Maximum demand consumption

To adjust the peak load of the countries, an additional function Eq. (22) is used, provided that the maximum of the target function $load(x)$ exceeds the value of $Peak^{tj}$.

$$y_{18} = a_{18} \sin^{n_{18}}(b_{18}x + c_{18}) + d_{18} \quad (22)$$

$$d_{18} = 0 \quad (22a) \quad n_{18} = 1 \quad (22b)$$

The length of the period and the phase of the shift are equivalent to the length of the period of the annual oscillations.

$$b_{18} = b_2 = \frac{2\pi}{8760} \quad (22c)$$

$$c_{18} = c_2 = 0.225 \cdot 2\pi \frac{lat}{|lat|} \quad (22d)$$

$$f_{a_{18}}^1(max(load(x))) := \begin{cases} 1, & max(load(x)) > Peak^{tj} \\ 0, & max(load(x)) < Peak^{tj} \end{cases} \quad (22e)$$

The amplitude is formed by an exponential function. Countries where the warmest temperature T_w^j can exceed 40 °C during the year have the following amplitude:

$$f_{a_{18}}^2(T_w^j) := \begin{cases} 1, & T_w^j \geq 40 \\ 0, & T_w^j < 40 \end{cases} \quad (22f)$$

$$a_{18}^1 = -Peak^{tj} \cdot \left(1 - e^{\frac{32.2 - T_w^{j_{month}}}{47.9}} \right) \quad (22g)$$

Eq (22h) defines the amplitude of the countries where the seasonal demand pattern exhibits higher consumption during winter than in summer. Therefore, the functions Eq. (6j) and Eq (6k) described in section 3.2.1 are used to determine the amplitude of the maximum demand oscillation.

$$a_{18}^2 = -0.1335 \cdot Peak^{tj} \cdot \left(1 - e^{-\frac{12.5 - T_{c\ month}^j}{15.2}} \right) \quad (22h)$$

$$a_{18} = a_{18}^1 \cdot f_{a_{18}}^1(max(load(x))) \cdot f_{a_{18}}^2(T_w^j) + a_{18}^2 \cdot f_{a_{18}}^1(max(load(x))) \cdot f_{a_2}^4(T_{c\ month}^j) \cdot f_{a_2}^5(lat^j) \quad (22i)$$

where $Peak^{tj}$ is the maximum electricity demand for the years 2017 to 2100 and $T_{c\ month}^j$ is the average temperature of the coldest month.

3.11 Calibration of total annual demand

The total annual demand is an input variable to the model and this last summand ensures that the integral of the annual load matches the total annual demand. To maintain the annual electricity demand, a bias constant is applied over all hours of the year.

$$Error = \frac{E_y^{tj} - \sum_i y_i(x)}{8760} \quad (23)$$

$$load(x) = \sum_i y_i(x) + Error \quad (24)$$

$$E_y^{tj} = \int_1^{8760} load(x) dx \quad (25)$$

where E_y^{tj} is the annual electricity consumption, y_i is the sum of sine functions (i denotes the number of sine functions), $Error$ is the mean absolute error, and $load(x)$ is the hourly synthetic electricity demand.

3.12 Estimation of future electricity demand and load profile

The model introduced in this section is well suited for founded estimates of the future electricity demand and the respective hourly demand profile for all countries in the world. The future electricity demand of countries is estimated by applying the model to an assumed future economic development level and related variables, such as electricity demand, peak load and GDP per capita as described in the data section. It is assumed that these explanatory variables are the most important for electricity demand and the load profile in long-term projections.

4. Results and application

4.1 Modeled load curve quality

The accuracy of the proposed model is tested using actual load values in hourly resolution as presented in the Appendix (Table A1). An error analysis, based on the R-squared error, is provided to estimate the model performance and its reliability. The R-squared error is calculated as follows:

$$R^2 = 1 - \frac{SSE}{SST} \quad (26)$$

where SSE is the sum square error and SST is the sum of squared total. These performance measures are defined as;

$$SSE = \sum_{i=1} (\text{load}_{r_i} - \text{load}_{m_i})^2 \quad (27)$$

$$SST = \sum_{i=1} (\text{load}_{r_i} - \overline{\text{load}_i})^2 \quad (28)$$

where load_{r_i} and load_{m_i} denote the actual values and modeled values of the load, respectively, for the i -th hour. The value $\overline{\text{load}_i}$ shows the average value of the hours of each day of the year. Equation (28) constrains the R-squared error to consider an annual oscillation, i.e. the line describing load passes through the average value of the hours of each day of the year.

The R-squared errors for 57 countries with available real load data are illustrated in Figure 8. The R-squared error values show satisfactory results.

Fig. 8. Values of R-squared error for countries with real load data. Abbreviations of countries relate to their internet endings.

The error values for all countries with real load profiles are summarised in the Appendix (Table A2).

4.2 Modeled peak load quality

To evaluate the modeled peak load quality, the actual peak load has been compared to model peak load results. The deviation (Dev) is provided as a measure of accuracy of the model in reproducing the peak load and defined as follow:

$$Dev = \left[\frac{Peak_m - Peak_r}{Peak_r} \right] \cdot 100 \quad (29)$$

where $Peak_m$ and $Peak_r$ are the modelled and real values of the load peak, respectively. Figure 9 illustrates the peak load deviation. A share of 41 % of the countries with real peak load data have peak load deviations within an error bar of $\pm 5\%$. As can be observed in Figure 9, countries with

electricity consumption varying between 300 and 5000 TWh have the smallest peak deviation, which means synthetic peak values are close to real peak load.

Fig. 9. Peak load deviation.

The deviations of the modeled and real load peaks are provided in detail in the Appendix (Table A3).

4.3 Model results for exemplarily countries and special impact variables

4.3.1 Impact variables

It was detected that specific economic, technical and climate characteristics have a significant influence on the quality of the results.

Tourism factor

The impact of tourism on electricity demand was examined for the example of Cyprus, where the share of tourism and travel in GDP equals 19.3%. It can be seen from Figure 10 that a lack of tourism impact in the model for Cyprus leads to growth of modelling error during the summer. The peak load deviation increased by 1.3%, i.e. the peak load values with and without the tourism factor are 689 MW and 601 MW, respectively, compared to the real peak load of 954 MW. As is depicted in Figure 10, the histogram of the modelling error is almost symmetrical around the zero value of the ordinate axis. However, the modelling error increases without the tourism factor and leads to a different appearance in the sides of the histogram.

Fig. 10. Actual load data and synthetic load data (i), the modelling error (ii), and histogram of the modelling error (iii) for Cyprus in the year 2015 with (left) and without (right) tourism impact.

Industrial production factor

Electricity consumption depends also on industrial production. In Russia, where 52% of total electricity consumption is industrial electricity consumption, this impact is significant. Figure 11 shows the actual and the synthetic load profiles, the modelling error and histogram of the modelling error for Russia in the year 2014. It can be noticed that the amplitude of the synthetic load significantly exceeds the real load amplitude. The graphical representation of the error illustrates the influence of the industrial impact on the load observed during the year. The difference between histograms of the modelling error with and without industrial production impact is significant. This can be explained by the magnification of the modelling error range due to the removal of the industrial production factor. The peak load deviation increased by 2.0%, i.e. the peak load values with and without the industrial production factor are 151 GW and 161 GW, respectively, compared to the real peak load of 155 GW. The main explanation of the high relevance of this factor is that industrial demand is closer to baseload due to 24/7 production conditions compared to the much higher relative demand during daytime and evening hours of private households. This is also true for commercial demand, such as retailers and many service businesses. Hence, the higher the industrial demand in the overall power sector, the less pronounced the relative minimum and maximum loads compared to the daily average.

Fig. 11. Actual load data and synthetic load data (i), the modelling error (ii), and histogram of the modelling error (iii) for Russia in the year 2014 with (left) and without (right) industrial production impact.

Air conditioning factor

Weather and climate conditions represent the most influential exogenous variables. Temperature is the most commonly used weather variable. Air conditioning in Japan as an example of the temperature influence is examined in the following. An increasing modelling error for the period between hours 3000 and 6000 can be observed based on the histograms in Figure 12. The elimination of air conditioning impact leads to an increased peak load deviation from -6.9% to -17%.

Fig. 12. Actual load data and synthetic load data (i), the modelling error (ii), and histogram of the modelling error (iii) for Japan in the year 2015 with (left) and without (right) air conditioning impact.

Electric heating factor

The ratio of electricity sourced from hydro, nuclear and geothermal power to total generated electricity in France is 89%. The inflexible nuclear baseload generation leads to electric heating systems, which can use the excess electricity during night hours, often stored for the following day, and leading to the strong temperature sensitivity of the French power sector. Figure 13 shows that the distribution of the modelling error in the histogram deviates towards negative values. This implies that the values of the real profile exceed the synthetic load values because of the elimination of the electric heating impact. The R-squared error increases from 0.97 to 0.98 by introducing the electric heating factor. In addition, the elimination of electric heating impact leads to an increased peak load deviation of 1.3%.

Fig. 13. Actual load data and synthetic load data (i), the modelling error (ii), and histogram of the modelling error (iii) for France in the year 2015 with (left) and without (right) electric heating impact.

Sunset hours factor

The time factor, such as sunset hours, affects electricity demand. The influence of sunset hours is shown for the example of New Zealand. As depicted in Figure 14, the exclusion of sunset hours for New Zealand results in an increase in the modelling error for the period between hours 3000 and 5000. The peak load deviation is increased from -7.5% to -17.5%.

Fig. 14. Actual load data and synthetic load data (i), the modelling error (ii), and histogram of the modelling error (iii) for New Zealand in the year 2015 with (left) and without (right) sunset hours impact.

4.3.2 Sweden

In Figure 15 the model results are presented for the example of Sweden, and the harmonics of the annual, diurnal and weekly variations for the year 2015 are displayed. The synthetic load demand achieves an R-squared error of 99% and the peak deviation is 0.8% compared to the actual peak. The electrical load pattern in the country varies for the different seasons. The electricity consumption is highest in January, and lowest during the holiday season in August.

Fig. 15. The synthetic and the actual demand of Sweden for the year 2015.

Figure 16 presents the synthetic and the actual demand of Sweden for the year 2015 as a matrix for all 8760 hours in a resolution for the 365 days and the 24 hours. The graphs for the actual and synthetic load show the daily minimum in the early morning hours at around 03:00. Furthermore, both graphs demonstrate two load peaks, one around noon and the second in the early evening around 19:00. In the winter months, the evening peak is substantially higher than the noon peak, whereas in summer months the peaks are very similar. It can be seen from the actual error plot that the maximum value of the absolute error is -7 GW, equal to -48%. A share of 47% of the load deviations are within an error bar of $\pm 5\%$.

Fig.16. Actual load data (top, left), synthetic load data (top, right), absolute error (bottom, left), and relative error (bottom, right) for Sweden in the year 2015.

Figure 17 shows for the resolution of one week in October, whereby both weekday and weekend intraday variations are reproduced. The weekly demand profile exhibits lower consumption during weekends. The peak demand switches from one peak in the late morning to a weaker peak in the afternoon.

Fig. 17. The synthetic and the actual demand for Sweden in the year 2015, for a representative week in October.

Figure 18 illustrates that the overall performance of the model is good for the example of Sweden. However, a closer look at Figure 18 indicates that the model values diverge more from the actual values in the modelled load region between 20 GW to 25 GW. At lower temperatures it is observed that the deviation of modelled values from the actual values is more significant. Warm summer days also show deviations since the model tends to project low load values compared to the fact that the Swedish power system does not tend to show load values significantly below 1 GW.

Fig. 18. The model performance for Sweden and the year 2015 depending on temperature.

Figure 19 depicts that the model is satisfactory for the example of Sweden. The graphical representation of the error is empirically reliable. The histogram shows the relative error sorted into a certain interval of error values. It can be seen from Figure 19 that the distribution is almost symmetrical around the zero error.

Fig. 19. Actual load data and synthetic load data (i), the modelling error (ii), and histogram of the modelling error (iii) for Sweden in the year 2015.

4.3.3 Iran

Projections have been created for annual electricity demand by applying the assumption of section 2.3. Figure 20 shows modeled values of annual electricity demand for the example of Iran for the years 2017 - 2100. The logistic growth of the electricity consumption can be observed reaching a plateau level at around the year 2070.

Fig. 20. The synthetic annual demand of Iran for the years 2017 - 2100.

The synthetic and the actual electricity demands of Iran for the year 2015 are presented in Figure 21. It can be seen from Figure 21 that consumption is highest in the summer period. There is a strong divergence between the curves in March. This is because the model does not include the influence of religious and public holidays. The Iranian New Year falls between 20 March and 24 March. The holidays last 5 days in general, and 14 days for schools and universities, resulting in a decrease in electricity demand during this period.

Fig. 21. The synthetic and the actual demand of Iran for the year 2015.

Figure 22 illustrates the actual load, the synthetic load, absolute error and relative error as a matrix for all 8760 hours in a resolution of 365 days and 24 hours for the year 2015. The increased demand during the summer can be easily observed from the actual load and the synthetic load graphs. In winter it can be noticed that the evening peak is higher than the noon peak in both graphs. The maximum of the errors is observed during the Iranian New Year, due to religious and public impacts not being included in the model. A share of 35 % of the load deviations are within an error bar of $\pm 5\%$.

Fig. 22. Actual load data (top, left), synthetic load data (top, right), absolute error (bottom, left), and relative error (bottom, right) for Iran in the year 2015.

An October week is illustrated in Figure 23. This shows the magnitude of the weekly and daily load curves. The load decreases on Thursday and Friday, and in the night hours of all weekdays. The weekend in Iran is Thursday and Friday, and the model correctly considers decreasing load during the Iranian weekend.

Fig. 23. The synthetic and the actual demand for Iran in the year 2015, for a representative week in October.

Figure 24 presents the performance of the model in the case of Iran for the year 2015. The maximum mismatch of loads is observed at minimum temperatures from 0 to 5 °C.

Fig. 24. The model performance for Iran and the year 2015 depending on temperature.

Figure 25 illustrates the actual and synthetic load profiles, the modelling error and histogram of the modelling error. The difference in the sides of the histogram and the increase of the modelling error during March can be explained by the exclusion of holidays in the model.

Fig. 25. Actual load data and synthetic load data (i), the modelling error (ii), and histogram of the modelling error (iii) for Iran in the year 2015.

All results for countries with real load and peak data can be found in the Appendix.

4.4 Projection of electricity demand and the respective load profile

The introduced model allows the estimation of annual electricity demand and its hourly resolution for all countries based on available data and assumptions for the period from 2017 to 2100. Estimates for the annual electricity demand for all countries in the world are presented for the years 2015, 2030, 2050, 2070 and 2090 in the Appendix (Table A4). Projections of the hourly electricity consumption as a matrix for 8760 hours in a resolution of 365 days and 24 hours are presented for all countries, regions, continents and the world for future decades in the Appendix (see spreadsheet files).

The model results are compared to the findings of Finnish research on future Finnish electricity consumption in baseline and vision scenarios used by the Finnish Ministry of Employment and the Economy [47]. The results are presented in Table 2 and Figure 26.

Table 2

Finnish electricity demand scenarios in TWh. Data for 2010 is historic data; for 2015 the projected data of the two VTT (Technical Research Centre of Finland) scenarios are shown as well as the historic demand for the case of this model.

Scenarios	2010	2015	2020	2030	2040	2050	2060	2070	2080	2090	2100
VTT baseline	87.5	98.1	103	108	113	116					
VTT vision	87.5	98.1	99	95	90	80					
This model	87.5	82.3	84.7	92.5	99.3	101.5	101.8	102.7	104.5	105.3	105.6

From Figure 26 it can be seen that the two scenarios and the model projection differ, in particular the VTT baseline and VTT vision scenarios, which project two diametrical trends, as a business-as-usual case and a scenario based on either very high efficiency gains or drastic economic decline. The projection of this research is comparable to the business-as-usual scenario but shifted to lower values. The result of this research shows an increasing trend till 2040/2050 and then a saturated plateau till the end of the century. The starting data of this model is from 2015, which takes into account the declining economic development of the recent years, which had been not possible to be anticipated by the VTT scenarios.

Fig. 26. Finnish electricity consumption scenarios.

Figure 27 depicts a relatively constant seasonal pattern of electricity consumption throughout the presented years for the case of Finland. It can be observed that electricity consumption is higher during the winter months. The diurnal electricity demand pattern shows a peak demand close to noon and in the evening for all years.

Fig. 27. The synthetic hourly electricity demand of Finland for the years 2030, 2050, 2070 and 2090.

5. Discussion

A long-term electricity projection model, based on the relationship between the electricity load and relevant driving parameters, has been developed in this paper. In the model the most commonly discussed driving parameters, such as existing load data, economic data, annual electricity consumption, annual peak load, temperature and some country-specific economic data are applied [33]. In addition to the common parameters mentioned in the literature, new parameters such as the time of sunset, tourism, travel share in GDP, and proportion of the electricity generation share of hydro, nuclear and geothermal power plants are introduced.

A multiple linear regression method is used in this research. The major concern with multiple linear regression is overfitting. A lot of predictors and a limited number of real load profiles can create such a problem. This arises from the target to develop an unified model for all countries. A further increased sample of real data and combining closely correlated predictors could reduce describing variables in further research.

The main difference between the proposed model and other multiple regression models [4,7-14] is that the electricity demand projection is developed in an hourly resolution, not annual. However, research about modelling demand in hourly resolution is being increasingly discussed in the

literature [3,7,12]. The main focus in the literature is on modelling the demand of one specific country and authors propose applying a similar methodology to other countries. In this research a projection model is proposed that can be used for all countries globally. Furthermore, in contrast to other studies, the approach projects an electricity demand for the period from 2017 - 2100.

The historical hourly load data of 57 countries [50-92] all around the world are compared with the modelled results for the same years to verify the results or the thus calibrated model parameters. It was found that specific economic, technical and climate characteristics, such as high shares of marginal cost generation, air conditioning, impact of tourism and industrial consumption, local temperature and seasonal effects have significant influence on the quality of results. For example, in Cyprus, a country with a high share of tourism in total GDP, it can be seen that if the tourism and travel share in GDP is not taken into account in the model, the modelling error of Cyprus is significantly increased during summer.

Meanwhile, the industrial consumption impact on the electricity demand pattern can be observed in Russia. Without this factor, the peak deviation of the model changes from -2.1% to 4.1%. The proportion of the electricity generation share of hydro, nuclear and geothermal power plants has a major impact on the results for France, where the electricity generation share of hydro, nuclear and geothermal equals 0.89, mainly driven by nuclear energy. The resulting R-square error varies between 0.97 and 0.98 depending on the inclusion of this parameter. Another important parameter is the influence of air conditioning on the electricity demand pattern. In countries such as Japan, where air-conditioning is used heavily, the peak load deviation of synthetic load increased from -6.9% to -17%. For New Zealand the impact of sunset hours leads to a larger modelling error in the winter.

Based on the obtained results of the case countries Sweden and Iran, it is obvious that the model shows satisfactory synthetic load profiles for countries with different geographic, socio-economic, climatic and technical conditions. The synthetic load demand achieves an R-squared error of 99% for both countries. This means that, despite the high availability of the real load profiles for European countries and less for emerging and developing countries, the model shows appropriate results for diverse countries without a bias towards developed countries. The strong impact of temperature is also covered well for the case of Iran.

The proposed electricity demand model, based on only a few easily accessible parameters, is the very first model that is applicable to all countries globally. The model can be also used to project future electricity demand and the respective load profile. This makes the model in particularly relevant for energy scenario research, which increasingly requires not only a projection for the annual electricity demand, but also an hourly resolution for entire years due the increasing share of variable renewable energy generation all around the world.

Long-term electricity demand forecasting is a crucial part of planning and expansion of electric power systems [2]. In fact, it plays an essential and important role in the planning of the construction of new generation facilities. The obtained results could have a significant impact and support energy transition studies towards sustainability. The results of this work can be applied to power network planning, and power networks can be analysed by this methodology over a long time period.

Future research dedicated to further improvements may be related to introducing a new temperature profile, taking temperature increase due to climate change into account. In addition, good data on country-wide vacation periods, holiday seasons and religious and cultural events may also further improve the model. Future energy technologies can have an influence on the electricity demand in the future. For instance, energy storage and flexible demand can decrease peak power demand while electric vehicles can increase the peak power demand. Electric vehicles will very likely penetrate the markets on a large scale in the future and will increase electricity demand. The impact of the heating and cooling load on the electricity demand pattern could be considered in more detail to improve the predictability of the model. Electricity consumption varies considerably between diverse types of buildings. For instance, in detached houses, more electricity is usually consumed per square meter compared to flats. Moreover, the buildings structure, the heating and cooling systems and the growth of area demand per capita in houses as a consequence of increasing GDP could be taken into account in future research.

Distributed generation will be one of the major trends in electricity networks in the long term. Solar will become the most important generation technology in the years to come [97]. The impact of the mentioned trends on the load curve may be better understood for improved modeling in further research. At the same time, the results of this research provide a good starting point from which these trends can be added or adaptations can be made. Research on the possible extent to which various flexible demands of the future can be incorporated into global energy systems must start from a basic knowledge of the potential peaks and valleys of future energy demand. A first step in projecting what future electricity demand may change to must involve projecting what it may change from. This research also provides such a starting point.

6. Conclusion

A model has been proposed, tested and illustrated to project electricity demand based on UN targets for all countries globally from present till the year 2100. The model is based on a linear regression method in terms of oscillations of the daily, weekly and seasonal variations [2]. Specific economic, technical and climate characteristics, such as high shares of marginal cost generation, air conditioning, impact of tourism and industrial consumption, local temperature and seasonal effects, which are important factors to improve modeling results, have been determined. The main advantage of the proposed model is the usage of the real load data of 57 countries for validation.

The main findings and contribution of the presented research are:

1. *The explanatory variables such as annual electricity demand, peak demand, temperature, GDP, population, industrial production, day duration matter for electricity load.* In addition to analyse the impact of oscillations of a different frequency (annual, weekly, weekend, diurnal), five main factors have been introduced: air conditioning, electric heating, tourism, industrial impact and day duration. All of these factors reduced the modelling error for a specific class of countries.
2. *Geographical coverage is caught in high resolution.* Synthetic load profiles are projected for 180 countries in hourly resolution and also for decades to come based on an applied

scenario. This feature of the introduced methodology may be of high value for energy system modelling in global-local resolution.

3. *The proposed method, multiple linear regression, is flexible enough to be applied to different socio-economic scenarios based on alternative assumptions.* It could help promote knowledge sharing and thus increase efficiency and transparency in the modelling community.
4. *The model performance was analysed based on 57 real load profiles and the R-square error.* The R-square error values for the modelled and actual loads vary between 0.968 and 0.998.

As future work, real temperature profiles in high resolution should be added in order to further improve the prediction accuracy of energy demand. Moreover, new technologies such as electric vehicles and energy storage may bring changes to the electricity load profile in the future. The result is that the effect on the load profile may be considerable and versatile, which should be considered in further research.

7. Acknowledgements

The authors gratefully acknowledge the public financing of Tekes (Finnish Funding Agency for Innovation) for the ‘Neo-Carbon Energy’ project under the number 40101/14. The authors would like to thank Michael Child for valuable feedback and proofreading.

8. Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.ijepes.2019.03.055>.

9. References

- [1] Fernandez Blanco Carramolino R., Careri F., Kavvadias K., Hidalgo Gonzalez I., Zucker A. and Peteves, E., 2017, Systematic mapping of power system models: Expert survey, Luxembourg;
- [2] Weron R., 2006. Modeling and Forecasting Electricity Loads and Prices: A Statistical Approach. Wiley Finance, New York;
- [3] Filik Ü. B., Gerek Ö. N., Kurban M., 2011. A novel modeling approach for hourly forecasting of long-term electric energy demand, *Energy Conversion and Management*, 52 (1), 199-211;
- [4] Hyndman R. J., Fan S., 2010. Density forecasting for long-term peak electricity demand, *IEEE Transactions Power Syst.*, 25 (2), 1142–53;
- [5] Kyriakides E., Polycarpou M., 2007. Short term electric load forecasting: A tutorial, in: K. Chen, L. Wang (Eds.), *Trends in Neural Computation, Studies in Computational Intelligence*, Springer, 35, 391–418;
- [6] Hong T., Fan S., 2016. Probabilistic electric load forecasting: A tutorial review, *International Journal of Forecasting*, 32 (3), 914–938;
- [7] Hong T., Wilson J., Xie J., 2014. Long-term probabilistic load forecasting and normalization with hourly information, *IEEE Transactions on smart grid*, 5 (1), 456-462;

- 1203 [8] Hor C.-L., Watson S. J., Majithia S., 2005. Analyzing the Impact of Weather Variables on
1204 Monthly Electricity Demand, *IEEE Transactions on power systems*, 20 (4), 2078-2085;
- 1205 [9] Bianco V., Manca O., Nardini S., 2009. Electricity consumption forecasting in Italy using
1206 linear regression models, *Energy*, 34 (9), 1413–1421;
- 1207 [10] Mohamed Z., Bodger P., 2005. Forecasting electricity consumption in New Zealand using
1208 economic and demographic variables, *Energy*, 30 (10), 1833–1843;
- 1209 [11] Kankal M., Akpınar A., Kömürcü M. İ., Özşahin T.Ş., 2011. Modeling and forecasting of
1210 Turkey's energy consumption using socio-economic and demographic variables, *Appl.*
1211 *Energy*, 88, 1927–1939;
- 1212 [12] Yukseltan E., Yucekaya A., Bilge A. H., 2017. Forecasting electricity demand for Turkey:
1213 Modeling periodic variations and demand segregation, *Applied Energy*, 193, 287-296;
- 1214 [13] Trotter I. M., Bolkesjø T. F., Féres J. G., Hollanda L., 2016. Climate change and electricity
1215 demand in Brazil: A stochastic approach, *Energy*, 102, 596-604;
- 1216 [14] Mirasgedis S., Sarafidis Y., Georgopoulou E., Lalas D.P., Moschovits M., Karagiannis F.,
1217 Papakonstantinou D., 2006. Models for mid-term electricity demand forecasting
1218 incorporating weather influences, *Energy*, 31, 208–227;
- 1219 [15] Amjady N., 2001. Short-Term Hourly Load Forecasting Using Time-Series Modeling with
1220 Peak Load Estimation Capability, *IEEE Trans. Power Syst.*, 16 (3), 498-505;
- 1221 [16] Clements A.E., Hurn A.S., Li Z., 2016. Forecasting day-ahead electricity load using a
1222 multiple equation time series approach, *European Journal of Operational Research*, 251 (2),
1223 522–530;
- 1224 [17] Fan, S. and Hyndman, R.J., 2012. Short-term load forecasting based on a semi-parametric
1225 additive model. *IEEE Transactions on Power Systems*, 27(1), 134-141;
- 1226 [18] Gould, P.G., Koehler, A.B., Ord, J.K., Snyder, R.D., Hyndman, R.J. and Vahid-Araghi, F.,
1227 2008. Forecasting time series with multiple seasonal patterns. *European Journal of*
1228 *Operational Research*, 191(1), pp.207-222;
- 1229
- 1230 [19] Boroojeni K. G., Amini M. H., Bahrami S., Iyengar S. S., Sarwat A. I., & Karabasoglu, O.,
1231 2017. A novel multi-time-scale modeling for electric power demand forecasting: From short-
1232 term to medium-term horizon. *Electric Power Systems Research*, 142, 58-73;
- 1233 [20] Taylor J. W., Snyder R. D., 2012. Forecasting intraday time series with multiple seasonal
1234 cycles using parsimonious seasonal exponential smoothing, *Omega*, 40 (6), 748-757;
- 1235 [21] Günay M. E., 2016. Forecasting annual gross electricity demand by artificial neural
1236 networks using predicted values of socio-economic indicators and climatic conditions: Case
1237 of Turkey, *Energy Policy*, 90, 92–101;
- 1238 [22] Ekonomou L., 2010. Greek long-term energy consumption prediction using artificial neural
1239 networks, *Energy*, 35, 512–517;
- 1240 [23] Song K. B., Baek Y. S., Hong D. H., Jang G., 2005. Short-term load forecasting for the
1241 holidays using fuzzy linear regression method, *IEEE Trans. Power Syst.*, 20 (1), 96–101;
- 1242 [24] Tzafestas S., Tzafestas E., 2001. Computational intelligence techniques for short-term
1243 electric load forecasting, *J Intell Robo Syst*, 31, 7–68;
- 1244 [25] Torrini F.C., Souza R.C., Oliveira F.L.C., Pessanha J.F.M., 2016. Long-term electricity
1245 consumption forecast in Brazil: a fuzzy logic approach, *Soc. Econ. Plan. Sci*, 54, 18–27;
- 1246 [26] Kucukali S., Baris K., 2010. Turkey's short-term gross annual electricity demand forecast by
1247 fuzzy logic approach, *Energy Policy*, 38 (5), 2438-2445;

- 1248 [27] Afshin M., Sadeghian A., 2007. PCA-based least squares support vector machines in week-
1249 ahead load forecasting, *Industrial and Commercial Power System Technical Conference*,
1250 IEEE, 1–6;
- 1251 [28] Hahn H., Meyer-Nieberg S., Pickl S., 2009. Electric load forecasting methods: Tools for
1252 decision making, *European Journal of Operational Research*, 199 (3), 902–907;
- 1253 [29] Wang, Y. and Bielicki, J.M., 2018. Acclimation and the response of hourly electricity loads
1254 to meteorological variables. *Energy*, 142, pp.473-485;
- 1255 [30] Do L. P. C., Lin K.-H., Molnára P., 2016. Electricity consumption modelling: A case of
1256 Germany, *Economic Modelling*, 55, 92–101;
- 1257 [31] Pérez-García J., Moral-Carcedo J., 2016. Analysis and long term forecasting of electricity
1258 demand through a decomposition model: A case study for Spain, *Energy*, 97, 127–143;
- 1259 [32] Moral-Carcedo, J. and Pérez-García, J., 2017. Integrating long-term economic scenarios into
1260 peak load forecasting: An application to Spain. *Energy*, 140, pp.682-695.;
- 1261 [33] Mustapha M., Mustafa M. W., Khalid S. N., Abubakar I., Shareef H., 2015. Classification of
1262 electricity load forecasting based on the factors influencing the load consumption and
1263 methods used: An-overview, *2015 IEEE Conf. Energy Conversion CENCON*, 442-447;
- 1264 [34] Squalli J., 2007. Electricity consumption and economic growth: Bounds and causality
1265 analyses of OPEC mem, *Energy Economics*, 29, 1192–1205;
- 1266 [35] Shiu A., Lam P-L., 2004. Electricity consumption and economic growth in China, *Energy*
1267 *Policy*, 32, 47–54;
- 1268 [36] Ghosh S., 2002. Electricity consumption and economic growth in India, *Energy Policy*, 30,
1269 125–129;
- 1270 [37] World Bank, 2017. GDP per capita, PPP (constant 2011 international \$), Washington DC.
1271 Available: <http://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD>. [Accessed
1272 02.06.2016];
- 1273 [38] Modis T., 2013. Long-term GDP forecasts and the prospects for growth, *Technological*
1274 *Forecasting and Social Change*, 80, 1557–1562;
- 1275 [39] [UN] – United Nations, 2015. Transforming our world: the 2030 Agenda for Sustainable
1276 *Development, Resolution adopted by the General Assembly*, New York;
- 1277 [40] [IEA] – International Energy Agency, 2015. Energy Balances of OECD Countries, Paris;
- 1278 [41] [IEA] – International Energy Agency, 2015. World Energy of non-OECD Countries, Paris;
- 1279 [42] Ferguson R., Wilkinson W., Hill R., 2000. Electricity consumption and economic
1280 development, *Energy Policy*, 28, 923-934;
- 1281 [43] [UN] – United Nations, 2015. Department of Economic and Social Affairs, Population
1282 Division, World Population Prospects, The 2015 Revision, New York. Available:
1283 <https://esa.un.org/unpd/wpp/DataQuery/>. [Accessed 02.06.2017];
- 1284 [44] Stackhouse P.W., Whitlock C.H., editors. 2008. Surface meteorology and solar energy
1285 (SSE) release 6.0, NASA SSE 6.0, earth science enterprise program. National Aeronautic
1286 and Space Administration (NASA), Langley. Available: <http://eosweb.larc.nasa.gov/sse/>.
1287 [Accessed 28.05.2015];
- 1288 [45] Stackhouse P.W., Whitlock C.H., editors. 2009. Surface meteorology and solar energy
1289 (SSE) release 6.0 Methodology, NASA SSE 6.0, earth science enterprise program, National
1290 Aeronautic and Space Administration (NASA), Langley. Available:
1291 <http://eosweb.larc.nasa.gov/sse/documents/SSE6Methodology.pdf>. [Accessed 28.05.2015];

- 1292 [46] Stetter D., 2012. Enhancement of the REMix energy system model: global renewable energy
1293 potentials optimized power plant siting and scenario validation. Dissertation, Faculty of
1294 Energy-, Process and Bio-Engineering, University of Stuttgart;
- 1295 [47] Koreneff G., Ruska M., Kiviluoma J., Shemeikka J., Lemström B., Alanen R., Koljonen T.,
1296 2009. Future development trends in electricity demand, VTT Tiedotteita – Research Notes
1297 2470. 79 p, Espoo;
- 1298 [48] World Bank, 2017b. Industry, value added (% of GDP), Washington DC. Available:
1299 <http://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD>. [Accessed 02.06.2016];
- 1300 [49] Knoema, 2017. World Data Atlas, Travel & Tourism Total Contribution to GDP - % share,
1301 McLean, VA. Available: [https://knoema.com/atlas/topics/Tourism/Travel-and-Tourism-](https://knoema.com/atlas/topics/Tourism/Travel-and-Tourism-Total-Contribution-to-GDP/Total-Contribution-to-GDP-percent-share)
1302 [Total-Contribution-to-GDP/Total-Contribution-to-GDP-percent-share](https://knoema.com/atlas/topics/Tourism/Travel-and-Tourism-Total-Contribution-to-GDP/Total-Contribution-to-GDP-percent-share). [Accessed
1303 02.06.2017];
- 1304 [50] Bejtullahu N, 2014. Common Electricity Market Kosovo – Albania, *Workshop on the future*
1305 *role of energy storage in South Eastern Europe, Tirana*, October 21 – 22. Available:
1306 [https://setis.ec.europa.eu/system/files/Common%20Electricity%20Market%20Kosovo-](https://setis.ec.europa.eu/system/files/Common%20Electricity%20Market%20Kosovo-Albania-USAID%20-%20BEJTULLAHU.pdf)
1307 [Albania-USAID%20-%20BEJTULLAHU.pdf](https://setis.ec.europa.eu/system/files/Common%20Electricity%20Market%20Kosovo-Albania-USAID%20-%20BEJTULLAHU.pdf). [Accessed 21.06.2017];
- 1308 [51] [ENTSO-E] – European Network of Transmission System Operators for Electricity, 2015.
1309 Data, Data Portal, Consumption, Brussels. Available: www.entsoe.eu/Pages/default.aspx.
1310 [Accessed 28.07.2016];
- 1311 [52] [CIGRE] – International council on large electric systems, 2015. The Electric Power System,
1312 Algeria Power System Paris. Available:
1313 [www.cigre.org/var/cigre/storage/original/application/1ec62202f27aaa674c271ace096089f3.](http://www.cigre.org/var/cigre/storage/original/application/1ec62202f27aaa674c271ace096089f3.pdf)
1314 [pdf](http://www.cigre.org/var/cigre/storage/original/application/1ec62202f27aaa674c271ace096089f3.pdf). [Accessed 12.02.2017];
- 1315 [53] [SAPP] – Southern African Pool, 2016. Annual report 2016, Harare;
- 1316 [54] [Cammesa] – Compañía Administradora del Mercado Mayorista Eléctrico, 2016. Diego
1317 Margulis, Private communication, Buenos Aires, October 10;
- 1318 [55] [AEMO] – Australian Energy Market Operator, 2016. National Electricity Market,
1319 Melbourne. Available: [www.aemo.com.au/Electricity/National-Electricity-Market-](http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Data-dashboard#aggregated-data)
1320 [NEM/Data-dashboard#aggregated-data](http://www.aemo.com.au/Electricity/National-Electricity-Market-NEM/Data-dashboard#aggregated-data). [Accessed 28.07.2016];
- 1321 [56] Blechinger, P. (ed.), 2015. Barriers and solutions to implementing renewable energies on
1322 Caribbean islands in respect of technical, economic, political, and social conditions, PhD
1323 thesis TU Berlin, Shaker Verlag, Berlin;
- 1324 [57] [BPC] – Botswana Power Corporation 2015. 2015 Annual Report, Gaborone Available:
1325 www.bpc.bw/about-us/Annual%20Reports/BPC%20Annual%20Report%202015.pdf.
1326 [Accessed 25.06.2017];
- 1327 [58] [ANEEL] – Agência Nacional de Energia Elétrica, 2016. Private communication, Brasília,
1328 October 7;
- 1329 [59] [ADB] – Asian Development Bank, Nam K.-Y., Cham M. R., Halili P. R. 2015. Power
1330 Sector Development in Myanmar, *ADB Economics Working Paper Series*, 460,
1331 Mandaluyong;
- 1332 [60] [ICA] – The Infrastructure Consortium for Africa 2011. Regional Power Status in African
1333 Power Pools Report, Cote d'Ivoire;
- 1334 [61] [ADB] – Asian Development Bank, 2012. Greater Mekong Subregion Power Trade and
1335 Interconnection, 2 Decades of Cooperation, Mandaluyong. Available:
1336 www.adb.org/sites/default/files/publication/29982/gms-power-trade-interconnection.pdf.
1337 [Accessed 22.06.2017];

1338 [62] [IESO] – The Independent Electricity System Operator, 2016. Private communication,
1339 Toronto. Available: www.ieso.ca/. [Accessed 28.07.2016];

1340 [63] [SaskPower] – Saskatchewan Power Corporation, 2016. Private communication,
1341 Saskatchewan. Available: www.saskpower.com/. [Accessed 28.07.2016];

1342 [64] [CDEC-SING] – Coordinador Eléctrico Nacional, 2016. Private communication, Santiago.
1343 Available: www.coordinadorelectrico.cl/. [Accessed 22.06.2017];

1344 [65] [IRENA] – International Renewable Energy Agency, 2014. Renewable Energy Prospects:
1345 China, Abu Dhabi. Available:
1346 https://irena.org/remap/IRENA_REmap_China_report_2014.pdf. [Accessed 22.06.2017];

1347 [66] Bedoya Díaz H.A., 2013. Private communication;

1348 [67] Arab Republic of Egypt, Ministry of Electricity and Renewable Energy, 2013. Annual report
1349 2014-2015., Cairo. Available: [www.moe.gov.eg/english_new/EEHC_Rep/2014-](http://www.moe.gov.eg/english_new/EEHC_Rep/2014-2015en.pdf)
1350 [2015en.pdf](http://www.moe.gov.eg/english_new/EEHC_Rep/2014-2015en.pdf). [Accessed 22.06.2017];

1351 [68] Ashenafi A. Demissie, Solomon A.A., 2016. Power system sensitivity to extreme
1352 hydrological conditions as studied using an integrated reservoir and power system dispatch
1353 model, the case of Ethiopia, *Applied Energy*, 182, pp. 442–463;

1354 [69] [GRIDCo] – Ghana grid company limited, 2011. 2014 Electricity supply plan, Tema.
1355 Available:
1356 www.gridcogh.com/media/photos/forms/supplyplan/2014_Electricity_Supply_Plan.pdf.
1357 [Accessed 22.06.2017];

1358 [70] [CEA] – Central Electricity Authority, 2016. Load Generation Balance Report 2016-17,
1359 New Delhi. Available: www.cea.nic.in/reports/annual/lgbr/lgbr-2016.pdf. [Accessed
1360 22.06.2017];

1361 [71] [IAEA-CNPP] – International Atomic Energy Agency, Country Nuclear Power Profiles,
1362 2016, Indonesia, Vienna. Available:
1363 <https://cnpp.iaea.org/countryprofiles/Indonesia/Indonesia.htm>. [Accessed 22.06.2017];

1364 [72] [IGMC] - Iran Grid Management Company, 2016. Definitive Report 1394 [in Persian],
1365 Tehran. Available: www.igmc.ir/Documents-Management?EntryId=305927. [Accessed
1366 19.04.2016];

1367 [73] Without author, 2015. Load curve for Israel, private communication;

1368 [74] [METI] – Ministry of Economy Energy and Industry, 2012. Load curve for Japanese grid
1369 areas, Tokyo. Available: www.meti.go.jp/setsuden/performance.html. [Accessed
1370 21.06.2016];

1371 [75] Baraza M., 2015. Private communication;

1372 [76] [KPX] – Korea Power Exchange, 2015. Private communication, Jeollanam-do. Available:
1373 www.kpx.or.kr/. [Accessed 21.06.2017];

1374 [77] Suruhanjaya Tenaga (Energy Commission), 2015. National Energy Balance 2014, Putrajaya.
1375 Available: www.st.gov.my/index.php/en/. [Accessed 21.06.2017];

1376 [78] [SENER] – Secretaria De Energia, 2010. Private communication, Mexico. Available:
1377 <http://sie.energia.gob.mx/bdiController.do?action=temas&fromCuadros=true>. [Accessed
1378 18.05.2016];

1379 [79] Giuliano S., Puppe M., Schenk H., Hirsch T., Moser M., Fichter T., Kern J., Trieb F.,
1380 Brakemeier D., Kretschmann J., Haller U., Klingler R., Engelhard M., Hurler S., Weigand
1381 A., Breyer Ch., Afanasyeva S., 2016. Techno-Economic Analysis and Comparison of CSP
1382 and Hybrid PV-Battery Power Plants, SolarPACES, Abu Dhabi, October 11-14;

1383 [80] [EMI] – Electricity Authority, 2016. Grid demand trend, Wellington. Available:
1384 www.emi.ea.govt.nz. [Accessed 20.09.2016];

1385 [81] [NTDC] – National Transmission And Despatch Company Limited, 2016. Power System
1386 Statistics 2013-2014, Lahore. Available:
1387 www.ppib.gov.pk/Power%20System%20Statistics%202013-14.pdf. [Accessed 22.06.2017];

1388 [82] [WESM] – Wholesale Electricity Spot Market, 2012. Downloads, Annual Market
1389 Assessment Report - 2015, Pasig. Available: www.wesm.ph/. [Accessed 22.06.2017];

1390 [83] [UES] – System Operator of the Unified Energy System, 2015. Generation and
1391 Consumption (hour) [in Russian], Moscow. Available: www.so-cdu.ru/. [Accessed
1392 22.12.2015];

1393 [84] [ECRA] – Electricity and Cogeneration Regulatory Authority, 2016. Private communication,
1394 Arriyadh. Available: www.ecra.gov.sa/en-us/dataandstatistics/pages/DataAndStatistics.aspx.
1395 [Accessed 22.06.2017];

1396 [85] [CEB] – Ceylon Electricity Board, 2015. Long Term Generation Expansion Plan 2015-2034,
1397 Colombo. Available: http://pucsl.gov.lk/sinhala/wp-content/uploads/2015/09/Long-Term-
1398 Generation-Plan-2015-2034-PUCSL.pdf. [Accessed 22.06.2017];

1399 [86] [EMA] – Energy Market Authority of Singapore, 2017. Statistics, Electricity, Demand,
1400 Bukit Merah. Available: www.ema.gov.sg/index.aspx. [Accessed 22.06.2017];

1401 [87] [EPPO] – Energy Policy and Planning Office, Ministry of Energy, 2016. Energy Statistics,
1402 Electricity, Bangkok. Available: www.eppo.go.th/index.php/en/. [Accessed 21.06.2017];

1403 [88] Dii, 2013. Common research on future energy options for Tunisia, Munich;

1404 [89] [TurkStat] – Turkish Statistical Institute, 2016. Private communication, Ankara. Available:
1405 www.turkstat.gov.tr/Start.do. [Accessed 21.06.2017];

1406 [90] [Statista] – The Statistical Portal, 2016. Industries, Energy & Environmental Services,
1407 Electricity, U.S. electric noncoincident peak load 1990-2013, New York. Available:
1408 www.statista.com/. [Accessed 21.06.2017];

1409 [91] Hà N.H., 2013. EVN Smart Grid Plan, *PEP-Fachveranstaltung*, Frankfurt, November 14.
1410 Available: www.giz.de/fachexpertise/downloads/2013-en-pep-fachveranstaltung-smart-
1411 grids-nguyen-hai-ha.pdf. [Accessed 21.06.2017];

1412 [92] [Statista] – The Statistical Portal, 2015. Industries, Energy & Environmental Services,
1413 Electricity, U.S. electric noncoincident peak load 1990-2013, New York. Available:
1414 www.statista.com/. [Accessed 21.06.2017];

1415 [93] [EIA] - The U.S. Energy Information Administration, 2015. International Energy Statistics,
1416 Statistics, Washington, DC. Available: www.eia.gov/ [Accessed 21.06.2017];

1417 [94] [IEA] - International Energy Agency, 2015a. Key World Energy Statistics 2015, Statistics,
1418 Paris;

1419 [95] [IEA] - International Energy Agency, 2015b. Key World Energy Statistics 2011, Statistics,
1420 Paris;

1421 [96] [IEA] - International Energy Agency, 2015c. Key World Energy Statistics 2012, Statistics,
1422 Paris;

1423 [97] Breyer Ch., Bogdanov D., Gulagi A., Aghahosseini A., Barbosa L.S.N.S., Koskinen O.,
1424 Barasa M., Caldera U., Afanasyeva S., Child M., Farfan J., Vainikka P., 2017. On the Role of
1425 Solar Photovoltaics in Global Energy Transition Scenarios, *Progress in Photovoltaics:*
1426 *Research and Applications*, 25, 727-745;

1427