# Exploratory data analysis of the electrical energy demand in the time domain in Greece

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**Abstract**: The electrical energy demand (EED) in Greece for the time period 2002-2016 is investigated. The aim of the study is to introduce a framework for the exploratory data analysis (EDA) of the EED in the time domain. To this end, the EED at the hourly, daily, seasonal and annual time scale along with the mean daily temperature and the Gross Domestic Product (GDP) of Greece are visualized. The forecast of the EED provided by the Greek Independent Power Transmission Operator (IPTO) is also visualized and is compared with the actual EED. Furthermore, the EED pricing system is visualized. The results of the study in general confirm and summarize the conclusions of previous relevant studies in Greece, each one treating a single topic and covering shorter and earlier time periods. Furthermore, some unexpected patterns are observed, which if not considered carefully could result to dubious models. Therefore, it is shown that the EDA of the EED in the time domain coupled with weather-, climate-related and socio-economic variables is essential for the building of a model for the short-, medium- and long-term EED forecasting, something not highlighted in the literature.

**Keywords**: electrical energy demand; energy forecasting; exploratory data analysis; Greece; Gross Domestic Product; temperature

## 1. Introduction

### *1.1 Electrical energy demand forecasting*

Electrical Energy Demand (EED) forecasting regards the prediction of hourly, daily, weekly, monthly, and annual values of the system demand and peak demand [1]. EED forecasts are classified into three categories, according to the horizon of the forecast. Short-term forecasts usually range from one hour to one week, medium-term forecasts usually range from one week to one year, and long-term forecasts are usually applied to time intervals longer than a year [2], albeit in the absence of a standard the time intervals may differ [3]. The short-term variation of the EED seems to depend mostly on fluctuations of the weather (e.g. [4]). On the other hand, concerning the long-term forecasting, there is a strong correlation between the EED and socio-economic variables, with a significant amount of studies examining their possible causal relationships (e.g. [5, 6]). Therefore, the investigation of the EED at various time scales and its relationship with weather- and climate-related and socio-economic variables is essential for its forecast.

The modelling and forecasting of the EED is important for formulating a sustainable energy policy [7]. The EED forecasting can serve short-, medium- and long-term objectives. Short-term forecasting is necessary for the daily operation (energy transactions, unit commitment, security analysis, and economic dispatch) of generation and distribution systems [2,8]. Medium-term forecasting is used by electrical energy producers and resellers for maintenance planning of grids and market researching [2]. Long-term forecasting is used for planning the expansion of the generation and distribution system [2,8].

Before modelling the EED in the time domain, it is important to understand its behaviour. To understand time series data a frequent approach adopted by data scientists is the exploratory data analysis (EDA) which emphasizes the graphical representation of the data. Based on the classical book of Tukey [9], Behrens and Yu [10] mention that in the context of EDA, data analysts and scientists work interactively in a cyclical process of pattern extraction and pattern interpretation. The aim is to complement the model building based on the findings of the EDA [11]. EDA also aims "to find the unexpected", e.g. to identify misleading patterns and to develop rich descriptions [10]. Chatfield [12] in a critique of Tukey's [9] work, adds a second objective of the EDA, i.e. the model formulation. Chatfield [12] and Behrens and Yu [10] also point out that in many studies the EDA is undervalued or neglected leading to the implementation of useless models (following the famous Box's [13] quote that "*all models are wrong, some are useful*").

### *1.2 Greek and international literature review on the electrical energy demand analysis*

In this study, the EED in the Greek Interconnected Electric System (GIES) is investigated. The GIES is part of the Greek Electric System (GES). The GIES consists of subsystems of generation, distribution and consumption of electrical energy. The GIES extends to the mainland Greece and the islands close to the mainland [14]. The GES also includes the electric systems in remote islands. The Independent Power Transmission Operator (IPTO) operates, maintains and develops the GES. The Operator of Electricity Market

(OEM) operates the process of the exchange between electricity producers and electricity consumers. The Regulatory Authority for Energy (RAE) supervises the OEM [15].

Several studies can be found, which analyse the energy demand in Greece. Amongst them, there exist studies of special interest for the present case study because their results are comparable to the present analysis. In most cases, these studies treat a single topic or they are applied to a short time interval. Psiloglou et al. [16] investigated the electrical energy demand of Athens for the period 1997-2001, and examined issues such as the relationship of the EED with the weather (e.g. the temperature) and socio-economic variables. Mirasgedis et al. [17] present a similar analysis about the EED in Greece for the time period 1993-2002. Pappas et al. [18] visualize the EED in Greece for the time period 2004-2005, and use the results to fit a stochastic model. Regarding the long-term forecasting, Ekonomou [19], Kalampalikas and Pilavachi [20], and Dagoumas and Kitsios [21] examine the relationship between the energy demand and socio-economic variables.

Additional published studies about the energy demand (or the EED) in Greece and in neighbouring Cyprus (with a Greek culture) include issues related to the energy market [15], the spatial analysis of the EED [22,23], the relationship between the energy demand and the economic activity [6,24–29], the relationship between the energy demand and climatic or geological variables [30–32], the renewable sources [33–35], the energy consumption for domestic use [36,37], the study of power system production [14], the exergy [38], the energy policy [39] and energy issues regarding Cyprus [4,40] or Greek regions [41].

The international literature also includes several studies concerning the EED analyses in the time domain. Such analyses include the examination of the causality relationship between the electrical energy consumption and the Gross Domestic Product (GDP) [42–44], the short- and long-term forecasting of energy demand and production [45–51], the relationship between the energy demand and the economic activity or socio-economic factors [7,52–55], the relationship between the energy demand and climatic or geological variables [56–59], the relationship between the energy demand and both socio-economic activities and climatic variables [60,61], the energy demand in various sectors of the economy [62,63], the distribution of the energy demand at different time scales [2,8], the domestic energy demand [64,65], the operation of grids [66] and many other topics. A review of the literature is presented in Jebaraj and Iniyan [67], Suganthi and Samuel [68] and recently in Hong and Fan [3] and Ghalehkhondabi et al. [69], while, regarding the causal relationship between electricity consumption and economic growth, Payne [5] presents a survey of the empirical literature. Furthermore, Aggarwal et al. [70] present a literature review on the related subject of electrical energy price forecasting.

### *1.3 Aim of the study*

In Section 1.1, the importance of the EED time series modelling and forecasting was emphasized. Furthermore, the importance of performing an EDA before modelling a time series was shown. An accurate forecast depends on the implementation of a useful model, which in turn depends on the correct description and use of available data. In Section 1.2, an extended literature on the EED analysis in the time domain was presented in which each paper treats a single or a couple of topics, regarding the relationship between the EED and other variables.

The present study has been motivated by the fact that in the EED forecasting literature little importance has been given to the integrated analysis of the data. Google Scholar returns 45 results when using simultaneously the terms "exploratory data analysis" and "energy forecasting", four results when using "exploratory data analysis" and "electricity forecasting" and 12 results when using the terms "exploratory data analysis" and "energy demand forecasting" (access: Saturday, August 13, 2016). Among them, the studies of Dudek [71], Hippert and Pedreira [72], Narayan et al. [73] and Vaghefi et al. [74] were distinguished, however their EDA still remains limited.

The number of original techniques for EED forecasting is still countable, i.e. within 100 and their applications in the literature have been exhausted [3]. Hong and Fan [3] also mention that a "*universally best technique simply does not exist*". Furthermore, they define three steps for EED forecasting, i.e. "*understanding of the business needs first, then analysing the data, and going through a trial and-error process, to figure out which is the best technique for a specific dataset in a specific jurisdiction*". Consequently, the selection of the best technique depends on the problem at hand, therefore the analysis of the data is crucial.

The R package MEFM (abbreviation for Monash Electricity Forecasting Model) based on Hyndman and Fan [1] models the EED as a function of observed EED, temperatures and seasonal socio-economic data and delivers a forecast using a combination of stochastic and machine learning methods. The package is flexible in the sense that various types of socio-economic data can be given as inputs. We emphasize that the forecast does not depend only on observed EED data. Indeed, in many studies, there is an attempt to apply time series models (from the families of autoregressive moving average (ARMA) models, [3]) to the data and use the fitted models to forecast the EED. However, neglecting the information from weather and climate data and socio-economic variables may be misleading for specific purposes (e.g. see Section 3.1.3, 3.1.4 and 3.1.9(2) in Hong and Fan [3] however, ARMAX models, which are generalizations of ARMA models, may include exogenous variables). The forecasts constitute an important part of the energy policy of a state, thus the procedure of forecasting must not be taken light-heartedly.

In this study, the EED in Greece for the time period 2002-2015 is investigated. The EED is visualized at the hourly, daily, seasonal and annual time scale along with the mean daily temperature, the GDP of Greece, the forecast of the EED provided by the IPTO and the EED pricing system. Furthermore, the forecast is compared with the actual EED. The aim of our study is to deliver a complete description of the data and to suggest a methodological EDA framework for application to EED forecasting techniques emphasising visualization methods.

We think that if we wish to deliver a valid short-, medium- or long-term forecast of the EED and avoid the implementation of useless models, we must at least perform an EDA similar to that of the present study. Before resorting to general models, possible hidden patterns must be revealed, which if not modelled sufficiently, they may invalidate the accuracy of the forecast. Furthermore, an interdisciplinary approach to the exploitation of all available information is also needed. Using the knowledge across several scientific fields may help to interpret the results of the visualization.

The results of our study confirm and summarize the conclusions of previous relevant studies in Greece, each one treating a single topic and covering shorter and earlier time periods. Some unexpected patterns are also revealed. The results of the analysis will be used in the development of an electrical energy forecasting system, which will be a part of a framework for optimal planning of a large-scale hybrid renewable energy system in which hydropower plays the dominant role.

The raw and wrangled data and code of the present study as well as additional Figures, associated with the present study but not included here for brevity, are available in Tyralis et al. [75]. The interested reader can use it to reproduce our analysis.

## 2. Data and methods

In Section 2, the data and methods used in the subsequent Sections are presented. EED, price, GDP and temperature data are used. The cleaning of the raw data is presented in Tyralis et al. [75]. In Table 1, the variables examined in the next Sections are summarized, along with their availability during the study time period. The IPTO [76] provided the weekly ahead load forecast.

Table 1. Variables examined in the study.

| Variable | Unit | Availability |
|---|---|---|
| Demand load | MW | 2002/09/01 - 2016/08/31 |
| Load forecast | MW | 2002/09/01 - 2016/08/31 |
| Ex-ante System Marginal Price (ex-ante SMP) | €/MWh | 2002/09/01 - 2016/08/31 |
| Ex-post System Marginal Price (ex-post SMP) | €/MWh | 2002/09/01 - 2016/08/31 |
| Gross Domestic Product (GDP) | $10^6$ € | 2002-2015 |
| Gross Domestic Product of hydrological year ($GDP_{hydr}$) | $10^6$ € | 2002 – 2014 (hydrological years) |
| Temperature | °C | 2005/09/01 - 2016/08/31 |
| Year | year | 2002-2016 |
| Hydrological year | year | 2002-2015, defined in eq. (1) |

### *2.1 Electrical energy demand*

The EED data used in this study were provided by the IPTO [76]. The hourly EED in Greece and its forecast are presented in Figure 1. The quality of the data was good with some missing values, which were substituted using interpolation. A seasonal periodicity of the EED is observed. The patterns of the EED and its forecast are similar. We also observe in Figure 2 that the histograms of the hourly EED and its weekly ahead forecast provided by the IPTO have two peaks at approximately 5 000 MW and 6 400 MW. Additionally, it is noted that the two histograms are bimodal while the histogram of load forecast is narrower and is shifted to the right compared to the histogram of the EED.

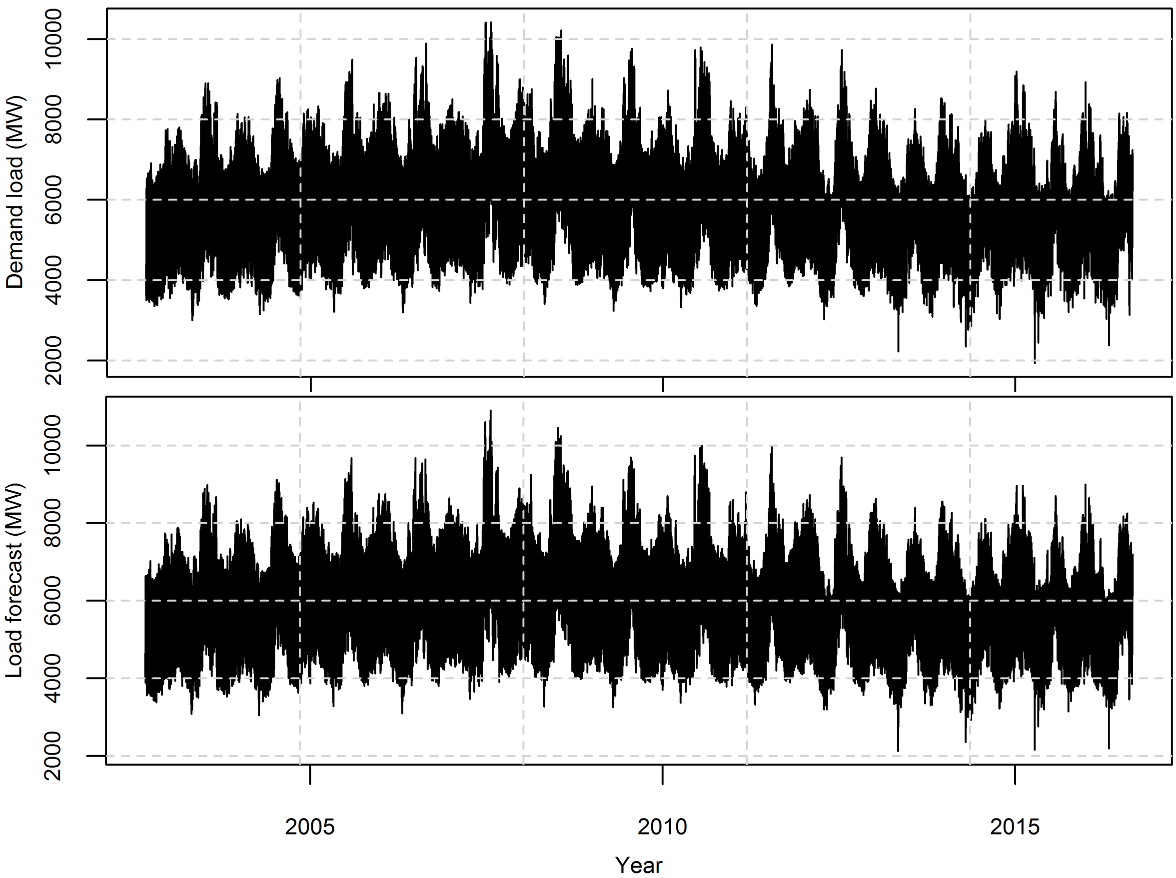


Figure 1. Hourly EED (top) and weekly ahead hourly forecasted load in Greece, provided by the IPTO (bottom) for the time period 2002/09/01 - 2016/08/31 (Data source: IPTO [76]).

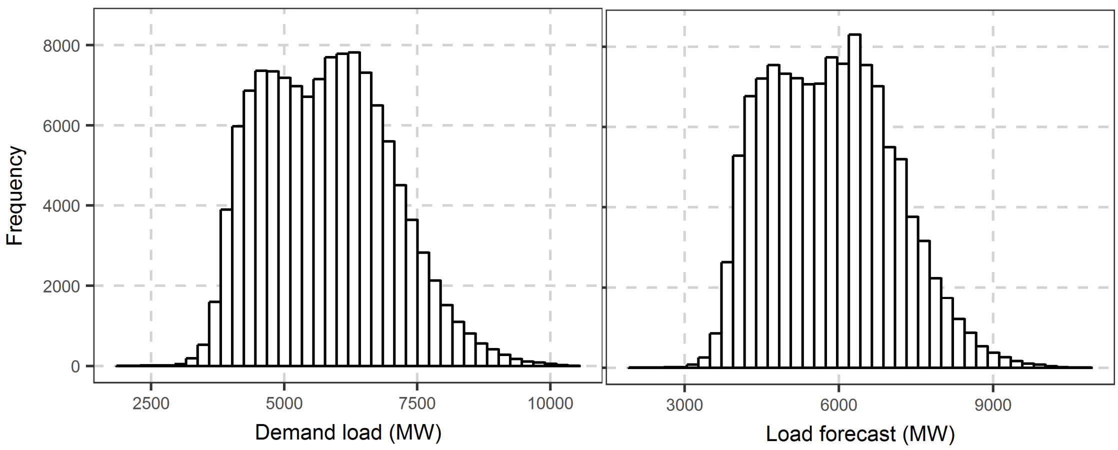


Figure 2. Histogram of the hourly EED (left) and the weekly ahead hourly forecasted load in Greece, provided by the IPTO (right) for the time period 2002/09/01 - 2016/08/31.

### *2.2 Gross Domestic Product*

The World Bank [77] provided the annual GDP of Greece (see Table 2). In this study, the hydrological year was defined, as the period between September 1st of one year and August 31st of the next. The present analysis will use the hydrological year as the reference time period because the results of the study will be used for optimal planning of a hybrid renewable energy system in which hydropower plays the dominant role. The annual GDP of the hydrological year was calculated according to (1).

$$\mathrm{GDP}_{\mathrm{hydr},i} = (1/3)\ \mathrm{GDP}_i + (2/3)\ \mathrm{GDP}_{i+1},\ i = 2002, 2003, \ldots \quad (1)$$

The annual GDP of the hydrological year is presented in Table 2. One could claim that the seasonality in the economic activity affects the computation of the $\mathrm{GDP}_{\mathrm{hydr}}$, however the approximation in eq. (1) could be accepted for the purpose of our analysis.

Table 2. Greek Annual Gross Domestic Product (Data source: The World Bank [77]).

| Year | Annual Gross Domestic Product ($10^6$ €) | Hydrological Year | Gross Domestic Product of Hydrological Year ($10^6$ €) |
|---|---|---|---|
| 2002 | 205 505 | 2002 | 213 443.7 |
| 2003 | 217 413 | 2003 | 224 748.3 |
| 2004 | 228 416 | 2004 | 229 328.7 |
| 2005 | 229 785 | 2005 | 238 443.7 |
| 2006 | 242 773 | 2006 | 248 071.7 |
| 2007 | 250 721 | 2007 | 250 160.3 |
| 2008 | 249 880 | 2008 | 242 716.0 |
| 2009 | 239 134 | 2009 | 230 398.7 |
| 2010 | 226 031 | 2010 | 212 269.7 |
| 2011 | 205 389 | 2011 | 195 393.0 |
| 2012 | 190 395 | 2012 | 186 335.0 |
| 2013 | 184 305 | 2013 | 185 109.0 |
| 2014 | 185 511 | 2014 | 185 224.3 |
| 2015 | 185 081 | | |

### *2.3 Temperature*

The Hydrological Observatory of Athens provided the temperature data [78]. Data from the Ilioupolis station were used. The Ilioupolis station is located in the administrative region of Attica (Figure 3). 35% of Greece's population resides in Attica. Furthermore, the country's main industrial activity is concentrated in Attica. Attica's climate is mild and the station is located near the sea, thus the variations of temperature are less sensitive to local weather extremes. Therefore, the station's temperature is representative of the temperature in Greece, at least for the purpose of the analysis, despite the high temperature variations of Greece due to its mountainous terrain. In addition, the choice of a single station for the analysis is justified by the choice of only two stations by Hyndman and Fan [1] in their advanced EED forecasting model.


Figure 3. Location of the meteorological station of Ilioupolis. The station is sited within the municipality of Ilioupolis installations in the foot of Ymittos mountain (ground altitude 206 m). The station operates since 2005/05/20 (Data source: The Hydrological Observatory of Athens [78]).

### *2.4 Pricing system*

In competitive electricity markets, the forecasted load has to meet each of the 24 hours of the day via day-ahead auctions between the electricity producers-suppliers. To ensure the forecasted load for each hour of the next day, the offer of every supplier is firstly classified in an ascending cost order (from the least to the most expensive one). At the next stage, producers' offers are accepted from the least to the most expensive until the predicted load demand is met.

The ex-ante System Marginal Price (ex-ante SMP) is formed by the offer of the last (and most expensive) supplier needed to meet the forecasted load. All the rest and more expensive offers are rejected. However, the ex-ante SMP depends on the forecasted load and its composition and not on actual observations. The final SMP is based on actual observations and is called ex-post SMP [79]. The IPTO [76] provided the electrical energy prices in Greece. Figure 4 presents the hourly ex-ante prices and the hourly ex-post prices. Similar patterns are observed for both prices until the year 2008, however after the year 2009 the ex-post SMPs are higher while many zero values for the ex-ante SMPs are also observed.

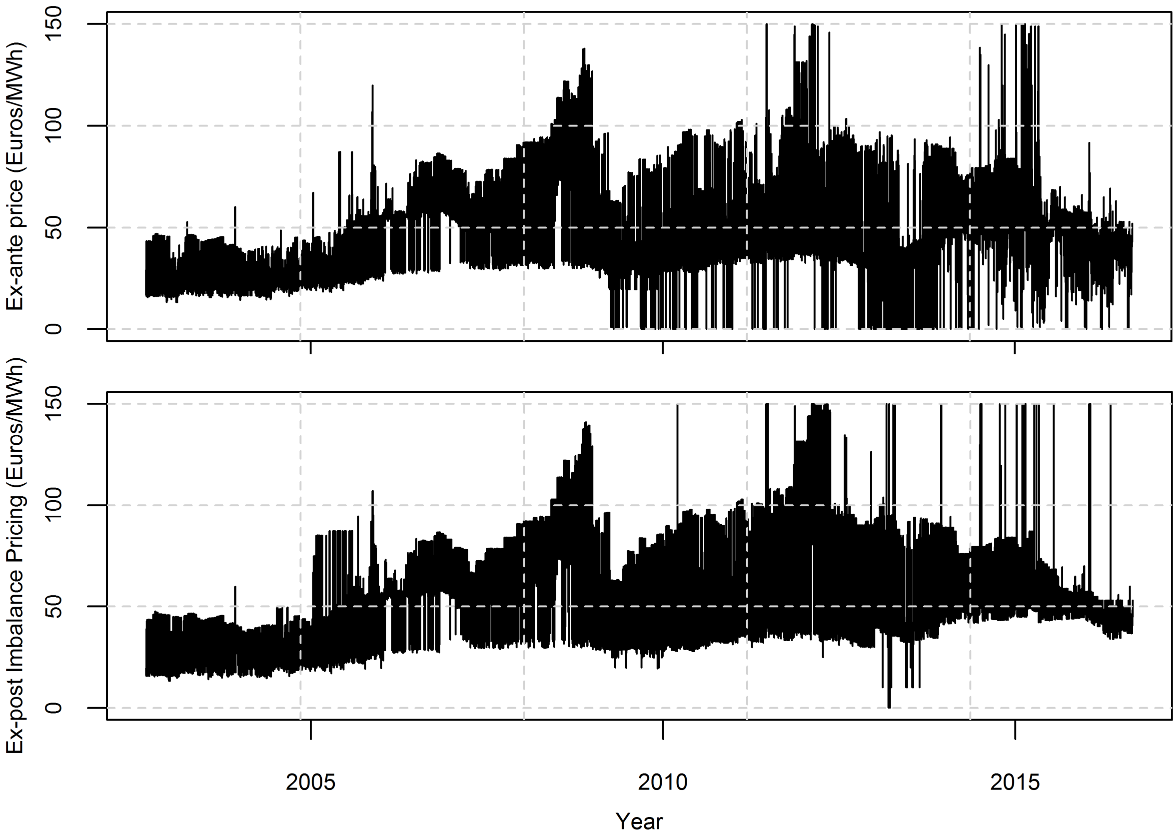

Figure 4. Hourly ex-ante electrical energy prices (top) and ex-post electrical energy prices (bottom) in Greece for the time period 2002/09/01 - 2016/08/31 (Data source: IPTO [76]).

### *2.5 Visualizations of the Exploratory Data Analysis*

In Table 3, the visualizations of the present study are summarized. Table 3 can be used as a guide for similar studies because it includes all the necessary visualizations to understand the data. These visualizations are the most frequently used in the literature, albeit we could not find any study including all of them.

Table 3. Figures of the present study. The examined variables and their time scale are also shown.

| Description | Time scale | Figures | Variables |
|---|---|---|---|
| Time series | hourly | 1, 4 | EED, forecasted load, prices |
| Time series | daily | 18 | EED, GDP, temperature |
| Time series | monthly | 13 | EED, forecasted load |
| Time series | annual | 16 | EED, GDP |
| Histogram | hourly | 2, 14, 21 | EED, forecasted load, prices |
| 3D plot | hourly | 5 | EED |
| ACF, PACF | hourly | 6 | EED |
| ACF, PACF | daily | 6 | EED |
| ACF, PACF | monthly | 6 | EED |
| Extreme values | hourly | 8 | EED |
| Daily distribution | monthly | 7 | EED |
| Weekly distribution | monthly | 9 | EED |
| Annual distribution | monthly | 10, 19 | EED, GDP, temperature |
| Boxplot | monthly | 12 | EED |
| Scatterplot | hourly | 20 | EED, GDP, temperature |
| Regression scatterplot | hourly | 15, 22, 23 | EED, forecasted load, prices |
| Regression scatterplot | annual | 17, 24 | EED, prices, GDP |

## 3. Visualization of the EED in the time domain

In Section 3, the EED in the time domain is visualized. In Figure 5, the data are illustrated in three dimensions. This representation provides a better insight and additional information about the EED variations, as proposed by Filik et al. [2]. One can observe two constant patterns, the first in the daily distribution and the second in the annual distribution of the EED. Furthermore, an increasing trend until day 2000 and a decreasing trend afterwards are observed. The autocorrelations will be examined and the EED at various time scales will be visualized in the next Sections, to better highlight the aforementioned observations.

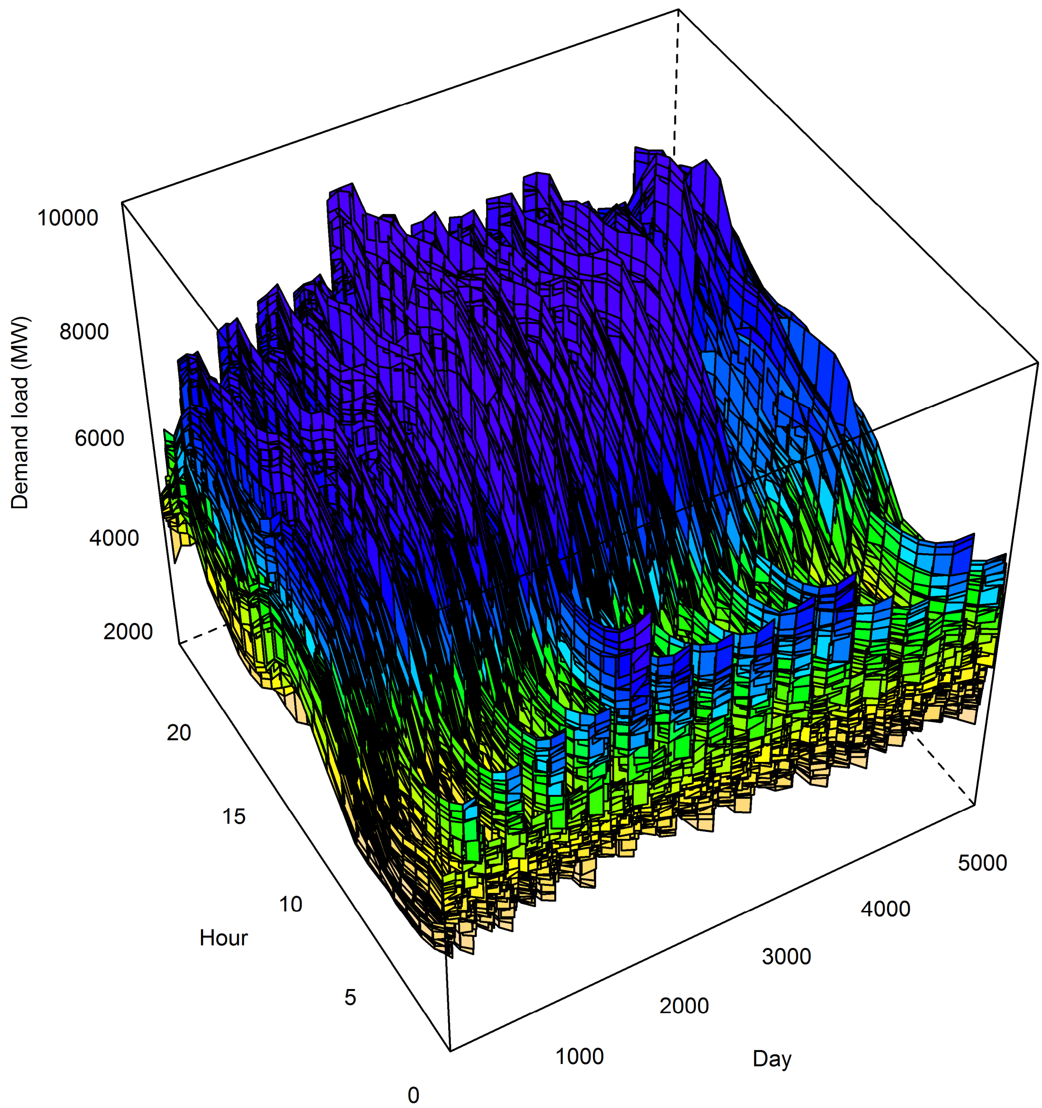


Figure 5. 3-D representation of the hourly EED for the time period 2002/09/01 - 2016/08/31.

### *3.1 Autocorrelation and partial autocorrelation function*

In Section 3.1, the sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of the EED at various time scales are calculated. The reader is referred to Wei ([80], p.20-23) for the calculation of the sample ACF and the sample PACF. The ACF and the PACF are useful in the recognition of the dependence structure and of periodic patterns. The use of the ACF in the identification of periodic patterns is straightforward. The reader is referred to Hamilton and Watts [81] for the use of the PACF in the recognition of periodic patterns.

Figure 6 represents the sample ACF and PACF for the hourly EED. The ACF is maximized every 24 hours and its multiples, i.e. there is a 24-hour periodicity. This result is confirmed by the corresponding spikes of the PACF in Figure 6. The sample ACF and the sample PACF of the mean daily EED are also shown in Figure 6. We observe a periodic pattern of 7 days. The dependence is strong even for time lags equal to 40 days. Furthermore, in Figure 6, both the sample ACF and PACF of the mean monthly EED are presented. A periodic pattern of 6 months is observed. However, the autocorrelation is stronger every 12 months.

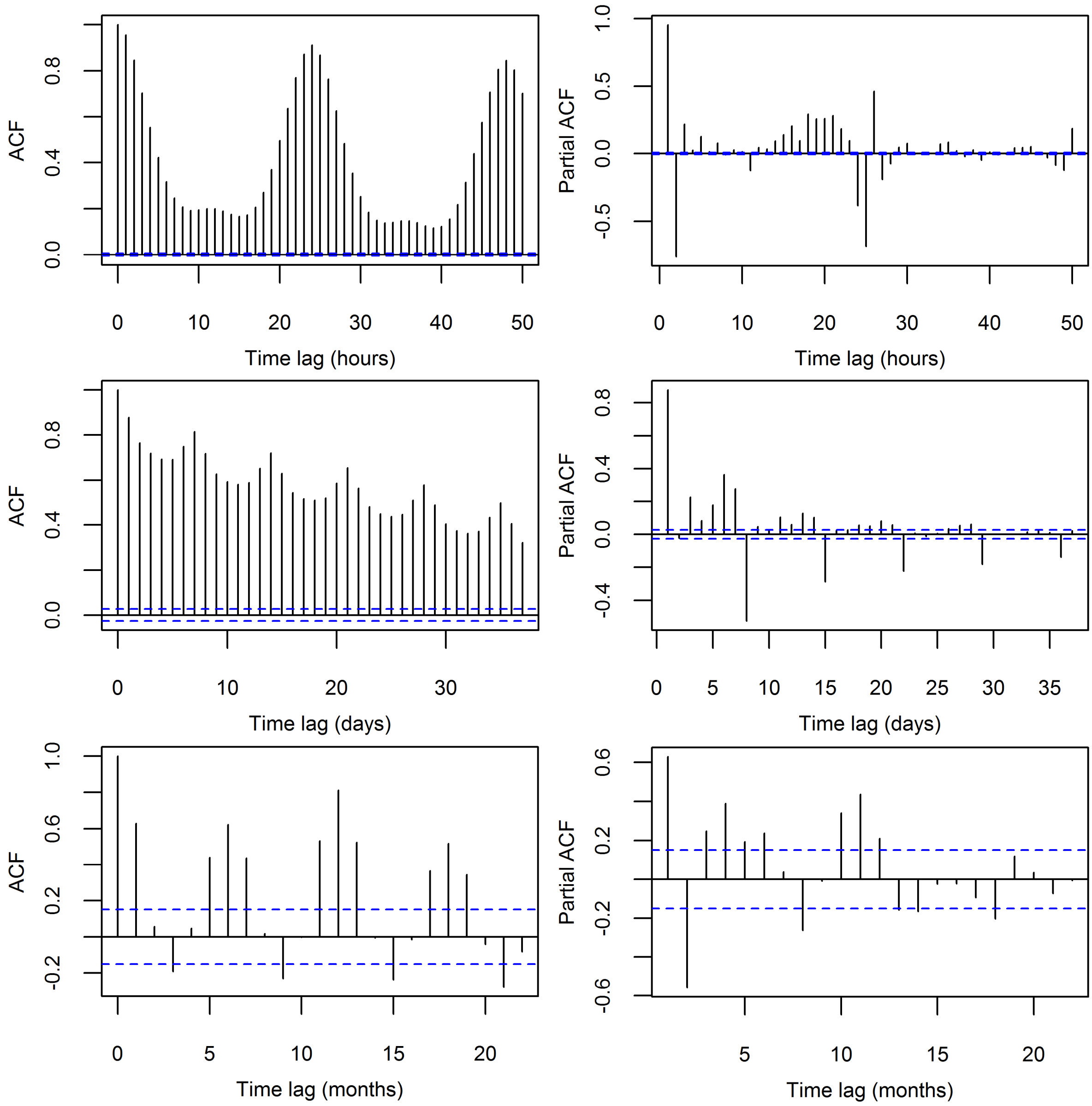


Figure 6. Sample ACF (left) and PACF (right) of the hourly (top), mean daily (middle) and mean monthly (bottom) EED for the time period 2002/09/01 - 2016/08/31.

### *3.2 Visualization at various time scales*

Based on the findings of Section 3.1, in Section 3.2 the EED at the hourly, daily, weekly and monthly time scale is visualized. The means at each time scale conditional on the month or the hydrological year are visualized. The results are compared with results reported in literature about Greece.

Figure 7 presents the mean EED per hour of day, conditional on the month of the year and the distribution of the EED during the day. While the results in Figure 7 (bottom) are scaled, thus they seem smoother, it can furthermore be observed that the EED varies over the year, thus a model, which considers the seasonality, is required. In the rest of Section 3.2, both the actual and the scaled EED for each time scale will be presented. In Figure 7, it is observed that the global minimum EED values appear at approximately 3:00 to 5:00, however another local minimum appears at approximately 16:00. Two local maxima are also observed. The first local maximum is observed at 12:00 regardless of the month, while the second local maximum moves from 18:00 in the winter months to 21:00 in the summer months. The first maximum is due to the increased EED for industries, services and household activities while the second maximum is due to household heating and cooling. Furthermore, the latter maximum is considerably higher compared to the former one in the winter months probably due to the increased need for heating in the night, whereas the two maxima are approximately equal in the summer months, in which cooling is mostly necessary in the afternoon hours. The increasing trend, observed between 06:00 and 07:00 in the summer, moves an hour earlier during the other months. The EED values range between these minima or maxima values during the spring and autumn. The results are similar to those of Figure 6 in Psiloglou et al. [16], which presents the EED distribution during the day, conditional on two months (January and July) or summarizing the results for all months. However, the second maximum is equal or higher than the first maximum in our study, whereas in Psiloglou et al. [16] the second maximum is lower. It is noted here that Psiloglou et al. [16] study the EED in Athens, which may differ compared to that of Greece.

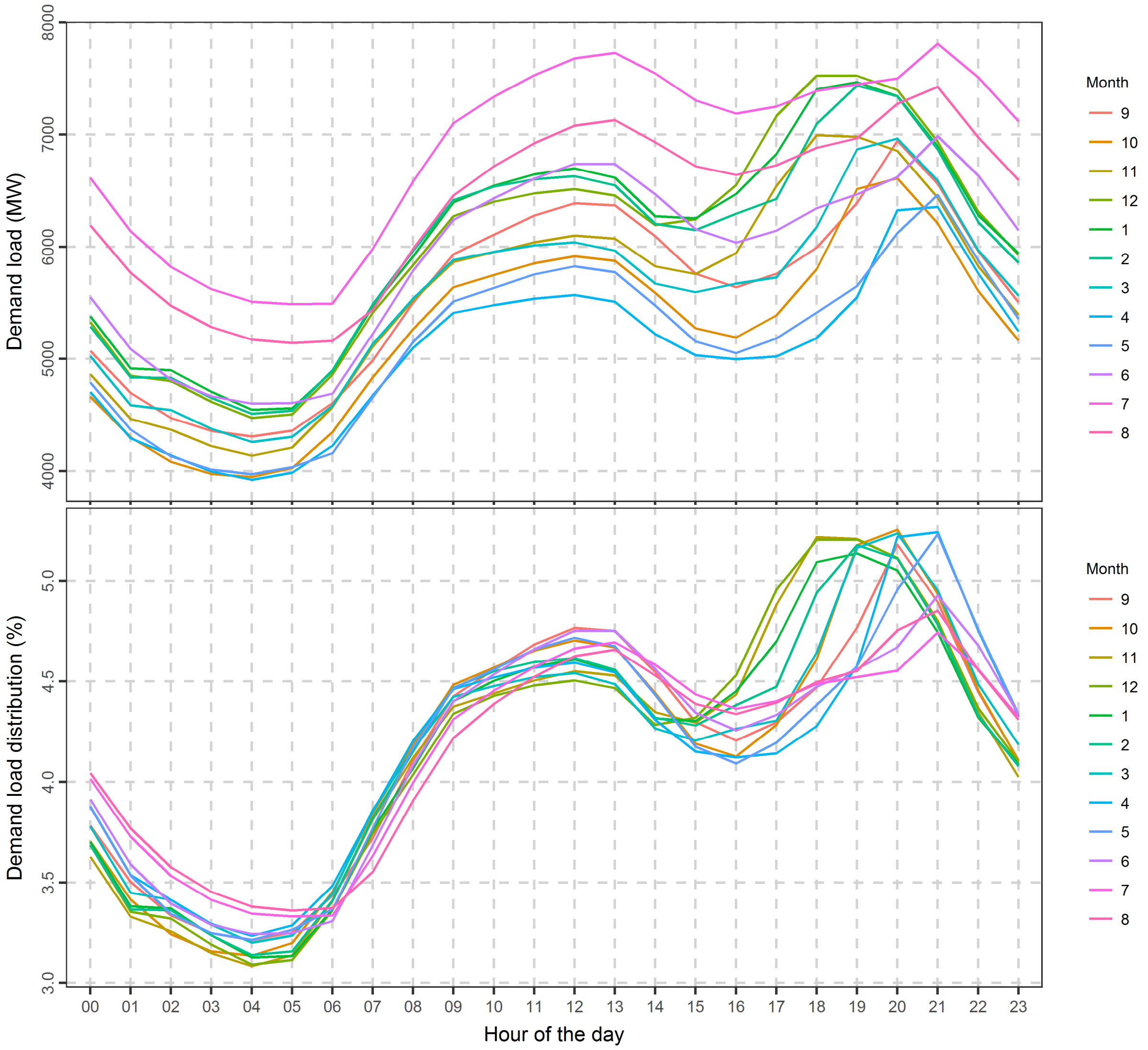

Figure 7. Mean EED per hour of day (top) and distribution of the EED during the day (bottom) presented for each month of the year (bottom). The data cover the time period 2002/09/01 - 2016/08/31.

In Figure 8, the 100 minimum and maximum hourly EED values for each hydrological year in the time period 2002 – 2015 are presented. A constant pattern of ascent in Figure 8 (left) and decay in Figure 8 (right) is observed, which is independent of the hydrological year. However, this pattern is shifted up and down, depending on the mean annual EED. Furthermore, in some cases the lines are intersecting, i.e. the extreme values significantly depend on other factors, e.g. the temperature. The mean annual EED will be discussed more thoroughly in Section 4.2.

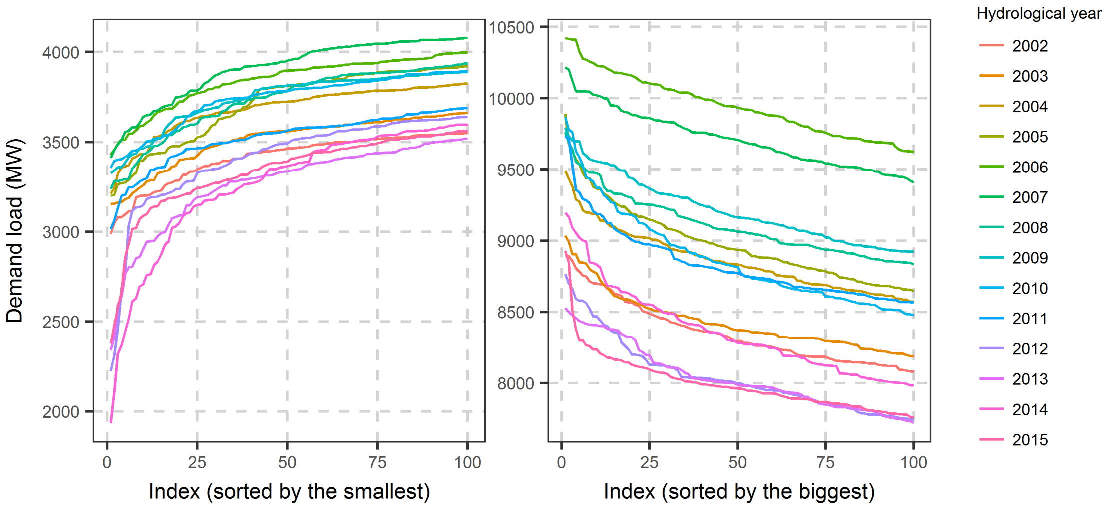

Figure 8. 100 minimum (left) and maximum (right) hourly EED values per hydrological year.

Figure 9 presents the mean EED per weekday, conditional on the month of the year and the distribution of the EED during the week. The pattern of the distribution is constant, conditional on the month, however the level of the EED is shifted up and down depending on the month. An unnatural decrease between Thursday and Friday in March is observed. Maxima of the mean daily EED are observed on Wednesdays or Thursdays and minima of the EED are observed on Sundays (and Saturdays), the latter due to the reduced economic activity in weekends [16]. The mean daily EEDs are equal in Mondays and Fridays, and the EED increases in the other working days of the week. The results are similar to those of Figure 1 in Mirasgedis et al. [17] which presents the EED distribution of the GIES during a particular week in March of 2002 and Figure 5 in Psiloglou et al. [16] which presents the EED distribution during the week, conditional on two months (January and July) or summarizing the results for all months.

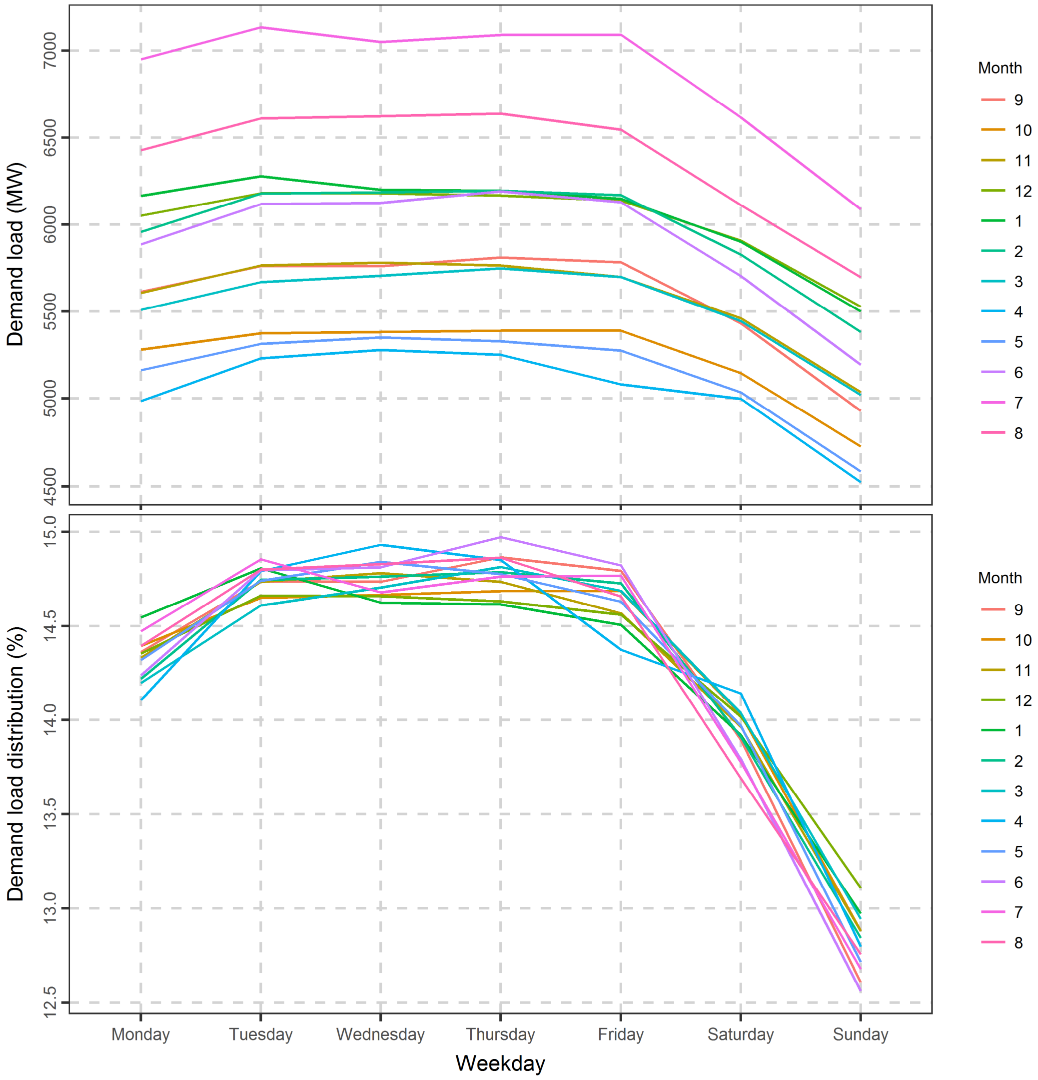


Figure 9. Mean EED per weekday (top) and distribution of the EED during the week (bottom) presented for each month of the year. The data cover the time period 2002/09/01 - 2016/08/31.

Figure 10 presents the mean EED per month, conditional on the hydrological year and the distribution of the EED during the hydrological year. Local maxima of the mean monthly EED are observed in January and July (which is also the global maximum) and local minima of the mean monthly EED are observed in October and April (which is also the global minimum). The increased demand observed in the winter (December, January, February) and the summer (June, July, August months) is associated with the increased needs for heating and cooling respectively [16]. The EED in August is significantly lower compared to July. This is explained by the fact that despite the mean temperatures of July and August are similar as shown in Figure 19, August is a vacations month for industries, which are high consumers of electrical energy [23]. The pattern is similar to that of Figure 1 in Mirasgedis et al. [17], which refers to the time period 1993-2002. However, in Figure

4 in Psiloglou et al. [16] a low value of the EED in August in Athens is observed. This is probably due to the fact that August is a vacations period for most people living in Athens.

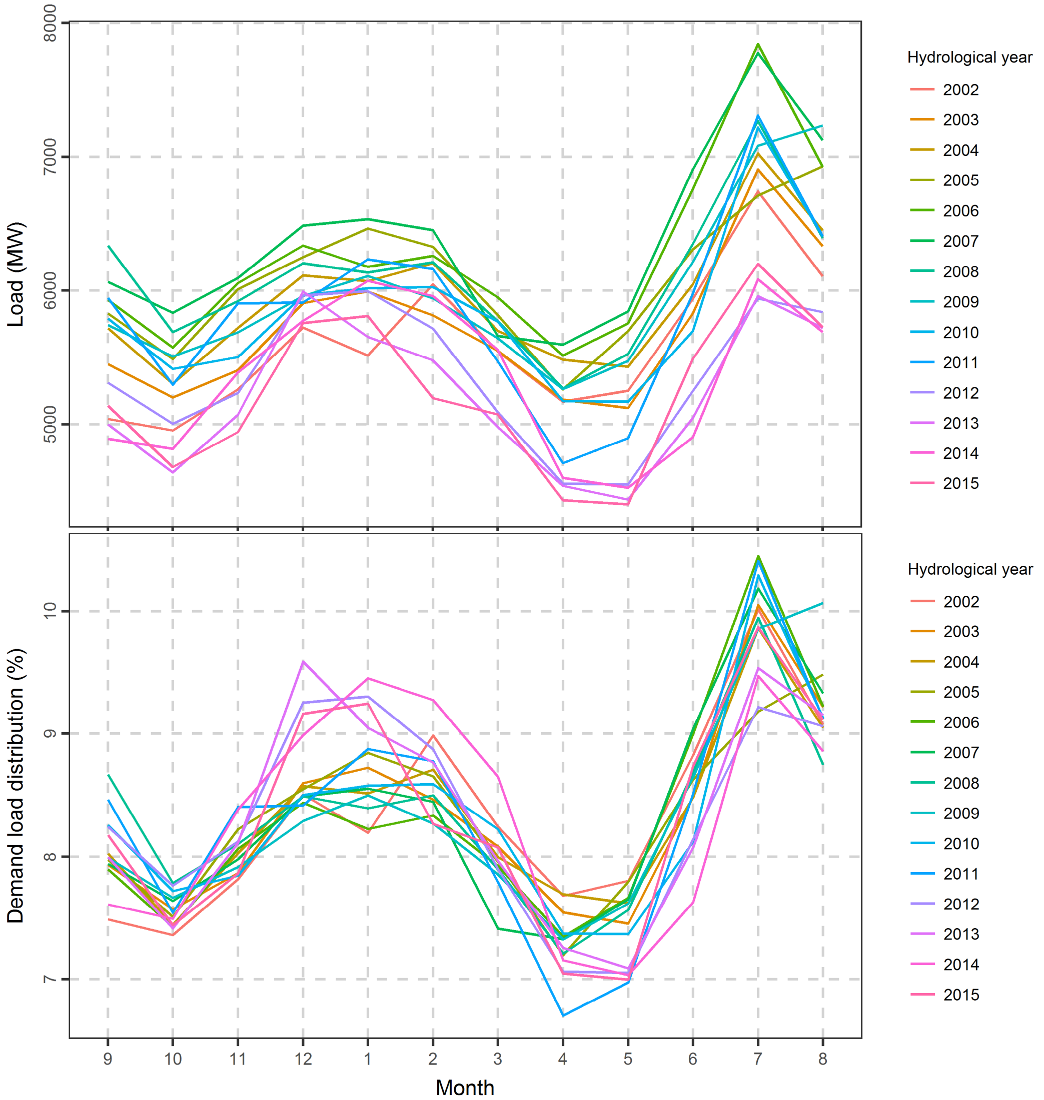


Figure 10. Mean EED per month (top) and distribution of the EED during the year (bottom) presented for each hydrological year.

In Figure 10, it is observed that the mean annual EED has reduced since the hydrological year 2008. This is more evident in Figure 11 in which intermediate hydrological years were omitted. This will be discussed more thoroughly in Section 4.2. In Figure 10, it is observed that the pattern of the mean monthly EED of December and January has changed considerably since the hydrological year 2012. This is again more evident in Figure 11, in which some intermediate hydrological years were again omitted. This was firstly observed by Dagoumas and Kitsios [21]. Their study refers to the hydrological year 2012, and they attributed this change to the considerable increase of tax on heating oil, which lead to an increase of use of electricity for heating purposes. The increase of tax on heating oil was a result of the economic policy adopted by the Greek government due to the decrease of the GDP and the economic crisis in Greece, which started the year 2010.

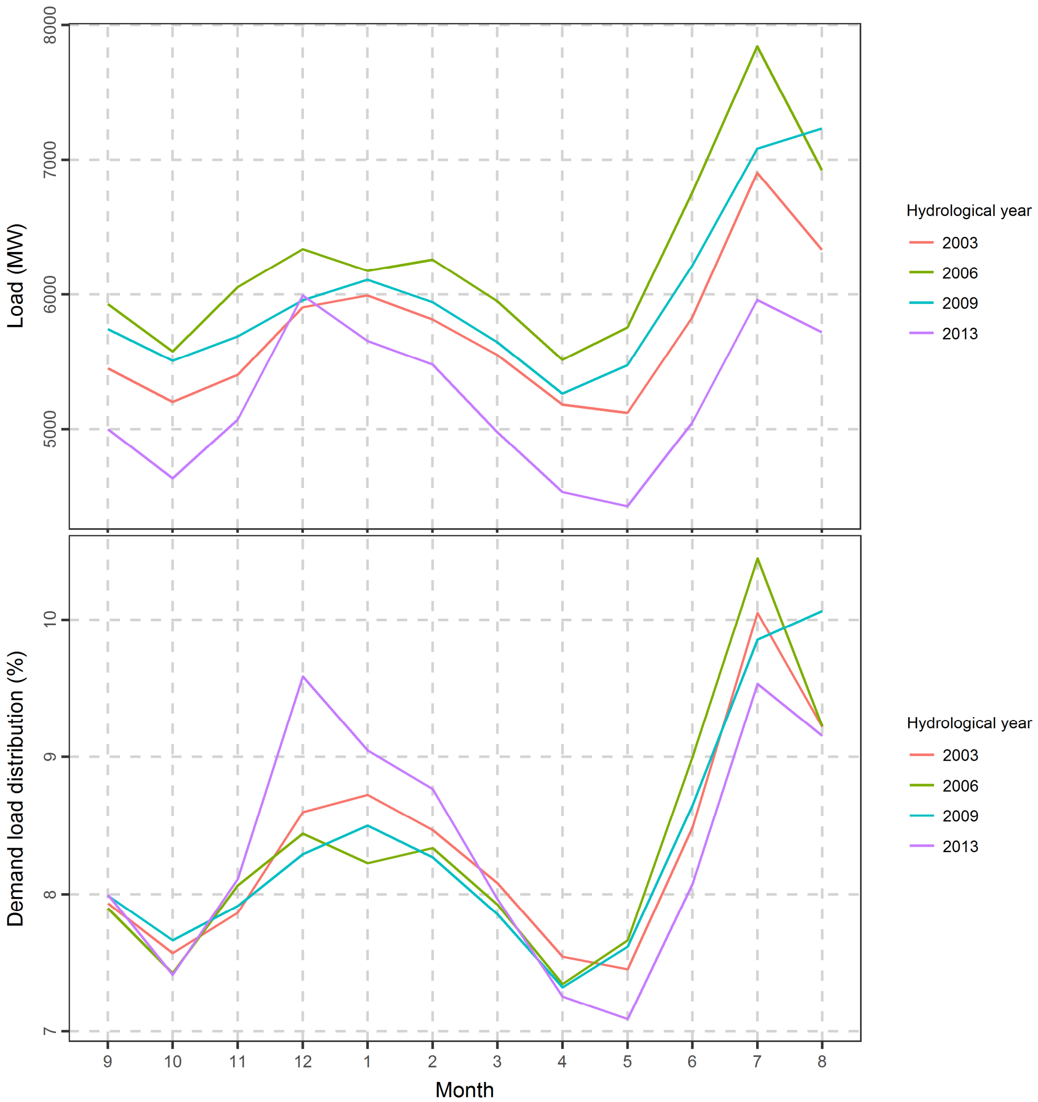


Figure 11. Mean EED per month (top) and distribution of the EED during the year (bottom) presented for the hydrological years 2003, 2006, 2009, 2013.

Figure 12 presents the variance of the mean monthly EED. The highest deviations from the mean occur in the summer months July and August. It is noted here that Figure 12 is not comparable to Figure 3 in Psiloglou et al. [16] who study the mean daily EED.

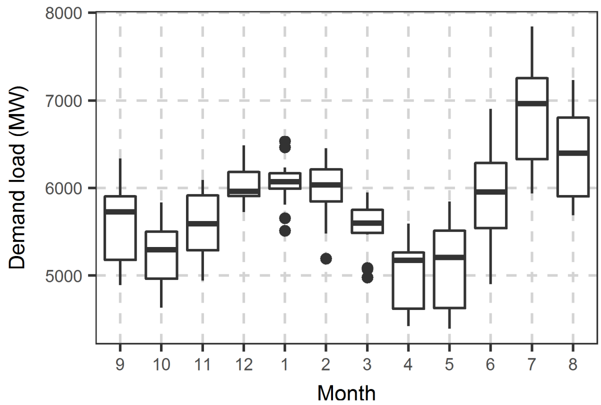

Figure 12. Boxplot with the percentiles 0.25 and 0.75 for the mean monthly EED.

## 4. Forecasting, GDP, temperature and pricing

In Section 4, the EED along with its forecast, the GDP, the temperature and the pricing system is visualized.

### *4.1 EED and IPTO forecasting*

In Figure 13, the mean monthly EED and its forecast are presented. It seems that in general the forecast is higher than the EED.

Figure 13. Mean monthly values of the EED and its forecast for the time period 2002/09/01 - 2016/08/31.

This overestimation is more evident in Figure 14, which presents an asymmetric to the right histogram of the differences of hourly values of the forecasted load minus the EED. The median of the difference is 45 MW. In Figure 15, the regression line between the EED and the forecasted load is presented. This line is above the red line, which bisects the angle between the axes, indicating that the EED is usually overestimated.

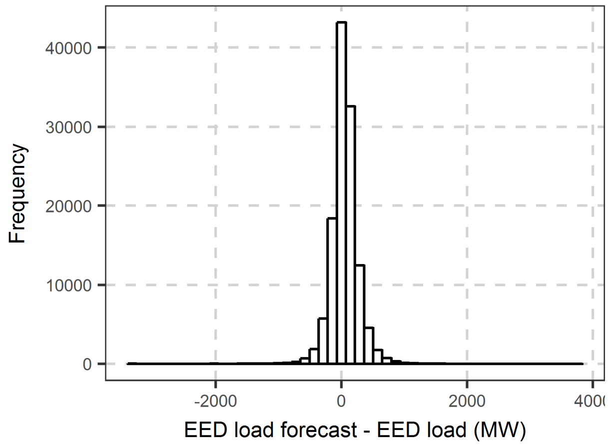

Figure 14. Histogram of hourly values of the forecasted load minus the EED for the time period 2002/09/01 - 2016/08/31.

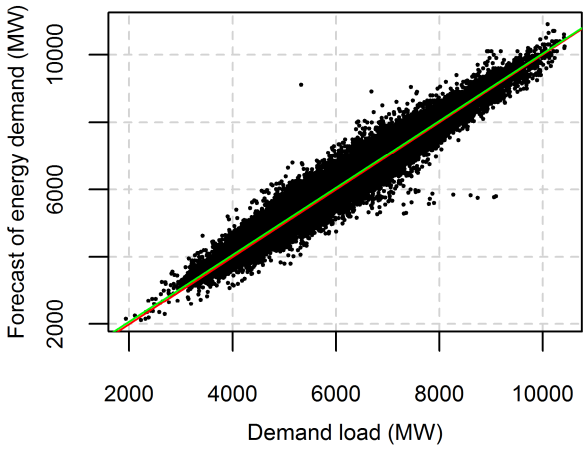

Figure 15. Hourly EED and the forecasted load. The red line is the bisector of the angle between the two axes. The green line is the regression line between the two variables. The data cover the time period 2002/09/01 - 2016/08/31.

### *4.2 EED and GDP*

In Figures 16 and 17, the annual GDP and the mean annual EED are presented. A linear model for the relationship between the GDP and the EED seems reasonable, as presented in Figure 17.

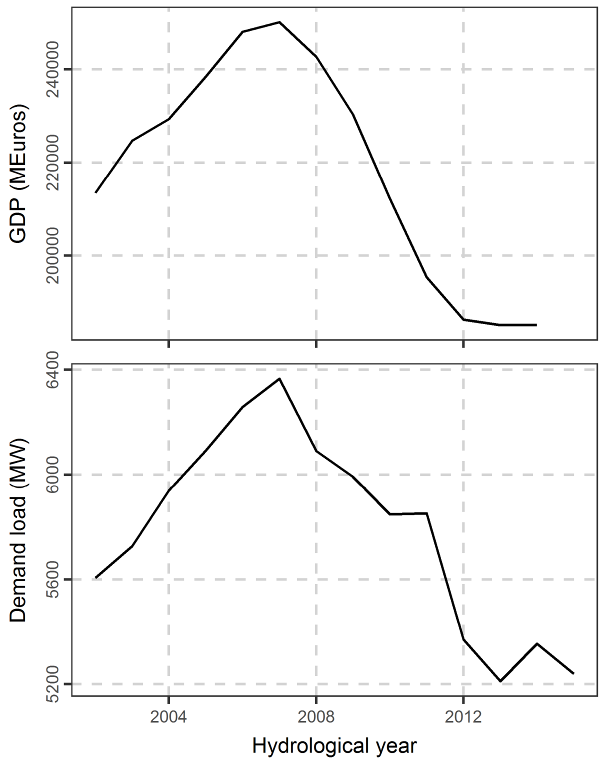


Figure 16. Annual GDP (top) and mean annual EED (lower) per hydrological year.

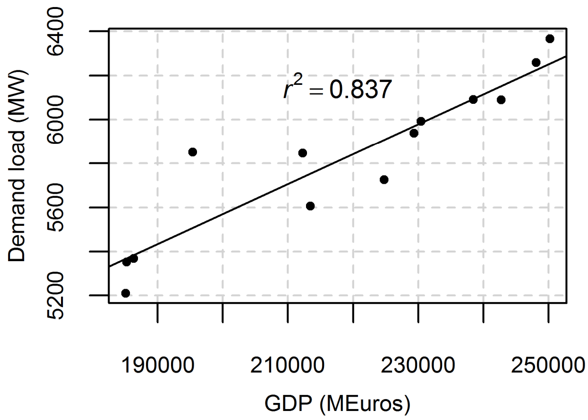


Figure 17. Annual GDP of hydrological year and mean annual EED. The continuous line is the regression line between the two variables. The coefficient of determination $r^2$ = 0.837. The data cover the time period 2002/09/01 - 2015/08/31.

The reduction of the mean annual EED presented in Figure 16 was firstly observed by Dagoumas and Kitsios [21] whose study ranges in the time period 1960-2012. Dagoumas and Kitsios [21] conclude that that the decrease in the electrical energy consumption seems to follow the economic crisis. Furthermore, the assumption of an annual increase from 2-5% of the EED in Kalampalikas and Pilavachi [20] for the development of a model of a power production system in Greece was not verified. Ekonomou [19] predicted an increase in the energy consumption in Greece until the year 2015, but his prediction may have not been verified. Regarding the Ekonomou's [19] forecast, it is noted that he models the energy consumption as a function of per resident electricity consumption. The electrical energy consumption is the highest part of the energy consumption, thus a decrease in EED may result in a decrease of energy consumption.

### *4.3 EED and temperature*

Figure 18 presents the mean daily temperature at the station of Ilioupolis and the ratios of the mean daily EED divided by the GDP of the respective year (calendar or hydrological). A periodicity of 12 months is observed in all cases (see also Section 3.1). In Figure 19, two local maxima of the mean monthly EED, occurring during the winter and the summer season are observed. The winter and the summer season in Greece are characterized by the highest and the lowest temperatures during the year respectively. This is also confirmed in Figure 20, which indicates that a useful model for the relationship between the mean daily temperature and the EED would be a convex curve. The maxima of this curve appear for low or high temperatures.

Furthermore, Figure 20 is similar to Figure 8 in Psiloglou et al. [16] for Athens, Figure 2 in Mirasgedis et al. [17] for Greece and Figure 2 in Moral-Carcedo and Vicens-Otero [58] for Spain with a similar climate to that of Greece. However, the pattern depends on the climate, thus a different pattern in Figure 3 in Hor et al. [57] for the United Kingdom and Figure 4 in Hyndman and Fan [1] for South Australia is observed.

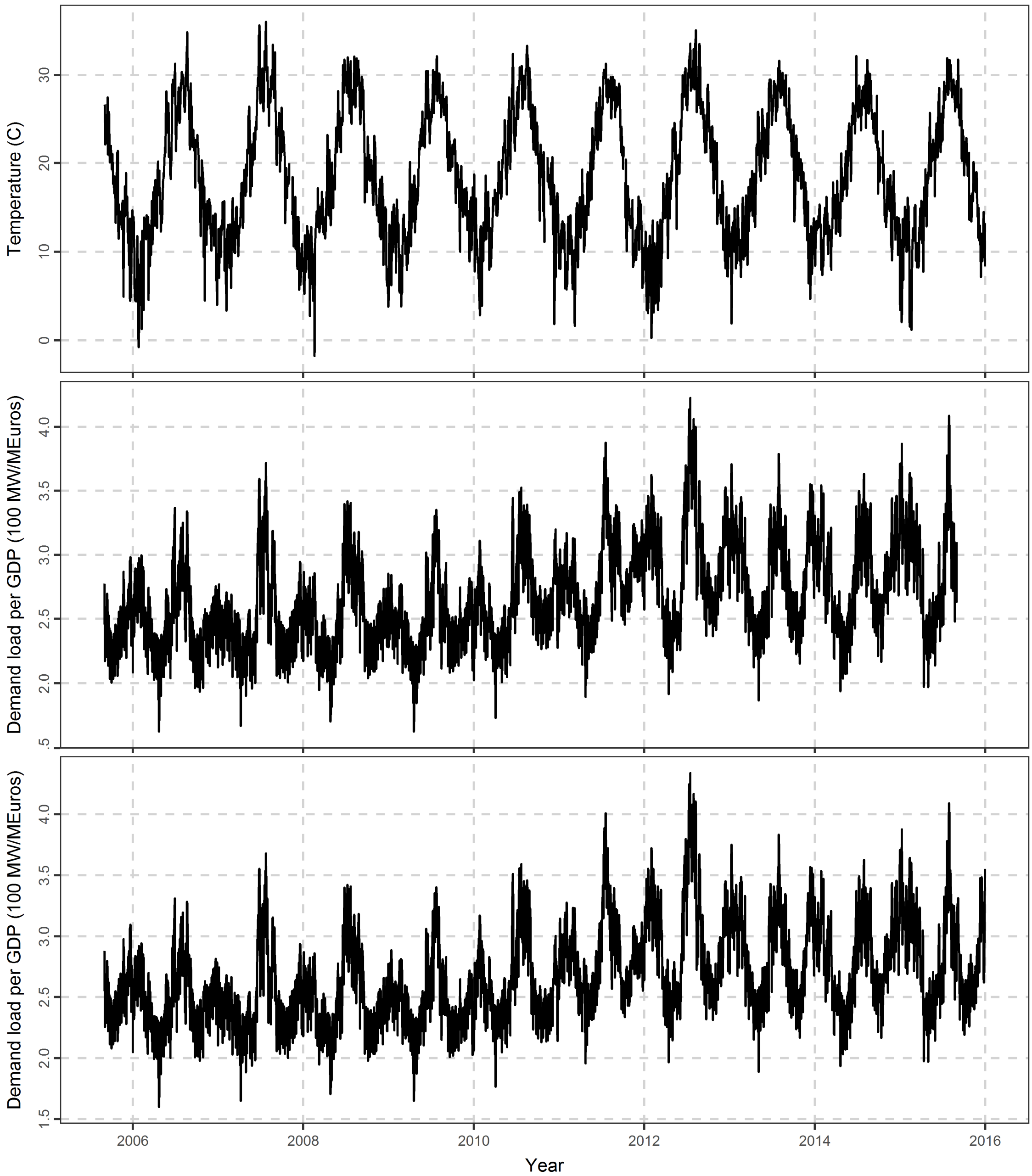


Figure 18. Mean daily temperature at the Ilioupolis station (top), hourly EED per GDP of the hydrological year (middle) and hourly EED per GDP of the calendar year (bottom).

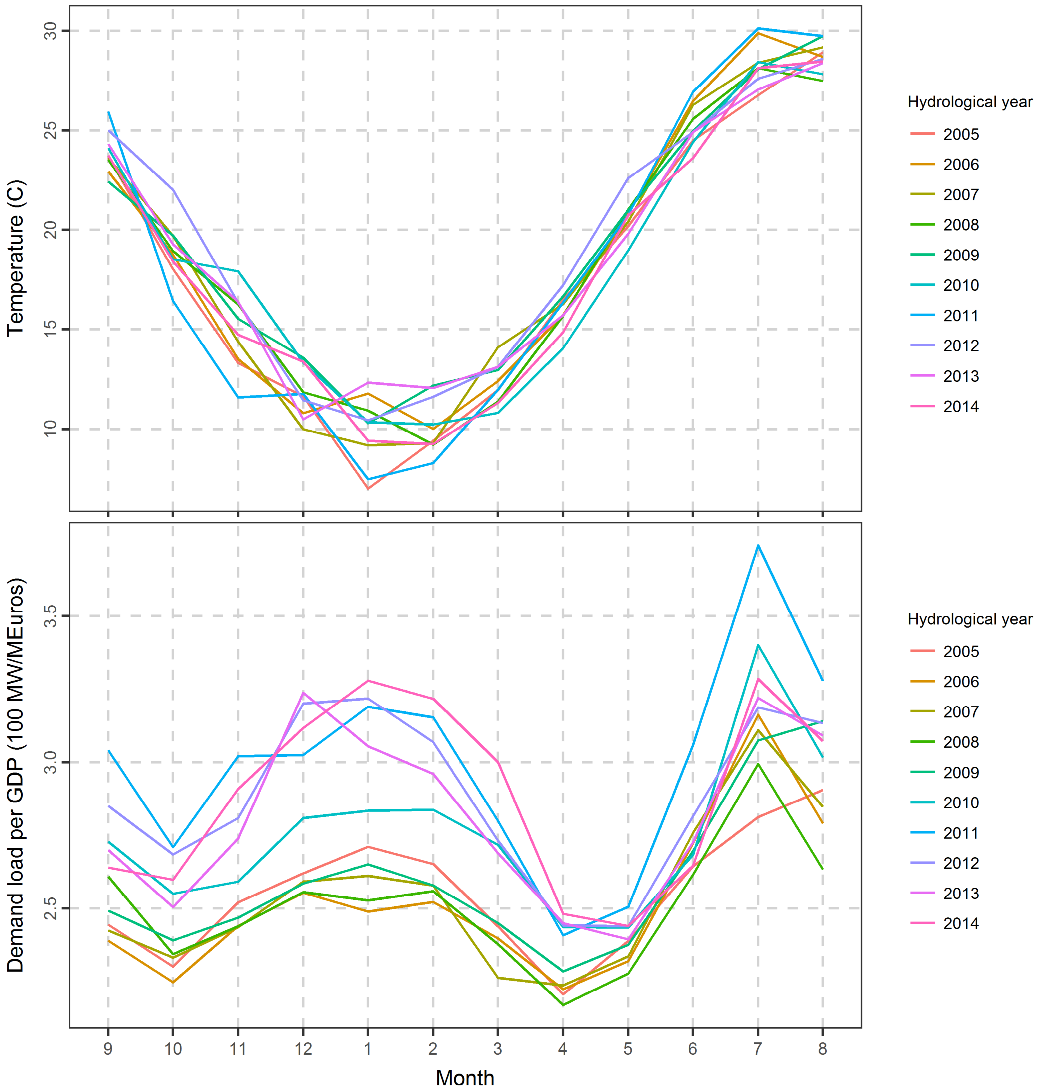


Figure 19. Mean monthly temperature at the Ilioupolis station (top) and mean EED per month (bottom). The means are presented for each hydrological year.

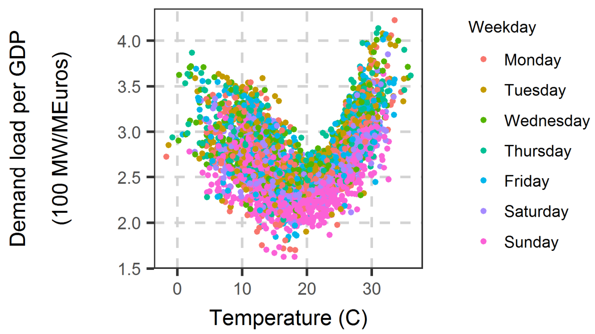


Figure 20. Mean daily temperature at the Ilioupolis station and mean EED per GDP of the hydrological year. The data cover the time period 2002/09/01 - 2015/08/31.

### *4.4 EED and the pricing system*

Significant differences are usually observed between the ex-ante and the ex-post SMP. However, the differences in prices are more intense due to the significant change of the load supply composition. In Figure 21, it is observed that the ex-post SMP values across the examined time period are much more dispersed, than the ex-ante SMP values. Furthermore, in the two histograms it is observed that the ex-post SMP values are higher than the ex-ante SMP values, thus the actual electrical energy price in Greece is systematically higher than the forecasted. Additionally, as observed in Figure 4, the deviations between the SMPs become more pronounced from the year 2009, starting to systemically affect significantly the ex-post SMP to higher values. An event which happened in the year 2009 was the significant introduction of renewables in the electricity mix. Thus, the difference between the ex-ante and ex-post SMPs maybe is due to this event, however it needs to be further investigated. The maximum SMP is 150 €/MWh as observed in Figure 21.

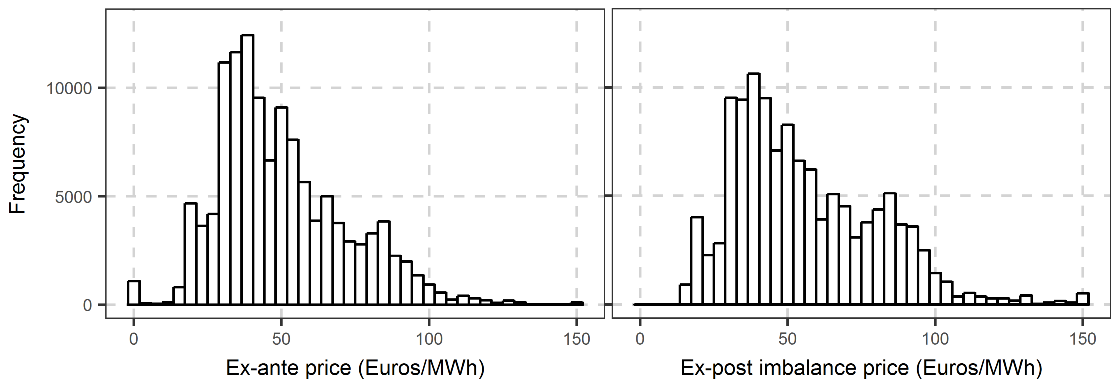

Figure 21. Histogram of the hourly ex-ante (left) and ex-post (right) electrical energy prices for the time period 2002/09/01 - 2016/08/31.

In Figure 22, the relationship between the EED and the ex-ante SMP, and the relationship between the EED and the ex-post SMP are presented. It is evident from the regression lines that the SMPs in general increase when the EED increases. In Figure 22, a cluster of zero ex-ante SMPs for a range of hourly EEDs between 3 000-6 500 MW, and another cluster of SMPs equal to 150 €/MWh for a range of hourly EEDs between 6 000-8 000 MW are observed. However, in Figure 22, there is not any cluster of zero ex-post SMPs, while the SMPs equal to 150 €/MWh range from 4 000 MW to 8 000 MW. This is an additional indication that the ex-post SMP is systematically higher than the ex-ante SMP. On the other hand, a linear relationship would not be a reasonable model for the relation between the SMP and the demand load, as it is also suggested by the low coefficient of determination $r^2$.

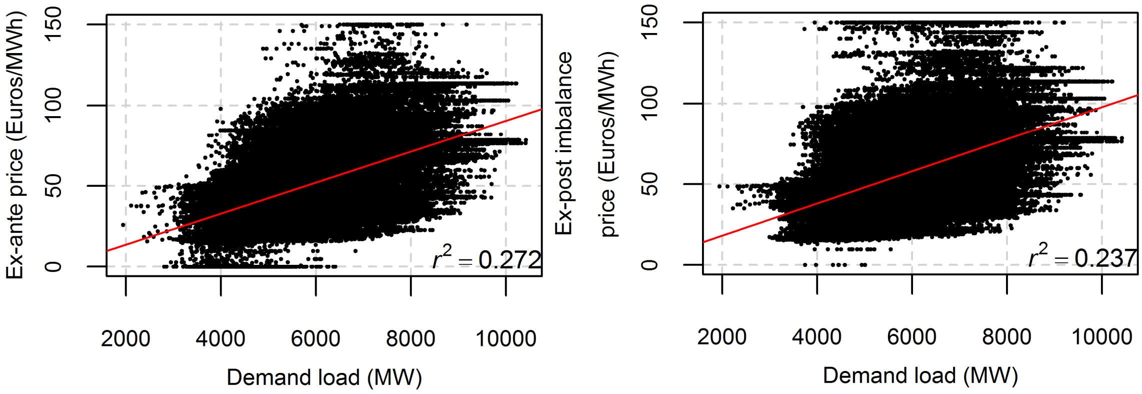

Figure 22. Hourly EED and ex-ante (left), ex-post (right) electrical energy prices for the time period 2002/09/01 - 2016/08/31. The red line is the regression line between the two variables.

Although it would be expected that high SMPs correspond to high EEDs, Figure 22 reveals a different behaviour, i.e. extremely high prices can be observed frequently even at relatively low or medium EEDs (4 000-6 000 MW). A possible explanation for this behaviour is that it is due to the peculiarities of the Greek electricity market with respect to the renewables. Furthermore, it is noted that the renewables' share in the electricity mix is higher for low or medium EEDs [82].

Figure 23 clarifies the indications of Figure 22. In Figure 21, it is observed that the main mass of SMPs is concentrated in values less than 115 €/MWh. The regression line in Figure 23 signifies that the ex-post SMP is systematically higher than the corresponding ex-ante SMP in the aforementioned region. The ex-ante SMP is higher than the corresponding expected ex-post SMP for ex-ante SMPs higher than approximately 115 €/MWh.

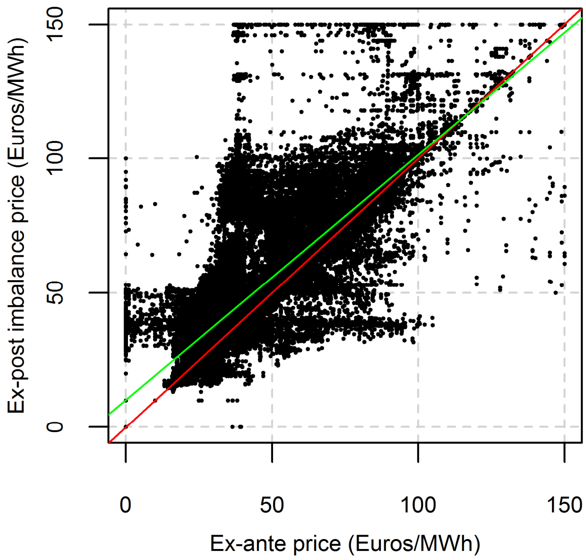


Figure 23. Hourly ex-ante and ex-post electrical energy prices for the time period 2002/09/01 - 2016/08/31. The red line bisects the angle between the two axes. The green line is the regression line between the two variables.

In Figure 24, it is observed that the mean annual demand load increases slightly with the increase of the mean annual SMP price. Pearson's $r$ is low, indicating that no linear relationship exists between the two variables, therefore the influence of the price should be examined using additional information from other variables.

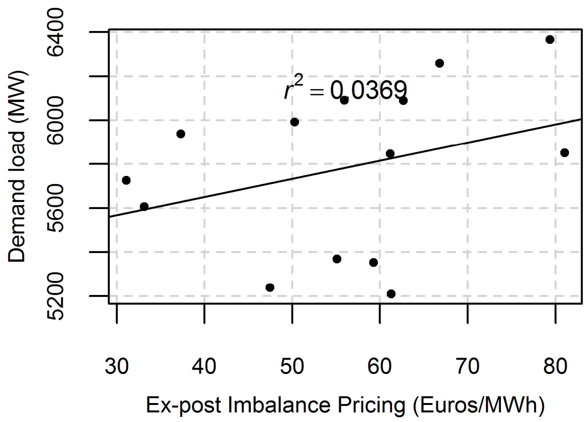


Figure 24. Mean annual EED and mean annual ex-post electrical energy price of hydrological year for the time period 2002/09/01 - 2016/08/31. The continuous line is the regression line between the two variables. The coefficient of determination $r^2$ = 0.04.

## 5. Discussion of results

To summarize the findings of the study, three types of periodicities, i.e. periodic patterns of 24 hours, 7 days and 12 months were observed. The distribution of the EED in the daily, weekly and annual time scale, along with the minimum and maximum values were visualized.

A linear model for the relationship between energy demand and GDP seems reasonable, i.e. the increase of the GDP results in increasing EED (or vice versa). The relationship between the mean daily temperature and the EED could be modelled with a convex curve. The maxima of this curve appear for low or high temperatures. This result is consistent with the result for the mean monthly EED values. Some side results of our analysis is that the IPTO forecast is usually higher than the observed EED, however, this difference is acceptable. Regarding the difference between the ex-ante and ex-post SMP values, it increases in favour of the ex-post SMP values since the year 2009.

Besides the expected patterns found, some details revealed by the EDA could considerably improve the building of forecasting models, thus highlighting its importance. One important result is that the price of oil may change the distribution of the EED during the year in a non-linear way. Thus, the price of fossil fuels should be considered in the modelling of the EED. Indeed, changes of variables such as the GDP, prices of heating oil etc., assumed to influence the EED in big time scales may also, influence the distribution of the EED during the year and consequently the maximum and minimum observed values and the mean weekly EEDs. Particularly, different economic variables may interact, e.g. the decrease of the GDP resulted in the increase of the price of fossil fuels as was explained in Section 3.2. This is important because time series models cannot model such deterministic changes. Therefore, the interaction of socio-economic factors and weather and climatic variables should always be considered, as well as their non-linear effects on the EED.

The varying levels of the variation of the EED from month to month should also been considered in the modelling, because the usual time series models, e.g. ARMA, ARIMA etc., are applied under the assumption of a constant standard deviation during the year, which is invalid in the present case.

## 6. Conclusions

Regarding the contributions of the present study, it is noticed that we found only one similar study in Greece, which investigated the electrical energy demand in Athens (the capital city) and used data from the time period 1997-2001, whereas in the present study a longer time period (2002-2015) is covered and more recent data are used. Furthermore, another study that presents in such detail the electrical energy demand in the time domain and its relationship to a big number of weather-, climate-related and socio-economic variables was not found.

The results of the present study confirm and summarize the conclusions of previous relevant studies in Greece with the exception of studies that forecasted the mean annual electrical energy demand. These studies failed to forecast the gross domestic product decrease, observed in recent years, and subsequently failed to forecast the electrical energy demand decrease. In addition, some unexpected behaviours were noticed, related to the change in the annual distribution of the electrical energy demand due to the increase in the oil prices and a non-stationarity regarding the variation of the mean monthly electrical energy demand, which if not modelled properly could result in dubious forecasts. These results highlight the importance of performing a detailed exploratory data analysis before modelling the electrical energy demand. Regarding the management of the GIES, its efficient operation in the short-term is noted, however there is still place for improvement.

On the other hand, special attention should be given to the short- and long-term planning due to the uncertainty in the forecasting of socio-economic variables, the interaction between the socio-economic variables and the modelling of the relationship between socio-economic variables and the electrical energy demand in small time scales. Indeed the socio-economic variables are subject to unexpected changes due to the unpredictability of the human behaviour therefore modelling of socio-economic variables is important and consequently an interdisciplinary approach is necessary.

The existence of software for electrical energy demand forecasting is noted, however its general use is not recommended, because the models are location-specific, hence not general. The exploratory data analysis of the electrical energy demand is necessary to investigate the usefulness of a model or a software in modelling the electrical energy demand, before using it. The framework introduced in the present study in which the electrical energy demand, the gross domestic product, the electricity price and the temperature were visualized in various time scales to highlight their interactions can serve as a blueprint for performing an exploratory data analysis.

We think that the results of our study are useful for building a model for short-, medium- and long-term electrical energy demand forecasting. This model could be applied in formulating a management policy for the daily operation, the maintenance planning and the expansion of the GIES. This model could also be used for the simulation of the GIES under various scenarios, regarding the installation of new energy systems, improving the planning strategy. It is also noted that the building of a model for the electrical energy demand in Greece is out of the scope of this study. In this manuscript, the code and the data are also provided, so that the reader can reproduce the results and create new work based on the present research.

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