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The influence of meteorological variability on the mid-term evolution of the electricity load

M.J. OrtizBeviá*, A. RuizdeElvira, F.J. Alvarez-García

Dpto Física, Edificio Ciencias, Campus, Universidad de Alcalá, Cra Barcelona km 32, Alcalá de Henares 28871, Madrid, Spain

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ABSTRACT

We investigate the relationships between Spain's electricity load and specific meteorological variables. Spain's electricity data consist of the country's aggregated network daily load for the period of 1993–2010. The meteorological variability is represented by an index based on temperature observations from meteorological stations across Spain. We use a monthly-fixed regression model to characterise the relationships between both indexes and investigate the sensitivity of the relationship. We propose also another regression model based on the relationship between the electricity load index and some indexes that characterize the variability of large scale climate signals. These signals are known to influence the meteorological variability in the Iberian sector, and include the North Atlantic Oscillation, the North Tropical Atlantic, the South Tropical Atlantic and the Pacific Decadal Oscillation, among others. We assess the predictive potential of both models through their monthly hindcast skill values and validate them with some complementary hindcast experiments.

1. Introduction

A recent study of the Spanish IDAE ('Institute for the Energetic Diversification and Efficiency') [1] indicates that only a small fraction (approximately 16%) of the energy used for heating-cooling purposes in homes in Spain is electrical. Although this fraction is small, in the last years, this sector has undergone rapid growth, partly due to the increasing demand for cooling. Additionally, the start of the 20/20/20 directive of the UE, which enforces the integration of the renewable energy in the electric system, requires a deeper knowledge of the factors that condition the electric demand. Along these lines, a recent study addresses the vulnerability of the energy demand to the changes produced by climate change [2].

The key factors that determine energy demand are economic and socio-economic. General models of the energy demand, such as the model proposed by Labandeira et al. [3] for Spain, include variables that are economic indicators, such as incomes and prices. They also include socio-economic variables that indicate the activity level of the day (workday or holiday). Moreover they include one variable or several variables representing 'the weather'. In a recent study of Spain's electricity load data, Blazquez et al. [4] investigate the influence of prices and weather on the electricity load in terms of certain 'elasticity' parameters. The calculated elasticities of the weather variables were greater than expected.

It is commonly accepted that the influence of the weather on the aggregated electricity load is conveyed mainly by the residential sector. Different studies ([5,6]) have shown that the outdoor temperature is the variable that controls the residential energy demand. In some studies, i.e. [5], this influence is represented by a simple regression of temperature values. However, most studies adopt another scheme that retains the nonlinear character of the electric demand by using the variable DD (degree-days), expressed as a defect HDD (heating degree-days) or excess CDD (cooling degree-days) of the daily temperature with respect to a comfort temperature. The comfort temperature is the temperature at which the electricity demand is at its minimum. To address the needs of the Spanish Market Operator, the consumption of a sample of Spanish homes was monitored daily by the Spanish Electricity Network REE (Red Eléctrica de España) from 1983 to 1999. Using these data [7], estimated a comfort temperature of $T = 18$ °C. Comfort temperatures have been calculated in many studies in other regions, and the values found generally agree with [7], although in a few studies the comfort temperatures are higher. Additionally, Moral-Carcedo and Vicens-Otero [8] propose a comfort zone between two temperature thresholds in which the demand is lowest. This two-level scheme is increasingly used [9]. In

* Corresponding author. Tel.: +34 18855056; fax: +34 18854942.
E-mail addresses: ortizbeviamr@gmail.es, mjose.ortiz@uah.es (M.J. OrtizBeviá).

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Table 1, we have summarised some temperature thresholds in the existing literature.

In analysing climate scenarios simulations, some studies propose the identification of temperature thresholds directly from the characteristics of the probability density function [14,15]. Moreover, in a recent study conducted in Spain [16], separating HDD (CDD) into nighttime HDD (CDD) and daytime HDD (CDD) was useful for analysing interannual variability.

Forecasting the mid- and long-term electricity loads can reduce costs and improve planning. Several forecast models with a lead of one month or greater have been proposed. These models usually target the total consumption ([13,17]), or the peak demand ([18–20]). Anticipating future needs, Taylor and Buizza [21] have pointed to the benefits of introducing a medium-term meteorological forecast of electricity demand. Recently, de Felice et al. [22] incorporated the ECMWF (European Center for Medium-Range Weather Forecasts) products to forecasts of the electricity load in Southern Italy during the summer.

In this paper, we investigate the empirical relationships between the evolution of Spain's electricity load and the temperature observed at a number of meteorological stations. We also consider the empirical relationship between that load and some large scale climate signals. We propose two different statistical models to predict the load evolution. Moreover we assess their potential for forecasting Spain's electricity demand at a one-month lead. In Section 1, we provide details regarding the data used to formulate the model's variables. In Section 2, we describe our methodology. The results are presented in Section 3, and Section 4 provides a summary and conclusions.

2. Data and preliminary treatment

The SEL (Spanish electric network load) data were supplied by the REE. The index has an upward trend that changes sign after 2008. This change has been detected in the electric load data of Italy [13] and in many other economic indicators such as the Spanish GDP (gross domestic product) index. The SEL data also present an important dependence on the level of activity of the day. Although some studies [13] introduce this dependence as a variable of the model, we filter it with the scheme proposed in [8]. The index thus obtained is represented by the upper curve in Fig. 1. Afterwards, we estimated the trend from the filtered index and removed it because we sought to eliminate most influences from economic factors. The trend in the first part of the record (before 2008) is approximated by the following logistic upward function:

$$f(t) = A + B\left(\frac{1}{1 + e^{-\sigma(t-t_a)}}\right)$$

where t and $t_a = 3139$ are given in days and the parameters A = 380 Gwh, B = 450 Gwh, $\sigma = 8.1 \times 10^{-4}$ day^{-1} and t_a are identified with a LSE (least-square minimisation) procedure.

Table 1
Different threshold values for HDD and CDD.

Author	Region	Thresholds
Sailor and Muñoz [5]	U.S.	18.3 °C except Florida: 21 °C
Valor et al. [6]	Spain	18 °C
Psiloglou et al. [10]	Athens and London,	Athens: 20 °C, London: 16 °C
Reiss and White [11]	California	HDD: 15.6 °C, CDD: 22 °C
Moral-Carcedo and Vicens Otero [8]	Spain	HDD:15.5 °C, CDD: 25 °C
Labandeira et al. [12]	Spain	HDD:18 °C, CDD: 22 °C
Blázquez et al. [4]	Spain	HDD:15 °C, CDD: 22 °C
Appadula et al. [13]	Italy	HDD: 4 °C, CDD: 25 °C

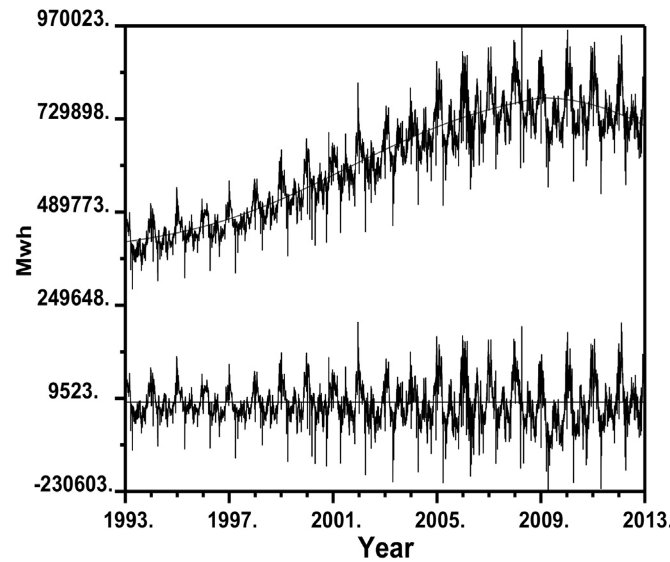

Fig. 1. Weighted data of electricity load by the REE (upper curve) and the corresponding detrended data (lower curve).

In the second part of the record, the trend is approximated by a downward parabola.

$$f(t) = C + D(t - t_0)^2$$

where C = 780 Gwh, D = -3.4×10^{-5} Gwh/day^2, and $t_0 = 5840$ days.

The filtered and detrended SEL index is depicted by the lower curve of Fig. 1. An annual cycle is apparent, with an absolute maximum in the first months of the year and a secondary maximum that corresponds to the peak of the cooling demand in August. An increase in the amplitude of the seasonal cycle and in the importance of the secondary maximum is also evident.

In one of the models the variables were chosen to represent the meteorological conditions throughout Spain. They were obtained from daily observations of the maximum, minimum and mean daily temperatures at 27 meteorological stations. The location of the stations is presented in Fig. 2. This dataset, from 1972 to 2012, was updated from the dataset used in [16] and was subjected to identical quality controls (recommended by [20]) that were applied to the latter.

In the other model the variables were chosen among some 'teleconnections indexes' associated to large scale signals. The influence of those indexes in the climatic variability of the Iberian peninsula sector has been assessed in a number of studies ([23,24]). Some of the indexes considered are defined as averages of the Sea Surface Temperature anomalies in a given region. Among these are the NTA (North Tropical Atlantic) Index and the STA (South Tropical Atlantic) Index [25], or the Pacific Decadal Oscillation Index [26]. Some others, like the NAO (North Atlantic Oscillation) Index [27] or the Indian Core Monsoon Index [28] were built from anomalies of meteorological observations at some meteorological station.

3. Methodology

In the construction of the two models used in the present study we followed five steps: identification of the possible variables of the model, selection of the most appropriate variables, determination of the model coefficients, assessment of the model skill and validation of the predictions.