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Summary

Since oil is a non-renewable resource with a high environmental impact, and its most common use is to produce combustibles for electricity, reliable methods for modelling electricity consumption can contribute to a more rational employment of this hydrocarbon fuel. In this paper we apply the Principal Components (PC) method to modelling the load curves of Italy, France and Greece on hourly data of aggregate electricity consumption. The empirical results obtained with the PC approach are compared with those produced by the Fourier and constrained smoothing spline estimators. The PC method represents a much simpler and attractive alternative to modelling electricity consumption since it is extremely easy to compute, it significantly reduces the number of variables to be considered, and generally increases the accuracy of electricity consumption forecasts. As an additional advantage, the PC method is able to accommodate relevant exogenous variables such as daily temperature and environmental factors, and it is extremely versatile in computing out-of-sample forecasts.

Keywords: Electricity, Load curves, Principal components, Fourier estimator, Constrained smoothing estimator, Temperature, Non-renewable resources, Hydrocarbon fuels, Environment

JEL: C51, C53, Q30, Q40

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Modelling the Load Curve of Aggregate Electricity Consumption

Using Principal Components

1. Introduction

In a Europe characterized by strong incentives towards the liberalization of national electricity markets, researchers and market operators are increasingly interested in obtaining reliable estimates and forecasts of the short-run demand for electricity.

The energy sector, which is intimately related with the oil and gas industry, is also crucial for its environmental implications. According to the European Energy Agency (2002), about 90% of the greenhouse effect is directly or indirectly attributable to the use of hydrocarbon fossils and deforestation. The International Energy Agency (2000) defines an important energy indicator, the so-called “total primary energy supply” (TPES), that is the total amount of energy produced by all existing sources. In 2002 the world TPES was about 10,000 mega-tons oil equivalent (MTOE), which are equivalent to $1.2 \times 10^8$ giga-Watt per hour. It is important to notice that crude oil only represents 35 % of the TPES, and that the sum of all fossil combustibles (i.e. oil, gas and coal) amounts to 76.2% of the TPES. Another crucial energy indicator is the “total final consumption” (TFC). Since no energy plant is 100% efficient, TFC is less than TPES, and has been estimated around 7,000 MTOE. Out of 7,000 MTOE, 75% is given by fossil combustibles, which is equivalent to $6 \times 10^4$ tera-Watt per hour.

Since oil is a non-renewable resource with a high environmental impact, academics, research institutions and public opinion are engaged in a fast-growing debate on how to reduce the dependence of national economic systems on oil. Besides the development of alternative and more
efficient ways to exploit renewable resources, the simplest method to control this type of
dependence is to reduce oil consumption. As the most common use of oil is to produce
combustibles for electricity and transportation, more reliable methods to model, estimate and
forecast electricity consumption can contribute to a more rational employment of this fundamental
hydrocarbon fuel.

Early studies on the analysis of the load curve (e.g. Cargill and Mayer, 1971) generally
concentrate only on the long-run features of electricity consumption. Alternative traditional
approaches which explicitly take into account the short-run movements in the load curve are spline
and Fourier models (see Hendricks et al., 1979; Mouchart and Roche, 1987), while a more recent
methodology which embeds both splines and Fourier is the constrained smoothing splines estimator
(see Rodriguez-Poo, 2000).

The Principal Components (PC) method, combined with traditional regression analysis, represents
a much simpler and attractive alternative to modelling and forecasting electricity consumption as it
is extremely easy to compute, significantly reduces the number of variables to be considered, and
generally contributes to more accurate electricity consumption forecasts.

In this paper we apply the PC method to model and forecast the load curves of three European
countries, namely Italy, France and Greece, using hourly aggregate electricity consumption data.
The empirical results obtained with the PC approach are compared with those produced by Fourier
and constrained smoothing spline estimators.

The paper is organized as follows. Section 2 provides a description of cubic splines, Fourier and
constrained smoothing estimators for modelling the loading curve. An illustration of the PC method
is given in Section 3. The data are presented in Section 4. In Section 5 the empirical results obtained
with the PC method are presented and compared with the Fourier and constrained smoothing
splines estimators. In Section 6 the PC method is used to obtain out-of-sample forecasts of
electricity consumption for the French market. Section 7 provides some concluding comments.
2. Classical models of the load curve

Early research on the daily load curve were generally based on a two-stage estimation approach (see, among others, Cargill and Mayer, 1971). In the first stage, a simple ARMA time series model is fitted to consumption data for each consumption unit (e.g. household, firm, or industrial plant). In the second stage, the estimated coefficients of each ARMA model are regressed on a set of residential, demographical and socio-economic variables. One limitation of this method is that it concentrates only on long-run features of the data, since the selected explanatory variables do not change within a single day. On the other hand, load curves, which are subject to physical as well as atmospheric conditions, are characterized by intra-day marked variations.

Alternative approaches which concentrate on short-run movements in the load curve are given by spline and Fourier models. In both cases, the general problem can be described as follows. Indicate with \( y_i, \ i=1,\ldots,n \), the electricity consumption between time \( t_{i-1} \) and time \( t_i \) for a given sample of data. The index \( i=1,\ldots,n \) denotes the data frequency. We are interested in the statistical model:

\[
(1) \quad y_i = m(t_i) + \varepsilon_i,
\]

where \( \varepsilon_i \) are independent and identically distributed error terms with zero mean and constant variance, \( t_i = i/n \) is a time index, \( n \) indicates the total number of observations, and the function \( m(t_i) \) is to be specified.
2.1. Cubic splines

A spline estimator to fit the hourly load curve has been used by Hendricks et al. (1979), and by Mouchart and Roche (1987). The function $m(t_i)$ is specified as a cubic spline, that is, a polynomial series with continuous first and second derivatives, and a step-wise third derivative. The polynomials are thus linked by a series of nodes which correspond to flex points. The number of flex points $q$ determines estimation accuracy. If $q=n$, a smoothing spline is obtained, while $q<n$ gives a parametric spline.

Assuming $q=n$, a cubic spline function can be interpreted as a non-parametric regression estimator which arises from the solution to the following problem:

$$
\min_{m \in W_2^{(2)}[0,1]} L_n(m),
$$

where

$$
L_n(m) = n^{-1} \sum_{i=1}^{n} w_i \left[ y_i - m(t_i) \right]^2 + \lambda \int_{0}^{1} \left[ \frac{d^2 m(t)}{dt^2} \right]^2 dt.
$$

In this context, $W_2^{(2)}[0,1]$ indicates the class of all twice periodic differentiable functions, whereas the loss function $L_n(m)$ is formed by two terms, the first being a weighted measure of goodness of fit, and the second a penalty.\(^1\) The solution to problem (2)-(3) yields an estimated $\hat{m}_\lambda = [\hat{m}_\lambda (t_1), \ldots, \hat{m}_\lambda (t_n)]'$ that, for given values of $\lambda$, is the best compromise between smoothness

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\(^1\) In our empirical application, we assume equal weights, i.e. $w_i = 1$ for all $i=1,\ldots,n$. 

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and goodness of fit (Rodriguez-Poo, 2000, p. 233). A model of this type is more sensible to changes in data structure than a standard parametric model.

2.2. Fourier estimator

Another classical method to model and forecast electricity consumption is provided by the Fourier estimator. Assuming that electricity consumption follows a daily pattern characterized by pronounced periodicity, a reasonable method to model the function $m(.)$ is to use sine and cosine polynomials at different frequencies. The aim is to estimate the parameters of the following function:

$$m(t) = \beta_{0\lambda} + \sum_{j=1}^{\lambda} \left[ c_{\lambda j} \cos\left(\frac{2\pi j t}{p}\right) + s_{\lambda j} \sin\left(\frac{2\pi j t}{p}\right) \right],$$

where $p$ is the periodicity.

The parameters $\beta_{0\lambda}$, $c_{\lambda j}$, $s_{\lambda j}$ and $\lambda$ can be estimated by exploiting the properties of the discrete Fourier transform (DFT). It is well known that the DFT of a period signal $y_m$ of period $n$ is the periodic sequence $F$ of period $n$, defined as:

$$F(k) = \sum_{m=0}^{n-1} y_m e^{-i\frac{2\pi k}{n} m},$$

for any $k=0,1,...,n-1$. Each complex element of the transform can be seen as the linear combination of the original data and a coefficient composed by a real (Re) and an imaginary (Im) part. If the original series is real-valued, the following property of the DFT holds:
(6) \( F(k) = c(k) - is(k) \)

where

(7) \( c(k) = \text{Re} F(k) = \sum_{m=0}^{n-1} y_m \cos \left( \frac{2\pi k}{n} m \right) \),

\( k=0,\ldots,n/2, \)

and

(8) \( s(k) = \text{Im} F(k) = \sum_{m=1}^{n-1} y_m \sin \left( \frac{2\pi k}{n} m \right) \),

\( k=1,\ldots,(n/2)-1. \)

Moreover, the inverse transform yields:

(9) \( y_m = \frac{1}{n} \left\{ b(0) + 2 \sum_{k=1}^{n-1} \left[ c(k) \cos \left( \frac{2\pi k}{n} m \right) + s(k) \sin \left( \frac{2\pi k}{n} m \right) \right] + c \left( \frac{n}{2} \right) \cos(km) \right\}. \)

In order to estimate the parameters \( \beta_{0k}, c_{jk}, s_{jk} \) and \( \lambda \), from the coefficients \( b(0), c(k), s(k) \) and \( c(n/2) \), we use the fast Fourier transform (FFT) algorithm and proceed as follows. First, recalling that the absolute value of the complex number \( F(k) \), \( |F(k)| \), is the “intensity” of the signal, we apply FFT on the original series \( y_i, i=1,\ldots,n \), to obtain the sequence of complex numbers \( F(k), k=0,\ldots,n \). Second, given the symmetric behaviour of \( F(k) \) when \( k=1,\ldots,(n/2)-1 \) and \( k=(n/2)+1,\ldots,n \), we calculate the standard deviation \( \sigma_{|F(k)|} \) of the series \( F(k), k=1,\ldots,(n/2)-1. \) Third, we select those
values of \( c(k) \) and \( s(k) \) which correspond to a significantly large signal intensity, according to the
criterion \(|F(k)| > 3\sigma_{|F(k)|}\). The estimated value of \( \lambda \) is given by the number of times the criterion
above is satisfied, while the estimated constant \( b(0) \) is, by definition, \( \hat{b}(0) = F(0) \). Moreover, we
set \( \hat{c}(n/2) = F(n/2) \) to zero since, in most of the empirical applications, the estimated value of
this parameter is negligible. Thus, the selected parameter values are \( \hat{\lambda}, \hat{c}(j), \hat{s}(j), \) and \( \hat{b}(0) \),
with \( j = 1, ..., \hat{\lambda} \). Finally, we calculate the “fitted” electricity consumption series as:

\[
(10) \quad \hat{m}(t) = \hat{b}(0) + \sum_{j=1}^{\hat{\lambda}} \left[ \hat{c}(j) \cos \left( \frac{2\pi j t}{n} \right) + \hat{s}(j) \sin \left( \frac{2\pi j t}{n} \right) \right].
\]

When the DFT is computed using the FFT algorithm on a given sample of observations, and the
subset of estimated parameters is selected appropriately, the original series can be interpreted as a
linear combination of sine and cosine functions whose parameters are the corresponding real and
imaginary parts of the transformed series. It is also clear from equations (4) and (10) that Fourier
polynomials are useful to model the behaviour of volumes in many energy markets as they are able
to accommodate marked seasonalities in the data. Nevertheless, this technique does not allow an
analysis of phenomena other than the daily load curve.

2.3. Constrained smoothing splines

Rodriguez-Poo (2000) proposes the Constrained Smoothing Spline Estimator (CSSE), which is
given by the combination of the Fourier estimator and the standard smoothing spline. The CSSE is
the solution to the following optimization problem:
(11) \( \min_{m \in W^2_2[0,1]} L_n(m) \)

where:

(12) \( L_n(m) = n^{-1}\sum_{i=1}^{n} w_i \left[ y_i - m(t_i) \right]^2 + \lambda_1 \int_0^1 \left[ \frac{d^2 m(t)}{dt^2} \right]^2 dt + \\
+ n^{-1} \lambda_2 \sum_{i=1}^{n} \left[ m(t_i) - g_0(t_i) \right]^2. \)

The resulting estimator takes into account goodness of fit (that is, the weighted residual sum of squares), smoothness (that is, the integral of the second derivative), and the distance of the function \( m(.) \) with respect to some periodic parametric function \( g_0(.) \).

The function \( g_0(.) \) in (12) is given by the Fourier function (4), while the function \( m(.) \) in (12) is the cubic spline which solves equations (2)-(3). Thus, the aim is to find estimates of \( \lambda_1 \) and \( \lambda_2 \) which minimize the distance between CSSE and \( g_0(.) \), since the underlying idea of CSSE is to maintain a structure which is similar to the Fourier. For this reason, the solution of equations (11)-(12) is between the standard smoothing operator (that is, \( \lambda_2 = 0 \)) and the Fourier polynomial when \( \lambda_1 = 0 \) and \( \lambda_2 \to \infty \).

3. Modelling the load curve with Principal Components

The method of Principal Components (PC) transforms the \( p \) variables of interest \( y_1, y_2, \ldots, y_p \), into a linear combination of other \( k \) variables, \( z_1, z_2, \ldots, z_k \), the so-called principal components, with \( k \leq p \). Notice that the only interesting case is when \( k < p \), that is, when we are able to represent \( p \) variables using a smaller number of linear combinations and with no loss of relevant
information. It must be stressed that, in our empirical application, \( y_r \) and \( z_s, r=1,...,p, s=1,...,k \), are column vectors of dimension \( d \times 1 \) of observations on electricity consumption, with \( d \) indicating the number of days in a year.

The first principal component is the linear combination with the largest variance. Define

\[(13) \quad z_1 = a_1 y_1 + a_{21} y_2 + \ldots + a_{p1} y_p = Y a_1,\]

where \( Y = (y_1, y_2, \ldots, y_p) \) is a \( d \times p \) matrix, and \( a_1' = (a_{11}, a_{21}, \ldots, a_{p1}) \) is a \( 1 \times p \) vector of coefficients. The variance of \( z_1 \) is given by

\[(14) \quad \sigma_{z_1}^2 = a_1'S a_1,\]

where \( S \) is the \( p \times p \) sample covariance matrix of \( y_1, y_2, \ldots, y_p \). It is well known that, in order for (13) to be the linear combination with the largest variance (14), \( a_1 \) should be the first eigenvector of the matrix \( S \), that is, the eigenvector which corresponds to the largest eigenvalue of \( S \), say \( \lambda_1 = a_1'S a_1 / a_1'a_1 \). The exercise is repeated to construct the \( d \times p \) matrix of principal components

\[Z = (z_1, z_2, \ldots, z_p), \quad k=p, \]

where \( z_s = a_{s1} y_1 + a_{s2} y_2 + \ldots + a_{sp} y_p = Y a_s, \quad s=1,...,k.\)

An important property of PC allows us to represent the variables simply as linear combinations of the components. Defining the \( p \times p \) matrix of eigenvectors of \( S \) as \( A = (a_1, a_2, \ldots, a_p) \), so that

\[(15) \quad Z = A Y.\]

Since the eigenvectors are orthogonal to each other, \( A^{-1} = A' \), which implies that \( A'A = AA' = I_p \). Hence, equation (15) can be represented as
(16) $Y = ZA^{-1} = ZA'$,

that is, $Y$ is expressed in terms of linear combinations of the components. If $k < p$, it is possible to partition the matrices $A$ and $Z$ as $A = (A_k, A_{p-k})$ and $Z = (Z_k, Z_{p-k})$, respectively. The $d \times k$ submatrix $A_k (Z_k)$ contains the first $k$ largest eigenvectors (principal components), while the $d \times (p-k)$ submatrix $A_{p-k} (Z_{p-k})$ is formed from the last $p-k$ eigenvectors (principal components). Using these partitioned matrices, we can rewrite expression (16) as

(17) $Y = Z_k A_k' + Z_{p-k} A_{p-k}' = Z_k A_k' + E'$,

where $E$ is the approximation error in representing the $p$ variables $Y$ using the first $k$ principal components $Z_k$ only. The term $Z_k A_k'$ is defined as the “fitted” load curve, $\hat{Y} = Z_k A_k'$.

If we want to improve the in-sample fit of the load curve without increasing the number of components $k$, we can combine the PC method with standard regression analysis. Specifically, given a $d \times g$ matrix $X$ of exogenous variables (with, in general, $g > k$), such as deterministic daily effects, holidays, seasonal patterns and weather conditions, we estimate $k$ separate regressions by OLS, which can be written compactly as follows:

(19) $Z_k = X \Pi + H$, 

where $\Pi$ is a $g \times k$ matrix of coefficients and $H$ a $d \times k$ matrix of error terms. Then, we can calculate the matrix of fitted values as
(20) \( \hat{Z}_i = Z_i \hat{\Pi}, \)

where \( \hat{\Pi} \) is the matrix of OLS estimated coefficients \( \Pi \). Finally, we reconstruct the estimated load curve as

(21) \( \hat{Y} = \hat{Z}_i A_i \).

4. Data description

In order to estimate the load curve with the PC method and compare the results with those obtained using the cubic spline and CSSE approaches, we use data on electricity consumption metered by the transmission system operators of three European countries: (i) the Italian “Gestore della Rete di Trasmissione Nazionale” (GRTN), (ii) the French “Gestionnaire du Réseau de Transport d’Électricité” (RTE), and (iii) the “Hellenic Transmission System Operator” (HTSO) for Greece. The unit of measurement is the Mega-Watt (MW), and the frequency for all data is hourly, although the sample period is not the same across countries. In particular, available observations span the period 1 January to 31 December 2001 for Italy, 1 January 2001 to 31 December 2002 for France, and 19 November 2001 to 25 November 2002 for Greece.

Figure 1 reports the observed load curves for Italy, France and Greece for one month of observations, namely January 2001. The three curves are very similar to each other, although measured on different scales. Specifically, the level of electricity consumption in Italy is directly comparable with that of France, the load curve in Greece is significantly lower. All three curves show the behaviour of the typical load curve, that is, a regular daily pattern within the first four days of each week and a change in the cycle approaching the week-end. Nevertheless, the French load
curve is flatter than the other two, since the MW difference between a peak and a trough is less pronounced.

5. Estimation results

5.1. The PC method

We have applied the PC approach described in Section 3 to daily observations on electricity consumption of Italy, France and Greece. In the empirical application, we use $p=24$ (the number of hours in a day), and $d=365$, the number of days in a year.

In Figure 2 we report, for each country, the percentages of total variation in electricity consumption explained by the PC method. The first component explains for all countries the largest part of the total variation (91%, on average), and represents the electricity consumption pattern within the typical week. The second and third components capture some specific aspects of electricity consumption, basically daily effects and environmental factors.

Concentrate on Italy, the mean aggregate load curve presented on Figure 3a exhibits a significant difference in consumption between night and day. On Figure 3b we show the eigenvectors associated with the first three components, $a_s$, $s=1,...,k=3$.

The 24 coefficients associated with the first component, $a_i$, mimic very closely the behaviour of the average load curve. This evidence confirms the explanatory power of this component. The daily curve, which is more “active” during working days and “less” active on week-ends and holidays, gives the general shape of the aggregate load curve. The contribution of the first component is to increase the imbalance effect in working days and, on the contrary, to flatten the load curve during week-ends. This last aspect can be visualized by graphing the values of the first component, $z_i$.

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2 In the graphs the first three components are indicated with Pc1, Pc2 and Pc3, respectively.
which are positive and almost constant during the first part of the week, while negative during the week-end (see Figure 5).

The coefficients of the second component, $a_2$, characterize more accurately the discrepancies between working days and week-ends within each week. For Italy, the second component captures the asymmetries in the load curve between morning and night hours. For France and Greece, this component helps define the shape of the load curve during working days (see Figures 4a-4d).

Although the third component explains, on average across countries, only a small part of the variability in electricity consumption, its interpretation is extremely interesting since it accounts for the effects of weather conditions and environmental factors. During winter, the days are shorter and the electricity consumption for heating and lighting is very high in late afternoon. On the contrary, in summer late afternoon consumption is lower, since daylight is intense and the average temperature is not as high as in the inside of the day to justify a massive use of air conditioning. This phenomenon is evident in all countries, although with different magnitudes (Figure 4).

We now calculate the “fitted” load curves, according to the procedure illustrated in Section 3. For each country, the matrix $X$ of exogenous regressors in equation (19) is formed by seven dummy variables indicating the seven days of the week (MON, TUE, WED, THU, FRI, SAT, SUN), two deterministic sine (SIN1, SIN2) and two cosine (COS1, COS2) variables with periods 1 and 2, respectively, in order to capture long-run seasonality effects, a dummy variable for national holidays (HOL), two variables measuring average temperature\(^3\) (TEMP) and its square (TEMP2), which capture the non-linearities in the relationship between electricity consumption and temperature.\(^4\)

The presence of non-linearities in the relationship between electricity consumption and temperature is well documented in the literature. For instance, Engle et al. (1986) provide empirical evidence in favour of a V-shaped relation between consumption and temperature, with a minimum

\(^3\) Average temperature is defined, for each country, as the arithmetic mean of daily temperatures recorded in three representative cities located in the North, Center and South.

\(^4\) The estimation results of equation (19) are reported, for each country, in Appendix 1.
around 18° C, for the US electricity market. This relation can be rationalized by noticing that temperature reductions increase electricity consumption through a more intense use of heating equipment, whereas a rise in temperature increases electricity consumption because of massive air conditioning.

The major drawback of this type of analysis is that it does not take into explicit consideration the shape of the load curve. Not only does temperature affect accumulated daily consumption (i.e. the area below the load curve), but also the shape of the consumption curve. Unfortunately, it is not easy to study the time series relationship between consumption and temperature, since the former is typically observed on an hourly base, whereas the latter is generally available with daily frequency. Using the PC method, we can overcome this problem by summarizing the shape of the load curve as the product between the hourly coefficients and the level of the corresponding principal component. Then we can model the relations between the components and a set of relevant exogenous variables, and analyze the changes in the daily accumulated electricity consumption, as well as the modifications of the shape of the load curve. If the daily temperature is included among the exogenous variables, it is also possible to concentrate attention on the impact of weather conditions on the shape of the load curve.

5.2. FFT, CSSE, and a comparison with the PC method

We have implemented the FFT estimator following the procedure described by equations (4)-(10) in Section 2.2. In the empirical application, the total number of observations is \( n = 8760 \) (i.e. 24 hours time 365 days), while the estimated values for the parameter \( \lambda \) in the Fourier model are 72 for Italy, 127 for France, and 115 for Greece. The estimated FFT consumption series has been constructed using expression (10).
The CSSE has been calculated along the lines illustrated in equations (11)-(12) of Section 2.3. The estimated CSSE consumption series has been calculated as the solution to the problems given in equations (2)-(3) and (11)-(12).

The results for Italy are reported in Figure 6, where the FFT and CSSE estimators (FFTIT and CSEIT, respectively) are compared with two versions of the PC method, namely with and without including the temperature variable as an exogenous variable in equation (19) (COMPTEMPIT and COMPIT, respectively). The scatter plot of the calculated (or “fitted”) values against actual consumption shows that the performance of each of the three methods is satisfactory, as all the data points for each of the four estimated models are very close to the 45° line. The squared correlation coefficients between the actual and fitted values indicate that the PC method which includes the temperature variable has the best fit ($R^2=0.96$), followed by the PC model without the temperature variable ($R^2=0.93$), while FFT and CSSE are very close (with $R^2$ values of 0.892 and 0.894, respectively). The estimated principal components seem to be more adaptable to the data, since they allow for long-run seasonality, daily and holiday effects. When the temperature variable is included, the principal components also capture modifications in the shape of the load curve.

Figure 7 reports the comparison between the PC method (without the temperature variable), FFT and CSSE for Greece and France. The motivation of this example is to emphasise the importance of the temperature variable in the PC approach. For both countries, the consumption series fitted by the PC method without the temperature variable has the lowest $R^2$. In particular, for Greece, the best performing $R^2$, which is associated with the FFT estimator, has an higher $R^2$ value by 0.15.

6. Forecasting the load curve with the PC method

Besides computational simplicity and the capability of accommodating relevant exogenous variables, such as daily temperature, one of the major advantages of the PC method is that it is

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5 The Matlab routine written to solve the problem given in (11)-(12) is reported in Appendix 2.
versatile when out-of-sample forecasts are required. For instance, if \( h \) additional out-of-sample observations on the exogenous variables are available, it is possible to define a matrix, \( \hat{X} \), of dimension \( h \times g \). Thus, given the matrix of estimated coefficients, \( \hat{\Pi} \), obtained from equation (19), we can calculate the \( k \) “out-of-sample” principal components as

\[
(22) \quad \hat{Z}_k = \hat{X}\hat{\Pi}.
\]

Finally, the out-of-sample predicted values of the load curve can be obtained as:

\[
(23) \quad \hat{Y} = \hat{Z}_k A_k^\prime.
\]

where \( A_k \) is the matrix of coefficients associated with the \( k \) “in-sample” principal components.

Given the availability of daily electricity consumption and temperature observations over the first three months of the year 2002 (i.e. \( g=90 \)), we have applied the approach described by equations (19), (22) and (23) to France.

The results in terms of forecasted consumption are encouraging, with a mean absolute error of 0.055 on an hourly base. In Figure 8, a scatter plot of the forecasted hourly consumption against actual consumption is reported. The forecasting performance of the PC method is satisfactory, since the dispersion around the 45° line is limited, with an informative \( R^2 \) value of 0.81. Figure 9 presents the graphical behaviour of the hourly load curve and the corresponding hourly observed consumption on a subperiod of the forecasting horizon, namely from 28 January 2002 to 19 February 2002. Again, the goodness of fit of the PC method is evident.
7. Conclusion

In this paper we have applied the Principal Components (PC) method to model the load curves of Italy, France and Greece on hourly data for aggregate electricity consumption. The empirical results obtained with the PC approach have been compared with those produced by the Fourier and constrained smoothing spline estimators.

The PC method represents a simple alternative to modelling electricity consumption since it is easy to compute, significantly reduces the number of variables to be considered, and generally contributes to greater accuracy of electricity consumption forecasts. As an additional advantage, the PC method is able to accommodate relevant exogenous variables such as daily temperature, and is versatile when true out-of-sample forecasts are required.

The squared correlation coefficients between actual and in-sample fitted values indicate that the PC method with the temperature variable has the best fit, followed by the PC model without the temperature variable, the Fourier model and the constrained smoothing spline estimator. Thus, the estimated principal components seem to be more adaptable to data since they allow for long-run seasonality, daily and holiday effects and, when the temperature variable is included, also capture modifications in the shape of the load curve. The out-of-sample forecasting performance of the PC method is also encouraging.
References


Figure 1. Load curves for Italy (IT), France (FR) and Greece (GR) measured in Mega-Watt (MW) (aggregate data, January 2001).
Figure 2. Percentage of total variation of electricity consumption explained by the principal components (PC1 = first principal component, PC2 = second principal component, PC3 = third principal component and OTHER = remaining 24-3=21 components).
Figure 3. Mean hourly consumption calculated as the sample mean of 365 daily observations (3a), and coefficients of the first three principal components PC1, PC2, and PC3 for Italy (3b).
Figure 4. Mean hourly consumption calculated as the sample mean of 365 daily observations (4a), and coefficients of the first three principal components PC1, PC2, and PC3 for France (4b).
Figure 4. Mean hourly consumption calculated as the sample mean of 365 daily observations (4c), and coefficients of the first three principal components PC1, PC2, and PC3 for Greece (4d).
Figure 5. First and second components (PC1 and PC2) for Italy, France and Greece.
\[ R^2 = 0.9288 \text{ (COMPTEMPIT)} \]
\[ R^2 = 0.8918 \text{ (COMPIT)} \]
\[ R^2 = 0.9579 \text{ (CSEIT)} \]
\[ R^2 = 0.8943 \text{ (FFTIT)} \]
Figure 7. Fitted (=forecasted) versus actual (=real) values for 4 competing models applied to Greece (GR) and France (FR). COMPW = PC model with no temperature, FFTW = Fourier model, CSEW = Constrained Smoothing Spline model; W=GR, FR. $R^2$ = squared correlation coefficients between fitted and actual values for each model.
Figure 8. Out-of-sample forecasted and actual (=real) values for the PC model applied to France (FR). COMPFR = PC model with temperature, $R^2$ = squared correlation coefficients between forecasted and actual values.
Figure 9. Out-of-sample fitted and actual load curves for France.
Appendix 1. OLS estimation of equation (19)

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Notes: * significant at 5%; ** significant at 1%;

$R^2$ = squared correlation coefficient between actual and fitted;
PC$k$ = $k$-th principal component, $k=1,2,3$;
IT = Italy; FR = France; GR = Greece.
Appendix 2. Matlab program for the CSSE algorithm

```matlab
function GCV=GCV(L);

global GG VETGRTG STIMFFTG % Define the global variables in the Workspace

Y=VETGRTG; % Y is the vector of historical hourly consumption
G0=STIMFFTG; % G0 is the previous estimates obtained using the FFT estimator
L1=L(1); % L1 indicates lambda1
L2=L(2); % L2 indicates lambda2

if L2==0 % Define the constraints on the parameters L1 and L2
    Lam=L1;
else
    Lam=(L2/(L1+L2)); % Define the smoothing values of the CSSE function
        % of L1 and L2
end

if Lam>1
    Lam=1
end

YS=csaps(GG,(Y+L2*G0)./(1+L2),Lam,GG); % Cubic smoothing spline
% function in Matlab, GG indicates days
GCV=((1/8760)*sum((Y-YS).^2))/(1-Lam)+((1/8760)*sum((YS-G0).^2))/(1-Lam));
% This is the revisited function of General Cross Validation to be
% minimized

assignin('base','YSA',YS); %The function returns to the Workspace
%the estimates
assignin('base','Lam',Lam); %and the solutions for lambda1 and lambda2
assignin('base','L1',L1);
assignin('base','L2',L2);
function end

After saving this function we set the follows instructions into the workspace:

fmins('GCV',[0.5 0.5],1)

Note: for each feasible solution, this process takes 1 min on a Celeron 400 Mhrz processor.
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