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Load Profile Analysis Tool for Electrical Appliances in Households Assisted by CPS

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Abstract

This paper presents a methodology to forecast the hourly and daily consumption in households assisted by cyber physical systems. The methodology was validated using a database of consumption of a set of 93 domestic consumers. Forecast tools used were based on Fast Fourier Series and Generalized Reduced Gradient. Both tools were tested and their forecast results were compared. The paper shows that both tools allow obtaining satisfactory results for energy consumption forecasting.

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Keywords: Energy consumption; Load management; Supply and demand; Smart meters; Predictive models.

1. Introduction

The electric grid is stated as arguably the world's largest engineered system, which is vital to significantly improve human life and is the motor of the economy and the major driver of progress [1]. Sustainable energy supply remains a main requirement of modern society in order to respond to the increased demand caused by the larger consumption and population growth.

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In this paper, predictive tools were developed for energy consumption forecast. Satisfactory results were obtained for forecasting electric appliance energy consumption. A database of energy consumption was used allowing the development of Short-term load forecasting (STLF).

In Portugal, the hourly average load curve structure is the following: the heating and cooling representing about 16% of the total electricity of housing consumption; the lights representing about 9% of the total electricity consumption; the refrigerators and chest freezers representing about 20% of the total electricity consumption; the washing and dishing machines representing about 11% of the total electricity consumption; the cooking representing about 12% of the total electricity consumption; for domestic hot water 5% are consumed. Computers and other electrical and electronic entertainment are one of the areas with greatest growth in household consumption of energy. These facilities represent 14% and miscellaneous appliances 13% of total electricity consumption in a household [2].

In Lisbon, Portugal, it was possible to identify the structure of the daily load profile for the residential sector disaggregated by major end uses. The structure of the daily load profile for the residential sector disaggregated by major end uses for a set of 93 households in Lisbon [2] are shown in Fig. 1.

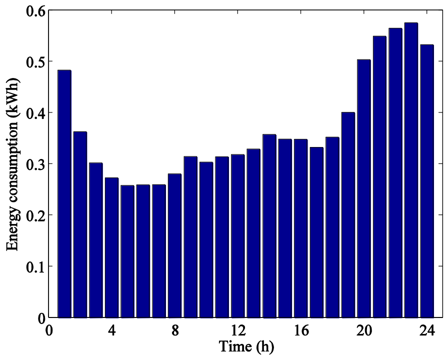

Fig. 1. The daily average electric consumption of a Portuguese set of 93 households.

Fig. 1 shows load the average hourly energy consumption. Vertical axes shows the hourly consumption which was averaged over a whole year. Horizontal axes represents the 24 hours of a day. In the evening peak period, there are three of the specific uses of electricity as lighting, cooling and audiovisual equipment that representing for more than a third of the total power required.

The database obtained provides the electricity consumption that was based on monitoring of 93 households held in Lisbon, Portugal and which characteristics are the below:

a) The distribution of apartments and villas in the samples were the following: 44% of the households are apartments. Moreover, the number of persons/household in the sample are 2.92, whereas in the country are 2.05 [3];
b) The number of inhabitants per household is always greater than the national averages. This is legitimate because they looked for households with the highest possible number of appliances, which usually are big and highly occupied households;
c) The average surface area of the households in the sample is 116.6 m^2;
d) The monitored households 66% used simple electricity tariffs and 28% were triphased. In the Portuguese sample only 6% of the households use electricity for domestic hot water (DHW). It is more common using the gas (Natural gas or LPG) for heating the DHW;
e) The average electric energy consumption in the Portuguese sample shown in Fig. 1 and is similar and have same profile as in [3].

The available database consists of 93 houses, where the electrical consumption was measured with a sampling time of 10 minutes during 6 weeks for each house. The measurements intervals among different houses partially overlap and the total time of monitoring was 18 months. The overall consumption was disaggregated into specific appliances: air conditioning; refrigerator; freezer; chest freezer; clothes-washer; dish-washer; clothes-dryer; air exhaust; audio-visual; TV; VCR; personal computer; hot waters production; lighting [3].

This work aims to identify the technical and behavioural patterns to produce predictive forecast. Thus, this paper will describe a method and results obtained with the predictive tools proposed.

The main contribution of this paper is to show the applicability of different tools as Fast Fourier Series (FFT) and Generalized Reduced Gradient (GRG) approach to develop a simple and reliable tool to forecast households' daily and hourly energy consumption for residential and small buildings.

This paper is organized as follows: Section 2 presents the state of the art. Section 3 presents the methodology used in the paper: the generalized reduced gradient or the Fourier series. Section 4 presents the simulation results. Finally, concluding remarks are given in Section 5.

2. State of the Art

The collection of information helps the system make smart decisions through sophisticated machine learning algorithms [4]. With possible real-time communication between the consumer and the electric grid, consumer could be able to adapt his consumption needs in advance. The real-time decision can be made more intelligent, electricity power can be distributed more evenly and the price of power can be charged more dynamically according to the different time durations and available power, reducing power fluctuation and smoothing the power diagram [5,6].

Reliable models for electric energy consumption and load profile are necessary under the paradigms of smart grid environment and cyber-physical systems (CPS) [7,8]. CPS use computations and communication deeply embedded in and interacting with physical processes to add new capabilities to physical systems. Applications of CPS introduce at different levels of integration, ranging from nation-wide electric grids, to medium scale, such as the smart home, and small scale, e.g. global appliance systems including home appliance and leisure devices.

Nowadays, in an existing electric grid, it is important to understand and forecast household daily or hourly consumption with a reliable and secure model for electric energy consumption and load profile in order to increase demand response programs required to adequate the profile of energy load diagram to generation [9]. Artificial neural networks (ANN) have been used together with an energy consumption database [10–15] for STLF.

The International Energy Agency (IEA) estimated that, even with a continuation of all existing appliance policy measures, the appliance electricity consumption will grow 25% by 2020 [16].

In all countries, four types of consumption seem to be rising particularly fast: a) domestic computers and peripherals; b) new domestic entertainment; c) standby power; d) lighting.

Usage patterns associated with different sections of the population and the variations in consumers' knowledge/attitudes can be identified. The usage pattern is related to the occupied period. For example, when people are not at home, most appliances will not be used. In daily appliance electricity profile, the occupants use virtually little power (stand by and fridge-freezer) during the night, may wake up and have breakfast, vacate the house during the morning and then return around mid-day for lunch, in the evening, the meal is cooked, television is watched, and showers are taken. Different households have different life styles.

The total load profile shape varies from day to day and house to house. The factors influencing the occupancy pattern are as follows:

a) the apartment area;
b) the number of occupants;
c) the time of the first person getting up in the morning and the last person going to sleep;
d) the period of the house unoccupied during the day.

It is important to identify the cluster of households when analyzing the load profile, because the load profile depends very much on the occupancy pattern. In the case of lack of information about household occupancy pattern, several scenarios, as proposed by [17] for household occupancy pattern, can be used.

The works [18,19] have demonstrated the role of monitoring in understanding the trends in electricity consumption in households and also established the need for qualitative and quantitative studies to explore the factors (technical, socio-demographic and behavioural) which influence these trends.

3. Methodology

This study creates a comprehensive residential energy consumption model based on a energy consumption database from a set of 93 houses, recorded in Portugal. Inputs include the apartment area, person/household, kitchen appliances, lighting, cooling and heating, DHW and entertainment appliances. The tool was trained using the mentioned database energy consumption. The trained model was then tested and compared with the annual energy consumption average.

Before using the tool, great part of the work was, firstly, to normalized the data in order to prepare the output layer for the training and testing. Six weeks of data, for every household, were used for validation. These values had an uninterrupted logged data along 6 weeks, which makes them adequate for the goals of this research.

The tool uses inputs from household and appliances (14 inputs), an array of 14×12, the first being the inputs of electrical column and lines the daytime hours (01:00 to 12:00 or 02:00 to 24: 00). For the calculation of each array value, and to analyse the best fit, the team research uses two models: the GRG algorithm; and the FFT.

3.1. Generalized Reduced Gradient

The GRG method is a popular state of the art technique for optimizing nonlinear problems. The original method, the Reduced Gradient Method has seen several different customizations due several researchers [20–23].

The GRG is a generalization of the reduced gradient method by allowing nonlinear constraints and arbitrary bounds on the variables is given by:

$$\max f(x) : h(x) = 0, L \leq x \leq U \tag{1}$$

where *h* has dimension *m*.

The method supposes that can be partition $x = (v, w)$ such that:

a) *v* has dimension m (and *w* has dimension *n-m*);
b) the values of *v* are strictly within their bounds: $Lv < v < Uv$ (this is a non degeneracy assumption);
c) $\nabla_v h(x)$ is non-singular at $x = (v, w)$.

As in the linear case, for any w there is a unique value, $v(w)$, such that $h(v(w), w) = 0$ (c.f., Implicit Function Theorem), which implies that given by:

$$\frac{dv}{dw} = (\nabla_v h(x))^{-1} \nabla_w h(x) \tag{2}$$

The idea is to choose the direction of the independent variables to be the reduced gradient, given by:

$$\nabla_w (f(x) - y^T h(x)) \tag{3}$$

where:

$$y = \frac{dv}{dw} = (\nabla_v\ h(x))^{-1} \nabla_w\ h(x) \tag{4}$$

The step size is chosen and a correction procedure applied to return to the surface, $h(x) = 0$.

The main steps (except the correction procedure) are the same as the reduced gradient method, changing the working set as appropriate.

The GRG method is quite efficient for problems of this type because it uses linear approximations to the problem functions at a number of stages in the solution process. Because the first derivative (or gradient) of the optimum cell measures its rate of change with respect to (each of) the adjustable cells, when all of the partial derivatives of the optimum cell are zero (that is, the gradient is the zero vector), the first-order conditions for optimality have been satisfied having found the highest (or lowest) possible value for the optimum cell. Of course, the solution obtained can be a local minima, not the global minimal. However this is a limitation of gradient methods.

For a cost function it was used the minimum square error (MSE) between the real consumption and the predicted consumption.

To performed de GRG, a matrix similar to the one presented in Table 1 was used to produce the weights for each appliance. The appliances are listed in the first column, and will weigh for each hour of day simulating the average consumption of each mentioned appliance. Data from the previous week's consumption of each household enabled the development of the matrix of weights applied in the following days.

To assign the minimum weight of each variable associated to the appliance in the matrix and, through GRG, calculate $\alpha_{i,i}$, it was set up a function in order to minimize the MSE of the electrical consumption and the real average consumption of each household.

The MSE can be estimated, is given by:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (\bar{\alpha}_i - \alpha_i)^2 \tag{5}$$

for the mean is the sample average given by:

$$\bar{\alpha} = \frac{1}{n} \sum_{i=1}^{n} \alpha_i \tag{6}$$

An MSE of zero, meaning that the weight of the $\alpha_{i,i}$ is with perfect accuracy, is the ideal, but is practically never possible, as show the results. The goal of using MSE was to experiments in such a way that when the observations are analyzed, the MSE is close to zero relative to the magnitude of the estimated forecasting.

3.2. Fourier Series

For analyzing the load profiles, the data were analysed in the time domain by FFT to produce the frequency spectrum. A FFT is an efficient algorithm for the calculation of the Discrete Fourier Transform

(DFT) any periodic and continuous function can be expressed as Fourier series, decomposing it into a sum of an infinite number of sine and cosine functions.

The FFT is a discrete Fourier transform algorithm which reduces the number of computations needed for N points from $2N^2$ to $2N\lg N$, where lg is the base 2 logarithm. The FFT algorithm was first discussed and proposed by Cooley and Tukey [24].

The basic idea is to break up a transform of length *N* into two transforms of length *N/2* using the identity given by:

$$F_{jk} = e^{2\pi ijk/n} = \omega^{jk} \tag{7}$$

for $j,k = 0,1,2,...,n-1$, where i is the imaginary number $i = \sqrt{-1}$ and normalized by is the $1/\sqrt{n}$, to make it a unitary.

A FFT is an efficient algorithm for the calculation of the DFT, giving the amplitudes, frequencies and phases φ_i for the cosine functions given by:

$$F(n) = a_0 + \sum_{\alpha=1}^{24} \left[a_\alpha \cos(2\alpha\pi n/24) + b_\alpha \sin(2\alpha\pi n/24) \right] \tag{8}$$

In this expression π is the frequency of the Fourier series, and a_0, a_k and b_k the fitting coefficient.

Once the Fourier series has been defined it was used to forecast future values of hourly energy consumption as the series presents a clear periodic behaviour.

For an optimization solution it was used the MSE, which has been found very useful for constraint variables to solve the model.

As it was done for GRG algorithm, to perform the FFT, Table 1 a matrix that is presented below was developed to produce the weights for each appliance, which are listed in the first column, and will weigh for each hour of day simulating the average consumption of each mentioned appliance. Data from the previous week’s consumption of each household enabled the development of the matrix of weights applied in the following days.

To assign the minimum weight of each variable associated to the appliance in the matrix and, through FFT, calculate $\alpha_{i,i}$, from Table 1, it was set up a function in order to minimize the MSE of the electrical consumption and the real average consumption of each household.

4. Simulation Results

The model of electric appliance load profile has been validated in [11] and used the database from [3]. From a random household and using the different tool the GRG and the FFT, this work was shown the ability to converge the forecasting function to the function of real consumption.

Table 1. Weights ($\alpha_{i,j}$) of daily average consumption of an household.

Household Nº x	α_1 01:00	α_2 02:00	α_3 03:00	--- ---	α_{22} 22:00	α_{23} 23:00	α_{24} 24:00
Area Inhabitants	A_x I_x	A_x I_x	A_x I_x	--- ---	A_x I_x	A_x I_x	A_x I_x
Appliance							
1	$\alpha_{1,1}$	$\alpha_{2,1}$	---	---	---	---	$\alpha_{24,1}$
...	$\alpha_{....}$	$\alpha_{...}$	---	---	---	---	$\alpha_{...}$
14	$\alpha_{1,14}$	$\alpha_{2,14}$	---	---	---	---	$\alpha_{24,14}$

4.1. Generalized Reduced Gradient

To find a solution it was used the GRG method used by Solver. The results showed that this tool can be used to forecast annual energy consumption average.

The comparison of an average annual consumption per day with accumulative energy consumption electric appliance forecasting are shown in Fig. 2.

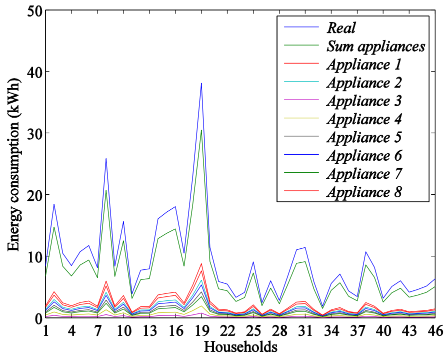

Fig. 2. Comparison of an average annual consumption per day with accumulative energy consumption.

Fig. 2 shows the modelling tested results of household average annual consumption per day. For sake of readability, the 14 appliances were aggregated in 8. The horizontal axis identifies the household number. Data was available for 93 houses. Half of them, actually 47, were used for computing the coefficients using GDG. These coefficients were used for forecasting the consumption of the remaining 46 houses. The vertical axis shows the average annual daily consumption in kWh/day. The straight blue line (from de top, first one) represents the total real average annual daily electric energy consumption. The green line (second) represents accumulated average annual electricity consumption from appliances forecasting. Other colours represent the contribution of each electric appliance forecasting energy consumption in each household. For this contribution, the values used by electric appliances are energy consumption forecasting from GRG computations.

The comparison of hourly energy consumption average using electric appliance forecasting is shown in Fig. 3.

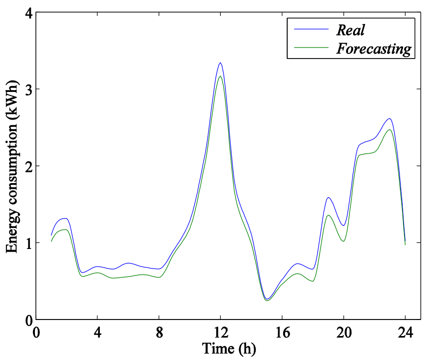

Fig. 3. Comparison of hourly energy consumption with forecasting by GRG.

Fig. 3 shows the modelling tested results of household hourly energy consumption average. The blue line represents the hourly electric energy consumption average and the green line represents the consumption weights and the contribution of each appliance in a household.

These results, which are the hourly and daily average energy consumption, have an important role in shaping the design of storage energy. Knowing the forecasting consumption, power production and hourly energy demand is possible shedding (anticipate or postpone) the consumption of electricity.

The tool developed can be used at the renewable energy system early design stage. It can also help the electricity supplier to forecast the likely future development of electricity demand in the whole sector of the community.

4.2. Fourier Series

The comparison of hourly energy consumption average using electric appliance forecasting is shown in Fig. 4.

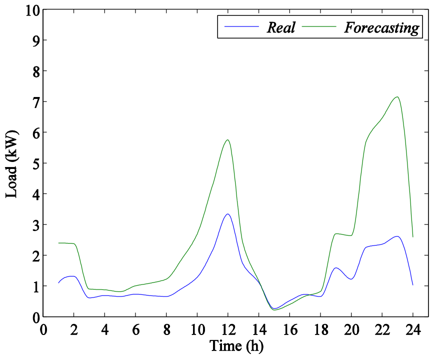

Fig. 4. Comparison of hourly energy consumption with forecasting by Fourier series.

These results show that the Fourier Series tool provided estimates for every hour of day (01:00-24:00), which present the same tendencies, but the forecast was above the real consumption. This may be due to the fact that Fourier Series can be applied to linear systems, and the model was surely non-linear.

4.3. Two Models Comparison

The models studied, GRG and FTT, show a reasonable behaviour for forecasting hourly, daily energy consumption and load curve profile for a randomly chosen household and under the conditions described above. However, when comparing the methods, it was observed that the best performance highlighted is the GRG method.

5. Conclusions

This paper presents a load profile forecast tool for electrical appliances in households. Optimization tools were analysed and tested. The paper shows that the tools are able to forecast hourly and daily average energy consumption, as well load profile. Generalized Reduced Gradient algorithm and Fourier Series were used. When comparing the methods, it was observed that the best performance was obtained by the GRG method.

Further work suggests that the daily and hourly energy consumption forecast can be useful to determine the required size of storage energy systems, delay and postpone energy consumption. These tools may be implementing into smart meters paving the way for Demand Response actions.

The used method can be used for improving Smart Grid performance. It can also help on the Demand-Side Management, such as electricity suppliers, to forecast the likely future development of electricity demand in the whole sector of the community. For the future, additional research may include renewable energy production (micro production) forecast. Moreover the models can be more accurate if they include different models for weekdays, weekends and holiday days, which correspond to different consumption patterns.

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