Load Profile Analysis Tool for Electrical Appliances in Households

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ABSTRACT

This paper presents a methodology to forecast the hourly and daily consumption in households. The methodology was validated for households in Lisbon region, Portugal. The paper shows that the forecast tool allows obtaining satisfactory results for forecasting. Models of demand response allow the support of consumer's decision in exchange for an economic benefit by the redefinition of load profile or changing the appliance consumption period. It is also in the interest of electric utilities to take advantage of these changes, particularly when consumers have an action on the demand-side management or production. Producers need to understand the load profile of households that are connected to a smart grid, to promote a better use of energy, as well as optimize the use of micro-generation from renewable sources, not only to delivering to the network but also in self-consumption.

KEYWORDS: Energy consumption, load management, supply and demand, smart grids, predictive models

1 INTRODUCTION

Nowadays, in an existing electric grid, it is important to understand and forecast household daily or hourly consumption with a reliable 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. In short-term load forecasting (STLF) model artificial neural networks (ANN) have been used together with an energy consumption database [1–3]. In this paper, the database uses a model with the whole week (workweek and weekend). Using smart devices such as cyber-physical systems monitoring, gathering and computing in real time a database with weekdays and weekends, the use of these groups of days allows the development of STLF models with better results than a model using the whole week. Nevertheless, this paper shows that developed predictive tool allows obtaining satisfactory results for forecasting.

The average household electric energy consumption per year, from a set of 93 houses in Lisbon, Portugal, is about 3.251 kWh, i.e., 1.142 kWh per person or 28 kWh/m^2 [4]. The maximum consumption per year is 16.000 kWh.

The energy consumption of domestic appliances can be classified as:

a) Brown goods: TVs, VCRs, DVDs;

b) Cold appliances: refrigerators, freezers and combined fridge-freezer;

c) Cooking appliances: electronic ovens, electric hobs, kettles and microwaves;

d) Wet appliances: washing machines, tumble dryers and dishwashers;

e) Artificial lighting: Fluorescent tube, halogen lamp and incandescent bulb;

f) Miscellaneous appliances: vacuum cleaners, irons, electric showers, central heating pumps and PCs.

Unlike domestic appliances, artificial lighting energy consumption is highly influenced by season. The electric lighting on/off pattern also depends on daylight and occupancy pattern. If the internal required lighting level is less than the available daylight luminance level then artificial lighting will be switched on when the room is occupied. In winter, people get up in the morning and need the lights on for the activities, but in summer, lighting is not required due to the daylight.

Cooking appliances and miscellaneous appliances like kettle (boiler), iron and vacuum cleaner, this usage pattern also depends on the household occupancy pattern and lifestyle.

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 [5].

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 [5] are shown in Fig. 1.

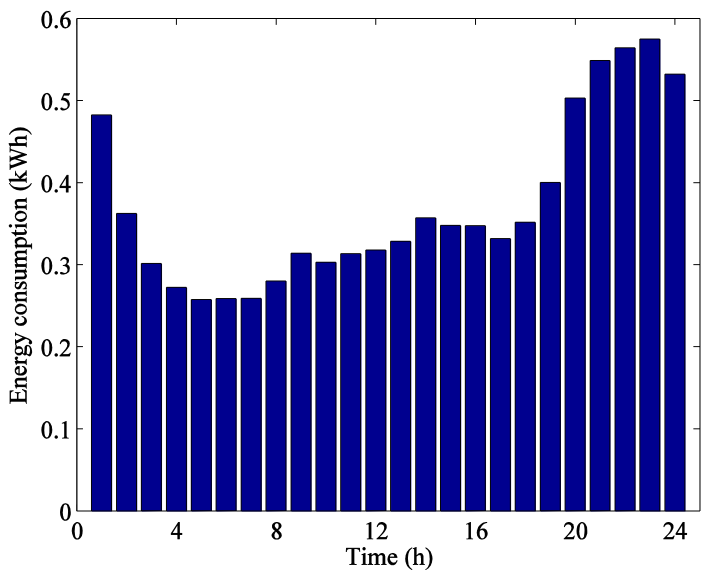

Fig. 1. The daily average electric consumption of a Portuguese set of 93 households.

In Fig. 1, 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.

Based on information gathered from monitoring carried out by [4], the structure of the daily load of a household in Portugal is similar to a typical day load in a household in Europe, as shown “Load curve structure (yearly average), from the grid point of view and a typical household on a day of the year in Portugal and Europe” [4].

The structure of the load profiles shows the average hourly energy demand, from the grid point of view. These curves are averaged over a whole year, values are consumptions per hour. For a system planning and strategic design, also shows the breakdown daily energy-consumption for an average size household that can be useful for the microgeneration renewables energy and smart grid.

In our research, the structure of electricity consumption disaggregated by major end-uses was based on monitoring of 93 households held in Lisbon, Portugal, in 2000 and 2001, and which results 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 [4].

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 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 [4].

The daily energy-consumption load profiles of electric appliance have been calculated using six weeks, including both workdays and weekend.

The predictive tool used is support by Solver that is a what-if analysis tool and dedicated to solve, among others, linear and non-linear optimization problems. It automatically finds close to optimal values for certain input cells, called decision variables. The solver ensures that these values satisfy limits, called constraints, on other cells calculated by formulas in the model. A designated formula cell, called the objective, is maximized or minimized at the near optimal solution.

2 STATE OF THE ART

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 [6].

In all countries, four types of consumption seem to be rising particularly fast:

1) The domestic computers and peripherals;

2) New domestic entertainment;

3) Standby power;

4) Some lighting technologies, such as halogen lamps.

According to IEA, 15% of total appliance electricity consumption in Europe, by 2030, could be due to stand-by functionality.

Usage patterns associated with different sections of the population and the variations in consumers' knowledge/attitudes need to be identified. Possible links between cultural values and energy use should be explored in order to identify feasible means for promoting energy-rational behavior. 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, etc. The different households have different life styles. The total load profile shape will of course vary 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 [7] for household occupancy pattern, can be used.

The works [8,9] 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 behavioral) which influence these trends.

This work and others from the authors of this paper on these themes seek to identify the technical and behavioral patterns to identify predictive methods. Thus, this paper will describe a method and results obtained with a predictive tool proposed.

3 METHODOLOGY

This study creates a comprehensive residential energy consumption model using a tool from an energy consumption database from a set of 93 houses, recorded in Lisbon, in the years 2000–2001. Inputs include the apartment area, person/household, kitchen appliances, lighting, cooling and heating, domestic hot water (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 x 12, the first being the inputs of electrical column and lines the daytime hours (01:00 to 12:00 or 02:00 - 24: 00). For the calculation of each array value, the solver uses the Generalized Reduced Gradient (GRG) Algorithm for optimizing nonlinear problems.

The GRG method is another popular state of the art technique. The original method, the Reduced Gradient Method has seen several different customizations due several researchers [10–13].

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

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

where h has dimension m. The method supposes that can be partition $x = (v, w)$ such that:

- v has dimension m (and w has dimension n-m);
- the values of v are strictly within their bounds: $L_v < v < U_v$ (this is a non degeneracy assumption);
- $\nabla_v\, h(x)$ is nonsingular 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:

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

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

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

where

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

Then, 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. For an optimization solution it was used the minimum square error (MSE), which has been found very useful for constraint variables to solve the model.

To performed de GRG, a matrix that is presented below was developed as Table 1 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 weeks' consumption of each household enabled the development of the matrix of weights applied in the following days.

Table 1. Matrix developed to produce weights (αi,j) of daily average consumption of an household

Household Nº x	α_1 01:00	α_2 02:00	α_3 03:00	α_4 04:00	α_5 05:00	α_6 06:00	α_7 07:00	α_8 08:00	α_9 09:00	α_{10} 10:00	α_{11} 11:00	α_{12} 12:00
Area	A_x	A_x	A_x	A_x	A_x	A_x	A_x	A_x	A_x	A_x	A_x	A_x
Inhabitants	I_x	I_x	I_x	I_x	I_x	I_x	I_x	I_x	I_x	I_x	I_x	I_x
Appliance												
1	$\alpha_{1,1}$	$\alpha_{2,1}$	---	---	---	---	---	---	---	---	---	$\alpha_{12,1}$
2	$\alpha_{1,2}$	$\alpha_{2,2}$	---	---	---	---	---	---	---	---	---	$\alpha_{12,2}$
3	$\alpha_{1,3}$	$\alpha_{2,3}$	---	---	---	---	---	---	---	---	---	$\alpha_{12,3}$
.	$\alpha_{1,.}$	$\alpha_{2,.}$	---	---	---	---	---	---	---	---	---	$\alpha_{12,.}$
.	$\alpha_{1,.}$	$\alpha_{2,.}$	---	---	---	---	---	---	---	---	---	$\alpha_{12,.}$
.	$\alpha_{1,.}$	$\alpha_{2,.}$	---	---	---	---	---	---	---	---	---	$\alpha_{12,.}$
14	$\alpha_{1,14}$	$\alpha_{2,14}$	---	---	---	---	---	---	---	---	---	$\alpha_{12,14}$

To assign the minimum weight of each variable associated to the appliance in the matrix and, through GRG, 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.

The MSE can be estimated by:

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

for the mean is the sample average

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

An MSE of zero, meaning that the weight of the $\alpha_{i,j}$ 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.

4 SIMULATION RESULTS

The study model and database, electric appliance load profile has been validated in [4] and based on information gathered from monitoring carried out by [2].

To optimize the solution and identify the type of function (linear or nonlinear) it was used the GRG method used by Solver. The results showed the functions of daily electricity consumption are nonlinear and the optimization tool can be used to forecast annual energy consumption average.

Using GRG, the research was shown the ability to converge the forecasting function to the function of real consumption with an error MSE ≅ 0.

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

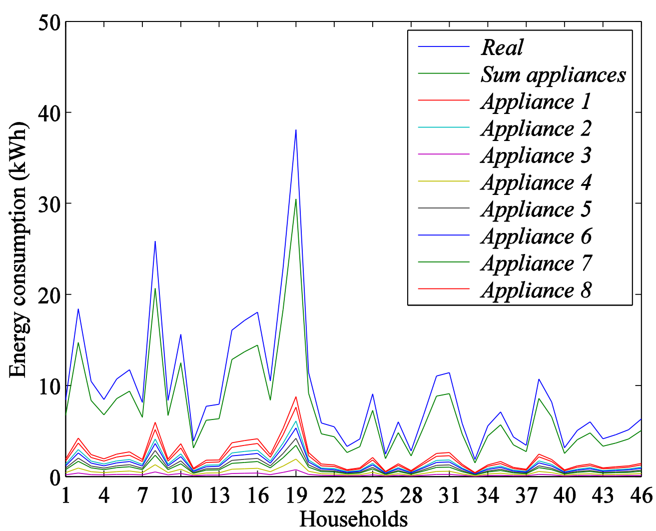

Fig 2. Comparison of an average annual consumption per day with accumulative energy consumption electric appliance forecasting.

Fig. 2 shows the modeling tested results of Portuguese household average annual consumption per day. The horizontal axis identifies the household number. The vertical axis shows the average annual daily consumption in kWh per 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 colors 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.

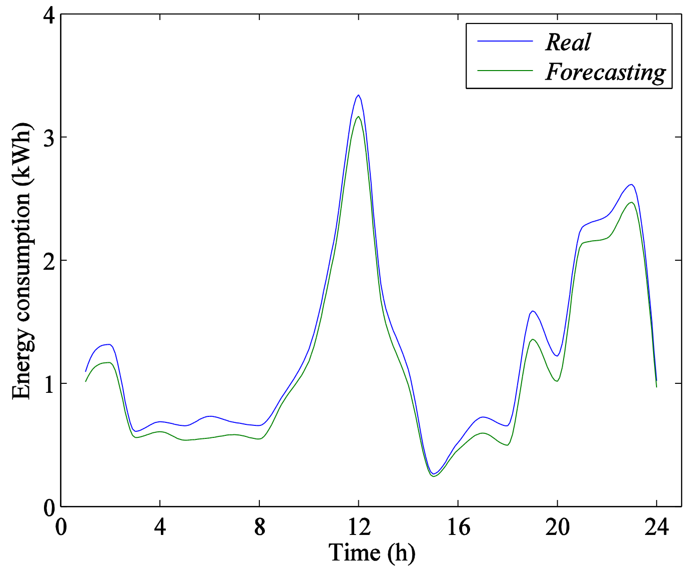

Fig 3. Comparison of hourly energy consumption average using electric appliance forecasting.

Fig. 3 shows the modeling 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.

5 CONCLUSION

This paper introduced simple forecast methods of daily and hourly average energy consumption, by using an optimization tool. The paper reveal that tool is able, after identifying the methods, forecast hourly and daily average energy consumption, as well load profile. This tool uses the Generalized Reduced Gradient method.

The input data included the apartment area, inhabitants, kitchen appliances, lighting, cooling and heating, domestic hot water and entertainment appliances.

The method is based on electric consumption and occupancy patterns. Hourly and daily measurements of end-users energy consumption are used for generalizing the load profile.

A load profile for 47 households, i.e., half of database has been generated for training. Verifying against the other half, the load forecasting kept close to the real consumption.

Forecast daily and hourly energy consumption can be useful in to determine the required size of a storage energy systems, delay and postpone energy consumption. The used method can be used at the renewable energy system early design stage and improve 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, an important step in continuing is additional research enhancing forecasting capability on the load profile renewable energy production (micro production), include testing the method for different day of the week (weekday, weekend and holiday days). The purpose of forecasting energy consumption daily and hourly is to identify an accurate, effective and sufficient, renewable energy production and energy storage.

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