Residential Electric Load Curve Profile Based on Fuzzy Systems

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Abstract**—Electric energy demand in residences represents around 30% of the global demand. This requires a detailed knowledge about the electrical load patterns, leading to a change in final consumer behavior to reduce the general demand. This work uses a fuzzy system, considering the quantity of occupants in a Brazilian family in different periods of day aiming to obtain the residential electric load profile.**

Index Term—Residential Load Curve, Active occupation, Fuzzy Logic.

I. Introduction

Electrical load forecasting is useful in managing electrical energy demand and it is imperative due to the increasing of the residential users [1]. The domestic electric demand is significant in the daily peaks. These load peaks influence the efficiency of the energy system, resulting in congestion of the electrical system [2]. Thus, it is necessary to know the electrical load curve principally in residences. This information allows the consumers to detect the wrong use of the electric energy reducing the demand and enabling the use in some hours of the day with the lowest price [3].

The specialized literature contains different types of models using the residential load curve. These models are classified in two principal groups: top-down and bottom-up [1].

The bottom-up models are not complex, but to implement them needs the use of a large empiric database [4], [5]. The data used are general information, like Gross National Product (GNP), unemployment rate, statistics about the population, predicted evolution, saturation appliance rate, etc.

The top-down models begin at the least unities of the system and successively aggregate these unities to achieve higher levels of the electrical system. The input data which characterize them are individual consume of the selected appliances, meteorological information, energy bills of the families, human behavior, etc. [6]-[8].

Gradjean et al. [1] presented a review and analysis of the residential load curve models. The Walker and Pokoski [8] was the first model to consider human behavior developing the residential load curve. The authors observed complexity in data acquisition and proposed considering only one individual living in the residence. This scenario is used to generate variations depending on probability distribution functions and changing times of the beginning of the principal activities. They also suggested the use of an inclination function based on other studies. This function is used to calculate the tendency of people to engage in some activities at a specific time of the day.

Capasso et al. [9] developed a model called ARGOS that improved the Walker and Pokoski model [8], which is a reference for other models developed, a posteriori, especially for those considering human behavior. ARGOS simulates the residential load curve by considering four domestic activities: 1) cooking; 2) domestic business; 3) leisure; and 4) personal care. Each member of the family is characterized by a scenario of presence and a specific tendency for each domestic activity.

Richardson et al. [10] approached a bottom-up model using aggregated familiar elements, specifying the appliances and the members of the family. The authors used data from studies containing detailed registers of domestic activities considering 21,000 houses. These registers created profiles for presence and activity for every 10 minutes interval. They also considered appliance data, such as penetration rate, annual consumption, occupation rate, and time of use, seasonal information, demographic statistical data, and the total load curves of 22 houses. Considering these data, they calculated the demand curve for one house based on the quantity of family members, the day of the week and the month of the year.

López-Rodríguez et al. [11] use information acquired by TUS (Time Use Survey) by the National Statistics Institute of Spain in 2009-2010 to obtain the active occupation profile of Spanish houses. These profiles, whose patterns present significant similarities with the typical profile for domestic electricity, were obtained to classify residences as a function of the quantity of inhabitants, considering houses with 1 to 6 persons, labor days and weekends. Three peaks of active occupation were identified: 1) morning; 2) afternoon and 3) night. This information was used at the input of a stochastic model based on the Markov chain and Monte Carlo techniques, where the active occupation profiles of the residences were generated to simulate the domestic consumption of electrical energy.

The models cited above emphasize the difficulties in modeling human behavior. Thus, Zúñiga et al. [2] proposed a model based on fuzzy logic, which was firstly introduced by Zadeh [12], to emulate the human behavior related to appliances and illumination in a home. They considered the characteristics of personal work and an agenda of leisure and domestic routines. Based on this model, the hourly activation profile for each appliance was obtained, and the residential load curve was calculated.

The electrical demand profile at residences is highly correlated with the occupation time of the residences [9]. Thus, this work aims to develop the use of a fuzzy system, considering the periods of the day and the home occupation. It is emphasized that this model considers the time when the occupants are in the house, even sleeping. The energy profile using an intelligent system can simulate the daily activities of the occupants in the residence and contribute to manage the demand response and in the future the smart grid. Based on the fuzzy model it is built the electric load profile of a Brazilian residence, considering the summer season, where the highest consume occurs due to the high temperatures.

II. BUILDING THE RESIDENTIAL LOAD CURVE

A fuzzy system based on fuzzy logic concepts is used to describe the residential load curve

A. *Fuzzy Logic*

Dr. Lofti A. Zadeh [10] developed Fuzzy logic in 1965 at California University. It aims to represent the uncertainties once the world does not contain only true or only false actions [10].

The membership functions is a graphical representation of each input representation. It associates one weight to each input processed, defining a functional superposition with the inputs, and finally determining an output answer. After the conclusions, the functions are defuzzified in real output (crisp) [11].

The fuzzy system is composed of three parts [10], [11], as shown in Figure 1.

1 Fuzzification: converts real variables (crisp) in linguistic variables;
2 Inference: consists in manipulating the rule base using declarations if-then, and fuzzy operations (AND, OR);
3 Defuzzification: converts the result (linguistic variables) in real variables (crisp);

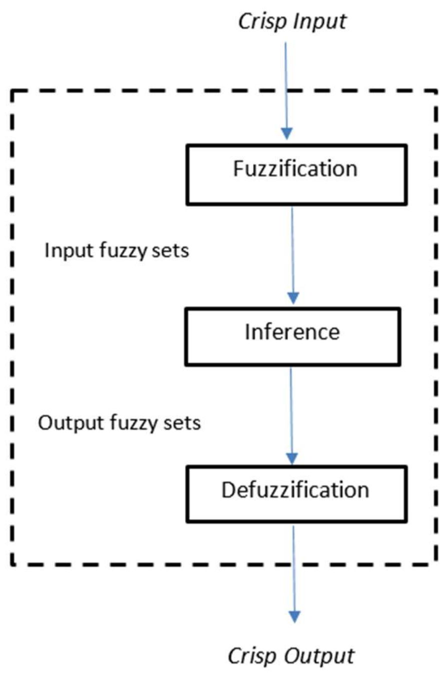

Fig. 1. Fuzzy System flowchart

B. *Fuzzy System Input*

The proposal considers a Brazilian residence with maximum five occupants, with a labor day of 8 hours.

Two input sets were created: *Period of the day* and *Occupation,* which will be used as inputs of the fuzzy system.

- Period of the day

To define the different periods of the day used as the fuzzy system input, the daily routine of the habitants working eight hours a day is considered. This is the characteristic of the majority of consumers of the Brazilian electric system. Thus, based on the daily routine eight different periods were created considering the interval [0, 24] hours.

The first period is the first sleeping period when the habitants are in home sleeping. This time, usually some air conditioner and fans are activated due to high temperatures in Brazil.

The second period is the breakfast, when the habitants wake up and begin to activate some appliances as illumination, electric shower, microwaves among others.

The next period is the work period, which is the third period of the day, when the habitants leave their residences to work. This time the majority of the appliances are deactivated, except refrigerators and freezers.

The fourth period is lunchtime, when the people having an interval of two hours come back home or not. Therefore, two different cases are considered, people who come back home consuming energy and those who do not come back home.

The fifth period is the second period of work, when the habitants come back to the respective work place.

Finishing the work time, the habitants come back to their respective homes activating several appliances as electric shower, illumination, TV set and begin to prepare dinner or something to eat. This is the sixth period considered.

The seventh period is rest time, when the habitants rest after a long day journey, activating some air conditioner, TV set among others. This time some habitants can go out home to a leisure or other thing.

The last period considered is the second period of sleeping, when the habitants deactivate almost all appliances except those of continuous use or refrigeration (air conditioner and fans).

Thus, eight membership functions with interval [0, 24] are defined to identify the different periods of the day, when the occupants are using the appliances, sleeping or out of home. Thus, the linguistic variable *Period of the day* has eight linguistic values, where each term is characterized by a membership function illustrated on Figure 2.

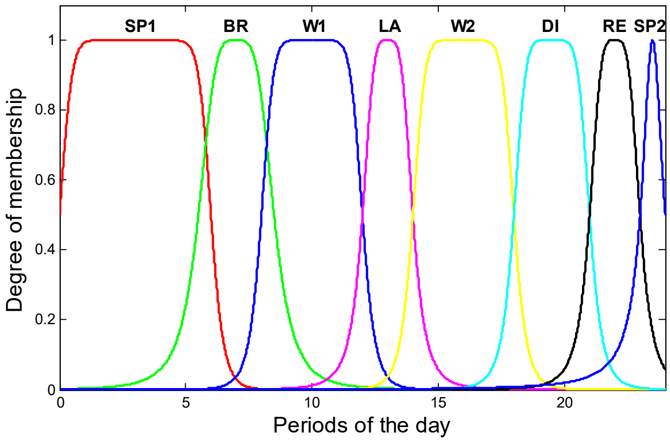

Fig. 2. Membership Function "Periods of the day".

where:

- First period of sleeping (SP1) : time that the occupants are sleeping [0, 6] h;
- Breakfast (BR) : time when the occupants realize the first meal [6, 8] h;
- First period of working (W1) : time when the occupants are at work [8, 12] h;
- Lunch (LA) : time when the occupants are taking lunch [12, 14] h;
- Second period of work (W2) : time when the occupants are at work [14, 18] h;
- Dinner (DI) : time when the occupants arrive from work and begin to prepare dinner [18, 21] h;
- Rest (RE) : period when the occupants rest [21,23] h;
-Second period of sleeping (SP2) : time when the occupants are sleeping [23, 24] h.

The membership function used to represent the input set was the bell function, and the choice is due to this function has a shape that better represents the periods and occupations of the residence.

• Occupation

Due to high correlation with the residential energy consume profile and the occupants of the house and the time they stay in home, the input set occupation is created.

The linguistic variable Occupation assumes seven linguistic values, determining if the occupation is high, medium or low, which depends on the quantity of the occupants on the house. A Brazilian residence with maximum five occupants is considered. The occupation is considered high when five or four occupants are on the house, medium when three or two occupants are on the house and low when only one or none is on the house. Each linguistic value is characterized by a membership function illustrated on Figure 3.

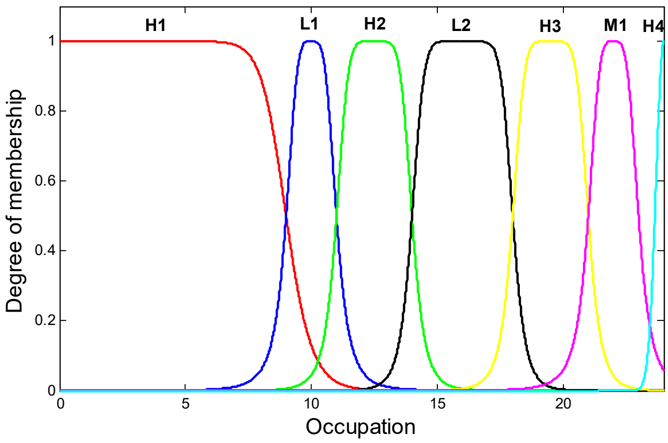

Fig. 3. Membership Function "Occupation".

where:

-High 1 (H1) : high occupation at period [0, 8] h;
-Low 1 (L1) : low occupation at period [8, 12] h;
-High 2 (H2) : high occupation at period [12, 14] h;
-Low 2 (L2) : low occupation at period [14, 18] h;
-High 3 (H3) : high occupation at period [18, 21] h;
-Medium 1(M1) : medium occupation at period [21, 23] h;
-High 4 (H4) : high occupation at period [23, 24] h.

C. *Fuzzy System Output*

The output of the fuzzy system considers the electrical energy consume within a period of 24 hours.

- Electrical Energy Consumption

Five membership functions are defined to represent the output of the fuzzy system Electrical Energy Consumption with the interval [0, 1]. Figure 4 illustrates the membership functions that are determined by the linguistic values (very high, high, medium, low, and very low) which are converted between zero "0"and one "1". A value near 1 means that there are many persons in the house to activate the appliances, illumination, while a value near 0 means that there are few persons in the house.

The Gaussian membership was the best one to represent the linguistic values for the system output.

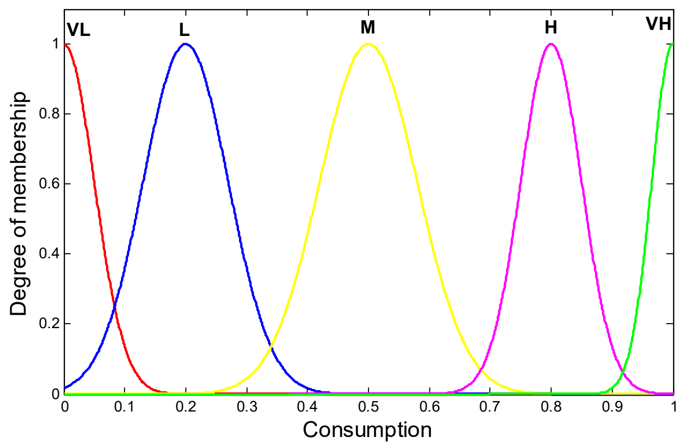

Fig. 4. Electrical Energy Consumption.

where:

- Very Low (VL) : the consumption is very low;
- Low (L) : the consumption is low;
- Medium (M) : the consumption is medium;
- High (H) : the consumption is high;
- Very High (VH) : the consumption is very high.

D. *Fuzzy System Rules*

After the input and output being defined by the linguistic variables, it is possible to create a set of rules to obtain the electrical load consumption. The database is one of the principal components of the fuzzy system [10]. These rules can be generated from the experience or by numerical data. The rules are defined according to the following relation:

$$IF\ X_1\ is\ BR\ and\ X_2\ is\ H1\ THEN\ Y\ is\ M$$

where X_1 and X_2 are the inputs and *Y*, the output.

Consider that X_1 is the linguistic variable "Period of the day", X_2 the linguistic variable "Occupation" and *Y* the linguistic variable of the output "Electrical Energy Consumption". Different rules are developed according to Table I.

Residences with maximum five occupants working eight hours per day are considered to create the fuzzy rules. Persons living in big cities, with excessive traffic are also considered, once they do not return at lunchtime.

The procedure used at the fuzzy input system is converted by the membership functions to the outputs. Applying the rules, an output fuzzy is obtained, which must be converted to a real value (crisp). This process is known as deffuzification. Several methods realize this conversion, and this work used the central area or centroid method [12].

Table I – Fuzzy System Rules.

Rule	X_1	X_2	Y
01	SP1	H1	H
02	SP1	M1	M
03	BR	H1	M
04	BR	L1	M
05	BR	M1	M
06	W1	H1	L
07	W1	L1	L
08	LA	L1	VL
09	LA	H2	L
10	LA	L2	L
11	W2	L2	VL
12	W2	L2	M
13	DI	H3	VH
14	DI	M1	H
15	RE	M1	H
16	RE	H4	H
17	SP2	H4	M
18	SP2	H4	L

The procedure of fuzzy system is to convert the inputs using the membership functions into the outputs. By applying the rules, an output is obtained whose value is a fuzzy number, which must then be converted into a real value (crisp). This process is known as defuzzification. There are different methods to convert the fuzzy outputs into real values; this work uses "Area Center" (AC), which is defined by equation (1) [21]:

$$AC = \frac{\sum_{i=1}^{n} u_i v_i}{\sum_{i=1}^{n} u_i} \qquad (1)$$

where:

n : quantity of rules;

u_i : membership grade of rule i;

v_i : recommended control activity according to rule i.

III. RESULTS

The obtained result is based on the definition of the input and output sets. It is also considered the rules defined based on the human behavior and the daily activities. The values of the input and output sets consider the variations of the daily period and the occupation.

Figure 5 represents the daily energy consumption profile on one day of the week, in a determined residence considering a maximum of 5 inhabitants working 8 hours per day that do not come home during lunchtime. The first peak occurs when the inhabitants awaken and begin their activities involved in leaving home and going to work, activating this time some appliances like illumination, electric shower among others. However, the maximum load peak occurs during night, increasing the consumption starting at 6:30 PM. when the inhabitants arrive from work and begin to prepare dinner and perform routine activities, activating several appliances as for example, illumination, electric shower, TV set, electric oven, among others. Table II resumes the peak times, when the occupation of the residence is considered high, i.e. time where most of the occupants are in their residences to activate the appliances.

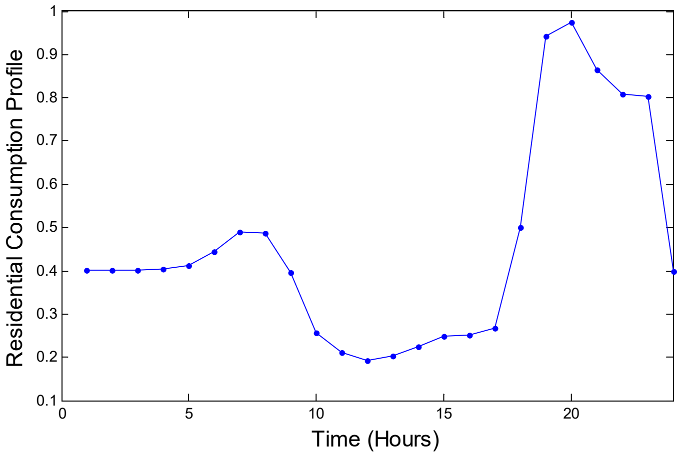

Fig. 5. Residential Load Curve.

Table II – Peak time and occupation for the days of the week

	Peak 1 Morning	Peak 2 Evening
Time	6:30 to 8:00	18:30 to 21:30
Occupation	High	High

An important observation is that the energy consumption is higher when the occupants are in the residence during the sleeping period than were out of the residence. This is due to the high temperatures of the Brazilian summer when the air conditioners are on, representing a high demand.

Analyzing the demand during the sleeping period is the contribution of this work. The literature only considers periods when the occupants are in the residence asleep activating their appliances, and the sleeping period is not considered [3]-[9].

Thus, the analysis of Figure 5 shows that the energy demand is higher on the period when the occupants are sleeping than when they are out of the residence.

IV. CONCLUSIONS

This paper proposes the use of a fuzzy system to build the residential electrical load profile. This method is chosen due to the simplicity not needing great quantity of input data to a detailed method.

It is emphasized that the linguistic variables of the fuzzy system consider a Brazilian residence with maximum five occupants working 8 hours daily. To obtain residential load curves considering more occupants even for less occupants than five, it is enough to change the input variable “Occupation”. The input variables “Period of Day” can also be modified if there are residences with a different routine, as for example with occupants working half a day.

This proposal is new and is based on developing a simple methodology with few input data, providing the residential load demand profile,

The energy consumption profile, using an intelligent system, can simulate the daily activities of users in their residences and can contribute to managing the energy demand, demand response, and in the near future, in the design of smart grids, performing a fundamental role in realizing environmental protection and reducing the consume among other advantages.

V. ACKNOWLEDGMENT

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