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Applying fuzzy logic and neural networks to forecasting in efficiency programs

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Abstract. This paper addresses the design and implementation of Fuzzy Inference System (FIS) and Artificial Neural Network (ANN) to determine daily demand curves of residential Electric Showers (ESs). To determine the daily curves were used two inputs: shower duration and number of showers. In Brazil the residential electricity corresponds to 25% of all demand. The use of ESs is widespread, it represents about 22% of the total residential consumption. This work evaluates the impacts of Energy Efficiency Programs (EEPs) in low-income communities located in the state of Rio de Janeiro in Brazil. Additionally, two different ESs devices are compared: the ES Temperature Control (ESTC) and the ES Heat Recovery (ESHR). This study was based on measurements made in 60 households in different low-income neighbourhoods. The results showed that ANN makes better predictions, however both FIS and ANN have the capacity to determine rapid changes in peak demand. These tools can be used in small and medium- sized areas with similar socio-economic features which allow determining the impact of EEPs in the communities in advance. Furthermore, the application of these techniques can be of help in the actions of Demand Side Management (DSM) mainly during the maximum demand period.

1 Introduction

The electricity consumption in the residential sector in Brazil corresponds to approximately 25% of the total electricity demand [1]. The ES represents on average about 21% of the total residential electricity consumption. In colder regions1, such as the southeast and south, the electricity demand of ESs is even higher, about 26% and 25% respectively [2]. About 110 million people live in these regions where the use of ES is widespread. The power consumption of ESs varies between 4-8 kW [3]. In residential sector the ESs are used mainly between 18:00 to 21:00 hours, which is accountable for the maximum peak demand in the Brazilian power system [4]. The use of ESs in terms of

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electricity costs is very significant, mainly in low- income households, where the electricity consumption of ESs represents about 23% of the monthly electricity bill [5].

Since 1998, electricity distribution utilities in Brazil have been required to invest in energy efficiency programs. These programs are evaluated by the Brazilian Electricity Regulatory Agency (ANEEL). About 100 electricity utilities were obliged to invest 0.5% of their revenue in energy efficiency projects. Between 1998 and 2014, the total investment in EEP is estimated to have been approximately USD 1.97 billion [4]. In 2008, ANEEL implemented regulation 3002 order to regulate the EEP investments guaranteeing 70% to low-income households. The EEPs have been applied to replace obsolete and inefficient appliances such as old refrigerators and incandescent lamps and also aimed to reduce the electricity consumption of ESs. To evaluate and to estimate the energy savings from the EEPs is a complex task. It includes measurement and verification (M&V) methodologies which define standard terms and suggest the best practices for quantifying the results of energy efficient investments according to the International Performance Measurement and Verification Protocol (IP- MVP).

In this paper we have two objectives: (1) to design and implement Fuzzy Inference System (FIS) and Artificial Neural Network (ANN) to predict daily load curves of residential ESs; and (2) to assess the results of EEPs using two devices, ESTC and ESHR.

2 Material and methods

Generally, two approaches have been applied to determine residential load demand, the Top-Down and the Bottom-Up methods [6;7]. The Top-Down approach uses general information related to macroeconomic variables such as GDP, population, energy consumption among other data related to countries, regions, cities or municipalities [8–10].

The Top-Down approach is based on econometric and statistical methods to predict demand. In contrast, Bottom-Up approach uses more detailed information, for instance, energy consumption for end-users [11–14] or technological features. Notwithstanding, in some cases, the Bottom-Up approach can be limited due to the impossibility of carrying out measurements due to high costs and difficulties to access data. To overcome these problems new approaches have been suggested to determine load curves using non-traditional approaches [15–17].

These new techniques using soft computing have been used in order to achieve more accurate predictions [18–21]. Fuzzy method has been widely used in predictions [22–24]. Some authors have implemented this method to predict load curves, for instance, Bakirtzis et al., [25] developed a FIS application short term forecasting. Senjyu et al., [26] proposed a fuzzy logic approach for next- day load curve forecasting. Pandian et al., [23] obtained closer results with fuzzy logic for the current consumption than other conventional methods.

Another method to solve load forecasting are ANNs. ANN is a robust and flexible, especially in non-linear systems [29]. Back- propagation (BP) is the most used algorithm in ANN for load forecasting. One of the most complex aspect in ANN correspond to determining the actual numerical weights assigned to output [30] [25–31]. In the scientific literature there are many works related to ANNs, using different types of architectures and algorithms to determine load forecasting [32–34].

Currently forecast models try to include aspects of human behavior. A first attempt to study and to understand consumer behavior was proposed by Walker and Pokoski [35]. They developed a residential electric load curve, which included the psychological factors that affect the use of several appliances. A novel modeling of electric load curve that included linguistic variables and a fuzzy logic approach was developed by Michalik [36]. Zúñiga et al. [37] calculated the energy demand curve for washing machines, stoves, and lights using fuzzy with the survey data from Statistics National Institute of Spain. Mamlook et al., [27] explores non-traditional variables, such as temperature and the kind of day (sunny, rainy and other weather conditions). Furthermore, Mamlook [28] proposed a methodology that decreases the calculated forecast error and the processing time.

2.1 Fuzzy logic

Zadeh [38] introduced the fuzzy logic theory. From 1965 to 1975, this theory was developed considering fuzzy multistage decision-making, fuzzy similarity relations, fuzzy restrictions, and linguistic hedges. Mamdani and Assilian [39] developed the first fuzzy logic controller. This fuzzy inference model is the most used complex system encountered by conventional tools and to observe 7that human reasoning can apply concepts and knowledge that do not have well-defined, sharp boundaries. There are several fuzzy style inferences, however the most widely used fuzzy methods used are Mamdani's model [39] and Sugeno's model [40].

2.1.1 Membership functions

In fuzzy control theory the most used membership functions are triangular, trapezoidal, Gaussian, sigmoidal-Z and S functions. The membership functions selected in this paper correspond to the Gaussian functions. According to Equation (1) as follows:

$$\int (x;\sigma,c)\text{-}e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{1}$$

The parameters correspond to standard deviation, σ, and mean, *c*.

2.1.2 Defuzzification

The output must be quantifiable in a numerical value (Zo). There are several methods, however, the center of area is also known as centroid or center of gravity is one the most used in defuzzification process [41]. This method calculates the center of area of the region under the curve defined by a fuzzy set, as written in Equation (2). If H is the set function, the results of the combination procedure and H is integrable the defuzzified value H is:

$$z_o = \frac{\int_a^b z\, H(z) d}{\int_a^b H(z)} \tag{2}$$

where $[a; b]$ is an interval that contains the support of *H*.

2.2 Artificial Neural Networks

Biological systems can perform complex tasks because they capability of learning gradually over time [42]. ANN is a mathematical model developed from the understanding of biological nervous systems. The mathematical model of an artificial neuron is based on the following assumptions according to McCulloch and Pitts [43]: (1) neurons are the elementary units in a nervous system; (2) the signals are passed between neurons or layers; (3) every connection between neurons has a weight that multiplies the signal transmitted; and (4) each neuron has an internal action, known as activation function. The Figure 1 shows the conceptual model of a neural network. Equation (3) describes mathematically the model for artificial neuron including the activation function. This equation contains the parameters $\theta = (w_1, \ldots, wn, b, f)$. The bias corresponds to the associated weight for an input xo. The output corresponds to 0 and 1 according to Equation (3).

$$f\ (\textstyle\sum_i^n (w_i x_i\text{-}b)) = \begin{Bmatrix} 0 \text{ if } \sum_i^n (w_i x_i) < b \\ 1 \text{ if } \sum_i^n (w_i x_i) \geq b \end{Bmatrix} \tag{3}$$

3. Proposed methodology

Figure 1 shows the flowchart to predict daily load curves for residential ESs. The flowchart has three main stages as follows: (1) input data, corresponds to the data samples (in blue); (2) methods related to the implementation of FIS and ANN algorithms (in yellow); and (3) output data, which are the prediction and error validation (in green). These outcomes are validated using Mean Absolute Error (MAE) and Mean Absolute Error Percentage (MAPE). These are two recognized methods to measure forecast error [44].

3.1 Data

The data were acquired by Light S.A. utility and International Energy Initiative (IEI) Non-governmental organization from an EEP in the state of Rio de Janeiro consisting of on measurements in 60 low-income households. Data logs every five minutes, the measured data in all samples were: electric power (W) and electricity consumption (Wh). Each sample data was placed in different neighbourhoods of Volta Redonda city, according to Table 1. Old ESs were replaced by new ESs with two different technologies: electric shower heat recovery (ESHR) and electric shower temperature control (ESTC) [45; 46]. The input data were duration and number of showers. The output data modeled through FIS and ANN was the electric power used in each shower, which was measured in the samples. These data were organized, for a period of one hour. Thus, there are 168 data per variable per household. Sample 1 before replacement ESs was used to develop FIS design and the trained ANN. This sample is considered the control sample.

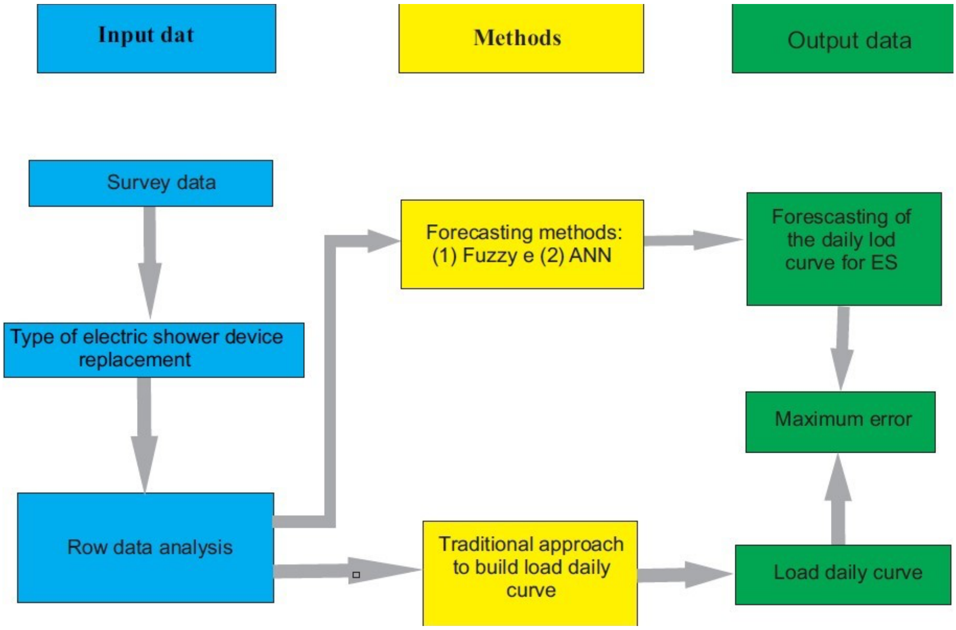


Fig. 1. FIS and ANN forecasting methodology.

The development and implementation of FIS for load forecasting consists of three stages: (1) to determine the membership functions; (2) constructing fuzzy rules; and (3) simulations. The fuzzy logic must have the capacity to capture consumer behavior from a limited amount of data and infer actions to develop a daily load curve with tolerable error. To characterize the membership functions required performing a basic statistical analysis of data, which allowed determining the appropriate functions. The FIS algorithm has two inputs: shower duration and number of showers per hour in one week. The first linguistic variable, "shower duration", was divided into 8 membership functions as shown in Figure 2a. The universe of discourse of "shower duration" has a range of [0 min, 30 min]. The 8 membership functions are defined as follows: Very-very low (VVL); Very low (VL; Normal (N); High (H); Very high (VH); Very-very high (VHH) and Upper (U).

Table 1. The samples description and ESs technologies used in this study.

Sample	Device	Quantity of households	Data before ES's replacement	Data after ES 's replacement
Sample 1 Neighbourhood 1 Volta Redonda	ESTC	37	From 9 Sept. to 15 Sept. 2013	From 18 Sept. to 24 Sept. 2013
Sample 2 Neighbourhood 2 Volta Redonda	ESHR	23	From 9 Sept. to 15 Sept. 2013	From 18 Sept. to 24 Sept. 2013

3.2 Design and implementation of FIS

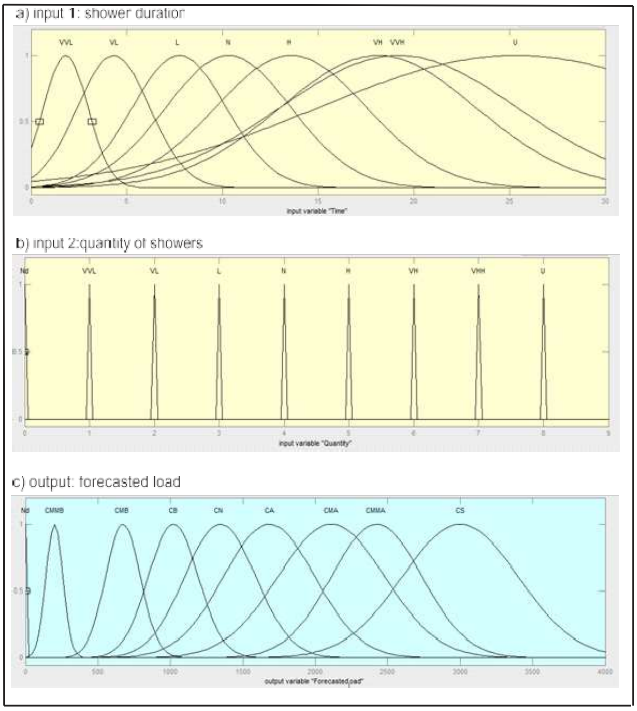


Fig 2. Membership functions: (a) shower duration; (b) number of showers; (c) forecasted load.

Figure 2b. shows the second linguistic variable, “number of showers”, which was divided into 9 membership functions. The universe of discourse of “number of showers” has a range of [0, 8]. The membership functions were defined as follows: Nothing (Nd); Very, Very Low (VVL - 1 showers); Very low (VL - 2 showers); Low (L - 3 showers); Normal (N - 4 showers); Very high (VH - 6 showers); Very-very high (VVH - 7 showers) and Upper (U - 8 showers).

The third linguistic variable, “forecasted load”, was divided into 9 membership functions according to Figure 2c. The universe of discourse of “forecasted load” has a range of [0 W, 4000 W]. They are defined as follows: Nothing (Nd); Very, very low consumption (VVLC); Very low consumption (VLC); Low consumption (LC); Normal consumption (NC); High consumption (HC); Very high consumption (VHC); Very, very high consumption (VVHC) and Upper consumption (UC).

The FIS model was implemented in Matlab using Fuzzy Logic Toolbox [47] with Mamdani type [39]. According to Figure 3 the FIS has three sub-processes: (1) fuzzification module, which converts crisp input values (e.g. 5 am) into linguistic values (time and number) through fuzzy sets where the membership functions are defined; (2) knowledge base (KB) module, which consists of a series of rules (72 in total) to yield the activation pro- files of ESs; and (3) defuzzification module, where the linguistic value of the output is converted in a numeric value of forecasted load (e.g 50 W). According to the membership functions determined at the beginning of this section, there is, for instance, rule 1, which says: if "shower duration" is VVL and "number of showers" is Nd, then forecasted load is Nd. In turn, rule 72 says: if "shower duration" is U and "number of shower" is U, the forecasted load is U. The fuzzy rules created are processed by the FIS, which formulates the mapping from a given input to an output.

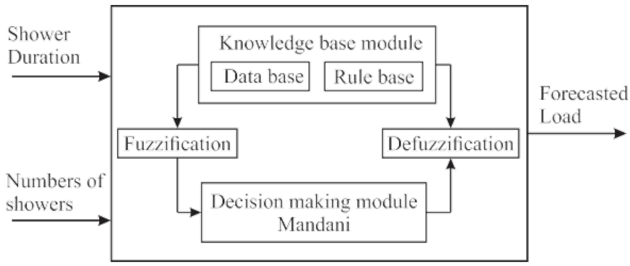


Fig 3. Fuzzy inference system (adapted from Jang [48])

3.2.1 Simulations of FIS:

In sample 1 was split into two parts, before and after the ES replacement. The FIS model was developed with sample 1 data before ES replacement.
The load curve prediction for ESTC was done using the FIS model with sample 1 data after the ES replacement.

In samples 2, before and after the ES replacement, the simulations were performed by using the FIs model. For these simulations, a cut off power in the ESHR device was applied, resulting in a reduction to 3000 W, without changing membership functions

3.3 Design and implementation of neural network

Several possible architectures were reviewed and the architecture selected was Feed-Forward Neural Network (FFNN). FFNNs are among most important and the most used architectures of neural network for time series and forecasting [49]. In general, the model developed is characterized by a network of three layers (input layer, hidden layer and output layer) of simple processing units connected by acyclic links, as shown below in Figure 4. Each layer has a weight matrix W, a bias vector unit b and out- put vector y. The hidden layer has 50 neurons and we used Levenber-Marquadt (LM) BP algorithm [50]. Through the learning algorithm, the ANN produces the output minimizing the discrepancies between its own output and the actual value. The Matlab neural network toolbox provides adequate built-in transfer functions that have been used for hidden and output layers.
The inputs correspond to shower duration and number of showers. Figure 5, shows the outputs y_i of each intermediate layer. The mathematical representations of the outputs y^1, y^2 and y^3 are given by Equations 4, 5. 6 and 7.

$$y^1 = f^1(IW^{1,1}x_i + b^1) \quad (4)$$

$$y^2 = f^2(IW^{2,1}x_i + b^2) \quad (5)$$

$$y^3 = f^3(IW^{3,1}x_i + b^3) \quad (6)$$

$$y = f^3(LW^{3,2}f^2(IW^{2,1}f^1(IW^{1,1}x_i + b^1) + b^2) + b^3) \quad (7)$$

where X_i is the number of inputs of the nodes; W_i (associated weight matrix between input layer and hidden layer) and y is the output.

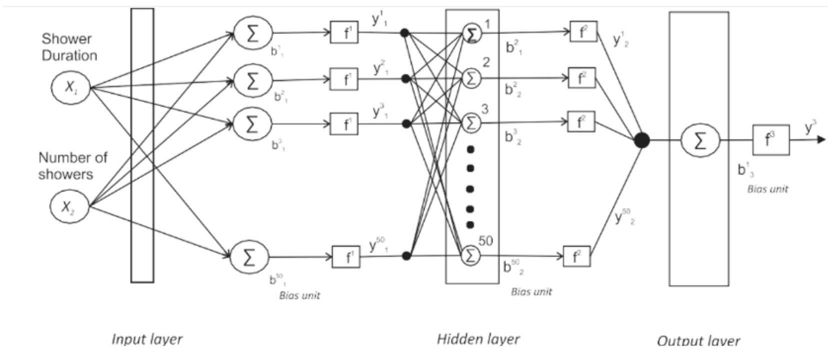


Fig 4. Architecture used in the modelled ANN.

3.3.1 Simulations of ANN:

In sample 1 was split into two parts, before and after ES replacement. The ANN model was developed with sample 1 data before the ES replacement.
The load curve prediction for ESTC was made by using ANN model with sample 1 data after the ES replacement.

In sample 2 before and after ES replacement, the simulations were performed by using ANN model.

For these simulations, a cut off power to 3000 W in ESHR device was applied.

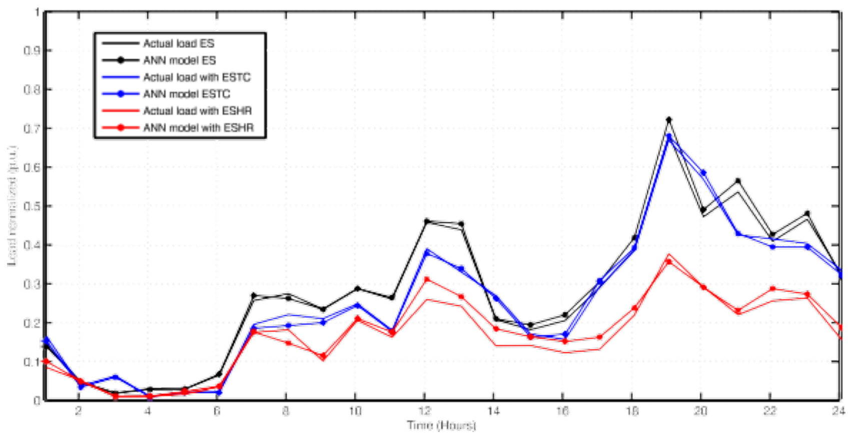
The training of an ANN is the process of finding not only a set of weights and bias units that are suitable but also finding outputs that are close to the actual outputs for the trained data. Appropriate weights and bias values are useful in the results of the prediction. Learning occurs through the adjustment of weights and node biases. In this ANN, the adjustment based on BP algorithm is used, which is the most commonly used for adjustment. BP can train multilayer FFNNs with differentiable transfer functions to obtain different kinds of approximate functions [47]. The "control sample" data are used for training the model. The data used correspond to the period from 9 September 2013 to 15 September 2013. They include the daily electricity consumption of ESs.

4. Results and discussion

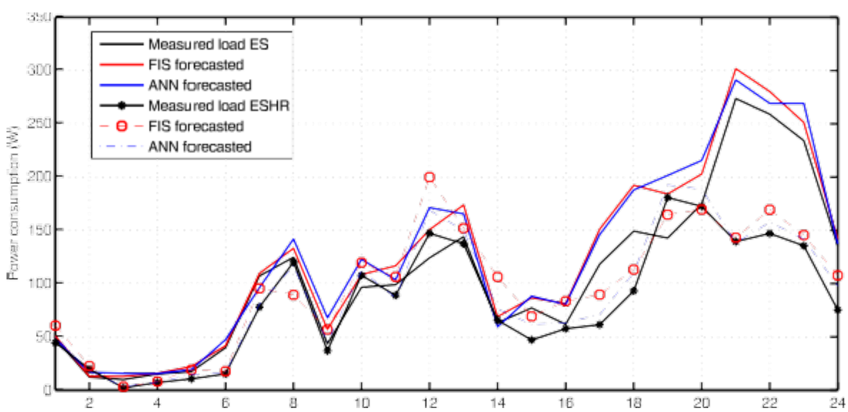
4.1 ESTC case

Figure 5a shows ex-ante and ex-post load curve estimations for the ESTC case. The mean daily load curve includes weekdays and weekends for seven days. Applying FIS in sample 1 with old ESs, the average MAE is 5.6 W and the average MAPE is 5.52%; applying the ANN model, the average MAE is 4.29 W and the average MAPE is 3.65%. In this case, the best result is obtained with the ANN method.

This result had an improvement of about 1.8% in MAPE error using the ANN method in comparison with FIS the method. Using FIS in sample 1 with ESTC, the average MAPE is 8.22%; using ANN, the average MAPE corresponds to 5.42%. The ANN prediction is better than FIS prediction of around 2.8%. In conclusion, in sample 1, the ANN model has the best forecasting behavior in the process than FIS, however FIS has also adequate forecasting results.



a)



b)

Fig. 5. a) Comparison between traditional load and forecasting methods in sample 1; and b) sample 2.

Finally, the ESTCs application resulted in an energy to 11.54 kWh saved per residence (i.e. 27.09% of saved energy). As for peak demand before replacing the ESs, as seen in Figure 5a, the first peak demand was 352.90 W at 12 o'clock and the maximum peak demand was 474.38 W at 19 o'clock. After ESTCs application, the peak demand was reduced to 283.04 W at 12 o'clock and the maximum peak demand was reduced to 333.29 W at 19 o'clock. This shows that the peak demand was reduced in 19.79% at 12 o'clock and in 29.74% at 19 o'clock.

4.2 ESHR case

Figure 5b shows ex-ante and ex-post load curve forecasting results regarding sample 2. In this sample, the ESs were replaced by ESHRs in 23 households. Before replacing the ESs, the FIS model predicts that the average MAE is 9.03 W and the average MAPE is 10.68%; the ANN model predicts that the average MAE is 5.58 W and the average MAPE is 7.04%. In the ESHR case, the error values of the average MAE are 6.77 W and 3.76 W and the average MAPE are 13.81% and 7.73% for FIS and ANN models respectively. Thus, the ANN prediction has the best results before and after of the replacement of ESs. Before replacing ESs: the average MAPE was less than 3.64% in the ANN model; afterwards, using ESHRs, the average MAPE was less than 6.08.

Figure 5b shows the actual first peak demand and the actual maximum demand for sample 2. In this sample, before replacing the ESs, the actual first peak demand ex-ante is 280.76 W and the actual maximum demand ex-ante is 401.93 W. In sample 2, ESHR case, the actual first peak demand ex-post and the actual maximum demand ex-post are 194.03 W and 333.29 W respectively. Table 3 shows the MAPE using the ANN method for the first peak demand is below 0.3% and for maximum demand is below 3.4%. In this case there are better predictors using the ANN method.

In sample 2, the ESHRs application resulted in an energy saving of 556.56 kWh per month, this result represents 24.19 kWh saved per residence saved (i.e. 50.04% of energy saved). The peak demand at 12 o'clock was reduced from 280.76 W to 110.5 W. This result corresponds to a reduction of 60.64%. At 19 o'clock, the reduction was from 401.93 W to 194.25 W, which represents reduction in energy consumption of 51.76%.

Table 2 gives the MAE and MAPE errors related to first peak load and maximum peak load for the FIS and ANN models respectively. Both methods Fuzzy as ANN are appropriate and adequate and their errors were below 5.2% for the first peak demand and below 3.4% for maximum demand. Figure 6 shows that the actual first peak demand is 352.90 W (ex-ante) and the actual first peak demand is 194.03 W (ex-post), related to the actual maximum demand they are 474.38 W and 333.29 W respectively.

Table 2. MAE and MAPE for peak load and maximum demand forecasted using FIS and ANN in ESTC device.

Type of event	Method	Sample 1	MAE (W)	MAPE (%)
First peak load	FIS	ex-ante	14.5	5.2
First peak load	ANN	ex-ante	8.1	3.0
First peak load	FIS	ex-post	7.2	3.8
First peak load	ANN	ex-post	6.3	3.4
Maximum peak load	FIS	ex-ante	15.9	3.4
Maximum peak load	ANN	ex-ante	17.3	3.5
Maximum peak load	FIS	ex-post	0.4	0.1
Maximum peak load	ANN	ex-post	5.4	1.6

5. Conclusions

This paper, proposed the design and implementation of daily load forecasting in the EEPs using FIS and ANN models, based on time duration and number of showers. Forecasting results were validated using MAE and MAPE errors of prediction. This validation showed that, in most of cases, the results were accurate. The use of non-traditional techniques, such as FIS and ANN, can contribute significantly to the investigation and assessment of EEPs in developing communities. These tools can be used in small and medium- sized with similar socio-economic and climate conditions, which allow to determine in advance the impact of EEPs in energy saving and reduction of peak demand on the communities.

According to the average MAPE using the ANN model, the results showed that ANN makes better predictions than FIS. In the sample 1 and the sample 2 applying the ANN method, the results showed the average MAPE ranging from 3% to 7%. Nevertheless, both ANN and FIS models have a good capacity to predict load demand in electric showers. Both methods are adequate and appropriate to forecast the first peak load and the maximum peak load.

These methods are efficacy as a reliable tool in DMS strategies. Regarding the EEPs in low-income communities, their results were positive because the consumption demand was reduced: in sample 1, the energy saved was 27.09% and in sample 2, the energy saved was 50.04%. Another important aspect of this work is the possibility of comparing two types of device to save energy in ESs. The results show that ESHR can be more efficient in energy saving by cutting off the power in electrical resistor. A relevant aspect to be considered in these EEPs is the relevant role of EE educational programs, which should include an active participation of the utilities, communities and local government in order to achieve the expected results the best use of ESs by consumers.

The method allows to predict the results of an EEP, in advance, applying FIS and ANN methods.

Additionally, we can calculate the maximum peak demand and the energy saved and we can characterize consumer behavior and reduce logistics costs in the application the EEPs.

These approaches based on soft computing achieves accurate models to forecast electricity consumption are indispensable for electric utilities in the process of design, planning and operating power systems. Furthermore, these forecasting approaches allow decision makers to implement EEP related targets. Furthermore, surveys and interviews design related with consumer behavior, regarding time duration and number of showers and the implementation of Fuzzy and ANN models can be useful and can help in the DSM actions.

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