Estimating Hourly Consumption for Residential Consumer Units Using Fuzzy Inference Systems and ANFIS

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***Abstract*—Over the last few decades, electricity consumption in the residential sector has been increasing and with the advance of technologies, different types of loads have been used and consumer behavior has changed. It is therefore important to improve electricity consumption models for residential consumer units, in order to incorporate changes in habits and consumer uncertainties. This article proposes the use of Fuzzy Inference Systems (FIS) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to estimate the electricity consumption of residential units, taking into account consumer behavior, climate and socio-economic factors. The dataset used for training and validation has 2073 hourly consumption samples that were collected from the 2019 Survey of Ownership and Habits of Use of Electrical Equipment in the Residential Class, drawn up by the *Programa Nacional de Conservação de Energia Elétrica*. The FIS and ANFIS models were implemented using the Fuzzy Logic toolbox and the ANFIS toolbox, both from MatLab. The results were evaluated in terms of mean absolute error (MAE), mean absolute percentage error (MAPE), mean square error (MSE) and root mean square error (RMSE). The proposed models were developed and validated, with the FIS model obtaining a MAPE of 40.55% and the ANFIS model 4.71%, proving to be best accuracy to the problem than the FIS model.**

***Index Terms*—intelligent systems, Fuzzy Inference Systems, Adaptive Neuro-Fuzzy Inference Systems, Estimating Residential Consumption, Hourly Consumption Model**

I. INTRODUCTION

Studies by the World Energy Council point to a transition in several countries, from centralized electricity systems to decentralized electricity systems, with the insertion of Distributed Energy Resources (DERs) [1], [2]. Although DERs connect to a distribution network, and in each case it is relatively small, it affects the system as a whole, i.e. the distribution system and the transmission system [3].

Technological advances in the energy sector and the wider dissemination of DERs will mean that consumers will no longer have the role of just consuming energy, but will play a more active role [4]. In this way, the agents involved will have different roles and consumers will no longer be passive, but will become prosumers [5].

In Brazil, with regard to changes in consumer behavior and the complexity of the system, in order to optimize the use of energy resources, the country will have to develop public policies that policies that take into account not only the growth in energy consumption, but also the new consumer behavior [4]. Within this new consumer behavior, one of the recommendations of the National Energy Plan - 2050 is to improve models for forecasting the electricity load curve, incorporating the greater participation of consumers and the associated uncertainties.

For decades, research into estimating electricity demand over a given period has focused on annual demand and on models that consider the power grid load as a total energy demand, without regard to the source of consumption [6], [7].

Therefore, in order to contribute to research into forecasting models that incorporate human aspects and the uncertainties related to the problem, this paper proposes integrating the estimation of electricity consumption for residential consumer units, correlating the climatic aspect, the economic-social aspect and the human behavioral aspect. This article combines the different aspects in a Fuzzy Inference System (FIS) and an Adaptive Neuro-Fuzzy Inference System (ANFIS).

The theory of fuzzy sets was created to deal with the vague aspect of information [8] and the theory of possibilities to deal with the imprecision of information [9]. These theories are closely linked and it is therefore possible to deal with both the imprecision and uncertainty of a set of information, and they are widely used in systems that use information provided by human beings [10]. In the literature found, a FIS can be used in several ways, the main ones being to perform intelligent home energy management [11]–[15] and to optimize energy use in the home [16]–[20]. The application of FIS for load curve estimation was found in some articles, being used to model the load curve of residential lighting [21], [22] and to model the profile or consumption of residential energy [23]–[25]. ANFIS' main applications are energy management [26]–[28] and estimating electricity consumption [29]–[33].

Next, in Section II, a brief overview will be given of the theories related to FIS and ANFIS. Section III presents the methodology used in this article, highlighting the dataset and pre-processing, the estimation models and the evaluation criteria. Section IV presents the results obtained and the relevant discussions. Finally, Section V concludes the work.

II. Related theories

A. FIS

In classical theory, the pertinence of an element is very well defined, and it can be classified as belonging or not belonging to the set. The pertinence function $\mu_A(x)$ expresses that given a universe X, the elements of this universe belong or do not belong to the set [34], [36], and is mathematically represented by Equation 1.

$$\mu_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{if } x \notin A \end{cases} \tag{1}$$

that is, the element has only two degrees of pertinence in relation to the set [0 or 1].

In fuzzy logic, an object can partially belong to a given set, because fuzzy sets have real values defined in the interval [0, 1] [8]. A fuzzy set A, defined in a universe of discourse I can be represented by Equation 2.

$$A = \{(x, \mu_A(x)) | x \in I\} \tag{2}$$

where $\mu_A(x)$ indicates how compatible x is with the set A.

A FIS has three main blocks: fuzzifier, inference and defuzzifier [35], illustrated in Figure 1.

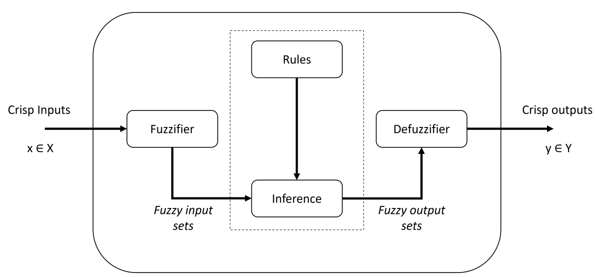

Fig. 1. Block diagram of an FIS (adapted from [36])

Normally, real values resulting from some measurement or observation are used as input to the FIS, commonly referred to as crisps values. The fuzzifier block is responsible for transforming the crisp value into a corresponding fuzzy value. It is at this stage that the linguistic values are assigned to the input variables [36].

The rules are fundamental to the good performance of a FIS and can be provided by experts. Thus, the rule base contains the set of rules that is responsible for all the fuzzy reasoning, using the linguistic variables. It is made up of rules of the type *if ... then* [36].

The inference block performs the operations of the fuzzy system according to what has been established in the rule base, which performs the fuzzy logic using the linguistic variables [36].

Finally, the defuzzifier block converts the information in the fuzzy domain into crisp output using the defuzzification methods [36], including the maximum criterion, the average of the maximum and the center of the area [35].

B. ANFIS

The main problem with fuzzy logic is that there is no organized process for transforming human knowledge or experience into a rule base, and, in order to minimize the output error, it is necessary to adjust the pertinence functions which makes validation difficult, as it requires the help of an expert. On the other hand, a neural network can learn from its environment and adapt interactively to it [37].

ANFIS is a multi-layer feedforward network that maps an input space to an output space using neural network learning algorithms and fuzzy reasoning, it can combine the word abstraction power of a fuzzy system with the numerical power of an adaptive neural network. This system is able to learn, build, count and classify, and its advantage is that it can extract rules from numerical data, or expert knowledge, and build a rule base based on the training data.

Figure 2 shows a simplified ANFIS for two inputs and one output. To represent the different adaptive capabilities, squares were used for nodes with parameters (adaptive nodes) and circles for nodes without parameters (fixed nodes) [37].

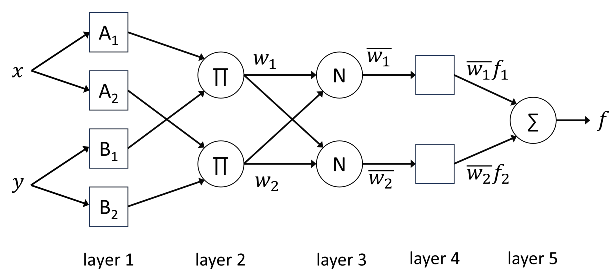

Fig. 2. ANFIS Architecture (adapted from [37])

According to [37], each of the layers has the following characteristics:

layer 1: Its output is the degree of pertinence of the respective input, based on the assumptions of the rules. Where x is the input of node i and A_i is the linguistic variable associated with its respective node, represented by Equation 3.

$$O_i^1 = \mu_{A_i}(x) \tag{3}$$

layer 2: The degree of pertinence for the consequent of each rule is calculated. The output of each node represents the degree of activation of a rule, given by Equation 4.

$$\omega_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \tag{4}$$

layer 3: The degree of activation of the rules is normalized according to Equation 5.

$$\overline{\omega_i} = \frac{\omega_i}{\omega_1 + \omega_2}, i = 1, 2, ... \tag{5}$$

layer 4: The output of this layer is calculated by the product between the normalized output of the previous layer and the degree of activation of the consequent, represented by Equation 6.

$$O_i^4 = \overline{\omega_i} f_i \tag{6}$$

layer 5: It outputs the system's crisp output, according to Equation 7.

$$O_i^5 = \sum_i \overline{\omega_i} f_i \tag{7}$$

In this way, a neuroadaptive system is built that is equivalent to an FIS of the type *Takagi-Sugeno* [37]. The ANFIS learning process is carried out iteratively until the stopping criterion is reached.

III. METHODOLOGY

A. Dataset and pre-processing

The dataset used in this work was collected from the 2019 Survey of Ownership and Usage Habits of Electrical Equipment in the Residential Class (PPH-2019), which was drawn up by the *Programa Nacional de Conservação de Energia Elétrica* [39]. As a result of this survey, various pieces of information can be obtained about the use and ownership of equipment in the residential class, such as load curves, consumption by equipment and others. The load curves can be classified according to the region of residence, federative unit, social class and month. The data was selected for the southeast region of Brazil, and hourly consumption information was obtained for each of the social classes and for each of the months.

The residential consumption data is shown in Figure 3, with a total of 1728 samples: 6 social classes, 12 average monthly temperatures (one for each month) and 24 hours per day. The data has a downward trend, as it is separated by social classes and in descending order, so the first samples refer to the highest social class and the last samples refer to the lowest social class, thus reflecting consumption for each of them.

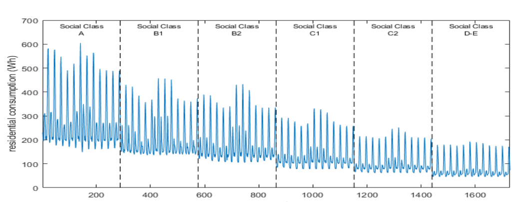

Fig. 3. Electricity consumption per hour in 2019, by social class and by month

B. Hourly consumption estimation models

1) FIS model: The research by [23]–[25] was used as a basis for estimating hourly consumption using FIS models. In the work by [23], [24], the author used the periods of the day and the occupancy of the home as inputs for the FIS and validated the system using the energy consumption measurements of just two homes as a reference.

In the work by [25], a FIS was used with "periods of the day" as input to estimate the consumption curve of the electric stove and washing machine. Another FIS was used with "day periods" and "day-night" as inputs, and this system was used to estimate the lighting consumption curve.

One of the models proposed by this research is a FIS model for estimating the hourly consumption of a home in southeastern Brazil, but with three inputs and validation using data from PPH-2019.

The inputs and outputs were classified in pertinence functions according to the specificity of each variable, the classification being as follows:

- Input "social class": "upper", "middle", "middle-lower" and "lower"
- Input "temperature": "low", "medium" and "high"
- Input "time": "sleep 1" (0-4h), "morning" (4-11h), "lunch" (11-15h), "afternoon" (15-18h), "night" (18-21h) and "sleep 2" (21-23h)
- Output "consumption": "low", "low-medium", "medium", "medium-high" and "high"

Figures 4, 5, 6 and 7 show the curves of the relevance functions for each of the inputs and outputs, respectively.

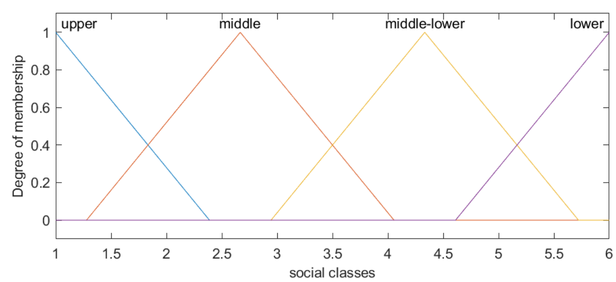

Fig. 4. Pertinence functions of the "social class" input

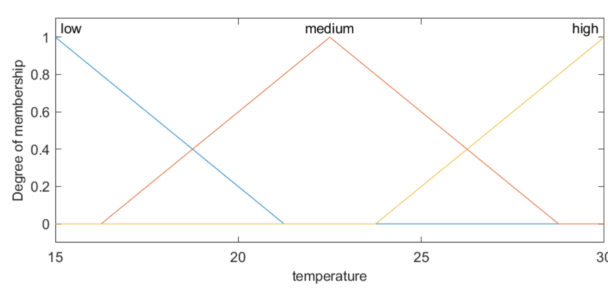

Fig. 5. Pertinence functions of the "temperature" input

2) ANFIS model: Some previous works, such as [29], [33], have already estimated energy consumption using ANFIS models. This work differs from the others in that it uses different input variables and is applied to the Brazilian scenario of residential electricity consumption.

To estimate hourly consumption using the ANFIS model, the FIS model was used as a base. As previously mentioned, the ANFIS system uses neural network learning algorithms to

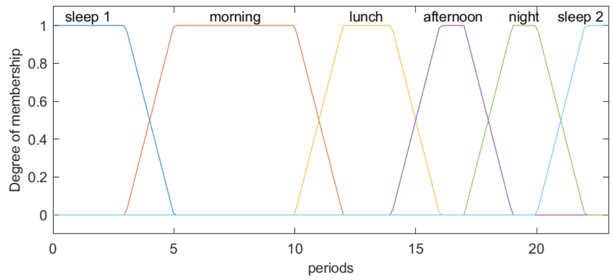

Fig. 6. Pertinence functions of the "time" input

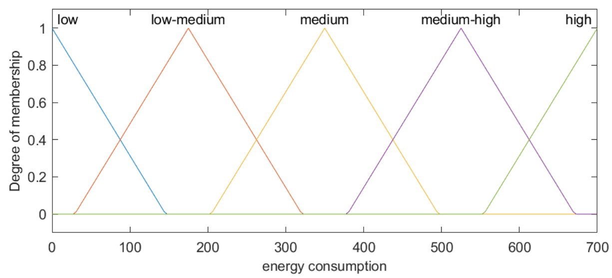

Fig. 7. Pertinence functions of the "consumption" output

train the parameters of a fuzzy system, for which the data must be separated into training and validation data. To train and validate the ANFIS model, the data was randomly separated into 80% for training and 20% for validation.

In order to make a comparison between the models proposed in this research, the ANFIS model used the same number of inputs and outputs as the FIS model, as well as the same number of pertinence functions for each of them. However, the system generated by the ANFIS model is of the *Sugeno* type, while the FIS model is of the *Mamdani* type.

C. Evaluation criteria

The results of the FIS and ANFIS models for estimating hourly electricity consumption for the residential sector are evaluated and compared using the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE) and Root Mean Square Error (RMSE). The following formulas are used to determine these evaluation criteria:

$$MAE = \frac{1}{n}\sum_{n}^{i=1}|Y_i - \hat{Y}_i| \quad (8)$$

$$MAPE = \frac{1}{n}\sum_{n}^{i=1}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \quad (9)$$

$$MSE = \frac{1}{n}\sum_{n}^{i=1}\left(Y_i - \hat{Y}_i\right)^2 \quad (10)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{n}^{i=1}\left(Y_i - \hat{Y}_i\right)^2} \quad (11)$$

where n is the number of validation samples, Y_i is the real value of the sample and $\hat{Y}_i$ is the estimated value of the sample.

IV. Results and Discussions

The results were obtained for each of the proposed models and according to the configuration of inputs and outputs previously defined. In order to obtain the result of the FIS model and make a comparison with the ANFIS model, the same data was used to validate the ANFIS model.

Figure 8 shows the expected values and the estimated values for each of the FIS model validation samples. It can clearly be seen that the FIS model had a high error. However, as presented by [37], the creation of the rule base and the adjustment of the pertinence functions does not follow an organized process and, most of the time, is carried out empirically.

By combining all the possible inputs, a rule base with 72 rules (4x3x6) was obtained. As the number of rules is high, the adjustment and combination process was very laborious and even then the error was considerable. To minimize the error, the rule base was redone several times, considering a logic between the input and output variables.

This model is a first version and the rule base can be improved with the help of an expert, working on the relationships between the inputs and the output. In this way, the model is expected to obtain better results.

Figure 9 shows the expected values and the estimated values for each of the ANFIS model validation samples. It can be seen that the error was much smaller and in most points the estimated value was very close to the expected value. This shows the power of the ANFIS tool in combining fuzzy systems with an artificial neural network.

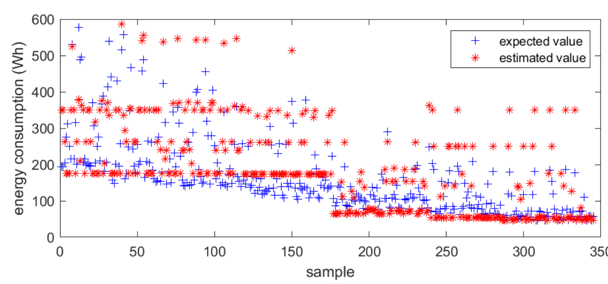

Fig. 8. Expected values *vs* estimated values for FIS model

Table I shows the error values used to evaluate and compare the models. These values corroborate what has already been observed. The ANFIS model performed better than the FIS model in all evaluation criteria. As the MAE, MSE and RMSE are absolute errors, they can be used to compare the models, but it is not possible to say that a model is good or bad by looking at these values. However, the MAPE has an independent scale, which is based on the relative error, and is therefore the most significant [41]. Thus, it can be said that the ANFIS model is very good, as it obtained a low MAPE of only 4.71%

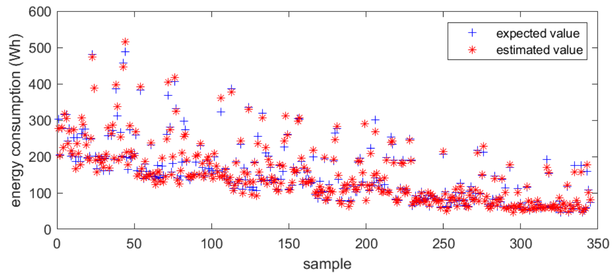

Fig. 9. Expected values *vs* estimated values for ANFIS model

TABLE I
ERRORS FOR EACH MODEL

Modelo	MAE	MAPE	MSE	RMSE
FIS	71,36	40,55%	8698,25	140,28
ANFIS	8,33	4,71%	211,12	14,53

V. CONCLUSION

This study aimed to estimate residential electricity consumption by correlating the climatic aspect, the economic-social aspect and the human behavioral aspect. Two estimation models were developed: a FIS and an ANFIS.

For both systems, the same inputs were considered, with the same number of pertinence functions for each one, as well as for the output of the models. Figures 8 and 9 show the validation of the models by comparing the expected value and the estimated value for each sample. The MAE, MAPE, MSE and RMSE indicators were used to metrify the evaluation of the models, and the results for each model are shown in the table I. The model using ANFIS showed a much better result than the model using FIS. As MAPE is a relative error, it can be said that the model using ANFIS performed very well for estimating hourly residential electricity consumption.

The models obtained through this work were able to correlate the behavioral-human aspect, the economic-social aspect and the climatic aspect for estimating hourly electricity consumption for the residential sector, with the model using ANFIS standing out the most. As this is a first version of the estimation of energy consumption considering these aspects of the Brazilian scenario, the work has fulfilled what was proposed. For future work, other aspects can be selected for use and the models can be improved.

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