Predicting Household Electricity Consumption in the Face of El Niño and La Niña Events: A Fuzzy Logic-Based Model

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***Resumen*—This study focuses on developing a fuzzy logic model for predicting household energy consumption, considering influential factors such as the El Niño and La Niña climate phenomena. As climate events increasingly impact energy usage patterns, understanding and forecasting their effects on electricity demand becomes crucial. The proposed model incorporates variables like the number of residents, outdoor temperature, and the intensity of climatic phenomena to anticipate monthly energy consumption. By addressing these dynamic influences, the model aims to contribute to efficient energy management strategies, particularly during climatic events, fostering a sustainable approach to residential energy consumption.**

I. Introduction

Undoubtedly, electricity represents one of the primary energy sources for humanity, as its application encompasses various daily activities, from domestic to industrial settings. However, the inadequate use of energy entails negative impacts on the environment, such as greenhouse gas emissions and depletion of natural resources. These impacts, together with the growing search for sustainability and resource optimization, underline the crucial importance of energy consumption prediction, control, and optimization models. These models not only allow for the precise quantification of energy use, but also play a fundamental role in promoting conscious and sustainable practices for the benefit of the environment and society.

Regarding residential energy consumption models, various methodologies have been developed, such as linear regression, neural network, time series, decision trees, support vector machines, and boosted tree ensembles, among others. Although these techniques have demonstrated good performance, their effectiveness is strongly tied to the quality of the database, unlike fuzzy models.

In (1) is proposal a comprehensive predictive control system that incorporates an optimized model based on Long Short-Term Memory (LSTM) to forecast both hourly load and electricity prices in a typical smart home. Additionally, a fuzzy logic-based controller for Demand Response is implemented, allowing optimal programming of household appliances. Compared to conventional prediction techniques such as linear regression, decision trees, and SVM, the proposed LSTM predictive model demonstrates superior performance. The Fuzzy controller has also proven effective in reducing electrical costs by selecting the optimal schedule for turning appliances on and off, highlighting how fuzzy logic emerges as an essential tool to efficiently model and control energy consumption in smart residential environments.

In (2) is developed an effective fuzzy logic algorithm to anticipate daily electric energy consumption and reduce associated costs. Unlike previous approaches, the construction of this model was based on a solidly structured database, recognized as essential due to the complexity of these electrical consumption systems. The proposed approach highlights the importance of anticipating consumption through fuzzy logic to efficiently manage costs and limit peak demand, providing flexibility without disrupting user comfort. The relevance of the data in this model could justify the possibility of errors in the approach presented in this article.

El Niño and La Niña climate phenomena are natural events that affect global weather patterns. During El Niño, warming of the Pacific Ocean waters leads to warmer and drier conditions, increasing the use of air conditioning, especially in tropical areas. In contrast, La Niña, with cooler waters, can generate an increase in humidity, also raising the demand for air conditioning. On the other hand, El Niño can cause colder winters in temperate zones, increasing the need for heating, while La Niña, by lowering summer temperatures, can lead to higher demand for heating.

These variations in the use of air conditioning systems during El Niño and La Niña generate a higher energy demand, challenging the electricity supply. Economically, this translates into higher bills and, environmentally, it contributes to increased emissions and air pollution. On the other hand, the El Niño phenomenon significantly affects the supply of electrical energy in Colombia approximately 70 % of electrical energy is generated through hydroelectric plants

(3). Therefore, efficient management of energy demand and efficiency practices are essential to mitigate these impacts on consumption during these climatic phenomena.

II. Mathematical Model

This fuzzy logic model aims to anticipate energy consumption levels in households, taking into account climatic phenomena such as La Niña and El Niño. As mentioned earlier, these phenomena can influence energy consumption patterns in homes. The relevance of addressing this issue lies in the need to understand and predict how these climatic events can impact the demand for electrical energy in households. Given the increasing climate variability and its impact on the availability and use of energy resources, having a model that incorporates these climatic variables would provide a valuable tool for planning and efficiently managing the energy supply. Furthermore, by anticipating energy consumption levels based on specific weather conditions, proactive strategies can be implemented to optimize resource distribution and mitigate potential impacts on the electrical infrastructure.

Variables

For the construction of this model, the following input variables are considered:

- Number of resident: The number of people in a household can directly impact the electrical load, as they are the ones using devices and appliances.
- Number of children: Although the number of children is included in the total number of residents, for this model, it is considered as an individual variable because children may have low energy awareness, which can be a reason for high consumption levels.
- Number of Rooms:This variable is crucial as it is strongly correlated with the number of devices and lighting. It also aims to represent the size of the dwelling.
- Quantity of Appliances: This factor is decisive, as the quantity and type of appliances in the home directly impact electrical consumption. Although this model does not specify the type of appliances, the quantity can provide an idea of what appliances are present.
- Frequency of use of household appliances: It represents how often non-essential or non-basic appliances are used in the home. Basic appliances refer to the refrigerator, electric stove, washing machine, blender, i.e., those that represent more of a necessity than a luxury.
- Outdoor temperature: Variations in temperature can influence the need for heating or cooling, directly affecting energy consumption.
- Intensity of El Niño Phenomenon: This climatic phenomenon can affect weather conditions and influence energy consumption patterns by increasing the demand for fan and air conditioning usage.
- Intensity of La Niña Phenomenon: Similar to El Niño, La Niña can have climatic effects that impact energy consumption, especially in the need for heating or cooling.

Outputs:

- Mensual Electric Energy Consumption: The output of this model is the monthly energy consumption in kilowatt-hours per month (kWh/month) for the household based on its characteristics.

Universe of Discourse

In this model, it is assumed that a Colombian household does not exceed 10 individuals, including 5 children, nor does it have more than 10 rooms. It is also assumed that the number of household appliances in a home does not exceed 30. It is important to note that these measurements are approximate and may vary; however, the most commonly encountered scenarios are addressed. The frequency of use of household appliances is measured as the number of hours per day for appliances that are not considered basic.

As mentioned, El Niño and La Niña phenomena are climatic disturbances that affect sea surface temperatures in the Pacific Ocean and global climate. The intensity of each phenomenon is measured based on anomalies in ocean temperature and climate. Currently, there is no global standard for classifying the intensity of these phenomena, as some experts rely on the magnitude of sea surface temperature anomalies, the Southern Oscillation Index, multivariate indices, the magnitude of climatic effects, or economic impact. For the purposes of this model, we will use the classification of events into Weak, Moderate, and Strong, as established by (4), based on the standard deviation or degrees Celsius of the sea surface temperature anomalies in the central region, also known as the Niño 3 region. Associated with positive anomalies, the intensity of the El Niño phenomenon will be greater than 1.03ºC, and the La Niña phenomenon will be less than -0.79ºC, associated with negative anomalies. Currently, there is no upper or lower limit; however, for the model's purposes, a small limit is considered.

- Number of resident $\in [0, 10]$
- Number of children $\in [0, 5]$
- Number of rooms $\in [0, 10]$
- Quantity of appliances $\in [0, 30]$
- Frequency of use of appliances $\in [0, 24]$[hours]
- Outdoor temperature $\in [0°C, 40°C]$
- Intensity of El Niño Phenomenon $\in [1.03°C, 2°C]$
- Intensity of La Niña Phenomenon $\in [-2°C, -0.79°C]$
- Electric Energy Consumption $\in [50, 500]$ [kWh/month]

Linguistic Categories

For the input variables such as Number of residents, Number of children, Quantity of household appliances, Frequency of use of household appliances, and Outdoor Temperature, we choose to use the three classical linguistic categories. This decision is justified as these categories adequately address a sufficient range of scenarios while avoiding redundancies and unnecessary complexities in the fuzzy system. The use of three categories strikes a suitable balance between model simplicity and the ability to effectively represent the various situations that may arise in the mentioned variables. For the variables Intensity of El Niño Phenomenon and Intensity of La Niña Phenomenon, the linguistic categories are established according to the classification of the phenomena given by (4).

- Number of resident:
  - Few
  - Moderate
  - Many
- Number of children
  - Few
  - Moderate
  - Many
- Quantity of household appliances
  - Low
  - Moderate
  - High
- Frequency of use of household appliances
  - Low
  - Moderate
  - High
- Outdoor temperature
  - Cold
  - Moderate
  - Hot
- Intensity of El Niño Phenomenon
  - Weak $\in [1.03°C, 1.48°C]$
  - Moderate $\in [1.49°C, 1.94°C]$
  - High: $> 1.94°C$
- Intensity of La Niña Phenomenon
  - Weak $\in [-0.79°C, -1.06°C]$
  - Moderate $\in [-1.07°C, -1.33°C]$
  - High: $< -1.33°C$
- Electric Energy Consumption
  - Very Low
  - Low
  - Moderate
  - High
  - Very High

Five linguistic categories are established for energy consumption, aiming for greater precision and communication of results. This choice allows addressing the diversity in residential consumption based on each home's specific characteristics, facilitating the segmentation of consumptions and enabling more precise analyses of energy consumption. It aligns with standards and regulations for specific evaluations, particularly in the context of energy efficiency.

Fuzzy Membership Function

The membership functions for each fuzzy set in this system are implemented using Gaussian, sigmoidal, and S-shaped functions. Each fuzzy set will employ one of these functions with variations in the parameter values, which will be detailed for each set later on.

- Gaussian Fuzzy Membership (gaussmf)

$$\mu(x, \mu_x, \sigma) = e^{-\frac{(x-\mu_x)^2}{\sigma^2}} \tag{1}$$

- Sigmoid Membership Function (sigmf(x,c,b))

$$\mu(x, c, b) = \frac{1}{1 + e^{-c(x-b)}} \tag{2}$$

- S-function fuzzy membership ($smf(x, a, b)$)

$$\mu(x, a, b) = \begin{cases} 0 & si \quad x \leq a \\ \frac{2(x-a)}{(b-a)^2} & si \quad a < x < \frac{a+b}{2} \\ 1 - \frac{2(x-b)}{(b-a)^2} & si \quad \frac{a+b}{2} < x < b \end{cases} \tag{3}$$

- **Number of Residents:** The membership function for the fuzzy set of Few Residents is defined as $1 - smf(x, 1, 5)$ and for the set of Many Residents it is established as $smf(x, 7, 10)$. The membership function for the set of a Moderate number of Residents it is modeled using a Gaussian function with the form $gaussmf(x, 6, 1)$.

- **Number of Childrens:** Similar to the membership functions for the variable Number of Residents, there is a membership function $1 - smf(x, 1, 3)$ for the Few Children set, $smf(x, 3, 5)$ for the Many Children set, and finally, a $gaussmf(x, 3, 0.3)$ for the Moderate Children set.

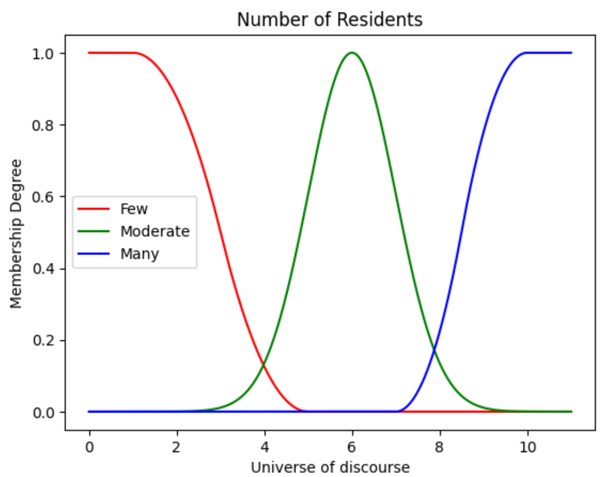

Figura 1: Membership Functions of Number of Residents

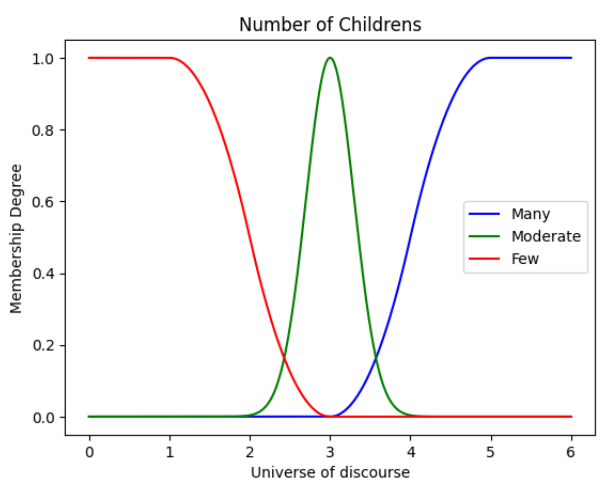

Figura 2: Membership Functions of Number of Chldrens

- **Number of Rooms:** The membership function for the Low Number of Rooms fuzzy set is $1 - smf(x, 1, 5)$, and $smf(x, 6, 1)$ for High Number of Rooms and finally, a $gaussmf(x, 7, 10)$ for the Moderate Number of Rooms set.

- **Quantity of Appliances:** Considering the information regarding the quantity of appliances in an average household, typically composed of two adults and two children, there is an estimated average of 18 to 20 electrical and electronic devices (5). In order to reflect a moderate level of appliances within the context of this fuzzy set, the mean is set at 15, as it positions itself in an intermediary stance between households with a low and high quantity of these devices. Consequently, for the Low Quantity fuzzy set, the membership function is

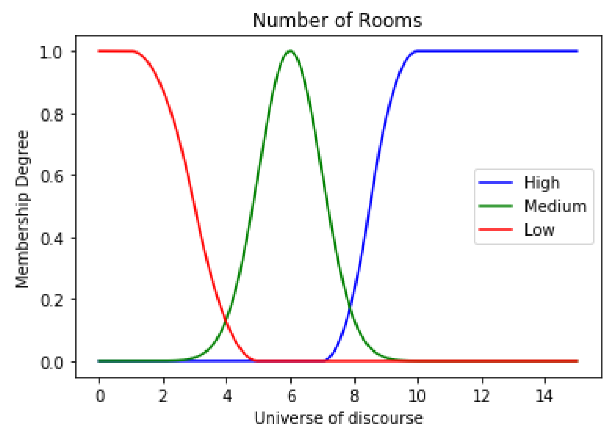

Figura 3: Membership Functions of Number of Rooms

set as $sigmf(x, 10, -1)$, for the High Quantity set, it is $sigmf(x, 20, 1)$, and finally, a $gaussmf(x, 15, 3)$ is employed for the 'Moderate Quantity' set.

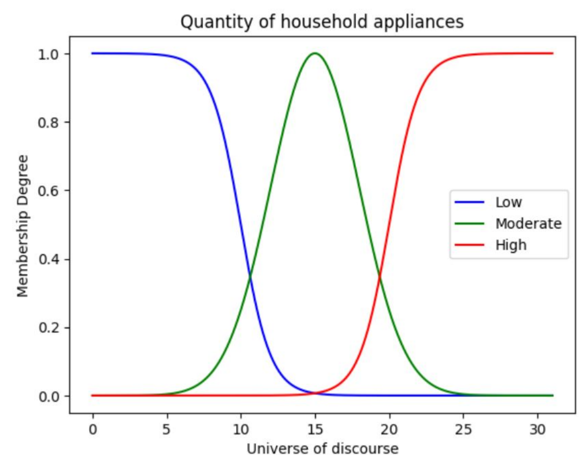

Figura 4: Membership Functions of Quantity of Appliances

- **Frequency of use of Appliances:** For the variable of usage frequency of non-basic household appliances, a membership function is defined as $sigmf(x, 6, -1)$ for the 'Low Use' set, and $sigmf(x, 17, 1)$ for the 'High Use' set. Additionally, for the 'Moderate Use' set, a $gaussmf(x, 12, 2)$ is employed.

- **Outdoor temperature:** For the fuzzy set ”Cold"the membership function is defined as $sigmf(x, 10, -1)$, for "Hot,ït is $sigmf(x, 30, 1)$, and for "Moderate,.ª $gaussmf(x, 20, 3)$ is utilized.

- **Intensity of El Niño Phenomenon** According to (4), the intensity of the El Niño

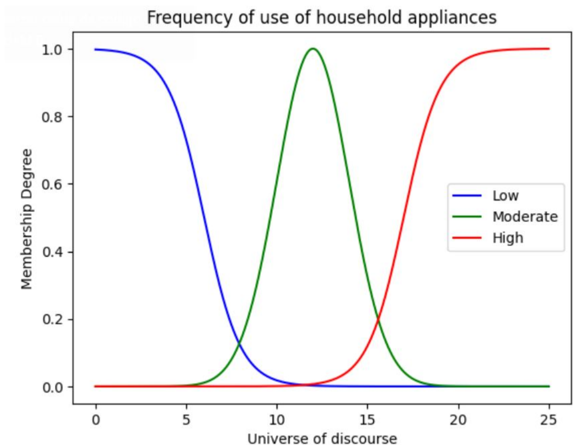

Figura 5: Membership Functions of Frequency of use of Appliances

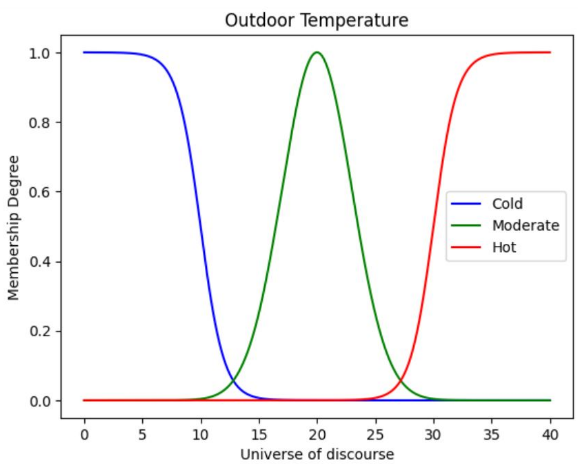

Figura 6: Membership Functions of Outdoor Temperature

phenomenon is considered weak when the standard deviation of the series of anomalies of sea surface temperature (ASST) in the central Pacific Ocean (Niño 3 Region) falls between $1\sigma < ASST \leq 1.5\sigma$, equivalent to temperatures in degrees Celsius ranging from 1.03ºC to 1.48ºC. It is considered moderate when $1.5\sigma < ASST \leq 2\sigma$, equivalent to temperatures from 1.49ºC to 1.94ºC, and it is considered strong when $ASST > 2\sigma$, corresponding to temperatures greater than 1.94ºC. Therefore, the membership function is defined as follows: for the 'Weak Intensity' set, it is $(1 - smf(x, 1, 1.48))$, for 'Strong Intensity' it is $smf(x, 1.6, 1.94)$, and for 'Moderate Intensity', a $gaussmf(x, 1.5, 0.05)$ is employed.

- **Intensity of La Niña Phenomenon:** According to (4), the intensity of the La Niña phenomenon is considered weak when the standard deviation of the series of anomalies of sea surface temperature

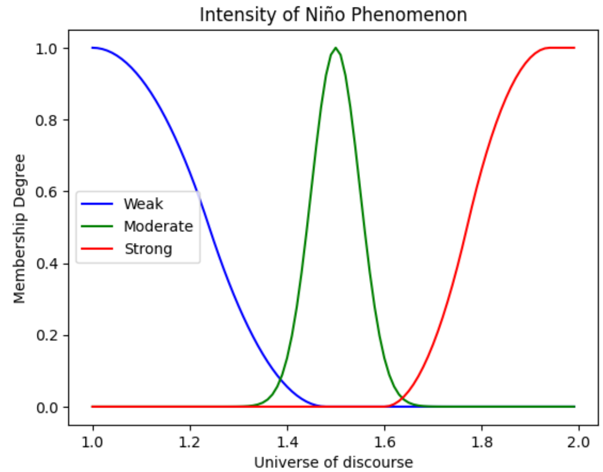

Figura 7: Membership Functions of El Niño Phenomenon Intensity

(ASST) in the central Pacific Ocean (Niño 3 Region) falls between $1\sigma < ASST \leq 1.3\sigma$, equivalent to temperatures in degrees Celsius ranging from -0.79ºC to -1.06ºC. It is considered moderate when $1.3\sigma < ASST \leq 1.6\sigma$, equivalent to temperatures from -1.07ºC to -1.33ºC, and it is considered strong when $ASST > 1.6\sigma$, corresponding to temperatures lower than -1.33ºC. Therefore, the membership function is defined as follows: for the 'Weak Intensity' set, it is $smf(x, -1.2, -0.8)$, for 'Strong Intensity' it is $smf(x, -2, -1.33)$, and for 'Moderate Intensity', a $gaussmf(x, -1.25, 0.1)$ is employed.

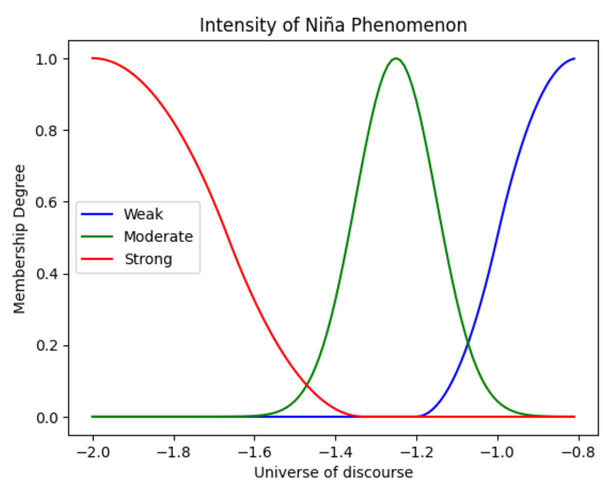

Figura 8: Membership Functions of La Niña Phenomenon Intensity

- **Electric Energy Consumption:** The membership functions for the .Electric Energy Consumption.output variable were designed using S and Gaussians functions.

For the "Very Low Consumption"set, the function $1 - smf(x, 60, 150)$ is employed. For the "Low Consumption"set, a Gaussian function gaussmf with parameters $(\mu = 180, \sigma = 20)$ is used. The "Moderate Consumption"set employs a Gaussian function (gaussmf) with parameters $(\mu = 250, \sigma = 20)$. Another Gaussian function (gaussmf) with parameters $(\mu = 350, \sigma = 20)$ is used for the "High Consumption"set. Finally, the function $smf(x, 350, 500)$ is utilized for the "Very High Consumption"fuzzy set.

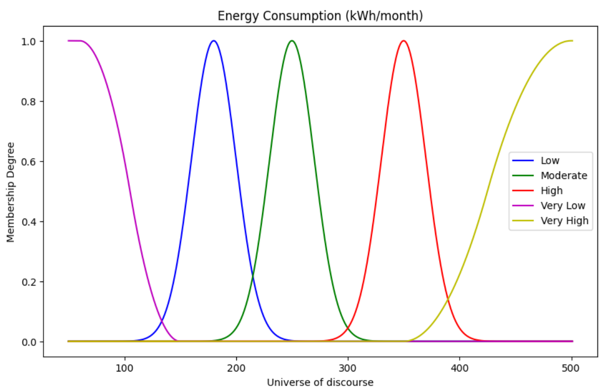

Figura 9: Membership Functions of Electric Energy Consumption

Model Assumptions

It is understood that there are several factors that can significantly impact energy consumption levels, which are not accounted for in this system. The reason for not considering these additional variables is to maintain the simplicity of the fuzzy logic-based model, as the objective at this stage is not to construct a complex model. However, there is a plan to include or exclude certain variables in future model enhancements. To minimize errors resulting from the absence of certain variables, the following assumptions are made:

- Homes with few appliances are assumed to have only basic appliances.
- Homes with a moderate or high quantity of appliances are assumed to have at least one ventilation or cooling element, such as a fan, air conditioner, or heater.
- The number of rooms in a home does not exceed the number of residents.

Rule Base

To write the some rules of the rule base, we will take into account some abbreviations: Number of Residents (NR), Number of childrens (NC), Number of rooms (NRM), Quantity of Appliances (NHA), Frequency of use of household appliances (FHA), Temperature (T), Intensity of El Niño Phenomenon (I-Niño), Intensity of La Niña Phenomenon (I-Niña), y Electric Energy Consumption (kWh).

- IF (NR is Few) and (NC is few) and (NRM is Low) and (NHA is Low) and (FHA is Low) and (T is Cold or T is Moderate or T is Hot) and (Not I-Niño) and (I-Niña is Weak or I-Niña is Moderate or I-Niña is Strong) THEN (kWh is Very Low)

- IF (NR is Few) and (NC is few) and (NRM is Low) and (NHA is Low) and (FHA is Low) and (T is Cold or T is Moderate or T is Hot), and (Not I-Niña) and(I-Niño is Weak or I-Niño is Moderate or I-Niño is Strong) THEN (kWh is Very Low)

- IF (NR is Few) and (NC is few) and (NRM is Low) and (NHA is Moderate) and (FHA is Low) and (T is is Moderate), and (Not I-Niña) and(I-Niño is Weak) THEN (kWh is Very Low)

- IF (NR is Few) and (NC is few) and (NRM is Low) and (NHA is Moderate) and (FHA is High) and (T is Hot), and (Not I-Niña) and(I-Niño is Strong) THEN (kWh is Moderate)

- IF (NR is Moderate) and (NC is Low) and (NRM is Moderate) and (NHA is Moderate) and (FHA is Moderate) and (T is Moderate), and (Not I-Niña) and(I-Niño is Weak) THEN (kWh is Moderate)

- IF (NR is Moderate) and (NC is Moderate) and (NRM is Moderate) and (NHA is Moderate) and (FHA is High) and (T is Moderate), and (Not I-Niña) and(I-Niño is Weak) THEN (kWh is High)

- IF (NR is Moderate) and (NC is Moderate) and (NRM is Moderate) and (NHA is Moderate) and (FHA is High) and (T is Cold), and (Not I-Niño) and(I-Niña is Strong) THEN (kWh is High)

- IF (NR is Moderate) and (NC is Many) and (NRM is Moderate) and (NHA is High) and (FHA is High) and (T is Cold), and (Not I-Niño) and(I-Niña is Strong) THEN (kWh is Very High)

- IF (NR is Many) and (NC is Many) and (NRM is High) and (NHA is High) and (FHA is High) and (T is Hot), and (Not I-Niña) and(I-Niño is Strong) THEN (kWh is Very High)

- IF (NR is Many) and (NC is Many) and (NRM is High) and (NHA is High) and (FHA is High) and (T is Hot), and (Not I-Niña) and(I-Niño is Strong) THEN (kWh is Very High)

- IF (NR is Few) and (NC is Few) and (NRM is High) and (NHA is High) and (FHA is High) and (T is Hot), and (Not I-Niña) and(I-Niño is Strong) THEN (kWh is Very High)

- IF (NR is Many) and (NC is Many) and (NRM is High) and (NHA is Low) and (FHA is Hgh) and (T is Moderate), and (Not I-Niña) and(I-Niño is Weak THEN (kWh is Moderate)

There may be a large rule base; however, the model will consider only some relevant rules that represent more probable scenarios.

T and S Norms

Two S-norms and two T-norms are considered as logical operators.The T-norms will be used to perform the intersection between fuzzy sets, and the S-norm for the union. The norms to be used are presented below, and a comparison of results with respect to the norms will be presented in the results section.

- T-Norms
  - Product: $T(a, b) = ab$
  - Minimum: $T(a, b) = Min(a, b)$
- S-Norms
  - Maximum: $S(a, b) = Max(a, b)$
  - Minimum : $S(a, b) = Min(a + b, 1)$

Defuzzification

Defuzzification is the process of converting an output fuzzy set into a single, crisp value. In this case, we will use three defuzzification methods:

- Centroid:Calculates the center of mass of the output fuzzy set.

- Mean of Maxima (MOM): Calculates the mean of the values with the highest membership degree in the output fuzzy set.

- Bisector: Divides the area under the curve of the fuzzy set into two equal areas, and the output corresponds to the value that divides the areas.

Scikit Fuzzy - Python

The fuzzy inference model was implemented in Python using the scikit-fuzzy (skfuzzy) library (6). This powerful library provides a wide variety of functions that simplify the construction of models based on fuzzy logic. It is important to note that, by default, Skfuzzy uses a Mamdani inference system and the Max-Min composition rule.

During the model construction process, essential membership functions were created, such as smf, sigmf, and gaussmf, which are fundamental for defining the fuzzy relationships between the variables involved. These functions allow for modeling the uncertainty and imprecision of the system's inputs and outputs.

In terms of structure, the fuzzy system was configured as a ControlSystem, in which the variables were specified as control variables, including both antecedents and consequents. When defining the kWh variable as a consequent, the defuzzification method that would determine the system output was also detailed. This output corresponds to the energy consumption prediction.

III. Results

Case of Study:

From a small database, we found households with different characteristics that can be useful for studying the performance of the fuzzy model. One of these cases is a household with 3 residents, one of whom is a child. They have 3 bedrooms, and around 12 appliances, and use them for around 14 hours a day. Due to the high intensity of the El Niño phenomenon at the beginning of this year (2024), we will assume an intensity of 1.8 and a temperature of around 21ºC. With this data, the model yielded the following results with variations in the norms and defuzzification methods. In this case, a consumption of 177 kWh/month would be expected.

Using the T-norm: Product and the S-norm: Minimum for the intersection and the union, respectively. The following results are obtained:

- Using the Centroid defuzzification method, a consumption of 184.79 kWh/month is obtained for this household.

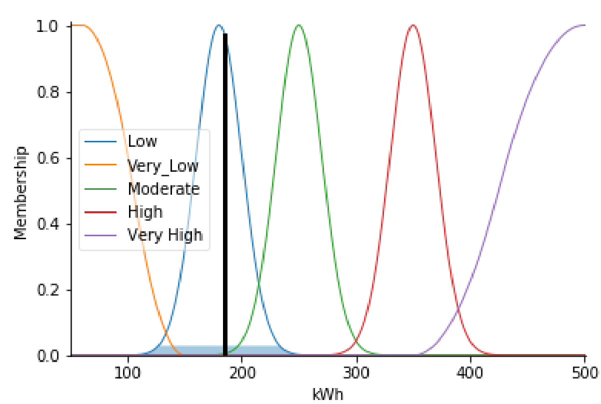

Figura 10: Output using Centroid defuzzifucation method and the norms, product and minimum

- Using the Bisector defuzzification method, the energy consumption estimate is 182.727 kWh/month.

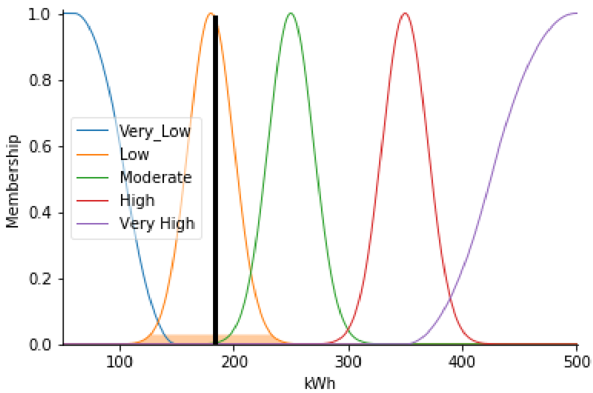

Figura 11: Output using Bisector defuzzifucation method and the norms, product and minimum

- Using the MOM as defuzzification method, the result is 179.994 kWh/month

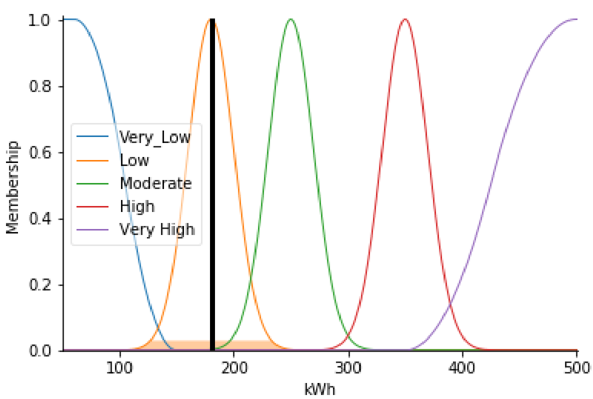

Figura 12: Output using MOM defuzzifucation method and the norms, product and minimum

Using the T-norm: Minimum and the S-norm: Maximum for the intersection and the union, respectively. The following results are obtained:

- Using Centroid defuzzification method, the consumption energy is 190.033 kWh/month
- Using the Bisector method the result is 184.890 kWh/month
- Using MOM method, the estimation is 180.003 kWh/month

The response areas differ significantly when using the two combinations of norms. When employing the T-norm of product and the S-norm of minimum, a considerably smaller response set is obtained compared to the result obtained when

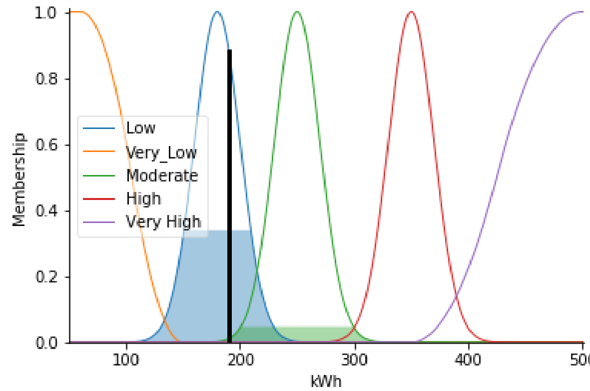

Figura 13: Output using Centroid defuzzifucation method and the norms, Minimum and Maximum

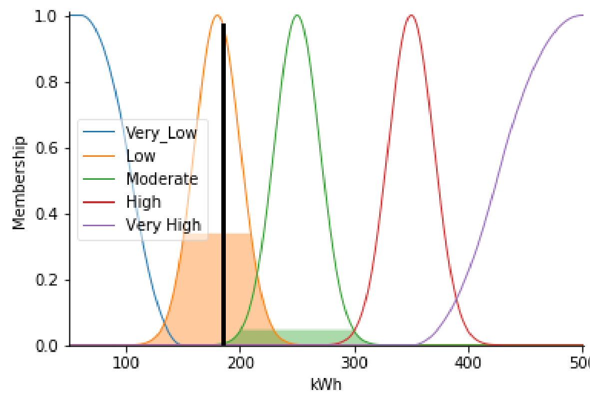

Figura 14: Output using Bisector defuzzifucation method and the norms, Minimum and Maximum

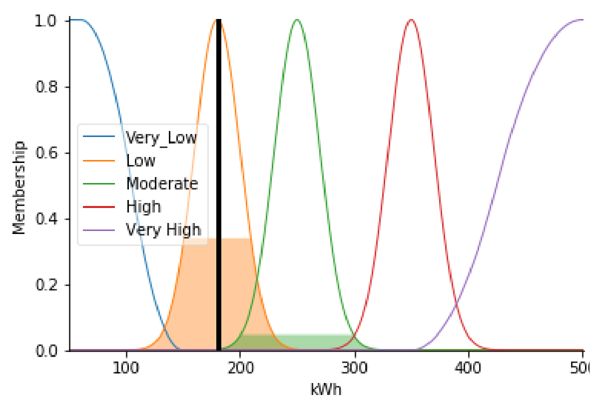

Figura 15: Output using MOM defuzzifucation method and the norms, Minimum and Maximum

using the T-norm of minimum and the S-norm of maximum. The latter covers a larger area, including two fuzzy sets: low consumption and moderate consumption.

In terms of the response set area, a larger dimension could offer various advantages by capturing greater uncertainty and providing more robust results against changes in system inputs. However, this approach could result in less precise outcomes. On the other hand, a smaller response area can generate more accurate results but also runs the risk of lacking robustness. This dichotomy is evident in the results obtained with different defuzzification methods, especially when using norms that lead to a smaller response set, such as the T-norm of product and the S-norm of minimum. With the various defuzzification methods employed, the results come closer to actual electricity consumption. Finally, the defuzzification methods Centroid, Bisector, and MOM lead to estimation errors ranging from 1 % to 7 %, with MOM yielding the lowest errors.

Response surface

To analyze the responses, two input variables were modified while keeping the others constant. In this case, the intensity of El Niño and La Niña phenomena, as well as the frequency of household appliance usage, were examined, with the latter being one of the most relevant variables when studying energy consumption. Although the responses clearly show how energy consumption increases with higher appliance usage in the home, when analyzing the influence of the intensity of each phenomenon, fluctuations or oscillations are observed in some segments. These fluctuations indicate that households that, under normal conditions, use their appliances intensively may experience increases in their energy consumption as the intensity of these phenomena grows.

However, in certain segments, the surfaces are too flat, highlighting the need to consider other variables and expand the rule base to obtain more accurate results.

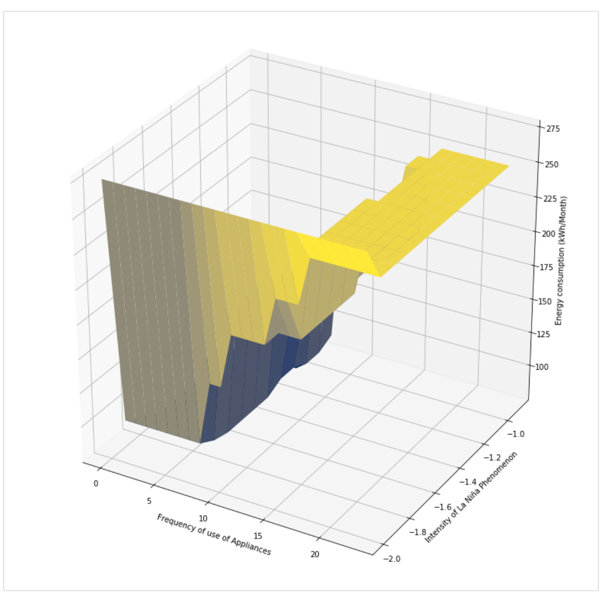

Figura 16: Response surface varying the Frequency of use of appliances and the intensity of La Niña phenomenon

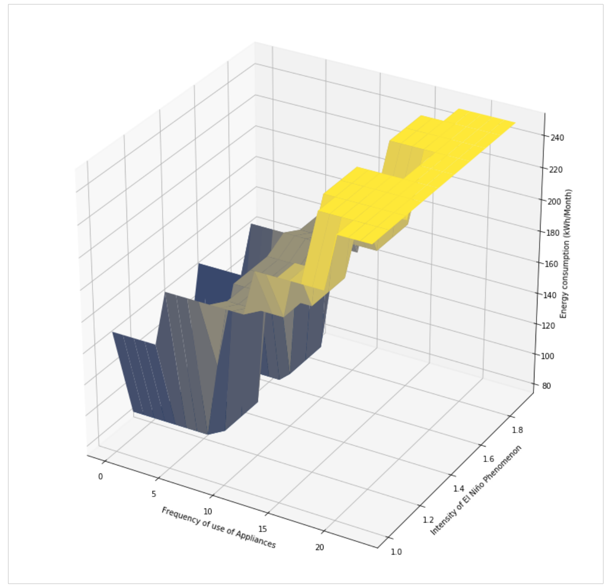

Figura 17: Response surface varying the Frequency of use of appliances and the intensity of El Niño phenomenon

Conclusion

The application of fuzzy logic emerges as a valuable alternative in data-scarce scenarios, particularly in contexts where the individual characteristics of households and the intensity of climatic phenomena, such as El Niño and La Niña, are unknown.

Based on the results obtained in the study, it is concluded that the defuzzification method MOM (Mean of Maximum) stands out as the most effective option for estimating energy consumption. Additionally, the use of T-Norm: Product and S-Norm: Minimum contributes to a more precise model. However, it is emphasized that these norms could compromise the robustness of the constructed model. In contrast, T-Norm: Minimum and S-Norm: Maximum could enhance robustness by providing a broader response area.

While the developed model demonstrates effectiveness in estimating energy consumption in certain scenarios, it is subject to significant improvements. The current limitation lies in the rule base of the fuzzy system, which does not encompass all possible cases. Expanding the number of rules emerges as a promising direction for future research, with the potential to achieve more robust results and the construction of a more resilient model. These limitations are reflected in the obtained response surfaces since, despite the variability of two parameters, it is evident that the model requires more decision rules or a greater number of variables to enhance its performance. Varying two parameters is not sufficient in this case to determine energy consumption levels adequately.

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