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**Article**

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# Localized Energy Poverty Index

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**ABSTRACT**

The impact of limited access to electricity varies based on the population. Our team evaluates the degree of deprivation experienced by different groups in order to identify energy poverty (EP). Through the use of a multi-criteria methodology such as technique for order performance by similarity to ideal solution and Shannon entropy methods, we then establish an EP index. This index allows us to compare populations and determine which are better or worse off. Our research produces a localized EP index, which outlines the various factors that contribute to the EP of a specific population. The localized index identifies poverty within a group while the EP index combines this information to provide an energy-specific index. This index is useful in determining the feasibility of improving electricity service provision.

**Keywords:** Energy Poverty, Energy Poverty Index, Colombia, Technique for Order Performance by Similarity to Ideal Solution, Shannon's Entropy
**JEL Classifications:** I32

## 1. INTRODUCTION

Energy poverty (EP) refers to the lack of access to essential services that can be obtained through the use of electricity. There are varying interpretations of the definition of EP. According to the United Nations Development Programme, EP is the inadequate access to affordable, dependable, high-quality energy services that are environmentally and health-friendly, and that provide opportunities for economic development in communities (Thompson and Bazilian, 2014). The International Energy Agency (IEA) defines EP as a lack of access to electricity and reliance on traditional biomass for cooking and heating (Khatib, 2011). The Asian Development Bank also defines EP as an inability to use modern cooking fuels (Sovacool, 2012).

Generally, EP is based on accessibility, availability, and affordability. These factors determine whether energy is accessible for use, whether the service is available, and if financing for energy services is affordable. Additionally, there are three reasons why households may lack access to energy services: energy may not be available, if it is available, it may not be affordable, and if it is available and affordable, it may not be acceptable to the household (Nathan and Hari, 2020).

Energy poverty (EP) is a serious issue that requires careful attention to identification. It occurs when households are unable to access vital energy services and products and is a leading cause of financial and health problems in some countries (Bouzarovski et al., 2012). Shockingly, almost 18% of the global population lacks access to electricity, with 85% of these individuals residing in rural and island areas (Kaygusuz, 2012). The IEA suggests that those without access will be harder to reach than those who are already connected. However, having access to electricity, fuels, and modern technologies can increase population equality by improving healthcare, education, and social relationships. This, in turn, can help reduce poverty in rural areas (Lillo et al., 2015). Notably, access to energy systems can improve living standards (Roy et al., 2022).

EP is a significant issue, and various indexes have been developed to measure it. The first measure that included a multidimensional poverty index was the Alkire-Foster (AF) method, which is a flexible technique for measuring poverty or well-being. Later, the researchers found that electricity deprivation is a common form of simultaneous deprivation that contributes to multidimensional poverty (Alkire et al., 2021). This study highlights the importance of considering more than just the three factors when assessing EP. Our work considers the unique circumstances of each population being analyzed and considers various indicators to identify the poverty index that best allows for comparisons between populations facing similar poverty situations. This approach helps to streamline both the identification and measurement of EP.

EP is the situation in which a household's energy needs are not met or only partially different depending on the place we are talking about, for example, a population can be considered in energy deprivation if they do not have access to any type of electronic device, however in other conditions another population has energy deprivation access to electricity in their home. Both are energy deprivations depending on the group that is asked; however, they are not comparable conditions, for this reason, it is necessary to consider an EP index that considers the poverty energy identification according to the population necessities as follows identify the population with more necessities and their reasons. During the VIII Energy Week, this fact was taken into consideration, and the following contribution was made: "For the energy transition to be just, the particular needs of affected communities must be recognized, particularly in developing countries."

In this paper, we propose the Localized Energy Poverty Index (LEPI) as a means of identifying and measuring poverty levels in a group of people who share similar energy deprivations, considering the particular needs of the group. LEPI uses relative measures to determine the EP index, which enables us to evaluate which individuals require more intervention to reduce social inequality. By using this aggregation method, we can recognize those who are in better conditions and determine the appropriate interventions to reduce the social gap.

In order to evaluate poverty levels, various indices have been developed to measure EP among countries, communities, or families. An Energy Poverty Index (EPI) is a composite measure that is used to estimate the poverty levels. The European Energy Poverty Index (EEPI) (Hub, 2022) utilizes the weighted average of four indicators, such as the share of income spent on energy, energy expenditure relative to income, heating degree days, and cooling degree days to estimate the measure. Multidimensional EP includes a range of indicators and does not consider the possibility of changing the measure according to the population that has been evaluated (Adeyonu et al., 2022; Alkire et al., 2021; Liu et al., 2023; Nussbaumer et al., 2011). In general, the EPI calculates the weighted average of indicators.

However, these indices do not consider the fact that criteria may differ depending on the group being evaluated. To address this issue, we propose the use of a LEPI, which considers multiple alternatives and important criteria to determine poverty levels. These alternatives and criteria can change according to the population, making it possible to compare populations with the same needs and identify specific groups that require more help to reduce the social gap.

To begin this process, we identify two stages: First, we determine which alternative is in the best condition. In this paper, we present a new index for measuring EP called the LEPI. This is an energy poverty index that allows identifying poverty in a localized way for groups of people to be compared through indicators that represent EP in the population and, based on this, establishing which population is in a better situation; this population is considered as a guide to establishing the poverty level of the other populations within the investigated group in order to reduce the social gap within it. By prioritizing efforts on the most affected population, we can analyze how the variation in different indicators affects the social gap. This helps in effectively reducing the gap and improving the situation for all populations in the group. The LEPI is constructed using multicriteria methods that consider the needs and characteristics of populations with similar conditions. Data is then normalized based on the technical conditions of a better-off population, followed by the determination of the LEPI.

The paper is organized as follows: Section 2. Background provides background information on the energy poverty index and discusses the need for a new one. Section 3. LEPI: A new technique to measure EP, describes how the LEPI is constructed. Finally, Section 4. Discussion presents the conclusions and future directions for this research.

## 2. BACKGROUND

To determine the energy poverty index, the initial step is to identify individuals who are living in poverty. Various indicators are available for identification purposes. The first is unidimensional poverty, which involves combining various welfare indicators into a single variable. The second indicator is the union, which identifies an individual experiencing deprivation in only one dimension as multidimensional poor. Lastly, the intersection indicator requires that the individual experiences deprivation in all dimensions (Alkire, n.d.).

To create a comprehensive poverty index, it is important to consider the unique qualities and overlooked aspects of each index. In order to include an index in an aggregation method for measuring poverty, it must satisfy certain properties. For this research, an energy poverty index will be developed that takes into account the identification and aggregation process.

Energy poverty indexes to aggregation process are utilized to assess the extent of EP. The initial index was introduced by Boardman in (Boardman, 1991), which is based on household income. If a household devotes more than 10% of its income to energy, then they are considered to be facing EP by Boardman's standards. However, it's essential to recognize that the EP index solely takes income into account and fails to consider the particular requirements of the populace.

EP indexes have been developed and used in literature, with the Boardman index being the most widely recognized. There are more than 41 composite indicators and 178 individual indicators used to measure EP (Jiglau et al., 2023). The most commonly used indexes are Theil Index, Low Income High Costs (LIHC), Multidimensional Energy Poverty Index (MEPI), and Composite Energy Poverty Index (CEPI), each with its own unique method of measurement.

The Theil Index is widely used to measure economic inequality between individuals or regions. It categorizes different subgroups or regions based on the concept of information entropy. This index uses proxy energy consumption to measure living standards and calculate inequality between rural and urban populations (Ma et al., 2021). It measures inequality within study groups and between groups. The owner EP index considers the entropy method and prioritizes according to criteria relevance in a group.

The LIHC indicator was introduced in (Hills, 2011). It defines fuel poverty as households pushed into poverty due to high fuel costs and low incomes. This index considers two criteria, one for income and one for costs, but it does not consider people's necessities.

The MEPI in (Nussbaumer et al., 2012) measures deprivation of access to modern energy services by different variables, including cooking technology, electricity access, and possession of household appliances. This index does not consider the possibility of including particular conditions according to the state.

A new approach to accessing EP was introduced in 2019 in (Khanna et al., 2019), known as the CEPI. This index considers accessibility (electricity rate and access to modern cooking), availability (total energy supply per capita), and affordability (total energy consumed per capita).

Traditional EP indices identify poverty in a multidimensional context, including factors such as limited access to clean cooking facilities, affordability issues, lack of access to electricity, and socio-economic development issues. However, the indices used did not account for the specific EP variables that should be considered based on the study population, which hinders poverty identification. In (Sareen et al., 2020), the authors discuss the various types of EP that exist and stress the importance of measuring it in order to address and alleviate it. They also emphasize the significance of involving the local population in the evaluation process to identify their needs and priorities.

Regional Observatory on Sustainable Energy (ROSE) and Energy Poverty Observatory (EPOV) are two leading organizations entrusted with the task of measuring EP in specific regions. ROSE measures EP in Latin America and the Caribbean, while EPOV measures it in Europe. Fuel poverty is measured through multidimensional indicators that involve experts conducting research to assess it from various perspectives. This approach is essential as fuel poverty is not only limited to energy access, but also involves aspects such as energy quality, affordability, and security.

EP is measured using different criteria. In Europe, the main indicators are energy security, climate change mitigation, and sustainable development (Thomson and Snell, 2013). To achieve this, various solutions have been proposed, such as the creation of entities that guide users when purchasing or changing appliances to reduce electricity consumption in their homes (Bouzarovski, 2011; Vondung and Thema, 2019). In addition to the relationship between EP and these indicators, studies, such as the one conducted by (Martiskainen et al., 2021), analyze new dimensions of EP, such as the relationship between energy and transport poverty.

Despite the impressive progress made by countries like India, which has improved coverage the fastest, it still has the largest number of people without electricity service. Similarly, China, despite being the country with the most significant progress in energy efficiency, has the largest number of people without access to clean fuels for cooking (Banco Mundial, n.d.). Countries such as Colombia or Mexico still have populations without electricity service in their homes.

The proposed index in this research can help identify which poverty indicators, whether suggested by experts or derived through participatory measurement, are contributing to EP in different populations. This index aims to identify the most pressing issue that needs to be addressed in the investigated group of the population that is most affected by EP.

In this research, we begin to identify poverty by analyzing the community to be studied, and, based on the information available for this study group, we identify the criteria that cause the population to be inequality and generate poverty in them. Thus, we obtain a method for the identification of poverty that adapts according to variable criteria.

In this research, we focus on the criteria that make a population to be considered in a state of EP. In considering the energy poverty index, it is important to recognize that access to electricity services can improve overall well-being and help reduce economic and social inequality. The index we present in this paper prioritizes the needs of those who are worst off, and we begin by identifying those who are considered better off.

The LEPI is a tool created to address fuel poverty. It does this by examining specific factors that apply to each group being evaluated. By comparing and assessing various options, the most suitable alternative is determined and ranked accordingly. It is important to include this index when measuring EP so that decision-makers can better understand the needs of different stakeholders. It is important to consider that different populations have different needs, and therefore, measures of poverty should reflect this reality. For instance, in areas where there is no availability of electricity, residents cannot be measured in the same way as those who can pay for electricity. However, both populations are important to consider as energy poor if they lack the ability to pay for it. This is why it is crucial to compare populations based on indicators that represent poverty according to their specific needs.

In order to bridge the gap between decision-makers and stakeholders, it is important to take into consideration the factors that they both find relevant to the final decision. This will generate the maximum benefit for all parties involved. The main objective of this research is to evaluate the reduction of EP to close this gap.

By measuring EP in a localized way, we can identify the factors that make a population energy-poor. This method of measurement helps us to determine the specific criteria to work on in order to reduce the fuel poverty rate. The localized poverty index helps to generate an EP index that can be used to compare populations based on their individual needs. To incorporate a LEPI, we use two multicriteria methods: TOPSIS and Shannon entropy, the illustration of these methods can be found in the following section.

## 3. LEPI: A NEW TECHNIQUE TO MEASURE ENERGY POVERTY

This section presents the process of constructing the LEPI, the methodology with which it was developed, and the results obtained for a given case study in Colombia. The construction of this index follows:

### 3.1. LEPI Methodology

The LEPI uses various selection criteria. To accurately measure the relevance of each criterion, multicriteria models like Analytic Hierarchy Process (Darko et al., 2019; Lin and Kou, 2021), Technique for Order Performance by Similarity to Ideal Solution (TOPSIS), VIKOR (Mardani et al., 2016; Wibawa et al., 2019), COPRAS (Complex PRoportional ASsessment) (Sriram and Vinodh, 2021; Varatharajulu et al., 2022), Shannon's Entropy (Shannon, 1996; Yang et al., 2018), and combinations thereof are employed.

According to research (Rojas-Zerpa and Yusta, 2015), using multiple criteria methods can make decision-making more robust, comprehensive, transparent, and in line with sustainable development requirements. However, when planning for electrification, the focus is often only on economic and technical aspects, with little attention paid to social and environmental consequences (Juanpera et al., 2020). To address this issue, this study uses a multicriteria model with the critical role played by all the dimensions of access, particularly affordability, accessibility, and availability tools. In order to calculate the poverty index, reliable information is needed for each criterion and alternative.

The localized fuel poverty index has two main processes, the first one is the identification of poverty, this process is a step 1 and a step 2, and it is different depending on the population we consider evaluating. In the initial stage, experts and the community can work together to determine the indicators that will be used to compare different populations. This participatory approach ensures that the community's input is taken into account. The process also involves identifying the importance of each indicator for the community being studied.

The second process is the overlooked and constant identification of the fuel poverty index in a defined population. For the construction of this index, we must follow the sequence of steps described in Figure 1. The weights given in the first process are used to identify the population with the least poverty for the selected indicators within the population being studied. Relevant indicators are then chosen to create an energy poverty index for these areas. The data is normalized based on the consideration that the least poor population identified above has an energy poverty index of 0. It is important to note that this does not mean the population is not poor, but rather that it has the lowest level of poverty within the group studied with the selected indicators. This allows for the comparison of the fuel poverty index in different populations and helps to identify areas for prioritization to reduce the social gap within the studied group.

To create an index for measuring EP, we start by gathering comprehensive data on various poverty and energy-related factors, taking into account the context in which the population to be assessed is situated. We ensure objectivity in assigning relevant values to each factor by calculating the weighting of each criterion based on its information vector using the Shannon entropy method. This method is preferred because it allows us to objectively calculate the weight of each criterion, ensuring both objectivity and replicability of the resulting index. This approach considers the available data to determine the relevance weightage for each criterion (Carcassi et al., 2021). When a variable or criterion has a high difference in values, its entropy is low, which means it provides more information. This methodology allows us to obtain the relevant weightage that should be considered based on the population under study and vary the weights accordingly.

The LEPI energy poverty index aims to improve the satisfaction of communities with high EP rates. This is done by prioritizing possessions for those in need, compared to those who are better off. To determine the best alternative, a multi-criteria prioritization method is used. This helps identify the most suitable option based on selected criteria. The TOPSIS method is applied to order the alternatives based on their relative proximity to the positive ideal solution and farthest distance from the negative ideal solution.

#### *3.1.1. Entropy method, determinations of the weight*

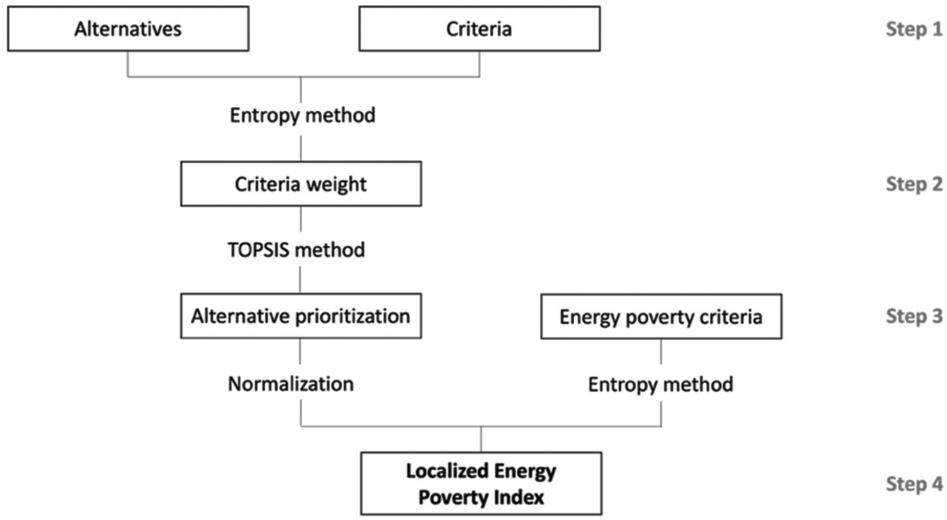
The goal of the entropy method is to determine the weight of each criterion involved in making a decision. The assumption is that the significance of a criterion is directly proportional to the amount of information that the alternatives provide concerning that criterion (Zeleny and Cochrane, 1982; Zhou et al., 2022). This approach is regarded as a reliable way to determine the distribution of weights (Aczél, 2006). To calculate the weight of the criteria, a full matrix with accurate data is required.

Before we can continue with LEPI construction, it's important to provide a thorough explanation of the entropy method.

The initial matrix has all data to a n alternatives and m criteria. The elements of initial data are represented as a_ij where i is the position in the row and j is the position in the column. The initial matrix can be visualized as (1).

$$A_{n\times m} = \begin{pmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{pmatrix} \quad (1)$$

**Figure 1:** Index construction




From the complete initial matrix, the steps to obtain the weights of each criterion by the entropy method are:

1. Normalize the initial matrix. The Eq. is (2)

$$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}}, j = 1,2,\ldots,n. \quad (2)$$

2. Calculate the entropy value, for this operation used an Eq. (3)

$$e_j = -k\sum_{i=1}^{m} r_{ij} \ln\left(r_{ij}\right), j = 1,2,\ldots,n.k = \frac{1}{\ln(m)} \quad (3)$$

3. Calculate the weight for all criteria's according to (4). $w_j$ represent a criteria weight and $\sum w_j = 1$

$$w_j = \frac{1-e_j}{\sum_{j=1}^{n}(1-e_j)}, j = 1,2,\ldots,n \quad (4)$$

The entropy method's weight is utilized to determine prioritization through the TOPSIS method. This method entails ranking alternatives based on their distance from the positive ideal solution and the negative ideal solution, with the goal of selecting the option with the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. There are some researches available that include a description of the TOPSIS method (Chakraborty, 2022; Hanine et al., 2016; Rahim et al., 2018).

#### *3.1.2. Detailed index construction*

The steps to construct a LEPI are outlined in Table 1.

For the LEPI construction is necessary to consider Entropy method, determinations of the weight, and TOPSIS methodologies. The order of its use and the proper construction of the LEPI (5) is described in Figure 1 and the step explication are in Table 1.

$$LEPI = |NEPC^{*}w_i| \quad (5)$$

**Table 1: Step definition**

| Step | Definition |
|---|---|
| 1 | Choose the alternatives on which the energy poverty index is to be determined and the socioeconomic criteria with which the population will be characterized, and which are relevant for the measurement of the electric energy service. |
| 2 | From the application of 1 Entropy method, determinations of the weight; the weights for each criterion are obtained. |
| 3 | On the one hand, the prioritization of alternatives is obtained from the application of the Technique for Order of preferenci by Similar to Ideal Solution (TOPSIS) method and on the other hand, criteria closely related to the electric power service must be chosen. |
| 4 | In this step, the criteria related to the provision of electric power service are considered and these criteria energy poverty criteria are normalized with respect to the best alternative. The Shannon entropy method is again applied to these criteria to obtain their new weights ($w_i$) and the Localized Energy Poverty Index is calculated with these data. |

In general, the LEPI methodology involves analyzing the relevant criteria or indicators used to compare alternatives. The data for these indicators should not be manipulated so as to ensure replicability. Once this is done, the LEPI method can be applied to obtain a valid analysis for the group under investigation. To demonstrate how the method is applied, an illustrative example is analyzed in the following section.

### 3.2. Localized EP Application

This section will provide a practical example using the method outlined in Table 1.

This example is to illustrate how the LEPI is implemented according to the criteria we established for this case study. Our study will focus on various regions in Colombia, a country located in northwestern South America, bordered by the Pacific Ocean and the Caribbean Sea. Colombia is renowned for its Andes Mountains, which are home to snow-capped peaks and volcanoes. Additionally, Colombia shares borders with Panama to the northwest, and with Brazil, Venezuela, Ecuador, and Peru to the east, south, and southeast, respectively.

Colombia is divided into thirty-two departments, a Capital District, and six natural regions. These regions are depicted in Figure 2. They are determined by physical geography criteria, most notably relief and, to a lesser extent, climate, hydrography, vegetation, soils, and other natural features. Each region has distinct characteristics, customs, cuisine, and music.

There is a problem in certain areas of Colombia where the zones are not connected to the National Interconnected System of energy (NIS). These areas are called non-interconnected zones (NIZ). In this study, we will focus on the NIZ in Amazonia, Orinoquia, Pacifica, Caribe, and Insula, as identified in the (GAS, 2020) report. There are 18 departments in Colombia with NIZ, with the following distribution per zone: Amazonia-6, Orinoquia-2, Pacifico-4, Norte-5, and Insular-1. The municipalities that fall under the NIZ are 83 in total and are distributed per region as follows: Amazonia-31, Orinoquia-5, Pacifico-37, Norte-8, and Insular-1.

If certain regions are included in the NIZ, it indicates that there are municipalities or localities that are deprived of access to electricity. This lack of access leads to specific energy necessities and demands in these areas. To tackle the underlying reasons for EP in these regions, it's crucial to assess and determine the most effective alternative solutions. Identifying the areas that need more intervention to enhance energy services is vital.

The primary reason for individuals or communities experiencing high EP is due to their lack of access to the NIS. This limits their ability to obtain reliable energy services in their homes. It is possible that residents in these locations may not have access to such services.

To establish a LEPI, we work with Colombia information for NIZ per Zone. According to a source referenced as (Superintendencia de Servicios Públicos, 2020), Colombia has distinct zones that are determined by geographic location and socio-cultural aspects. These zones are Amazonian, Orinoquia, Pacific, Caribbean, and Andean, and they provide us with alternative options. The criteria that we consider relevant to stablish the best alternative is according to information in "Informe sectorial de la prestación del servicio de energía eléctrica 2021" (GAS, 2020) the definition for each criterian can be found in Table 2.

In this step, we need to consider certain criteria to determine the best alternative. It's important to note that this alternative may not be perfect, but it has the shortest distance from the ideal solution and the greatest distance from the negative ideal solution when compared to the other alternatives.

The criteria for the LEPI can vary depending on the decision makers and the necessities and opportunities of the regions. This means that the LEPI can be adjusted based on the specific study group and its poverty situation, which is an advantage compared to other EP indices.

Our criteria definition to evaluate the alternatives are in Table 2. In this case study, various indicators have been taken into account to identify the population with the lowest level of EP within the study group. This information can then be used as a reference point for further analysis within the group. The decision matrix values for this case study are presented in Table 3 were obtained from (Superintendencia de Servicios Públicos, 2020).

**Figure 2:** Colombia regions


**Table 2: Criteria description**

| Criteria | Definition |
|---|---|
| Coverage ratio (%) | The electric power coverage index of the "Unidad de planeación minero energética" |
| Family expenses ($/month) | Family expenses per month |
| Availability of payment ($/month) | Availability of payment for energy consumption |
| Locations (#) | Localities per zone |
| Total housing (#) | Number of houses by zone |
| Billing (%) | Percentage of electricity billed by zone |
| Certified subsidies (%) | Average percentage subsidized by the government |
| Average unit cost per zone ($) | Unit cost of service provision |
| Installed Diesel capacity (MW) | Installed Diesel capacity by zone |
| Installed FNCER capacity (MW) | Installed Non-conventional renewable energy sources (FNCER) by zone |
| Interruptions per year (#) | Service interruptions based on telemetry and power generation |
| Energy generated from diesel (MWh) | Energy generated from diesel by zone |

**Table 3: Criteria values**

| Criteria | Amazonia | Orinoquia | Pacífico | Norte | Insular |
|---|---|---|---|---|---|
| Coverage ratio (%) | 0.571 | 0.614 | 0.890 | 0.850 | 1.000 |
| Family expenses ($/month) | 681057 | 614692 | 251825 | 284178 | 251825 |
| Availability of payment ($/month) | 9508 | 24000 | 14000 | 9805 | 9508 |
| Locations (#) | 396 | 13 | 1549 | 122 | 2 |
| Total housing (#) | 105150 | 77714 | 1002465 | 1006918 | 22355 |
| Billing (%) | 0.183 | 0.151 | 0.307 | 0.018 | 0.341 |
| Certified subsidies (%) | 0.177 | 0.129 | 0.415 | 0.003 | 0.276 |
| Average unit cost per zone ($) | 1413.22 | 1205.24 | 1535.12 | 947.77 | 947.77 |
| Installed diesel capacity (MW) | 63.8 | 25.5 | 106.2 | 0.4 | 68.5 |
| Installed FNCER capacity (MW) | 13494 | 0.125 | 0.275 | 0.290 | 0.000 |
| Interruptions per year (#) | 11 | 8 | 129 | 3 | 0 |
| Energy generated from diesel (MWh) | 52166.5 | 18803.9 | 95496 | 1.3 | 176985.1 |

In Figure 3, the criteria values have been normalized. From the graphical representation, it is evident that there is no alternative that stands out dominantly in all criteria. Therefore, we proceed with prioritization to determine the alternative with the shortest distance from the ideal solution and the longest distance from the negative ideal solution.

### *3.2.1. Step 1*

Table 3 includes the values for all the alternatives in all the criteria, the data is taken from information shared by a public entity in Colombia (Superintendencia Delegada para la energía y Gas combustible). We reviewed all the data and compared them with information from other public pages and the data are the same, in addition to this we reviewed value by value and analyzed the valuation against the criteria and verified the consistency of the data.

Because of this we consider that the data is preserved we consider that these are reliable data, for this reason, we can apply an Entropy method, determinations of the weight, this method evaluates the measures values dispersion in decision-making, and for the criteria to evaluate the best alternative we have the weights for each criterion are given in Table 4. According to the Shannon entropy method, a criterion's weight increases with the amount of information it provides. This is because a criterion with a high difference between values has high entropy (Lee and Chang, 2018; Zou et al., 2006) For our case study, the criterion with the highest dispersion in data is Installed FNCER capacity. This criterion is given more weight for this reason.

### *3.2.2. Step 2*

We evaluate each criterion and determine which attributes are desirable and which are not, with the goal of selecting the best alternative. We use the entropy method to establish weights, and then calculate the proximity of each alternative to the positive and negative ideal solutions using the TOPSIS method. Based on the results of the TOPSIS multi-criteria analysis, we rank the alternatives as follows: Amazonia is the top priority, followed by Insular, Orinoquia, Norte, and Pacífico.

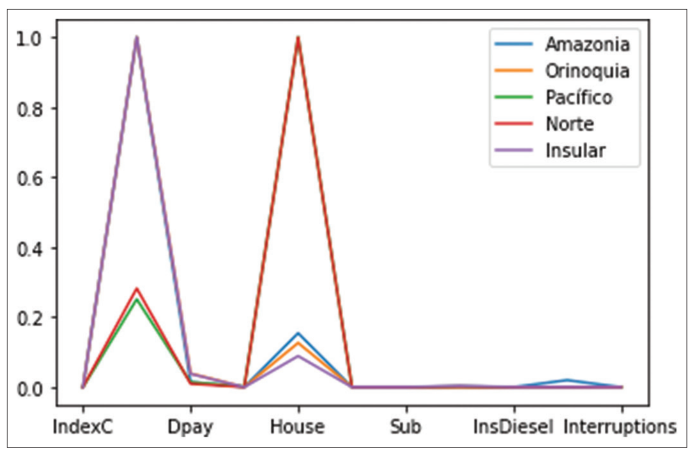
Next, select among the criteria already listed, which ones are related to the definition of EP and then we obtain the Energy Poverty Criteria (EPC), which means the criteria that are reliable to energy and poverty, this criterion can change according to the expert's decision. For the EPC applying Shannon's method to obtain the weights of Criteria weight ($w_i$), this information is in Table 5.

The data for each zone with regards to EPC is compared to Amazonia, which is considered the best-performing zone based on TOPSIS analysis. The resulting normalized data is referred to as NEPC. It's important to note that being the best among the compared alternatives doesn't necessarily mean it's free from EP. The best alternative is determined by having the shortest distance from the ideal solution and the greatest distance from the negative ideal solution.

**Table 4: Weight criteria**

| Criteria | Criteria weight |
|---|---|
| Coverage ratio | 0.056 |
| Family expenses | 0.061 |
| Availability of payment | 0.059 |
| Locations | 0.108 |
| Total housing | 0.090 |
| Billing | 0.067 |
| Certified subsidies | 0.073 |
| Average unit cost per zone | 0.055 |
| Installed Diesel capacity | 0.074 |
| Installed FNCER capacity | 0.154 |
| Interruptions per year | 0.119 |
| Energy generated from diesel | 0.083 |

**Figure 3:** Data normalized



*3.2.3. Step 3*

The energy poverty index for each location is calculated with respect to the area that is in the best condition. This place on which the data is normalized results in LEPI=0 because it is a best-performing alternative.

This value of zero does not imply that this alternative has no energy poverty index, but that it is the best performing within the compared group. The other values represent how poor the other zones of the group analyzed are with respect to the criteria determined to define energy poverty within the group of alternatives; in this case, we can see that the Pacific zone has the highest energy poverty index among the zones.

The data obtained are replaced in Eq. (5) to obtain the LEPI. The LEPI value is in Table 6 and indicates respect to in this case Amazonia which is the energy poverty index in the other zones.

Amazonia is the region with better conditions in comparison with Orinoquia, Pacifico, Caribe, and Insular, for this reason, the LEPI value is cero. With the criteria and their respect weight that we consider in Table 5, Pacifico is the region that needs investment prioritization because is the region with more energy poverty index in Colombia.

## 4. DISCUSSION

The energy poverty index results provide insight into the level of energy poverty based on specific criteria shared by the population. This index helps identify which criteria have the most significant impact on EP in a particular population. It also helps determine which areas need improvement to reduce the social gap caused by inadequate access to electricity services, as indicated by the energy poverty index.

Through the use of LEPI, decision-makers can gain valuable insights into ways to improve the energy poverty index of a population. By changing a criterion, they can see how it directly affects the index. Adding a criterion, such as implementing an electric microgrid in a specific area, can also impact the index.

**Table 5: Criteria weight**

| Energy poverty criteria | Criteria weight (wi) |
|---|---|
| Coverage ratio | 0.087 |
| Family expenses | 0.106 |
| Availability of payment | 0.100 |
| Billing | 0.132 |
| Certified subsidies | 0.154 |
| Average unit cost per zone | 0.086 |
| Interruptions per year | 0.335 |

**Table 6: Localized energy poverty index value**

| Zone | Localized energy poverty index |
|---|---|
| Amazonia | 0 |
| Orinoquia | 0.02 |
| Pacifico | 3.93 |
| Caribe | 0.56 |
| Insular | 0.16 |

Another option is to consider the effects of renewable generation sources on the energy poverty index. These decisions can help improve the energy situation of a population.

Providing safe and affordable electric service in non-interconnected areas can be expensive, and often the residents in these areas have low incomes and cannot afford the service. Therefore, it is not typically feasible to implement a solution to provide this service in these zones. However, with the use of LEPI, we can determine how the energy poverty index would be impacted by the installation of secure electric service. This approach aims to achieve not only financial returns but also social improvement. Additionally, reducing the energy poverty index can alleviate poverty in these areas overall.

The aim of this research is to identify the primary causes of poverty in a community and prioritize interventions accordingly. By distinguishing the needs of the population and analyzing the factors that contribute to the highest poverty index, we can rank the necessary improvements and reduce the social gap. Our focus is to improve the energy poverty index and make it a priority for decision-making.

Poverty arises when basic physical and psychological needs are not met, including food, housing, education, healthcare, drinking water, and electricity. To ensure that these needs are met, various criteria must be evaluated depending on the community being studied. For example, the energy poverty index varies depending on the location and the level of poverty. By reviewing the criteria that impact poverty, we can determine which areas require the most attention.

This index can assist communities in making various decisions, such as developing a national policy to implement local changes. This can be done by prioritizing investments and attention based on the community's need for equal treatment. To implement this index, similar needs and opportunities must be considered, and budget capacity, laws, and subsidies should be shared within the same country.

## 5. CONCLUSIONS

In literature we find how different indicators influence the construction of the EP index in different countries, with the LEPI it is possible to compare in a localized way, i.e. under the same context what is the EP indicator and which populations are more affected with respect to the determined indicators. Therefore, this index is useful for comparing localities with similar needs.

The decision maker can evaluate the feasibility of reducing the EP rate by assessing how a possible improvement may impact the energy poverty index in a specific community. This information can also help identify the varying needs of different populations and determine poverty levels based on their characteristics. Therefore, this index is useful for comparing localities with similar needs.

For future studies, the proposed poverty index can be utilized to measure various localized forms of poverty. It is important to evaluate the criteria that define poverty, considering the diverse needs of different groups. In order to accomplish this, we aim to involve professionals from various fields, including sociologists, anthropologists, economists, public policy experts, political scientists, and others. Additionally, we plan to conduct fieldwork that allows the participation of the communities to be evaluated, so that the index can be applied in accordance with their specific needs and desires. This participatory approach will enable us to effectively serve the communities in question.

This index shows us that although poverty measures can be compared across different groups based on their priorities, the resulting index may vary depending on the group and context being evaluated. This provides a relative approach to measuring and understanding poverty, which helps us identify the indicators that need to be prioritized in order to reduce social inequality in the studied context.

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