International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(2), 270-283.

Optimizing Energy Alternatives in Colombia's Isolated Regions: A Multi-Criteria Evaluation

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Received: 15 September 2024 **Accepted:** 13 January 2025 **DOI:** https://doi.org/10.32479/ijeep.18048

ABSTRACT

Access to affordable, reliable, and sustainable energy is crucial for achieving the Sustainable Development Goals, improving quality of life, combating poverty, and fostering socioeconomic growth. However, a significant portion of the global population still struggles with energy poverty, lacking access to basic services such as electricity and clean cooking. Current strategies to combat this issue often rely on fossil fuels, which are costly and have negative environmental and health impacts. Hybrid energy systems offer a promising solution, but designing and evaluating them is complex. This study proposes an integrated approach for tackling that problem using Hybrid Optimization of Multiple Energy Resources (HOMER) software, along with the Criteria Importance Through Inter-Criteria Correlation (CRITIC) and multi-criteria decision making method (VIKOR). The methodology was applied to a case study in a remote region of Colombia. Results demonstrate that this approach enhances decision-making and identifies viable alternatives for energy-poor regions, providing a valuable tool for energy planning in developing contexts.

Keywords: HOMER, VIKOR, CRITIC, Energy Poverty, Colombia, MCDM
JEL Classification: Q20, Q42, D70

1. INTRODUCTION

Energy is an essential resource for human progress, playing a crucial role in improving people's quality of life and socioeconomic development (Bhandari et al., 2021; Peng et al., 2021). Universal access to energy has been established as a primary objective for sustainable development (Dehays and Schuschny, 2019), and several countries have directed their efforts towards achieving this goal (Elkadeem et al., 2021). However, in 2022 there were still 685 million people without access to electricity and 2.1 billion without access to clean cooking in the world (International Energy Agency [IEA] et al., 2024).

The IEA predicts that by 2030, 660 million people will still lack access to electricity and 1.8 billion will continue relying on biomass, kerosene or charcoal for cooking (IEA et al., 2024). This challenge mainly affects rural areas in developing countries (Gómez et al., 2023; Juanpera et al., 2022; Leduchowicz et al., 2022), where lack of access to reliable and sustainable energy sources adversely impacts health, education, economic growth and the environment (Abbas et al., 2020; Kaur et al., 2023).

IEA recognizes lack of access to modern energy services as energy poverty (Bonatz et al., 2019), and the main strategy for tackling it has been to extend electricity grids. However, this approach is economically and technically unfeasible in mountainous or remote regions, due to difficult terrain, low population density, and low energy consumption levels (Juanpera et al., 2020). As a result, traditional solutions often rely on diesel power plants, chosen for their affordability in initial investment, ease of construction, and operational maintenance (da Ponte et al., 2021; Kaur et al., 2023).

Despite the apparent convenience of diesel-based systems, they have significant drawbacks such as high operational and maintenance costs due to fuel expenses and supply chain complexities. Furthermore, such systems generate negative environmental impacts and pose health risks, particularly when installed near residential areas (da Ponte et al., 2021; Fuso et al., 2014).

While acknowledging negative impacts of diesel, its use in power generation is expected to grow by 2030. This trend is mainly driven by the need for developing countries to expand energy access on a cost-effective way (Gómez et al., 2023; Juanpera et al., 2022). Furthermore, since renewable sources face challenges, such as supply variability, high initial costs, and their requirement for substantial land area for installation (Ullah et al., 2021).

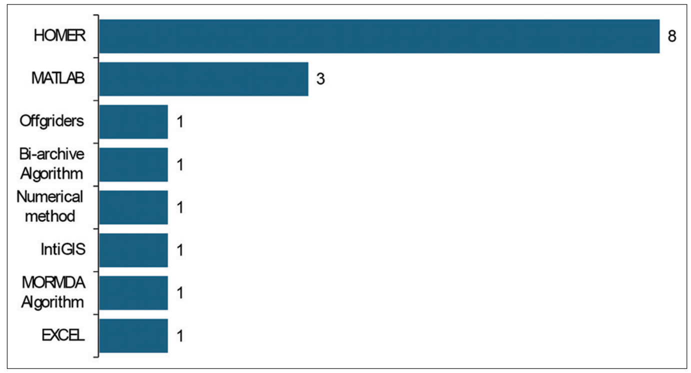
Since both, traditional and renewable energy sources, have inherent disadvantages, the integration of multiple technologies into hybrid energy systems offers a promising solution, potentially enhancing sustainability performance and ensuring a more reliable, cost-effective energy supply (Aberilla et al., 2020; Mallek et al., 2024; Ullah et al., 2021). However, hybrid systems introduce complexity in selecting and designing optimal solutions due to factors such as the numerous variables involved, uncertainties from non-linear component behavior, and variability in renewable resources and energy demand (Elkadeem et al., 2021; Ridha et al., 2022).

Designing and sizing hybrid generation systems require meticulous attention to ensure system reliability. Meeting demand consistently and cost-effectively involves considering various technical and economic parameters. Several sizing methods can be employed for this purpose, including intuitive, numerical, analytical, stochastic, computer tools, and hybrid methods. The intuitive method is recognized for its simplicity, while software tools are noted for their user-friendliness. Additionally, software tools are highly effective in solving multi-objective optimization problems and are well-suited for conducting feasibility and sensitivity analyses (Ridha et al., 2021).

Recently, various software tools have been used for the design and sizing of generation systems, including HOMER, improved Hybrid Optimization by Genetic Algorithms (IHOGA), HYBRID2, HYBRIDS, System Advisor Model (SAM), Transient System Simulation Tool (TRNSYS), Renewable-energy and Energy-efficiency Technology Screening software (RETScreen), Visual Investment Planning Optimization & Revision (ViPOR), Offgridders, and Open-Source energy Modelling System (OseMOSYS) (Juanpera et al., 2020, 2022; Ridha et al., 2021; Rituraj et al., 2024). HOMER is a popular choice and, alongside ViPOR, is widely used in developing countries (Juanpera et al., 2020; Rituraj et al., 2024). HOMER stands out because it enables users to consider numerous technologies in their designs and supports detailed system modeling (Juanpera et al., 2020).

Figure 1 illustrate the distribution of software and algorithms identified from the literature review. HOMER was found to be the leading software for addressing challenges in rural electrification. Additionally, a variety of tools used to optimize generation systems in rural settings were identified. These tools can be categorized into two groups: software packages such as Matrix Laboratory (MATLAB), Offgridders, IntiGIS, and Excel, and optimization algorithms including Multi-objective Ranking Mutant Dragonfly Algorithm (MORMDA), Bi-archive, and numerical methods.

Figure 1: Tools used for sizing solutions



Software tools enable technical-economic evaluation of energy projects. However, despite their capabilities, they may not fully encompass all critical aspects inherent to rural electrification challenges (Juanpera et al., 2020; 2022). Electrification projects are inherently multidimensional, involving diverse stakeholders with specific needs and expectations (Juanpera et al., 2020). The literature on energy alternative evaluations typically considers various criteria, including economic, technical, environmental, and social dimensions. Some studies also incorporate political and risk criteria. Table 1 presents the most relevant sub-criteria within these main dimensions. Prioritizing electrification projects should take these criteria into account to assess their potential success (Gómez et al., 2023).

Addressing multidimensional issues requires an interdisciplinary approach that considers all relevant aspects during evaluation. Multi-criteria methodologies play a crucial role in tackling these challenges by enabling the resolution of complex tasks and the identification of appropriate solutions. These tools help to mitigate the inherent uncertainties and complexities associated with multi-objective problems (Kotb et al., 2021; Peng et al., 2021; Ullah et al., 2021).

Ridha et al. (2021), identify Multi-Objective Optimization based on ratio analysis (MULTIMOORA), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Analytic Hierarchy Process (AHP), Combined Distance-Based Assessment (CODAS), VIKOR, and Complex Proportional Assessment (COPRAS) as some of the most cited and well-known multi-criteria methods. The literature review corroborates these findings. AHP, Best-Worst Method (BWM), and equal weighting are the most used methods for criteria weighting, as shown in Figure II. Figure III presents the methods used for alternative selection, with TOPSIS, VIKOR, MULTIMOORA, CODAS, and AHP being predominantly employed. Further details of these results are available in Table A1 in Appendix A.

This paper uses CRITIC and VIKOR methods to evaluate feasibility of different energy alternatives in a Colombian region.

Table 1: Commonly considered criteria for the evaluation of energy alternatives.

Criteria	Sub-criteria	Source
Environmental	GHG emissions (GHG)	Ali et al., 2020; Bhandari et al., 2021; Bilal et al., 2022; Das et al., 2022; Elkadeem et al., 2021; Elkadeem et al., 2021; Gómez et al., 2023; Juanpera et al., 2020, 2022; Kotb et al., 2021; Mallek et al., 2024; Mwanza and Ulgen, 2020; Ridha et al., 2021; Tariq et al., 2021; Ukoba et al., 2020; Ullah et al., 2021; Wang et al., 2022
	Land requirement (LR)	Bhandari et al., 2021; Bilal et al., 2022; Elkadeem et al., 2021; Kotb et al., 2021; Mwanza and Ulgen, 2020; Peng et al., 2021; Ullah et al., 2021
	Renewable fraction (RF)	Ali et al., 2020; Das et al., 2022; Elkadeem et al., 2021; Elkadeem et al., 2021; Kotb et al., 2021; Tariq et al., 2021
Economic	Cost of energy (COE)	Ali et al., 2020; Ali et al., 2020; Bhandari et al., 2021; Bilal et al., 2022; Das et al., 2022; Elkadeem et al., 2021; Elkadeem et al., 2021; Gómez et al., 2023; He et al., 2021; Kotb et al., 2021; Mallek et al., 2024; Peng et al., 2021; Tariq et al., 2021; Ukoba et al., 2020
	Operation and Maintenance Cost (O&M)	Ali et al., 2020; Ali et al., 2020; Bhandari et al., 2021; Bilal et al., 2022; Das et al., 2022; Elkadeem et al., 2021; Elkadeem et al., 2021; He et al., 2021; Juanpera et al., 2020, 2022; Kotb et al., 2021; Mallek et al., 2024; Ukoba et al., 2020
	Investment Cost (IC)	Ali et al., 2020; Ali et al., 2020; Bhandari et al., 2021; Bilal et al., 2022; Das et al., 2022; Elkadeem et al., 2021; Elkadeem et al., 2021; He et al., 2021; Juanpera et al., 2020, 2022; Mallek et al., 2024; Mwanza and Ulgen, 2020; Ukoba et al., 2020
Social	Social acceptance (SA)	Aberilla et al., 2020; Ali et al., 2020; Bilal et al., 2022; Elkadeem et al., 2021; Juanpera et al., 2020, 2022; Mallek et al., 2024
	Job creation (JC)	Aberilla et al., 2020; Bilal et al., 2022; Elkadeem et al., 2021, 2021; Mallek et al., 2024; Mwanza and Ulgen, 2020
	Social Benefit (SB)	Ali et al., 2020; Bhandari et al., 2021; Peng et al., 2021
Technical	Reliability (Re)	Ali et al., 2022; Ali et al., 2020; Ali et al., 2020; Bhandari et al., 2021; Bilal et al., 2022; Gómez et al., 2023; Juanpera et al., 2020, 2022
	Efficiency (Ef)	Ali et al., 2020; Ali et al., 2020; Bhandari et al., 2021; Bilal et al., 2022; Peng et al., 2021; Wang et al., 2022
	Technological maturity (M)	Ali et al., 2020; Elkadeem et al., 2021; Peng et al., 2021; Ukoba et al., 2020

Figure 2: Multi-Criteria methods used for criteria weighting

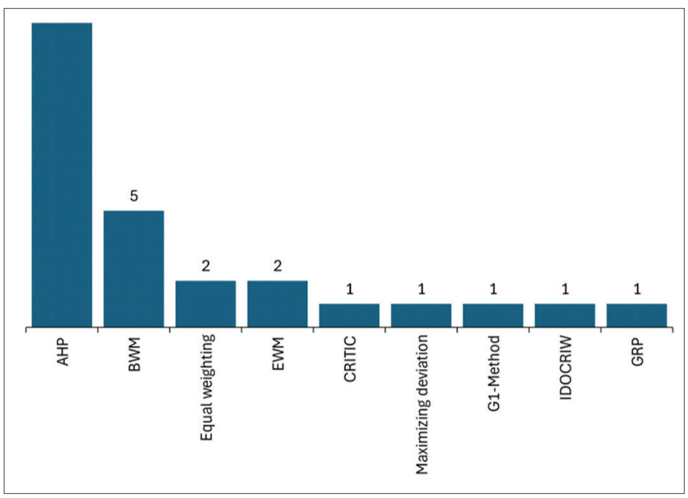
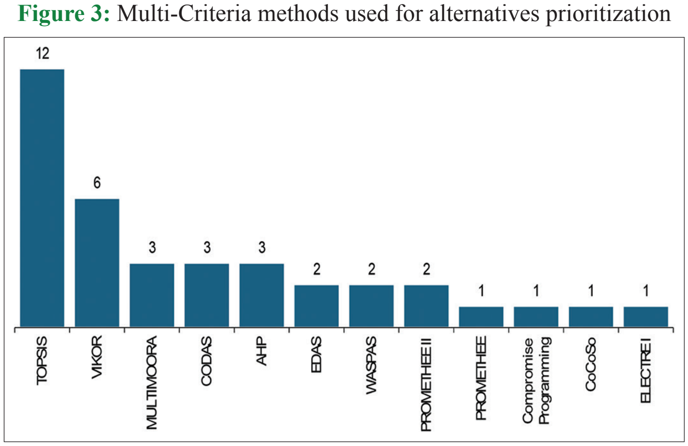


Figure 3: Multi-Criteria methods used for alternatives prioritization



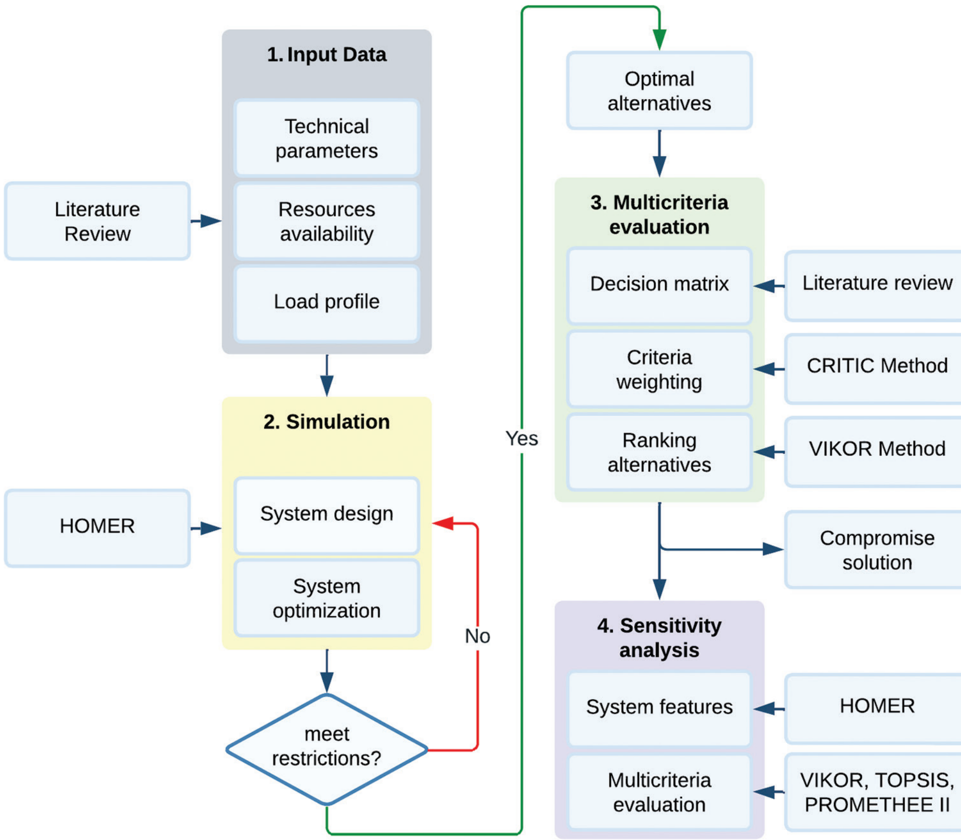
The analysis integrates different technologies within hybrid systems to offer sustainable, reliable, and viable energy solutions. HOMER software was used for system design and sizing, CRITIC for criteria weighting and VIKOR for alternatives evaluation and prioritization.

CRITIC stands out as one of the most widely used approaches for criteria weighting. It is an objective method based on an algorithm that impartially calculates weight without incorporating decision-makers' preferences or biases. This method can deliver realistic and accurate weights, offering enhanced reliability compared to traditional objective weighting methods such as entropy and standard deviation (Ali et al., 2020).

On the other hand, VIKOR is a widely used method in evaluating energy alternatives, it was designed to address challenges involving conflicting criteria and differing units of measurement. It assesses the superiority of alternatives and identifies compromise solutions by measuring their proximity to the ideal solution. One of its main features is its ability to maximize group benefits while minimizing individual regrets, enhancing acceptance of compromise solutions by decision-makers (Lee and Chang, 2018). Additionally, VIKOR ensures result stability even with slight variations in criteria weights (Muñoz and Romana, 2016).

To show these methods' applications and main findings, this paper is structured as follows: Section 2 outlines methodology for multi-criteria analysis, detailing tools employed. Section 3 presents key findings derived from applying this methodology to design and evaluate different energy alternatives. Finally, Section 4 discusses principal conclusions drawn from analysis.

Figure 4: Study methodology



2. MATERIALS AND METHODS

This study employed a four-phase approach to design and evaluate an optimal power generation system for the target region, as illustrated in Figure 4. The first phase focused on gathering essential information for energy generation system design. This information included characteristics of the study region, available energy resources, energy demand profile, and technical specifications and cost data for potential system components.

The second phase employed HOMER software for system modeling and optimization. This phase allowed the identification of optimal configurations, which were later evaluated to find the most suitable alternative for the region. The optimization process was conducted from an economic viability standpoint, with optimal alternatives for each configuration selected based on the lowest COE.

The third phase employed a multi-criteria decision-making (MCDM) approach to determine the optimal configuration for the region. This phase was subdivided into three stages. In sub-stage 1, a decision matrix was constructed using optimization results from HOMER and supplemented with relevant data from literature review for aspects not covered by the software. In sub-stage 2, the CRITIC method was used to weight evaluation criteria, and, in sub-stage 3, alternatives were evaluated using VIKOR method, incorporating weighted criteria from the previous stage, HOMER optimization results, and literature review findings.

Finally, in phase four, a sensitivity analysis was conducted to validate the reliability of results. This analysis examined the sensitivity of the decision to key solution characteristics, including energy resources availability and fuel cost, as well as the impact of criteria weighting on the evaluation of optimal solutions derived from HOMER.

2.1. Input Data

A critical challenge when using HOMER software is to find the necessary input data for simulation and optimization. This includes data on load profiles, geographical conditions, available renewable resources, and techno-economic characteristics of system components. The comprehensive collection of this information is crucial for accurate modeling and reliable results (HOMER Energy, 2020).

Different sources can provide the necessary data for simulation and optimization. Solar radiation and wind speed data can be extracted from organizational websites like National Renewable Energy Agency (NREL), National Aeronautics and Space Administration (NASA), and the National Climatic Data Center (NCDC). Platforms like Solargis and Solcast supply solar radiation data, while Weatherbase and Windustry offer wind speed data (HOMER Energy, 2020). Renewables.ninja provides access to both solar radiation and wind speed, while PVGIS focuses on solar radiation for any location in the world (Rituraj et al., 2024). In Colombia, the Geo-Open data catalog managed by the Institute of Hydrology, Meteorology, and Environmental Studies (IDEAM) provides access to meteorological data, including solar radiation, wind speed, and temperature (IDEAM, n.d.), among others.

To determine the load profile, HOMER uses data from Open Energy Information (OpenEI), which includes profiles for 16 types of reference buildings across the 16 different climate zones in the United States. HOMER identifies the analyzed climate zone by approximating it based on the Koeppen Geiger climate classification to a predefined one (HOMER Energy, 2020). The profile can be established by importing or entering existing data, or by allowing the software to synthesize profiles using average daily load data that can be scaled to match the specific load under analysis (Lambert et al., 2006).

Technical and economic data on generation system components can be obtained from distributors' websites such as Alternative Energy Store, and Solar Energy as well as from reports such as Renewable Energy Technology Characterizations and SolarBuzz (HOMER Energy, 2020). These data can also be obtained from previous studies, as done by Fontalvo et al. (2023) in their work.

2.2. Software HOMER

HOMER, developed by NREL in the United States, is an easy-to-use simulation software used for modeling grid-connected and off-grid systems, considering electrical and thermal loads for individual users or communities (Fontalvo et al., 2023). It integrates various generation technologies such as solar photovoltaic, wind turbines, energy cells, fossil fuels, alongside storage options like batteries, hydrogen storage, and supercapacitors (Qiblawey et al., 2022).

HOMER is commonly used for techno-economic analyses and provides insights into environmental impacts by estimating greenhouse gas emissions (Qiblawey et al., 2022). It facilitates comparison among different generation system design options based on technical and economic criteria, while also evaluating the effects of input variable uncertainties. HOMER's core functionalities include simulation, optimization, and sensitivity analysis (Lambert et al., 2006).

Fundamental HOMER's capability is long-term simulation of micro-energy systems. The simulation process allows for observation of how a system would work, considering specific components and a defined operating strategy. HOMER can model two different strategies to determine the interaction of generators with battery banks, the first, called Load Following (LF), in which only renewable sources charge the battery and the second, called Cyclic Charging (CC), in which when a generator is required it runs at full capacity, recharging the batteries with the surplus energy (Lambert et al., 2006).

During the simulation process, HOMER performs calculations of the energy balance between supply and demand, deciding how to manage the surplus of renewable energy or how to generate additional energy when needed (Lambert et al., 2006). These calculations are performed in simulation times of 1 year with a minimum resolution of one minute (Qiblawey et al., 2022). The fundamental outcome of this phase is to determine whether a system is viable by assessing its ability to meet the electrical or thermal load and other user-defined constraints, and to calculate the life-cycle cost of the system (Lambert et al., 2006).

Based on simulation results, HOMER evaluates and organizes various configurations, highlighting those with the best technical and economic performance through its optimization process (Fontalvo et al., 2023; Lambert et al., 2006). The goal of this process is to determine the optimal values for each decision variable to establish the most cost-effective system, which satisfies the load requirements and user-defined constraints, while minimizing the total net present cost (NPC) (Lambert et al., 2006).

Among the decision variables considered by HOMER are the size of the solar array, number of wind turbines, generator sizes, number of batteries, and dispatch strategy, among others. The software can automatically determine optimal sizes or quantities for each component, or alternatively, users can input multiple values for each decision variable within the search space, which are then considered during optimization (HOMER Energy, 2020; Lambert et al., 2006).

Users can also adjust key parameters for the optimization process, such as simulation time step duration, number of simulations, design accuracy, NPC sensitivity, and focus factor (HOMER Energy, 2020). These parameters enable the refinement and adjustment of software operations to achieve results aligned with the objectives and required accuracy. Fontalvo et al. (2023) indicate that utilizing short time intervals and a focus factor close to 1 can prevent the occurrence of local optima, although this may decelerate the simulation and optimization processes.

In parallel with the optimization process, HOMER can conduct sensitivity analyses on different numerical variables, such as energy resources behavior and fuel prices, which are beyond user control. This optional step allows the software to analyze any number of sensitive variables, perform optimization for each case, and present the results in various formats, either tabular or graphical. Sensitivity analysis primarily mitigates uncertainty and supports trade-off analyses, decision-making processes, and addressing critical questions (Lambert et al., 2006).

2.3. CRITIC Method

The CRITIC method, introduced by Diakoulaki et al. (1995), performs correlation analysis to identify differences between criteria (Ali et al., 2020). This method involves seven steps, outlined as follows:

Step 1: Construct the decision matrix.

$$A = a_{ij} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} = [a_{ij}]_{m\times n} \quad (1)$$

Where a_{ij} ($a_{ij} \geq 0$) represents performance of i^{th} alternative on j^{th} criterion.

Step 2: Normalize the decision matrix.

$$\bar{a}_{ij} = \frac{a_{ij} - a_j^{Worst}}{a_j^{Best} - a_j^{Worst}} \quad (2)$$

For non-beneficial criteria, minimum value will be the best and maximum value will be the worst. On the other hand, for beneficial criteria, maximum value will be the best, and minimum value will be the worst.

Step 3: Estimate standard deviation (σ_j) of each criterion.

Step 4: Create a symmetric matrix (*nxn*) with a generic factor r_{jk}, which is the linear correlation coefficient vector between a_j and a_k.

Step 5: Determine the measure of conflict caused by criterion j.

$$\sum_{k=1}^{m}(1-r_{jk}) \tag{3}$$

Step 6: Calculate the quantity of information concerning each criterion.

$$C_i = \sigma_j \sum_{k=1}^{m}(1-r_{jk}) \tag{4}$$

Step 7: Estimate objective weights of each criterion.

$$W_j = \frac{C_j}{\sum_{k=1}^{m} C_j} \tag{5}$$

2.4. VIKOR Method

The VIKOR method is developed in 4 stages, which are described as follows (Lee and Chang, 2018):

Step 1: Determine the positive and negative ideal solutions (A+) and (A$^-$).

$$A^+ = f_j^+ = \{\max_i f_{ij} \mid j \in I_1\}, f_j^+ = \{\min_i f_{ij} \mid j \in I_2\}, \forall j \tag{6}$$

$$A^- = f_j^- = \{\min_i f_{ij} \mid j \in I_1\}, f_j^- = \{\max_i f_{ij} \mid j \in I_2\}, \forall j \tag{7}$$

Where I_1 and I_2 correspond to sets of benefit and cost criteria respectively.

Step 2: Calculate the values S_i and R_i.

$$S_i = \sum_{j=1}^{n} w_j \frac{(f_i^+ - f_{ij})}{(f_i^+ - f_j^-)} \tag{8}$$

$$R_i = \max_j [w_j \frac{(f_i^+ - f_{ij})}{(f_i^+ - f_j^-)}] \tag{9}$$

Where w_j represents the criteria weights.

Step 3: Calculate Q_i.

$$Q_i = v(\frac{S_i - S^+}{S^- - S^+}) + (1-v)(\frac{R_i - R^+}{R^- - R^+}) \tag{10}$$

Where $S^+ = min(S_i)$, $S^- = max(S_i)$, $R^+ = min(R_i)$, $R^- = max(R_i)$, and *v* is introduced as a weight of the strategy of maximum group utility, while (1−*v*) is the weight of individual opposition. The value of *v* ranges between 0 and 1. A value of $v = 0.5$ implies a consensus strategy between both positions. If $v < 0.5$ the minority decides, that is, the individual position takes on greater importance. Whereas, if $v > 0.5$, the majority decides (Muñoz and Romana, 2016).

Step 4: Order the alternatives in decreasing order according to Si, R_i, and Q_i. The result obtained in this step is three lists, with which the one with the minimum Q ($A^{(1)}$) can be defined as the compromise solution, if the following conditions are met (Muñoz and Romana, 2016):

Condition 1: Acceptable advantage

$$Q(A^{(2)}) - Q(A^{(1)}) \geq DQ \tag{11}$$

Where $A^{(2)}$ is the second alternative according to the classification of the values of Q and DQ.

$$DQ = \frac{1}{(j-1)} \tag{12}$$

Where *j* is the number of alternatives.

Condition 2: Acceptable stability in the decision-making process. It must be fulfilled that alternative $A^{(1)}$ must be the best classified in the lists of S and/or R values.

If any of the conditions are not met, the process suggests moving to the definition of a compromise set of solutions, as follows:

- If condition 2 is not met, alternatives $A^{(1)}$ and $A^{(2)}$.
- If condition 1 is not met, the set consists of the alternatives $A^{(1)}$, $A^{(2)}$, $A^{(3)}$,… $A^{(M)}$ is determined by considering the relationship shown in Equation 13. These alternatives are close to the ideal solution.

$$Q(A^{(M)}) - Q(A^{(1)}) < DQ \tag{13}$$

3. RESULTS

3.1. Load Estimation

The study focuses on the community of Cañado in Alto Baudó, a municipality in Colombia's Chocó region. It is classified as a type 3 locality according to the Planning and Promotion Institute for Energy Solutions in Non-Interconnected Zones (IPSE), indicating it has between 51 and 150 subscribers or users (National Monitoring Center [CNM], 2021). The Mining and Energy Planning Unit (UPME), as quoted by Fontalvo et al. (2023), estimates an average Colombian household of four people consumes approximately 157 kWh of electricity per month. Considering the previous information and assuming the standard household consumption per subscriber in Cañadó, the estimated total community demand ranges from 0.26 to 0.79 Mwh/day.

Figure 5 illustrates the load profile used for analysis. Given Colombia's equatorial location, the profile is expected to remain relatively uniform throughout the year, without significant seasonal variations (Fontalvo et al., 2023). The community's average annual energy demand is approximately 32.7 kW, with peak demand reaching 97.1 kW. Weekday average demand is 33.7 kW, while weekend demand averages 30.2 kW.

Figure 5: Community load profile, on weekday and weekend

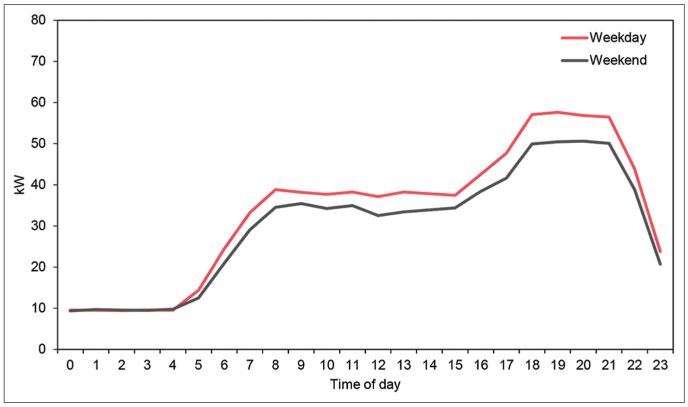


Figure 6: Average solar radiation per month in Alto Baudó – Chocó

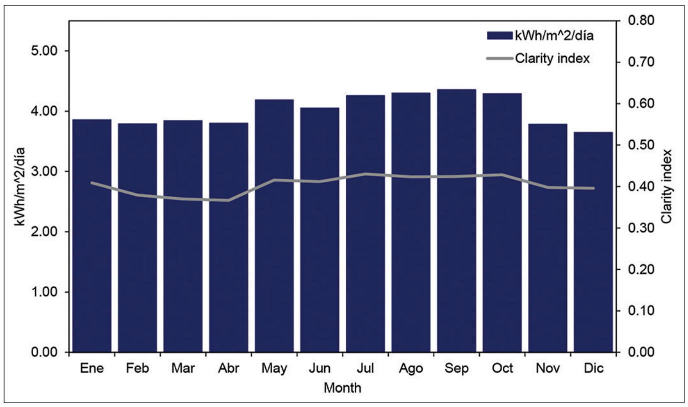
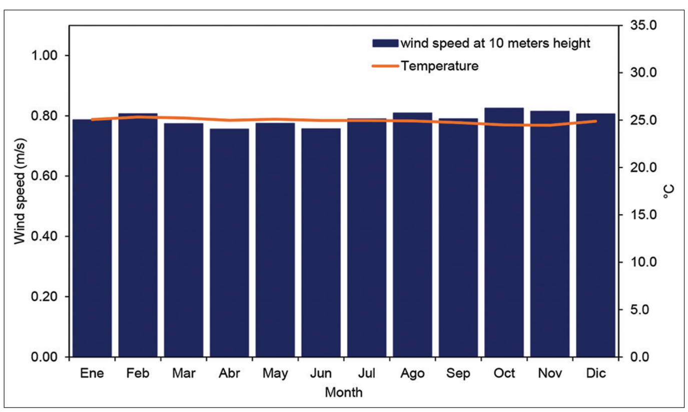


Figure 7: Wind speed and average temperature per month in Alto Baudó - Chocó

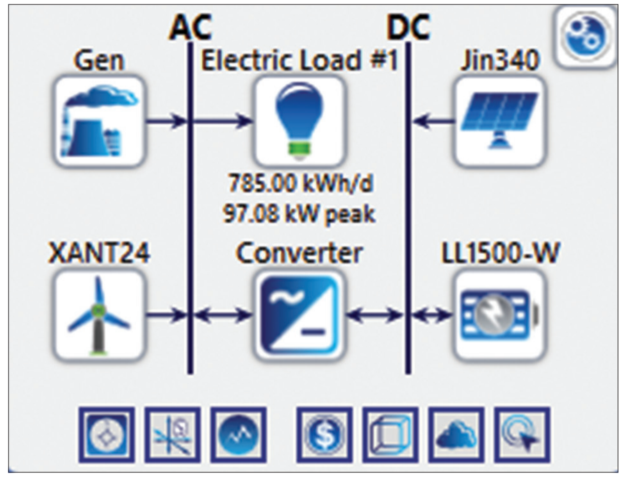


3.2. Analysis of Available Resources

Weather and climate data for Alto Baudó were extracted from NASA's Prediction Of Worldwide Energy Resources (POWER) database for the period from January 2018 to March 2022 (NASA, n.d.). Figure 6 illustrates the average monthly global horizontal radiation (GHI). Peak radiation occurs between August and October, with the region receiving an average GHI of 4 kWh/m^2/day. The clarity index varies between 0.32 and 0.46 and is relatively uniform throughout the year.

Figure 7 presents the average wind speed at 10 meters height and the average temperature in the region. The average wind speed is approximately 0.8 m/s. The average monthly temperature is 24.94°C, with minimal seasonal variation. Temperatures range from a maximum of 25.33°C to a minimum of 24.46°C, indicating a stable tropical climate.

Figure 8: Schematic of the system designed in HOMER



3.3. System Design

The case study focuses on an integrated energy system that comprises several key components: the community's energy demand profile, a diesel generator, wind turbines, solar panels, an energy converter system, and a storage system. Figure 8 presents a schematic diagram of the system as modeled in HOMER software.

The design incorporates both alternating current (AC) and direct current (DC) buses, which serve as the main power distribution pathways. The AC generation systems are connected to the grid via the AC bus, while auxiliary systems such as batteries and solar panels are connected via the DC bus. This dual-bus configuration allows for efficient integration of various power sources and storage systems. Table 2 provides detailed technical specifications and cost characteristics for each component used in the system design.

3.4. Optimization with HOMER

HOMER software was used to optimize a hybrid (PV-WT-DG-Bat-Conv) power generation system. The optimization considered a projected diesel price of US $2.7/gallon by the end of 2024 (UPME, 2023), an inflation of 5%, and a discount rate of 10%. The evaluation period was 25 years, corresponding to the project's life cycle. LF and CC control strategies were tested, and each component was optimized based on the minimum NPC and the minimum COE.

The optimization was conducted in 60-min intervals with a focus factor of 5. From the simulation, various combinations of equipment were obtained that represent feasible alternatives for energy supply in the study region. Combinations were excluded if they were infeasible, posed stability risks in demand coverage, or lacked essential components like the converter or battery bank. Each alternative considered represents the most economically viable option among the possible combinations. Table 3 presents the different configurations selected from the optimization process.

Table 2: Equipment considered for analysis

Component	Initial Cost	Replacement	OandM	Service Life	Source
PV	$1,159/kW	$747/kW	$17/year	25 years	Munoz et al., 2021
WT	$147,250/t	$147,250/t	$2945/year	20 years	Fontalvo et al., 2023
DG	$665/kW	$535/kW	$0.027/h	15,000 h	Fontalvo et al., 2023
Conv	$300/kW	$300/kW	$0/year	15 years	Fontalvo et al., 2023
Bat	$5,406/Bat	$5,406/Bat	$108/year	Degradation cycle	Fontalvo et al., 2023

Table 3: Selected Settings

System	Components
S1	PV-DG-Bat-Conv
S2	PV-WT-DG-Bat-Conv
S3	DG-Bat-Conv
S4	WT-DG-Bat-Conv
S5	PV-Bat-Conv
S6	PV-WT-Bat-Conv

Table 4 presents the configurations derived from HOMER for each of the six alternatives, along with their corresponding NPC, COE, IC, O&M, RF, and GHG. COE values range from $0.345/kWh to $0.602/kWh. Among the alternatives, S1 is the most economically viable, whereas S5 and S6 demonstrate the lowest GHG due to their reliance on renewable sources.

3.5. Multi-criteria Selection of Energy Alternatives

The selected alternatives were evaluated across economic, environmental, social, and technical dimensions, considering a total of 9 sub-criteria detailed in Table 5. For the evaluation of alternatives, the JC subcriterion was divided into two categories: Job Creation in the Construction and Installation stage (JCCI) and Job Creation in the Operation and Maintenance stage (JCOM). To ensure a comprehensive assessment, the results obtained from HOMER were supplemented with technical data sourced from the literature review.

Based on the data presented in Table 6 and additional findings from the literature review, a decision matrix was constructed (Table 6) to prioritize the different criteria and sub-criteria. The CRITIC method was employed to rank the criteria based on their importance. Table 7 presents the results of criteria weighting. The Technical dimension was ranked as the most critical, with a weight of 35%, whereas the economic dimension ranked lowest, with 10%. It is important to consider that the technical dimension included three sub-criteria, while the economic included only one sub-criterion.

Among the sub-criteria, the most relevant were Reliability and Land requirement, each carrying a weight of 12.6%, followed by Efficiency with 12.5%, and the renewable fraction with 10.8%. In contrast, Technological maturity and Cost of energy were ranked lowest, with weights of 10.0% and 9.7%, respectively.

Subsequently, the VIKOR method was used to prioritize the alternatives. Alternative S1 emerged as the compromise solution. This configuration includes a photovoltaic system, diesel generator, battery set, and converter (Table 8). Figure 9 illustrates the operational details of S1, demonstrating its capability to meet the required load with a 13.3% surplus of electricity, providing storage for batteries and backup in case of system failure. A detailed cost breakdown for S1 is shown in Figure 10, indicating that 34% of its expenses are attributable to fuel costs, highlighting its vulnerability to fluctuations in diesel prices.

4. SENSITIVITY ANALYSIS

4.1. Power Generation System

A sensitivity analysis was conducted using HOMER to evaluate the impact of variations in solar radiation, wind speed, and diesel cost on the optimization of solutions. The analysis revealed a positive correlation between diesel cost and the Cost of Energy (COE). Additionally, it demonstrated that improved availability of renewable resources contributes to reducing the COE, as illustrated in Figure 11.

Regression analysis was performed to quantify the relationships between these variables and the COE. Results indicated that diesel prices have the most significant influence on the energy cost outcome. Analysis of variance yielded an F-statistic of approximately 232, with a critical F-value of 3.61E-12. When considered alongside the R^2 value, these statistics suggest a good model fit and indicate coefficients of independent variables are jointly significant. Detailed results of regression analysis are presented in Table A2 and A3 in Appendix B.

4.2. Multi-Criteria Assessment

Finally, a sensitivity analysis was conducted to evaluate the influence of criteria weights on the ranking of alternatives. This analysis also compared results across different multi-criteria methods, including VIKOR, TOPSIS, and Preference Ranking Organization Method for Enrichment Evaluation II (PROMETHEE II). Various weighting scenarios were assessed, such as Shannon's Entropy for objective weighting and equal weighting for each criterion. Additionally, scenarios were constructed using AI assistants like ChatGPT, Gemini, Claude, Microsoft Copilot, and Leo, from Environmental, Social, Economic, and Technical perspectives. These scenarios are summarized in Table 9.

The results of the sensitivity analysis are presented in Table 10. Using VIKOR, alternative S1 emerged as the most preferred option, ranking first in 5 out of 7 scenarios, and was part of the compromise set in 6 scenarios, excluding only the Technical perspective. S5 ranked first in the Environmental

Table 4: Optimization results

System	Components					Characteristics					
	PV (kW)	WT (Qty.)	DG (kW)	Bat (Qty.)	Conv (kW)	NPC (MM $)	COE ($/kWh)	IC (MM $)	OandM (M$/y)	RF (%)	GHG (Ton/y)
S1	176.3	0.0	110.0	35.0	56.2	1.43	0.345	0.50	13.008	42.9	122.4
S2	175.4	1.0	110.0	35.0	55.6	1.61	0.390	0.65	15.753	45.0	118.0
S3	0.0	0.0	110.0	15.0	34.1	1.78	0.430	0.17	17.815	-	247.6
S4	0.0	1.0	110.0	15.0	33.5	1.96	0.474	0.32	20.597	-	241.7
S5	747.0	0.0	0.0	120.0	96.3	2.30	0.557	1.57	25.658	100.0	-
S6	753.4	1.0	0.0	116.0	101.1	2.49	0.602	1.71	28.281	100.0	-

Table 5: Selected evaluation criteria

Criteria	ID	Sub-criteria	Unit	Source
Economic	C1	COE	U$	HOMER
Environmental	C2	RF	%	HOMER
	C3	GHG	Ton/yr	HOMER
	C4	LR	m^2/kWh	Marques et al., 2021
Social	C5	JCCI	Job-year/MW	Marques et al., 2021
	C6	JCOM	Job/MW	Marques et al., 2021
Technical	C7	M	Scale 1–5	Lee and Chang, 2018
	C8	Ef	%	Marques et al., 2021
	C9	Re	%	Rahman et al., 2013

Table 6: Decision matrix for multi-criteria evaluation

System/ Sub-criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
S1	0.345	42.9	122.4	0.0058	15.26	0.85	5.00	46.1	24.7
S2	0.390	45.0	118.0	0.0058	15.20	0.85	4.98	45.2	24.8
S3	0.430	-	247.6	0.0003	1.30	0.14	5.00	80.0	40.0
S4	0.474	-	241.7	0.0003	1.35	0.14	4.97	78.6	40.0
S5	0.557	100.0	-	0.0100	26.00	1.40	5.00	20.0	13.0
S6	0.602	100.0	-	0.0099	25.80	1.39	4.99	20.0	13.2

Table 7: Criteria weighting

Criteria	Weight	ID	Sub-criteria	Weight
Economic	10%	C1	COE	9.7%
Environmental	34%	C2	RF	10.8%
		C3	GHG	10.6%
		C4	LR	12.6%
Social	21%	C5	JCCI	10.6%
		C6	JCOM	10.6%
Technical	35%	C7	M	10.0%
		C8	Ef	12.5%
			Re	12.6%

Table 8: Ranking of alternatives

System	Metric		
	Si	Ri	Qi
S1	0.42	0.07	0.00
S2	0.52	0.08	0.42
S3	0.46	0.11	0.45
S5	0.46	0.13	0.62
S6	0.51	0.13	0.78
S4	0.57	0.11	0.83

scenario, while S3 led in the Technical scenario and was identified as part of the Ideal Solution in the Shannon's Entropy weighting scenario. Alternative S2 was part of the compromise solution in the Environmental and Social scenarios, while S6 was part of the compromise solution in the Environmental perspective.

Comparisons between VIKOR, TOPSIS, and PROMETHEE II methods revealed significant impacts of methodological choices on decision outcomes. TOPSIS produced notably different rankings compared to VIKOR. For instance, S1, often identified as the Most Preferred Solution using VIKOR, was only first in two scenarios with TOPSIS: Shannon's Entropy and Economic. Conversely, S5, less favored by VIKOR, ranked first in three scenarios under TOPSIS: CRITIC, Equal Weights, and Economic.

Figure 9: S1 alternative operation details

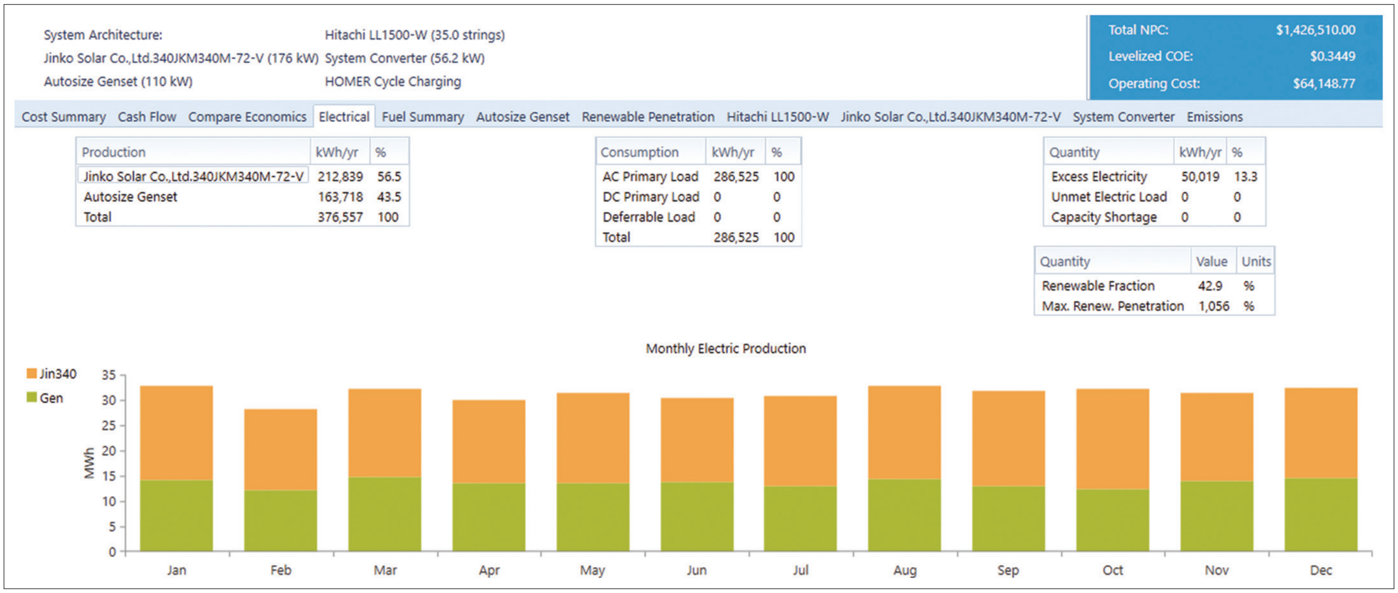


Figure 10: Cost structure of the S1 alternative

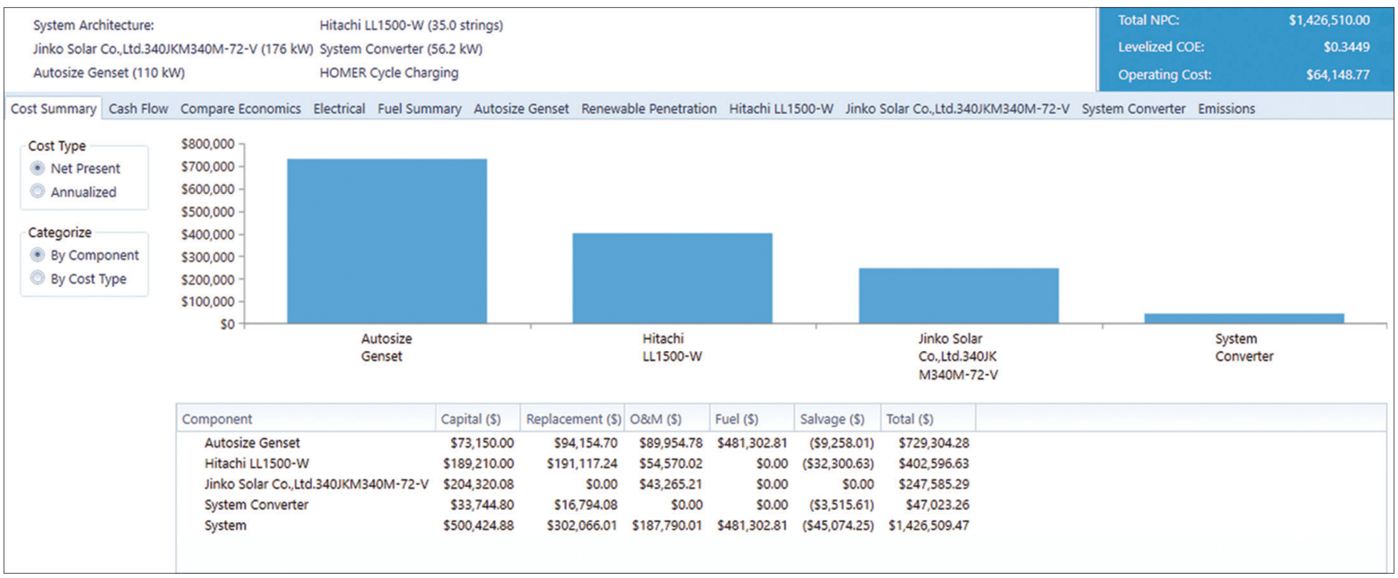


Table 9: Weighting scenarios

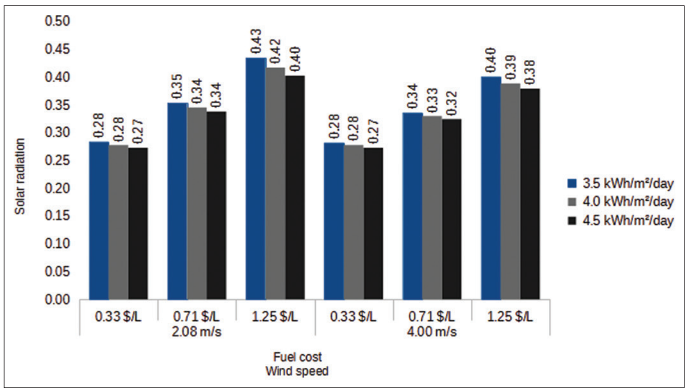
ID	CRITIC	Shannon Entropy	Equal Weights	Environmental	Social	Economic	Technical
C1	9.7	16.4	11.1	5.1	18.4	28.8	9.6
C2	10.8	5.1	11.1	25.0	9.4	7.5	10.8
C3	10.6	5.5	11.1	26.0	9.0	2.5	7.0
C4	12.6	8.1	11.1	16.0	7.2	4.3	6.8
C5	10.6	9.0	11.1	3.1	21.0	13.9	3.5
C6	10.6	10.8	11.1	1.9	16.0	11.9	2.1
C7	10.0	16.8	11.1	4.9	3.1	7.9	18.0
C8	12.5	13.6	11.1	11.4	4.9	14.8	22.0
C9	12.6	14.6	11.1	6.6	11.0	8.5	20.2
	100	100	100	100	100	100	100

On the other hand, PROMETHEE II showed greater alignment with VIKOR results. S1 ranked first in four scenarios: CRITIC, Shannon's Entropy, Equal Weights, and Economic. S5 led in the Environmental and Social scenarios, whereas S3 ranked first in the Technical scenario. In pairwise comparisons, TOPSIS matched VIKOR 31% of the time, while PROMETHEE II matched VIKOR

Table 10: Multicriteria Sensitivity Analysis Results

Scenario	VIKOR						Topsis						PROMETHEE II					
	Position						Position						Position					
	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
CRITIC	S1	S2	S3	S5	S6	S4	S5	S6	S2	S1	S3	S4	S1	S3	S5	S6	S2	S4
Ent. Shannon	S1	S3	S2	S5	S4	S6	S1	S3	S4	S2	S5	S6	S1	S3	S5	S2	S4	S6
Equal Weights	S1	S5	S2	S3	S6	S4	S5	S6	S2	S1	S3	S4	S1	S5	S3	S6	S2	S4
Environmental	S5	S6	S1	S2	S3	S4	S6	S5	S2	S1	S4	S3	S5	S6	S1	S2	S3	S4
Social	S1	S2	S5	S6	S3	S4	S5	S6	S1	S2	S3	S4	S5	S1	S6	S2	S3	S4
Economic	S1	S2	S3	S4	S5	S6	S1	S2	S5	S6	S3	S4	S1	S2	S3	S5	S4	S6
Technical	S3	S1	S2	S4	S5	S6	S3	S4	S1	S2	S5	S6	S3	S1	S4	S2	S5	S6

Figure 11: Sensitivity analysis in HOMER



60% of the time. All three methods placed the alternatives in the same positions 29% of the time.

Regardless of differences or similarities between methods, it's crucial to note that a key advantage of VIKOR is its ability to assess decision significance and determine the superiority of alternatives. For instance, in the Environmental scenario, it provided a set of four solutions, while in the Social scenario, it offered two. This indicates similar performance across options for these perspectives, allowing for greater flexibility in decision-making.

5. DISCUSSION AND CONCLUSION

This study proposes a multi-criteria evaluation model for energy solutions, comprising two fundamental stages: E3 design and optimization of alternatives using HOMER software, followed by evaluation using the CRITIC and VIKOR multi-criteria methods. HOMER facilitated the identification of the best combinations of generation technologies for the study region at the best possible cost, while MCDM allowed for a comprehensive evaluation.

The combined use of these tools identified alternative S1 as the optimal solution for Alto Baudó, Colombia. This system integrates Solar Photovoltaic technology with a Diesel Generator and a Battery Bank. By combining renewable and non-renewable sources, this hybrid system offers both reliability and affordability, leveraging the advantages of each component.

Beyond identifying the best-cost alternatives, the analysis revealed the importance of considering multiple dimensions when addressing energization problems, given their multidimensional nature. It was possible to recognize the relevance of complementing the technical-economic analysis, obtained from HOMER, with the analysis of social and environmental variables using multi-criteria methods.

The CRITIC method was employed to determine objective weights of the evaluation criteria, mitigating the risk of biases since it eliminates human interaction in this step. This method utilized available information from the criteria against different alternatives to establish the importance of each indicator.

On the other hand, methods such as VIKOR become formidable tools to address rural energization problems, allowing the evaluation of different dimensions in decision making. Since HOMER limits its analysis to technical and economic aspects, multi-criteria tools become a fundamental complement to perform a comprehensive evaluation.

The sensitivity analysis revealed how decision outcomes can be influenced by the perspective used to define criteria weights and the chosen evaluation method. Then, decision-makers are responsible for determining the multi-criteria tool for the evaluation of energy projects. Selecting the multi-criteria method can be a complex step in the decision-making process; however, it is advisable to research and learn about the tools to choose the one that best aligns with the objectives pursued.

To explore different perspectives, this study used artificial intelligence tools to build weighting scenarios and verify how the preferred alternatives varied according to different standpoints in criteria weighting. This does not replace subjective evaluation, which can enrich this process by allowing the priorities of different stakeholders to be reflected and solutions to be tailored to the context of the country and region where the evaluation is being conducted.

Another finding of the sensitivity analysis is that the availability of renewable resources significantly enhances the affordability and stability of energy solutions by mitigating the risks associated with fuel cost fluctuations, such as diesel. These findings suggest that expanding the range of renewable alternatives, considering alternatives such as hydrogen, biomass, thermal energy, and hydropower, could further improve the robustness and sustainability of the energy solutions proposed in this study. Moreover, a deeper exploration of the energy-water-food nexus in the Colombian context could provide valuable insights into the interrelationships and potential benefits of integrating improvements across these sectors.

The proposed evaluation model demonstrates the efficacy of integrating simulation and optimization tools with multi-criteria evaluation methods. This integrated approach enables the identification and prioritization of sustainable, context-appropriate energy solutions, supporting energy planning processes in countries such as Colombia, which aspire to achieve universal energy access, a valuable strategy for addressing energy poverty in remote areas of developing countries.

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APPENDICES

A. Literature Review Results

The table presents the results of the literature review, detailing the methods and tools utilized by each author during each stage of their research.

Table A1: Methods and tools for energy optimization and evaluation

Method/Tool			Source
Weighting of criteria	**Ranking of alternatives**	**Optimization**	
Equal weighting	VIKOR		Aberilla et al., 2020
CRITIC	CODAS		Ali et al., 2020
AHP	CODAS, EDAS, WASPAS, MULTIMOORA		Ali et al., 2020
BWM, IDOCRIW	Cocoso		Ali et al., 2022
AHP	AHP		Bhandari et al., 2021
AHP	AHP		Bilal et al., 2022
AHP	TOPSIS		da Ponte et al., 2021
Equal weighting	TOPSIS	HOMER	Das et al., 2022
BWM	VIKOR, TOPSIS	HOMER, MATLAB	Elkadeem et al., 2021
AHP	VIKOR, WASPAS, CODAS, TOPSIS	HOMER	Elkadeem et al., 2021
		MATLAB	Fioriti et al., 2021
		MOPOSO algorithm	
AHP	VIKOR	IntiGIS	Gómez et al., 2023
EWM	MULTIMOORA, TOPSIS, EDAS		He et al., 2021
G1-Method			
Weight Assignment	Commitment Programming	Offgriders	Juanpera et al., 2020
EWM	TOPSIS		Kaur et al., 2023
AHP	VIKOR	HOMER	Kotb et al., 2021
AHP	PROMETHEE	HOMER	Mallek et al., 2024
AHP, BWM	VIKOR, TOPSIS	Numerical Method	Ridha et al., 2022
AHP	AHP		Mwanza and Ulgen, 2020
Maximizing Deviation	ELECTRE I		Peng et al., 2021
BWM	PROMETHEE II, TOPSIS	Bi-Archive Algorithm	Ridha et al., 2023
AHP, BWM	TOPSIS, PROMETHEE II	MORMDA algorithm	Ridha et al., 2024
	TOPSIS	HOMER, MATLAB, EXCEL	Tariq et al., 2021
AHP	TOPSIS	HOMER	Ukoba et al., 2020
AHP	MULTIMOORA, TOPSIS, EDAS	HOMER	Ullah et al., 2021
GRP	GRP		Wang et al., 2022

B. Regression Analysis Results

The tables present linear regression results. The first table provides a measure of the model's fit. The second table details the significance of the regression coefficients for each independent variable.

Table A2: Regression analysis results

Regression results	
Multiple correlation coefficient	0.990
Coefficient of determination R^2	0.980
R^2 Adjusted	0.976
Typical error	0.008
F	232.000
F Critical value	3.16E-12

Table A3: Reliability of regression coefficients

Variables	Coefficients	Typical error	Statistic t	Probability
Interception	0.33	0.02	15.69	2.80E-10
D	0.14	0.01	25.87	3.20E-13
S	−0.02	0.00	−3.55	3.22E-03
W	−0.01	0.00	−3.76	2.13E-03