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Energy Planning: A Fuzzy Multi-Objective Tool for Sustainable Energy Mixes in Colombia

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ABSTRACT

This study introduces a computational tool developed to identify the most sustainable alternative for integrating a hybrid renewable energy system. The approach brings together a fuzzy optimisation model, focused on minimising both the Net Present Value and carbon dioxide emissions, with the Fuzzy Analytical Hierarchy Process, incorporating economic, technical, environmental, and social criteria. To enhance usability, the tool includes an Excel-based module that allows users to adjust quantitative parameters, while qualitative aspects can be modified through editable comparison matrices in the main graphical interface. This flexibility makes it adaptable to a wide range of geographical and contextual scenarios. The proposed framework was applied in a pilot-scale case study in the municipality of Tona, Colombia. The selected energy mix consists of 57.56% photovoltaic solar energy, 35.42% biomass-based generation, and 7.02% diesel generation, achieving a Net Present Value of 1,765.68 US Dollars and total emissions of 1,216.08 kg of carbon dioxide.

KEYWORDS

Energy planning tool, Energy transition, Fuzzy analytical hierarchy process, Fuzzy optimisation model, Power grid, Renewable energy system.

INTRODUCTION

The rapid socio-economic growth of communities worldwide continues to drive a steady increase in global energy demand. This demand is predominantly met through fossil fuels such as oil, coal, and natural gas. These are finite resources and among the primary contributors to greenhouse gas emissions [1]. The energy sector is one of the main drivers of climate change, accounting for approximately 25.93% of global carbon dioxide (CO_2) emissions [2]. In response, the United Nations has established the Sustainable Development Goals [3] and the Paris Agreement [4], both aiming to promote the adoption of renewable and sustainable energy sources to slow down climate change and move toward carbon neutrality.

In this context, Colombia introduced Law 1715 in 2014 to encourage the integration of renewable energy through economic incentives [5]. However, the country's complex geography,

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which includes mountainous regions, constitutionally protected areas, and territories affected by internal conflict, presents significant challenges. As a result, approximately 53% of the national territory corresponds to non-interconnected areas, while only 47% is connected to the National Interconnected System (SIN) [6]. In these non-interconnected zones, electricity is supplied predominantly by diesel generators, which make up 84% of the energy mix, while renewables account for only 14%. This reliance on diesel leads to high CO_2 emissions and limited electricity service, often restricted to five to ten hours per day [7]. In areas connected to the SIN, electricity generation depends heavily on hydroelectric power plants, which provide around 70% of the national supply. This dependence increases the vulnerability of the energy system to climatic variability, particularly during droughts and periods of intense rainfall [8]. To address these vulnerabilities, institutions such as the Mining and Energy Planning Unit (UPME) and the Institute for the Planning and Promotion of Energy Solutions in Non-Interconnected Zones (IPSE) have developed the National Energy Plan. This strategy seeks to expand and diversify the national electricity matrix by promoting renewable energy sources [9].

Energy planning projects are inherently complex, as they must consider a wide range of interdependent factors. These include the availability of renewable energy resources such as solar, wind, and biomass, land suitability for infrastructure development, technical and financial parameters of the technologies involved, and the specific energy demands of local communities. All these factors are critical in determining when and how much capacity should be added over the planning horizon [10].

Such planning problems are typically approached using bottom-up methodologies. These rely on models that account for energy demand and local resource availability to optimise system configuration at the community level [11]. As noted in [12], most optimisation models in the literature focus on minimising a single economic objective function. Only a few adopt multi-objective formulations that combine economic goals with reliability or environmental performance, with the latter gaining increasing relevance in the context of energy transition.

One of the major challenges of integrating renewable energy lies in its intermittent and variable nature throughout the day [13]. These limitations often make it unfeasible to rely exclusively on renewable sources. To ensure a reliable and continuous electricity supply, conventional technologies like diesel generators are still necessary to provide backup. This combination of conventional and renewable technologies is commonly referred to as a hybrid renewable energy system (HRES) [14].

To address the complexity of energy planning, a number of computational tools have been developed. These tools aim to optimise the use of renewable energy potential while meeting community energy needs, whether in isolated or interconnected settings. Among the most widely used commercial tools are HOMER (Hybrid Optimization Model for Multiple Energy Resources), RETScreen, and iHOGA (Hybrid Optimization by Genetic Algorithms).

In addition to these, several open-source tools have been identified in various comprehensive reviews. In [15], 97 free computational tools were examined and highlighted some of the most relevant and functional platforms, including Balmorel, Calliope, ELMOD, EMMA, EnergyPLAN, EnergyScope, GENeSYS-MOD, H2RES, LUT-ESTM, OSeMOSYS, Oemof Family, PLEXOS Open EU, PyPSA, Renpass, REMix, and Temoa. In [16], 203 commercial tools and 40 open-source tools were reviewed, identifying among their main shortcomings characteristics such as scalability, interoperability between different software, integration of IoT and blockchain technologies, advanced analysis, multivector energy systems, among others. In [17], it was found that most tools include economic, technical, and environmental indicators, for the design and optimisation of renewable energy systems. However, none of these consider social factors, such as job creation or social acceptance.

In addition to the aforementioned shortcomings, most optimisation models still rely on a single cost-based objective, treating CO_2 emissions as constraints rather than objectives. Tools that do apply multi-objective optimisation typically present relative comparisons between objectives but fall short in integrating broader decision-making frameworks [15]. To better support decision-makers, it is essential to include multi-attribute decision-making methods (MADM). These allow for the selection of the most sustainable options along the Pareto frontier by incorporating both quantitative and qualitative aspects that may not be fully captured in the optimisation process due to computational limitations or definitional complexity [18].

Among the available MADM, the Analytical Hierarchy Process (AHP), TOPSIS, and VIKOR are commonly applied. AHP stands out for its intuitive structure, internal consistency checks, and user-friendly nature, especially for stakeholders with limited technical backgrounds [19]. Still, a persistent challenge in energy planning and MADM applications is the stochastic nature of input data and expert judgment. Fuzzy logic offers a valuable way to represent these uncertainties using ranges of possibility, rather than relying solely on historical data as required by probabilistic methods [20].

One relevant contribution in this area is the Energy Fuzzy-On tool. This platform enables the selection of sustainable electricity generation alternatives for non-interconnected zones in Colombia, incorporating economic, technical, environmental, and social criteria under a fuzzy environment. While it is the only tool that currently integrates optimisation models, MADM methods, and fuzzy logic, its scope is limited to isolated regions without grid access [21].

Based on the above, this study introduces a new computational tool called "Energy On Planning". This proposal differs from existing tools, with the exception of Energy Fuzzy-On, by integrating MADM methods with fuzzy logic techniques. Its purpose is to incorporate expert judgement into the decision-making process, facilitating the selection of the most sustainable Pareto alternative. It also allows for the management of uncertainty associated with both qualitative and quantitative parameters, both in the optimisation model and in the MADM process.

Compared with Energy Fuzzy-On, the proposed tool incorporates additional functionalities, such as the analysis of interconnected zones and the possibility of considering the sale of surplus energy within the optimisation model, in accordance with Resolution 174 of 2021 of the Colombian Energy and Gas Regulatory Commission (CREG). It also enables annual assessments over longer planning horizons (up to 20 years), defined according to the useful life of the technologies. As an open-source Python-based tool, it includes predefined case-study zones, particularly in high-mountain regions, highlighting the importance of reducing CO_2 emissions and protecting strategic ecosystems such as the páramos.

Moreover, its scalable and flexible architecture allows application in diverse geographical contexts and facilitates the integration of new conventional and unconventional technologies with minimal modifications to the code. Through the incorporation of a MADM, the tool also accounts for social criteria, including job creation and social acceptance.

DESIGN RATIONALE AND FUNCTIONAL STRUCTURE OF THE ENERGY ON PLANNING TOOL

The following sections describe the structure and components of the computational tool developed to support the selection of the most sustainable alternative for integrating a HRES in grid-connected areas of Colombia. This hybrid system includes technologies such as photovoltaic solar panels, biomass gasifiers, wind turbines, and diesel generators. Although biomass gasifiers are costly and associated with relatively high CO_2 emissions, they remain relevant due to their ability to process local agricultural waste, thereby contributing to the reduction of excess biomass accumulation in rural areas [22]. Battery storage technologies were not included in the optimisation model due to the assumption of reliable grid connectivity, which provides sufficient flexibility to balance supply and demand. In this context, the grid acts as a virtual storage system, enabling both energy export and import. As a result, storage does not provide a clear economic advantage in terms of improving the Net Present Value (NPV), since its additional investment and operational costs are not offset by sufficient benefits under the studied conditions. Therefore, its exclusion is consistent with the scope of this work. Nevertheless, storage may become relevant under scenarios with higher renewable penetration, demand variability, limited grid capacity, or lower technology costs, which is identified as future work.

The Energy On Planning tool was developed in Python using the Pyomo library for the optimisation model and Tkinter for the graphical user interfaces [23]. The Gurobi solver, under an academic license, was used to resolve the optimisation problem [24]. Additionally, an Excel-based sub-tool was incorporated to allow users to modify the quantitative parameters employed in the optimisation model.

Excel sub-module for configuring quantitative input parameters

The quantitative parameters provided through the Excel module and used as input data for the fuzzy optimisation model were categorised into financial, technical, and environmental variables, depending on the technology and study region. These parameters include investment and operational costs for each technology, emission factors, availability factors, electricity demand, and the availability of local resources, among others. All parameters were projected over a 20-year planning horizon. Baseline values were estimated using data from national and international sources, including databases from the UPME [25], the International Energy Agency (IEA) [26], the International Renewable Energy Agency (IRENA) [27], the Ministry of Agriculture and Rural Development [28], and the doctoral dissertation of Rosso-Cerón [29].

Optimisation model

The structured optimisation model corresponds to a multi-objective Mixed-Integer Linear Programming (MILP) problem, subject to design, operational, and budgetary constraints. The input parameters represent the techno-economic and operational characteristics of each technology considered in the system. The mathematical expressions of the MILP formulation are detailed as follows.

Objective functions. The model aims to minimise two key objectives: the NPV (eq. (1)) and the total CO_2 emissions (eq. (2)) associated with the energy mix.

The NPV aggregates all discounted economic cash flows over the planning horizon, using a discount rate (TD) that reflects the financial risks associated with the development of sustainable energy projects, as typically estimated by major financial institutions. This formulation includes parameters such as unit investment costs, fixed and variable operation and maintenance (O&M) costs, unit costs of primary fuel consumption, and unit revenues from the sale of surplus electricity.

To ensure consistency in the minimisation of both objective functions (NPV and CO_2 emissions), a sign convention was adopted in which all costs are defined as positive values, while revenues from electricity sales are represented as negative values. Under this formulation, minimising the NPV leads to more negative values, which, by convention, correspond to higher economic benefits.

Therefore, NPV results are presented as negative values in the Pareto front plots, whereas for discussion and analysis purposes, absolute values are used to facilitate interpretation and avoid conceptual inconsistencies:

$$NPV = \sum_t \frac{1}{(1+TD)^t} \times \begin{bmatrix} \sum_p InvCo_{p,t} \times CaA_{p,t} + \sum_p FixCo_{p,t} \times CaT_{p,t} + \\ \sum_p VarCo_{p,t} \times EnG_{p,t} + \\ \sum_p FuCo_{p,t} \times FuR_{p,t} - \sum_p SellCo_{p,t} \times EnVe_{p,t} \end{bmatrix} \tag{1}$$

Similarly, CO_2 emissions associated with each technology are estimated based on their emission factors and the amount of energy generated, thereby penalising high-emission technologies within the optimisation model. These emission factors depend on the type of primary fuel consumed to generate 1 kWh, particularly for diesel and biomass-based technologies. In the case of biomass, the emission factor further depends on its chemical composition:

$$CO_2 = \sum_t \left[\sum_p Em_p \times EnG_{p,t} \right] \tag{2}$$

Therefore, based on the parameters defining the objective functions and their inherent trade-off, the MILP model is expected to favour technologies with lower investment costs or lower CO_2 emissions, depending on the relative prioritisation of economic versus environmental objectives.

<u>Operational constraints</u>. These constraints ensure that both electricity demand and peak power requirements are met, while also accounting for surplus generation that enhances system reliability and allows for the commercialisation of excess electricity. The constraints considered are described as follows.

Electricity demand constitutes the primary driver for sizing the hybrid energy system, requiring the model to install higher capacities under higher demand scenarios, and vice versa. Therefore, the total energy generated must satisfy the electricity demand as well as the energy sold to the grid:

$$\sum_p EnG_{p,t} = DE_t + \sum_p EnVe_{p,t} \tag{3}$$

To ensure system reliability, both the peak power demand and a 6% reserve margin must be satisfied. Peak power demand represents the maximum instantaneous electricity requirement, measured in kW. Incorporating a reserve margin helps maintain system stability under unforeseen events, such as outages or sudden load variations, preventing failures in generation units or transmission infrastructure due to abrupt power changes.

Consequently, this constraint leads to the installation of additional capacity beyond what is strictly required to meet the average electricity demand:

$$\sum_p PoG_{p,t} \geq (1 + \rho) \times DP_t \tag{4}$$

For each proposed technology, the energy generated must correspond to the installed power output, adjusted by the fraction of time the plant is operational, as defined by the availability factor. This factor accounts for scheduled maintenance and climate-related variability and reflects the capability of each technology to reliably supply electricity demand, as well as the potential need for complementary or backup technologies. Additionally, since the MILP model is formulated on an annual basis, the total number of hours in a year is incorporated through the parameter DB:

$$EnG_{p,t} = Fd_p \times DB_t \times PoG_{p,t} \tag{5}$$

The power generated by the conversion technologies must not exceed the ratio between the average power actually produced and the power that would be generated under ideal conditions, as defined by the capacity factor. Therefore, this factor ensures that the model installs sufficient capacity to produce feasible energy outputs under real operating conditions, considering climate variability, resource availability, and the operational characteristics of each technology:

$$PoG_{p,t} \leq Fc_p \times CaT_{p,t} \tag{6}$$

Design constraints. These constraints ensure that installed capacities are not oversized, considering predefined capacity limits, construction lead times, and the availability of primary energy resources.

The total installed capacity must equal the sum of the pre-existing capacity in the region and the newly added capacity. Additionally, each plant must comply with the required construction lead time (T_p) before becoming operational. As a result, the model is driven to install sufficient capacity in advance to ensure energy supply continuity, accounting for the delay between investment decisions and the actual availability of new generation capacity. This temporal constraint influences planning decisions by requiring earlier investments to meet future demand while respecting construction timelines:

$$CaT_{p,t} = ICa_{p,t} \times Op_{p,t} + \sum\nolimits_{v \leq t - T_p} CaA_{p,t} \tag{7}$$

The added capacities must be within the established limits to avoid oversizing and installation of very low capacities. This constraint ensures that only feasible solutions are considered, taking into account commercially available equipment and the geographical conditions of the study area:

$$Camin_p \times In_{p,t} \leq CaA_{p,t} \leq Camax_p \times In_{p,t} \tag{8}$$

The additional installed capacities must fall within predefined upper and lower bounds to prevent both oversizing and the installation of capacities that are too small to be technically or economically viable:

$$\sum\nolimits_t CaA_{p,t} \leq Camax_p \tag{9}$$

The primary resources consumed for electricity generation must not exceed the available primary resources in each target region, including solar radiation, wind speed, agricultural residues, and commercially available diesel. Furthermore, this constraint depends on the specific consumption of each primary resource required to generate 1 kWh, taking into account operational factors such as the efficiency of each technology:

$$Rw_{r,p} \times EnG_{p,t} \leq PriT_{r,t} \tag{101}$$

The amount of primary resource consumed by diesel power plants to generate electricity corresponds to the quantity of fossil fuel (diesel) or agricultural residues purchased in the market:

$$Rw_{r,p} \times EnG_{p,t} = FuR_{r,t} \tag{11}$$

Budgetary constraints. This constraint limits the amount of funding allocated to each region for the implementation of energy planning projects. The budget parameter plays a critical role in the optimisation model, as it restricts the maximum capital that can be invested, even in cases where more favourable hybrid system configurations are identified over the planning horizon but require higher upfront investment. The available budget is estimated based on the guidelines established by the Financial Support Fund for Electrification of Interconnected Rural Areas (FAER) [30]:

$$\sum_t \frac{1}{(1+r)^t} \times \left[\sum_p InvCo_{p,t} \times CaA_{p,t} \right] \leq BugCo \tag{12}$$

Uncertainty management

The stochastic nature of the quantitative parameters used as input data in the optimisation model is addressed through the application of fuzzy mathematics, which is implemented in the following steps:

<u>Fuzzification</u>. The original data for the input parameters supplied to the optimisation model, also known as crisp values (X), are transformed to incorporate the uncertainty associated with their estimation. This process, known as fuzzification, consists of converting each crisp value into a fuzzy number $\tilde{X}$ using a membership function (μ), which takes values in the interval [0,1].

Among the various forms of membership functions, the most widely used and recommended is the triangular function, due to its simplicity and adequate representation of uncertainty. In this case, the crisp value is represented by a triangular fuzzy number defined by three values (X_1, X_2, X_3) (eq. (13)):

$$X \to \tilde{X} = (X_1, X_2, X_3) \tag{13}$$

Where X_1, X_2, and X_3 represent the pessimistic, most likely, and optimistic values, respectively. In addition, to incorporate these fuzzy numbers into the optimisation model, the method known as the α-cut is used (Figure 1) [31].

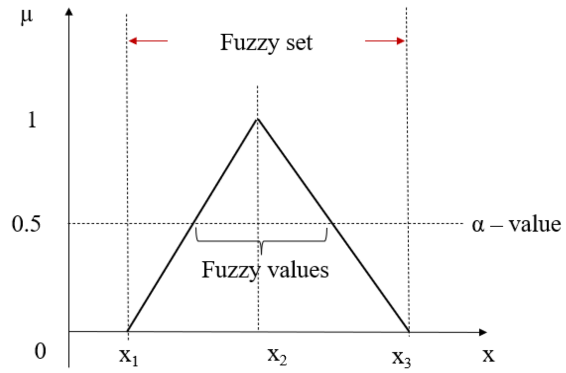

Figure 1. α-cut method

This method involves selecting a membership level α ∈ [0,1], which defines the range of acceptable values within the fuzzy number. From this level, the bounded values of the fuzzy number $(X_1^\alpha, X_2^\alpha, X_3^\alpha)$ are obtained, defined as:

$$X_1{}^\alpha = \alpha \times (X_2 - X_1) + X_1 \quad if \quad X_1 \leq X \leq X_2 \tag{14}$$

$$X_2{}^\alpha = X_2 \quad if \quad X = X_2 \tag{15}$$

$$X_3{}^\alpha = X_3 - \alpha \times (X_3 - X_2) \quad if \quad X_2 \leq X \leq X_3 \tag{16}$$

Accordingly, low values of α (close to 0) broaden the range of uncertainty considered, allowing for the exploration of a greater number of possible scenarios within the model, even if they include potentially less realistic solutions. Conversely, high values of α progressively narrow this range until α = 1 is reached, at which point the model is reduced to the original crisp value, completely eliminating uncertainty. In this regard, selecting an intermediate value, such as α = 0.5, allows for an appropriate balance to be maintained between scenario exploration and realism in the results.

Defuzzification. To incorporate fuzzy values into the structure of the optimisation model, the following methodologies are applied.

Fuzzy parameters within the objective functions are defuzzified using the expected value method [32], defined as:

$$X^{\alpha} = \frac{{X_1}^{\alpha} + 2{X_2}^{\alpha} + {X_3}^{\alpha}}{4} \tag{17}$$

Fuzzy parameters appearing in the constraints are defuzzified using the methodology proposed by Lai and Hwang (1992) [33]. When these parameters are located on the left-hand side of the constraint, Equation (18) is applied. If fuzzy parameters are present on both sides of the expression, Equation (19) is used instead:

$$\frac{1}{6}\left({X_1}^{\alpha} + 4{X_2}^{\alpha} + {X_3}^{\alpha}\right) \times x_i \leq b \tag{18}$$

$$\tilde{X} \times x_i \leq \tilde{b} = \begin{cases} {X_1}^{\alpha} \times x_i \leq {b_1}^{\alpha} \\ {X_2}^{\alpha} \times x_i \leq {b_2}^{\alpha} \\ {X_3}^{\alpha} \times x_i \leq {b_3}^{\alpha} \end{cases} \tag{19}$$

The structured fuzzy optimisation model was solved using the ε-constraint method [34], generating a set of 10 alternatives and considering the NPV as the primary objective function. The resulting Pareto front is used as input data for the fuzzy MADM.

Fuzzy Analytical Hierarchy Process

The Energy On Planning tool incorporates the Fuzzy Analytical Hierarchy Process (FAHP) to select the most sustainable Pareto alternative based on expert judgment. To construct the pairwise comparison matrices, a hierarchical structure composed of criteria, subcriteria, and alternatives was defined, as shown in Figure 2.

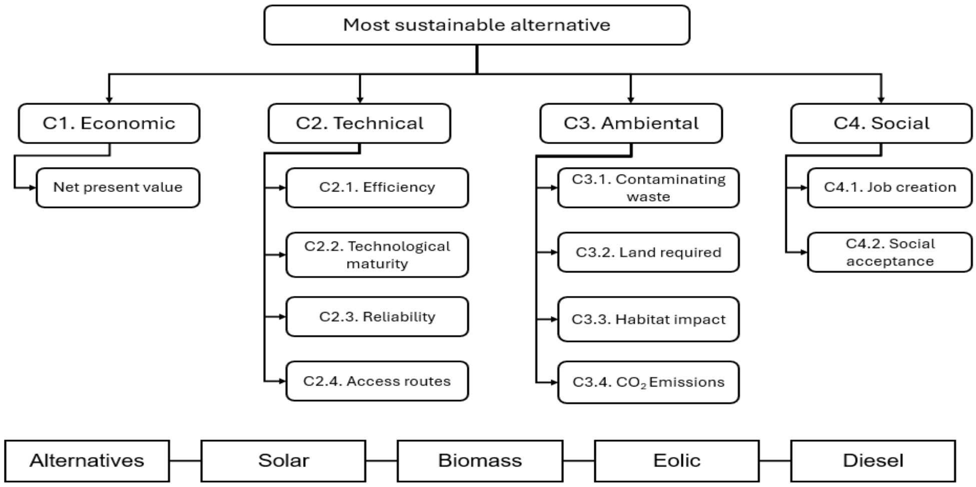

Figure 2. Hierarchical structure of the FAHP method

Given that these matrices rely on expert judgment, the assigned values may involve a certain degree of uncertainty, particularly when using the Saaty scale, where experts may hesitate between adjacent preference levels. To address this issue, fuzzy logic is incorporated using the Buckley method [35].

In this approach, each crisp value provided by the expert is transformed into a triangular fuzzy number. The lower and upper bounds are defined by decreasing or increasing the original Saaty value by one unit, respectively, while the central value corresponds to the original judgment. Exceptions are made for the extreme values (1 and 9), which are represented as single-point fuzzy numbers to preserve consistency. The resulting fuzzy scales used in the analysis are presented in Table 1.

Table 1. Fuzzy sets and numbers

Linguistic variable	Fuzzy values	Reciprocal fuzzy values
Equal importance	(1, 1, 1)	(1, 1, 1)
Moderate importance	(2, 3, 4)	(1/2, 1/3, 1/4)
Strong importance	(4, 5, 6)	(1/4, 1/5, 1/6)
Very strong importance	(6, 7, 8)	(1/6, 1/7, 1/8)
Extreme importance	(9, 9, 9)	(1/9, 1/9, 1/9)
Intermediate importance	(1, 2, 3)	(1, 1/2, 1/3)
	(3, 4, 5)	(1/3, 1/4, 1/5)
	(5, 6, 7)	(1/5, 1/6, 1/7)
	(7, 8, 9)	(1/7, 1/8, 1/9)

Subsequently, once the crisp pairwise comparison matrices have been converted into fuzzy matrices, the geometric mean is calculated for each row of each fuzzy comparison matrix, using the following expression:

$$r_i = (a_{i1} \times a_{i2} \times \ldots \times a_{in})^{\frac{1}{n}} \tag{202}$$

Where r_i is the fuzzy geometric mean for row i, a_{in} is the fuzzy value in row i and column n. Then, the weights (w_i) are estimated for each row of the matrices:

$$w_i = r_i \times (r_1 + r_2 + \cdots + r_n)^{-1} \tag{21}$$

The fuzzy weights are defuzzified by applying the area centre method, using the following equation:

$$\widetilde{w_i} = \frac{w_{l_i} + w_{m_i} + w_{u_i}}{3} \tag{22}$$

Where w_{l_i}, w_{m_i} and w_{u_i} are the weights calculated for the most pessimistic, probable, and optimistic values, respectively. Finally, the most sustainable Pareto alternative, according to expert judgment, is selected using the following expression:

$$A_i = \sum_p \left(EnG_p \times w_p\right) \tag{23}$$

Where A_i is the weight or ranking of Pareto alternative i, EnG_p is the energy generated by power plant p, and w_p are the weights of each power plant p.

Sensitivity analysis

The robustness of the optimisation model and the identification of the most influential parameters were assessed through a sensitivity analysis, which examined their impact on the variation in NPV and CO_2 emissions across the Pareto-optimal alternatives. The analysis considered changes in the fuzzy parameter (α-level) in high-uncertainty (α = 0) and low-uncertainty (α = 1) scenarios, using the base case (α = 0.5) as a reference. In addition, based on historical price volatility and findings reported in previous studies of the Colombian energy sector, a variation of ± 20% was applied to the main input parameters, including investment costs, fixed O&M costs, variable O&M costs, electricity demand, fuel price and the electricity selling price. These parameter variations were applied for each uncertainty level (α = 0, 0.5 and 1.0) in order to assess the model's sensitivity under different uncertainty conditions.

Graphical interfaces and functionality

The Energy On Planning tool consists of a set of graphical interfaces that allow users to interact with the system throughout the entire process, from entering input data for the optimisation model to modifying the qualitative parameters used in the FAHP method. The main window enables users to select which conventional or non-conventional technologies to integrate, define the regions of interest (Pamplona, Silos, Tona, or a custom option), and specify the value of the membership level or α parameter (Figure 3. Main window).

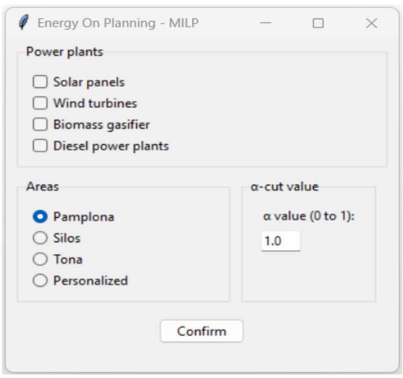

Figure 3. Main window

After selecting the desired options and clicking the "Confirm" button, the second interface is displayed, showing the results of the fuzzy optimisation model. These results include the

Pareto diagram and a table that allows users to identify the exact values associated with each alternative (Figure 4).

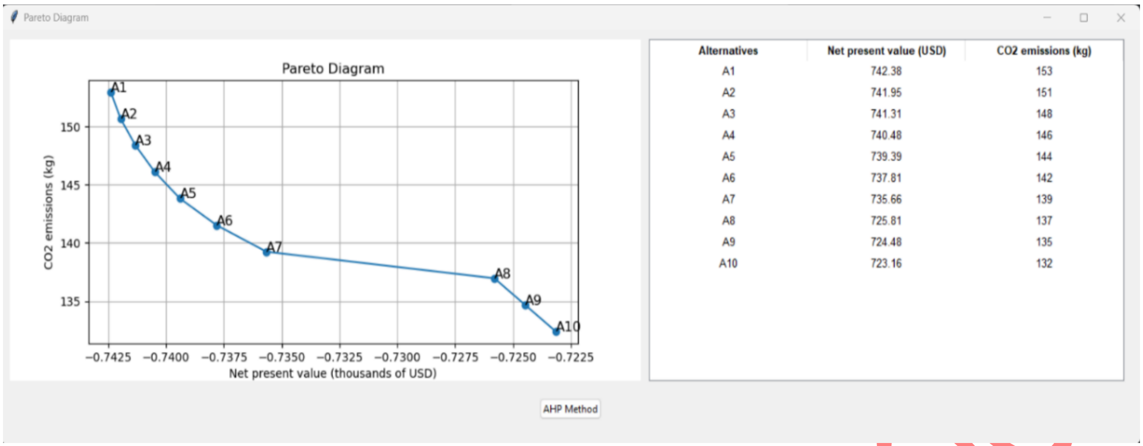

Figure 4. Results window of the fuzzy optimisation model

The tool also provides detailed information for each alternative regarding the decision variables related to installed capacity and energy generation throughout the entire planning horizon (Figure 5).

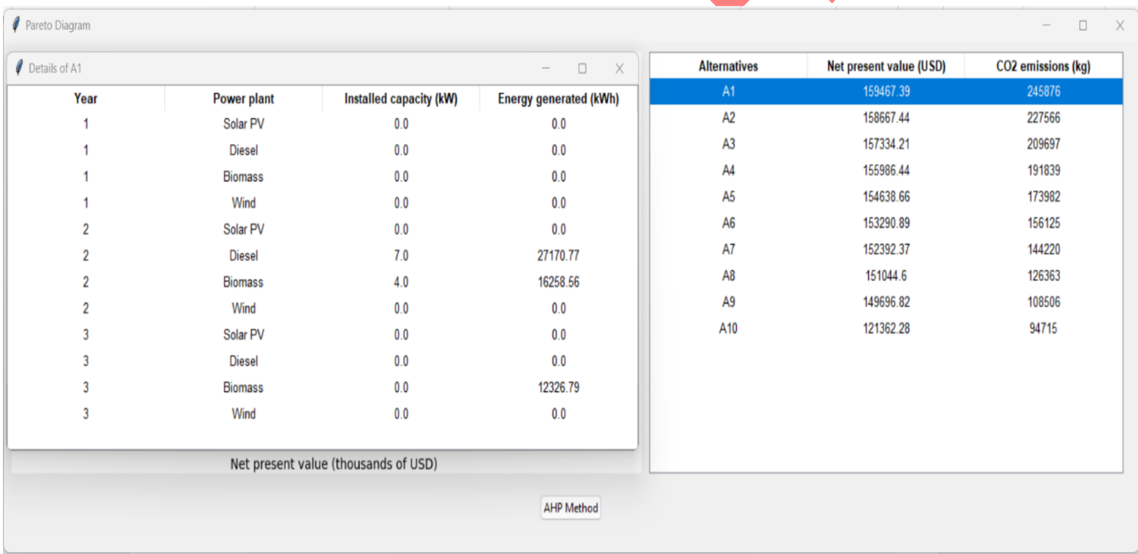

Figure 5. Decision variables window

After reviewing the results and selecting the "AHP Method" button, the comparison matrix interface is displayed. This interface allows the user to input qualitative values for the criteria and sub-criteria defined in the hierarchical structure, using the Saaty scale [36]. It also provides the option to use "Default values," which were obtained from a collection of expert opinions identified by the author (Figure 6). Expert judgments were elicited through structured surveys designed under the Delphi method, involving participants with extensive experience in energy transition technologies and energy planning. The panel was primarily composed of university professors holding doctoral degrees, with proven involvement in national and international projects related to clean energy and sustainable transitions. Additionally, postgraduate students whose research is specifically focused on these fields were included.

The survey was developed following the FAHP, enabling experts to provide pairwise comparisons of the selected criteria and sub-criteria. A total of nine experts participated in the process, and their judgments were aggregated using the arithmetic mean to construct the comparison matrix applied in the FAHP analysis.

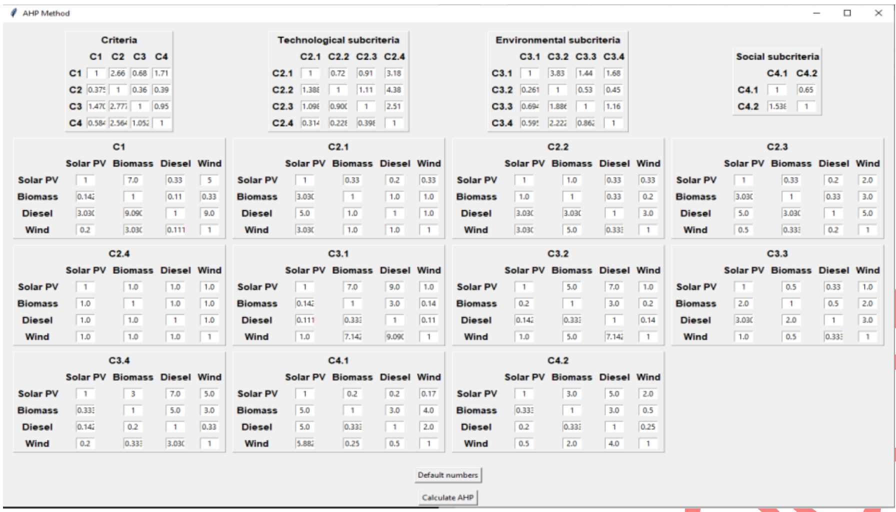

Figure 6. Comparison matrix window of the FAHP method

Finally, by clicking the "Calculate AHP" button, the last interface is displayed. This screen presents the selected sustainable alternative along with its prioritisation value. It also shows the values of the financial parameters, the objective functions, the energy generated, the initial and installed capacities, and a pie chart illustrating either the percentage of energy generated by each plant in the energy mix or the percentage distribution of the financial parameters (Figure 7).

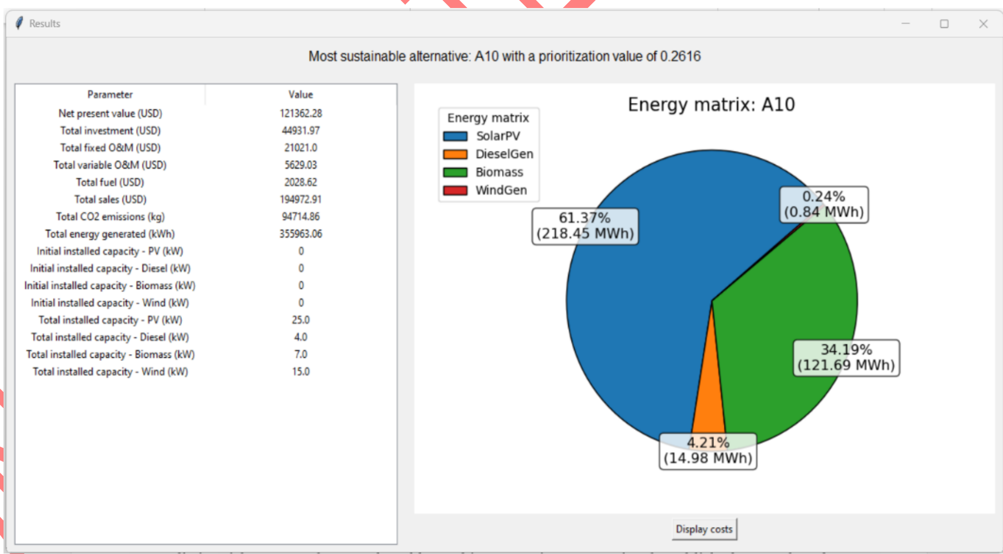

Figure 7. Results window of the most sustainable alternative

Case studies

The case studies implemented in the computational tool focused on the pilot-scale case study of municipalities of Pamplona, Santo Domingo de Silos, and Tona, all located in high-mountain regions of Colombia. These areas are of particular interest due to their proximity to the Santurbán Páramo, a region of high biodiversity that provides water to approximately 2.5 million people [37]. All three municipalities are connected to Colombia's SIN and include both rural and urban zones, with agriculture as their primary economic activity.

In addition, the Energy On Planning tool offers a "Custom" option that enables users to explore alternative geographical contexts by modifying the quantitative parameters used as input for the optimisation model. This customisation is carried out through the integrated Excel sub-tool.

RESULTS AND ANALYSIS

The Energy On Planning computational tool was implemented for the municipality of Tona, a small town with 6,680 inhabitants located in the department of Santander, Colombia [38]. According to reports from IPSE, Tona is connected to the SIN. To ensure the use of representative real-world data, a sample of 15 households was selected from rural areas of the municipality. These households correspond to low-income strata (levels 1–3), with an average of approximately three inhabitants per dwelling, reflecting typical demographic conditions of the region. Electricity demand was estimated through surveys conducted with the selected households, collecting information on the number of electrical appliances and their average operating hours. The base year was defined as 2018, corresponding to the period in which the survey data were collected within the framework of the research project acknowledged in this study. During this year, the estimated electricity demand reached 7,666.73 kWh and was fully supplied by the national grid, primarily based on hydroelectric generation. This grid connection allows for the commercialisation of electricity surpluses based on wholesale market prices, which averaged 0.095 USD per kWh in 2018 [39].

Although the analysis is based on real demand data from 15 households, the proposed tool is fully scalable, allowing the modification of input parameters to evaluate larger systems, such as community-scale or municipal energy systems.

Tona's primary energy resources include annual solar radiation ranging from 6.99 kWh/m^2 to 7.10 kWh/m^2, wind speeds between 1.86 and 1.92 m/s, and agricultural residues from bean, potato, and onion crops with a combined energy potential of 933,771.45 GJ per year. Given these conditions, technologies such as photovoltaic solar panels and biomass gasifiers were deemed feasible in the area. The agricultural waste selected for use as fuel was bean residue, due to its moisture content below 40%, which makes it suitable for efficient use in biomass gasifiers [40]. The expected population growth in Tona projects an increase in electricity demand and peak power requirements, reaching 11,205.42 kWh and 2.46 kW, respectively.

The collected data were used as input for the fuzzy optimisation model, with the membership level α set to 0.5. The resulting Pareto front is shown in Figure 8. Pareto diagram for the pilot-scale case study in the municipality of Tona. The curve presents 10 alternatives with a linear trade-off between the prioritisation of the objective functions. Over the planning horizon, the NPV ranged from 1,765.68 USD to 1,853.89 USD, while CO_2 emissions from the energy matrix varied from 1,759 kg CO_2 to 1,216 kg CO_2.

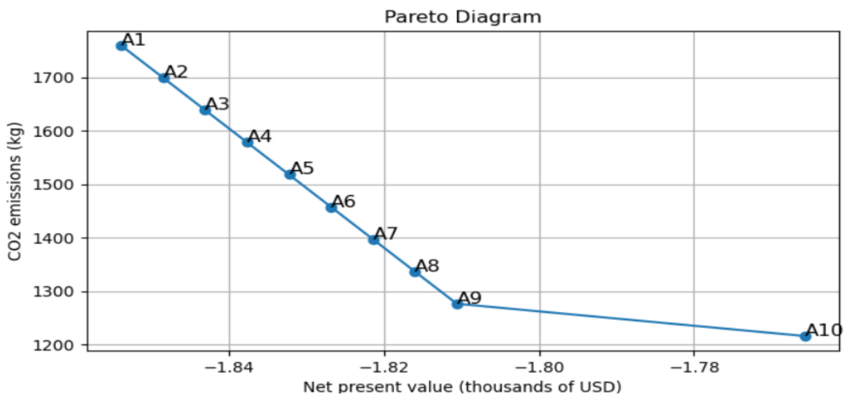

Figure 8. Pareto diagram for the pilot-scale case study in the municipality of Tona

Figure 9 illustrates the distribution of newly installed capacities throughout the planning horizon. In 2019, all alternatives included the installation of biomass gasifiers and diesel generators, with capacities of 0.08 kW and 0.04 kW, respectively. The only exception was alternative A10, which installed 0.06 kW of biomass and 0.07 kW of diesel. Additionally, in 2022, photovoltaic solar systems were installed, with capacities varying across the different alternatives. As the environmental objective gains more weight in the optimisation, the installed capacity of solar panels increases accordingly.

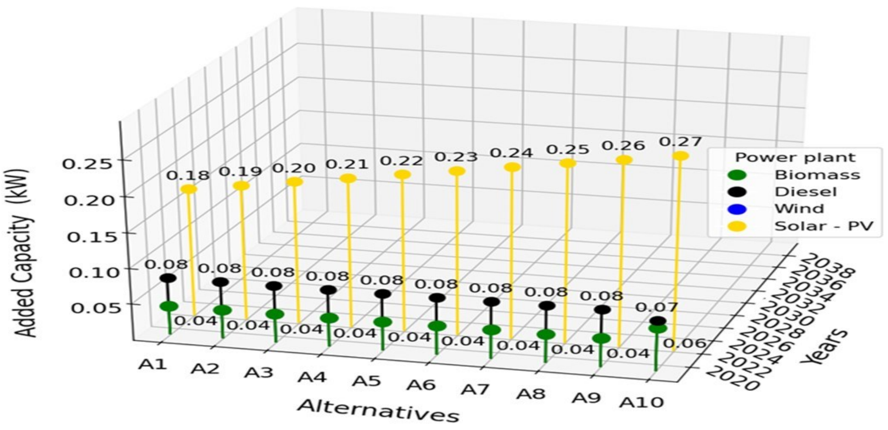

Figure 9. Installed capacities added during the planning horizon

Figure 10 presents, for each alternative, the percentage distribution of energy generation from the installed plants within the energy mix. Throughout the planning horizon, energy generation from diesel power plants remains constant due to their role as a backup system, with the exception of alternative A10, where a reduction in their contribution is observed. The increase in energy generation from solar panels leads to a corresponding decrease in the use of biomass gasifiers, which contributes to the reduction of CO_2 emissions. For alternatives A7 through A10, solar panels account for more than 50% of the total energy generation. These results indicate that in the pilot-scale case study in the municipality of Tona, it is not feasible to meet electricity demand with a fully renewable energy mix, due to the intermittent nature of solar panels, the inability to install wind turbines, and the high costs and CO_2 emissions associated with diesel power plants.

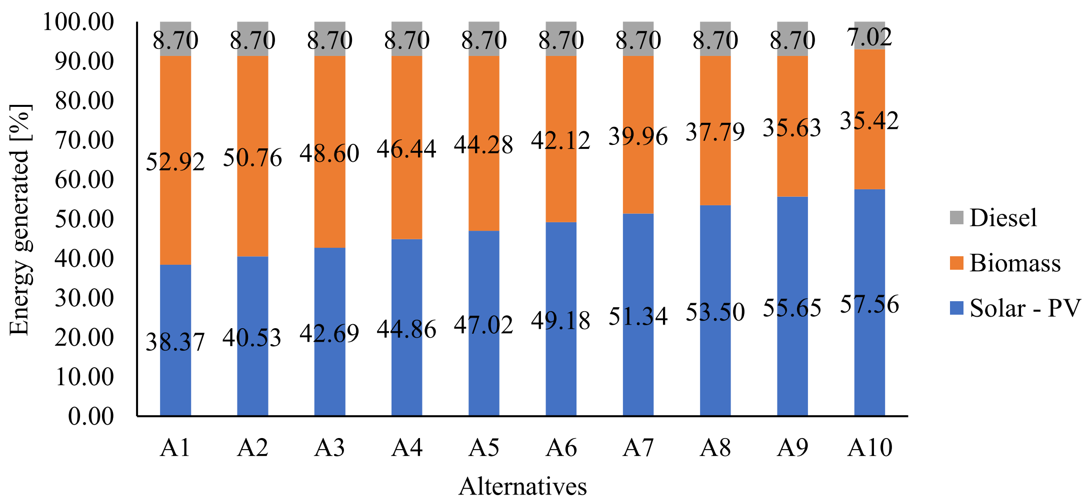

Figure 10. Percentage energy generation mix of Pareto alternatives

The most sustainable alternative was selected using the values established under the "Default Values" option. According to expert judgment, the selected alternative was A10, with a prioritisation score of 0.26. This configuration includes photovoltaic panels with an installed capacity of 0.27 kW, supported by a backup system composed of biomass gasifiers and diesel generators, with capacities of 0.06 kW and 0.07 kW, respectively. Solar panels contribute 57.56% of total electricity generation, followed by biomass gasifiers with 35.42% and diesel generators with 7.02% (Figure 11).

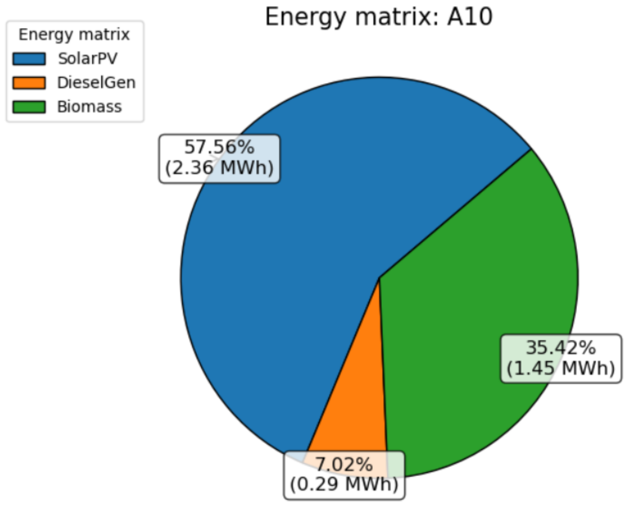

Figure 11. Energy generation mix of selected alternative A10

The NPV of the energy matrix results in a profit of 1,765.68 USD, with total CO_2 emissions of 1,216.08 kg CO_2. Investment costs represent the largest share of the total, accounting for 57.27%. These are followed by fixed and variable O&M costs, with shares of 24.57% and 11.54%, respectively. Finally, the costs related to fuel acquisition make up the smallest portion, representing 6.62% (Figure 12).

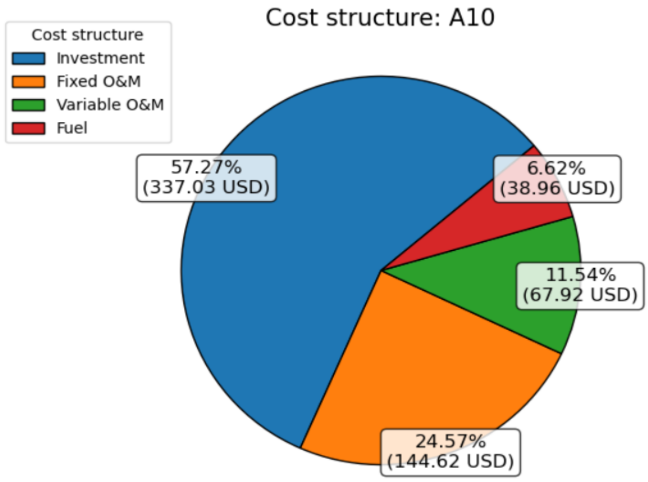

Figure 12. Cost structure of the energy matrix for alternative A10

The installed capacities and associated costs of the energy matrix are relatively low, as the initial estimated electricity demand is already met by the existing power grid. Therefore, the newly installed capacities are intended solely to cover the projected increase in demand.

To synthesise the results and provide a clearer quantitative comparison across alternatives, Table 2 and Table 3 present the main techno-economic indicators and the disaggregated cost structure, respectively.

Table 2 highlights a clear trade-off between economic and environmental performance. A progressive reduction in CO_2 emissions, from 1,759 kg CO_2 to 1,216 kg CO_2, is accompanied by a decrease in the magnitude of the NPV (i.e., lower economic benefit). This behaviour is mainly driven by the gradual increase in installed photovoltaic capacity, which rises from 0.18 kW in A1 to 0.27 kW in A10. In contrast, biomass and diesel capacities remain relatively stable, with only minor adjustments in the most environmentally prioritised alternative.

Table 2. Objective function values and installed capacity

Alternatives	NPV [USD]	CO_2 emissions [kg CO_2]	Installed capacity [kW]		
			PV	Biomass	Diesel
A1	1853.89	1759.00	0.18	0.04	0.08
A2	1848.48	1699.00	0.19	0.04	0.08
A3	1843.06	1639.00	0.2	0.04	0.08
A4	1837.65	1578.00	0.21	0.04	0.08
A5	1832.24	1518.00	0.22	0.04	0.08
A6	1826.83	1457.00	0.23	0.04	0.08
A7	1821.41	1397.00	0.24	0.04	0.08
A8	1816.00	1337.00	0.25	0.04	0.08
A9	1810.59	1276.00	0.26	0.04	0.08
A10	1765.68	1216.00	0.27	0.06	0.07

Table 3 further illustrates the economic implications of this transition. As optimisation increasingly prioritises environmental performance, investment costs rise steadily (from 245.97 USD to 337.03 USD), reflecting the higher capital requirements associated with renewable technologies, particularly solar PV. This trend is accompanied by an increase in fixed O&M costs, which are directly linked to installed capacity.

Conversely, variable O&M costs show a consistent decrease across the alternatives, indicating a reduced reliance on dispatchable technologies such as biomass and diesel. Similarly, fuel costs slightly decrease in the most environmentally favourable alternative (A10), reinforcing the shift away from conventional generation sources.

Table 3. Cost structure of the hybrid energy system

Alternatives	Cost structure [USD]				
	Investment	Fixed O&M	Variable O&M	Fuel	Revenue
A1	245.97	103.80	102.25	48.32	2354.22
A2	253.69	105.67	98.07	48.32	2354.22
A3	261.41	107.54	93.89	48.32	2354.22
A4	269.12	109.41	89.71	48.32	2354.22
A5	276.84	111.28	85.54	48.32	2354.22
A6	284.56	113.15	81.36	48.32	2354.22
A7	292.28	115.02	77.18	48.32	2354.22
A8	300.00	116.90	73.00	48.32	2354.22
A9	307.72	118.77	68.83	48.32	2354.22
A10	337.03	144.62	67.92	38.96	2354.22

Sensitivity analysis

The main findings of the sensitivity analysis are presented below:

Variation in the fuzzy parameter. The results associated with variations in the fuzzy parameter towards scenarios of higher uncertainty ($\alpha = 0$) and lower uncertainty ($\alpha = 1$) are presented in Table 4. Results indicate that, by widening the range of uncertainty of the parameters, the optimisation model has a greater degree of freedom, which allows it to explore more favourable combinations and, consequently, achieve higher NPV values. In contrast, when restricting the range of variation ($\alpha = 1$), the NPV results tend to be higher, as only central or more probable values are considered.

In this context, selecting an intermediate value ($\alpha = 0.5$) is appropriate, as it strikes a balance between uncertainty and the realism of the parameters, avoiding both overestimation and excessive restriction of the results.

Furthermore, Table 4 demonstrates that the variation in NPV with respect to the base case is relatively symmetrical for values of α both below and above 0.5, with changes ranging from 1.48% to 2.12%. This behaviour suggests that the model exhibits adequate stability in the face of variations in membership levels, demonstrating a consistent response in the management of fuzzy uncertainty.

Additionally, as shown in Figure 13, a change in the parameter α causes the Pareto front to shift mainly along the economic axis (NPV), whilst CO_2 emissions remain constant. This behaviour indicates that the structure of the optimal energy system, including the selected technologies and their share of generation, is not affected by the level of uncertainty considered. Consequently, changes in the NPV are due solely to variations in the economic parameters, without altering the system's technological configuration.

These results demonstrate that the model exhibits robust behaviour in the face of fuzzy uncertainty, as the optimal solutions remain stable and variations in the results are limited.

Table 4. Effect of membership level variation on the Pareto front

	α = 0.0	**α = 0.5 (base)**	**α = 1.0**	**α = 0.0**	**α = 0.5 (base)**	**α = 1.0**	
Alter.	NPV [USD]	NPV [USD]	NPV [USD]	CO_2 Em. [kg CO_2]	CO_2 Em. [kg CO_2]	CO_2 Em. [kg CO_2]	ΔNPV [%]
A1	1826.56	1853.89	1881.22	1759.00	1759.00	1759.00	± 1.48
A2	1820.29	1848.48	1876.66	1699.00	1699.00	1699.00	± 1.52
A3	1814.02	1843.06	1872.11	1639.00	1639.00	1639.00	± 1.58
A4	1807.75	1837.65	1867.55	1578.00	1578.00	1578.00	± 1.63
A5	1801.48	1832.24	1863.00	1518.00	1518.00	1518.00	± 1.68
A6	1795.21	1826.83	1858.44	1457.00	1457.00	1457.00	± 1.73
A7	1788.94	1821.41	1853.89	1397.00	1397.00	1397.00	± 1.78
A8	1782.67	1816.00	1849.33	1337.00	1337.00	1337.00	± 1.84
A9	1776.40	1810.59	1844.78	1276.00	1276.00	1276.00	± 1.89
A10	1728.23	1765.68	1803.13	1216.00	1216.00	1216.00	± 2.12

Variation in input parameters. The results of a ± 20% variation in the most influential input parameters, assuming a fixed level of uncertainty ($\alpha = 0.5$), are presented in Table 5. In general, the variations in investment costs, fixed and variable O&M costs and the price of fuel result in insignificant changes on the Pareto front, with variations ranging from 0.43% to 4.33% in NPV values.

Moreover, there are no changes in CO_2 emissions, indicating that installed capacities and the proportion of energy generated by each technology remain constant. In this regard, variations in costs affect only the economic structure of the system, increasing or decreasing the NPV depending on the modified parameter, without altering the optimal energy configuration.

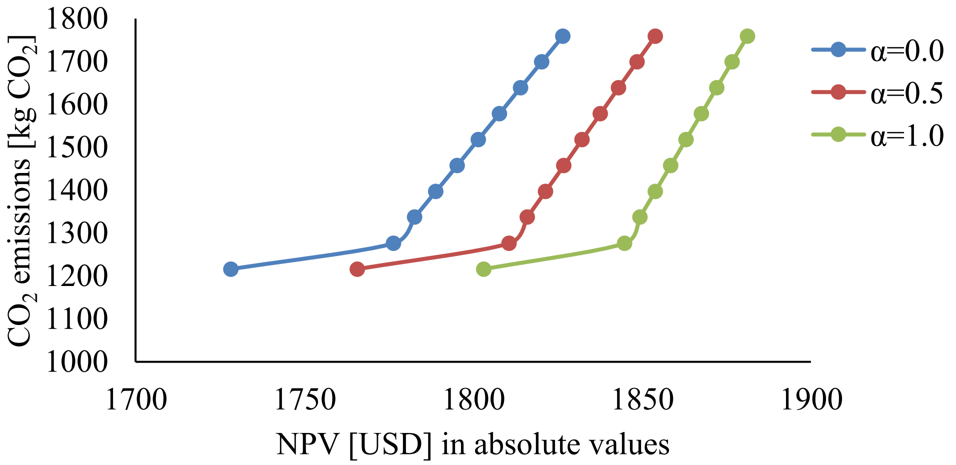

Figure 13. Pareto alternatives at different membership levels

In contrast, the most sensitive parameters identified are electricity demand and the unit selling price of surplus electricity. Electricity demand directly influences the objective function, as an increase in demand requires the installation of greater capacity and higher energy generation, whilst a reduction in demand produces the opposite effect. However, despite these changes, the relative contribution of each technology within the energy mix remains virtually unchanged, indicating a stable solution structure.

Meanwhile, the selling price of surplus electricity has the greatest impact on the NPV and is identified as the most critical parameter in the model. However, although this parameter leads to significant variations in economic benefits, it does not result in changes to the configuration of the energy system but only affects the level of revenue generated.

Finally, the results show that the most sustainable alternatives selected coincide with those of the baseline scenario, maintaining both the same alternative and its level of prioritisation. Overall, these results indicate that the optimisation model exhibits high robustness, as variations in the input parameters (± 20%) generate limited changes in the results and do not affect the selection of the optimal solutions.

Table 5. Sensitivity analysis of input parameters under different uncertainty levels

	α = 0.0		α = 0.5		α = 1.0	
Parameter	ΔNPV [%]	ΔCO_2 Em. [%]	ΔNPV [%]	ΔCO_2 Em. [%]	ΔNPV [%]	ΔCO_2 Em. [%]
Investment costs	2.99 - 4.33	0.00	2.65 - 3.81	0.00	2.32 - 3.32	0.00
Fixed O&M costs	1.14 - 1.67	0.00	1.12 - 1.64	0.00	1.10 - 1.60	0.00
Variable O&M costs	0.79 - 1.12	0.00	0.77 - 1.10	0.00	0.75 - 1.09	0.00
Electricity demand	20.00 - 21.37	19.98 - 32.23	20.00 - 21.18	19.98 - 32.23	20.00 - 20.99	19.98 - 32.23
Fuel price	0.45 - 0.53	0.00	0.44 - 0.52	0.00	0.43 - 0.51	0.00
Electricity sale price	27.25 - 25.78	0.00	25.40 - 26.67	0.00	26.11 - 25.03	0.00

The results obtained from the proposed optimisation model were qualitatively compared with those reported in previous studies in the literature. In particular, different energy system configurations were analysed, including: (i) isolated systems based on photovoltaic panels, wind turbines, and battery storage [41]; (ii) grid-connected hybrid systems integrating photovoltaic generation, diesel units, and batteries [42]; and (iii) microgrid configurations combining photovoltaic systems with combined heat and power (CHP) units [43].

Despite the differences in system configurations, a consistent trend can be identified between the reported studies and the results obtained in this work. Specifically, photovoltaic technology emerges as the dominant option for electricity supply, while complementary technologies such as energy storage systems and grid electricity support the balance between supply and demand. Additionally, technologies such as diesel generators and biomass gasifiers are typically employed as backup or supplementary units and therefore contribute only a small share to the overall energy mix. Similarly, wind turbines are used as complementary technologies when local wind conditions are low and do not provide sufficient energy to ensure their effective operation.

It is important to note that quantitative differences in the results are expected due to the variability in case study conditions, including resource availability, electricity demand, and techno-economic parameters. These differences directly influence the optimal installed capacity of each technology. However, the consistency observed in the overall behaviour of the system and in the selection of technologies across the various studies ensures that the proposed optimisation model yields realistic and reliable results. Therefore, this comparative analysis provides additional confidence that the model captures the key techno-economic drivers governing energy system design and can be reliably applied for decision-making purposes.

Although a direct comparison with dedicated optimisation platforms (e.g., HOMER or EnergyPLAN) is beyond the scope of this study, the consistency of the obtained results with widely reported energy system configurations in the literature provides a qualitative consistency check of the proposed modelling approach.

This implementation demonstrates that the developed computational tool is a valuable instrument for guiding decision-makers in the selection of alternatives for integrating HRES into the energy infrastructure of high-mountain regions in Colombia. Furthermore, it offers the flexibility to adapt the analysis to other geographical contexts by modifying the quantitative parameters used in the fuzzy optimisation model.

CONCLUSIONS

The developed computational tool, Energy On Planning, enhances the selection of the most sustainable alternative for integrating a HRES into the local energy network, with the objective of meeting the electricity demand of the target area. The tool integrates two robust methodologies: a fuzzy multi-objective MILP model and the FAHP. The optimisation framework generates multiple Pareto alternatives, combining conventional and non-conventional technologies while optimising economic and environmental objectives within the bounds of design, operational, and budgetary constraints. The FAHP method then systematically selects the most sustainable option based on the opinions of diverse experts, considering economic, technical, environmental, and social criteria.

By default, the proposed framework analyses three high-mountain regions in Colombia. Nevertheless, it also includes an Excel sub-tool that empowers users to explore alternative geographic scenarios by modifying the quantitative input parameters of the optimisation model. Energy On Planning also facilitates the adjustment of qualitative parameter values according to expert judgment through a user-friendly graphical interface for editing comparison matrices covering criteria, subcriteria, and alternatives.

Applied to the pilot-scale case study in the municipality of Tona, the tool produced a set of Pareto alternatives with absolute NPV values ranging from 1,765.68 USD to 1,853.89 USD, and CO_2 emissions varying between 1,759 kg CO_2 and 1,216 kg CO_2. Experts identified alternative A10 as the preferred choice, with the highest prioritisation score of 0.26. This solution generates a profit of 1,765.68 USD and features a cost structure comprising 57.27% initial investment, 24.57% fixed O&M costs, 11.54% variable O&M costs, and 6.62% fuel acquisition costs. The energy matrix of this alternative is composed of 57.56% solar panels, 35.42% biomass gasifiers, and 7.02% diesel generators. These results indicate that, within Tona, achieving a fully renewable energy mix is currently unfeasible, necessitating the installation of diesel generator capacity as a reliable backup.

The sensitivity analysis confirms the consistency of the optimisation model in the presence of uncertainty and variations in input parameters. Changing the membership level (α) shows that, although extreme values affect the NPV, they do not alter the technological configuration or CO_2 emissions. Similarly, variations of ± 20% in the main parameters generate limited economic changes, leaving the system structure and the selection of optimal alternatives unchanged. It was also found that electricity demand and the selling price of surplus energy are the factors that most influence the NPV. Overall, these results demonstrate the stability and qualitative consistency of the proposed framework with existing literature.

Energy On Planning provides a novel and comprehensive framework for the development of energy planning tools in interconnected zones by integrating fuzzy optimisation with fuzzy MADM. These methodologies address the complexity and variability often encountered when estimating qualitative parameters, which are typically avoided in traditional optimisation models. For future work, it is advisable to incorporate emerging technologies and dynamic demand profiles to explore additional primary resources within the study areas.

Ultimately, this computational tool can serve as a strategic guide for decision-makers responsible for designing and evaluating energy planning projects in Colombia, supporting the country's energy transition objectives.

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NOMENCLATURE

Symbols

α	Membership level
X	Crisp value
$\tilde{X}$	Fuzzy value

Financial parameters - MILP

InvCo	Initial unit investment cost	[USD/kW]
FixCo	Fixed unit O&M cost	[USD/kW]
VarCo	Variable unit O&M cost	[USD/kWh]
FuCo	Fuel cost	[USD/unit of fuel]
SellCo	Electricity sales price	[USD/kWh]
BugCo	Budget	[USD]

Continuous decision variables - MILP

CaA	Added capacity	[kW]
CaT	Total installed capacity	[kW]
EnG	Energy generated	[kWh]
FuR	Fuel consumed	[fossil fuel unit]
EnVe	Surplus energy sold	[kWh]
PoG	Power generated	[kW]

Binary decision variables - MILP

Op	If the installed capacity is operational	
In	If new capacity is installed	

Environmental parameters - MILP

Em	CO_2 emissions factor	[kg CO_2/kWh]

Technical parameters - MILP

DE	Electricity demand	[kWh]
DP	Power demand	[kW]
Fc	Capacity factor	
Fd	Availability factor	
Camin-Camax	Capacity limits	
Rw	Primary energy consumption factor	
Tp	Construction lead time	[h]
ρ	Reserve margin	
DB	Annual operating hours	[h]
ICa	Initial installed capacity	[kW]
PriT	Primary resources available in the area	[kg/unit of primary resource]

SUBSCRIPTS - MILP

p	Power plants
t,v	Time period
r	Primary resources

ACRONYMS

NPV	Net Present Value
FAHP	Fuzzy Analytical Hierarchy Process
SIN	National Interconnected System
UPME	Mining and Energy Planning Unit
IPSE	Institute for Planning and Promotion of Energy Solutions for Non-Interconnected Areas
CREG	Energy and Gas Regulatory Commission
HRES	Hybrid Renewable Energy System
IRENA	International Renewable Energy Agency
MILP	Mixed-Integer Linear Programming
FAER	Financial Support Fund for the Electrification of Interconnected Rural Areas
HOMER	Hybrid Optimization Model for Multiple Energy Resources
iHOGA	Hybrid Optimization by Genetic Algorithms

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