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# Integrated multi-criteria decision-making approach for power generation technology selection in sustainable energy systems

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ABSTRACT

Increasing global energy demands and sustainability challenges necessitate effective selection frameworks for power generation technologies (PGTs) that balance economic, technical, and environmental factors. This research proposes a novel methodology based on a hybrid multi-criteria decision-making (MCDM) approach to facilitate informed decision-making in PGT selection. The methodology combines expert evaluations with a tailored rubric to assess the suitability of different technologies across a range of criteria.

The methodology is applied to a real-world case study framed in the Reffect Africa Project. It was used to evaluate the suitability of different power generation systems for a remote industrial off grid plant. Results revealed gasification as the most suitable alternative, despite its higher upfront costs. This finding highlights the potential of renewable energy sources to serve not only for domestic applications in microgrids but also industrial purposes in isolated areas, emphasizing the alignment of life-cycle and environmental impact with the growing recognition of renewable energy as a key driver of sustainable development in underdeveloped areas. This case study validates the robustness of the proposed framework for industrial energy applications. The findings underscore the flexibility of the methodology, which can adapt to diverse scenarios, including grid-connected and disconnected contexts, while providing decision-makers with systematic tools to achieve optimal energy solutions.

## 1. Introduction

Amidst a growing global energy demand, the current energy landscape faces challenges in balancing supply with demand. Conventional energy sources are insufficient and contribute to environmental issues, necessitating a shift towards cleaner and sustainable alternatives such as renewables.

The industrial sector, constituting 41.9 % of final electricity consumption, stands as the most energy-intensive sector [1], thus playing a critical role in reducing energy consumption and emissions. Despite the significant advancements in power technologies' efficiency, the relentless upward trajectory of global energy demand presents crucial challenges in attaining sustainable development goals. Empirical evidence underscores that despite the swift proliferation of Renewable Energy Sources (RES), this trend fails to adequately curb fossil fuel consumption [1,2]. Particularly in highly industrialized and developing regions, traditional industrial models hinge on fossil fuel utilization, driven by combustion power generation systems esteemed for their expediency, reliability, flexibility and affordability [3,4]. Nonetheless, recent developments have rendered this approach less feasible due to erratic fuel price fluctuations and mounting concerns regarding their environmental impact [5,6].

Energy planning deals with the selection from the pool of diverse alternative energy sources and technologies for promotion and implementation. The increasing preference for RES vis-à-vis fossil fuels is evident in recent comparative studies focusing on energy supplies [7–9]. Nevertheless, renewable sources do not always emerge as the most appropriate or feasible alternatives considering economic, environmental and technical requirements [10].

The transition towards sustainable energy sources presents unique challenges for industrial applications, particularly in the judicious selection of the most appropriate power generation technology. Opting for the most suitable technology for an industrial project is a crucial decision that must be made during the project's nascent stages. At this

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juncture, industrial requirements can vary greatly, contingent upon factors such as size, location, sector, resource pricing and availability, or politics [11]. The decision requires a comprehensive evaluation of alternatives based on efficiency [12], cost [13], life-cycle analysis [14,15], and reliability [16,17]. Multi-criteria decision-making (MCDM) methods are effective tools for this process, enabling stakeholders to make informed and objective decisions [18].

Following an extensive review of the literature on power generation technologies (PGT) selection methods and tools, two facts are apparent: the existence of a wide variety of approaches and the conspicuous absence of a universally accepted decision-making protocol. This work proposes a consistent methodology guided by current specialized literature.

This paper is organized as follows: Section 2 presents a comprehensive literature review identifying research gaps, establishing precise research objectives, and clarifying the paper's contributions. Subsequently, a description of the proposed methodology and the tools for its implementation are presented in Section 3. A detailed description of the case study is presented in Section 4. The results of applying the proposed methodology and tools are presented and discussed in Section 5. Finally, Section 6 presents the conclusions, literature review, research gaps, aim and contributions.

## 2. Literature review, research gaps, aim and contributions

### 2.1. Literature review

The study of power generation technologies' planning presents a complex challenge. Encompassing energy production, system operation, technology selection, and management. MCDM methods are commonly employed to deal with the selection of diverse PGTs.

The first group, "general comparison of technologies", is composed of works focused on comparing technologies from a broad perspective, comparing the adequacy or benefits of renewable with fossil fuel technologies. For instance, C. Ghenai et al. [19] developed a sustainability assessment of renewable energy systems using a MCDM model with a hybrid SWARA/ARAS method. In their study, land-based wind energy systems ranked as the most sustainable option, followed by solid oxide fuel cell, phosphoric acid fuel cell, and solar energy systems. C. Wang et al. [20] developed a hybrid fuzzy MCDM model in Vietnam to successfully select an optimal wind turbine supplier whilst maintaining growth, aiming for a balance between traditional and new alternative energy sources. D. Aikhuele et al. [21] developed an integrated model to evaluate renewable energy technologies, ranking the most suitable energy technologies by taking into consideration their socio-technical and economic attributes. Kaya and Kahraman [22] used a Fuzzy-MCDM model to compare technologies such as wind, biomass, solar, CHP, hydraulic and nuclear, from a general perspective. Their model outperforms general comparisons which do not permit the differentiation between individual assets and their suitability to different contexts. Solangi et al. [23] outperformed a double MCDM method designed to evaluate strategies for the implementation of sustainable energy sources. F. Dell'Anna et al. [24] explored the use of multi-criteria decision-making analysis to select a near-zero-energy building type in line with European and international sustainability goals. They employed the PROMETHEE II method to rank alternatives based on energy considerations, in addition to economic, and non-economic criteria. While these general comparisons offer valuable insights, their generalization might limit applicability in specific industrial contexts. Additionally, these projects favour the use of fuzzy techniques. The integration of fuzzy methodologies into MCDM tools does simplify decision analysis but compromises precision due to their inherent ambiguity. The use of generic rubric exacerbates this issue, underscoring the need for a balanced approach between simplicity and accuracy in complex decision-making processes.

The second group, "validation and/or optimization of already defined models and systems", involves works utilizing MCDM techniques to validate predefined models or specific characteristics of established systems, technologies or facilities. These contributions focused on how decisions were made during the finishing stages of a project as opposed to at its initiation. For instance, Arslan et al. [25] employed a hybrid MCDM methodology to validate the Simav Integrated Geothermal Energy System. Similarly, Mojaver et al. [26] assessed a combined heat and power solid oxide fuel cell-system in comparison to experimental data from the literature. Using HOMER software supported with MATLAB, H. Yazdani et al. [2] proposed the optimization of hybrid renewable energy systems for large energy-consuming complexes, identifying the Pareto-optimal mix of units and the most influential variables on the system's net cost. M. Elkadeem et al. [27] developed a decision-making framework integrating spatial investigation, energy-economy-ecology design optimization and multi-criteria decision-making analysis to select the site and optimal design of a hybrid renewable energy system in Kenya, leading to the selection a hybrid solar/wind/diesel/battery system. Y. Ke et al. [28] proposed a fuzzy framework to select an integrated energy system plan for urban areas considering residents' lives, limited energy resources, and energy efficiency. O. Taylan et al. [29] focused on compressor selection in the petrochemical industry as a multi-attribute decision-making (MADM) problem. Fuzzy analytical hierarchy process (FAHP) and methodologies using fuzzy technique for order performance by similarity to an ideal solution (TOPSIS) for decision-making in a vague and imprecise environment. Scenario III, which involved turbo compressors of an active system with low specific energy consumption and heat recovery potential, is identified as the best option among the six scenarios under consideration.

Despite their valuable insights in the study of decision-making processes and their fine-tuning details, it's necessary to highlight that since they are employed retrospectively these processes might display inherent biases.

The third category, "methods for decision-making", encompasses works focused on the use of diverse decision-making methods in the energy technology field without adhering to a standardized and polyvalent methodology. For instance, L. Kiser and L. Otero [30] developed a holistic approach using an Analytic Hierarchy Process model to facilitate the decision-making process for selecting a feasible nuclear power plant type. Although that study identified potential areas for expansion and future research, it remained confined to nuclear power plant selection. B. Nsafon et al. [31] proposed a hybrid model integrating AHP-VIKOR aiming at renewable energy plans in African rural communities. Their focus was on hybrid energy systems offering reliability and economic benefits, providing substantial income from power sales in addition to savings from carbon pricing. Their study took place within a tightly defined framework which meant it was overly conditioned to fit the case study that was utilised. Similarly, the study of T. Witt et al. [32] proposed a combination of scenario planning, multi-criteria decision-making, and energy system analysis for the transition to a renewable electricity supply in Lower Saxony, Germany. While this approach enhanced problem structuring and fostered stakeholder discussions, its methodology was somewhat constrained by a focus on renewable technologies. S. Rekik and S. El Alimi [33] proposed a preliminary assessment of suitable locations for large-scale wind power plants and solar photovoltaic plants in Tunisia using GIS and MCDM. The study identified large suitable areas, providing estimated annual energy outputs and thereby aiding policymakers in proactively developing solar and wind farms. Despite addressing some of the previous studies' shortcomings, these comparisons predominantly restrict themselves to closed technology groups (e.g., nuclear technologies [30], renewable energies [26,27], wind and solar [33]), overlooking alternatives with diverse characteristics.

Table 1 presents a synthesis of pertinent literature on MCDM applications for PGT selection, classified into the described three main groups defined by their objectives, the methods used in each study and the

**Table 1**
Review of papers regarding the use of MCDM for PGT selection.

| Approach | Ref. | Methods Used | Technologies analysed | | | | |
|---|---|---|---|---|---|---|---|
| | | | Biomass | Solar | Wind | Battery | Others |
| General comparison of technologies | [19] | Hybrid SWARA/ARAS | | ✓ | ✓ | | ✓ |
| | [20] | Hybrid fuzzy MCDM model. | | | ✓ | | |
| | [21] | Integrated MCDM model. | | ✓ | ✓ | | ✓ |
| | [22] | Fuzzy-MCDM model. | ✓ | ✓ | ✓ | ✓ | |
| | [23] | Double MCDM | ✓ | ✓ | ✓ | ✓ | |
| | [24] | PROMETHEE II | | | | | ✓ |
| Validation and/or optimization | [25] | Hybrid MCDM methodology. | | | | | ✓ |
| | [26] | Experimental data comparison, HOMER and MATLAB. | | | | ✓ | |
| | [2] | HOMER with Pareto optimization. | | ✓ | ✓ | ✓ | ✓ |
| | [27] | MCDM. with energy-economy-ecology optimization, | ✓ | ✓ | ✓ | ✓ | ✓ |
| | [28] | Fuzzy framework. | ✓ | ✓ | ✓ | ✓ | ✓ |
| | [29] | Fuzzy AHP/TOPSIS. | | | | | ✓ |
| Decision-making | [30] | AHP | | | | | ✓ |
| | [31] | Hybrid AHP-VIKOR. | | ✓ | ✓ | ✓ | ✓ |
| | [32] | Scenario planning, MCDM, and energy system analysis. | | ✓ | ✓ | | ✓ |
| | [33] | GIS integrated with MCDM. | | ✓ | ✓ | | |

technologies analysed in each study.

### 2.2. Research gaps

The literature review highlights the diverse applications of MCDM techniques in the renewable energy sector. However, several research gaps concerning the decision-making processes for electricity production technologies in engineering projects were found:

- Limited applicability: The comparisons of technologies are valuable for providing a general perspective, yet may lack applicability in specific case studies within industries and practical contexts [22]. These studies tend to focus on comparing types of technologies, the most common broad comparisons being those between renewable and non-renewable [20,23] or those among several renewables [19,21]. Additionally, these comparisons employ variables, considerations and conditions that might be described as overly particular. It can be observed in Refs. [14–19].
- Inherent biases in retrospective studies: The validation and optimization of predefined models and systems [20–25] using MCDM techniques, while valuable for fine-tuning decision-making details, may harbour inherent biases due to their retrospective nature, and their predominant focus on highly specific study cases [24,25], a factor which may limit their objectivity and relevance.
- Lack of consensus for techniques and tools: Specially detected in Refs. [26–29]. A lack of consensus prevails despite generally following a common process, each study implements different MCDM techniques and tools. Each MCDM technique exhibits a particular context-sensitive suitability. Nevertheless, the lack of consensus may provoke confusion among end-users seeking guidance.

These gaps and problems highlight the need for more adaptable and comprehensive approaches to facilitate the decision-making process in the power generation sector, especially when addressing specific case studies and integrating different technology options for end users.

### 2.3. Aim and contribution

This study aims to develop a systematic framework for the early-stage design and selection of power generation technologies (PGTs) in industrial applications. The primary objective is to facilitate these processes in engineering projects by prioritizing a structured decision-making approach over purely quantitative outputs. This work proposes a closed methodology comprising a specific rubric designed to gather the necessary data for implementing an AHP-TOPSIS model. This methodology is tailored to avoid biases in the selection and design processes and mitigate the risks of misguided methodology or parameter choices. By focusing on the decision-making processes, itself, this study emphasizes transparency and robustness in selecting PGTs, aligning with the broader aim of promoting better-informed and sustainable design choices.

The primary contributions of this study include:

- Identification of ways to streamline processes in order to simplify the selection of PGTs potentially reducing both costs and time during the early stages when PGT installation projects are under study.
- Creation of a comprehensive tool to facilitate the evaluation of various PGTs, offering valuable guidance and support during the decision-making process. This tool consists of a closed rubric specifically designed to gather the necessary data to implement an AHP-TOPSIS model. By utilizing the rubric, project developers and decision-makers can systematically assess and compare different technologies, ensuring an optimal alignment with the specific project requirements.
- Proposal of a closed widely applicable model that takes into consideration evaluations from multiple experts to reach a consensus.
- Evaluation of the designed rubric and the hybrid AHP-TOPSIS model through implementation in a real case study involving the selection of an optimal technology for an olive oil mill in Morocco and the subsequent sensitivity analysis. This demonstrates the practicality and effectiveness of the proposed approach, further emphasizing the significance of the rubric in enabling informed decision-making within the field of power engineering.

## 3. Materials and methods

MCDM methodologies are most commonly used to structure and solve decision and planning problems involving multiple criteria. In general, methodologies employed to solve these problems are structured following the steps described in Fig. 1. In the first step, the problem is defined with the establishment of needs and objectives. Step two involves the identification of decision variables. It includes the selection of options to be contrasted in addition to the criteria on which that comparison will be based. In step three, the most suitable context-dependant MCDM technique is selected: a needs-specific model focused on the particular problem and only the relevant variables. The fourth step is concerned with gathering data and defining the data-collecting tool (commonly, a rubric, a questionnaire, a test, etc.). Once this tool is

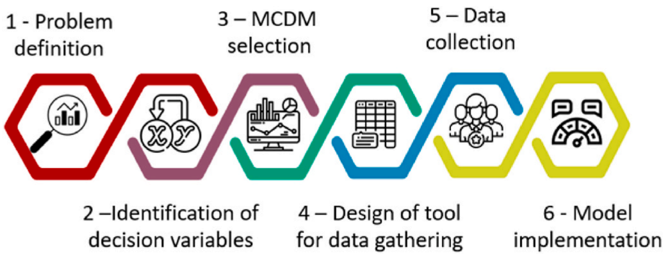

**Fig. 1.** Flowchart of generic methodology.

prepared, step five requires data collection. In the final step, the MCDM model, is used to perform the comparison, providing an ordered list of alternatives.

Building upon the general methodology, this article proposes a specific model to be applied to solve the case of PGT selection in real cases. By adapting the methodology to a specific problem, it is possible to streamline the process and provide a readily useable solution for end-users and researchers.

This involves identifying relevant decision-making variables and criteria, selecting an appropriate MCDM technique, and creating a data aggregation tool. Determining the decision variables and criteria is crucial for the other tasks, so it should be done first. A purpose-built rubric is an effective tool for data gathering, enabling objective assessment of scores. Selecting the most suitable MCDM method ensures the technique aligns with the specific problem.

Given that the rubric must accommodate the chosen MCDM, it is first necessary to choose the most appropriate MCDM technique for the purpose of PGT selection. Among the MCDM, the TOPSIS technique is extensively used to solve problems related to the design of engineering systems [2,34]. This technique ascertains the optimal design solution by evaluating its proximity in comparison to hypothetical ideal solutions. Implementing TOPSIS requires two main sets of data, namely, the weights of the different criterion and the value of each alternative for each criterion.

In multivariate decision-making, the weight of attributes serves as a crucial input parameter. Various techniques exist for calculating the weight of each criterion. The simplest of these involves subjective weight assignment based on the preferences of decision makers, ensuring the summation of coefficients equals unity [35]. In contrast, using mathematical approaches, alternative exist. Hybrid approaches, such as the AHP technique, incorporate a combination of decision-maker tendencies and mathematical principles to determine weighting [36]. Furthermore, the literature for MCDM demonstrates that algorithms from AHP-based TOPSIS have been utilised extensively [37,38]. Generally, AHP offers a higher degree of sensitivity as it permits experts to scale the importance of criteria.

Despite some limitations like dependence on expert selection, The study selects AHP and TOPSIS as suitable MCDM approaches due to their proven effectiveness in handling complex decisions with multiple conflicting criteria in varied contexts [39–41]. AHP provides a structured framework for systematically weighting diverse criteria, unilaterally determining the order of convergence to the best solution. TOPSIS complements this by excelling in decision-making by its use of mathematical ranking procedures, offering a straightforward ranking mechanism based on the proximity of alternatives to ideal solutions. Consequently, the hybridization of these two methods can yield more robust and effective outcomes The proposed hybridization is carried out using the convergence values obtained from AHP as the weights in the TOPSIS model [25], creating a robust decision-making framework. Additionally, it mitigates inherent subjectivity by combining different evaluations and performing a comprehensive sensitivity analysis to test the robustness of results against variations in criteria weights.

Based on these considerations, this study advocates an integrated methodology underscored by purpose-built tools tailored for PGT selection. Specifically, this work proposes and describes an AHP-TOPSIS hybrid model supported by a unique rubric to collate data for PGT selection. Fig. 2 encapsulates the reduction in workload achieved through the implementation of the proposed methodology.

To enhance comprehension, the remainder of this section is structured according to the implementation process of the devised methodology. Firstly, the rubric used to obtain the income data is described. AHP, which is used to obtain the weights of TOPSIS' criteria, is subsequently presented. Then, the TOPSIS model, is explained and finally, the implementation of the proposed methodology and the sensitivity analysis are highlighted.

### 3.1. *Rubric development*

The rubric serves as a comprehensive tool for evaluating the suitability of various electricity generation technologies, providing valuable guidance and support during the decision-making process. Previous studies have analysed the distribution and relevance of the primary criteria governing energy evaluation. In their review, Kaya et al. [42] examine the distribution of key criteria percentages in energy decision-making, considering Economic, Social/Political, Environmental, Land use, Risk and Quality Efficiency factors as the main criteria. Additionally, other studies [7,8,22,43] favoured the selection of four to five aspects or criteria, namely, Energy, Economic, Technological, Environmental and Social factors which are commonly split into a set of two to five indicators or sub-criteria.

Furthermore, given the dual-purpose nature of this rubric, it is necessarily organized into two distinct sections. The first is dedicated to outperforming a pairwise comparison of the criteria, while the second section is tailormade to address the technical questions necessary for an objective evaluation of each indicator. A description of each criterion and their respective indicators ensues.

Based on authors' technical expertise and the review of relevant literature, this rubric is composed by six criteria (Cost, Flexibility, Life-Cycle Impact, Efficiency, Robustness, and Resource Availability), each with five specific indicators, except cost with four. It requires objective analysis of specific system data, avoiding general assumptions. Supplier technical data and machinery specifications are used for some indicators.

This structured approach aligns with best practices in multi-criteria decision-making, as highlighted by previous research, and provides a robust framework for assessing the diverse factors that influence the suitability and sustainability of energy systems. Below, each criterion and indicator are described.

Cost. Composed by the indicators: acquisition, installation, maintenance, and fuel costs. It ensures a complete economic assessment, from

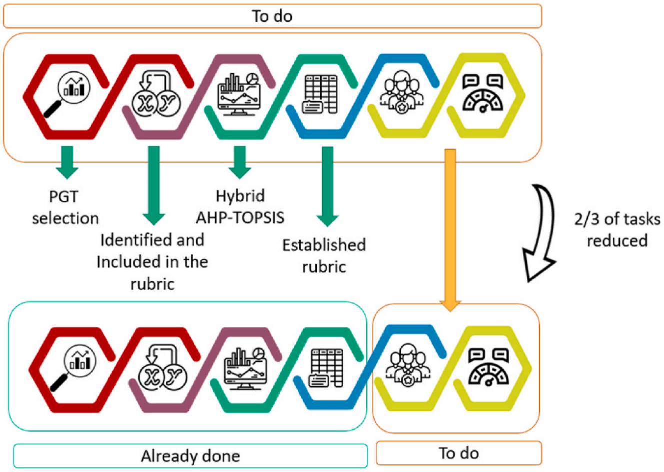

**Fig. 2.** Proposed methodology flowchart.

capital expenditures (CAPEX) to ongoing operational costs (OPEX). This cost breakdown provides a clear view of both short, and long, term economic feasibility.

Flexibility: Its indicators comprise power variation, energy source replaceability, maximum and minimum load, and modification delay, assessing technology's ability to adapt to changing operational conditions. Flexibility is key in integrating energy sources and managing variable energy loads, for grid stability and operational agility.

Life-Cycle Impact: The inclusion of NOx emissions, waste generation, recyclability, and contamination risk provide a holistic environmental evaluation. Life-cycle assessments (LCA) of pollutants and waste handling are crucial for minimizing long-term environmental impacts.

Efficiency: Composed by performance, working capacity, energy losses, performance improvements, and Energy Return on Investment (EROI) measure a technology's ability to efficiently convert energy. A higher EROI ensures better energy sustainability, making efficiency a key metric in comparing technologies.

Robustness: Indicators like adaptability, maintainability, weather restrictions, and redundancies assess a system's reliability and resilience, ensuring consistent performance and reducing downtime.

Resource Availability: Composed by Weather-dependence, fuel compatibility, energy source access, storage, and renewable potential reflect the availability and sustainability of resources needed for long-term operation.

### 3.2. AHP

The Analytic Hierarchy Process (AHP) is a decision-making technique that allows for a structured and systematic approach to complex decision-making problems. Introduced in the 1970s by Thomas Saaty [44], AHP subsequently gained extensive application in diverse fields including business, engineering, and social sciences.

The AHP technique entails breaking down a complex decision into a hierarchical structure of smaller, more manageable sub-problems. The hierarchy is composed of a goal, a set of criteria, and a set of alternatives, as shown in Fig. 3. The goal represents the ultimate objective of the decision, the criteria are the factors that are important in achieving the goal, and the alternatives are the options available for achieving the goal.

AHP utilizes pairwise comparisons to determine the relative importance or priority of criteria and alternatives, assigning numerical values based on decision maker's subjective judgments. AHP then calculates the relative weights of both criteria and alternatives, allowing for a ranked decision. This structured and transparent framework proves advantageous in scenarios encompassing multiple decision criteria and involving stakeholders with differing priorities.

AHP analysis was conducted to determine the criteria weighting for evaluating the performance scores of different PGTs using the TOPSIS method. The assessment of criteria weights using AHP involved the following sequential steps [45]:

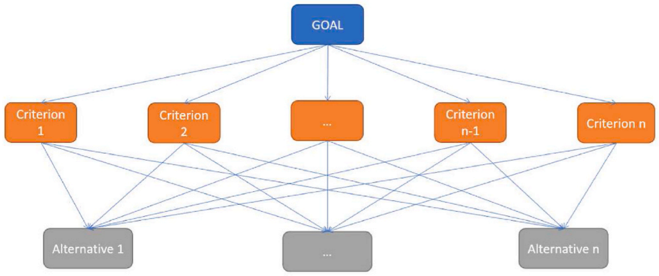

**Fig. 3.** AHP structure.

1. Establishing the analysis objective and breaking down the MCDM into its constituent parts, delineating the aim, the criteria and the alternatives.
2. Designing the pairwise comparison matrix to assess the relative significance of one criterion in relation to another. Saaty's nine-point scale, which is illustrated in Table 3 [23], is used for this purpose. The pairwise comparison matrix is structured as shown in Table 4. The data obtained from the rubric is used to fill the matrix. Based on the values of the upper diagonal (from 1 to 9), the lower diagonal values are obtained making its complementary value (1/X), X being the value of its opposing value in the matrix.
3. Normalization of the pairwise comparison matrix and calculating the criteria weight. Table 3 represents a normalized pairwise comparison matrix and the weights of each criterion. The normalized pairwise comparison matrix and weights are calculated using Eq. (1).

$$\omega_j = \frac{1}{n}\sum_{j=1}^{n}\frac{a_{ij}}{\sum_{i=1}^{a} a_{ij}}; i,j = 1,2,3,\ldots,n \tag{1}$$

where $\omega_j$ is the value of the jth criterion, $a_{ij}$ is the comparative importance of the ith criterion regarding to the jth criterion, $n$ is the non-defined number that represents the number of criteria.

4. Evaluating the consistency ratio (CR) of the matrix and verifying its acceptability. The CR is calculated using Eq. (2).

$$CR = \frac{CI}{RI} \tag{2}$$

where $RI$ is the random consistency index, whose value is obtained based on Table 5 and $CI$ is the consistency index, which is obtained according to Eq. (3).

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{3}$$

where $\lambda_{\max}$, is the maximum eigen value according to Eq. (4).

$$\lambda_{max} = \sum_{i=1}^{n}\frac{\sum_{i=1}^{a} a_{ij} \times \omega_j}{\omega_i}; i,j = 1,2,3,\ldots,n \tag{4}$$

### 3.3. TOPSIS

When resolving multivariate decision-making problems, the application of MCDA models is a common approach. In this regard, TOPSIS ascertains the optimal design solution by evaluating its proximity to ideal solutions and ranking alternatives based on multiple criteria [18]. Fig. 4, displays the concept of distance from the ideal alternative and the negative ideal alternative. The TOPSIS approach is relatively simple, logical, and comprehensive compared to other methods [19].

The TOPSIS process is encompassed by the following steps: Creation of the initial TOPSIS matrix (1); normalization of criteria (2); indicator weight allocation (3); identification of the hypothetical ideal and negative ideal solutions (4); evaluation of geometric distances between alternatives and ideal and negative ideal solutions (5); quantification of relative distances (6); and finally, the organization of alternatives over a lower-scored counterpart (7). These steps are described below:

1. Construction of the decision matrix, T, with a $m \times n$ order. This matrix is composed, as shown in Table 6, by four main elements, $A_i$, $C_j$, $W_j$, $X_{ij}$, where:
   - $A_i$ *is the column of alternatives, it corresponds to the column* 1, *so* $A_i = T_{i1}$
   - $C_j$ *is the row of criteria, it corresponds to the row* 1, *so* $C_j = T_{1j}$
   - $W_j$ *is the row of the weights associated to the corresponding criterion, it corresponds to the row* 2, *so* $W_j = T_{2j}$

**Table 2**
Rubric, second section.

| Crit. | Index | Indicator | Question | Input type & Range | Normalization |
|---|---|---|---|---|---|
| Cost ($C_1$) | $I_{11}$ | Acquisition cost | What is the total cost needed to acquire the system, including purchase, transport, and associated fees? | Numerical: 0–$10^7$ | 5*Input/budget |
| | $I_{12}$ | Installation cost | What is the cost of installing the system, as a percentage of the acquisition cost? | Numerical: 0–100 | 5*(Input/100* $I_{11}$)/budget |
| | $I_{13}$ | Maintenance cost | What is the estimated annual maintenance cost, expressed as a percentage of the acquisition cost? | Numerical: 0–100 | 5*(Input/100* $I_{11}$)/budget |
| | $I_{14}$ | Fuel cost | What is the projected cost of fuel required to operate the system over a year, expressed as a percentage of the acquisition cost? | Numerical: 0–100 | 5*(Input/100* $I_{11}$)/budget |
| Flexibility ($C_2$) | $I_{21}$ | Power variation capacity | What is the maximum variation in power output that the system can handle without experiencing performance degradation, expressed as a percentage? | Numerical: 0–100 | Input/100 |
| | $I_{22}$ | energy source replaceability | Can the system's energy source be replaced or substituted with another type of energy source? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |
| | $I_{23}$ | Maximum load | What is the highest load that the system can reliably support, expressed as a percentage of its rated capacity? | Numerical: 0–100 | Input/100 |
| | $I_{24}$ | Minimum load | What is the lowest load at which the system can operate reliably, expressed as a percentage of its rated capacity? | Numerical: 0–100 | 1-(Input/100) |
| | $I_{25}$ | Working regime modification delay | How much time is required for the system to modify its operating regime to accommodate a change in load demand? | Text: milliseconds/ seconds/ minutes | If input = milliseconds, Norm. Value = 1,<br>If input = seconds, Norm. Value = 0.75,<br>If input = minutes, Norm. Value = 0.25 |
| Life-cycle Impact ($C_3$) | $I_{31}$ | NOx & COx pollutants | Do the system's emissions contain significant amounts of nitrogen oxides (NOx) and/or carbon oxides (COx)? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |
| | $I_{32}$ | Waste generation | Does the system generate solid wastes during its operation? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |
| | $I_{33}$ | Wastes recyclability | If the system generates solid waste, are these wastes recyclable or reusable? | Text: Yes/No | If $I_{32}$ input = Yes and $I_{33}$ input = Yes, Norm. Value = −1,<br>If $I_{32}$ input = Yes and $I_{33}$ input = No, Norm. Value = 1,<br>If $I_{32}$ input = No, $I_{33}$ Norm. Value = 0 |
| | $I_{34}$ | Contamination risk | Could a potential leakage from the system pose a pollution risk to the soil or the environment? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |
| | $I_{35}$ | Secondary pollution | Does the system produce secondary pollution, such as noise, light, or impact on the surrounding landscape? | Numerical: 0–3 | Input/3 |
| Efficiency ($C_4$): | $I_{41}$ | Performance | What is the theoretical maximum efficiency of the system, expressed as a percentage? | Numerical: 0–100 | Input/100 |
| | $I_{42}$ | Working capacity | Can the system operate continuously, 24/7, without interruption? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |
| | $I_{43}$ | Energy losses | What is the average percentage of energy lost during the system's operation or conversion processes? | Numerical: 0–100 | 1-(Input/100) |
| | $I_{44}$ | Performance increase | Can supplementary components, such as an ORC or heat recovery systems, be added to improve the system's performance? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |
| | $I_{45}$ | EROI | What is the system's EROI? | Numerical: 0–100 | 1/Input |
| Robustness ($C_5$): | $I_{51}$ | Adaptability for modifications | Can the system be easily modified to meet specific project requirements? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |
| | $I_{52}$ | Maintainability and operability | Is the system designed for easy maintenance and operation by low qualified workers? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |
| | $I_{53}$ | Weather restrictions | Do weather conditions affect the operation or performance of the system? | Text: Yes/No | If input = No, Norm. Value = 1,<br>If input = Yes, Norm. Value = 0 |
| | $I_{54}$ | Replacements | Are replacements readily available and easily accessible? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |
| | $I_{55}$ | Redundancies | Does the system include built-in redundancies to ensure reliable operation? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |

(*continued on next page*)

**Table 2** (*continued*)

| Crit. | Index | Indicator | Question | Input type & Range | Normalization |
|---|---|---|---|---|---|
| Resources availability ($C_6$): | $I_{61}$ | Weather- dependant resource | Does the system rely on weather-dependent resources, such as wind or solar power? | Text: Yes/No | If input = No, Norm. Value = 1,<br>If input = Yes, Norm. Value = 0 |
| | $I_{62}$ | Compatibility with different fuel types | Can the system operate using a variety of fuel types or energy sources? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |
| | $I_{63}$ | Energy sources access | Are the required energy resources easily accessible near the facility? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |
| | $I_{64}$ | Energy storage | Does the system have the ability to store energy for use during peak demand periods or when production dips? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |
| | $I_{65}$ | Renewable sources | Is the system powered by renewable energy sources? | Text: Yes/No | If input = Yes, Norm. Value = 1,<br>If input = No, Norm. Value = 0 |

**Table 3**
Saaty's point scale.

| Point scale | Complementary | Definition |
|---|---|---|
| 1 | 1 | Equally preferred |
| 3 | 1/3 | Moderately preferred |
| 5 | 1/5 | Strongly preferred |
| 7 | 1/7 | Very strongly preferred |
| 9 | 1/9 | Extremely preferred |

**Table 4**
Pairwise comparison matrix $A = [a_{ij}]$

| | $C_1$ | $C_2$ | … | $C_n$ |
|---|---|---|---|---|
| $C_1$ | 1 | $C_1 - C_2$ | … | $C_1 - C_n$ |
| $C_2$ | $^1/_{C_1 - C_2}$ | 1 | … | $C_2 - C_n$ |
| … | … | … | 1 | … |
| $C_n$ | $^1/_{C_1 - C_n}$ | $^1/_{C_2 - C_n}$ | … | 1 |

- $X_{ij}$ *is the Sub matrix of values*, *representing* the assessment of alternative $A_i$ with respect to criterion $C_j$, *so* $X_{ij} = T_{ij}$, *where* $i = 1, 2, \ldots, n$; *and* $j = 1, 2, \ldots, n$:.

2. Normalization of criteria. The standardization of the decision matrix allows to non-dimensionalize disparate indicators since the elements of the decision matrix may not be defined in the same domain. The standard used is given by Eq. (5), where $r_{ij}$ are the normalized values of each criterion for each alternative:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}\ j \in [1, \ldots, m] \tag{5}$$

3. Construction of the weighted standardized decision matrix: By allocating the weights to each indicator. Thus every $r_{ij}$ is replaced by a new $v_{ij}$, which is obtained as follows:

$$v_{ij} = w_j \cdot r_{ij} \tag{6}$$

4. Identification of the hypothetical positive-ideal $\left(A_j^+\right)$ and negative-ideal $\left(A_j^-\right)$ solutions. These solutions are calculated using Eqs. (7) and (8), respectively.

$$A_j^+ = \{best\ (v_{ij})\}_{i=1}^{n} \tag{7}$$

$$A_j^- = \{worst\ (v_{ij})\}_{i=1}^{n} \tag{8}$$

where the expression "best" is the minimum operator for non-beneficial attributes such as cost, and it is the maximum operator for beneficial indicators. This argument is the opposite for the expression "worst".

5. Evaluation of the geometric distance between alternatives and positive-ideal and negative-ideal solutions using Eqs. (9) and (10).

$$D_i^+ = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^+\right)^2} \tag{9}$$

$$D_i^- = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^-\right)^2} \tag{10}$$

where $D_i^+$ and $D_i^-$ are the Euclidean distance from alternative $i$ to the positive-ideal and negative-ideal solutions, respectively. They are used to calculate the geometric distance between each design and ideal solutions.

6. Quantification of the relative distances by using Eq. (11).

$$C_i^+ = \frac{d_i^-}{d_i^+ + d_i^-} \tag{11}$$

where $C_i^+$ is the overall performance coefficient. It is used to measures the relative proximity of each alternative to the positive-ideal solutions, producing a score between 0 and 1.

7. Organization of alternatives in relation to a lower-scoring counterpart: the alternatives appear in descending order, starting with the closest to the positive-ideal solution (the greater relative proximity).

### 3.4. *Methodology implementation and sensitivity analysis*

The proposed methodology commences by distributing the rubric for completion among experts actively engaged in the project. Experts are requested for evaluations using a close rubric they have to follow. This rubric requests for close answers (yes/no or a number, usually in the 0–100 or 1–9 ranges) as inputs. The data obtained from these experts serves a dual purpose. First, one section of the rubric gathers input data for the implementation of the AHP analysis. Second, the remaining rubric provides the values of the criteria associated with those alternatives considered in the TOPSIS analysis. The interaction between these tools is depicted in Fig. 5, illustrating their synergy in the decision-making process. This figure shows how the rubric is divided into two main sections. The first is used to gather data for AHP, while the second focuses on the evaluation of characteristics of alternatives according to the established criteria. AHP results determine criterion weights for TOPSIS. Subsequently, the resulting values of the assessments, criteria and alternatives are implemented in the TOPSIS model, which determines the adequacy of each alternative for the case study.

After applying the methodology to the case study, a dual sensitivity analysis is conducted to explore the effects of varying the most influential parameters. Firstly, through an iterative process, the two parameters with the highest relative weights are systematically adjusted within a range of −25 % to +25 %, while the third parameter served as a pivot. Variations were implemented in increments of 5 % from their initial values. The objective is to evaluate the impact of incremental variations of the criteria on the suitability of each alternative. This enables a thorough examination of the model calibration. Secondly, AHP is replaced by FAHP to analyse how the experts' evaluation would vary when using linguistic assessments for comparison instead of numerical ones. In this case, the use of a shorter variety of options, together with a more natural answers is the key to the study.

Finally, a validation process is performed using HOMER Pro software to determine whether the results of the proposed methodology and AHP-TOPSIS analysis against the technical analysis are consistent.

To develop a Fuzzy Analytic Hierarchy Process (FAHP) model from a traditional Analytic Hierarchy Process (AHP) framework, the following modifications are essential. FAHP extends AHP by incorporating fuzzy set theory to manage the vagueness and uncertainty inherent in human judgment. The traditional AHP, based on crisp pairwise comparisons, is modified to incorporate fuzzy logic using linguistic terms, fuzzy numbers, and specific defuzzification processes, as described below.

1. Transformation of Pairwise Comparisons into Fuzzy Numbers: In traditional AHP, decision-makers express preferences between criteria using crisp values from a scale of 1–9. In FAHP, linguistic terms such as "very important," "equally important," or "moderately less important" are used. These linguistic terms are then converted into fuzzy numbers. Typically, triangular fuzzy numbers (TFNs)
   - l: lower bound, representing the lowest possible value.
   - m: middle value, representing the most likely value.
   - u: upper bound, representing the highest possible value.

The pairwise comparison matrix $A = [a_{ij}]$ in AHP is thus transformed into a fuzzy pairwise comparison matrix $\widetilde{A} = [\widetilde{a}_{ij}]$

2. Construction of Fuzzy Comparison Matrices: Expert judgments are aggregated to form a fuzzy comparison matrix, $\widetilde{A}$, where each $\widetilde{a}_{ij}$ is a TFN representing the relative importance of criterion, like in traditional AHP. The fuzzy numbers capture the uncertainty in decision-makers' subjective evaluations.
3. Fuzzy Synthetic Extent Analysis: To derive weights from the fuzzy comparison matrix, the fuzzy synthetic extent analysis method is utilised. For each criterion $i$, the fuzzy synthetic extent $\widetilde{S}_i$ is calculated as indicated in Equation (12):

$$\widetilde{S}_i = \frac{\sum_{j=1}^{n} \widetilde{a}_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} \widetilde{a}_{ij}} \tag{12}$$

The operations on fuzzy numbers, such as addition, multiplication, and reciprocal, are performed to compute the synthetic extent values. The fuzzy arithmetic used is governed by fuzzy set theory rules, specifically focusing on α-cut operations and the extension principle.

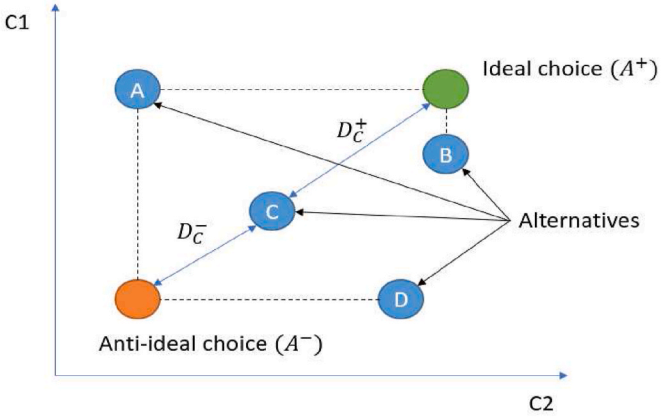

**Fig. 4.** Graphic depiction of the TOPSIS method [46].

**Table 6**
Theoretical TOPSIS decision matrix.

| | $C_1$ | $C_2$ | … | $C_1$ |
|---|---|---|---|---|
| | $W_1$ | $W_2$ | … | $W_n$ |
| $A_1$ | $x_{11}$ | $x_{12}$ | … | $x_{1n}$ |
| $A_2$ | $x_{21}$ | $x_{22}$ | … | $x_{2n}$ |
| … | … | … | … | … |
| $A_m$ | $x_{m1}$ | $x_{m2}$ | … | $x_{mn}$ |

**Table 5**
Saaty's random consistency index (RI).

| N° of alternatives (n) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| RI | 0.00 | 0.00 | 0.058 | 0.90 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 | 1.51 | 1.48 |

4. Defuzzification: The fuzzy values obtained from synthetic extent analysis must be converted into crisp values to determine priority weights. Defuzzification is typically done using the centroid method or mean of maximum method, as shown in Equation (13), yielding a crisp score:

$$\widetilde{w}_i = \frac{l_i + m_i + u_i}{3} \tag{13}$$

The crisp values are normalized to derive the final priority weights for each criterion.

Consistency Check: The consistency of the pairwise comparisons is verified by calculating the Fuzzy Consistency Index (FCI). The fuzzy consistency ratio (FCR) is derived in a manner similar to AHP's consistency ratio (CR), ensuring that the judgments provided are sufficiently consistent.

## 4. Study case

The validation of this study's proposition was substantiated through its practical application in designing a demonstration installation within the EU-funded project "Reffect Africa" [47]. Specifically, the methodology was applied to the pilot plant in Morocco: the DARA olive mill (Rehamna province, Marrakesh-Safi). This plant exhibits the following characteristics: it requires industrial power, it has an isolated electrical supply, and has convenient, cost-effective access to biomass resources.

The olive mill comprises several buildings and other facilities: an olive mill building, an enclosed space where the extraction of olive oil takes place; a water pond in addition to an olive tree plantation. Currently, as it is off-grid, a locally-rented diesel generator supplies the electrical energy demands of the olive mill throughout the production campaign. The description of each system evaluated until the implementation of the MCDM methodology is provided bellow in Table 7:

To account for the specific context of the olive mill, the methodology considered the availability of solar radiation, agri-food waste availability, the limited technical expertise of the workforce and the remoteness of the closest city, 110 km far from the plant. The power consumption of the olive oil mill during normal operation is around 20–30 kWe. The peak power consumption is near 55 kWe [48]. Regarding PGTs, photovoltaic system, gasification, biomass, and the existing diesel generator were evaluated as energy systems. A panel of ten experts assisted the case study by following the proposed methodology. By assessing their evaluations in accordance with the proposed rubric and implementing the data in the designed MCDM model, the options were ranked based on their suitability. The selection of experts was based on availability and literature [2], ensuring well-rounded representation. Experts cover different fields such as maintenance, machinery reliability, energy management, power generation, renewable energies, power plant construction and project management. This ensured coverage of critical perspectives relevant to the research problem.

## 5. Results and discussion

This section is structured to replicate the implementation process. The incoming data and results of each technique employed (AHP, TOPSIS) are presented sequentially and followed by a sensitivity analysis.

### 5.1. AHP

The initial step involves obtaining values for each criterion. To accomplish this, a pairwise comparison between the alternatives as outlined in Tables 3 and 4 and is performed. Experts provide the assessment data shown in Table 8, in accordance with Table 3. By inputting this data into the AHP model, the values of each criterion obtained by each expert are displayed in Table 9 together with their individual consistency ratios.

Despite the obvious disparity in assessment among the experts, a common tendency is discernible. Expert 3 consistently gives similar scores in most comparisons, while experts 1 and 2 exhibit the greatest relevant disparities regarding cost and flexibility, cost and life-cycle impact, and cost and efficiency.

Individually, the analysis of experts' evaluations $(E_1, E_2, \ldots, E_{10})$ reveals a diversity of criteria preferences. While most of the experts $(E_1, E_2, E_3, E_5, E_8)$ prioritize cost-efficiency, reflecting a pragmatic approach, others $(E_4, E_6, E_9)$ emphasize life-cycle analysis, highlighting the relevance of sustainability. Meanwhile, there is another group of experts $(E_2, E_7, E_9)$ placing resources availability at the forefront, emphasizing a reliable availability of energy. In general, flexibility and robustness hold moderate importance for all, while resource availability appears relatively less significant. These varied preferences underscore the need for informed, customized technology selection processes that align with

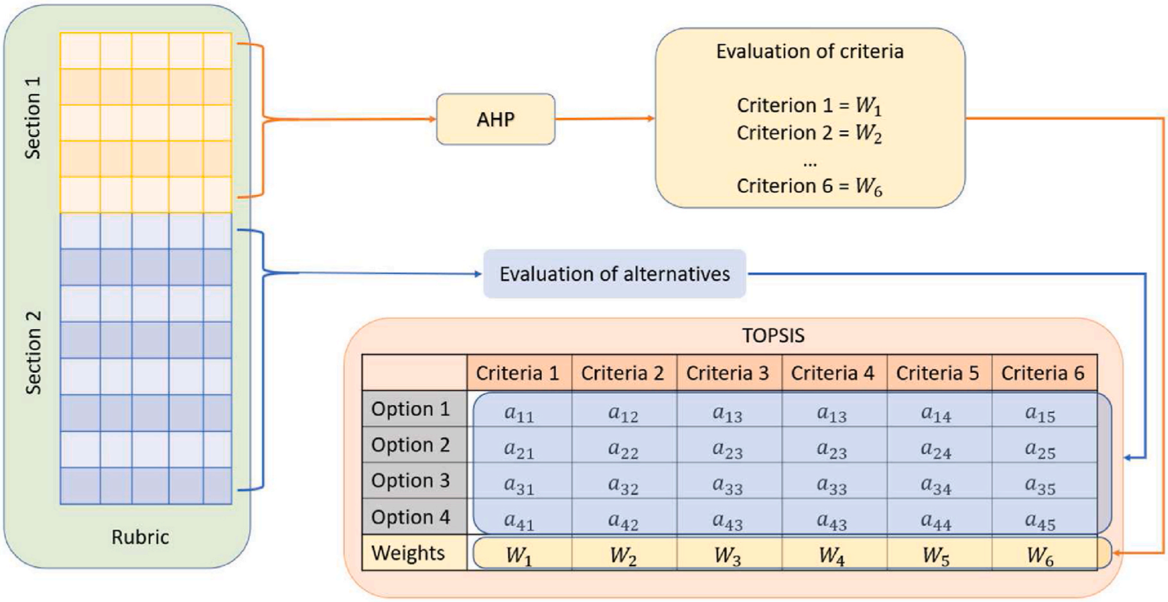

**Fig. 5.** Model structure.

**Table 7**
Evaluated system's description.

| System | Description |
|---|---|
| Biomass Gasification | Converts biomass into syngas via high-temperature, oxygen-limited conditions. Capital cost is 110k EUR, with low operational costs if agricultural residues are used. Efficiency is 25–30 %. Life-cycle analysis involves carbon-neutral potential if residues are sustainably sourced but has emissions associated with transport and syngas combustion. Robust, but dependent on biomass availability. Reliability is good for continuous power, moderate flexibility for variable loads. Heat recovery systems can enhance performance. |
| PV-Solar | A 60 kW solar system with 15 kW battery storage. It converts solar energy to AC power for industrial use. Capital cost is 60k EUR, with minimal operational costs. The system lacks enough storage for 24/7 operation, which limits its reliability during non-sunny periods. It is cost-effective during operation (zero fuel cost) but has environmental impacts related to panel production and disposal. The system's flexibility is suitable for a single-shift operation schedule. |
| Biomass combustion | Burns organic material (e.g., olive pits) to generate thermal energy. Capital cost is 80k EUR. It is simple to operate and relies on locally available biomass, ensuring low fuel costs and carbon-neutral potential if biomass is sourced sustainably. However, NOx emissions and waste generation require consideration. The system is reliable for steady power but lacks flexibility in responding to rapid load changes. |
| Diesel genset | Uses diesel to produce electricity via an internal combustion engine. Capital cost is 65k EUR, high operational costs due to fuel dependency. Efficiency is around 30–40 %. Life-cycle impact is negative due to significant greenhouse gas emissions and diesel extraction/refining processes. Highly flexible and capable of meeting variable power demands quickly. Reliable under most conditions but faces robustness challenges with fuel logistics and maintenance requirements. |

*In the case study, the possibility of connecting the plant to the electric grid was considered initially, but since the implementation cost was over the budget, making this alternative unfeasible, it was rejected and no longer considered.

**Table 8**
Rubric's AHP evaluation data.

| | $C_1 - C_2$ | $C_1 - C_3$ | $C_1 - C_4$ | $C_1 - C_5$ | $C_1 - C_6$ | $C_2 - C_3$ | $C_2 - C_4$ | $C_2 - C_5$ | $C_2 - C_6$ | $C_3 - C_4$ | $C_3 - C_5$ | $C_3 - C_6$ | $C_4 - C_5$ | $C_4 - C_5$ | $C_5 - C_6$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $E_1$ | 4 | 2 | 5 | 2 | 2 | 1/3 | 3 | 1/2 | 1/3 | 5 | 2 | 1 | 1/3 | 1/3 | 1/2 |
| $E_2$ | 7 | 5 | 7 | 3 | 1/2 | 2 | 1 | 1 | 1/5 | 2 | 3 | 1/7 | 1/7 | 1/7 | 1/4 |
| $E_3$ | 3 | 2 | 4 | 5 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 1 | 2 | 1 | 1/2 |
| $E_4$ | 4 | 1 | 1 | 2 | 2 | 1/4 | 3 | 1/2 | 1/3 | 5 | 2 | 4 | 1/2 | 1/3 | 1/2 |
| $E_5$ | 3 | 2 | 4 | 5 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 1 | 2 | 1 | 1/2 |
| $E_6$ | 5 | 1 | 5 | 2 | 2 | 1/6 | 3 | 1/2 | 1/3 | 6 | 2 | 2 | 1/4 | 1/3 | 1/2 |
| $E_7$ | 7 | 5 | 5 | 3 | 1/3 | 2 | 2 | 1 | 1/4 | 2 | 3 | 1/3 | 1/6 | 1/7 | 1/3 |
| $E_8$ | 6 | 4 | 3 | 2 | 1 | 1/5 | 2 | 1 | 1/6 | 5 | 3 | 1 | 1/2 | 1/6 | 1/3 |
| $E_9$ | 3 | 1/2 | 3 | 3 | 1/2 | 1/4 | 1 | 2 | 1/4 | 3 | 4 | 1/2 | 2 | 1/4 | 1/3 |
| $E_{10}$ | 6 | 3 | 4 | 2 | 1 | 1/2 | 1 | 1/3 | 1/5 | 2 | 3 | 1/6 | 1/5 | 1/7 | 1/4 |

project goals and values. It highlights the importance of a balanced approach, considering diverse perspectives in MCDM for PGT.

According to Ref. [44], the consistency ratios show a value below 0.1, signifying reasonable consistency. Furthermore, the experts, each with their own perspective, present personal criteria preferences, highlighting the significance of opinion, individual background and technical analysis. Nevertheless, analysing the results taking into account the different criteria, $C_1$ exhibits the most consistent value while $C_2$ and $C_4$ display the largest deviation between experts 1 and 2 compared to expert 3. In the final stage the criteria values are combined. To do so, the geometrical average (GA) calculated by Eq. (12) is used. Table 10 shows the results obtained.

$$GA = \sqrt[n]{\prod_{i=1}^{N} x_i} \tag{12}$$

Once the combined weights associated to each criterion are obtained, it is possible to observe that $C_1$ (costs) is the most relevant, as is typically the case in engineering works. It represents one third of the total weightage. The next criterion is $C_6$ (availability of resources) with a score of 24 %, reflecting its significance in the project, with the obligatory reuse of local biomass as its a power source which also aids local economic development. The third criterion are $C_2$, $C_3$ and $C_5$ with a score between 10 and 15 %, representing an intermediate level of relevance. Finally, $C_4$ (Efficiency) emerges as least relevant criterion. Despite efficiency typically being one the most relevant criteria, the context of this particular project prioritizes the local economy and sustainable energy sources. This leads experts to compromise on efficiency.

**Table 9**
AHP evaluation results.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | CR Value |
|---|---|---|---|---|---|---|---|
| $E_1$ | 0.321 | 0.084 | 0.216 | 0.048 | 0.132 | 0.199 | 0.031 |
| $E_2$ | 0.335 | 0.078 | 0.091 | 0.042 | 0.109 | 0.349 | 0.059 |
| $E_3$ | 0.380 | 0.083 | 0.117 | 0.043 | 0.110 | 0.266 | −0.027 |
| $E_4$ | 0.273 | 0.080 | 0.314 | 0.049 | 0.122 | 0.160 | −0.024 |
| $E_5$ | 0.358 | 0.195 | 0.145 | 0.103 | 0.068 | 0.129 | −0.027 |
| $E_6$ | 0.282 | 0.070 | 0.299 | 0.043 | 0.134 | 0.171 | −0.039 |
| $E_7$ | 0.292 | 0.092 | 0.109 | 0.039 | 0.109 | 0.357 | 0.085 |
| $E_8$ | 0.305 | 0.063 | 0.217 | 0.051 | 0.091 | 0.273 | 0.022 |
| $E_9$ | 0.187 | 0.081 | 0.257 | 0.085 | 0.062 | 0.327 | −0.009 |
| $E_{10}$ | 0.274 | 0.050 | 0.122 | 0.049 | 0.131 | 0.131 | 0.026 |

### 5.2. TOPSIS

Employing the TOPSIS model requires two primary datasets: weights and evaluations. The former, weights were obtained in the previous subsection. Data collection for evaluations is also required. To this end, the second section of the rubric presented in Table 1 asks each expert to evaluate each indicator for each alternative, and their assessments are presented in Table 11. The entire dataset is accessible in [49].

After analysing the income data shown in Table 10 and applying the rules from Table 2, the normalized indicator scores are obtained from each expert. Then, the scores of the indicators associated to each criterion are aggregated. This process is carried out separately, obtaining the individual scores of each criterion for each expert. Finally, to consolidate scores, the geometric average is employed as detailed above. The values for each criterion and alternative are shown in Table 12.

As previously mentioned, the evaluations provided by the panel of experts reveal distinctive profiles and perspectives when assessing the various criteria for the alternatives. These differences highlight the need for a multidisciplinary approach. By incorporating a range of perspectives, a more robust and comprehensive evaluation can be achieved in decision-making processes.

Once all the data has been collected, it is combined as outlined in the

**Table 10**
Weights obtained by AHP (in per unit).

| Criteria | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| Weight | 0.2959013 | 0.08169287 | 0.05249577 | 0.10391747 | 0.10391747 | 0.24527352 |

**Table 11**
Experts' evaluation of criteria through rubric usage.

| | | Alternative 1 | | | | Alternative 2 | | | | Alternative 3 | | | | Alternative 4 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $E_1$ | $E_2$ | | $E_{10}$ | $E_1$ | $E_2$ | | $E_{10}$ | $E_1$ | $E_2$ | | $E_{10}$ | $E_1$ | $E_2$ | | $E_{10}$ |
| $C_1$ | $I_{11}$ | 110k | 110k | … | 110k | 90k | 90k | … | 90k | 80k | 80k | … | 80k | 65k | 65k | … | 65k |
| | $I_{12}$ | 20 | 20 | | 20 | 10 | 15 | | 20 | 20 | 20 | | 20 | 10 | 15 | | 20 |
| | $I_{13}$ | 3 | 3 | | 5 | 0.5 | 0.5 | | 5 | 3 | 3 | | 5 | 5 | 5 | | 5 |
| | $I_{14}$ | 0.5 | 0.5 | | 0.5 | 0 | 0 | | 0 | 0.5 | 0.5 | | 0.5 | 0.5 | 0.5 | | 0.5 |
| $C_2$ | $I_{21}$ | 20 | 20 | … | 50 | 100 | 100 | … | 80 | 20 | 20 | … | 80 | 90 | 30 | … | 90 |
| | $I_{22}$ | Yes | Yes | | Yes | No | No | | No | Yes | Yes | | Yes | No | No | | No |
| | $I_{23}$ | 80 | 85 | | 100 | 100 | 100 | | 100 | 90 | 90 | | 100 | 95 | 100 | | 95 |
| | $I_{24}$ | 30 | 30 | | 10 | 0 | 1 | | 0 | 30 | 10 | | 0 | 25 | 1 | | 25 |
| | $I_{25}$ | Min | Min | | Min | Ms | Ms | | Ms | Min | Seg | | Seg | Seg | Seg | | Seg |
| $C_3$ | $I_{31}$ | No | No | … | No | No | No | … | No | Yes | Yes | … | Yes | Yes | Yes | … | Yes |
| | $I_{32}$ | Yes | Yes | | Yes | No | No | | No | Yes | Yes | | No | No | No | | No |
| | $I_{33}$ | No | No | | No | No | No | | No | No | Yes | | Yes | Yes | Yes | | Yes |
| | $I_{34}$ | Yes | Yes | | No | No | No | | No | yes | Yes | | Yes | No | No | | Yes |
| | $I_{35}$ | 1 | 2 | | 1 | 1 | 2 | | 1 | 1 | 2 | | 1 | 1 | 1 | | 1 |
| $C_4$ | $I_{41}$ | 60 | 60 | … | 60 | 25 | 25 | … | 30 | 45 | 45 | … | 40 | 65 | 65 | … | 40 |
| | $I_{42}$ | Yes | Yes | | Yes | No | No | | No | Yes | Yes | | Yes | Yes | Yes | | Yes |
| | $I_{43}$ | 15 | 15 | | 0 | 10 | 10 | | 0 | 15 | 15 | | 10 | 12.5 | 12.5 | | 10 |
| | $I_{44}$ | Yes | Yes | | Yes | No | Yes | | yes | Yes | Yes | | Yes | No | Yes | | Yes |
| | $I_{45}$ | 6 | 7 | | 10 | 1 | 1 | | 10 | 4 | 5 | | 20 | 20 | 15 | | 10 |
| $C_5$ | $I_{51}$ | Yes | Yes | … | No | Yes | Yes | … | Yes | No | No | … | No | No | No | … | Yes |
| | $I_{52}$ | Yes | Yes | | No | No | No | | Yes | Yes | Yes | | No | Yes | Yes | | Yes |
| | $I_{53}$ | No | No | | No | Yes | Yes | | Yes | No | No | | No | No | No | | No |
| | $I_{54}$ | Yes | Yes | | No | No | No | | No | Yes | Yes | | No | Yes | Yes | | Yes |
| | $I_{55}$ | No | No | | Yes | No | No | | No | No | No | | No | No | No | | Yes |
| $C_6$ | $I_{61}$ | No | No | … | No | Yes | Yes | … | Yes | No | No | … | No | No | No | … | No |
| | $I_{62}$ | Yes | Yes | | Yes | No | No | | No | Yes | Yes | | Yes | Yes | No | | Yes |
| | $I_{63}$ | Yes | No | | Yes | No | No | | No | Yes | No | | Yes | Yes | No | | No |
| | $I_{64}$ | Yes | Yes | | Yes | Yes | Yes | | Yes | Yes | Yes | | Yes | Yes | Yes | | Yes |
| | $I_{65}$ | Yes | Yes | | Yes | Yes | Yes | | Yes | Yes | Yes | | Yes | No | No | | No |

methodology, yielding the results shown in Table 13, which represents the initial TOPSIS model matrix. To enhance data comprehension and visualization, Fig. 6 presents a radar chart displaying the data as polygons. To facilitate chart interpretation, all criteria are considered with a minimum punctuation of 0 and a maximum of 5, so that, the ideal option would correspond to the polygon with the largest area.

Finally, based on the data displayed in Table 12 and applying equations (5)–(11) described in the methodology, the values in Table 14 present TOPSIS suitability and ranking rate results. In this table, each alternative obtains a performance coefficient with a value below 1. The highest coefficient, corresponds to the gasification alternative, followed by biomass, PV-Solar and finally, with the lowest suitability, the diesel option.

## 5.3. *Sensitivity analysis*

### 5.3.1. *Coefficients' variation*

Sensitivity analysis is carried out as defined in the methodology section. This analysis yields consistent results in favour of selecting gasification as the most suitable alternative, ranking first 46.28099 % of the time, (56 out of 121 cases), highlighting it as a generally dominant preference. Biomass follows as the second-placed choice, ranked first in 33.8843 %, or 41 out of 121 cases. The PV-solar alternative emerged as favourable in 21 cases and finally, the Diesel generator ranked first in 3 cases.

Surface diagrams were employed to present and interpret the outcomes of parameter variations, illustrating changes in suitability of each alternative as criterion weights were adjusted. Additionally, a distribution map was presented, to highlight the optimal alternative for each step of the parameter variation analysis.

Fig. 7 and Table 15 showcase the results for the first-placed gasification alternative. The surface diagram in Fig. 7 provides a visual representation of the adequacy scores obtained throughout the sensitivity analysis. By juxtaposing this data with those of the alternatives, a comparative ranking of each alternative can be established. Correspondingly, Table 15 presents the ranked positions of the gasification alternative based on its adequacy scores. Notably, there is a direct correlation between the highest scores depicted in Fig. 7 and the rankings presented in Table 15. However, it is important to acknowledge that despite achieving the highest rate of first positions, the gasification alternative exhibits dramatic fluctuations, occasionally shifting from first to third place.

Similarly, Fig. 8, and Table 16 scope the results for the biomass alternative. The surface diagram in Fig. 8 represents the adequacy scores obtained throughout the sensitivity analysis. Correspondingly, Table 16 presents the ranked positions of the biomass alternative based on its adequacy scores. There is a direct correlation between the shape of the diagram from Fig. 8 and rankings presented in Table 16. The wider middle section of the surface diagram is represented by the bigger transition region observed in Table 16.

The disparities among the evaluated technologies are noteworthy. The gasifier exhibited positive attributes, notably reduced life-cycle impact and efficient resource utilization, albeit with drawbacks in terms of cost and flexibility. The biomass option demonstrated similar results but with less variability between positive and negative aspects. The photovoltaic energy option showcased strengths in terms of flexibility and life-cycle, while the diesel generator excelled in cost advantages despite its negative environmental impact.

**Table 12**
Pondered values for criteria and alternatives.

| | | Alternative 1 | Alternative 2 | Alternative 3 | Alternative 4 |
|---|---|---|---|---|---|
| $C_1$ | $E_1$ | 3.66025 | 2.59875 | 2.735 | 1.99063 |
| | $E_2$ | 3.2818 | 2.48625 | 2.47 | 1.885 |
| | … | … | … | … | … |
| | $E_{10}$ | 3.72625 | 2.6325 | 2.71 | 2.03125 |
| $C_2$ | $E_1$ | 2.7 | 4 | 2.8 | 3.35 |
| | $E_2$ | 3 | 3.99 | 3.75 | 3.04 |
| | .. | … | … | … | … |
| | $E_{10}$ | 1.8 | 4 | 1.9 | 3.45 |
| C3 | $E_1$ | 1.333 | 0.3333 | 1.3333 | 2.3333 |
| | $E_2$ | 1.666 | 0.666 | 2.666 | 2.3333 |
| | … | … | … | … | … |
| | $E_{10}$ | 1.3333 | 0.3333 | 1.3333 | 2.3333 |
| $C_4$ | $E_1$ | 3.61666 | 2.15 | 3.55 | 2.575 |
| | $E_2$ | 3.59285 | 2.25 | 3.5 | 3.725 |
| | … | … | … | … | … |
| | $E_{10}$ | 3.7 | 1.275 | 3.55 | 2.565 |
| $C_5$ | $E_1$ | 4 | 1 | 3 | 3 |
| | $E_2$ | 4 | 1 | 3 | 3 |
| | … | … | … | … | … |
| | $E_{10}$ | 4 | 1 | 4 | 4 |
| $C_6$ | $E_1$ | 5 | 2 | 5 | 4 |
| | $E_2$ | 4 | 2 | 4 | 2 |
| | | … | … | … | … |
| | $E_{10}$ | 5 | 2 | 5 | 4 |

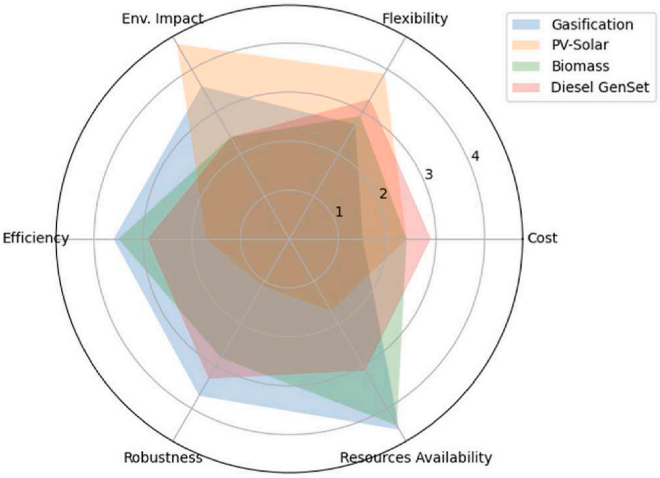

**Fig. 6.** TOPSIS initial data displayed as a radar diagram.

**Table 14**
TOPSIS Suitability and raking rates.

| Alternative | Suitability rate | Ranking |
|---|---|---|
| Gasification | 0.558469353 | 1 |
| PV-Solar | 0.496339513 | 3 |
| Biomass | 0.51305338 | 2 |
| Diesel | 0.489877483 | 4 |

### 5.3.2. *Modified fuzzy methodology*

To further validate the robustness of the initial sensitivity analysis, a second sensitivity analysis was conducted using the FAHP in place of the previous AHP method. As described in the methodology section this approach incorporates linguistic evaluations to address subjective uncertainties and variability in expert judgments, providing an additional layer of insight into the consistency and reliability of the decision-making process.

The same experts were requested to perform the pairwise comparisons as before, but this time using linguistic variables instead of numerical ones to assess the evaluation criteria. The FAHP values were translated into triangular fuzzy numbers and their reciprocals. The fuzzy ratings are represented through respective triangular fuzzy sets. These fuzzy sets were then used to derive comparative weights for the evaluation criteria (C1 to C6) across the experts' evaluations, ensuring consistency with the previously described fuzzy logic approach. This process resulted in distinct sets of consistency ratio (CR) values, which are detailed in Table 17. Linguistic terminology and second experts' evaluation are detailed in the Appendix (Table 21 and Table 22).

Considering these modifications, the suitability rates and rankings of the alternatives derived from FAHP are presented in Table 18. These results indicate that gasification continues to emerge as the most favourable alternative, with a suitability rate of 0.5934 and ranking first across all scenarios, reinforcing the previous conclusions from the AHP analysis, validating the proposed methodology. Biomass ranks second, while the PV Solar alternative and the diesel generator exchange positions compared to the AHP results. This shift is attributable to the fuzzification process, which adjusts the weight priorities. However, the differences between these options remain marginal in terms of suitability. Notably, the rankings derived from FAHP exhibit minor changes in the relative positioning of the alternatives. However, the differences between the first and second options are more pronounced, making the top-ranked choice appear clearer.

Notably, the FAHP rankings reveal minor changes in the relative positioning of PV Solar and biomass.

Overall, the FAHP analysis substantiates the dominance of gasification while providing further insights into the stability of intermediate alternatives under uncertainty. By incorporating linguistic assessments, FAHP allows for a more nuanced understanding of expert preferences, accommodating the variability inherent in human judgment, as seen in the smoother transition patterns and increased consistency across evaluations.

**Table 13**
Combined TOPSIS results.

| | min<br>Cost | max<br>Flexibility | min<br>LCI | max<br>Efficiency | max<br>Robustness | max<br>Resources |
|---|---|---|---|---|---|---|
| Gasification | 3.54167768 | 2.7649674 | 1.4578161 | 3.61793873 | 3.66925902 | 4.57305052 |
| PV-Solar | 2.61348408 | 3.94997768 | 0.43983597 | 1.66025446 | 1.07177346 | 1.74110113 |
| Biomass | 2.59423944 | 2.91100568 | 2.59050094 | 3.48436535 | 2.84706168 | 4.3734483 |
| Diesel Genset | 2.06838324 | 3.32101854 | 2.54952753 | 2.96223765 | 3.34421259 | 3.15687306 |
| Ideal | 2.06838324 | 3.94997768 | 0.43983597 | 3.61793873 | 3.66925902 | 4.57305052 |
| Anti-ideal | 3.54167768 | 2.7649674 | 2.59050094 | 1.66025446 | 1.07177346 | 1.74110113 |
| Weight | 0.29594013 | 0.08169287 | 0.17252544 | 0.05249577 | 0.10391747 | 0.24527352 |

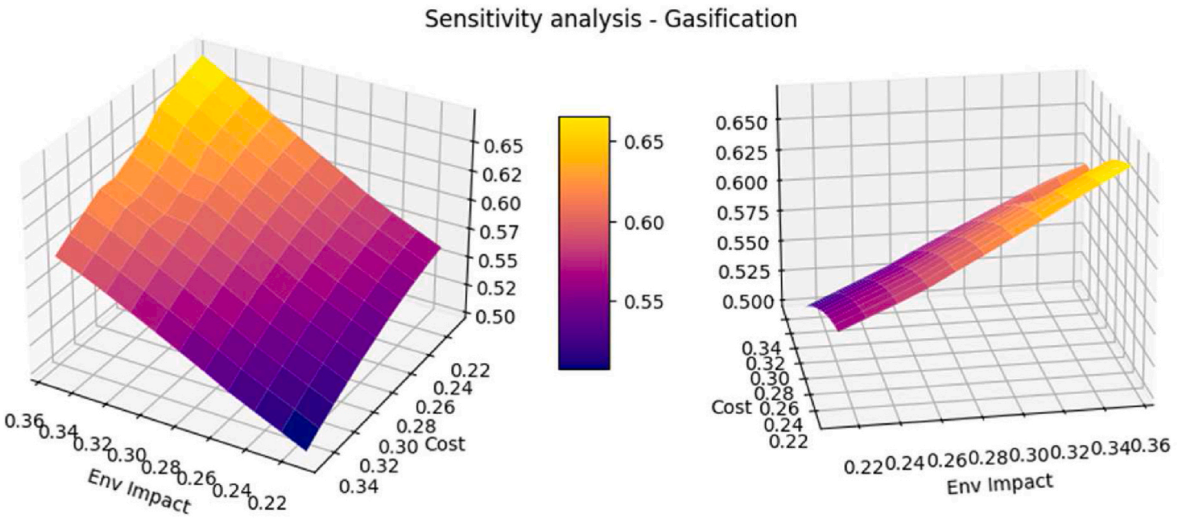

**Fig. 7.** Sensitivity analysis - Gasification.

**Table 15**
Sensitivity analysis - gasification.

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.3699 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 0.3551 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 0.3403 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 0.3255 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 0.3107 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 2 |
| 0.2959 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 2 | 2 | 2 |
| 0.2811 | 2 | 2 | 1 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 |
| 0.2663 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 |
| 0.2515 | 2 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| 0.2367 | 2 | 2 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| 0.2219 | 4 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| | 0.2200 | 0.2347 | 0.2494 | 0.264 | 0.2787 | 0.2934 | 0.3081 | 0.3227 | 0.3374 | 0.3521 | 0.3667 |

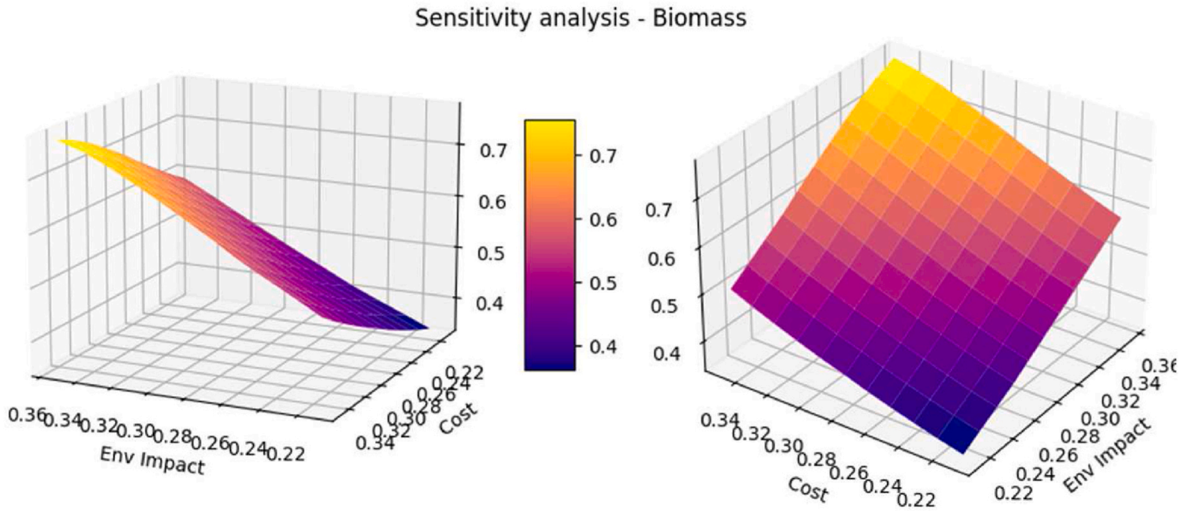

**Fig. 8.** Sensitivity analysis - Biomass.

### *5.4. Validation*

The validation process in this study compares the outcomes of the AHP-TOPSIS analysis with results from HOMER Pro (Version 3.16.2), a well-regarded simulation software for microgrid design and optimization. Its capability to model, simulate, and optimize hybrid energy systems based on economic, efficiency, and environmental metrics makes it ideal for validating complex energy assessments. This comparison ensures the reliability of the MCDM process by verifying if AHP-TOPSIS rankings align with a detailed technical analysis of cost, performance, and emissions. Fig. 9 illustrates the modelled system and energy configurations used.

**Table 16**

Sensitivity analysis - biomass.

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.3699 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 2 | 2 | 2 | 2 |
| 0.3551 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 2 | 2 | 2 | 2 |
| 0.3403 | 3 | 3 | 3 | 3 | 3 | 3 | 2 | 2 | 2 | 2 | 2 |
| 0.3255 | 3 | 3 | 3 | 3 | 3 | 2 | 2 | 2 | 2 | 2 | 2 |
| 0.3107 | 3 | 3 | 3 | 3 | 3 | 2 | 2 | 2 | 2 | 2 | 1 |
| 0.2959 | 3 | 3 | 3 | 3 | 2 | 2 | 2 | 2 | 1 | 1 | 1 |
| 0.2811 | 4 | 3 | 3 | 2 | 2 | 2 | 1 | 1 | 1 | 1 | 1 |
| 0.2663 | 4 | 3 | 3 | 2 | 2 | 1 | 1 | 1 | 1 | 1 | 1 |
| 0.2515 | 4 | 4 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 0.2367 | 4 | 3 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 0.2219 | 3 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 0.2200 | 0.2347 | 0.2494 | 0.264 | 0.2787 | 0.2934 | 0.3081 | 0.3227 | 0.3374 | 0.3521 | 0.3667 |

**Table 17**

FAHP evaluation data and comparison against AHP.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | CR Value |
|---|---|---|---|---|---|---|---|
| $E_1$ | 0.234 | 0.096 | 0.234 | 0.036 | 0.184 | 0.217 | 0.0295 |
| $E_2$ | 0.298 | 0.064 | 0.096 | 0.047 | 0.109 | 0.385 | 0.0432 |
| $E_3$ | 0.314 | 0.123 | 0.159 | 0.123 | 0.120 | 0.160 | −0.0451 |
| $E_4$ | 0.2391 | 0.1219 | 0.1997 | 0.0580 | 0.1609 | 0.2204 | 0.0263 |
| $E_5$ | 0.2909 | 0.1220 | 0.1550 | 0.1220 | 0.1550 | 0.1550 | 0.0666 |
| $E_6$ | 0.2550 | 0.1586 | 0.1926 | 0.0339 | 0.1539 | 0.2061 | 0.0597 |
| $E_7$ | 0.2942 | 0.0696 | 0.1038 | 0.0495 | 0.1063 | 0.3767 | 0.0698 |
| $E_8$ | 0.2954 | 0.0715 | 0.2001 | 0.0536 | 0.0966 | 0.2828 | 0.0769 |
| $E_9$ | 0.2652 | 0.0991 | 0.2301 | 0.0702 | 0.0702 | 0.2652 | −0.0577 |
| $E_{10}$ | 0.2607 | 0.0492 | 0.1110 | 0.0501 | 0.1567 | 0.3724 | 0.0712 |
| Overall AHP | 0.29594013 | 0.08169287 | 0.17252544 | 0.05249577 | 0.10391747 | 0.24527352 | |
| Overall FAHP | 0.2746 | 0.0975 | 0.168 | 0.0643 | 0.1313 | 0.2641 | |
| Variation (%) | −7.194 | 19.337 | −2.547 | 22.543 | 26.312 | 7.659 | |

**Table 18**

TOPSIS Suitability and raking rates using criteria from FAHP.

| Alternative | Suitability rate | Ranking |
|---|---|---|
| Gasification | 0.59345405 | 1 |
| PV-Solar | 0.46372339 | 4 |
| Biomass | 0.53362621 | 2 |
| Diesel | 0.49574548 | 3 |

The results obtained from HOMER Pro displayed in two tables: Table 19 presents economic data and Table 20 details emissions' results.

The results obtained from HOMER Pro reveal a notable alignment between the cost-related and emissions factors of different energy systems, and the outcomes of the AHP-TOPSIS methodology. Specifically, the gasification system emerged as the top-ranked option in both analyses. According to HOMER, the gasification system offers the lowest Net Present Cost (NPC) and Levelized Cost of Energy (LCOE) compared to other hybrid and fossil-based configurations, along with moderate emissions, making it a cost-effective and relatively environmentally friendly solution. The second and third-ranked alternatives, biomass and PV + gasification, follow a similar pattern where their costs and emissions are moderately favourable. Diesel-based systems, including combinations with PV, were consistently ranked lowest due to their high costs and substantial carbon and sulfur emissions, aligning with the MCDM ranking which placed diesel at the bottom. These findings suggest that the AHP-TOPSIS analysis is consistent with the more detailed technical evaluation provided by HOMER Pro, thereby enhancing the robustness of the MCDM results and providing confidence in recommending gasification-based systems for regions like Morocco.

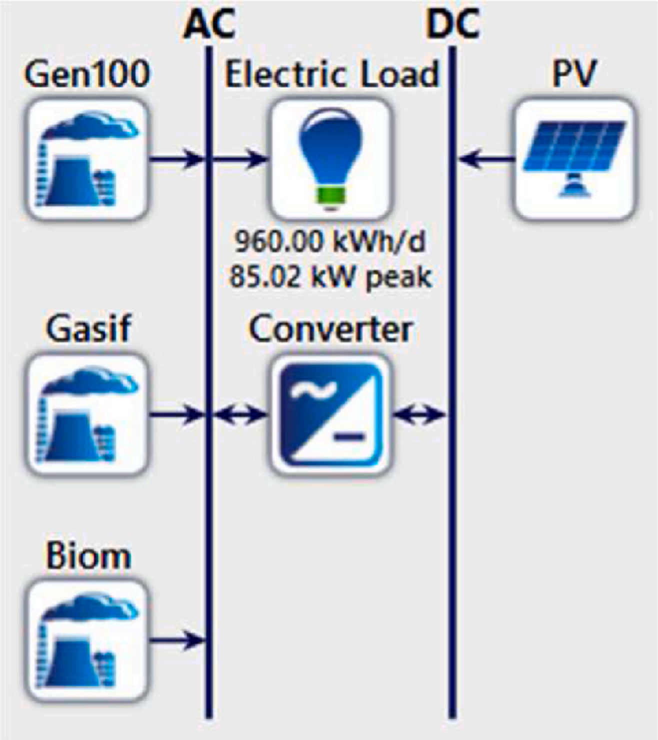

**Fig. 9.** System configuration in HOMER.

**Table 19**
HOMER economic results.

| System | Power (kW) | NPC (€) | LCOE (€/kWh) | Operating cost (€/yr) | CAPEX (€) |
|---|---|---|---|---|---|
| Gasification | 65 | 299590.6 | 0.08957043 | 16529.37 | 110000 |
| biomass | 65 | 350691.9 | 0.1048485 | 23600.15 | 80000 |
| PV + gasification | 60+65 | 371179.8 | 0.1108799 | 14924.62 | 199995.7 |
| PV + biomass | 60+65 | 413266.9 | 0.1234523 | 21142.47 | 170764.4 |
| Diesel engine + gasification | 100+65 | 452297.7 | 0.1350458 | 24176.07 | 175000 |
| PV + Diesel engine | 60+100 | 2160147 | 0.6449707 | 174617.1 | 157301.9 |
| Diesel engine | 100 | 2194352 | 0.6551836 | 185646.6 | 65000 |

**Table 20**
Homer emissions results.

| System | Carbon Dioxide (kg/year) | Carbon Monoxide (kg/year) | Unburned Hydrocarbons (kg/year) | Particulate Matter (kg/year) | Sulfur Dioxide (kg/year) | Nitrogen Oxides (kg/year) |
|---|---|---|---|---|---|---|
| Gasification | 169,545 | 6,691 | 295 | 40.1 | 48 | 6,289 |
| biomass | 131,940 | 1,147 | 50.5 | 6.88 | 137 | 1,078 |
| PV + gasification | 141,616 | 5,589 | 246 | 33.5 | 40.1 | 5,253 |
| PV + biomass | 109,603 | 953 | 42 | 5.71 | 114 | 896 |
| Diesel engine + Gasification | 173,320 | 6,382 | 281 | 38.1 | 79.5 | 5,916 |
| PV + Diesel engine | 243,850 | 1,659 | 67.1 | 6.64 | 598 | 133 |
| Diesel engine | 265,062 | 1,803 | 73 | 7.22 | 650 | 144 |

## 6. Conclusions

This study introduces a systematic approach aimed at facilitating the evaluation and selection of optimal PGTs. Within this scope, MCDM techniques play a pivotal role. These techniques demand careful and systematic consideration. The expert perspective is crucial at this stage, making AHP one of the most valuable tools in this context. Combining the AHP solutions with the TOPSIS analysis would be a more convenient way to solve energy planning problems. Thus, an integrated methodology based on an AHP-TOPSIS model supported by a tailormade rubric was proposed to outline a comprehensive evaluation framework that ensures transparency, reduces biases, and emphasizes the decision-making process over solely quantitative outputs, as highlighted in the aims of this study.

This methodology was put into practice in a case study involving the installation of a power generation plant in a developing area. While the case study focuses on an isolated power supply, the methodology is versatile and adaptable to both off-grid and grid-connected systems. Isolated systems such as the DARA olive mill highlight the potential for decentralized energy solutions in regions lacking reliable grid access. However, the same approach can be applied to grid-connected environments, evaluating different energy sources under varying conditions.

Considering the specific characteristics and requirements of the study case, four distinct installation alternatives were considered: PV-Solar, biomass, gasification and a diesel genset. The gasification exhibited positive attributes such as reduced life-cycle impact and efficient resource utilization and emerged as the best alternative. According to HOMER Pro simulations, the gasification system offers the lowest Net Present Cost (NPC) of $2.5 million and a Levelized Cost of Energy (LCOE) of $0.12 per kWh, compared to higher costs in other configurations, along with moderate emissions, making it a cost-effective and relatively environmentally friendly solution. These findings suggest that the AHP-TOPSIS analysis is consistent with the more detailed technical evaluation provided by HOMER Pro, thereby enhancing the robustness of the MCDM results and providing confidence in recommending gasification-based systems for regions like Morocco. AHP analysis scoped *Cost* as the most relevant criterion representing one third of the total weight. Additionally, the score of 24 % for *Availability of Resources* reflects its significance in the project. This is due to the reusability of local biomass, a pivotal power source and a catalyst of local economic development. Scoring between 10 and 15 %, *Flexibility, Life-cycle analysis and Robustness* represent the intermediate criteria in terms of relevance, with *Efficiency* deemed to be the least relevant criteria. While efficiency is generally a key criterion, the project context prioritizes local economic development in addition to the use of sustainable energy sources. Hence, with these contextual considerations in mind, in this case the experts placed efficiency below other criteria.

A sensitivity analysis was conducted to evaluate the robustness of the methodology, and to evaluate the result volatility according to the experts' evaluations. Considering these modifications, the suitability rates and rankings of the alternatives derived from FAHP indicated that gasification continues to emerge as the most favourable alternative, with a suitability rate of 0.5934 and ranking first across all scenarios, reinforcing the previous conclusions from the AHP analysis. The gasification alternative ranked first in 46.28 % of cases displaying its general dominance, followed by biomass, which ranked first in 33.28 % of cases. Finally, PV-solar and diesel were considered residual options. This finding highlights the potential of renewable energy sources to serve not only domestic applications in microgrids but also industrial purposes in isolated areas. Results of the case study emphasis on life-cycle impact aligns with the growing recognition of renewable energy as a key driver of sustainable development in underdeveloped areas. Additionally, the results align with the broader goal of supporting decentralized energy solutions in regions lacking reliable grid access, while the methodology's flexibility enables its use in grid-connected environments under different conditions.

AHP is widely used for weighting criteria. Consequently, the obtained weights may vary across methodologies due to discrepancies in expert assessments. Nevertheless, working with several experts and integrating diverse evaluations to derive a consensual single value for each criterion, together with the application of the proposed closed rubric totally integrated into the MCDM model, enables a more robust and reliable decision-making process. This process, while inherently subjective due to the involvement of expert opinions, is made more objective through the imposition of the proposed rubric and the integration of various evaluations. Consequently, decisions are not solely reliant on expert opinion but are also supported by a rigorous and systematic approach. The proposed methodology could set a precedent, or potentially establish a standardized solution for the specific case of PGT selection.

## CRediT authorship contribution statement

**José Antonio Hernández-Torres:** Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Daniel Sánchez-Lozano:** Writing – original draft, Validation, Software, Investigation, Data curation, Conceptualization. **Reyes Sánchez-Herrera:** Validation, Supervision, Project administration, Formal analysis. **David Vera:** Supervision, Resources, Project administration, Methodology, Funding acquisition. **Juan P. Torreglosa:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition.

## Data availability

Publicly available datasets analysed in this study. Can be found in https://zenodo.org/records/14271098.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jose Antonio Hernandez-Torres, Daniel Sanchez Lozano, Reyes Sanchez-Herrera, David Vera Candeas and Juan P. Torreglosa report financial support and article publishing charges were provided by European Union's Horizon 2020.

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## Appendix

**Table 21**
Linguistic scale and equivalent triangular fuzzy numbers.

| Linguistic variable | Triangular fuzzy numbers | Triangular fuzzy reciprocal numbers |
|---|---|---|
| Equally Important (E) | (1,1,1) | (1,1,1) |
| Slightly More Important (S) | (2, 3, 4) | (1/2, 1/3, 1/4) |
| Moderately More Important (M) | (4,5, 6) | (1/4, 1/5, 1/6) |
| Highly More Important (H) | (6, 7, 8) | (1/6, 1/7, 1/8) |
| Critically More Important (C) | (8, 9, 9) | (1/8, 1/9, 1/9) |

When the second parameter in a comparison is evaluated as more important, the letter 'R' is added in front.

**Table 22**
Expert's evaluation using Linguistic terms

| | $C_1 - C_2$ | $C_1 - C_3$ | $C_1 - C_4$ | $C_1 - C_5$ | $C_1 - C_6$ | $C_2 - C_3$ | $C_2 - C_4$ | $C_2 - C_5$ | $C_2 - C_6$ | $C_3 - C_4$ | $C_3 - C_5$ | $C_3 - C_6$ | $C_4 - C_5$ | $C_4 - C_5$ | $C_5 - C_6$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $E_1$ | M | S | M | S | S | RS | S | RS | RS | M | S | E | RS | RS | RS |
| $E_2$ | H | M | H | S | RH | S | E | E | RM | S | S | RH | RH | RH | RM |
| $E_3$ | S | S | M | M | S | S | S | S | S | S | S | E | S | E | RS |
| $E_4$ | S | E | M | E | E | S | S | E | RS | M | E | S | E | RS | E |
| $E_5$ | S | E | S | M | E | E | E | E | E | E | E | E | E | E | E |
| $E_6$ | M | E | M | E | E | S | S | E | RS | 4 | E | E | RS | RS | E |
| $E_7$ | H | M | M | S | RS | E | E | E | RS | E | S | RS | RH | RH | RS |
| $E_8$ | H | S | S | E | E | E | E | E | RS | M | S | E | E | RH | RS |
| $E_9$ | S | E | S | S | E | E | E | E | RS | S | S | E | E | RS | RS |
| $E_{10}$ | H | S | S | E | E | E | E | RS | RM | E | S | RH | RM | 0.25 | RS |

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.renene.2025.122481.

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