Operational Research in Engineering Sciences: Theory and Applications
Vol. 7, Issue 1, 2024, pp. 348-371
ISSN: 2620-1607
eISSN: 2620-1747
DOI: https://doi.org/10.5281/zenodo.15080786

AN ANALYTIC HIERARCHY PROCESS MULTI-CRITERIA DECISION-MAKING MODEL TO EVALUATE RENEWABLE ENERGY SOURCES IN PALESTINIAN TERRITORIES

Mohammad Kanan[1*], Dalal Al-Nabulsi[2], Mohammed Alsayed[3*], Yahya Saleh[4], Ramiz Assaf [4*], Giacomo Scelba[5], Naglaa Ibrahim Khamis[6]

[1]Industrial Engineering Department, Faculty of Engineering, University of Business and Technology (UBT), Jeddah 21448, Saudi Arabia

[2]Engineering Management program, An- Najah National University, P.O. Box 7, Nablus, Palestine.

[3]Energy Engineering and Environment department, An-Najah National University, P.O. Box 7, Nablus, Palestine.

[4]Industrial Engineering Department, An-Najah National University, P.O. Box 7, Nablus, Palestine.

[5]Dipartimento di Ingegneria Elettrica Elettronica e Informatica, University of Catania, Catania, Italy.

[6]Faculty of Financial and Administrative Sciences, Pharos University in Alexandria, Egypt

Received: 08 November 2023
Accepted: 22 March 2024
First Online: 30 March 2024

Research Paper

Abstract: *With numerous renewable energy technologies available worldwide, the selection process must be meticulous to address specific needs effectively. Given the precarious dependency of Palestinian territories (PTs) on imported energy, surpassing 90% of its electricity requirements, there is a pressing need to explore sustainable solutions, particularly renewable energy sources, to achieve energy self-sufficiency. In response to this challenge, the present research employs a Multi-Criteria Decision-Making (MCDM) approach, specifically leveraging the Analytic Hierarchy Process (AHP). The primary objective is to comprehensively investigate, select, and rank eight renewable energy sources in PTs, including solar photovoltaic (PV), solar water heaters (SWH), concentrated solar power (CSP), wind, geothermal, biomass, biogas, and waste-to-energy (WTE) alternatives. Utilizing the MCDM approach, the AHP assessment model is structured around five main criteria (technical, economic, environmental, socio-political, and risk) and 22 sub-criteria, aligned with the eight renewable energy alternative solutions. The findings underscore solar PV as the most promising renewable energy alternative solution in the*

---

*Corresponding Author: m.kanan@ubt.edu.sa (M. Kanan),
malsayed@najah.edu (M. Alsayed), ramizassaf@najah.edu (R. Assaf)

PTs, followed by SWH, WTE, geothermal, biogas, and CSP, respectively. Following a sensitivity analysis, the prioritization and ranking of the renewable energy alternative solutions portfolio offer valuable insights for the formulation of long-term energy roadmaps and policies aimed at achieving sustainability. Furthermore, the study employs the AHP model alongside corresponding comparison matrices to discern local and global preferences across hierarchical tree levels, encompassing criteria, sub-criteria, and final selection alternatives. Notably, technical and economic criteria are paramount, each with a weight of 33.3%, while socio-political, risk, and environmental criteria follow, each with a weight of 11.1%. The study's pioneering use of the AHP method for prioritizing renewable alternatives in the Palestinian context significantly enhances informed decision-making and strategic energy planning in the region.

Keywords: *RE Sources, Multi-Criteria Decision Making, Analytic Hierarchy Process, Palestinian Territories.*

1. Introduction

Renewable Energy (RE), often referred to as green energy, plays a pivotal role in advancing sustainable development objectives and augmenting overall societal well-being. It has garnered significant attention within the scientific community as a potent tool in addressing CO2 emission challenges. The rapid evolution of technology, coupled with the burgeoning global population and an enduring quest for heightened living standards, has precipitated an increasing demand for both fossil fuels and renewable energy sources (Abu-Madi, 2013). In recent times, the proliferation of mature and economically viable RE technologies across diverse sectors including residential, commercial, agricultural, and industrial, has empowered numerous nations to realize their strategic objectives. These technologies have facilitated the attainment of dependable and cost-effective energy sources, thereby fostering development while ameliorating energy price fluctuations (Casanova-Peláez et al., 2015). Furthermore, the imperative to mitigate CO2 emissions underscores the critical importance of deploying diverse solar energy-based technologies (Farooq et al., 2020). This underscores the pressing need for transitioning towards renewable energy sources to mitigate environmental degradation and promote sustainable practices.

The PTs, comprising the West Bank and Gaza Strip, are located in the Middle East region. PTs confront a plethora of energy-related challenges owing to limitations in natural resources and intricate regional political dynamics. A significant reliance on imported electricity and petroleum products exacerbates these challenges, with over 93% of electricity consumption imported in 2018, primarily sourced from Israel, supplemented by marginal percentages from Jordan and Egypt (Palestinian Central Bureau of Statistics, 2020). The comparatively high energy prices in PTs, in contrast to other Middle Eastern regions, exacerbate these complexities. The administrative division of lands, notably delineated by the Oslo peace agreement into Zones A, B, and C in the West Bank, introduces further obstacles, particularly with the C region (comprising 60% of the West Bank region) under complete Israeli control. These circumstances constrain the Palestinian Authority (PA)’s capacity to advance the energy sector, underscoring the imperative of transitioning towards RE sources to establish a sustainable energy framework in PTs (International Renewable Energy Agency, 2013).

A MCDM approach is recognized as an essential decision-making tool, adept at efficiently addressing the socio-economic, environmental, institutional, and technical challenges inherent in energy system design (Mateo, 2012). The primary aim of this research is to conduct a comprehensive comparative analysis of energy source development alternatives in the PTs, with a specific focus on RE. This analysis seeks to elucidate the PA capacity to achieve its strategic objectives related to the energy sector and renewable energy. The main objective is to provide decision-makers with a robust framework that enhances their realism and flexibility in adopting corrective actions during the development and implementation of strategic energy plans. This framework will enable them to concentrate on the most sustainable and applicable RE technologies.

Utilizing the AHP within a MCDM approach, the analysis prioritizes criteria, subcriteria, and RE alternatives. The study evaluates eight potential RE sources. The primary criteria are categorized into technical, economic, socio-political, risk, and environmental factors. The remainder of this paper is structured as follows: Section II provides a comprehensive literature review. Section III outlines the energy sector landscape in the PTs. Section IV details the research methodology employed in this study. Section V presents the results and discussion. Finally, Section VI offers recommendations and suggests avenues for future research.

2. Related Work

Since the beginning of the 21st century, the application of MCDM in energy planning has gained significant popularity. This approach enables decision-makers to comprehensively assess all potential options, thereby facilitating more informed decisions through effective prioritization. Numerous algorithms have been developed for the evaluation and planning of energy systems, accommodating both single and multiple criteria optimization (Kumar et al., 2014; Yang & Nehorai, 2014).

Numerous prior studies have investigated the applications of MCDM in the energy sector. For instance, Streimikiene et al. (2012) employed two MCDM methods, the Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS) and the MULTIMOORA approach, to evaluate economic, environmental, and social dimensions for selecting the most sustainable electricity production technologies. Similar investigations can be found in (Amer & Daim, 2011; Kaya & Kahraman, 2010).

In addressing the global challenge of energy transition, determining effective strategies amidst conflicting factors is crucial. The study by Das et al. (2024) provides a comprehensive review of SWOT-MCDM methods, highlighting their applicability and future directions in diverse fields, particularly within the realm of energy transition. Integrating SWOT analysis with MCDM offers a novel approach for prioritizing energy strategies, facilitating a more sustainable transition. Moreover, the study by Santos et al. (2024) introduces an innovative approach by integrating Geographic Information Systems (GIS) and Building Information Modelling (BIM) with MCDM to optimize infrastructure investment planning. Through simulations and comprehensive analysis, it identifies effective alternatives for infrastructure projects, considering environmental, cost, and safety criteria. While acknowledging limitations in data quality and overlooking certain variables, the proposed method automates decision-making, reduces subjectivity, and demonstrates adaptability across various infrastructures, offering significant advancements in prioritization techniques. This study by Parvaneh and Hammad (2024) presents a hybrid MCDM model to aid power-generating plant owners in selecting sustainable technology for new projects. Sixteen criteria, categorized under economic, social, environmental, and technical pillars, are identified. With input from experts in the field, the model offers a comprehensive approach to rational decision-making in construction projects, contributing to sustainability efforts.

Table 1: Utilization of multi-criteria approaches for the assessment and prioritization of sustainable energy technologies has gained prominence in recent years.

Year	Criteria Used in Energy Planning							References
	Tech.	Eco.	Envir.	Soc.	Pol.	Rk.	Flex.	
2016	✓	✓	✓	✓	✓			(Al Garni et al., 2016)
2017	✓	✓	✓	✓		✓		(Algarín et al., 2017)
2018	✓	✓	✓	✓				(Lee & Chang, 2018)
2018	✓	✓	✓					(Ishfaq et al., 2018)
2021	✓	✓	✓	✓	✓		✓	(Saraswat & Digalwar, 2021)
2022	✓	✓	✓	✓				(Effatpanah et al., 2022)
2023	✓	✓	✓	✓				(Akpahou & Odoi-Yorke, 2023)
2024	✓	✓	✓	✓	✓			(Gupta et al., 2024)
2024	✓	✓	✓	✓	✓	✓		Current Work

Note: Tech.: Technological, Eco.: Economic, Envir.: Environmental, Soc.: Social, Pol.: Political, Rk.: Risk, Flex.: Flexible.

The work in Dioba et al. (2024) addresses barriers to Energy Communities (ECs) by employing the AHP model. Through interviews and surveys, it identifies and ranks key barriers, categorizing them into financial, regulatory, technical, and social aspects. Regulatory complexity and financial constraints emerge as the most significant barriers hindering stakeholder participation in ECs, as indicated by the AHP methodology. Moreover, the study by Cho et al. (2024) presents an LCOE-integrated AHP model for assessing renewable energy certificate (REC) multipliers, focusing on cost-effectiveness and social concerns. Their findings reflect market conditions and policy objectives, informing revisions to REC multipliers by the government. Stakeholder interests, institutional consistency, and market stability are considered in the decision-making process. The AHP method has been utilized across various fields. Its applicability and effectiveness in energy planning projects, particularly those related to renewable energy, have been demonstrated in several studies (Al Garni et al., 2016; Shahroodi et al., 2012; Xu et al., 2024).

2.1 Energy Sector Situation in PTs

Energy prices in the PTs are recognized as among the highest in the region. According to statistics published by Palestinian Central Bureau of Statistics. (2020), PTs are heavily dependent on imported fossil fuels. Approximately 59%, 29%, and 12% of the total energy consumption come from fossil fuels, electricity, and RE, respectively. The term "fossil fuels" encompasses diesel, gasoline, LPG, bitumen, and other fuels (kerosene, fuel oil, and lubricants), accounting for 57%, 20%, 20%, 2%, and 1% of total fossil fuel consumption, respectively. In terms of total RE consumption, solar energy, wood and charcoal, and biomass olive cake make up 59%, 36%, and 5%, respectively. The majority of the electricity consumed in PTs is imported from Israel, with smaller portions coming from Egypt and Jordan to supply the Gaza Strip and West Bank, respectively. This reliance burdens the local economy, weakening the socio-political fabric of the community. Concurrently, it places strains on Israel's power generation plants and distribution network master plans. For a comprehensive overview of the history, strategy, and potential opportunities within the Palestinian energy sector, see (El-Kilani & Zaid, 2015; Juaidi et al., 2022)

3. Research Methodology

3.1 Multiple Criteria Decision Analysis (MCDM)

MCDM, a discipline within operations research, encompasses various well-established methods, among which the AHP is prominently utilized in energy planning and decision-making. AHP is favoured for its simplicity, flexibility, adaptability, and its avoidance of complex mathematical computations. By employing a hierarchical structure, AHP enables a focused evaluation of each criterion and sub-criterion (Ishizaka & Labib, 2009; Shahroodi et al., 2012). The AHP method involves the following steps:

1. Hierarchically defining the analysis goals, alternatives, criteria, and sub-criteria.
2. Assigning ratings to the parameters at each level using a nine-point integer scale, as illustrated in Table 2.
3. Constructing a pairwise comparison matrix.
4. Determining the weights of parameters at each level within the decision hierarchy.
5. Validating the results through the calculation of consistency levels.
6. Computing the comprehensive weight of each criterion, sub-criterion, and alternative.

Table 2: AHP measurement scale (Saaty et al., 2012)

Level of Importance	9	8	7	6	5	4	3	2	1
Definition	Extremely More Important	Strongly to Extremely Important	Very Strongly More Important	Strong to Very Strongly More Important	Strongly More Important	Moderately to Strongly More Important	Moderately More Important	Equal to Moderately More Important	Equally Important

According to the AHP, weights are deemed consistent if their consistency ratio falls below or equals 10%; if not, the data are regarded as inconsistent, requiring a reassessment of the decision-makers inputs.

3.2 RE Alternatives, Criteria, and Sub-criteria

In alignment with the Palestinian energy strategy for 2017-2022 Mender and Rcree (2020) and drawing from insights gleaned from prior scholarly investigations, this study assessed eight RE technologies. A thorough review of literature on energy planning dilemmas employing MCDM tools yielded an initial compilation of 51 sub-criteria, categorized into five groups: technical, economic, socio-political, environmental, and risk. To refine this list into a final set of sub-criteria, three steps were undertaken. Firstly, non-influential sub-criteria were excluded from consideration for evaluating RE alternatives in PTs. Secondly, sub-criteria were selected based on their frequency of appearance in the reviewed literature. Lastly, consultation with local energy experts was conducted to incorporate or omit sub-criteria deemed pertinent to the Palestinian context. Following these procedures, a refined group of 22 sub-criteria was identified, organized under the aforementioned five primary criteria, as depicted in Figure 1.

The AHP model employed in this study, as illustrated in Figure 1, comprises four hierarchical levels: goal, criteria, sub-criteria, and alternatives. The primary aim of this decision model is to streamline the process of selecting, assessing, and prioritizing RE technologies to promote sustainable development in PTs.

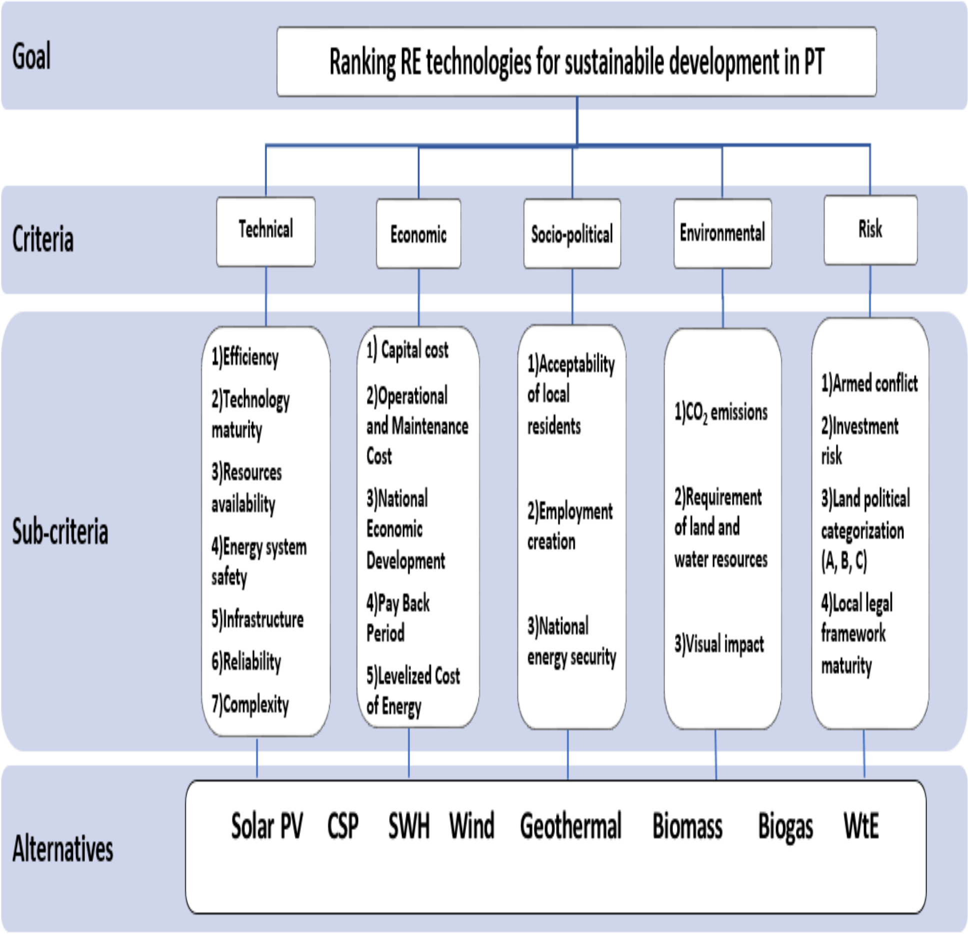


Figure 1: The proposed AHP model.

Table 3: The scoring system used for evaluating qualitative sub-criteria.

Sub-Criteria Score	Maturity	Reliability	Safety of Energy System	Complexity	Acceptability of Local Residents
1	Least mature	Concept level: it needs to be validated.	Highest mortality	Less than 1 year	It limits or prevents the local community from utilizing surrounding lands.
2	Very low maturity	Small prototype level: it is a technology without a clear design, and its prototype needs validation in testing conditions.	High mortality	Between 1 and 2 years	It has visual pollution and important noise.
3	Low maturity	Large prototype level: prototype of a given technology proven at scale and ready for deployment.	Moderate mortality	More than 2 years	It provides economic benefits to local communities.
4	Moderate maturity	Demonstration phase: it is tested in real-world environments.	Low mortality	-	-
5	High maturity	Early adoption phase: it is validated at the demonstration and prototype phases.	Lowest mortality	-	-
6	Very high maturity	Mature technology phase: technology that is close to reaching the theoretical efficiency limits.	-	-	-
7	Most mature	-	-	-	-

Table 4: Data inventory collected and applied in the research.

Sub-Criteria	WTE	Biogas	Biomass	Geothermal	Wind	SWH	CSP	PV	References
Efficiency (%) (2010-2020)	20-25	55.8	77.7	83.8	30.64	35	35.64	16.3	(Stefanidies, 2021) & experts' judgments
Reliability	Early adoption phase (5)	Early adoption phase (5)	Early adoption phase (5)	Mature technology phase (6)	Early adoption phase (5)	Mature technology phase (6)	Early adoption phase (5)	Early adoption phase (5)	(IEA, 2020)& experts' judgments
Availability (%)	≥ 91	≥ 90	80	95	34.8- 38	50-75	20-50	20- 24.5	(Chludziński & Duda, 2018; Funk et al., 2013; Saver, 2022)& experts' judgments

Table 4: Continued

Sub-Criteria	WTE	Biogas	Biomass	Geothermal	Wind	SWH	CSP	PV	References
Complexity	More than 2 years (3)	Between 1 and 2 years (2)	Between 1 and 2 years (2)	Between 1 and 2 years (2)	Less than 1 year (1)	Less than 1 year (1)	Less than 1 year (1)	Less than 1 year (1)	(Baris & Kucukali, 2012)& experts' judgments
Technology Maturity	High maturity (5)	High maturity (5)	Most mature (7)	Very high maturity (6)	High maturity (5)	Very High maturity (6)	Least mature (1)	Very high maturity (6)	(S & A. Brown, 2011;IEA, 2020) & experts' judgments
Safety of Energy System	Highest mortality (1)	Highest mortality (1)	Highest mortality (1)	Moderate mortality (3)	Moderate mortality (3)	Low mortality (4)	Low mortality (4)	Lowest mortality (5)	(Al Garni et al., 2016; Burgherr & Hirschberg, 2014; Funk et al., 2013) & experts' judgments
Capital Cost($/kW)	4672	1563	4097	2521	1265	1000	7221	1313	(Sha et al., 2020; Tayeh et al., 2021)& experts' judgments
Operational and Maintenance Cost($/kW-year	82	20.1	125.72	128.544	26.34	15.25	85.4	15.25	
Pay Back Period (years)	≥8.5	6-10	6-10	6-12	4-8	4-6	8-14	3-4	(Tayeh et al., 2021)& experts' judgments
Levelized Cost of Energy (USD/kWh) (2020)	0.05	0.066	0.066	0.071	0.039	0.0127	0.11	0.057	(Tayeh et al., 2021; Stefanidies, 2021)& experts' judgments
Employment creation (Total jobs - 2019 year	39	342	764	99	1165	5600	30	3755	(Irea, 2013) & experts' judgments
Acceptability of Local Residents	2	2	3	2	2	3	2	2	(Achillas et al., 2011) & experts' judgments
CO2 Emissions (lb/MMBtu)	67	117	206	0	0	0	0	0	(Tayeh et al., 2021; Stefanidies, 2021)& experts' judgments
Land and Water Requirements (m^2/kW)	25	4000	4000	100	200	5	10	10	(Troldborg et al., 2013) & experts' judgments

4. Data Inventory

To ensure a strong basis for comparative analysis, extensive searches were conducted through previous publications, reports from international organizations, and inputs provided by local experts. Emphasis was placed on quantitative data obtained from previously published materials, while qualitative sub-criteria were evaluated through expert assessments, employing specific score scaling techniques. As part of this process, maturity (SC12), safety of the energy system (SC14), reliability (SC16), complexity (SC17), and acceptability by local residents (SC31) were subjected to evaluation using scoring systems delineated in Table 3. These scoring methodologies were derived from relevant literature and international reports, as demonstrated in Table 4.

The dataset utilized in this study is presented in Table 4, offering a detailed breakdown of diverse sub-criteria linked to specific renewable energy technologies.

4.1 Application of AHP Model

Within the AHP, sub-criteria data are classified as either quantitative or qualitative. Quantitative data can be measured through international databases or documented in literature from similar projects, whereas qualitative data depends on expert judgments. Evaluating the five criteria aligned with their overarching goal and assessing sub-criteria in relation to their parent node necessitates a synthesis of expert inputs and quantitative data. In this study, priority is accorded to utilizing quantitative data whenever feasible to alleviate inconsistencies stemming from divergent opinions.

To integrate expert opinions, a carefully crafted questionnaire was distributed, consisting of sixteen sequentially arranged sections.

1. Part one: The questionnaire elucidates the study's objectives, delineates the adopted scale and evaluation mechanism, and requests personal information from the respondent, including job title and experience.
2. Part two: Enables the surveyed expert to evaluate the criteria in relation to each other with regard to the overarching goal.
3. Parts three to seven: Assists the expert in prioritizing technical, economic, socio-political, environmental, and risk sub-criteria, thereby deriving local weights for each sub-criterion in relation to its parent node, as well as global weights relative to the overarching goal.
4. Parts eight to fifteen: Empowers the expert to assign weights to alternatives concerning sub-criteria devoid of quantitative data, such as armed conflict and visual impact.
5. Part sixteen: Enables experts to introduce additional criteria they deem significant or eliminate any they consider unnecessary.

A non-probability convenient sample comprising 35 questionnaires was distributed to or sent to the most nationally relevant experts in PTs. The specifics of the received questionnaire sample are delineated in Table 5.

After finalizing the data collection phase, the responses from experts were amalgamated, and the geometric mean was computed to establish the ranking of alternatives. Subsequently, pairwise comparisons of alternatives, employing the AHP scale, were conducted using Equation 3. Lastly, Expert Choice software was employed to compute local weights, global weights, and CRs, alongside conducting a sensitivity analysis. The flow chart illustrating the prioritization process is presented in Figure 3.

Table 5: Questionnaire filled sample description.

Institution/Working Field/Sector of the Expert	Number
Private Sector (People who work in the private sector exclusively).	4
Non-governmental organizations (NGO's)	2
Academics	6
Energy Research Centre- An Najah National University	4
Electricity Distribution Company (EDC)	5
Palestinian Electricity Transmission Company (PETC)	8
Palestinian Energy and Natural Resources Authority (PENRA)	6
Total Number	35

The Rank Number of Alternative (RNA), a flexible scaling technique suitable for both qualitative and quantitative inputs, streamlines the data aggregation process. It replaces the traditional direct pairwise comparison with an assessment on a nine-point scale, thereby diminishing the quantity of pairwise comparisons among each pair of elements and enhancing the precision of responses. The computational process unfolds in the subsequent steps:

1. Establishing the step value (h) through Equation 1, where Omax represents the maximum value and Omin denotes the lowest value among all the compared alternatives.
2. $\frac{O_{max}-O_{min}}{9}$ Equation (1)
3. Ranking alternatives involves assigning values from one to nine according to the numerical scale outlined in Table 3. The RNA (i) is computed and translated into an integer value using Equation 2, wherein the alternative demonstrating the superior performance is allocated the highest RNA value, and conversely.
4. $\mathrm{RNA(i)}=\begin{cases} \mathrm{INT}\left(9-\frac{\mathrm{Oi-Omin}}{\mathrm{h}}\right), \text{If Omin is the best} \\ \mathrm{INT}\left(\frac{\mathrm{Oi-Omin}}{\mathrm{h}}\right), \quad \text{If Omax is the best} \end{cases}$ Equation (2)
5. Subsequently, generating a pairwise comparison matrix between two alternatives (one and two) utilizing the AHP numerical scale by employing the scoring value equation (SV1→2) depicted in Equation 3.
6. $\mathrm{SV1} \rightarrow 2 = \begin{cases} \frac{1}{(\mathrm{RNA(2)-RNA(1)+1})}, & \text{If } \mathrm{RNA(1)} - \mathrm{RNA(2)} < 0 \\ (\mathrm{RNA(1)} - \mathrm{RNA(2)} + 1), & \text{If } \mathrm{RNA(1)} - \mathrm{RNA(2)} \geq 0 \end{cases}$ Equation (3)
7. Table 6 depicts the conversion of the LCOE into Rank Number of Alternative (RNA), where alternatives with minimum values are favoured.

Table 6: Ranking of Alternatives by LCOE.

Renewable Energy Technologies	Levelized Cost of Energy ($/KWh)	RNA
WTE	0.0500	5
Biogas	0.0660	4
Biomass	0.0660	4
Geothermal	0.0710	3
Wind	0.0390	6
SWH	0.0127	9
CSP	0.1100	1
Solar PV	0.0570	4

Table 7 displays the pairwise comparison matrix for the examined alternatives regarding the LCOE, derived from Equation 3.

Table 7: Pairwise comparison matrix of alternatives concerning LCOE sub-criteria.

Renewable Energy Technologies	Solar PV	CSP	SWH	Wind	Geothermal	Biomass	Biogas	WTE
Solar PV	1.00	4	0.16	0.33	2.00	1.00	1.00	0.50
CSP	0.25	1	0.11	0.16	0.33	0.25	0.25	0.20
SWH	6.00	9	1.00	4.00	7.00	6.00	6.00	5.00
Wind	3.00	6	0.25	1.00	4.00	3.00	3.00	2.00
Geothermal	0.50	3	0.14	0.25	1.00	0.50	0.50	0.33
Biomass	1.00	4	0.16	0.33	2.00	1.00	1.00	0.50
Biogas	1.00	4	0.16	0.33	2.00	1.00	1.00	0.50
WTE	2.00	5	0.20	0.50	3.00	2.00	2.00	1.00

In situations requiring qualitative evaluation, such as assessing visual impact, experts employed a nine-level scale for each alternative relative to its parent node. Following this, the geometric mean was computed, and responses were rounded to integer values, yielding the RNA (i). Similar to the quantitative parameter analysis, pairwise comparison matrices were constructed using Equation 3. Table 8 exhibits the RNA for each criterion in relation to the overarching objective. Subsequently, the geometric mean was calculated and rounded to an integer value, determining the rank number for each criterion. The prioritization of criteria aligned with their goal is presented in Table 10.

Table 8: Rank Number of each crterion concerning goal

Criteria	Geometric Mean	RNA
Risk	5.54	5
Environmental	5.82	5
Socio-Political	5.51	5
Economic	7.73	7
Technical	7.97	7

Table 9: Pairwise comparison matrix of criteria.

Criteria	Technical	Economic	Socio-Political	Environmental	Risk
Technical	1.00	1.00	3	3	3
Economic	1.00	1.00	3	3	3
Socio-Political	0.33	0.33	1	1	1
Environmental	0.33	0.33	1	1	1
Risk	0.33	0.33	1	1	1

This research involved the creation of 28 comparison matrices, integrating both quantitative and qualitative data.

Verifying the outcomes through the calculation of the CI and CR utilizing Equations 4 and 5, respectively. A noteworthy benefit of the AHP is its ability to evaluate consistency, recognizing the inherent inconsistency in individuals' judgments.

$$\mathrm{CI} = \frac{\lambda\mathrm{max} - \mathrm{n}}{\mathrm{n} - 1} \qquad \text{Equation (4)}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \qquad \text{Equation (5)}$$

Where λmax represents the largest eigenvalue, known as the principal eigenvalue, while RI denotes the random consistency index, calculated as an average of CIs across a large set of matrices with random inputs. Table 10 furnishes the corresponding RI values for various n parameters (Saaty et al., 2012).

Table 10: Random Consistency Index (RI).

n	RI
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0

5. Research Implementation Steps

The research implementation adhered to a structured sequence of steps, as depicted in Figure 2. These steps were systematically executed to efficiently accomplish the research objectives.

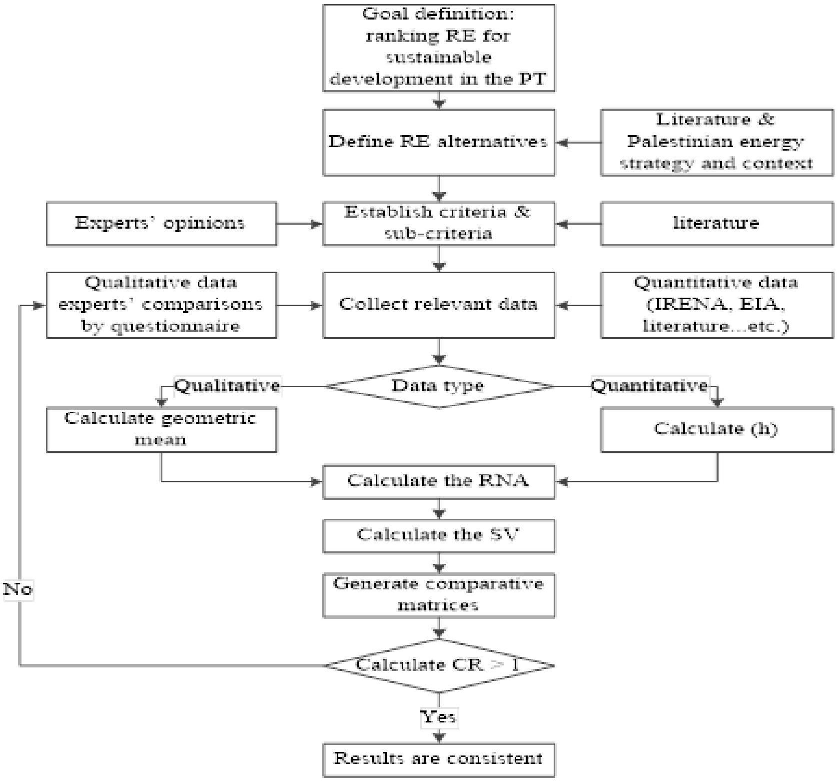


Figure 2: Research calculation methodology.

6. Results and Discussion

The AHP model, accompanied by the relevant comparison matrices, was constructed to ascertain both local and global preferences across hierarchical levels within the decision tree, encompassing criteria, sub-criteria, and ultimate selection alternatives. The employment of the Expert Choice software package, renowned for its contribution to collaborative decision-making endeavours within the AHP framework, streamlined this procedure. Expert Choice efficiently structures intricate problems in an easily understandable format, precisely gauging the relative importance of competing alternatives and objectives by amalgamating knowledge, expertise, and viewpoints. Furthermore, the software facilitates sensitivity analyses and exploration of hypothetical scenarios.

The findings indicated that both technical and economic criteria occupied the leading positions, each carrying an equal weight of 33.3%. Following closely, socio-political, risk, and environmental criteria attained the second position, each bearing equal weights of 11.1%. The parity in weights among the second-place criteria may be attributed to legislative constraints and priority limitations, thereby mitigating their relative significance. The CR for this comparison was 0, indicating acceptable consistency. These outcomes align with those reported in Al Garni et al. (2016), where technical and economic criteria were prioritized, each with a relative weight of 35.1%, while socio-political and environmental criteria were assigned weights of 18.9% and 10.9%, respectively. Similarly, Algarín et al. (2017) prioritized RE sources for rural areas in the Caribbean region of Colombia, assigning weights of 24.7%, 21.7%, 19.6%, 17.9%, and 16.3% to technical, environmental, social, economic, and risk criteria, respectively. Conversely, contrasting findings were observed in the study by Rojas and Yusta (2014) which focused on electric supply planning in rural remote areas. Here, technical (30.14%), social (26.65%), environmental (22.48%), and economic (20.72%) criteria were prioritized. Ahmad and Tahar (2014), examining RE alternatives for sustainable development in Malaysia, identified economic criteria as paramount with a weight of 52%, followed by technical (26%), environmental (15%), and social (7%) criteria. Similarly, economic criteria received the highest weights of 35% in the research conducted by (Amer & Daim, 2011), while technical, environmental, social, and political criteria were allocated weights of 26%, 15%, 12%, and 12%, respectively. These disparities in criteria ranking underscore the contextual dependence on country-specific circumstances, priorities, and interests.

5.1 Local and Global Weights Analysis for Sub-criteria

Table 11 offers a glimpse into the local weights attributed to each group of sub-criteria relative to the parent criteria. The cumulative local weights per criterion should amount to 100%, thereby emphasizing the relative significance of each sub-criterion within its corresponding criteria sector. In the majority of criteria sectors, no individual sub-criterion exerts dominance over the weights, with the exceptions being SC53 in the risk sector and SC33 in the socio-political sector. These findings highlight the imperative of contemplating each sub-criterion in the decision-making process.

Emphasizing the global weights of sub-criteria is crucial. These global weights, spanning from SC11 to SC54, must collectively add up to 100%. They signify the most influential sub-criteria in the ranking of alternatives concerning the established objective. Calculating the global priority weight involves multiplying the local weight of each sub-criterion in relation to its parent node by the weight of each decision criterion in relation to the goal. Figure 3 visually illustrates the global weights of the research sub-criteria. Remarkably, environmental sub-criteria are anticipated to have minimal effects owing to the absence of pertinent laws and legislation in PTs.

Table 11: Local weights of sub-criteria concerning each parent criterion.

Criteria	Sub-Criteria	Local Weight (%)	CR (%)
C1. Technical	SC_{11}. Efficiency/ capacity factor	17.1	0.11 %
	SC_{12}. Technology maturity	8.95	
	SC_{13}. Resource availability	17.1	
	SC_{14}. Safety of energy system	17.1	
	SC_{15}. Infrastructure	17.1	
	SC_{16}. Reliability	17.1	
	SC_{17}. Complexity	5.55	
	Total local weights	100%	
C2. Economic	SC_{21}. Capital cost	25	0.00
	SC_{22}. Operational and maintenance cost (O&M)	12.5	
	SC_{23}. National economic development	12.5	
	SC_{24}. Payback period	25	
	SC_{25}. Levelized cost of energy (LCOE)	25	
	Total Local Weights	100%	
C3. Socio-Political	SC_{31}. Acceptability of local residents	25	0.00
	SC_{32}. Employment creation	25	
	SC_{33}. National energy security	50	
	Total local weights	100%	
C4. Environmental	SC_{41}. CO_2 emissions	40	0.00
	SC_{42}. Requirement of land and water resources	40	
	SC_{43}. Visual impact	20	
	Total local weights	100%	
C5. Risk	SC_{51}. Armed conflict	12.2	0.39 %
	SC_{52}. Investment risk	22.7	
	SC_{53}. Land political categorization (A, B, C)	42.4	
	SC_{54}. Local legal framework maturity	22.7	
	Total local weights	100%	

5.2 Local and Global Weights Examination for Alternatives

The assessment of the eight RE technologies followed a hierarchical structure with four levels for each studied sub-criterion. Quantitative data guided evaluations for tangible sub-criteria, while qualitative inputs from decision-makers directed assessments for intangible ones. Table 13 delineates the local weights allocated to alternatives for each sub-criterion, ensuring that the summation equals 100% for each sub-criterion's alternatives. The performance of each RE technology across sub-criteria determined the score of RE alternatives toward the goal. CRs at this stage remained within the acceptable limit of 10%. Notably, PV and SWH alternatives demonstrated relatively high scores across all sub-criteria compared to other alternatives, attributed to PTs' abundant solar energy potential. Conversely, newer technologies in the Palestinian context, such as WTE, CSP, biomass, and biogas, achieved lower scores compared to their counterparts.

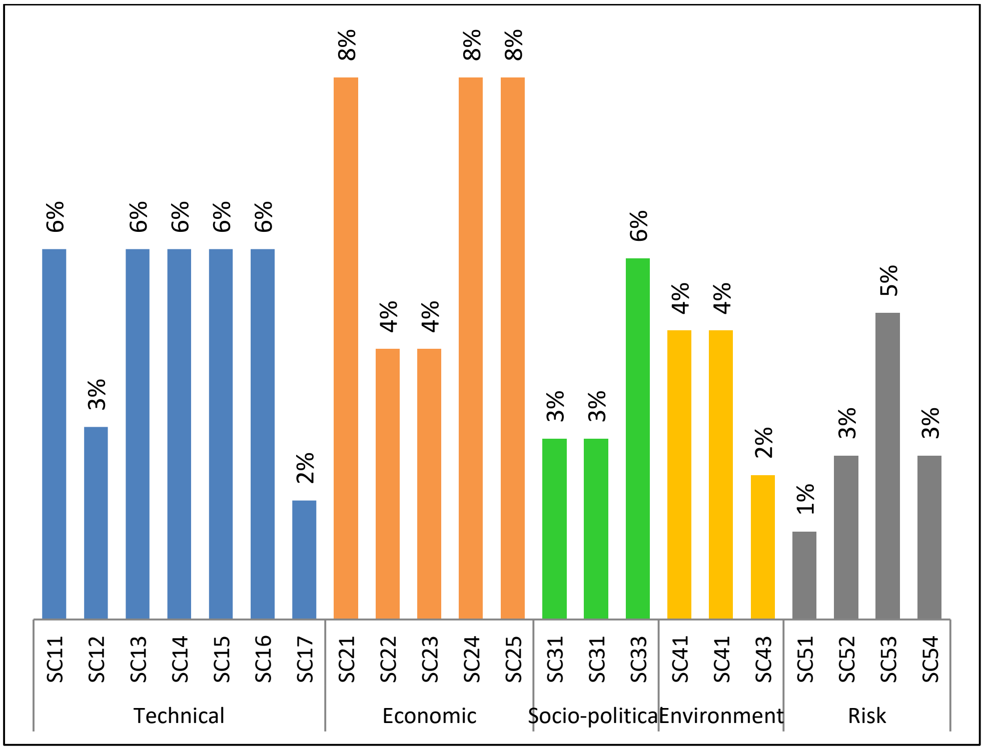
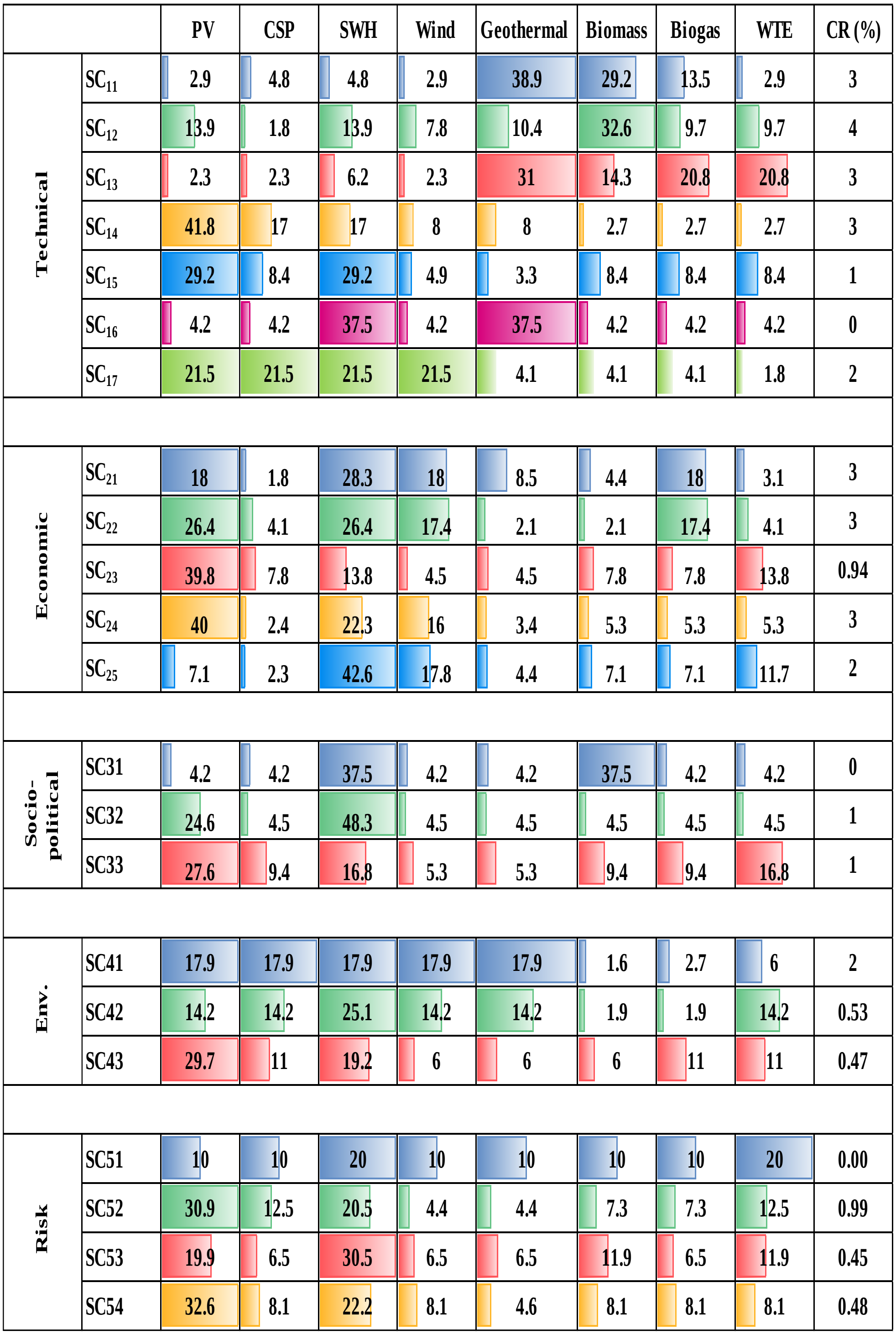


Figure 3: Overall Importance of Sub-Criteria Relative to the Objective.

The matrix derived from the relative weights of alternatives obtained in the previous step, multiplied by the local weights of each sub-criterion concerning each criterion, yielded the relative weights of each alternative regarding each criterion (as per Equation 6). Figure 4 visually represents the performance of each alternative across each criterion.

$$\begin{pmatrix}\text{Relative weights of}\\ \text{alternatives with}\\ \text{respect to each criterion}\end{pmatrix} = \begin{pmatrix}\text{Relative weights of} & \\ \text{alternatives with} & - \text{criterion}\\ \text{respect to each sub} & \end{pmatrix} \times \begin{pmatrix}\text{Relative}\\ \text{weights of subcriteria}\\ \text{with respect to each criterion}\end{pmatrix} \quad \text{Equation} \quad (6)$$

Figure 5 depicts the local weights attributed to each RE alternative source within each decision criterion. Following the assessment of each alternative against every sub-criterion locally, it becomes imperative to evaluate their performance concerning each analytical criterion. The eight considered alternatives were categorized into two primary groups based on the final product: SWH, geothermal, and biomass comprised systems producing heat, while the remaining alternatives constituted systems generating electric power. Figure 6 illustrates the performance of each group of alternatives concerning each criterion. Once more, SWH among thermal energy generation systems and PV among electric power generation systems emerged as superior performers.



		PV	CSP	SWH	Wind	Geothermal	Biomass	Biogas	WTE	CR (%)
Technical	SC_{11}	2.9	4.8	4.8	2.9	38.9	29.2	13.5	2.9	3
	SC_{12}	13.9	1.8	13.9	7.8	10.4	32.6	9.7	9.7	4
	SC_{13}	2.3	2.3	6.2	2.3	31	14.3	20.8	20.8	3
	SC_{14}	41.8	17	17	8	8	2.7	2.7	2.7	3
	SC_{15}	29.2	8.4	29.2	4.9	3.3	8.4	8.4	8.4	1
	SC_{16}	4.2	4.2	37.5	4.2	37.5	4.2	4.2	4.2	0
	SC_{17}	21.5	21.5	21.5	21.5	4.1	4.1	4.1	1.8	2
Economic	SC_{21}	18	1.8	28.3	18	8.5	4.4	18	3.1	3
	SC_{22}	26.4	4.1	26.4	17.4	2.1	2.1	17.4	4.1	3
	SC_{23}	39.8	7.8	13.8	4.5	4.5	7.8	7.8	13.8	0.94
	SC_{24}	40	2.4	22.3	16	3.4	5.3	5.3	5.3	3
	SC_{25}	7.1	2.3	42.6	17.8	4.4	7.1	7.1	11.7	2
Socio-political	SC31	4.2	4.2	37.5	4.2	4.2	37.5	4.2	4.2	0
	SC32	24.6	4.5	48.3	4.5	4.5	4.5	4.5	4.5	1
	SC33	27.6	9.4	16.8	5.3	5.3	9.4	9.4	16.8	1
Env.	SC41	17.9	17.9	17.9	17.9	17.9	1.6	2.7	6	2
	SC42	14.2	14.2	25.1	14.2	14.2	1.9	1.9	14.2	0.53
	SC43	29.7	11	19.2	6	6	6	11	11	0.47
Risk	SC51	10	10	20	10	10	10	10	20	0.00
	SC52	30.9	12.5	20.5	4.4	4.4	7.3	7.3	12.5	0.99
	SC53	19.9	6.5	30.5	6.5	6.5	11.9	6.5	11.9	0.45
	SC54	32.6	8.1	22.2	8.1	4.6	8.1	8.1	8.1	0.48

Figure 4: Alternatives comparison based on sub-criteria local weights.

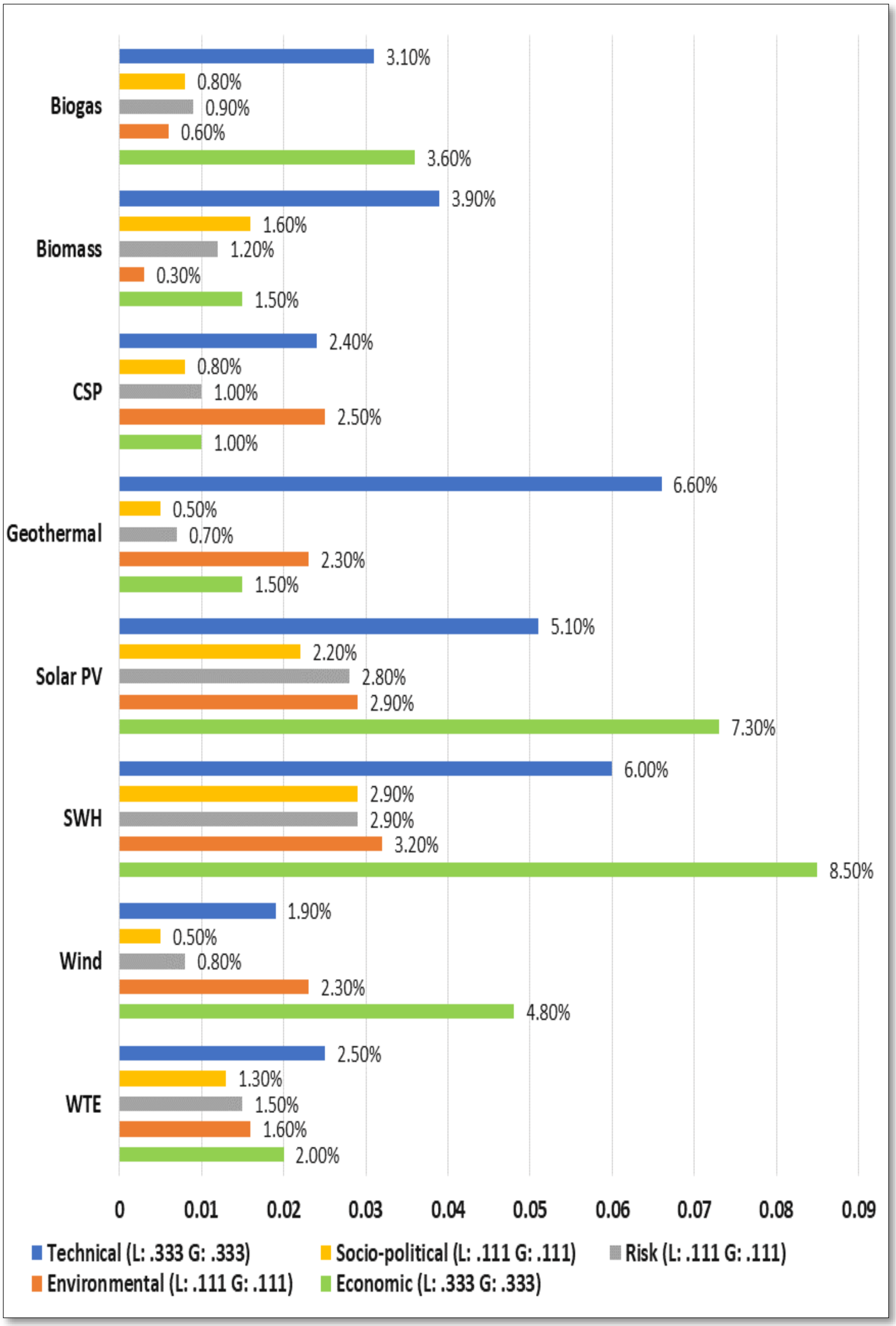


Figure 5: Allocation of weights to individual alternatives within each decision criterion.

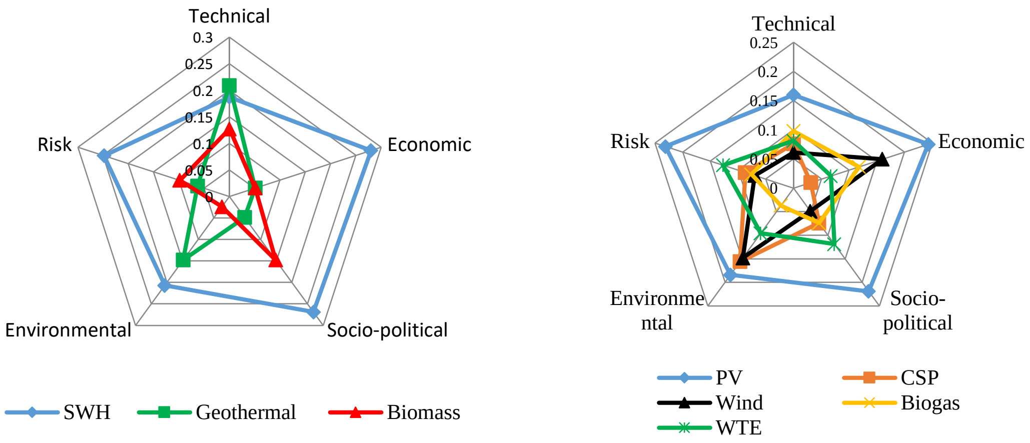


Figure 6: Evaluation of each alternative's performance across all criteria

$$\begin{bmatrix} \text{Technical} & \text{Economic} & \text{Socio}-\text{political} & \text{Environmental} & \text{Risk} \\ 0.160 & 0.243 & 0.219 & 0.184 & 0.231 \\ 0.076 & 0.031 & 0.074 & 0.156 & 0.087 \\ 0.187 & 0.280 & 0.269 & 0.207 & 0.248 \\ 0.061 & 0.160 & 0.049 & 0.148 & 0.070 \\ 0.209 & 0.051 & 0.049 & 0.148 & 0.063 \\ 0.127 & 0.051 & 0.148 & 0.024 & 0.098 \\ 0.098 & 0.118 & 0.074 & 0.037 & 0.076 \\ 0.081 & 0.067 & 0.119 & 0.096 & 0.127 \end{bmatrix} \times \begin{bmatrix} \text{Criteria weights} \\ 0.333 \\ 0.333 \\ 0.111 \\ 0.111 \\ 0.111 \end{bmatrix} = \begin{bmatrix} \text{Alternatives weights} \\ 0.203 \\ 0.076 \\ 0.234 \\ 0.104 \\ 0.118 \\ 0.087 \\ 0.089 \\ 0.089 \end{bmatrix} \qquad \text{Equation (7)}$$

After establishing the relative weights of RE alternatives throughout the hierarchy, consolidating these weights across various levels of the proposed model generated global weights for alternatives. The overall priority of all alternatives is computed by multiplying the alternative weights concerning criteria by the relative weights of criteria in relation to the goal. Equation 7 delineates the pertinent matrix calculations.

While prior analyses provided in-depth insights into the performance of each alternative across criteria and sub-criteria, decision-makers are ultimately interested in the final ranking of each alternative for comparative purposes, aligning with national objectives and strategic planning. In this context, Figure 7a illustrates the overall rankings of the examined alternatives, with a CR of 1%. As inferred from the analysis of sub-criteria, solar-dependent alternatives/technologies attained the highest rankings.

Intriguingly, geothermal energy secured the third position. Presently, geothermal energy applications in PTs are primarily limited to basic internal space heating in buildings. Survey participants, considering the high costs of electricity and fossil fuels, positively evaluated geothermal energy due to its anticipated low life cycle cost. For a more precise comparison between alternatives, two sub-groups underwent reassessment, and the rankings of alternatives were adjusted accordingly. Figures 7b and 7c depict the total rankings for each subgroup, focusing on thermal and electric energy generation systems, respectively.

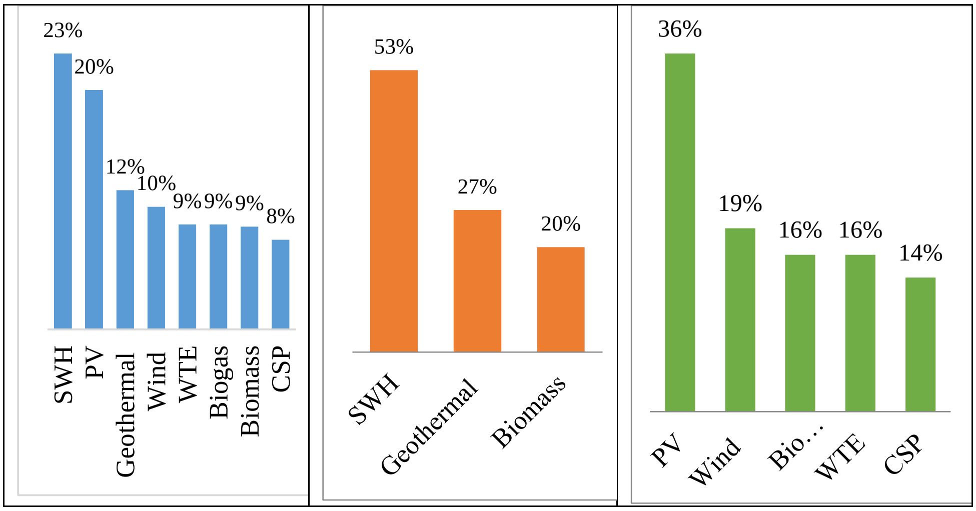


Figure 7: (a) RE alternatives overall ranks (b) RE total ranks for thermal energy generation systems (c) RE total ranks for electric power generation systems.

In a study assessing renewable power generation technologies for electrification in Saudi Arabia, solar PV emerged as the most prominent with a percentage of 25.6%, followed by solar thermal (23.6%), wind (22.1%), geothermal (13.2%), and biomass (15.5%) (Al Garni et al., 2016). A similar trend was observed in a study focused on energy planning for rural electrification in the Caribbean region of Colombia (Algarín et al., 2017). Solar PV once again dominated with the highest percentage at 45.3%, while wind, biomass, and SHPP followed with percentages of 23.8%, 15.5%, and 15.4% respectively. These findings align with other studies where solar PV was identified as the most relevant alternative (Ahmad & Tahar, 2014; Amer & Daim, 2011)

6. Conclusion

This study utilized MCDM with AHP to prioritize renewable energy options in Palestine, a novel application in this context. Eight alternatives were assessed against 22 sub-criteria across technical, economic, socio-political, environmental, and risk dimensions. Quantitative data and expert opinions guided the evaluation, resulting in a comprehensive ranking of alternatives based on nuanced criteria. The assessment highlights the economic significance of parameters like PBP, LCOE, and capital cost, crucial for navigating the Palestinian economic landscape. Meanwhile, technical aspects prioritize efficiency, system safety, infrastructure, and reliability, pivotal for sustainable energy projects. Among the alternatives, SWH and solar PV emerge as front-runners, echoing past energy strategies aiming to generate 10% of electricity through RE sources by 2020, with solar PV at 34.6% and wind energy at 33.8%. However, future strategies should elevate biogas alongside waste-to-energy, while lowering the emphasis on CSP.

7. Study Limitations

The study's applicability is constrained to the Palestinian context, limiting broader generalization. It may have overlooked emerging renewable alternatives, potentially impacting its comprehensiveness. The complexity of the decision-making model, like AHP, could pose challenges for users' understanding and application. Additionally, the static analysis may not fully reflect the dynamic nature of evolving energy systems over time.

8. Implications

The findings of this study have significant implications for energy policy and planning in the Palestinian territories. The prioritization of renewable energy alternatives, particularly solar PV and SWH, provides a strategic pathway for achieving energy self-sufficiency and reducing dependency on imported energy. By emphasizing technical and economic criteria, the study offers a robust framework for decision-makers to allocate resources effectively and develop sustainable energy policies. The use of the AHP model also highlights the importance of incorporating multi-criteria decision-making tools in regional energy.

9. Future Work

In charting future research trajectories, there exists potential for augmenting the authenticity and precision of the model through the integration of localized data into the analysis framework. Additionally, diversifying the exploration of multi-criteria decision-making tools for comparative analyses could substantially enrich the research domain. A recognized limitation in this study is the scarcity of local technical and economic data pertaining to certain considered alternatives, attributable to their limited implementation in Palestine.

References

Abu-Madi, M. (2013). Estimation of main greenhouse gases emission from household energy consumption in the West Bank, Palestine. *Environmental pollution*, *179*, 250-257. https://doi.org/10.1016/j.envpol.2013.04.022

Achillas, C., Vlachokostas, C., Moussiopoulos, N., Banias, G., Kafetzopoulos, G., & Karagiannidis, A. (2011). Social acceptance for the development of a waste-to-energy plant in an urban area. *Resources, Conservation and Recycling*, *55*(9-10), 857-863. https://doi.org/10.1016/j.resconrec.2011.04.012

Ahmad, S., & Tahar, R. M. (2014). Selection of renewable energy sources for sustainable development of electricity generation system using analytic hierarchy process: A case of Malaysia. *Renewable Energy*, *63*, 458-466. https://doi.org/10.1016/j.renene.2013.10.001

Akpahou, R., & Odoi-Yorke, F. (2023). A multicriteria decision-making approach for prioritizing renewable energy resources for sustainable electricity generation in Benin. *Cogent Engineering*, *10*(1), 2204553. https://doi.org/10.1080/23311916.2023.2204553

Al Garni, H., Kassem, A., Awasthi, A., Komljenovic, D., & Al-Haddad, K. (2016). A multicriteria decision making approach for evaluating renewable power generation sources in Saudi Arabia. *Sustainable energy technologies and assessments*, *16*, 137-150. https://doi.org/10.1016/j.seta.2016.05.006

Algarín, C. R., Llanos, A. P., & Castro, A. O. (2017). An analytic hierarchy process based approach for evaluating renewable energy sources. *International Journal of Energy Economics and Policy*, *7*(4), 38-47. http://hdl.handle.net/11159/1258

Amer, M., & Daim, T. U. (2011). Selection of renewable energy technologies for a developing county: a case of Pakistan. *Energy for sustainable development*, *15*(4), 420-435. https://doi.org/10.1016/j.esd.2011.09.001

Baris, K., & Kucukali, S. (2012). Availibility of renewable energy sources in Turkey: Current situation, potential, government policies and the EU perspective. *Energy policy*, *42*, 377-391. https://doi.org/10.1016/j.enpol.2011.12.002

Burgherr, P., & Hirschberg, S. (2014). Comparative risk assessment of severe accidents in the energy sector. *Energy policy*, *74*, S45-S56. https://doi.org/10.1016/j.enpol.2014.01.035

Casanova-Peláez, P. J., Palomar-Carnicero, J. M., Manzano-Agugliaro, F., & Cruz-Peragón, F. (2015). Olive cake improvement for bioenergy: the drying kinetics. *International journal of green energy*, *12*(6), 559-569. https://doi.org/10.1080/15435075.2014.880347

Chludziński, D., & Duda, M. (2018). Technological solutions applied in biogas plants-a case study. E3S Web of Conferences, https://doi.org/10.1051/e3sconf/20184900012

Cho, S., Kim, J., & Lim, D. (2024). Optimal design of renewable energy certificate multipliers using an LCOE-Integrated AHP model: A case study of South Korea. *Renewable Energy*, *226*, 120386. https://doi.org/10.1016/j.renene.2024.120386

Das, S., De, S., & De, S. (2024). Application of MCDM Tool Integrated with SWOT Analysis for Prioritization of Strategies to Optimize Distributed Hybrid Energy Systems for Better Sustainability. In *Challenges and Opportunities of Distributed Renewable Power* (pp. 9-34). Springer. https://doi.org/10.1007/978-981-97-1406-3_2

Dioba, A., Giannakopoulou, A., Struthers, D., Stamos, A., Dewitte, S., & Fróes, I. (2024). Identifying Key Barriers to joining an Energy Community using AHP. *Energy*, 131478. https://doi.org/10.1016/j.energy.2024.131478

Effatpanah, S. K., Ahmadi, M. H., Aungkulanon, P., Maleki, A., Sadeghzadeh, M., Sharifpur, M., & Chen, L. (2022). Comparative analysis of five widely-used multi-criteria decision-making methods to evaluate clean energy technologies: A case study. *Sustainability*, *14*(3), 1403. https://doi.org/10.3390/su14031403

El-Kilani, R. J., & Zaid, A. I. (2015). Geothermal energy in Palestine practical applications. 2015 Power Generation System and Renewable Energy

Technologies (PGSRET), https://doi.org/10.1109/PGSRET.2015.7312223

Farooq, W., Khan, A. D., Khan, A. D., & Noman, M. (2020). Enhancing the power conversion efficiency of organic solar cells. *Optik*, *208*, 164093. https://doi.org/10.1016/j.ijleo.2019.164093

Funk, K., Milford, J., & Simpkins, T. (2013). *Waste not, want not: Analyzing the economic and environmental viability of waste-to-energy (WTE) technology for site-specific optimization of renewable energy options*. https://doi.org/10.1016/b978-0-12-815497-7.00019-1

Gupta, S., Kumar, R., & Kumar, A. (2024). Green hydrogen in India: Prioritization of its potential and viable renewable source. *International Journal of Hydrogen Energy*, *50*, 226-238. https://doi.org/10.1016/j.ijhydene.2023.08.166

IEA. (2020). *Clean Energy Innovation, IEA, Paris*. https://www.iea.org/reports/clean-energy-innovation/innovation-needs-in-the-sustainable-development-scenario

International Renewable Energy Agency. (2013). Renewable power generation costs in 2012: An overview. https://www.irena.org/publications/2013/Jan/Renewable-Power-Generation-Costs-in-2012-An-Overview

Ishfaq, S., Ali, S., & Ali, Y. (2018). Selection of optimum renewable energy source for energy sector in Pakistan by using MCDM approach. *Process Integration and Optimization for Sustainability*, *2*, 61-71. https://doi.org/10.1007/s41660-017-0032-z

Juaidi, A., Anayah, F., Assaf, R., Hasan, A. A., Monna, S., Herzallah, L., Abdallah, R., Dutournié, P., & Jeguirim, M. (2022). An overview of renewable energy strategies and policies in Palestine: Strengths and challenges. *Energy for sustainable development*, *68*, 258-272. https://doi.org/10.1016/j.esd.2022.04.002

Kaya, T., & Kahraman, C. (2010). Multicriteria renewable energy planning using an integrated fuzzy VIKOR & AHP methodology: The case of Istanbul. *Energy*, *35*(6), 2517-2527. https://doi.org/10.1016/j.energy.2010.02.051

Kumar, A., Bam, G., Sah, B., & Kumar, P. (2014). A hybrid micro grid for remote village in Himalayas. 3rd Renewable Power Generation Conference (RPG 2014), https://doi.org/10.1049/cp.2014.0928

Lee, H.-C., & Chang, C.-T. (2018). Comparative analysis of MCDM methods for ranking renewable energy sources in Taiwan. *Renewable and Sustainable Energy Reviews*, *92*, 883-896. https://doi.org/10.1016/j.rser.2018.05.007

Mateo, J. R. S. C. (2012). *Multi criteria analysis in the renewable energy industry*. Springer Science & Business Media. https://doi.org/10.1001/978-1-4471-2346-0_1

Medener, & Rcreee. (2020). *Country report on energy efficiency and renewable energy investment climate – Palestinian territories*. https://meetmed.org/wp-content/uploads/2022/02/A31_PalestineClimate_FINAL.pdf

Palestinian Central Bureau of Statistics. (2020). Energy tables 2020. https://www.pcbs.gov.ps/Portals/_Rainbow/Documents/energy-tables-2020-ar.pdf

Parvaneh, F., & Hammad, A. (2024). Application of Multi-Criteria Decision-Making (MCDM) to Select the Most Sustainable Power-Generating Technology. *Sustainability*, *16*(8), 3287. https://doi.org/10.3390/su16083287

Rojas-Zerpa, J. C., & Yusta, J. M. (2014). Methodologies, technologies and applications for electric supply planning in rural remote areas. *Energy for Sustainable Development, 20*, 66-76. https://doi.org/10.1016/j.esd.2014.03.003

S, M., & A. Brown. (2011). Best and Future Policy Practice. *Renewable Energy Markets and Policies. The International Energy Agency (IEA). Paris*. https://doi.org/10.1787/9789264124912-en

Saaty, T. L., Vargas, L. G., Saaty, T. L., & Vargas, L. G. (2012). The seven pillars of the analytic hierarchy process. *Models, methods, concepts & applications of the analytic hierarchy process*, 23-40. https://doi.org/10.1007/978-1-4614-3597-6_2

Santos, P. A. S., Cortez, B., & Carvalho, M. T. M. (2024). Integrating GIS and BIM with MCDM for infrastructure planning: a comprehensive framework. *Engineering, Construction and Architectural Management*. https://doi.org/10.1108/ECAM-08-2023-0830

Saraswat, S., & Digalwar, A. K. (2021). Evaluation of energy alternatives for sustainable development of energy sector in India: An integrated Shannon's entropy fuzzy multi-criteria decision approach. *Renewable Energy*, *171*, 58-74. https://doi.org/10.1016/j.renene.2021.02.068

Saver, E. (2022). Estimating the Cost and Energy Efficiency of a Solar Water Heater *Department of Energy*. https://www.energy.gov/energysaver/estimating-cost-and-energy-efficiency-solar-water-heater

Sha, F., Gallagher, K., Gandiglio, M., García, M., Gatellier, B., Gogan, K., Gutzwiller, L., Stignor, C., Handelsman, J., & Hauer, A. (2020). Energy Technology Perspectives 2020—Special Report on Clean Energy Innovation. *Energy Technology Perspectives*, *185*. https://doi.org/10.1787/ab43a9a5-en

Shahroodi, K., Keramatpanah, A., Amini, S., & Sayyad Haghighi, K. (2012). Application of analytical hierarchy process (AHP) technique to evaluate and selecting suppliers in an effective supply chain. *Kuwait Chapter of Arabian Journal of Business Management Review*, *1*(8). https://platform.almanhal.com/Files/2/37972

Stefanides, M. (2021). *Renewable power generation costs in 2020: Cost declines and record capacity additions*. https://policycommons.net/artifacts/3140372/renewable-power-generation-costs-in-2020/3933628/

Streimikiene, D., Balezentis, T., Krisciukaitienė, I., & Balezentis, A. (2012). Prioritizing sustainable electricity production technologies: MCDM approach. *Renewable and Sustainable Energy Reviews*, *16*(5), 3302-3311. https://doi.org/10.1016/j.rser.2012.02.067

Tayeh, R. A., Alsayed, M. F., & Saleh, Y. A. (2021). The potential of sustainable municipal solid waste-to-energy management in the Palestinian Territories. *Journal of cleaner production*, *279*, 123753. https://doi.org/10.1016/j.jclepro.2020.123753

Troldborg, M., Heslop, S., & Hough, R. L. (2014). Assessing the sustainability of renewable energy technologies using multi-criteria analysis: Suitability of approach for national-scale assessments and associated uncertainties. *Renewable and Sustainable Energy Reviews, 39*, 1173-1184. https://doi.org/10.1016/j.rser.2014.07.160

Xu, N., Wan, A., Elahi, E., & Peng, B. (2024). Evaluating investment risks in overseas renewable energy projects: A WSR and D-AHP based approach.

Environmental Progress & Sustainable Energy, *43*(3), e14306. https://doi.org/10.1002/ep.14306

Yang, P., & Nehorai, A. (2014). Joint optimization of hybrid energy storage and generation capacity with renewable energy. *IEEE Transactions on Smart Grid*, *5*(4), 1566-1574. https://doi.org/10.1109/TSG.2014.2313724