energies

Article

Evaluation and Prioritization of Power-Generating Systems Using a Life Cycle Assessment and a Multicriteria Decision-Making Approach

Busola D. Akintayo [1,*], Oluwafemi E. Ige [1], Olubayo M. Babatunde [2] and Oludolapo A. Olanrewaju [1]

[1] Department of Industrial Engineering, Durban University of Technology, Durban 4001, South Africa; phemmyigoh@yahoo.com (O.E.I.); oludolapoo@dut.ac.za (O.A.O.)
[2] Department of Electrical Electronics Engineering, University of Lagos, Akoka, Lagos 100213, Nigeria; mobabatunde@unilag.edu.ng
* Correspondence: olaginjubusola52@gmail.com

Abstract: Millions of people in Asia and sub-Saharan Africa still lack access to power, which emphasizes the need for sustainable and clean energy solutions. This study attempts to address this issue by integrating a life cycle assessment (LCA) and a multicriteria decision-making (MCDM) analysis to determine the preferred energy technology for electrification. This research focuses on the environmental implications and long-term viability of various energy system options. The LCA evaluates midpoint characterization containing 18 environmental impact categories; the COPRAS and ARAS methods of MCDM analysis are then used to rank the energy alternatives based on their environmental performance. This study's key finding is that the gas-powered power plant is the most preferred energy system alternative, while the geothermal power plant is the least preferred. This midpoint characterization study provides in-depth insights into how various stages contribute to major environmental impact categories like global warming, ozone depletion, and ecotoxicity. By considering environmental impacts and sustainability requirements, informed decisions may be made to encourage clean and cost-effective power generation, thereby contributing to climate change mitigation and supporting economic growth and human development. Future research may include analysis from cradle-to-grave compared to cradle-to-gate.

Keywords: life cycle assessment (LCA); multicriteria decision making (MCDM); power plant; decision making; energy systems

Citation: Akintayo, B.D.; Ige, O.E.; Babatunde, O.M.; Olanrewaju, O.A. Evaluation and Prioritization of Power-Generating Systems Using a Life Cycle Assessment and a Multicriteria Decision-Making Approach. *Energies* **2023**, *16*, 6722. https://doi.org/10.3390/en16186722

Academic Editors: Abdul Matin Ibrahimi and Danish Mir Sayed Shah

Received: 7 August 2023
Revised: 6 September 2023
Accepted: 15 September 2023
Published: 20 September 2023

1. Introduction

Energy, especially electricity, is no doubt a key element in the sustenance of modern civilization because it powers almost every service and human activity [1]. Aside from this, it serves as an input to many products that provide comfort for modern humans [2]. Although electricity has been commercialized for quite a long time, a sizeable number of people residing in Asia and sub-Saharan Africa still do not have access to electricity. It is reported that 600 million people in Africa live in areas that are yet to be electrified [3]. The electrification of these communities must be established on the framework of sustainability. Traditionally, electricity is generated using fossil fuel; however, as the world has begun to feel the effects of climate change, scientists have proposed that the adoption of clean sources of energy is essential for mitigating climate change [4]. Aside from preventing greenhouse gases, sustainable energy systems also follow the principle of sustainability, which argues that the present generation must not disfranchise the upcoming generation by consuming resources that are meant for the upcoming generation. As regards sustainability, proponents of environmental justice argue that decarbonization of the energy-consuming sectors, especially electricity and transportation that account for 52% of greenhouse gases, would result in a significant reversal of climate change [5]. The commitment to clean energy and sustainability is evident and clearly spelled out in the United Nations SDG number 7, which solicits support for ensuring availability of clean, cost-effective energy to all [6,7]. Sustainable and cost-effective electricity is critical to the development of agriculture, business, communications, education, healthcare, and transportation. Energy scarcity suppresses economic growth and human development.

Given that it is a good idea to initiate decarbonization in the electrical sector from the supply side, researchers have suggested replacing carbon-intensive power plants with clean coal technology, renewable energy, and nuclear power plants [8,9]. On the one hand, there is rising concern about the long-term viability of fossil fuels such as oil, which has continued to decline, resulting in increased scarcity and higher prices [10]. Renewable energy sources such as wind and solar, on the other hand, can make substantial impacts on the reduction of cost associated with electricity generation in off-grid systems and the mitigation of greenhouse gas emissions (GHGs) [11,12]. Moreso, these systems operate independently from the primary utility grid [13], and the cost per watt installed for photovoltaic and wind systems has consistently reduced over the years [14]. Thus, one may be tempted to jump the gun to agree to an immediate replacement without a thorough evaluation of the overall impact. To select the most preferred energy technology for electrification, there are various criteria that must be considered; these include technological maturity, social acceptance and consequences, cost, available policies, legal frameworks, and environmental consequences of the technologies [15–17].

2. Literature Review

Researchers frequently employ a life cycle assessment (LCA) [18,19] to evaluate the effects and effectiveness of technologies and scenarios because it offers a comprehensive evaluation of various aspects and potential impacts that arise during the entire life cycle of a product, service, or activity, thereby providing valuable indicators in this regard. However, these indicators are often measured using units that differ from those used for project decision making. This difference makes it challenging to compare them with economic and political indicators. In addition, life cycle impact assessments of the power plant are essential for quantifying the effect of the power plant on the environment. There are various attributes and life cycle impact assessments that researchers usually consider when selecting a product; some of these impact assessment approaches include cradle-to-grave, cradle-to-gate, cradle-to-cradle, gate-to-gate, economic input–output, ecologically based LCA, and exergy-based LCA, each of which has its own merits [20–22].

LCA is a widely used method to assess the environmental impact of energy systems, especially in areas where environmental protection is important [23–25]. The methodology considers the environmental impact of an energy system throughout its life cycle, from the extraction of raw materials to the disposal of waste. This allows for a more comprehensive assessment of the environmental impact of energy systems than traditional methods, which typically only consider the operational phase. LCA has been conducted in several countries to compare the results of the environmental impact of different electricity generation technologies. These countries include Mexico [26], Poland [27], Belgium [28,29], Portugal [30,31], Pakistan [32], Denmark [33,34], Brazil [35,36], China [37,38], Chile [39], and Turkey [40].

Mahmud et al. [41] conducted an LCA of solar photovoltaic (PV) and solar thermal systems to compare their environmental impacts. They used 16 indicators to assess the impacts of the two systems and found that the solar thermal system has a more significant environmental impact than the PV system. However, the solar thermal system also has a longer lifespan than the PV system, so the environmental impact of each system over its lifetime is comparable.

Kabayo et al. [30] used LCA to evaluate the environmental and socioeconomic impact of electricity generation in Portugal. They considered the environmental impact of five types of electricity generation technologies: coal, natural gas, large hydro and small hydro, wind, and photovoltaic power plants. Wind power has the highest impact on metal depletion;

coal has the highest impact on fossil fuel depletion, global warming, terrestrial acidification, freshwater eutrophication, and aquatic acidification; natural gas has the highest impact on ozone depletion; large hydro has the highest impact on the water scarcity footprint; and photovoltaic has the highest impact on toxicity.

Wu et al. [37] combined LCA with other modeling techniques to provide a more comprehensive assessment of the environmental impact of different policy scenarios in China from 2016 to 2050. Under the deep CO_2 emission reduction scenario designed to achieve emission reduction and carbon neutrality goals in China by 2050, CO_2, PM10, PM2.5, NOx, CO, and SO_2 emissions are expected to be reduced by more than 71.4% compared to 2016.

The results of these LCAs have shown that the environmental impact of electricity generation varies depending on the technology used. Coal-fired power plants typically have the highest environmental impact and are major contributors to climate change and global warming, followed by natural gas-fired power plants. Nuclear power plants and wind power have relatively low environmental impacts. The operation and maintenance of coal-fired power plants is a major contributor to CO_2 emissions [38].

Another important consideration in the implementation of LCA is the use of midpoint indicators, which are intermediate measures of environmental impact that indicate changes in the natural environment induced by emissions or resource consumption. For example, greenhouse gas emissions can be quantified as carbon dioxide equivalents (CO_2e), which show the global warming potential of certain gases. Midpoint indicators are frequently easier to compute and interpret than endpoint indicators because they are closer to the source of the impact and are less affected by uncertainties and assumptions. In addition, midpoint indicators are easier to comprehend for most audiences, making them reliable and reputable for communication and teaching. They also enable a more thorough and focused study of the many environmental impact categories, which can assist in pinpointing problem areas and suggesting chances for improvement. As such, they are applicable in the process of selecting the most preferred electricity generation alternative based on environmental attributes because thy look at the impact earlier along the cause–effect chain before the endpoint is reached. Midpoint indicators are more comparable and consistent across various studies and databases because of their acceptance and standardization within the LCA community [42,43].

Multicriteria decision-making (MCDM) methods are extensively employed to address problems that involve ranking alternatives and selecting the most preferred alternative after considering various indicators. These methods facilitate the normalization of data and enable the evaluation of multiple alternatives by assigning varying weights to each, ultimately generating a ranking of preference for the alternatives. Several MCDM methods are available for use, including the analytic network process (ANP), analytic hierarchic process (AHP), multicriteria optimization and compromise solution (VIKOR), elimination et choix tradusiant la realité (ELECTRE), technique for order performance by similarity to ideal solution (TOPSIS), and data envelopment analysis (DEA) [44].

Zhou et al. [45] conducted a study highlighting the primary areas in which MCDM analysis have been mainly utilized, which include energy policies, electricity planning, and project assessment. Bhandari et al. [46] analyzed a methodology for evaluating various energy technologies in Niger using an MCDM approach, utilizing 40 indicators across six dimensions. This evaluation provides a ranked list of suitable technologies to guide stakeholders in making informed decisions for future projects in Niger. Shaaban et al. [47] used two MCDA methods, the analytical hierarchy process and the weighted sum method, to assess the sustainability of seven energy technologies: coal, natural gas, wind, concentrated solar power, photovoltaics, biomass, and nuclear in Egypt. Natural gas power plants were ranked as the most sustainable technology, followed by renewable energy technologies. MCDM methods present a different approach to incorporating multiple dimensions into the decision-making process, including environmental, economic, and social aspects. It is important to emphasize that MCDM facilitates decision making in a structured and unbiased manner, even when dealing with many variables. Hence, the significance becomes evident in the context of energy, as it encompasses multiple sustainability-related criteria. MCDM is a well-suited tool for environmental decision making, especially when comparing social, economic, and environmental indicators. This is because MCDA can help decision makers systematically consider multiple criteria and their trade-offs and make informed decisions aligned with their values and objectives [48–50]. MCDM analysis is more effective when it uses quantitative-based methodologies. MCDM methods, which encompass a range of techniques, can be integrated with LCA to assess the sustainability of systems [51]. LCA is one of the most important tools and methodologies that can be used in MCDA because it provides a comprehensive assessment of the environmental impact of a product. LCA is a well-established method for assessing the environmental impact of products, systems, and services [52,53]. It evaluates different decision alternatives based on various environmental indicators [54]. However, the results of LCA can be difficult to interpret and use for decision making. Integrating LCA with MCDM can solve this problem practically [55]. MCDM is a method for making decisions in the presence of multiple criteria. By integrating LCA and MCDM, decision makers can better understand the trade-offs between different environmental impacts and make more informed decisions.

As mentioned earlier, the MCDA approach alone cannot identify efficient levels of pollution production or resource use [56]. Myllyviita et al. [57] agree that MCDA often needs input from other tools and methods, such as LCA, to support sustainability assessments. Therefore, combining LCA and MCDA is a common approach for assessing sustainability scenarios. This combination has been used in several studies and applications, such as Bogacka in coal production [58], Burchart-Korol et al. in steel production [59], and Von Doderer and Kleynhans in bioenergy systems [52].

De Souza et al. [55] introduced a new approach to evaluating and prioritizing sustainable waste electrical and electronic equipment (WEEE) management systems in Brazil using an integrated method. They combined qualitative evaluations of an MCDM with LCA, targeting situations with limited data and a small group of evaluators. Their results highlighted the need for statistical inference to improve the accuracy of results, which requires a larger sample of evaluators. The proposed method fills a gap in the field by integrating LCA, qualitative evaluation, and MCDM without relying on many experts.

Zanghelini et al. [60] reviewed the use of MCDM and LCA to assess the environmental impact of different systems and processes. They focused on how effectively MCDM techniques can be used in the context of LCA to help evaluate the environmental impact of these systems and processes. Their findings suggest that the combination of MCDM and LCA can be a valuable tool for environmental impact assessment, but more research is needed to explore its potential fully.

Myllyviita et al. [61] used a combined LCA-MCDM approach to assess the environmental impact of biomass production chains in Finland. They used LCA to calculate the environmental impact of each chain in terms of various impact categories, while MCDM was used to normalize LCA results. This allowed them to compare the environmental impact of the different biomass production chains on a common scale. The study results showed that the environmental impact of biomass production chains vary depending on the type of biomass used and the production process.

Domingues et al. [62] combined MCDM and LCA to assess the environmental impact of different vehicle fuel types in Portugal. They used both approaches to determine the optimal fuel solution, considering multiple environmental impact categories.

Sohn et al. [63] evaluated the environmental impacts of different insulation levels of industrial buildings using two life cycle impact assessment (LCIA) methods: ReCiPe endpoints and MCDA. These methods allowed them to generate two single-score assessments and rank the insulation scenarios. The study found that the most effective level of insulation for industrial buildings varied depending on the climate and the type of building.

Martín-Gamboa et al. [44] reviewed the use of LCA approaches and DEA in MCDM for the sustainability assessment of energy systems. They identified the most commonly used criteria, data sources, and tools for the sustainability assessment of energy systems and reviewed the available LCA and DEA approaches. They found that this combination is very effective for assessing case studies.

LCA and MCDM share common characteristics as robust methodologies enabling both qualitative and quantitative assessments. Additionally, they allow the consideration of various perspectives and preferences held by stakeholders, thereby minimizing uncertainties in the results. These attributes make LCA and MCDM practical approaches for selecting sustainable solutions [64]. The integration of LCA ensures that the decision-making process considers both environmental impact and other relevant criteria. The efficacy of multi-criteria decision-making analysis can be combined with a midpoint-indicators approach to rank and select the most preferred energy technology for electrification. However, a comprehensive review of the existing literature indicates that there is a knowledge gap in the hybridization of MCDM and midpoint approach in the ranking and selection of the most preferred electricity generation alternative.

This research was inspired by the critical importance of finding solutions to the problems associated with energy generation and the associated environmental effect. Considering the growing risks posed by climate change and resource depletion, nations around the world must move toward renewable energy. However, due to the wide variety of energy options and the complexity of their environmental impact, an in-depth assessment framework is required. The purpose of this study is to evaluate the environmental impact of various energy systems across a broad spectrum of impact categories by analyzing factors other than greenhouse gas emissions, such as stratospheric ozone depletion, ionization radiation, and others. The goal is to provide a comprehensive understanding of the complex relationships between energy production processes and their diverse environmental impact.

As such, in this study, we took the initiative to employ the integration of LCA and MCDA to evaluate the sustainability of different electricity generation alternatives by considering their entire life cycle. We conducted a life cycle assessment of seven energy system alternatives based on the midpoint approach and identified the most and least preferred energy system based on the 18 impact categories using the multi-criteria decision-making approach. Further analysis was carried out on the most preferred and least preferred system to identify specific phases in the predefined production process that contributed the most to the impact of the selected system. This study will assist decision makers in selecting the most sustainable option by examining essential criteria and implementing measures to enhance existing processes.

3. Methodology

The methodology employed in this study involved the integration of LCA and MCDA, which combines the environmental perspective provided by LCA with the decision-making tools of MCDM. This integration allows decision makers to consider environmental impact alongside other economic, social, and technical criteria when evaluating different alternatives. By integrating LCA and MCDM, decision makers can make more informed and balanced decisions that consider environmental, economic, social, and technical aspects, promoting sustainability and responsible resource management. However, it is essential to involve relevant stakeholders and ensure transparency in the decision-making process to achieve meaningful results.

The decision to use an integrated methodology that combines life cycle assessment (LCA) and multicriteria decision making (MCDM) is supported by a number of compelling justifications that collectively improve the rigor, comprehensiveness, and practicability of evaluating and ranking various energy systems.

The use of life cycle assessment (LCA) is primarily driven by its inherent ability to provide a comprehensive evaluation of environmental impact, encompassing the whole life cycle of energy systems from their raw material mining to their disposal. This approach ensures a comprehensive examination of all aspects of environmental impact, hence preventing the omission of interconnected stages and hidden repercussions. MCDM adoption, on the other hand, addresses the intrinsic complexity of energy system assessments. The multidimensional characteristics of these evaluations necessitate a structured way to weigh multiple criteria at the same time. MCDM provides this framework, allowing for the integration of quantitative and qualitative data as well as strong comparisons across options. The combination of LCA and MCDM yields a decision-making tool that combines the strengths of both approaches thanks to the quantitative accuracy of LCA and the ability of MCDM to consider subjective attributes. This combination emphasizes the value of empirical evidence while also recognizing that some criteria cannot be quantified in terms of numbers. Furthermore, the adopted methodology supports transparency and reproducibility. Both the LCA and the MCDM techniques are well-known and have established protocols. By using a structured approach, the evaluation process is made transparent, and the outcomes are verifiable, giving the conclusions validity and reliability.

3.1. LCA Assessment

LCA is based on gathering inputs and outputs related to the environmental, economic, and social impact of a product, goods, or services over their life cycle [65]. Interpreting LCA results can be challenging because there are often trade-offs between the impact in different categories when evaluating various scenarios [66]. These results can sometimes conflict with each other, creating challenges in decision making; two approaches have been identified to address this problem: the initial approach involves assigning importance to and combining the LCA results for each impact category to generate a single scoring indicator. The second approach suggests using a limited set of impact categories to simplify the interpretation of the results [67].

LCA consists of four stages, which are as follows: "goal and scope definition, life cycle inventory analysis (LCI), life cycle impact assessment (LCIA) and interpretation". Based on the International Organization for Standardization (ISO) standards [18,19], LCA examines each electricity generation technology under consideration, provides quantitative data on the environmental performance of each technology, and involves assessing the possible environmental impact at various stages of a product's life cycle, from raw materials extraction through production, usage, operation, end-of-life treatment, recycling, and final disposal. This approach, often called "cradle-to-grave," is divided into four phases, as illustrated in Figure 1.

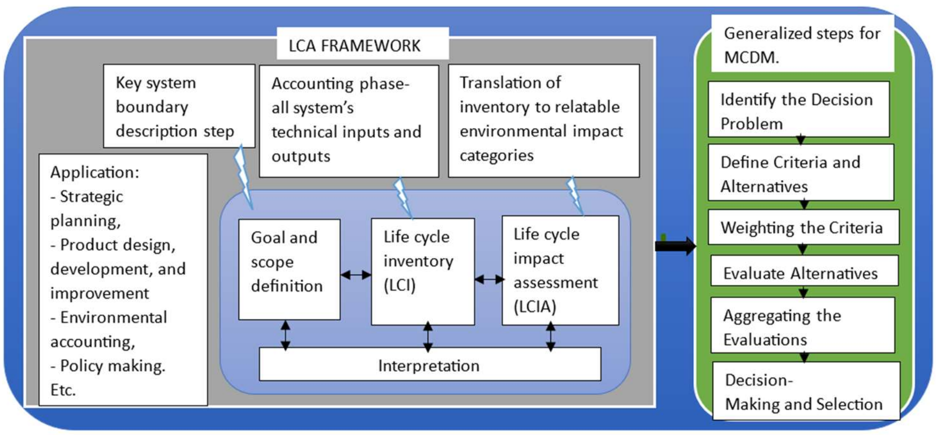

Figure 1. LCA and MCDM framework.

Goal and scope definition: This stage involves clearly defining the goal and scope of the LCA study. The goal defines the purpose and intended application of the assessment, while the scope identifies the system boundaries, functional unit, and life cycle stages to be included. In this case, the goal of this study is to carry out LCA on seven energy system alternatives, while the functional unit considered in this study is 100 MW electricity produced. In addition, the dataset used for this analysis was from the extraction of raw material through to the building of the energy system to the point of electricity production. This study only covered the "cradle-to-gate" assessment of the electricity systems; the operational stages, use, disposal/end-of-life or waste treatment data were not taken into consideration in this study.

Inventory analysis: This stage involves data on the material inputs, emissions and other outputs associated with the life cycle of a product, and process of the system under assessment. This considers all technical inputs and outputs of what it takes to build the systems from scratch up to the point of producing electricity. This study made use of secondary data from the Ecoinvent database to carry out the assessment (See Table S9 for details).

Impact assessment: The LCIA stage involves evaluating and quantifying the potential environmental impact associated with the life cycle inventory data collected in the previous stage. It includes assessing various impact categories such as global warming potential, acidification potential, and eutrophication potential. This study makes use of the midpoint impact assessment approach for the characterization of the impact categories using SimaPro 9.2.

Interpretation: The interpretation stage involves analyzing and summarizing the results of the LCA study. It includes identifying the key findings, assessing the uncertainties and limitations of this study, and drawing conclusions.

3.2. Multicriteria Decision-Making Assessment

MCDM is a mathematics-based protocol for analyzing and interpreting inputs that guide decision making across various fields [68]. However, a significant limitation arises when measuring the impact criteria, as decision makers commonly employ qualitative scales [69]. While qualitative scales are often suitable for evaluating social aspects, studies have shown that they may not accurately and precisely represent the environmental and economic performance of the assessed alternatives [70]. Therefore, it is crucial to adopt structured tools that can effectively evaluate the performance of alternatives across multiple criteria to promote sustainability [69]. An MCDM model is constructed by incorporating the identified criteria and their respective weights, which reflect the relative importance of each criterion in the decision-making process [71]. Various MCDM methods, such as AHP, TOPSIS, ELECTRE, and WSM, can be used. But this study will consider the complex proportional assessment (COPRAS) method. Aside from computational efficiency advantage over other types of MCDM methods [72], COPRAS also addresses criterion interdependence, allowing decision makers to assess how changes in one criterion affect others [73]. This feature aids in the capturing of complicated interactions between diverse criteria, resulting in more realistic and accurate judgments. To validate the results obtained from the COPRAS method for consistency, the results obtained from COPRAS will be compared with those of the additive ratio assessment (ARAS) MCDM method, which is also computationally efficient and more specifically presents a ratio-based strategy for dealing with both positive and unfavorable criteria, making it more appropriate for complicated decision issues [74,75].

3.2.1. Complex Proportional Assessment (COPRAS) Method

The complex proportional assessment (COPRAS) method is a multicriteria decision-making tool widely employed for multicriteria decision making and is highly valuable. It compares and evaluates alternatives according to multiple criteria as part of the decision-making process. The COPRAS method ranks the available options according to different and related weight criteria. It consists of the following steps:

Step 1: development of the initial decision matrix.

The decision matrix (Equation (1)) provides the alternatives to be evaluated and the evaluation criteria for a decision-making process. Stakeholders and experts are typically involved in developing the decision matrix.

$$x = [x_{ij}]_{mxn} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{1}$$

Step 2: normalization of the decision matrix.

Normalization of the decision matrix (Equation (2)) converts each element in a decision matrix to a single scale by a reference value to prevent prejudice in the decision-making process. Doing this gives all criteria equal weight and importance during the evaluation process.

$$R = [r_{ij}]_{mxn} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{2}$$

Step 3: weighted normalization of the decision matrix.

The weight of each criterion is determined by its relative importance during the decision-making process (Equation (3)). After that, the normalized decision matrix is multiplied by the weights corresponding to the decision matrix.

$$\begin{gathered} D = [y_{ij}]_{mxn} = r_{ij} \times w_j \\ i = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, n \end{gathered} \tag{3}$$

Step 4: summing of weighted normalization of the decision matrix.

For each alternative, an overall score is determined by summing the weighted normalized decision matrix across all criteria as shown in Equations (4) and (5). There is a need to separate the sum of the beneficial and nonbeneficial attributes.

$$S_{+i} \sum_{j=1}^{n} y_{+ij} \tag{4}$$

$$S_{-i} \sum_{j=1}^{n} y_{-ij} \tag{5}$$

Step 5: determination of the relative significance of alternatives (Equation (6)).

Based on the overall scores, each alternative is ranked in terms of its relative significance.

$$\begin{gathered} Q_i = S_{+i} + \frac{S_{-min} \sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} (S_{-min}/S_{-i})} \\ (i = 1, 2, \dots, m) \end{gathered} \tag{6}$$

where $S_{-min} = S_{-i}$.

Step 6: calculation of the quantitative utility.

Lastly, each alternative's quantitative utility is determined (Equation (7)) according to its rank and the relative relevance of the alternatives.

$$U_i = \left\lfloor \frac{Q_i}{Q_{max}} \right\rfloor \times 100\% \tag{7}$$

The potential of COPRAS to manage complicated decision-making scenarios involving several criteria and decision makers is well established. Nevertheless, it is crucial to remember that the approach mainly depends on subjective analysis and expert opinion. The reference values and weighting schemes employed in the evaluation process may influence the results.

3.2.2. Additive Ratio Assessment (ARAS) MCDM Method

The additive ratio assessment (ARAS) method is a multicriteria decision-making method that can rank a finite number of decision alternatives based on different decision criteria. The method involves several steps, which are as follows:

Step 1: development of the initial decision matrix (see Equation (8)).

$$x = \begin{bmatrix} x_{01} & \cdots & x_{0j} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \quad i = \overline{0,m};\ j = \overline{1,n} \tag{8}$$

where m is the number of alternatives and n is the number of criteria, x_{ij} is the value representing i performance value alternative in terms of the j criterion, and x_{01} is the optimal value of j the criterion.

Step 2: normalization of the decision matrix (Equations (9) and (10)).

$$Beneficial\ attributes\ \overline{x_{ij}} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \tag{9}$$

$$Non-beneficial\ attributes\ x_{ij} = \frac{1}{x_{ij}^{*}};\ \overline{x_{ij}} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \tag{10}$$

Step 3: weighted normalized decision matrix (Equation (11)).

$$\hat{x}_{ij=}\overline{x_{ij}}w_j \tag{11}$$

Step 4: S_i-optimality function for ith alternative (Equation (12)).

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij};\ i = \overline{0,m}, \tag{12}$$

where S_i is the overall index value of the i-th alternative. There is a need to separate the sum of the beneficial and nonbeneficial attributes.

Step 5: calculation of the utility degree.

$$K_i = \frac{S_i}{S_0} \tag{13}$$

where S_i and S_0 are the optimality criterion values.

3.3. Integration of MCDM into LCA in Electricity Generation

LCA and MCDM are decision-support tools with different methodologies vide supra (Sections 3.1 and 3.2) [60], which do not follow a similar order (Figure 1). MCDM is a technique used to evaluate alternatives based on multiple criteria or objectives, while LCA is a methodology for assessing the environmental impacts of a product or system throughout its life cycle. LCA focuses on measuring impact indicators that require accurate interpretation, whereas MCDM considers real-world contexts for decision making that should rely on indicators [76]. LCA is characterized by its objectivity, reproducibility, and standardization. On the other hand, MCDM often incorporates subjectivity, allowing for the inclusion of multiple perspectives that offer a more comprehensive understanding of the study context [76]. However, they possess complementary characteristics, and for this reason, they can be effectively utilized together. Integrating MCDM with LCA for electricity generation involves combining these two methodologies to support decision-making processes in the energy sector. The combination of LCA (especially the midpoint method) and MCDM has not been extensively investigated as a comprehensive assessment method for ranking and selection of alternatives. This integration addresses the individual limitations of LCA and MCDM, making it a promising methodology. When applying MCDM with LCA to electricity generation, the goal is to select the most sustainable and environmentally friendly option among various electricity generation technologies. By integrating MCDM with LCA, decision makers can go beyond a single-dimensional analysis and consider multiple perspectives when evaluating electricity generation options. This approach facilitates a more comprehensive assessment, promoting sustainable and environmentally friendly choices in the energy sector.

MCDM can be integrated into this stage by applying decision-making methods to analyze and compare the alternatives based on their aggregated environmental impact. These methods help stakeholders or decision makers in selecting the most environmentally preferable option. MCDM can be integrated by assigning weights to the different impact categories based on their relative importance. This weighting allows for the aggregation of impact and facilitates the comparison of other alternatives. MCDM can be integrated here by considering the criteria identified in the goal and scope definition stage and determining which environmental indicators and parameters should be included in the inventory analysis. MCDM can be integrated into this stage by involving stakeholders or decision makers to identify the relevant criteria and the importance of their weights for the assessment.

4. Results

This section discusses the results obtained from the LCA and MCDM approach. For midpoint characterization analysis of the seven energy systems, 18 impact categories were obtained (See Table S1 for details). These impact categories were used as inputs into the COPRAS and ARAS methods to obtain the ranking of the energy systems. The details of the MCDM is given in Tables S2–S8.

4.1. Multicriteria Analysis

Using the 18 impact categories obtained from the midpoint approach for LCA, the energy alternatives were ranked. To start with, the weights of the impact categories were obtained using the entropy weight method. The impact categories were specified as the criteria while the various energy technologies were the alternatives. Based on the entropy method, except for global warming with 4.98%, the other 17 criteria had the same weight of 5.59% (Figure 2). This shows that most of the criteria were equally important in the ranking of the energy alternatives based on environmental factors.

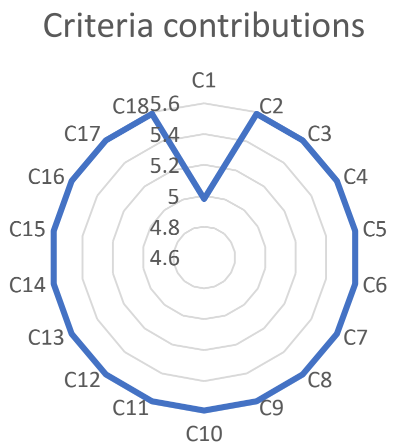

Figure 2. Weight of criteria.

Using the COPRAS method, the energy alternatives were ranked based on the 12 criteria obtained from the LCA, and the results of the COPRAS method were then compared to those returned by the ARAS method, as shown in Table 1. From the results, both the COPRAS and ARAS methods point to the gas-powered power plant as the most preferred energy system alternative with utility degree of 100 and 1, respectively, and the geothermal power plant as the least preferred alternative. With regard to the COPRAS method, the second most preferred energy system is the oil power plant followed by the hard coal power plant, wind power plant, nuclear power plant, solar power plant, and geothermal plant, respectively. The ARAS method shows that the second most preferred energy system is the oil power plant, followed by the hard coal power plant, solar power plant, wind power plant, nuclear power plant, and geothermal plant, respectively.

Table 1. Results of the MCDM method.

Energy System	COPRAS			ARAS		
	Qi	Ui	Rank	Si	ki	Rank
Geothermal power plant	0.0014	0.2817	7	0.0009	0.0026	7
Hard coal power plant	0.1274	25.3246	3	0.0733	0.2196	3
Gas power plant	0.5032	100.0000	1	0.3337	1.0000	1
Nuclear power plant	0.0811	16.1135	5	0.0442	0.1323	6
Oil power plant	0.1488	29.5744	2	0.0841	0.2520	2
Solar thermal	0.0550	10.9322	6	0.0658	0.1972	4
Wind power plant	0.0830	16.4954	4	0.0644	0.1931	5

4.2. Midpoint Characterization

The detailed midpoint characterization results showing the contribution of four production processes/strategies to each environmental impact category of the least and most preferred energy alternatives are discussed in this section. The processes are as follows:

Extraction: all mining processes required in mining operation which are not limited to emission of gases, different production processes, composite, and waste.

Processing: all processes required for converting extracted raw materials to the required final state for energy conversion, which may range from purification of gases to heat production, etc.

Transportation: all transportation required right from extraction site to busbar.

Energy conversion: all processes required for electricity production which also include the construction of the power plant itself.

From Figure 3, it can be observed that energy conversion, with a 41.4% share, is the major contributor to global warming; this is followed by the processing stage (35.3%), extraction (22.9%), and transportation (0.4%), respectively. The processing stage (with 56%) is the main cause of stratospheric ozone depletion, while extraction, energy conversion, and transportation contribute 30.6%, 10.4%, and 3%, respectively, to the depletion of the stratospheric ozone. Only two stages contribute to ionization radiation; these are extraction (99.5%) and energy conversion (0.5%). The processing stage of the energy system accounts for 46.2% of the fine particulate matter formation; this is followed by extraction (26.3%), energy conversion (24%), and transport (3.5%). Furthermore, processing (42.4%) contributes the most to terrestrial acidification, while transportation contributes the least (7%). The biggest contributor to freshwater eutrophication, marine eutrophication, terrestrial ecotoxicity, freshwater ecotoxicity, marine ecotoxicity, human carcinogenic toxicity, human noncarcinogenic toxicity, land use, fossil resource scarcity, and water consumption is extraction. With regard to ozone formation, human health, and ozone formation terrestrial, the processing stage contributes the same value and is also the highest contributor.

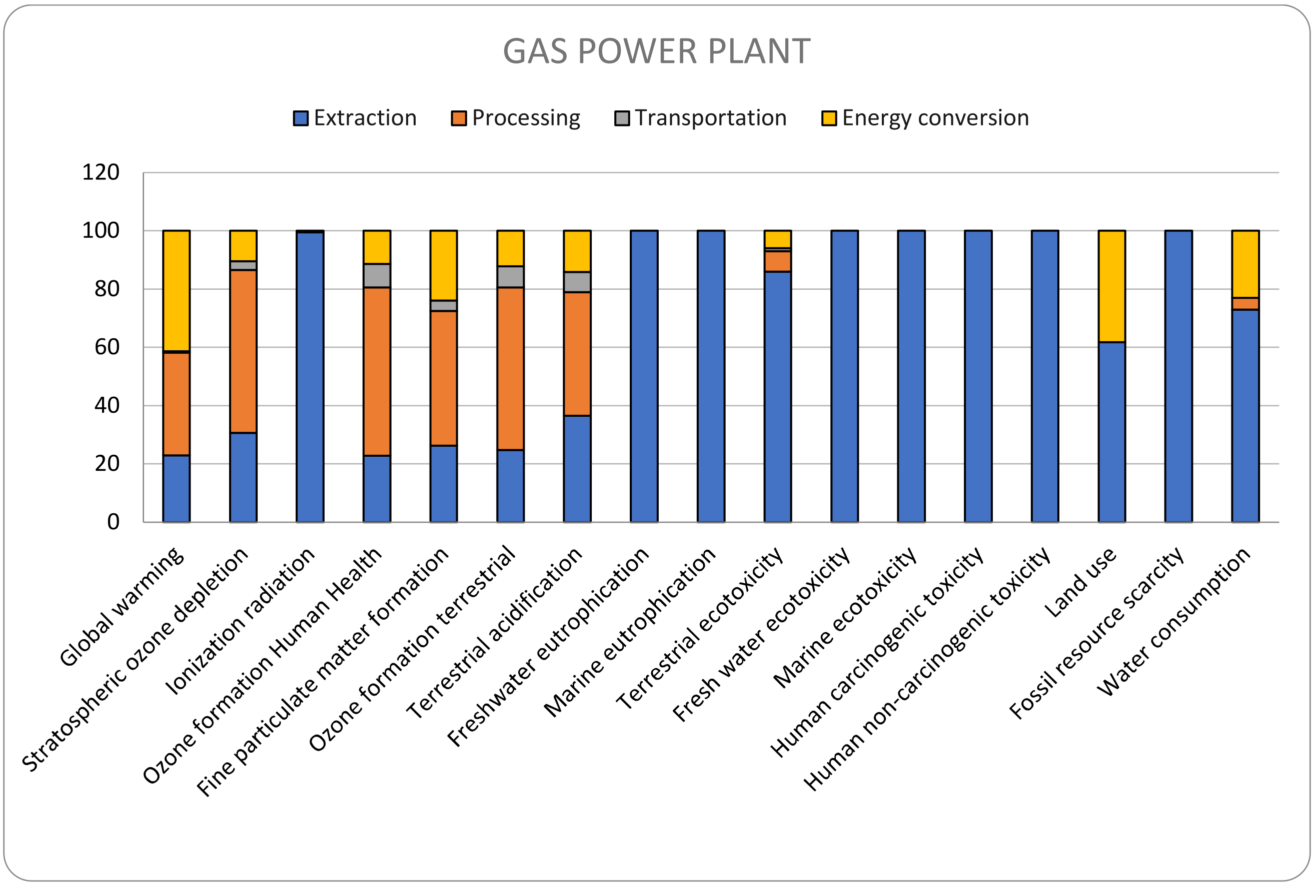

Figure 3. The midpoint characterization of the gas-powered power plant.

Figure 4 shows the midpoint characterization of the geothermal power plant. With regard to the geothermal plant, the largest contributor to global warming is energy conversion with 78%; this is followed by extraction with 17.9%. Processing contributes 3.8% to global warming, while transportation is the lowest contributor to global warming with less than 1% input. Energy conversion and processing contribute almost the same share to the depletion of the stratospheric ozone with 42.8 and 42.7%, respectively, and transportation contributes the least with 3.6%. Concerning ozone formation, human health, and ozone formation terrestrial, energy conversion is seen to contribute to the largest share (53.6% and 58%, respectively) while transportation with contributions of 11% and 9%, respectively, contributes the least. Like the result obtained for the gas-powered plant, the extraction process is the major contributor to ionization radiation, and energy conversion contributes the least; transportation and processing do not contribute to the ionization of radiation. The energy conversion stage of the geothermal energy system accounts for 57% of the fine particulate matter formation; this is followed by extraction (27.6%), processing (12.2%), and transport (3.2%). Furthermore, energy conversion (68.5%) contributes the most to terrestrial acidification, while transportation contributes the least (7%). The results further show that extraction is the main cause of freshwater eutrophication, marine eutrophication, terrestrial ecotoxicity, freshwater ecotoxicity, marine ecotoxicity, human carcinogenic toxicity, human noncarcinogenic toxicity, land use, fossil resource scarcity, and water consumption.

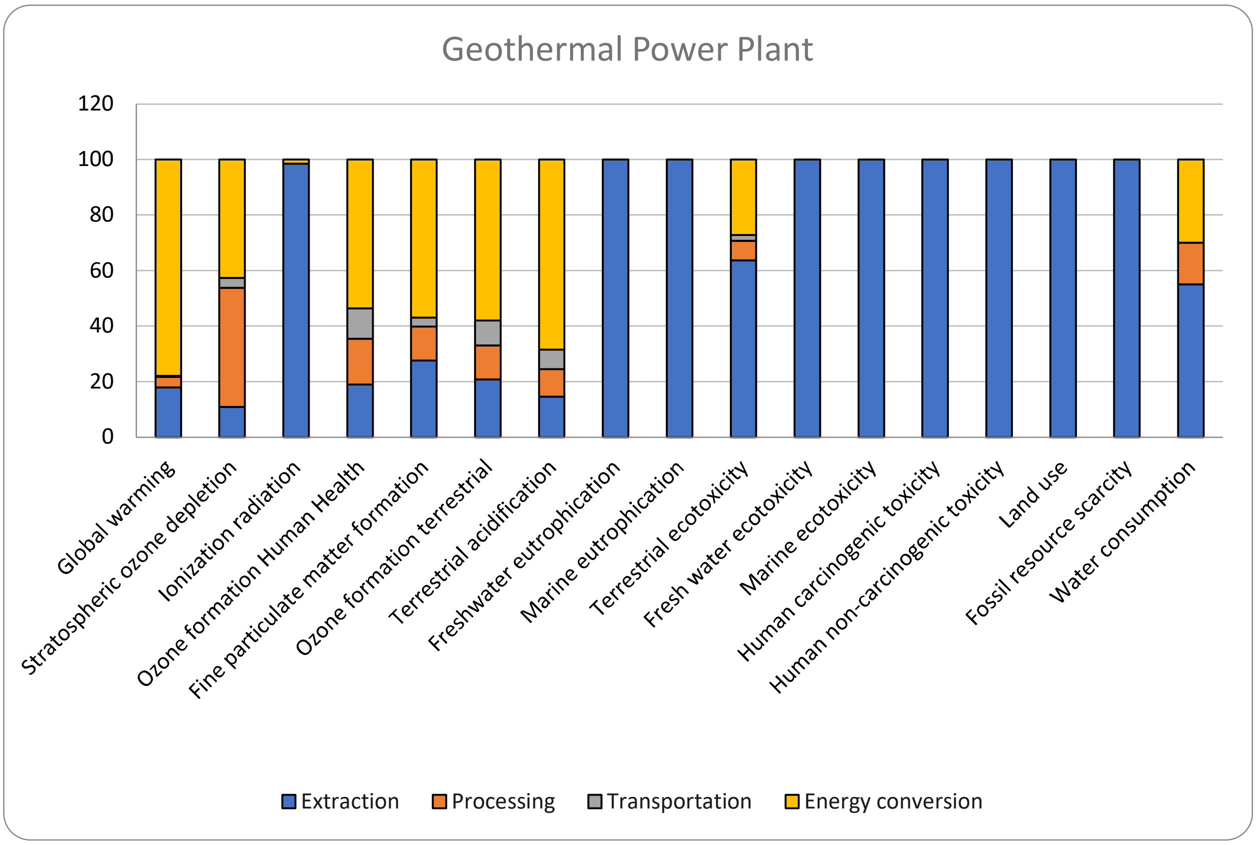

Figure 4. The midpoint characterization of the geothermal power plant.

5. Discussion

This study took a comprehensive approach, combining the LCA approach, which evaluates the environmental impact of various energy systems over their life cycles, with the MCDM approach to rank these systems based on a set of 18 impact categories. This integrated analysis provides a comprehensive understanding of the environmental impact associated with each energy option and a distinct ranking that can direct decision makers toward sustainable energy options.

This study's multicriteria analysis (MCDM) offered a structured framework for assessing the energy alternatives based on multiple environmental criteria. These criteria, which encompass a wide range of environmental impact attributes, are the outputs of the LCA's midpoint characterization process. To ensure an inclusive and objective evaluation, this study used the entropy weight approach to give each criterion a specific weight, and the results showed that all the criteria had a significant role in determining the relative environmental impact of each energy source. The utilization of this particular methodology enhances the reliability of this study's findings by ensuring that no individual criterion exerts excessive influence over the decision-making process.

The examination of energy alternatives in the study, utilizing both COPRAS and ARAS techniques, highlights the strength and reliability of the research findings. The gas-powered power plant has been identified as the most favored alternative based on both methodologies, highlighting its potential as an environmentally advantageous choice. On the other hand, the geothermal power plant, despite its classification as a renewable energy source, was determined to be the least preferred option. The paradoxical nature of this finding implies the existence of potential operational or environmental barriers related to geothermal energy, which warrant additional research and examination. Although the gas-powered and geothermal facilities had the same scores in both techniques, variations were observed in the intermediate rankings. This suggests that although there may be a general agreement regarding the environmental consequences of certain technologies, others necessitate a more intricate examination, as the selected methodology could potentially shape the result.

The comprehensive analysis of midpoint characterization provided a more in-depth examination of the contributions made by diverse production processes to distinct categories of environmental impact. This component of this study offers significant insights into the focal areas of each energy system's life cycle. The contribution of various phases of energy production, from extraction to energy conversion, offers invaluable insight into where interventions may be most effective. The predominance of the energy conversion process in global warming impact, particularly for gas-powered plants, indicates the need for enhanced efficiency and possibly the implementation of carbon capture and storage technologies. The geothermal power plant's ranking as the lowest performer can be attributed to the significant environmental impact associated with energy conversion. This finding implies that the perceived environmental footprint of establishing and operating geothermal facilities may be underestimated. This phenomenon may be attributed to several sources such as land use changes, ecosystem disruptions, or emissions associated with drilling operations.

6. Conclusions

In conclusion, this study has shown how choosing the most suitable energy technology for electrification may be accomplished by integrating life cycle assessment (LCA) and multicriteria decision-making (MCDM) analysis. Decision makers can make well-informed decisions that support efficient and affordable power generation by taking the environmental effects and sustainability features of various energy system alternatives into consideration. The midpoint characterization study utilizing LCA yielded insightful findings regarding the environmental effects of various energy technologies. The 18 impact categories considered in this study allowed for an in-depth assessment of the possible consequences on, among other impacts, global warming, ozone depletion, ionizing radiation, particle creation, acidification, eutrophication, ecotoxicity, and resource scarcity.

These results emphasize the need to fully comprehend the environmental impact of energy systems by considering every stage of their life cycles, from resource extraction to energy generation. This study used MCDM analysis to rate the alternative energy systems according to how well they performed overall when compared to several other factors. The options were evaluated using the COPRAS and ARAS methodologies, which considered both positive and negative features. In all MCDM evaluations, the gas-powered power plant emerged as the most preferred choice, followed by the oil- and hard coal-fired power plants. The geothermal power plant, on the other hand, was deemed to be the least recommended option.

The in-depth midpoint characterization analysis revealed details about the exact phases of the chosen energy systems that were most responsible for their environmental effects. These data are necessary for identifying problem regions and putting effective mitigation measures in place. For instance, in a gas-powered power plant, energy conversion and processing steps were found to be key drivers of global warming, whereas extraction was a major factor in ozone depletion and ecotoxicity. The key findings include the following points:

- The integration of LCA and MCDM analysis enabled an in-depth assessment of the effects of energy systems on the environment and their sustainability.
- The most preferred energy system was identified to be a gas-powered power plant, while the least preferred option was a geothermal power plant.
- With respect to the gas-powered power plant, energy conversion and processing phases were a key cause of global warming.
- Across most of the energy systems, extraction had a considerable impact on ecotoxicity and ozone depletion.
- This study emphasizes how crucial it is to consider an energy system's complete life cycle, from resource extraction to end of life, to fully comprehend its environmental

impact. This study, however, considered the system from resource extraction to the point of getting the system operational based on the available dataset.

While it is true that renewable energy sources like wind and solar have shown considerable promise in lowering GHG emissions, it is also crucial to note that this study employed cradle-to-gate analysis, which involves building the seven highlighted energy systems from the ground up (beginning with raw material extraction). Considering the cradle-to-grave/cradle study of these systems, which will include the operational-stage end of life of the systems, further research is needed in this area. Overall, the integration of LCA and MCDM analysis provides decision makers with an excellent basis for determining the best energy technology for electrification. We can make educated decisions that promote clean and cost-effective power generation while protecting the well-being of current and future generations by considering environmental implications and sustainability criteria.

The findings from this research are extremely important and of significance because they shed light on a variety of issues related to sustainable energy planning and environmental decision making. The integration of life cycle assessment (LCA) and multicriteria decision-making (MCDM) approaches offers a systematic approach for stakeholders and policy makers to prioritize energy sources by evaluating their comprehensive environmental impact. In addition to guiding present choices, this study paves the way for investments in sustainable energy infrastructure in the future. Second, the unanticipated findings, such as the paradoxical environmental impact of geothermal energy, challenge the prevailing assumptions. These findings highlight the need to evaluate energy systems holistically, considering not only direct emissions but also the complex relationships between various production processes and their contributions to various impact categories. This challenges industry standards and prompts a reevaluation of energy options, leading to a more nuanced comprehension of environmental trade-offs.

Finally, the midpoint characterization study delves further into the contributions of individual production stages to distinct effect types. With this level of detail, players in the energy sector can zero in on specific areas for environmental improvement. The findings allow for individualized mitigation measures to address the most pressing environmental concerns by highlighting the steps that contribute most to specific impacts, such as extraction to terrestrial ecotoxicity. The findings of this study are significant because they provide actionable, data-driven guidance for making sustainable energy decisions that consider a wide range of convoluted environmental concerns. Based on the findings of this study, the following are suggested as areas of further studies:

Temporal considerations: As technology advances, the environmental impact of energy systems may change over time. It would be useful to consider how rankings might change as technology develops.

All-inclusive sustainability metrics: while the focus of this study was on environmental effects, integrating social and economic sustainability aspects could give an improved understanding.

Operational vs. construction impacts: considering the cradle-to-grave/cradle study of these systems, which will include the operational-stage end of life of the systems, further research is needed in this area.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/en16186722/s1, Table S1: Impact categories of the energy systems; Table S2: Decision matrix; Table S3: Normarlized decision matrix for COPRAS; Table S4: Weighted Normarlized Decision Matrix (COPRAS); Table S5: Result of COPRAS method; Table S6: Normarlized decision matrix for ARAS; Table S7: Weighted Normarlized Decision Matrix (ARAS); Table S8: Result of ARAS method; Table S9: Dataset used for analysis.

Author Contributions: Conceptualization, B.D.A.; Methodology, O.E.I.; Software, B.D.A. and O.M.B.; Validation, B.D.A., O.E.I. and O.M.B.; Formal analysis, O.E.I. and O.M.B.; Investigation, O.M.B. and O.A.O.; Resources, O.E.I.; Data curation, B.D.A.; Writing–original draft, B.D.A. and O.E.I.; Writing–review & editing, B.D.A. and O.E.I.; Visualization, B.D.A. and O.M.B.; Supervision, O.A.O.; Project administration, O.A.O.; Funding acquisition, O.A.O. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by DUT SCHOLARSHIP SCHEME 2023.

Data Availability Statement: The data presented in this study are available in the supplementary material.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Oyedepo, S.O. Energy and sustainable development in Nigeria: The way forward. *Energy Sustain. Soc.* **2012**, *2*, 15. [CrossRef]
2. Akinbulire, T.O.; Oluseyi, P.O.; Babatunde, O.M. Techno-economic and environmental evaluation of demand side management techniques for rural electrification in Ibadan, Nigeria. *Int. J. Energy Environ. Eng.* **2014**, *5*, 375–385. [CrossRef]
3. Mekonnen, Y.; Sarwat, A.I. Renewable energy supported microgrid in rural electrification of Sub-Saharan Africa. In Proceedings of the 2017 IEEE PES PowerAfrica, Accra, Ghana, 27–30 June 2017; pp. 595–599.
4. Krishna, K.S.; Kumar, K.S. A review on hybrid renewable energy systems. *Renew. Sustain. Energy Rev.* **2015**, *52*, 907–916. [CrossRef]
5. Tian, X.; An, C.; Chen, Z. The role of clean energy in achieving decarbonization of electricity generation, transportation, and heating sectors by 2050: A meta-analysis review. *Renew. Sustain. Energy Rev.* **2023**, *182*, 113404. [CrossRef]
6. Agency, I.E. Access to Electricity. 2020. Available online: https://www.iea.org/reports/sdg7-data-and-projections/access-to-electricity (accessed on 22 July 2023).
7. Adebisi, J.; Ibili, P.; Emezirinwune, M.; Abdulsalam, K. Comparative Study of Hybrid Solar Photovoltaic-Diesel Power Supply System. *Afr. J. Inter/Multidiscip. Stud.* **2023**, *5*, 1–15. [CrossRef]
8. Yu, B.; Fang, D.; Xiao, K.; Pan, Y. Drivers of renewable energy penetration and its role in power sector's deep decarbonization towards carbon peak. *Renew. Sustain. Energy Rev.* **2023**, *178*, 113247. [CrossRef]
9. Ziegler, M.S.; Mueller, J.M.; Pereira, G.D.; Song, J.; Ferrara, M.; Chiang, Y.-M.; Trancik, J.E. Storage requirements and costs of shaping renewable energy toward grid decarbonization. *Joule* **2019**, *3*, 2134–2153. [CrossRef]
10. Vis, I.F.; Ursavas, E. Assessment approaches to logistics for offshore wind energy installation. *Sustain. Energy Technol. Assess.* **2016**, *14*, 80–91. [CrossRef]
11. Kumar, M. Social, economic, and environmental impacts of renewable energy resources. In *Wind Solar Hybrid Renewable Energy System*; IntechOpen: London, UK, 2020; Volume 1.
12. Razmjoo, A.; Kaigutha, L.G.; Rad, M.V.; Marzband, M.; Davarpanah, A.; Denai, M. A Technical analysis investigating energy sustainability utilizing reliable renewable energy sources to reduce CO_2 emissions in a high potential area. *Renew. Energy* **2021**, *164*, 46–57. [CrossRef]
13. Maleki, A.; Askarzadeh, A. Optimal sizing of a PV/wind/diesel system with battery storage for electrification to an off-grid remote region: A case study of Rafsanjan, Iran. *Sustain. Energy Technol. Assess.* **2014**, *7*, 147–153. [CrossRef]
14. Kolhe, M.L.; Ranaweera, K.I.U.; Gunawardana, A.S. Techno-economic sizing of off-grid hybrid renewable energy system for rural electrification in Sri Lanka. *Sustain. Energy Technol. Assess.* **2015**, *11*, 53–64. [CrossRef]
15. Kamari, M.L.; Isvand, H.; Nazari, M.A. Applications of multi-criteria decision-making (MCDM) methods in renewable energy development: A review. *Renew. Energy Res. Appl.* **2020**, *1*, 47–54.
16. Ali, T.; Ma, H.; Nahian, A.J. An analysis of the renewable energy technology selection in the southern region of Bangladesh using a hybrid multi-criteria decision making (MCDM) method. *Int. J. Renew. Energy Res.* **2019**, *9*, 1838–1848.
17. Lee, H.-C.; Chang, C.-T. Comparative analysis of MCDM methods for ranking renewable energy sources in Taiwan. *Renew. Sustain. Energy Rev.* **2018**, *92*, 883–896. [CrossRef]
18. *ISO 14040*; Environmental Management: Life Cycle Assessment. Principles and Framework; ISO: Geneva, Switzerland, 2006. Available online: https://www.iso.org/obp/ui/#iso:std:iso:14040:ed-2:v1:en (accessed on 31 July 2023).
19. *ISO 14044*; Environmental Management: Environmental Management: Life Cycle Assessment. Requirements and Guidelines; ISO: Geneva, Switzerland, 2006. Available online: https://www.iso.org/obp/ui/#iso:std:iso:14044:ed-1:v1:en (accessed on 31 July 2022).
20. Jordaan, S.M.; Combs, C.; Guenther, E. Life cycle assessment of electricity generation: A systematic review of spatiotemporal methods. *Adv. Appl. Energy* **2021**, *3*, 100058. [CrossRef]
21. Barros, M.V.; Salvador, R.; Piekarski, C.M.; de Francisco, A.C.; Freire, F.M.C.S. Life cycle assessment of electricity generation: A review of the characteristics of existing literature. *Int. J. Life Cycle Assess.* **2020**, *25*, 36–54. [CrossRef]
22. Mahmud, M.P.; Farjana, S.H. Comparative life cycle environmental impact assessment of renewable electricity generation systems: A practical approach towards Europe, North America and Oceania. *Renew. Energy* **2022**, *193*, 1106–1120. [CrossRef]

23. de Haes, H.A.U.; Heijungs, R. Life-cycle assessment for energy analysis and management. *Appl. Energy* **2007**, *84*, 817–827. [CrossRef]
24. Bhat, I.; Prakash, R. LCA of renewable energy for electricity generation systems—A review. *Renew. Sustain. Energy Rev.* **2009**, *13*, 1067–1073.
25. Muench, S.; Guenther, E. A systematic review of bioenergy life cycle assessments. *Appl. Energy* **2013**, *112*, 257–273. [CrossRef]
26. Santoyo-Castelazo, E.; Gujba, H.; Azapagic, A. Life cycle assessment of electricity generation in Mexico. *Energy* **2011**, *36*, 1488–1499. [CrossRef]
27. Dzikuć, M.; Piwowar, A. Ecological and economic aspects of electric energy production using the biomass co-firing method: The case of Poland. *Renew. Sustain. Energy Rev.* **2016**, *55*, 856–862. [CrossRef]
28. Rodríguez, M.R.; Cespón, M.F.; De Ruyck, J.; Guevara, V.O.; Verma, V. Life cycle modeling of energy matrix scenarios, Belgian power and partial heat mixes as case study. *Appl. Energy* **2013**, *107*, 329–337. [CrossRef]
29. Messagie, M.; Mertens, J.; Oliveira, L.; Rangaraju, S.; Sanfelix, J.; Coosemans, T.; Van Mierlo, J.; Macharis, C. The hourly life cycle carbon footprint of electricity generation in Belgium, bringing a temporal resolution in life cycle assessment. *Appl. Energy* **2014**, *134*, 469–476. [CrossRef]
30. Kabayo, J.; Marques, P.; Garcia, R.; Freire, F. Life-cycle sustainability assessment of key electricity generation systems in Portugal. *Energy* **2019**, *176*, 131–142. [CrossRef]
31. Garcia, R.; Marques, P.; Freire, F. Life-cycle assessment of electricity in Portugal. *Appl. Energy* **2014**, *134*, 563–572. [CrossRef]
32. Akber, M.Z.; Thaheem, M.J.; Arshad, H. Life cycle sustainability assessment of electricity generation in Pakistan: Policy regime for a sustainable energy mix. *Energy Policy* **2017**, *111*, 111–126. [CrossRef]
33. Turconi, R.; Tonini, D.; Nielsen, C.F.; Simonsen, C.G.; Astrup, T. Environmental impacts of future low-carbon electricity systems: Detailed life cycle assessment of a Danish case study. *Appl. Energy* **2014**, *132*, 66–73. [CrossRef]
34. Laurent, A.; Espinosa, N. Environmental impacts of electricity generation at global, regional and national scales in 1980–2011: What can we learn for future energy planning? *Energy Environ. Sci.* **2015**, *8*, 689–701. [CrossRef]
35. Barros, M.V.; Piekarski, C.M.; De Francisco, A.C. Carbon footprint of electricity generation in Brazil: An analysis of the 2016–2026 period. *Energies* **2018**, *11*, 1412. [CrossRef]
36. Silva, D.A.L.; Delai, I.; Montes, M.L.D.; Ometto, A.R. Life cycle assessment of the sugarcane bagasse electricity generation in Brazil. *Renew. Sustain. Energy Rev.* **2014**, *32*, 532–547. [CrossRef]
37. Wu, X.; Wu, K.; Zhang, Y.; Hong, Q.; Zheng, C.; Gao, X.; Cen, K. Comparative life cycle assessment and economic analysis of typical flue-gas cleaning processes of coal-fired power plants in China. *J. Clean. Prod.* **2017**, *142*, 3236–3242. [CrossRef]
38. Li, H.; Jiang, H.-D.; Dong, K.-Y.; Wei, Y.-M.; Liao, H. A comparative analysis of the life cycle environmental emissions from wind and coal power: Evidence from China. *J. Clean. Prod.* **2020**, *248*, 119192. [CrossRef]
39. Gaete-Morales, C.; Gallego-Schmid, A.; Stamford, L.; Azapagic, A. Life cycle environmental impacts of electricity from fossil fuels in Chile over a ten-year period. *J. Clean. Prod.* **2019**, *232*, 1499–1512. [CrossRef]
40. Günkaya, Z.; Özdemir, A.; Özkan, A.; Banar, M. Environmental performance of electricity generation based on resources: A life cycle assessment case study in Turkey. *Sustainability* **2016**, *8*, 1097. [CrossRef]
41. Mahmud, M.P.; Huda, N.; Farjana, S.H.; Lang, C. Environmental impacts of solar-photovoltaic and solar-thermal systems with life-cycle assessment. *Energies* **2018**, *11*, 2346. [CrossRef]
42. Olagunju, B.D. Life Cycle Assessment of the Production of Cement: A South African Case Study. Master's Thesis, Durban University of Technology, Durban, South Africa, 2021.
43. Goedkoop, M.; Heijungs, R.; Huijbregts, M.; De Schryver, A.; Struijs, J.; Van Zelm, R. ReCiPe 2008. In *A Life Cycle Impact Assessment Method Which Comprises Harmonised Category Indicators at the Midpoint and the Endpoint Level*; Ministry of VROM. ReCiPe: The Hague, The Netherlands, 2009; Volume 1, pp. 1–126.
44. Martín-Gamboa, M.; Iribarren, D.; García-Gusano, D.; Dufour, J. A review of life-cycle approaches coupled with data envelopment analysis within multi-criteria decision analysis for sustainability assessment of energy systems. *J. Clean. Prod.* **2017**, *150*, 164–174. [CrossRef]
45. Zhou, P.; Ang, B.; Poh, K. Decision analysis in energy and environmental modeling: An update. *Energy* **2006**, *31*, 2604–2622. [CrossRef]
46. Bhandari, R.; Arce, B.E.; Sessa, V.; Adamou, R. Sustainability assessment of electricity generation in Niger using a weighted multi-criteria decision approach. *Sustainability* **2021**, *13*, 385. [CrossRef]
47. Shaaban, M.; Scheffran, J.; Böhner, J.; Elsobki, M.S. Sustainability assessment of electricity generation technologies in Egypt using multi-criteria decision analysis. *Energies* **2018**, *11*, 1117. [CrossRef]
48. Dias, L.C.; Domingues, A.R. On multi-criteria sustainability assessment: Spider-gram surface and dependence biases. *Appl. Energy* **2014**, *113*, 159–163. [CrossRef]
49. Motuzienė, V.; Rogoža, A.; Lapinskienė, V.; Vilutienė, T. Construction solutions for energy efficient single-family house based on its life cycle multi-criteria analysis: A case study. *J. Clean. Prod.* **2016**, *112*, 532–541. [CrossRef]
50. Myllyviita, T.; Leskinen, P.; Seppälä, J. Impact of normalisation, elicitation technique and background information on panel weighting results in life cycle assessment. *Int. J. Life Cycle Assess.* **2014**, *19*, 377–386. [CrossRef]
51. Jeswani, H.K.; Azapagic, A.; Schepelmann, P.; Ritthoff, M. Options for broadening and deepening the LCA approaches. *J. Clean. Prod.* **2010**, *18*, 120–127. [CrossRef]

52. Von Doderer, C.; Kleynhans, T. Determining the most sustainable lignocellulosic bioenergy system following a case study approach. *Biomass Bioenergy* **2014**, *70*, 273–286. [CrossRef]
53. Boufateh, I.; Perwuelz, A.; Rabenasolo, B.; Jolly-Desodt, A.-M. Multiple criteria decision-making for environmental impacts optimisation. *Int. J. Bus. Perform. Supply Chain. Model.* **2011**, *3*, 28–42. [CrossRef]
54. Rowley, H.V.; Peters, G.M.; Lundie, S.; Moore, S.J. Aggregating sustainability indicators: Beyond the weighted sum. *J. Environ. Manag.* **2012**, *111*, 24–33. [CrossRef]
55. de Souza, R.G.; Clímaco, J.C.N.; Sant'Anna, A.P.; Rocha, T.B.; do Valle, R.d.A.B.; Quelhas, O.L.G. Sustainability assessment and prioritisation of e-waste management options in Brazil. *Waste Manag.* **2016**, *57*, 46–56. [CrossRef]
56. Zagonari, F. Four sustainability paradigms for environmental management: A methodological analysis and an empirical study based on 30 Italian industries. *Sustainability* **2016**, *8*, 504. [CrossRef]
57. Myllyviita, T.; Antikainen, R.; Leskinen, P. Sustainability assessment tools—Their comprehensiveness and utilisation in company-level sustainability assessments in Finland. *Int. J. Sustain. Dev. World Ecol.* **2017**, *24*, 236–247. [CrossRef]
58. Bogacka, M. Multicriteria analysis of coal mine. In Proceedings of the 15th International Multidisciplinary Scientific Geoconference SGEM 2015, Albena, Bulgaria, 18–24 June 2015; pp. 493–500.
59. Burchart-Korol, D.; Korol, J.; Fugiel, A. Development of Eco-Efficiency Evaluation with Multicriteria Analysis for Steel Production. In Proceedings of the 23rd International Conference on Metallurgy and Materials METAL, Brno, Czech Republic, 21–23 May 2014.
60. Zanghelini, G.M.; Cherubini, E.; Soares, S.R. How multi-criteria decision analysis (MCDA) is aiding life cycle assessment (LCA) in results interpretation. *J. Clean. Prod.* **2018**, *172*, 609–622. [CrossRef]
61. Myllyviita, T.; Holma, A.; Antikainen, R.; Lähtinen, K.; Leskinen, P. Assessing environmental impacts of biomass production chains–application of life cycle assessment (LCA) and multi-criteria decision analysis (MCDA). *J. Clean. Prod.* **2012**, *29*, 238–245. [CrossRef]
62. Domingues, A.R.; Marques, P.; Garcia, R.; Freire, F.; Dias, L.C. Applying multi-criteria decision analysis to the life-cycle assessment of vehicles. *J. Clean. Prod.* **2015**, *107*, 749–759. [CrossRef]
63. Sohn, J.L.; Kalbar, P.P.; Birkved, M. Life cycle based dynamic assessment coupled with multiple criteria decision analysis: A case study of determining an optimal building insulation level. *J. Clean. Prod.* **2017**, *162*, 449–457. [CrossRef]
64. Kumar, A.; Sah, B.; Singh, A.R.; Deng, Y.; He, X.; Kumar, P.; Bansal, R. A review of multi criteria decision making (MCDM) towards sustainable renewable energy development. *Renew. Sustain. Energy Rev.* **2017**, *69*, 596–609. [CrossRef]
65. Hauschild, M.Z. Introduction to LCA methodology. In *Life Cycle Assessment: Theory and Practice*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 59–66.
66. Owsianiak, M.; Bjørn, A.; Laurent, A.; Molin, C.; Ryberg, M.W. LCA applications. In *Life Cycle Assessment: Theory and Practice*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 31–41.
67. Torkayesh, A.E.; Rajaeifar, M.A.; Rostom, M.; Malmir, B.; Yazdani, M.; Suh, S.; Heidrich, O. Integrating life cycle assessment and multi criteria decision making for sustainable waste management: Key issues and recommendations for future studies. *Renew. Sustain. Energy Rev.* **2022**, *168*, 112819. [CrossRef]
68. Esmail, B.; Geneletti, D. Multi-criteria decision analysis for nature conservation: A review of 20 years of applications. *Methods Ecol. Evol.* **2018**, *9*, 42–53. [CrossRef]
69. Campos-Guzmán, V.; García-Cáscales, M.S.; Espinosa, N.; Urbina, A. Life Cycle Analysis with Multi-Criteria Decision Making: A review of approaches for the sustainability evaluation of renewable energy technologies. *Renew. Sustain. Energy Rev.* **2019**, *104*, 343–366. [CrossRef]
70. Tziolas, E.; Bournaris, T.; Manos, B.; Nastis, S. Life cycle assessment and multi-criteria analysis in agriculture: Synergies and insights. In *Multicriteria Analysis in Agriculture: Current Trends and Recent Applications*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 289–321.
71. Taherdoost, H.; Madanchian, M. Multi-criteria decision making (MCDM) methods and concepts. *Encyclopedia* **2023**, *3*, 77–87. [CrossRef]
72. Thakkar, J.J.; Thakkar, J.J. Complex Proportion Assessment Method (COPRAS). In *Multi-Criteria Decision Making*; Springer: Singapore, 2021; Volume 336, pp. 219–237. [CrossRef]
73. Thakur, P.; Kizielewicz, B.; Gandotra, N.; Shekhovtsov, A.; Saini, N.; Sałabun, W. The Group Decision-Making Using Pythagorean Fuzzy Entropy and the Complex Proportional Assessment. *Sensors* **2022**, *22*, 4879. [CrossRef]
74. Liu, N.; Xu, Z. An overview of ARAS method: Theory development, application extension, and future challenge. *Int. J. Intell. Syst.* **2021**, *36*, 3524–3565. [CrossRef]
75. Martin, N.; Deepak, F.E. Application of new additive ratio assessment (NARAS) method in selection of material for optimal design of engineering components. *Mater. Today Proc.* **2019**, *11*, 1049–1053. [CrossRef]
76. Dias, L.C.; Freire, F.; Geldermann, J. Perspectives on multi-criteria decision analysis and life-cycle assessment. In *New Perspectives in Multiple Criteria Decision Making: Innovative Applications and Case Studies*; Springer: Berlin/Heidelberg, Germany, 2019; pp. 315–329.