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Research Article

INTEGRATING FUZZY-MACHINE LEARNING AND BIBLIOMETRIC ANALYSIS FOR SDG-ALIGNED RENEWABLE ENERGY STRATEGIES

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Sustainable Development Goals (SDGs), renewable energy, Fuzzy-Analytical Hierarchy Process (F-AHP), Fuzzy-TOPSIS, machine learning, and bibliometric analysis

ABSTRACT

This research aims to analyze and predict the most suitable renewable energy source using a machine learning model aligned with the Sustainable Development Goals (SDGs). A bibliometric analysis is conducted to select relevant literature from Scopus and Web of Science databases to identify key sustainability criteria. The criteria weights are determined using the fuzzy Analytical Hierarchy Process (AHP), while prediction is performed using a logistic regression model combined with fuzzy TOPSIS. This approach ensures a data-driven selection of renewable energy sources. The results highlight 'Technological Innovation' as the most critical criterion, while 'Concentrating Solar' emerges as the best-suited renewable energy option. The proposed model offers a structured framework to aid policy-makers in selecting appropriate renewable energy solutions for different regions. This study provides a systematic decision-making model for renewable energy selection, incorporating advanced machine learning and fuzzy MCDM techniques. Future research can explore additional machine learning models to enhance prediction accuracy and decision-making efficiency.

1 INTRODUCTION

Renewable energy sources (RES) are among the cleanest options available, as they do not harm the environment. They are also considered a renewable form of energy, capable of being replenished over time. Despite this, their full potential is not yet realized, primarily due to a limited understanding and insufficient technological advancements. Choosing the right renewable energy source can be challenging because of the many options available, each with its benefits, limitations, and impacts. Traditional methods for selecting energy sources often depend on isolated factors or expert opinions, which do not provide the comprehensive, data-driven insights necessary to address the complex and varied needs of today's energy landscape. This study aims to fill this gap by creating a machine learning model that predicts the most suitable renewable energy sources based on criteria derived from bibliometric analysis, to support Sustainable Development Goals (SDGs) related to energy and climate action[1].

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The "United Nations (UN)" set up 17 Sustainable Development Goals (SDGs) in 2015, addressing social, economic, and environmental issues. The main objectives of these SDGs are to safeguard the environment and foster peace and stability in the least developed countries by following UN guidelines [2]. The seventh goal of the Sustainable Development Goals (SDGs), "Affordable and Clean Energy," seeks to ensure that every household has access to power at a lower cost while protecting the environment by 2030 [3]. Each country, local area, or organization has the flexibility to determine its approach to meet these SDGs. However, there are numerous challenges to achieving these goals, including sustainable urban development, job creation, access to quality education, industrial growth, climate action, and health and well-being, among others. [4].

According to the Ministry of New and Renewable Energy, Government of India (November 2023), India has seen a remarkable 396% increase in its non-fossil fuel capacity over the past 8.5 years, now exceeding 179.57 GW. Nuclear and large hydropower sources contribute to about 42% of this total capacity (MNRE| India, n.d.). In 2022, India made significant strides by achieving a 9.83% rise in renewable energy installations, marking an important step towards sustainable energy development. The solar energy capacity has surged 30 times in the last nine years, reaching 74.30 GW as of January 2024 (MSPI | Government Of India, n.d.). Despite this progress, fossil fuels continue to dominate the global energy landscape, making up approximately 70% of total energy consumption in 2023. This emphasizes the urgency of accelerating efforts to achieve the objectives of Sustainable Development Goal 7, which seeks to ensure “affordable and clean energy for all” [7]. Researchers have developed a variety of methods and techniques for selecting renewable energy sources. Carbon emissions pose a significant challenge that directly influences the choice of renewable energy options.

Researchers are exploring advanced methods to tackle the intricate challenges related to renewable energy, aiming for global sustainability. This study introduces a sophisticated energy prediction technique focused on sustainability. By combining machine learning methods with fuzzy multi-criteria decision-making (MCDM), a structured system is created to address complex decision-making issues. [8]. To promote sustainability, various criteria derived from bibliometric analysis are applied to this integrated approach. The research includes a case study that leverages insights from the bibliometric analysis to identify current trends in technology and methods for predicting optimal renewable energy sources. The findings indicate that fuzzy MCDM [9] in conjunction with machine learning techniques is effective in this field. This research merges these techniques to support sustainable development goals. The study is organized into three main sections. The first part presents a comprehensive bibliometric analysis to identify key tools and techniques using targeted keywords [10]. The second part involves assigning weights to the criteria derived from the bibliometric analysis through fuzzy AHP [11]. Finally, the weighted criteria are applied to eight renewable energy sources using a logistic regression machine learning technique to determine the most suitable renewable energy option.

The subsequent research is organized as follows: a literature review was conducted to investigate studies related to renewable energy selection, utilizing bibliometric analysis to identify various tools, techniques, and sustainable criteria. The methods discussed in the literature section, such as fuzzy AHP, TOPSIS, and machine learning [12] are applied in the methodology section. The results and discussion section presents the outcomes and findings of the methodology, along with in-depth discussions on these results. It also highlights how Sustainable Development Goal 7 aligns with the renewable energy selection process. Finally, the conclusions offer a comprehensive summary of the research, including its implications, limitations, and suggestions for future work related to the proposed research.

2 Literature review

"Multi-criteria decision-making" (MCDM) is a widely used approach in research, particularly for selecting or predicting the most suitable renewable energy sources. Different types of MCDM tools have been developed based on the specific conditions and factors involved in the decision-making process. Techniques such as the "Analytic Hierarchy Process (AHP)" (Saaty, T.L. (1977) Scientific Research Publishing, n.d.). "Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)," "Elimination and Choice Translating Reality (ELECTRE)," and "VIsekriterijumsko KOmpromisno Rangiranje (VIKOR)" are commonly utilized in this field. These various MCDM techniques enable researchers and stakeholders to rank renewable energy options using both qualitative and quantitative data [14]. Additionally, MCDM techniques can be combined with fuzzy methods, which enhance the relevance and applicability of results in real-world scenarios [15]. The integration of fuzzy techniques with MCDM is beneficial as it allows for the management of uncertainty, vagueness, and ambiguity when addressing real-life situations [16].

The benefit of employing fuzzy logic with MCDM is that it can handle uncertainty, vagueness, and ambiguity while handling an actual situation. [17]. The data, be it linguistically discrete or numerical, can be further divided, employing a fuzzy scale, which can be highly beneficial for researchers or policymakers to resolve decision-making issues. Current research indicates that "Artificial Intelligence (AI)" and "Machine Learning (ML)" are being applied in combination with the MCDM and fuzzy approach. This hybrid method can be employed to enhance the performance and efficiency of the current prediction model, or can be employed to create a new one for the same selection process [8,18]. "Support Vector Machine (SVM)" is a renowned ML method that is employed for ranking and prediction, how the renewable energy sector operates based on various types of data [19,20]. "Decision Trees and Random Forest" can also be applied to explore complex decision-making issues, which provides an insight into the different factors affecting the choice of renewable energy sources [21,22].

Sustainable Development Goal 7 focuses on clean and affordable energy for all and places special emphasis on renewable energy [23]. Sustainable criterion selection poses a challenge on its own, especially in the context of renewable energy. This is because selection criteria can be global, socioeconomic, geographical, environmental, as well as cultural (Büyüközkan et al., 2018a; Sitorus & Brito-Parada, 2022). There has been great effort in the research of renewable energies and energies associated with it. Numerous IP scholars have proposed different models and policies to resolve this problem. MCDM is considered a highly suitable technique for resolving decision-making problems [26,27]. It can help to assign values of weights and ranks (AHP and TOPSIS methods) to elements in a defined system of selection processes [28]. The AHP and TOPSIS methods have been used in this field by many researchers [12]. A study where AHP and Delphi Methods were used for ranking renewable energies in India was done successfully [29]. For assessment of criteria and alternative options in different blocks of the region, [30] conducted similar research using AHP.[31] claims that researchers also applied AHP Shannon Entropy to the MOORA evaluation in the renewable energy project. Another study was conducted in Iran [32], that uses AHP, TOPSIS, and SAW to determine the best appropriate criterion and renewable energy in five climatic zones. Research also employs AHP to conduct our study on finding smart cities in western India [33].

When the MCDM technique is applied to a real-life scenario, it might result in uncertainty, ambiguity, and confusion [34]. These can be addressed by combining fuzzy sets with the MCDM approach [16,35,36]. There are other occasions where these two strategies have been combined and employed in the energy selection process. The authors use "Fuzzy-TOPSIS" and demonstrate that ambiguity and uncertainty were effectively addressed when determining the most appropriate renewable energy [37]. The authors compare "Fuzzy TOPSIS and Fuzzy PROMETHEE" after rating the renewable energy sources. A study used AHP and Fuzzy TOPSIS to identify the most critical elements in determining the ranking of renewable energy in Pakistan [38]. [39] successfully employed "interval type-2 fuzzy sets (IT2FSs)" and TOPSIS to identify renewable energy.

Decision-making can be more effective if it is done in a hesitant environment where the decision-maker is reluctant to share his or her opinions. Some of the researchers have investigated the "Hesitant Fuzzy Linguistic set" along with "AHP and COPRAS" operating on many criteria and sub-criteria while attaining the "Sustainable Development Goals" [40–42]. One introduced a new fuzzy aggregation operator for aggregating decision-makers' evaluations, using fuzzy weights rather than crisp ones [43]. To demonstrate how good the improved CODAS method is, the authors apply a case study on choosing renewable energy sources in Turkey by several criteria. They contrast this technique with two alternative CODAS approaches in existing studies that apply interval-valued intuitionistic fuzzy logic. "Type-2 fuzzy sets and Hesitant fuzzy TOPSIS" were used to find out the relative importance of each criterion for identifying appropriate renewable energy alternatives. They then tested the sensitivity of the results to changes in those criteria[36].

3 METHODOLOGY ADOPTED

This research is structured in a series of phases designed in such a way as to predict suitable renewable energy sources based on key criteria aligning with Sustainable Development Goal 7. The methodology is shown in Figure 1, which is organized as follows:

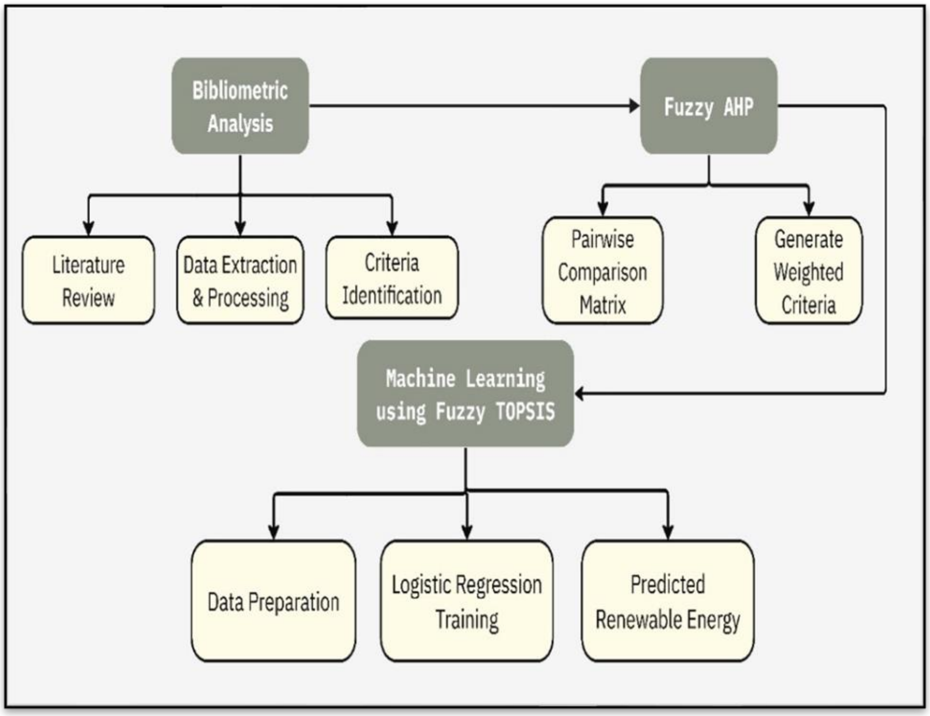

Figure 1: Renewable Energy Prediction Model

3.1 BIBLIOMETRIC ANALYSIS

The study begins with a bibliometric analysis to systematically review and identify the most relevant literature, criteria, methods, and tools commonly used in renewable energy selection research. It involves collecting and analyzing relevant documents from Scopus and Web of Science (WoS) databases, followed by describing the search syntax, filters, and bibliometric tool used to conduct the study, as shown in Figure 2.

An R programming tool called "Bibliometrix" with a web-based interface called "Biblioshiny" is used in the current work to perform the analysis. To ensure coverage of all pertinent papers in this field of study, the search employed a keyword string that included phrases as illustrated in Figure 3. A total of 2,017 research articles were obtained from Web of Science (WoS) and 2,292 from Scopus. The various criteria aligned with Sustainable Development Goal 7 are selected from these articles under expert guidance from academia, the environment, and industry. The graphs and charts from this study are analyzed, and some are explained in the results section. To prepare the literature for in-depth examination, filters are applied to the original dataset. To examine changing approaches, studies from the year 2000 onward were included.

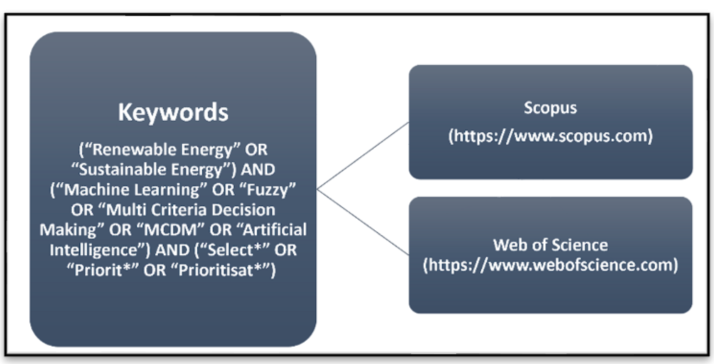

Figure 3: Search Syntax for Carrying Bibliometric Analysis

After the English language filter was applied, a total of 1,936 articles from WoS and 2,151 articles from Scopus were chosen. R's mergeDbSources () function was used to look for overlap between the datasets from the two databases, and 1,321 common articles were found.

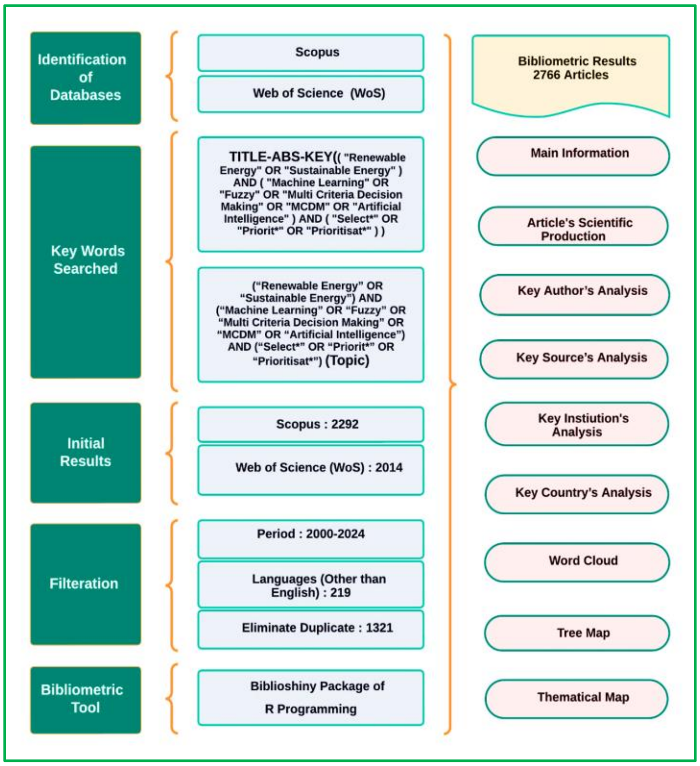

Figure 2: Steps Involved in Bibliometric Analysis

3.2 FUZZY ANALYTIC HIERARCHY PROCESS (FUZZY AHP) FOR CRITERIA WEIGHTING

After identifying the criteria fulfilling Sustainable Development Goal 7, the Fuzzy AHP method will be applied to assign weights to each criterion. The identified criteria are 'Environmental Impact', 'Resource Availability', 'Community Support and Acceptance', 'Technological Innovation and Research Opportunities', and 'Socio-Economic Impact Assessment'. A Fuzzy AHP can handle the uncertainty and subjective judgment involved in weighing complex criteria. A pairwise comparison is conducted, where experts rate the importance of each criterion relative to others as per the linguistic fuzzy Table 1. The output of this step is a set of weighted criteria, which will serve as inputs for the machine learning model. The process is done as follows:

3.3 WEIGHT CALCULATION VIA NORMALIZATION

Given a defuzzified matrix M, where each element represents the relative importance between criteria, we first calculate the sum of each column, sum_j. Each element M_{ij} is then normalized by dividing by its column sum, forming a normalized matrix M_{norm}:

$$M_{norm}[i,j] = \frac{M_{ij}}{sum_j} \quad (1)$$

The average of each row in M_{norm} gives the final weight W_i for each criterion:

$$W_i = \frac{\sum_j M_{norm}[i,j]}{number\ of\ columns} \quad (2)$$

Table 1: Linguistic Fuzzy Scale Table

Linguistic Term	Abbreviation	Triangular Fuzzy Number
Extremely High Significant	EHS	(4,5,6)
Very High Significant	VHS	(3,4,5)
Moderately High Significant	MHS	(2,3,4)
High Significant	HS	(1,2,3)
Close Significant	CS	(1,1,1)
Low Significant	LS	$(\frac{1}{3}, \frac{1}{2}, 1)$
Moderately Low Significant	MLS	$(\frac{1}{4}, \frac{1}{3}, \frac{1}{2})$
Very Low Significant	VLS	$(\frac{1}{5}, \frac{1}{4}, \frac{1}{3})$
Extremely Low Significant	ELS	$(\frac{1}{6}, \frac{1}{5}, \frac{1}{4})$

3.4 CONSISTENCY EVALUATION

To assess consistency, the maximum eigenvalue λ_{max} of M is calculated. The Consistency Index (CI) is then derived:

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (3)$$

where n is the number of criteria. The Consistency Ratio (CR) is calculated using the Random Index (RI), a constant based on n:

$$CR = \frac{CI}{RI} \quad (4)$$

3.5 MACHINE LEARNING WITH TOPSIS FOR PREDICTIVE ANALYSIS

The next step is to apply machine learning integrated with TOPSIS to predict the most suitable renewable energy source. Eight renewable energies, namely: solar PV, solar thermal, concentrating solar, wind, hydropower, biomass, waste-to-energy, and geothermal, are considered in this case study. In this step, machine learning models use weighted criteria to identify patterns and relationships among renewable energy options. TOPSIS is applied within the machine learning model to evaluate the degree to which each energy option aligns with an ideal solution based on the weighted criteria. This will allow the model to predict the renewable energy source that best meets the specified conditions without ranking them in a traditional sense. The logistic regression machine learning algorithm has been tested for final analysis. The method is mentioned as follows:

3.5.1 FUZZY DECISION MATRIX AND NORMALIZATION

The initial matrix, representing energy options and criteria, uses fuzzy triangular numbers to account for uncertainty. Each criterion is normalized by dividing elements by a computed normalization factor to make values comparable.

3.5.2 WEIGHT APPLICATION AND IDEAL SOLUTIONS (TOPSIS)

The weighted matrix is obtained by the various weight combinations applied to the normalized matrix. The maximum (FPIS) and minimum (FNIS) values for each criterion are then calculated. For each alternative, distances to FPIS d_{pos} and FNIS d_{neg} are computed using Euclidean distance, where:

$$d_{pos}[i] = \sqrt{\sum (w[i,j] - FPIS_j)^2} \quad (5)$$

$$d_{neg}[i] = \sqrt{\sum(w[i,j] - FNIS_j)^2} \quad (6)$$

The closeness coefficient for each alternative is given by:

$$Closeness[\mathrm{i}] = \frac{d_{pos}[i]}{d_{pos}[i] + d_{neg}[i]} \quad (7)$$

This value ranks alternatives based on their proximity to the ideal solution.

3.6 LOGISTIC REGRESSION FOR PREDICTION

After ranking the alternatives, logistic regression predicts the best choice based on the criteria weights. Logistic regression estimates the probability of each alternative being the best by using the formula:

$$P = \frac{1}{1+e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_0 x_n)}} \quad (8)$$

where β represents the model coefficients and x the input features (criteria weights).
In the analysis, a logistic regression classifier is used to evaluate the rankings of renewable energy alternatives based on environmental impact, resource availability, Technological innovation, social acceptance, and socio-economic influence. The model is trained on a dataset created from rankings generated under varying priority combinations of these criteria. Each unique weighting defines a different prioritization, allowing the model to detect patterns in the rankings based on how criteria are valued. The dataset is split into 80:20 ratios for training and testing. To maintain uniformity, our data is divided and split into 42 random states that give proper regeneration of subsets for training and testing, with almost 200 iterations performed for better analysis, as shown in Figure 4 below, implemented using Python code. Sensitivity analysis is used to validate or authenticate the results by considering the various cases where the weights of all considered criteria are varied systematically. This will also help to check the robustness and efficiency of the proposed model under varying conditions.

Figure 4: Python Code for Model Prediction

4 RESULTS AND DISCUSSIONS

The results obtained for the three phases are discussed in sub-sections as follows:

4.1 BIBLIOMETRIC RESULTS

The main bibliometric information for the renewable energy selection is obtained using the "biblioshiny program". A total of 2766 research documents were obtained from 1042 sources between the years 2000 and 2024. The total number of authors who published the related articles is 6748, and 117 documents were single-authored. The average citation per document is 23.23.

Figure 5 shows the word cloud obtained from the bibliometric analysis, which identifies keywords like "renewable energy," "selection," "optimization," and "multicriteria decision-making" as the most frequently mentioned keywords for the related research. The figure highlights the most important research area, developing renewable energy selection techniques, and the important theme working in this research area. To work for sustainable development, integrating concepts like fuzzy logic and machine learning is essential for decision-making in renewable energy systems.

Figure 5: Word Cloud Representing Most Frequent Research Words

Our bibliographic study shows that "machine learning" has emerged as the leading topic in renewable energy selection, with a notable rise in interest from the years 2018 to 2022, as illustrated in Figure 6. This trend highlights the increasing focus on advanced algorithms to enhance efficiency, support sustainable development, and improve decision-making in renewable energy systems. The growing density of data points reflects the expanding scholarly attention on the intersection of machine learning and sustainability in this field.

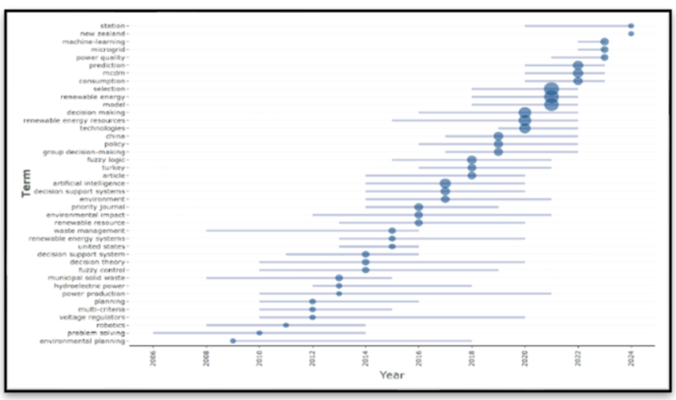

Figure 6: Trending topic in RE selection research

Figure 7 presents a bibliometric network visualization for renewable energy selection, with "renewable energy selection" as the central node connected to key terms like "multicriteria decision-making," "analytic hierarchy process," "optimization," and "site selection." Color clusters highlight thematic groupings and connections between these concepts, providing an overview of current research themes and trends in the field.

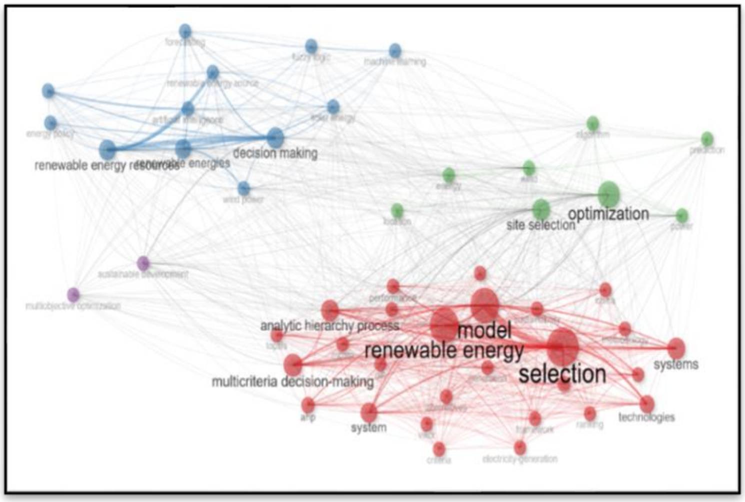

Figure 7: Co-occurrence Network showing Mapping of Various Research Themes

Figure 8 displays a dendrogram illustrating clusters of research articles focused on renewable energy preferences. In this visual, horizontal lines connect related studies, while each vertical line represents an individual study. Studies that branch closer together are more similar in content. Distinct clusters center around major topics like "wind power," "renewable energy resources," and "sustainable development," pinpointing primary areas of interest. The close link between "renewable energy resources" and "sustainable development" underscores a significant research focus on integrating sustainability with renewable energy applications. This diagram offers a clear view of core themes and connections, helping to direct future research efforts.

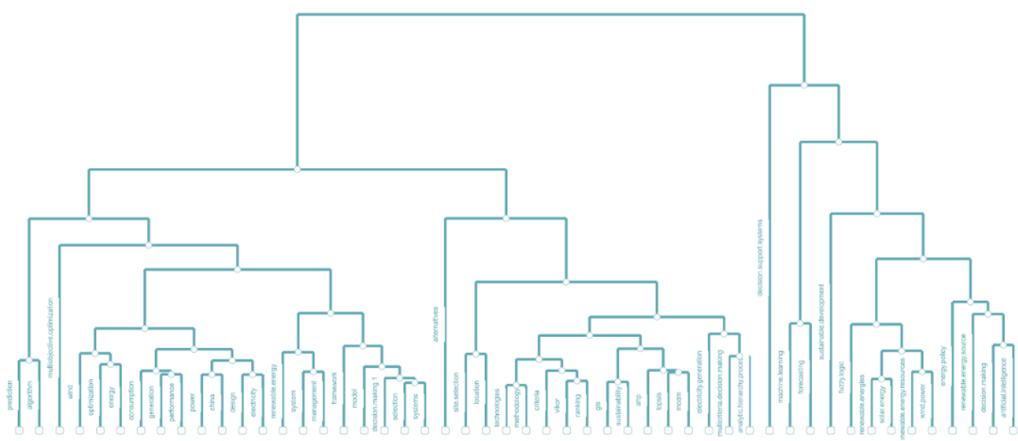

Figure 8: Dendrogram Showing the Relationship of the Renewable Energy Selection Studies

The bibliometric analysis in this study has identified the techniques for predicting renewable energy, like the fuzzy AHP for weighing criteria and TOPSIS for evaluating options. These methods allow for clear and structured decision-making by assessing renewable energy alternatives based on multiple factors and handling uncertainties. Additionally, machine learning has emerged as a significant area in renewable energy research, with an increasing focus on using predictive models to support energy system optimization and enhance decision-making. Together, these approaches align with sustainable development goals by promoting the selection of renewable energy options that are efficient, environmentally friendly, and tailored to regional needs. The findings highlight the value of combining decision-making tools with machine learning to advance sustainable and data-driven energy solutions. The five criteria shortlisted from the literature are socio-economic assessment, technological innovation & research opportunities, community support and acceptance, resource availability, and environmental impact.

4.2 CRITERIA WEIGHTS USING FUZZY AHP

Figure 9 shows the weights obtained using fuzzy AHP for the five criteria. The weight of technological innovation and research opportunities (0.285) is the highest, whereas the weight of community support and acceptance (0.071) is the lowest. The weight of other criteria in ascending orders is 0.236 (environmental impact), 0.206 (resource availability), and 0.202 (socio-economic assessment). The calculation involved in the whole process is done in Python coding.

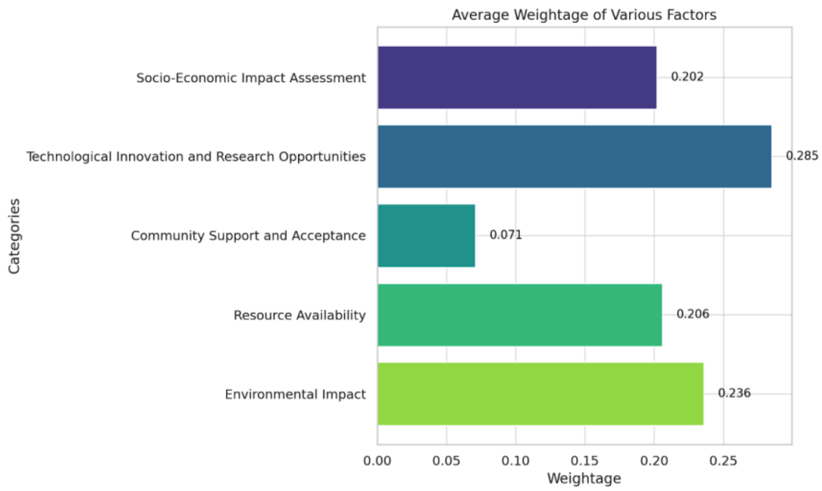

Figure 9: Weights of Criteria Using Fuzzy AHP

4.3 MACHINE LEARNING PREDICTION USING FUZZY TOPSIS

The weights obtained from the fuzzy AHP are used to analyze all renewable energies and the closeness coefficients are obtained through fuzzy TOPSIS. Further, this closeness coefficient is used to find the most appropriate energy. The user can input the weight of criteria once the model is trained to prioritize or rank all the considered energies, as shown in Figure 10.

A thousand cases were formed by varying the weights of the criteria. A baseline scenario where all criteria are weighted equally (each factor has identical importance), leads to an objective of ranking renewable energy sources.

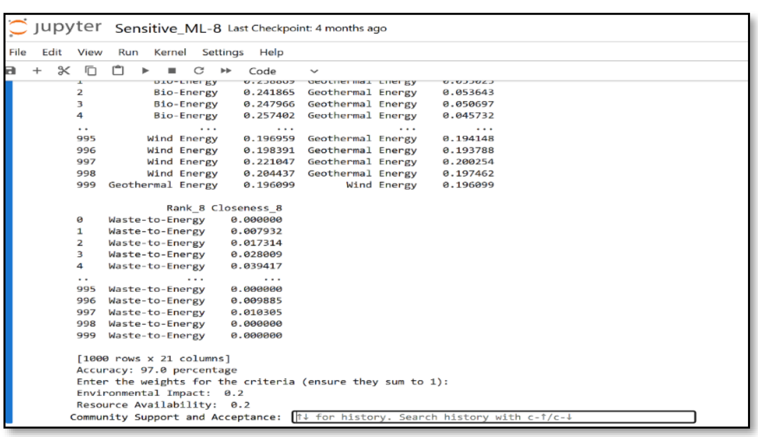

Figure 10: Renewable Energy Prediction Based on User Input

The results show that concentrating solar has a maximum closeness index of 0.8433, whereas waste-to-energy has a minimum closeness index of 0.0498. The value of the closeness index for all the renewable energy is shown in Figure 11. This setup allows the model to evaluate alternatives like "Solar PV" or "Wind Energy" without bias, as no single criterion is emphasized.

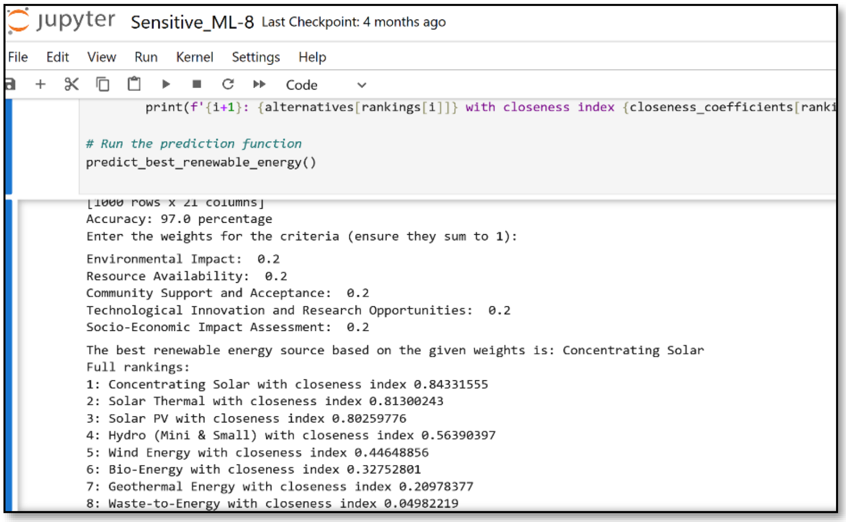

Figure 11: Closeness Index of all Criteria Using Python

To check the robustness and flexibility, a sensitivity analysis is performed considering the various cases, wherein Table 2 shows how the weights of primary criteria are varied. Results highlight the comparative performance of each renewable energy source under different weighted criteria, with closeness coefficients indicating how well each option aligns with ideal evaluation conditions. Concentrating solar and Solar PV consistently achieve high closeness coefficients, ranking them as top choices across most cases. This trend suggests these options are highly adaptable and effective in diverse decision-making scenarios, likely due to their strong performance in areas like environmental impact and technological innovation. Solar Thermal also ranks well, especially in cases 3 and 6, implying that it excels when criteria like Socio-Economic impact and technological opportunities are given higher weights. Hydro (Mini & Small) shows mixed performance, with notably higher scores in cases where community support and resource availability are prioritized, such as in case 4. Wind Energy demonstrates moderate closeness values but rises in ranking in cases 4 and 5, suggesting its suitability under specific priorities, particularly when innovation and resource availability are emphasized. Bio-energy and geothermal energy generally achieve lower rankings, indicating they may not be as effective under the selected criteria but still hold potential in specialized contexts.

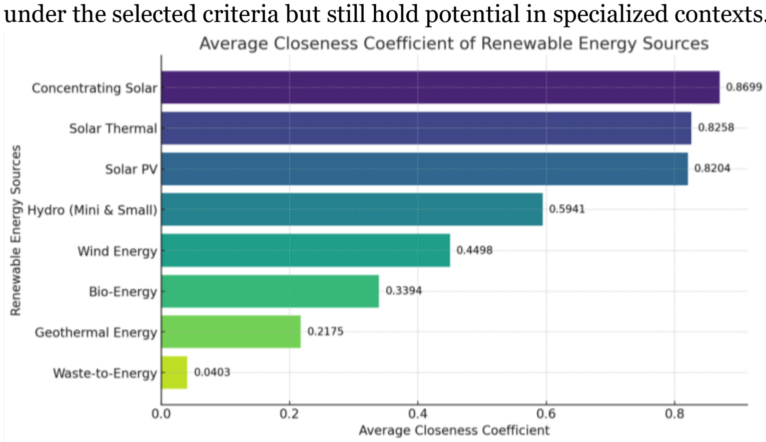

Figure 12: Renewable Energy Preference Based on Sensitivity Analysis

Waste-to-energy with consistently low closeness indices, ranks as the least favourable option overall, suggesting that it may not perform well under most priority conditions compared to the other renewable options. The average closeness coefficients for all renewable energy sources were calculated, allowing for a final ranking as illustrated in Figure 12. This study suggests a preferred sequence of renewable energy options, listed in descending order of preference as follows: concentrating solar, solar thermal, solar PV, hydro (mini & small), wind energy, bio-energy, geothermal energy, and waste-to-energy.

Tab le 2: Closeness Coefficient of Renewable Energies for the Six Cases

		Renewable Energies							
		Solar PV	Concentrating Solar	Solar Thermal	Hydro (Mini & Small)	Bio-Energy	Wind Energy	Geothermal Energy	Waste-to-Energy
Cases	1	0.81001	0.848676	0.81928	0.576364	0.34463	0.45913	0.22388	0.04613
	2	0.92538	0.939627	0.755419	0.708969	0.46293	0.28310	0.22956	0.01826
	3	0.76954	0.773885	0.936593	0.53449	0.50268	0.51721	0.28261	0.01615
	4	0.72029	0.940982	0.721632	0.841921	0.12834	0.80007	0.40571	0.08039
	5	0.93718	0.949205	0.777452	0.548398	0.31996	0.33752	0.07478	0.06389
	6	0.76197	0.765739	0.940414	0.354455	0.2781	0.29773	0.08849	0.01515

The model demonstrates a strong preference for the three solar-based technologies, followed by a moderate preference for hydro (mini & small), wind, and bio-energy, while geothermal and waste-to-energy options receive the lowest preference.

5 Conclusion and Future Work

The bibliometric analysis of renewable energy selection techniques offers important insights. By reviewing 2,766 research documents from 1,042 sources published between 2000 and 2024, authored by 6,748 researchers, our study emphasizes the significant research activity and increasing interest in renewable energy selection. It identifies key methods such as fuzzy AHP for weighing criteria and TOPSIS for evaluating options, which provide structured decision-making processes for a thorough assessment of renewable energy alternatives. Additionally, the growing use of machine learning techniques has been crucial in improving predictive models and optimizing energy systems. This research aligns with Sustainable Development Goal 7 by selecting various sustainable criteria from the literature.

The results of the proposed model demonstrate its potential benefits for decision-makers. The SDG 7 initiative aims to ensure energy access for all, achievable through the integrated application of fuzzy AHP, TOPSIS, and machine learning. A decision-making framework is established using a fuzzy MCDM approach, minimizing uncertainty and hesitancy. By considering various environmental, social, economic, and technological impacts, the research outlines a comprehensive decision-making process for policymakers. It also highlights advanced techniques like machine learning, which can significantly enhance decision-making capabilities.

This research has utilized two databases, but a more thorough bibliometric analysis could be conducted by incorporating additional databases to capture more research. The model may yield different results when applying other MCDM techniques such as VIKOR, MOORA, or ELECTRE. Furthermore, the same model can be adapted to consider other sustainable criteria based on specific local or regional contexts. Advanced machine-learning techniques could also be employed to improve the effectiveness of the existing model.

Declarations

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Conflicts of interest: The authors have no conflicts of interest to declare that are relevant to the content of this article and have no relevant financial or non-financial interests to disclose.

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