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An Empirical Study on Enhancing Renewable Energy Efficiency through Information Entropy

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Abstract: - One of the most important things that many countries might do to solve their energy crises and their environmental problems is to promote the usage of renewable energy sources (RES). As the global population and economy continue to expand, more energy would be required, making diversification of energy sources essential to provide a reliable supply, stimulate economic growth, and promote the creation of a more sustainable energy infrastructure. In this research, a model is developed based on integrated Shannon entropy and Evaluation based on distance from average solution (EDAS) to find the optimal RES among the various sources for sustainable development planning. The results that are obtained from the integrated Shannon and EDAS are optimized using a Genetic Algorithm (GA) to obtain the optimal ranking. Finally, the obtained result demonstrated that the Solar Photo-voltaic (PV) and Wind energy sources obtained the highest ranking among all the other RES. The obtained appraisal score of solar PV and wind energy before the optimization is 0.8242 and 0.7864 respectively and after optimization, the appraisal score is 0.8412 and 0.8405. This shows that solar PV and wind energy are the optimum solutions for sustainable development and meeting future demand.

Keywords: Sustainable development, Renewable energy sources, Integrated Shannon entropy, Genetic algorithm, EDAS.

I. Introduction

Renewable Energy Sources (RES), when used sensibly, might help reduce emissions from fossil fuel sources and lessen dependency on fuel provided by countries outside the European Union (EU) [1]. In general, RES is trusted for its steady supply of power. However, for Renewable Energy Technology (RET) to correlate to a practical and dependable RET infrastructure, several factors, norms, and constraints must be considered [2], [3]. Before concluding the kind of RET development that would be most suited to a particular location, it is necessary to consider a wide range of factors, as appropriate RET development requires. It is important to remember that RES are natural resources that cannot be used up. However, some years might have less sunlight and less wind, which means that RET might not be able to provide the same amount of electricity [4]. Figure 1 shows a microgrid of the RET center as given below.

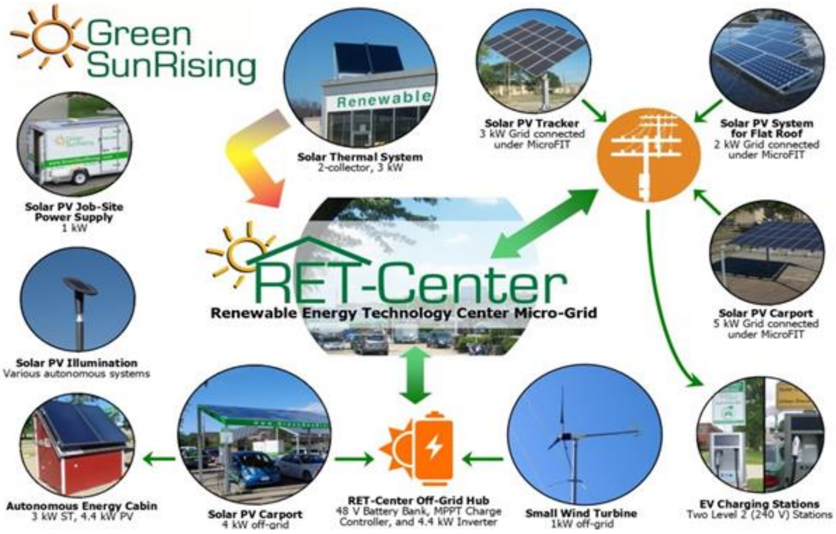

Figure 1. RET [5].

A RES power system needs both flexible and solid capacities to balance the changeable RES output. Long-term planning is possible because of the many factors involved in RET development, including the increase in transmission, and generating capacity across international borders, the well-accomplished incorporation of request-side technology, the introduction of energy-saving events, the widespread mobilization of existing resources, and the inevitable increase in expenditures [6,7].

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A. Information Entropy

Entropy, a concept first used by Clausius in thermodynamics, is a useful method for characterizing the degree of disarray. When entropy increases, uncertainty and randomness also increase. Numerous research subsequently evolved to apply entropy to other fields [8]. A classification of IE is shown in Figure 2 as given below.

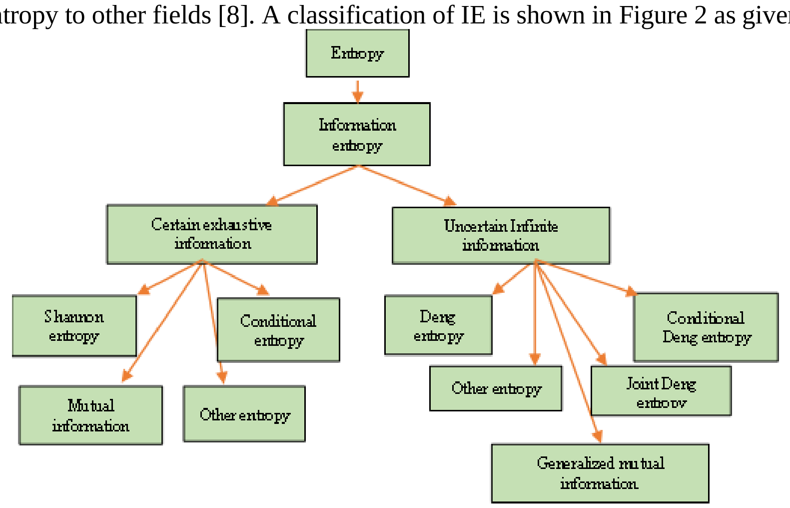


Figure 2. Information Entropy Classification [8]

Shanon entropy is one of the most used entropies. Shanon introduced the concept of "information entropy" (IE) in the 1940s to evaluate the degree of uncertainty associated with various information sources [9]. Ever since it was first developed, the IE theory has been an important factor in determining how to measure uncertainty. Recently, academics have shown curiosity in employing it to represent the unpredictability of the electricity generated by RES [10, 11]. This degree of unpredictability is one of the expenses associated with the price of RES markets. In the meantime, electric vehicles need to be led by price signals in the day-ahead (DA) market so that they could be charged in an orderly way [12]. A regional low-carbon emission electricity market (LCEM) might be easier to set up if electric vehicles and RES could trade with each other [13, 14].

The expansion of nations' energy resources is one of the primary drivers of economic growth in today's world [15]. As the need for energy develops due to economic and population growth, diversifying energy sources is crucial to provide a safer option, create more employment opportunities, and contribute to the development of sustainable energy [16]. Energy might be defined as the capacity to carry out a task, in addition to the fact that it is the origin of all forms of life. Energy is directly derived from primary energy sources in nature, such as coal, oil, natural gas, uranium, biomass, geothermal, hydro, solar, and wind. Secondary energy sources include wind, sun, and hydro. The remaining options are forms of renewable energy [17]. There is no need for any industrial procedures to be carried out to get renewable energy [18].

B. Renewable Energy

In many nations, one of the most significant options for addressing both the energy crisis and the environmental challenges that they are facing would be to encourage the use of RES. To guarantee the long-term growth of RES, it is necessary to implement the proper policies and strategic solutions, which would cut emissions of greenhouse gases and boost energy efficiency. The overall structure of "green" projects is shown in Figure 3, which aims to strike a healthy balance between the environment, economic activity, and renewable energy sources [19].

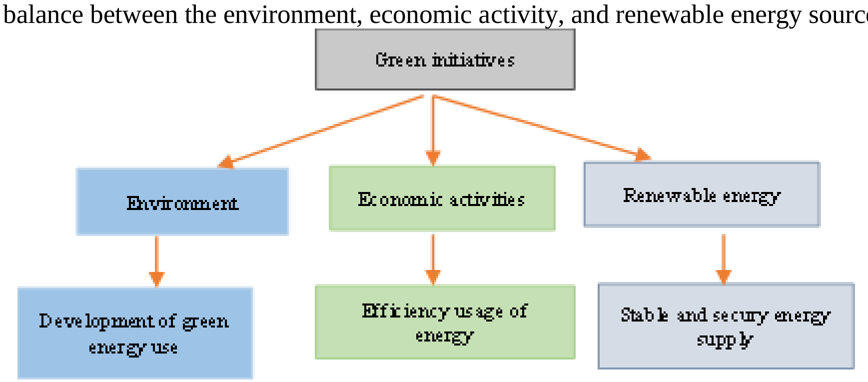


Figure 3. Green Initiatives [19]

- Renewable Energy Sources

Wind, sun, biomass, geothermal, biogas, tides and ocean, and hydrogen energy are all forms of RES that might be found on a global scale (Figure 4) [20].

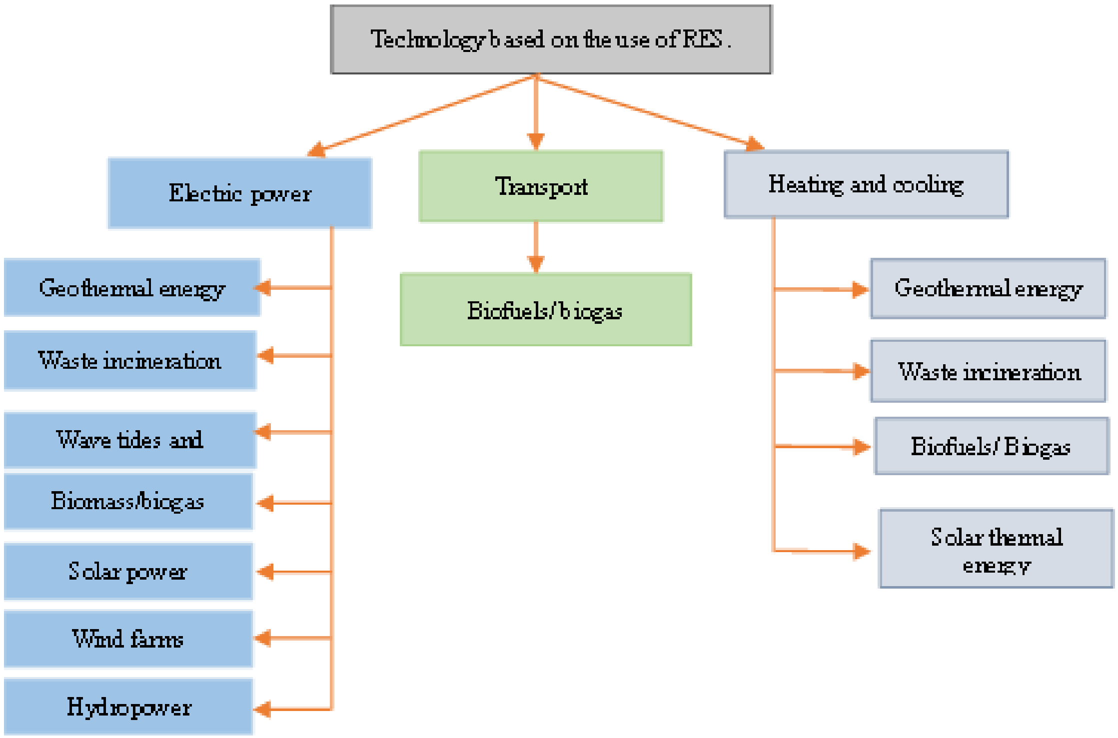


Figure 4. RES [19]

Unfortunately, in the case of Lithuania, this list of potentially useable RES is shrinking owing to objective causes. As a result, the RESs that are the most promising and important for Lithuania are given below [21].

i. Hydropower
ii. Wind
iii. Biomass
iv. Solar
v. Hydrogen
vi. Geothermal

II. Review of Literature

In this analysis, some related research based on information entropy in RES is discussed below:

Sitorous et. al., (2022) [22] developed a hybrid multi-criteria decision-making (MCDM) strategy that could overcome these challenges by taking into consideration quantitative and qualitative data within a probabilistic setting within the framework of group decision-making. The findings suggest that the technique that was developed could reduce the amount of valuable objective information that is lost because of the subjective bias of qualitative weights that occurs during the evaluations. This is done by changing the hybrid model's correlation factors while the calculations are being done.

Tekin et. al., (2021) [23] used the maximum entropy model (MaxEnt) in conjunction with geographic information systems (GIS) to identify the probable best sites for renewable energy. As a result, investors in the renewable energy industry would have guidance in the form of the framework that was established by the results. According to the calculations, solar energy has an area under the curve (AUC) value of 0.87, whereas wind energy has an AUC value of 0.95.

Wang et. al., (2021) [24] proposed the G1-anti-entropy weight complete assessment method, which uses 23 indicators distributed over 4 criteria levels to evaluate performance in the areas of technology, environment, economics, and society. A hospital in Henan is analyzed using this thorough assessment methodology to determine the best course of action for the facility's distributed energy system. The findings of the empirical study confirm the soundness of the complete assessment model and offer a foundation for future evaluations of distributed energy systems.

Seterus, et. al., (2020) [25] introduced a novel, more comprehensive form of the Shannon Entropy known as Integrated Constrained Fuzzy Shannon Entropy (IC-FSE), whereby criterion weights are derived from ambiguous input data. The results show that IC-FSE could provide practical fuzzy solutions for appropriately balancing sustainability requirements for RES. It follows that the proposed technique has broad applicability in the field of RES and has the potential to aid in the formation of more informed consumer choices.

Rani et. al., (2019) [26] created a unique approach to RET evaluation by combining the Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) with the discrepancy and entropy measurements of Pythagorean fuzzy sets (PFSs). As a result, the initial step of the work is to create original data measures for PFSs. “Finally, an assortment issue of RETs is provided in which the assessment of the energy options vs each criterion is described in terms of Pythagorean Fuzzy Numbers, demonstrating the effectiveness of the suggested technique (PFNs). The research's findings showed that the suggested PF-VIKOR was useful for selecting and assessing RET."

Ceci et. al., (2019) [27] developed a set of criteria based on entropy to address the issue. The introduction of spatially situated sensors results in autocorrelation, which occurs when the data acquired by the sensors exhibit a correlation only owing to their relative physical closeness. To solve these problems, a novel approach to teaching artificial neural networks has been developed. To account for spatial autocorrelation, the technique conducts online adaptive training and enhances the entropy measures with spatial data from the data. As shown by experimental findings on two solar power production datasets, entropy-based metrics that account for spatial autocorrelation perform well, even when compared to state-of-the-art approaches.

Suharevska et. al., (2019) [28] developed the technique for order of preference by similarity to the ideal solution (TOPSIS) model with the help of IE, which is a key part of the proposed MCDM technique by serving as a criterion weighting tool. The research explores seven primary criteria from the realms of technology, economics, ecology, and society. First, the selected RET criteria were used to conduct an in-depth analysis of each potential host nation. To get a better idea of how things are going, specific data is compared to the MCDM of RET outcomes in Latvia. The study's findings indicate that although hydropower facilities are still important in Latvia.

Lee and Ching (2018) [29] presented an evaluation of four MCDM techniques TOPSIS for ranking RES for electricity production in Taiwan. Each criterion for rating RES is given a weight based on its relative value, with the Shannon entropy weight technique being utilized. The rankings place hydro as the top energy source in Taiwan, ahead of solar, wind, biomass, and geothermal. Additionally, susceptibility analysis of the weights was carried out since the weight of the criteria has a considerable impact on the results of the ranking. The results of the sensitivity analysis show that hydropower is the best RES in Taiwan since it has the most sophisticated technology and the lowest cost, regardless of whether technical or financial factors are considered.

There is a wide range of authors who used the technique and presented their discoveries, as could be found in Table 1.

Table 1. Summary of Related Work

Authors and Year	Techniques	Results
Sitorous et. al., (2022)	MCDM	The findings suggest that the technique that was developed could reduce the amount of valuable objective information that is lost because of the subjective bias of qualitative weights that occurs during the evaluations.
Tekin et. al., (2021) [22]	MaxEnt Model	According to the findings of the energy suitability site maps, only 3.39% (1554 km2) of the overall research area is extremely suitable for wind energy, while only 8% (3.42 km2) of the total study area is suitable for solar energy.
Wang et. al., (2021) [23]	G1-anti-entropy weight complete assessment method	The findings of the empirical study confirm the soundness of the complete assessment model and offer a foundation for future evaluations of distributed energy systems.
Sitorus, et. al., (2020) [24]	IC-FSE	The results show that IC-FSE may provide valuable fuzzy solutions for appropriately balancing RES sustainability requirements.
Rani et. al., (2019) [25]	VIKOR	The research's findings showed that the suggested PF-VIKOR was useful for selecting and assessing RET.
Ceci et. al., (2019) [26]	Artificial neural networks	As shown by experimental findings on two solar power production datasets, entropy-based metrics that account for spatial autocorrelation perform well, even when compared to state-of-the-art approaches.
Suharevska et. al., (2019) [27]	TOPSIS model	The study's findings indicate that although hydropower facilities are still important in Latvia, the country's most prospective RET development is based on biofuels and wind power.
Lee, and Ching (2018) [28]	MCDM	According to the conclusions of the sensitivity analysis, regardless of whether financial or technical factors are included, hydropower is indeed the best RES in Taiwan due to its most technological advancements and lowest cost.

III. BACKGROUND STUFY

This research aims to identify the best green energy options for long-term development strategies. In the analysis, an integrated MCDM assessment known as the entropy TOPSIS is used to evaluate various energy sources as well as storage methods, such as underground salt caverns. The information that is associated with energy parameters is never exact. As a result, the entropy approach is utilized to handle the imprecision that exists while obtaining judgments on the preferences of criteria. After that, the TOPSIS approach is applied to choose the best sources. According to the findings, solar photovoltaics is the best option for a green energy source because it has the maximum score number, and yearly generation is the factor that was given the most weight. The reliability of the selection approach could also be seen to be demonstrated through sensitivity analysis [30].

IV. PROBLEM FORMULATION

It is essential to diversify energy sources to attain a safer choice, produce more employment, and promote the advancement of sustainable energy as the requirement for energy rises because of demographic and economic expansion. Non-renewable energy sources such as coal and natural gas are limited resources that are also the primary contributor to the production of greenhouse gases. The term RES refers to organic sources or processes that are continuously renewed. In this context, RES is regarded as a feasible choice for incorporation with traditional power plants that run on fossil fuels, and these resources are promising to take up a considerable portion of the energy market. Also, in this research, a model is developed to find the optimal RES among the various sources for sustainable development planning and the results are quite promising.

V. RESEARCH OBJECTIVES

- To enhance the efficacy of the energy region and the execution of renewable energy systems.
- To propose a model for investigating the most appropriate source among the many renewable sources of energy for sustainable development.
- To circumvent the imprecision that might arise while soliciting judgments on the preferences of criteria the entropy approach is utilized.

VI. METHODOLOGY

Research strategies are discussed about the idea of planned architecture. Based on the literature survey, the RES criteria are defined. By using integrated Shannon entropy and EDAS the appraising and ranking of optimum RES are performed. Then the genetic algorithm is used to optimize the generated results. Finally, the efficiency of the proposed framework is analyzed based on accuracy and sensitivity analysis.

A. Technique Used

In the proposed model various techniques are used in the designed architecture. All these techniques are described below.

- **Shannon entropy**

The Shannon Entropy method is a weighted MCDM model used for calculation. Decision criterion weights are calculated using the original decision matrix in the following steps:

Step 1: Normalization is accomplished followed by the initial matrix:

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} xij} \qquad i = 1,2,..,m \tag{1}$$

Step 2: For each criterion, entropy is estimated as:

$$e_j = -K\sum_{i=1}^{m} r_{ij}\log r_{ij} \qquad j = 1,2,\dots,n \tag{2}$$

his formula $K = \frac{1}{\log m}$is a constant that makes sure $0 \le e_j \le 1$, in this e_j shows the entropy value for the criterion C_j, while m is the number of alternatives.

Step 3: Now the weight of the objective for each criterion is defined as:

$$W_j = \frac{1-e_j}{\sum_{i=1}^{m}(1-e_j)}, \qquad j = 1,2,\dots,n \tag{3}$$

Where W_j implies the weights of the objectives of each criterion C_j.

- **EDAS**

EDAS is utilized to rank the various RES in order of importance. PDA and NDA are introduced as baseline statistics in this method as the positive and negative distances from the mean, respectively. With the help of these metrics, the degree to which each solution (alternative) differs from the typical option is determined. As a result, a solution is considered ideal when it has larger numbers of PDA and lesser values of NDA [31] [32]. EDAS algorithm is stated below.

Step 1: The first version of the decision matrix should be built with the help of actual data.

Step 2: With the help of Eqn. 4 and 5 mean values for each criterion are determined.

$$AV = \left[AV_j\right]_{1\times m} \tag{4}$$

$$AV_j = \frac{\sum_{i=1}^{n} X_{ij}}{n} \tag{5}$$

Step 3: The PDA and NDA could be determined by applying equations 6 and 7.

$$PDA = \left[PDA_{ij}\right]_{n\times m} \tag{6}$$

$$NDA = \left[NDA_{ij}\right]_{n\times m} \tag{7}$$

Step 4: For all substituted of PDA and NDA the weighted sum is calculated using equations 8 and 9.

$$PDA = \left[PDA_{ij}\right]_{n\times m} \tag{6}$$

$$NDA = \left[NDA_{ij}\right]_{n\times m} \tag{7}$$

$$SP_i = \sum_{j=1}^{m} w_j PDA_{ij} \quad (8)$$

$$SN_i = \sum_{j=1}^{m} w_j NDA_{ij} \quad (9)$$

Step 5: In step 5, by using equations 10 and 11 the normalized values are determined.

$$NSP_i = \frac{SP_i}{\max_i(SN_i)} \quad (10)$$

$$NSN_i = 1 - \frac{SN_i}{\max_i(SN_i)} \quad (11)$$

Step 6: Finally, the evaluation score (AS), for each possibility is determined using equation 12.

$$AS_i = \frac{1}{2}(NSP_i + NSN_i) \quad (12)$$

- **Genetic Algorithm (GA)**

Genetic method (GA) is a probabilistic search method that is based on Darwin's ideas about natural selection and heredity. The algorithm deviates from the norm in that it could probe a more extensive data collection. GA works effectively with huge ensembles, complicated issues, and many probabilistic parameters, as well as the more challenging kinds of functions, including linear, nonlinear, continuous, discontinuous, and others. Figure 5 shows the working principle of the genetic algorithm [33].

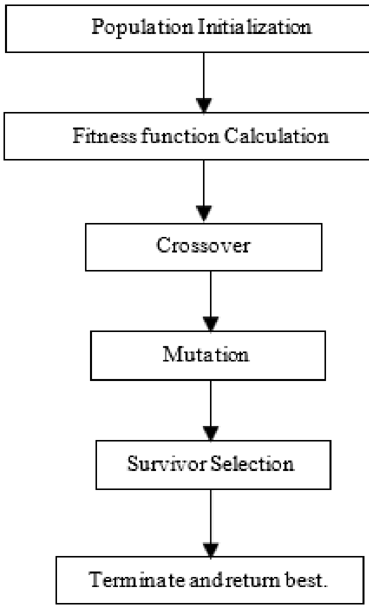


Figure 5. Schematic illustration of the genetic algorithm [34].

B. Proposed Algorithm

Start

1. Define various RES → as input variables; RES = renewable energy sources, GA = genetic algorithm
2. Perform ranking of → RES using integrated Shannon entropy & EDAS."
3. Result optimization using → GA
4. If (stopping criteria not matched)

Perform step 3 again.

5. Else

Perform performance evaluation based on → (Accuracy, Sensitivity)

End

C. Proposed Methodology

Figure 6 depicts the proposed methodology in flowchart form.

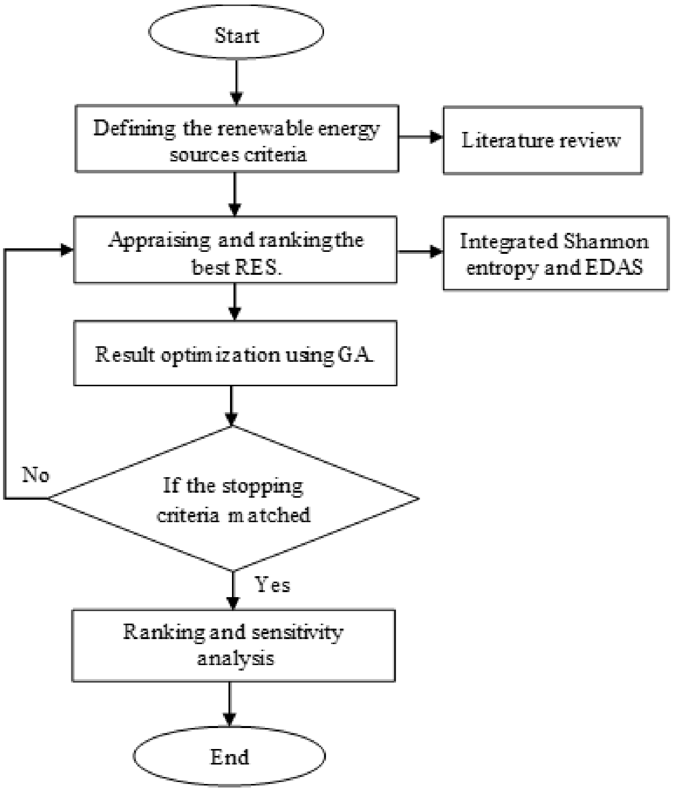


Figure 6. Flowchart of the proposed methodology

Step 1: Defining the renewable energy sources criteria.

At the beginning of the process, various RES criteria are first defined. The RES criteria are evaluated based on a literature survey.

Step 2: Appraising and ranking the sources.

After defining the RES criteria based on the literature survey, in this step appraising and ranking of the sources are performed. The appraising and ranking of the sources are done by using the integrated Shannon entropy and EDAS. This is done so that the optimal sources could be obtained to plan for sustainable energy.

Step 3: Result optimization

In step 3, after appraising and ranking the various optimum sources the result optimization is performed. The GA technique is employed for result optimization. The GA suggests the optimal source from various RES for sustainable energy planning.

Step 4: Checked for stopping criteria.

After the result optimization using the GA technique in this step, the stopping criteria are checked to proceed further. If the stopping criteria are not matched, then again, the process moves to step 3 to optimize the result, and if the stopping criteria are matched it moves to the next step for evaluating the system performance.

Step 5: Performance evaluation

In the last step of the proposed methodology, the robustness of the designed architecture is investigated. The performance of the designed architecture is evaluated by considering the various performance measuring parameters such as accuracy and sensitivity analysis

VII. Results and Discussion

- **Dataset**

In this analysis, the dataset that is used is generated from primary sources based on the consumption and generation of renewable sources. This dataset contains information regarding renewable sources and their generation and consumption value.

A. Results

In this section, the results are discussed that are obtained after the implementation of the research methodology. Initially, the ranking of the RES is obtained using the integrated Shannon entropy and EDAS. It is clearly shown in the results that the GA algorithm optimized the overall ranking of the RES. Finally, the sensitivity analysis is performed of all the energy criteria.

- **Before optimization using GA**

First, the Entropy approach is used to calculate the weights of the criterion. The entropy approach employs the decision matrix that is displayed in Table 2. Efficiency (R7), which weighs 14.25 percent, is the weighted factor that is given the highest priority. Capital cost (R1), which weighs 14.38%, is listed as the second most significant criterion, almost equivalent to efficiency. With a weight of 11.9%, emission (R6) is the third most significant criterion. With a combined score of 12.76%, the fourth prioritized criteria of energy cost (R3) and land usage (R5) are both chosen. The fifth and sixth criteria are total job/year (R4) and resource availability (R8), respectively. With a weight of 10.2%, operational cost (R2) is the least significant criterion. Using the EDAS and integrated Shannon entropy, the RES is ranked. The findings indicate that of all the energy sources, solar energy came out on top.

Table 2. Decision matrix

RES	R1	R2	R3	R4	R5	R6	R7	R8
Solar PV	3625	3823	0,29	0,88	152	0,09	14	2223
Wind	2468	23,54	0,07	0,16	205	0,06	33	568
Hydropower	3675	1980	0,03	0.08	135	0,05	25	328
Geothermal	6248	135	0,05	0,21	97	0,06	19	102
Biomass	8500	463,42	0,07	0,24	23	0,09	23	195

Equations (6) and (7) are used to calculate the weighted PDA and NDA for all the energy sources denoted as SP_i and SN_i. Further SP_i and SN_i values are normalized using equations (8) and (9) respectively. Finally, the appraisal score is calculated to obtain the rank of the resources using equation (10). The results show that solar energy obtained the highest rank among all the energy sources. The obtained results are shown in Table 3 for all energy sources.

Table 3. Obtained results

RES	SP_i	SN_i	NSP_i	NSN_i	AS_i	Ranking
Solar PV	0.5840	0.2254	1	0.6432	0.8242	1
Wind	0.4974	0.1538	1	0.6154	0.7864	2
Hydropower	0.3584	0.1258	0.8354	0.5201	0.6989	3
Geothermal	0.1158	0.1489	0.5232	0.6758	0.4725	4
Biomass	0.1085	0.781	0.5212	0	0.2014	5

- **After optimization using GA**

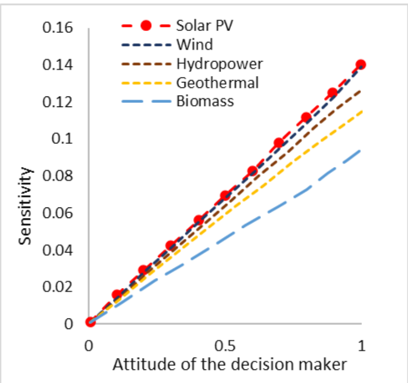
The results that are obtained above are further optimized using the GA technique and the results show that solar energy and wind energy have approximately both are acquiring the same value followed by other energy sources. Table 4 shows the further results that are obtained after the optimization.

Table 4. Ranking obtained after optimization.

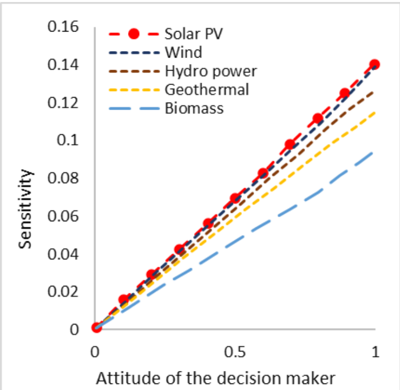
RES	SP_i	SN_i	NSP_i	NSN_i	AS_i	Rank
Solar PV	0.5920	0.2263	1	0.6578	0.8412	1
Wind	0.5978	0.2258	1	0.6523	0.8405	2
Hydropower	0.3601	0.1408	0.8954	0.5512	0.7345	3
Geothermal	0.1375	0.1378	0.5199	0.6854	0.4725	4
Biomass	0.1105	0.832	0.5014	0	0.2105	5

- **Sensitivity analysis**

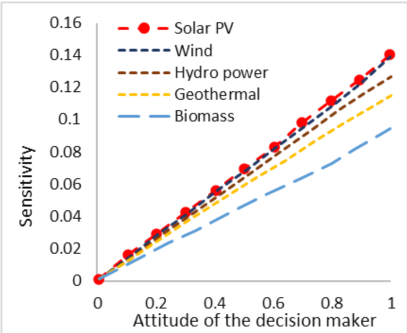
The sensitivity analysis is obtained in this part by using an adequate selection of RES, which incorporated energy cost, CO2 emission, resource availability, and efficiency. This study analyses the selection of optimal RES in a specific method that involves the decision attitude, and makers concerning the relative efficacy of the sourcing options. The key rationale for choosing RES is to increase electricity output from green resources for ecosystem protection and to achieve a cleaner future. The final decision would be made in terms of the criteria (C3, C6, C7, and C8) used in this study to assess the efficacy of the proposed integrated Shannon entropy EDAS+GA approach. Figure 7 (a) to (d) depicts the sensitivity index in terms of resource availability, efficiency, energy cost, and CO2 emission, with the remaining criteria held constant.



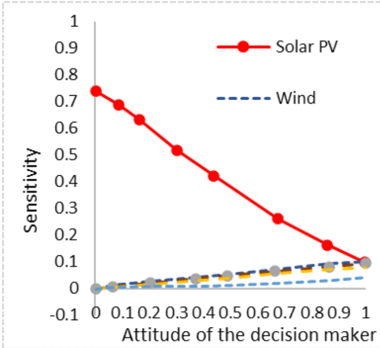
(a) Resource availability



(b) Efficiency



(c) Energy cost



(d) Co2 Emission

VIII. Conclusion and Future Scope

In conclusion, encouraging the use of RES is a major step that many nations may take to address their energy and environmental issues. The optimal RES for long-term sustainability is identified using an integrated Shannon entropy and EDAS in this study. Eventually, solar photovoltaic (PV) and wind energy sources ranked top among all RES. Before optimization, solar PV and wind energy appraisal scores were 0.8242 and 0.7864, respectively. After optimization, they were 0.8412 and 0.8405. Solar PV and wind energy are best for sustainable development and meeting future demand. In future works, using quantitative methods, this study could be broadened to cover all the characteristics that allow robustness and long-term technological progress in energy supply in each province and core region. The suggested integrated decision-making tool is not limited to the energy industry but could be applied to any complex MCDM situation. The Shannon Entropy approach could be combined with other weight-calculating methods to estimate the aggregate weight of criteria, improving the process's dependability and consistency.

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