Towards Efficient Energy Solutions: MCDA-Driven Selection of Hybrid Renewable Energy Systems

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Abstract—**In these days of growing awareness on Renewable Energy Sources and their benefits, there is a major issue that needs to be considered, which is selection of suitable Hybrid Renewable Energy System (HRES) among the vast multitude of choices. In this paper, multiple Multi Criteria Decision Analysis (MCDA) techniques are proposed to select the best among a choice of six HRES Systems using different criteria including but not limited to net present cost (NPC), operating cost, renewability fraction, CO_2 & NO_x emissions etc. The criteria weights are obtained using Analytical Hierarchy Process (AHP) based on the preference order of the criteria. The decision matrix is obtained from the statistical data of the different HRES and using different MCDA techniques such as Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), rankings are given to the HRES systems based on their closeness to the ideal solution. These rankings are helpful in the selection of suitable HRES configuration for normal household purposes. Since cost aspects are given greater preference, the obtained rankings lean more towards economically affordable solutions without compromising on the number of units generated.**

Index Terms—**Hybrid Renewable Energy System (HRES), Multi Criteria Decision Analysis (MCDA), Analytical Hierarchy Process (AHP), Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)**

I INTRODUCTION

As the global community confronts the pressing requirement to tackle climate change and shift towards sustainable energy resources, the significance of renewable energy systems has risen remarkably. Within the array of choices accessible, hybrid renewable energy systems (HRES) have garnered substantial focus and are seen as a promising avenue for fulfilling our energy requirements while curbing emissions of greenhouse gases.

A hybrid renewable energy system melds two or more renewable energy sources, capitalizing on their individual merits to establish a power generation system that is more effective and dependable. By amalgamating diverse sources such as solar, hydro, wind, geothermal or biomass energy, a hybrid system can optimize the production of energy and elevate the general reliability of the system.

One of the primary advantages of hybrid renewable energy systems is their ability to capitalize on the complementary characteristics of different energy sources. For example, solar energy production is highest during daylight hours when the sun is shining, while wind energy tends to peak at different times of the day. By integrating these two sources, a hybrid system can smooth out the fluctuations and ensure a more consistent and reliable power supply throughout the day. This integration allows for a more stable energy output, reducing the reliance on a single source and enhancing the system's resilience.

Apart from enhancing energy generation, hybrid renewable energy systems frequently integrate energy storage solutions, like batteries, to store surplus energy generated during periods of peak production. This accumulated energy can subsequently be employed during periods of increased demand or when renewable sources are not actively generating electricity. Energy storage enhances the flexibility and reliability of hybrid systems, enabling a continuous power supply and reducing dependence on conventional backup systems. It also enables the utilization of renewable energy during non-peak hours, making the system more efficient and reducing wastage.

Moreover, hybrid renewable energy systems offer significant environmental benefits by reducing carbon emissions compared to conventional fossil fuel-based

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energy generation. By harnessing clean, renewable sources, these systems help mitigate climate change and reduce air pollution, contributing to a more sustainable and low-carbon future. Incorporating renewable sources additionally contributes to broadening the energy composition, lessening reliance on limited fossil fuel reserves, and bolstering energy stability.

Furthermore, as technology advances and economies of scale are achieved, hybrid renewable energy systems are becoming increasingly feasible and cost-effective. The decreasing costs of renewable energy technologies, coupled with government incentives and supportive policies, have accelerated the adoption of hybrid systems. They are being deployed in various settings, ranging from remote off-grid locations to urban areas and industrial complexes, showcasing their versatility and adaptability.

One of the main challenges faced during installation of hybrid renewable energy systems is choosing the suitable configuration among the many types of HRES systems available for any given scenario. We can rely on expert opinion and judgement, but it might not always be valid for the situation. An approach to address the aforementioned issue involves the utilization of multi-criteria decision analysis methods to select the optimal HRES system from a provided array of alternatives.

Multi-criteria decision analysis techniques are a set of methodologies and tools used to make decisions in situations where multiple criteria or objectives need to be considered. These techniques are particularly useful when faced with complex problems involving conflicting objectives and limited resources.

In conventional decision-making procedures, choices are generally determined by a solitary standard or goal. Nevertheless, numerous real-world scenarios, spanning fields like business, engineering, and policymaking, necessitate the consideration of multiple criteria. For instance, when opting for a product supplier, it’s imperative to factor in aspects beyond just cost, encompassing attributes like quality, dependability, and delivery timelines.

Methods for MCDM offer a methodical approach to assess and contrast alternatives by taking into account numerous criteria using a series of steps as depicted in Fig. 1. These methodologies are designed to aid decision-makers in comprehending the trade-offs amid distinct objectives and in selecting the most fitting alternative.

There are several commonly used MCDM techniques, each with its own strengths and limitations. Some of the popular ones include:

- Analytic hierarchy process (AHP): AHP dissects a decision quandary into a hierarchical framework consisting of criteria and alternatives. Through pairwise comparisons, it gauges the comparative significance of both criteria and alternatives, subsequently deriving mathematical priority weights that establish the ranking of these alternatives.
- Technique for order of preference by similarity to ideal solution (TOPSIS): In TOPSIS, alternatives are evaluated by measuring their proximity to the ideal solution and their distance from the worst solution. This assessment yields a relative closeness coefficient for each alternative, facilitating the identification of the optimal selection.
- Preference ranking organization method for enrichment evaluation (PROMETHEE): PROMETHEE is an outranking-based method that compares alternatives pairwise using predefined criteria. It assigns preference indices and net flows to evaluate the relative performance of alternatives.
- Elimination and choice expressing reality (ELECTRE): ELECTRE is a family of methods that ranks alternatives by eliminating those that fail to meet specific criteria thresholds. It considers partial or complete outranking relationships among alternatives.
- Weighted sum model (WSM): WSM aggregates criteria using weighted sums to generate a single score for each alternative. The weights reflect the relative importance of each criterion, and the alternative with the highest score is chosen.
- Grey relational analysis (GRA): GRA is based on grey system theory and measures the similarity between alternatives and a reference alternative. It evaluates alternatives in terms of the grey relational coefficient and ranks them accordingly.

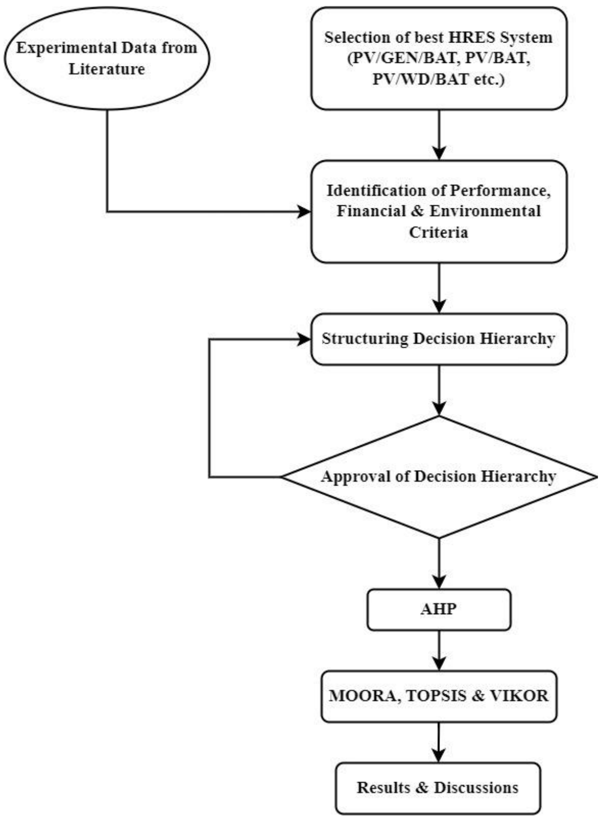

Fig. 1. Flowchart for MCDA methods.

These are just a few examples of MCDM techniques, and there are many more available, each with its own unique approach. The choice of technique depends on the specific decision problem, the availability of data, and the preferences of the decision-makers.

In this study, we opted for the AHP approach to establish the hierarchy of selection criteria by assigning weights to the criteria based on their relative preferences when compared to each other. The derived criterion weights are subsequently applied in conjunction with the multi-objective optimization on the basis of ratio analysis (MOORA), TOPSIS, and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) methods to identify the optimal alternative from the provided options.

A. MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis)

MOORA is a decision-making technique that aims to rank alternatives based on multiple criteria. It involves two main steps: normalization and the calculation of the weighted normalized values. In the normalization step, the criteria are transformed into dimensionless ratios. This allows for fair comparison between criteria that may have different measurement scales. During the subsequent phase, the computation involves weighted normalized values, achieved by multiplying the normalized values of the alternatives by their respective weights. Subsequently, the alternatives are ranked according to their cumulative weighted normalized values. MOORA proves especially beneficial when the criteria exhibit varying measurement units, necessitating transformation into a shared scale to enable effective comparison.

B. TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)

TOPSIS is a decision-making approach that compares potential outcomes to the best and worst possible ones. It zeroes in on the option that’s the furthest away from the worst possible solution while still being relatively close to the ideal one. In the case of TOPSIS, the initial step entails normalizing the decision matrix, akin to other MCDM techniques. Subsequently, the optimal and worst solutions are established by pinpointing the most favorable and unfavorable values for each criterion. Following this, the Euclidean distance is computed for each alternative’s normalized values concerning the ideal and worst solutions. The coefficient of relative proximity is then obtained by incorporating these distances to establish the hierarchy of alternatives. The alternative with the highest proximity coefficient is deemed the most appropriate. TOPSIS is frequently applied when the decision at hand necessitates a selection that is as near to the ideal solution as possible while simultaneously being as distant from the worst solution as feasible.

C. VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje)

VIKOR presents a decision-making approach that seeks equilibrium between the utmost "group utility" and the minimal "individual regret" within alternatives. It encompasses an evaluation of both the average performance and the level of concession across criteria. VIKOR entails four principal stages: normalization, derivation of "utility" and "regret" values, computation of the VIKOR index, and arrangement of the alternatives. The initial step involves normalizing the decision matrix to establish a common scale for all criteria. Subsequently, utility and regret values are computed to assess the performance of alternatives concerning the best and worst solutions. The VIKOR index is deduced by taking into account the trade-off between utility and regret, ultimately guiding the ranking of alternatives. The compromise solution aims to minimize the regret for the worst-performing criteria while achieving a good overall performance. VIKOR is suitable when decision-makers need to strike a balance between overall group performance and individual criteria regret.

As the previous studies have not done analysis with multiple MCDA methods applied for this scenario, this study takes the Decision Matrix from the survey conducted in [1] and applies the above three methods to obtain the rankings. The final rankings are then compared and the final conclusion on the order of the preferability of the alternatives is drawn based on the comparisons.

II. Literature Survey

Babatunde *et al.* [1] presented a multi-criteria approach for optimal hybrid renewable energy system (HRES) selection, incorporating energy-efficient equipment and utilizing hybrid optimization and multi-criteria analysis to inform decision-making for low-income households. Manoj *et al.* [2] introduced an integrated approach employing the PROMETHEE method alongside AHP to effectively determine the optimal site for Wind energy projects. Utilizing seven criteria, including wind power, hub height, distance, cost, CO_2 emissions, wind speed, and blade height, the study evaluated six wind energy projects in India. The AHP-PROMETHEE II analysis identifies the Muppandal wind farm in Kanyakumari as the most favorable location for the wind power project among the options considered. Wu *et al.* [3] examined the diverse applications of multi-criteria decision analysis (MCDA) in evaluating the performance and impacts of renewable energy systems (RES), highlighting the need for future research in RES feasibility and MCDA method selection for effective alternative energy decision-making. In the context of the green economy, intricate energy planning incorporating technical, social, economic, and environmental standards presents challenges for optimal energy resource utilization, further compounded by geographical constraints on renewable systems. Manoj *et al.* [4] employed multi criteria decision making techniques like AHP, TOPSIS, and VIKOR to evaluate and select the most suitable hydro power project in India, utilizing factors like capacity, reservoir metrics, and cost, as demonstrated through a comprehensive case study of Indian hydropower facilities. Løken [5] described about MCDA methods integrated into energy planning facilitate holistic decision-making by considering technical, economic, environmental, and social aspects, with diverse techniques like AHP, TOPSIS, and PROMETHEE addressing transparency, criteria weighting, robustness, and stakeholder engagement. Manoj *et al.* [6] utilized analytical hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS) to determine the optimal site for a wind turbine in India among six projects based on criteria including wind power, hub height, distance, cost, CO_2 emissions, wind speed, and blade height, ultimately identifying the Muppandal wind farm in Kanyakumari as the most favorable location.

Rajavelu *et al.* [7] introduced a modified energy system integrating renewable sources in an existing building, identifying Grid-PV-Wind as the optimal hybrid configuration to address reliability, cost-effectiveness, and sustainable development goal criteria by utilizing multicriteria decision analysis (MCDA) and HOMER software. Goswami *et al.* [8] utilized the MEREC-PIV MCDM tool to propose a suitable RE power plant for India based on climatic conditions and six crucial factors, identifying hydroelectric power as the optimal choice through sensitivity analysis addressing the complexity of selecting the best renewable energy source. Pang *et al.* [9] presented a comprehensive evaluation framework for selecting battery energy storage systems (BESS) using the intuitionistic uncertain language Choquet ordered weighted aggregation operator (IULCWA) within a fuzzy multi-criteria decision-making (MCDM) approach, addressing challenges in indicator measurement and expert correlation in renewable energy integration. Alavi *et al.* [10] employed multiple criteria decision-making methods, ranking options based on 13 criteria and utilizing Shannon entropy weighting and methods like SAW, TOPSIS, and ELECTRE to determine optimal sites while highlighting sensitivity differences assessing wind farm feasibility in Iran's eastern provinces.

Alsayed *et al.* [11] employed a multi criteria decision analysis (MCDA) optimization approach to address the intricate task of designing optimal grid-connected hybrid PV-WT power generation systems, considering uncertain variables and criteria weights to achieve reduced emissions, total costs, and social acceptability. Vishnupriyan *et al.* [12] introduced an integrated approach combining AHP and HOMER Energy® simulation to optimize grid-connected renewable energy systems for meeting electricity demand in Tamil Nadu, India, with emphasis on annual optimum tilt photovoltaic systems based on multi-criteria decision analysis. Ali *et al.* [13] evaluated MCDA techniques to select optimal renewable energy sources for Msallata city, Libya, favoring a wind and solar combination, followed by standalone solar, and indicating COPRAS or VIKOR as suitable methods. Indrajayanthan *et al.* [14] addressed India's coal-heavy electricity mix by employing multi-criteria decision analysis to evaluate clean energy transition potential across seven key states, identifying Gujarat as the most favorable and Uttar Pradesh as the least conducive. Wang *et al.* [15] introduced a novel DANP-VIKOR approach to sustainable supplier selection (SSS) in Taiwan's electronic manufacturing industry, accommodating complex multidimensional criteria interrelationships addressing the escalating demand for sustainability in supply chains. Hassan *et al.* [16] proposed a hybrid framework integrating MCDM techniques to assess suitable sites for large-scale solar PV systems in five Saudi Arabian cities, with Riyadh ranking highest, facilitating informed decisions for solar power plant placement and grid expansion.

Babatunde *et al.* [17] examined the implementation of an off-grid hybrid renewable energy system for a Nigerian high-rise building, emphasizing single and multiple criteria analyses and their implications for economic feasibility and sustainability. Zheng *et al.* [18] established evaluation criteria and ranks renewable energy system schemes in tourist resorts, aiding decision-makers in optimal selection based on economic, technological, and environmental factors using the VIKOR method. Abu-Taha *et al*. [19] showcased that renewable energy's sustainability and cost-effectiveness are driving its adoption, with multi-criteria decision analysis methods like AHP prominently utilized in the renewable energy field, in a review of 90+ papers. Sahabuddin *et al.* [20] identified COPRAS and WPM as the most robust for assessing electricity generation sustainability, underscoring the complex nature of multi-criteria decision-making in energy planning. comparing seven MCDA methods. Ergul *et al*. [21] employed the MOORA method to determine optimal wind energy plant sites, highlighting the intricate decision-making process and selecting the most suitable site (RES_2) in Amasya amid Turkey's energy transition. Dadda *et al*. [22] introduced a novel hybrid MCDM-METHOD for selecting optimal renewable energy projects, employing hierarchical levels, weighted criteria, and validation stages, while requiring comprehensive understanding of the energy landscape and relevant stakeholders. Wątróbski *et al.* [23] proposed a dynamic MCDA framework, utilizing the Temporal VIKOR method and data variability measurement, for assessing sustainable cities over time addressing sustainability in policy with the UN's SDG 11.

Alsayed *et al.* [24] introduced an optimal sizing method using Multi Criteria Decision Analysis (MCDA) for hybrid PV/WT grid-connected power systems, addressing the intricate nature of variable interactions, and applies it to a practical case. Kim *et al.* [25] proposed a novel parent selection algorithm for wireless sensor networks employing analytical hierarchy process and additive weighting to objectively balance performance metrics and achieve flexible trade-offs. Ijtihadie *et al.* [26] proposed an AHP-based method for optimizing container distribution among servers by considering resource availability and determining server shutdown based on specified parameters. Rong *et al.* [27] presented a novel streamlined spherical fuzzy TODIM approach, analyzing a paradox, developing a generalized version, and demonstrating its validity and advantages through examples and comparisons with existing methods. Raos *et al*. [28] presented a holistic simulation-based evaluation model for enhanced geothermal system projects, integrating diverse criteria and multi-criteria decision-making for comprehensive assessment and comparison of project options.

The prevailing literature primarily concentrates on broader case studies at national, regional, and rural levels, often neglecting the energy needs of low-income households. A significant research gap exists in thoroughly investigating how energy-efficient practices influence the technical, economic, and environmental dimensions of HRES. Previous studies have highlighted that many HRES options inadequately address energy challenges due to a historical emphasis on single criteria, such as technical or economic factors.

As a result, a comprehensive assessment and ranking of HRES alternatives based on multiple criteria, especially in household contexts, remains underexplored. Factors like renewable energy generation and environmental considerations play pivotal roles in the selection of appropriate HRES alternatives.

This study makes a substantial contribution by introducing a range of multi-criteria methodologies to evaluate and select the most suitable HRES system from predefined alternatives. Employing established methods like AHP, MOORA, TOPSIS, and VIKOR, the study demonstrates the advantages of energy efficiency in HRES. These advantages include cost reductions, energy savings, and emissions mitigation. By integrating multiple criteria, optimal solutions are achieved, addressing various performance aspects and stakeholder priorities.

In conclusion, this research fills gaps by exploring HRES selection at the household level with a multi-criteria approach, highlighting energy efficiency's significance and enhancing understanding of complex HRES decision-making, thus advancing sustainable energy solutions.

III. Methodology

The HRES system considered in this paper is one of the many possible configurations that are available in the market which include all the necessary components that are required for a normal low-income household. This configuration includes both a PV System as well as a DC wind turbine Along with a diesel generator and a battery storage device to store the excess energy.

The provided system takes advantage of the available energy resources on the study site, presenting a proposed configuration that includes photovoltaic panels (PV), a wind turbine, a gasoline generator, and a battery bank as depicted in Fig. 2. This section furnishes comprehensive details regarding the cost and technical specifications of these components within the system. The projected operational span of the project amounts to 25 years, accompanied by an annual real interest rate of 6%. The specific technical and cost details for each element of the system are detailed here.

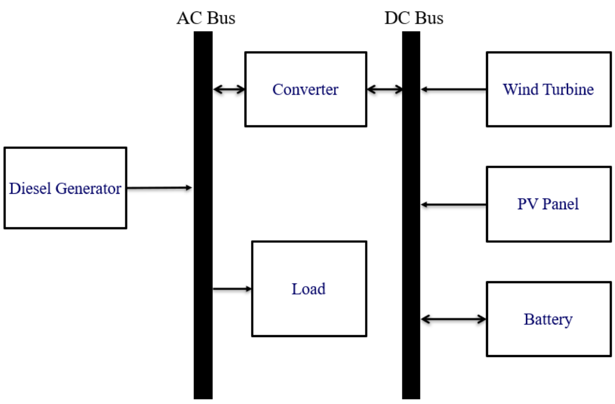

Fig. 2. HRES system configuration [1].

Photovoltaic (PV) panel: The investment cost for each kilowatt (kW) of PV panel capacity is established at $4250. Further, the replacement expense is designated at $4200 per kW, with an assumed zero operational and maintenance cost annually. The solar panel's size can be anywhere from 0 kW to 5 kW, and it has a 25-year expected lifespan. Without a tracking system, the PV panel's output is considered direct current (DC). A derating factor of 80% and a ground reflectance of 20% are incorporated into this setup.

Wind turbine: A DC wind turbine with a rating of 3 kW is specified, having an estimated initial investment cost of $1200 and a replacement cost of $1100. The operational lifespan of the wind turbine is anticipated to be 25 years, with an annual maintenance cost of $20. The turbine is positioned at a height of 25 m above sea level. The range explored for the quantity of turbines spans from 0 to 3.

Gasoline generator: A generator rated at 2.6 kW is described, carrying a capital cost of $1000. The software employs interpolation or extrapolation to ascertain the generator's cost within the optimal system configuration. Operating and maintenance expenses for the generator are set at $0.04 per hour. Replacing the gasoline generator incurs a cost of $1000, and its projected operational span extends to 15,000 hours. The generator's key specs include a 30% minimum load ratio, a 0.08 L/h/kW rated intercept coefficient, and a 0.25 L/h/kW output slope. The range of possible power output from the generator is between 0.4 and 1 kW.

Battery bank: The analyzed battery is characterized by specifications of 4 V and 1900 Ah, with a capital cost of $269 and a replacement cost of $260. The range of evaluated battery quantities varies from 0 to 40, with a lifespan spanning 4 years. Annual maintenance expenses for each individual battery amount to $5.

Converter: A 3-kW converter is priced at approximately $200, with a replacement cost of $225. Additional parameters encompass an annual operational and maintenance cost of $1, inverter efficiency at 90%, rectifier efficiency at 85%, and an anticipated operational span of 15 years. The converter sizes considered include 0kW, 1kW, 2kW, 3kW, and 4 kW.

A. Criteria

The criteria utilized for the decision analysis in this paper and the alternatives considered, as shown in Fig. 3, have been chosen from the perspective of a typical low-income household. The following of the section provides a description of these criteria.

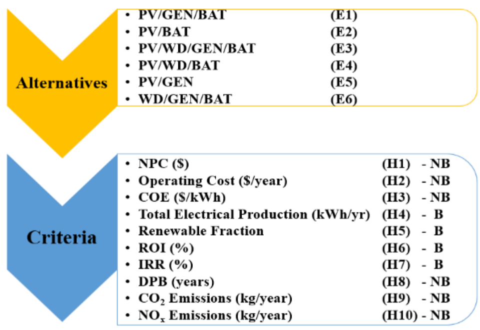

Fig. 3. Nomenclature.

The criteria are categorized into two distinct types: beneficial criteria and non-beneficial criteria. The former are considered advantageous, it is favorable to have a higher value for these criteria. The latter are regarded as unfavorable, it is preferable to have a lower value for these criteria.

Net present cost: The net present cost encompasses the summation of all costs incurred by the system throughout its operational lifespan. This value is reduced by subtracting the present value of generated revenues. A higher total net present cost implies greater expenses outweighing the revenue, thus categorizing it as a non-beneficial criterion.

Operating cost: Operating costs encompass the ongoing expenditures linked with the system's day-to-day functionality. Higher operating costs signify increased financial strain, making it a non-beneficial criterion. Efficient systems typically exhibit lower operating costs.

Cost of energy: Cost of energy refers to the expenditure associated with producing each unit of energy. A higher cost of energy directly affects the economic viability of the system, making it a non-beneficial criterion. Lower energy production costs are desired for sustainable operations.

Total electrical production: Total electrical production signifies the cumulative amount of electrical energy generated within a year. Higher values indicate increased energy generation, a beneficial criterion that supports energy sustainability and reliability.

Renewable fraction: The renewable fraction denotes the proportion of power generated from renewable sources, such as solar or wind energy. A higher renewable fraction aligns with environmental conservation and resource sustainability, categorizing it as a beneficial criterion.

Return on investment (ROI): Return on investment is the ratio of net profit to the total cost of investment. A higher ROI indicates that the investment's gains are more favorable compared to its cost. Achieving a higher ROI is desirable and serves as a beneficial criterion in evaluating investment success.

Internal rate of return (IRR): IRR signifies the discount rate at which the net present value of all cash flows becomes zero within the framework of discounted cash flow analysis. A higher IRR signifies a more attractive investment opportunity, making it a beneficial criterion for selecting financially viable projects.

Discounted payback period: The discounted payback period evaluates the duration required for the initial project cost to match the discounted worth of expected cash flows. A shorter payback period is favored as it signifies a swifter recuperation of the investment, thereby labeling it as a non-beneficial criterion.

CO_2 emissions: CO_2 emissions constitute a major portion of greenhouse gas emissions, contributing to environmental degradation. Minimizing CO_2 emissions is imperative for mitigating climate change impacts, making it a non-beneficial criterion.

NO_x emissions: NO_x emissions comprise NO and NO_2 gases, known for their harmful effects on air quality and health. Reducing NO_x emissions is crucial for environmental and human health, making it a non-beneficial criterion.

In pursuit of an optimal solution, the objective is to minimize the values of beneficial criteria and maximize the values of non-beneficial criteria to achieve the most favorable outcomes, both economically and environmentally. The data for this study is taken from [1] while the methods are implemented using MATLAB Software.

TABLE I: DECISION MATRIX [1]

Alter-natives	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10
E1	6919	87	0.28	2818	0.97	24.4	25.2	4.77	84	2
E2	7738	75	0.313	4107	1	19.2	19.6	6.08	0	0
E3	11087	196	0.452	2562	0.95	11.7	11.1	11.1	138	3
E4	11766	173	0.476	3799	1	10.4	9.5	15.1	0	0
E5	11778	640	0.477	3512	0.39	23.6	24.1	4.83	2667	59
E6	12752	414	0.512	2493	0.43	9.99	9.04	15.8	1254	28

B. Decision Matrix

The presented information in Table I outlines the decision matrix with the system data for all the alternatives obtained from [1], which is a data table that correlates the various alternatives being observed with the selected criteria. The mapping of all the selected alternatives with the chosen criteria is done as shown in Fig. 4.

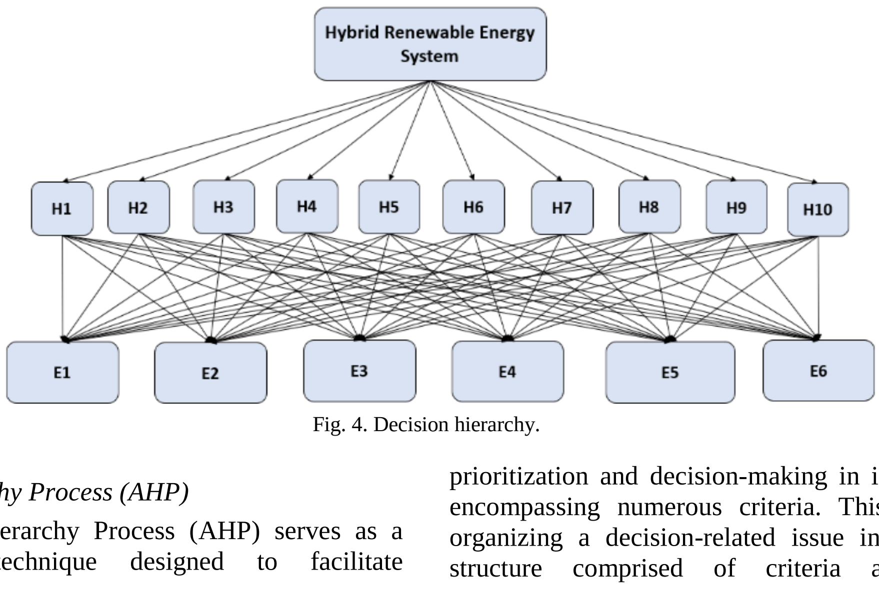

Fig. 4. Decision hierarchy.

C. Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) serves as a decision-making technique designed to facilitate prioritization and decision-making in intricate scenarios encompassing numerous criteria. This method entails organizing a decision-related issue into a hierarchical structure comprised of criteria and alternatives.

Subsequently, it involves assigning quantitative values to gauge the relative significance of criteria and the efficacy of alternatives [29]. Herein, a detailed breakdown of the AHP approach is provided, encompassing the associated formulas and stepwise elucidation with the same illustrated in Fig. 5.

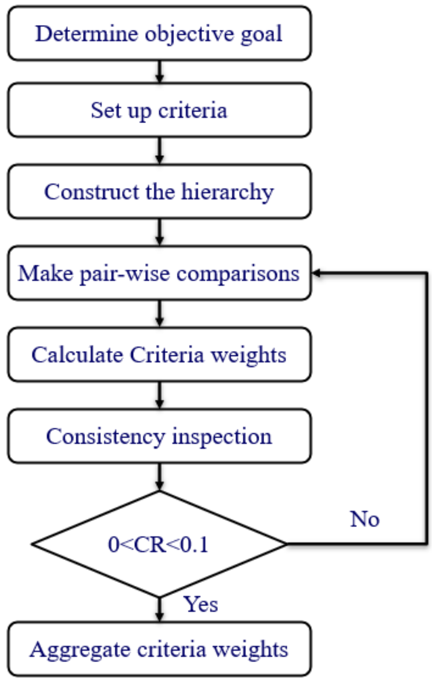

Fig. 5. Flowchart of AHP.

Step 1: Decision problem definition

Identify the decision problem and the objectives or criteria that you need to consider in order to make a decision. These criteria need to be precise, quantifiable, and pertinent to the problem.

Step 2: Create a hierarchy

Construct a hierarchical structure that breaks down the decision problem into levels. The top level consists of the main goal, followed by intermediate levels containing criteria, and the lowest level containing alternatives.

Step 3: Pairwise comparisons

For each pair of criteria or alternatives within the same level, perform pairwise comparisons to determine their relative importance or performance. Assign numerical values to express the relative importance or preference of one criterion or alternative over another. The values are usually based on a scale, such as Saaty's 1 to 9 scale [3].

Step 4: Pairwise comparison matrix construction

Create a pairwise comparison matrix for each level of the hierarchy. Within the matrix, the entry at the intersection of row *i* and column *j* denotes the comparative significance of criterion *i* in relation to criterion *j*, or the effectiveness of alternative *i* when contrasted with alternative *j*. If *A* holds greater importance than *B*, then *A/B* equals *k*, with *k* being the value assigned via the pairwise comparison.

$$\mathbf{A} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \tag{1}$$

Step 5: Calculate the priority vector

Compute the normalized priority vector for every matrix of pairwise comparisons. This vector signifies the relative significance of each criterion or the effectiveness of each alternative within the corresponding tier. Normalize each column of the matrix by dividing each element by the sum of the elements in that particular column.

Step 6: Calculate the weighted sum

For each level, calculate the weighted sum of the priority vectors of the lower level. Multiply the normalized priority vector of each criterion by its corresponding value from the parent's priority vector. Sum up these weighted vectors to obtain the overall priority vector for the next higher level.

Step 7: Consistency check

Assess the coherence of the matrices for pairwise comparisons by employing the consistency index (CI) and the corresponding consistency ratio (CR). The calculation of the consistency ratio involves dividing the CI by the random index (RI) [2]. If CR is below a certain threshold (e.g., 0.1), the comparisons are considered consistent. If not, adjustments to the comparisons are needed.

Step 8: Calculate the final priority vector

Repeat the steps for each level of the hierarchy until you reach the top level. The final priority vector at the top level represents the relative importance of the alternatives or the performance of the criteria.

Step 9: Perform sensitivity analysis (optional)

Perform sensitivity analysis to assess the impact of potential changes in the pairwise comparisons on the final results. This step helps evaluate the robustness of the decisions made.

AHP offers a methodical strategy for decision-making that encompasses both qualitative and quantitative elements. It offers a systematic way to compare criteria and alternatives while considering their relative importance, resulting in a well-informed and rational decision.

D. MOORA Method

MOORA technique is a multi-criteria decision-making method applied to prioritize alternatives by evaluating their performance across numerous criteria. This approach includes computing relative scores for each alternative and subsequently arranging them in order of preference. Here's a step-by-step explanation of the MOORA method, including the formulas involved with the overall process demonstrated in Fig. 6.

Step 1: Decision problem definition

Recognize the decision quandary and the criteria that will be employed to appraise the alternatives. These criteria must be quantifiable, pertinent, and suitable for the context of the decision.

Step 2: Normalize the Criteria

Normalize the criteria to bring them to a common scale.

This ensures that criteria with different units or measurement scales can be compared effectively. Divide each criterion value by the total number of values for that criterion to normalise.

Formula for Normalization:

$$N_{i,j} = \frac{X_{i,j}}{\sum_{i=1}^{n} X_{i,j}} \tag{2}$$

where $N_{i,j}$ is the normalized value of alternative i on criterion j, $X_{i,j}$ is the original value of alternative i on criterion j, and n is the total number of alternatives.

Step 3: Decide which values are the best and worst

Determine the optimal and worst values for each criterion among all possible options. These values will be used to calculate the relative scores.

Step 4: Calculate the relative scores

Calculate the relative scores for each alternative on each criterion by comparing their normalized values to the best and worst values. The relative score represents how close each alternative is to the best or worst performance on each criterion.

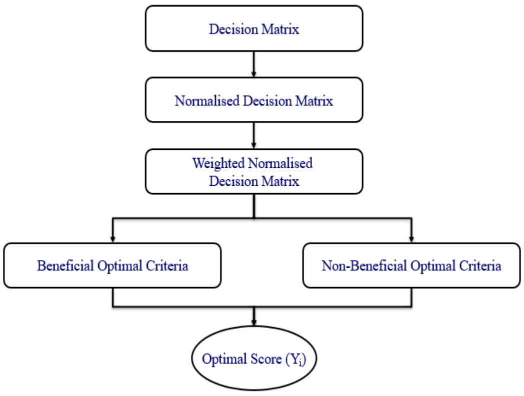

Fig. 6. Flowchart of MOORA.

Formula for Relative Score:

$$S_{i,j} = \frac{X_{i,j} - \min_i N_{i,j}}{\max_i N_{i,j} - \min_i N_{i,j}} \tag{3}$$

where $S_{i,j}$ is the relative score of alternative i on criterion j, $N_{i,j}$ is the normalized value of alternative i on criterion j, $\max_i N_{i,j}$ is the maximum normalized value for criterion j among all alternatives, and $\min_i N_{i,j}$ is the minimum normalized value for criterion j among all alternatives.

Step 5: Calculate the performance scores

Calculate the performance scores for each alternative by summing up their relative scores across all criteria. Each alternative's overall performance is represented by the performance score.

Formula for Performance Score:

$$Y_i = \sum_{i=1}^{m} S_{i,j} \tag{4}$$

where Y_i is the performance score of alternative i and m is the total number of criteria.

Step 6: Rank the alternatives

Arrange the alternatives according to their computed performance scores. The alternative with the most elevated performance score attains the top rank, while the one with the lowest performance score obtains the lowest rank.

MOORA offers a systematic method for making decisions involving multiple criteria, taking into account the relative performance of alternatives across various criteria. It enables decision-makers to objectively rank alternatives based on their overall performance, facilitating effective and informed decision-making.

E. TOPSIS Method

In order to rank a group of alternatives in terms of how closely they resemble the ideal answer, TOPSIS is a multi-criteria decision-making technique. Finding the best alternative, which is located farthest from the negative ideal solution and closest to the positive ideal solution, is the main goal of this approach [30]. Here's a step-by-step explanation of the TOPSIS method, including the formulas involved as well as its flowchart shown in Fig. 7:

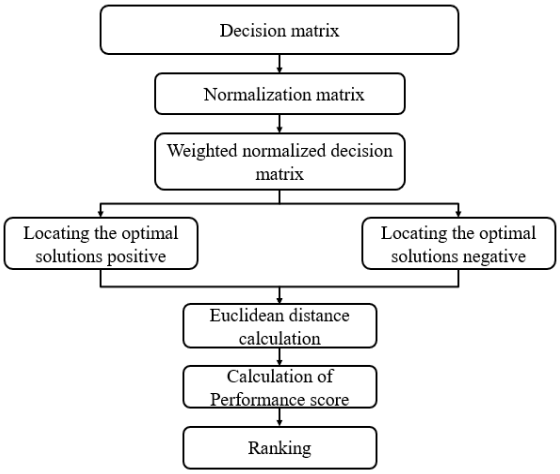

Fig. 7. Flowchart of TOPSIS.

Step 1: Define the problem and criteria

Recognize the decision problem's nature and decide on the standards that will be used to evaluate the available options. These standards must be quantifiable and relevant to the choice being made.

Step 2: Normalize the decision matrix

Create a decision matrix with the criteria in columns and the alternatives given in rows. By dividing each value in the matrix by the square root of the sum of the squares of the values within the corresponding column, the decision matrix is normalized. This procedure guarantees the uniformity of the criteria scale.

Formula for Normalization:

$$\bar{X}_{i,j} = \frac{X_{i,j}}{\sqrt{\sum_{i=1}^{n} X_{i,j}^2}} \tag{5}$$

where $X_{i,j}$ is the value of alternative i on criterion j and n is the total number of alternatives.

Step 3: Weighted normalized decision matrix determination

Allocate weights to each criterion according to their relative significance, ensuring that the sum of the weights equals 1. Multiply the normalized decision matrix by the corresponding criterion weights to derive the matrix of weighted normalized decisions.

Formula for weighted normalization:

$$W_j = \frac{w_j}{\sum_{j=1}^{m} w_j}, \; V_{i,j} = W_j \bar{X}_{i,j} \tag{6}$$

where w_j is the weight of criterion j and m is the total number of criteria.

Step 4: Find the best possible positive and negative solutions

For every criterion, determine the highest (maximum) and lowest (minimum) values across all alternatives. Formulate vectors for the positive and negative ideal solutions by amalgamating the optimal values for all criteria to constitute the positive ideal solution vector, and amalgamating the least favourable values for all criteria to constitute the negative ideal solution vector.

Step 5: Calculate the distance from the ideal solutions

Compute the Euclidean distance separating each alternative from both the positive and negative ideal solutions.

Formula for positive ideal solution distance:

$$S_i^+ = \sqrt{\sum_{j=1}^{m} \left(V_{i,j} - V_j^+\right)^2} \tag{7}$$

Formula for negative ideal solution distance:

$$S_i^- = \sqrt{\sum_{j=1}^{m} \left(V_{i,j} - V_j^-\right)^2} \tag{8}$$

where V_j^+ is the jth element of the positive ideal solution vector and V_j^- is the jth element of the negative ideal solution vector.

Step 6: Calculate the relative closeness to the ideal solution

Compare the distance between each option and the positive and negative ideal solutions to get a sense of how close they are to the optimal one. The option with the highest degree of similarity is ultimately chosen.

Formula for relative closeness:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{9}$$

where C_i is the relative closeness of alternative i, S_i^+ is the distance from the positive ideal solution for alternative i, and S_i^- is the distance from the negative ideal solution for alternative i.

Step 7: Rank the alternatives

Arrange the alternatives in order according to their computed relative closeness values. The alternative with the utmost relative closeness value attains the highest rank, while the one with the lowest relative closeness value secures the lowest rank.

TOPSIS offers a structured method for multi-criteria decision-making that takes into account both the positive and negative ideal solutions. It takes into account the trade-offs between criteria and allows decision-makers to choose the alternative that strikes the best balance between them.

F. VIKOR Method

The VIKOR technique is a method for multi-criteria decision-making employed to choose the most suitable compromise alternative among a range of options, considering various criteria. It aims to balance the best and worst aspects of each alternative to find a solution that satisfies both optimistic and pessimistic decision-makers. Here's an illustration of the VIKOR method in Fig. 8 along with a detailed explanation, including the formulas involved:

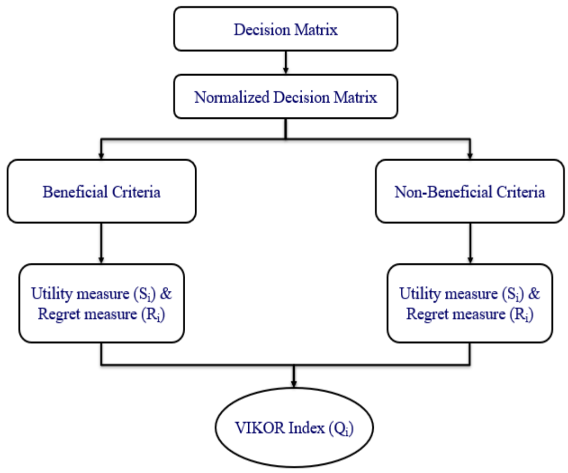

Fig. 8. VIKOR flowchart.

Step 1: Decision problem definition

Recognize the decision quandary and determine the criteria that will be utilized to assess the alternatives. These criteria should be measurable and mirror the context of the decision.

Step 2: Normalize the criteria

Normalize the criteria to bring them to a common scale, just like in the MOORA method. Normalize each criterion value by dividing it by the sum of all values for that criterion.

Formula for normalization:

$$N_{i,j} = \frac{X_{i,j}}{\sum_{i=1}^{n} X_{i,j}} \tag{10}$$

where $N_{i,j}$ is the normalized value of alternative i on criterion j, $X_{i,j}$ is the original value of alternative i on criterion j, and n is the total number of alternatives.

Step 3: Determine the best and worst values

Identify the best and worst values for each criterion among all alternatives. These values will be used to calculate the compromise solution.

Step 4: Calculate the S-values

Calculate the S-values for each alternative on each criterion by comparing their normalized values to the best and worst values. The S-value represents the compromise between the best and worst performance on each criterion.

Formula for S-Value:

$$S_{i,j} = \frac{N_{i,j} - \min_i N_{i,j}}{\max_i N_{i,j} - \min_i N_{i,j}} \quad (11)$$

where $S_{i,j}$ is the S-value of alternative i on criterion j, $N_{i,j}$ is the normalized value of alternative i on criterion j, $\max_i N_{i,j}$ is the maximum normalized value for criterion j among all alternatives, and $\min_i N_{ij}$ is the minimum normalized value for criterion j among all alternatives.

Step 5: Calculate the Q-value

Calculate the Q-value for each alternative by considering the distance between its S-values and the ideal compromise solution. The alternative with the smallest Q-value is the best compromise solution.

Formula for Q-value:

$$Q_i = \lambda\left(\sum_{j=1}^{m} w_j (S_{i,j} - S_j^-)^2\right) + (1-\lambda)\left(\sum_{j=1}^{m} w_j (S_{i,j} - S_j^+)^2\right) \quad (12)$$

where Q_i is the Q-value of alternative i, λ is the weight that balances the compromise between the best and worst aspects (typically set between 0.5 and 1), w_j is the weight of criterion j, S_{ij} is the S-value of alternative i on criterion j, S_j^- is the S-value of the worst value for criterion j, and S_j^+ is the S-value of the best value for criterion j.

Step 6: Rank the alternatives

Arrange the alternatives in order according to their computed Q-values. The alternative with the lowest Q-value is positioned at the top rank, signifying the optimal compromise solution.

VIKOR offers a comprehensive approach for multi-criteria decision-making by considering both the optimistic and pessimistic aspects of each alternative. By balancing the compromise solution, it helps decision-makers make more informed and well-rounded choices in complex decision scenarios.

IV. Results and Discussions

A. AHP

The pairwise comparison matrix for the selected criteria is formed according to consumer preferences. Table II shows the results by applying the aforementioned steps for AHP method.

TABLE II: AHP RESULTS

	H1	H2	H3	H4	H5	H6	H7	H8	H9	H10	Weighted Sum Value	Criteria Weights	λ
H1	0.29	0.46	0.44	0.42	0.28	0.39	0.23	0.34	0.18	0.14	3.16	0.29	10.95
H2	0.10	0.15	0.22	0.11	0.20	0.24	0.17	0.23	0.14	0.12	1.67	0.15	10.98
H3	0.07	0.08	0.11	0.07	0.16	0.16	0.14	0.17	0.12	0.11	1.18	0.11	10.80
H4	0.14	0.30	0.33	0.21	0.24	0.32	0.20	0.28	0.16	0.14	2.32	0.21	11.04
H5	0.04	0.03	0.03	0.03	0.04	0.03	0.06	0.03	0.06	0.06	0.40	0.04	10.12
H6	0.06	0.05	0.05	0.05	0.12	0.08	0.11	0.11	0.10	0.09	0.83	0.08	10.55
H7	0.03	0.02	0.02	0.03	0.02	0.02	0.03	0.02	0.04	0.05	0.28	0.03	10.05
H8	0.05	0.04	0.04	0.04	0.08	0.04	0.08	0.06	0.08	0.08	0.58	0.06	10.31
H9	0.03	0.02	0.02	0.03	0.01	0.02	0.01	0.01	0.02	0.03	0.20	0.02	10.10
H10	0.03	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.16	0.02	10.21

The criteria weights obtained using AHP method are demonstrated in Fig. 9. The CR value obtained is 0.03806 which is lesser than the threshold value of 0.1 which signifies that our pair-wise comparison is consistent.

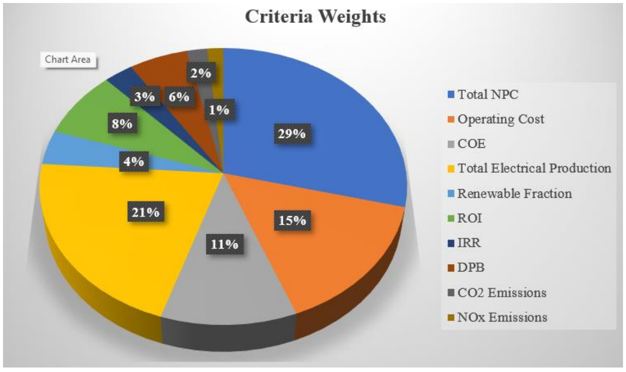

Fig. 9. Pie chart of criteria weights.

The initial step involved employing the AHP method to determine the relative importance of the ten evaluation criteria. Through pairwise comparisons, the criteria were assigned weights that reflect their hierarchical significance (refer Table II). This process enabled the establishment of a well-structured framework for evaluating the HRES systems.

B. MOORA

Using the above-mentioned Step 2 to Step 4 for MOORA method on the decision matrix, we can obtain the rankings for the alternatives as given in Table III.

TABLE III: MOORA RANKING

Alternatives	E1	E2	E3	E4	E5	E6
Y_i	0.0198	0.0289	−0.1188	−0.1015	−0.1848	−0.2244
Rank	2	1	4	3	5	6

The MOORA method employed the concept of ratios to evaluate the performance of the HRES alternatives. The Y_i values in Table III, which represent the ratios of each alternative's performance to the best performance, were used to derive rankings. The MOORA results uncovered the following insights:

- PV/BAT secured the top rank, consistently outperforming the other alternatives in terms of Y_i values.
- PV/GEN/BAT demonstrated competitive performance, securing the second rank across the criteria evaluations.

- PV/WD/BAT and PV/WD/GEN/BAT obtained mid-tier positions, indicating their balanced attributes.
- PV/GEN and WD/GEN/BAT found themselves towards the lower end of the rankings, suggesting potential areas for improvement.

C. TOPSIS

The ranking for all the alternatives obtained by using the Step 5 to Step 9 in the TOPSIS method are given Table IV.

The TOPSIS technique evaluated the proximity of every alternative to the ideal solution by employing the C_i values, as demonstrated in Table IV. The TOPSIS rankings provided the following insights:

- PV/BAT clinched the top rank, signifying its consistent proximity to the ideal solution across the evaluation criteria.
- PV/GEN/BAT and PV/WD/BAT closely followed, implying their potential as strong contenders.

PV/WD/GEN/BAT, PV/GEN, and WD/GEN/BAT exhibited relatively higher C_i values, positioning them further down the rankings.

TABLE IV: TOPSIS RANKING

	D_i^+	D_i-	C_i	Rank
E1	0.034	0.132	0.796	2
E2	0.014	0.134	0.903	1
E3	0.074	0.089	0.547	4
E4	0.071	0.098	0.580	3
E5	0.124	0.046	0.271	6
E6	0.111	0.044	0.284	5

D. VIKOR

Final rankings for all the alternatives using the steps mentioned in (10) to (12) in the VIKOR method are given below:

The VIKOR method aimed to find the best compromise solution by considering optimistic and pessimistic perspectives using Q_i values (see Table V). The VIKOR rankings revealed the following perspective:

TABLE V: VIKOR RANKING

	S_i	R_i	Q_i	Rank
E1	0.174427	0.168077	0.302	2
E2	0.101135	0.040566	0	1
E3	0.653390	0.206445	0.672	3
E4	0.556131	0.240076	0.680	4
E5	0.645417	0.240670	0.736	5
E6	0.917851	0.288913	1	6

- PV/BAT led the rankings once more, highlighting its robustness under both optimistic and pessimistic scenarios.
- PV/GEN/BAT and PV/WD/BAT maintained their competitive positions, showcasing their capacity for compromise solutions.
- PV/WD/GEN/BAT, PV/GEN, and WD/GEN/BAT displayed higher Q_i values, positioning them at a lower rank.

E. DISCUSSIONS

As seen in the previous section, we have found the system among the shortlisted HRES systems closest to the optimal solution through three different methods namely MOORA, TOPSIS & VIKOR. The comparison of rankings obtained from the 3 methods is given in Table VI.

TABLE VI: RANKS COMPARISON

Alternatives	MOORA		TOPSIS		VIKOR	
	Y_i	Rank	C_i	Rank	Q_i	Rank
PV/GEN/BAT	0.019783	2	0.79614	2	0.3016	2
PV/BAT	0.028917	1	0.90291	1	0	1
PV/WD/GEN/BAT	-0.11878	4	0.54712	4	0.6721	3
PV/WD/BAT	-0.10152	3	0.58045	3	0.6802	4
PV/GEN	-0.18476	5	0.27066	6	0.7361	5
WD/GEN/BAT	-0.22439	6	0.28405	5	1	6

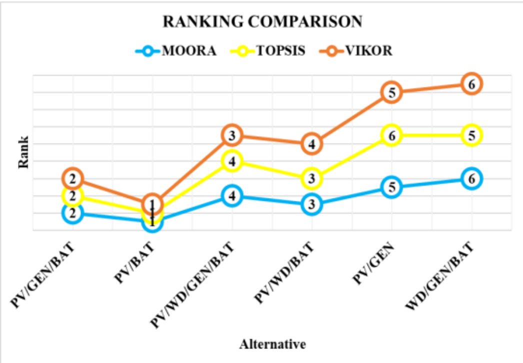

Fig. 10. Comparison of rankings.

The comprehensive evaluation of six Hybrid Renewable Energy Systems (HRES) utilizing the Analytic Hierarchy Process (AHP), Multi-Objective Optimization on the basis of Ratio Analysis (MOORA), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) methods has yielded a nuanced understanding of their attributes, strengths, and compromises. This multifaceted analysis involved ten distinct evaluation criteria and aimed to provide a holistic view for informed decision-making.

Comparing the rankings and scores obtained from the three methods underscores both consistencies and variations (refer Fig. 10). Notably, the PV/BAT system secured the top rank across all methodologies, affirming its exceptional performance. PV/GEN/BAT and PV/WD/BAT consistently held strong positions, indicating their competitive attributes. In contrast, PV/WD/GEN/BAT, PV/GEN, and WD/GEN/BAT consistently occupied the lower ranks, suggesting potential areas for improvement.

This multifaceted analysis highlights the importance of a comprehensive evaluation approach. The AHP method provided a foundation for criteria weighting, while MOORA, TOPSIS, and VIKOR facilitated a thorough assessment of the alternatives' attributes. While the rankings and scores vary between methods due to their distinct evaluation frameworks, the common thread lies in the consistent performance of the PV/BAT system.

V. CONCLUSIONS

A comprehensive multi-criteria evaluation using MOORA, TOPSIS, and VIKOR techniques across six alternative systems has been presented. The assessment involved the consideration of Y_i, C_i, and Q_i values, yielding distinct ranks for each alternative under the respective methodologies. Upon analysis, it is evident that the PV/BAT configuration emerges as the unequivocal leader across all three methods. Its consistent attainment of the top rank underscores its remarkable performance. This alternative, characterized by its Y_i and C_i values, demonstrates superior efficiency and effectiveness, positioning it as the prime choice.

Following suit, the PV/GEN/BAT and PV/WD/BAT alternatives secure commendable positions, consistently performing well across the evaluation methods. Their balanced ranking averages further bolster their candidacy as viable options. While they may fall short of the PV/BAT system's pinnacle, their collective merit indicates their potential in various scenarios.

On the other hand, the WD/GEN/BAT system emerges as the least favored alternative in this comparison. Its consistently inferior rank across all methods points to potential shortcomings in terms of Yi, Ci, and Qi values. Though it may have specific use cases, its overall performance lags behind the other alternatives.

In summation, the PV/BAT system garners the spotlight as the most advantageous choice, backed by its steadfast top-ranking performance due to its high electrical energy production with low operating cost when compared to the rest in all three methodologies. While PV/GEN/BAT and PV/WD/BAT hold promise as well-rounded contenders, the WD/GEN/BAT system lags behind as the least optimal choice. This assessment empowers decision-makers to make informed choices based on a holistic understanding of these alternatives' multi-faceted performance, ultimately driving more effective and efficient system selections in line with varying priorities and contexts.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

The concept and research were developed by Vasupalli Manoj and Ramana Pilla. Data collection and analysis of the methods used for this study were carried out by Krishna Koushik Bhogi and Y. Narendra Kumar. Contributions to the introduction and methodology sections in the paper were made by Chetna Sinha, Somarouthu V G V A Prasad, and M. Kalyan Chakravarthi. All authors reviewed and approved the final version of the paper.

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