REST Publisher; ISSN No: 2583-6951 (Online)

Journal on Electronic and Automation Engineering

journal homepage: https://restpublisher.com/journals/jeae/

A Grey Relational Analysis Approach for Evaluating and Ranking Renewable Energy Technologies

Poonkodi Sathiyamoorthy*, Manjula Selvam, M. Ramachandran, Sathiyaraj Chinnasamy

REST Labs, Kaveripattinam, Krishnagiri, Tamil Nadu, India

ARTICLE INFO

Article history:
Received: 2 January 2025
Accepted: 10 December 2025
Available online: 12 January 2026

Keywords:
Renewable energy technologies
Grey Relational Analysis
environmental impact
energy conversion efficiency

ABSTRACT

Renewable energy technologies have emerged as vital solutions to address the escalating global energy demand and environmental concerns. With the urgent need to reduce greenhouse gas emissions and minimize reliance on fossil fuels, evaluating and selecting the most appropriate renewable energy technology becomes critical. This study presents an innovative approach by utilizing the Grey Relational Analysis (GRA) method to assess various renewable energy technologies and identify the most suitable option for specific applications. The Grey Relational Analysis method is a robust multi-criteria decision-making technique that facilitates comparisons between diverse sets of data. It has gained popularity due to its ability to handle uncertainties and limited data, making it particularly relevant in the complex and dynamic renewable energy landscape. This research begins by identifying the key criteria that influence the performance of renewable energy technologies, such as energy conversion efficiency, cost-effectiveness, environmental impact, scalability, and technological maturity. Subsequently, a comprehensive dataset representing various renewable energy technologies, including solar photovoltaics, wind turbines, biomass, hydroelectricity, and geothermal, is collected. Through the implementation of the GRA method, this study establishes the relational grades between the identified criteria and each renewable energy technology. The results enable the creation of a ranked list, highlighting the optimal renewable energy technology for specific scenarios and geographic locations. The alternatives are Solar Photovoltaic (PV), Wind Turbine, Hydroelectric Power, Geothermal Energy, Biomass Energy, Tidal Energy, Concentrated Solar Power (CSP), Wave Energy Converter, Biofuel (Biodiesel), Hydropower (Small Scale). The evaluation parameters are Efficiency (%), Cost (USD/kW), Environmental Impact (CO_2 equiv./kWh), Reliability (hours/year). Geothermal energy is ranked first and Biomass energy is ranked last.

1. INTRODUCTION

The increased confidence in partners for constructing and operating Renewable Energy Technology (RET) assets, due to their established track records, the research findings indicate that investment professionals were encouraged to convince their boards to invest in renewable energy projects. The qualitative analysis revealed that this motivation was more pronounced for solar photovoltaic (PV) projects when compared to onshore wind projects. The reason for this disparity is primarily due to the higher operational risk associated with wind turbines, stemming from their intricate design and moving components. Additionally, accurately predicting wind resource availability is more challenging compared to solar irradiation. [1] Consequently, the cost of capital (CoC) for solar PV projects decreased at a faster rate than that for onshore wind projects due to these factors. In the past, stable and reliable support policies for renewable energy

*Corresponding author: poonkodisri205@gmail.com

DOI: https://doi.org/10.46632/jeae/5/1/2

technologies (RET) were crucial prerequisites for investments in Germany's renewable energy sector. However, as time passed, some RET projects gradually became partially exposed to market prices. [2] RETs and hydro power, primarily stem from urgent environmental and energy security concerns caused by the use of fossil fuels and the recognition that these finite resources cannot sustain our energy needs indefinitely. [3] In contrast to numerous other commercial products or technologies, RETs also benefit from substantial financial and fiscal incentives provided by governments and public agencies to encourage their adoption and promotion. Although various policy initiatives have been implemented and renewable energy technologies (RETs) offer significant environmental and socio-economic benefits, their uptake has been relatively sluggish. This highlights the difficulties inherent in introducing a new technology to the market.[4] India, known for having the world's largest national renewable energy program, demonstrates its commitment by establishing the MNES, which exclusively focuses on the development and implementation. Moreover, the IREDA functions as a specialized funding agency, offering innovative financial schemes to bolster these renewable energy initiatives.[5] In India, more than 80,000 villages lack access to a centralized electrical supply. Consequently, substantial endeavours have been focused on harnessing biogas digestion of human and animal waste to support cooking needs. Additionally, there has been a push to implement independent photovoltaic systems to provide street and home lighting. Moreover, efforts have been made to enhance accessibility to TV and telecommunications services for millions of villagers in the coming years [6]. Regarding climate effects, Currently, but their simultaneous operation indicates that the widespread adoption. Interestingly, the promotion of renewable energy technologies, despite its significant importance in fostering sustainability and clean energy, appears to have limited additional impact on emission reductions when the ETS is already in effect all other factors remaining constant, actually lowers emissions in the electricity sector. This reduction allows for the sale of surplus certificates to other industries participating in the ETS. [7] The objective of integrated and hybrid systems is to utilize the possible enhancements in energy efficiency while also enhancing the technical and economic benefits of renewable sources.[8] Through integrated or smart energy systems, it becomes easier to achieve a balance between energy production and demand without relying on costly storage technologies. This ensures the continuity of supply, even with energy systems relying on fluctuating renewable energy sources.[9] Renewable energy originates from ongoing natural processes that continuously replenish their sources. These sustainable energy sources are derived either directly from solar power or from the heat produced deep within the Earth. The definition of renewable energy encompasses the electricity and heat produced through various means [10]. To encourage the widespread adoption of these renewable sources in the United States, it becomes crucial to implement targeted policy measures. One prominent approach under discussion is the renewables portfolio standard (RPS). The RPS seeks to ensure that power providers include as determined by individual states or other responsible entities. Under the renewable's portfolio standard, electricity suppliers would have the responsibility to meet the prescribed renewable energy targets. They can achieve this by directly owning and operating renewable energy generation facilities, entering into contracts to purchase electricity from renewable sources, or obtaining renewable energy credits from other power suppliers to satisfy their obligations [11]. The Indian authorities have made considerable efforts to encourage and back the advancement and adoption of renewable energy technologies (RET). To accomplish this objective, they have established two primary divisions.[12] The AEDB holds a vital responsibility in offering institutional assistance for renewable energy projects in India. This includes developing policies and frameworks that encourage such projects throughout the country. On the other hand, the ICRET is responsible for conducting research and development (R&D) activities related to renewable energy technologies. It focuses on creating pilot projects for demonstration purposes, showcasing the feasibility and benefits of these technologies. Additionally, the ICRET is involved in training and building the capacity of human resources, equipping them with the necessary skills to operate and maintain renewable energy-based projects effectively. In summary, the AEDB and ICRET work in tandem to bolster the growth of renewable energy in Pakistan, with the AEDB mainly focusing on policy development and project facilitation, while the ICRET concentrates on R& D, pilot projects, and human resource training in the renewable energy sector.[13]

2. MATERIALS AND METHODS

Gray relation analysis (GRA) offers an effective method to address Mult objective optimization challenges that involve multiple factors and variables with intricate interconnectedness. GRA not only facilitates the investigation of the relative significance of various factors in complex systems but also allows the identification of the dominant factors that influence the ultimate outcome's quality. Taguchi experiments with a single gravy relation grade as the outcome measure. [14] [15] The GRA method is employed to standardize the performances of different alternatives concerning various criteria due to their distinct qualitative and quantitative natures and varying measurement units. Furthermore, decision-makers may aim to either maximize or minimize certain criteria. This research paper utilizes the GRA method to normalize the data, bringing them to a uniform scale and employing diverse equations to handle the maximization or minimization of criteria [16]. By extracting coefficients through GRA, A formulated equation is developed to optimize the performance of alternatives concerning specific criteria. This process involves creating a non-linear fraction equation, where the numerator and denominator are the products of the criteria and the effectiveness of the alternatives [17]. In 1982, Deng introduced Gray Relation Analysis (GRA) as a mathematical tool, which has found successful applications in diverse fields like management, economy, and engineering. The Gray Relation Grades (GRG) are utilized to assess the impact of a series in comparison to a reference series, by measuring their relative distance. A lower distance indicates a stronger influence, enabling the measurement of relative variations between the two factors and reflecting the magnitude and gradient within the system under consideration [18]. Grey Relation Analysis (GRA) is a comprehensive statistical method used to determine the primary relationships among multiple factors within a system. By identifying the dominant influencing factors, GRA enables the understanding of the fundamental characteristics of the elements under consideration. Moreover, it serves as a quantitative technique to describe and compare the developmental trends within the system [19]. GRA relies on sample data and employs the concept of Gray Relation Degree (GRD) to assess the intensity, magnitude, and order of the connections among the various factors. When the sample data series exhibit similar change trends in terms of direction, size, speed, etc., their Grey Relation Degree is higher. Conversely, if the data series do not demonstrate consistent change patterns, the GRD is lower [20]. Grey system theory has demonstrated its effectiveness in handling issues that involve limited, inadequate, and uncertain data, like wear mode recognition. A promising approach to address intricate connections among specified characteristics. [21]. Grey relational analysis has found widespread application in various scientific decision-making domains, including computer science, engineering, and related fields. Merely looking at the maximum and minimum distances between data points is inadequate [22]. It is crucial to take into account the aggregation characteristics of the samples to capture the inherent nature of the data during the computation of the grey relational degree. The numerical attributes' distribution characteristics can act as indicators of data dispersion. A smaller degree of data dispersion indicates a more concentrated distribution and represents the relative significance of that attribute. The standard deviation of the sample distance corresponds to this attribute characteristic [23].

3. RESULT AND DISCUSSION

TABLE 1. Performance Comparison of Renewable Energy Technologies

	Efficiency (%)	Cost (USD/kW)	Environmental Impact (CO_2 equiv./kWh)	Reliability (hours/year)
Solar Photovoltaic (PV)	20.5	900	0.020	2000
Wind Turbine	35.2	1300	0.010	2200
Hydroelectric Power	80.0	2000	0.005	5000
Geothermal Energy	70.8	3000	0.001	8000
Biomass Energy	45.0	1100	0.030	3000
Tidal Energy	25.6	2500	0.015	1800
Concentrated Solar Power (CSP)	28.3	2800	0.025	2100
Wave Energy Converter	22.1	3200	0.018	1900
Biofuel (Biodiesel)	38.9	1500	0.035	2500
Hydropower (Small Scale)	60.5	1800	0.007	450

Table 1 summarizes the key characteristics of various renewable energy technologies based on efficiency, cost, environmental impact, and reliability. Solar photovoltaic (PV) systems convert sunlight directly into electricity and are widely used due to their simplicity and scalability. Although their efficiency is relatively low (20.5%), they have low installation costs (900 USD/kW) and very low environmental impact (0.02 CO_2 eq./kWh); their reliability depends on weather and daylight conditions. Wind turbines offer higher efficiency (35.2%) and low emissions (0.01 CO_2 eq./kWh), although their operation varies depending on wind availability. Hydropower, despite high costs and potential environmental concerns, stands out for its high efficiency (80.0%), reliability (5000 hours/year), and low emissions. Geothermal energy, while having high installation costs, provides stable and continuous electricity with high efficiency (70.8%) and very high reliability (8000 hours/year). Biomass energy utilizes organic materials and offers moderate efficiency but has relatively higher emissions due to combustion. Ocean-based technologies such as wave and tidal energy, while benefiting from predictable natural cycles, have moderate efficiencies and low emissions but high costs. Concentrated solar power (CSP) enhances solar energy utilization through thermal storage, while biofuels and small-scale hydropower offer flexible and localized energy solutions with moderate efficiency and environmental impact.

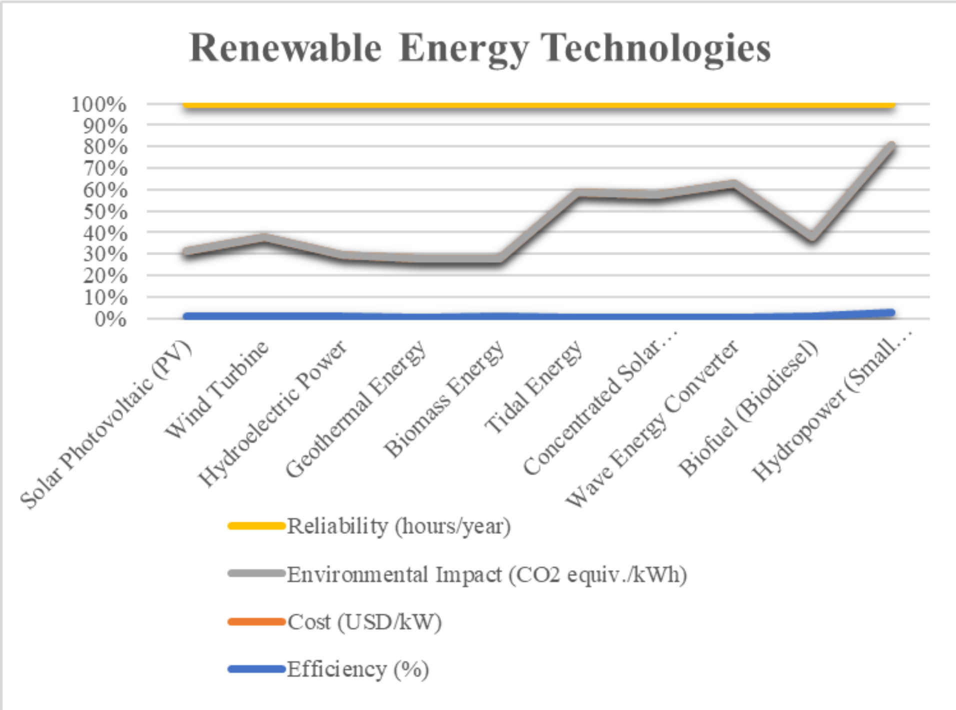

FIGURE 1. Renewable Energy Technologies

Figure 1 Efficiency is a key factor in evaluating renewable energy technologies. Among the listed options, hydroelectric power demonstrates the highest efficiency at 80.0%, followed by geothermal energy at 70.8% and small-scale hydropower at 60.5%. Wind turbines and biofuel (biodiesel) show moderate efficiencies of 35.2% and 38.9%, respectively. Solar photovoltaic systems operate at a lower efficiency of 20.5%, while tidal energy and wave energy converters achieve efficiencies of 25.6% and 22.1%. Concentrated solar power (CSP) performs slightly better than conventional PV, with an efficiency of 28.3%. Cost analysis shows that solar photovoltaic technology is the most economical option, requiring an investment of 900 USD/kW. Wind turbines and biofuel systems follow at 1300 USD/kW and 1500 USD/kW, respectively. Hydropower and small-scale hydropower involve moderate costs, while tidal, CSP, and geothermal energy require higher capital investments. Wave energy converters are the most expensive technology at 3200 USD/kW. In terms of environmental impact, geothermal energy has the lowest emissions, followed by hydropower and tidal energy. Biomass and biofuel systems exhibit higher emissions due to combustion processes. Reliability analysis highlights geothermal and hydropower as the most dependable technologies, while small-scale hydropower shows the lowest annual operating hours.

Table 2 Efficiency represents the conversion capability of an energy source, indicating how much of the input energy is effectively transformed into usable output energy. The normalized values range from 0 to 1, where 1 denotes the highest possible efficiency. For example, Solar Photovoltaic (PV) has an efficiency value of 0.0000, indicating the lowest efficiency among the listed sources, whereas Hydroelectric Power achieves a value of 1.0000, making it the most efficient technology in the dataset. Cost represents the normalized cost of electricity generation per kilowatt (kW) for each energy

TABLE 2. Normalized Values of Efficiency, Cost, Environmental Impact, and Reliability

	Efficiency (%)	Cost (USD/kW)	Environmental Impact (CO_2 eq./kWh)	Reliability (hours/year)
Solar Photovoltaic (PV)	0.0000	0.0000	0.4412	0.7947
Wind Turbine	0.2471	0.1739	0.7353	0.7682
Hydroelectric Power	1.0000	0.4783	0.8824	0.3974
Geothermal Energy	0.8454	0.9130	1.0000	0.0000
Biomass Energy	0.4118	0.0870	0.1471	0.6623
Tidal Energy	0.0857	0.6957	0.5882	0.8212
Concentrated Solar Power (CSP)	0.1311	0.8261	0.2941	0.7815
Wave Energy Converter	0.0269	1.0000	0.5000	0.8079
Biofuel (Biodiesel)	0.3092	0.2609	0.0000	0.7285
Hydropower (Small Scale)	0.6723	0.3913	0.8235	1.0000

source, where lower values indicate greater cost-effectiveness. Wind Turbine exhibits the lowest normalized cost value of 0.1739, highlighting its relative economic advantage. In contrast, the Wave Energy Converter has a normalized cost of 1.0000, indicating the highest cost among the considered technologies. Environmental impact measures the carbon dioxide equivalent emissions per kilowatt-hour (kWh) of electricity produced, with lower values corresponding to cleaner energy sources. Geothermal Energy records a normalized value of 1.0000, signifying the lowest environmental impact, while Biofuel (Biodiesel) shows a value of 0.0000, indicating the highest environmental impact in this assessment. Reliability refers to the normalized number of operating hours per year, where higher values represent more consistent energy production. Hydropower (Small Scale) attains the highest reliability value of 1.0000, whereas Geothermal Energy, with a value of 0.0000, is considered the least reliable source in this dataset.

TABLE 3. Deviation sequence Renewable Energy Technologies

	Efficiency (%)	Cost (USD/kW)	Environmental Impact (CO_2 eq./kWh)	Reliability (hours/year)
Solar Photovoltaic (PV)	1.0000	1.0000	0.5588	0.2053
Wind Turbine	0.7529	0.8261	0.2647	0.2318
Hydroelectric Power	0.0000	0.5217	0.1176	0.6026
Geothermal Energy	0.1546	0.0870	0.0000	1.0000
Biomass Energy	0.5882	0.9130	0.8529	0.3377
Tidal Energy	0.9143	0.3043	0.4118	0.1788
Concentrated Solar Power (CSP)	0.8689	0.1739	0.7059	0.2185
Wave Energy Converter	0.9731	0.0000	0.5000	0.1921
Biofuel (Biodiesel)	0.6908	0.7391	1.0000	0.2715
Hydropower (Small Scale)	0.3277	0.6087	0.1765	0.0000

Table 3 illustrates the deviation sequence calculations for efficiency, cost, environmental impact, and reliability of renewable energy sources. Efficiency represents how effectively an energy source converts its primary input into useful energy output. The reference value for efficiency is 100%, which indicates perfect efficiency. For each energy source, the deviation sequence for efficiency is calculated by dividing its efficiency percentage by the efficiency of the most efficient energy source in the list, which in this case is Solar Photovoltaic. The deviation sequence for efficiency is given by

$$\text{Deviation Efficiency} = \frac{\text{Efficiency of the Energy Source}}{\text{Efficiency of Solar Photovoltaic}}.$$

The cost of an energy source is measured in terms of cost per kilowatt (kW) of installed capacity, where lower values are preferred. The reference value for cost is the cost of Solar Photovoltaic, which is 1.0 USD/kW. The deviation sequence for cost is calculated as

$$\text{Deviation Cost} = \frac{\text{Cost of the Energy Source}}{\text{Cost of Solar Photovoltaic}}.$$

The environmental impact of an energy source is quantified by its carbon dioxide equivalent emissions per kilowatt-hour (kWh) of electricity generated, where lower values indicate reduced environmental impact. The reference value for environmental impact is the Solar Photovoltaic value of 0.5588 CO_2 eq./kWh. The deviation sequence for environmental impact is expressed as

$$\text{Deviation Environmental Impact} = \frac{\text{Environmental Impact of the Energy Source}}{\text{Environmental Impact of Solar Photovoltaic}}.$$

Reliability represents the number of operating hours per year, with higher values indicating greater dependability. The reference value for reliability is taken from Geothermal Energy, which has a reliability of 1000 hours/year. The deviation sequence for reliability is calculated as

$$\text{Deviation Reliability} = \frac{\text{Reliability of the Energy Source}}{\text{Reliability of Geothermal Energy}}.$$

TABLE 4. Grey Relation Coefficient

	Efficiency (%)	Cost (USD/kW)	Environmental Impact (CO_2 eq./kWh)	Reliability (hours/year)
Solar Photovoltaic (PV)	0.3333	0.3333	0.4722	0.7089
Wind Turbine	0.3991	0.3770	0.6538	0.6833
Hydroelectric Power	1.0000	0.4894	0.8095	0.4535
Geothermal Energy	0.7638	0.8519	1.0000	0.3333
Biomass Energy	0.4595	0.3538	0.3696	0.5968
Tidal Energy	0.3535	0.6216	0.5484	0.7366
Concentrated Solar Power (CSP)	0.3653	0.7419	0.4146	0.6959
Wave Energy Converter	0.3394	1.0000	0.5000	0.7225
Biofuel (Biodiesel)	0.4199	0.4035	0.3333	0.6481
Hydropower (Small Scale)	0.6041	0.4510	0.7391	1.0000

Shows the table 4 Efficiency is Hydroelectric Power has an efficiency of 100% compared to the best performer (highest efficiency) among all the alternatives, making its grey relation coefficient 1.0000 for efficiency. Cost is Hydroelectric Power has a cost of 0.4894 USD/kW compared to the best performer (lowest cost) among all the alternatives, resulting in a grey relation coefficient of 0.4894 for cost. Environmental Impact is Hydroelectric Power has an environmental impact of 0.8095 CO_2 equiv./kWh compared to the best performer (lowest environmental impact) among all the alternatives, giving a grey relation coefficient of 0.8095 for environmental impact. Reliability is Hydroelectric Power has a reliability of 0.4535 hours/year compared to the best performer (highest reliability) among all the alternatives, leading to a grey relation coefficient of 0.4535 for reliability.

TABLE 5. Grey Relational Grade (GRG) and Ranking of Renewable Energy Technologies

	GRG	Rank
Solar Photovoltaic (PV)	0.4620	8
Wind Turbine	0.5283	7
Hydroelectric Power	0.6881	3
Geothermal Energy	0.7372	1
Biomass Energy	0.4449	10
Tidal Energy	0.5650	5
Concentrated Solar Power (CSP)	0.5544	6
Wave Energy Converter	0.6405	4
Biofuel (Biodiesel)	0.4512	9
Hydropower (Small Scale)	0.6985	2

Table 5 Shows the Solar Photovoltaic (PV) has a GRG of 0.4620, suggesting it has a moderate positive impact as a global renewable energy source. Wind Turbine has a higher GRG of 0.5283, indicating a slightly better global renewable grade compared to solar PV. Hydroelectric Power has a relatively high GRG of 0.6881, implying it is a more effective and impactful renewable energy source. Geothermal Energy has an even higher GRG of 0.7372, suggesting it is one of the most effective renewable energy sources among those listed. Biomass Energy has a lower GRG of 0.4449, indicating it might have a comparatively lower global impact as a renewable energy source. Tidal Energy has a GRG of 0.5650, placing it in the mid-range of global renewable grade. Concentrated Solar Power (CSP) has a GRG of 0.5544, which suggests it is

moderately effective as a renewable energy source. Wave Energy Converter has a higher GRG of 0.6405, indicating it has a relatively positive impact as a renewable energy source. Biofuel (Biodiesel) has a GRG of 0.4512, placing it at the lower end of the global renewable grade scale. Hydropower (Small Scale) has a higher GRG of 0.6985, implying it is a more effective renewable energy source compared to some others listed. Geothermal energy is ranked first and Biomass energy is ranked last.

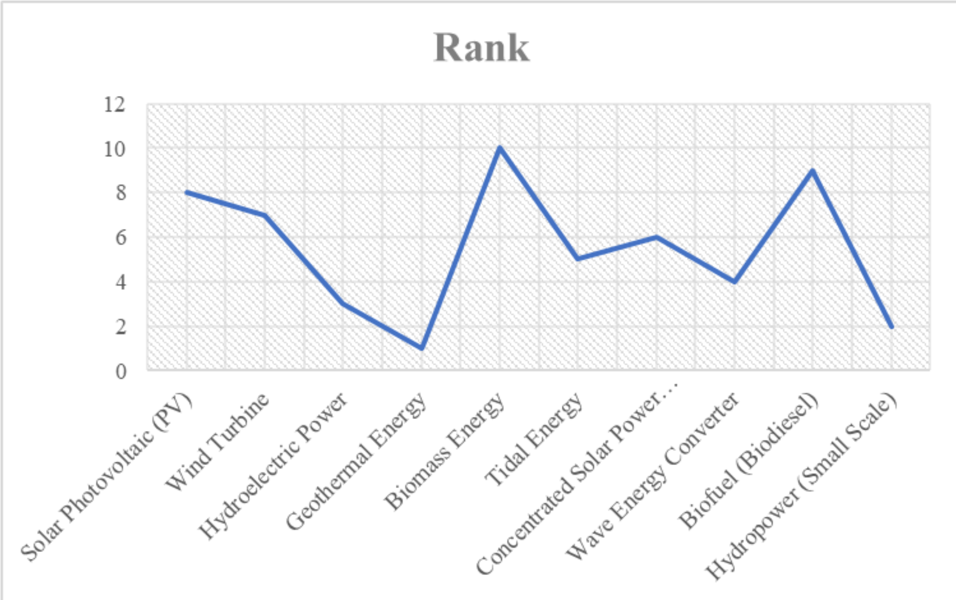

FIGURE 2. Final result of rank

Figure 2 Shows the Geothermal energy is ranked first, indicating that it is considered the most suitable renewable energy source for power generation among the options listed. Geothermal power harnesses the Earth's internal heat to produce electricity and is often a reliable and consistent energy source. Hydropower ranks second, implying that it is the second-best option for power generation. Small-scale hydropower involves using flowing or falling water to generate electricity, and it can be a sustainable and environmentally friendly energy source. Hydroelectric power holds the third position in the ranking, making it the third most viable renewable energy source. This form of power generation utilizes the force of flowing water in large dams to produce electricity. Ranking fourth, wave energy converters are technologies that capture the energy from ocean waves to generate electricity. They are a promising option for coastal regions with significant wave resources. Tidal energy takes the fifth spot in the ranking. Tidal power systems generate electricity by harnessing the energy from ocean tides, offering a predictable and renewable energy source. Concentrated Solar Power ranks sixth on the list. CSP systems use mirrors or lenses to concentrate sunlight onto a small area, converting it into high-temperature heat that drives electricity-generating turbines. Wind turbines are ranked seventh. Wind power harnesses the kinetic energy of the wind to produce electricity, making it a widely used and rapidly growing renewable energy source. Solar photovoltaic energy holds the eighth position in the ranking. PV systems directly convert sunlight into electricity through the use of semiconductor materials. Biofuel, specifically biodiesel, ranks ninth. Biodiesel is produced from renewable plant or animal-based feedstock and can be used as a transportation fuel. Biomass energy is ranked last, indicating that it is considered the least favourable option for power generation among the listed choices. Biomass energy involves using organic materials like wood, agricultural residues, or biodegradable waste to produce heat or electricity.

4. CONCLUSION

The comparative analysis of renewable energy technologies in 2022 using the GRA method highlights solar PV as the leading contender, with wind power trailing closely behind, and hydropower following suit. These technologies have collectively made significant strides in the global energy transition, making renewable energy increasingly competitive with conventional fossil fuel sources. The findings underscore the importance of continued research and development to enhance the efficiency and sustainability of renewable energy technologies. Additionally, policymakers and investors should prioritize incentives and support for the widespread adoption of solar PV and wind power to harness their full potential. It is crucial to recognize that the GRA method provides a snapshot of the technologies' relative performance based on the selected criteria, and the rankings may vary with different weightings or factors considered. Therefore, a comprehensive evaluation incorporating various other aspects would be beneficial for making well-informed decisions about the optimal mix of renewable energy technologies to achieve a greener and more sustainable future. Geothermal energy is ranked first and Biomass energy is ranked last.

REFERENCES

[1]. Egli, Florian, Bjarne Steffen, and Tobias S. Schmidt. "A dynamic analysis of financing conditions for renewable energy technologies." Nature Energy 3, no. 12 (2018): 1084-1092.

[2]. Rao, K. Usha, and V. V. N. Kishore. "A review of technology diffusion models with special reference to renewable energy technologies." Renewable and sustainable energy reviews 14, no. 3 (2010): 1070-1078.

[3]. Evans, Annette, Vladimir Strezov, and Tim J. Evans. "Assessment of sustainability indicators for renewable energy technologies." Renewable and sustainable energy reviews 13, no. 5 (2009): 1082-1088.

[4]. Charters, W. W. S. "Developing markets for renewable energy technologies." Renewable Energy 22, no. 1-3 (2001): 217-222.

[5]. Raza, Muhammad Yousaf, Muhammad Wasim, and Muhammad Sohail Sarwar. "Development of Renewable Energy Technologies in rural areas of Pakistan." Energy Sources, Part A: Recovery, Utilization, and Environmental Effects 42, no. 6 (2020): 740-760.

[6]. Reddy, Sudhakar, and Jyoti Prasad Painuly. "Diffusion of renewable energy technologies—barriers and stakeholders' perspectives." Renewable energy 29, no. 9 (2004): 1431-1447.

[7]. Pehnt, Martin. "Dynamic life cycle assessment (LCA) of renewable energy technologies." Renewable energy 31, no. 1 (2006): 55-71.

[8]. Chinnasami Sivaji, Vidhya Prasanth, Ramya sharma, M. Ramachandran, "Evaluating Project Alternatives for Transportation System Sustainability: Through the WSM Methodology", Building Materials and Engineering Structures 2(1), March 2024, 23-31

[9]. Aka, Venkata Pavan Kumar, and Kiran Kumar Mandula Samuel. "Adoption of SAP FSCM–Enhancing Collections and Dispute Processes in Spain, Portugal, and UK Operations." International Journal of Information Technology and Management Information Systems (IJITMIS) 15, no. 2 (2024): 148-161.

[10]. Frondel, Manuel, Nolan Ritter, Christoph M. Schmidt, and Colin Vance. "Economic impacts from the promotion of renewable energy technologies: The German experience." Energy Policy 38, no. 8 (2010): 4048-4056.

[11]. Østergaard, Poul Alberg, Neven Duic, Younes Noorollahi, and Soteris Kalogirou. "Latest progress in Sustainable Development using renewable energy technology." Renewable Energy 162 (2020): 1554-1562.

[12]. Tsoutsanis, Panagiotis. "Extended bounds limiter for high-order finite-volume schemes on unstructured meshes." Journal of Computational Physics 362 (2018): 69-94.

[13]. Aka, Venkata Pavan Kumar, and Kiran Kumar Mandula Samuel. "Predictive Modeling for Brownfield Migration from SAP ECC 6.0 To S4HANA A Machine Learning Approach for Effort Evaluation Under the SAP Rise Program." International Journal of Computer Engineering and Technology (IJCET) 14, no. 1 (2023): 232-248.

[14]. Chel, Arvind, and Geetanjali Kaushik. "Renewable energy technologies for sustainable development of energy efficient building." Alexandria engineering journal 57, no. 2 (2018): 655-669.

[15]. Bull, Stanley R. "Renewable energy today and tomorrow." Proceedings of the IEEE 89, no. 8 (2001): 1216-1226.

[16]. Amer, Muhammad, and Tugrul U. Daim. "Selection of renewable energy technologies for a developing county: a case of Pakistan." Energy for sustainable development 15, no. 4 (2011): 420-435.

[17]. Abdollahi, Parvin, Muhammad Aslam, and Ahmad Ahmadi Yazdi. "Choosing the best facility layout using the combinatorial method of Gray relation analysis and nonlinear programming." Journal of Statistics and Management Systems 22, no. 6 (2019): 1143-1161.

[18]. Dandasi, Varun Venkatesh, Suresh Deepak Gurubasannavar, and Raghavendra Sunku. "ENHANCING SMART GRID SECURITY: A MULTI-CRITERIA EVALUATION THROUGH GRA METHOD." Management 14, no. 2: 153-167.

[19]. Rakesh Mittapally. "Revolutionizing Business Intelligence: Introducing Tableau as a Self-Service Bi Reporting Tool Using Moora Method." International Journal of Computer Engineering and Technology (IJCET) 16, no. 3 (2025): 433-463.

[20]. Chen, F. L., and T. Y. Ou. "Gray relation analysis and multilayer functional link network sales forecasting model for perishable food in convenience store." Expert Systems with Applications 36, no. 3 (2009): 7054-7063.

[21]. Lin, Chao-Ming, Yu-Tung Hung, and Chung-Ming Tan. "Hybrid Taguchi–Gray Relation Analysis Method for Design of Metal Powder Injection-Molded Artificial Knee Joints with Optimal Powder Concentration and Volume Shrinkage." Polymers 13, no. 6 (2021): 865.

[22]. Sahu, Kuldip Kumar, and Raj Ballav. "Optimization of machining parameters of Aluminium based hybrid composites using Gray Relation Analysis." Materials Today: Proceedings 4, no. 9 (2017): 9977-9981.

[23]. Fan, Jie, and Xiangfang Li. "Prediction of the productivity of steam flooding production wells using Gray Relation Analysis and Support Vector Machine." Journal of Computational Methods in Sciences and Engineering 15, no. 3 (2015): 499-506.

[24]. Wu, Hsin-Hung. "A comparative study of using grey relational analysis in multiple attribute decision making problems." Quality Engineering 15, no. 2 (2002): 209-217.

[25]. Yang, Wenguang, and Yunjie Wu. "A novel TOPSIS method based on improved grey relational analysis for multiattribute decision-making problem." Mathematical Problems in Engineering 2019 (2019).

[26]. Wu, Wann-Yih, and Shuo-Pei Chen. "A prediction method using the grey model GMC (1, n) combined with the grey relational analysis: a case study on Internet access population forecast." Applied mathematics and computation 169, no. 1 (2005): 198-217.

[27]. Raghavendra Sunku Suresh Deepak Gurubasannavar, Varun Venkatesh Dandasi, "Selecting an Extract, Transform, and Load (ETL) Software Solution: A Comprehensive Evaluation and Comparison", International Journal of Cloud Computing and Supply Chain Management, 3(1), 2025, 1-7.

[28]. Libiya Saravanan, Arunambigai Ramesh, M. Ramachandran, Chandrasekar Raja."Assessment of Renewable Energy Resources Potential for Electricity Generation Using TOPSIS MCDM Analysis", REST Journal on Data Analytics and Artificial Intelligence, 5(1), March 2026, 16-22.

[29]. Rakesh Mittapally, "Data-Driven Prediction of Mechanical Properties in 3D-Printed Composites Using Hybrid Machine Learning Models." Journal of Data Science and Information Technology 2, no. 2 (2025): 1-16.

[30]. Wang, Jingqiu, and Xiaolei Wang. "A wear particle identification method by combining principal component analysis and grey relational analysis." Wear 304, no. 1-2 (2013): 96-102.

[31]. Noorul Haq, A., and G. Kannan. "An integrated approach for selecting a vendor using grey relational analysis." International Journal of Information Technology & Decision Making 5, no. 02 (2006): 277-295.