Neutrosophic Systems with Applications, Vol. 22, 2024
https://doi.org/10.61356/j.nswa.2024.22388

# Evaluation of Renewable Energy Sources for a Sustainable Future: A Multi-Criteria Decision-Making Approach

**Mai Mohamed [1,*] and Asmaa Elsayed [2]**

[1] Faculty of Computers and Informatics, Zagazig University, Zagazig 44519, Sharqiyah, Egypt.
Emails: mmgaafar@zu.edu.eg; aa.ahmed023@eng.zu.edu.eg.

* Correspondence: mmgaafar@zu.edu.eg.

**Abstract:** The urgent global challenges of climate change, energy security, and environmental degradation highlight the need for sustainable energy solutions. Renewable energy sources (RES) present a viable pathway towards sustainability by mitigating greenhouse gas emissions, reducing reliance on fossil fuels, and fostering economic resilience. Purpose: The purpose of this paper is to propose an advanced Multi-Criteria Decision-Making (MCDM) approach to evaluate various RES by integrating environmental, economic, technological, social acceptance, and resource availability criteria, to identify the most suitable RES for sustainable energy solutions. Methodology: The study employs a hybrid method combining Type-2 Neutrosophic Numbers (T2NN) with LOPCOW (Logarithmic Percentage Change Operator Weighting) and MAIRCA (Multi-Attributive Ideal-Real Comparative Assessment) to rank the suitability of different RES, including solar, wind, hydropower, and geothermal energy. Findings: The case study results reveal wind energy as the top-ranked alternative, supported by consistent findings across comparative methods such as COPRAS, MABAC, EDAS, and TOPSIS. Sensitivity analysis further confirms the stability of the proposed model under various scenarios. Originality: The originality of this study lies in the integration of T2NN, LOPCOW, and MAIRCA to address the limitations of traditional MCDM approaches in handling uncertainty and imprecision in data. The study demonstrates the efficacy of the proposed framework in providing a robust evaluation of RES, and its value lies in its potential to inform decision-making in the field of sustainable energy solutions.

**Keywords:** Solar; Wind; Hydropower; Geothermal; T2NN; LOPCOW; MAIRCA; MCDM; RES; COPRAS; MABAC; EDAS; TOPSIS.

## 1. Introduction

The transformation into renewable energy is crucial in tackling the complex problems of this century including climate change, depletion of resources, and energy security are among them [1]. Over the last century, due to the dependency on fossil fuels, the pace of industrialization and economic growth has been very swift, paralleling acute environmental degradation problems [2]. Global warming, air pollution, and the disruption of ecosystems have some connection or relationship with the consumption of fossil fuels [3]. However, these are costlier in environmental footprints because they are finite resources in the long term [4]. RES which are naturally replenished and have a minimal environmental impact, offer a promising solution to these challenges that can significantly reduce greenhouse gas emissions and promote environmental stewardship [5]. This paper provides an in-depth analysis of various renewable energy sources, including solar, wind, hydro, and geothermal and their potential to contribute to a sustainable future and their potential to contribute to a sustainable future. Renewable energy is very important for mitigating the problem of climate change and ensuring energy safety all over the world [6]. Unlike fossil fuels, which are finite and concentrated in specific regions, renewable energy is abundant and widely distributed [7]. By transitioning to RES, nations can reduce their dependence on imported fuels, enhance their state of energy security, and stimulate economic development by creating green jobs.

Solar energy, derived from the sun's radiation, is one of the most abundant and widely recognized RES [8]. Photovoltaic (PV) systems and solar thermal technologies are the primary methods of harnessing solar energy [9]. These systems have significant advancements in efficiency and cost reduction, making solar energy more accessible and economically viable [10]. Wind energy is harnessed through wind turbines that convert the kinetic energy of wind into electricity [11]. Wind farms can be located onshore or offshore, with offshore wind farms generally benefiting from stronger and more consistent winds [12]. Wind energy is a clean, renewable source with a relatively low environmental impact during operation [13]. It has become increasingly cost-competitive with traditional energy sources, making it a vital component of the global energy mix [14]. Hydropower is generated by using the gravitational force of falling or flowing water to produce electricity [15]. It is one of the oldest and most widely used forms of renewable energy [16]. Hydropower is a reliable and consistent source of energy, with the ability to generate large amounts of electricity [17]. It also provides additional benefits such as water supply, flood control, and recreational opportunities [18]. Geothermal energy is derived from the Earth's internal heat, which can be harnessed for electricity generation or direct heating purposes [19]. This energy source is particularly effective in regions with high geothermal activity, such as Iceland and parts of the United States [20]. Geothermal energy provides a consistent and reliable energy source with minimal greenhouse gas emissions [21]. It can operate independently of weather conditions and has a small land footprint, making it suitable for a variety of applications [21].

The integration of RES into the global energy mix is essential for achieving a sustainable future [22]. Continuous research and development are necessary to improve the efficiency and cost-effectiveness of renewable energy technologies [23]. Innovations in energy storage, grid management, and smart grids are particularly crucial for managing the variability of RES [24]. The transition to renewable energy requires significant investment in infrastructure, including the expansion of transmission networks, the development of energy storage systems, and the modernization of the energy grid [22]. Government policies and incentives play a crucial role in promoting the adoption of renewable energy. Investments in renewable energy infrastructure, research, and development are necessary to accelerate the transition and overcome the technical and economic challenges associated with renewable energy deployment.

In decision-making processes, handling uncertainty and ambiguity is a critical part [25]. Traditional crisp numbers and even fuzzy sets often fall short of capturing the complexity and uncertainty inherent in real-world problems. Neutrosophic Sets, particularly T2NN, offer a more flexible framework to handle uncertainty in decision-making [26]. This paper proposes the integration of T2NN with the LOPCOW [27] and MAIRCA [28] methods, enhancing their capability to handle complex decision problems. Evaluating RES requires a comprehensive approach that considers a multitude of environmental, economic, technological, social, and resource availability criteria as in Figure 1. The inherent uncertainty in predicting energy outputs, costs, and environmental impacts adds complexity to this task. Traditional decision-making methods often struggle to accommodate these uncertainties, leading to less reliable outcomes. By incorporating T2NN, decision-makers can better model the uncertainty and ambiguity in RES evaluations. T2NNs extend the capabilities of standard fuzzy and neutrosophic sets by allowing each element to be represented with a second layer of membership functions, providing a more detailed depiction of uncertainty [29]. This paper also emphasizes the importance of applying comparative analysis and sensitivity testing to validate the proposed framework. Comparative analysis helps in understanding how different RES alternatives rank against each other under varying conditions, while sensitivity testing ensures that the decision-making model remains robust even when input parameters are altered. This approach not only enhances the reliability of the evaluation but also provides deeper insights into the resilience and effectiveness of the decision-making process.

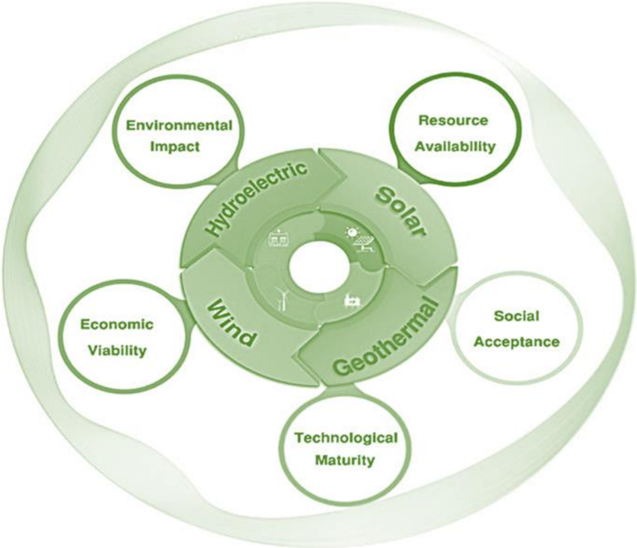


**Figure 1.** Renewable energy sources.

### *1.1 Objectives*

The primary objective of this paper is to develop and validate an enhanced MCDM framework that integrates T2NN with LOPCOW and MAIRCA methods to evaluate the sustainability of various Renewable Energy Sources. The framework aims to:

- Address the inherent uncertainty and ambiguity in RES evaluations by utilizing T2NNs, which allow for a more flexible representation of truth, indeterminacy, and falsity.
- Apply the LOPCOW method to systematically prioritize environmental, economic, and social criteria hierarchically, reflecting their relative importance in decision-making.
- Utilize the MAIRCA method to compare and rank RES alternatives based on their performance against the prioritized criteria, considering both ideal and real scenarios.
- Offer a robust and reliable decision-support tool for policymakers, investors, and other stakeholders involved in the selection and implementation of sustainable energy projects.
- Perform comparative analysis and sensitivity testing to validate the framework's effectiveness and robustness. This step ensures that the framework is not only accurate in its assessments but also resilient to changes in input parameters, thereby increasing its reliability in different decision-making contexts.

### *1.2 Motivations and Contributions*

The motivation behind a research paper or study is the reason or driving force that prompts the researcher to investigate a particular topic or problem. It is often related to a gap in existing knowledge, a practical problem, or a theoretical issue that needs to be addressed. This paper arises from the growing need to make informed and sustainable decisions in the evaluation of renewable energy sources. Traditional decision-making methods often fall short of adequately addressing the uncertainty and complexity inherent in such evaluations. Renewable energy projects involve numerous variables, ranging from fluctuating environmental impacts to varying economic costs and social implications. The limitations of conventional MCDM methods, particularly in handling uncertainty and indeterminacy, highlight the need for more advanced tools. This paper contributes to the field of MCDM by proposing a novel integration of T2NN with the LOPCOW and MAIRCA methods. This integration enhances the ability to handle uncertainty, indeterminacy, and the hierarchical structure of criteria in decision-making processes. Specifically, the paper introduces a robust methodology for evaluating and ranking the sustainability of various RES by considering environmental, economic, and social criteria. By leveraging the strengths of T2NNs, LOPCOW, and MAIRCA, the proposed approach provides a more accurate and reliable framework for decision-makers dealing with complex and uncertain scenarios.

This paper is structured as follows: Section 2: Literature Review: This section reviews existing MCDM methods, particularly those used for renewable energy selection. It also discusses the use of MCDM with T2NN, providing an overview of the LOPCOW and MAIRCA methods. Section 3: Basic Concepts: This section introduces the concept of T2NN and explains its operation within the context of the proposed MCDM framework. Section 4: Methodology: This section details the methodology for applying the proposed framework. Section 5: Case Study: This section presents a case study that applies the proposed framework to evaluate a set of RES alternatives, Section 6: Results and Discussion: This section discusses the outcomes of the case study, including a thorough analysis of the results. It also covers the comparative analysis and sensitivity testing procedures. Section 7: Managerial implications: Section 8: Challenges and Future Work. Section 9: Conclusions.

## 2. Literature Review

The literature review section provides an overview of the existing research on the use of MCDM techniques in evaluating the sustainability of RES. The section is divided into several sub-sections, each focusing on a specific aspect of the literature.

### *2.1 MCDM Techniques in RES Evaluation*

The importance of renewable energy in achieving sustainable development goals has been extensively documented in the literature. Previous studies have employed various MCDM techniques to assess the sustainability of RES, including VIKOR [30], AHP [31], and EDAS [32]. Tao Li et al. [33] studied how to profit from the renewable energy industry in sustainable development, using a comparison of MCDM methods. Narayanamoorthy et al. [34] employed the MULTIMOORA method to identify the best location to build a renewable energy station. Meng Shao et al. [35] also used the AHP approach to choose sites for renewable energy. Goswami et al. [36] utilized integrated MEREC-PIV MCDM to choose India's top renewable green energy source. Sarkodie et al. [37] utilized MCDM techniques such as TOPSIS, MABAC, and MOORA to rank Ghana's renewable energy resources for the production of electricity. Romain Akpahou et al. [38] evaluated potential solutions to Benin's renewable energy deployment obstacles using the fuzzy-TOPSIS technique. Sahand Hosouli et al. [39] also utilized numerous MCDM techniques, such as VIKOR, TOPSIS, EDAS, and PROMETHEE II, to choose the best Photovoltaic thermal collector optimization for renewable energy systems. Fazıl Gökgöz et al. [40] examined how RES might be used to lessen the consequences of climate change by employing the TOPSIS and COPRAS methodologies. Mohsen Ramezanzade et al. [41] ranked renewable energy projects in a fuzzy environment by using MCDM techniques like VIKOR, EDAS, ARAS, and MOORA. However, the integration of LOPCOW with MAIRCA under T2NN provides a novel approach that combines the strengths of both methods.

### *2.2 T2NN in MCDM*

T2NN is a mathematical tool used to handle uncertain and incomplete information in decision-making processes. It also can deal with indeterminate and ambiguous data by using a membership function with a range of values [26]. T2NN sets can capture the degree of truthiness, falsity, and indeterminacy, making it a useful tool for handling complex decision-making problems [29]. T2NN is an extension of the concept of a T1NN to a higher level of indeterminacy [43]. The neutrosophic sets proved to be a valid workspace in describing incompatible and indefinite information. $Z(T, I, F)$ is a Type-1 Neutrosophic Number. But $Z((T_t, T_i, T_f), (I_t, I_i, I_f), (F_t, F_i, F_f))$ is a T2NN, which means that each neutrosophic component T, I, and F is split into its truth, indeterminacy, and falsehood subparts [42]. Vladimir Simic et al. [43] presented integrated CRITIC-MABAC under T2NNs in the selection of public transportation pricing systems. İsmail Önden et al. [29] applied T2NN-CRITIC-MABAC to businesses offering micro-mobility services. Vladimir Simic et al. [44] implemented an integrated MEREC-MARCOS method using a T2NN environment in Urban Transportation. Umit Cali et al. [42] used EDAS with T2NN. Muhammet Deveci et al. [45] applied the T2NN MABAC method for the USA's offshore wind project site selection. Alshehri et al. [46] utilized the T2NN-AHP model for evaluating the impact of the security IOT framework. Vladimir Simić et al. [47] selected the best sustainable route of petroleum transportation using T2NN-ITARA-EDAS.

### *2.3 LOPCOW Method*

Despite these advancements, the integration of the LOPCOW method with the MAIRCA approach under T2NN is a novel approach that combines the strengths of both methods, addressing the limitations of traditional MCDM techniques in handling uncertainty and ambiguity. LOPCOW is an advanced weighting method used in MCDM that determines criteria weights based on logarithmic percentage changes [27]. This method is advantageous for its ability to emphasize the relative importance of criteria by considering both the absolute and relative differences in criteria values [48]. Fatih Ecer et al. [27] proposed a novel LOPCOW-DOBI MCDM in the banking sector. Aparajita Sanyal et al. [48] utilized LOPCOW with the EDAS method to select Organic Food. Biswas et al. [49] also used LOPCOW with EDAS but in the consumer durable sector. Furkan [50] also applied LOPCOW-CRADIS to analyze the performances of G7 Countries. Integrating T2NN with the LOPCOW method can effectively handle the uncertainty in criteria weighting. The T2NN framework allows the LOPCOW method to consider the imprecise nature of data by utilizing interval values in the weighting process. This leads to a more robust and flexible weighting system that can adapt to uncertain decision environments. Vladimir Simic et al. [51] introduced LOPCOW in the T2NN environment with the ARAS method in the Industry 4.0 field.

### *2.4 MAIRCA Method*

MAIRCA is a decision-making method that evaluates alternatives by comparing them to an ideal solution and a real solution, taking into account the deviation of each alternative from both these reference points [28]. The method focuses on minimizing the distance from the ideal solution while maximizing the distance from the real (worst) solution [52]. Dmitri Muravev et al. [28] utilized the DEMATEL-MAIRCA method for Optimizing CR Express International Logistics Center Locations. Dragan Pamucar et al. [53] also utilized the DEMATEL-MAIRCA method for sustainable site selection for the construction of a multimodal logistics hub. Soumava Boral et al. [54] applied the MAIRCA method with fuzzy. Rana Sami Ul Haq et al. [55] applied MAIRCA using interval-valued neutrosophic. Ecer, F. et al. [56] utilized the MAIRCA method using intuitionistic fuzzy sets. Tayfun Öztaş et al. [57] integrated LOPCOW with MAIRCA. By incorporating T2NN into MAIRCA, the method can better address the uncertainty and imprecision in the evaluation of alternatives. The interval values in T2NN allow for a more comprehensive analysis of the deviation of alternatives from the ideal and real solutions, accounting for the inherent uncertainty in the data.

## 3. Basic Concepts

Unlike fuzzy sets, neutrosophic sets assign a truth-membership degree, indeterminacy-membership degree, and falsity-membership degree [26, 29].

### *3.1 Structure of T2NN [43]*

**Definition 3.1.** Suppose that $X$ is a limited universe of discourse and R [0,1] is the set of all triangular neutrosophic numbers on R [0,1].
A T2NNS $\tilde{S}$ in X is represented by $\tilde{S}$ =

$$\left\langle \left(T_{T_{\tilde{S}}}(x), T_{I_{\tilde{S}}}(x), T_{F_{\tilde{S}}}(x)\right), \left(I_{T_{\tilde{S}}}(x), I_{I_{\tilde{S}}}(x), I_{F_{\tilde{S}}}(x)\right), \left(F_{T_{\tilde{S}}}(x), F_{I_{\tilde{S}}}(x), F_{F_{\tilde{S}}}(x)\right) \right\rangle \tag{1}$$

Where $\breve{T}_{\tilde{S}}(x) : X \to R[0,1]$ , $\tilde{I}_{\tilde{S}}(x) : X \to R[0,1]$ , $\breve{F}_{\tilde{S}}(x) : X \to R[0,1]$ .
The T2NN $\breve{T}_{\tilde{S}}(x) = \left(T_{T_{\tilde{S}}}(x), T_{I_{\tilde{S}}}(x), T_{F_{\tilde{S}}}(x)\right)$ , $\tilde{I}_{\tilde{S}}(x) = \left(I_{T_{\tilde{S}}}(x), I_{I_{\tilde{S}}}(x), I_{F_{\tilde{S}}}(x)\right)$ , $\breve{F}_{\tilde{S}}(x) = \left(F_{T_{\tilde{S}}}(x), F_{I_{\tilde{S}}}(x), F_{F_{\tilde{S}}}(x)\right)$ defined as the truth, indeterminacy, and falsity of memberships of x in $\tilde{S}$.

### *3.2 Operations on T2NN [43]*

**Definition 3.2.** Let two T2NN $\tilde{S}_1, \tilde{S}_2$ be defined as the following:

$$\tilde{S}_1 = \left\langle \left(T_{T_{\tilde{S}_1}}(x), T_{I_{\tilde{S}1}}(x), T_{F_{\tilde{S}1}}(x)\right), \left(I_{T_{\tilde{S}1}}(x), I_{I_{\tilde{S}1}}(x), I_{F_{\tilde{S}1}}(x)\right), \left(F_{T_{\tilde{S}1}}(x), F_{I_{\tilde{S}1}}(x), F_{F_{\tilde{S}1}}(x)\right) \right\rangle,$$

$$\tilde{S}_2 = \left\langle \left(T_{T_{\tilde{S}_2}}(x), T_{I_{\tilde{S}2}}(x), T_{F_{\tilde{S}2}}(x)\right), \left(I_{T_{\tilde{S}2}}(x), I_{I_{\tilde{S}2}}(x), I_{F_{\tilde{S}2}}(x)\right), \left(F_{T_{\tilde{S}2}}(x), F_{I_{\tilde{S}2}}(x), F_{F_{\tilde{S}2}}(x)\right) \right\rangle$$

Then: T2NN Addition:

$$\tilde{S}_1 \oplus \tilde{S}_2 = \left\langle \begin{array}{c} \begin{pmatrix} T_{T_{\tilde{S}_1}}(x) + T_{T_{\tilde{S}_2}}(x) - T_{T_{\tilde{S}_1}}(x).T_{T_{\tilde{S}_2}}(x),\ T_{I_{\tilde{S}1}}(x) + T_{I_{\tilde{S}2}}(x) - T_{I_{\tilde{S}1}}(x).T_{I_{\tilde{S}2}}(x), \\ T_{F_{\tilde{S}1}}(x) + T_{F_{\tilde{S}2}}(x) - T_{F_{\tilde{S}1}}(x).T_{F_{\tilde{S}2}}(x) \end{pmatrix}, \\ \left(I_{T_{\tilde{S}1}}(x).I_{T_{\tilde{S}2}}(x), I_{I_{\tilde{S}1}}(x).I_{I_{\tilde{S}2}}(x), I_{F_{\tilde{S}1}}(x).I_{F_{\tilde{S}2}}(x)\right), \\ \left(F_{T_{\tilde{S}1}}(x).F_{T_{\tilde{S}2}}(x), F_{I_{\tilde{S}1}}(x).F_{I_{\tilde{S}2}}(x), F_{F_{\tilde{S}1}}(x).F_{F_{\tilde{S}2}}(x)\right) \end{array} \right\rangle \tag{2}$$

T2NN Multiplication: $\tilde{S}_1 \otimes \tilde{S}_2$=

$$\left\langle \begin{array}{c} \left(\left(T_{T_{\tilde{S}_1}}(x).T_{T_{\tilde{S}_2}}(x), T_{I_{\tilde{S}1}}(x).T_{I_{\tilde{S}2}}(x), T_{F_{\tilde{S}1}}(x).T_{F_{\tilde{S}2}}(x)\right)\right), \\ \left(\left(I_{T_{\tilde{S}1}}(x) + I_{T_{\tilde{S}2}}(x) - I_{T_{\tilde{S}1}}(x).I_{T_{\tilde{S}2}}(x)\right), \left(I_{I_{\tilde{S}1}}(x) + I_{I_{\tilde{S}2}}(x) - I_{I_{\tilde{S}1}}(x).I_{I_{\tilde{S}2}}(x)\right), \begin{pmatrix} I_{F_{\tilde{S}1}}(x) + I_{F_{\tilde{S}2}}(x) - \\ I_{F_{\tilde{S}1}}(x).I_{F_{\tilde{S}2}}(x) \end{pmatrix}\right) \\ \left(\left(F_{T_{\tilde{S}1}}(x) + F_{T_{\tilde{S}2}}(x) - F_{T_{\tilde{S}1}}(x).F_{T_{\tilde{S}2}}(x)\right), \left(F_{I_{\tilde{S}1}}(x) + F_{I_{\tilde{S}2}}(x) - F_{I_{\tilde{S}1}}(x).F_{I_{\tilde{S}2}}(x)\right), \begin{pmatrix} F_{F_{\tilde{S}1}}(x) + F_{F_{\tilde{S}2}}(x) - \\ F_{F_{\tilde{S}1}}(x).F_{F_{\tilde{S}2}}(x) \end{pmatrix}\right) \end{array} \right\rangle \tag{3}$$

**Definition 3.3.** The score function $S(\tilde{S}_1)$ is defined as follows:

$$S(\tilde{S}_1) = \frac{1}{12}\left\langle 8 + \left(T_{T_{\tilde{S}_1}}(x) + 2\left(T_{I_{\tilde{S}_1}}(x)\right) + T_{F_{\tilde{S}_1}}(x)\right) - \left(I_{T_{\tilde{S}1}}(x) + 2\left(I_{I_{\tilde{S}1}}(x)\right) + I_{F_{\tilde{S}1}}(x)\right) - \left(F_{T_{\tilde{S}1}}(x) + 2\left(F_{I_{\tilde{S}1}}(x)\right) + F_{F_{\tilde{S}1}}(x)\right)\right\rangle \tag{4}$$

**Definition 3.4.** In essence, this formula is used to combine the opinions of multiple decision-makers into a single, aggregated T2NN value. This can be useful in decision-making scenarios where multiple stakeholders have different opinions or perspectives on a particular issue. $\widetilde{X_{ip}}$ =

$$\frac{[T_{T_{ip}}(x), T_{I_{ip}}(x), T_{F_{ip}}(x), I_{T_{ip}}(x), I_{I_{ip}}(Z), I_{F_{ip}}(x), F_{T_{ip}}(x), F_{I_{ip}}(Z), F_{F_{ip}}(x)]}{n} \tag{5}$$

Where n represents the number of decision-makers.

### *3.3 Linguistic Values of T2NN [43]*

In the context of T2NN, linguistic values are used to express subjective assessments or evaluations in decision-making processes. These linguistic values are used to capture the uncertainty and imprecision associated with human judgments, opinions, and preferences as in Table 1.

**Table 1.** T2NN for evaluating criteria.

| Linguistic Variables | T2NN |
|---|---|
| Very Bad (VB) | ((0.20,0.20,0.10), (0.65,0.80,0.85), (0.45,0.80,0.70)) |
| Bad (B) | ((0.35,0.35,0.10), (0.50,0.75,0.80), (0.50,0.75,0.65)) |
| Medium Bad (MB) | ((0.50,0.30,0.50), (0.50,0.35,0.45), (0.45,0.30,0.60)) |
| Medium (M) | ((0.40,0.45,0.50), (0.40,0.45,0.50), (0.35,0.40,0.45)) |
| Medium Good (MG) | ((0.60,0.45,0.50), (0.20,0.15,0.25), (0.10,0.25,0.15)) |
| Good (G) | ((0.70,0.75,0.80), (0.15,0.20,0.25,), (0.10,0.15,0.20)) |
| Very Good (VG) | ((0.95,0.90,0.95), (0.10,0.10,0.05), (0.05,0.05,0.05)) |

## 4. Proposed Hybrid Model: T2NN-LOPCOW-MAIRCA

Integrating T2NN with LOPCOW and MAIRCA methods can enhance decision-making processes by effectively handling uncertainty and hierarchical criteria. T2NN allows for a nuanced representation of uncertainty, LOPCOW provides a structured way to prioritize criteria in multi-level decisions, and MAIRCA offers a robust approach to comparing alternatives based on their ideal and real scenarios. Combining these techniques could yield more accurate and reliable outcomes in complex decision-making contexts. This hybrid model is structured into four phases, each designed to handle uncertainty, prioritize criteria, and evaluate alternatives effectively as represented in Figure 2.

***Phase 1: Problem Definition and Criteria Identification:***

**Step 1.1.** Problem Definition: Clearly define the decision-making problem, including the specific RES alternatives to be evaluated. Then identify and define Criteria.

**Step 1.2.** Decision Matrix Construction: Determine the alternatives $(A1, A2, \dots, Am)$, criteria $(C1, C2, \dots, Cn)$ and decision-makers $Dm = \{Dm_1, Dm_2, \dots., Dm_k\}$ involved in the decision-making process.

**Step 1.3.** Define Linguistic Values: Assign linguistic values to the criteria and alternatives using T2NN to handle uncertainty and ambiguity as is in Table 1.

***Phase 2: T2NN Representation:***

**Step 2.1.** Define T2NN Initial Matrix: Represent the linguistic values using T2NN, which encapsulate the truth, indeterminacy, and falsity of each criterion. Convert expert judgments or subjective evaluations into T2NN values.

**Step 2.2.** Obtain T2NN Aggregated Decision Matrix: Combine the individual T2NN values from multiple decision-makers into a collective T2NN value for each criterion using Eq. (5).

**Step 2.3.** Convert T2NN to Crisp Values: Use a score function in Eq. (4) to convert T2NNs into crisp values, and create a decision matrix as in Eq. (6) that can be used in subsequent phases.

$$\mathrm{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{im} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix} \tag{6}$$

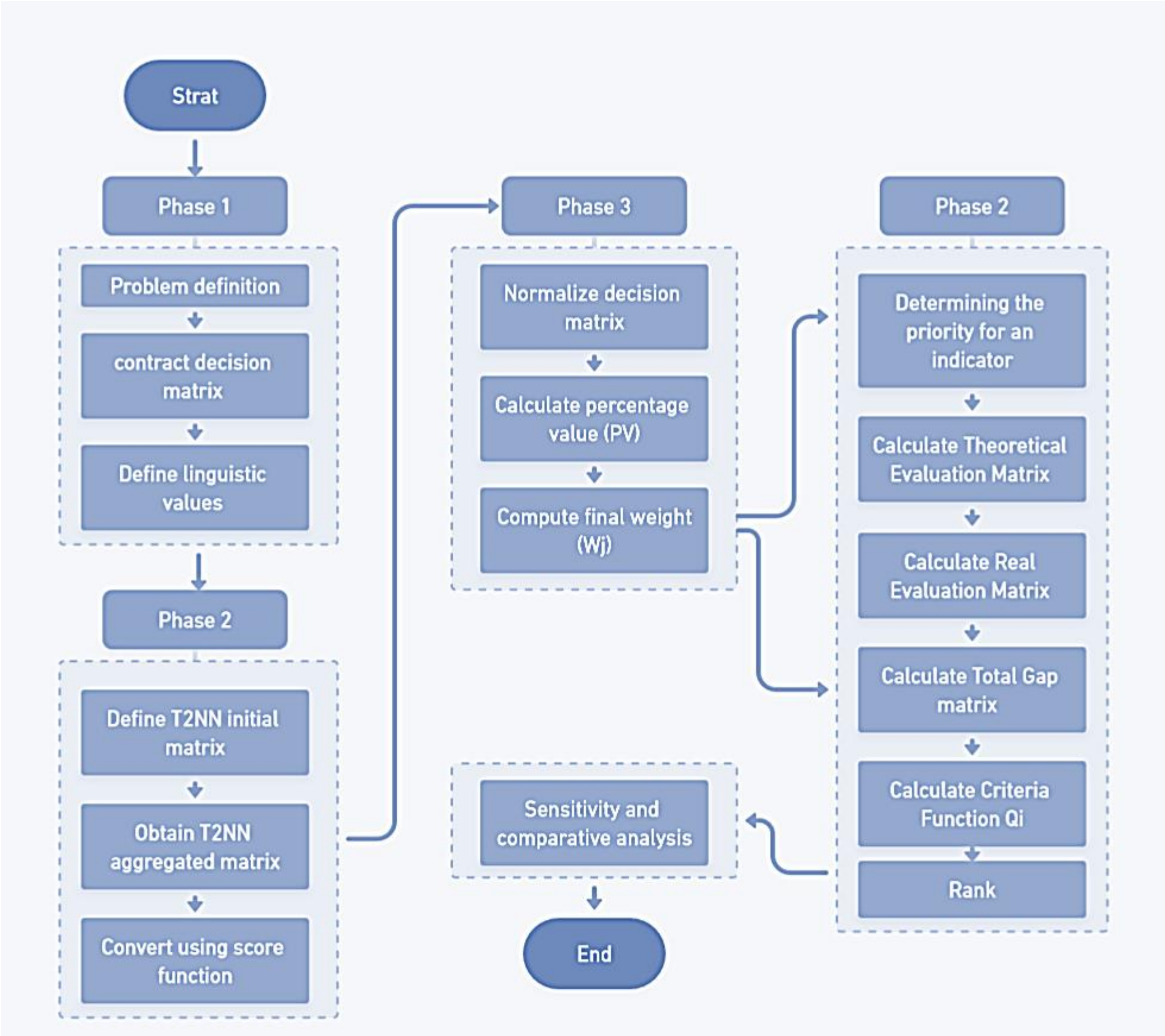


**Figure 2.** T2NN based proposed model.

***Phase 3: Criteria Weighting with T2NN-LOPCOW***

**Step 3.1.** A normalized decision matrix which obtained from the previous phase for both beneficial and non-beneficial criteria, where $n_{ij}$ the normalized value for alternative $i$ and criterion $j$, $x_{ij}$ is the original value of alternative $i$ for criterion $j$, $x_{max}$ maximum value among all alternatives for criterion j and $x_{min}$ minimum value among all alternatives for criterion j

$$n_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \quad \text{for B} \tag{7}$$

$$n_{ij} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}} \quad \text{for NB} \tag{8}$$

**Step 3.2.** Calculate Percentage Value (PV). Compute the percentage value (PV) for each criterion using the elements of the normalized matrix, standard deviation (σ), and number of alternatives (m) using Eq. (9).

$$PV_{ij} = \left| \ln\left(\frac{\sqrt{\sum_{i=1}^{m} n_{ij}^2}}{\sigma}\right) . 100 \right| \tag{9}$$

**Step 3.3.** Compute Criteria Weights: the weight of each criterion is calculated using the $PV$ values. The criteria weights ($wj$) are obtained as follows:

$$w_j = \frac{PV_{ij}}{\sum_{i=1}^{n} PV_{ij}} \tag{10}$$

***Phase 4: Alternatives Evaluation***

Each alternative is evaluated against the criteria using the MAIRCA method. This step involves calculating the deviation of each alternative from the ideal and real solutions using the following steps:

**Step 4.1.** Determining the priority for an indicator. Neutral Priority Calculation as follows:

$$p_{A_j} = \frac{1}{m}, \quad j = 1, 2\ldots, n \tag{11}$$

**Step 4.2.** Calculate Theoretical (Ideal) Evaluation Matrix $t_{pij}$ According to the equation:

$$t_{pij} = p_{A_j} \cdot w_j, \quad i = 1,2,\cdots,m; j = 1,2\cdots,n \tag{12}$$

Where $w_j$ Is the weight of the j-th criterion.

**Step 4.3.** Calculate Real (Observational) Evaluation Matrix $t_{rij}$ According to the equations:

$$t_{rij} = t_{pij} \cdot \left(\frac{x_{ij} - x_i^-}{x_i^+ - x_i^-}\right) \quad \text{for B} \tag{13}$$

$$t_{rij} = t_{pij} \cdot \left(\frac{x_{ij} - x_i^+}{x_i^- - x_i^+}\right) \quad \text{for NB} \tag{14}$$

**Step 4.4.** Calculate the total Gap matrix $g_{ij}$ According to the equation:

$$g_{ij} = t_{pij} - t_{rij} \tag{15}$$

**Step 4.5.** Calculate Criteria Function $Q_i$

$$Q_i = \sum_{i=1}^{m} g_{ij} \tag{16}$$

Rank the alternatives based on the $Q_i$ values, where the alternative with the smallest $Q_i$ is considered the best option.

## 5. Case Study

The world is facing an unprecedented energy crisis, driven by increasing energy demand, depleting fossil fuel resources, and growing concerns about climate change. RES has emerged as a viable alternative to traditional fossil fuels, offering a cleaner, more sustainable, and environmentally friendly option. However, the selection of a suitable RES project is a complex decision-making problem, involving multiple stakeholders, conflicting criteria, and uncertain outcomes. This case study illustrates the application of the T2NN-LOPCOW-MAIRCA model to select the most suitable renewable energy project from a set of alternatives. The decision-making problem involves evaluating and ranking a set of RES project alternatives, each with its unique characteristics, advantages, and disadvantages.

### *5.1 Application of the T2NN-LOPCOW-MAIRCA Model*

***Phase 1: Problem Definition***

**Step 1.1.** The decision-making problem involves evaluating and ranking a set of RES project alternatives, each with its unique characteristics, advantages, and disadvantages.

**Step 1.2.** Three DMs will evaluate the sustainability of various RES based on five decision criteria. The alternatives and criteria are defined as follows: Alt1: Solar Energy. Alt2: Wind Energy. Alt3: Hydropower. Alt4: Geothermal Energy. The decision criteria impacting sustainability include:

- Environmental Impact (C1): Assesses the potential environmental effects, such as greenhouse gas emissions, land use, and water usage.
- Economic Viability (C2): Evaluate the economic feasibility, including costs, revenue, and return on investment.
- Technological Maturity (C3): Assesses the level of technological advancement and readiness.
- Social Acceptance (C4): Evaluates the level of social acceptance and support, including public perception and community engagement.
- Resource Availability (C5): Assesses the availability of resources, such as land, water, and materials required for the project.

**Step 1.3.** Assign linguistic labels to each criterion to capture uncertainty and imprecision as represented in Table 2.

*Phase 2: T2NN Representation*

**Step 2.1.** Represent the linguistic values using T2NN, which include degrees of truth, indeterminacy, and falsity from Table 1.

**Step 2.2.** Aggregate the individual T2NN values from multiple decision-makers to obtain a collective T2NN value for each criterion using Eq. (5).

**Step 2.3.** Use Eq. (4) to convert T2NN into crisp values, resulting in a decision matrix as in Table 3.

**Table 2.** DMs evaluation.

| DMs | Alt | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|---|
| DM1 | Alt1 | VB | M | B | MB | G |
| | Alt2 | VG | VG | VG | B | MB |
| | Alt3 | MB | VG | M | MB | VG |
| | Alt4 | B | MB | MB | M | B |
| DM2 | Alt1 | G | G | M | MG | MB |
| | Alt2 | M | M | VB | B | B |
| | Alt3 | VB | MG | B | MB | M |
| | Alt4 | G | M | M | VB | MG |
| DM3 | Alt1 | M | M | B | B | MB |
| | Alt2 | M | M | MB | B | M |
| | Alt3 | MB | MG | M | MB | MG |
| | Alt4 | G | G | MG | M | G |

**Table 3.** Crisp decision matrix.

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| **Alt1** | 0.524 | 0.622 | 0.383 | 0.531 | 0.652 |
| **Alt2** | 0.665 | 0.665 | 0.581 | 0.308 | 0.473 |
| **Alt3** | 0.464 | 0.782 | 0.458 | 0.578 | 0.724 |
| **Alt4** | 0.636 | 0.637 | 0.606 | 0.435 | 0.606 |

*Phase 3: Criteria Weighting with T2NN-LOPCOW*

**Step 3.1.** Normalized decision matrix for beneficial criteria (C1, C2, C3, C5) and non-beneficial (C4) criteria using Eq. (7) and Eq. (8) to get normalized matrix as in Table 4.

**Step 3.2.** Calculate Percentage Value (PV) by Eq. (9) as shown in Table 5.

**Step 3.3.** Calculate the weights for each criterion using Eq. (10) to get the final weight as in Table 5.

**Table 4.** Normalized decision matrix.

| | C1 + | C2 + | C3 + | C4 - | C5 + |
|---|---|---|---|---|---|
| **Alt1** | 0.296 | 0.000 | 0.000 | 0.171 | 0.713 |
| **Alt2** | 1.000 | 0.269 | 0.888 | 1.000 | 0.000 |
| **Alt3** | 0.000 | 1.000 | 0.336 | 0.000 | 1.000 |
| **Alt4** | 0.855 | 0.092 | 1.000 | 0.530 | 0.529 |

**Table 5.** Final weight.

| | C1 | C2 | C3 | C4 | C5 |
|---|---|---|---|---|---|
| $\boldsymbol{PV_{ij}}$ | 5.65959 | 5.43442 | 5.67997 | 5.55636 | 5.76097 |
| $\boldsymbol{W_j}$ | 0.20147 | 0.19346 | 0.2022 | 0.1978 | 0.20508 |

*Phase 4: Alternatives Evaluation*

**Step 4.1.** Determine Priority for an Indicator using Eq. (11) as m= 4 then, $p_{A_j}$=1/4.

**Step 4.2.** Calculate the theoretical evaluation for each alternative using weight obtained from the previous phase by Eq. (12) to get Table 6.

**Step 4.3.** Get real evaluation matrix using Eq. (13), and Eq. (14) for both beneficial and non-beneficial criteria as in Table 7.
**Step 4.4.** Calculate the gap between the theoretical and real matrix by Eq. (15) as represented in Table 8.
**Step 4.5.** Calculate the criteria function for alternatives using Eq. (16) to get the final rank as Table 8.

**Table 6.** Theoretical matrix.

| | C1 + | C2 + | C3 + | C4 - | C5 + |
|---|---|---|---|---|---|
| **Alt1** | 0.050368 | 0.048364 | 0.050549 | 0.049449 | 0.05127 |
| **Alt2** | 0.050368 | 0.048364 | 0.050549 | 0.049449 | 0.05127 |
| **Alt3** | 0.050368 | 0.048364 | 0.050549 | 0.049449 | 0.05127 |
| **Alt4** | 0.050368 | 0.048364 | 0.050549 | 0.049449 | 0.05127 |

**Table 7.** Real matrix.

| | C1 + | C2 + | C3 + | C4 - | C5 + |
|---|---|---|---|---|---|
| **Alt1** | 0.014888 | 0 | 0 | 0.008471 | 0.036548 |
| **Alt2** | 0.050368 | 0.013033 | 0.044884 | 0.049449 | 0 |
| **Alt3** | 0 | 0.048364 | 0.016997 | 0 | 0.05127 |
| **Alt4** | 0.043063 | 0.004456 | 0.050549 | 0.02623 | 0.027113 |

**Table 8.** Gap matrix and final rank.

| | C1 + | C2 + | C3 + | C4 - | C5 + | $Q_i$ | Rank |
|---|---|---|---|---|---|---|---|
| **Alt1** | 0.03548 | 0.048364 | 0.050549 | 0.040978 | 0.014722 | 0.190093 | 4 |
| **Alt2** | 0 | 0.035331 | 0.005666 | 0 | 0.05127 | 0.092267 | 1 |
| **Alt3** | 0.050368 | 0 | 0.033553 | 0.049449 | 0 | 0.133369 | 3 |
| **Alt4** | 0.007305 | 0.043908 | 0 | 0.023219 | 0.024157 | 0.098589 | 2 |

The application of the T2NN-LOPCOW-MAIRCA model in this case study effectively handles the complexities of selecting a suitable renewable energy project. By incorporating uncertainty, prioritizing criteria, and comparing alternatives against both ideal and real scenarios, the model provides a comprehensive evaluation framework. The result is a well-informed decision that balances environmental, economic, technological, social, and resource-related considerations, guiding stakeholders toward the most sustainable and viable renewable energy project.

## 6. Results and Discussion

Based on the final ranking, Alt2: Wind Energy is the top-ranked alternative, followed by Alt4: Geothermal Energy, Alt3: Hydropower, and Alt1: Solar Energy. The results of this study highlight the strengths and weaknesses of each renewable energy source based on the selected criteria. Wind energy emerged as the top-ranked alternative due to its balanced performance across economic, social, and resource-based criteria. Geothermal energy also performed well, particularly in terms of environmental impact and technological maturity, but its limited resource availability affected its overall ranking. Hydropower, despite being a reliable and mature technology, was ranked third due to its environmental impact and the specific geographic requirements needed for its implementation. Solar energy ranked last due to challenges related to economic viability and resource availability. This ranking underscores the importance of considering a broad range of criteria when evaluating renewable energy sources. While each energy source has its strengths, the decision-making process must balance these against potential challenges to select the most suitable option for specific contexts. The results of the case study demonstrate the effectiveness of the T2NN-LOPCOW-MAIRCA model in handling complex decision problems under uncertainty. The integration of T2NN allows for a more nuanced and flexible evaluation of alternatives, leading to more reliable decision-making outcomes. The hybrid model is particularly useful in scenarios where the decision data is imprecise or where expert opinions vary significantly.

### *6.1 Comparative Analysis*

In addition to the T2NN-LOPCOW-MAIRCA model, a comparative analysis was conducted using four other well-known MCDM methods: COPRAS, MABAC, EDAS, and TOPSIS. This comparison aims to validate the robustness and consistency of the results obtained through the T2NN-LOPCOW-MAIRCA model. COPRAS [38] This method focuses on evaluating alternatives by considering both the beneficial and non-beneficial criteria. MABAC [45] involves determining the distance of alternatives from the positive and negative ideal solutions, ranking them based on their relative closeness. EDAS [43] evaluates alternatives based on their distance from an average solution, considering both positive and negative distances. TOPSIS [39] ranks alternatives by measuring the Euclidean distance between an ideal solution and an anti-ideal solution, prioritizing those closest to the ideal and farthest from the anti-ideal. The results of the comparative analysis, as summarized in Table 9 and illustrated in Figure 3, show the rankings of the alternatives across the different MCDM methods. Figure 4 also displays comparative score values of alternatives across MCDM methods used in these analyses.

**Table 9.** Comparative analysis rank.

| Rank | MAIRCA | COPRAS | MABAC | EDAS | TOPSIS |
|---|---|---|---|---|---|
| **Alt1** | 4 | 4 | 4 | 4 | 4 |
| **Alt2** | 1 | 1 | 1 | 1 | 1 |
| **Alt3** | 3 | 3 | 3 | 3 | 3 |
| **Alt4** | 2 | 2 | 2 | 2 | 2 |

The ranking of alternatives is consistent across all methods, with Wind Energy (Alt2) consistently ranked as the top choice, followed by Geothermal Energy (Alt4), Hydropower (Alt3), and Solar Energy (Alt1). This consistency across different MCDM methods highlights the robustness of the results. The alignment of results from the T2NN-LOPCOW-MAIRCA model with those from COPRAS, MABAC, EDAS, and TOPSIS provides confidence in the validity and effectiveness of the proposed model. The model's ability to handle uncertainty and incorporate hierarchical criteria is corroborated by its consistent ranking results. The consistent top ranking of Wind Energy across various methods reinforces its suitability as the most favorable renewable energy project based on the defined criteria. This provides a strong foundation for decision-making, ensuring that the selection process is well-supported by multiple analytical perspectives.

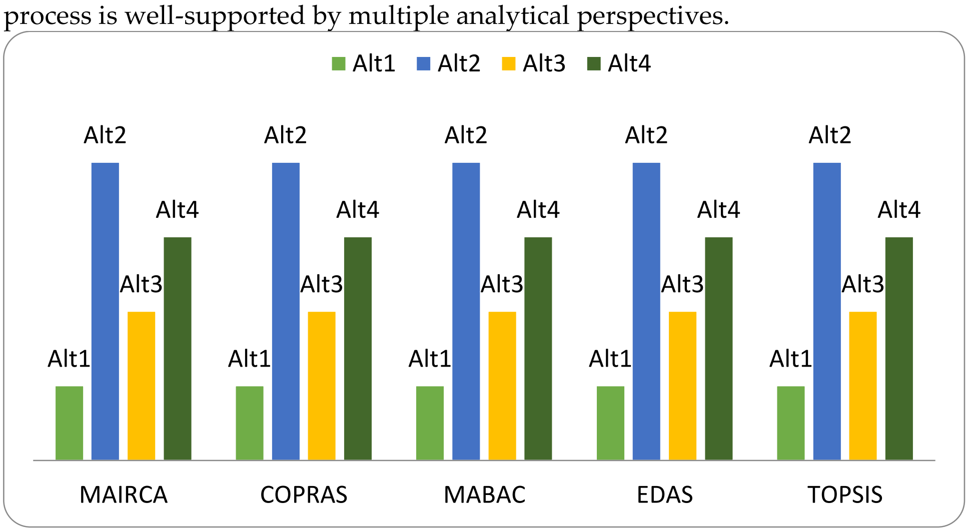


**Figure 3.** Ranking of alternatives from the various MCDM methods.

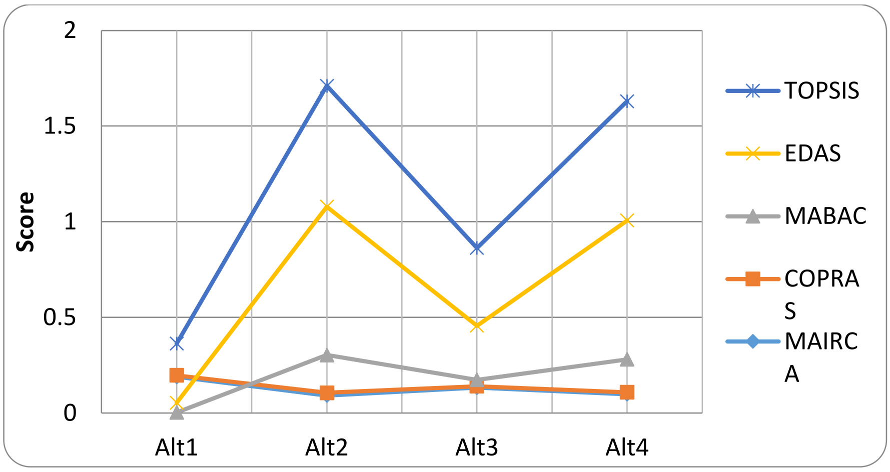


**Figure 4.** Values of alternatives via MCDM methods.

### *6.2 Sensitivity Analysis*

Sensitivity analysis is crucial for assessing the robustness of the decision-making framework by evaluating how changes in criteria weights impact the final rankings of alternatives. In this study, sensitivity analysis was performed to examine the stability of the rankings derived from the T2NN-LOPCOW-MAIRCA model. The goal was to determine whether small variations in criteria weights or input data would significantly alter the ranking of renewable energy sources. The weights assigned to each criterion (Environmental Impact, Economic Viability, Technological Maturity, Social Acceptance, and Resource Availability) were varied within a specified range as following scenarios:

- Case 1: Each criterion weight was set to 0.2, ensuring an equal weight distribution across all criteria.
- Case 2: Increase the weight of C1 by 0.10 and decrease the weight of C2 by 0.10 while keeping other weights unchanged. The resulting weights were: (C1= 0.301, C2= 0.09346, C3= 0.2022, C4= 0.1978, C5= 0.20508).
- Case 3: Increase the weight of C1 and proportionally decrease the weights of the other criteria. The resulting weights were: (C1= 0.25, C2= 0.175, C3= 0.2, C4=0.175, C5=0.2).
- Case 4: Increase the weight of C5 while keeping other weights constant. The resulting weights were: (C1= 0.18, C2=0.1, C3=0.18, C4=0.18, C5=0.28).
- Case 5: Assign random values within a specified range to the weights of all criteria. The resulting weights were: (C1= 0.22, C2=0.18, C3=0.21 C4=0.19, C5=0.2).

Table 10 represents the value of $Q_i$ Across different cases and Figure 5 visually represents the results of your sensitivity analysis in these cases.

**Table 10.** $Q_i$ Values.

| Qi | Baseline | Case 1 | Case 2 | Case 3 | Case 4 | Case 5 |
|---|---|---|---|---|---|---|
| **Alt1** | 0.190093 | 0.191012 | 0.182703 | 0.188388 | 0.17909 | 0.189963 |
| **Alt2** | 0.092267 | 0.09213 | 0.074004 | 0.087565 | 0.107917 | 0.088758 |
| **Alt3** | 0.133369 | 0.133188 | 0.158369 | 0.139438 | 0.119869 | 0.137347 |
| **Alt4** | 0.098589 | 0.099681 | 0.079518 | 0.092885 | 0.101492 | 0.094693 |

Wind Energy (Alt2) remained the top-ranked alternative across all variations in criteria weights. This stability indicates that Wind Energy consistently performs well relative to the other alternatives, even when the importance of different criteria changes. Geothermal Energy (Alt4): Generally remained the second-ranked alternative, though it occasionally shifted to the top position when the weight of Environmental Impact was increased significantly. The model's rankings are stable with changes in criteria weights, suggesting that the T2NN-LOPCOW-MAIRCA approach is effective in handling variations in criteria importance.

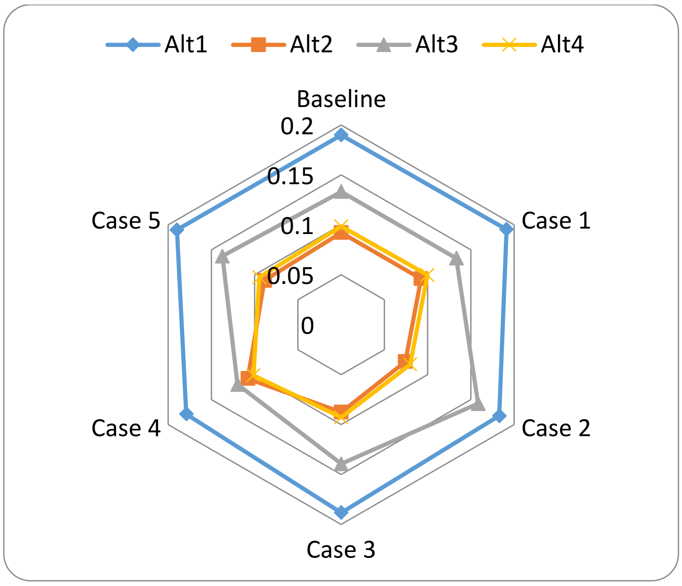


**Figure 5.** Sensitivity analysis.

## 7. Managerial Implications

Prioritizing renewable energy in national economic policies allows governments to drive economic growth, reduce unemployment, and ensure a smooth transition for workers shifting from traditional energy sectors. By investing in specialized training programs, governments can also ensure that the workforce gains the necessary skills to succeed in the renewable energy industry. The T2NN-LOPCOW-MAIRCA framework offers energy companies and corporations a strategic tool to effectively identify and prioritize renewable energy investments that align with long-term sustainability goals. Through systematic evaluation of different alternatives, organizations can make informed decisions that promote business growth while minimizing environmental impact. Governments can utilize this framework to design and implement energy policies that prioritize renewable energy projects based on their sustainability potential, supporting both national and regional shifts towards cleaner energy sources and contributing to long-term energy security and climate mitigation efforts. This framework also helps direct capital towards renewable energy initiatives with the highest economic viability and environmental benefits, ensuring efficient use of resources and maximizing returns on investments in green technologies. The integration of T2NN within the framework strengthens an organization's ability to manage risks and uncertainties in energy investments, resulting in more resilient and robust decision-making. Considering social factors in energy decisions allows companies to address community concerns effectively and gain public support for renewable energy projects, improving the likelihood of successful implementation and enhancing corporate reputations. Adopting advanced decision-making frameworks like T2NN-LOPCOW-MAIRCA places organizations at the forefront of innovation in the renewable energy sector, providing a competitive edge by demonstrating a commitment to cutting-edge, sustainable business practices. Governments that apply sophisticated evaluation frameworks for renewable energy can attract international attention and investment, positioning themselves as leaders in the global energy transition.

## 8. Challenges and Future Work

### *8.1 Challenges*

Evaluating renewable energy options requires a comprehensive approach considering environmental, economic, and social factors. However, integrating these diverse perspectives into a cohesive decision-making framework is a significant challenge. One of the main hurdles is coordinating and managing collaboration among experts from different fields. This interdisciplinary nature of sustainable energy evaluation demands effective communication and teamwork. Another primary challenge is dealing with uncertain and imprecise data. While the T2NN framework offers a robust way to manage this uncertainty, defining accurate membership functions and intervals for truth, indeterminacy, and falsity can be complex. The integration of T2NN with LOPCOW and MAIRCA adds layers of computational complexity, making it difficult to handle large datasets or real-time decision-making processes efficiently. Although the proposed framework has been validated through case studies, its effectiveness in real-world scenarios, particularly in dynamic and rapidly changing environments, remains a challenge. Further validation is needed to ensure the framework's applicability across different domains and under varying conditions.

### *8.2 Future Work*

The T2NN-LOPCOW-MAIRCA framework could be applied to various domains such as healthcare, finance, urban planning, and environmental management. These fields often involve complex decision-making scenarios that require consideration of multiple criteria and the management of high levels of uncertainty. As global challenges evolve, incorporating new criteria and methodologies into the framework will be essential to address emerging issues and enhance its decision-support capabilities. Conducting more real-world case studies across different industries and geographical regions would be crucial for validating the effectiveness and robustness of the T2NN-LOPCOW-MAIRCA framework. These studies could provide valuable insights into the practical challenges and benefits of using the framework in various contexts. Integrating other MCDM methods, such as DEMATEL, ANP, or ELECTRE, could enhance the T2NN-LOPCOW-MAIRCA framework's ability to address complex interdependencies among criteria and alternatives. These methods can offer more sophisticated tools for modeling relationships between criteria and refining decision-making processes. Future research could focus on refining the T2NN approach, especially in terms of defining and calibrating neutrosophic membership functions.

These challenges and future directions highlight the potential for further research and development in improving the T2NN-LOPCOW-MAIRCA framework. By addressing these challenges and exploring new applications and methods, the framework can be refined and expanded to better support complex decision-making in various domains.

## 9. Conclusion

RES offers a viable pathway to a sustainable future by reducing dependence on fossil fuels, mitigating climate change, and promoting energy security. While challenges remain, including technological, economic, and social barriers, the potential benefits of renewable energy far outweigh these obstacles. A concerted effort by governments, industries, and individuals is necessary to accelerate the transition to a renewable energy future, ensuring a sustainable and resilient world for generations to come. This paper presents a novel MCDM framework that integrates T2NN with LOPCOW and MAIRCA methods to evaluate the sustainability of various RES. The primary objectives were to address the inherent uncertainties and ambiguities in RES evaluations, systematically prioritize criteria, and provide a robust decision-support tool for selecting sustainable energy projects. T2NN enhances the ability to model complex uncertainties by providing a detailed representation of truth, indeterminacy, and falsity. The proposed framework was applied to evaluate four RES alternatives: Solar Energy, Wind Energy, Hydropower, and Geothermal Energy, using criteria such as Environmental Impact, Economic Viability, Technological Maturity, Social Acceptance, and Resource Availability. The analysis revealed that Wind Energy (Alt2) consistently ranked as the most favorable alternative, demonstrating its superior performance in terms of economic viability, social acceptance, and resource availability. A comparative analysis with four other well-known MCDM methods (COPRAS, MABAC, EDAS, and TOPSIS) confirmed the robustness and consistency of the T2NN-LOPCOW-MAIRCA model. The rankings obtained from the proposed model were consistent across different methods, validating the effectiveness of the integrated approach. Sensitivity analysis demonstrated the stability of the rankings under varying criteria weights and input data variations. Wind Energy remained the top choice across different scenarios, indicating that the model's conclusions are reliable and resilient to changes in input parameters. The proposed framework offers a valuable decision-support tool for policymakers, investors, and stakeholders involved in the selection and implementation of sustainable energy projects. It helps in systematically evaluating and prioritizing RES based on a comprehensive set of criteria.

### *9.1 Recommendations*

Based on the findings of this study, the following recommendations are made:

- Policymakers should prioritize investments in wind and geothermal energy due to their high sustainability rankings.
- Further research should explore the integration of multiple RES to enhance overall energy system resilience.
- Future studies should consider additional criteria, such as lifecycle costs and energy storage, to provide a more comprehensive assessment of RES sustainability.

**Declarations**

**Ethics Approval and Consent to Participate**

The results/data/figures in this manuscript have not been published elsewhere, nor are they under consideration by another publisher. All the material is owned by the authors, and/or no permissions are required.

**Consent for Publication**

This article does not contain any studies with human participants or animals performed by any of the authors.

**Availability of Data and Materials**

The data that support the findings of this study are available from the corresponding author upon reasonable request.

**Competing Interests**

The authors declare no competing interests in the research.

**Funding**

This research was not supported by any funding agency or institute.

**Author Contribution**

All authors contributed equally to this research.

**Acknowledgment**

The author is grateful to the editorial and reviewers, as well as the correspondent author, who offered assistance in the form of advice, assessment, and checking during the study period.

## References

1. Alghassab, M. (2023). A computational case study on sustainable energy transition in the Kingdom of Saudi Arabia. *Energies*, *16*(13), 5133. https://doi.org/10.3390/en16135133
2. Yang, J., Yu, Y., Ma, T., Zhang, C., & Wang, Q. (2021). Evolution of energy and metal demand driven by industrial revolutions and its trend analysis. *Chinese Journal of Population Resources and Environment*, *19*(3), 256–264. https://doi.org/10.1016/j.cjpre.2021.12.028
3. Ramanathan, V. (2020). Climate change, air pollution, and health: common sources, similar impacts, and common solutions. In *Springer eBooks* (pp. 49–59). https://doi.org/10.1007/978-3-030-31125-4_5
4. Wang, J., & Azam, W. (2024). Natural resource scarcity, fossil fuel energy consumption, and total greenhouse gas emissions in top emitting countries. *Geoscience Frontiers*, *15*(2), 101757. https://doi.org/10.1016/j.gsf.2023.101757
5. Bathaei, A., & Štreimikienė, D. (2023). Renewable Energy and Sustainable Agriculture: Review of Indicators. *Sustainability*, *15*(19), 14307. https://doi.org/10.3390/su151914307
6. Elkhatat, A., & Al-Muhtaseb, S. (2024). Climate Change and Energy Security: A comparative analysis of the role of energy policies in Advancing environmental sustainability. *Energies*, *17*(13), 3179. https://doi.org/10.3390/en17133179
7. Lak, S. Z., Rezaei, J., & Rahimpour, M. R. (2024). Health and pollution Challenges of fossil fuels utilization. In *Elsevier eBooks*. https://doi.org/10.1016/b978-0-323-93940-9.00202-4
8. Kumar, K. P., Atchuta, S., Prasad, M. S., Barshilia, H. C., & Sakthivel, S. (2024). Review on selective absorber coatings: A catalyst for enhanced solar energy conversion efficiency. *Solar Energy Materials and Solar Cells*, *277*, 113080. https://doi.org/10.1016/j.solmat.2024.113080
9. Qamili, A., & Kapia, S. (2024). Evaluation and integration of photovoltaic (PV) systems in Albanian energy landscape. *Solar Compass*, 100070. https://doi.org/10.1016/j.solcom.2024.100070
10. Hazim, H. I., Baharin, K. A., Gan, C. K., & Sabry, A. H. (2024). Techno-Economic optimization of photovoltaic (PV)-inverter power sizing ratio for Grid-Connected PV systems. *Results in Engineering*, 102580. https://doi.org/10.1016/j.rineng.2024.102580
11. Ouerghi, F. H., Omri, M., Menaem, A. A., Taloba, A. I., & El-Aziz, R. M. A. (2024). Feasibility evaluation of wind energy as a sustainable energy resource. *Alexandria Engineering Journal*, *106*, 227–239. https://doi.org/10.1016/j.aej.2024.06.055
12. Yanez-Rosales, P., Del Río-Gamero, B., & Schallenberg-Rodríguez, J. (2024). Rationale for selecting the most suitable areas for offshore wind energy farms in isolated island systems. Case study: Canary Islands. *Energy*, *307*, 132589. https://doi.org/10.1016/j.energy.2024.132589
13. Wang, X., Ali, D. A., & Zhao, W. (2024). Urban energy transition and quality of life: A comprehensive statistical study on the nexus of wind clean energy adoption, job creation, and livability. *Sustainable Cities and Society*, 105436. https://doi.org/10.1016/j.scs.2024.105436
14. Annoukoubi, M., Essadki, A., & Akarne, Y. (2024). Model Predictive Control of Multilevel Inverter used in a Wind Energy Conversion System Application. *e-Prime - Advances in Electrical Engineering Electronics and Energy*, 100717. https://doi.org/10.1016/j.prime.2024.100717
15. Aryal, S., Ghimire, S., Tiwari, S., Baaniya, Y., & Pandey, V. P. (2024). Evolution and future prospects of hydropower sector in Nepal: A review. *Heliyon*, *10*(10), e31139. https://doi.org/10.1016/j.heliyon.2024.e31139
16. Vagnoni, E., Gezer, D., Anagnostopoulos, I., Cavazzini, G., Doujak, E., Hočevar, M., & Rudolf, P. (2024). E. Vagnoni et al.: The new role of sustainable hydropower in flexible energy systems and its technical evolution through innovation and digitalization. *Renewable Energy*, 120832. https://doi.org/10.1016/j.renene.2024.120832
17. Yu, S., Zhang, J., Cheng, C., & Shen, J. (2024). Bidding optimization for cascade hydropower plants in multi-regional electricity markets. *Journal of Cleaner Production*, *435*, 140477. https://doi.org/10.1016/j.jclepro.2023.140477
18. Zhou, S., Wang, Y., Chang, J., Su, H., Huang, Q., & Li, Z. (2024). Quantifying the effects of future environmental changes on water supply and hydropower generation benefits of cascade reservoirs in the

Yellow River Basin within the framework of reservoir water supply and demand uncertainty. *Journal of Hydrology Regional Studies*, *52*, 101729. https://doi.org/10.1016/j.ejrh.2024.101729

19. Assareh, E., Sahrakar, M., Parvaz, M., Agarwal, N., Firozzadeh, M., & Lee, M. (2024). A Multi-Energy production system utilizing an absorption refrigeration cycle, and a PEM electrolyzer powered by geothermal energy: Thermoeconomic Assessment and Optimization. *Renewable Energy*, 120744. https://doi.org/10.1016/j.renene.2024.120744
20. Edwards, B. A., Outridge, P. M., & Wang, F. (2024). Mercury from Icelandic geothermal activity: High enrichments in soils, low emissions to the atmosphere. *Geochimica Et Cosmochimica Acta*. https://doi.org/10.1016/j.gca.2024.06.026
21. Bashir, M. A., Qing, L., Syed, Q. R., Barwińska-Małajowicz, A., & Hashmi, S. M. (2024). Resources policy from extraction to innovation: The interplay of minerals, geothermal energy, technological advancements, and ecological footprint in high-ecological footprint economies. *Resources Policy*, *95*, 105182. https://doi.org/10.1016/j.resourpol.2024.105182
22. Ang, T., Salem, M., Kamarol, M., Das, H. S., Nazari, M. A., & Prabaharan, N. (2022). A comprehensive study of renewable energy sources: Classifications, challenges and suggestions. *Energy Strategy Reviews*, *43*, 100939. https://doi.org/10.1016/j.esr.2022.100939
23. Shangguan, Z., Li, H., Yang, B., Zhao, Z., Wang, T., Jin, L., & Zhang, C. (2024). Optimization of alkaline electrolyzer operation in renewable energy power systems: A universal modeling approach for enhanced hydrogen production efficiency and cost-effectiveness. *International Journal of Hydrogen Energy*, *49*, 943–954. https://doi.org/10.1016/j.ijhydene.2023.10.057
24. Kumar, M. J., Sampradeepraj, M., Sivajothi, M., & Singh, G. (2024). An Efficient Hybrid Technique for Energy Management System with Renewable Energy System and Energy Storage System in Smart Grid. *Energy*, 132454. https://doi.org/10.1016/j.energy.2024.132454
25. Sahoo, S. K., & Goswami, S. S. (2023). A comprehensive review of multiple Criteria Decision-Making (MCDM) methods: advancements, applications, and future directions. *Decision Making Advances*, *1*(1), 25–48. https://doi.org/10.31181/dma1120237
26. Wang, Z., Cai, Q., & Wei, G. (2023). Modified TODIM method based on cumulative prospect theory with Type-2 neutrosophic number for green supplier selection. *Engineering Applications of Artificial Intelligence*, *126*, 106843. https://doi.org/10.1016/j.engappai.2023.106843
27. Ecer, F., & Pamucar, D. (2022). A novel LOPCOW-DOBI multi-criteria sustainability performance assessment methodology: An application in developing country banking sector. *Omega*, *112*, 102690. https://doi.org/10.1016/j.omega.2022.102690
28. Muravev, D., Hu, H., Zhou, H., & Pamucar, D. (2020). Location optimization of CR Express International Logistics Centers. *Symmetry*, *12*(1), 143. https://doi.org/10.3390/sym12010143
29. Önden, İ., Deveci, M., Kara, K., Yalçın, G. C., Önden, A., Eker, M., & Hasseb, M. (2024b). Supplier selection of companies providing micro mobility service under Type-2 Neutrosophic number based Decision making model. *Expert Systems With Applications*, *245*, 123033. https://doi.org/10.1016/j.eswa.2023.123033
30. Ighravwe, D. E., Babatunde, M. O., Mosetlhe, T. C., Aikhuele, D., & Akinyele, D. (2021). A MCDM-based framework for the selection of renewable energy system simulation tool for teaching and learning at university level. *Environment Development and Sustainability*, *24*(11), 13035–13056. https://doi.org/10.1007/s10668-021-01981-1
31. MCDM for renewable energy projects: criteria weighting with traditional entropy and novel hierarchy in combination with conventional and structured in blocks AHP approaches. (2022, February 23). IEEE Conference Publication | IEEE Xplore. https://ieeexplore.ieee.org/document/9804553
32. Akpahou, R., & Odoi-Yorke, F. (2023). A multicriteria decision-making approach for prioritizing renewable energy resources for sustainable electricity generation in Benin. *Cogent Engineering*, *10*(1). https://doi.org/10.1080/23311916.2023.2204553
33. Li, T., Li, A., & Guo, X. (2020). The sustainable development-oriented development and utilization of renewable energy industry——A comprehensive analysis of MCDM methods. *Energy*, *212*, 118694. https://doi.org/10.1016/j.energy.2020.118694

34. Narayanamoorthy, S., Parthasarathy, T. N., Pragathi, S., Shanmugam, P., Baleanu, D., Ahmadian, A., & Kang, D. (2022). The novel augmented Fermatean MCDM perspectives for identifying the optimal renewable energy power plant location. *Sustainable Energy Technologies and Assessments*, *53*, 102488. https://doi.org/10.1016/j.seta.2022.102488
35. Shao, M., Han, Z., Sun, J., Xiao, C., Zhang, S., & Zhao, Y. (2020). A review of multi-criteria decision making applications for renewable energy site selection. *Renewable Energy*, *157*, 377–403. https://doi.org/10.1016/j.renene.2020.04.137
36. Goswami, S. S., Mohanty, S. K., & Behera, D. K. (2022). Selection of a green renewable energy source in India with the help of MEREC integrated PIV MCDM tool. *Materials Today Proceedings*, *52*, 1153–1160. https://doi.org/10.1016/j.matpr.2021.11.019
37. Sarkodie, W. O., Ofosu, E. A., & Ampimah, B. C. (2022). Decision optimization techniques for evaluating renewable energy resources for power generation in Ghana: MCDM approach. *Energy Reports*, *8*, 13504–13513. https://doi.org/10.1016/j.egyr.2022.10.120
38. Akpahou, R., Mensah, L. D., Quansah, D. A., & Kemausuor, F. (2024). Long-term energy demand modeling and optimal evaluation of solutions to renewable energy deployment barriers in Benin: A LEAP-MCDM approach. *Energy Reports*, *12*, 1888–1904. https://doi.org/10.1016/j.egyr.2024.07.055
39. Hosouli, S., Gaikwad, N., Qamar, S. H., & Gomes, J. (2024). Optimizing photovoltaic thermal (PVT) collector selection: A multi-criteria decision-making (MCDM) approach for renewable energy systems. *Heliyon*, e27605. https://doi.org/10.1016/j.heliyon.2024.e27605
40. Gökgöz, F., & Yalçın, E. (2021). Can renewable energy sources be a viable instrument for climate change mitigation? Evidence from EU countries via MCDM methods. In *Elsevier eBooks* (pp. 19–39). https://doi.org/10.1016/b978-0-12-823767-0.00002-1
41. Ramezanzade, M., Karimi, H., Almutairi, K., Xuan, H. A., Saebi, J., Mostafaeipour, A., & Techato, K. (2021). Implementing MCDM Techniques for Ranking Renewable Energy Projects under Fuzzy Environment: A Case Study. *Sustainability*, *13*(22), 12858. https://doi.org/10.3390/su132212858
42. Cali, U., Deveci, M., Saha, S. S., Halden, U., & Smarandache, F. (2022). Prioritizing energy blockchain use cases using Neutrosophic Number-Based EDAS. *IEEE Access*, *10*, 34260–34276. https://doi.org/10.1109/access.2022.3162190
43. Simic, V., Gokasar, I., Deveci, M., & Karakurt, A. (2022). An integrated CRITIC and MABAC based type-2 neutrosophic model for public transportation pricing system selection. *Socio-Economic Planning Sciences*, *80*, 101157. https://doi.org/10.1016/j.seps.2021.101157
44. Simic, V., Gokasar, I., Deveci, M., & Švadlenka, L. (2024). Mitigating climate change effects of urban transportation using a type-2 neutrosophic MEREC-MARCOS model. *IEEE Transactions on Engineering Management*, *71*, 3233–3249. https://doi.org/10.1109/tem.2022.3207375
45. Deveci, M., Erdogan, N., Cali, U., Stekli, J., & Zhong, S. (2021). Type-2 neutrosophic number based multi-attributive border approximation area comparison (MABAC) approach for offshore wind farm site selection in USA. *Engineering Applications of Artificial Intelligence*, *103*, 104311. https://doi.org/10.1016/j.engappai.2021.104311
46. Alshehri, M. D. (2023). An integrated AHP MCDM based Type-2 Neutrosophic Model for Assessing the Effect of Security in Fog-based IoT Framework. *International Journal of Neutrosophic Science*, *20*(2), 55–76. https://doi.org/10.54216/ijns.200205
47. Simić, V., Milovanović, B., Pantelić, S., Pamučar, D., & Tirkolaee, E. B. (2023). Sustainable route selection of petroleum transportation using a type-2 neutrosophic number based ITARA-EDAS model. *Information Sciences*, *622*, 732–754. https://doi.org/10.1016/j.ins.2022.11.105
48. Sanyal, A., Biswas, S., & Sur, S. (2024). An integrated full consistent LOPCOW-EDAS framework for modelling consumer decision making for organic food selection. *Yugoslav Journal of Operations Research*, *00*, 22. https://doi.org/10.2298/yjor240315022s
49. Biswas, S., Bandyopadhyay, G., & Mukhopadhyaya, J. N. (2022). A multi-criteria framework for comparing dividend pay capabilities: Evidence from Indian FMCG and consumer durable sector. *Decision Making Applications in Management and Engineering*, *5*(2), 140–175. https://doi.org/10.31181/dmame0306102022b

50. Altintaş, F. F. (2023). Analysis of the prosperity performances of G7 countries: an application of the LOPCOW-based CRADIS method. *Alphanumeric Journal*. https://doi.org/10.17093/alphanumeric.1360478
51. Simic, V., Dabic-Miletic, S., Tirkolaee, E. B., Stević, Ž., Ala, A., & Amirteimoori, A. (2023). Neutrosophic LOPCOW-ARAS model for prioritizing industry 4.0-based material handling technologies in smart and sustainable warehouse management systems. *Applied Soft Computing*, *143*, 110400. https://doi.org/10.1016/j.asoc.2023.110400
52. Rani, P., Chen, S., & Mishra, A. R. (2023). Multiple attribute decision making based on MAIRCA, standard deviation-based method, and Pythagorean fuzzy sets. *Information Sciences*, *644*, 119274. https://doi.org/10.1016/j.ins.2023.119274
53. Pamucar, D. S., Tarle, S. P., & Parezanovic, T. (2018). New hybrid multi-criteria decision-making DEMATEL-MAIRCA model: sustainable selection of a location for the development of multimodal logistics centre. *Economic Research-Ekonomska Istraživanja*, *31*(1), 1641–1665. https://doi.org/10.1080/1331677x.2018.1506706
54. Boral, S., Howard, I., Chaturvedi, S. K., McKee, K., & Naikan, V. (2020). An integrated approach for fuzzy failure modes and effects analysis using fuzzy AHP and fuzzy MAIRCA. *Engineering Failure Analysis*, *108*, 104195. https://doi.org/10.1016/j.engfailanal.2019.104195
55. Haq, R. S. U., Saeed, M., Mateen, N., Siddiqui, F., & Ahmed, S. (2023b). An interval-valued neutrosophic based MAIRCA method for sustainable material selection. *Engineering Applications of Artificial Intelligence*, *123*, 106177. https://doi.org/10.1016/j.engappai.2023.106177
56. Ecer, F. (2022). An extended MAIRCA method using intuitionistic fuzzy sets for coronavirus vaccine selection in the age of COVID-19. *Neural Computing and Applications*, *34*(7), 5603–5623. https://doi.org/10.1007/s00521-021-06728-7
57. Öztaş, T., & Öztaş, G. Z. (2023). G20 ülkelerinin i̇novasyon performans analizi: COVID-19 dönemini i̇çeren yeni bütünleşik LOPCOW-MAIRCA ÇKKV yaklaşımı. *Verimlilik Dergisi*. https://doi.org/10.51551/verimlilik.1320794

**Received:** 26 Aug 2024, **Revised:** 24 Sep 2024,

**Accepted:** 29 Sep 2024, **Available online:** 01 Oct 2024.