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Comparative Analysis of Multi-Criteria Techniques in Neutrosophic Environment and their Applications to Economic Condition Assessment

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

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

* Correspondence: aa.ahmed023@eng.zu.edu.eg.

Abstract: In economic decision-making, the challenge of evaluating multiple, often conflicting criteria necessitates advanced Multi-Criteria Decision-Making (MCDM) techniques. Traditional methods can struggle with the inherent uncertainty, ambiguity, and imprecision of real-world data. This paper addresses these challenges by investigating the effectiveness of various MCDM techniques within neutrosophic environments, with a particular focus on the Criteria-wise Alternatives Ranking and Correlation Analysis for Composite Scoring (CARCACS) method. Neutrosophic sets, which incorporate truth, falsity, and indeterminacy, provide a robust framework for addressing the vagueness and inconsistencies found in economic indicators such as GDP growth, employment levels, inflation rates, trade balances, investment activity, and government fiscal policy. This paper conducts a comparative analysis of several MCDM techniques, including N-PROMETHEE II, N-COPRAS, N-GRA, N-ARAS, N-WSM, N-MOORA, N-TOPSIS, and N-WASPAS, assessing their performance using Single-Valued Triangular Neutrosophic Numbers (SVTrNN) in the context of economic condition analysis. The study details the strengths and weaknesses of these methods in managing ambiguous and imprecise data and highlights the neutrosophic CARCACS method's effectiveness in capturing the intricate interactions between criteria and offering a comprehensive evaluation of alternatives. The results reveal the comparative advantages of different MCDM techniques and provide insights into their application in decision-making (DM) under uncertainty. This study contributes to the existing literature by demonstrating how neutrosophic environments can enhance economic DM and by introducing a novel approach for handling economic conditions through the CARCACS method. It aims to assist policymakers and analysts in selecting the most suitable MCDM techniques for complex and uncertain scenarios, leading to more informed and effective decisions. In evaluating MCDM techniques within neutrosophic environments, several sensitivity and comparative challenges arise. The diversity in methods, such as N-PROMETHEE II, N-COPRAS, and N-TOPSIS, introduces variability in handling criteria weightings and alternatives, leading to different results under similar conditions. Sensitivity analysis of the N-CARCACS method also highlights its robustness challenges, particularly how fluctuations in input parameters and criteria weights affect decision outcomes.

Keywords: MCDM; SVTrNN; CARCACS; PROMETHEE II; COPRAS; GRA; ARAS; WSM; MOORA; TOPSIS; WASPAS.

1. Introduction

MCDM techniques are widely used to evaluate and select the most appropriate alternatives by considering multiple, often conflicting criteria [1]. In the real world, most decision-making problems involve evaluating different qualitative criteria that can be vague, ambiguous, fuzzy, or imprecise [2]. To address these challenges, soft computing techniques, such as fuzzy logic and rough sets, are used in MCDM [3]. MCDM methods can be classified into classical and non-classical approaches. Classical methods are based on traditional decision-making approaches, while non-classical methods, such as fuzzy interval and intuitionistic fuzzy (IF), are used to handle complex and uncertain decision-making problems [4, 5]. Fuzzy set theory is a major research area that describes decisions in terms of both tribe optimization and preference analyses [6]. Researchers have proposed different approaches that are integrated to represent the uncertainty of attributes of alternatives upon the model to give the weights by using the uncertainty in the decision [7]. One of these is non-classical MCDM methods, which aim to select the best alternative as a decision problem using the vague, ambiguous, and imprecise data that decision-makers employ in their preferences using a neutrosophic set [8].

Neutrosophic MCDM techniques are a powerful tool for analyzing decision problems under uncertainty [9]. These techniques utilize neutrosophic sets, which can handle indeterminate and inconsistent information, making them well-suited for complex scenarios [10]. In the realm of decision-making, the integration of multiple criteria has become increasingly crucial, particularly in complex economic environments. The incorporation of neutrosophic theory, which encompasses the concepts of truth, falsity, and indeterminacy, has further enhanced the ability to address the uncertainties inherent in such processes [11]. Numerous MCDM techniques have been developed and applied to various economic domains, each with its strengths and limitations [12,13]. The selection of an appropriate MCDM technique is crucial, as it can significantly impact the outcome of the decision-making process. Different methods, when applied to the same problem with similar data, can often produce varying results, highlighting the importance of choosing the technique that best fits the specific decision-making scenario [14].

MCDM is a widely used analytical approach in economics to evaluate and make decisions based on multiple, often conflicting criteria [15]. Many researches provide an overview of how MCDM methods can be applied to economic data and problems [15, 16]. MCDM methods consider various quantitative and qualitative factors to determine the most suitable solution or alternative [17]. These methods can be used to address a wide range of economic problems, including investment decisions, policy analysis, and resource allocation [17]. Moreover, the choice of appropriate method, normalization technique, and data type has been identified as the most effective impact factor for the success of MCDM methods [18]. Some common MCDM techniques used in economics include ARAS [19] and TOPSIS [20]. By considering multiple, sometimes conflicting criteria, MCDM analysis can provide a more comprehensive and nuanced understanding of economic conditions and aid in the decision-making process [17]. The application of MCDM in economics has been growing, as it allows for a more holistic evaluation of complex economic scenarios. Economic conditions refer to the overall state of an economy at a given point in time. They can be measured using a range of indicators such as Gross Domestic Product (GDP) growth, employment levels, inflation rates, trade balances, and investment activity [21].

When considering neutrosophic environments, characterized by imprecise, incomplete, and inconsistent information, the choice of decision-making techniques becomes crucial [10]. This paper delves into a comparative analysis of various MCDM techniques in neutrosophic environments and their application to economic condition analysis. A SVTrNN is a special type of neutrosophic number that is represented by a triangular membership function. It is an extension of triangular fuzzy numbers and IF numbers [22]. This allows for a more nuanced understanding of economic conditions and the decision-making process [23]. SVTrNN provides a powerful tool for representing and handling uncertain and imprecise information in complex systems. They have the potential to be applied in a wide range of fields where uncertainty and imprecision are inherent [24]. When applying MCDM techniques like the CARCACS method to economic condition analysis, the capacity for detailed analysis and insight is evident [15]. Economic indicators such as the consumer price index (CPI), gross domestic product (GDP), and trade balance can be effectively incorporated into the N-CARCACS method to provide a comprehensive assessment of economic conditions.

The application of neutrosophic environments to economic condition analysis, particularly through the N-CARCACS method, offers a distinct advantage in managing ambiguous and vague data, challenging traditional economic modeling assumptions [25]. By embracing the uncertainties inherent in neutrosophic environments, policymakers can gain a more nuanced understanding of economic conditions, leading to more refined and accurate decision-making [24]. However, employing MCDM techniques in these environments presents both challenges and opportunities. Key issues such as the quality, reliability, and availability of data can significantly affect decision-making outcomes. If these challenges are not adequately addressed, they can result in flawed policy decisions. Nevertheless, by overcoming these hurdles, policymakers can enhance the accuracy and credibility of economic condition analyses, ultimately facilitating more informed and effective decisions. Traditional economic modeling assumptions often fall short when dealing with the complexities of neutrosophic environments, leading to suboptimal policy decisions. In response, MCDM techniques have been proposed as a solution, providing a more sophisticated approach to understanding economic conditions under uncertainty, focusing on the N-CARCACS method. This paper conducts a comparative analysis of various MCDM techniques in a neutrosophic atmosphere, including N-PROMETHEE II, N-COPRAS, N-GRA, N-ARAS, N-WSM, N-MOORA, N-TOPSIS, and N-WASPAS. The goal is to evaluate their impact on economic analysis and provide insights into their application in assessing economic conditions. By focusing on the application of these techniques to economic condition analysis, this study aims to identify the strengths and limitations of each method when dealing with vague, ambiguous, and imprecise data and by examining their correlation. A special emphasis is placed on the N-CARCACS method to evaluate its effectiveness in handling economic indicators under uncertainty. The ultimate goal is to provide a comprehensive evaluation of how different MCDM methods can be utilized to enhance decision-making in complex economic scenarios.

1.1 Contributions of the Study

i). This study demonstrates how MCDM techniques can be effectively applied to economic condition analysis, offering a more nuanced and comprehensive understanding of economic indicators such as GDP growth, employment levels, and trade balances.

ii). The paper presents a detailed comparative analysis of various MCDM techniques, specifically within the context of neutrosophic environments. This comparison helps to select the most appropriate technique for specific needs when dealing with uncertain, vague, and imprecise data.

iii). The paper introduces the CARCACS method in the neutrosophic environment (N-CARCACS) for the first time in economic condition analysis. This method is shown to be particularly effective in managing the ambiguities and uncertainties inherent in economic data.

iv). The paper highlights the ability of MCDM techniques, especially the N-CARCACS method, to effectively manage ambiguous and vague data. This addresses a common challenge in economic condition analysis, where traditional models may struggle with imprecise information.

v). Beyond economics, the study’s findings and proposed framework have potential applications in other fields that involve decision-making under uncertainty, such as finance, healthcare, and environmental management. This broad applicability underscores the versatility of the approach and promotes the development of more effective decision-making tools across various domains.

This paper is structured as follows: Background and Literature Review of MCDM Techniques and Neutrosophic Environment in Economic Condition Analysis. Section 3: Theoretical Framework of SVTrNN and N-CARCACS Method. Section 4: Case Study. Section 5: Comparative and Sensitivity

Analysis of MCDM Techniques in Neutrosophic Environment. Section 6: Displays challenges and future work. Section 7: Conclusion.

2. Background and Literature Review

This section provides an overview of MCDM techniques and a review of neutrosophic theory and their application in economic condition analysis.

2.1 MCDM Techniques and Neutrosophic in Decision-Making

MCDM techniques have been widely used in various fields to evaluate and pick the optimal alternative from a variety of possibilities [1]. MCDM techniques consider multiple criteria or attributes that are often conflicting and incommensurable [2]. The goal of MCDM is to provide a structured approach to decision-making, enabling decision-makers to evaluate and prioritize alternatives based on their performance across multiple criteria [3]. Over the years, various MCDM techniques have been developed, including ARAS [19], TOPSIS [20], PROMETHEE II [26], Elimination and Choice Expressing Reality (ELECTRE) [27] and WASPAS [28]. Singh R et al. [7] apply MOORA to a fuzzy environment and analyze it for different applications. Sukanta Malakar et al. [29] apply WSM MCDM with AHP for Calculating seismic. Bhavna Pandey et al. [30] propose SWARA-COPRAS in the Pythagorean fuzzy environment to evaluate Industry 4.0. Xianliang Liu et al. [31] apply sensitivity analysis to the PROMETHEE II method. Gang Kou et al. [32] evaluate TOPSIS, ELECTRE, GRA, VIKOR, and PROMETHEE using Spearman's rank correlation coefficient. These techniques have been successfully applied in various fields, including business, engineering, healthcare, and environmental management [33]. MCDM techniques have been also applied to a wide range of economic problems [14]. These techniques, among others, offer flexibility in addressing decision-making problems by accommodating various forms of data, including quantitative, qualitative, and fuzzy information [4, 5].

The neutrosophic theory extends traditional fuzzy set theory by introducing the concept of indeterminacy, allowing for a more nuanced representation of uncertainty [10]. Neutrosophic logic deals with three types of membership functions, with the ranges [0, 1] normally representing truth, indeterminacy, and falsity membership [8]. Smarandache developed neutrosophic logic in 1995 as a generalization of IF logic and fuzzy logic. [22]. This allows for the representation of incomplete, uncertain, and inconsistent information in decision-making problems [9]. In recent years, applications of neutrosophic logic to decision-making issues have been made, especially in MCDM. Zolfani, S. H. et al. [33] integrated GRA with Type-2 neutrosophic fuzzy sets. Ibrahim M. et al. [34] applied COPRAS with MASWIP using an SVN environment. Vladimir Simic et al. [35] proposed ARAS with Neutrosophic LOPCOW in industry 4.0. Amirhossein Nafei et al. [36] presented TOPSIS with neutrosophic in Sustainable Manufacturing. One key aspect examined in this paper is the comparative capacity of different neutrosophic MCDM approaches. Mahmut Baydas et al. [37]. Aimed to evaluate the performance of different MCDM methods for evaluating the financial performance of companies. They compared 10 MCDM methods, including PROMETHEE, FUCA, TOPSIS, GRA, S-, WSA, SAW, COPRAS, MOORA, and LINMAP, by examining their correlation with actual stock prices, which were used as a proxy for financial performance. Chao Tian et al. [38] introduced new operators for single-valued neutrosophic (SVN) information and applied them to solve MCDM problems. In the context of COVID-19 vaccine prioritization, research has also explored the use of neutrosophic MCDM techniques like TOPSIS to evaluate and rank alternatives [39]. An improved multi-criteria group decision-making (MCGDM) strategy has been developed in a pentagonal neutrosophic environment using MEREC compared to the GRA technique and is effective for agricultural-based decision problems [40]. An interval-valued neutrosophic MAIRCA method has been proposed for selecting optimal materials in design problems with quantitative measurements [41]. GRA is also applied using fuzzy environments for select pest control [42]. Amit R. Patil et al. [43]

applied GRA with the AHP method. S.S. Mohanrasu et al. [44] provided the COPRAS method for select Text Classification. Farhad Hosseinzadeh et al. [45] introduced COPRAS in Uncertainty Environment. Also, ARAS has been integrated with many environments as T-Spherical Fuzzy [46] and Pythagorean fuzzy environment [47]. Victor Rosemberg et al. [48] provided a new BWM-MOORA technique. Subhanshu Goyal et al. [49] applied WASPAS in SVN sets.

2.2 Applications of MCDM in Economic Condition Analysis

MCDM techniques have been widely applied in economic condition analysis to evaluate the performance of countries, regions, or organizations [50]. Economic condition analysis involves evaluating various economic indicators, such as GDP growth rate, inflation rate, unemployment rate, and income inequality [21]. MCDM techniques have been used to evaluate the economic performance of countries and regions, identify the most important economic indicators, and prioritize policy interventions [51]. Recent studies have also applied neutrosophic MCDM techniques to economic analysis [52]. The integration of neutrosophic logic with MCDM in economic condition analysis provides a robust framework for decision-making under uncertainty, particularly in dynamic and volatile markets. The case study analysis of the economic situation is an important approach to examine and understand the complex economic conditions in a given context. A technical note presents an example of the approach to the economic analysis of a health project, which can serve as a guide for future projects [53]. Alexandra provided a case study comparing economic growth (GDP) with economic development using different indicators [54].

3. Theoretical Framework and Methodology

3.1 Concepts SVTrNN and Their Properties [22, 23]

In this section, we present several key components of SVTrNN.
A SVTrNN [24] is represented as $\breve{S} = (s_1, s_2, s_3); T_{\breve{s}}, I_{\breve{s}}, F_{\breve{s}}, where\ s_1, s_2, s_3$ are the lower, middle, and upper parts of a neutrosophic number. Also, $T_{\breve{s}}$ is the truth, $I_{\breve{s}}$ is the indeterminacy, and $F_{\breve{s}}$ is the falsity of membership degrees.

3.1.1 SVTrNN Definitions

On the real line R, SVTrNN is a neutrosophic set, represented as $\breve{S} = ((s_1, s_2, s_3): T_{\breve{s}}, I_{\breve{s}}, F_{\mathrm{s}})$ where s_1, s_2, s_3 are real numbers and $(T_{\breve{s}}, I_{\breve{s}}, F_{\mathrm{s}})$ are membership functions. The definition of the membership functions is [52]:

$$T_s(x) = \begin{cases} \dfrac{(x - s_1)T_s}{(s_2 - s_1)} & (s_1 \le x \le s_2) \\ T_s & (x = s_2) \\ \dfrac{(s_3 - x)T_s}{(s_3 - s_2)} & (s_2 \le x \le s_3) \\ 0 & otherwise \end{cases}$$

$$I_s(x) = \begin{cases} \dfrac{(s_2 - x + I_s(x - s_1))}{(s_2 - s_1)} & (s_1 \le x \le s_2) \\ I_s & (x = s_2) \\ \dfrac{(x - s_2 + I_s(s_3 - x))}{(s_3 - s_2)} & (s_2 \le x \le s_3) \\ 1 & otherwise \end{cases}$$

$$F_a(x) = \begin{cases} \dfrac{(s_2 - x + F_s(x - s_1))}{(s_2 - s_1)} & (s_1 \le x \le s_2) \\ F_s & (x = s_2) \\ \dfrac{(x - s_3 + F_s(s_3 - x))}{(s_3 - s_2)} & (s_1 \le x \le s_3) \\ 1 & otherwise \end{cases}$$

Where $T_s, I_s, F_s \in [0,1]$ and $s_1, s_2, s_3 \in$ R, $s_1 \le s_2 \le s_3$.

3.1.2 Operations on SVTrNN

Let X = $((a_1, a_2, a_3) : T_1, I_1, F_1)$ and Y = $((b_1, b_2, b_3) : T_2, I_2, F_2)$ be two SVTrNNs and Then,

- Addition $X \oplus Y = \langle (a_1 + b_1, a_2 + b_2, a_3 + b_3);, \min(T_1, T_2), \max(I_1, I_2), \max(F_1, F_2) \rangle$
- Multiplication $X \otimes Y = ((a_1 b_1, a_2 b_2, a_3 b_3) \min(T_1, T_2), \max(I_1, I_2), \max(F_1, F_2))$

3.1.3 Score and Accuracy Functions

let $a = ((a_1, a_2, a_3) : T_a, I_a, F_a)$ be SVTrNN. The accuracy and score functions respectively are:

$$S(\mathrm{a}) = \left(\frac{1}{12}\right)[a_1 + 2a_2 + a_3] * [2 + T_a - I_a - F_a] \quad (1)$$

$$A(\mathrm{a}) = \left(\frac{1}{12}\right)[a_1 + 2a_2 + a_3] * [2 + T_a - I_a + F_a] \quad (2)$$

3.2 N-CARCACS Technique

The CARCACS method is a MCDM technique [25]. The extended version of the CARCACS method in neutrosophic environment (N-CARCACS) will be as follows:

i). Problem Definition: Identify the decision-making problem, criteria, and alternatives. Define expert as $Ex_k = \{Ex_1, Ex_2, \ldots, Ex_k\}$.

ii). Collect Expert Opinions: Gather expert evaluations of each alternative against each criterion, represented as SVTrNN $\widetilde{A_1} = ((a_1, a_2, a_3); T_1, I_1, F_1)$ using linguistic terms as represented in Table 1.

iii). Decision Matrix Construction: Create a decision matrix R = $[\mathrm{x_{ij}}]_{\mathrm{mxn}}$ where $\mathrm{x_{ij}}$ represents the SVTrNN assigned to alternative i concerning criterion j. The number of alternatives chosen by the decision makers is represented by m, and n is the number of criteria used to rank those alternatives.

iv). Conversion of SVTrNN to Crisp Numbers: Convert SVTrNNs to crisp values using the score function as in Eq. (1).

v). Aggregate the Decision Makers' Matrices: The expert's matrices can be aggregated using a suitable aggregation method, such as the average method to construct the decision matrix.

$$\text{Aggre} = \frac{\sum_{i=1}^{k} \mathrm{Ex}}{\mathrm{N}} \quad (3)$$

where N numbers of Exs.

vi). Rank Matrix Construction: Rank the alternatives based on each criterion (beneficial and non-beneficial attributes). For each criterion, Beneficial attributes: The highest value is assigned the first rank and the ranking decreases as the values decrease. Non-beneficial attributes: The lowest value is assigned the first rank and the ranking increases as the values increase. Equal values: In cases where two or more alternatives have equal values, an average rank is assigned.

vii). Correlation Calculation: Compute the linear correlation between criteria denoted as $Corr_{ab}$ Using the formula:

$$Corr_{ab} = \frac{(m \sum_{i=1}^{m} a_i b_i) - (\sum_{i=1}^{m} a_i \sum_{i=1}^{m} b_i)}{\sqrt{m \sum_{i=1}^{m} a_i^2 - (\sum_{i=1}^{m} a_i)^2} \sqrt{m \sum_{i=1}^{m} b_i^2 - (\sum_{i=1}^{m} b_i)^2}} \quad (4)$$

Where, a_i and b_i refer to the performance values of the ith alternative based on the a and b criteria, respectively, for assessing their inter-criteria correlation, m denotes the number of alternatives. Notice that the value of $Corr_{ab}$ is from $-1 \ to \ +1$.

viii). Deviation Calculation: Calculate the deviation:

$$\varphi_{ij} = 1 - Corr_{ab} \quad (5)$$

ix). Overall Correlation Value: Sum the deviation values to find the overall correlation θ_j for each criterion.

$$\theta_j = \sum_{i=1}^{m} \varphi_{ij} \quad (6)$$

x). Criterion Weights: Calculate the weights w_j for each criterion.

$$w_j = \frac{\theta_j}{\sum_{j=1}^{n} \theta_j} \quad (7)$$

xi). Weighted Rank Performance Matrix: Construct the weighted rank matrix $\check{R} = [r_{ij}]_{mxn}$ using the criterion weights. $\check{R}$ is derived by

$$r_{ij} = w_j \, . R \quad (8)$$

xii). Composite Score Calculation: Calculate the composite score S_c for each alternative by summing the weighted rank values using

$$S_c = \sum_{j=1}^{n} r_{ij} \quad (9)$$

, and rank the alternatives based on this score with the lowest S_c being the best choice.

The N-CARCACS method provides a systematic approach to evaluating alternatives based on multiple criteria, taking into account the correlation between criteria and the relative importance of each criterion.

Table 1. SVTrNN scale.

Linguistic Scale	SVTrNN Values
Very Low (VL)	((0.2, 0.5, 0.8); 0.30, 0.70, 0.40)
Low (L)	((0.8, 2, 3.2); 0.20, 0.85, 0.60)
Medium (M)	((2.5, 4.5, 6.5); 0.60, 0.30, 0.35)
High (H)	((5.5, 7.5, 9.5); 0.80, 0.20, 0.20)
Very High (VH)	((8.5, 9.5, 10); 0.95, 0.05, 0.05)

4. Case Study

In the modern economic landscape, decision-making is increasingly complex due to the presence of multiple, and conflicting criteria. Traditional decision-making approaches may fall short in handling the ambiguity, imprecision, and uncertainty that characterize real-world economic conditions. MCDM techniques have emerged as powerful tools to address these challenges by providing a structured framework for evaluating and selecting the most appropriate alternatives based on various criteria. Economic conditions refer to the overall state of an economy at a given point in time, measured using various indicators such as Gross Domestic Product (GDP) growth, employment levels, inflation rates, trade balances, investment activity, and government fiscal policy [21]. Analyzing these conditions requires considering multiple criteria that may have conflicting impacts on the decision-making process. The main problem addressed in this study is the selection of the most effective MCDM method for analyzing economic conditions in a neutrosophic environment. Traditional economic models may not adequately capture the uncertainty and vagueness inherent in economic data, leading to suboptimal policy decisions. The paper will employ a comparative analysis of various MCDM techniques within a neutrosophic environment, focusing on the N-CARCACS method. The analysis will be conducted using a case study involving five alternatives and six economic criteria. Process Steps for Applying the N-CARCACS Method Using SVTrNN in Economic Condition Analysis:

Step 1: Describe the problem of decision-making:

Identify the decision-making problem: Evaluate the economic conditions of 5 alternatives $A1, A2, A3, A4, A5$ based on 6 criteria and four experts to express their opinions using the SVTrNN Linguistic Scale.

Define the criteria (6):

C1: Gross Domestic Product (GDP) growth

C2: Employment levels

C3: Inflation rates

C4: Trade balances

C5: Investment activity

C6: Government fiscal policy

Step 2: Construct the Decision Matrix: Create a decision matrix R with SVTrNN Linguistic Scale from Table 1 for each alternative concerning each criterion as represented in Table 2.

Step 3: Convert SVTrNN into Crisp Numbers: Use the Score function (Eq. (1)) to convert the SVTrNN values into crisp numbers. This step simplifies the decision matrix into a crisp format for further analysis. Then use the aggregation method (Eq. (3)) to aggregate the crisp format to establish the decision matrix as in Table 3.

Step 4: Construct the Rank Matrix: Rank the alternatives for each criterion using the crisp numbers obtained in Step 3 as in Table 4.

Beneficial Criteria (C1, C2, C3, C4, C5): Higher values receive higher ranks.

Non-beneficial Criteria (C6): Lower values receive higher ranks.

Step 5: Calculate Correlation and Deviation:

Calculate the linear correlation $Corr_{ab}$ between criteria using Eq. (4) and the deviation in correlation values φ_{ij} using Eq. (5) as in Table 5.

Step 6: Compute Overall Correlation and Criterion Weights:

Sum the deviation values θ_j for each criterion j to obtain the overall correlation using Eq. (6) and calculate the criterion weights $W_j$using Eq. (7) as in Table 5. Ensure that $\sum w_j$=1.

Step 7: Establish the Weighted Rank Performance Decision Matrix:

Multiply the rank values by the corresponding criterion weights to construct the weighted rank performance matrix $\check{R}$ using Eq. (8) as in Table 6.

Step 8: Calculate the Composite Score for Each Alternative using Eq. (9). Then Rank the alternatives based on the increasing values of Sc. The alternative with the lowest Sc is considered the best choice for the final rank as shown in Table 6 where A4 > A2 > A5 > A3 > A1.

Table 2. SVTrNN decision matrix.

Exs		C1	C2	C3	C4	C5	C6
EX1	A1	L	L	L	M	M	H
	A2	H	VL	M	M	H	H
	A3	L	VH	M	H	VL	VH
	A4	M	M	H	VL	VH	M
	A5	M	H	H	VH	VH	L
EX2	A1	L	L	VL	M	H	H
	A2	VL	M	M	H	H	VH
	A3	M	VL	VL	H	VH	VH
	A4	VL	H	H	VL	VH	L
	A5	H	H	VH	VH	L	L
EX3	A1	M	M	H	H	VH	VH
	A2	VH	H	H	VH	VH	M
	A3	H	VL	VH	VH	L	L

	A4	H	VH	VH	L	M	L
	A5	VH	VH	L	L	L	M
EX4	A1	M	H	H	VH	VL	L
	A2	H	H	VL	VH	L	VL
	A3	L	VL	VH	L	M	L
	A4	VH	VH	L	VL	VL	VH
	A5	VH	L	L	L	M	M

Table 3. Decision matrix.

	C1	C2	C3	C4	C5	C6
A1	1.7125	2.33125	2.875	4.890625	4.209375	4.903125
A2	4.828125	3.48125	2.8625	6.2375	4.903125	4.209375
A3	2.33125	2.228125	4.9375	4.903125	2.984375	4.40625
A4	4.209375	6.2375	4.903125	0.275	4.9375	3.059375
A5	6.2375	4.903125	3.678125	4.40625	3.059375	1.7125

Table 4. Rank matrix.

	C1	C2	C3	C4	C5	C6
A1	5	4	4	3	3	5
A2	2	3	5	1	2	3
A3	4	5	1	2	5	4
A4	3	1	2	5	1	2
A5	1	2	3	4	4	1

Table 5. Correlation and deviation.

$Corr_{ab}$	C1	C2	C3	C4	C5	C6
C1	1	0.6	-0.2	-0.1	0.1	0.9
C2	0.6	1	-0.1	-0.7	0.7	0.8
C3	-0.2	-0.1	1	-0.4	-0.4	0.1
C4	-0.1	-0.7	-0.4	1	-0.3	-0.5
C5	0.1	0.7	-0.4	-0.3	1	0.2
C6	0.9	0.8	0.1	-0.5	0.2	1
θ_j	3.7	3.7	6	7	4.7	3.5
w_j	0.129370629	0.129370629	0.20979021	0.244755245	0.164335664	0.122377622

Table 6. Weighted matrix and final rank.

	C1	C2	C3	C4	C5	C6	Sc	rank
A1	0.646853147	0.517482517	0.839160839	0.734265734	0.493006993	0.611888112	3.842657343	5
A2	0.258741259	0.388111888	1.048951049	0.244755245	0.328671329	0.367132867	2.636363636	3
A3	0.517482517	0.646853147	0.20979021	0.48951049	0.821678322	0.48951049	3.174825175	4
A4	0.388111888	0.129370629	0.41958042	1.223776224	0.164335664	0.244755245	2.56993007	1
A5	0.129370629	0.258741259	0.629370629	0.979020979	0.657342657	0.122377622	2.776223776	2

5. Comparative and Sensitivity Analysis of MCDM Techniques in Neutrosophic Environment

This section presents a comparative analysis focusing on economic condition analysis using different MCDM techniques applied in a neutrosophic environment (i.e. using the proposed scale for constructing decision matrices by considering any uncertainty, the same aggregation equation, and score function for obtaining crisp decision matrix and complete remaining steps as classical methods).

5.1 Evaluation of Criteria Weight

Economic indicators, such as GDP growth, employment levels, inflation rates, trade balances, investment activity, and government fiscal policy, are used as criteria. The methods are compared based on their ability to handle uncertainty, provide accurate rankings, and deal with the interdependence of criteria. In MCDM the weighting of criteria is a critical step that significantly influences the final ranking of alternatives [3]. N-CARCACS and N-CRITIC, are used to determine the weights of different economic indicators (criteria) in a decision-making process. The weights represent the relative importance of each criterion as in Table 7. Figure 1 shows the weights (w_j) obtained using each method for the six economic indicators.

N-CARCACS vs. N-CRITIC:

- N-CARCACS
- A novel MCDM method was designed. It involves calculating weights for each criterion based on the correlation between the criteria and the alternatives.
- N-CRITIC

A classical CRITIC method is used for objective weight determination by considering the contrast intensity and conflict among criteria. It calculates weights based on the standard deviation and correlation coefficient of each criterion [47]. In neutrosophic CRITIC we applied the first five steps as in the proposed method and applied the remaining calculations on the aggregated crisp matrix as in the classical CRITIC method.

Table 7. Comprehensive analysis of weighting methods.

	C1	C2	C3	C4	C5	C6
w_j N-CARCACS	0.129370629	0.129370629	0.20979021	0.244755245	0.164335664	0.122377622
w_j N-Critic	0.152597129	0.154198518	0.19236763	0.16994195	0.168100338	0.164607052

By comparing the weights obtained from both methods, you can analyze the differences in the importance assigned to each criterion. This can help you understand the strengths and weaknesses of each method and choose the most suitable approach for your decision-making problem.

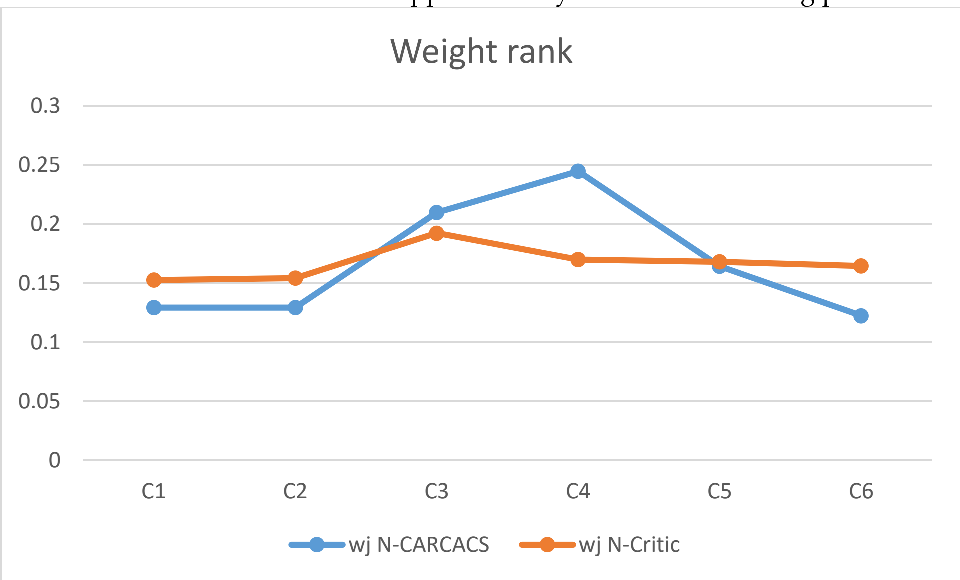

Figure 1. Comprehensive analysis of weighting methods.

N-CARCACS is particularly effective in scenarios where criteria are interdependent. By incorporating correlation, it adjusts weights to reflect the real-world interactions between criteria, making it well-suited for complex decision environments like economic condition analysis. N-CARCACS can be adapted to handle neutrosophic data, which includes uncertainty, indeterminacy, and inconsistency, providing a nuanced approach to decision-making in uncertain environments. N-CRITIC offers a purely objective method for weight determination, free from subjective bias. It is grounded in statistical measures, which enhances the reliability of the weights in data-rich environments. By focusing on criteria that provide unique and substantial information, N-CRITIC ensures that the most informative criteria are given more importance in the decision-making process. The choice between these two methods should be based on the specific characteristics of the decision-making problem, including the nature of the criteria, the availability and quality of data, and the level of complexity involved.

5.2 Sensitivity Analysis of N-CARCACS

The goal of sensitivity analysis in the context of the N-CARCACS method is to assess how changes in the input data affect the results of the DM process. This helps in understanding the robustness of the N-CARCACS method against variations in the input parameters and in identifying which alternatives are most sensitive to changes. The provided data in Table 8 includes different cases with variations in weights of criteria and their impact on the final rank of the five alternatives across twelve cases. Figure 2 visually represents the sensitivity analysis of score values of Sc for all twelve cases.

Case 1: We assume that the weight of the six criteria are equal and each of them = 0.166667. As a result, it was found that the alternatives have been ranked in the following order: $A4 > A5 > A2 > A3 > A1$.

Case 2: Let the weight of the first criterion = be 0.229371 and the weights of the other criteria are 0.154126 for each of them. The alternatives have been ranked in the following order: $A4 > A5 > A2 > A3 > A1$.

Case 3: Let the weight of the second criterion = be 0.229371 and the weights of the other criteria are 0.154126 for each of them. The alternatives have been ranked in the following order: $A4 > A5 > A2 > A3 > A1$.

Case 4: Let the weight of the third criterion = be 0.229371 and the weights of the other criteria are 0.154126 for each of them. The alternatives have been ranked in the following order: $A4 > A5 > A2 > A3 > A1$.

Case 5: Let the weight of the fourth criterion = be 0.229371 and the weights of the other criteria are 0.154126 for each of them. The alternatives have been ranked in the following order: $A4 > A2 > A5 > A3 > A1$.

Case 6: Let the weight of the fifth criterion = be 0.229371 and the weights of the other criteria are 0.154126 for each of them. The alternatives have been ranked in the following order: $A4 > A5 > A2 > A3 > A1$.

Case 7: Let the weight of the six criteria = 0.229371 and the weights of the other criteria are 0.154126 for each of them. The alternatives have been ranked in the following order: $A4 > A5 > A2 > A3 > A1$.

Case 8: Let the weight of criteria be as follows C1= 0.244755, C2= 0.129370, C3= 0.209790, C4 = 0.129370, C5= 0.164335, and C6= 0.122377. The alternatives have been ranked in the following order: $A4 > A5 > A2 > A3 > A1$.

Case 9: Let the weight of criteria be as follows C1= 0.129370, C2 = 0.244755, C3= 0.209790, C4 = 0.129370, C5= 0.164335, and C6= 0.122377. The alternatives have been ranked in the following order: $A4 > A5 > A2 > A3 > A1$.

Case 10: Let the weight of criteria are as follows C1= 0.129370, C2 = 0.129370, C3= 0.244755, C4 = 0.209790, C5= 0.164335, and C6= 0.122377. The alternatives have been ranked in the following order: $A4 > A5 > A2 > A3 > A1$.
Case 11: Let the weight of criteria are as follows C1= 0.129370, C2 = 0.129370, C3= 0.209790, C4 = 0.164335, C5= 0.244755, and C6= 0.122377. The alternatives have been ranked in the following order: $A4 > A2 > A5 > A3 > A1$.
Case 12: Let the weight of criteria are as follows C1= 0.129370, C2 = 0.129370, C3= 0.209790, C4 = 0.122377, C5= 0.164335, and C6= 0.244755. The alternatives have been ranked in the following order: $A4 > A5 > A2 > A3 > A1$.

Table 8. Sensitivity analysis of weight and its impact on rank.

	Base Case	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12
A1	5	5	5	5	5	5	5	5	5	5	5	5	5
A2	2	3	3	3	3	2	3	3	3	3	3	2	3
A3	4	4	4	4	4	4	4	4	4	4	4	4	4
A4	1	1	1	1	1	1	1	1	1	1	1	1	1
A5	3	2	2	2	2	3	2	2	2	2	2	3	2

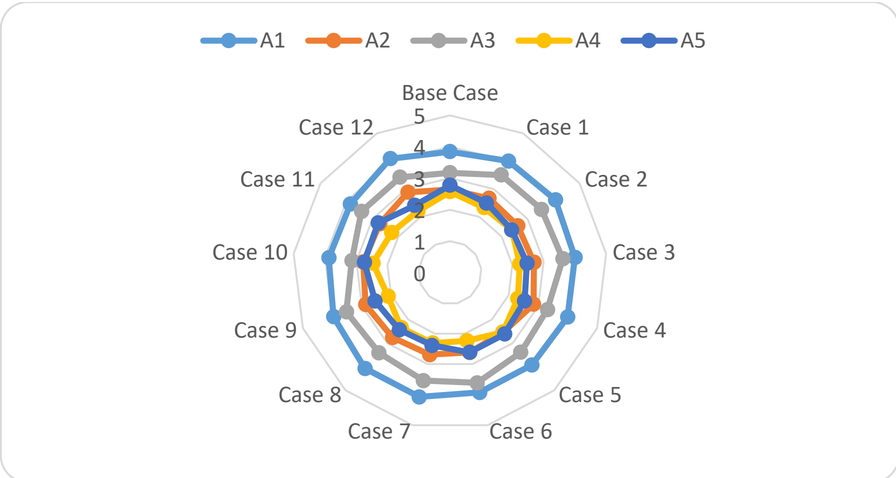

Figure 2. Score values of alternatives regarding 12 cases.

Alternatives A1, A3, and A4 have no variability in their scores, indicating that their rankings will remain constant regardless of the case. Alternatives A2 and A5 have variability in their scores. Indicates that their rankings are sensitive to changes in input data. Figure 3 shows how each alternative's rank changes across different cases.

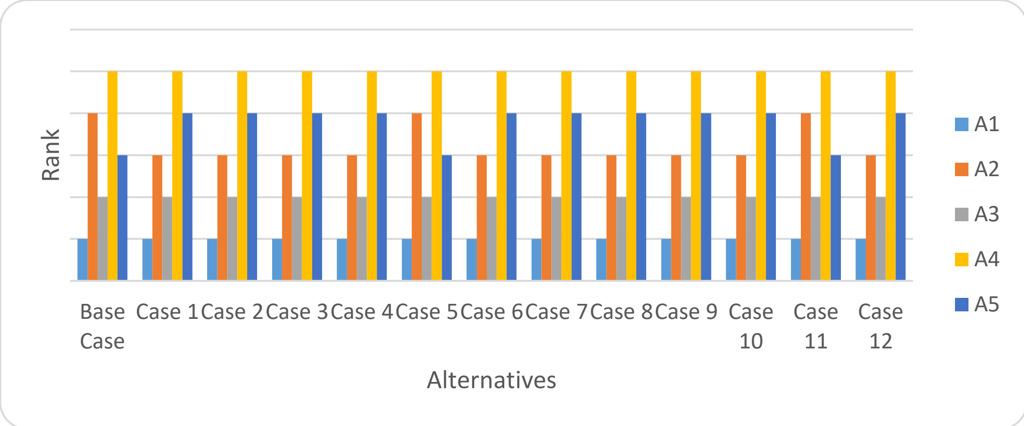

Figure 3. The rank of alternatives across different cases.

By systematically analyzing how variations in cases impact the alternatives, you can identify which alternatives are most sensitive to changes in input and make more informed decisions based on the N-CARCACS method.

5.3 Comparative Analysis of Techniques

Evaluating the performance of different MCDM methods, including N-CARCACS, in handling complex decision-making problems involving interrelated criteria and uncertain data.

- N-CARCACS: Provides a composite score based on weighted ranks, making it adaptable to situations where criteria are interrelated. Also, effective in handling neutrosophic data, that involves truth, indeterminacy, and falsity components.
- Other MCDM Techniques using weight obtained from the N-CRITIC method:
- N-COPRAS: COPRAS focuses on proportional dependencies of criteria [30]. Effective in determining the importance of alternatives based on the criteria dependencies.
- N-GRA: GRA can handle incomplete information and find relational degrees among alternatives [40].
- N-ARAS: The Additive Ratio Assessment approach focuses on utility degree determination [19] and is capable of ranking alternatives by their total performance scores.
- N-WSM: WSM is simple and easy to implement [29, 56]. Lacks the sophistication needed for complex, interdependent criteria
- N-MOORA: Multi-Objective Optimization by Ratio Analysis, a method that provides a clear ranking of alternatives. Also, offers straightforward computations, and clear rankings [7].
- N-TOPSIS: TOPSIS considers the distance from an ideal solution [20].
- N-WASPAS: Weighted Aggregated Sum Product Assessment, which combines the benefits of WSM and TOPSIS [28].
- N-PROMETHEE II: An outranking method that uses pairwise comparisons to rank alternatives based on criteria preferences [26, 32]. Effective in handling both quantitative and qualitative criteria and offers flexibility in pairwise comparisons.

Table 9 shows the results of each method for the five alternatives. The values represent the scores obtained from each method. By comparing the results in Figures 4 and 5, evaluate the performance of each method in handling complex decision-making problems.

Table 9. Comprehensive analysis of ranking methods.

	N-PROMETHEE II	N-CARCACS	N-COPRAS	N-GRA	N-ARAS	N-WSM	N-MOORA	N-TOPSIS	N-WASPAS
A1	0.039936374	3.842657	0.157588	0.072628	0.541175	0.125302	0.031419	0.177706	0.522492
A2	0.068760619	2.636364	0.211676	0.103262	0.761294	0.166646	0.104746	0.339881	0.700644
A3	-0.307527444	3.174825	0.174502	0.089065	0.643606	0.142093	0.071476	0.277984	0.578982
A4	0.205581473	2.56993	0.210006	0.122477	0.856478	0.347182	0.305971	0.772669	0.609422
A5	-0.006751022	2.776224	0.24804	0.109909	1.291171	0.22059	0.21346	0.569672	0.798926

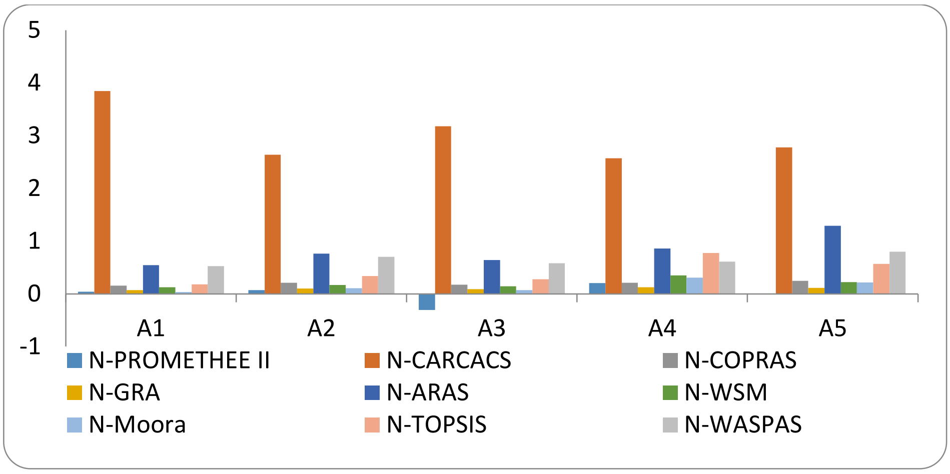

Figure 4. Values of alternatives via various methods.

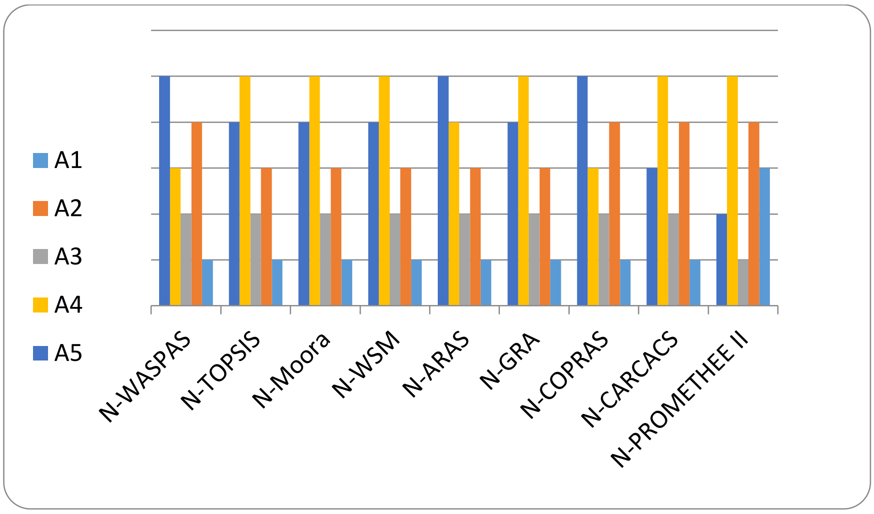

Figure 5. Rank of alternatives via various methods.

To evaluate the consistency of the rankings obtained from each MCDM method, Corrl (also known as Spearman's rank correlation coefficient) is calculated between each pair of methods [58]. Table 10 shows the Corrl between each pair of MCDM methods using weight calculated by N-CARCACS and N-Critic weight applied to remain ranking method. Figure 6, also shows this analysis.

Table 10. Corrl between proposed and other methods.

Corrl	N-PROMETHEE II	N-COPRAS	N-GRA	N-ARAS	N-WSM	N-Moora	N-TOPSIS	N-WASPAS
N-CARCACS	0.7	0.6	0.9	0.7	0.9	0.9	0.9	0.6

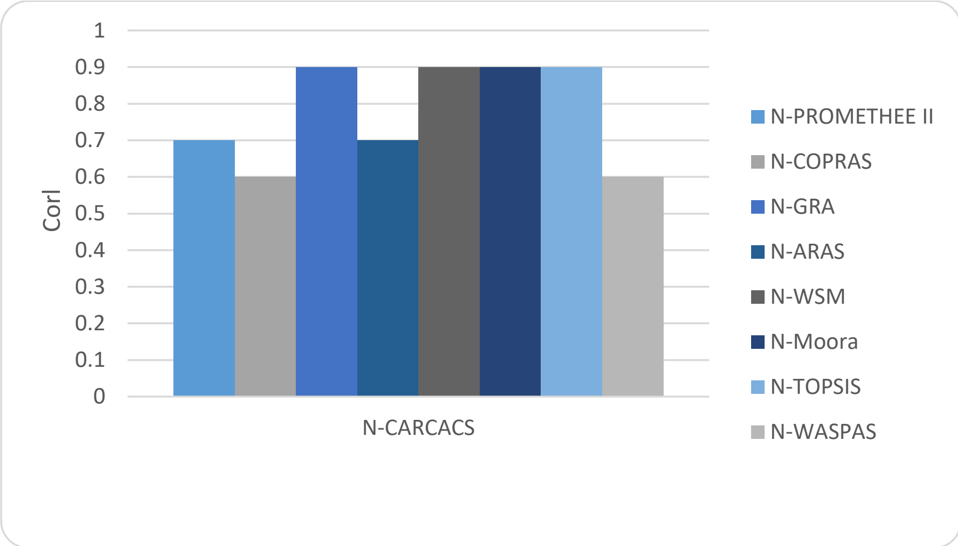

Figure 6. Corrl between proposed and other MCDM methods.

Based on the correlation matrix in Table 10:

- **High Correlation** (0.9): The Corrl shows a high correlation between N-CARCACS and several other methods including N-GRA, N-WSM, N-MOORA, and N-TOPSIS, all with a value of 0.9. This suggests that the rankings produced by N-CARCACS are highly similar to those generated by these methods, indicating that they may share common decision-making principles.
- **Moderate Correlation** (0.7, 0.6): N-PROMETHEE II and N-ARAS moderately correlate with N-CARCACS (0.7). N-COPRAS and N-WASPAS also show a moderate correlation with N-CARCACS (0.6). While there is some agreement, it is less pronounced than the methods showing a 0.9 correlation, suggesting that these methods may incorporate additional factors or weightings that slightly alter the rankings.

The analysis suggests that while there is generally good agreement between N-CARCACS and several other methods, certain methods like N-COPRAS and N-WASPAS may yield different rankings, offering unique perspectives in decision-making processes. This underscores the importance of selecting the appropriate MCDM method based on the specific context and criteria of the decision-making scenario. The Corrl among proposed and other methods appears in Table 11 and Figure 7.

Table 11. Corrl between MCDM methods.

Corrl	N-PROMETHEE II	N-CARCACS	N-COPRAS	N-GRA	N-ARAS	N-WSM	N-MOORA	N-TOPSIS	N-WASPAS
N-CARCACS	0.7	1	0.6	0.9	0.7	0.9	0.9	0.9	0.6
N-PROMETHEE II	1	0.7	0.1	0.5	0.2	0.5	0.5	0.5	0.1
N-COPRAS	0.1	0.6	1	0.7	0.9	0.7	0.7	0.7	1
N-GRA	0.5	0.9	0.7	1	0.9	1	1	1	0.7
N-ARAS	0.2	0.7	0.9	0.9	1	0.9	0.9	0.9	0.9
N-WSM	0.5	0.9	0.7	1	0.9	1	1	1	0.7
N-MOORA	0.5	0.9	0.7	1	0.9	1	1	1	0.7
N-TOPSIS	0.5	0.9	0.7	1	0.9	1	1	1	0.7
N-WASPAS	0.1	0.6	1	0.7	0.9	0.7	0.7	0.7	1

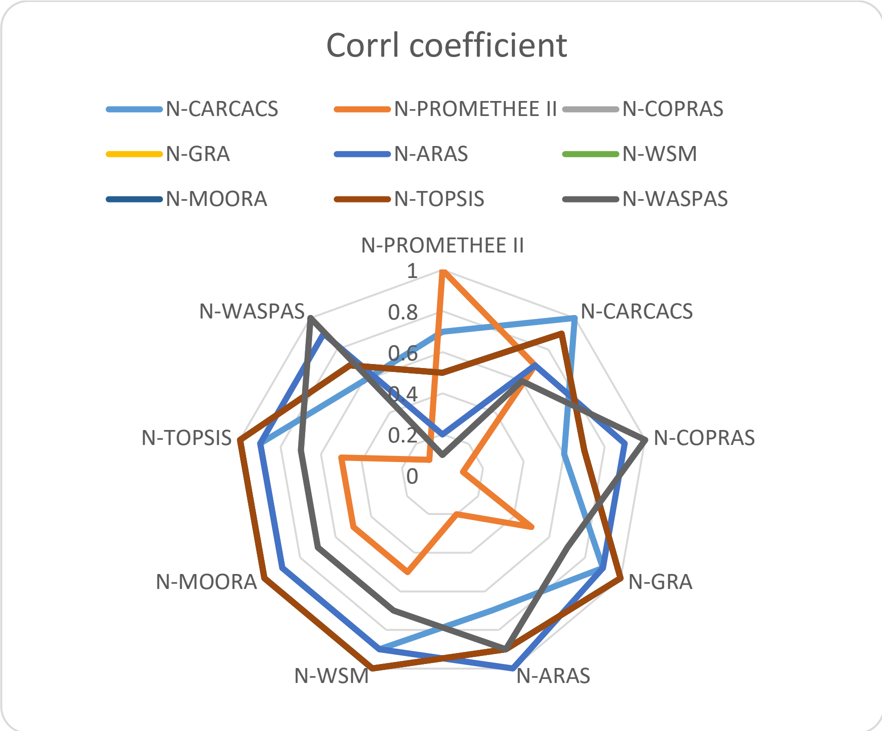

Figure 7. Corrl between MCDM methods.

Methods like N-GRA, N-WSM, N-MOORA, and N-TOPSIS are highly consistent with each other, making them reliable choices when seeking consistency in decision-making. N-PROMETHEE II, N-COPRAS, and N-WASPAS show significant divergence from other methods, suggesting that they may be better suited for specific decision-making contexts where their unique strengths are more applicable. The choice of the MCDM method can significantly influence decision outcomes. Understanding the correlations between methods allows decision-makers to select the most appropriate method based on the specific needs of their analysis, especially in the context of neutrosophic environments. Methods like N-CARCACS, which show strong correlations with established methods while handling neutrosophic data, may offer a valuable balance of innovation and reliability, making them ideal for decision-making in complex, uncertain environments.

6. Challenges and Future Work

6.1 Challenges

Handling neutrosophic data introduces complexities due to its inherent uncertainty, indeterminacy, and inconsistency. Accurately modeling and processing such data can be challenging, requiring sophisticated methods and techniques. Combining different MCDM methods and approaches, such as integrating N-CARCACS with other techniques, can be complex. Ensuring compatibility and consistency among diverse methods requires careful design and validation. MCDM methods are sensitive to parameter settings, such as weight assignments and preference functions. Variations in these parameters can significantly impact the results, posing challenges in achieving consistent and reliable outcomes. As the number of alternatives and criteria increases, the computational complexity of MCDM techniques can grow exponentially. Efficient algorithms and scalable solutions are needed to handle large-scale problems. Addressing these challenges will contribute to the advancement of MCDM methods and their effective application in various domains, enhancing decision-making processes and outcomes.

6.2 Future Work

Future research could explore the application of MCDM techniques to other domains beyond economics, such as healthcare, environmental management, and finance. This would involve adapting the methodologies to different types of data and decision-making contexts. The integration of emerging MCDM techniques and soft computing methods with neutrosophic environments could also provide new insights and enhance decision-making processes. Future studies could investigate the combination of N-CARCACS with other advanced methods to address specific challenges in various fields. Further sensitivity analysis with a broader range of cases and scenarios could provide deeper insights into the robustness of different MCDM techniques. This could involve examining how variations in data quality, criterion interdependencies, and other factors impact the results. Applying the N-CARCACS method and other MCDM techniques to real-world case studies in different economic contexts could validate their effectiveness and offer practical insights. This would involve collaborating with industry experts and policymakers to test the methodologies in real-world scenarios.

7. Conclusions

This study provides a comprehensive comparative analysis of various MCDM techniques applied within neutrosophic environments, specifically focusing on economic condition analysis. The study highlights the performance of several MCDM methods, including N-PROMETHEE II, N-COPRAS, N-GRA, N-ARAS, N-WSM, N-MOORA, N-TOPSIS, and N-WASPAS. Each technique offers unique advantages in handling complex decision-making problems under uncertainty, with N-CARCACS demonstrating notable effectiveness in managing ambiguous and imprecise data. The N-CARCACS method, with its ability to incorporate correlation among criteria and handle neutrosophic data, shows a robust approach to economic condition analysis. It provides a nuanced ranking of alternatives based on weighted ranks and correlations, making it particularly useful for scenarios involving interdependent criteria and uncertain data. The comparative analysis underscores the importance of selecting an appropriate MCDM technique based on the specific characteristics of the decision-making problem. The study's findings have significant implications for economic analysis and policy-making. By applying MCDM techniques in neutrosophic environments, policymakers can achieve a more comprehensive and accurate understanding of economic conditions, leading to more effective and informed policy decisions. The application of MCDM techniques in neutrosophic environments provides policymakers with a more nuanced understanding of economic conditions, helping to make better-informed decisions. By accounting for uncertainties and interdependencies, policies can be designed to address complex economic challenges more effectively. Conducting empirical validation studies in various real-world contexts will be crucial for assessing the practical effectiveness of neutrosophic MCDM techniques. These studies should aim to test the methods in diverse scenarios and compare their performance against traditional approaches to ensure their practical utility and effectiveness.

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.

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Author Contribution

All authors contributed equally to this research.

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