An Enhanced MCDM Model for Cloud Service Provider Selection

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***Abstract*—Multi-Criteria Decision-Making (MCDM) techniques are often used to aid decision-makers in selecting the best alternative among several options. However, these systems have issues, including the Rank Reversal Problem (RRP) and decision-making ambiguity. This study aimed to propose a selection model for a Cloud Service Provider (CSP) that addresses these issues. This research used the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to rank the alternatives. The entropy technique is utilized to determine the weight of the criteria, and Single Valued Neutrosophic (SVN) is employed to address uncertainty. To select the best cloud provider based on Quality of Service (QoS) criteria, we used a dataset from Cloud Harmony for this study. The results indicated that the suggested model could effectively resolve the RRP under conditions of uncertainty. This research is novel and is the first to address both the problem of uncertainty in decision-making and RRP in MCDM.**

Keywords—MCDM; TOPSIS; neutrosophic set; single valued neutrosophic; cloud services provider; quality of service

I. Introduction

Cloud computing, an emerging paradigm, offers users pay-per-use or on-demand services. It provides users with three primary categories of service models: infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS). IaaS offers computational assistance to cloud clients. PaaS provides a framework for application development. SaaS gives users access to pre-made apps. Due to the vast number of software products and flexibility in utilizing cloud services, many large firms, such as Microsoft and Google, are investing significant amounts of money in offering various cloud services. However, finding and identifying a CSP has become a challenging task for cloud users due to the growing number of cloud providers.

Cloud benchmarking service providers, such as Cloud Harmony and Cloud Spectator [1, 2], analyze the performance of multiple CSPs and publish their findings online, serving as the foundation of the simple method cloud customers use to select the optimal CSP. However, the execution environment used by cloud customers may differ from the performance assessed by a third party in a given context. As a result, professionals or cloud users must evaluate multiple CSPs based on their experience to choose the optimal CSP.

The above issue has motivated researchers to design a mechanism for selecting the optimal CSP, which requires a set of QoS criteria to assess cloud services and a methodology for rating them according to these criteria [3].

MCDM is a structured and formal decision-making approach used to deal with complex problems and conflicting criteria.

There are several MCDM approaches used in related works, such as TOPSIS, Decision-Making Trial and Evaluation Laboratory (DEMATEL), Simple Additive Weightage (SAW), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Analytic Hierarchy Process (AHP), Elimination Et Choice Translating Reality (ELECTRE), Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), Complex Proportion Assessment Method (COPRAS), Analytic Network Process (ANP), Multi-objective Optimization on the Basis of Ratio Analysis Method (MOORA), Stepwise Weight Assessment Ration Analysis (SWARA), and others [4], [5], [6], [7] and [8].

Generally, TOPSIS is the most popular technique for handling MCDM problems [9]. It depends on synthesizing the criteria and dividing the alternatives into two subsets: positive and negative solutions. The optimal solution has the shortest distance from the positive set of solutions and the longest distance from the negative set of solutions [10].

Due to its advantages over other fuzzy extensions, SVN Set has been taken into consideration for handling vagueness. The membership function, used in fuzzy set theory developed by Zadeh et al. [11], translates linguistic terms into membership values. However, the value of membership for a term may vary among experts. For example, one expert may give a value of two to express the linguistic term "low," while another may give a value of three.

To address this issue, a Neutrosophic Set (NS) is employed. With the condition that the three membership values must be less than or equal to three, NS allows decision-makers to judge in three degrees: truth, indeterminacy, and falsity. As a generalization of all fuzzy set versions, NS has been combined with several MCDM techniques and aids decision-makers in resolving ambiguity in their judgment [12].

The main contributions of this research can be summarized as follows:

- A comprehensive analysis of the robustness of MCDM models against the RRP.
- An evaluation of the suggested model's resistance to RRP.
- The integration of SVN theory with a modified Entropy-based TOPSIS method.
- A comparative analysis between the proposed model and other MCDM models.

The rest of the paper is organized as follows: Section II discusses related work. Section III presents the methodology used in the proposed model. In Section IV, we present the results and validation of our model. Section V summarizes the conclusions of our research, and Section VI outlines future work.

II. Related Work

The increasing number of CSPs has attracted the interest of researchers in evaluating their performance in different applications. The primary objective of this research is to assess CSP performance and develop techniques for finding the most effective and optimal CSP. MCDM techniques have been extensively utilized in previous publications to handle decision-making problems in various industries, such as supplier and employee selection. Since the current proposed methodology combines TOPSIS with NS to identify the optimal CSP, we first explored MCDM-based techniques. Then we reviewed numerous publications that used NS in conjunction with MCDM to tackle different decision-making problems. After that, we highlighted the drawbacks of the MCDM-based TOPSIS technique.

Zulqarnain et al. [13] applied neutrosophic TOPSIS to select the most suitable supplier and found that neutrosophic can handle uncertainty in decision-making. However, they did not consider the RRP in TOPSIS.

Garcia et al. [14] discovered that the TOPSIS technique suffers from RRP due to changing the normalized value of the judgment matrix when an alternative is added. They proposed two hypothetical values representing the minimum and maximum values for each criterion, and the modified technique can handle some cases of RRP.

Abdel-Basset et al. [15] developed a hybrid technique combining neutrosophic set theory and AHP to evaluate cloud services. They implemented a function to convert linguistic terms into crisp values. The hybrid technique is effective when classical AHP fails due to an inconsistent pairwise decision matrix; however, it does not address RRP.

Kumar et al. [16] developed a hybrid technique by combining AHP and TOPSIS. AHP is used to obtain each criterion's weight, and TOPSIS is used to rate CSPs based on cloud benchmarking reports. A significant limitation of this research is that it cannot handle the uncertainty problem, or RRP, in MCDM.

Jatoth et al. [17] developed an integrated model that consists of AHP and grey TOPSIS. The grey set is used to handle uncertainty in decision-making. The proposed model considers both functional and non-functional requirements of cloud services but does not consider the RRP.

Aires et al. [18] proposed R-TOPSIS, a modified version of TOPSIS. This model requires a judgment matrix, criteria weights, and domains for each criterion. It uses the domain of each criterion with a max or max-min normalization approach to normalize the judgment matrix. The Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) are computed using a novel method. The results showed that the model fails to handle RRP when removing a non-distinct criterion.

Goswami et al. [19] proposed a technique for choosing the optimal steel grades and their corresponding heat treatment procedures using a hybrid technique based on entropy and TOPSIS. The limitation of this model is that it cannot handle uncertainty or RRP.

Tiwari et al. [12] developed a framework based on neutrosophic TOPSIS to handle uncertainty in decision-making. The framework is validated against only two types of RRP: the insertion and deletion of alternatives from the decision matrix.

Hezam et al. [20] developed an MCDM model based on neutrosophic AHP and TOPSIS to identify the priority groups for the COVID-19 vaccine. The model was able to handle uncertainty, but it has not been validated against the RRP.

Trabay et al. [21] built a mathematical model based on MCDM to rate the trustworthiness of cloud services based on various opinions. The results showed that fuzzy TOPSIS provides more accurate results than TOPSIS, fuzzy AHP, and AHP.

Saha et al. [22] proposed a hybrid MCDM model consisting of ANP and VIKOR, where ANP is used to obtain the local rank of CSP, and VIKOR is used to obtain the global rank. The major disadvantage of this model is that it cannot handle uncertainty or RRP.

Dani et al. [23] developed a technique to assess the efficiency of educational boards. They used a linear weighted model and TOPSIS. The results showed that the ranks obtained by both models were very similar.

Dhand et al. [24] developed a network selection model consisting of fuzzy AHP and ELECTRE, where fuzzy AHP is utilized to obtain the weight of each criterion, and ELECTRE is utilized to rate networks. Results showed that the model could effectively select the optimal network, but it has not been validated against the RRP.

According to previous research, we can consider CSPs ranking as a decision problem. The majority of researchers employed MCDM to select the optimal CSP. Some techniques are extended to fuzzy or NS theories to handle uncertainty. The previously discussed related works addressed either the RRP or uncertainty, but none tried to address both rank reversal and uncertainty simultaneously.

NS has become essential in solving decision problems because it can more efficiently handle uncertainty problems in decision-making. Therefore, we used a neutrosophic set with an integrated Entropy-TOPSIS technique to choose the optimal CSP. The novel model is effective and robustly selects CSPs in the neutrosophic state. Our research is the first to apply the integrated Entropy-TOPSIS technique to CSP ranking.

III. METHODOLOGY

A. Basic Concepts

This section introduces Entropy, TOPSIS and some basic definitions of NS and SVN.

1) Neutrosophic set theory: This theory considers every idea <X> along with its negation <Anti-X> and a group of "neutralities," <Neut-X>, which lies between the two boundaries and supports neither <X> nor <Anti-X> [11].

a) Single valued neutrosophic set: Let X be a space of objects, $x \in X$. A neutrosophic set N on X is defined by a truth membership T_N, an indeterminacy membership I_N, and a falsity membership F_N. $T_N(x)$, $I_N(x)$ and $F_N(x)$ are subsets of $]0^-, 1^+[$, and the sum of their values is between $^-0$ and 3^+ [12].

b) Score function: Junaid et al. [25] proposed the following score functions S ($x_{i,j}$) to transform the neutrosophic numbers into crisp numeric value.

$$S\,(x_{i,j}) = \frac{L_{x_{i,j}} + M_{x_{i,j}} + U_{x_{i,j}}}{3} + \left(T_{x_{i,j}} - I_{x_{i,j}} - F_{x_{i,j}}\right) \qquad (1)$$

$$S\,(x_{i,j}) = \frac{1}{S\,(x_{i,j})} = \frac{1}{\frac{L_{x_{i,j}} + M_{x_{i,j}} + U_{x_{i,j}}}{3} + \left(T_{x_{i,j}} - I_{x_{i,j}} - F_{x_{i,j}}\right)} \qquad (2)$$

Where *L*, *M*, and *U* are the lower, medium, and upper values of the neutrosophic numbers, and *T*, *I*, and *F* are the degrees of truthiness, indeterminacy, and falsity. If there is more than one decision expert, then the average of all experts' scores should be calculated to obtain the aggregated matrix [25].

2) Entropy: Entropy is an objective weighting method developed by Shannon [26]. It is used to calculate the weight of criteria for a multi-objective decision problem without considering the decision-makers' opinions. Weights are identified using the entropy method, which automatically computes the weight of criteria based on the judgment matrix, i.e., the significance of the parameter in relation to the other parameters. The steps of entropy are listed in [19].

3) TOPSIS: TOPSIS is the most widely used MCDM method, which ranks alternative solutions based on increasing the distance from the negative ideal point and reducing the distance from the positive ideal point. The steps involved in the TOPSIS method are listed in [19].

B. Proposed Model

Aires et al. [18] determined that an effective solution for the RRP in TOPSIS technique should take the following factors into account at the same time:

- Selecting a normalization method that reduces the consequences of alternative dependence.
- Using fixed NIS and PIS even if the set of alternatives is modified.

In addition to that, a lot of related works used the neutrosophic set to eliminate uncertainty in decision-making [25]. Therefore, we proposed a model based on SVN numbers to handle uncertainty problems, and we modified the normalization procedure in the Original TOPSIS technique. Moreover, a normal Gaussian distribution for normalization [27] and fixed PIS and NIS were used to calculate the rank of alternatives.

The steps of the proposed model are given in Algorithm 1, and a schematic diagram of the proposed model is presented in Fig. 1.

Algorithm 1: Proposed Model

A. Phase I: Modified Entropy

Input: The decision matrix *D (m x n)* which contains the performance values and is represented in linguistic terms. 'm' denotes the number of alternatives, and 'n' denotes the number of criteria.

Output: The weight of each criterion.

Step 1: Create a Decision Matrix D.

$$D = \begin{bmatrix} x_{1,1} & \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{m,1} & \cdots & x_{m,n} \end{bmatrix} \qquad (3)$$

Step 2: Map each linguistic term to its equivalent SVN value using Table I.

TABLE I. MAPPING BETWEEN LINGUISTIC TERM AND SVNS

Linguistic terms	SVNs
Extremely Low (EL)	<(1, 2, 3); (0.3, 0.75, 0.7)>
Very Low (VL)	<(2, 3, 4); (0.4, 0.6, 0.65)>
Low (L)	<(3, 4, 5); (0.6, 0.35, 0.4)>
Medium Low (ML)	<(4, 5, 6); (0.7, 0.3, 0.35)>
Medium/Fair (M/F)	<(1, 1, 1); (0.5, 0.5, 0.5)>
Medium High (MH)	<(5, 6, 7); (0.8, 0.25, 0.3)>
High (H)	<(6, 7, 8); (0.85, 0.2, 0.25)>
Very High (VH)	<(7, 8, 9); (0.9, 0.15, 0.2)>

Step 3: Convert the SVN into crisp numbers using score function given in Equation 1.

Step 4: Compute normalized decision matrix ‘ $r_{i,j}$ ’.

$$r_{i,j} = \frac{x_{i,j}}{\sum_{i=1}^{m} x_{i,j}} \quad (4)$$

Step 5: Calculate the entropy value ‘e_j' for each criterion.

$$e_j = - h \sum_{i=1}^{m} r_{i,j} \ln(r_{i,j}) \quad (5)$$

where h=1/ln(m) and m is the number of alternatives.

Step 6: Compute the degree of divergence ‘G_j’ for each criterion.

$$G_j = \left|1 - e_j\right| \quad (6)$$

Step 7: Compute the weight of each criterion ‘w_j’.

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

B. *Phase II: Modified TOPSIS*

Input: The same decision matrix in (phase I) and the criterion weightages ‘ w_j ’ from (phase. I).

Output: The rank of each alternative.

Step 1: Calculate the normalized decision matrix ‘M ’ using the normal Gaussian distribution function $F(x_{i,j})$.

$$m_{i,j} = F(x_{i,j}) = \int_{-\infty}^{x_{i,j}} e^{-(x-\mu)^2/2\sigma^2} dx \quad (8)$$

Step 2: Calculate the weighted normalized decision matrix.

$$W_{i,j} = w_j * m_{i,j} \quad (9)$$

Step 3: Calculate the PIS and NIS using the following equations.

$$v_j^+ = \{v_1^+ \dots v_m^+\} = \begin{cases} v_j^+ = w_j \;\; if \;\; j \in \text{Benefit Criteria} \\ v_j^+ = 0 \;\; if \;\; j \in \text{Cost Criteria} \end{cases} \quad (10)$$

$$v_j^- = \{v_1^- \dots v_m^-\} = \begin{cases} v_j^- = 0 \;\; if \;\; j \in \text{Benefit Criteria} \\ v_j^- = w_j \;\; if \;\; j \in \text{Cost Criteria} \end{cases} \quad (11)$$

Step 4: Compute the Euclidean distance S_i^+ and S_i^- of each alternative from the PIS and NIS.

$$S_i^+ = \left[\sum_{j=1}^{m} \left(v_{i,j} - v_j^+\right)^2\right]^{1/2} \quad (12)$$

$$S_i^- = \left[\sum_{j=1}^{m} \left(v_{i,j} - v_j^-\right)^2\right]^{1/2} \quad (13)$$

Step 5: Calculate the closeness index (P_i) for each alternative.

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (14)$$

Step 6: Rank each alternative based on its relative closeness index (P_i) in descending order.

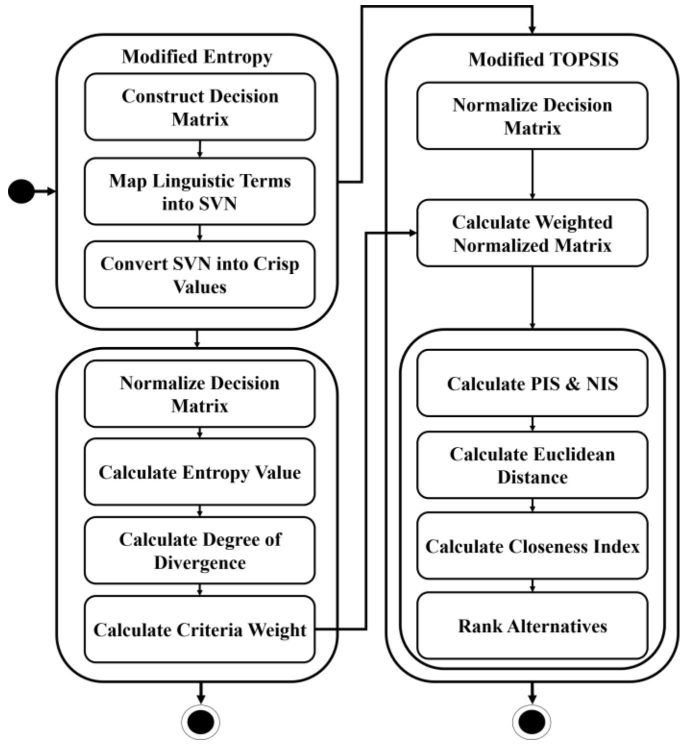

Fig. 1. Schematic diagram of the proposed model

IV. CASE STUDY

The proposed CSP selection methodology assists cloud users in choosing the appropriate cloud service for their needs. A case study was carried out to validate its reliability, where we applied the proposed model using a real dataset obtained from Tiwari et al. [12]. This dataset was obtained from reports issued by Cloud Harmony [1], a cloud benchmarking service provider. In addition to applying our proposed model in the case study, we conducted sensitivity and performance studies on the proposed model. Furthermore, the model was compared and validated with other studies.

A. Data Set

The dataset contains ten QoS parameters from six real-world CSPs. The QoS parameters used are Cost (C), Latency of Network (NL), Sequential Disk RW Performance Consistency (SDRWPC), Random Disk RW Performance Consistency (RDRWPC), CPU Integer Performance (CPUIP), CPU Floating Point Performance (CPUFPP), Memory Performance on Scale (MPS), Memory Performance on Triad (MPT), Sequential RW Disk Performance (SRWDP) & Random RW Disk Performance (RRWDP). The first four criteria are costly, while the others are benefit criteria. Table II shows the dataset, where all values are represented in linguistic terms [12].

TABLE II. DATA SET [12]

CSP	C	NL	SDRWPC	RDRWPC	CPUIP	CPUFPP	MPS	MPT	SRWDP	RRWDP
Soft Layer	L	VL	L	F	L	L	H	H	F	F
Rack Space	F	F	F	F	L	L	H	H	H	L
Ms. Azure	L	F	L	L	VL	VL	F	F	L	L
Google	L	H	L	L	L	L	H	H	VL	VL
Digital Ocean	L	F	VL	VL	L	L	H	H	L	L
Amazon EC2	L	VL	L	L	L	L	H	H	L	L

B. Cloud Service Ranking

The proposed model was used to calculate the rank of CSPs. Table II presents the judgment matrix for the dataset used in this study, which was formed based on 10 QoS measures and 6 CSPs. After applying the proposed model shown in (Algorithm 1), the rank of each CSP was calculated using the closeness index. Rack space was ranked as the optimal CSP, while Amazon EC2 was the worst CSP.

C. Sensitivity Analysis

The analysis was conducted to evaluate the proposed model's reliability and consistency in different RRP scenarios. This analysis had two objectives: the first was to determine the RRP when changing the number of alternatives, and the second was to test the proposed model's reliability. This was achieved by performing a complete test to observe a variation in each case. The ranking model is considered to be reliable if it consistently ranked CSPs.

The Five types of RRP are discussed as follows:

1) The first type: Deletion of an alternative from the dataset: This rank reversal analysis was carried out by deleting only one CSP. Six experiments were performed on the Cloud Harmony dataset (Table. 2). In each experiment, a single CSP was deleted. No changes were observed in the closeness index and rank of alternatives, demonstrating that the proposed model is resistant to the RRP found in the first type.

2) The second type: Addition of an alternative to the dataset: This rank reversal analysis was carried out by adding a CSP alternative. Four experiments were performed, and the closeness index and rank were calculated each time. The rank of alternatives was not affected by adding any alternatives, demonstrating that the proposed model is resistant to the RRP found in the second type.

3) The third type: Addition of an irrelevant alternative: The third type of RRP is carried out by adding an irrelevant alternative to the dataset to assess the reliability of the proposed model. We added an irrelevant $(CSP)_x$ with the same criteria as Rack Space alternative which exists in the data set (Table II). The Closeness index and rank were computed, and we observed that rank was the same before adding an irrelevant alternative $(CSP)_x$.

4) The fourth type: Testing the property of transitivity by dividing the existing matrix into two sub-decision matrices: In the Fourth type, the decision matrix was divided into two subsets, then the rank was calculated in each sub set and compared to the rank of the original decision matrix. After performing this test, we found out that the rank obtained from the two subsets was the same as the rank obtained from the original matrix.

5) The fifth type: The deletion of a non-distinct criterion: The Fifth type was carried out by deleting a non-distinct criterion from the existing dataset. A non-distinct criterion is a criterion with the lowest standard deviation. In our experiment the third criterion named SDRWPC was removed since it had the lowest standard deviation, then we observed that rank obtained after removing the non-distinct criterion was the same as the rank obtained before removing this criterion, which demonstrates that the proposed model is resistant to RRP found in type five.

The above rank reversal sensitivity analysis for all test cases showed that the proposed model is resistant to the RRP.

D. Results Validation

A validation was conducted to verify the accuracy of the rank calculated by the proposed model as follows:

1) Firstly, comparative analysis was performed to validate the proposed model. Fig. 2 demonstrates the ranking of each CSP obtained using the model and related work. Rack space was ranked first in all techniques, Google second, Digital Ocean third, Ms. Azure fourth, and soft layer and Amazon EC2 sixth and fifth, respectively, in all techniques except the technique proposed by Kumar et al. [16]. In addition, the model ranked the alternatives almost identically to those developed by Goswami et al. [19] and Aires et al. [18]. In contrast, it slightly differed from the model developed by Kumar et al. [16]. Therefore, it could be concluded that the proposed model accurately ranks CSPs.

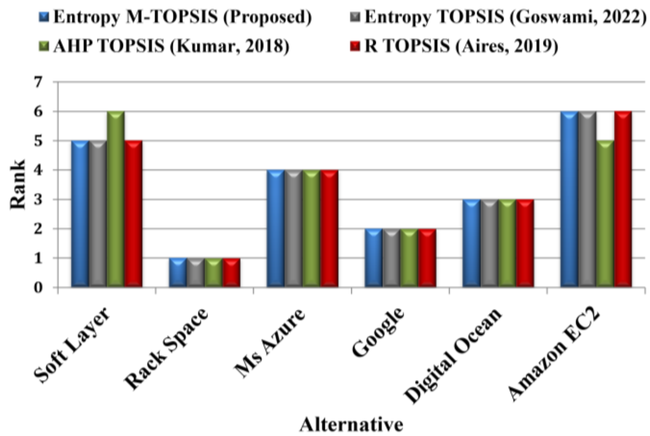

Fig. 2. The rank of CSP for the proposed model & related work

2) Secondly, the suggested model and other related work were compared [18], [19], and [16]. Table III shows the resistance to the RRP for the proposed model and related work. The proposed model could handle all five types of RRP, while the original TOPSIS, Entropy-TOPSIS, and AHP-TOPSIS techniques could not handle all kinds of RRP. R-TOPSIS, developed by Aires et al. [18], could handle all types of RRP except type five.

TABLE III. THE RRP ANALYSIS FOR THE PROPOSED MODEL AND RELATED WORK

Method	Type 1	Type 2	Type 3	Type 4	Type 5
Proposed Model	√	√	√	√	√
Entropy-TOPSIS	X	X	X	X	X
AHP-TOPSIS	X	X	X	X	X
R-TOPSIS	√	√	√	√	X
TOPSIS	X	X	X	X	X

3) Thirdly, statistics of dispersion and similarity were used to compare the techniques in related work with the proposed model. The following statistical methods were applied in validation phase [18], [28] and [29]:

- *Similarity:* Mean Absolute Error of Rank (MAER) and Spearman's Rank Correlation (SRC).
- *Dispersion*: The Standard Deviation of the closeness coefficient for each rank (SD), the difference between the closeness coefficient of the best alternative and the worst (BWD), and the difference between closeness coefficient of the 1st and 2nd alternative (FSD).

The simulation was implemented in MATLAB. Table IV compares the proposed model and its other variants, considering similarity (SRC and MAER) statistics and dispersion (SD, BWD and FSD) statistics. An average of four simulation cycles was used for 4,000 simulated cases.

Comparing the dispersion measures for each technique, the proposed model generally had smaller values for (SD, BWD and FSD) than the other models. Furthermore, based on the statistical methods used to compute the similarity degree between the ranks obtained by the four techniques, it was observed that there is a very high degree of similarity between the rankings, indicating that the suggested model corresponds to the other methods. Fig. 3 and Fig. 5 show that the MAER value between the proposed model (M1) and method (M2) is the lowest. In contrast, Fig. 4 and Fig. 6 show that the SRC value between (M1) and (M2) is the highest. Moreover, method (M4) deviated from the proposed model more than the other methods. Therefore, it can be concluded that the proposed model is more similar to the method (M2) according to all similarity measures.

TABLE IV. DISPERSION AND SIMILARITY STATISTICS

Method	SD	BWD	FSD	SRC	MAER
Entropy M-TOPSIS (M1)	0.0582	0.1106	0.0569	0.8120	0.0823
Entropy TOPSIS (M2)	0.1959	0.3740	0.1946		
Entropy M-TOPSIS (M1)	0.0582	0.1106	0.0569	0.2295	0.3420
AHP-TOPSIS (M3)	0.2109	0.3989	0.1946		
Entropy M-TOPSIS (M1)	0.0582	0.1106	0.0569	0.1080	0.3963
R TOPSIS (M4)	0.1504	0.2858	0.1674		

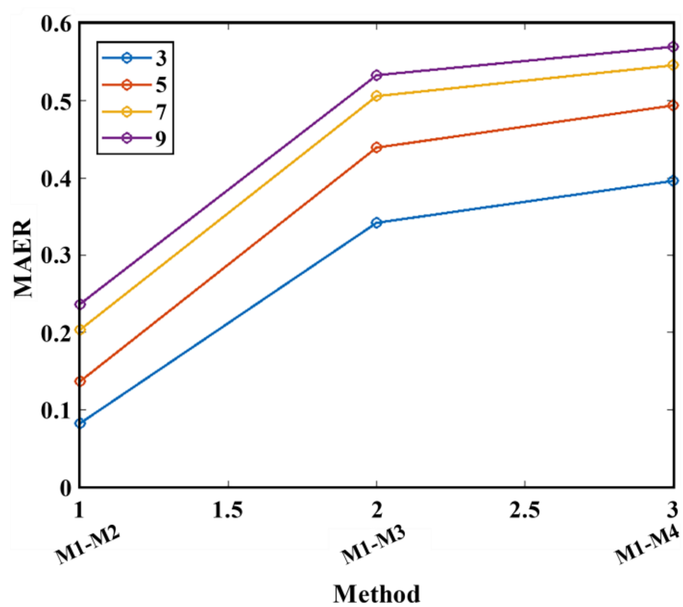

Fig. 3. MAER by number of alternatives

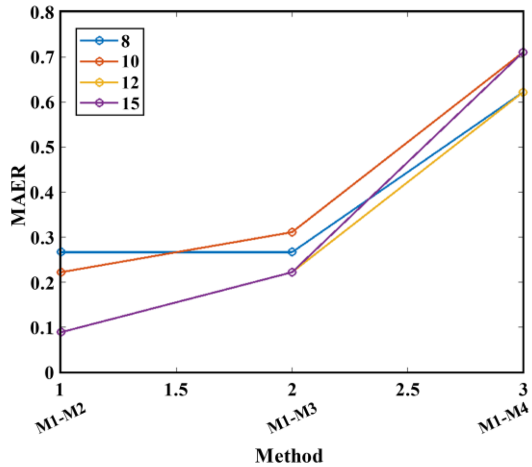

Fig. 4. MAER by number of criteria

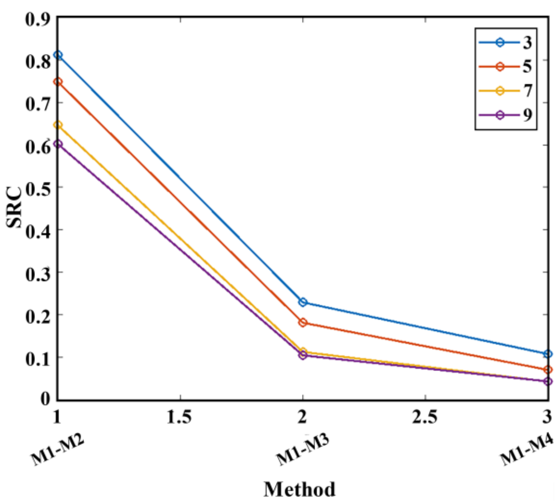

Fig. 5. SRC by number of alternatives

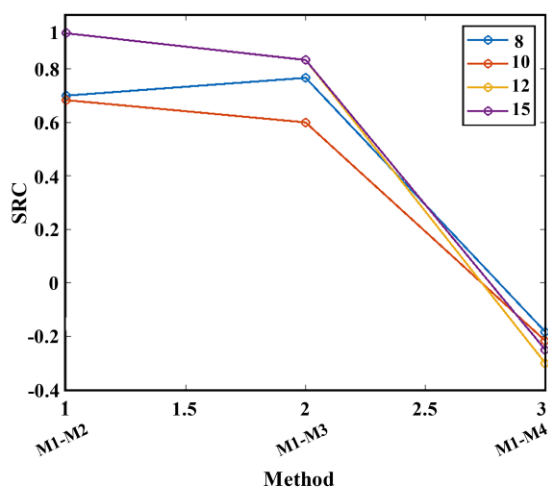

Fig. 6. SRC by number of criteria

4) *Fourthly*, the execution time of the proposed model and related work was measured with increasing the number of alternatives. The analysis was carried out using a Core i5 (8^{th} Gen.) PC, with WIN 10 (64-bit) OS, and 8 G.B RAM. Linguistic terms for about 1,500 alternatives and ten criteria were randomly generated. Fig. 7 shows the execution time of the proposed model and other related work. It can be noted The proposed model took less time to execute than Entropy-TOPSIS and AHP-TOPSIS and only slightly more time than R-TOPSIS, by just a few milliseconds.

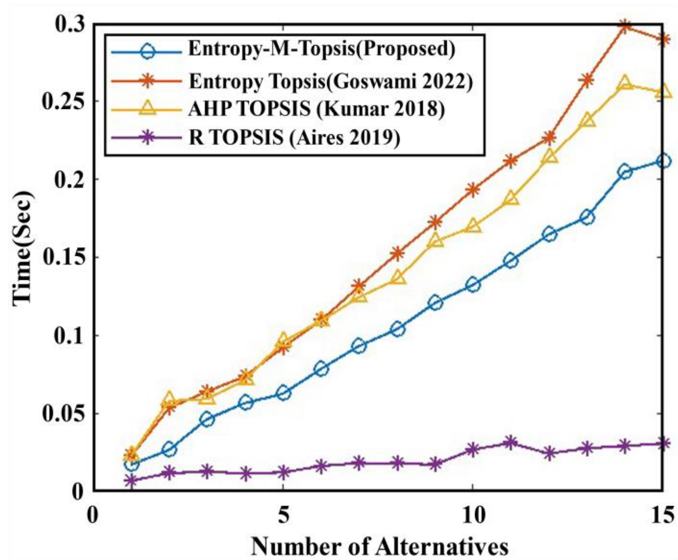

Fig. 7. Analysis of the execution time

V. Conclusion

The analysis of RRP in TOPSIS presented in this study is comprehensive. We have identified that the normalization process and the selection of PIS and NIS are the leading causes of RRP in TOPSIS. To address these issues, we utilized the normal Gaussian distribution function for normalization and introduced a new approach for calculating PIS and NIS. Moreover, we proposed a novel extension to handle insufficient information, including degrees of truth, indeterminacy, and falsity, by integrating SVNs with the suggested model. The proposed model was validated through sensitivity analysis, comparative analysis, and statistical measures of similarity and dispersion. The results indicated that the proposed model could improve the decision-making process under uncertainty with high accuracy and robustness against RRP, making it applicable to any multi-criteria decision problem. One limitation of this research is that it did not consider subjective weighting-based approaches that determine criteria weights based on the judgments of decision-makers. Table V summarizes the overall results of this research work.

TABLE V. SUMMARY OF THE OVERALL RESULTS

Model	Evaluation Criteria	
	Handling Uncertainty	Handling All Types of RRP
Proposed model	√	√
Entropy-TOPSIS	x	x
R-TOPSIS	x	x
AHP-TOPSIS	x	x

VI. FUTURE WORK

New extensions of neutrosophic sets can be utilized to solve the uncertainty problem and provide more accurate results to support the decision-making process. In addition, the output from various MCDM techniques, such as COPRAS, PROMETHEE, and others, can be compared to the results of the current research. Finally, other subjective and objective weighting-based approaches can be utilized, and the difference in rank can be assessed.

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