

A COMPARATIVE ANALYSIS OF HAMMING AND EXTENDED HAUSDORFF DISTANCE MEASURES FOR SUPPLIER SELECTION USING SINGLE-VALUES NEUTROSOPHIC SETS

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Abstract: *An effective supplier selection strategy is essential for ensuring business success, particularly because suppliers play a significant role in an organization's operational performance and competitiveness. However, selecting the most suitable supplier can be challenging due to uncertainty, imprecision, and hesitation in the decision-making process. This study focusses on comperative analysis between distance measure-based approach for selecting the best supplier under uncertain conditions using Single-Valued Neutrosophic Sets (SVNS). Several important supplier selection criteria are considered to facilitate a comprehensive evaluation of potential suppliers. The proposed approach incorporates three distance measures, namely Hamming distance, normalized Hamming distance, and extended Hausdorff distance, together with a similarity measure. A three-phase decision-making framework is developed and applied to a supplier selection problem, followed by a comparative analysis of the resulting rankings. The results indicate that a lower value is preferred for the distance measures, whereas a higher value is preferred for the similarity measure. The proposed approach provides a simple, systematic, and effective decision-making tool for supplier selection in an uncertain environment.*

Keywords: *Single-Valued Neutrosophic Sets; Neutrosophic Distance Measure; Multi-Criteria Decision-Making; Supplier Selection; Similarity Measure; Ranking Method*

Introduction

In the real world, the business sector is highly competitive, and organizations continuously strive to improve their performance, maintain competitiveness, and achieve sustainable growth. One of the key factors contributing to business success is the selection of an appropriate supplier. Supplier selection is a strategic decision because suppliers can significantly influence an organization's cost, product quality, delivery performance, operational efficiency, and overall competitiveness. Luo et al. (2023) stated that businesses consider not only the direct economic benefits provided by suppliers at the commercial level but also the potential indirect economic benefits arising from suppliers' sustainable development. Therefore, selecting an appropriate supplier is essential for organizations seeking to improve their operational performance and maintain a competitive position.

Supplier selection is closely associated with Supply Chain Management (SCM), particularly because procurement is one of the fundamental activities within the supply chain. According to Cakar and Çavuş (2021), SCM is a management process that involves obtaining raw materials through the selection of suitable suppliers, processing the raw materials into final products, and ensuring customer satisfaction. Since the procurement of raw materials is an important function of supply chain management (SCM), selecting appropriate suppliers is crucial to the effectiveness of the overall supply chain system. Supplier selection can influence several important organizational outcomes, including cost, product quality, delivery performance, and customer satisfaction (Kannan & Tan, 2002; Sarkis, 2002). Consequently, supplier selection has become an important multi-criteria decision-making (MCDM) problem in supply chain management, as suppliers are generally evaluated based on multiple quantitative and qualitative criteria rather than a single factor such as cost (Ho et al., 2010). In this context, identifying and evaluating appropriate supplier selection criteria is essential because different criteria may have different levels of importance and influence the final supplier selection decision (Abdolshah, 2013; Aouadni et al., 2019).

However, supplier selection is often challenging because decision-makers must deal with ambiguity, imprecision, incomplete information, and uncertainty. In real-world decision-making environments, experts may not always have sufficient information or may be unable to express their judgments with complete certainty. Different experts may also provide conflicting evaluations when assessing the same supplier (Ho et al., 2010). These conditions make it difficult to obtain a reliable decision using conventional decision-making approaches. Therefore, an appropriate mathematical framework is required to represent and process uncertain information effectively.

To address uncertainty in decision-making, Zadeh (1965) introduced the concept of fuzzy sets, which has subsequently been applied extensively in various real-world applications. Fuzzy set theory provides an effective means of representing the degree of membership of an element to a set. Nevertheless, conventional fuzzy sets have limitations when information involves indeterminacy, inconsistency, incompleteness, or conflicting opinions. In particular, the uncertainty associated with whether information is true, false, or indeterminate cannot be explicitly represented within the conventional fuzzy set framework. Such limitations become particularly relevant in supplier selection, where experts may be uncertain about their evaluations of supplier performance.

To overcome these limitations, Smarandache (1999) introduced the concept of Neutrosophic Sets (NS), which provides a framework for representing uncertain, incomplete, indeterminate,

and inconsistent information. Unlike conventional fuzzy sets, a neutrosophic set explicitly incorporates three independent components: truth-membership (T), indeterminacy-membership (I), and falsity-membership (F). These three components enable decision-makers to express not only the degree to which a statement is true or false but also the degree of uncertainty associated with the statement. The incorporation of indeterminacy provides greater flexibility in representing uncertain and ambiguous information in real-world decision-making problems.

Several extensions of neutrosophic sets have been introduced, including Single-Valued Neutrosophic Sets (SVNS) and Interval Neutrosophic Sets (INS). Among these, SVNS has received considerable attention because it provides a relatively simple and practical framework for representing uncertain information using numerical membership degrees. Wang et al., 2010 formalised SVNS and established its set-theoretic operators and properties, providing a technically tractable representation of neutrosophic information. SVNS has been applied in various fields, including social management, pattern recognition, decision-making, data analysis, medical diagnosis, and financial investment (Zhang et al., 2020). Chai et al. (2021) stated that SVNS is an effective model for handling imprecise, inconsistent, and incomplete information systematically because it simultaneously considers the degrees of truth, indeterminacy, and falsity associated with each piece of information. Therefore, SVNS provides a suitable framework for decision-making problems in which experts' evaluations contain uncertainty and hesitation, such as supplier selection.

In an SVNS-based decision-making environment, an important issue is how to determine the degree of closeness or separation between alternatives. Distance and similarity measures are particularly important in this context because they provide quantitative information regarding the relationship between alternatives and an ideal solution. A distance measure determines the degree of separation between two alternatives, whereas a similarity measure evaluates their degree of closeness. In supplier selection, these measures can be used to determine how closely each potential supplier corresponds to an ideal supplier. Generally, a smaller distance indicates that an alternative is closer to the ideal solution and is therefore preferable, whereas a higher similarity value indicates a stronger degree of resemblance to the ideal solution (Jin et al., 2018; Chai et al., 2021).

Although SVNS has been widely applied to various MCDM problems, the selection and application of appropriate distance and similarity measures remain important issues. Different measures may produce different numerical evaluations of the same alternatives and may consequently lead to different supplier rankings. This issue is particularly relevant in supplier selection because the decision usually involves multiple criteria and uncertain assessments from decision-makers. An inappropriate or unsuitable measurement approach may affect the resulting ranking and, ultimately, the selection of the preferred supplier (Jin et al., 2018; Chai et al., 2021).

Furthermore, existing studies may focus on a particular distance or similarity measure without providing a systematic comparison of different measurement approaches within a common supplier selection framework. The resulting rankings obtained from different measures may therefore vary, and decision-makers may not have sufficient information to determine the extent to which these approaches produce consistent results. A comparative investigation involving Hamming distance, normalized Hamming distance, extended Hausdorff distance, and similarity measure within the same SVNS-based supplier selection problem can provide useful insights into the behaviour and applicability of these measures. Hence, there is a research gap in

developing a systematic framework that integrates and compares different SVNS-based distance and similarity measures for supplier selection under uncertain conditions.

Motivated by this research gap, this study develops a three-phase framework for supplier selection using Single-Valued Neutrosophic Sets. The proposed framework incorporates Hamming distance, normalized Hamming distance, extended Hausdorff distance, and a similarity measure to evaluate potential suppliers based on multiple selection criteria. The framework consists of the representation of decision-makers' evaluations using SVNS, the computation of distance and similarity values between alternatives and the ideal solution, and the subsequent ranking and comparison of suppliers. By applying different measurement approaches to the same supplier selection problem, the study enables a systematic comparison of the resulting rankings.

The main contribution of this study is the integration of several SVNS-based distance and similarity measures into a common three-phase supplier selection framework. Rather than introducing a new distance measure, this study focuses on the comparative application of existing measures and examines their effects on supplier evaluation and ranking. The study also provides a systematic comparison between distance-based and similarity-based approaches, where lower distance values and higher similarity values indicate preferable suppliers. This comparative perspective can assist decision-makers in understanding the behaviour of different measurement approaches and selecting an appropriate approach for supplier selection problems involving uncertain information. The proposed framework may also provide a practical decision-support tool for organizations that need to evaluate and rank suppliers in environments characterized by imprecision, uncertainty, and incomplete information.

Methodology

This study proposes a systematic three-phase framework for solving the supplier selection problem using Single-Valued Neutrosophic Sets (SVNS). The framework incorporates four measurement approaches, namely Hamming distance, normalized Hamming distance, extended Hausdorff distance, and similarity measure. These measures are applied to evaluate the degree of closeness or separation between potential suppliers and the ideal supplier under multiple selection criteria. The data of supplier selection used in this study were adopted from Keshavarz Ghorabae et al. (2016).

The proposed methodology is designed to handle uncertainty, imprecision, and indeterminacy in the evaluation of suppliers. In the first phase, the evaluations provided by decision-makers are represented using Single-Valued Neutrosophic Numbers (SVNNs) to construct the decision matrix. In the second phase, the distance and similarity values between each supplier and the ideal solution are calculated using the respective measurement approaches. In the third phase, the suppliers are ranked based on the calculated values, where a smaller distance value indicates a preferable supplier, while a higher similarity value indicates a preferable supplier. Finally, the rankings obtained from the different measurement approaches are compared to examine the consistency of the decision outcomes.

The overall methodology consists of the following three phases:

Phase 1: Construction of the SVNS Decision Matrix

In the first phase, the decision-makers evaluate each supplier with respect to the selected criteria. The linguistic evaluations are used to establish the relationships between the

alternatives and criteria, as well as between the decision makers and criteria. These linguistic evaluations are then converted into Single-Valued Neutrosophic Numbers (SVNNs), which represent the truth-membership, indeterminacy-membership, and falsity-membership degrees of each evaluation.

Step 1: Construction of the Alternative–Criteria and Decision Maker–Criteria Relationships

The relationship between the alternatives and the selected criteria is established based on the aggregated linguistic evaluations. The resulting alternative–criteria relationship is presented in Table 1.

Table 1: Relationship between Alternatives and Criteria

Criteria	A1	A2	A3	A4	A5
C1	VL	M	H	VH	M
C2	H	H	MH	VH	H
C3	ML	VH	VH	ML	VH
C4	MH	VH	VL	L	H
C5	H	H	L	ML	VH
C6	H	MH	VL	H	MH

The relationship between the decision makers and the selected criteria represents the linguistic assessment of the importance of each criterion by the respective decision makers. The resulting relationship is presented in Table 2.

Table 2: Relationship between Decision Makers and Criteria

Criteria	DM1	DM2	DM3	DM4	DM5
C1	VH	H	H	VH	VH
C2	H	H	H	MH	M
C3	ML	ML	ML	M	M
C4	VL	VL	L	L	VL
C5	VH	VH	H	VH	H
C6	VL	L	ML	ML	L

Step 2: Conversion of Linguistic Evaluations into SVNNs

The linguistic evaluations obtained in Step 1 are converted into Single-Valued Neutrosophic Numbers (SVNNs) based on the linguistic scale presented by Biswas et al. (2016). Each linguistic term is represented by a triplet consisting of truth-membership, indeterminacy-membership, and falsity-membership degrees.

The resulting SVNN representations of the alternative–criteria relationship and the decision maker–criteria relationship is presented in Table 3 and Table 4, respectively.

Table 3: Relationship between Alternatives and Criteria in SVN Form

Criteria	A1	A2	A3	A4	A5
C1	(0.10, 0.85, 0.90)	(0.50, 0.50, 0.45)	(0.80, 0.20, 0.15)	(0.90, 0.10, 0.05)	(0.50, 0.50, 0.45)
C2	(0.80, 0.20, 0.15)	(0.80, 0.20, 0.15)	(0.65, 0.35, 0.30)	(0.90, 0.10, 0.05)	(0.80, 0.20, 0.15)
C3	(0.35, 0.65, 0.60)	(0.90, 0.10, 0.05)	(0.90, 0.10, 0.05)	(0.35, 0.65, 0.60)	(0.90, 0.10, 0.05)
C4	(0.65, 0.35, 0.30)	(0.90, 0.10, 0.05)	(0.10, 0.85, 0.90)	(0.20, 0.75, 0.80)	(0.80, 0.20, 0.15)
C5	(0.80, 0.20, 0.15)	(0.80, 0.20, 0.15)	(0.20, 0.75, 0.80)	(0.35, 0.65, 0.60)	(0.90, 0.10, 0.05)
C6	(0.80, 0.20, 0.15)	(0.65, 0.35, 0.30)	(0.10, 0.85, 0.90)	(0.80, 0.20, 0.15)	(0.65, 0.35, 0.30)

Table 4: Relationship between Decision Makers and Criteria in SVN Form

Criteria	DM1	DM2	DM3	DM4	DM5
C1	(0.90, 0.10, 0.05)	(0.80, 0.20, 0.15)	(0.80, 0.20, 0.15)	(0.90, 0.10, 0.05)	(0.90, 0.10, 0.05)
C2	(0.80, 0.20, 0.15)	(0.80, 0.20, 0.15)	(0.80, 0.20, 0.15)	(0.65, 0.35, 0.30)	(0.50, 0.50, 0.45)
C3	(0.35, 0.65, 0.60)	(0.35, 0.65, 0.60)	(0.35, 0.65, 0.60)	(0.50, 0.50, 0.45)	(0.50, 0.50, 0.45)
C4	(0.10, 0.85, 0.90)	(0.10, 0.85, 0.90)	(0.20, 0.75, 0.80)	(0.20, 0.75, 0.80)	(0.10, 0.85, 0.90)
C5	(0.90, 0.10, 0.05)	(0.90, 0.10, 0.05)	(0.80, 0.20, 0.15)	(0.90, 0.10, 0.05)	(0.80, 0.20, 0.15)
C6	(0.10, 0.85, 0.90)	(0.20, 0.75, 0.80)	(0.35, 0.65, 0.60)	(0.35, 0.65, 0.60)	(0.20, 0.75, 0.80)

The SVN decision matrices obtained in this phase are subsequently used in Phase 2 to calculate the Hamming distance, normalized Hamming distance, extended Hausdorff distance, and similarity measures between each supplier and the ideal solution.

Phase 2: Computation of Distance and Similarity Measures

In the second phase, the Hamming distance, normalized Hamming distance, extended Hausdorff distance, and similarity measures are applied to evaluate the degree of closeness between each supplier and the ideal solution. These measures provide quantitative assessments of the separation or similarity between the supplier alternatives and the ideal supplier represented in the Single-Valued Neutrosophic Set (SVNS) environment.

A Single-Valued Neutrosophic Set represents uncertain information using three independent membership degrees: truth-membership, indeterminacy-membership, and falsity-membership. Each element is represented by a Single-Valued Neutrosophic Number (SVNN), expressed as

$$A = \{(x, T_A(x), I_A(x), F_A(x)) : x \in X\},$$

where $T_A(x)$, $I_A(x)$, and $F_A(x)$ represent the truth, indeterminacy, and falsity membership values, respectively.

The Ideal solution vector:

$$A^* = (a_1^*, a_2^*, \dots, a_n^*)$$

where

$$a_j^* = \max\{a_{ij}\}, j = 1, 2, \dots, n$$

for benefit criteria, with the corresponding minimum formulation for cost criteria.

The Weighted distance:

$$dw(A_i, A^*) = \sum_{j=1}^n w_j d(A_{ij}, a_j^*)$$

where W_j denotes the weight of criterion j , and $d(A_{ij}, a_j^*)$ represents the distance between the evaluation of alternative A_i and the ideal solution for criterion j .

Aggregation of decision-makers:

$$D(A_i, A^*) = k = \frac{1}{\sum_{k=1}^K \lambda_k} dw(k)(A_i, A^*)$$

where K is the number of decision-makers, $dw(k)(A_i, A^*)$ is the weighted distance obtained from decision-maker k , and λ_k is the weight assigned to decision-maker k , satisfying

$$\sum_{k=1}^K \lambda_k = 1.$$

To evaluate the closeness of each supplier to the ideal solution, three distance measures are considered. The Hamming distance between two SVNSSs, (A) and (B), is defined as

$$d_H(A, B) = \sum_{i=1}^n [|T_A(x_i) - T_B(x_i)| + |I_A(x_i) - I_B(x_i)| + |F_A(x_i) - F_B(x_i)|].$$

The normalized Hamming distance is given by

$$d_{NH}(A, B) = \frac{1}{3n} \sum_{i=1}^n [|T_A(x_i) - T_B(x_i)| + |I_A(x_i) - I_B(x_i)| + |F_A(x_i) - F_B(x_i)|].$$

The extended Hausdorff distance is calculated as

$$d_{EH}(A, B) = \frac{1}{n} \sum_{i=1}^n \max\{|T_A(x_i) - T_B(x_i)|, |I_A(x_i) - I_B(x_i)|, |F_A(x_i) - F_B(x_i)|\}.$$

The Hamming and normalized Hamming distance formulations adopted in this study are based on Majumdar and Samanta (2014), whereas the extended Hausdorff distance formulation follows Mustapha et al. (2021).

The similarity measures adopted in this study are based on the formulations proposed by Majumdar and Samanta (2014). The corresponding similarity measures are derived from the calculated distance values. For the Hamming distance, the similarity measure is expressed as:

$$S_H(A, B) = \frac{1}{1 + d_H(A, B)}.$$

For the normalized Hamming distance and extended Hausdorff distance, the similarity measure is calculated as:

$$S(A, B) = 1 - d(A, B).$$

where $d(A, B)$ denotes the corresponding normalized Hamming distance or extended Hausdorff distance.

For all three measures, a lower distance value indicates that the supplier is closer to the ideal solution and is therefore preferable. Conversely, a higher similarity value indicates a greater degree of closeness to the ideal solution and represents a preferable supplier.

As a discussion the distance for DM1 of Hamming distance is

$$d_H(A,B) = |0.1-0.9| + |0.85-0.1| + |0.9-0.05| + |0.8-0.8| + |0.2-0.2| + |0.15-0.15| + |0.35-0.35| + |0.65-0.65| + |0.6-0.6| + |0.65-0.1| + |0.35-0.85| + |0.3-0.9| + |0.8-0.9| + |0.2-0.1| + |0.15-0.05| + |0.8-0.1| + |0.2-0.85| + |0.15-0.9|$$

$$d_H(A,B) = 2.40 + 0.00 + 0.00 + 1.65 + 0.30 + 2.10$$

$$d_H(A,B) = 2.40 + 0.00 + 0.00 + 1.65 + 0.30 + 2.10 = 6.45$$

and the similarity of Hamming distance measure is

$$S_H(A,B) = 1 / (1 + d_H(A,B)) = 1 / (1 + 6.45) = 1 / 7.45 = 0.1342.$$

The calculation of distance for DM1, normalized Hamming distance is

$$d_{NH}(A,B) = 1/(3(6)) [(|0.1-0.9| + |0.85-0.1| + |0.9-0.05|) + (|0.8-0.8| + |0.2-0.2| + |0.15-0.15|) + (|0.35-0.35| + |0.65-0.65| + |0.6-0.6|) + (|0.65-0.1| + |0.35-0.85| + |0.3-0.9|) + (|0.8-0.9| + |0.2-0.1| + |0.15-0.05|) + (|0.8-0.1| + |0.2-0.85| + |0.15-0.9|)]$$

$$d_{NH}(A,B) = 1/18 (2.40 + 0.00 + 0.00 + 1.65 + 0.30 + 2.10) = 1/18 (6.45) = 0.3583.$$

Hence, the similarity of normalized Hamming is

$$S_{NH}(A,B) = 1 - d_{NH}(A,B) = 1 - 0.3583 = 0.6417.$$

While the calculation of distance for DM1 extended Hausdorff distance is as follows

$$d_{EH}(A,B) = 1/6 [\max(0.85, 0.75, 0.85) + \max(0, 0, 0) + \max(0, 0, 0) + \max(0.55, 0.50, 0.60) + \max(0.10, 0.10, 0.10) + \max(0.70, 0.65, 0.75)]$$

$$d_{EH}(A,B) = 1/6 (0.85 + 0 + 0 + 0.60 + 0.10 + 0.75) = 1/6 (2.30) = 0.3833$$

and the similarity of extended Hausdorff is

$$S_{EH}(A,B) = 1 - d_{EH}(A,B) = 1 - 0.3833 = 0.6167.$$

Phase 3: Supplier Ranking and Comparative Analysis

In the third phase, the calculated distance and similarity values are used to determine the ranking of the supplier alternatives. For the distance-based measures, a lower distance value indicates that the supplier is closer to the ideal solution and is therefore considered preferable. Conversely, for the similarity measure, a higher similarity value indicates a greater degree of closeness to the ideal solution and is considered preferable.

The supplier rankings obtained using the Hamming distance, normalized Hamming distance, and extended Hausdorff distance measures are compared to examine the consistency of the

ranking results. The corresponding similarity-based rankings are also compared with the distance-based rankings to determine whether they provide consistent supplier preferences. The results of the comparison are presented and discussed in the following section.

Result and Discussion

This section presents the results obtained from the application of the three distance measures and their corresponding similarity measures for the supplier selection problem. The results are presented in tabular form and discussed comparatively to evaluate the consistency of the supplier alternatives under the Single-Valued Neutrosophic Set (SVNS) framework.

Distance and Similarity Measures

The results obtained from the three distance measures are presented in Tables 5–7. Table 5 reports the results based on the Hamming distance measure, while Table 6 presents the results obtained using the normalized Hamming distance measure. Table 7 presents the results based on the extended Hausdorff distance measure.

Table 5: Hamming Distance Measure

Alternative	DM1	DM2	DM3	DM4	DM5	Distance Average	Similarity Average
A1	6.45	5.85	4.80	6.30	7.20	6.12	0.1404
A2	7.20	6.66	5.55	6.15	7.05	6.52	0.1330
A3	4.50	4.50	4.95	4.65	4.65	4.65	0.1770
A4	4.35	4.35	3.30	4.20	5.11	4.26	0.1901
A5	6.60	6.00	5.55	5.55	7.05	6.15	0.1399

Based on Table 5, A4 obtained the lowest average Hamming distance of 4.26, indicating that it is the closest supplier to the ideal solution and is therefore ranked as the preferable supplier. The resulting ranking is $A4 > A3 > A1 > A5 > A2$. A3 was ranked second, followed by A1 and A5, while A2 was ranked as the least preferable supplier with the highest average distance value of 6.52.

The similarity measure produced the same ranking as the Hamming distance measure. A4 obtained the highest similarity value of 0.1901, confirming its position as the most preferable supplier. In contrast, A2 obtained the lowest similarity value of 0.1330, indicating the lowest degree of similarity to the ideal solution. Therefore, both the distance and similarity measures consistently identify A4 as the most preferable supplier and A2 as the least preferable supplier.

Table 6: Normalized Hamming Distance Measure

Alternative	DM1	DM2	DM3	DM4	DM5	Distance Average	Similarity Average
A1	0.3583	0.3100	0.2667	0.3500	0.4000	0.3370	0.6630
A2	0.4000	0.3667	0.3083	0.3417	0.3917	0.3617	0.6383
A3	0.2500	0.2500	0.2750	0.2583	0.2250	0.2517	0.7483
A4	0.2417	0.2417	0.1833	0.2337	0.2833	0.2367	0.7633
A5	0.3667	0.3333	0.3083	0.3083	0.3917	0.3417	0.6583

Table 6 presents the results obtained using the normalized Hamming distance measure. The overall ranking remains unchanged compared with the Hamming distance measure, although the distance values are normalized to the interval [0, 1]. From Table 6, A4 obtained the lowest average distance value of 0.2367, indicating that it is the closest supplier to the ideal solution. Therefore, A4 is ranked as the most preferable supplier, followed by A3, A1, A5, and A2. The resulting ranking is $A4 > A3 > A1 > A5 > A2$. A2 obtained the highest distance value of 0.3617, placing it as the least preferable supplier.

For the similarity measure, A4 obtained the highest value of 0.7633, whereas A2 obtained the lowest value of 0.6383. These results are consistent with the distance-based ranking. Thus, the normalized Hamming distance measure also identifies A4 as the most preferable supplier and A2 as the least preferable supplier.

Table 7: Extended Hausdorff Distance

Alternative	DM1	DM2	DM3	DM4	DM5	Distance Average	Similarity Average
A1	0.3833	0.3500	0.2833	0.3667	0.4250	0.3617	0.6383
A2	0.4167	0.3833	0.3167	0.3500	0.4083	0.3750	0.6250
A3	0.2583	0.2583	0.2917	0.2750	0.2333	0.2633	0.7367
A4	0.2500	0.2500	0.1833	0.2333	0.2917	0.2417	0.7583
A5	0.3833	0.3500	0.3167	0.3167	0.4083	0.3550	0.6450

Table 7 presents the results obtained using the extended Hausdorff distance measure. A slight difference can be observed in the ranking of the intermediate alternatives compared with the Hamming and normalized Hamming distance, which may be attributed to variations in the decision-maker ratings and the way these ratings are captured by the respective distance measures. Nevertheless, A4 remains the most preferable supplier.

Based on the distance measure, A4 obtained the lowest average distance value of 0.2417, followed by A3 with 0.2633, A5 with 0.3550, A1 with 0.3617, and A2 with 0.3750. Therefore, the resulting ranking is $A4 > A3 > A5 > A1 > A2$.

In comparison with Table 5 and Table 6, A5 and A1 exchange their positions under the extended Hausdorff distance measure. This indicates that the choice of distance may influence the relative ranking of some intermediate alternatives, although the most and least preferable suppliers remain unchanged.

For the similarity measure, A4 obtained the highest value of 0.7583, while A2 obtained the lowest value of 0.6250. The similarity-based ranking is therefore consistent with the distance-based ranking, with A4 ranked as the most preferable supplier and A2 as the least preferable supplier.

Comparative Analysis of Supplier Rankings

To further evaluate the consistency of the proposed approach, the average distance and similarity values obtained from the three distance measures are summarized in Table 8, while the corresponding supplier rankings are presented in Table 9.

Table 8: Average Distance and Similarity Values for Supplier Alternatives

Alternative	Hamming Distance	Similarity	Normalized Hamming Distance	Similarity	Extended Hausdorff Distance	Similarity
A1	6.12	0.1404	0.3370	0.6630	0.3617	0.6383
A2	6.52	0.1330	0.3617	0.6383	0.3750	0.6250
A3	4.65	0.1770	0.2517	0.7483	0.2633	0.7367
A4	4.26	0.1901	0.2367	0.7633	0.2417	0.7583
A5	6.15	0.1399	0.3417	0.6583	0.3550	0.6450

Table 9: Comparison of Supplier Rankings Based on the Three Distance Measures

Supplier	Hamming Distance	Normalized Hamming Distance	Extended Hausdorff Distance
A1	3	3	4
A2	5	5	5
A3	2	2	2
A4	1	1	1
A5	4	4	3

The comparison in Table 9 shows that A4 consistently ranks first, while A2 consistently ranks fifth across all three distance measures. A3 also maintains a stable second position throughout the three approaches. However, a difference is observed between A1 and A5. Under the Hamming and normalized Hamming distance measures, A1 ranks third and A5 ranks fourth. In contrast, the extended Hausdorff distance measure places A5 in third position and A1 in fourth position. This difference demonstrates that the choice of distance measure can affect the ranking of intermediate alternatives. Nevertheless, the consistent identification of A4 as the most preferable supplier and A2 as the least preferable supplier indicates that the overall supplier selection decision is stable across the three approaches.

Furthermore, the similarity measures provide rankings consistent with their corresponding distance measures. Suppliers with lower distance values generally obtain higher similarity values, indicating greater closeness to the ideal solution. Therefore, the use of both distance and similarity measures provides complementary perspectives for evaluating supplier alternatives under uncertain and imprecise conditions. Overall, the results demonstrate that the proposed SVNS-based framework can effectively distinguish between the supplier alternatives. The comparative analysis also highlights the importance of considering more than one distance measure, as different distance formulations may produce variations in the ranking of intermediate alternatives even when the best and least preferable suppliers remain unchanged.

Conclusion and Recommendations

This study presented an SVNS-based approach for addressing the supplier selection problem under uncertain and imprecise decision-making conditions. A three-phase framework was developed to systematically implement the proposed approach. The framework involved the construction of the SVNS decision matrix, the computation of three distance measures and their corresponding similarity measures, and the ranking and comparative analysis of the supplier alternatives. Three distance measures, namely the Hamming distance, normalized Hamming distance, and extended Hausdorff distance, were applied to evaluate the closeness of each supplier to the ideal solution. The corresponding similarity measures were also employed to

provide an additional assessment of supplier preference. The results demonstrated that lower distance values and higher similarity values consistently indicate preferable supplier alternatives.

Based on the results, A4 was consistently identified as the most preferable supplier, while A2 was consistently identified as the least preferable supplier across all three distance measures. The Hamming and normalized Hamming distance measures produced the same ranking, namely $A4 > A3 > A1 > A5 > A2$, whereas the extended Hausdorff distance produced $A4 > A3 > A5 > A1 > A2$. The difference between A1 and A5 indicates that the choice of distance measure may influence the ranking of intermediate alternatives. Nevertheless, the best and least preferable suppliers remained unchanged. Overall, the findings demonstrate that the proposed SVNS-based distance and similarity measures provide a systematic and practical approach for supplier selection in the presence of uncertainty, imprecision, and indeterminacy. The comparative analysis of different distance measures also provides decision-makers with a broader perspective when evaluating the robustness and consistency of supplier rankings.

For future research, the proposed framework can be extended by incorporating other distance and similarity measures to further examine their effects on supplier rankings. The use of alternative Multi-Criteria Decision-Making (MCDM) techniques and different weighting approaches may also provide further insights into the robustness of the supplier selection results. In addition, future studies may consider more complex supplier selection problems involving a larger number of alternatives, criteria, and decision makers. Sensitivity analysis could also be incorporated to examine how changes in criteria weights and decision-maker evaluations affect the final supplier rankings. Furthermore, the proposed approach can be extended to other neutrosophic environments, such as Interval-Valued Neutrosophic Sets (IVNS), to better accommodate vague, incomplete, and inconsistent information commonly encountered in real-world decision-making.

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