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RAPID PROTOTYPE PROCESS SELECTION USING MULTI ATTRIBUTE DECISION MAKING USING ADVANCED ENTROPY WEIGHT BASED FUZZY SINGLE VALUED NEUTROSOPHIC SET

Nital Pravinbhai Nirmal¹, Jignesh Girishbhai Parmar² and Mehul Gunvantrai Mehta³

¹ Shantilal Shah Engineering College (A State Govt. Institute), Affiliated with Gujarat Technological University, Ahmedabad.

^{2,3} Shantilal Shah Engineering College (A State Govt. Institute), Bhavangar affiliated with Gujarat Technological University, Ahmedabad.

¹<https://orcid.org/0000-0002-8657-4253>, ²<https://orcid.org/0000-0002-8533-8304>, ³<https://orcid.org/0009-0002-2219-0848>

Email: nital.nirmal@gmail.com, jigneshparmarssec@gmail.com, mehulgmehta@gmail.com

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ABSTRACT

This paper presents a novel methodology for Multi-Attribute Decision Making (MADM) based on Single-Valued Neutrosophic Sets (SVNS), a specialized extension of Neutrosophic sets that incorporates three distinct membership functions: truth, indeterminacy, and falsehood. The objective is to develop an advanced decision-making framework that improves rapid prototype process selection, particularly when handling imprecise, uncertain, and inconsistent information commonly encountered in real-world applications. The proposed method integrates the conversion of crisp and fuzzy data into SVNS and employs an advanced entropy weight-based approach to enhance the selection process. The effectiveness of the approach is demonstrated through case studies drawn from existing literature on rapid prototyping, showing that the new methodology yields more accurate results with reduced computational effort when compared to traditional MADM methods. The results validate the superiority of the proposed approach in addressing indeterminacies and uncertainties, offering more reliable and precise decision-making outcomes in complex environments.



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I. INTRODUCTION

In the context of globalization, significant advancements are being made in the manufacturing sector to optimize product development and minimize lead times. One of the most prominent technologies driving this evolution is Rapid Prototyping (RP), a method that enables the creation of physical models through layer-by-layer deposition, guided by Computer-Aided Design (CAD) data, without the need for traditional cutting tools. Researchers are actively working to optimize various aspects of the RP process, including material selection, path planning, and process efficiency, using advanced mathematical modeling techniques. Typically, the RP process can be divided into three key stages: the first stage involves the "sub-active" phase, where initial material preparation takes place; the second stage is "additive," where material is added to the workpiece layer by layer; and the third stage is "virtual," involving the digital validation and optimization of the prototype.

Rapid prototyping has proven instrumental in reducing costs and accelerating product development cycles, making it a valuable tool across industries such as aerospace, automotive, and consumer goods. The commercialization of new RP techniques continues to expand its application globally, offering manufacturers a competitive edge in design and production. Rapid prototype technique is the production of physical model from computer aided design (CAD) data layer by layer deposition without using cutting tool and the rapid prototype has been established to reduce cost and product development [1].

II. EXISTING LITERATURE ON RAPID PROTOTYPE PROCESS RANKING USING MULTI-ATTRIBUTE DECISION MAKING (MADM)

II.1 ANALYTICAL HIERARCHY PROCESS (AHP)

The method developed by [2] employs a normalization approach that treats both beneficial and non-beneficial criteria in the same manner. It utilizes the Euclidean distance principle for decision-making, but one of its limitations is that it does not account for the potential correlation between attributes. Additionally, this method requires expert or research-based input to determine the weights for each attribute, which can lead to variations in the rankings, particularly if the weightings assigned to the attributes differ. Table 1 illustrates the application of the Analytical Hierarchy Process (AHP) methodology across various manufacturing and supply chain functions, including its use in selecting rapid prototyping layered manufacturing processes [3]. This highlights the widespread adoption of AHP in optimizing decisions where multiple criteria must be balanced, despite its limitations in handling attribute correlations and weight assignment variations.

II.2 VISEKRITERIJSKA OPTIMIZACIJA I KOMOROMISNO RESENJE (VIKOR)

The ViseKriterijska Optimizacija I Komoromisno Resenje (VIKOR) method, investigated by [4], focuses on a weight strategy for calculating rankings, where the values are constrained within the range of [0, 1]. However, this weight strategy can lead to different ranking outcomes even when the attribute weights remain the same. As an outranking method, VIKOR lacks a self-evident foundation, which limits its interpretability in certain decision-making contexts. In this regard, [5] introduced the Fuzzy VIKOR (F-VIKOR) approach for robot selection, which incorporates fuzzy logic to handle uncertainty in the decision-making process. Furthermore, [6] applied various decision-making methods to select rapid prototyping technologies, while [7] utilized the Fuzzy VIKOR methodology to optimize the selection of rapid prototyping technologies in an agile environment. These studies demonstrate the versatility and application of VIKOR-based methods in complex decision-making scenarios, particularly in the selection of manufacturing technologies and processes.

II.3 COMPLEX PROPORTIONAL ASSESSMENT (COPRAS)

The method investigated by [8] also employs a similar normalization technique for both beneficial and non-beneficial criteria. Like other approaches, it requires input from decision makers, experts, or researchers to assign weights to the attributes, which can lead to variations in the ranking solutions based on differing weight assignments. A potential issue with this method arises during the normalization process, as some attribute values may become zero, which can significantly alter the overall ranking outcome. In a related study, [9] applied an improved version of the Complex Proportional Assessment (COPRAS) method, which is designed to handle qualitative information in the context of rapid prototype system selection. This demonstrates the continued evolution of decision-making methods, particularly in the realm of rapid prototyping, where both qualitative and quantitative factors must be considered.

II.4 HYBRID MADM TECHNIQUES FOR RAPID PROTOTYPE TOOL SELECTION

The selection of rapid prototyping processes has been addressed through various decision-making methodologies in recent studies. For instance, [10] employed the DEMATEL (Decision-Making Trial and Evaluation Laboratory) and VIKOR methods to evaluate and select three-dimensional printer service providers. In contrast, [1] applied a modified version of the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) methodology to solve the rapid prototyping selection problem. Building on this, [11] proposed the Generalized TOPSIS (GTMA) methodology to address the same issue, offering an alternative approach to ranking rapid prototyping processes. Additionally, [12] tackled the rapid prototyping selection problem by integrating the Grey Relational Analysis (GRA) method with Fuzzy TOPSIS, combining the strengths of both techniques to handle uncertainty and improve decision accuracy. The Fuzzy TOPSIS with GRA method, as implemented by [12], demonstrated its utility in optimizing rapid prototyping selection. In another advancement, the Fuzzy Single-Valued Neutrosophic Set Entropy Weight-based Multi-Attribute Decision Making (F-SVNS EW-MADM) method was introduced by [13, 14], providing a robust framework for handling uncertain, indeterminate, and fuzzy information in the decision-making process. Furthermore, [15] utilized the Analytical Network Process (ANP) and TOPSIS methodologies to assess and select appropriate rapid prototyping processes, further diversifying the range of techniques applied to this problem. These studies reflect the ongoing development and application of sophisticated decision-making models to improve the selection of rapid prototyping technologies.

III. PROPOSED METHODOLOGY FUZZY-SINGLE VALUED NEUTROSOPHIC SET ENTROPY WEIGHT BASED MULTI ATTRIBUTE DECISION MAKING TECHNIQUE (F-SVNS EW-MADM)

The Fuzzy Single-Valued Neutrosophic Set Advanced Entropy Weight-based Multi-Attribute Decision Making (F-SVNS AEW-MADM) methodology follows a structured approach to decision-making. The key steps involved in this process are outlined below:

- Step 1: Define the objective of the selection process, clearly establishing the goal or desired outcome for the decision-making task.
- Step 2: Identify the various alternatives available for selection, along with the relevant attributes (criteria) that will influence the decision. This step involves determining the factors that will be used to evaluate and compare the alternatives in the context of the selection problem.
- Step 3: All alternatives and attributes (criteria) in matrix form with comparative performance are known as *decision* matrix. Let us consider set of alternatives as $A = \{A_i, i = 1, 2, 3, \dots, m\}$ & set of criteria as $C = \{C_j, j = 1, 2, 3, \dots, n\}$, X_{ij} is the performance of alternatives A_i for relative criteria C_j . X_{ij} are having qualitative/ quantitative values. The structure of decision matrix is illustrated in Table 1.

Table 1: Decision Matrix for F-SVNS AEW-MADM.

Alternatives	C ₁	C ₂	C ₃	C _n
A ₁	X ₁₁	X ₁₂	X ₁₃	X _{1n}
A ₂	X ₂₁	X ₂₂	X ₂₃	X _{2n}
A ₃	X ₃₁	X ₃₂	X ₃₃	X _{3n}
....
A _m	X _{m1}	X _{m2}	X _{m3}	X _{mn}

Source: Authors, (2025).

Step 4: Conversion of Qualitative Data to Quantitative Data

The qualitative (linguistic) information is systematically transformed into quantitative (crisp) values, as outlined in Table 2. This process enables the representation of subjective, descriptive information in a measurable form, facilitating more precise analysis and interpretation

Table 2. Conversion of Linguistic Terms in to Classic (Crisp) Set.

Linguistic terms of selection attributes	Fuzzy number	Crisp value of selection attribute
Exceptionally low	M1	0.045
Extremely low	M2	0.135
Very low	M3	0.255
Low	M4	0.335
Below average	M5	0.410
Average	M6	0.500
Above average	M7	0.590
High	M8	0.665
Very high	M9	0.745
Extremely high	M10	0.865

Source: Authors, (2025).

Data collected from sources [13, 14, 16, 17, 18].

If the input matrix consists solely of quantitative data, this conversion step can be omitted.

Step 5. Generalization/ normalization of matrix

As outlined in sources [13] and [14], each attribute associated with the alternatives presents distinct values. To ensure consistency, the data is standardized within the range [0, 1] through the application of the Vector Normalization Method (VNM). For beneficial criteria, where higher values are advantageous (such as quality and profit), normalization is achieved using Equation (1).

$$R_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}}; \forall i, j \tag{1}$$

For non-beneficial criteria, where lower values are preferable (e.g., price, lead time), normalization is conducted using Equation (2).

$$R_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}}; \forall i, j \tag{2}$$

Normalized decision matrix is shown in Table 3.

Table 3. Normalized Decision Matrix.

Alternative	C ₁	C ₂	C ₃	C _n
A ₁	R ₁₁	R ₁₂	R ₁₃	R _{1n}
A ₂	R ₂₁	R ₂₂	R ₂₃	R _{2n}
A ₃	R ₃₁	R ₃₂	R ₃₃	R _{3n}
....
A _m	R _{m1}	R _{m2}	R _{m3}	R _{mn}

Source: Authors, (2025).

Step 6: Conversion of Classic Set/Fuzzy Set to Single-Valued Neutrosophic Set (SVNS)

The normalized decision matrix for F-SVNS AEW-MADM is presented in Table 4, where classic or fuzzy sets are converted into a Single-Valued Neutrosophic Set (SVNS). This transformation allows for a more comprehensive representation of uncertainty in decision-making scenarios.

Table 4. SVNS Normalized Decision Matrix for F-SVNS AEW-MADM

A	C ₁	C _n
A ₁	< T ₁₁ (x), I ₁₁ (x), F ₁₁ (x) >	< T _{1n} (x), I _{1n} (x), F _{1n} (x) >
A ₂	< T ₂₁ (x), I ₂₁ (x), F ₂₁ (x) >	< T _{2n} (x), I _{2n} (x), F _{2n} (x) >
A ₃	< T ₃₁ (x), I ₃₁ (x), F ₃₁ (x) >	< T _{3n} (x), I _{3n} (x), F _{3n} (x) >
....
A _m	< T _{m1} (x), I _{m1} (x), F _{m1} (x) >	< T _{mn} (x), I _{mn} (x), F _{mn} (x) >

Source: Authors, (2025).

According to sources [13], [14], and [21], the conversion rules for transforming classic or fuzzy sets to Single-Valued Neutrosophic Sets (SVNS) for both beneficial and non-beneficial criteria are outlined in [14]. For beneficial criteria, where higher values of performance measures are desirable (e.g., profit, quality), the Positive Ideal Solution (PIS) is defined as $\langle T_{\max}^*(x), I_{\min}^*(x), F_{\min}^*(x) \rangle$. In this context, the normalized input matrix treats the beneficial criteria as the degree of truthfulness, while the degree of indeterminacy and degree of falsehood are represented as $I_A(x) = F_A(x) = 1 - T_A(x)$ respectively. The SVNS conversion is performed using Equation (3).

$$\langle T_{ij}(x), I_{ij}(x), F_{ij}(x) \rangle = \langle R_{ij}(x), (1 - R_{ij}(x)), (1 - R_{ij}(x)) \rangle \tag{3}$$

Step 7: Identification of Ideal Solution for Beneficial and Non-Beneficial Attributes

According to sources [13], [14], and [21], the ideal solution for beneficial attributes—where higher values are advantageous (e.g., quality, profit)—is identified by determining the Positive Ideal Solution (PIS) here by Equation (4) and (5).

$$\text{BAIS} = \langle T_{\max}^*(x), I_{\min}^*(x), F_{\min}^*(x) \rangle = \langle 1, 0, 0 \rangle \tag{4}$$

Non beneficial attributes ideal solution

$$\text{NBAIS} = \langle T_{\min}^*(x), I_{\max}^*(x), F_{\max}^*(x) \rangle = \langle 0, 1, 1 \rangle \tag{5}$$

Step 8: Calculation of the entropy value of attribute E_j

Find the entropy value for attribute with Equation (6).

$$E_j = 1 - \frac{1}{n} \sum_{i=1}^m \left(T_{ij}(x_i) + F_{ij}(x_i) \right) \left| 2 \left(I_{ij}(x_i) \right) - 1 \right| \tag{6}$$

Step 9: Calculation of the entropy weight of attribute W_j

Find the entropy weight of attribute by Equation (7).

$$W_j = \frac{1 - E_j}{\sum_{j=1}^n (1 - E_j)} \tag{7}$$

Here, we get weight vector $W = (w_1, w_2, w_3, \dots, w_n)^T$ of attributes, $C = \{C_j; \text{ for } j = 1, 2, 3, \dots, n\}$ with $W_j \geq 0$ and $\sum_{j=1}^n W_j = 1$.

Step 10: Calculate the entropy weight of alternative A_w

Find the alternative weight by Equation (8).

$$A_w = \sum_{j=1}^n W_j * \left((T_{ij}(x) * T_{ij}^*(x)) + (I_{ij}(x) * I_{ij}^*(x)) + (F_{ij}(x) * F_{ij}^*(x)) \right) \tag{8}$$

Here, for beneficial attributes $\text{PIS} = \langle T_{\max}^*(x), I_{\min}^*(x), F_{\min}^*(x) \rangle = \langle 1, 0, 0 \rangle$ and for non-beneficial attributes $\text{NIS} = \langle T_{\min}^*(x), I_{\max}^*(x), F_{\max}^*(x) \rangle = \langle 0, 1, 1 \rangle$.

Step 11: Ranking of Alternatives

Upon the calculation of alternative weight A_w , the alternatives are ranked in descending order. The alternative with the highest correlation coefficient A_w is assigned the first rank, while the alternative with the lowest A_w is assigned the last rank. This ranking method ensures that alternatives are ordered based on their relative performance and suitability according to the calculated weights.

IV. COLLECTED CASE EXAMPLE OF RAPID PROTOTYPE PROGRAM SELECTION

Step 1: A case study on the selection of a rapid prototype program for industrial applications was presented by [1] using a modified TOPSIS methodology. Table 5 provides the quantitative data illustrating the expected performance of each rapid prototype (alternative) in relation to the respective process parameters (attributes). This case serves as the foundation for the new proposed approach, demonstrating its application in an industrial context.

Step 2: The same case example was further analyzed by [19] and [20] using various multi-criteria decision-making methods, including GTMA, SAW, WPM, AHP, TOPSIS, and a modified version of TOPSIS. These approaches were employed to evaluate and compare the performance of the alternatives under the given process parameters.

Step 3: The decision matrix comprises six rapid prototype systems as alternatives and six attribute measures: C1 (accuracy), C2 (surface roughness), C3 (tensile strength), C4 (elongation), C5 (cost of part), and C6 (build time). Based on the published input data, the beneficial attributes are identified as C3 (tensile strength) and C4 (elongation), while the non-beneficial attributes are C1 (accuracy), C2 (surface roughness), C5 (cost of part), and C6 (build time). Although accuracy (C1) is typically considered a beneficial attribute, for the purpose of comparison with previously published rankings, and in accordance with the research assumptions, it is treated as a non-beneficial attribute in this study.

For implementation and initial validation purposes, the proposed methodologies were applied to the collected case examples, which were sourced from peer-reviewed journals and books. The results were then compared with and explained in the context of the published rankings, while the original data from the sources remained unchanged.

Step 4: The decision matrix utilized in this study was collected from sources [1] and [20], as presented in Table 5. This matrix provides the necessary data for evaluating the alternatives based on the defined attributes.

Table 5. Rapid Prototype Selection Input Matrix (Collected Case Example).

Alternative	C1 (-)	C2 (-)	C3 (+)	C4 (+)	C5 (-)	C6 (-)
A1	120	6.5	65	5	0.745	0.5
A2	150	12.5	40	8.5	0.745	0.5
A3	125	21	30	10	0.665	0.745
A4	185	20	25	10	0.59	0.41
A5	95	3.5	30	6	0.745	0.41
A6	600	15.5	5	1	0.135	0.255

Source: Authors, (2025).

The data is collected from sources [1, 11, 20].

Step 5: Conversion of Qualitative Data to Quantitative Data

In this case, the input information consists solely of quantitative data. Therefore, there is no need to convert any qualitative values into quantitative form. As a result, this step is not applicable and has been excluded from the current case example.

Step 6: Normalization of Table 5 is carried out with the Equation (1) / (2). Rapid prototype selection normalized matrix is shown in Table 6.

Table 6. Rapid Prototype Selection Normalized Matrix using VNM.

Sr. No.	C1 (-)	C2 (-)	C3 (+)	C4 (+)	C5 (-)	C6 (-)
A1	0.8223	0.8192	0.7145	0.2735	0.5263	0.5857
A2	0.7778	0.6522	0.4397	0.4649	0.5263	0.5857
A3	0.8148	0.4158	0.3298	0.5470	0.5772	0.3826
A4	0.7260	0.4436	0.2748	0.5470	0.6249	0.6602
A5	0.8593	0.9026	0.3298	0.3282	0.5263	0.6602
A6	0.1113	0.5688	0.0550	0.0547	0.9142	0.7887

Source: Authors, (2025).

Step 7: Convert crisp normalized matrix into SVNS decision matrix: Crisp data is converted in SVNS $\langle T_{ij}(x), I_{ij}(x), F_{ij}(x) \rangle$ degree of truthness, indeterminate and falsehood form is carried out with Equation (3).

Non-beneficial attributes i.e. Alternative A1 and attribute C1 having value **0.8223** converted in SVNS gives the value $\langle (1 - 0.8223), 0.8223, 0.8223 \rangle = \langle 0.1777, 0.8223, 0.8223 \rangle$. The same calculation is also is carried out for attributes C2, C5 and C6.

Beneficial attributes i.e. Alternative A1 and attribute C3 having value 0.7145 converted in SVNS gives the value $\langle 0.7145, (1 - 0.7145), (1 - 0.7145) \rangle = \langle 0.7145, 0.2855, 0.2855 \rangle$. The same calculation is also carried out for attribute C4.

Step 8: Find the beneficial attribute ideal solution and non-beneficial attribute ideal solution.

Beneficial attribute ideal solution and non-beneficial attribute ideal solution is discovered with Equation (4)/ (5), where $BAIS(A^*) = \langle T_{max}^*(x), I_{min}^*(x), F_{min}^*(x) \rangle = \langle 1, 0, 0 \rangle$ and

$NBAIS(A^*) = \langle T_{min}^*(x), I_{max}^*(x), F_{max}^*(x) \rangle = \langle 0, 1, 1 \rangle$.

Step 9: Calculate the entropy value for attribute (E_j)

Calculate the attribute value with the Equation (6) is as shown in Table 7. i.e. consider calculation of the entropy value for attribute A1.

$$E_{j1} = 1 - \frac{1}{6} [\{(0.1777 + 0.8223) * |2(0.8223) - 1|\} + \{(0.2222 + 0.7778) * |2(0.7778) - 1|\} + \{(0.1852 + 0.8148) * |2(0.8148) - 1|\} + \{(0.2740 + 0.7260) * |2(0.7260) - 1|\} + \{(0.1407 + 0.8593) * |2(0.8593) - 1|\} + \{(0.8887 + 0.1113) * |2(0.1113) - 1|\}] = 0.3704$$

The same calculation is also is carried out for remaining attributes.

Step 10: Calculate the entropy weight of attribute W_j

Calculate the attribute value with the Equation (7) is as shown in Table 7. i.e. consider calculation of the alternative entropy value for attribute A1.

$$W_{j1} = \left[\frac{(1 - 0.3704)}{(1 - 0.3704) + (1 - 0.6388) + (1 - 0.5715) + (1 - 0.6758) + (1 - 0.7683) + (1 - 0.7007)} \right] = 0.2768$$

The same calculation is also is carried out for W_{j2} to W_{j6} .

$$\text{Where, } \sum_{j=1}^n W_j = 0.2768 + 0.1588 + 0.1884 + 0.1019 + 0.1884 + 0.1316 = 1$$

Step 11: Calculate the entropy weight of alterative A_w

Find the alternative weight by Eq. (7) is as shown in Table 7

$$A_{w1} = [0.2768 * \{(0.1777 * 0) + (0.8223 * 1) + (0.8223 * 1)\} + 0.1588 * \{(0.1808 * 0) + (0.8192 * 1) + (0.8192 * 1)\} + 0.1884 * \{(0.7145 * 1) + (0.2855 * 0) + (0.2855 * 0)\} + 0.1019 * \{(0.2735 * 1) + (0.7265 * 0) + (0.7265 * 0)\} + 0.1884 * \{(0.4737 * 0) + (0.5263 * 1) + (0.5263 * 1)\} + 0.1316 * \{(0.4143 * 0) + (0.5857 * 1) + (0.5857 * 1)\}] = 1.1503$$

The same calculation is also is carried out for remaining alternatives.

Table 7. F-SVNS-AEW-MADM Ranking for Rapid Prototype Selection.

Step 12: Ranking of alternatives

The rank is calculated with F-SVNS-AEW-MADM is as shown in Table 7. The alternatives rank is given according to alternative weight A_w in descending order, $1.1523 > 1.1503 > 1.0482 > 0.9736 > 0.9416 > 0.6542$. Alternatives ranking order is $A5 > A1 > A2 > A4 > A3 > A6$ as shown in Table 7.

V. PERFORMANCE MEASURES COMPARISON: RAPID PROTOTYPE RANKING

The results of the proposed three methodologies are compared with published results to validate their effectiveness in the selection of rapid prototypes. To facilitate the comparison, all rapid prototype alternatives are ranked based on their respective alternative weight values, as shown in Table 8. The alternative with the highest weight value is ranked first, followed by the alternative with the second-highest weight value in second place, and so on. The ranking order obtained using the three proposed methodologies is then compared with the ranking order reported in the literature. The comparison of results is presented in Table 8.

The result comparisons presented in Table 8 indicate that the outcomes obtained from the proposed methodologies are largely consistent with the results reported in the literature. The same rapid prototype selection problem was addressed by [19] using the GTMA, SAW, WPM, AHP, and VIKOR methodologies. All methods, except for TOPSIS and modified TOPSIS, identified alternative A5 as the top choice. This discrepancy is attributed to the fact that these methodologies take attribute weights into account, and the weight assignment is dependent on the decision maker, which results in different ranking outcomes.

Furthermore, the second-ranked alternative, as determined by all proposed methods, aligns with the published results, with the exception of the TOPSIS and modified TOPSIS methodologies, due to their distinct approach to weight calculation. For the fourth-ranked alternative, the proposed methods match the rankings obtained by the VIKOR and GTMA methods. In contrast, other MADM approaches such as SAW, AHP, TOPSIS, and modified TOPSIS report a slight variation in the 4th rank, primarily due to differences in weight criteria calculation, assumptions, and expert opinions.

The proposed methodologies demonstrate a consistent ranking of alternative A6, aligning with published results where alternative A6 holds a similar position. This indicates that, although

Table 7: F-SVNS-AEW-MADM Ranking for Rapid Prototype Selection.

Sr. No.	C1 (-)	C2 (-)	C3 (+)	C4 (+)	C5 (-)	C6 (-)	A_w	Rank
A1	<0.1777, 0.8223, 0.8223>	<0.1808, 0.8192, 0.8192>	<0.7145, 0.2855, 0.2855>	<0.2735, 0.7265, 0.7265>	<0.4737, 0.5263, 0.5263>	<0.4143, 0.5857, 0.5857>	1.1503	2
A2	<0.2222, 0.7778, 0.7778>	<0.3478, 0.6522, 0.6522>	<0.4397, 0.5603, 0.5603>	<0.4649, 0.5351, 0.5351>	<0.4737, 0.5263, 0.5263>	<0.4143, 0.5857, 0.5857>	1.0482	3
A3	<0.1852, 0.8148, 0.8148>	<0.5842, 0.4158, 0.4158>	<0.3298, 0.6702, 0.6702>	<0.5470, 0.4530, 0.4530>	<0.4228, 0.5772, 0.5772>	<0.6174, 0.3826, 0.3826>	0.9416	5
A4	<0.2740, 0.7260, 0.7260>	<0.5564, 0.4436, 0.4436>	<0.2748, 0.7252, 0.7252>	<0.5470, 0.4530, 0.4530>	<0.3751, 0.6249, 0.6249>	<0.3398, 0.6602, 0.6602>	0.9736	4

A5	<0.1407, 0.8593, 0.8593>	<0.0974, 0.9026, 0.9026>	<0.3298, 0.6702, 0.6702>	<0.3282, 0.6718, 0.6718>	<0.4737, 0.5263, 0.5263>	<0.3398, 0.6602, 0.6602>	1.1523	1
A6	<0.8887, 0.1113, 0.1113>	<0.4312, 0.5688, 0.5688>	<0.0550, 0.9450, 0.9450>	<0.0547, 0.9453, 0.9453>	<0.0858, 0.9142, 0.9142>	<0.2113, 0.7887, 0.7887>	0.6542	6
A*	<0.0000, 1.0000, 1.0000>	<0.0000, 1.0000, 1.0000>	<1.000, 0.0000, 0.0000>	<1.000, 0.0000, 0.0000>	<0.0000, 1.0000, 1.0000>	<0.0000, 1.0000, 1.0000>		
E _j	0.3704	0.6388	0.5715	0.6758	0.7683	0.7007		
W _j	0.2768	0.1588	0.1884	0.1425	0.1019	0.1316	1	

Source: Authors, (2025).

Table 8: Rapid Prototype Selection Performance Measures Comparison.

Alternatives (Sr. No.)	F-SVNS AEW-MADMs	Data Collected from the source [19]						
		GTMA	SAW	WPM	AHP	TOPSIS	ModifiedTOPSIS	VIKOR
A1	2	2	2	2	2	1	1	2
A2	3	3	3	3	3	3	3	3
A3	5	5	4	4	4	4	4	5
A4	4	4	5	5	5	5	5	4
A5	1	1	1	1	1	2	2	1
A6	6	6	6	6	6	6	6	6

Source: Authors, (2025).

The weight criteria influence the rankings of other alternatives, the proposed approaches maintain strong consistency with the published findings for the top-ranked alternative, thereby affirming the robustness and reliability of the methods.

VI. CONCLUSIONS

The proposed methodology offers a streamlined approach with minimal computational complexity, eliminating the need to calculate the relative importance of attributes. It does not require resizing the assignment matrix and is capable of converting simple or linguistic sets into F-SVNS. Furthermore, the suggested methodology outperforms established methods such as GTMA, SAW, WPM, AHP, TOPSIS, Modified TOPSIS, and VIKOR. This chapter introduces the F-SVNS AEW-MADM technique, developed and implemented to evaluate its feasibility in the selection and ranking of rapid prototyping processes. The key conclusions of the proposed method are as follows:

- The methodology effectively converts both crisp data and fuzzy information provided by the decision maker into SVNS form, resulting in more efficient and reliable ranking solutions.
- It is robust in handling decision-making scenarios involving inconsistent, incomplete, and indeterminate information.
- The proposed approach facilitates more efficient negotiation and selection of the best alternative with reduced computational effort.
- The calculation and normalization process ensures no loss of information, and no attribute value is reduced to zero during the process.
- The F-SVNS AEW-MADM technique incorporates attribute weight calculation, and comparison with existing published results demonstrates its validity, applicability, and reliability in rapid prototyping selection for manufacturing environments. This leads to enhanced manufacturing performance and function.
- Overall, the proposed methodology provides a valuable tool for improving decision-making processes in manufacturing, specifically in the selection of rapid prototyping systems.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Nital Pravinbhai Nirmal, Jignesh Girishbhai Parmar and Mehul Gunvantrai Mehta.

Methodology: Nital Pravinbhai Nirmal, Jignesh Girishbhai Parmar and Mehul Gunvantrai Mehta.

Investigation: Nital Pravinbhai Nirmal, Jignesh Girishbhai Parmar and Mehul Gunvantrai Mehta.

Discussion of results: Nital Pravinbhai Nirmal, Jignesh Girishbhai Parmar and Mehul Gunvantrai Mehta.

Writing – Original Draft: Nital Pravinbhai Nirmal, Jignesh Girishbhai Parmar and Mehul Gunvantrai Mehta.

Writing – Review and Editing: Nital Pravinbhai Nirmal, Jignesh Girishbhai Parmar and Mehul Gunvantrai Mehta.

Resources: Nital Pravinbhai Nirmal, Jignesh Girishbhai Parmar and Mehul Gunvantrai Mehta.

Supervision: Nital Pravinbhai Nirmal, Jignesh Girishbhai Parmar and Mehul Gunvantrai Mehta.

Approval of the final text: Nital Pravinbhai Nirmal, Jignesh Girishbhai Parmar and Mehul Gunvantrai Mehta.

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