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RANKING AND SELECTION OF ROBOT USING ADVANCE CORRELATION COEFFICIENT SINGLE-VALUED NEUTROSOPHIC SET MULTI-ATTRIBUTE DECISION-MAKING TECHNIQUE

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ABSTRACT

Industrial robot selection plays a critical role in modern manufacturing systems, as the choice of an appropriate robot directly affects productivity, operational efficiency, product quality, and overall cost performance. However, selecting a suitable robot is a challenging task due to the presence of multiple conflicting criteria and the inherent uncertainty in decision data, making it a complex Multi-Attribute Decision-Making (MADM) problem. This study proposes an advanced decision-making framework that integrates Single-Valued Neutrosophic Sets (SVNS) with the Advanced Correlation Coefficient (ACC) to enhance the reliability and effectiveness of robot ranking and selection. The proposed approach transforms conventional decision data into the SVNS domain, where each alternative is represented through three independent membership degrees: truth, indeterminacy, and falsity, allowing a more realistic handling of uncertainty and incomplete information. The ACC measure is then used to determine the closeness of each alternative to the ideal solution, enabling a structured ranking process. A standard robot selection case study is employed to demonstrate the applicability of the method. The results show strong agreement with existing techniques, confirming its validity and robustness. The method is computationally simple and does not require complex weight calculations, making it suitable for practical engineering decision-making applications.



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I. INTRODUCTION

Robotics plays a crucial role in advancing modern technology by enhancing efficiency, accuracy, and safety across various sectors. Robots are capable of performing repetitive and complex tasks with high precision, reducing human effort and minimizing errors in industrial processes. They are especially valuable in hazardous environments where they help prevent risks to human life. In addition, robotics contributes to increasing productivity, cost effectiveness and consistent quality in manufacturing, healthcare, agricultural, pharmaceutical, oil industries and service industries. Overall, the importance of robotics lies in its ability to improve performance, ensure safety, and support innovation in a rapidly evolving technological world. Robotic system offers both benefits and limitations, making the identification of the most appropriate robot for the application a critical task. [1] briefly explain that the selection becomes even more complex due to their diverse capabilities, design specifications, adaptability, cost, and performance. Therefore, selecting a suitable robot can be viewed as a multi-attribute decision-making (MADM) problem, where several parameters must be evaluated simultaneously to reach an optimal decision. [2] Explained that selecting the right robot requires evaluating multiple, often conflicting criteria. [3] explained that selecting the right robot for a manufacturing environment from a large set of alternatives makes the decision making process difficult. [3] author also tried to explained that robot selection involves evaluating multiple attributes such as material availability, configurations, cost, space requirements, load capacity, human interaction, degree of freedom, control type, programming methods, work volume, speed, movement and quality of robot.

Existing ranking and selection MADM techniques for order preference by similarity to Ideal Solution (TOPSIS), Preference Ranking Index (PSI), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), and Isekriterijumsko KOmpromisno Rangiranje (VIKOR), etc. have been widely used, but they face challenges in handling uncertainty and imprecise information. To address this gap, the present work proposes a Fuzzy Single Value Neutrosophic Set (F-SVNS) based Advanced Correlation Coefficient (ACC) MADM technique for effective robot ranking and selection. The objective of this paper is to develop a simple and reliable decision-making approach that can yield more accurate ranking results. This method is applied to standard case study to validate its performance. At the end, compare the ranking with existing approaches. This finding indicates that the proposed method offers more consistent and practical results, making it suitable for real-world manufacturing decision-making, although its effectiveness depends on the robot selection of criteria and available data.

II. LITERATURE REVIEW

II.1 SELECTION THROUGH MADM TECHNIQUES

The enumerations of citations in the body of the article must be sequenced in the order in which they appear, according to the example shown below. [4] implemented Fuzzy Entropy weight based SVNS MADM for Rapid prototype ranking and selection. [3] implemented ranking and selection of automated guided vehicle (AGV) using F-SVNS MADM technique. The application of neutrosophic-based MADM techniques has proven to be highly effective in handling uncertainty in supplier selection problems [5] Supplied selection method was proposed by [6] applied fuzzy inference decision support system for supplier selection in industrial environment. [7] implemented modelling of vendor selection problem using fuzzy inference decision support system. Industrial drilling machine different parts collected and assembled from the vendor and this study is implemented by using fuzzy inference decision support system with diagrammatic figure. [8] also showed the importance of MADM in selection methodology. [9] also tried to show the importance of selection methodology in supply chain management field. [10] investigated F-SVNS selection methodology gives best result to improve manufacturing and supply chain functions.

II.2 ROBOT SELECTION THROUGH MADM TECHNIQUES

Applications of existing MADM techniques for robot selection, gathered from reviewed journals and international books, are listed here. [11] investigated best worst method for robot selection. FBWM-PROMETHEE approach for industrial robot selection was implemented by [12]. [13] has carried out the comparative analysis of robot selection using two newly developed hybrid MCDM models, namely TOPSIS-ARAS and COPRAS-ARAS. [14] explained the key consideration of industrial robot selection. [15] has tried to insight the robot selection importance through MADM techniques. [16] worked to select the military robot selection through Fuzzy AHP and TOPSIS methodology this was the hybrid approach of MADM technique. [17] worked to select the robotic gripper under multi criteria/ attribute environment. [18] developed and applied an extended version of the PROMETHEE method to address robot selection decision-making. [19] proposed a fuzzy extended VIKOR-based model for mobile robot selection in hospital pharmacy applications.

III. PROPOSED METHODOLOGY- FUZZY SINGLE VALUED NEUTROSOPHIC SET SVNS ADVANCE CORRELATION COEFFICIENT MULTI ATTRIBUTE DECISION MAKING TECHNIQUE (F-SVNS-ACC-MADM)

Fuzzy Single Valued Neutrosophic Set Advance Correlation Coefficient Multi Attribute Decision Making (F-SVNS ACC-MADM) methodological steps are as below.

- Step 1.** Define the objective of MADM i.e. ranking/ sorting/ evaluation/ selection in decision making.
- Step 2.** Identification of various alternatives and relative attributes (criteria) involved in selection problem.
- Step 3.** Preparation of the decision matrix

All alternatives and attributes (criteria) in matrix form with relative performance are known as decision matrix. Let us consider set of alternatives $A = \{A_i, i = 1, 2, 3, \dots, m\}$ & set of criteria as $C = \{C_j, j = 1, 2, 3, \dots, n\}$, Here, X_{ij} is the performance of alternatives A_i for relative criteria C_j . X_{ij} are having qualitative/ quantitative values. Table 1 shows the decision matrix.

Table 1: Decision Matrix.

	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, (2026).

- Step 4.** Conversion of qualitative data into quantitative data.
Convert qualitative (linguistic) information into quantitative (crisp) values with the help of Table 2. If the input matrix contains only quantitative information, then skip this step.
- Step 5.** Generalization/ normalization of matrix

In [20], As per [21], each relative attributes of alternatives are having different values. Normalization is carried out to make the information in range [0, 1]. Here, the normalization is carried out with Vector Normalization Method (VNM). For beneficial criteria; where highest values are desirable (i. e. quality, profit, etc.) normalization is carried out with Equation (1)

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

and for non-beneficial criteria where lower values are desirable (i.e. price, lead time etc.) normalization is carried out with Equation (2)

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

Normalized decision matrix is shown in Table 2.

Table 2: Normalized Decision matrix for F-SVNS ACC- MADM.

	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, (2026).

Step 6. Conversion of classic set/ fuzzy set to Single Valued Neutrosophic (SVNS)

SVNS normalized decision matrix for F-SVNS ACC-MADM is as shown in Table 3.

Table 3: SVNS Normalized Decision Matrix for F-SVNS ACC-MADM.

	C ₁	C ₂		C _n
A ₁	< T ₁₁ (x), I ₁₁ (x), F ₁₁ (x) >	< T ₁₂ (x), I ₁₂ (x), F ₁₂ (x) >		< T _{1n} (x), I _{1n} (x), F _{1n} (x) >
A ₂	< T ₂₁ (x), I ₂₁ (x), F ₂₁ (x) >	< T ₂₂ (x), I ₂₂ (x), F ₂₂ (x) >		< T _{2n} (x), I _{2n} (x), F _{2n} (x) >
A ₃	< T ₃₁ (x), I ₃₁ (x), F ₃₁ (x) >	< T ₃₂ (x), I ₃₂ (x), F ₃₂ (x) >		< T _{3n} (x), I _{3n} (x), F _{3n} (x) >
....				
A _m	< T _{m1} (x), I _{m1} (x), F _{m1} (x) >	< T _{m2} (x), I _{m2} (x), F _{m2} (x) >		< T _{mn} (x), I _{mn} (x), F _{mn} (x) >

Source: Authors, (2026).

In [20], as per [21], the conversion rule for classic or fuzzy set to SVNS for beneficial and non-beneficial criteria [21] is explained below.

- In [19], as per [20], beneficial criteria: (higher value of performance measures of selection criteria is desirable. i.e. quality, profit, etc.) considering positive ideal solution (PIS) as < T_{max}^{*}(x), I_{min}^{*}(x), F_{min}^{*}(x) >; normalized input matrix beneficial criteria are considered as degree of truthness T_A(x), while degree of indeterminacy, degree of falsity as I_A(x) = F_A(x) = 1 – T_A(x) respectively. SVNS conversion is carried out with this Equation (3).
- In [19], as per [20], non-beneficial criteria: (lower value of performance measure of selection criteria is desirable i.e. cost, lead time, etc.): Considering negative ideal solution (NIS) as < T_{min}^{*}(x), I_{max}^{*}(x), F_{max}^{*}(x) >; normalized input matrix non-beneficial criteria are considered as degree of indeterminacy and falsehood as I_A(x) = F_A(x) while degrees of truthness is considered as T_A(x) = 1 – I_A(x) = 1 – F_A(x). SVNS conversion is carried out with this Equation (4).

Step 7. Find the ideal solution for beneficial and non-beneficial attributes

Beneficial attributes ideal solution BAIS = < T_{max}^{*}(x), I_{min}^{*}(x), F_{min}^{*}(x) > = < 1, 0, 0 >

Non-beneficial attributes ideal solution NBAIS = < T_{min}^{*}(x), I_{max}^{*}(x), F_{max}^{*}(x) > = < 0, 1, 1 >

Step 8. Calculation of the Advance Correlation Coefficient function of Alternatives

Find the Advance Correlation Coefficient function for each alternative with Equation (5)

$$W(A_j) = \frac{\sum_{j=1}^n [T_{ij}T_j^* + I_{ij}I_j^* + F_{ij}F_j^*]}{\max\{\sum_{j=1}^n [(T_{ij}T_j^*)^2 + (I_{ij}I_j^*)^2 + (F_{ij}F_j^*)^2], \sum_{j=1}^n [T_j^{*2} + I_j^{*2} + F_j^{*2}]\}} \quad (6)$$

Step 9. Ranking of alternatives

After calculation of alternative weight A_w the alternatives are ranked according to descending order. i.e. highest alternatives correlation coefficient A_w is considered as leading rank, while lowest alternative score . A_w is considered as last ranked

IV. COLLECTED CASE STUDY: ROBOT SELECTION

Step 1: One case example of robot selection was adopted and demonstrate by[22] with regression analysis. The case example was implemented further and illustrated by [2] with fuzzy regression model, [23] by with multivariate procedure, [24] was worked on the same problem with TOPSIS methodology, [25] were worked on the same case example with PROMETHEE-II.

Step 2: Here are twenty-seven robot alternatives with four attributes and their attributes measures are C1: velocity (m/s), C2: load capacity (Kg), C3: cost (Dollar) and C4: Repeatability (mm). Here, beneficial attributes are C1 and C2; whereas Non-beneficial attributes are C3 and C4. Actually repeatability of robot must be considered as positive attribute but, for comparison with other published ranking and as per assumption from section 1.6 with 2nd point, data collected from the source is not changed.

Step: 3 Decision matrix was collected from [26], [2], [27], [25] and [24] is as shown in Table 4.

Table 4: Robot Selection Input Matrix (Collected Case Example).

Sr. No. Alternatives	C1 (+)	C2 (+)	C3(-)	C4 (-)
A1	1.35	60	7.2	0.15
A2	1.1	6	4.8	0.05
A3	1.27	45	5	1.27
A4	0.66	1.5	7.2	0.025
A5	0.05	50	9.6	0.25
A6	0.3	1	1.07	0.1
A7	1	5	1.76	0.1
A8	1	15	3.2	0.1
A9	1.1	10	6.72	0.2
A10	1	6	2.4	0.05
A11	0.9	30	2.88	0.5
A12	0.15	13.6	6.9	1
A13	1.2	10	3.2	0.05
A14	1.2	30	4	0.05
A15	1.2	47	3.68	1
A16	1	80	6.88	1
A17	2	15	8	2
A18	1	10	6.3	0.2
A19	0.3	10	0.94	0.05
A20	0.8	1.5	0.16	2
A21	1.7	27	2.81	2
A22	1	0.9	3.8	0.05
A23	0.5	2.5	1.25	0.1
A24	0.5	2.5	1.37	0.1
A25	1	10	3.63	0.2
A26	1.25	70	5.3	1.27
A27	0.75	205	4	2.03

Source: [22], [2], [27], [25], [24].

Step 6. Conversion of qualitative data in to quantitative data

Here, the input information contains quantitative information only, so there is no need to convert qualitative value in to quantitative value. So, this step is eliminated in the current case example.

Step 7. Normalization of Table 4 is carried out with the Equation 1/ Equation 2. Robot selection normalized matrix is shown in Table 5.

Table 5: Robot Selection Normalized Matrix using VNM.

Alternatives (Sr. No.)	C1 (+)	C2 (+)	C3(-)	C4 (-)
A1	0.2516	0.2310	0.7154	0.9686
A2	0.2050	0.0237	0.8103	0.9895
A3	0.2367	0.1781	0.8023	0.7344
A4	0.1230	0.0059	0.7154	0.9948
A5	0.0093	0.1979	0.6205	0.9477
A6	0.0559	0.0040	0.9577	0.9791
A7	0.1864	0.0198	0.9304	0.9791
A8	0.1864	0.0594	0.8735	0.9791
A9	0.2050	0.0396	0.7344	0.9582
A10	0.1864	0.0237	0.9051	0.9895
A11	0.1678	0.1187	0.8862	0.8954
A12	0.0280	0.0538	0.7272	0.7909
A13	0.2237	0.0396	0.8735	0.9895
A14	0.2237	0.1187	0.8419	0.9895
A15	0.2237	0.1860	0.8545	0.7909
A16	0.1864	0.3166	0.7280	0.7909
A17	0.3728	0.0594	0.6838	0.5818
A18	0.1864	0.0396	0.7510	0.9582
A19	0.0559	0.0396	0.9628	0.9895
A20	0.1491	0.0059	0.9937	0.5818
A21	0.3169	0.1069	0.8889	0.5818
A22	0.1864	0.0036	0.8498	0.9895
A23	0.0932	0.0099	0.9506	0.9791
A24	0.0932	0.0099	0.9458	0.9791
A25	0.1864	0.0396	0.8565	0.9582
A26	0.2330	0.2770	0.7905	0.7344
A27	0.1398	0.8114	0.8419	0.5755

Source: Authors, (2026).

Step 6. 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.

- Beneficial attributes i.e. Alternative A1 and attribute C1 having value 0.2516 converted in SVNS gives the value $\langle 0.2516, (1 - 0.2516), (1 - 0.2516) \rangle = \langle 0.2516, 0.7484, 0.7484 \rangle$. The same calculation is also carried out for attribute C2.
- Non-beneficial attributes i.e. Alternative A1 and attribute C3 having value 0.7154 converted in SVNS gives the value $\langle (1 - 0.7154), 0.7154, 0.7154 \rangle = \langle 0.2846, 0.7154, 0.7154 \rangle$. The same calculation is also carried out for attribute C4.

Step 7. 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 3/ Equation 4, where $BAIS(A^*) = \langle T_{max}^*(x), I_{min}^*(x), F_{min}^*(x) \rangle = \langle 1, 0, 0 \rangle$ and $NBAIS(A^*) = \langle T_{min}^*(x), I_{max}^*(x), F_{max}^*(x) \rangle = \langle 0, 1, 1 \rangle$. The calculations of step 8 and step 9 directly calculated and shown in the Table. are shown in following table. The rank is calculated with F-SVNS-ACC-MADM is as shown in Table 6.

Table 6: F-SVNS ACC-MADM Ranking of Robot Selection.

Alternatives (Sr. No.)	C1 (+)	C2 (+)	C3(-)	C4 (-)	A_w	Rank
A1	$\langle 0.2516, 0.7484, 0.7484 \rangle$	$\langle 0.2310, 0.7690, 0.7690 \rangle$	$\langle 0.2846, 0.7154, 0.7154 \rangle$	$\langle 0.0314, 0.9686, 0.9686 \rangle$	0.6418	12
A2	$\langle 0.2050, 0.7950, 0.7950 \rangle$	$\langle 0.0231, 0.9759, 0.9759 \rangle$	$\langle 0.1897, 0.8103, 0.8103 \rangle$	$\langle 0.0105, 0.9895, 0.9895 \rangle$	0.6380	14
A3	$\langle 0.2367, 0.7633, 0.7633 \rangle$	$\langle 0.1733, 0.8267, 0.8267 \rangle$	$\langle 0.1977, 0.8023, 0.8023 \rangle$	$\langle 0.2656, 0.7344, 0.7344 \rangle$	0.5806	22
A4	$\langle 0.1230, 0.8770, 0.8770 \rangle$	$\langle 0.0058, 0.9942, 0.9942 \rangle$	$\langle 0.2846, 0.7154, 0.7154 \rangle$	$\langle 0.0052, 0.9948, 0.9948 \rangle$	0.5915	20
A5	$\langle 0.0093, 0.9907, 0.9907 \rangle$	$\langle 0.1925, 0.8075, 0.8075 \rangle$	$\langle 0.3795, 0.6205, 0.6205 \rangle$	$\langle 0.0523, 0.9477, 0.9477 \rangle$	0.5564	24
A6	$\langle 0.0559, 0.9441, 0.9441 \rangle$	$\langle 0.0039, 0.9961, 0.9961 \rangle$	$\langle 0.0423, 0.9577, 0.9577 \rangle$	$\langle 0.0209, 0.9791, 0.9791 \rangle$	0.6556	9
A7	$\langle 0.1864, 0.8136, 0.8136 \rangle$	$\langle 0.0193, 0.9807, 0.9807 \rangle$	$\langle 0.0696, 0.9304, 0.9304 \rangle$	$\langle 0.0209, 0.9791, 0.9791 \rangle$	0.6708	1
A8	$\langle 0.1864, 0.8136, 0.8136 \rangle$	$\langle 0.0578, 0.9422, 0.9422 \rangle$	$\langle 0.1265, 0.8735, 0.8735 \rangle$	$\langle 0.0209, 0.9791, 0.9791 \rangle$	0.6582	8
A9	$\langle 0.2050, 0.7950, 0.7950 \rangle$	$\langle 0.0385, 0.9615, 0.9615 \rangle$	$\langle 0.2656, 0.7344, 0.7344 \rangle$	$\langle 0.0418, 0.9582, 0.9582 \rangle$	0.6048	18
A10	$\langle 0.1864, 0.8136, 0.8136 \rangle$	$\langle 0.0231, 0.9769, 0.9769 \rangle$	$\langle 0.0949, 0.9051, 0.9051 \rangle$	$\langle 0.0105, 0.9895, 0.9895 \rangle$	0.6665	4
A11	$\langle 0.1678, 0.8322, 0.8322 \rangle$	$\langle 0.1155, 0.8845, 0.8845 \rangle$	$\langle 0.1138, 0.8862, 0.8862 \rangle$	$\langle 0.1046, 0.8954, 0.8954 \rangle$	0.6411	13
A12	$\langle 0.0280, 0.9720, 0.9720 \rangle$	$\langle 0.0524, 0.9476, 0.9476 \rangle$	$\langle 0.2728, 0.7272, 0.7272 \rangle$	$\langle 0.2091, 0.7909, 0.7909 \rangle$	0.5194	26
A13	$\langle 0.2237, 0.7763, 0.7763 \rangle$	$\langle 0.0385, 0.9615, 0.9615 \rangle$	$\langle 0.1265, 0.8735, 0.8735 \rangle$	$\langle 0.0105, 0.9895, 0.9895 \rangle$	0.6647	5
A14	$\langle 0.2237, 0.7763, 0.7763 \rangle$	$\langle 0.1155, 0.8845, 0.8845 \rangle$	$\langle 0.1581, 0.8419, 0.8419 \rangle$	$\langle 0.0105, 0.9895, 0.9895 \rangle$	0.6670	2
A15	$\langle 0.2237, 0.7763, 0.7763 \rangle$	$\langle 0.1810, 0.8190, 0.8190 \rangle$	$\langle 0.1455, 0.8545, 0.8545 \rangle$	$\langle 0.2091, 0.7909, 0.7909 \rangle$	0.6159	16
A16	$\langle 0.1864, 0.8136, 0.8136 \rangle$	$\langle 0.3081, 0.6919, 0.6919 \rangle$	$\langle 0.2720, 0.7280, 0.7280 \rangle$	$\langle 0.2091, 0.7909, 0.7909 \rangle$	0.5887	21

A17	<0.3728, 0.6272, 0.6272>	<0.0578, 0.9422, 0.9422>	<0.3162, 0.6838, 0.6838>	<0.4182, 0.5818, 0.5818>	0.4936	27
A18	<0.1864, 0.8136, 0.8136>	<0.0385, 0.9615, 0.9615>	<0.2490, 0.7510, 0.7510>	<0.0418, 0.9582, 0.9582>	0.6072	17
A19	<0.0559, 0.9441, 0.9441>	<0.0385, 0.9615, 0.9615>	<0.0372, 0.9628, 0.9628>	<0.0105, 0.9895, 0.9895>	0.6665	3
A20	<0.1491, 0.8509, 0.8509>	<0.0058, 0.9942, 0.9942>	<0.0063, 0.9937, 0.9937>	<0.4182, 0.5818, 0.5818>	0.5510	25
A21	<0.3169, 0.6831, 0.6831>	<0.1040, 0.8960, 0.8960>	<0.1111, 0.8889, 0.8889>	<0.4182, 0.5818, 0.5818>	0.5604	23
A22	<0.1864, 0.8136, 0.8136>	<0.0035, 0.9965, 0.9965>	<0.1502, 0.8498, .8498>	<0.0105, 0.9895, 0.9895>	0.6448	10
A23	<0.0932, 0.9068, 0.9068>	<0.0096, 0.9904, 0.9904>	<0.0494, 0.9506, 0.9506>	<0.0209, 0.9791, 0.9791>	0.6604	6
A24	<0.0932, 0.9068, 0.9068>	<0.0096, 0.9904, 0.9904>	<0.0542, 0.9458, 0.9458>	<0.0209, 0.9791, 0.9791>	0.6588	7
A25	<0.1864, 0.8136, 0.8136>	<0.0385, 0.9615, 0.9615>	<0.1435, 0.8565, 0.8565>	<0.0418, 0.9582, 0.9582>	0.6424	11
A26	<0.2330, 0.7670, 0.7670>	<0.2696, 0.7304, 0.7304>	<0.2095, 0.7905, 0.7905>	<0.2656, 0.7344, 0.7344>	0.5921	19
A27	<0.1398, 0.8602, 0.8602>	<0.7894, 0.2106, 0.2106>	<0.1581, 0.8419, 0.8419>	<0.4245, 0.5755, 0.5755>	0.6273	15
A*	<1.000, 0.0000, 0.0000>	<1.0000, 0.0000, 0.0000>	<0.0000, 1.0000, 1.0000>	<0.0000, 1.0000, 1.0000>		

Source: Authors, (2026).

V. PERFORMANCE MEASURES COMPARISON: ROBOTS RANKING DISCUSSIONS

The result of proposed three methodologies is compared with the published results to validate them for robot selection. To compare the result, all Robot alternatives are ranked according to alternatives weight values is as shown in Table 6. The Robot alternatives are ranked first whose alternative weight value is highest; Robot alternative is ranked second whose alternatives weight values is second highest. Finally the ranking order obtained by the proposed three different methodologies is compared with the ranking order published in the literature and result comparisons are shown in Table 7.

Table 7: Robot Selection Performance Measures Comparison.

Alternatives (Sr. No.)	Proposed Methodology	Collected ranking from [26]		Collected ranking from [2]	
	F-SVNS MADM- ACC	Regression method	Fuzzy Regression method	PROMETHEE-II (Equal criteria weight)	PROMETHEE-II (Unequal criteria weight)
A1	12	2	3	6	4
A2	14	4	6	13	7
A3	22	22	22	21	19
A4	20	8	14	23	21
A5	24	10	18	26	25
A6	9	24	15	15	17
A7	1	9	5	1	1
A8	8	6	7	5	6
A9	18	11	13	17	11
A10	4	5	4	4	5
A11	13	16	17	12	10
A12	26	26	23	27	27
A13	5	3	2	3	3

A14	2	1	1	2	2
A15	16	21	20	16	18
A16	21	15	19	22	20
A17	27	25	26	25	24
A18	17	13	16	19	12
A19	3	7	9	10	15
A20	25	27	27	24	26
A21	23	23	25	20	22
A22	10	14	8	9	8
A23	6	19	11	7	13
A24	7	20	12	11	14
A25	11	12	10	8	9
A26	19	17	21	18	16
A27	15	18	24	14	23

Source: Authors, (2026).

The result comparisons presented in Table 7 shows that the result obtained from the proposed methodologies are roughly similar to the result reported in the literature. Initially robot selection problem was solved by [26] using regression and fuzzy regression method which showed that robot with alternative A14 is the first choice, which is based on mathematical modeling. The same robot selection problem was solved by [2] using PROMETHEE-II considering equal weight criteria and unequal weight criteria and it is showed that robot with alternative A7 is the first choice. Both methodologies differ from the proposed methodology and it has been found that the first robot ranking solution given by the two methodologies is nearer to each other. Hence, ranking solution using the proposed method is obviously more genuine. Further, 2nd rank is calculated by F-SVNS N-MADM and F-SVNS ACC-MADM matched with published results of PROMETHEE-II with equal and unequal criteria weight consideration. While for 4th rank is calculated by proposed methods matched with published results of fuzzy regression and PROMETHEE-II equal criteria weight method. Where, actually regression method is not a part of MADM method though it shows similarity in ranking. While, regression method and PROMETHEE-II with unequal weight method published results their selves not match among each other, due to different weight criteria calculation/ assumption/ expert opinion. It also shows that if there are more numbers of alternatives its gives comparative good ranking solutions. Proposed methodologies work with minimum calculations, without calculating any kind of relative importance of attributes, without need to resize the assignment matrix and it is gifted to convert simple set or linguistic set to F-SVNS. Here, Proposed methodology F-SVNS ACC-MADM, work without calculating attribute weight among other MADM methodology. With comparison with other published results show that proposed methods prove the validity, applicability and reliability for the robots selection for manufacturing environment which leads to improve manufacturing function.

VI. CONCLUSIONS

This study develops a practical and reliable approach for robot ranking and selection by combining Single-Valued Neutrosophic Sets (SVNS) with the Advanced Correlation Coefficient (ACC) within a Multi-Attribute Decision-Making framework. The method represents each alternative using three independent measures like degree of truthness, degree of indeterminacy, and degree of falsity, these helps in capturing uncertainty and incomplete information more effectively than many traditional techniques. By working in the neutrosophic environment, the proposed approach allows decision-makers to express hesitation and ambiguity in a more realistic way. The use of the Advanced Correlation Coefficient further supports the evaluation process by providing a clear measure of how closely each alternative matches the ideal solution. Together, these features make the method both flexible and logically sound. The effectiveness of the approach is demonstrated through a standard robot selection example. The results are consistent with those obtained using existing methods, which confirms the validity of the proposed framework. At the same time, the ranking outcomes remain stable across different evaluation conditions, showing that the method is dependable and not overly sensitive to changes in input data. Another important advantage of this method is its simplicity. It avoids complicated calculations and does not rely heavily on difficult weight determination procedures, making it easier to apply in practical situations. This is particularly useful in industrial environments where decisions often need to be made quickly and efficiently. Overall, the proposed SVNS-ACC-based MADM approach provides a useful decision-support tool for selecting robots in manufacturing systems. Its ability to handle uncertainty, produce consistent results, and remain computationally simple makes it valuable for real-world applications. In addition, the framework can be extended to other multi-criteria decision-making problems in engineering and management, offering scope for further research and development.

VII. AUTHOR'S CONTRIBUTION

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