A Hybrid Triangular Fuzzy MCDM Model for Evaluating and Selecting the Optimal Industrial Robot for Manufacturing Plants Based on Fuzzy AHP and Fuzzy ARAS

Ngoc Tien Tran
School of Mechanical and Automotive Engineering, Hanoi University of Industry, Hanoi, Vietnam
tientn@haui.edu.vn

Van Long Trinh
School of Mechanical and Automotive Engineering, Hanoi University of Industry, Hanoi, Vietnam
longtv@haui.edu.vn (corresponding author)

Tien Sy Nguyen
School of Mechanical and Automotive Engineering, Hanoi University of Industry, Hanoi, Vietnam
nguyentiensy@haui.com.vn

Viet Hoi Tran
School of Mechanical and Automotive Engineering, Hanoi University of Industry, Hanoi, Vietnam
hoitv@haui.edu.com

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ABSTRACT

Selecting the optimal industrial robot is a crucial factor in enhancing production efficiency and reducing operational costs. However, conflicts among evaluation criteria make this process challenging, requiring a structured decision-making approach. The present study proposes a hybrid Multi-Criteria Decision-Making (MCDM) model that integrates the Fuzzy Analytic Hierarchy Process (FAHP) and the Fuzzy Additive Ratio Assessment (FARAS). The model consists of six main steps: constructing the pairwise contribution matrix from experts regarding the relationships between criteria, developing the fuzzy pairwise comparison matrix for weights, determining the fuzzy weights of each criterion, obtaining expert evaluations of the alternatives, normalizing the data, and ranking the alternatives. Industrial robot selection must achieve a balance between performance and cost considerations. High-performance robots offer superior accuracy and reliability but come with high investment costs, whereas low-cost options may not meet technical requirements. The proposed approach utilizes fuzzy set theory to address the uncertainties inherent in expert evaluations. FAHP determines the criterion weights, whereas FARAS ranks robots based on aggregated performance scores. A case study involving ten industrial robots was conducted to validate the model's effectiveness. The results indicate that Robot 1 is the optimal choice, whereas Robot 6 ranks the lowest. The findings of the study demonstrate that the hybrid fuzzy MCDM approach not only improves accuracy but also provides a comprehensive decision-support tool, enabling manufacturing organizations to select suitable robots based on scientifically grounded data.

Keywords-MCDM methods; fuzzy AHP; fuzzy ARAS; industrial robots

I. INTRODUCTION

The evaluation and decision-making process is characterized by its inherent complexity. The evaluation of criteria is a challenging process, due to the complexity of the assessment process. To address this issue, it is necessary to employ a combination of modern methodologies, including mathematics, economic theory, and various statistical methods. This integration not only facilitates the computation and estimation of solutions to decision-making problems but also provides deep insights into the complex interactions among the problem's components. One of the most widely adopted approaches for addressing such problems is Multi-Criteria Decision Making (MCDM) [1-4]. MCDM provides a comprehensive analytical framework for evaluating decisions related to multiple criteria. This method considers both qualitative and quantitative factors, thereby overcoming the limitations of single-criterion evaluations and yielding more balanced and optimal outcomes. MCDM has been applied extensively across various fields. For instance, MCDM has been used to select the optimal location and technology for solar power plants [5]. Additionally, MCDM has been applied to rank the economic status of 22 districts in Tehran for establishing financial and commercial centers [6]. Furthermore, MCDM has been used to select material handling equipment in industry by using the entropy in combination with MCDM techniques [7]. Finally, MCDM tools have been applied for selecting industrial robots for industrial manufacturing [8]. This study offers a comprehensive evaluation of various weight assignment strategies, including average weighting, standard deviation, and the entropy method. The analysis aims to assess their impact on the final outcomes. The MCDM has become an indispensable tool across a wide range of fields to select the most appropriate alternative in multi-criteria decisions. A substantial number of researchers have adopted traditional MCDM methods, including the Analytic Hierarchy Process (AHP) [9], the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [10], and the Decision-Making Trial and Evaluation Laboratory (DEMATEL) [11]. Furthermore, the integration of traditional MCDM methods with fuzzy logic has yielded substantial benefits in decision-making processes [12]. This hybridization reduces the influence of expert subjectivity during evaluations, thereby promoting fairer and more objective outcomes. Additionally, it provides a flexible mechanism to manage uncertainty, thereby minimizing its influence on the final decision. One such study proposed a hybrid model combining the Fuzzy Analytic Hierarchy Process (FAHP) and the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS) to evaluate and select the most appropriate robot among several alternatives. This model processes fuzzy expert input to determine criterion weights and ranks robot alternatives accordingly [13]. Additionally, MCDM methods, including FAHP, FTOPSIS, and the Simple Multi-Attribute Rating Technique (SMART), have been employed to select industrial robots for a flexible assembly station [14]. New hybrid MCDM models have also been developed, such as TOPSIS–Additive Ratio Assessment (ARAS) [15] and TOPSIS–Entropy [16], further enhancing the robustness and flexibility of robot selection methodologies.

The present paper proposes a novel hybrid MCDM model of FAHP and Fuzzy Additive Ratio Assessment (FARAS) for application in the manufacturing industry, with the objective of selecting the optimal industrial robot for the factory. This integrated approach is applied in a fuzzy environment, where fuzzy information is processed based on expert evaluations to determine the priority weights of each criterion. Subsequent to the acquisition of these weights, the alternatives are prioritized through a process of ranking based on the evaluated factors.

II. METHODOLOGICAL STUDY

The FAHP method is carried out through the following steps:

- Step 1: Establishing the relationship between the criteria. The decision-maker employs the linguistic terms presented in Table I to compare the criteria. The linguistic terms are defined using a triangular fuzzy scale as follows: If criterion 1 is considered to be of significant importance relative to criterion 2, the corresponding triangular fuzzy scale is (6, 7, 8). Conversely, when criterion 2 is compared to criterion 1, the inverse triangular fuzzy scale is (1/8, 1/7, 1/6).

TABLE I. LINGUISTIC TERMS AND THE CORRESPONDING TRIANGULAR FUZZY NUMBERS

Linguistic variable	Corresponding triangular fuzzy number	Inverse of the triangular fuzzy number
Extreme vital importance (EXI)	(9, 9, 9)	(1/9, 1/9, 1/9)
Very vital importance (VEI)	(6, 7, 8)	(1/8, 1/7, 1/6)
Essential importance (ESI)	(4, 5, 6)	(1/6, 1/5, 1/4)
Moderate importance (MOI)	(2, 3, 4)	(1/4, 1/3, 1/2)
Equally importance (EQI)	(1, 1, 1)	(1, 1, 1)
Moderate unimportance (MOU)	(1/4, 1/3, 1/2)	(2, 3, 4)
Essential unimportance (ESU)	(1/6, 1/5.1/4)	(4, 5, 6)
Very unimportance (VEU)	(1/8, 1/7, 1/6)	(6, 7, 8)
Extreme unimportance (EXU)	(1/9, 1/9, 1/9)	(9, 9, 9)

- Step 2: Constructing the pairwise contribution matrix:

$$\tilde{A}_k = \begin{bmatrix} \tilde{d}_{12}^k & \cdots & \tilde{d}_{1n}^k \\ \tilde{d}_{21}^k & \cdots & \tilde{d}_{2n}^k \\ \cdots & \cdots & \cdots \\ \tilde{d}_{n1}^k & \cdots & \tilde{d}_{nn}^k \end{bmatrix}_{n\times n} \quad (1)$$

where $\tilde{d}_{ij}^k$ denotes the preference of the *k*-th decision-maker when evaluating criterion *i* compared to criterion *j* using triangular fuzzy scales.

- Step 3: Constructing the pairwise comparison matrix. If multiple decision-makers are involved, their respective preference values are averaged as follows:

$$\tilde{d}_{ij} = \frac{\sum_{k=1}^{k} \tilde{d}_{ij}^k}{k} \quad (2)$$

The pairwise comparison matrix is constructed as follows:

$$\tilde{A} = \begin{bmatrix} \tilde{d}_{11} & \dots & \tilde{d}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{d}_{n1} & \dots & \tilde{d}_{nn} \end{bmatrix}_{n\times n} \quad (3)$$

- Step 4: Calculating the geometric mean of the fuzzy comparison values for each criterion:

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{d}_{ij}\right)^{\frac{1}{n}} \quad (4)$$

- Step 5: Determining the fuzzy weight of each criterion:

$$\tilde{w}_i = \tilde{r}_i \times (\tilde{r}_1 + \tilde{r}_2 + \tilde{r}_3 + \cdots + \tilde{r}_n)^{-1} = (lw_i, mw_i, uw_i) \quad (5)$$

- Step 6: $\tilde{w}_i$ is a triangular fuzzy number, which necessitates defuzzification using the centroid method to obtain a non-fuzzy number:

$$M_i = \frac{lw_i, mw_i, uw_i}{3} \quad (6)$$

- Step 7: Normalizing the weights M_i:

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \quad (7)$$

The aforementioned steps are performed to determine the normalized weights of the criteria and the alternatives. Subsequently, the score for each alternative is calculated by multiplying each alternative's weight by the corresponding criteria weights. The alternative with the highest score is then recommended to the decision-maker.

The steps for implementing FARAS are as follows:

- Step 1: Establishing the fuzzy decision matrix:

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{01} & \tilde{x}_{02} & \cdots & \tilde{x}_{0n} \\ \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix}_{m \times n} \quad (8)$$

where $i = 0, 1, 2, ..., m$ represents the number of alternatives and $j = 1, 2, 3, ..., n$ represents the number of criteria describing each alternative. $\tilde{x}_{ij}$ denotes the fuzzy performance value of the *i*-th alternative according to the *j*-th criterion. x_{0j} represents the optimal level of performance ranking for the *j*-th criterion. The benefit criteria are optimized by maximization, whereas the cost criteria are optimized by minimization. Typically, the performance values $\tilde{x}_{ij}$ and the weights are determined by experts (Table II).

TABLE II. LINGUISTIC TERMS DESCRIBING ATTRIBUTE RATINGS

Linguistic variable	**Corresponding triangular fuzzy number**
Very poor (VP)	(0, 0, 1)
Poor (P)	(0, 1, 3)
Medium poor (MP)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Medium good (MG)	(5, 7, 9)
Good (G)	(7, 9, 10)
Very good (VG)	(9, 10, 10)

- Step 2: Constructing the normalized decision matrix. The normalized decision matrix is represented as follows:

$$\tilde{\bar{X}} = \begin{bmatrix} \tilde{\bar{x}}_{01} & \tilde{\bar{x}}_{02} & \cdots & \tilde{\bar{x}}_{0n} \\ \tilde{\bar{x}}_{11} & \tilde{\bar{x}}_{12} & \cdots & \tilde{\bar{x}}_{1n} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{\bar{x}}_{m1} & \tilde{\bar{x}}_{m2} & \cdots & \tilde{\bar{x}}_{mn} \end{bmatrix}_{m \times n} \quad (9)$$

For criteria where the priority value is maximized: $\tilde{\bar{x}}_{ij} = \frac{\tilde{x}_{ij}}{\sum_{i=0}^{m} \tilde{x}_{ij}}$. For criteria where the priority value is minimized: $\tilde{\bar{x}}_{ij} = \frac{1/\tilde{x}_{ij}}{\sum_{i=0}^{m} 1/\tilde{x}_{ij}}$.

- Step 3: Calculating the weighted fuzzy normalized matrix:

$$\tilde{\hat{X}} = \begin{bmatrix} \tilde{\hat{x}}_{01} & \tilde{\hat{x}}_{02} & \cdots & \tilde{\hat{x}}_{0n} \\ \tilde{\hat{x}}_{11} & \tilde{\hat{x}}_{12} & \cdots & \tilde{\hat{x}}_{1n} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{\hat{x}}_{m1} & \tilde{\hat{x}}_{m2} & \cdots & \tilde{\hat{x}}_{mn} \end{bmatrix}_{m \times n} \quad (10)$$

The weighted normalized values for all criteria are calculated as follows:

$$\tilde{\hat{x}}_{ij} = \tilde{\bar{x}}_{ij} \times \tilde{w}_j \quad (11)$$

where $\tilde{w}_j$ is the fuzzy weight of criterion *j*, and $\tilde{\bar{x}}_{ij}$ is the fuzzy normalized evaluation of criterion *j*.

- Step 4: Calculating the performance index $\tilde{S}_i$ for each alternative:

$$\tilde{S}_i = \sum_{j=1}^{n} \tilde{\hat{x}}_{ij} \quad (12)$$

Since $\tilde{S}_i$ is a fuzzy number in the form $\tilde{S}_i = (s_{i1}, s_{i2}, s_{i3})$, defuzzification is performed to obtain:

$$S_i = \frac{(s_{i1} + s_{i2} + s_{i3})}{3} \quad (13)$$

- Step 5: Calculating the final ranking. The utility degree K_i of an alternative is calculated as follows:

$$K_i = \frac{S_i}{S_0} \quad (14)$$

where S_i and S_0 are the optimal criterion values. The values of K_i fall within the range $[0,1]$ and can be arranged in ascending order, representing the desired priority ranking.

III. RESULTS AND DISCUSSION

Selecting the appropriate industrial robot for different purposes is a significant challenge in the manufacturing field. Determining the right robot requires considering multiple conflicting qualitative and quantitative criteria. Both qualitative and quantitative criteria are considered when selecting an industrial robot. Qualitative criteria include factors such as the human-machine interface, programming flexibility, and vendor service quality. Quantitative criteria include cost, velocity, and vertical reach. Table III shows the four criteria used to evaluate industrial robot selection.

TABLE III. CRITERIA FOR INDUSTRIAL ROBOT SELECTION

No	Criterion	Unit	Criterion type
1	Velocity (VE)	m/s	Max
2	Load capacity (LC)	Kg	Max
3	Cost (CO)	$	Min
4	Repeatability (RE)	mm	Max

This study focuses on selecting a robot that maximizes the VE, LC, and RE benefit criteria by evaluating and ranking ten selected robots, as shown in Table IV.

TABLE IV. NUMERICAL DATA FOR INDUSTRIAL ROBOT SELECTION

Robot	VE	LC	CO	RE
Robot 1	1.35	60	7.20	0.150
Robot 2	1.10	6.0	4.80	0.050
Robot 3	1.27	45.0	5.0	1.270
Robot 4	0.66	1.5	7.20	0.025
Robot 5	0.05	50.0	9.60	0.250
Robot 6	0.30	1.0	1.07	0.100
Robot 7	1.00	5.0	1.76	0.100
Robot 8	1.00	15.0	3.20	0.100
Robot 9	1.10	10.0	6.72	0.200
Robot 10	1.00	6.0	2.40	0.050

In the proposed method, experts play a crucial role in assessing the criteria using linguistic variables. Each linguistic variable corresponds to a set of fuzzy values, accurately reflecting the inherent vagueness in human decision-making. The objective of this evaluation is to determine the weights of the criteria for selecting an industrial robot. To ensure the breadth and depth of our research, we consulted three experts in the field of mechatronics and automation. Each of these experts has at least 10 years of experience in researching and teaching industrial robotics at universities. The hybrid FAHP–FARAS method is comprised of three fundamental steps. First, the definition of objectives and criteria is undertaken, including the incorporation of alternative robots and their associated data. Second, the expert evaluation stage is initiated, during which a pairwise comparison matrix is constructed to determine the fuzzy weights. Third, the decision matrix and ranking stage follows, wherein FARAS is utilized to rank the alternatives. The detailed process is illustrated in Figure 1 and is described as follows:

- Step 1: Based on Table I and (1), we obtain the pairwise contribution matrices from the experts regarding the relationships between the criteria, as shown in Tables V, VI, and VII.
- Step 2: Constructing the fuzzy pairwise comparison matrix for weights. Based on (2) and (3), we obtain the fuzzy pairwise comparison matrix for weights, as shown in Table VIII.

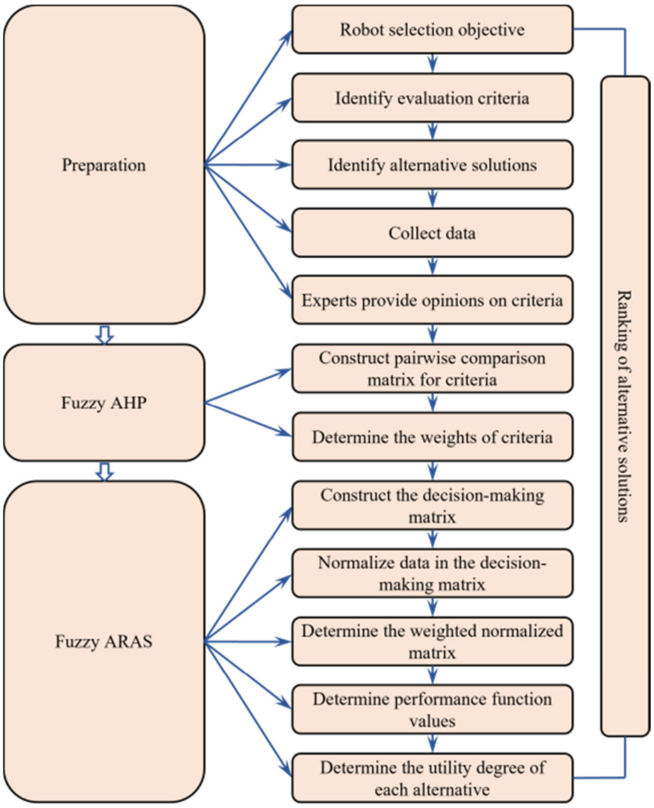

Fig. 1. Evaluation structure diagram.

TABLE V. EVALUATION OF CRITERIA BY EXPERT 1

Criteria	VE	LC	CO	RE
VE	(1, 1, 1)	(4, 5, 6)	(6, 7, 8)	(2, 3, 4)
LC	-	(1, 1, 1)	(4, 5, 6)	(2, 3, 4)
CO	-	-	(1, 1, 1)	(1/4, 1/3, 1/2)
RE	-	-	-	(1, 1, 1)

TABLE VI. EVALUATION OF CRITERIA BY EXPERT 2

Criteria	VE	LC	CO	RE
VE	(1, 1, 1)	(4, 5, 6)	(4, 5, 6)	(2, 3, 4)
LC	-	(1, 1, 1)	(4, 5, 6)	(1, 1, 1)
CO	-	-	(1, 1, 1)	(1/4, 1/3, 1/2)
RE	-	-	-	(1, 1, 1)

TABLE VII. EVALUATION OF CRITERIA BY EXPERT 3

Criteria	VE	LC	CO	RE
VE	(1, 1, 1)	(2, 3, 4)	(6, 7, 8)	(2, 3, 4)
LC	-	(1, 1, 1)	(2, 3, 4)	(2, 3, 4)
CO	-	-	(1, 1, 1)	(1/6, 1/5, 1/4)
RE	-	-	-	(1, 1, 1)

TABLE VIII. FUZZY PAIRWISE COMPARISON MATRIX FOR WEIGHTS

Criteria	VE	LC	CO	RE
VE	(1, 1, 1)	(10/3, 13/3, 16/3)	(16/3, 19/3, 22/3)	(2, 3, 4)
LC	-	(1, 1, 1)	(10/3, 13/3, 16/3)	(5/3, 7/3, 3)
CO	-	-	(1, 1, 1)	(2/9, 13/45, 5/4)
RE	-	-	-	(1, 1, 1)

- Step 3: Determining the fuzzy weights of each criterion. Using (4) and (5), we calculate the fuzzy weight matrix for the criteria, as shown in Table IX.
- Step 4: Expert evaluation of alternatives. Based on Table II, the expert evaluations of the alternatives are presented in Tables X-XIII.
- Step 5: Constructing the fuzzy decision-making matrix for all criteria, outlined in Table XIV.
- Step 6: Calculating the performance index S_i for each alternative. Table XV presents the final performance index S_i determined using (12) and defuzzification using (13).

TABLE IX. FUZZY WEIGHT MATRIX FOR EACH CRITERION

Criterion	**Fuzzy weight ($\tilde{w}_i$)**
VE	(0.369, 0.557, 0.835)
LC	(0.153, 0.229, 0.35)
CO	(0.042, 0.059, 0.122)
RE	(0.077, 0.155, 0.255)

TABLE X. EXPERT'S ASSESSMENT OF ALTERNATIVES ACCORDING TO THE VELOCITY CRITERION

Criterion	**Alternative**	**DM1**	**DM2**	**DM3**
VE	Robot 1	VG	VG	G
	Robot 2	MG	G	MG
	Robot 3	G	G	VG
	Robot 4	MP	MP	F
	Robot 5	VP	P	MP
	Robot 6	P	MP	MP
	Robot 7	F	F	MP
	Robot 8	F	F	MP
	Robot 9	MG	G	MG
	Robot 10	F	F	MP

TABLE XI. EXPERT'S ASSESSMENT OF ALTERNATIVES ACCORDING TO THE LOAD CAPACITY CRITERION

Criterion	**Alternative**	**DM1**	**DM2**	**DM3**
LC	Robot 1	VG	VG	VG
	Robot 2	P	MP	MP
	Robot 3	MG	MG	G
	Robot 4	VP	P	MP
	Robot 5	G	G	VG
	Robot 6	VP	P	MP
	Robot 7	P	MP	MP
	Robot 8	F	F	MP
	Robot 9	MP	MP	F
	Robot 10	P	MP	MP

TABLE XII. EXPERT'S ASSESSMENT OF ALTERNATIVES ACCORDING TO THE COST CRITERION

Criterion	**Alternative**	**DM1**	**DM2**	**DM3**
CO	Robot 1	P	MP	MP
	Robot 2	F	MG	F
	Robot 3	MP	MP	P
	Robot 4	P	MP	MP
	Robot 5	VP	P	MP
	Robot 6	VG	VG	G
	Robot 7	G	G	VG
	Robot 8	F	MG	F
	Robot 9	MP	MP	P
	Robot 10	MG	G	MG

TABLE XIII. EXPERT'S ASSESSMENT OF ALTERNATIVES ACCORDING TO THE REPEATABILITY CRITERION

Criterion	**Alternative**	**DM1**	**DM2**	**DM3**
RE	Robot 1	F	F	F
	Robot 2	P	P	MP
	Robot 3	MG	MG	F
	Robot 4	VP	P	MP
	Robot 5	VG	VG	G
	Robot 6	MP	MP	F
	Robot 7	MP	MP	F
	Robot 8	MP	MP	F
	Robot 9	G	G	VG
	Robot 10	P	P	MP

TABLE XIV. DECISION MATRIX FOR ALL CRITERIA

Alternative	**VE**	**LC**	**CO**	**RE**
Robot 1	(25/3, 29/3, 10)	(9, 10, 10)	(2/3, 7/3, 13/3)	(3, 5, 7)
Robot 2	(17/3, 23/3, 28/3)	(2/3, 7/3, 13/3)	(11/3, 17/3, 23/3)	(1/3, 5/3, 11/3)
Robot 3	(23/9, 28/3, 10)	(17/3, 23/3, 28/3)	(2/3, 7/3, 13/3)	(13/3, 19/3, 25/3)
Robot 4	(5/3, 11/3, 17/3)	(1/3, 4/3, 3)	(2/3, 7/3, 13/3)	(1/3, 4/3, 3)
Robot 5	(1/3, 4/3, 3)	(23/9, 28/3, 10)	(1/3, 4/3, 3)	(25/3, 29/3, 10)
Robot 6	(2/3, 7/3, 13/3)	(1/3, 4/3, 3)	(25/3, 29/3, 10)	(5/3, 11/3, 17/3)
Robot 7	(7/3, 13/3, 19/3)	(2/3, 7/3, 13/3)	(7, 9, 10)	(5/3, 11/3, 17/3)
Robot 8	(7/3, 13/3, 19/3)	(7/3, 13/3, 19/3)	(11/3, 17/3, 23/3)	(5/3, 11/3, 17/3)
Robot 9	(17/3, 23/3, 28/3)	(5/3, 11/3, 17/3)	(2/3, 7/3, 13/3)	(23/9, 28/3, 10)
Robot 10	(7/3, 13/3, 19/3)	(2/3, 7/3, 13/3)	(17/3, 23/3, 28/3	(1/3, 5/3, 11/3)

TABLE XV. PERFORMANCE INDEX FOR EACH ALTERNATIVE

Alternative	$\tilde{S}_i$	S_i
Robot 1	(0.1699, 0.1746, 0.2201)	0.1882
Robot 2	(0.0720, 0.0990, 0.1591)	0.1100
Robot 3	(0.0859, 0.1637, 0.2216)	0.1571
Robot 4	(0.0288, 0.0567, 0.1120)	0.0658
Robot 5	(0.0593, 0.1080, 0.1564)	0.1079
Robot 6	(0.0157, 0.0449, 0.0984)	0.0530
Robot 7	(0.0372, 0.0705,0.1297)	0.0791
Robot 8	(0.0484, 0.0820, 0.1434)	0.0913
Robot 9	(0.0907, 0.1364, 0.1993)	0.1421
Robot 10	(0.0331, 0.0642, 0.1221)	0.0731

The utility degree of an alternative is determined by measuring its importance in achieving the final objective. A higher utility degree K_i indicates that the alternative is more favorable, as it contributes more to meeting the criteria. Figure 2 illustrates the utility degree K_i of the alternatives using (14).

Our case study considered 10 industrial robots with diverse specifications, allowing us to simulate the realistic trade-offs commonly encountered in industry. Specifically, Robot 1 ranked highest due to its strong performance in all benefit criteria: high speed (1.35 m/s), large payload (60 kg), and high precision (0.150 mm), all while maintaining an acceptable cost ($7,200). Conversely, Robot 6, which ranked lowest, has a minimal load capacity (1 kg) and velocity (0.30 m/s), despite having the lowest cost ($1,070), illustrating that cost alone is insufficient for effective selection. The FAHP–FARAS model proved effective in capturing the inherent uncertainty in expert judgments and systematically aggregating evaluations. The FAHP method determined that velocity and load capacity are the most influential criteria, with fuzzy weights of (0.369, 0.557, 0.835) and (0.153, 0.229, 0.350), respectively, reflecting their critical role in production and task suitability. The cost criterion, although important, received relatively lower weight, suggesting that decision-makers prioritize operational performance over initial investment when selecting industrial robots for long-term deployment. Expert input was crucial in this process. Three robotics experts provided linguistic evaluations of each robot's performance on all criteria. These evaluations were converted into triangular fuzzy numbers and processed through FARAS to obtain the performance indices and a final ranking. The highest-ranked robots (Robot 1, Robot 3, and Robot 9) achieved balanced performance across all dimensions. Lower-ranked robots generally excelled in only one or two criteria but performed poorly in others (e.g., Robot 5 had a high payload capacity but very low velocity).

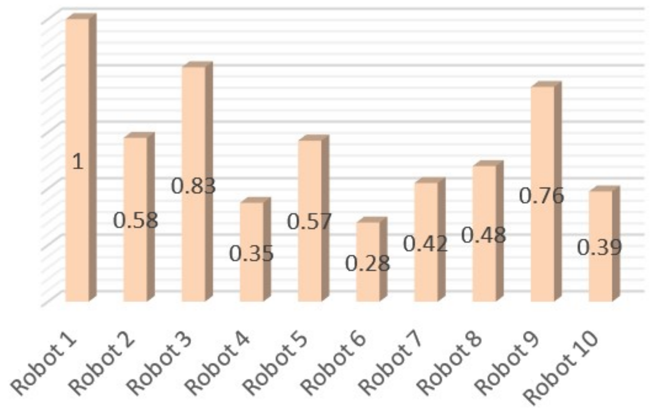

Fig. 2. Ranking of alternatives.

IV. CONCLUSION

The present study proposes a hybrid fuzzy Multi-Criteria Decision-Making (MCDM) approach to facilitate the selection of industrial robots in manufacturing. The proposed model integrates expert knowledge with fuzzy sets to address the conflicting nature of multiple criteria and the vagueness inherent in human judgment. The decision-making process incorporated both quantitative data, including velocity, load capacity, cost, and repeatability, and qualitative expert evaluations. This comprehensive approach enabled a realistic assessment of the available alternatives. The results indicated that Robot 1 was the optimal alternative, demonstrating a well-balanced performance across all key criteria. Conversely, Robot 6 exhibited the poorest performance, despite its cost-effectiveness, due to its limited capabilities. These findings emphasize that robot selection should not rely on any single criterion but must be guided by a multi-dimensional evaluation process. The Fuzzy Analytic Hierarchy Process (FAHP)–Fuzzy Additive Ratio Assessment (FARAS) model demonstrates notable strengths in addressing uncertainty management through the use of fuzzy representation of expert input. It offers a structured and transparent methodology for calculating criteria weights and ranking alternatives, while also exhibiting flexibility in adapting to different industrial contexts and selection priorities. The findings are consistent with previous research that has employed fuzzy MCDM models (e.g., FAHP–Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)–Entropy), yet the integration of FAHP and FARAS offers a more efficient computational framework while maintaining decision robustness, making it suitable for industrial applications.

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