A Novel Application of FDOSM for Industrial Robot Selection Using MCDM Techniques

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Abstract: Industrial robots offer a range of capabilities and specifications depending on their intended applications. The role of robots in industries, especially in manufacturing, logistics, and related fields, has become increasingly important. As a result, selecting an industrial robot creates a complex decision-making challenge due to the vast array of options available and the absence of uniform performance standards. Decision by Opinion Score Method (FDOSM) is a reliable and consistent method that work in a fuzzy environment, presenting greater flexibility and less computational effort than previous methods. It efficiently addresses challenges by evaluating multiple alternatives according to multiple criteria, enhancing decision-making accuracy. It relies on the use of an opinion matrix to aggregate expert judgments, helping to resolve differences and reduce computational complexity. FDOSM consists of three phases: data input, transformation, and processing units, and both individual and group decision-making contexts are applied to FDOSM. A case study on industrial robot selection demonstrates FDOSM's ability to logically rank alternatives. The R3 (Cybotech V15 Electric) achieved the highest ranking with a score of 2.0944, demonstrating its suitability for pick and place operations in manufacturing systems. Also, among the robots evaluated, the R5 (Unimation PUMA 500/600) achieved the lowest ranking with a score of 3.6. The results demonstrate the effectiveness of the method utilized, as it agrees well with expert opinions and demonstrates the ability to improve decision reliability by addressing discrepancies in expert judgments. The study validates its findings by comparing the mean scores of the two groups, demonstrating that the method provides consistent and logical rankings.

1 INTRODUCTION

In recent years, industrial robots have seen a significant increase in their popularity and applications. To enhance production efficiency while maintaining product quality and speeding up workflow, industries rely on industrial robots. Robots are now used in processes such as assembly, finishing, and welding. However, choosing the most appropriate robot is complicated by varying performance criteria and the lack of uniform, globally agreed upon manufacturing standards. To address this problem, several MCDM methods have been used, allowing the best alternative to be selected by considering various conflicting criteria. Therefore, this paper presents the use of a modern decision model to simplify the industrial robot selection process, the FDOSM method, which provides a systematic approach to more accurately evaluate and select the most appropriate alternative [1],[2].

Multi-criteria decision making (MCDM) is a fundamental field in operations research and expert systems. It involves identifying the best alternative from among several alternatives by evaluating multiple criteria [3]–[5], a number of alternatives are compared based on different criteria [6]. It uses computational and mathematical approaches to evaluate performance criteria from the decision maker's perspective [7]. Given the complexity of decision-making scenarios, MCDM methods provide a structured approach for systematically evaluating multiple alternatives, criteria, and preferences [8]. These techniques have been widely used in a variety of fields, including engineering and healthcare, to efficiently address complex decision-making problems [10], [11]. MCDM is divided into two main approaches: the human approach and the mathematical approach. Both approaches aim to rank alternatives and assign weights to different criteria [12]. The human approach relies on expert opinion and includes techniques such as the AHP [13], ANP [14], and BWM [12]. As for the mathematical approach, it is based on mathematical operations and includes techniques such as TOPSIS [15] and WSM [16]. MCDM techniques, whether human or mathematical, present substantial challenges when dealing with ambiguous and confusing data. Decision-makers typically convey their opinions in words rather than precise numerical values, complicating the assigning of specific weights to criteria. This uncertainty influences the final ranking of options and has been widely investigated in MCDM research [13], [17], [18]. To address this issue, MCDM has evolved inside a fuzzy set framework, effectively managing uncertainty and imprecise decision-making. Lotfi A. Zadeh's current notion of fuzzy sets paved the path for new approaches to solve the inadequacies of traditional MCDM techniques, leading to the development of fuzzy MCDM (FMCDM) techniques [18-20]. One of the most recent advancements in this industry is the FDOSM, which was revealed in 2020. FDOSM was created particularly for fuzzy environments, ranking alternatives using an opinion matrix, and the concept of an ideal solution. It effectively addresses core MCDM difficulties such as contradicting expert opinions, time-consuming comparisons, and unrealistic criterion evaluations. FDOSM also reduces the number of mathematical operations required, while increasing decision accuracy. It also addresses the issue of distance measurement by including both positive and negative ideal solutions, which eliminates the requirement for explicit criteria weighting. FDOSM improves decision-making by addressing issues with normalization and weight determination that are frequent in traditional mathematical techniques, resulting in a very efficient and accurate method [18]. Because FDOSM is generalizable, it can be applied to other MCDM problems, and compared to other fuzzy MCDM methods, FDOSM is less complex and maintains accuracy. Therefore, it was adopted in this study because of its novelty, simplicity, and effectiveness, and because it has not previously been used for optimal industrial robot selection.

A new application of FDOSM on a new case study to verify its effectiveness and reliability in solving MCDM problems.

2 MULTI CRITERIA DECISION MAKING (MCDM)

MCDM is a multidisciplinary field that has received significant interest in recent years, especially in situations where different options need to be comprehensively evaluated using multiple criteria [21], [22]. The basic goal of MCDM methods is to provide a systematic structure that enables decision makers to form rational, transparent, and well-supported choices [23]. The challenges of MCDM frequently arise in a variety of business and decision-making scenarios. Complexities arise from considering a large number of options, each evaluated according to a set of criteria, including factors such as cost, efficiency, and sustainability, depending on the specific decision-making context [24]. MCDM breaks down the problem into smaller, more manageable parts so that the DM can better understand it [25]. The main steps of the MCDM methodology include defining the problem, defining criteria, identifying alternatives, constructing a decision matrix, determining criterion weights, and ranking the alternatives. Decision criteria are typically divided into two categories. The first is the benefit criterion, where higher alternative scores indicate better performance, such as profits. The second is the cost criterion, where lower alternative scores indicate better performance, such as price [6, 26, 27]. The decision matrix (DM) is a commonly used approach in the MCDM, in which alternatives and criteria are presented clearly and systematically. It enhances the clarity of the decision-making problem and forms the basis for applying various techniques. Each alternative is evaluated under specific criteria, enabling a comprehensive analysis of each alternative's performance against these criteria. The decision matrix can be represented as follows:

$$DM = \begin{array}{c c} & \begin{array}{ccc} C_1 & \ldots & C_n \end{array} \\ \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \end{array}$$

The decision matrix is a two-dimensional (Q×H) matrix, with (Q) rows representing alternatives (A1, A2,...) and (H) columns representing criteria (C1, C2,...Cn) [4]. The alternatives (A1,..., Am) are the possibilities that an experts may evaluate, whereas the criteria (C1,..., Cn) are the standards utilized to assess each alternative, and (x_{ij}) represents the evaluation of alternative (A_i) against criterion (C_j) [23], [28].

This matrix is a useful tool for experts to arrange and evaluate their alternatives methodically [27].

3 FUZZY DECISION BY OPINION SCORE METHOD (FDOSM)

The Fuzzy Decision by Opinion Score Method (FDOSM) is a new improved approach to MCDM, introduced in 2020 [18] to address the shortcomings of previous techniques. Designed to operate in a fuzzy environment, FDOSM uses an opinion matrix composed of expert opinions to provide an optimal value that serves as a benchmark for evaluating other values that meet the same criteria This method simplifies the decision-making process through aggregation using the arithmetic mean. Its advantages include reducing complex mathematical calculations and inconsistencies, which were common in previous techniques, and increasing decision accuracy and efficiency by addressing issues such as missing data, normalization, and weighting without the need for explicit criterion weights [18], [22]. Consequently, it provides a more logical and consistent ranking of options compared to other MCDM techniques. This method can be applied to both single and group (internal and external aggregations) decision-making scenarios.

3.1 FDOSM Steps

The FDOSM steps are outlined as follows [18], [26], [29]:

Step 1: Construct the Decision Matrix.

Step 2: Choose the ideal solution for each criteria such as minimum, maximum, or a critical value.

Step 3: To generate the opinion matrix, Compare the ideal solution to the values of the alternatives per criteria depending on the decision-maker's opinions.

Step 4: Transform the opinion matrix into triangular fuzzy numbers.

Step 5: Involves aggregation through arithmetic mean.

Step 6: Concludes with the selection of the lowest option as the optimal decision.

3.2 FDOSM Unit

There are three primary parts to FDOSM.: data input, data transformation, and data processing. below explain each unit, including its steps and mathematical formulae [18], [25]:

3.2.1 Phase One: Data Input Unit

Although it is comparable to previous MCDM methods, the suggested MCDM method involves a set of m alternatives, A_1,..., A_m, and a set of n criteria, C_1,..., C_n.These two elements are represented in a decision matrix, defined as:

$$D = \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}. \quad (1)$$

This decision matrix is the product of the initial stage. Afterward, this decision matrix is converted to an opinion matrix in the next phase.

3.2.2 Phase Two: Data Transformation Unit

Once the decision matrix has been built (as the result of the initial phase), FDOSM performs a transformation phase by choosing an ideal solution depending on one of following factors: minimum, maximum, or critical value:

- Minimum Value. Utilized for cost-related criterion; the smallest value represents the preferred solution.
- Maximum Value. Utilized for benefit-related criterion, where higher values are preferred.
- Critical Value. Used in situations where the ideal solution fails to fit into the minimum or maximum categories, such as blood pressure, where an optimal range is preferred.

This step of FDOSM enables the selection of an ideal solution for values that are otherwise difficult to measure. The following steps in this stage are outlined and described [18, 29]:

Step 1: Choose the ideal solution. The selection of the ideal solution in FDOSM is given below:

$$A^* = \Big\{\Big[\Big(\underset{i}{max} v_{ij} \mid j \in J\Big), \Big(\underset{i}{min} v_{ij} \mid j \in J\Big), \big(Op_{ij} \in IJ\big) \mid i = 1,2,3, \ldots .m\Big]\Big\}. \quad (2)$$

Where: $\underset{i}{max} v_{ij}$represents the ideal solution for benefit criteria (higher values are preferred), $\underset{i}{min} v_{ij}$ represents the ideal solution for cost criteria (lower values are preferred), Op_{ij} is a critical value for cases where the ideal value is between $\underset{i}{max} v_{ij}$ and $\underset{i}{min} v_{ij}$.

Step 2: Comparing Ideal Solution to other values per criterion. In this step will perform comparison the ideal solution with each alternative’s values per criterion. Here, weights are assigned to evaluation criteria implicitly. Decision-makers (DMs) evaluate whether differences between the ideal solution and alternative values have a significant impact on their opinion, based on a set of five linguistic which facilitates this comparison, the DM selects ideal solution vectors (V_{31}, V_{22}, V_{43}, and V_{14}) to serve as benchmarks. After choosing the ideal solution, the alternatives are compared to it (reference comparison process is expressed) as follows:

$$Op_{\text{Lang}} = \left\{\left(\left(\tilde{v}_{ij} \otimes v_{ij} \mid j \in J\right) \cdot \mid i = 1.2.3 \ldots m\right)\right\}, \quad (3)$$

where $\otimes$ represents this reference comparison

This comparison yields a linguistic opinion matrix, which will then be turned to fuzzy numbers by utilizing fuzzy membership.

$$Op_{\ Lang} = \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} \begin{bmatrix} op_{11} & \cdots & op_{1n} \\ \vdots & \ddots & \vdots \\ op_{m1} & \cdots & op_{mn} \end{bmatrix}. \quad (4)$$

When $Op_{\ Lang}$ represents the value of an alternative after it has been transformed into an opinion linguistic term [22].

3.2.3 Phase Three: Data Processing Unit

This process is detailed as follow:

Step 1: Fuzzify the opinion matrix by replacing opinion terms with triangular fuzzy numbers to form the fuzzy opinion decision matrix (FD_{ij}).

Step 2: Use arithmetic mean as an aggregation operator, to aggregate the outcomes from the fuzzy opinion decision matrix for every alternative. Once generating the fuzzy decision matrix, the procedure of aggregation is applied to choose the optimal alternative. This can be done by following equation:

$$\text{Arithmetic mean } A_{m(x)} = \frac{\sum_{i=1}^{n} x_i}{n} \quad (5)$$

Step 3**:** Apply defuzzification to the aggregated results to obtain a crisp value, which is computed as follows:

$$\frac{(a+b+c)}{3} \quad (6)$$

3.3 FDOSM Context

There are two types of processes applied to the opinion matrix in decision-making contexts:

3.3.1 Single Decision Making

In this case, the decision-making problem is handled by a single person who uses their experience to assess and then select the finest alternative from a list of alternatives based on preset criteria. This individual's judgment alone determines the final decision [18].

3.3.2 Group Decision Making

Group MCDM (G-MCDM) includes many decision-makers working together to identify the best alternative depending on expert experience and judgments[18]. It assists organizations in addressing complicated decision-making challenges, to achieve a unified solution. It includes two stages, internal and external aggregation, and we will use the external context in this work through the following (7):

$$External\ aggregation\ = \oplus A^{*}, \quad (7)$$

where $\oplus$ denotes the arithmetic mean, and A^{*} indicates the ultimate outcome for every expert.

4 FUZZY SET

Fuzzy set theory, presented by Lotfi A. Zadeh, which is a mathematical structure to handling with uncertainty and vagueness in real-life situations [19]. Fuzzy sets are a kind of logic used to describe principles or phenomena that do not have a definite value. A fuzzy set uses a membership function to assign integer values ranging from 0 to 1 to represent an element's degree of belonging to a set. This approach allows for more precise and efficient reasoning when dealing with ambiguity. grasp fuzzy sets requires a foundational grasp of classical set theory. So, the classical set is a collection of well defined items, each of which either belongs to the set or does not [30]. The membership of an element x in a classical set A is determined by a characteristic function $\mu_A(x)$, which assigns a value of either 1 (if $x \in A$) or 0 (if $x \notin A$) [30, 31]:

$$\mu_A(x) = \begin{cases} 1 & \text{for } x \in A \\ 0 & \text{for } x \notin A \end{cases} \quad (8)$$

In contrast, a fuzzy set allows partial membership, where $\mu_{\mathrm{T}}(\mathrm{x})$ can take any value in the range [0,1] to denote the degree to which x relates to the fuzzy set T.

A fuzzy set T is outlined as:

$$T = \{(\mathrm{x}, \mu_{\mathrm{T}}(\mathrm{x}))/\mathrm{x} \in \mathrm{A}, \mu_{\mathrm{T}}(\mathrm{x}) \in [0,1]\} \quad (9)$$

Here, $\mu_{\mathrm{T}}(\mathrm{x})$ is the membership function that quantifies the level of membership of x in T.

5 TRIANGULAR FUZZY NUMBERS (TFN)

Triangular fuzzy numbers, represented as A = (a, b, c), are among the most commonly used types of fuzzy numbers in fuzzy MCDM. They are favored in practical applications for its conceptual clarity and ease of computation. The membership function of triangular fuzzy numbers is displayed in Figure 1. TFNs are outlined by their below membership function[32]:

$$\mu A(x) = \begin{cases} 0 & \text{if } x < a \\ \frac{x-a}{b-a} & \text{if } a \le x \le b \\ \frac{c-x}{c-b} & \text{if } b \le x \le x \\ 0 & \text{if } x > c \end{cases} \text{.where } a \le b \le c \quad (10)$$

Assume $\tilde{x}$ = (a1, b1, c1) and $\tilde{y}$ = (a2, b2, c2) are two nonnegative triangular fuzzy numbers, and α ∈ R+..The arithmetic operations can be illustrated in Table 1.

Table 2 shows the values of linguistic terms with TFN.

6 CASE STUDY

Bhangale et al.[34] examined an issue related to Choosing the most appropriate industrial robot for (pick-and-place actions) while avoiding certain obstacles. In this study, they identified five key attributes for robot selection: load capacity (LC), maximum tip speed (S), repeatability (RE), memory capacity (C), and manipulator reach (MR). Among these attributes, (LC, S, C, MR) are considered beneficial, meaning greater values are preferable. In contrast, (RE) is categorized as a cost attribute since a smallest value is desirable. Consequently, the robotics selection issue involves five criteria and seven robots, as detailed in Table 3.

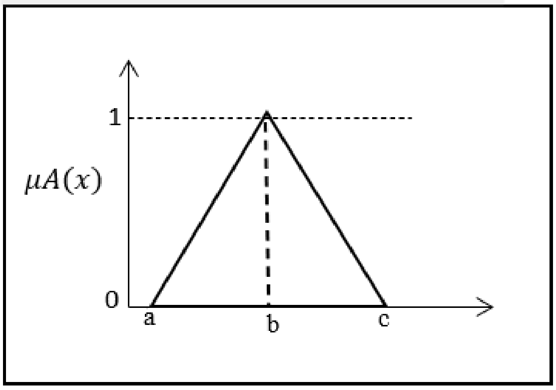

Figure 1: The triangular membership [33].

7 RESULTS AND DISCUSSION

7.1 Data Transformation Unit

In this step, to ensure practical application, we consulted with three experts in the field of industrial robotics, who have sufficient knowledge and experience in this field, every expert identifies the ideal solution for each criterion and evaluates it against other values based on the same criterion by using the five Likert scale. The comparisons result is linguistic terms (No difference, Slight difference, difference, Big difference, Huge difference). Consequently, the decision matrix is transformed to opinion matrix utilizing these linguistic phrases, as illustrated in the Table 4.

Table 1: The arithmetic operations TFN [33].

Linguistic terms	TFNs
No Difference (NO. D)	(0.00, 0.10, 0.30)
Slight Difference (S.D)	(0.10, 0.30, 0.50)
Difference (D)	(0.30, 0.50, 0.75)
Big Difference (B.D)	(0.50, 0.75, 0.90)
Huge Difference (H.D)	(0.75, 0.90, 1.00)

Table 2: The linguistic terms values with TFN [33].

Operations	Equations
Addition	$\tilde{x} + \tilde{y} = (a_1 + a_2, b_1 + b_2, c_1 + c_2)$ (11)
Subtraction	$\tilde{x} - \tilde{y} = (a_1 - c_2, b_1 - b_2, c_1 - a_2)$ (12)
Multiplication	$\alpha\tilde{x} = (\alpha \mathrm{a}_1, \alpha \mathrm{b}_1, \alpha \mathrm{c}_1)$ (13)
Division	$\tilde{x}/\tilde{y} \cong (\mathrm{a}_1/\mathrm{c}_2, \mathrm{b}_1/\mathrm{b}_2, \mathrm{c}_1/\mathrm{a}_2)$ (14)

Table 3: Robot Decision Matrix [34].

Alternative	LC	S	C	MR	RE
ASEA-IRB 60/2	60	2540	500	990	0.4
Cincinnati Milacrone T3-726	6.35	1016	3000	1041	0.15
Cybotech V15 Electric Robot	6.8	1727.2	1500	1676	0.1
Hitachi America Process Robot	10	1000	2000	965	0.2
Unimation PUMA 500/600	2.5	560	500	915	0.1
United States Robots Maker 110	4.5	1016	350	508	0.08
Yaskawa Electric Motoman L3C	3	1778	1000	920	0.1

Table 4: Opinion Matrix for three experts.

	Opinion matrix (Expert 1)					Opinion matrix (Expert 2)					Opinion matrix (Expert 3)				
Alterna-tive	LC	MTS	MC	MR	RE	LC	MTS	MC	MR	RE	LC	MTS	MC	MR	RE
R1	NO.D	NO.D	H. D	S. D	H. D	NO.D	NO.D	H. D	S. D	H. D	NO.D	NO.D	H. D	D	H. D
R2	H. D	B. D	NO.D	S. D	S. D	B. G	D	NO.D	S. D	D	H. D	H. D	NO.D	S. D	B. D
R3	H. D	D	D	NO.D	S. D	B. G	S. D	D	NO.D	S. D	B. G	S. D	D	NO.D	S. D
R4	B. G	B. D	D	D	B. D	B. G	D	S. D	D	H. D	D	H. D	S. D	D	B. D
R5	H. D	H. D	H. D	D	S. D	H. D	H. D	H. D	B. D	S. D	H. D	H. D	H. D	B. D	S. D
R6	H. D	B. D	H. D	H. D	NO.D	H. D	D	H. D	H. D	NO.D	H. D	D	H. D	H. D	NO.D
R7	H. D	D	B. D	D	S. D	H. D	S. D	B. D	B. D	S. D	H. D	S. D	D	B. D	S. D

Table 5: Fuzzy Opinion Matrix for three experts.

Fuzzy opinion matrix (Expert 1)															
Alternative	LC			S			C			MR			RE		
R1	0	0.1	0.3	0	0.1	0.3	0.75	0.9	1	0.1	0.3	0.5	0.75	0.9	1
R2	0.75	0.9	1	0.5	0.75	0.9	0	0.1	0.3	0.1	0.3	0.5	0.3	0.5	0.75
R3	0.75	0.9	1	0.3	0.5	0.75	0.3	0.5	0.75	0	0.1	0.3	0.1	0.3	0.5
R4	0.5	0.75	0.9	0.5	0.75	0.9	0.3	0.5	0.75	0.3	0.5	0.75	0.5	0.75	0.9
R5	0.75	0.9	1	0.75	0.9	1	0.75	0.9	1	0.3	0.5	0.75	0.1	0.3	0.5
R6	0.75	0.9	1	0.5	0.75	0.9	0.75	0.9	1	0.75	0.9	1	0	0.1	0.3
R7	0.75	0.9	1	0.3	0.5	0.75	0.5	0.75	0.9	0.3	0.5	0.75	0.1	0.3	0.5
Fuzzy opinion matrix (Expert 2)															
Alternative	LC			S			C			MR			RE		
R1	0	0.1	0.3	0	0.1	0.3	0.75	0.9	1	0.1	0.3	0.5	0.75	0.9	1
R2	0.5	0.75	0.9	0.3	0.5	0.75	0	0.1	0.3	0.1	0.3	0.5	0.3	0.5	0.75
R3	0.5	0.75	0.9	0.1	0.3	0.5	0.3	0.5	0.75	0	0.1	0.3	0.1	0.3	0.5
R4	0.5	0.75	0.9	0.3	0.5	0.75	0.1	0.3	0.5	0.3	0.5	0.75	0.75	0.9	1
R5	0.75	0.9	1	0.75	0.9	1	0.75	0.9	1	0.5	0.75	0.9	0.1	0.3	0.5
R6	0.75	0.9	1	0.3	0.5	0.75	0.75	0.9	1	0.75	0.9	1	0	0.1	0.3
R7	0.75	0.9	1	0.1	0.3	0.5	0.5	0.75	0.9	0.5	0.75	0.9	0.1	0.3	0.5
Fuzzy opinion matrix (Expert 3)															
Alternative	LC			S			C			MR			RE		
R1	0	0.1	0.3	0	0.1	0.3	0.75	0.9	1	0.3	0.5	0.75	0.75	0.9	1
R2	0.75	0.9	1	0.75	0.9	1	0	0.1	0.3	0.1	0.3	0.5	0.5	0.75	0.9
R3	0.5	0.75	0.9	0.1	0.3	0.5	0.3	0.5	0.75	0	0.1	0.3	0.1	0.3	0.5
R4	0.3	0.5	0.75	0.75	0.9	1	0.1	0.3	0.5	0.3	0.5	0.75	0.5	0.75	0.9
R5	0.75	0.9	1	0.75	0.9	1	0.75	0.9	1	0.5	0.75	0.9	0.1	0.3	0.5
R6	0.75	0.9	1	0.3	0.5	0.75	0.75	0.9	1	0.75	0.9	1	0	0.1	0.3
R7	0.75	0.9	1	0.1	0.3	0.5	0.3	0.5	0.75	0.5	0.75	0.9	0.1	0.3	0.5

7.2 Data Processing Unit

This involves three phases:

1) First, the opinion matrix is transformed to fuzzy opinion matrix. This is done by changing the linguistic terms with triangular fuzzy numbers pursuant to Table 2. As a result, we obtain a fuzzy opinion matrix, as illustrated in the above Table 5.
2) Second, use an addition (11) to combine the results from the prior procedure for each alterna-ative. as illustrated in Table 6.
3) Third, the defuzzification (6) is used to the preceding matrix to present the end outcomes for every individual decision maker, as illustrated in Table 7.

Table 8 illustrates the application of group decision-making, where the individual decisions of several experts are aggregated to produce a unified group decision. This process employs external group decision-making methods by using (7). By utilizing this approach, we can address the variability in expert opinions and resolve any inconsistencies that may arise.

Pursuant to the FDOSM concept, the appropriate alternative is the one nearest to the no-difference linguistic phrase describing the ideal solution, denoted by the smallest value, and the opposite is true. Table 6 displays the final findings for each expert (Individual Decision Making) based on the Opinion Matrix. So, based on these results, the ideal alternative for the first decision-maker is "R1(ASEA-IRB 60/2)" with a score of "2.33333333". In contrast, " R3(Cybotech V15 Electric Robot)" is the favored alternative for both the second and third experts, obtaining score of "1.966666667" for both. The variance arises from experts having differing opinions based on their experiences and perspectives when evaluating robots according to specific criteria. On the other hand, the least favored alternative for the first decision-maker, with a score, is "R6(United States Robots Maker 110)," with a score of "3.5" while for the second and third decision-maker, the least preferred alternative is "R5(Unimation PUMA 500/600)," with scores of "3.666666667" for both.

Table 6: Aggregation step for three experts.

Aggregation step (Expert 1)			
Alternative	Scores		
R1	1.6	2.3	3.1
R2	1.65	2.55	3.45
R3	1.45	2.3	3.3
R4	2.1	3.25	4.2
R5	2.65	3.5	4.25
R6	2.75	3.55	4.2
R7	1.95	2.95	3.9
Aggregation step (Expert 2)			
Alternative	Scores		
R1	1.6	2.3	3.1
R2	1.2	2.15	3.2
R3	1	1.95	2.95
R4	1.95	2.95	3.9
R5	2.85	3.75	4.4
R6	2.55	3.3	4.05
R7	1.95	3	3.8
Aggregation step (Expert 3)			
Alternative	Scores		
R1	1.8	2.5	3.35
R2	2.1	2.95	3.7
R3	1	1.95	2.95
R4	1.95	2.95	3.9
R5	2.85	3.75	4.4
R6	2.55	3.3	4.05
R7	1.75	2.75	3.65

Table 7: Final result for three experts.

Expert 1		
Alternative	Score	Rank
R1	2.333333333	1
R2	2.55	3
R3	2.35	2
R4	3.183333333	5
R5	3.466666667	6
R6	3.5	7
R7	2.933333333	4
Expert 2		
Alternative	Score	Rank
R1	2.333333333	3
R2	2.183333333	2
R3	1.966666667	1
R4	2.933333333	5
R5	3.666666667	7
R6	3.3	6
R7	2.916666667	4
Expert 3		
Alternative	Score	Rank
R1	2.55	2
R2	2.916666667	4
R3	1.966666667	1
R4	2.933333333	5
R5	3.666666667	7
R6	3.3	6
R7	2.716666667	3

Table 8: Final result for three experts.

Group expert		
Alternative	Score	Rank
R1	2.4056	2
R2	2.55	3
R3	2.0944	1
R4	3.0167	5
R5	3.6	7
R6	3.3667	6
R7	2.8556	4

Table 9: Validation for basic-FDOSM.

Group	Industrial robot	Means
first Group	R3	2.476389
	R1	
	R2	
	R7	
second Group	R4	3.327778
	R6	
	R5	

In the Group decision-making, pursuant to Table 7, the best alternative is "R3(Cybotech V15 Electric Robot)", with a score of "2.0944". The least favorable alternative is "R5(Unimation PUMA 500/600)", which got a score of "3.6". The difference in ranking scores reflects decision-makers diverse perspectives. However, when the GDM findings are compared to the individual decision-makers opinion matrices, the robot model rankings remain constant. The usage of GDM increases flexibility and effectively handles uncertainty in opinion matrices, resulting in a more accurate comparison of the group's final choice and individual judgments. Limitations of this method include: Converting the opinion matrix to a fuzzy decision matrix is limited to using only one fuzzy number at a time. The quality of the input data must be ensured to obtain consistent and reliable results.

8 VALIDATION

In this study, validation is employed to substantiate the decision-making outcomes derived from the basic-FDOSM method. Objective validation entails partitioning the alternatives into distinct groups, a technique that has been utilized in various MCDM studies [14], [18].

To validate the results, the following steps are undertaken: first: the alternatives are sorted based on the decision-making outcomes from the Group basic-FDOSM, second: the sorted alternatives are divided into two groups, and third: the groups mean is calculated based on the group decision-making (GDM) findings, as defined in the (15) [14]:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (15)$$

The comparison results are contingent upon the mean values of each group as it forms the basis for comparison, with the lowest mean value representing the optimal solution for each criterion (desirable groups), in accordance with the FDOSM concept. Conversely, a higher mean value signifies a less favorable alternative. In this context, the first group is analyzed for having the minimal mean, which is utilized to evaluate the validity of the results. This first group is then contrasted with the second group to further assess the validity of the findings. The second group's mean should be greater than or at least equal to that of the first group. Once the assessment results are consistent, they can be deemed valid. Table 9 presents the validation outcomes for the industrial robot selection case study utilizing basic-FDOSM. The first group exhibits a lower average of 2.476389 compared to the second group's average of 3.327778. Validation results confirm that the basic-FDOSM findings for identifying the optimal robots, as presented by the groups, are valid and can be systematically ranked.

9 CONCLUSIONS

Selecting the optimal alternative based on many performance factors is important for daily life and work. The problem is handled with the FDOSM. FDOSM efficiently tackles issues such as inconsistent human judgment and unnecessary computing complexity by combining expert opinion with fuzzy logic. The approach simplifies decision-making by using an opinion matrix and arithmetic mean aggregation to ensure a logical and accurate ranking of alternatives. The ranking results of the case study proved that FDOSM is a methodical and efficient method for selecting the best industrial robot, including individual and group decision-making scenarios.So, the results, the ideal alternatives for the individual decision-makers are “R1(ASEA-IRB 60/2)", and R3(Cybotech V15 Electric Robot)", In the Group decision-making, the best alternative is "R3(Cybotech V15 Electric Robot)”. The validation demonstrated that FDOSM improves decision dependability by reducing uncertainty in expert evaluations. Future research could be applying FDOSM to other industrial and engineering issues, demonstrating its adaptability and significance in broader applications.

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