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A HOMOGENEOUS GROUP DECISION MAKING FOR SELECTION OF ROBOTIC SYSTEMS USING EXTENDED TOPSIS UNDER SUBJECTIVE AND OBJECTIVE FACTORS

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Abstract: *Selection of the best robotic system considering subjective and objective factors is very imperative decision making procedure. This paper presents an extended TOPSIS based homogeneous group decision making algorithm for the selection of the best industrial robotic systems under fuzzy multiple criteria decision making (FMCDM) analysis. FPIS, FNIS, positive and negative separation measures, subjective factor measure, and objective factor measure and robot selection index are computed. A case study has been conducted and illustrated for better clarification and verification of proposed algorithm.*

Key words: *FMCDM, robotic system selection, homogeneous group decision making, subjective factor measure, objective factor measure.*

1. Introduction

Multi Criteria Decision Making (MCDM) is an analysis dealing with the evaluation of alternatives and identifying the best alternative out of a finite number of available alternatives. MCDM procedure can be categorized into classical Multi Criteria Decision Making (MCDM) (Feng & Wang, 2000; Wang & Lee, 2007) and Fuzzy Multiple Criteria Decision Making (FMCDM) (Wang et al., 2003). The selection criteria on the basis of which all these decisions are made are objective, subjective and critical in nature. Objective criteria can be measured and quantified. Subjective criteria are qualitative but neither measurable nor quantifiable. Subjective criteria are associated to ambiguity, imprecision, vagueness and uncertainty and realized by human perception and feelings (Zadeh, 1965; Zimmermann, 1991). Critical criteria are those which decide the requirement of further evaluation of data of an alternative. Critical criteria of an alternative must be satisfied before further assessment for final selection.

While decision making is based on objective criteria with certainty, it is classical MCDM. The MCDM problems are generally solved using a variety of techniques that include TOPSIS method, the total sum (TS), the AHP, SAW, DEA, ELECTRE and

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PROMETHEE (Wang et al., 2003; Hwang & Yoon, 1981). The fuzzy set theory is applied while assessment of alternative and importance of criteria are not possible to determine exactly. The concept of fuzzy is integrated with MCDM and the concerned technique is termed as FMCDM approach.

In FMCDM, linguistic term is used to measure performance assessment of alternative and importance of criteria. Linguistic term is converted into fuzzy number. In reality where objective measurement is unsatisfactory or insufficient, fuzzy sets considering subjective factors are applied for the evaluation of alternatives. A crisp sets can be defined to express an element is either member or not member in a universe of discourse. A fuzzy set is defined by assigning a value to each individual belonging in its universe of discourse. In the fuzzy sets this value represents its grades of membership (Klir & Yuan, 1995; Majumdar et al., 2004).

Chodha et al. (2022) applied entropy based TOPSIS for ranking of robots for industrial purpose (Chodha et al., 2022). Narayanamoorthy et al. (2019) implemented intuitionstic hesitant FVIKOR approach and entropy for selection of industrial robots. Fu et al. (2019) advocated industrial robot selection technique using group stochastic multiple criteria acceptability analysis. Nasrollahi et al. (2020) applied PROMETHEE method based on FBWM for ranking and selection of industrial robot[13]. Ali and Rashid (2020) applied best–worst method for appropriate robots selection in performing definite task in industry. Yalçin and Nuşin (2020) used EDAS approach for proper decision making in selection of industrial robots .

Shih (2008) proposes an algorithm to explain the procedure of robot selection. The author first divided the criteria into two categories: benefit and cost. The evaluation of alternatives was done using incremental benefit-cost ratio. Group TOPSIS was used to find rank of the candidate. Selection of robot is based on the incremental benefit-cost ratio. Though the proposed algorithm is suitable for more than one decision maker, it is too complex for one decision maker. The algorithm is not only complex but also tedious while the alternatives are required to be ranked.

Chu et al. (2003) proposed a FTOPSIS method. The purpose is to make sure the matching amid linguistic rating and related objective values. Internal arithmetic was used to rank the robots and to defuzzy of rating into crisp values and closeness coefficient. Parkan and Wu (1999) suggested a technique that illustrates and judges against a number of MADM as well as assessment procedure using a robot selection process. These papers are incapable for handling both objective and subjective factors together. Bhattacharyya et al. (2002) suggested a technique for selection of material handling equipment under MCDM Environment. A TOPSIS based fuzzy hierarchical algorithm was employed for selection of robotic systems for industrial application (Kahraman et al., 2007).

The gap analysis of the above literature review exposes that previous researchers have attempted to apply MCDM techniques for selection of robots. Still, this endeavor is not enough for extensive decision making regarding evaluation and selection of appropriate robots from several available alternatives under MCDM.

In the current study, qualitative (subjective) criteria have been considered for performance evaluation of robotic systems. Due to existence of ambiguity and imprecision, decision criteria are expressed in terms of linguistic variables which are then converted into suitable fuzzy numbers for quantification. Hence the solution procedure of the present study deserves the implementation of fuzzy set theory. In selection of robotic systems, multiple criteria are generally considered. Therefore, MCDM technique is appropriate for solving such a problem on robotic system selection. TOPSIS is one of the most well-known MCDM techniques that past researches have used successfully in similar decision making environment. So in the decision making process of the current study, TOPSIS is applied in combination with fuzzy set theory to ensure better applicability of the approach towards the right solution of the problem.

The objective of the paper is to aid decision makers by providing a decision making framework that can considers both objective factors and subjective factors with homogeneous group decision making strategy.

The remaining part of the paper is arranged in the following manner. Section 2 describes the proposed algorithm. Section 3 elaborates the case study and furnishes the calculation and discussion in details. Section 4 is dedicated for some essential concluding remarks with the direction of future research.

2. Proposed Algorithm

Let 'm' alternatives to be ranked based on assessment of 'n' number of criteria among those 'p' number of criteria are subjective (qualitative) and remaining 'q' number of criteria are objective (quantitative), where p + q = n; 'O' is the (15th letter of the English alphabet) number of homogeneous decision makers of a committee employed in the selection procedure.

Step1. (a): Form a decision matrix with fuzzy performance ratings expressed with linguistic variables offered by every expert to every alternative for every qualitative factor.

$$D = \begin{array}{c} \\ A_1 \\ \cdots \\ A_i \\ \cdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & \cdots & C_j & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11}^k & \cdots & x_{1j}^k & \cdots & x_{1n}^k \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i1}^k & \cdots & x_{ij}^k & \cdots & x_{in} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{m1}^k & \cdots & x_{mj}^k & \cdots & x_{mn}^k \end{bmatrix} \end{array} \tag{1}$$

Here, x_{ij}^k represents rating of i^{th} alternative (A_i) for j^{th} criterion (C_j) offered by decision maker D^k. For subjective criteria, performance ratings of alternatives will be expressed with seven degree of linguistic terms depicted in Table 1. Each linguistic term is converted into a corresponding TFN as per Table 1. For objective criteria, performance ratings are represented in crisp value. Here, $i \subset N$, i is less than or equal to m; $j \subset N$, j is less than or equal to n; $k \subset N$, k is less than or equal to O. N is the set of natural number. Every decision maker forms such a decision matrix.

Step 1.b: Form of fuzzy weight matrix by the decision makers by assigning linguistic variables to each subjective (qualitative) criterion.

$$W = \begin{array}{c} \\ D_1 \\ \cdots \\ D_k \\ \cdots \\ D_O \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & \cdots & C_j & \cdots & C_n \end{array} \\ \begin{bmatrix} w_1^1 & \cdots & w_j^1 & \cdots & w_n^1 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ w_1^k & \cdots & w_j^k & \cdots & w_n^k \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ w_1^O & \cdots & w_j^O & \cdots & w_n^O \end{bmatrix} \end{array}$$

(2)

w_j^k denotes importance for criterion *j,* estimated by DM *k*. Where, w_j^k is fuzzy and is represented by trapezoidal number for its simplicity. If the criterion is objective then its weight expressed in fuzzy number is transformed into crisp value by defuzzification.

Step 2: Convert linguistic variable into triangular fuzzy number. Form average decision matrix in fuzzy numbers (AFDM) and average weight matrix in fuzzy numbers (AFWM).

Element of average fuzzy decision matrix is

$$r_{ij} = \frac{1}{k}\sum_{k=1}^{O}\left(x_{ij}^k\right) \tag{3}$$

Element of average fuzzy weight matrix is

$$w'_{ij} = \frac{1}{k}\sum_{k=1}^{O}\left(w_j^k\right) \tag{4}$$

where Here, $i \subset N$, i is less than or equal to m; $j \subset N$, i is less than or equal to *n*; $k \subset N$, k is less than or equal to *O,* N is the set of natural number. In the case of objective criteria, operation of finding average performance rating can be debarred. As the weight of objective criteria is fuzzy and qualitative in nature, the operation of finding average weight must be determined. Here, $r_{ij} = \left(\alpha_{ij}, \beta_{ij}, \gamma_{ij}\right)$ is a triangular fuzzy number.

Step 3**:** Determine normalized average fuzzy decision matrix using the Eq. (5a) and Eq. (5b)

$$r'_{ij} = \left(\alpha^*_{ij}, \beta^*_{ij}, \gamma^*_{ij}\right) = \left(\frac{\alpha_{ij}}{\phi^*}, \frac{\beta_{ij}}{\phi^*}, \frac{\gamma_{ij}}{\phi^*}\right), \qquad j \in B \tag{5a}$$

$$r'_{ij} = \left(\alpha^*_{ij}, \beta^*_{ij}, \gamma^*_{ij}\right) = \left(1 - \frac{\gamma_{ij}}{\phi^*}, 1 - \frac{\beta_{ij}}{\phi^*}, 1 - \frac{\alpha_{ij}}{\phi^*}\right), \quad j \in NB \tag{5b}$$

where $\phi^* = \max\left(\gamma_{ij}\right) \ \forall i, j$

Step 4: Determine weighted normalized average fuzzy decision matrix using the following Eq. (6).

$$r''_{ij} = r'_{ij} * w'_{ij} = \left(\alpha'_{ij}, \beta'_{ij}, \gamma'_{ij}\right) \tag{6}$$

Step 5: Find Fuzzy Positive Ideal Solution (FPIS) as $v^+ = (1,1,1)$ and Fuzzy Negative Ideal Solution (FNIS) as $v^- = (0,0,0)$

Step 6: Find the Euclidean distances from FPIS and FNIS for every alternative using following Eq. (7) and Eq. (8).

$$S_i^+ = \sum_{j=1}^{p} \sqrt{\frac{1}{3}\left[\left(1-\alpha'_{ij}\right)^2 + \left(1-\beta'_{ij}\right)^2 + \left(1-\gamma'_{ij}\right)^2\right]} \quad (7)$$

$$S_i^- = \sum_{j=1}^{p} \sqrt{\frac{1}{3}\left[\left(\alpha'_{ij}\right)^2 + \left(\beta'_{ij}\right)^2 + \left(\gamma'_{ij}\right)^2\right]} \quad (8)$$

Where *i* is natural number less than or equal to m; and *j* is natural number less than equal to *n*.

Step 7: Determine relative closeness (RC_i) or Subjective Factor Measure (SFM_i) for each alternative using Eq. (9).

$$RC_i = \frac{S_i^-}{S_i^+ + S_i^-} = SFM_i \quad (9)$$

Where, *i* is natural number less than or equal to *m*. In the paper Relative Closeness (RC_i) is considered as Subjective Factor Measure (SFM_i) owing to RC_i is the performance measure of i^{th} alternative on the basis of subjective criteria.

Step 8: Determine Objective Factor Measure (OFM) from Objective Factor Cost (OFC). OFM and OFC are inter-related by the following well known mathematical Eq. (10) (Feng & Wang, 2000).

$$OFM_i = \left[OFC_i \times \left(\sum_{i=1}^{m} OFC_i^{-1}\right)\right]^{-1} \quad (10)$$

OFC_i = OFC for i^{th} alternative, OFM_i = OFM for i^{th} alternative; *i* is natural number less than or equal to *m*.

Step 9: Evaluate overall Robot Selection Index RSI_i using following Eq. (11).

$$RSI_i = \alpha \times SFM_i + (1-\alpha) \times OFM_i \quad (11)$$

α is coefficient of attitude having the value in the range $0 \le \alpha \le 1$.

Step 10: Organize the alternatives in decreasing order of the Robot Selection Indices and select the alternative with maximum RSI value as the best one.

3. Case Study

The above algorithm is illustrated for solving the following case study. The illustration is presented by dividing it into two subsections such as problem definition, calculation and discussion.

3.1 Problem Definition

An Eastern Indian based automotive manufacturing organization decides to install robotic systems for its new plant. Keeping the ever increasing global market competitiveness in view, the management of the organization is searching the way of making correct decision with scientific basis in every step associated with financial investment and future impact. The management also would like to involve its experts (decision makers) and incorporate their knowledge, experience, and opinion in the decision making procedure. The top managerial authority forms a decision making committee with three experts, one from marketing department, one from department of financial management and the remaining expert is from the manufacturing unit. Each of the experts has experience more than ten years in the respective department. Due to having almost equal experience, same age and organizational positions, the competent authority of top management decides to put equal importance to the decision makers. Since there are multiple decision makers with equal importance, hence it may be termed as homogeneous group decision making process. The decision makers are reluctant to reveal their introduction and they are comfortable to be mentioned by D1, D2, and D3 respectively. The three homogeneous personnel of the committee bear the responsibility of making decision regarding the selection of decision criteria and estimation of their respective importance weights. Through discussions and exchanging personal opinions, the decision making committee identifies and lists five significant subjective decision criteria for assessment and selection of industrial robotic systems. The listed five criteria are Programming flexibility (C_1), Vendor's service quality (C_2), user friendliness (C3), Reputation of manufacturer (C4) and Cost (C5). Out of the five significant criteria, Programming flexibility (C_1), Vendor's service quality (C_2), user friendliness (C3), Reputation of manufacturer (C4) are subjective and the remaining criterion Cost (C5) is objective in nature. Provisional

The decision making committee executes a rigorous market survey for a feasible set of industrial robotic systems. Based on the minimum requisite fulfillment of the considered criteria a screening test is conducted and a set of five industrial robotic systems is provisionally identified by the decision making committee. They designate the set of five robots by Robot1 (R1), Robot2 (R2), Robot3 (R3), Robot4 (R4) and Robot5 (R5) which are to be ranked and the best robotic system is to be selected under FMCDM atmosphere for performing specific function in the automatic manufacturing organization.

3.2 Calculation and Discussions

Due to vagueness, imprecision and ambiguity associated with the four criteria viz. programming flexibility, vendor's service quality, user friendliness and reputation of manufacturer seven grades of linguistic variables have been used for assessment of alternatives with respect to the above mentioned criteria. Since the linguistic assessment of the alternatives is inappropriate in decision making, the linguistic variables used for assessing performance rating are required to transform into suitable fuzzy numbers for quantification. This investigation suggests triangular fuzzy numbers (TFNs) due to its ease of application, simple calculation and proven capability of conveying information. The linguistic variables along with the acronyms and corresponding TFNs for performance rating are presented in Table 1.

Table 1. Linguistic variables for assessment of performance rating

Linguistic Terms	Acronym	TFNs
Extremely Poor	EP	(0, 0, 1)
Poor	P	(0, 1, 3)
Slightly Poor	SP	(1, 3, 5)
Medium	M	(3, 5, 7)
Slightly Good	SG	(5, 7, 9)
Good	G	(7, 9, 10)
Extremely Good	EG	(9, 10, 10)

While selecting a robotic system the different criteria in general have a varying impact on the selection and decision making. Therefore it is very important to estimate appropriate importance weights for the criteria under consideration. In this paper, five grades of different linguistic variables have been used for the assessment of criteria weights by the decision makers. The linguistic variables to be utilized for assessing criteria weights along with the associated acronyms and the corresponding triangular fuzzy numbers (TFNs) are presented in Table 2.

Table 2. linguistic variables for assessment of criteria weight

Linguistic variable	Acronyms	TFNs
Extremely Low	EL	(0, 0, 0.1)
Low	L	(0, 0.1, 0.3)
Slightly Low	SL	(0.1, 0.3, 0.5)
Medium	M	(0.3, 0.5, 0.7)
Slightly High	SH	(0.5, 0.7, 0.9)
High	H	(0.7, 0.9, 0.1)
Very High	EH	(0.9, 0.1, 0.1)

The decision making committee consists of three experts with diverse decision making attitude towards assessing performance ratings of the alternative robotic systems due to ambiguous nature of subjective decision criteria. This is equally true for estimation of the importance weights of the criteria with subjective nature. Each decision maker assess each alternative robotic system with respect to every subjective criterion using one of the seven degrees of prescribed linguistic variables which are collectively arranged in a matrix form known as decision matrix consisting of performance ratings of the alternatives.

There are five alternatives R1, R2, R3, R4 and R5 to be assessed with respect to four criteria C1, C2, C3 and C4. The assessment is to be accomplished by three decision makers D1, D2 and D3. Therefore the decision matrix consists of $5 \times 4 \times 3=60$ entries or performance ratings. For example, decision maker D1 assesses alternative robotic system R1 with SG, G, EG and G with respect to criteria C1, C2, C3 and C4 respectively. Decision maker D2 evaluates alternative robotic system R1 with G, G, G and SG with respect to criteria C1, C2, C3 and C4 respectively. Similarly decision maker D3 evaluates alternative robotic system R5 with P, G, EG and SG with respect to criteria C1, C2, C3 and C4 respectively. Thus each alternative robotic system is assessed by each decision makers with respect to each criterion with performance ratings which are accommodated in the decision matrix presented in Table 3.

Table 3. Fuzzy decision matrix

Alternatives	Criteria	Decision Makers D1	D2	D3
R1	C 1	SG	G	SG
	C 2	G	G	SG
	C 3	EG	G	P
	C 4	G	SG	G
R2	C 1	EG	EG	EG
	C 2	SG	G	EG
	C 3	P	G	G
	C 4	EG	EG	G
R3	C 1	G	SG	EG
	C 2	EG	G	EG
	C 3	EG	EG	EG
	C 4	G	EG	SG
R4	C 1	P	P	P
	C 2	EG	SG	G
	C 3	G	G	SG
	C4	SG	G	SG
R5	C1	G	SG	P
	C2	P	G	G
	C3	SG	G	EG
	C4	G	G	SG

The criteria weights in linguistic variables estimated by the members of the experts of the decision making committee is presented in a criteria versus decision makers in a matrix form known as weight matrix and shown in Table 4.

Table 4. Fuzzy weight matrix in linguistic variable

Criteria	Decision Makers D1	D2	D3
C1	H	VH	SH
C2	VH	VH	VH
C3	VH	H	H
C4	VH	VH	H
C5	H	VH	VH

Cost is an objective criterion. In the current problem on industrial robotic system evaluation and selection, the cost criterion is composed of five components viz. cost of acquisition, cost of installation, cost of operation, cost of maintenance and cost of transportation expressed in the unit of $\$ \times 10^5$. The cost of acquisition for the alternative robotic system selections are 2, 1, 0.9, 0.8, 0.9 unit respectively. The total costs with the five components for each of the five alternative robotic systems are shown in Table 5.

Table 5. Cost of alternatives in details: Reproduced with permission from Bhattacharya et al. (2002)

Robots	R_1	R_2	R_3	R_4	R_5
Cost of acquisition ($\$ \times 10^5$)	2.00	1.00	0.90	0.80	0.90
Cost of installation ($\$ \times 10^5$)	0.40	0.30	0.25	0.20	0.45
Cost of operation ($\$ \times 10^5$)	0.30	0.20	0.35	0.30	0.35
Cost of maintenance ($\$ \times 10^5$)	0.80	0.60	0.25	0.25	0.50
Cost of transportation($\$\times10^5$)	0.20	0.10	0.05	0.05	0.14
Total costs ($\$ \times 10^5$)	3.8	2.2	1.8	1.6	2.34

The above data is originally taken from Bhattacharya et al. (2002). The solution and result of the given example with step by step by illustration have been furnished below.

Decision makers like to assess alternatives using linguistic variables because of ease of expression with linguistic variables and unavailability of accurate information. However, linguistic variable is not suitable for correct decision making. That is why linguistic variables are then converted into suitable fuzzy numbers. The current algorithm suggests triangular fuzzy numbers as the medium for the quantification of linguistic variables used for the assessment of alternative robotic systems. Conversion of linguistic variable to triangular fuzzy number is accomplished as per the suggested scale in the paper. The average fuzzy performance rating is calculated from the assessment individual decision makers. For example Robotic system R1 is assessed against the criterion C1 (Programming flexibility) with SG, G, and SG by the three decision makers D1, D2 and D3 respectively. Now following the conversion scales SG is converted into (5, 7, 9), G into (7, 9, 10) and G into (5, 7, 9). The average fuzzy performance rating is calculated as follows.

$$\left(\frac{5+7+5}{3},\frac{7+9+7}{3},\frac{9+7+9}{3}\right)=(5.7,7.7,9.3)$$

The average fuzzy performance ratings of other alternatives with respect to each criterion is calculated in the similar way and average fuzzy decision matrix is constructed as shown in Table 6.

Table 6. Average fuzzy decision matrix

Ri	C1			C2			C3			C4		
R1	(5.7	7.7	9.3)	(6.3	8.3	9.7)	(6.7	8.0	9.0)	(6.3	8.3	9.7)
R2	(9.0	10.0	10)	(7.0	8.7	9.7)	(5.7	7.7	9)	(8.3	9.7	10)
R3	(6.7	8.7	9.7)	(8.3	9.7	10)	(9	10	10)	(7	8.7	9.7)
R4	(3.0	5.0	7.0)	(7	8.7	9.7)	(6.3	8.3	9.7)	(5.7	7.7	9.3)
R5	(5.0	7.0	8.7)	(5.7	7.7	9)	(8.3	9.7	10)	(6.3	8.3	9.7)

The weights of criterion C1 in linguistic variables assessed by the decision makers D1, D2, and D3 are H, VH and SH respectively. These linguistic weights are converted into the TFNs (0.7, 0.9, 0.1), (0.9, 0.1, 0.1) and (0.5, 0.7, 0.9) respectively as per the prescribed conversion school. The average fuzzy weight for criterion C1is computed as follows.

$$\left(\frac{0.7+0.9+0.5}{3},\frac{0.9+1+0.7}{3},\frac{1+1+0.9}{3}\right)=(0.7,0.87,0.97)$$

The average fuzzy weights (AFW) for other subjective criteria C2, C3 and C4 are calculated as (0.90, 1.0,1), (0.83, 0.97,1) and (0.83, 0.97,1) respectively using same procedure. The average fuzzy weight performance ratings are inserted in Table 7.

Table 7. Average fuzzy weight matrix

	C1			C2			C3			C4		
W_a	(0.7	0.87	0.97)	(0.90	1.00	1)	(0.83	0.97	1)	(0.83	0.97	1)

Average fuzzy performance rating of each alternative with respect to ach criteria is normalized to ensure the range of lower, middle and upper values of all average fuzzy performance ratings from 0 (zero) to 1 (one). To accomplish the operation, every points of each average fuzzy performance rating is divided by the greatest point of all which is 10. The fuzzy performance ratings of robotic system R1 under subjective criteria C1, C2, C3 and C4 are (5.7, 7.7, 9.3), (6.3, 8.3, 9.7), (6.7, 8.0, 9.0) and (6.3, 8.3, 9.7) respectively. When each lower, middle and upper point is divided by the greatest point 10, the normalized fuzzy performance ratings for the same are obtained as (0.57, 0.77, 0.93), (0.63, 0.83, 0.97), (0.67, 0.80, 0.90) and (0.63, 0.83, 0.97) respectively. In this way the normalized average performance rating of all alternatives with respect to every criterion is calculated and the related values of normalized average performance ratings are arranged in Table 8.

Table 8. Normalized average fuzzy decision matrix

Ri	C1			C2			C3			C4		
R1	(0.55	0.77	0.93)	(0.63	0.83	0.97)	(0.67	0.80	0.9.0)	(0.63	0.83	0.97)
R2	(0.90	1.0	0.1)	(0.70	0.87	0.97)	(0.57	0.77	0.9)	(0.83	0.97	1.0)
R3	(0.67	0.87	0.97)	(0.83	0.97	1.0)	(0.9	1.0	1.0)	(0.7	0.87	0.97)
R4	(0.30	0.50	0.70)	(0.7	0.87	0.97)	(0.63	0.83	0.97)	(0.57	0.77	0.93)
R5	(0.50	0.70	0.87)	(0.57	0.77	0.9)	(0.83	0.97	1.0)	(0.63	0.83	0.97)

Normalized average performance rating of each alternative robotic system is integrated with the respective criteria as per the algorithm and the weighted normalized average performance rating for the same is calculated for each alternative versus each criterion. For example, normalized average performance rating of the alternative robotic systems are (0.57, 0.77, 0.93), (0.90, 1, 0.1), (0.67, 0.87, 0.97), (0.30, 0.50, 0.70) and (0.50, 0.70, 0.87) respectively. While these normalized average performance ratings are integrated with importance fuzzy weight (0.7, 0.87, 0.97), for criterion C1, then the resultant weighted normalized average performance ratings (WNAPR) of the alternatives with respect to Criteria C1 are (0.39, 0.67, 0.90), (0.63, 0.87, 0.97) ,(0.47, 0.87, 0.94), (0.21, 0.75, 0.68) and (0.35, 0.43, 0.84) respectively.

The calculation of the weighted normalized average performance rating for alternative robotic system R1 with respect to criterion C1 is as follows.

$(0.57 \times 0.7, 0.77 \times 0.87, 0.93 \times 0.97) = (0.39, 0.67, 0.90)$

$(0.90 \times 0.7, 1.0 \times 0.87, 1.0 \times 0.97) = (0.63, 0.87, 0.97)$

$(0.67 \times 0.7, 0.87 \times 0.87, 0.97 \times 0.97) = (0.47, 0.87, 0.94)$

$(0.30 \times 0.7, 0.50 \times 0.87, 0.70 \times 0.97) = (0.21, 0.75, 0.68)$

$(0.50 \times 0.7, 0.70 \times 0.87, 0.93 \times 0.97) = (0.35, 0.43, 0.84)$

It is noted that all non-benefit subjective criteria are normalized in such a way that it is converted into benefit category. Therefore we choose Fuzzy Positive Ideal Solution (FPIS) as (1, 1, 1) and Fuzzy Negative Ideal Solution (FNIS) as (0, 0, 0) for all subjective criteria. Weighted normalized average performance ratings (WNAPR), FPIS and FNIS value for each subjective criterion in terms of TFN are shown in Table 9.

Table 9. Weighted normalized average fuzzy decision matrix

Ri	C1			C2			C3			C4		
R1	(0.39	0.67	0.90)	(0.57	0.83	0.97)	(0.55	0.77	0.90)	(0.52	0.80	0.97)
R2	(0.63	0.87	0.97)	(0.63	0.87	0.97)	(0.47	0.75	0.90)	(0.69	0.94	1.0)
R3	(0.47	0.87	0.94)	(0.74	0.97	1.0)	(0.75	097	1.0)	(0.58	0.84	0.97)
R4	(0.21	0.75	0.68)	(0.63	0.87	0.97)	(0.52	0.80	0.97)	(0.47	0.75	0.93)
R5	(0.35	0.43	0.84)	(0.51	0.77	0.9)	(0.69	0.94	1.0)	(0.40	0.80	0.97)
FPIS	(1,	1,	1)	(1,	1,	1)	(1,	1,	1)	(1,	1,	1)
FNIS	(0,	0,	0)	(0,	0,	0)	(0,	0,	0)	(0,	0,	0)

Positive separation measure (PSM) denoted by S^+ and negative separation measure (NSM) denoted by S^+ for each alternative robotic system are calculated by the Euclidian distance of each alternative from the FPIS and FNIS respectively. Positive separation measure (S_1^+) for alternative robotic system R1 is computed as follows.

$$S_1^+ = \sqrt{\frac{1}{3}\left\{(1-0.39)^2+(1-0.67)^2+(1-0.90)^2\right\}} + \sqrt{\frac{1}{3}\left\{(1-0.57)^2+(1-0.83)^2+(1-0.97)^2\right\}}$$
$$+\sqrt{\frac{1}{3}\left\{(1-0.55)^2+(1-0.77)^2+(1-0.90)^2\right\}} + \sqrt{\frac{1}{3}\left\{(1-0.52)^2+(1-0.80)^2+(1-0.97)^2\right\}}$$
$$S_1^+ = 1.2550$$

Similarly positive separation measures for the alternative robotic systems R2, R3, R4 and R5 are computed as $S_2^+ = 0.9795$, $S_3^+ = 0.8915$, $S_4^+ = 1.4572$ and $S_5^+ = 1.3126$ respectively. It is noted that positive separation measures are determined by crisp values. Negative separation measure (S_1^-) for robotic system R1 is computed as follows.

$$S_1^- = \sqrt{\frac{1}{3}\left\{(0-0.39)^2+(0-0.67)^2+(0-0.90)^2\right\}} + \sqrt{\frac{1}{3}\left\{(0-0.57)^2+(0-0.83)^2+(0-0.97)^2\right\}}$$
$$+\sqrt{\frac{1}{3}\left\{(0-0.55)^2+(0-0.77)^2+(0-0.90)^2\right\}} + \sqrt{\frac{1}{3}\left\{(0-0.52)^2+(0-0.80)^2+(0-0.97)^2\right\}}$$
$$S_1^- = 3.0192$$

Similarly, Negative separation measures for the alternative robotic systems R2, R3, R4 and R5 are computed as $S_2^- = 3.2056$, $S_3^- = 3.3880$, $S_4^- = 2.7216$ and $S_5^- = 3.0831$ respectively. It is noted that negative separation measures are determined and expressed in terms of crisp number.

Positive separation measures and negative separation measures are combined to determine relative closeness (RC) or subjective factor measure (SFM) for each alternative robotic system. The calculation procedure is illustrated as follows.

$$RC_1 = \frac{3.0912}{1.2550+3.0912} = 0.7094 = SFM_1$$

$$RC_2 = \frac{3.2056}{1.2550+3.2056} = 0.7660 = SFM_2$$

$$RC_3 = \frac{3.3880}{0.8915 + 3.3880} = 0.7917 = SFM_3$$

$$RC_4 = \frac{2.7216}{1.3126 + 2.7216} = 0.6513 = SFM_4$$

$$RC_5 = \frac{3.0831}{1.3126 + 3.0831} = 0.7014 = SFM_5$$

The calculated positive separation measure, negative separation measures, relative closeness (RC_i) are presented in Table 10.

Table 10. Positive and negative separation measures, Relative Closeness (RC_i)

Robots	S_i^+	S_i^-	Objective Factor Measure
R1	1.2550	3.0912	0.7094
R2	0.9795	3.2056	0.7660
R3	0.8915	3.3880	0.7917
R4	1.4572	2.7216	0.6513
R5	1.3126	3.0831	0.7014

RC1, RC2, RC3, RC4 and RC5 denote the relative closeness of the robotic systems R1, R2, R3, R4 and R5 respectively. SFM1, SFM2, SFM3 SFM4 and SFM5 denote the subjective factor measure of the robotic systems R1, R2, R3, R4 and R5 respectively. In this paper subjective factor measure is defined as the relative closeness determined from subjective criteria. Relative closeness of robotic systems is depicted in Figure 1.

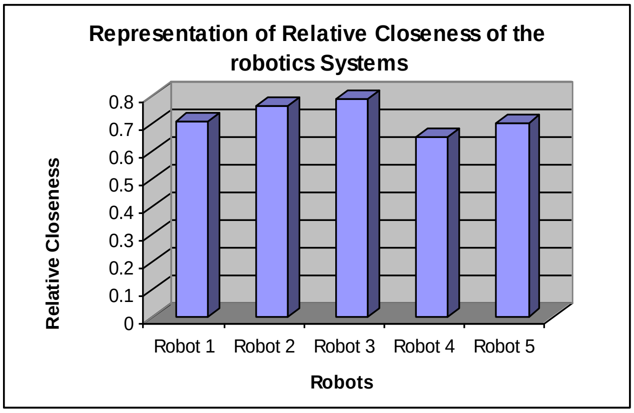

Figure 1. Relative closeness of robotic systems

Objective Factor Measure (OFM) for each alternative robotic system is calculated from the quantitative assessment of objective criterion which is in this case costs. There are five costs components for each alternative robot. The total cost or objective factor cost (OFC) is calculated for each robotic system. This objective factor cost (OFC) is used to compute objective factor measure (OFM) as follows.

$$OFM_1 = \left[3.8\left(\frac{1}{3.8} + \frac{1}{2.2} + \frac{1}{1.8} + \frac{1}{1.6} + \frac{1}{2.7}\right)\right]^{-1} = 0.1132$$

$$OFM_2 = \left[2.2\left(\frac{1}{3.8}+\frac{1}{2.2}+\frac{1}{1.8}+\frac{1}{1.6}+\frac{1}{2.7}\right)\right]^{-1} = 0.1954$$

$$OFM_3 = \left[1.8\left(\frac{1}{3.8}+\frac{1}{2.2}+\frac{1}{1.8}+\frac{1}{1.6}+\frac{1}{2.7}\right)\right]^{-1} = 0.2389$$

$$OFM_4 = \left[1.6\left(\frac{1}{3.8}+\frac{1}{2.2}+\frac{1}{1.8}+\frac{1}{1.6}+\frac{1}{2.7}\right)\right]^{-1} = 0.2687$$

$$OFM_5 = \left[2.7\left(\frac{1}{3.8}+\frac{1}{2.2}+\frac{1}{1.8}+\frac{1}{1.6}+\frac{1}{2.7}\right)\right]^{-1} = 0.1838$$

The difference between objective factor cost and objective factor measure is that objective factor cost is of cost category and objective factor measure of benefit category. Objective factor measures of robotic systems are presented in Figure 2.

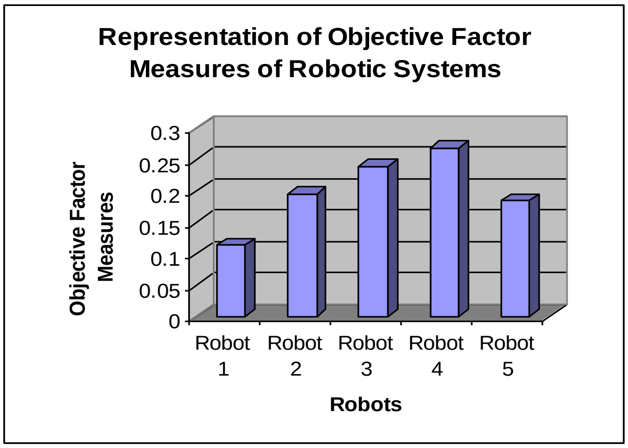

Figure 2. Objective Factor Measure of Robotic Systems

At last, subjective factor measure (SFM) and objective factor measure (OFM) are combined together to compute robot selection index for each alternative robot. Based on the importance of the subjective factor and number of subjective factor a coefficient of decision making attitude $\alpha = 0.67$ is assigned towards the subjective factor measure and $(1-\alpha) = 0.33$ towards objective factor measures. The Subjective factor measure and the objective measure of the robotic system R1 are SFM_1=0.7094, and OFM_1= 0.1132 respectively. The corresponding robot selection index for R1 is calculated as follows.

$$RSI_1 = 0.7094 \times 0.67 + 0.1132 \times 0.33 = 0.5127$$

Similarly the robot selection indices for the other robotic systems R2, R3, R4 and R5 are also calculated below.

$$RSI_2 = 0.7660 \times 0.67 + 0.1954 \times 0.33 = 0.5777$$

$$RSI_3 = 0.7917 \times 0.67 + 0.2389 \times 0.33 = 0.6093$$

$$RSI_4 = 0.6513 \times 0.67 + 0.2687 \times 0.33 = 0.5250$$

$$RSI_5 = 0.7014 \times 0.67 + 0.1838 \times 0.33 = 0.5306$$

Relative closeness (subjective factor measure), objective factor measure, robot selection index are presented in Table 11.

Table 11. Relative Closeness, Objective Factor Measure, Robot Selection Index

Robot (Ri)	Subjective Factor Measure (SFMi)	Objective Factor Measure (OFM_i)	Robot Selection Index (RSI_i)
R1	0.7094	0.1132	0.5127
R2	0.7660	0.1954	0.5777
R3	0.7917	0.2389	0.6093*
R4	0.6513	0.2687	0.5250
R5	0.7014	0.1838	0.5306

It is observed that robot selection indices for the robotic systems are in the following order. $RSI_3 > RSI_2 > RSI_5 > RSI_4 > RSI_1$ Higher robot selection index is better and desirable. Robot selection indices of the robotic systems are shown in Figure 3.

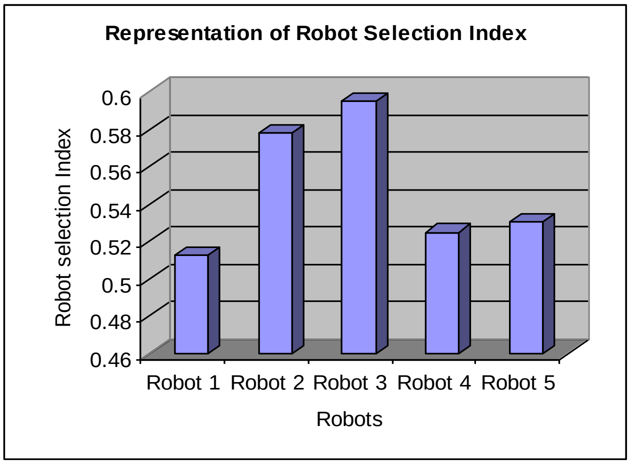

Figure 3. Robot selection indices of robotic systems

Therefore decision makers of the committee can rank the robots as $R_3 > R_2 > R_5 > R_4 > R_1$ and they can make the conclusion that R_3 is the best robotic system of the five.

4. Conclusions

Proper selection of robotic system under subjective and objective factors is very hard. In fuzzy environment, due to existence of imprecision, vagueness and ambiguity in information regarding performance of alternatives and weight of criteria the decision making procedure becomes more complex. In the present work, an effort has been made to turn the complexity into simplicity. To assess the performance of the robot an FMCDM method has been proposed, which can tackle subjective criteria, objective criteria as well as group decision.

This model considers subjective criteria of benefit category only and objective criteria of cost category only. The proposed algorithm can help decision makers to select robots and similar alternatives with subjective and objective criteria under fuzzy MCDM environment. Manual calculation of the data may make the present model tedious and time consuming. The present methodology can be easily be implemented into computer program by the application of Visual basic, Visual C++ and many more. Consideration of interdependent factors and heterogeneous group decision making and can be a new direction of future research and development.

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