Rank Assessment of Robots Using m-Polar Fuzzy ELECTRE-I Algorithm

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Abstract

Extension in bi-polar fuzzy set results in m-Polar fuzzy (mF) set. It is a methodology developed over the years since 2014. Integrated with various multi-criteria decision making (MCDM) techniques, several hybrid algorithms developed to improve the accuracy of the mF set algorithm used for decision making. Algorithms like mF TOPSIS and mF ELECTRE-I are widely used algorithms. In this paper, we aim to solve a selection of robots with the mF ELECTRE-I method. It is implemented in a stepwise manner and elaborated as an mF ELECTRE-I algorithm. We have collected Robot selection data from a previously published research article. Results obtained using mF ELECTRE-I are compared and validated with the same research article. We found that the mF ELECTRE-I method is well resulted in getting the rank solution of robot selection. The rank obtained by mF ELECTRE-I is more consistent with the original research done for robot selection. Graphically presented results are with outranking relations. We can solve a wide range of industry problems starting from pole=1 to available subgroups to implement mF set techniques.

Keywords
Bi-polar, Fuzzy sets (FS), m-polar fuzzy ELECTRE-I, MCDM, and robot.

1. Introduction
This research explores applications of mF sets in industrial selection problems and validates results with existing techniques. The mF set is a recent technique to solve multi-criteria group decision-making problems. It solves issues having uncertainty, multiple subgroups to multiple parameters, multiple parameters, multiple decision-makers, multipolar information, or/and limit process. Now day's mF set methodology is used in various selection problems where data is vague or linguistic. This research will elaborate scope of implementation of mF ELECTRE-I and introduce this methodology to researchers to solve similar types of issues from Industries. For example, the selection of robots in the Industry is one of the MCDM problems. In this paper, selected problems from the literature have five parameters for selecting robots from seven available robots. As the problem is not having subgroups to the parameters, we can consider this as pole=1.

1.1 Objectives

- To solve the problem of robot selection using the mF ELECTRE-I method.
- To explain outranking between alternate robots.
- To validate results with the available results obtained using different techniques.
- To explore the scope of the mF set method for various application domains.

2. Literature Review

Chen et.al, (2014) extended the notion of bipolar fuzzy sets (FSs) to m-polar FSs (mFSs). In an mFS, an element's membership value ranges over $[0, 1]^m$ interval, shows all *m* features of an element (Akram et al., 2019). This FSs fit numerous real-life problems wherein information arrives as of *n* agents ($n \geq 2$). Researchers have used the m-polar FSs while modeling practical problems which involve multiple parameters, multiple alternatives, multiple decision-makers, and uncertainty. These multipolar data further complicate the decision-making procedure in realistic scenarios, thus initiating the MCDM problem. (Akram et al., 2019) introduced the mF ELECTRE-I method for MCDM problems using mFSs. They aimed at exploiting m-polar FSs as a robust tool in depicting uncertainty and fuzziness under multipolar data. In their approach, the decision-maker evaluated the ranking of alternatives under critical conditions and their standardized weights. They applied their proposed m-polar FS method for addressing MCDM problems in three practical-world scenarios like selecting the desired location of the airport, selecting a convenient site for a diesel power plant, and performance assessment of instructors in university administration. They presented alternatives via a graph that indicated the best preferable alternative under the m-polar fuzzy condition for decision making and addressed the complexity faced by existing FS methods in handling ambiguous information under multipolar data. (Akram et al., 2017) provided a multifaceted decision-making approach using m-polar FSs. They presented the m-polar FSs implementation in three real-world decision-making problems: hotel selection, tour selection, and house selection. (Adeel et al., 2019) proposed the m-polar linguistic fuzzy ELECTRE-I technique to solve MCDM and group MCDM problems by assessing alternatives under appropriate linguistic values. (Adeel et al., 2019) analyzed the m-polar FS-based technique's decision-making efficacy to various real-life instances like companies' salary analysis and corrupted country selection.

(Karande and Chakraborty, 2012;Chakraborty, 2011; Brauers and Zavadskas, 2006) studied beneficial and non-beneficial criteria and implemented alternatives from available options using multi-objective optimization based on the ratio analysis (MOORA) method in multi-objective optimization. (Karande,2016)studied six MCDM methods to understand sensitivity while changing values of weights for the essential and critical criteria to solve real-time robot selection problems. The six methods studied are a multiplicative form of MOORA method (MULTIMOORA), MOORA and reference point approach method, WPM, WASPAS, and WSM. Weights obtained for criteria and performance data are the factors that affect the output in the MCDM method (Zavadskas et al., 2006). In MCDM methods, Weights obtained are varies for different approaches. Decision-maker's opinion concerning various weights and uncertain calculations for the various systems like the AHP approach is biased and subjective. A study of MCDM methods shows for the fix alternatives and same criteria, and other MCDM techniques result in various ranks of alternatives (Lourenzutti and Krohling, 2013; Podvezko and Sivilevičius, 2013; Tavana et al., 2013; Chai et al., 2013; Ruzgys et al., 2014). MCDM can be improved to achieve quality in decision making by dealing with it explicitly, efficiently, and more rationally.

3. Method

Akram et al. (2019) explained the novelty of the m-Polar Fuzzy ELECTRE-I method and used it for solving real-life problems. The m-polar fuzzy ELECTRE-I is explained step by step as below:

1) Let $O = \{ o_1, o_2, o_3 \ldots\ldots\ldots o_n \}$ set of options (Alternatives) available with $S = \{ s_1, s_2, s_3, \ldots\ldots\ldots s_n \}$ set of criteria.
2) Representation of the Decision Matrix as alternatives and values of criteria with the help of $H = (h_{ij}) = \{h_{ij}^1, h_{ij}^2, h_{ij}^3 \ldots\ldots\ldots h_{ij}^m\}$
3) Weights are to be normalized and taken from experts, $1 = \sum_{j=1}^{n} w_j$.
4) Applying weight to m-polar decision matrix $X = (x_{ij})$ is formed.
$$X = (x_{ij}) = (x_{ij}^1, x_{ij}^2, x_{ij}^3 \ldots\ldots\ldots x_{ij}^m) \text{ here } x_{ij} = w_j h_{ij} .$$
5) Concordance sets for m-polar fuzzy given by

$$L_{pq} = \{1 \le j \le t : y_{pj} \ge y_{qj},\ p \ne q;\ p,q = 1,2..........n\}$$

Here $y_{ij} = h_{ij}^1 + h_{ij}^2 + h_{ij}^3 .... + h_{ij}^m$,

6) Discordance sets for m-polar fuzzy given by

$$R_{pq} = \{1 \le j \le t : y_{pj} \le y_{qj},\ p \ne q;\ p,q = 1,2..........n\}$$

Here $y_{ij} = h_{ij}^1 + h_{ij}^2 + h_{ij}^3 .... + h_{ij}^m$,

7) Concordance value of indices is formed as

$$l_{pq} = \sum_{j \in L_{pq}} w_j \text{ , for all p,q.}$$

8) Concordance matrix can present as L for the m-polar fuzzy set given as :

$$L = \begin{pmatrix} - & l_{12} & l_{13} & l_{1n} \\ l_{21} & - & .. & l_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ l_{n1} & l_{n2} & \cdots & - \end{pmatrix}$$

9) Discordance indices value is formed as :

$$r_{pq} = \frac{\max_{j \in R_{pq}} \sqrt{\frac{1}{m}\left[\left(x^1{}_{pj} - x^1{}_{qj}\right)^2 + \left(x^2{}_{pj} - x^2{}_{qj}\right)^2 + \ldots + \left(x^m{}_{pj} - x^m{}_{qj}\right)^2\right]}}{\max_j \sqrt{\frac{1}{m}\left[\left(x^1{}_{pj} - x^1{}_{qj}\right)^2 + \left(x^2{}_{pj} - x^2{}_{qj}\right)^2 + \ldots + \left(x^m{}_{pj} - x^m{}_{qj}\right)^2\right]}} \text{ for all p,q}$$

10) Discordance matrix can present as R for the m-polar fuzzy set given as:

$$R = \begin{pmatrix} - & r_{12} & r_{13} & r_{1n} \\ r_{21} & - & .. & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & - \end{pmatrix}$$

11) Levels of Concordance and Discordance can formulate as,

$$\bar{l} = \frac{1}{n(n-1)} \sum_{\substack{p=1 \\ p \ne q}}^{n} \sum_{\substack{q=1 \\ q \ne p}}^{n} l_{pq}$$

$$\bar{r} = \frac{1}{n(n-1)} \sum_{\substack{p=1 \\ p \ne q}}^{n} \sum_{\substack{q=1 \\ q \ne p}}^{n} r_{pq}$$

12) From concordance and discordance levels, we can form K as concordance dominance matrix and U as discordance dominance matrix as,

$$K = \begin{pmatrix} - & k_{12} & k_{13} & k_{1n} \\ k_{21} & - & .. & k_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ k_{n1} & k_{n2} & \cdots & - \end{pmatrix}$$

Here

$$k_{pq} = \begin{cases} 1, \text{ and } l_{pq} \ge \bar{l} \\ 0, \text{ and } l_{pq} \le \bar{l} \end{cases}$$

$$U = \begin{pmatrix} - & u_{12} & u_{13} & u_{1n} \\ u_{21} & - & .. & u_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ u_{n1} & u_{n2} & \cdots & - \end{pmatrix}$$

Here

$$u_{pq} = \begin{cases} 1, \text{ and } r_{pq} \ge \bar{r} \\ 0, \text{ and } r_{pq} \le \bar{r} \end{cases}$$

13) To obtain aggregate dominance matrix V, perform point to point multiplication of K and U matrix values

$$V = \begin{pmatrix} - & v_{12} & v_{13} & v_{1n} \\ v_{21} & - & .. & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{n1} & v_{n2} & \cdots & - \end{pmatrix}$$

Above 13 steps is to be followed for solving the selection problem with the m-polar fuzzy ELECTRE-I method. Matrices K, U, and V are used for outranking relations between alternatives.

4. Robot selection problem:

The selection of robots for operations of pick-n-place with avoiding obstacles is an industrial problem (Bhangale et al., 2004). For a sample from seven different robots, five parameters were selected, such as memory capacity (MC), manipulator reach (MR), repeatability (RE), maximum tip speed (MTS), and load capacity (LC). RE is the non-beneficial parameter from the abovementioned parameters, while the remaining all are the beneficial parameters. Data for problem is collected from case study solved by (Bhangale et. al., 2004). In table 1, seven robots available are o_1 = (A) ASEA-IRB 60/2, o_2 = (B) Cincinnati Milacrone T3-726, o_3 = (C) Cybotech V15 Electric Robot, o_4 = (D) Hitachi America Process Robot, o_5 = (E) Unimation PUMA 500/600, o_6 = (F) United States Robots Maker 110 and o_7 = (G) Yaskawa Electric Motoman L3C. Parameters for robot selection are s_1 = LC, s_2 = RE, s_3 = MTS, s_4 = MC and s_5 = MR. AHP method (Rao et al., 2007) used to calculate weights, as shown in Table 2.

Table 1. problem decision matrix (Bhangale et al.,2004)

Name of robot	s_1	s_2	s_3	s_4	s_5
A	60	0.4	2540	500	990
B	6.35	0.15	1016	3000	1041
C	6.8	0.1	1727.2	1500	1676
D	10	0.2	1000	2000	965
E	2.5	0.1	560	500	915
F	4.5	0.08	1016	350	508
G	3	0.1	1778	1000	920

Table 2. Criteria weights for robot selection parameters (Rao et.al.,2007)

Criteria	s_1	s_2	s_3	s_4	s_5
Weight	0.036	0.192	0.326	0.326	0.12

Table 3 (Karande et al., 2016) showed normalization of criteria values based on techniques of normalization used while solving MCDM problems with the WASPAS method. Table 4, shown below, was obtained by multiplying the normalization matrix with criteria weights. Table 4 is the weight-born matrix and used for all calculations.

Table 3. WASPAS normalization of problem (Karande et al., 2016)

Robot	s_1	s_2	s_3	s_4	s_5
A	1.0000	0.2000	1.0000	0.1667	0.5907
B	0.1058	0.5333	0.4000	1.0000	0.6211
C	0.1133	0.8000	0.6800	0.5000	1.0000
D	0.1667	0.4000	0.3937	0.6667	0.5758
E	0.0417	0.8000	0.2205	0.1667	0.5459
F	0.0750	1.0000	0.4000	0.1167	0.3031
G	0.0500	0.8000	0.7000	0.3333	0.5489

Table 4. Weight multiplied matrix (Karande et al., 2016)

Robot	s_1	s_2	s_3	s_4	s_5
A	0.036	0.0384	0.326	0.0543442	0.070884
B	0.0038088	0.102394	0.1304	0.326	0.074532
C	0.0040788	0.1536	0.22168	0.163	0.12
D	0.0060012	0.0768	0.128346	0.217344	0.069096
E	0.0015012	0.1536	0.071883	0.0543442	0.065508
F	0.0027	0.192	0.1304	0.0380442	0.036372
G	0.0018	0.1536	0.2282	0.108656	0.065868

5. Results and Discussion

Applying m-polar Fuzzy ELECTRE-I methodology to the industrial robot selection problem, we obtained Table 5 and Table 6, which shows the concordance set and discordance set. Matrix L and matrix R below represent the concordance matrix and discordance matrix obtained from the respective group.

5.1 Numerical Results

Concordance and discordance set shown in table 5 and table 6, respectively, evaluated from conditions mentioned in steps five and step six from the methodology. Then, matrix L and matrix R evaluate based on equations mentioned in step 7 and step 9 of the method.

Table 5. Concordance set for robot selection

j	1	2	3	4	5	6	7
B_{1j}	-	{1,3}	{1,3}	{1,3,5}	{1,3,4,5}	{1,3,4,5}	{1,3,5}
B_{2j}	{2,4,5}	-	{4}	{2,3,4,5}	{1,3,4,5}	{1,3,4,5}	{1,4,5}
B_{3j}	{2,4,5}	{1,2,3,5}	-	{2,3,5}	{1,2,3,4,5}	{1,3,4,5}	{1,2,4,5}
B_{4j}	{2,4}	{1}	{1,4}	-	{1,3,4,5}	{1,4,5}	{1,4,5}
B_{5j}	{2,4}	{2}	{2}	{2}	-	{4,5}	{2}
B_{6j}	{2}	{2,3}	{2}	{2,3}	{1,2,3}	-	{1,2}
B_{7j}	{2,4}	{2,3}	{2,3}	{2,3}	{1,2,3,4,5}	{3,4,5}	-

Table 6. Discordance set for robot selection

j	1	2	3	4	5	6	7
E_{1j}	-	{2,4,5}	{2,4,5}	{2,4}	{2}	{2}	{2,4}
E_{2j}	{1,3}	-	{1,2,3,5}	{1}	{2}	{2}	{2,3}
E_{3j}	{1,3}	{4}	-	{1,4}	{}	{2}	{3}
E_{4j}	{1,3,5}	{2,3,4,5}	{2,3,5}	-	{2}	{2,3}	{2,3}
E_{5j}	{1,3,5}	{1,3,4,5}	{1,3,4,5}	{1,3,4,5}	-	{1,2,3}	{1,3,4,5}
E_{6j}	{1,3,4,5}	{1,4,5}	{1,3,4,5}	{1,4,5}	{4,5}	-	{3,4,5}
E_{7j}	{1,3,5}	{1,4,5}	{1,4,5}	{1,4,5}	{}	{1,2}	-

$$L=\begin{bmatrix} - & 0.362 & 0.362 & 0.482 & 0.808 & 0.808 & 0.482 \\ 0.638 & - & 0.326 & 0.964 & 0.808 & 0.808 & 0.482 \\ 0.638 & 0.674 & - & 0.638 & 1 & 0.808 & 0.674 \\ 0.518 & 0.036 & 0.362 & - & 0.808 & 0.482 & 0.482 \\ 0.518 & 0.192 & 0.192 & 0.192 & - & 0.446 & 0.192 \\ 0.192 & 0.518 & 0.192 & 0.518 & 0.554 & - & 0.228 \\ 0.518 & 0.518 & 0.518 & 0.518 & 1 & 0.772 & - \end{bmatrix}$$

$$R=\begin{bmatrix} - & 1 & 1 & 0.824674 & 0.453334 & 0.785276 & 1 \\ 0.720029 & - & 0.56 & 0.0201775 & 0.188497 & 0.311181 & 0.449978 \\ 0.905556 & 1 & - & 0.582256 & 0 & 0.307309 & 0.119976 \\ 1 & 1 & 1 & - & 0.471166 & 0.642499 & 0.918716 \\ 1 & 1 & 1 & 1 & - & 1 & 1 \\ 1 & 1 & 1 & 1 & 0.497907 & - & 1 \\ 0.848958 & 1 & 1 & 1 & 0 & 0.392638 & - \end{bmatrix}$$

Concordance level and Discordance level are $\bar{l} = 0.529238$ and $\bar{r} = 0.738098$. Matrix K and matrix U are outcomes from matrix L and matrix R by comparing values of concordance level and discordance level with each element from matrix L and matrix R.

$$K = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

$$U = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

$$V = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

From Matrix V, robot B is the Best alternative. Values from Matrix K, U, and V are utilized in Table 7 to compare robots. In table 7, the first column is pair of robots. Outranking relation between these robots is obtained based on values of elements from matrix K, U, and matrix V. Values of matrix K, U, and matrix V are equal to one. Therefore, we can show that pairs of robots are comparable. On the other hand, if one element is different from one, it means the team of robots is incomparable. Therefore, robot B is more comparable with other robots and has more advantages than the other robots.

Table 7. Outranking relationship within alternatives of problem.

pair of Robots	B_{pq}	E_{pq}	b_{pq}	e_{pq}	k	u	v	Ranking
(A,B)	{1,3}	{2,4,5}	0.362	1	0	0	0	Incomparable
(A,C)	{1,3}	{2,4,5}	0.362	1	0	0	0	Incomparable
(A,D)	{1,3,5}	{2,4}	0.482	0.824674	0	0	0	Incomparable
(A,E)	{1,3,4,5}	{2}	0.808	0.453334	1	1	1	A → E
(A,F)	{1,3,4,5}	{2}	0.808	0.785276	1	0	0	Incomparable
(A,G)	{1,3,5}	{2,4}	0.482	1	0	0	0	Incomparable
(B,A)	{2,4,5}	{1,3}	0.638	0.720029	1	1	1	B → A
(B,C)	{4}	{1,2,3,5}	0.326	0.56	0	1	0	Incomparable
(B,D)	{2,3,4,5}	{1}	0.964	0.0201775	1	1	1	B → D
(B,E)	{1,3,4,5}	{2}	0.808	0.188497	1	1	1	B → E
(B,F)	{1,3,4,5}	{2}	0.808	0.311181	1	1	1	B → F
(B,G)	{1,4,5}	{2,3}	0.482	0.449978	0	1	0	Incomparable
(C,A)	{2,4,5}	{1,3}	0.638	0.905556	1	0	0	Incomparable
(C,B)	{1,2,3,5}	{4}	0.674	1	1	0	0	Incomparable
(C,D)	{2,3,5}	{1,4}	0.638	0.582256	1	1	1	C → D
(C,E)	{1,2,3,4,5}	{}	1	0	1	1	1	C → E
(C,F)	{1,3,4,5}	{2}	0.808	0.307309	1	1	1	C → F
(C,G)	{1,2,4,5}	{3}	0.674	0.119976	1	1	1	C → G

(D,A)	{2,4}	{1,3,5}	0.518	1	0	0	0	Incomparable
(D,B)	{1}	{2,3,4,5}	0.036	1	0	0	0	Incomparable
(D,C)	{1,4}	{2,3,5}	0.362	1	0	0	0	Incomparable
(D,E)	{1,3,4,5}	{2}	0.808	0.471166	1	1	1	D → E
(D,F)	{1,4,5}	{2,3}	0.482	0.642499	0	1	0	Incomparable
(D,G)	{1,4,5}	{2,3}	0.482	0.918716	0	0	0	Incomparable
(E,A)	{2,4}	{1,3,5}	0.518	1	0	0	0	Incomparable
(E,B)	{2}	{1,3,4,5}	0.192	1	0	0	0	Incomparable
(E,C)	{2}	{1,3,4,5}	0.192	1	0	0	0	Incomparable
(E,D)	{2}	{1,3,4,5}	0.192	1	0	0	0	Incomparable
(E,F)	{4,5}	{1,2,3}	0.446	1	0	0	0	Incomparable
(E,G)	{2}	{1,3,4,5}	0.192	1	0	0	0	Incomparable
(F,A)	{2}	{1,3,4,5}	0.192	1	0	0	0	Incomparable
(F,B)	{2,3}	{1,4,5}	0.518	1	0	0	0	Incomparable
(F,C)	{2}	{1,3,4,5}	0.192	1	0	0	0	Incomparable
(F,D)	{2,3}	{1,4,5}	0.518	1	0	0	0	Incomparable
(F,E)	{1,2,3}	{4,5}	0.554	0.497907	1	1	1	F → E
(F,G)	{1,2}	{3,4,5}	0.228	1	0	0	0	Incomparable
(G,A)	{2,4}	{1,3,5}	0.518	0.848958	0	0	0	Incomparable
(G,B)	{2,3}	{1,4,5}	0.518	1	0	0	0	Incomparable
(G,C)	{2,3}	{1,4,5}	0.518	1	0	0	0	Incomparable
(G,D)	{2,3}	{1,4,5}	0.518	1	0	0	0	Incomparable
(G,E)	{1,2,3,4,5}	{}	1	0	1	1	1	G → E
(G,F)	{3,4,5}	{1,2}	0.772	0.392638	1	1	1	G → F

The directed graph is shown below, drawn from the above table for the robot. For example, the final ranking obtained from the implementation of the 1-Polar Fuzzy ELECTRE-I method is B-C-G-D-A-F-E.

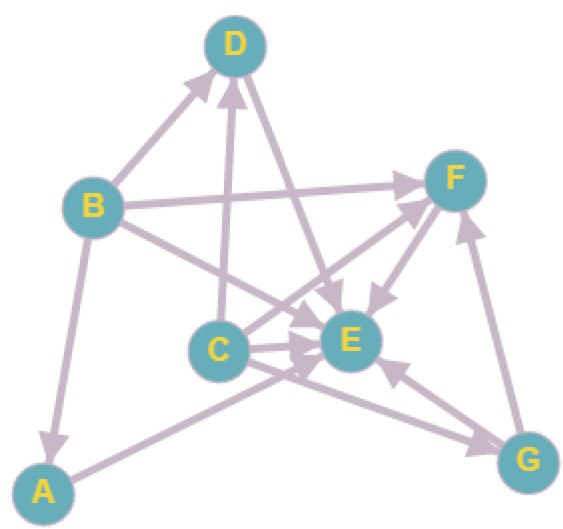

Figure 1. Directed graph of outranking relation of the robot (WPM, WASPAS normalization)

5.2Graphical Results

Directed graph for robots above in figure 1, inferred following points.

1. There are direct edges from B to A, E, F, and D; therefore, robot B is the best selection.
2. Robot C is preferred over D, E, and G robots.
3. Robot G is the best over E and F robots.
4. For robot E, no edge exists from it; It is Incomparable with others.
5. Similarly, robot D is good over robot E.
6. Similarly, robot F is good over robot E.

5.3Proposed Improvements

With the various normalized matrix, the ranking of the robot changes. For example, the decision Matrix normalized for the MOORA method is having a different order than the normalized matrix of WPM and WASPAS. Table 8, shown below, is the decision matrix based on the MOORA normalization method. Figure 2 below shows a directed graph obtained after solving MOORA normalized decision matrix with the 1-Polar Fuzzy ELECTRE-I method.

Table 8. Normalized decision matrix for MOORA (Karande; 2016)

Robot	s_1	s_2	s_3	s_4	s_5
A	0.9705	0.7861	0.6355	0.1217	0.3557
B	0.1027	0.2948	0.2542	0.7304	0.3740
C	0.1100	0.1965	0.4321	0.3652	0.6022
D	0.1618	0.3931	0.2502	0.4869	0.3467
E	0.0404	0.1965	0.1401	0.1217	0.3288
F	0.0728	0.1572	0.2542	0.0852	0.1825
G	0.0485	0.1965	0.4449	0.2435	0.3306

For the above-normalized decision, matrix directed graph will appear as below,

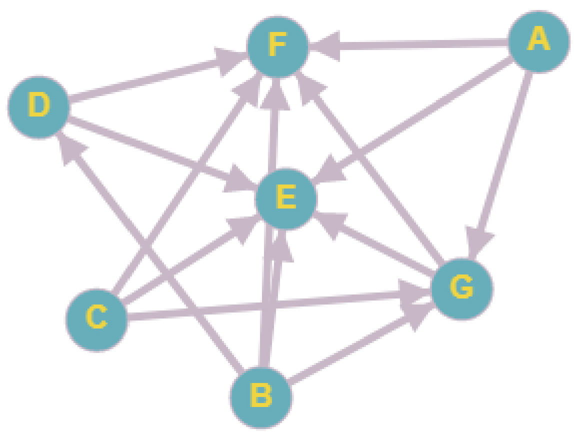

Figure 2. Directed graph of outranking relation of the robot (MOORA normalization). The above figure shows that the ranking of robot A and robot G gets affected by changing the Normalized decision matrix.

5.4 Validation

Various Methods implemented over the year result in multiple rankings of robots. (Karande et al.,2016) Analysis of WSM, Ratio System, WPM, fully multiplicative form, WASPAS, and Reference point found that Ranks have appeared slightly different from (Bhangale et al.,2004). 1-Polar ELECTRE-I with WPM normalization and MOORA normalization methods have the same ranking (Bhangale et al., 2004).

Table 9. Validation of results with previous researchers

ROBOT	Bhangale et al. (2004)	Karande et al. (2016) WSM	Karande et al. (2016) WPM	Karande et al. (2016) WASPAS	Karande et al. (2016) Ratio System	Karande et al. (2016) Reference point	Karande et.al. (2016) Fully multiplicative form	1-polar ELECTRE-1 (WPM-norm)	1-polar ELECTRE-1 (MOORA-norm)
A	3	4	5	5	5	5	2	5	3
B	1	2	2	2	1	2	3	1	1
C	2	1	1	1	2	1	1	2	2
D	6	5	4	4	4	3	4	4	4
E	7	7	7	7	7	5	7	7	7
F	4	6	6	6	6	7	6	6	6
G	5	3	3	3	3	4	5	3	5

6. Conclusions

The m-polar Fuzzy ELECTRE-I method solves the industrial robot selection problem. Earlier researchers have solved robot selection problems with various MCDM techniques. Rankings of the robot selection problem are well-validated with ranks obtained by previous researchers. Directed graphs which explain outranking between robots are the advantage of the ELECTRE-I method for the preference ranking of robots. Decision Matrix normalized as WSM, WPM, and WASPAS form and in MOORA form shows different elements obtained. In robot selection, the way of normalization of the decision matrix affects the final ranking. Results obtained with mF ELECTRE-I are more consistent in scale compared with the original research. The current study scope of the application of mFS is broad in the Industrial selection of robots. In the future, there is vast scope for mFS ELECTRE-I in group decision-making problems.

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