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A Rough Multi-Attributive Border Approximation Area Comparison Approach for Arc Welding Robot Selection

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Abstract

In the present day, automated industries, such as arc welding robots have found immense applications in manufacturing of steel furniture, automobile components, agricultural machineries etc. Selection of the most appropriate robot for a specific welding application can be treated as a multi-criteria decision making problem where the best alternative needs to be identified with respect to a set of conflicting evaluation criteria. In this paper, rough numbers are integrated with multi-attributive border approximation area comparison (MABAC) approach for solving an arc welding robot selection problem. The opinions of five decision makers are aggregated together using rough numbers to avoid subjectivity in the decision making process, while MABAC method is employed to rank the candidate alternatives and choose the best robot for the given welding application. The criteria weights are determined using rough entropy method, which reveals that welding performance and payload are the two most important arc welding robot selection criteria, followed by cost of the robot. The application of rough-MABAC method identifies robot A6 as the most suitable choice and robot A2 as the least preferred option.

Keywords: Arc welding robot; MABAC method; Rank; Rough set theory; Selection;

1. Introduction

According to ISO 8373:2012, an industrial robot can be defined as 'an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications'. Due to their ability to perform dangerous, monotonous and repetitive tasks with unswerving precision and accuracy, industrial robots are now of increasing demands in diverse manufacturing applications under challenging environments. As their various functionalities are automatically controlled by programmed software, they can be operated round the clock while releasing the occupied manpower to other activities, and relieving the manpower from those activities which may cause physical strain and injury to them. Their implementation thus increases productivity and profitability of the present day manufacturing industries while reducing delivery time and improving work environment [1, 2].

Although the primary task of industrial robots is to move materials from one place to another, they can also be adopted for carrying out other programmed tasks in different industrial settings, like welding (arc and spot), machine loading and unloading, spray painting, assembly operation, picking, packing and palletizing, machining and cutting operations, etc. At the same time, the number of industrial robot manufacturers has also shown an increasing trend, each offering a wide range of robots to fulfil the customers' end requirements. Thus, with the availability of different types and models of industrial robots having separate specifications, it now becomes a difficult and challenging assignment to the decision makers to identify the most appropriate robot to perform the specified industrial operation. This robot selection task now becomes more and more intricate as diverse complex features and facilities are being continuously added to the robots by different manufacturers. Changing manufacturing environment, investment plan, product design and manufacturing system often influence the industrial robot selection decision. Thus, selection of the best-suited industrial robot having the desired functional ability can be treated as a multi-criteria decision making (MCDM) problem [3]. It has been often noticed that an ill-selected robot may adversely affect the productivity and profitability of a manufacturing organization. The application of an MCDM method for robot selection basically consists of three stages, i.e. identification and assessment of various robot alternatives and evaluation criteria, determination of the criteria weights and prioritization of the candidate robots. Presence of subjective evaluation criteria expressed in linguistic terms, mutually conflicting criteria and large number of selection criteria make the industrial robot selection task more and more difficult. It can be interestingly noted that Bhangale et al. [4] recognized a total of 83 criteria for performance appraisal of industrial robots.

While applying any MCDM method for identification of the most apposite robot for a given industrial application, valuable opinions of the decision makers/experts are often

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sought to evaluate the performance of the candidate robots with respect to various criteria. These expert opinions are subjectively expressed using linguistic terms and they also considerably vary from one expert to another. These varied judgements of the participating experts need to be aggregated to arrive at the final selection decision. There also exists ambiguity and uncertainty in evaluating weights of various evaluation criteria. In this paper, a maiden endeavour is put forward to evaluate the performance of arc welding robots and identify the best choice for a given task while applying rough multi-attributive border approximation area comparison (MABAC) approach. In order to avoid any biasness in the decision making process, rough entropy method is implemented to determine the priority weights of the considered selection criteria. Arc welding is a joining process which utilizes an electric arc between an electrode and a metal base. Arc welding robots employ this process to generate intense heat to the metal at a joint, causing the metal to melt and intermix. There are several advantages of arc welding robots over the manual welders. They can provide consistent performance throughout the weld, and have extremely high repeatability, causing high quality welds. They can also save the manual welders from toxic fumes and risk of arc burns. They can significantly reduce cycle time and increase productivity. It has been observed that arc welding robots have typically about 75-80% arc-on time, and for larger parts with long seams, they can have more than 95% arc-on time. On the other hand, human welders have less than 50% arc-on time and with fatigue, it may further decrease as the shift progresses. Arc welding robots have found wide ranging applications in manufacturing of steel furniture, automobile components, agricultural machineries etc.

This paper is organized as follows: After providing a brief introduction on the need of arc welding robot selection in Section 1, Section 2 presents a review on various MCDM methods applied for robot selection. Section 3 highlights the mathematics behind rough set theory and MABAC approach. An arc welding robot selection problem is solved in Section 4. Discussions are provided in Section 5 and conclusions are drawn in Section 6.

2. Literature review

It can be revealed that selection of industrial robots for varying applications has already caught the attention of the researchers since several years. Various MCDM techniques, mainly in the form of weighted sum method (WSM), weighted product method (WPM), simple multi-attribute rating technique (SMART), weighted aggregated sum product assessment (WASPAS), multi-objective optimization on the basic of ratio analysis (MOORA), analytic hierarchy process (AHP), technique for order preference by similarity to the ideal solution (TOPSIS), evaluation based on distance from average solution (EDAS), preference ranking organization method for enrichment evaluation (PROMETHEE), TOmada de Decisao Interativa Multicriterio (TODIM) (an acronym in Portuguese for interative multi-criteria decision making) etc. have been adopted for identifying suitable robots for performing simple pick-n-place operations. Table 1 presents a review of the existent literature on industrial robot selection along with the number of alternative robots, evaluation criteria and MCDM techniques employed for solving those problems.

Those MCDM techniques have been deployed under the circumstances where the performance of the alternative robots with respect to various evaluation criteria can be numerically expressed in absolute units. On the other hand, it can also be noticed that some of those MCDM techniques have been integrated with different models of fuzzy set theory, like interval type-2 fuzzy sets, interval-valued hesitant fuzzy theory, cloud model etc. to quantify the qualitative assessment of different robot selection criteria under group decision making environment. Those fuzzy models usually convert the crisp information into fuzzy values to deal with the vagueness present in the decision making process. In fuzzy set theory, identification of the appropriate membership functions mainly depends of the subjective judgments of the concerned decision makers. Auxiliary information is also required in most of the fuzzy models. The introduction of rough numbers instead of fuzzy numbers can more efficiently address the subjectivity and ambiguity in the data because they mainly confide in the original data without any additional information. Rough numbers are able to deal with the vagueness and uncertainty in the data with the help of boundary region of a set instead of membership functions [20-23]. Application of rough numbers in decision making does not require any preliminary or additional information about the primary data (like, probability distributions, membership functions or possibility value). It has been pointed out that the integration of rough numbers with MCDM methods would provide more acceptable and reliable results while solving complex decision making problems [24, 25]. The above-cited literature review also reveals the fact that the application of MCDM methods for solving welding robot selection problems is really scarce. Thus, in this paper, rough numbers are harmonized with MABAC method to identify the most apposite industrial robot for performing arc welding operations in real time manufacturing environment. The rough-MABAC method also identifies the positive and negative attributes for each of the arc welding robot alternatives. This integrated approach would classify the competing robot alternatives into efficient (best performers) and inefficient (underperformers) ones, and would also identify the relative strengths of the best performing robots and weaknesses of the underperforming robots. It would finally rank the competing arc welding robots from the best to the worst. In order to avoid subjectivity in the decision making process, the priority weights of the considered robot selection criteria are determined using rough entropy method. Compared to other subjective weighting models, like best worst method (BWM), step-wise weight assessment ratio analysis (SWARA), factor relationship (FARE), level based weight assessment (LBWA), full consistency method (FUCOM) etc., the major advantage of entropy weighting method is the avoidance of interference of human factors during estimation of criteria weights, thereby increasing objectivity of weight measurement results [26]. Based on the disorder degree of a system (randomness), it can extract valuable information using the data provided. In a decision matrix, when the difference in performance scores of the candidate alternatives with respect to a specific criterion is high, the corresponding entropy would be low providing more useful information and the weight of that criterion would be set as high. On the other hand, if the difference is small, the entropy is high and the relative weight would be low. Thus, the application of rough-MABAC method would help a manufacturing organization in arriving at the most proactive decision with respect to robot selection for a specific welding task. Based on the identified research gap, this paper contributes to the followings:

1. to assess the relative performance of 14 arc welding robot alternatives with respect to 12 evaluation criteria based on the valued opinions of five decision makers/experts using rough numbers,
2. to propose the application of MABAC method to rank all the alternative robots from the best to the worst based on their calculated performance scores,
3. to segregate all the alternative robots into best performing (efficient) and underperforming (inefficient) clusters using their corresponding criteria function values,
4. to identify the relative strengths and weaknesses of each of the robots with respect to all the evaluation criteria so that the concerned manufacturers can modify/upgrade the existing specifications of the underperforming robots to make them more comparable and appropriate for a specific welding task, and
5. to prove the accuracy of the ranking results derived using rough-MABAC method against other popular rough MCDM techniques.

Table 1. List of alternative robots, evaluation criteria and MCDM techniques considered by the past researchers

Sl. No.	Author(s)	Number of alternative robots	Evaluation criteria	MCDM technique(s)
1.	Sen et al. [5]	7, 14	Velocity, load capacity, cost, repeatability, maximum tip speed, memory capacity, manipulator reach, vendor's service quality, programming flexibility	PROMETHEE II
2.	Ghorabaee [6]	8	Inconsistency with infrastructure, man-machine interface, programming flexibility, vendor's service contract, supporting channel partner's performance, compliance, stability	Fuzzy VIKOR with interval type-2 fuzzy sets
3.	Gitinavard et al. [7]	3	Man-machine interface, programming flexibility, vendor's service contract, load capacity, positioning accuracy, cost	Interval-valued hesitant fuzzy distance-based group decision model
4.	Karande et al. [8]	7,12	Load capacity, maximum tip speed, repeatability, memory capacity, manipulator reach, cost, handling coefficient, velocity	WSM, WPM, WASPAS, MOORA, MULTIMOORA
5.	Sen et al. [9]	7	Load capacity, repeatability, maximum tip speed, memory capacity, manipulator reach, man-machine interface, programming flexibility, vendor's service contract, positioning accuracy, safety, environmental performance, reliability, maintainability	Fuzzy PROMETHEE
6.	Sen et al. [10]	7	Load capacity, repeatability, maximum tip speed, memory capacity, manipulator reach, velocity, cost	TODIM
7.	Xue et al. [11]	3	Man-machine interface, programming flexibility, vendor's service contract, cost, load capacity, positioning accuracy	Linguistic MCDM approach
8.	Breaz et al. [12]	3	Load capacity, reach, weight, repeatability, power consumption, dexterity, service	AHP
9.	Wang et al. [13]	4	Inconsistency with infrastructure, man-machine interface, programming flexibility, vendor's service contract, supporting channel partner's performance, compliance, stability	Cloud TODIM
10.	Liu et al. [14]	3	Freedom, work space, velocity, load capacity, accuracy, warranty period, protection class	Linguistic MCDM model
11.	Yalçin and Uncu [15]	3, 5, 7	Load capacity, repeatability, vertical reach, degrees of freedom, maximum tip speed, memory capacity, manipulator reach, man-machine interface, programming flexibility, vendor's service contract	EDAS
12.	Nasrollahi et al. [16]	4	Cost, load capacity, repeatability, man-machine interface, programming flexibility, velocity ratio	Fuzzy BWM-PROMETHEE
13.	Suszynski and Rogalewicz [17]	5	Lifting capacity, weight, working range, repeatability, range of movement, price, velocity	Fuzzy AHP, fuzzy TOPSIS, SMART
14.	Zhang et al. [18]	3	Price, energy consumption, external configuration, accuracy, speed, work raio, programming difficulty	AHP, TOPSIS
15.	Rashid et al. [19]	5	Load capacity, repeatability, velocity ratio, degree of freedom	BWM-EDAS
16.	This paper	14	Payload, horizontal reach, vertical reach, repeatability, weight, power rating, cost, flexibility, safety, welding performance, maintainability, ease of programming	Rough-MABAC

3. Methods

3.1. Rough set theory

A rough number can be expressed with respect to rough boundary interval, comprising lower limit and upper limit [27]. Suppose, in the universe, U with all the objects, Y is an arbitrary object of U, and R is a set of t classes $\{G_1,G_2,...,G_t\}$ encompassing all the objects in U. If these t classes are arranged as $\{G_1<G_2<...<G_t\}$, then $\forall Y \in U, G_q \in R$, $1 \le q \le t$, where $R(Y)$ represents the class to which the object belongs. The lower approximation $(\underline{Apr}(G_q))$, upper approximation $(\overline{Apr}(G_q))$ and boundary region $(Bnd(G_q))$ of class G_q can be denoted as follows:

$$\underline{Apr}(G_q)=\{Y \in U / R(Y) \le G_q\} \tag{1}$$

$$\overline{Apr}(G_q)=\{Y \in U / R(Y) \ge G_q\} \tag{2}$$

$$\begin{aligned} Bnd(G_q)&=\{Y \in U / R(Y) \ne G_q\}= \\ &\{Y \in U / R(Y) > G_q\} \cup \{Y \in U / R(Y) < G_q\} \end{aligned} \tag{3}$$

Then G_q can be defined as rough number $(RN(G_q))$, which can be expressed by its corresponding lower limit $(\underline{Lim}(G_q))$ and upper limit $(\overline{Lim}(G_q))$, as shown below [25]:

$$\underline{Lim}(G_q)=\frac{1}{M_L}\sum\left\{Y \in \underline{Apr}(G_q)\right\}R(Y) \tag{4}$$

$$\overline{Lim}(G_q)=\frac{1}{M_U}\sum\left\{Y \in \overline{Apr}(G_q)\right\}R(Y) \tag{5}$$

$$RN(G_q)=\left[\underline{Lim}(G_q),\overline{Lim}(G_q)\right]=\left[x_{ij}^L,x_{ij}^U\right] \tag{6}$$

where M_L and M_U are the numbers of objects contained in $(\underline{Apr}(G_q))$ and $(\overline{Apr}(G_q))$ respectively, and x_{ij}^L and x_{ij}^U are the lower evaluation and upper evaluation limits of j^{th} criterion with respect to i^{th} alternative respectively.

The difference between the upper and lower evaluation limits is known as the rough boundary interval.

$$IRBnd(G_q)=\overline{Lim}(G_q)-\underline{Lim}(G_q) \tag{7}$$

More vagueness present in the data has a larger rough boundary interval, whereas, more preciseness is represented by the smaller value of this interval.

3.2. Rough number-based entropy method

While solving any MCDM problem, determination of the weights (relative importance) of the considered criteria always plays an important role. Any variation in the criteria weights may result in different ranking orders of the candidate alternatives. It has already been mentioned that the conventional approaches of criteria weight measurement, like AHP, BWM, LBWA, SWARA, FUCOM etc, suffer from a major disadvantage of being affected by the subjective preferences of the decision makers. In order to avoid this subjectivity in human judgements, information entropy theory has now become a well-accepted approach where the estimation of the criteria weights mainly depends on the randomness in the data itself. Thus, rough set theory is combined here with entropy theory to aggregate the individual judgements of the decision makers while estimating the weights of various arc welding robot selection attributes. Determination of the criteria weights based on rough entropy method has the following procedural steps [28]:

- *Step 1*: For k number of decision makers, k number of decision matrices can be developed, each representing the performance of candidate arc welding robots with respect to different attributes under consideration. Based on the information of those decision matrices and rough set theory, the following decision matrix (X) can be formulated:

$$X=\begin{bmatrix} (x_{11}^L,x_{11}^U) & (x_{12}^L,x_{12}^U) & \cdots & (x_{1n}^L,x_{1n}^U) \\ (x_{21}^L,x_{21}^U) & (x_{22}^L,x_{22}^U) & \cdots & (x_{2n}^L,x_{2n}^U) \\ \vdots & \vdots & \ddots & \vdots \\ (x_{m1}^L,x_{m1}^U) & (x_{m2}^L,x_{m2}^U) & \cdots & (x_{mn}^L,x_{mn}^U) \end{bmatrix} \tag{8}$$

where x_{ij} ($1 \le i \le m$, $1 \le j \le n$) is the performance score of i^{th} alternative with respect to j^{th} criterion, m is the number of alternatives and n is the number of attributes.

- *Step 2*: From the initial rough decision matrix (X), the corresponding normalized rough decision matrix, $N=([r_{ij}^L,r_{ij}^U])_{m\times n}$ is now developed. For this normalization process, any of the following two equations can be deployed depending on the type of the considered criterion.

For beneficial criteria:

$$r_{ij}^L=\left[x_{ij}^L-\min(x_{ij}^L)\right]/\left[\max(x_{ij}^U)-\min(x_{ij}^L)\right] \tag{9}$$

(for $1 \le i \le m$, $1 \le j \le n$)

$$r_{ij}^U=\left[x_{ij}^U-\min(x_{ij}^L)\right]/\left[\max(x_{ij}^U)-\min(x_{ij}^L)\right] \tag{10}$$

For non-beneficial criteria:

$$r_{ij}^L=\left[\max(x_{ij}^U)-x_{ij}^U\right]/\left[\max(x_{ij}^U)-\min(x_{ij}^L)\right]$$

(for $1 \le i \le m$, $1 \le j \le n$) (11)

$$r_{ij}^U=\left[\max(x_{ij}^U)-x_{ij}^L\right]/\left[\max(x_{ij}^U)-\min(x_{ij}^L)\right] \tag{12}$$

- *Step 3*: *The* entropy of the rough numbers is now computed using the following expressions:

$$E_j^L=-k\sum_{i=1}^{m} f_{ij}^L \ln(f_{ij}^L) \tag{13}$$

$$E_j^U=-k\sum_{i=1}^{m} f_{ij}^U \ln(f_{ij}^U) \tag{14}$$

where $f_{ij}^L=r_{ij}^L/\sum_{i=1}^{m} r_{ij}^U$, $f_{ij}^U=r_{ij}^U/\sum_{i=1}^{m} r_{ij}^U$, $k = 1/\ln(n)$, supposing $f_{ij}=0$, $f_{ij}\ln f_{ij}=0$.

Now, the weight for j^{th} criterion can be estimated as follows:

$$w_j^L=\frac{1-E_j^U}{\sum_{j=1}^{n}\left(1-E_j^U\right)} \tag{15}$$

$$w_j^U = \frac{1-E_j^L}{\sum_{j=1}^{n}\left(1-E_j^L\right)} \quad (16)$$

where w_j^L and w_j^U respectively represent the lower and upper limits of the entropy weight for j^{th} criterion.

3.3. Rough number-based MABAC method

The implementation procedure of rough number-based MABAC approach for identifying the best alternative based on a set of conflicting criteria has the following steps [29-34]:

- *Step 1*: *Using* the normalized rough decision matrix and rough entropy weights, the corresponding weighted normalized rough decision matrix (V) is formulated.

$$\begin{cases} V = \left(\left[v_{ij}^L, v_{ij}^U\right]\right)_{m\times n} \\ v_{ij}^L = w_j^L\left(n_{ij}^L + 1\right) \\ v_{ij}^U = w_j^U\left(n_{ij}^U + 1\right) \end{cases} \quad (17)$$

where $[n_{ij}^L, n_{ij}^U]$ are the elements of the normalized rough decision matrix (N) and $[w_j^L, w_j^U]$ are the rough entropy weights of j^{th} criterion.

- *Step 2*: Based on the geometric aggregation procedure for interval numbers, the border approximation area (BAA) for each criterion is calculated as follows:

$$\begin{cases} G = [g_1, g_2, ..., g_n], \text{ where } g_j = [g_j^L, g_j^U] \\ g_j^L = \left(\prod_{i=1}^{m} v_{ij}^L\right)^{1/m} \\ g_j^U = \left(\prod_{i=1}^{m} v_{ij}^U\right)^{1/m} \end{cases} \quad (18)$$

- *Step 3*: Calculate the distances of the candidate alternatives from the BAA to obtain the related distance matrix (Q) while employing the Euclidean distance operator for interval numbers.

$$Q = (q_{ij})_{m\times n} = ([q_{ij}^L, q_{ij}^U])_{m\times n} \quad (19)$$

where for beneficial criteria:

$$q_{ij} = \begin{cases} d_E(v_{ij}, g_j) & \text{if } RN(v_{ij}) > RN(g_j) \\ -d_E(v_{ij}, g_j) & \text{if } RN(v_{ij}) < RN(g_j) \end{cases} \quad (20)$$

For non-beneficial criteria:

$$q_{ij} = \begin{cases} -d_E(v_{ij}, g_j) & \text{if } RN(v_{ij}) > RN(g_j) \\ d_E(v_{ij}, g_j) & \text{if } RN(v_{ij}) < RN(g_j) \end{cases} \quad (21)$$

and

$$d_E(v_{ij}, g_j) = \sqrt{(v_{ij}^L - g_j^U)^2 + (v_{ij}^U - g_j^L)^2}$$ for beneficial criteria (22)

$$d_E(v_{ij}, g_j) = \sqrt{(v_{ij}^L - g_j^L)^2 + (v_{ij}^U - g_j^U)^2}$$

for non-beneficial criteria (23)

where $[g_j^L, g_j^U]$ is the BAA for j^{th} criterion.

Now, if $q_{ij} = 0$, an alternative A_i belongs to the BAA (G); if $q_{ij} > 0$, it belongs to upper approximation area (G^+), and if $q_{ij} < 0$, it belongs to lower approximation area (G^-). The ideal alternative (A^+) should be positioned in the upper approximation area (G^+), and location of the anti-ideal alternative (A^-) should be in the lower approximation area (G^-). An alternative (A_i) with as many criteria belonging to the upper approximation area (G^+) should be treated as the best choice.

- *Step 4*: For *determination* of the criteria function values (final scores) of the alternatives, the distances of the alternatives from the BAA vector are added together.

$$S(A_i) = \sum_{j=1}^{n} q_{ij}, \; i = 1,2,...,m \quad (24)$$

The candidate alternatives are now ranked based on the descending values of $S(A_i)$. Hence, the alternative having the highest $S(A_i)$ value is obviously the best suited option.

4. Selection of an arc welding robot

Due to wide ranging applications of arc welding robots in various manufacturing industries, it becomes an ardent need for the decision makers to evaluate the performance of the available robots with respect to some of the important criteria, and to identify the most apposite robot for a said welding application. As the deployment of an arc welding robot is a capital intensive task, any wrong decision during the robot procurement and installation stage may negatively affect the productivity and goodwill of the manufacturing organizations. While selecting an arc welding robot, the judgments of the individual decision makers (experts) are often predisposed. Hence, in order to avoid this biasness in the decision making process, the opinions of five decision makers are sought. These decision makers, engaged in an automobile industry and having more than 10 years of industrial experience, have enough expertise in joining/welding processes, operation and control of arc welding robots, robot programming, part/product geometry, safety and environmental hazards during the welding operation. Each of those decision makers has to assess the performance of 14 candidate arc welding robots with respect to 12 evaluation criteria based on a 9-point scale (where 1 = very low, 3 = low, 5 = moderate, 7 = high and 9 = very high). For this arc welding robot selection problem, the considered evaluation criteria are payload (PL), horizontal reach (HR), vertical reach (VR), repeatability (R), weight (W), power rating (PR), cost (C), flexibility (FL), safety (S), welding performance (WP), maintainability (M) and ease of programming (EP). Amongst these 12 evaluation criteria, PL, HR, VR, R, FL, S, WP, M and EP are beneficial attributes, always requiring their higher values. On the other hand, W, PR and C are non-beneficial criteria where lower values are preferred. Performance of an arc welding robot by the concerned decision makers is usually appraised based on the manufacturers' brand name, service facility provided, features in the robot, complexity of the welding operation to be performed, compactness of the robot etc. Payload is the maximum weight that a robot can lift and manipulate over a specified working space with ease and desired repeatability. It includes weight of the end arm tooling with the necessary welding attachments. Horizontal reach can be defined as the distance from the centre of the robot to the fullest extension of its arm in horizontal direction. On the other hand, vertical reach is the maximum work envelope in vertical direction where a robotic arm with the welding attachments can reach. Repeatability is the measure of variability of a robotic arm's positioning under the specified conditions of load, temperature etc. Weight is the overall weight of an arc welding robot. It plays a crucial role when there is a load constraint in the job floor. Power rating signifies the amount of power required by a robot for performing a seamless welding operation. Cost of an arc welding robot consists of the expenditure incurred during its procurement and installation. Flexibility is the ability of an arc welding robot to perform a variety of different welding tasks regardless of the size, shape or position of the job. Safety is determined on the basis of various safety features present in an arc welding robot to allow safe human-robot interaction. Welding performance indicates the quality and consistency of the welding operation by a robot. Maintainability represents the ease with which it can be ensured that the robots are welding/functioning properly and can be repaired in case of any failure/malfunction. Ease of programming is an important feature for an arc welding robot through which it is instructed to perform a sequence of steps. The robot can be easily reprogrammed to perform a different set of steps as and when desired.

Thus, based on the evaluation of the candidate arc welding robots with respect to 12 assessment criteria by the five decision makers, five decision matrices are developed. Table 2 shows one such decision matrix representing the preference of the first decision maker while evaluating the performance of the considered arc welding robots. Other four decision matrices are also similarly formed. Thus, the first decision maker assesses the performance of robot A_1 with PL = very low (1), HR = very low (1), VR = very low (1), R = very low (1) and so on. Rough set theory is now applied to aggregate the individual judgments of the five decision makers. For example, the set of performance ratings of robot A_1 with respect to PL as evaluated by the five decision makers is represented as x_{11} = {very low, very low, low, low, very low} = {1, 1, 3, 3, 1}. Using Eqs. (4)-(6), this set of subjective linguistic information is transformed into the corresponding rough numbers, as explained below:

For the element $\tilde{x}_{11}$ = {1, 1, 3, 3, 1}

$$\underline{Lim}(1) = 1.00, \overline{Lim}(1) = \frac{1}{5}(1+1+3+3+1) = 1.80$$

$$\underline{Lim}(3) = \frac{1}{5}(1+1+3+3+1) = 1.80, \overline{Lim}(3) = 3.00$$

$$RN(x_{11}^1) = [1.00,1.80], RN(x_{11}^2) = [1.00,1.80],$$
$$RN(x_{11}^3) = [1.80,3.00], RN(x_{11}^4) =$$
$$[1.80,3.00], RN(x_{11}^5) = [1.00,1.80]$$

$$x_{11}^L = \frac{x_{11}^1 + x_{11}^2 + x_{11}^3 + x_{11}^4 + x_{11}^5}{5} =$$
$$\frac{1.00 + 1.00 + 1.80 + 1.80 + 1.00}{5} = 1.32$$

$$x_{11}^U = \frac{x_{11}^1 + x_{11}^2 + x_{11}^3 + x_{11}^4 + x_{11}^5}{5} =$$
$$\frac{1.80 + 1.80 + 3.00 + 3.00 + 1.80}{5} = 2.28$$

Based on the above-demonstrated calculations, all the entries from the decision matrices of the five individual decision makers are converted into a rough decision matrix, $X = ([x_{ij}^L, x_{ij}^U])_{14\times 12}$, as provided in Table 3. It is worthwhile to mention here that among the 12 evaluation criteria, some are beneficial (larger-the-better) in nature and some are non-beneficial (smaller-the-better) attributes. Thus, while taking into consideration both these types of attributes, the rough decision matrix is now normalized applying Eqs. (9)-(12). The corresponding normalized rough decision matrix $N = ([r_{ij}^L, r_{ij}^U])_{14\times 12}$ is shown in Table 4. Similarly, while employing Eqs. (13)-(16), the rough entropy weights for the 12 arc welding robot selection criteria are estimated, as exhibited in Table 5. Amongst these 12 robot selection criteria, WP and PL are observed to have maximum rough entropy weights, followed by C and S. On the other hand, WP is identified having the maximum rough boundary interval, where the five decision makers have opined quite differently.

After developing the normalized rough decision matrix and calculating the rough entropy weights for the considered assessment criteria, the corresponding weighted normalized rough decision matrix is formulated, as shown in Table 6. This matrix is developed by multiplying rough entropy weights with the elements of the normalized rough decision matrix, using Eq. (17). Now, rough-MABAC method is implemented to identify the best arc welding robot from a set of 14 candidate alternatives. Using the geometric aggregation operator for rough numbers and Eq. (18), the related border approximation area (BAA) for each of the robot selection criteria is computed, as presented in Table 7. For example,

g_1^L =
(0.038×0.040×0.048×0.069×0.046×0.056×0.037×0.039×0.036×0.056×0.036×0.036×0.055×0.036)$^{(1/14)}$ = 0.0439

g_1^U =
(0.447×0.469×0.548×0.757×0.531×0.627×0.436×0.497×0.409×0.627×0.409×0.428×0.640×0.412)$^{(1/14)}$ = 0.5070

g_1 = [0.0439,0.5070]

The distances of all the arc welding robot alternatives from the BAA are now calculated to form the corresponding distance matrix, Q, while employing the rough-valued Euclidean distance operator of Eqs. (20)-(23). This distance matrix is provided in Table 8, from which the final score, $S(A_i)$ for each of the arc welding robots is computed. The $S(A_i)$ values are then arranged in descending order to provide a ranking list of the robots from the best to the worst. For example,

S(AR700) = –0.6186 – 0.3759 – 0.4031 – 0.4030 – 0.0822 – 0.0300 + 0.0953 + 0.5566 – 0.5303 + 0.9243 + 0.6042 + 0.6022 = 0.3394

S(AR900) = –0.6321 – 0.3759 – 0.4137 – 0.4030 – 0.0899 – 0.0300 + 0.0953 – 0.4789 + 0.6156 – 0.7685 + 0.6101 + 0.6085 = –1.2624

The final scores of all the 14 arc welding robot alternatives are exhibited in Table 9. Based on these scores as computed using rough-MABAC method, it can be revealed that A_6 robot occupies the top position in the ranking list, followed by robot A_3. The entire ranking list is obtained as $A_6 \rightarrow A_3 \rightarrow A_{13} \rightarrow A_{10} \rightarrow A_5 \rightarrow A_9 \rightarrow A_4 \rightarrow A_{11} \rightarrow A_1 \rightarrow A_{14} \rightarrow A_7 \rightarrow A_{12} \rightarrow A_8 \rightarrow A_2$. The positions of all these alternative arc welding robots in the lower, upper and border approximation areas are depicted in Figure 1. From this figure, it can be noticed that there are two arc welding robots, i.e. A_7 and A_{14} almost positioning on the border approximation area, and the locations of three robots, i.e. A_2, A_8 and A_{12} are in the lower approximation area. The remaining nine arc welding robots are positioned in the upper approximation area. Based on the positions of the alternative robots in the upper and lower approximation areas, they can be definitely categorized as efficient and inefficient ones respectively for the given welding task. Thus, it can be concluded that the arc welding robots, A_6, A_3, A_{13}, A_{10}, A_5, A_9, A_4, A_{11} and A_1 can be efficiently deployed to perform the required welding task in a real time manufacturing environment.

Table 2. Arc welding robot performance evaluation matrix by decision maker 1

Arc welding robot	PL	HR	VR	R	W	PR	C	FL	S	WP	M	EP
A_1	1	1	1	1	1	1	7	7	3	7	7	7
A_2	1	1	1	1	1	1	7	3	7	3	7	7
A_3	3	3	3	3	3	1	3	3	3	7	3	7
A_4	9	5	5	3	5	3	3	3	9	3	3	7
A_5	3	5	5	5	5	3	3	7	3	3	3	7
A_6	7	5	5	3	5	3	9	9	7	7	7	9
A_7	1	3	3	5	3	1	7	7	3	9	9	3
A_8	3	5	5	5	5	3	3	3	3	3	7	3
A_9	1	9	9	9	9	5	3	3	3	7	7	3
A_{10}	7	9	9	9	9	9	7	7	7	7	3	3
A_{11}	1	3	3	5	3	1	9	7	9	3	9	7
A_{12}	1	3	3	5	3	1	7	7	7	3	9	3
A_{13}	7	5	5	5	7	7	3	7	3	7	3	3
A_{14}	1	3	3	5	3	1	7	7	3	7	9	3

Table 3. Rough decision matrix for arc welding robot selection problem

Arc welding robot	PL	HR	VR	R	W	PR	C	FL	S	WP	M	EP
A_1	[1.32,2.28]	[1.08,1.72]	[1.08,1.72]	[1.32,2.28]	[1.32,2.28]	[1.08,1.72]	[7.08,7.72]	[7.08,7.72]	[3.08,3.72]	[7.08,7.72]	[5.72,6.68]	[5.72,6.68]
A_2	[1.72,2.68]	[1.08,1.72]	[1.32,2.28]	[1.32,2.28]	[1.08,1.72]	[1.08,1.72]	[7.08,7.72]	[3.32,4.28]	[5.72,6.68]	[3.08,3.72]	[6.28,6.92]	[6.28,6.92]
A_3	[3.08,3.72]	[3.08,3.72]	[3.32,4.28]	[3.32,4.28]	[3.08,3.72]	[1.32,2.28]	[3.32,4.28]	[3.32,4.28]	[3.32,4.28]	[5.72,6.68]	[1.72,2.68]	[5.72,6.68]
A_4	[8.28,8.92]	[5.32,6.28]	[5.08,5.72]	[3.08,3.72]	[4.28,4.92]	[3.32,4.28]	[3.72,4.68]	[3.08,3.72]	[8.28,8.92]	[3.32,4.28]	[1.72,2.68]	[5.32,6.28]
A_5	[3.08,3.72]	[5.32,6.28]	[5.32,6.28]	[5.08,5.72]	[5.32,6.28]	[3.32,4.28]	[3.08,3.72]	[5.72,6.68]	[1.72,2.68]	[3.32,4.28]	[3.08,3.72]	[5.32,6.28]
A_6	[6.28,6.92]	[5.72,6.68]	[5.08,5.72]	[3.08,3.72]	[5.08,5.72]	[3.08,3.72]	[7.72,8.68]	[8.28,8.92]	[5.72,6.68]	[6.28,6.92]	[7.32,8.28]	[7.72,8.68]
A_7	[1.32,2.28]	[3.08,3.72]	[3.32,4.28]	[5.08,5.72]	[3.32,4.28]	[1.08,1.72]	[7.08,7.72]	[6.28,6.92]	[3.08,3.72]	[8.28,8.92]	[8.28,8.92]	[3.08,3.72]
A_8	[3.32,4.28]	[5.08,5.72]	[5.32,6.28]	[5.08,5.72]	[3.72,4.68]	[3.32,4.28]	[3.32,4.28]	[3.08,3.72]	[3.08,3.72]	[3.32,4.28]	[6.28,6.92]	[3.32,4.28]
A_9	[1.08,1.72]	[8.28,8.92]	[8.28,8.92]	[7.72,8.68]	[8.28,8.92]	[3.72,4.68]	[3.72,4.68]	[3.08,3.72]	[3.32,4.28]	[5.72,6.68]	[5.72,6.68]	[3.72,4.68]
A_{10}	[6.28,6.92]	[7.72,8.68]	[7.72,8.68]	[8.28,8.92]	[8.28,8.92]	[7.72,8.68]	[6.28,6.92]	[7.08,7.72]	[5.72,6.68]	[5.72,6.68]	[3.08,3.72]	[3.32,4.28]
A_{11}	[1.08,1.72]	[3.32,4.28]	[3.32,4.28]	[5.08,5.72]	[3.32,4.28]	[1.32,2.28]	[8.28,8.92]	[7.32,8.28]	[7.72,8.68]	[3.32,4.28]	[8.28,8.92]	[5.72,6.68]
A_{12}	[1.32,2.28]	[3.32,4.28]	[3.08,3.72]	[5.08,5.72]	[3.32,4.28]	[1.32,2.28]	[7.08,7.72]	[7.08,7.72]	[7.32,8.28]	[3.72,4.68]	[7.72,8.68]	[3.72,4.68]
A_{13}	[5.72,6.68]	[5.32,6.28]	[5.32,6.28]	[5.32,6.28]	[7.08,7.72]	[7.08,7.72]	[3.08,3.72]	[7.32,8.28]	[3.08,3.72]	[5.72,6.68]	[3.08,3.72]	[3.08,3.72]
A_{14}	[1.08,1.72]	[3.08,3.72]	[3.32,4.28]	[5.32,6.28]	[3.32,4.28]	[1.32,2.28]	[7.32,8.28]	[7.08,7.72]	[3.08,3.72]	[6.28,6.92]	[7.08,7.72]	[3.32,4.28]

Table 4. Normalized rough decision matrix for arc welding robot selection problem

Arc welding robot	PL	HR	VR	R	W	PR	C	FL	S	WP	M	EP
A_1	[0.036,0.181]	[0,0.096]	[0,0.096]	[0.036,0.181]	[0.819,0.964]	[0.904,1.000]	[0,0.096]	[0.904,1.000]	[0.301,0.398]	[0.904,1.000]	[0.699,0.843]	[0.699,0.843]
A_2	[0.096,0.241]	[0,0.096]	[0.036,0.181]	[0.036,0.181]	[0.904,1.000]	[0.904,1.000]	[0,0.096]	[0.337,0.482]	[0.699,0.843]	[0.301,0.398]	[0.783,0.88]	[0.783,0.880]
A_3	[0.328,0.448]	[0.328,0.448]	[0.373,0.552]	[0.373,0.552]	[0.552,0.672]	[0.821,1.000]	[0.448,0.627]	[0.373,0.552]	[0.373,0.552]	[0.821,1.000]	[0.075,0.254]	[0.821,1.000]
A_4	[0.911,1.000]	[0.500,0.633]	[0.467,0.556]	[0.189,0.278]	[0.556,0.644]	[0.644,0.778]	[0.589,0.722]	[0.189,0.278]	[0.911,1.000]	[0.222,0.356]	[0,0.133]	[0.5000,0.633]
A_5	[0.274,0.403]	[0.726,0.919]	[0.726,0.919]	[0.677,0.806]	[0.081,0.274]	[0.484,0.677]	[0.597,0.726]	[0.806,1.000]	[0,0.194]	[0.323,0.516]	[0.274,0.403]	[0.726,0.919]
A_6	[0.548,0.658]	[0.452,0.616]	[0.342,0.452]	[0,0.110]	[0.548,0.658]	[0.890,1.000]	[0.041,0.205]	[0.890,1.000]	[0.452,0.616]	[0.548,0.658]	[0.726,0.89]	[0.795,0.959]
A_7	[0.031,0.153]	[0.255,0.337]	[0.286,0.408]	[0.510,0.592]	[0.592,0.714]	[0.918,1.000]	[0.153,0.235]	[0.663,0.745]	[0.255,0.337]	[0.918,1.000]	[0.918,1.000]	[0.255,0.337]
A_8	[0.063,0.313]	[0.521,0.688]	[0.583,0.833]	[0.521,0.688]	[0.583,0.833]	[0.688,0.938]	[0.688,0.938]	[0,0.167]	[0,0.167]	[0.063,0.313]	[0.833,1.000]	[0.063,0.313]
A_9	[0,0.082]	[0.918,1.000]	[0.918,1.000]	[0.847,0.969]	[0,0.082]	[0.541,0.663]	[0.541,0.663]	[0.255,0.337]	[0.286,0.408]	[0.592,0.714]	[0.592,0.714]	[0.337,0.459]
A_{10}	[0.548,0.658]	[0.795,0.959]	[0.795,0.959]	[0.890,1.000]	[0,0.110]	[0.041,0.205]	[0.342,0.452]	[0.685,0.795]	[0.452,0.616]	[0.452,0.616]	[0,0.110]	[0.041,0.205]
A_{11}	[0,0.082]	[0.286,0.408]	[0.286,0.408]	[0.510,0.592]	[0.592,0.714]	[0.847,0.969]	[0,0.082]	[0.796,0.918]	[0.847,0.969]	[0.286,0.408]	[0.918,1.000]	[0.592,0.714]
A_{12}	[0,0.130]	[0.272,0.402]	[0.239,0.326]	[0.511,0.598]	[0.598,0.728]	[0.870,1.000]	[0.130,0.217]	[0.783,0.87]	[0.815,0.946]	[0.326,0.457]	[0.870,1.000]	[0.326,0.457]
A_{13}	[0.508,0.692]	[0.431,0.615]	[0.431,0.615]	[0.431,0.615]	[0.108,0.231]	[0.108,0.231]	[0.877,1.000]	[0.815,1.000]	[0,0.123]	[0.508,0.692]	[0,0.123]	[0,0.123]
A_{14}	[0,0.089]	[0.278,0.367]	[0.311,0.444]	[0.589,0.722]	[0.556,0.689]	[0.833,0.967]	[0,0.133]	[0.833,0.922]	[0.278,0.367]	[0.722,0.811]	[0.833,0.922]	[0.311,0.444]

Table 5. Rough entropy weights for arc welding robot selection criteria

PL	HR	VR	R	W	PR	C	FL	S	WP	M	EP
[0.036,0.378]	[0.026,0.223]	[0.025,0.236]	[0.025,0.230]	[0.026,0.205]	[0.020,0.142]	[0.036,0.304]	[0.022,0.233]	[0.027,0.282]	[0.020,0.377]	[0.029,0.272]	[0.025,0.271]

Table 6. Weighted normalized rough decision matrix for arc welding robot selection problem

Arc welding robot	PL	HR	VR	R	W	PR	C	FL	S	WP	M	EP
A_1	[0.038,0.447]	[0.026,0.245]	[0.025,0.258]	[0.026,0.271]	[0.047,0.402]	[0.039,0.285]	[0.036,0.333]	[0.042,0.466]	[0.035,0.395]	[0.038,0.755]	[0.049,0.502]	[0.042,0.500]
A_2	[0.040,0.469]	[0.026,0.245]	[0.026,0.278]	[0.026,0.271]	[0.050,0.410]	[0.039,0.285]	[0.036,0.333]	[0.030,0.345]	[0.046,0.520]	[0.026,0.527]	[0.051,0.512]	[0.044,0.510]
A_3	[0.048,0.548]	[0.035,0.323]	[0.034,0.366]	[0.035,0.356]	[0.041,0.342]	[0.037,0.285]	[0.052,0.494]	[0.030,0.361]	[0.037,0.438]	[0.037,0.755]	[0.031,0.341]	[0.045,0.542]
A_4	[0.069,0.757]	[0.039,0.365]	[0.037,0.366]	[0.030,0.293]	[0.041,0.337]	[0.033,0.253]	[0.057,0.523]	[0.026,0.298]	[0.051,0.565]	[0.025,0.511]	[0.029,0.309]	[0.037,0.443]
A_5	[0.046,0.531]	[0.045,0.429]	[0.043,0.452]	[0.042,0.415]	[0.028,0.261]	[0.030,0.239]	[0.057,0.524]	[0.040,0.466]	[0.027,0.337]	[0.027,0.572]	[0.037,0.382]	[0.043,0.521]
A_6	[0.056,0.627]	[0.038,0.361]	[0.033,0.342]	[0.025,0.255]	[0.040,0.339]	[0.038,0.285]	[0.037,0.366]	[0.042,0.466]	[0.039,0.456]	[0.031,0.625]	[0.049,0.515]	[0.044,0.531]
A_7	[0.037,0.436]	[0.033,0.299]	[0.032,0.332]	[0.038,0.365]	[0.042,0.351]	[0.039,0.285]	[0.041,0.375]	[0.037,0.406]	[0.034,0.377]	[0.039,0.755]	[0.055,0.545]	[0.031,0.363]
A_8	[0.039,0.497]	[0.040,0.377]	[0.039,0.432]	[0.038,0.387]	[0.041,0.375]	[0.034,0.276]	[0.060,0.588]	[0.022,0.272]	[0.027,0.329]	[0.021,0.495]	[0.053,0.545]	[0.026,0.356]
A_9	[0.036,0.409]	[0.050,0.447]	[0.048,0.471]	[0.047,0.452]	[0.026,0.221]	[0.031,0.237]	[0.055,0.505]	[0.028,0.311]	[0.035,0.398]	[0.032,0.647]	[0.046,0.467]	[0.033,0.396]
A_{10}	[0.056,0.627]	[0.047,0.438]	[0.045,0.461]	[0.048,0.459]	[0.026,0.227]	[0.021,0.172]	[0.048,0.441]	[0.037,0.418]	[0.039,0.456]	[0.029,0.61]	[0.029,0.302]	[0.026,0.327]
A_{11}	[0.036,0.409]	[0.034,0.315]	[0.032,0.332]	[0.038,0.365]	[0.042,0.351]	[0.037,0.280]	[0.036,0.329]	[0.040,0.447]	[0.050,0.556]	[0.026,0.531]	[0.055,0.545]	[0.039,0.465]
A_{12}	[0.036,0.428]	[0.033,0.313]	[0.031,0.312]	[0.038,0.367]	[0.042,0.354]	[0.038,0.285]	[0.040,0.370]	[0.039,0.435]	[0.049,0.549]	[0.027,0.550]	[0.054,0.545]	[0.033,0.395]
A_{13}	[0.055,0.640]	[0.037,0.361]	[0.036,0.380]	[0.036,0.371]	[0.029,0.252]	[0.022,0.175]	[0.067,0.607]	[0.040,0.466]	[0.027,0.317]	[0.030,0.638]	[0.029,0.306]	[0.025,0.305]
A_{14}	[0.036,0.412]	[0.033,0.305]	[0.033,0.340]	[0.040,0.395]	[0.041,0.346]	[0.037,0.280]	[0.036,0.344]	[0.041,0.448]	[0.034,0.386]	[0.035,0.683]	[0.053,0.523]	[0.032,0.392]

Table 7. BAA matrix for arc welding robot selection problem

PL	HR	VR	R	W	PR	C	FL	S	WP	M	EP
[0.0439, 0.5070]	[0.0363, 0.3388]	[0.0346, 0.3603]	[0.0356, 0.3532]	[0.0374, 0.3205]	[0.0335, 0.2552]	[0.0458, 0.4278]	[0.0346, 0.3942]	[0.0369, 0.4265]	[0.0297, 0.6119]	[0.0427, 0.4412]	[0.0349, 0.4246]

Table 8. Distance matrix for arc welding robot selection problem

Arc welding robot	PL	HR	VR	R	W	PR	C	FL	S	WP	M	EP
A_1	-0.6186	-0.3759	-0.4031	-0.4030	-0.0822	-0.0300	0.0953	0.5566	-0.5303	0.9243	0.6042	0.6022
A_2	-0.6321	-0.3759	-0.4137	-0.4030	-0.0899	-0.0300	0.0953	-0.4789	0.6156	-0.7685	0.6101	0.6085
A_3	0.6815	-0.4183	0.4646	0.4521	-0.0220	-0.0297	-0.0666	-0.4891	0.5594	0.9253	-0.5076	0.6338
A_4	0.8365	0.4447	0.4635	-0.4134	-0.0165	0.0021	-0.0959	-0.4522	0.6475	-0.7595	-0.4908	0.5628
A_5	0.6705	0.4903	0.5243	0.4903	0.0603	0.0167	-0.0970	0.5580	-0.4998	-0.7978	-0.5282	0.6178
A_6	0.7372	0.4428	-0.4487	-0.3944	-0.0191	-0.0299	0.0622	0.5568	0.5711	0.8318	0.6135	0.6253
A_7	-0.6120	-0.4031	-0.4427	0.4562	-0.0308	-0.0300	0.0530	0.5157	-0.5198	0.9241	0.6333	-0.5121
A_8	-0.6515	0.4534	0.5106	0.4721	-0.0550	-0.0207	-0.1613	-0.4411	-0.4953	-0.7518	0.6348	-0.5116
A_9	-0.5959	0.5019	0.5368	0.5172	0.0997	0.0185	-0.0780	-0.4591	-0.5327	0.8467	0.5800	-0.5325
A_{10}	0.7372	0.4963	0.5308	0.5223	0.0940	0.0845	-0.0134	0.5237	0.5711	-0.8222	-0.4874	-0.4944
A_{11}	-0.5959	-0.4131	-0.4427	0.4562	-0.0308	-0.0255	0.0998	0.5436	0.6415	-0.7713	0.6333	0.5774
A_{12}	-0.6074	-0.4124	-0.4309	0.4572	-0.0337	-0.0299	0.0583	0.5352	0.6366	-0.7827	0.6342	-0.5322
A_{13}	0.7485	0.4430	0.4743	0.4615	0.0690	0.0807	-0.1809	0.5579	-0.4881	0.8418	-0.4893	-0.4823
A_{14}	-0.5976	-0.407	-0.4480	0.4770	-0.0255	-0.0251	0.0841	0.5437	-0.5250	0.8719	0.6182	-0.5303

Table 9. Final scores for the arc welding robots

Arc welding robot	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}
Score	0.3394	-1.2624	2.1833	0.7288	1.5054	3.5485	0.0316	-1.0175	0.9026	1.7425	0.6725	-0.5076	2.0361	0.0365
Rank	9	14	2	7	5	1	11	13	6	4	8	12	3	10

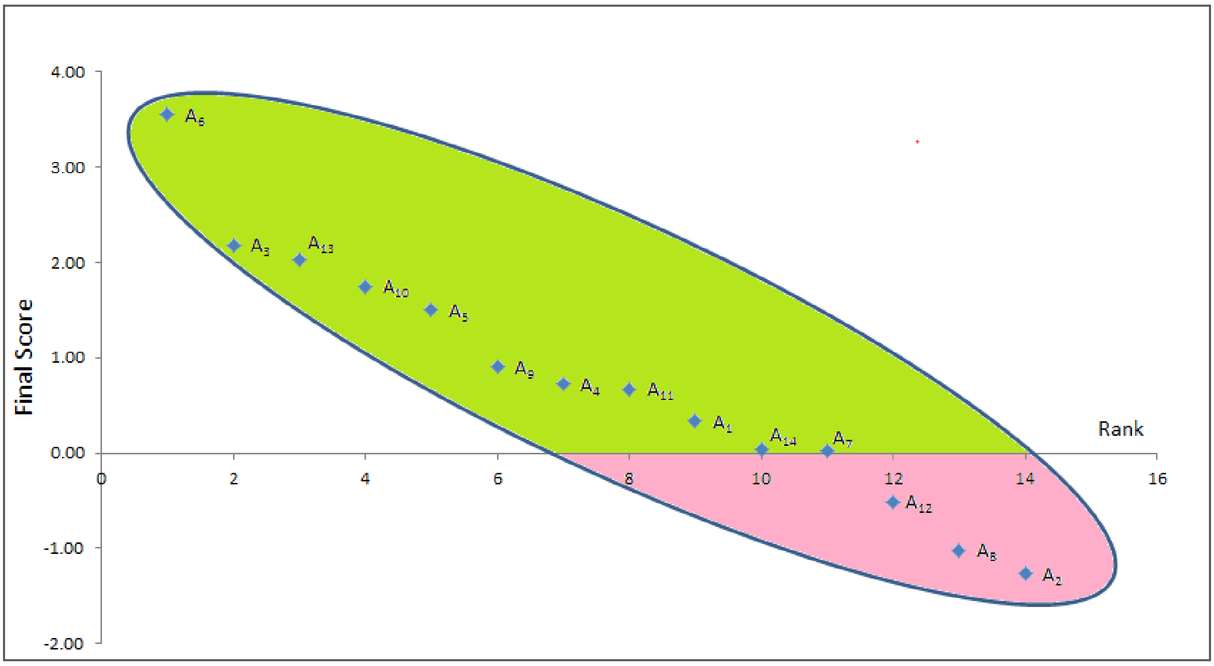

Figure 1. Positions of the arc welding robots in the lower, upper and border approximation areas

Now, in order to analyze the capabilities of each of the considered arc welding robots as well as their strengths and weaknesses, Tables 10 and 11 are developed. In Table 9, the locations of all the arc welding robots in the upper and lower approximation areas with respect to various evaluation criteria are portrayed. In this industrial robot selection problem, it has already been stated that PL, HR, VR, R, FL, S, WP, M and EP are the beneficial criteria, whereas, W, PR and C are the non-beneficial criteria. From Table 10, it can be observed that for the beneficial attributes, the locations of almost all the efficient arc welding robots are in the upper approximation area. In the similar way, those efficient arc welding robots are positioned in the lower approximation area for the non-beneficial criteria. In Table 11, the locations of 12 robot selection criteria in the upper and lower approximation areas for the 14 arc welding robots are shown. For the efficient robots, almost all the beneficial criteria are located in the upper approximation area and the positions of the non-beneficial attributes are in the lower approximation area. It can be propounded that robot A_6 (the top ranked alternative) is quite strong with respect to PL, HR, C, FL, S, WP, M and EP criteria, whereas, it has weaknesses only in VR, R, W and PR criteria. Thus, it has relatively low vertical reach, low repeatability, high weight and high power rating. On the other hand, the major strengths of A_3 (second ranked robot) are with respect to PL, VR, R, S, WP and EP, and it is weak with respect to HP, W, PR, C, FL and M criteria. It has poor horizontal reach, flexibility and maintainability. Similarly, the last ranked arc welding robot A_2 has only four criteria (C, S, M and EP) in its favour. It has major weaknesses with respect to PL, HR, VR, R, W, PR, FL and WP criteria. The identification of the strengths and weaknesses of each of the alternative arc welding robots would thus guide the decision makers in choosing the most appropriate robot for a given welding task.

In order to study the solution accuracy of rough-MABAC method in solving this arc welding robot selection problem, its ranking performance is finally compared with that of other rough-MCDM methods, i.e. rough-WASPAS, rough-SAW, rough-TOPSIS and rough-VIKOR, as shown in Table 12. It can be observed from this table that the positions of the top two and last arc welding robots remain unchanged in most of the rough-MCDM methods, although there are variations in the intermediate rankings of the considered alternatives. It proves the applicability of rough-MABAC method as an effective and sound mathematical tool for solving diverse problems in group decision making environment where the individual judgements of the decision makers are subjectively expressed.

Table 10. Positions of arc welding robots with respect to different evaluation criteria

Evaluation criteria	Position of the arc welding robot	
	Upper approximation area	Lower approximation area
PL	A_3, A_4, A_5, A_6, A_{10}, A_{13}	A_1, A_2, A_7, A_8, A_9, A_{11}, A_{12}, A_{14}
HR	A_4, A_5, A_6, A_8, A_9, A_{10}, A_{13}	A_1, A_2, A_3, A_7, A_{11}, A_{12}, A_{14}
VR	A_3, A_4, A_5, A_8, A_9, A_{10}, A_{13}	A_1, A_2, A_6, A_7, A_{11}, A_{12}, A_{14}
R	A_3, A_5, A_7, A_8, A_9, A_{10}, A_{11}, A_{12}, A_{13}, A_{14}	A_1, A_2, A_4, A_6
W	A_5, A_9, A_{10}, A_{13}	A_1, A_2, A_3, A_4, A_6, A_7, A_8, A_{11}, A_{12}, A_{14}
PR	A_4, A_5, A_9, A_{10}, A_{13}	A_1, A_2, A_3, A_6, A_7, A_8, A_{11}, A_{12}, A_{13}
C	A_1, A_2, A_6, A_7, A_{11}, A_{12}, A_{14}	A_3, A_4, A_5, A_8, A_9, A_{10}, A_{13}
FL	A_1, A_5, A_6, A_7, A_{10}, A_{11}, A_{12}, A_{13}, A_{14}	A_2, A_3, A_4, A_8, A_9
S	A_2, A_3, A_4, A_6, A_{10}, A_{11}, A_{12}	A_1, A_5, A_7, A_8, A_9, A_{13}, A_{14}
WP	A_1, A_3, A_6, A_7, A_9, A_{13}, A_{14}	A_2, A_4, A_5, A_8, A_{10}, A_{11}, A_{12}
M	A_1, A_2, A_6, A_7, A_8, A_9, A_{11}, A_{12}, A_{14}	A_3, A_4, A_5, A_{10}, A_{13}
EP	A_1, A_2, A_3, A_4, A_5, A_6, A_{11}	A_7, A_8, A_9, A_{10}, A_{12}, A_{13}, A_{14}

Table 11. Positions of different evaluation criteria for arc welding robots

Arc welding robot	Position of the evaluation criteria	
	Upper approximation area	Lower approximation area
A_1	C, FL, WP, M, EP	PL, HR, VR, R, W, PR, S
A_2	C, S, M, EP	PL, HR, VR, R, W, PR, FL, WP
A_3	PL, VR, R, S, WP, EP	HR, W, PR, C, FL, M
A_4	PL, HR, VR, PR, S, EP	R, W, C, FL, WP, M
A_5	PL, HR, VR, R, W, PR, FL, EP	C, S, WP, M
A_6	PL, HR, C, FL, S, WP, M, EP	VR, R, W, PR
A_7	R, C, FL, WP, M	PL, HR, VR, W, PR, S, EP
A_8	HR, VR, R, M	PL, W, PR, C, FL, S, WP, EP
A_9	HR, VR, R, W, PR, WP, M	PL, C, FL, S, EP
A_{10}	PL, HR, VR, R, W, PR, FL, S	C, WP, M, EP
A_{11}	R, C, FL, S, M, EP	PL, HR, VR, W, PR, WP
A_{12}	R, C, FL, S, M	PL, HR, VR, W, PR, WP, EP
A_{13}	PL, HR, VR, R, W, PR, FL, WP	C, S, M, EP
A_{14}	R, C, FL, WP, M	PL, HR, VR, W, PR, S, EP

Table 12. Comparison of rankings based on different rough-MCDM methods

Arc welding robot	Rough MCDM method				
	Rough-MABAC	Rough-WASPAS	Rough-SAW	Rough-TOPSIS	Rough-VIKOR
A_1	9	12	11	13	4
A_2	14	14	14	9	14
A_3	2	1	1	6	1
A_4	7	4	4	1	2
A_5	5	3	3	7	6
A_6	1	2	2	2	5
A_7	11	5	10	12	3
A_8	13	9	7	14	8
A_9	6	6	5	10	10
A_{10}	4	8	6	3	13
A_{11}	8	7	8	4	11
A_{12}	12	10	9	5	12
A_{13}	3	13	12	11	9
A_{14}	10	11	13	8	7

5. Discussions

As selection of the most apposite robot for a specific welding operation is a capital intensive task, this decision making process must be formulated seeking opinions of a group of experts to avoid biasness/partiality in the final selection decision. A wrongly selected robot may negatively influence productivity of a manufacturing organization. In this paper, an attempt is put forward to rank 14 arc welding robot alternatives based on 12 evaluation criteria using an integrated approach combining rough numbers and MABAC method. The performances of all the robots are first assessed with respect to the considered criteria using the judgements of five decision makers/experts. As criteria weights play a pivotal role in any decision making process, rough entropy method having the advantage of determining importance of the criteria based on randomness of the dataset itself is employed here. The MABAC is later adopted to provide a complete ranking of the candidate arc welding robots from the best to the worst along with the strengths and weaknesses of each of the alternatives. It is observed that among the considered alternatives, A_6 is the best performing robot, followed by A_3. On the other hand, robot A_2 is the worst preferred choice. Arc welding robot A_6 has the strengths with respect to PL, HR, C, FL, S, WP, M and EP evaluation criteria, whereas, VR, R, W and PR are its major weaknesses. It has low vertical reach and repeatability, and high weight and power rating. Similarly, for robot A_2, C, S, M and EP are its favourable properties and it lags behind with respect to PL, HR, VR, R, W, PR, FL and WP criteria. In the similar direction, application of rough-MABAC method segregates all the candidate robots as the best performing and underperforming ones with respect to each of the evaluation criteria. For example, robots A_3, A_4, A_5, A_6, A_{10} and A_{13} are the best performing alternatives (positioned in upper approximation area) with respect to PL criterion. On the contrary, robots A_1, A_2, A_7, A_8, A_9, A_{11}, A_{12} and A_{14} are underperforming (located in lower approximation area) against criterion PL. Identification of the deficiencies of the inefficient arc welding robots (underperformers) would help the concerned manufacturers to modify the existing specifications and/or add new technical features to make them more comparable and appropriate for a specific welding task. In this context, the advantageous features of the best performing robots can act as an appraisement module (benchmark) to others with respect to product variety, reliability and safe functionality.

Application of this integrated MCDM methodology thus proves itself as an efficient decision making tool while accurately providing complete ranking order of the considered arc welding robots. It can thus assist the decision makers/managers in understanding and improving the selection process of the most suitable arc welding robot from available alternatives along with process enhancement and adaptation of business intelligence leading to conceptualization of Industry 4.0 approach.

6. Conclusions

It has already been pointed out by the previous researchers that integration of rough set theory with any of the MCDM methods would provide more accurate and reliable ranking solutions to varied decision making problems. Keeping this objective in mind, the present paper dealt with the application of rough-MABAC method for evaluation and selection of the most appropriate arc welding robot based on a set of 12 conflicting criteria. In order to avoid subjectivity in human judgements, the weights of the considered evaluation criteria are estimated using rough entropy method. Based on this analysis, all the 14 arc welding robots are classified as efficient and inefficient ones based on their positions in the upper and lower approximation areas respectively. The robot A_6 is identified as the best option for performing the given welding task with eight favourable (PL, HR, C, FL, S, WP, M and EP) and only four unfavourable criteria (VR, R, W and PR). On the other hand, A_2 is the least preferred robot with only four favourable (C, S, M and EP) and eight unfavourable criteria (PL, HR, VR, R, W, PR, FL and WP). A comparison study of the ranking performance with the other rough-MCDM methods proves the efficacy of rough-MABAC approach in solving complex decision making problems. However, rough-MABAC method suffers from some drawbacks. It is unable to provide satisfactory results when the criteria weights are completely unknown. It is assumed that all the evaluation criteria are independent to each other which may not be true in real time welding environment. During information aggregation using rough numbers, it is also supposed that all the participating decision makers have equal importance. But, based on its several attractive advantages, it can be effectively applied as a flexible and comprehensive tool for solving real time decision making problems, such as selection of appropriate machine tool, flexible manufacturing system, cutting fluid, materials for engineering components etc. As a further future scope, the applicability of MABAC method using interval rough number or intuitionistic fuzzy sets may be explored.

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