The Implementation of MABAC Approach for Arc Welding Robot Selection with Rough Approach Integration

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Abstract: In the current days, several immense applications in the agricultural machineries, automobile components, manufacturing process of steel furniture and some other applications can be found by the automated industries like the arc welding. Actually, the selection of the most suitable robot for a certain welding application may be handled as a critical decision making with multi-criteria, where the optimal alternative needs must be chosen based on a certain conflicting evaluation criteria. In this study, an approach "multi-attributive-border-approximation-area-comparison (MABAC)" has been integrated with rough numbers to solve a certain problem, which is arc welding robot selection. Five certain decision makers gave their opinions that have been aggregated to each other by using the rough numbers in order to mitigate the subjectivity and the personality in the process of decision maker. However, MABAC approach is used to rank the proposed alternatives in addition to select the optimal robot for a certain welding application. Moreover, the criteria weights were calculated based on the rough entropy approach that reveals that both of welding payload and welding performance are considered as the most essential robot-selection criteria in the arc welding application, followed by the robot cost. In this paper, the usage of the rough MABAC approach indicated that robot A6 is the most proper choice, while the worst selection is for A2.

Keywords: *Welding Application, MABAC, Arc Welding Robot Selection, Welding Payload, Welding Performance.*

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I. INTRODUCTION

A. Overview

Based on ISO number 8373:2012, the industrial developed robot is known as reprogrammable, controllable, and an adaptable manipulator that can be programmed for three or more axes, which are stationary in a certain area or another option is that it may be mobile to be used in the industrial automation field. Because of their ability to achieve some monotonous, repetitive, and dangerous tasks with unswerving accuracy and precision, the industrial robots become these days highly demand in diverse manufacturing field with the existence of several environments challenges. Since their different functionalities can be automatically monitored and, therefore, controlled through a programmed software (Arents & Greitans, 2022). These industrial robots may be worked nearby the clock during sending the workers into other activities, and protect the workers from their works that could lead to produce physical stress as well as harms. Hence, inserting the industrial developed robots enhance the profitability and the productivity of these days manufacturing industries and decreasing the delivery time in addition to enhancing the work environment (Wu, et al., 2022).

However, the goal of the main task of the industrial developed robots is to change the place of something by moving it from location to another, but they can be used to carry out some other programmed responsibilities in several industrial settings like the cutting and machining operations, palletizing and packing, picking, assembly operation, spray painting, machine unloading and loading, welding (spot and arc). Simultaneously, the overall number of the industrial robot's manufacturers has become a trend because it provides extensive range of applications to accomplish the clients' end necessities. Hence, with the existence of these several kinds and models of industrial-robots that have several conditions, this makes the selection of the most proper robot a relatively challenging and difficult task. The

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most proper robot requires the identification of the most suitable robot that can perform a special industrial operation.

Fig 1 Robot used for Arc Welding *(Kah, et al., 2015)*.

Now, the selection of the robot becomes core complicated since these robots diverse some complex characteristics. However, several facilities are being added into the robot through several manufacturers. By the way, there are several factors that contribute in the robot selection decision such as: manufacturing system and product design, investment plan, varying the manufacturing environment. Therefore, the optimal selection of the suited industrial developed robots, who have the preferred goal that is the capability, which could be handled as a multi-criteria decision making (MCDM) (Tan, et al., 2021). It has been observed that the inaccurate selection of robot leads to, adversely, affect the profitability as well as productivity of the manufacturing organization. Three stages are proposed for robot selection based on the MCDM, which are 1- the assessment and the identification of several robot options besides the evaluation criteria 2-calculating the criteria weights and 3- the ranking regarding the candidate and proposed robots. Existence of subjectivity in evaluation criteria is expressed in several approaches such as: the linguistic terms, the mutually-conflicting criteria, in addition to the selection criteria for large number. This makes the task of industrial selection of robot becomes, relatively, difficult.

However, (Agrawal, et al., 2004) stated that there are a total number of criteria regarding the performance appraisal of the industrial robots equal to 80 criteria. During applying the MCDM approach for identifying the most proper robot to a certain industrial; field, several valuable opinions obtained from the decision experts/makers are required in order to make an evaluation for the candidate-robots performance depending on several criteria. The opinions of these experts were subjectively provided based on the linguistic terms, and these opinions was varied from expert to another. Whatever, the varied opinions of the experts have been aggregated at the end of the decision selection stage, some uncertainties and ambiguity were existed during the evaluation of some criteria weights. In this study, the first endeavour is selected to assess the performance of the robot welding by arc and to classify the optimal selection of a certain task during implementing rough multi-attributive-border-approximation-area-comparison (MABAC) method. Rough entropy method was used to calculate the considered selection criteria priority weights in order to mitigate the biasness during decision making.

In general, the welding process by arc is defined as a linking process that uses an arc between a metal base and an electrode. Similarly, arc welding industrial robots generates an intense temperature and heat into the metal, especially at the joint point, which causes the melt of metal and therefore the intermixing. Different advantages are obtained from the arc welding by robots that cannot be achieved by the manual-welders. For instance, arc welding by robots can give a reliable performance and behaviour during the weld process, provide an extremely high repeatability, which causes a high quality of weld. Moreover, it can protect the manual welders from arc burns risks and toxic fumes, increasing the productivity and minimising the cycle time. It was observed that the on-time of an arc welding by robots is around 75-80 %, while for larger portions with a relatively long seams, the on time is more than, approximately, 95%. In contrast, manual welding by humans may have an on time, which is less than 50% and with the fatigue this percentage may be decreased.

Arc welding by robots can be used in several applications, especially in the manufacturing process of the steel furniture, agricultural machineries, and the automobile components. The structure of this paper is: the first stage is providing a brief description regarding the necessity of the selection of arc welding by robots in the first section, then several MCDM approaches that are applied in robot selection are reviewed in the second section. The mathematical behind the rough theory and the MABAC method is highlighted in section number 3, while the solution of the selection problem of arc welding-robot is shown in section number 4. In the fifth section, the discussions are clarified and the conclusions are illustrated in the sixth section.

B. Components of Robots Arc Welding System

Welding is considered as an essential process especially in advanced industrial manufacturing. In addition, robots are considered as the essential component in modern welding technique. In the newest application of the robot arc welding, which is also known as the first generation G_1 robot arc welding. With the continuous development of technology, the arc robot came with the G_2. However, the up-to-date technology in robot arc welding is G_3. However, Figure 2 represents the main components of any robot arc welding scheme (Kah, et al., 2015). While Figure 3 clarifies the structure of any welding robot environment (Yang, et al., 2017).

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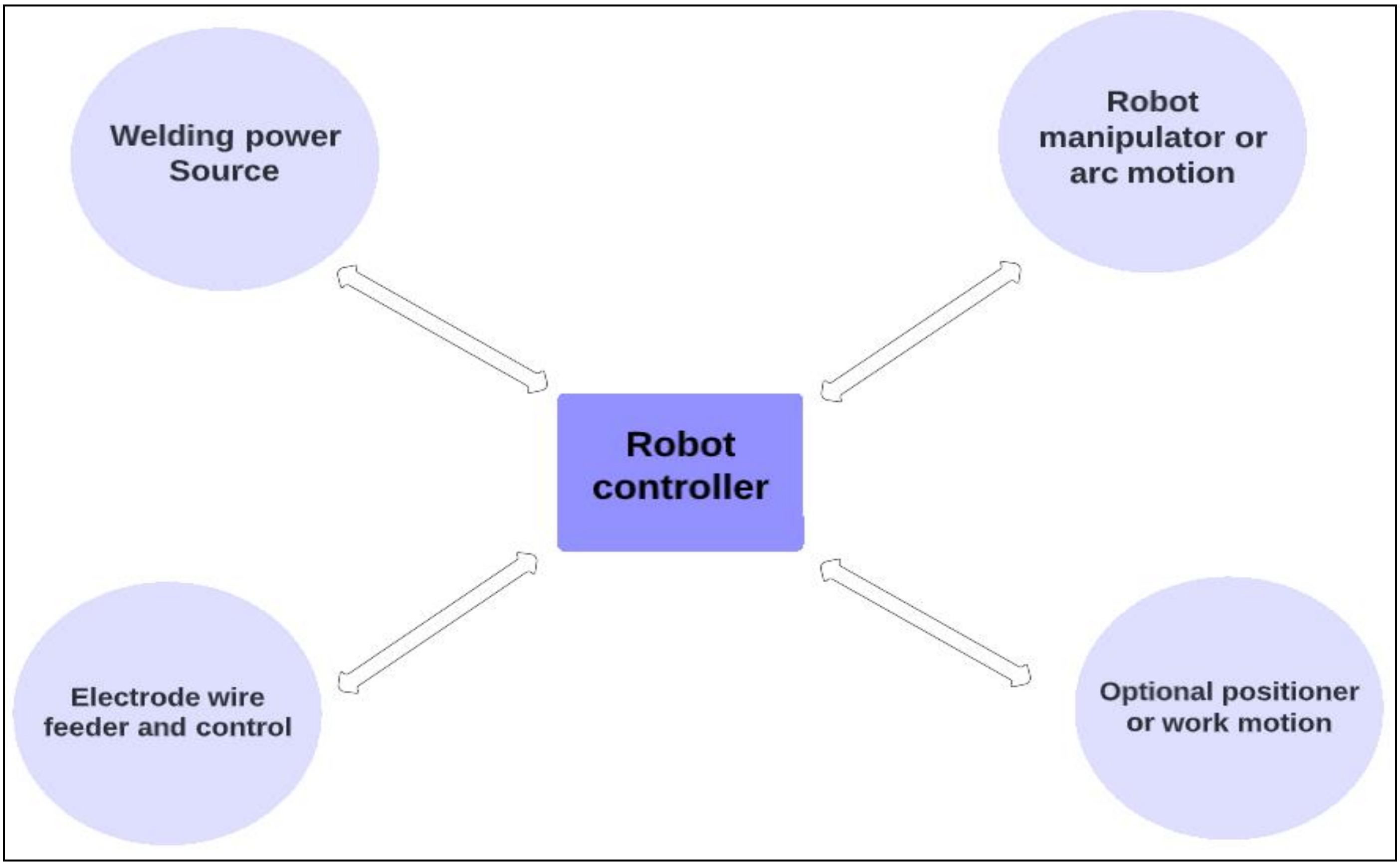

Fig 2 Components in Any Robot Arc Welding *(Kah, et al., 2015)*.

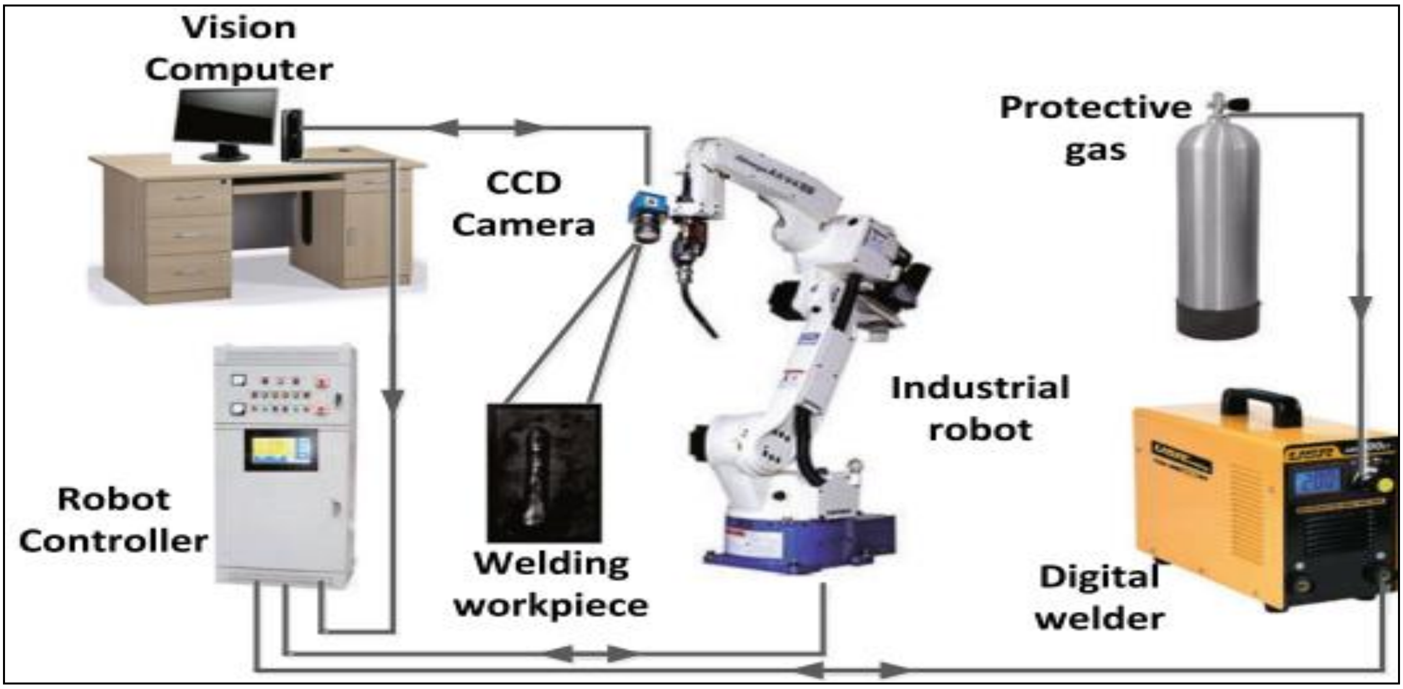

Fig 3 Structure of Any Welding Robot Environment (Yang, et al., 2017).

C. Technological Challenges in Robotic Arc Welding

As mentioned in the previous subsections, arc welding process is used in several industrial applications. The only thing that differs between the robot arc welding and the welding process is the manipulation. However, several challenges are considered in arc welding, such as: the type of material may not be suitable to be arced, further, this technique require a large number of interrelated components and parameters. Moreover, the wrong selection of the position which should be very accurate is also considered as a big challenge for arc welding by robots. The control process of the arc welding by the robots is also considered as a big deal. Finally, how to start running of the process is not as easy as can be imagined (Bolmsjö & Olsson, 2002).

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II. LITERATURE REVIEW

The industrial developed robot's selection for several uses owned huge attention in the research. Different techniques of MCDM were adopted to identify the proper robots to perform a simple pick-n-place task. Some of these techniques are: PROMETHEE, TOPSIS, WSM, WPM, WASPAS, TOPSIS, TODIM, EDAS, AHP, MOORA, and MOORA. Several studies that investigated the industrial selection of robot, in corresponding number with the other robots, the criteria that are used in the evaluation, in addition to the MCDM that were used to resolve the problem of robot selection are clarified in Table 1.

Table 1 List of MCDM Techniques, Evaluation Criteria, and the Number of Alternative Robots.

Authors	# of robots options	Criteria of Evaluation	techniques of MCDM
(Ali, et al., 2021)	5	Degree of freedom, velocity ratio, repeatability, load capacity.	BWM-EDAS
(Rogalewicz & Suszynski, 2020)	5	Velocity, price, range of movement, repeatability, working range, weight, lifting capacity.	SMART, fuzzy TOPSIS, Fuzzy AHP.
(Datta & Sen, 2015)	7,14	Programming flexibility, vendor's quality of service, manipulator reach, memory capacity, repeatability, cost, load capacity, and velocity.	PROMETHEE II
(Guo, et al., 2019)	3	Protection class, warranty period, accuracy, load capacity, velocity, work space, freedom.	Linguistic MCDM.
(Nasrollahi, et al., 2020)	4	Velocity ratio, programming flexibility, man-machine interface, repeatability, load capacity, and cost.	Fuzzy BWM-PROMETHEE
(Ghorabaee, 2016)	8	Stability, compliance, supporting-channel-partner's behaviour, programming flexibility, man-machine Interface, Inconsistency with infrastructure.	Fuzzy VIKOR with Type two fuzzy type.
(Zhao, et al., 2019)	3	Programming difficulty, work ratio, speed, external configuration, energy consumption, accuracy, and price.	TOPSIS, AHP.
(Siadat, et al., 2016)	3	Cost, locating accuracy, capacity of the load, programming flexibility, interface of the machine.	Interval Fuzzy depending on a group of decision model.
(Yalçin & Uncu, 2019)	3, 5, 7	Vendor's service contract, flexibility, programming, man-machine interface, manipulator reach, memory capacity, degrees of freedom, vertical reach, repeatability, load capacity.	EDAS
(Chakraborty, et al., 2016)	7, 12	Velocity, handling coefficient, cost, manipulator reach, memory capacity, repeatability, load capacity.	MULTIMOORA, MOORA, WASPAS, WPM, WSM
(Guo, et al., 2019)	3	protection class, warranty period, accuracy, load capacity, velocity, work space, freedom	Linguistic MCDM
(Mahapatra, et al., 2016)	7	Maintainability, reliability, environmental performance, safety, positioning accuracy, programming flexibility, manipulator reach, memory capacity, repeatability, load capacity	Fuzzy PROMETHEE
(Liu, et al., 2018)	4	Stability, compliance, programming flexibility, Inconsistency with the infrastructure.	Cloud TODIM
(Liu, et al., 2016)	3	Positioning accuracy, load capacity, cost, programming flexibility, Man-machine interface.	Linguistic MCDM
(Mahapatra, et al., 2016)	7	Maintainability, safety, reliability, positioning accuracy environmental performance, programming flexibility, manipulator reach.	TODIM
(Racz, et al., 2017)	3	Service, dexterity, power consumption, repeatability, weight, reach, load capacity.	AHP

The mentioned MCDM techniques were organised under certain situations where the behaviour of the other robots could be mathematically expressed in the absolute units with respect to several evaluation criteria. In addition, these MCDM techniques were integrated with several fuzzy models in order to quantify the whole qualitative assessment for several selection criteria of robot. Some of these models are: cloud model, interval-valued hesitant fuzzy theory, type two fuzzy groups. For clarifications, the fuzzy models always transform a crisp input to some values of fuzzy to handle the obscurity present within the process of decision making (Chach, 2018). In fuzzy concept, the definition of the most suitable MF relies on the decision maker's judgments. In most of the fuzzy models some Auxiliary information will be required. Introducing the RN instead of the FN could set an ambiguity in addition to the subjectivity in the data since they trust the origin data with no need to add to any extra information. RNs are commonly capable to handle uncertainty as well the vagueness within the data

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with guidelines of the limit region of the set rather than the MFs (Au & Chan, 2001).

No initiatory or added information for the main data like the possibility value or MFs, and probability distributions will be required for applications of rough numbers, especially in decision making (Jia, et al., 2019). It was noticed that the integration of MCDM method as well as the rough numbers will deliver more reliable and acceptable outcomes during solving the complicated decision making issues (Pamucar, et al., 2019).

The mentioned studies showed that applying a certain method, which is MCDM, in order to solve the selection of welding robot issues is considered as a scarce issue. Hence, in this work, the rough numbers were harmonised with the MABAC approach in order to choose the most proper industrial developed robot to achieve the operation of arc welding within the real time of manufacturing environment. MABAC approach identify the negative and positive features of any welding process by arc. The mentioned method will categorise the competition of robots options for inefficient (underperformers) and efficient (best performers) ones. Further, it will identify relative strengths for the best behaviour of the robots in addition to weaknesses of the poor performance robots. Finally, this method will rank the competition between the welding by the arc based on the performance of the robot (from best to worst). The preference weights of the measured selection criteria of robot were determined by using rough entropy approach to mitigate the bias in decision making.

Comparing subjective weighting to each other, such as FUCOM, LBWA, FARE, SWARA, and BWM, the main benefit of the EW approach is mitigating the human influences interference while estimating the weights of the criteria, therefore, rising the subjectivity of the weight values outcomes (Park, et al., 2017). Depending on the system disorder degree, in other words “randomness”, valuable information can be extracted by the provided data. If the variation in behaviour marks of the proposed options for a certain studied criterion is relatively large in a decision matrix, the parallel entropy is expected to be minimum, that provides additional valuable data and the CW will be high. In contrast, if the variation in behaviour marks of the proposed options for a certain criterion is small, the EM would be large while the weight will be minimal. Therefore, applying the MABAC approach will guide the manufacturing organization to get the best proactive decision based on the selection of robot of certain task of welding. Depending on the mentioned researches gaps, the contribution of this study are:

- To identify and introduce the relative weaknesses and strength for each robot, based on the evaluation criteria. Therefore, the manufacturers could upgrade/modify the current conditions of poor performing robots in order to remake the robots more suitable and comparable of certain welding duty,
- Isolating the whole alternative robots to the efficient in addition to inefficient groups by utilizing their function values parallel criteria.
- To verify the accuracy, which is for the ranking outcomes that are derived by using MABAC approach,
- To propose and suggest the performance and the behaviour of the fourteen robot welding by arc options according to the twelve performance indicators, which relies on the views of the 5 experts by using RNs,
- Suggesting MABAC approach in order to make a rank for the whole robot’s options from the optimal into poorest depending on the determined scores of the performance,

III. METHEMATICAL MODELLING

A. RS Principle

The RN could be represented in terms of the interval of rough boundary, involving both the lower limit as well as the upper limit (Tiwari, et al., 2016). Assuming that the “Y” represents the autocratic object of the symbol U, while the symbol R represents a set of several periods (from 1 to t) $\{G_1, G_2, \dots, G_t\}$ involving the whole objects within U. if the periods are ranked like $\{G_1 \text{ lower than } G_2 \text{ lower than } G_3 \dots \text{lower than } G_t\}$, then for $\forall\, Y \in U, G_q \in R, 1 \leq q \leq t$, where the symbol $R(Y)$ denotes the classes that the object belongs. However, the upper approximation is ($\overline{Apr}\,(G_q)$), while the lower approximation is ($\underline{Apr}\,(G_q)$), while the boundary region, which is denoted by ($Bnd\ (G_q)$) could be expressed as:

$$\underline{Apr}\,(G_q) = \{Y \in U / R(Y) \leq G_q\} \dots\dots\dots\dots\dots\dots (1)$$

$$\overline{Apr}\,(G_q) = \{Y \in U / R(Y) \geq G_q\} \dots\dots\dots\dots\dots\dots (2)$$

$$Bnd\,(G_q) = \left\{Y \in \frac{U}{R(Y)} \neq G_q\right\} = \{Y \in U/R(Y) > G_q\} \cup \left\{Y \in \frac{U}{R(Y)} < G_q\right\} \dots\dots (3)$$

Therefore, the symbol Gq could be expressed in terms of a RN ($RN\,(G_q)$), that could be written with the help of its upper limit, which is denoted by ($\overline{Lim}\ (G_q)$), and lower limit, which is denoted by ($\underline{Lim}\ (G_q)$) as clarified in the following equations (Zhai, et al., 2009):

$$\underline{Lim}\,(G_q) = \frac{1}{M_L} \sum \{Y \in \underline{Apr}\,(G_q)\}\, R(Y) \dots\dots (4)$$

$$\overline{Lim}\,(G_q) = \frac{1}{M_U} \sum \{Y \in \overline{Apr}\,(G_q)\} R(Y) \dots . (5)$$

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

Where MU and ML are the objects number in ($\overline{Apr}\ (G_q)$) and ($\underline{Apr}\ (G_q)$) respectively, while x_{ij}^U and x_{ij}^L represents the upper assessment and the lower assessment limits for the j^{th} criterion depending on the i^{th} alternative.

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

More ambiguity exists within the data that consist of large interval of rough boundary, and the preciseness is characterised by the minimal value of the interval.

B. *RN Entropy Approach*

In resolving the MCDM issue, the most important role is determining the criteria weights that were selected. Any alteration in the weights of the criteria could result in several ranking for the candidate alternatives. Further, it was noticed that the traditional methods of the criteria measurements of weight such as the FUCOM, SWARA, LBWA, BWM, and the AHP suffer from the main difficulty of being influenced via the subjectivity preference for each selection maker. To mitigate the subjectivity in human personality judgements, the theory of information entropy has become an accepted method, while the estimated weights of the selected criteria relies on how random is the obtained data. Therefore, the RS is consisted of the entropy theory in order to aggregate with the individual decision obtained from a decision maker, during the estimation of the weights for several selection of welding-robot features. Calculating the weights of each criteria depending on the RE approach is applied by the next steps (Çalışkan, et al., 2013):

- The first step: For a certain number of experts, k, the amount of DM could be modified. Each k represents the robot arc welding behaviour based on several attributes that are taken into account. The following matrix has been obtained by the information obtained from the decision matrices.

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

X_{ij} represents a score for the performance of the option i^{th} based on the criterion of j^{th} ($1 \le i \le m$, $1 \le j \le n$), m is the options number, while n describes the features numbers.

- The second step: Starting from a starting RDM (X), the parallel RDM that has been normalized, $N = ([n_{ij}^L, n_{ij}^U])_{m\times n}$ is developed. Hence, for the mentioned normalised process, the following two equations (equation (9) and equation (10)) can be applied based on the considered criterion type.

For the beneficial criteria:

$$n_{ij}^L = [(x_{ij}^L - min(x_{ij}^L)] / [\max(x_{ij}^U) - min(x_{ij}^L)] \ldots\ldots\ldots (9)$$

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

$$n_{ij}^U = [(x_{ij}^U - min(x_{ij}^L)] / [\max(x_{ij}^U) - min(x_{ij}^L)] \ldots\ldots\ldots (10)$$

While for the non-beneficial criteria:

$$n_{ij}^L = \frac{[max(x_{ij}^U) - x_{ij}^U]}{[max(x_{ij}^U) - min(x_{ij}^L)]} \ldots\ldots\ldots (11)$$

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

$$n_{ij}^U = \frac{[max(x_{ij}^U) - x_{ij}^L]}{[max(x_{ij}^U) - min(x_{ij}^L)]} \ldots\ldots (12)$$

- Step # 3: the rough numbers entropy is now calculated by using the next formulas:

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

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

Where $f_{ij}^L = \frac{n_{ij}^L}{\sum_{i=1}^m n_{ij}^U}, f_{ij}^U = \frac{n_{ij}^L}{\sum_{i=1}^m n_{ij}^U}, k = 1/\ln(n),$ assuming $f_{ij} = 0, f_{ij} \ln f_{ij} = 0$

Hence, the j^{th} weight criterion could be assessed as follows:

$$W_j^L = \frac{1 - E_j^U}{\sum_{i=1}^n (1 - E_j^U)} \ldots\ldots\ldots\ldots\ldots (15)$$

$$W_j^U = \frac{1 - E_j^L}{\sum_{j=1}^n (1 - E_j^L)} \ldots\ldots\ldots\ldots (16)$$

Where W_j^U and W_j^L respectively represent the higher in addition to the minor bounds for the entropy criterion weightiness of j^{th}.

C. *RNMABAC Approach*

RN based MABAC method remains applied to identify the optimal options depending on the optimal alternative depending on a group of differing criteria own the next steps (Sharma, et al., 2018):

- The first step: Utilising the RDM that has been normalized in conjunction with the weights of the entropy, the consistent weighted for the normalized RDM (V) has been formulated.

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

Where $[n_{ij}^L, n_{ij}^U]$ are defined as the components of the RDM normalized (N) $[w_j^L, w_j^U]$ of the RE weights for the j^{th} factor.

- The second step: Depending on a procedure of the GA of the interval limits, and the BA area, which is denoted by (BAA) of each criterion was determined as:

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

- The third step: calculate the proposed alternatives distances from the BAA in order to get the correlated distance-matrix, which is denoted by (Q) during the implementation of the ED operator of the interval limits.

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

For the beneficial criteria:

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

While for the non-beneficial criteria:

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

Besides,

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

And the beneficial criteria:

$$d_E(v_{ij}, g_j) = \sqrt{(v_{ij}^L + g_j^L)^2 + (v_{ij}^U - g_j^U)^2} \ldots \ldots \ldots \ldots (23)$$

For the non-beneficial criteria. $[g_j^L, g_j^U]$ are the $BAA\ (G)$ of the j^{th} criterion.

However, when q_{ij} is requal to 0, an alternative of Ai will belong to $BAA\ (G)$; while when $q_{ij} > 0$, Ai will be belonged with the higher approximation area, which is denoted by (G^+), and when q_{ij} is less than zero, this will indicates that it belonged with a minor approximation area, which is denoted by (G^-). The optimal alternative (A^+) must be located within (G^+), while the location of the anti-optimal must be in the (G^-). An option of (A_i) linked with several criteria that are belonged with (G^+) must be addressed as the optimal choice.

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

The alternatives, which are considered as the proposed, were ranked in descending manner. Thus, the optimal suited option is selected based on the alternative which will have the greatest $S\ (A_i)$.

IV. RESULTS AND DISCUSSION

Because of the wide range of the arc welding applications in several manufacturing, it is considered as an essential need to facilitate the process of decision making. Therefore, this will help in evaluate the behaviour and the performance of the robots, which are available, based on some important criteria. Further, this will also help in identifying the best robot for welding applications (for example). However, arc welding deployment has an intensive capital cost, and any improper decision within the installation and robot procurement stage could affect and impact negatively the goodwill and the productivity of a manufacturing organization. During the robot arc selection, each decision maker provides his own opinion and the judgment of this opinion would be predisposed. Therefore, to mitigate the biasness in decision making process the whole opinions will be sought. The decision makers are selected such that each one will have about 10 years' experiences.

Moreover, these experts should have deep knowledge and expertise in welding/joining process. In addition, a well background regarding the control of robot arc welding is required and robot programming will be also required. The most important thing that should be taken into account is the environmental and safety hazards and risks when the welding process is conducted. Each decision maker should assess the behaviour of 14 are welding robots based on a number of evaluation criteria, which is equal to twelve. These indicators are relied on a number of point measure that is equal to 9 (where 9 means very high, 7 means high, 5 means moderate, 3 indicates low, and 1 indicates very low).

In this paper, the selected evaluation criteria are: ease of programming (EP), maintainability (M), welding performance (WP), safety (S), flexibility (FL), cost (C), power rating (PR), weight (W), repeatability (R), vertical reach (VR), horizontal reach (HR) and the payload (PL). The most beneficial evaluation criteria are: EP, M, WP, S, FL, R, VR, HR, and PL. In contrast, C, PR, and W are considered as non- beneficial. The performance of the robot arc welding is often appraised depending on the brand name of the manufacturers, robot compactness, welding operation complexity, robot features, and the provided service facility. The PL is defined as the highest weight, which the robot may manipulate and lift over a certain working region with the desired and the ease of the repeatability.

However, the HRE may be identified as a distance between a robot centre and a whole extension of the arm (horizontally). While the vertical reach may be defined as the highest work that can be enveloped in a vertical direction. The measure of the robotic arm's is known as the repeatability where some conditions are considered regarding the temperature and the load.

The whole weight for the robot welding via arc, has a character that is considered as a crucial role. Without doubt, the PowerRating is the needed power by the robot to perform the welding task that is seamless. In general, the cost of the robot arc welding involves the payment incurred during the installation. The flexibility is known as the capability of arc welding to achieve several welding tasks with several position, shape and size of the job.

Table 2 One Decision Matrix Represents the Priority Corresponding to the First Decision Maker

Arch 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	9	9	9	7	7	7	9
A_7	1	3	3	5	3	7	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	3	3	3	3	7	7	3
A_{10}	7	9	9	9	9	7	7	7	7	7	3	3
A_{11}	1	3	3	5	3	9	9	7	9	3	9	7
A_{12}	1	3	3	5	3	7	7	7	7	3	9	3
A_{13}	7	5	5	5	7	3	3	7	3	7	3	3
A_{14}	1	3	3	5	3	7	7	7	3	7	9	3

Regarding the safety, it can be determined based on several features which are presenting during the robot arc welding that achieve the human-robot interactions. Regarding the performance of welding process, it shows the consistency and the quality of the robot welding operation. Regarding the EP it is an essential feature in robot arc welding, the robot could simply be reprogrammed in order to perform several set of steps. Finally, regarding the maintainability it represents the ease that could be ensured if the robots are functioning in a proper manner or not, and if it can be repaired if a failure occurred.

Therefore, depending on the robot arc welding performance according to the number of assessment indicators, which =12, an amount of decision matrices that is equal to 5. Table 2 clarifies the one decision matrix that represents the priority that is corresponding to the first decision maker during the evaluation of the behaviour of the robot welding by arc.

The rest 4 DM have been also shaped. Hence, expert 1 evaluated the behaviour of A1. The next step was to aggregate the whole judgments for the five experts. For clarification, the ratings performance set of robot A1 depending on PL represented by $x_{11} = \{1; 1: 3; 3: 1\}$. By utilizing equation (4), equation (5), and equation (6), the group of linguistic data has been converted to the RN as represented:

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

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

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

$$RN(x^1_{11}) = [1.00, 1.80], RN(x^2_{11}) = [1.00, 1.80],$$

$$RN(x^3_{11}) = [1.80, 3.00], RN(x^4_{11}) = [1.80, 3.00], RN(x^5_{11}) = [1.00, 1.80]$$

$$x^L_{11} = \frac{x^1_{11} + x^2_{11} + x^3_{11} + x^4_{11} + x^5_{11}}{5}$$

$$= \frac{1.00 + 1.00 + 1.80 + 1.80 + 1.00}{5} = 1.32$$

$$x^U_{11} = \frac{x^1_{11} + x^2_{11} + x^3_{11} + x^4_{11} + x^5_{11}}{5}$$

$$= \frac{1.80 + 1.80 + 3.00 + 3.00 + 1.80}{5} = 2.28$$

According to the illustrated calculations, the whole entries extracted from the decision matrices were converted to rough decision matrix $X = \left(\left[x^L_{ij}, x^U_{ij}\right]\right)_{14\times 12}$. Between twelve EC, some of them were considered as beneficial while the rest were non- beneficial. Hence, when these two types are considered the rough-decision-matrix will be normalized by applying the equations (9) -(12).

However, when the equations (13) -(16) are employed the weights of the RE of the whole robot's selection were assessed. The selection criteria were expected exactly as clarified in Table 3.

Table 3 Selection Criteria Expectation

PL	HR	VR	R	W	PR	C	FL	S	WP	M	EP
[0.036, 0.378]	[0.026, 0.233]	[0.025, 0.236]	[0.025, 0.23]	[0.026, 0.205]	[0.2, 0.142]	[0.036, 0.304]	[0.22. 0.233]	[0.027, 0.282]	[0.02. 0.377]	[0.029, 0.272]	[0.025, 0.271]

Between the mentioned twelve SC of robot, PL as well WP were noticed to own the highest RW, tracked by S as well C. In contrast, WP has been identified to have the maximum boundary interval that is rough.

However, after developing the rough-decision-matrix that has been normalized and after calculating the weights of the RE of the EC that were considered, the normalized RDM of the corresponding weighted was shaped. The development of the matrix has been done through multiply the RE weights by the components of the matrix of the RD that has been normalized by using Eq. (17). Then, an approach which is known with rough-MABAC has been implemented in order to clarify the optimal robot welding via arc from the group of the 14 alternative candidate.

By utilizing Eq. (18) and the operator of geometric aggregation for the rough numbers the related approximation border area (ABA) for any selection-criteria of a robot has been calculated. For instance,

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

$$g_1^U = (0.047 \times 0.469 \times 0.547 \times 0.757 \times 0.0531 \times 0.627 \times 0.436 \times 0.497 \times 0.409 \times 0.627 \times 0.409 \times 0.428 \times 0.640 \times 0.412)^{1/14} = 0.5070$$

$$g_1 = [0.0439 , 0.5070]$$

The overall distances of the robot welding through arc from ABA have been determined in order to form a distance matrix, which is denoted by Q, during the employment of the rough value of ED operator from Eq (20) to Eq (23). Regarding the DM, a last score S(Ai) of any robot welding through arc has been calculated. The values of S(Ai) have been ranked in descending way to give the arrangement list of the robots beggining from an optimal one to the poorest performance one. For instance,

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

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

The last scores of the fourteen robot arc welding alternatives were shown in Table 9. According to the shown scores that were calculated by using the RMABAC approach, it could be understood that robot A6 has the ultimate location within a franking list, the next stage is given into A3. However, the whole ranking list has been obtained:

$$A_6 \text{ then } A_3 \text{ then } A_{13} \text{ then } A_{10} \text{ then } A_5 \text{ then } A_9 \text{ then } A_4 \text{ then } A_{11} \text{ then } A_1 \text{ then } A_{14} \text{ then } A_7 \text{ then } A_{12}$$

$$\text{then } A_8 \text{ then } A_2$$

The corresponding locations for the whole alternatives robot arc welding within the upper, lower, and the BAA have been clarified in Figure 4.

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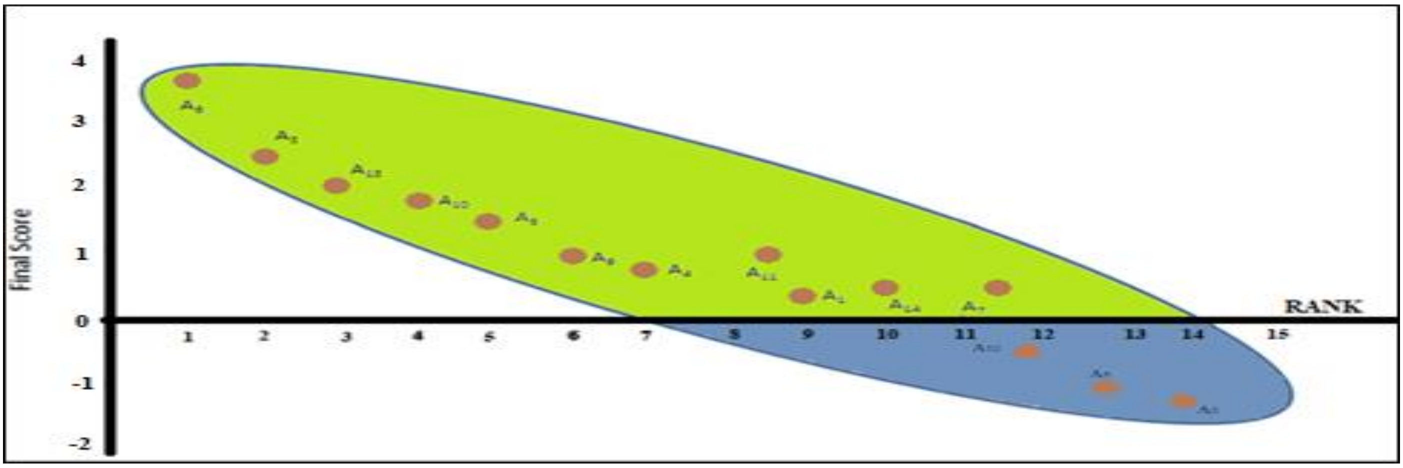

Fig 4 Positions of the Robots Welding Via Arc in the Upper, Lower and the Border AA.

Based on Figure 4, it could be seen that two robot welding via arc (A14 and A7) have almost positioning area. And the locations for the listed robots (A_{12}, A_8, as well A_2) are within the LAA area. The rest 9 robots welding via arc have been located within the UA of approximation. According to the alternatives positions of robots within the lower and upper approximation areas. According to the alternative robot's positions within the lower and upper AA, they could be classified as an EAI respectively of a certain welding tasks. Hence, it could be understood that robots welding via arc (A1, A11, A4, A9, A5, A10, A13, A3, and A6) may be professionally deployed in order to conduct the desired welding task in the real time of the manufacturing environment. Table 4 shows the exact location for the robots welding via arc within the LAUAA depending on several evaluation criteria.

Table 4 The Exact Location for the Robots Welding Via Arc within the LAUAA

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

In the industrial selection problem of robot, it was stated that M, WP, EP, S, FL, R, VR, HR, and PL are selected as the most beneficial indicators, while C, PR, and W are considered as the NBC. It could be noticed that for beneficial features of the corresponding positions for the whole effective robot welding via arc are within the UAA. Similarly, the robots arc welding have been positioned within the LAA of the NB criteria. The whole of the mentioned beneficial criteria of the effective robots are positioned within the UAA while the NB features have been located within LAA. It could be noticed that the A6 robot is relatively strong based on EP, M, WP, S, FL, C, HR, and PL criteria. In contrast, the weaknesses are PR, W, R, and VR. Therefore, it has high power rating, high weight, low repeatability, and low vertical reach.

However, the main strength for A3 are based on EP, WP, S, R, VR, and PL. it has a relatively poor horizontal reach, maintainability, and flexibility. Likewise, the latest robot arc welding rank, which is A2 owns four criteria, which are EP, M, S, and C. In contrast, it has the main weakness based on WP, FL, PR, W, R, VR, HR, and PL criteria.

The weaknesses and strengths identification for each alternative robot arc welding help the experts in selecting the most suitable robot of a given task. However, the accuracy of the solution has been studied by the MABAC approach. The ranking performance of it is linked with the other methods of RMCDM such as rough-VIKOR, rough-TOPSIS, rough-SAW, and rough-WASPAS is studied. It could be noticed that the location of the last and top 2 robot arc welding remained unchanged and kept the same in most of rough-MCDM approaches, although there are several intermediate rankings in the considered alternatives. Hence, this verifies the rough-MABAC applicability and demonstrate the effectiveness of these approaches.

The choice of the most suitable robots of a certain process of welding is considered as a relatively severe and critical job. The process of DM should be shaped through following some views of several specialists in order to mitigate the partiality/biasness in the latest selection decision. If the selection was not accurate enough this would affect the productivity of the manufacturing company. In this research, a trial has been put to rank a number of robot arc welding, which is 14, depending on twelve evaluation criteria by utilizing an integrated method that combines and links the MABAC and rough-numbers method. The robots' performance has been assessed depending on the selected criteria by utilizing the judgements that were provided by five decision experts/makers.

A role which is an important one is played via the weights of the criteria regarding the process of decision making. For instance, the rough-entropy approach having the benefit of calculating how important is the criteria depending on the dataset randomness. The method MABAC is then adopted in order to give a completed rank for the proposed robot welding by arc from the optimal into the worst in juxtaposition with a weakness as well strengths for each option. It was noticed that between the whole considered alternatives A6 was the optimal robot, the A3 has come in the second stage, while A2 has been considered as the worst selection.

The outcomes showed that robot A6 owns the best performance with respect to EP, M, WP, S, FL, C, HR, and PL evaluation criteria. In contrast, depending on PR, W, R, and VR A6 has a weakness. While regarding A2, based on the evaluation criteria EP, M, S, and C it has the most favourable properties, while this robot (A2) lags behind depending on WP, FL, PR, W, R, VR, HR, and PL.

V. CONCLUSION

In this research, it was pointed out that the integration of MCDM approach with rough ST can suggest an explanation regarding the DM selection with more accuracy. This research dealt with rough-MABAC approach application to assess and choose the most suitable robot arc welding depending on a number of conflicting criteria, which is 12. However, mitigate the human decision subjectivity, the considered evaluation criteria weights were expected by utilizing the RE approach. According to this evaluation, the whole 14 robots arc welding were classified as inefficient and efficient ones depending on their locations in the LAA and UAA. It was found that sixth A6 robot was the optimal choice to perform the required task with 8 favourable criteria, which are EP, M, WP, S, FL, C, HR, and Pl in addition to only 4 unfavourable criteria which are PR, W, R, and VR. In contrast, the robot A2 has been assigned to be the last preferred one since there was only 4 favourable criteria, which are (EP, M, S, and C) and a relatively large number of unfavourable criteria, which are (WP, FL, PR, W, R, VR, HR, and PL). When a comparison between some MCDM approaches regarding these performances were conducted, the effectiveness of these MCDM approaches was verified.

The most weakness point that was found in the MABAC approach is that this approach suffers from the disadvantages. The weights of the criteria have to be set, otherwise the satisfactory outcomes will not be provided. It is supposed that each evaluation criteria have a certain weight which differs from the other evaluation criteria. Further, when the information was aggregated by the rough numbers, it was assumed that the whole participating experts have an identical importance. Finally, as a future scope, the MABAC approaches can be explored by using intuitionistic fuzzy sets.

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