Multi-criteria Decision Making Model for Industrial Arc Welding Robot

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Abstract

Industrial robots have made it possible for manufacturers to make elevated low-cost products, which are thus major elements of advanced production technologies. Welding, cleaning, assembling, dismantling, slotting for computer chips, labeling requirements, stacking pallets, quality inspection, and monitoring are just a few of the applications for robotic systems. All the features are completed with a high level of endurance, speed, and accuracy. Multiple and competing criteria must be assessed simultaneously in a comprehensive selection analysis to identify the effectiveness of robots. To provide an automated machine for such arc machining operation, simple multi-criteria decision-making (MCDM) technique based on the COPRAS method is described in this work. The COPRAS method calculates significance weights using objective preferences and ranks the options. The COPRAS technique was used to determine the ranking order. The findings revealed that MCDM techniques for robot selection are extremely useful. The study's peculiarity is that it uses COPRAS MCDM approaches to select industrial arc welding robots.

Keywords: MCDM; Robot; Industrial; COPRAS

1. Introduction

The term "industrial robot" relates to a robot that is typically used in production environments. Materials management, welding processes, arc welding, arrangement, cutting force, quality assurance and checking, offloading, repainting, and entire product are just a few of the many applications where robots are used to automate tedious, dangerous and time-consuming tasks. The sole goal of using the robotic system in the manufacturing process is to reduce operating costs and improve productivity. When it comes to an industrial robot's robotic weight, payload ability, repeatability, and so forth.[1]. An MCDM issue arises as a result of these specifics. There is no manufacturing sector where welding isn't the most in-demand application. Since the advent of industrial robots, there has been a significant increase in the demand for robotic systems for welding applications. In the construction of steel constructions and manufacturing fabrication, the gas metal arc is among the most commonly used welding methods.

The different types of arc welding are as follows: electrical, carbon arc, steel, Metal inert gas, erythrocytes, immersed, and electro-slag[2]. The programming of an arc welding robotic allows it to conduct all forms of arc welding tasks. Electrodes and conductive metals are brought together to form an arc in arc welding[3]. Arc welding industrial robots are manufactured by a variety of businesses, including YASKAWA ELECTRIC CORP and FANUC, KAWASAKI, ABB, PANASONIC, KUKA, and so on[4]. Robots' ability to execute a variety of jobs has made them a popular replacement for traditional welding equipment since they can accomplish tasks seamlessly and even go beyond their intended use. Robotic aided manufacturing (RAM) is becoming more commonplace in manufacturing firms as a result of technological advancements and a rising demand for goods[5]. Include a standard

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layout so that automakers can choose among a variety of arc welding robots. Prioritizing manufacturing arc welding robots will be the focus of this research.

Increased product assessment methods should push the use of industrial robots for welding at a lower cost, while yet producing a high-quality weld. A wide range of robots is available from a number of manufacturers. The key distinction between these models is identifying the optimal one based on the most important criteria. The TOPSIS approach is used to investigate industrial robot choice for arc welding operations in the current research. In order to implement eight distinct robots with six controllable axes and various controllers from their individual manufacturing businesses, the information for arc welding robotics was gathered.

We can classify these eight robots according to a set of five traits/criteria. Multiple data sheets offered by robot manufacturing businesses to explain their goods were reviewed to determine the selection criteria. The views of industry professionals are also taken into account. The selection criteria were decided after a meeting between the research team and an industry specialist. The ultimate choice matrix was based on the combined judgment of both teams, and the major qualities of every robotic were regarded factors for assessment. The packet of a robot, for example, is an example of useful criteria in decision-making. A smaller amount, such as the power consumption of the robotic, is subject to the non-beneficial rules.

Section 2 provides a summary of the most important research papers used to pick various robots and emphasizes the relevance of MCDM approaches in the remainder of the study. Section 3 provides the methodology. Section 4 provides the application and results. This investigation's management ramifications are discussed in Section 5, and summarised in Section 6.

2. Related Work

Robots are becoming more widespread in commercial arc welding processes, as shown by a survey of robotics in use [6]. There are several aspects to consider while selecting the finest robotic technology for arc welding[7]. Arc welding activities [8] showed how robotic systems may help manage the expansion of welding processes. To choose a robot for taking activities, MCDM approaches such as ELECTRE, VIKOR, and compromises rating techniques were used. The decision matrix took into account seven possible outcomes, each with its own set of five criteria [9]. In order to pick the right automated machine among four possibilities, a distance-based technique was designed and deployed. The TOPSIS and Digraph & Matrix methods were used to compare the rankings. There'd been a sensitive analysis done [10]. Robot selection and assessment use the fuzzy digraph approach. For each criterion, both positivist and interpretivist weights were calculated. Also included in [11] were two statistical illustrations of industrial uses.

Robot choice was done using a fuzzy regression model. There were 27 industrial robots evaluated against each other using four different criteria. As a consequence, the findings were compared to those of prior studies [12]. MULTIMOORA and interval-valued gray's test were presented to help choose the most relevant standards for robotic systems to be evaluated.
The notion of dominance was used to evaluate and contrast the fifty-nine criteria that made up the suggested assessment. With this data, we were able to determine what the best robot selection criteria were [13]. Industrial robotics' seven choices were compared and evaluated using theAHP and TOPSIS methods [14]. In order to manage successful robot selection when unclear and insufficient information is provided, an interval 2-tuple linguistic TOPSIS approach was employed.

A sample calculation was used to explain mathematically how positivist and interpretive assessments might be applied to real-world situations [15]. Selecting robots was made easier by combining the Fuzzy Delphi method (FDM), the FAHP, the Fuzzy Modified TOPSIS or the Fuzzy VIKOR, and the Brown-Gibson model. A total of fifteen numerical and seven mainly characterized [16] were taken into account, including both positivist and interpretive ones. To pick a robot, a PROMETHEE II approach was used that relied on objective data. 4 and 5 factors were used to compare 14 and 7 robotic technology, correspondingly, in two numerical results [17].

It was determined that fuzzy axiomatic design concepts might be used to help solve a robot selection issue. Nine factors [18] were used to evaluate 7 commercial robots designed for light assembly lines. Robot choice difficulties with inadequate weight information may be handled by a combined model that uses hesitant 2-tuple linguistic word sets and an enhanced QUALIFLEX technique. HSA, ITL-

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TOPSIS, IF-VIKOR, and IVF-COPRAS were compared with current MCDM techniques to ease the MCDM [19].

Using the VIKOR technique with a type-2 fuzzy sets methodology, 7 factors were used to assess 8 robotic technology. [20] The outcomes of the new approach were compared to various current methods. Industrial robot selection was used to test the efficiency of several MCDM techniques from the WSM through the MOORA and MULTIMOORA families. In this study, 7 robotics were assessed according to 5 factors, and findings were acquired using various MCDM methodologies and thus evaluated[21].

A strategy based on the AHP was presented for selecting robotic arms for milling applications. It was determined that three milling robotics were evaluated on the basis of seven distinct factors[22]. Based on a comparison of seven actual models of robotic systems, WASPAS was presented as an MCDM technique for picking the best robotic[23]. In order to assess mobile robot choice for a pharmacy department, a fuzzy extended VIKOR approach was created by merging fuzzy AHP and VIKOR-based methodologies. Given the following relevant parameters, three distinct robotic arms were evaluated [24]. Sifting through industrial robots for usage in Arc welding applications in the military was offered as a case study. The AHP approach for MCDM was used to analyze the fifteen possibilities based on three criteria and their additional sub-criteria [25].

The MCDM selection of robots was suggested to use the grey relational analysis approach. Four important criteria [26] were evaluated for five possible robot options. The cloud concept and the TODIM approach were used to construct a decision support model for selecting robots. The approach was shown to be successful in coping with uncertainty and inaccurate judgments made by decision-makers [27] by evaluating four alternative robotics. Rating distinct robots according to five primary criteria was made possible by using an interval-valued intuitionistic fuzzy VIKOR technique [28]. For the choice of four robotics based on 5 factors, a team decision-making approach was presented. In addition, the Shannon entropy, CRITIC, the ideal point, and the way away approach were all given and contrasted [29] as objective techniques. [30] A real-world application of the Fuzzy BWM and PROMETHEE was used to solve the robot choice challenge. The assembly segment of the MCDM issue was studied using the DEMATEL method to identify dangers. A total of fifteen of that kinds of variables were taken into account and examined [31].
To find the best industrial robots, the BWM, combined with the EDAS method, was proposed. Based on 4 evaluation standards, four different drones were equated to each other.

There was also a sensitivity analysis [32]. For multi-objective enhancement of milling processes, the AHP and Entropy weight technique was being used in conjunction with the TOPSIS approach [33]. It was hoped that a review study would demonstrate the advantages of the Entropy Weight Technique in the multi-objective enhancement of machining processes. Entropy weights are beneficial in academic papers, journals, and story arcs in research books [34]. It was suggested to use an MCDM approach that is based on the TOPSIS method to find the best hoover on the market. There were eight brand names and twenty-six models to choose from when it came to the selection process[35]. Various decision-making strategies are used in engineering to reach decisions[36]. A WASPAS MCDM approach was used to compare twenty-four up in diverse hard disc drives in search of the best one premised on eight various qualities [37].

The AHP and VIKOR methods of MCDM were used to optimize process variables all through CNC turning in a different way. In the end, the results were compared to those obtained using the TOPSIS approach [38]. It is clear from the literature review that MCDM methods are being used successfully for selecting applicants. The MCDM methods are also used in the selection of robotic systems for various tasks. Choosing an arc welding robot does not make use of a decision-making approach. As a result of this strategy, TOPSIS has been effectively used in a wide range of industries. Using the best possible answer, it calculates the final combined measure. Judgment is not involved in the entropy weights method's computation of weights. So, the TOPSIS-Entropy technique is used to choose arc welding robots in the current study.

3. Decision Making Methodology

In this section, we proposed the MCDM COPRAS method to select the best robot. The model building could be done by focusing on the benefits of different MCDM methodologies. The MCDM strategies used in this study are briefly reviewed below. Zavadskas et al. [39]proposed the COPRAS approach

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as a strong Methodology. It has several benefits, including the capacity to calculate both cost and benefit criteria, demonstrating which option is the best when options are tried to compare, and aiding in determining the similarity among each option and the ideal option using utility grades. Figure 1 shows the decision-making methodology.

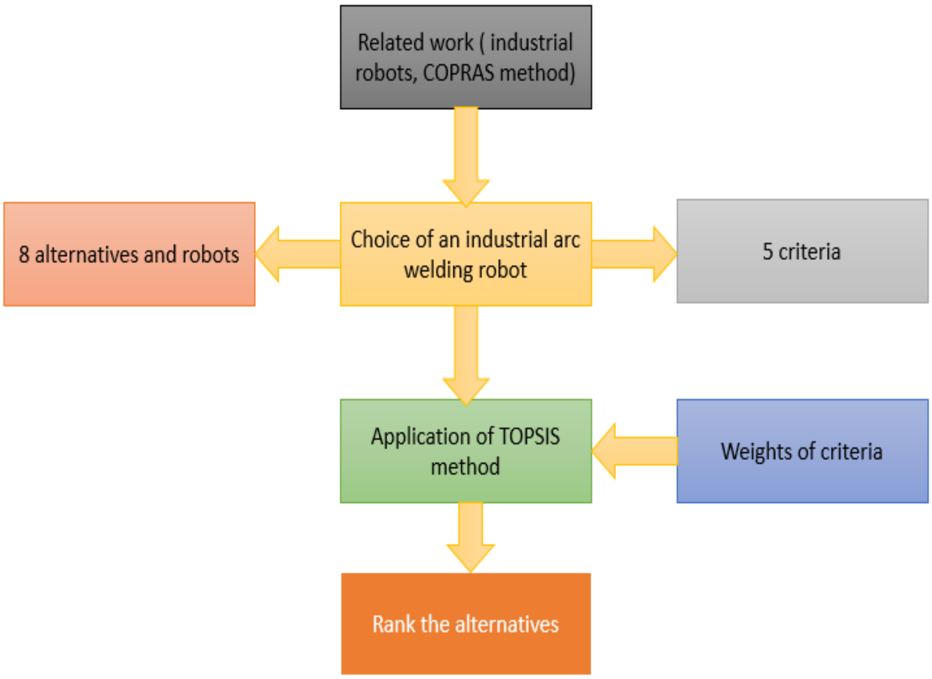

Figure 1. Decision-making methodology

Step 1: Generate the decision judgment matrix in step one. If there is more than one decision-maker, so need to aggregate their opinions by the average method
The decision judgment matrix X is being prepared based on element i in the alternative j.

$$X = [x_{ij}]_{m\times n} = \begin{pmatrix} x_{11} & x_{12} & x_{13} & x_{14} & \dots & x_{1n} \\ x_{12} & x_{22} & x_{23} & x_{24} & \dots & x_{2n} \\ x_{13} & x_{32} & x_{33} & x_{34} & \dots & x_{2n} \\ x_{14} & x_{42} & x_{43} & x_{44} & \dots & x_{4n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{m3} & x_{m4} & \dots & x_{mn} \end{pmatrix} \quad (1)$$

Where $i = 1,2,3 \dots .m; j = 1,2,3 \dots ..n; m$ is the number of attributes and n is the number of options

Step 2: Perform a normalization of the decision judgment matrix X.

$$N_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (2)$$

Step 3: Build the normalized decision matrix

$$N = [N_{ij}]_{m\times n} = \begin{pmatrix} N_{11} & N_{12} & N_{13} & N_{14} & \dots & N_{1n} \\ N_{12} & N_{22} & N_{23} & N_{24} & \dots & N_{2n} \\ N_{13} & N_{32} & N_{33} & N_{34} & \dots & N_{2n} \\ N & N_{42} & N_{43} & N_{44} & \dots & N_{4n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ N_{m1} & N_{m2} & N_{m3} & N_{m4} & \dots & N_{mn} \end{pmatrix} \quad (3)$$

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Step 4: Generate the weighted normalized decision judgment matrix in step four.

$$WN_{ij} = N_{ij} w_j \tag{4}$$

Where w_j refers to the weights of criteria

Step 5: Compute the max and min value for the benefit and cost criteria

$$MB_i = \sum_{j=1}^{n} WN_{ij} \ benefit \tag{5}$$

$$MC_i = \sum_{j=1}^{n} WN_{ij} \ cost \tag{6}$$

Step 6: Calculate the related weights to every alternative

$$R_i = MB_i + \frac{\sum_{i=1}^{m} MC_i}{MC_i \sum_{i=1}^{m} \frac{1}{MC_i}} \tag{7}$$

Step 7: Determine the index of performance

$$PR_i = \left[\frac{R_i}{R_{max}}\right] 100\% \tag{8}$$

Step 8: Rank the options according to the greatest value of PR_i

4. Results and discussion

list the various criteria for choosing arc welding robots. As below:

Criteria	Alternatives
Mechanical weight WRC1	WRA1 Robot-1
Repeatability WRC2	WRA2 Robot-2
Payload capacity WRC3	WRA3 Robot-3
Maximum reach WRC4	WRA4 Robot-4
Average power consumption WRC5	WRA5 Robot-5
	WRA6 Robot-6
	WRA7 Robot-7
	WRA8 Robot-8
	The name of robot is hidden due to the marketing

There are 3 experts to evaluate the criteria and alternatives. Tables 1-3 show the data collected on the eight Arc Welding Robots (AWR) using the five criteria. The aggregated decision matrix in Table 4 is based on Eq (1).

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Table 1: The opinions of the first expert

	WRC_1	WRC_2	WRC_3	WRC_4	WRC_5
WRA_1	68	68	68	68	50
WRA_2	83	38	68	50	68
WRA_3	38	83	50	50	68
WRA_4	38	68	50	38	16
WRA_5	50	38	68	16	38
WRA_6	50	83	83	38	50
WRA_7	68	68	68	68	68
WRA_8	68	83	50	16	83

Table 2: The opinions of the second expert

	WRC_1	WRC_2	WRC_3	WRC_4	WRC_5
WRA_1	68	68	68	68	50
WRA_2	83	38	68	50	68
WRA_3	38	83	50	50	68
WRA_4	38	68	50	38	16
WRA_5	50	38	68	16	38
WRA_6	50	83	83	38	50
WRA_7	68	68	68	68	68
WRA_8	68	83	50	16	83

Table 3: The opinions of the third expert

	WRC_1	WRC_2	WRC_3	WRC_4	WRC_5
WRA_1	68	50	38	68	50
WRA_2	83	38	50	68	68
WRA_3	83	38	16	83	68
WRA_4	68	16	68	83	38
WRA_5	38	68	83	50	16
WRA_6	38	68	68	50	38
WRA_7	16	68	68	83	68
WRA_8	38	83	50	38	83

Table 4: The opinions of all expert

	WRC_1	WRC_2	WRC_3	WRC_4	WRC_5
WRA_1	62	56	58	62	61
WRA_2	72	38	67	56	68
WRA_3	63	53	44.66667	67	58
WRA_4	48	55.66667	62	63	23.33333
WRA_5	34.66667	58	63	49.66667	30.66667
WRA_6	42	63	63	57	52
WRA_7	50.66667	73	50.66667	78	68
WRA_8	58	68	38.66667	40.66667	72

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The weights of criteria are computed by the normalization of opinions of experts by every criterion. Let experts evaluate the criteria. Then normalized their values to compute the weights of the criteria. Figure 3 shows the weights of five criteria. The WRC3 is the higest weight of criteria followed by WRC5. The lowets weight in the five weight if WRC2.

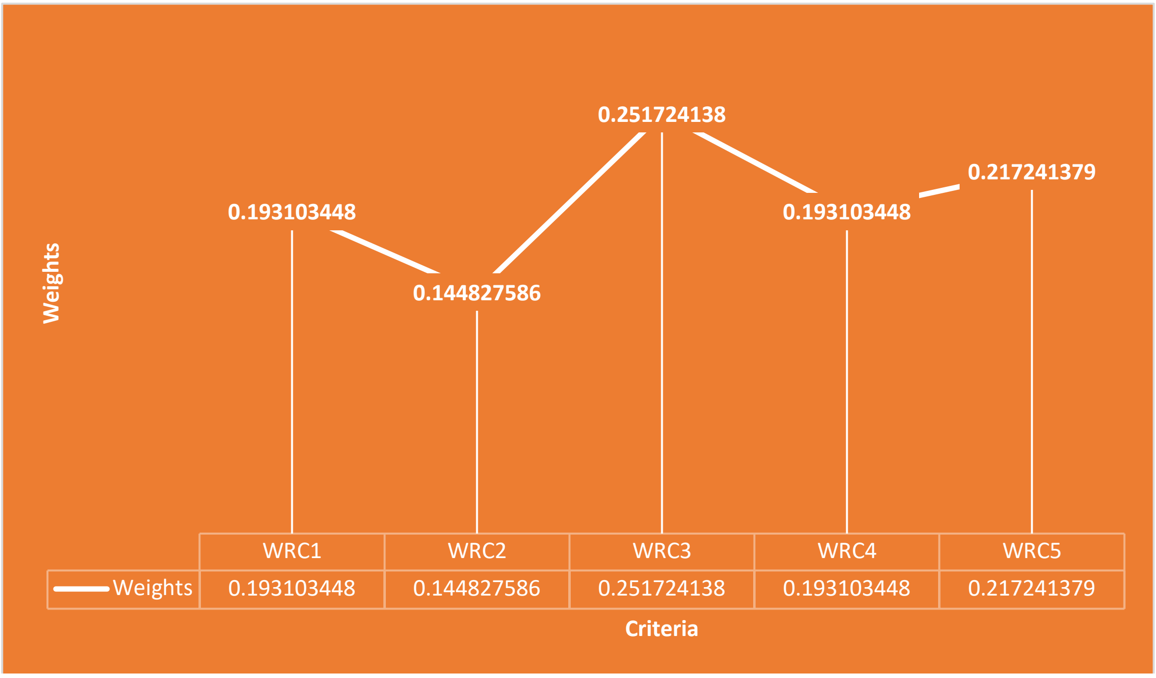

Figure 3. The weights of criteria.

The arithmetic mean of every analysis of each characteristic is computed using Eqs. (2,3) from step 2, and the results are shown in Table 5 as the normalized matrix.

Table 5: The normalization matrix

	WRC1	WRC2	WRC3	WRC4	WRC5
WRA1	0.144074	0.120516	0.129754	0.130986	0.140878
WRA2	0.167312	0.081779	0.149888	0.11831	0.157044
WRA3	0.146398	0.11406	0.099925	0.141549	0.133949
WRA4	0.111541	0.119799	0.138702	0.133099	0.053888
WRA5	0.080558	0.124821	0.14094	0.10493	0.070824
WRA6	0.097599	0.135581	0.14094	0.120423	0.120092
WRA7	0.117738	0.157102	0.113348	0.164789	0.157044
WRA8	0.134779	0.146341	0.086503	0.085915	0.166282

By using the weights of criteria, we computed the normalized weight. Using Eq. (4) to compute the weighted normalized matrix, by multiplying the weights of criteria by the normalization matrix is in the previous steps. Table 6. Show weighted normalized decision matrix.

Table 6: The weighted normalization matrix

	WRC1	WRC2	WRC3	WRC4	WRC5
WRA1	0.027821	0.017454	0.032662	0.025294	0.030604
WRA2	0.032309	0.011844	0.03773	0.022846	0.034116
WRA3	0.02827	0.016519	0.025154	0.027334	0.029099
WRA4	0.021539	0.01735	0.034915	0.025702	0.011707
WRA5	0.015556	0.018077	0.035478	0.020262	0.015386
WRA6	0.018847	0.019636	0.035478	0.023254	0.026089
WRA7	0.022736	0.022753	0.028532	0.031821	0.034116
WRA8	0.026026	0.021194	0.021775	0.016591	0.036123

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By using Eqs. (5,6) the maximum and minimum values for the benefit and cost criteria are computed in Table 7. Eq. (7) is used to compute the relative weight in table 7. Eq. (8) is used to compute the index of performance. In the case of cost and benefit criteria, the WRC_1 and WRC_1 are the cost criteria and other criteria are benefit criteria. The 8 alternatives are ranked based on the highest value of the index of performance. Figure 3 shows the rank of alternatives. Form figure 3. The WRA_1 is the best robot followed by WRC_4 and WRC_6. The lowest rank of alternatives is WRC_8.

Table 7: The maximum and minimum values

	Benefit	Cost	Relative weight	Index of performance
WRA1	0.07541	0.058426	0.117233	76.7286
WRA2	0.07242	0.066425	0.109206	71.47542
WRA3	0.069006	0.057369	0.111599	73.04139
WRA4	0.077967	0.033246	0.151465	99.13386
WRA5	0.073818	0.030942	0.152789	100
WRA6	0.078368	0.044936	0.132746	86.88187
WRA7	0.083106	0.056852	0.126087	82.52349
WRA8	0.05956	0.06215	0.098876	64.71434

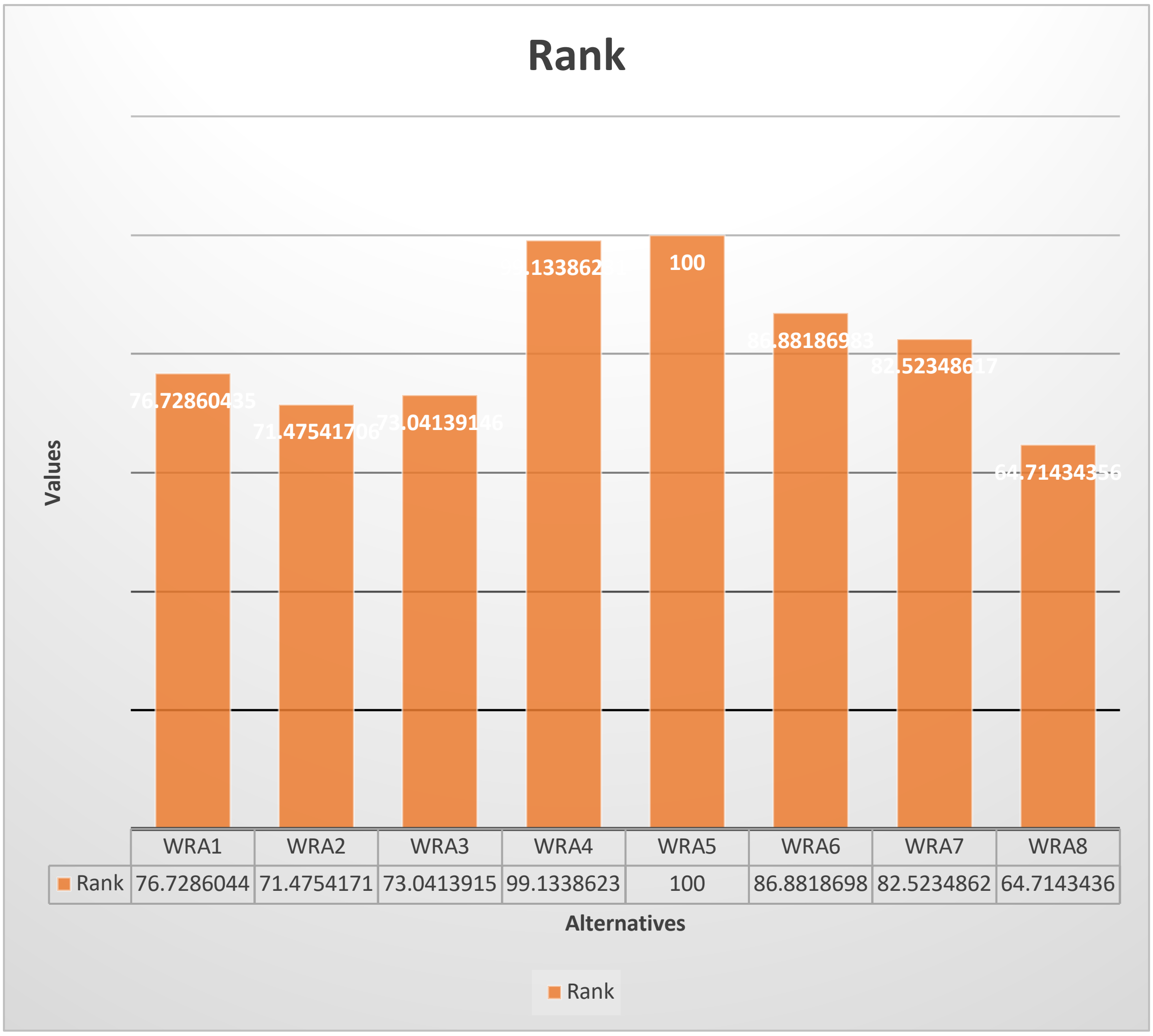

Figure 3. The rank of alternatives.

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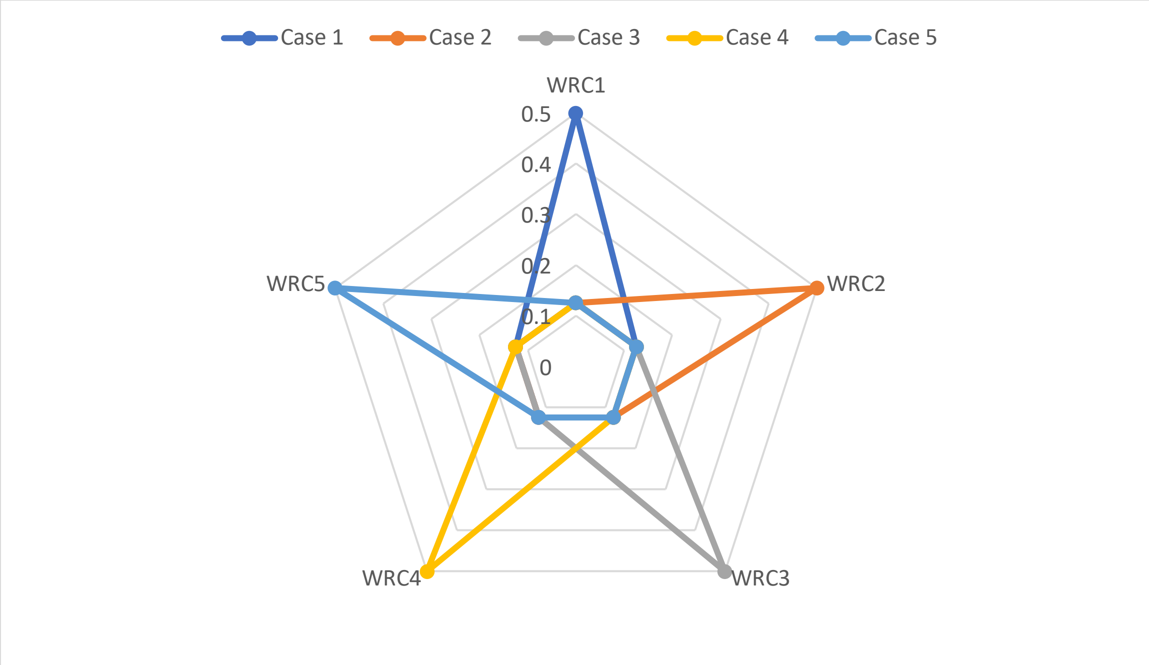

Figure 4. The five cases in change the weights of criteria

Senisitivity Analysis

In this study, we change the weights of criteria under five cases to show the rank of alternatives. The five cases in figure 4. In the five cases put the one criteria with weight 0.5 and other 0.125 to compute the sum of all criteri 1. Then shows the rank of alternatives under these modifications. Under five cases the rank of alternatives is shown in figure 5. The cases 1,2 the WRA5 is the best alternative and WRA2 is the worst alternative. In Case 3 The WRA5 is the best alternative and WRA8 is the worst alternative. In cases 4,5 the WRA4 is the best alternative and WRA8 is the worst alternative.

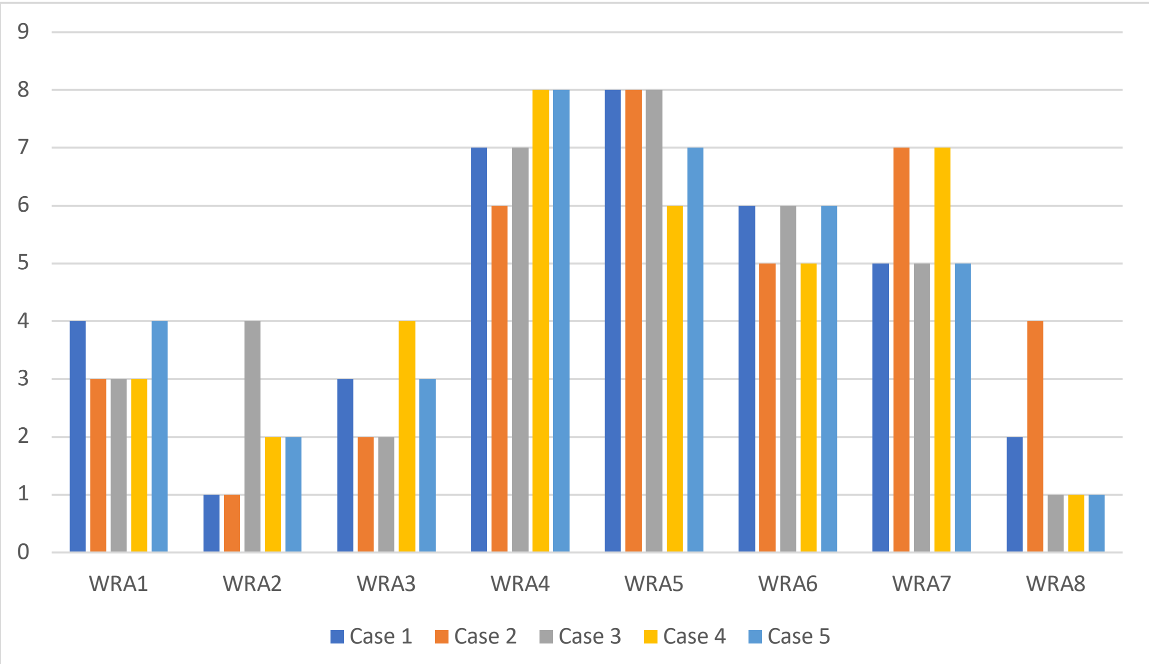

Figure 5. The rank of alternatives under five cases.

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5. Managerial Implications

The use of fully automated Welding equipment is no longer a cutting-edge idea thanks to the advent of robotic systems and the industrial revolution. Even so, the initial capital outlay in this equipment is still quite large, which necessitates a high degree of precision when selecting and purchasing a product.

The current study conceivably wants to introduce the necessity of utilizing MCDM implementations to better understand the criteria. Theoretical considerations alone are not enough to produce the desired results. Robot-5 is the most effective of the eight different robotic welding automatic appliances currently being tested. As a result of this research, industrial companies can choose from a variety of other options based on their accessibility and economic ability. This research has largely made a significant contribution to the existing literature on the judgment in the selection of a manufacturing arc welding robot with the COPRAS MCDM technique, allowing manufacturing residences to make good decisions even without hassle.

6. Conclusion

The purpose of this study is to determine which industrial robot is best suited for welding processes. When making decisions, eight options were weighed against five factors/attributes. Based on its requirements, the COPRAS method is used to select the best robot available. The attributes and criteria are given a numerical weighting based on their relative importance. According to the research results, the Robot (WRA_5) is the first candidate to be chosen using the COPRAS method. It's possible to get more reliable data with the COPRAS method because it's simpler to use. More options and attributes can be added to the Robots' product line in the future. The important task weights can be viewed as having both open to interpretation and identical weights.

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