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Application of MEREC in Multi-Criteria Selection of Optimal Spray-Painting Robot

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Abstract: Robots are being increasingly utilized for various operations in industrial and household applications. One such application is for spray painting, wherein atomized paint particles are sprayed on a surface to coat the surface with paint. As there are different models of robots available for the job, it becomes crucial to select the best among them. Multi-criteria decision-making (MCDM) techniques are widely used in various fields to tackle selection problems where there are many conflicting criteria and several alternatives. This work focuses on selecting the best robot among twelve alternatives based on seven criteria, among which payload, speed, and reach are beneficial criteria while mechanical weight, repeatability, cost, and power consumption are cost criteria. Five MCDM techniques, namely combination distance-based assessment (CODAS), complex proportional assessment (COPRAS), combined compromise solution (CoCoSo), multi-attributive border approximation area comparison (MABAC), and višekriterijumsko kompromisno rangiranje (VIKOR) were used for the selection while a weight calculation was performed using an objective weight calculation technique called MEREC. HY1010A-143 was found to be the most suitable robot for spray-painting applications by four of the five techniques used. Correlation studies showed a significant level of correlation among all the MCDM techniques.

Keywords: robot selection; compromise solution; multi-criteria; optimization; ranking

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Citation: Shanmugasundar, G.; Sapkota, G.; Čep, R.; Kalita, K. Application of MEREC in Multi-Criteria Selection of Optimal Spray-Painting Robot. *Processes* **2022**, *10*, 1172. https://doi.org/10.3390/pr10061172

Academic Editor: Raul D.S.G. Campilho

Received: 2 May 2022
Accepted: 8 June 2022
Published: 10 June 2022

1. Introduction

With massive progress in the field of engineering and information technology, robots have become an integral part of industries, primarily in the automobile and manufacturing sector. Robots are self-controlled machines which are reprogrammable and can perform a diverse range of operations. In industries, the applications of a robot include loading, finishing, welding, assembly, spray painting, etc. Spray painting involves directing atomized paint particles toward a surface that needs to be coated [1]. The paint particles are carried to the surface in a gaseous medium, which is usually compressed air [2]. Robots are employed for this process primarily because of the hazardous nature of the process, especially because of the involvement of atomized paint particles, which are damaging to the human body. Because there are many robots available for spray painting, it becomes a challenging task to select the most appropriate robot for the job [3].

Multi-criteria decision-making (MCDM) techniques provide us with the tools that are required for the decision-making process when there are many criteria and alternatives to choose from. MCDM has been employed in various domains of study where decision making becomes crucial for selection among several alternatives based on contrasting criteria. Poongavanam et al. [4] conducted a comparative study between various MCDM techniques for the selection of refrigerants in automobile air conditioning systems. Their decision matrix consisted of fourteen alternatives and thirteen criteria, and the Shannon entropy method was used for weight determination while the ranking was done using an evaluation based on the distance from average solution (EDAS), multi-objective optimization based on ratio analysis (MOORA), and the technique for order of preference by similarity to ideal solution (TOPSIS). Ozkaya et al. [5] used nine MCDM techniques to rank 40 countries based on numerous criteria related to science and technology. They also performed a comparative study of the MCDM techniques using a globally accepted dataset, which showed significant overlap and confirmed the utility of the MCDM techniques used. They stated a few advantages and disadvantages of the MCDM techniques used in their study. Liu et al. [6] used the hybrid decision-making trial and evaluation laboratory (DEMATEL), the analytical network process (ANP), and the višekriterijumsko kompromisno rangiranje (VIKOR) MCDM techniques to select the best low-carbon energy plan among four alternatives. Fifteen criteria were considered as a measure for four types of properties. DEMATEL analysis showed interactions of various properties among each other while ANP was used for the calculation of criteria weights. The ranks obtained using the hybrid technique were compared with the ranks obtained using grey relational analysis (GRA) and TOPSIS, which had also ranked the alternatives similarly. Badi et al. [7] employed the combination distance-based assessment (CODAS) MCDM technique to select a supplier based on four criteria among six alternatives. They made a quality decision using the employed CODAS technique. They had considered both quantitative and qualitative criteria for their study. The robustness of the method was verified by the same authors in their subsequent work by comparing the results of different techniques. Popovic et al. [8] selected the best option among 30 candidates based on six criteria. The weight calculation was done using the stepwise weight assessment ratio analysis (SWARA) method while the ranking was done using the combined compromise solution (CoCoSo) MCDM technique. They also stated that the CoCoSo technique, which is a comparatively new technique, is a highly reliable and simple technique for MCDM problems. Hamdia et al. [9] carried out a damage assessment of reinforced buildings using a fuzzy analytic hierarchy process (AHP).

MCDM techniques are also widely used for the selection of robots for industrial applications because of the complexity and consequences associated with the process of decision making. Chatterjee et al. [10] used MCDMs in the selection of pick-and-place robots. They selected load capacity, maximum tip speed, repeatability, memory capacity, manipulator reach, velocity, vendor's service quality, program flexibility, and cost as the criteria. They relied on VIKOR and élimination et choix traduisant la realité (ELECTRE) to carry out the analysis. Athawale and Chakraborty [11] carried out one of the preliminary works in pick-and-place robot selection by comparing several MCDMs. They compared the weighted sum model (WSM), weighted product model (WPM), AHP, TOPSIS, VIKOR, ELECTRE, the preference ranking organization method for enrichment evaluation (PROMETHEE), and the GRA method. Athawale et al. [12] used AHP in conjunction with the VIKOR method to select the best pick-and-place robot. For similar problems, Omoniwa [13] used the GRA method whereas Sen et al. [14] used the PROMETHEE II. In another work, Sen et al. [15] used the TODIM method. Parameshwaran et al. [16] developed fuzzy VIKOR and fuzzy TOPSIS frameworks to carry out robot selection in an uncertain decision-making environment. Xue et al. [17] developed a hybrid hesitant 2-tuple linguistic-term-infused MCDM approach for robot selection. Ghorabaee [18] developed an interval type-2 fuzzy set and deployed it with VIKOR for robot selection. Karande et al. [19] used WSM, WPM, WASPAS, and MOORA to solve an industrial robot-selection problem. Goswami et al. [20] used criteria importance through inter-criteria correlation (CRITIC) for weight calculation and employed hybrid COPRAS–ARAS and TOPSIS–ARAS methods to select the best industrial robot based on three beneficial and two non-beneficial criteria. They further validated their newly developed hybrid MCDM techniques using several pre-existing MCDM techniques. Rashid et al. [21] used the BW–EDAS method to select the best robot for industrial applications. Four criteria and five alternatives were included in the decision matrix for the decision-making process. They also compared their results with other MCDM techniques to validate their approach, and a sensitivity analysis was done to check the robustness of their approach. Very recently, Kumar et al. [22] used the SWARA–CoCoSo MCDM approach to select the best industrial robot for spray-painting applications. Three beneficial and four non-beneficial criteria were chosen to decide among twelve alternatives by various manufacturers. They concluded that Fanuc P-350iA/45 was the best choice among the considered alternatives for their study. Choda et al. [23] very recently used an entropy-TOPSIS approach for arc-welding robot selection. Simion et al. [24] selected the best possible arc-welding robot by evaluating the robot's motion, repeatability, allowable loading moment, payload, robot mass, reach, power rating, cost, and flexibility. They used AHP to achieve the best compromise solution. Similarly, Agarwal et al. [25] considered payload, horizontal reach, vertical reach, repeatability, weight, power rating, cost, flexibility, safety, welding performance, maintainability, and ease of programming as the criteria for the evaluation of robots. They relied on the entropy method to set the weights for the criteria and MABAC to select the appropriate robot.

As evidenced from the discussion of the literature above, MCDM techniques involve determining the weights of all the criteria that are taken into consideration. A weighted normalized decision matrix is considered based on the quantitative data available for each alternative for all the criteria. Various weight-determination criteria, such as the mean weight method, the standard deviation method, the entropy method, CRITIC, MEREC, etc., have been proposed in the literature. Among these methods, MEREC is the most recent one. MEREC was proposed by Ghorabaee et al. [26], where the authors state that it is based on the removal effect of criteria. They compared the weights calculated by their proposed MEREC method with other pre-existing methods, such as CRITIC, the entropy method, and the standard deviation method, to validate the effectiveness of their method. It was observed that MEREC could successfully assign criteria weights. A correlation analysis showed significant overlap with existing weight-determining methods.

The objective of this research was to determine the best spray-painting robot based on the qualitative features of the robots. To avoid any bias in the decision-making process, a newly developed objective weight allocation method called MEREC was used in this work. To the best of our knowledge, this is the first use of MEREC for robot-selection problems. In this work, an attempt has been made to apply the MEREC method for robot selection in a spray-painting application. Moreover, the literature survey also revealed that there is a dearth of works where newer methods such as CoCoSo and MABAC have been applied to robot-selection problems. Thus, in this paper, CoCoSo and MABAC are compared with VIKOR, a widely popular traditional MCDM method applied to robot-selection problems. Furthermore, two other algorithms, namely CODAS and COPRAS, are also considered in this work. The rest of the paper is arranged as follows. The next section details the criteria weight calculation method MEREC, followed by the mathematical frameworks and descriptions of CODAS, COPRAS, CoCoSo, MABAC, and VIKOR. The problem description of the case study considered in this paper is discussed in Section 3. Section 4 presents detailed discussions of the results, and finally, some conclusions based on this study are drawn in Section 5.

2. Methodology

2.1. MEREC

Ghorabaee et al. [26] proposed a weight-determination method based on the removal effects of criteria. While most of the other weight-determining methods check for variance in the alternative's performance associated with the criteria to assign the weights of the criteria, MEREC checks for the effect of the removal of criteria to assign a weight to each criterion. The steps involved in weight determination using MEREC as described by the original author are stated as follows:

Step 1: The decision matrix is constructed. The matrix will be a $n \times m$ matrix, where m is the number of criteria and n is the number of alternatives for the problem, and each row and column will contain a performance value associated with the corresponding alternative and criterion. From here on, x_{ij} is the denomination used to refer to elements in the decision matrix in the i^{th} row and j^{th} column.

Step 2: The decision matrix is normalized. The formula used to normalize the decision matrix is as follows:

$$n_{ij}^{x} = \begin{cases} \frac{\min\limits_{k} x_{kj}}{x_{ij}} & \text{if } j \in B \\ \frac{x_{ij}}{\max\limits_{k} x_{kj}} & \text{if } j \in C \end{cases} \tag{1}$$

where B is the set of beneficial criteria and C is the set of non-beneficial (cost) criteria.

Step 3: The overall performance of the alternatives (S_i) is calculated as

$$S_i = \ln\left(1 + \left(\frac{1}{m} \sum_j \left|\ln\left(n_{ij}^{x}\right)\right|\right)\right) \tag{2}$$

Step 4: The performance of the alternatives is calculated by removing each criterion $\left(S'_{ij}\right)$:

$$S'_{ij} = \ln\left(1 + \left(\frac{1}{m} \sum_{k,k \neq j} |\ln(n_{ik}^{x})|\right)\right) \tag{3}$$

Step 5: The absolute deviation is calculated and is summed up to calculate E_j:

$$E_j = \sum_i |S'_{ij} - S_i| \tag{4}$$

Step 6: The weights of the criteria are determined using the following formula:

$$w_j = \frac{E_j}{\sum_k E_k} \tag{5}$$

In this equation, w_j is the weight assigned to each criterion for all the MCDM techniques used in this paper.

2.2. CODAS

Ghorabaee et al. [27] proposed a combination distance-based assessment (CODAS) technique to effectively solve MCDM problems in 2016. This technique considers two measures to rank the alternatives from best to worst. The primary measure is the Euclidean distance of the alternatives from the negative-ideal solution. This distance is associated with the L2-norm indifference space for criteria. CODAS also considers taxicab distance, which is associated with L1-norm indifference space for criteria. The steps as proposed by the Ghorabaee et al. [27] are stated as follows:

Step 1: The decision matrix is constructed. The matrix will be a $n \times m$ matrix, where m is the number of criteria and n is the number of alternatives, and each row and column will contain a performance value associated with the corresponding alternative and criterion.

Step 2: The decision matrix is normalized. Linear normalization is considered in CODAS. It is calculated as follows:

$$n_{ij}^{x} = \begin{cases} \frac{x_{ij}}{\max\limits_{i} x_{ij}} & \text{if } j \in B \\ \frac{\min\limits_{i} x_{ij}}{x_{ij}} & \text{if } j \in C \end{cases} \tag{6}$$

Step 3: The weighted normalized decision matrix is calculated as $r_{ij} = w_j n_{ij}$, where w_j is the weight of j^{th} criterion.

Step 4: The negative ideal solution point is determined as follows:

$$ns = [ns_j]_{1xm}, \text{ where } ns_j = \min_i r_{ij}. \tag{7}$$

Step 5: The Euclidean and taxicab distances of the alternatives are computed using the following formulas:

$$E_i = \sqrt{\sum_{j=1}^{m} (r_{ij} - ns_j)^2} \tag{8}$$

$$T_i = \sum_{j=1}^{m} |r_{ij} - ns_j| \tag{9}$$

Step 6: The relative assessment matrix $Ra = [h_{ik}]_{nxn}$ is defined as follows:

$$h_{ik} = (E_i - E_k) + (\psi(E_i - E_k) \text{ x } (T_i - T_k)) \tag{10}$$

where $k \in \{1, 2, \ldots, n\}$, and ψ denotes a threshold function that is either 0 or 1 depending on the necessity to compute the taxicab distance:

$$\psi(x) = \begin{cases} 1 \text{ if } |\, x \,| \geq \tau \\ 0 \text{ if } |\, x \,| < \tau \end{cases} \tag{11}$$

where τ is set by the decision maker.

Step 7: The assessment score is computed as follows:

$$H_i = \sum_{k=1}^{n} (h_{ik}) \tag{12}$$

and alternatives are ranked in descending values of the assessment score.

Consequently, the alternative with the highest H_i is the best choice among the alternatives.

2.3. COPRAS

COPRAS was introduced by Zavadskas et al. [28] in 1994 as an MCDM technique to select construction sites. It uses stepwise ranking in terms of the utility and significance of the alternatives to rank the available alternatives. Very little computational work makes COPRAS one of the simplest and most effective MCDM techniques currently. The steps involved in the decision-making process are discussed as follows:

Step 1: As with all the other MCDM techniques, the first step is to define a decision matrix.

Step 2: Normalization of the decision matrix is done to transform the performance values into comparable dimensionless values. The following formula is used for normalization in COPRAS:

$$n_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{13}$$

Step 3: The weighted normalized decision matrix is calculated by multiplying the corresponding weight (w_j) with each element of the normalized decision matrix:

$$D = [d_{ij}];\ d_{ij} = n_{ij} \text{x } w_j \tag{14}$$

Step 4: Each alternative is categorized as minimizing the (S_-) and maximizing the (S_+) indices using the formulas

$$S_+ = \sum_{j=1}^{k} d_{ij} \tag{15}$$

$$S_{-} = \sum_{j=k+1}^{n} d_{ij} \tag{16}$$

Step 5: The relative weight (Q_i) of the i_{th} alternative is calculated as follows:

$$Q_i = S_{+} + \frac{\min_i S_{-} \sum_{i=1}^{m} S_{-}}{S_{-} \sum_{i=1}^{m} \frac{\min S_{-}}{\frac{1}{S_{-}}}} \tag{17}$$

Step 6: The priority order of the alternatives is ranked using the value of Q_i in descending order. The highest relative weight is the most acceptable alternative.

2.4. CoCoSo

Yazdani et al. [29] proposed a technique called the combined compromise solution (CoCoSo) for an MCDM problem which is based on integrated simple additive weighing and an exponentially weighted product model. Consistency and accuracy are the main advantages of the CoCoSo decision-making process. The steps involved, as suggested by the original authors, are as follows:

Step 1: As with all the other MCDM techniques, the first step is to determine the decision matrix with m rows and n columns.

Step 2: A compromise normalization equation is used to normalize the decision matrix. The formula is stated as follows:

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}; j \in B \tag{18}$$

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}; j \in H \tag{19}$$

Step 3: Performance indices following the grey relation generation approach and the WASPAS approach are calculated as S_i and P_i, respectively. The calculation formula is stated below:

$$S_i = \sum_{j=1}^{n} w_j r_{ij} \tag{20}$$

$$P_i = \sum_{j=1}^{n} (r_{ij})^{w_j} \tag{21}$$

Step 4: Three appraisal scores for each alternative are calculated using the following formula:

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)} \tag{22}$$

$$k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i} \tag{23}$$

$$k_{ia} = \frac{(1-\lambda)P_i + \lambda S_i}{\lambda \max_i S_i + (1-\lambda)\max_i P_i} \tag{24}$$

Step 5: The alternatives are calculated and ranked in descending order based on k_i:

$$k_i = (k_{ia} k_{ib} k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \tag{25}$$

2.5. MABAC

Pamucar et al. [30] proposed a multi-attributive border approximation area comparison (MABAC) method to tackle MCDM problems. They applied their newly proposed method for the selection of forklifts. The distance of the criterion function from the border approximation area was used to rank the alternatives using the MABAC method. A sensitivity analysis and comparison with SAW, COPRAS, TOPSIS, and MOORA were also done to confirm the validity of the newly proposed method. The primary advantage of MABAC as stated by the authors is the consistency, accuracy and simplicity of the mathematical apparatus used. The steps involved in MABAC are stated below:

Step 1: The decision matrix is determined, as with all the other MCDM techniques.
Step 2: The decision matrix is normalized using the following equations:

$$t_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-}; j \in B \tag{26}$$

$$t_{ij} = \frac{x_{ij} - x_i^+}{x_i^+ - x_i^-}; j \in H \tag{27}$$

where x_i^+ and x_i^+ are the maximum and minimum values of the observed criterion in the decision matrix.

Step 3: The weighted normalized matrix is determined as

$$V = \left[v_{ij}\right]_{mxn}; \; v_{ij} = w_j.t_{ij} + w_j \tag{28}$$

Step 4: The border approximation area matrix is determined as

$$G = [g_i]_{1xn}; g_i = \left(\prod_{j=1}^{m} v_{ij}\right)^{1/m} \tag{29}$$

Step 5: The distances of the alternatives from the border approximation area are calculated as

$$Q = V - G \tag{30}$$

where V and G are the matrices defined in Steps 3 and 4.

Step 6: The criterion function is calculated as

$$Si = \sum_{j=1}^{n} q_{ij} \tag{31}$$

Alternatives are ranked in descending order by the criterion function. That is, the highest value of the criterion function is to be ranked as 1.

2.6. VIKOR

Opricovic and Tzeng [31] developed the višekriterijumsko kompromisno rangiranje (VIKOR) technique to solve MCDM problems involving conflicting and non-commensurable criteria. This model proposes a compromise solution that is closest to the ideal solution with an acceptable degree of accuracy. The steps involved in the VIKOR process are discussed below:

Step 1: The decision matrix is determined, as with the other MCDM techniques.
Step 2: The best f_i^+ and the worst f_i^- performance values are determined for all criteria.
Step 3: The S_j and R_j values are calculated using the following relations:

$$S_j = \sum_{i=1}^{n} w_i \frac{f_i^+ - f_{ij}}{f_i^+ - f_i^-} \tag{32}$$

$$R_j = \max_i \left[w_i \frac{f_i^+ - f_{ij}}{f_i^+ - f_i^-} \right] \quad (33)$$

where w_i is the weight of the criterion.

Step 4: The value of Q_i is calculated as follows:

$$Q_i = v\left[\frac{S_i - (S_i)_{min}}{(S_i)_{max} - (S_i)_{min}}\right] - (1 - v)\left[\frac{R_i - (R_i)_{min}}{(R_i)_{max} - (R_i)_{min}}\right] \quad (34)$$

where $(R_i)_{max}$ and $(R_i)_{min}$ represent the maximum and minimum values of R_j while $(S_i)_{min}$ and $(S_i)_{max}$ represent the maximum and minimum values of S_j.

The value of v is given by the decision maker and it represents the weight of the strategy of maximum group utility in the decision-making process. The term $(1 - v)$ represents individual regret.

Step 5: Ranking is performed in ascending order of Q_i.

3. Problem Description

Modern-day industries need to be safe, fast, efficient, and precise. Thus, most painting applications in industrial settings now use robotic systems. However, numerous alternatives with varying configurations and complexities are available to choose from. At times, due to end user bias, an improper robotic system may be selected for a particular application which could have been performed more efficiently and cost-effectively by another robot. Often, a robotic system is selected without adequate examination of the application necessities. Therefore, it is imperative that, while selecting an appropriate robotic system for spray-painting applications, due consideration is given to the specifications and capabilities of the robotic systems. These could include checking functional features such as production rate, speed, or ability to work with different materials, or checking physical features such as space requirements, power consumption, availability of spare parts, etc. The selection of an appropriate robotic system from a set of viable alternatives by comparing their various features (criteria), which may have conflicting requirements, is a typical multi-criteria decision-making (MCDM) problem. The presence of conflicting requirements, such as high power consumption due to high speed or high capital cost due to better brand/better efficiency, means that spray-painting robot selection is a non-trivial problem.

An industrial spray-painting robot-selection problem was considered in this study. The data for the analysis were collected from Kumar et al. [22]. In total, 12 robots from six different manufacturers were considered. All the robots were capable of movement in six degrees of freedom. Payload (P), mass (M), speed (S), repeatability (RE), reach (RC), cost (C), and power consumption (PC) were the seven deciding factors, or criteria, for the selection of the optimal robot. Payload (P), speed (S), and reach (RC) were the beneficial criteria and mass (M), repeatability (RE), cost (C), and power consumption (PC) were the cost criteria. Payload (P) was the total weight of the paint and spray gun, as well as the end arm tooling, that the robot could lift. It was measured in kg. Speed (S) was a measure of the robot's productivity and was defined as the rate at which the robot could carry out the spray-painting operation. It was measured in m/sec. Repeatability (RE) was a measure of the robot's ability to consistently perform the same task with minimum deviation. It was measured in +/− mm. Reach (R) was a measure of the robot's work envelope. It was the distance from the centre of a robot to the fullest extension of its arm. It was measured in mm. Cost (C) was the upfront capital investment for the procurement of the robot. It was measured in USD. Power consumption (C) was the total electric power required to operate the robot. It was measured in kVA.

4. Results and Discussion

Weight determination in past work was done using subjective weight-determining techniques such as SWARA, and comparisons were made with other similar techniques such as AHP, PIPRECIA, BWM, and FUCOM. Although subjective methods have their own merits, they rely heavily on the assumption that an expert decision maker is competent enough to assign weights to each criterion without any error, which may or may not always be true. Thus, this work focused on the application of the MCDM techniques CODAS, COPRAS, CoCoSo, MABAC, and VIKOR for the selection of robots in a spray-painting application. The weights of the various criteria considered in this study were calculated using an objective weight-determining method based on the removal effect of criteria (MEREC), and all the alternatives were ranked using the MCDM techniques discussed above.

The first step in any MCDM problem is the formulation of a decision matrix. Table 1 shows the list of 12 alternatives to choose from, based on seven different criteria. Three of the seven criteria, namely payload (P), speed (S), and reach (RC), were required to be maximized (beneficial criteria), while mechanical weight (M), repeatability (RE), cost (C), and power consumption (PC) were to be minimized (cost criteria). For weight calculations, the normalized decision matrix was calculated using Equation (1). Normalization was done to ensure that the performance values conformed to the same standard. The overall performance values of alternatives were calculated using Equation (2) and are shown in Table 2. The performance value of each alternative upon removing each criterion was calculated using Equation (3). Table 3 shows the S_{ij} determined by the matrix. E_j, or the absolute deviation, was calculated using Equation (4) and the weights of criteria were calculated using Equation (5). It can be observed that M > RE > C > P > PC > RC > S was the order of weight assigned to each criterion using the MEREC method. The mechanical weight of the robot was selected as the most significant criteria for spray-painting robot selection using the MEREC technique.

Table 1. Decision matrix consisting of various robot models and their features [22].

Manufacturer	Model	Alternative	P	S	RC	M	RE	C	PC
Kawasaki	KF121	A1	12	1	2668	770	0.5	52,186	5
	KJ264	A2	15	2	2640	540	0.5	58,137	7
ABB	IRB 5500-22	A3	13	1	2975	780	0.2	20,167	6
	IRB 5510	A4	13	1	2600	767	0.2	12,550	5
YASKAWA	Motoman MPX-3500	A5	15	2	2700	590	0.2	39,000	3
	Motoman EPX-2800	A6	20	2	2779	650	0.5	44,000	5
Haosheng	HS-6-1722	A7	20	2	1722	220	0.1	54,000	4
	HS-6-1640	A8	10	2	1640	185	0.1	50,000	6
Fanuc	P-250iB/15	A9	15	2	2800	530	0.2	22,500	4
	P-350iA/45	A10	45	2	2606	590	0.1	25,000	3
Yooheart	HY1010A-143	A11	10	2	1430	170	0.1	23,000	3
	HY1050A-200	A12	50	2	2000	520	0.1	25,000	8

Table 2. Calculations of the performance values of alternatives using MEREC.

Alternative	P	S	RC	M	RE	C	PC	Si
A1	0.83	1.00	0.54	0.99	1.00	0.90	0.64	0.03
A2	0.67	0.80	0.54	0.69	1.00	1.00	0.91	0.11
A3	0.77	0.86	0.48	1.00	0.30	0.35	0.78	0.27
A4	0.77	0.86	0.55	0.98	0.30	0.22	0.66	0.36
A5	0.67	0.60	0.53	0.76	0.30	0.67	0.38	0.37
A6	0.50	0.60	0.51	0.83	1.00	0.76	0.63	0.19
A7	0.50	0.60	0.83	0.28	0.12	0.93	0.55	0.55
A8	1.00	0.60	0.87	0.24	0.10	0.86	0.71	0.51
A9	0.67	0.67	0.51	0.68	0.40	0.39	0.55	0.36
A10	0.22	0.67	0.55	0.76	0.20	0.43	0.39	0.54
A11	1.00	0.75	1.00	0.22	0.12	0.40	0.38	0.61
A12	0.20	0.75	0.72	0.67	0.16	0.43	1.00	0.51

Table 3. Weight calculations using MEREC.

Alternative	P	S	RC	M	RE	C	PC
A1	0.01	0.03	0.10	0.09	0.03	0.16	0.09
A2	0.05	0.08	0.14	0.48	0.11	0.13	0.12
A3	0.24	0.26	0.35	1.05	0.13	0.15	0.25
A4	0.33	0.34	0.41	1.28	0.23	0.19	0.31
A5	0.33	0.32	0.43	1.12	0.24	0.33	0.27
A6	0.11	0.13	0.27	0.23	0.19	0.27	0.18
A7	0.49	0.50	0.56	1.33	0.35	0.54	0.49
A8	0.51	0.46	0.52	1.32	0.28	0.49	0.48
A9	0.31	0.31	0.42	1.07	0.26	0.26	0.29
A10	0.40	0.50	0.59	1.40	0.39	0.47	0.46
A11	0.61	0.58	0.61	1.62	0.43	0.53	0.53
A12	0.36	0.48	0.54	1.28	0.34	0.43	0.51
E_j	0.6441	0.3872	0.5481	7.8821	1.4014	0.9029	0.5554
Weight	0.0523	0.0314	0.0445	0.6397	0.1137	0.0733	0.0451

E_j The selection of the best robot among 12 alternatives was done using five MCDM techniques, namely CODAS, COPRAS, CoCoSo, MABAC, and VIKOR. The procedural steps discussed in Section 2.2 were religiously followed for the rank calculation using CODAS. Normalization of the decision matrix was done using Equation (6). The weights determined using MEREC were multiplied by the performance value associated with the corresponding criterion for all available alternatives to determine the weighted normalized matrix, as shown in Table 4. The negative ideal solution was calculated using Equation (8), and the Euclidian and taxicab distances were calculated using Equations (9) and (10), respectively. The H assessment matrix was determined using Equation (11) and the value of τ was selected as x for the computation of the H values presented in Table 5. The ranking was done in descending order of the H values computed using Equation (13). The ranks obtained using the CODAS technique are tabulated in Table 5. According to the CODAS technique, HY1010A-143 was the best robot in the lot for spray-painting applications, while HS-6-1640 and HS-6-1722 were ranked 2nd and 3rd, respectively. KF121 was selected to be the least desirable for spray-painting applications according to the CODAS technique. Similarly, robots were also ranked using COPRAS by following the procedural steps discussed in Section 2.3. The normalization procedure was slightly different for the COPRAS method and was done using Equation (14). The weighted normalized matrix was determined using Equation (15). The S_+ and S_- values were calculated by summing up the elements in the weighted normalized matrix under beneficial and cost criteria, respectively, as shown in Equations (16) and (17). The relative weights of each alternative were calculated using Equation (18) and the alternatives were ranked in descending order of Q_i. The calculation of ranks using COPRAS is shown in Table 6; HY1010A-143 was ranked first by COPRAS while KF121 was ranked last. It can be seen that CODAS also ranked the same two robots as the best and the worst alternatives.

Following the procedural steps discussed in Section 2.4, robots for spray-painting applications were also ranked using CoCoSo. The compromise normalization of the decision matrix was done using Equation (19). The performance indices S_i and P_i were calculated from the weighted normalized matrix and the exponentially weighted normalized matrix, respectively, using Equations (20) and (21). The calculations of S_i and P_i are shown in Tables 7 and 8, respectively. Three appraisal scores were calculated using these two performance indices and Equations (22)–(24), which were aggregated together in Equation (25) to calculate the ranking index k. The calculated values of performance indices and ranks are presented in Table 9. Alternatives were ranked in decreasing order of k as shown in the table. CoCoSo ranked HS-6-1722 as the best robot for spray-painting applications. CoCoSo, as with COPRAS and CODAS, also predicted KF121 as the least favourable alternative for spray-painting applications.

Table 4. Normalized decision matrix for CODAS.

Alternative	P	S	RC	M	RE	C	PC
A1	0.0125	0.0189	0.0399	0.1412	0.0114	0.0176	0.0265
A2	0.0157	0.0236	0.0395	0.2014	0.0114	0.0158	0.0185
A3	0.0136	0.0220	0.0445	0.1394	0.0379	0.0456	0.0218
A4	0.0136	0.0220	0.0389	0.1418	0.0379	0.0733	0.0255
A5	0.0157	0.0314	0.0404	0.1843	0.0379	0.0236	0.0451
A6	0.0209	0.0314	0.0416	0.1673	0.0114	0.0209	0.0270
A7	0.0209	0.0314	0.0257	0.4943	0.0948	0.0170	0.0307
A8	0.0105	0.0314	0.0245	0.5878	0.1137	0.0184	0.0237
A9	0.0157	0.0283	0.0419	0.2052	0.0284	0.0409	0.0307
A10	0.0470	0.0283	0.0390	0.1843	0.0569	0.0368	0.0436
A11	0.0105	0.0251	0.0214	0.6397	0.0948	0.0400	0.0451
A12	0.0523	0.0251	0.0299	0.2091	0.0711	0.0368	0.0169

Table 5. Rank calculations using CODAS.

Alternative	Euclidean	Taxicab	H	Rank	Alternative	Euclidean	Taxicab	H	Rank
A1	0.0211	0.0338	−4.0193	12	A7	0.3652	0.4807	5.4204	3
A2	0.0650	0.0916	−2.5983	9	A8	0.4602	0.5759	7.7019	2
A3	0.0466	0.0906	−3.0066	10	A9	0.0773	0.1569	−1.9929	6
A4	0.0664	0.1188	−2.4180	8	A10	0.0835	0.2017	−1.6040	5
A5	0.0642	0.1442	−2.2923	7	A11	0.5086	0.6423	9.0798	1
A6	0.0398	0.0863	−3.2666	11	A12	0.1036	0.2070	−1.0041	4

Table 6. Weighted normalized matrix, with performance metrics and rank calculations using COPRAS.

Alternative	P	S	RC	M	RE	C	PC	S_+	S_-	Q	Rank
A1	0.0047	0.0033	0.0084	0.0105	0.0414	0.0466	0.0074	0.0164	0.1060	0.0495	12
A2	0.0058	0.0042	0.0083	0.0074	0.0414	0.0519	0.0106	0.0183	0.1113	0.0498	11
A3	0.0051	0.0039	0.0094	0.0106	0.0124	0.0180	0.0090	0.0183	0.0501	0.0883	6
A4	0.0051	0.0039	0.0082	0.0105	0.0124	0.0112	0.0077	0.0171	0.0418	0.1010	4
A5	0.0058	0.0055	0.0085	0.0080	0.0124	0.0348	0.0044	0.0199	0.0597	0.0786	7
A6	0.0078	0.0055	0.0088	0.0089	0.0414	0.0393	0.0073	0.0221	0.0969	0.0583	10
A7	0.0078	0.0055	0.0054	0.0030	0.0050	0.0482	0.0064	0.0187	0.0626	0.0747	8
A8	0.0039	0.0055	0.0052	0.0025	0.0041	0.0447	0.0083	0.0146	0.0596	0.0734	9
A9	0.0058	0.0050	0.0088	0.0072	0.0166	0.0201	0.0064	0.0196	0.0503	0.0893	5
A10	0.0175	0.0050	0.0082	0.0080	0.0083	0.0223	0.0045	0.0307	0.0432	0.1119	2
A11	0.0039	0.0044	0.0045	0.0023	0.0050	0.0206	0.0044	0.0128	0.0322	0.1217	1
A12	0.0195	0.0044	0.0063	0.0071	0.0066	0.0223	0.0116	0.0302	0.0477	0.1037	3

Table 7. S_i calculations for CoCoSo.

Alternative	P	S	RC	M	RE	C	PC	S_i
A1	0.0026	0.0000	0.0356	0.0105	0.0000	0.0096	0.0261	0.0845
A2	0.0065	0.0118	0.0348	0.2517	0.0000	0.0000	0.0063	0.3112
A3	0.0039	0.0079	0.0445	0.0000	0.0885	0.0610	0.0162	0.2220
A4	0.0039	0.0079	0.0337	0.0136	0.0885	0.0733	0.0243	0.2452
A5	0.0065	0.0314	0.0366	0.1993	0.0885	0.0308	0.0451	0.4381
A6	0.0131	0.0314	0.0388	0.1363	0.0000	0.0227	0.0270	0.2694
A7	0.0131	0.0314	0.0084	0.5873	0.1112	0.0067	0.0325	0.7905
A8	0.0000	0.0314	0.0060	0.6240	0.1137	0.0131	0.0207	0.8090
A9	0.0065	0.0236	0.0394	0.2622	0.0758	0.0573	0.0325	0.4973
A10	0.0457	0.0236	0.0339	0.1993	0.1011	0.0533	0.0442	0.5010
A11	0.0000	0.0157	0.0000	0.6397	0.1112	0.0565	0.0451	0.8682
A12	0.0523	0.0157	0.0164	0.2727	0.1062	0.0533	0.0000	0.5165

Table 8. P_i calculations for CoCoSo.

Alternative	P	S	RC	M	RE	C	PC	P_i
A1	0.8550	0.0000	0.9902	0.0721	0.0000	0.8614	0.9757	3.7545
A2	0.8970	0.9696	0.9892	0.5506	0.0000	0.0000	0.9152	4.3216
A3	0.8734	0.9574	1.0000	0.0000	0.9718	0.9867	0.9550	5.7442
A4	0.8734	0.9574	0.9877	0.0853	0.9718	1.0000	0.9726	5.8481
A5	0.8970	1.0000	0.9913	0.4742	0.9718	0.9384	1.0000	6.2727
A6	0.9301	1.0000	0.9940	0.3720	0.0000	0.9178	0.9772	5.1911
A7	0.9301	1.0000	0.9286	0.9468	0.9974	0.8387	0.9853	6.6269
A8	0.0000	1.0000	0.9150	0.9842	1.0000	0.8814	0.9656	5.7462
A9	0.8970	0.9910	0.9947	0.5652	0.9549	0.9821	0.9853	6.3702
A10	0.9930	0.9910	0.9879	0.4742	0.9867	0.9769	0.9991	6.4088
A11	0.0000	0.9785	0.0000	1.0000	0.9974	0.9811	1.0000	4.9570
A12	1.0000	0.9785	0.9566	0.5795	0.9922	0.9769	0.0000	5.4837

Table 9. Rank calculations using CoCoSo (Lambda = 0.5).

Alternative	k_a	k_b	k_c	k	Rank	Alternative	k_a	k_b	k_c	k	Rank
A1	0.053	2.000	0.512	1.234	12	A7	0.103	11.125	0.990	5.114	1
A2	0.064	4.835	0.618	2.416	10	A8	0.091	11.109	0.875	4.984	3
A3	0.083	4.158	0.796	2.328	11	A9	0.095	7.585	0.916	3.736	5
A4	0.084	4.461	0.813	2.460	8	A10	0.096	7.639	0.922	3.762	4
A5	0.093	6.858	0.895	3.444	7	A11	0.081	11.600	0.777	5.052	2
A6	0.076	4.573	0.729	2.424	9	A12	0.083	7.576	0.801	3.615	6

The MABAC technique was also used to rank the alternatives. Firstly, the decision matrix was normalized using Equations (26) and (27) depending on the type of criteria. The weights calculated with MEREC were used to calculate the weighted normalized matrix by using Equation (28). The border approximation area matrix G was calculated using Equation (29), as shown in Table 10, and the distances of the performance values from the border approximation area were calculated using Equation (30). The criterion function S_i was calculated using Equation (31) and the alternatives were ranked in decreasing order of S_i, as shown in Table 11. HY1010A-143 was ranked number one by the MABAC technique, while KF121 was ranked last.

Table 10. Weighted normalized decision matrix for MABAC.

Alternative	P	S	RC	M	RE	C	PC
A1	0.0549	0.0314	0.0801	0.6502	0.1137	0.0828	0.0712
A2	0.0588	0.0432	0.0793	0.8914	0.1137	0.0733	0.0514
A3	0.0562	0.0393	0.0890	0.6397	0.2022	0.1343	0.0613
A4	0.0562	0.0393	0.0782	0.6533	0.2022	0.1466	0.0694
A5	0.0588	0.0628	0.0811	0.8390	0.2022	0.1040	0.0902
A6	0.0653	0.0628	0.0833	0.7760	0.1137	0.0960	0.0721
A7	0.0653	0.0628	0.0529	1.2270	0.2250	0.0799	0.0775
A8	0.0523	0.0628	0.0505	1.2637	0.2275	0.0864	0.0658
A9	0.0588	0.0550	0.0839	0.9019	0.1896	0.1306	0.0775
A10	0.0980	0.0550	0.0783	0.8390	0.2148	0.1266	0.0893
A11	0.0523	0.0471	0.0445	1.2794	0.2250	0.1298	0.0902
A12	0.1046	0.0471	0.0609	0.9124	0.2199	0.1266	0.0451
G	0.0634	0.0496	0.0702	0.8801	0.1812	0.1069	0.0703

The VIKOR MCDM technique was also used to determine the ranks of the alternatives using the steps discussed in Section 2.6. The worst and best performance values for each criterion were noted and Equations (32) and (33) were used to calculate the S and R values. The Q values were calculated with the S_j and R_j values obtained using Equation (34), and ranking was done in ascending order of the Q values. Table 12 shows the ranks of all the alternatives calculated using VIKOR. HY1010A-143 was selected as the best robot by the VIKOR technique, which agreed with the CODAS, COPRAS, and MABAC techniques as discussed above. KF121 was placed at the bottom of the ranks by VIKOR.

Table 11. Q matrix and ranks using MABAC.

Alternative	P	S	RC	M	RE	C	PC	S_i	Rank
A1	−0.0085	−0.0181	0.0100	−0.2299	−0.0675	−0.0241	0.0009	−0.3372	12
A2	−0.0046	−0.0064	0.0092	0.0113	−0.0675	−0.0337	−0.0189	−0.1105	8
A3	−0.0072	−0.0103	0.0188	−0.2404	0.0210	0.0274	−0.0090	−0.1997	11
A4	−0.0072	−0.0103	0.0080	−0.2268	0.0210	0.0396	−0.0009	−0.1765	10
A5	−0.0046	0.0133	0.0109	−0.0411	0.0210	−0.0029	0.0199	0.0164	7
A6	0.0019	0.0133	0.0132	−0.1041	−0.0675	−0.0109	0.0018	−0.1522	9
A7	0.0019	0.0133	−0.0173	0.3469	0.0437	−0.0270	0.0072	0.3688	3
A8	−0.0111	0.0133	−0.0196	0.3836	0.0463	−0.0206	−0.0045	0.3873	2
A9	−0.0046	0.0054	0.0138	0.0218	0.0084	0.0236	0.0072	0.0756	6
A10	0.0346	0.0054	0.0082	−0.0411	0.0336	0.0196	0.0190	0.0793	5
A11	−0.0111	−0.0024	−0.0257	0.3993	0.0437	0.0228	0.0199	0.4465	1
A12	0.0412	−0.0024	−0.0093	0.0323	0.0387	0.0196	−0.0252	0.0948	4

Table 12. Rank calculations using VIKOR.

Alternatives	P	S	RC	M	RE	C	PC	S	R	Q	Rank
A1	12	1.2	2668	770	0.5	52,186	5.1	0.9155	0.6292	0.9911	12
A2	15	1.5	2640	540	0.5	58,137	7.3	0.6888	0.3880	0.6411	8
A3	13	1.4	2975	780	0.15	20,167	6.2	0.7780	0.6397	0.9123	11
A4	13	1.4	2600	767	0.15	12,550	5.3	0.7548	0.6261	0.8859	10
A5	15	2	2700	590	0.15	39,000	3	0.5619	0.4405	0.6048	7
A6	20	2	2779	650	0.5	44,000	5	0.7306	0.5034	0.7659	9
A7	20	2	1722	220	0.06	54,000	4.4	0.2095	0.0666	0.0618	3
A8	10	2	1640	185	0.05	50,000	5.7	0.1910	0.0602	0.0445	2
A9	15	1.8	2800	530	0.2	22,500	4.4	0.5027	0.3775	0.5135	5
A10	45	1.8	2606	590	0.1	25,000	3.1	0.4990	0.4405	0.5647	6
A11	10	1.6	1430	170	0.06	23,000	3	0.1318	0.0523	< 0.0001	1
A12	50	1.6	2000	520	0.08	25,000	8	0.4835	0.3671	0.4923	4

All the MCDM techniques employed were consistent in choosing the least preferable robot as the KJ121 robot. Also, HY1010A-143 was ranked the best by four of the MCDM techniques, while the two Haosheng-made robots were ranked among the top three by all the MCDM techniques—among which four techniques ranked HS-6-1640 as the better of the two. The ranks obtained using all the MCDM techniques are tabulated in Table 13.

Table 13. Ranks obtained using various MCDM techniques.

Alternatives	CODAS	COPRAS	CoCoSo	MABAC	VIKOR
A1	12	12	12	12	12
A2	9	9	10	8	8
A3	10	10	11	11	11
A4	8	8	8	10	10
A5	7	7	7	7	7
A6	11	11	9	9	9
A7	3	3	1	3	3
A8	2	2	3	2	2
A9	6	6	5	6	5
A10	5	5	4	5	6
A11	1	1	2	1	1
A12	4	4	6	4	4

A correlation analysis has also been done to study the overlap and mismatch in the MCDM techniques used. The Pearson correlation coefficient was chosen as the measure to check the association of the ranks. It is a well-established measure of correlation for checking the linear association between two arrays. It is calculated as:

$$\text{Correlation coefficient}(X, Y) = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sqrt{\sum(x - \bar{x})^2 \sum(y - \bar{y})^2}}$$

The "correl" function of MS Excel was used to obtain the correlation coefficients shown in Figure 1. Figure 1 shows the correlation matrix among the five techniques used. All the techniques used showed more than 90% correlation, validating the rankings obtained in this study.

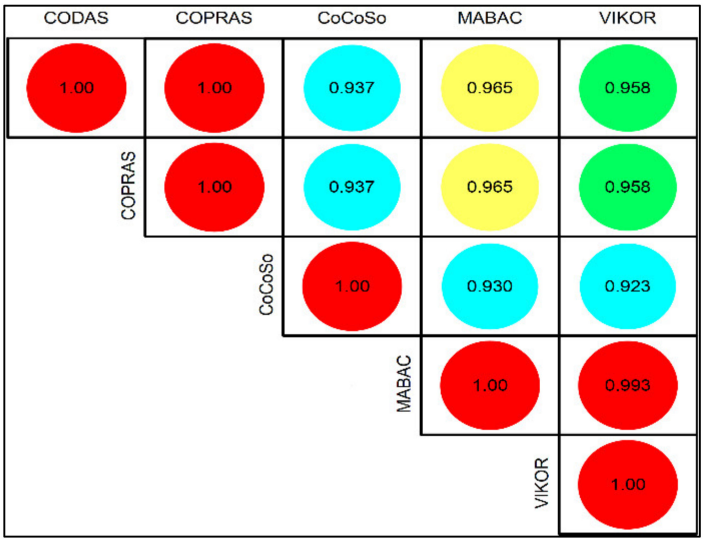

Figure 1. Correlation matrix of the ranks obtained using various MCDMs.

From the obtained results, it was observed that the five different MCDMs selected in this work had a high correlation in terms of the best robot predicted. This indicates that the methods are likely to give the same best solution. In general, there was no conflict seen in the predicted best and predicted worst robots by the different MCDMs. However, owing to the difference in the methodology of the calculation of performance scores, the internal ranks (except the top and bottom 1%) showed some conflicts. Nevertheless, MCDMs are generally used only to select the best compromise solution or avoid the worst possible solution. In this regard, all five methods were found to be reliable.

5. Conclusions

In this paper, twelve spray-painting robots were compared based on three beneficial and four cost criteria to select the best one for the job. The MCDM techniques COPRAS, CODAS, CoCoSo, MABAC, and VIKOR were used to tackle the selection problem. The weights of the criteria were calculated by using an objective weight-determination technique called MEREC. Based on the rigorous analysis, the following conclusions can be made from the current work:

- HY1010A-143 was the best robot for spray-painting applications, followed by HS-6-1640 and HS-6-1722 according to most of the MCDM techniques used in the current work.
- KF121 was the least desirable robot for spray-painting applications.
- The MEREC weight calculation was successfully employed with diverse MCDM techniques for the selection of industrial robots for spray-painting applications. This method was observed to be less cumbersome as compared to subjective methods.

- A correlation analysis showed a high degree of correlation among all five MCDM techniques used in this analysis.

Thus, it can be concluded that the MEREC method can be applied for similar robot/machinery selection problems, where it is desired that the weights are not affected by the preference of the decision makers. The MEREC weights were purely qualitative, as they are dependent on the traits and specifications of the robots. Moreover, the ranking performance of various MCDM methods has been contrasted here, which builds high reliability in the obtained results. This work could be further extended to include newer methods such as MARCOS, MARICA, the Rao method, etc. Furthermore, since the methodology is data-driven, it can be easily applied to other research problems such as site selection, machinery selection, material selection, etc., as well.

Author Contributions: Conceptualization, G.S. (G. Shanmugasundar), R.Č. and K.K.; data curation, G.S. (G. Shanmugasundar) and G.S. (Gaurav Sapkota); formal analysis, G.S. (G. Shanmugasundar) and G.S. (Gaurav Sapkota); investigation, G.S. (Gaurav Sapkota); methodology, G.S. (G. Shanmugasundar) and G.S. (Gaurav Sapkota); software, R.Č. and K.K.; supervision, R.Č. and K.K.; visualization, K.K.; writing—original draft, G.S. (G. Shanmugasundar) and G.S. (Gaurav Sapkota); writing—review and editing, R.Č. and K.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available through email upon request to the corresponding author.

Acknowledgments: The authors thank M. Ramachandran, lead research scientist, REST Labs, India, for his help in the data curation and some of the analyses.

Conflicts of Interest: The authors declare no conflict of interest.

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