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The Significance of Weighting in Multicriteria Decision-Making Methods: A Case Study on Robot Selection

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ABSTRACT
Multi-Criteria Decision-making (MCDM) is employed in many fields of engineering decision-making including robot selection challenges. Researchers are very interested in using the MCDM technique for robot selection difficulties. The current study employs four common MCDM methods: COCOSO, TOPSIS, VIKOR, and MOORA are utilized to determine the better robot choices. Furthermore, in MCDM, weight allocation is critical in selecting the optimal choices. Thus, five distinct objective weight allocation approaches are utilized to fix a real-time robot selection issue with five selection criteria and seven alternative robots: Entropy method (EM), Mean weight method (MW), Criteria Importance Through Inter Criteria Correlation (CRITIC), Standard deviation method (SD), and Analytic Hierarchy Process (AHP). The primary goal of this work is to compare the relative performance of the 20 most well-known combinations (four MCDM approaches and five alternative weight allocation methods) in terms of observed ranks. The ranks produced from the 20 permutations are not uniform, which must be considered. In this study, the Rank Average (Mean) approach is utilized to aggregate the 20 collected rankings into a single composite rank, which is then compared to the rankings produced by the other 20 permutations. The performance of the MOORA combination techniques (MOORA-MW, MOORA-CRITIC, and MOORA-AHP) is adequate for handling selection difficulties. It is impractical to expect a freshly designed MCDM, such as a COCOSO, to outperform well-tested -and-true approaches such as TOPSIS, VIKOR, and MOORA. Decision mistakes may occur if just one MCDM-TOOL (MCDM method - WEIGHT method) is used to pick the options without also considering the other MCDM-TOOLS.

Keywords:. *Robot Selection Problem; COCOSO; MOORA; TOPSIS; VIKOR.*

1. Introduction

Managers have significant difficulty in the proper selection of machines and robots, which is essential for sustaining a competitive edge. The term "robot selection criteria" refers to the factors that play a role in deciding which robot will be used in a certain industrial setting. Criteria like these that influence the choice of a robot may be divided to two categories: good and bad. Positive features, such as load-bearing capability and programming versatility, are ideally aimed at higher values, while negative characteristics, such as cost and repeatability error, are intended to be lower. Many key strategic factors, including maximum tip speed, purchase cost, supplier service quality, memory capacity, repeatability, adaptability, etc. have recently received more attention. With so many models to choose from, finding the right robot for a certain job and manufacturing setting has become a challenging endeavor. In light of this tendency, it's clear that we need a system for comparing and contrasting different robots to choose the best one. Numerous precision-based approaches to robot selection have been developed for the same purpose.

A variety of engineering fields, from design to production, have used MCDM strategies. In terms of robots, it's really useful. For instance, there are literature available MCDM models for choosing appropriate robots. There are several MCDM strategies for choosing a robot that have been published in the literature. Because the topic of this study is the selection of robots, previously succeeded MCDM applications incorporated into a crisp data set will be presented.

Agrawal, et al. [1] suggested steps to the rank of robot selection of the alternates in a shortlist using the

TOPSIS technique. The improved expert system was used to help the decision maker at various stages to establish vantages and visualize the selection process. Khouja [2] used data envelopment analysis (DEA) to select the best robots with vendor specifications combinations depending on the robots' performance parameters. Then, an MCDM method was utilized to choose the best robot. Zhao, et al. [3] merged a first-fit bin packing algorithm with a multi-chromosome genetic algorithm for a computer-integrated manufacturing system workstation solving the robot selection and assignment problems. Goh, et al. [4] created a refined weighted sum decision model which considers both subjective and objective properties while selecting a robot. Baker and Talluri [5] developed a methodology for selecting industrial robots based on cross efficiencies in DEA without taking into account the decision maker's preferences or the criteria weights. Goh [6] used the AHP for robot selection that could take into consideration both the subjective attributes and objectives simultaneously. Braglia and Petroni [7] developed a technique for industrial robot selection using DEA, which endeavors to recognize the best robot by measuring each robot's relative efficiency through linear-programming problem resolution. Parkan and Wu [8] investigated the TOPSIS methods rating and operational competitiveness applications and interrelationship in a selection problem of the robot and compared their efficiency with other approaches. Khouja [9] developed a model of robot selection, which would, in turn, provide the decision maker, with the replacement, of the selected robot option with a better one throughout the product's life with uncertain demand. Braglia and Gabbrielli [10] treated the mathematical method applicability depending on dimensional analysis theory to solve the robot selection problems. Talluri and Yoon [11] applied the cone-ratio DEA combination, which would consolidate the decision maker's preferences with a new DEA methodological extension for industrial robot selection. Bhangale, et al. [12] investigated a methodology of robot selection using graphical and TOPSIS methods. They contrasted the relative classifications of the alternate robots as derived using the two methods. Bhattacharya, et al. [13] combined quality function deployment (QFD) and AHP methods for solving the selection problems of industrial robots while taking into consideration four alternative robots and seven technical requirements. Karsak and Ahiska [14] utilized a practical MCDM common weight methodology with a robot selection enhanced discriminating power. It was noticed that the methodology used could further grade the units of DEA-efficient decision-making with a markable economy in computations compared with cross-efficiency analysis. Rao and Padmanabhan [15] employed the matrix and digraph methods for estimating and rating alternative robots. Chatterjee, et al. [16] utilized two MCDM methods and ELECTRE II for solving robot selection problems. Kumar and Garg [17] proposed a deterministic quantitative model that depended on a distance-based technique for ranking, selecting, and evaluating robots. Chatterjee, et al. [16] applied compromise and outranking methods, ELECTRE II and VIKOR. Kentli and Kar [18] used a distance measurement technique and a satisfaction function to solve problems of robot selection. Rao, et al. [19] developed objective and subjective integrated multiple-attribute decision-making techniques for robot selection. Athawale and Chakraborty [20] while resolving a selection problem of industrial robots, examined the ten renowned MCDM methods and summarized ranking performance that WPM, TOPSIS, and GRA applied marginally better than others. Mondal and Chakraborty [21] performed four-DEA models to select the optimal robots. Azimi, et al. [22] utilized the MADM polygon area method. Karande, et al. [23] surveyed the six popular MCDM methods ranking performance for problems selection industrial robots. Yazdani, et al. [24] disbanded the selection problem of a robot by fulfilling the COPRAS and MOORA methods. Xue, et al. [25] investigated an integrated linguistic MCDM approach, merging extended QUALIFLEX for appraisal robot selection problems with incomplete weight information. Bairagi, et al. [26], Kamble and Patil [27], and Sharaf [28] used a new TOPSIS, multiplicative MCDM model, and an ellipsoid algorithm based on the MCDM approach, respectively to dissolve the selection problem of a robot. Wang, et al. [29] created a decision support model merged with the entropy weighting method that utilizes the TODIM and cloud model to treat robot selection problems. Banerjee, et al. [30] developed a novel multiple-criteria analysis process for industrial robots' selection and evaluation. Kumar and Raj [31] performed an inserted technique of modified GRA and AHP to choose the best mobile and material-handling robot. Horňáková, et al. [32] emphasized that mobile robots are the superior material handling equipment in an industrial setup. Rashid, et al. [33] proposed a hybrid methodology MCDM, to choose the best industrial robot alternatives by merging the EDAS and BWM methods, followed by sensitivity analysis, and comparing them with distance-based techniques, such as TOPSIS and VIKOR. Goswami, et al. [34] investigated the analysis of the robots' selection problem by using two newly proposed hybrid MCDM models of COPRAS-ARAS and TOPSIS-ARAS

There are several approaches to MCDM, and as the relative relevance of different criteria varies for evaluating alternatives, many of these approaches rely on assigning either objective or subjective weights to those criteria. The criterion weights are often estimated using subjective weighing algorithms like AHP, BWM, etc., which might result in biased findings and discrepancies. The literature shows that objective weighting approaches are widely utilized in the decision-making disciplines to assess parametric weight. Ma, et al. [35] discussed an approach to determining objective and subjective attribute weights using the mathematical programming of a model. More objective weight attribution methods are proposed such as the CRITIC, Diakoulaki, et al. [36], the MW, Deng, et al. [37], the EM, Shanian and Savadogo [38], and preference Selection Index, Maniya and Bhatt [39]. Fusion of some of these methods is proposed by Wang and Luo [40] to submit a weight attribution using correlations coefficient (CC) and SD method.

In order to determine the best robot for the job numerous studies using a variety of MCDM approaches have been carried out. However, more investigation is needed to examine how various MCDM approaches to robot selection problem-solving handle the assignment of weights to criteria. Moreover, none of the researchers have previously tried to join various MCDM approaches and different weight calculation methods, to develop a robust MCDM system. Twenty distinct permutations of five weight calculation methods (MW, SDV, EM, CRITIC, and AHP) and four MCDM approaches (COCOSO, TOPSIS, VIKOR, and MOORA) were taken into account in this study to evaluate the consistency of the ranking outcomes in robot selection challenges. When a single rating is to be proclaimed, it is urgent to note that the many permutations each supply their distinct perspective on the ranking process. There is no standard to choose the best option. Using the MEAN approach, can be combined these individual rankings into one more accurate overall score.

Figure 1 shows the flowchart model which represents the complete analysis's overall structure.

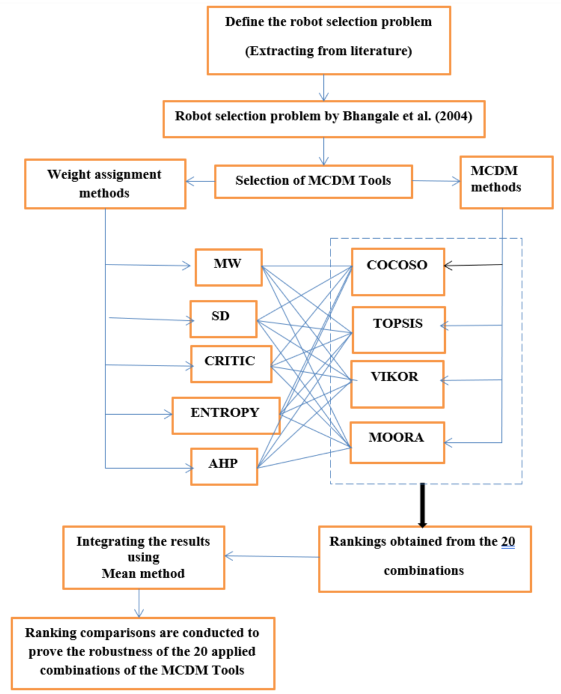

Figure.1 Flowchart model of the MCDM analysis whole robot selection.

2. Illustrative Case Study and Methodology

2.1. A Case Study on Robot Selection Problem

In this study, Bhangale, et al. [12] quantitative dataset for the robot selection issue. As can be seen in Table (1), five requirements must be met, and seven possible solutions. Here, repeatability is a negative criterion when, in general, all criteria are positive. The AHP technique is used to estimate the weights of the criterion. But the total weight of these criteria is more than one. Using the robot selection issue defined by Bhangale, et al. [12], Athawale and Chakraborty [20] re-normalized the criterion weights to be C1 = 0.1574, C2 = 0.1825, C3 = 0.2385, C4 = 0.2172, and C5 = 0.2043.

Table 1- Robot Selection of Quantitative Data Bhangale, et al. [12]

	Robot	C1	C2	C3	C4	C5
R1	ASEA-IRB 60/2	60	0.40	2540	500	990
R2	Cincinnati Milacrone T3-726	6.35	0.15	1016	3000	1041
R3	Cybotech V15 Electric Robot	6.8	0.10	1727.2	1500	1676
R4	Hitachi America Process Robot	10	0.20	1000	2000	965
R5	Unimation PUMA 500/600	2.5	0.10	560	500	915
R6	United States Robots Maker 110	4.5	0.08	1016	350	508
R7	Yaskawa Electric Motoman L3C	3	0.10	177	1000	920

It should be noted that Bhangale, et al. [12] used five different robot selection attributes are considered as C1- Load capacity (kg),C2- Repeatability(mm), C3- Maximum tip speed (mm/s) . C4- Memory capacity, C5- Manipulator reach (mm). In the current article, we re-use the robot selection issue and discuss four MCDM techniques for solving it. The alternatives to robots are ranked using COCOSO, TOPSIS, VIKOR, and MOORA, and the weights of the criteria are assessed using one of five weight estimate techniques (MW, SD, EM, CRITIC, or AHP).

2.2 MCDM Tools

The steps of the mathematical calculations for the applied MCDM tools are discussed in the upcoming sub-sections.

2.2.1 A Brief Review of the Assignment of Weight Methods Used in this Work.

2.2.1.1 Mean Weight Method

The implied weight depends on the assumption that all criteria are of equal importance. This can be declared by using the use of an equation.

$$w_j = \frac{1}{n} \tag{1}$$

where (n) is the criteria number.

2.2.1.2 SD Method

Having m alternatives and n criteria, a decision matrix is proposed by decision-makers presenting the relationship between criteria and alternatives. The decision-making matrix can be expressed as:

$$X = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{bmatrix} \tag{2}$$

Here Ai (i= 1,2.... m) signifies the possible alternatives, Cj (j= 1,2....... n) represents the criteria relating to alternative performance, and xij is the performance of Ai concerning attribute C j SD technique determines the weights of the standards in terms of their standard deviations. The weighting factor can be calculated as

$$w_j = \frac{\sigma_j}{\sum_{j=1}^{n} \sigma_j} \tag{3}$$

Where σj is the standard deviation for criterion j.

2.2.1.3 Entropy Method

In information theory, entropy serves as a criterion for the degree of uncertainty represented by a discrete random distribution, with the consensus being that a more loosely packed distribution better captures the essence of uncertainty than a more tightly packed one. Following is a description of how to use the entropy weight technique for a decision-making issue, as given by (Eisa [41]):

The weight is computed using the EM by the following steps.

Step 1. Determine the normalized decision matrix ($\boldsymbol{p_{ij}}$) using equation (4):

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} p_{ij} \tag{4}$$

Where j= 1, 2, …, n and i= 1, 2, …, m

Step 2. Determine the entropy value for each criterion ($\boldsymbol{E_j}$) using equation (5) :

$$E_j = -h \sum_{i=1}^{m} p_{ij} \ln(p_{ij}) \tag{5}$$

where $\boldsymbol{h} = \frac{\mathbf{1}}{\boldsymbol{ln(m)}}$ is constant and $0 \le \boldsymbol{E_j} \le 1$

Step 3. For each criterion, the weight $\boldsymbol{W_j}$ is computed as:

$$W_j = \frac{d_j}{\sum_i^n (dj)} \tag{6}$$

Where $\boldsymbol{d_j}$ is the divergence degree of the average intrinsic information found in each criterion computed as:

$$d_j = 1 - E_j \tag{7}$$

Compute the weight (Wj) representing the importance of criteria as:

$$\sum_{j=1}^{n} W_j \quad = 1, j = 1, \dots, n. \tag{8}$$

2.2.1.4 Criteria Importance through inter criteria Correlation

As part of this research, the CRITIC technique is used to make a weighted judgment of the criteria objectively. The choice problem's contrast intensity and conflict assessment are taken into consideration to determine the weights to be applied. In addition, this approach does not need human involvement in the evaluation stage, which helps to further automate the decision-making process. Herein follows a brief overview of the procedure (details can be seen in Diakoulaki, et al. [36]).

Step 1. Normalize the decision matrix as follows.

$$r_{ij}=\frac{x_{ij}-\min(x_{ij})}{\max(x_{ij})-\min(x_{ij})} \quad (9)$$

where r_{ij} is the normalized performance value of the ith alternative on the jth criterion.

Step 2: Determine the standard deviation (σ_j) of each criterion.

Step 3. Determine the amount of information contained in the jth criterion through the following multiplicative formula.

$$C_j=\sigma_j \sum_{j=1}^{n}\left(1-r_{ij}\right) \quad (10)$$

where r_{ij} is the correlation coefficient between two different criteria

Step 4. Determine the objective weights of each criterion by normalizing Cj with the following formula.

$$W_j=\frac{C_j}{\sum_{j=1}^{n} C_j} \quad (11)$$

where W_j is the objective weight of the jth criterion. It is worth mentioning that this method gives high weights to those criteria with high standard deviation and low correlation with other criteria.

2.2.2 A Brief Review of the MCDM Approaches Used in This Work

COCOSO, TOPSIS, VIKOR, and MOORA are all MCDM techniques that are used to analyze information. Both benefits and drawbacks may be associated with any approach. No one approach can be said to be superior to the others. In most cases, the analyst's preferences will determine which approach is used.

2.2.2 .1 Combined Compromise Solution COCOSO Method

Yazdani, et al. [24] offer the COCOSO technique. When the weighted sum approach and the exponentially weighted product method are combined, you get the COCOSO method. Here, we provide the computational specifics of the COCOSO approach used in this paper:

Step 1 The normalization of criteria values is accomplished based on the compromise normalization equation

$$r_{ij}=\frac{x_{ij}-\min(x_{ij})}{\max(x_{ij})-\min(x_{ij})} \quad ; \text{for benefit} \quad (12)$$

$$r_{ij}=\frac{\max(x_{ij})-x_{ij}}{\max(x_{ij})-\min(x_{ij})} \quad ; \text{for cost}$$

Step 2 Determination of the sum of the weighted comparability sequence Si and the power weight of comparability sequences Pi

$$S_i=\sum_{j=1}^{n}\left(W_j\ r_{ij}\right) \quad (13)$$

$$p_i=\sum_{j=1}^{n}(r_{ij})^{wj} \quad (14)$$

Step 3 Three appraisal scores are used to generate relative weights of other options derived using equations (15), (16), and (17):

$$k_{ia}=\frac{p_i+s_i}{\sum_{i=1}^{m}(p_i+s_i)} \quad (15)$$

$$k_{ib}=\frac{s_i}{\min_{si}}+\frac{p_i}{\min_{pi}} \quad (16)$$

$$k_{ic}=\frac{\lambda(s_i)+(1-\lambda)(p_i)}{\lambda\max_{si}+(1-\lambda)\max_{pi}} \quad (17)$$

In Equation (17), λ (usually λ=0.5) is chosen by decision-makers.

Step 4. The ranking of all the alternatives is found based on ki values from higher to lower.

$$k_i=(k_{ia}k_{ib}k_{ic})^{\frac{1}{3}}+(k_{ia}+k_{ib}+k_{ic}) \quad (18)$$

2.2.2.2 TOPSIS Method

For this technique to work, the optimal option must be the one that is farthest away from the negative ideal solution and has the least Euclidean distance to it. Abeer S. Eisa [41]. lays forth the fundamental procedures of the TOPSIS approach as follows:

Step 1. Constitute the matrix D using priority scores given to each alternative on each criterion.

Step 2. Compute the weight (Wj) indicating the importance of criteria as equation (11)

Step 3. Determine the normalized decision matrix (r_{ij}):

$$r_{ij}=\frac{x_{ij}}{\sqrt{\sum_{j=1}^{n}(x_{ij})^2}}, i=1,\dots,m; j=1,\dots,n. \quad (19)$$

Step 4. Compute the weighted normalized decision matrix:

Multiply the columns by$\boldsymbol{r_{ij}}$ the corresponding weights (wj) as:

$$v_{ij}=W_j * r_{ij}, \quad (20)$$

where is $\boldsymbol{W_j}$the weight of its attribute.

Step 5. Determine the positive ideal solution (A^+) and the negative ideal solution (A^-) by using the following formulas:

$$\begin{aligned} A_j^+ &= \{v_1^+, v_2^+, \dots, v_m^+\} \\ &= \{(\max_i v_{ij}/j \in B), \min_i v_{ij}/j \in C)\} \end{aligned} \quad (21)$$

$$A_j^- = \{v_1^-, v_2^-, \dots, v_n^-\} = \{(\min_i v_{ij}/j \in B), \max_i v_{ij}/j \in C)\} \quad (22)$$

Where B and C correspond to the benefit and cost criteria set, respectively.

Step 6. Use the Euclidean distance to compute the measures of separation S_i^+ and S_i^- of each alternative from the A_j^+ and A_j^- :

$$S_i^+ = \sqrt{\sum_{i=1}^{m}(V_{ij} - A_j^+)^2} \quad (23)$$

$$S_i^- = \sqrt{\sum_{i=1}^{m}(V_{ij} - A_j^-)^2} \quad (24)$$

Step 7. Find the ideal alternatives by the computation of the relative closeness coefficient (RCCi) as:

$$RCCi = \frac{S_i^-}{S_i^+ + S_i^-}, i = 1, 2, \dots, m; 0 \le RCCi \le 1 \quad (25)$$

Step 8. Rank the alternatives according to their RCCi relative closeness coefficient to the ideal alternatives: the upper value of RCCi ,the better the alternative Ai.

2.2.2.3 VIKOR Method for MCDM

Abeer S. Eisa [41] lays forth the theoretical foundations of VIKOR, which will be used in this investigation. With the VIKOR approach, a decision matrix is the starting point. The following are the stages of the VIKOR algorithm.

Step 1 : Determine the best and the worst values of all the criteria using Equations (21 and 22).

Step 2 : Determine the average Sj and the worst group score Rj of i-th alternative as defined by Equations (26) and (27):

$$S_i = \sum_{j=1}^{m}(W_j * \frac{x_i^+ - x_{ij}}{x_i^+ - x_i^-}) \quad (26)$$

$$R_i = \mathrm{Max}_j(W_j * \frac{x_i^+ - x_{ij}}{x_i^+ - x_i^-}) \quad (27)$$

Step 3 : Determine the overall ranking index for each alternative (Qi) using the following formula:

$$Q_i = v * \left(\frac{S_i - S^*}{S^- - S^*}\right) + (1 - v) * \left(\frac{R_i - R^*}{R^- - R^*}\right) \quad (28)$$

Where: $S^* = \mathrm{Min}_i S_i$, $S^- = \mathrm{Max}_i S_i$.$R^* = \mathrm{Min}_i R_i$, $R^- = \mathrm{Max}_i R_i$, and ν is the significance of the strategy of criteria (objectives) majority whose value is usually set to be 0.5.

2.2.2.4 MOORA method

The following section describes the methodological basis of MOORA to be applied in this work. The steps of the MOORA method are described as follows: Abeer S. Eisa [41].

MOORA method starts with a decision matrix as expressed previously. The procedure for using MOORA for ranking alternatives is described here.

Step 1: Compute the normalized decision matrix by vector method as defined by Equation (29):

$$X'_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}(x_{ij})^2}} \quad (29)$$

where: i=1 , …,m ; j=1,…,n

Step 2: Calculate the composite score as expressed in Equation (30):

$$Z_i = \sum_{j=1}^{b} X'_{ij} - \sum_{j=b+1}^{n} X'_{ij} \quad (30)$$

Where $\sum_{j=1}^{b} X'_{ij}$ and $\sum_{j=b+1}^{n} X'_{ij}$ are, respectively, the benefit and non-benefit (cost) criteria.

The overall grade may be represented as in Equation (31) if certain characteristics are weighted more heavily than others.

$$Z_i = \sum_{j=1}^{b} W_j \; X'_{ij} - \sum_{j=b+1}^{n} W_j \; X'_{ij}, i = 1, \dots, m \quad (31)$$

Where W_j is the weight of j^{th} the criterion.

Step 3: Sort the alternatives by Z_i value, which may be positive or negative based on whether or not the alternatives' maxima (benefit characteristics) or minima (non-benefit attributes) sum to more than zero in the decision matrix. Ultimately, one's choice is derived from an ordinal ranking of Z_i, with the greatest Z_i value being the best option and the lowest Z_i value representing the worst.

3. RESULTS and DISCUSSION

3.1 Weight Allocation Methods

In this study, the weight of the robot criterion using many different approaches, including the mean weight technique, the standard deviation method, the entropy method, and the CRITIC method was calculated.

Each criterion is given the same amount of consideration in the equal weight technique, and the formula for doing so is provided in the next sentence. There are a total of five criteria, and each one has an equal amount of weight (0.2).

Each criterion's weight was determined using the standard deviation approach and was recorded in Table (2) using equation (3).

The relative importance of each criterion was determined using the entropy technique (equations (5 - 8)), and the results are provided in Table (3)

Table 2- Criterion Weight According to the SD Method

	C1	C2	C3	C4	C5
SD j	0.360 8	0.352 8	0.352 8	0.367 3	0.295 7
Wj	.2171	.2123	0.204 1	0.178	0.178

Table 3- Criterion Weight According to Entropy Method

	C1	C2	C3	C4	C5
Ej	0.6430	0.9113	0.9487	0.8749	0.9747
Dj	0.3570	0.0887	0.0513	0.1251	0.0253
Wj	0.5515	0.1370	0.0792	0.1932	0.0391

The procedure of the CRITIC method for the calculation of the criteria weight is depicted in the following steps

Step 1: Normalize the decision matrix using Equation (9) to determine the standard deviation of each criterion and as shown in Table 4

Table 4- Normalized Matrix for CRITIC Method

	C1	C2	C3	C4	C5
R1	1.0000	0.0000	1.0000	0.0566	0.4127
R2	0.0670	0.7813	0.2303	1.0000	0.4563
R3	0.0748	0.9375	0.5895	0.4340	1.0000
R4	0.1304	0.6250	0.2222	0.6226	0.3913
R5	0.0000	0.9375	0.0000	0.0566	0.3485
R6	0.0348	1.0000	0.2303	0.0000	0.0000
R7	0.0087	0.9375	0.6152	0.2453	0.3527
SD	0.3608	0.3528	0.3392	0.3673	0.2957

Step 2: A symmetric matrix is built according to Equation (10) as shown in Table (5)

Table 5- Symmetric Matrix

	C1	C2	C3	C4	C5
C1	1.0000	-0.9609	0.7615	-0.2699	0.0242
C2	-0.9609	1.0000	-0.6605	0.0616	-0.0191
C3	0.7317	-0.6605	1.0000	-0.2197	0.3151
C4	-0.2699	0.0768	-0.2197	1.0000	0.3711
C5	0.0242	-0.0191	0.3151	0.3711	1.0000

Step 3: The measure of conflict is determined using Equation (11) as shown in Table (6)

Table 6- The Measure of the Conflict

	C1	C2	C3	C4	C5	Conflict measure
C1	0.000	1.960	0.238	1.269	0.975	4.4451
C2	1.960	0.000	1.660	0.938	1.019	5.5789
C3	0.268	1.660	0.000	1.219	0.684	3.8334
C4	1.269	0.923	1.219	0.000	0.628	4.0417
C5	0.975	1.019	0.684	0.628	0.000	3.3088
Conflict Measure	4.445	5.578	3.833	4.041	3.308	

Step 4: Finally, according to Equation (12), objective weights are computed. The final objective criteria weights are shown in Table (7).

Table 7 - Criterion Weight According to the CRITIC Method

	C1	C2	C3	C4	C5
Wj	0.2186	0.2683	0.1773	0.2024	0.1334

A ranking is determined based on the weights assigned to each criterion through the various methods, as shown in Table (8). According to the CRITIC technique, as shown in Table (8) and Fig. (1), C2 is the most crucial criterion, followed by C1, C3, C4, and C5

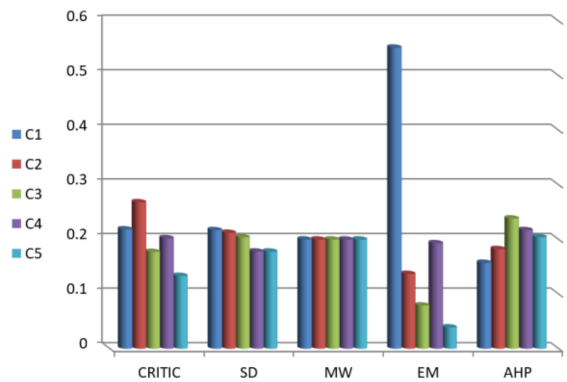

Figure 2- The Weight for each Criterion and Their Ranking in Terms of Different Approaches

Table 8- The Weight for each Criterion and Their Ranking in Terms of Different Approaches

Criteria	**CRITIC Method**		**SD Method**		**MW Method**		**Entropy Method**		**AHP Method**	
	Weight	Rank	Weight	Rank	Weight	Rank	Weight	Rank	Weight	Rank
C1	0.2186	2	0.2171	1	0.2	1	0.5515	1	0.1574	5
C2	0.2683	1	0.2123	2	0.2	1	0.1370	3	0.1825	4
C3	0.1773	4	0 .2041	3	0.2	1	0.0792	4	0.2385	1
C4	0.2024	3	0.178	4	0.2	1	0.1932	2	0.2172	2
C5	0.1334	5	0.178	5	0.2	1	0.0391	5	0.2043	3

3.3 Impact of Criteria Weights Techniques on Ranking Order

A comparison study is carried out to illustrate how the ranking of robots shifts as a result of variations in criterion weights.

3.3.1 Computational data of COCOSO Method Using CRITIC Weight

Table (9) indicates that R3 is the top robot and R6 is the bottom. Thus, the robot selection problem assessment choice is phrased as R3 > R2 > R4 > R7 > R1 > R5 > R6. Table (10) displays the results of the COCOSO approach, and five different weight assignment methods used to evaluate the robot's final ranking. Table (10) and Figure (2) reveal that, except for the EM approach, all of the applied weighting strategies agree that R6 is the poorest option and R3 is the best. The first two spots are consistent across all methods except EM. The findings of this approach are constant enough to yield the same best and worst outcomes in all circumstances, despite slight differences in the rankings of the middle-order options. The same calculation steps can be performed for all criteria Weights Techniques.

Using the information in Table (1), the power-weighted comparability sequence and the sum of the weighted comparability sequence of the ith option by solving the corresponding systems of equations (12 - 18) can be determined. Table (9) includes the calculated values for the three combined evaluation scores (Kia, kib, and Kic). The ki-based ranking score is used to determine where each option falls on the final ranking list

Table 9- The Computational Data of COCOSO Method Using CRITIC Method

Robot	Si	Pi	Ka	Kb	Kc	Ki	RANK
R1	0.4939	3.4008	0.1424	3.4591	0.7891	2.1922	5
R2	0.5070	4.1344	0.1697	3.8360	0.9404	2.4964	2
R3	0.6071	4.3284	0.1805	4.3179	1.0000	2.7514	1
R4	0.3983	4.0544	0.1628	3.3711	0.9022	2.2686	3
R5	0.2685	2.3602	0.0961	2.1072	0.5326	1.3875	6
R6	0.2530	2.2563	0.0918	2	0.5084	1.3198	7
R7	0.4319	3.8486	0.1565	3.4125	0.8673	2.2513	4

Table 10 -The Robot Rankings Using COCOSO Method and Five Weight Assignment Methods

Weight Method	Ranking	BEST	WORST
MW	R3 > R2 > R4> R7> R1 > R5 > R6	R3	R6
SD	R3 >R2 >R7 >R4 >R1 >R5> R6	R3	R6
CRITIC	R3 >R2 >R4 >R7 >R1> R5> R6	R3	R6
EM	R1 >R2 >R3 >R4 >R7 >R5 >R6	R1	R6
AHP	R3 >R2 > R7 >R4 >R1 >R5 >R6	R3	R6

Table 11- Spearman rank correlation coefficient for COCOSO Method and the five Weigh Assignment Methods

Method	MW	SD	CRITIC	EM	AHP
MW		0.9643	1	0.6071	0.9643
SD			0.9643	0.5714	1
CRITIC				0.6071	0.9643
EM					0.5714

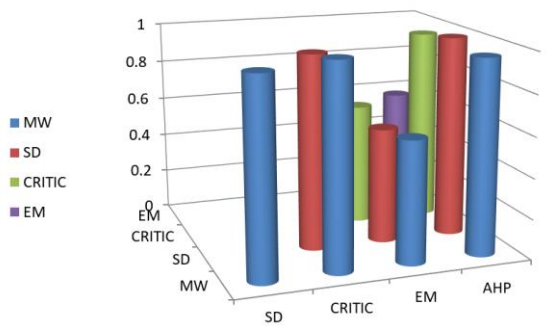

Figure (3) The Spearman's rank Correlation Coefficient for COCOSO Method and the five Weight Assignment Methods

The coefficient of Spearman rank correlation is more than 0.8 in six instances (MW-SD, MW-CRITIC, MW-AHP, SD-CRITIC, SD-AHP, and CRITIC - AHP) (see Table (11) and Fig (3) for details), indicating a substantial rank connection between the existing proposed ranks. In addition, Spearman's rank Correlation Coefficient (SCC) of all the used weight techniques is more than 0.9, and their ultimate placement in the ranking reflects their efficacy in the continuing inquiry into the decision-making process.

3.4 Impact of the MCDM Methods and Criterion Weights Techniques on the Ranking of Robots

Since the robot ranking is affected by the MCDM approaches, a comparison study to show how changing the MCDM method and the weight assignment method affects the robot ranking was conducted.

3.4.1Computational data of TOPSIS Method Using CRITIC Method

The TOPSIS process, as described above, will be used in the following:

Equation (19) allows one to determine the normalized worth of each option. By plugging the original decision matrix into Eq. (20), we can get the weighted normalized version.

The optimal and suboptimal solutions for each criterion have been calculated and given in Table (12) using Eqs (21and 22)

Then, using Eq. (24), the distances Si(+) and Si(-) between each possible solution and the best and worst ones, respectively. At last, Eq. (25) to get the rank of all the experiments and the relative proximity values RCCi between them. The findings are shown in Table (13)

Table 13- Computational data of TOPSIS Method Using CRITIC method

Robot	S+j	S-j	Ci	RANK
R1	0.2115	0.2228	0.5130	1
R2	0.2070	0.1889	0.4771	2
R3	0.2056	0.1852	0.4739	3
R4	0.2086	0.1389	0.3997	6
R5	0.2562	0.1595	0.3837	7
R6	0.2515	0.1700	0.4034	5
R7	0.23	0.1713	0.4269	4

3.4.2 Computational data of VIKOR Method Using CRITIC Method

The VIKOR method implementation described earlier will be used here:

At first, the Equation determines the optimal and suboptimal values for each criterion. Using equations (26) and (27), the individual regret value and the group utility Si for each option. The value of $S^- = \max_i S_i$, $S^* = \min_i S_i$, $R^- = \max_i R_i$, and $R^* = \min_i R_i$ can be also found. then the compromise value Q_i for each alternative can be computed using equation (28) and the rank of each experiment is determined. The results are shown in Table (14)

Table 14- The Computational data of the VIKOR Method using the CRITIC method.

Robot	Si	Ri	Qi	RANK
R1	0.3171	0.1689	0.7309	7
R2	0.6189	0.4768	0.2036	2
R3	0.6326	0.4728	0.0778	1
R4	0.6772	0.4443	0.3163	3
R5	0.8344	0.5110	0.6822	6
R6	0.8032	0.4932	0.6208	5
R7	0.8198	0.5065	0.4066	4

Table 12- The Best and the Worst Solutions for all Criteria

	C1	C2	C3	C4	C5
Best(Ai+)	0.2122	0.0422	0.1127	0.1478	0.0803
Worst(Ai-	0.0088	0.2109	0.0248	0.0172	0.0243

3.4.3 Computational data of MOORA Method Using CRITIC Method

A description of the MOORA technique has been provided and will be followed here:

In the first stage, Eq. (29). to get a normalized value for each option

In the second step, Equation (31) to get the total score across all criteria. In Table (15), the aggregate score for all criteria and the resultant rank of each option are recorded.

Table 15- The Computational data of the MOORA Method using the CRITIC method

Robot	Beneficial	Non-Beneficial	Zi	RANK
R1	0.3969	0.2109	0.1860	3
R2	0.2652	0.0791	0.1861	2
R3	0.2549	0.0527	0.2022	1
R4	0.2245	0.1054	0.1190	5
R5	0.1021	0.0527	0.0494	7
R6	0.1025	0.0421	0.0603	6
R7	0.1828	0.0527	0.1301	4

3.4.4 Comparison of the Robot Ranks in Terms of Different MCDM Methods and Different Weights of Criteria Methods

Concerning the alternative robots spotted rankings for the Bhangale, et al. [12] case study, the major purpose of this paper is to compare the outcomes of the 20 most common combinations (MCDM method - WEIGHT method). The relative rankings of the options are shown in Table (16) for each of the 20 possible permutations of the MCDM techniques and the criteria weights.

Table 16- The Robot Ranks in Terms of Different MCDM Methods and Different Weights of Criteria Methods

	COCOSO					TOPSIS				
	MW	SD	CRIT	ENT.	AHP	MW	SD	CRIT	ENT.	AHP
Comb.#	1	2	3	4	5	6	7	8	9	10
R1	5	5	5	1	5	1	1	1	1	1
R2	2	2	2	2	2	3	3	2	2	3
R3	1	1	1	3	1	2	2	3	4	2
R4	3	4	3	4	4	5	5	6	3	5
R5	6	6	6	6	6	7	7	7	7	7
R6	7	7	7	7	7	6	6	6	6	6
R7	4	3	4	5	3	4	4	4	5	4

	VIKOR					MOORA					Integration Method
	MW	SD	CRIT	ENT.	AHP	MW	SD	CRIT	ENT.	AHP	Mean Composite
Comb.#	11	12	13	14	15	16	17	18	19	20	Rank
R1	4	4	7	1	4	2	1	3	1	2	3
R2	3	3	2	2	3	3	3	2	2	3	2
R3	1	1	1	4	1	1	2	1	4	1	1
R4	2	2	3	3	5	5	5	5	3	5	4
R5	6	7	6	7	7	7	7	7	7	7	7
R6	7	6	5	6	6	6	6	6	6	6	6
R7	5	5	4	5	2	4	4	4	5	4	5

Drawing on data in Table (16) and Figure (4). Considering that Robot 3 is the top-ranked robot in 11 out of the 20 possible permutations and Robot 1 is the top-ranked robot in 9 of those permutations, it is safe to say that both Robot 3 and Robot 1 are middle-of-the-road answers (each of them can be as the best option). A comparison study suggests we choose Robot 5 as the least significant robot even though the worst robot fluctuates between Robot 5 and Robot 6. Results from this approach are stable enough to yield the same best and worst outcomes in all scenarios, despite minor ranking fluctuations in the middle-order robots.

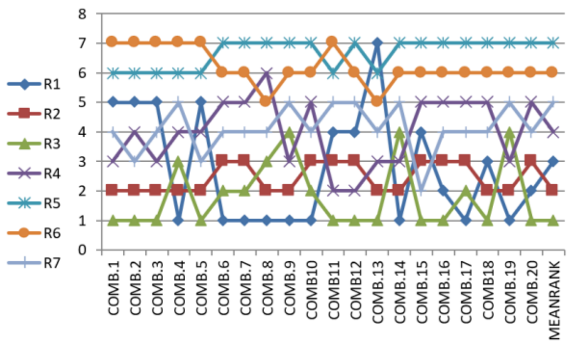

Figure 4- Robot Ranking Variations for the 20 Different Combinations of (the MCDM method – WEIGHT method)

The ranking performance of the robots obtained using the 20 different combinations is compared, and it is found that some combinations share the same ranking performance as others. For example, the four combinations (TOPSIS-MW, TOPSIS-SD, TOPSIS-AHP, and MOORA-SD) all rank the same (R1 > R3 > R2 > R4 > R3 > R7 > R6>R5), as do the combinations (COM.9,14, and 19), which all rank the same (R1 > R2

3.4.5 Integrate the Obtained Ranks Using the Rank Average (Mean) Method

The rankings derived from the 20 permutations are not uniform, and this must be taken into account. The dilemma that emerges in such a scenario is what specific combinations need to be picked. For this research, determining which of 20 possible permutations yields the proper ranking is impossible. Methods such as the Rank Average (Mean), Broda, and Copeland Integration may be used to deal with the issue Ghafari, et al. [42]. and then assess the efficiency of each of the 20 possible permutations to choose the best. In this study, the Rank Average (Mean) technique of integration to combine the 20 acquired rankings into a single composite rank (composite rank). This technique uses an average of the determined rankings from all 20 permutations to determine the robots' final order. This is the simplest method for determining a median rank from the 20 possible permutations (composite rank). According to the results in Table (16), the composite rank is (R3 >R2 >R1 >R4 >R7 >R6 >R5). In this article, the results of the 20 combinations are not similar to the composite rank, hence it can choose the composite rank as the best rank.

The best rank, determined by using a composite ranking, is compared to the rankings determined by using the other 20 permutations. Spearman's rank correlation coefficient (SCC) is utilized to determine the two groups here. Between 0.64 to 0.96, the SCC value is measured. Based on the data, we can deduce that combination 18 has a perfect correlation with the composite rank, while combinations 16 and 20 are only moderately correlated, combinations 1 through 7 and 10 through 12 and 17 have a fair correlation, and combinations 8 through 9 and 13 through 15 and 19 have a terrible correlation. The results suggest that the performance of the MOORA combination strategies (MOORA-MW, MOORA-CRITIC, and MOORA-AHP) is adequate for addressing the selection issues. This research shows that although the COCOSO approach is novel, it only has a modest correlation with the composite rank, making it potentially inappropriate for application in the selection issue. Thus, it is unrealistic to assume that any newly developed MCDM approach would be superior to tried-and-true techniques like TOPSIS, VIKOR, and MOORA. Decision mistakes may occur if just one MCDM-TOOL (MCDM method - WEIGHT method) is used to pick the options without also considering the other MCDM-TOOLS.

4. Conclusions

For inspecting a robot selection problem ,the following conclusion can be draw twenty different combinations between five weight calculation techniques (MW, SD, EM, CRITIC, and AHP) and four MCDM approaches (COCOSO, TOPSIS, VIKOR, and MOORA).

1- The ranking result for MCDM issues is sensitive to changes in the MCDM - Tools (MCDM methodologies and weight determination methods.

2- The Rank Average (Mean) technique of integration to combine the 20 acquired rankings into a single composite rank (composite rank) has been developed.

3- The results obtained have shown that the performance of the MOORA combination strategies (MOORA-MW, MOORA-CRITIC, and MOORA-AHP) is adequate for addressing the selection issues.

4- The obtained results shown that robot 3 is the top-ranked robot in 11 out of the 20 permutations,

5- The COCOSO approach, although of recent origin, correlates only somewhat with the composite rank.

6- Decision mistakes may occur if just one MCDM-TOOL is used to pick the options without also considering the other MCDM-TOOLS.

Possible future work including this study may include evaluating the longevity of various hybrid MCDM approaches to robot selection issues. Only clean datasets are discussed in this article. Robot selection is fraught with uncertainty, but this research may be expanded to address MCDM procedures based on intuitionistic fuzzy sets in a single-valued neutrosophic setting.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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