Article

Decision Models for Selection of Industrial Robots—A Comprehensive Comparison of Multi-Criteria Decision Making

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Abstract: Due to increased demands of production capacity and higher quality requirements, industries are automating at a fast pace. Industrial robots are an important component of the industrial automation ecosystem. However, the selection of appropriate robots is a challenging task due to the sheer number of alternatives present and their varied specifications. The various characteristics or attributes of industrial robots that need due consideration before selection of an optimal robot for a given application are found to be conflicting in nature. Thus, in this paper, several multi-criteria decision-making (MCDM) methods are deployed to select an optimal robot depending on the application. Three different industrial robot selection problems are solved in this paper by using Simple Additive Weighing (SAW), the Technique for Order of Preference by Similarity to Ideal Solution (TOP-SIS), the Linear Programming Technique (LINMAP), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Elimination and Choice Translating Priority III (ELECTRE-III), and the Net Flow Method (NFM).

Keywords: optimization; robots; MCDM; decision making; optimal selection

1. Introduction

A robot is a collaboration of interdisciplinary fields integrating together to provide automatic or semiautomatic assistance to humans, and the study of these robots' operation, design, and use is all about robotics. The term robot comes from the Czech word robots, which means forced or slave laborer, as it performs the work that is programmed accordingly or work that is assigned to it. According to the International Organization for Standardization, a robot is an automatically controlled, reprogrammable multipurpose manipulator that is programmable in three or more axes [1,2], which can be either fixed in place or mobile for use in industrial automation applications. Industries are moving toward robotic functions because of the repeated and continuous work needed to be carried out with more precision and accuracy [3]. The advancement in robotics has helped researchers and industries work in the hazardous and difficult environments where human operations are dangerous to perform. Robots are performing repetitious, difficult, and hazardous tasks with precision [4]. Robots are also playing a vital role in different segments of industries, for example, machining [5], hospitality [6], space science [7], automotive industries [8], medical [9], and sports segments [10]. Different robots have different types of autonomy as per human intervention ranging from fully human-controlled robots, to an assisting robot helping in reducing human work, to a fully autonomous one that does not require any external help. Day by day, increasing demands and increasing competitions in the

market can be a suitable area in which robots will play an important role by increasing productivity and quality.

Booth et al. [11] carried out an evaluation and selection of robots on the basis of environmental condition, performance, and cost of the robots. Chatterjee et al. [12] mentioned the various attributes of robot selection, i.e., subjective and objective attributes. Subjective attributes can be defined as qualitative attributes such as material quality and serviceability, and objective attributes are those that are quantitative parameters such as load capacity, reach, and memory capacity. These attributes can also be categorized as beneficial and non-beneficial attributes. Beneficial attributes are those in which higher values are always desirable, for example, load capacity, reach, maximum top speed, and memory capacity. Non-beneficial attributes, which are also referred to as cost attributes in the literature, are those in which lower values are preferable, for example, economic cost, repeatability error, weight, and power consumption. Table 1 lists several attributes that are often considered in robot selection. The definition and utility of these attributes are also discussed in Table 1.

Table 1. Various attributes of industrial robots.

Attribute	Type	Definition
Economic cost	Non-beneficial	The initial set-up cost including purchase, installation, and training cost
Load capacity	Beneficial	Maximum load the manipulator arm can carry without affecting its performance
Repeatability error	Non-beneficial	Error associated with the robot's inability to return back to its initial fixed position
Top Speed	Beneficial	The maximum speed that the robot arm tip can attain
Kinematic structure (degree of freedom)	Beneficial	Number of independent actuators that can be controlled to position the robotic arm
Vertical reach	Beneficial	Maximum vertical distance that the manipulator arm can reach to grasp objects
Horizontal reach	Beneficial	Maximum horizontal distance that the manipulator arm can reach to grasp objects
Memory capacity	Beneficial	Number of steps/points that a robot can store while in operation
Weight	Non-beneficial	Weight of the structure in kg
Power consumption	Non-beneficial	Total power requirement per unit time by the robot in KWh

Multi-criteria decision making has widespread applications [13,14]. Its application ranges from stock selection [15] to manufacturing and construction [16] to Industry 4.0 [17]. Various methods have been proposed to determine an optimal robot for a given application. Owing to the presence of several criteria that must be analyzed before selecting an optimal robot, robot selection is a non-trivial problem. Moreover, since the criteria often conflict with each other, multi-criteria decision-making (MCDM) methods are especially apt for such applications. In the literature, different MCDM methods have been used by researchers to solve such robot selection problems. Bhalaji et al. [18] used DEMATEL (decision-making trial and evaluation laboratory) to analyze the risk factors influencing the human–robot interaction and found that automation level and reliability of the robot are the major factors that need to be carefully checked to reduce the risk factor for efficient assembly. Parameshwaran et al. [19] worked on an integrated fuzzy MCDM-based approach for robot selection considering objective and subjective criteria. Fu et al. [4] used MCDM for group decision making for handling the multiple criteria for selection and focused on three main procedures: identifying the experts, implementing the MCDM method, and achieving a group consensus. Further, they used two MCDM methods called VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) and Elimination and Choice Translating Priority II (ELECTRE II) for demonstrating the effectiveness and validity of the methodology. Zhou et al. [20] developed fuzzy extended VIKOR to choose the best robot with different specifications with respect to multiple conflicting criteria. Liu et al. [21], too, tackled robot section by using a MCDM framework. In this regard, they presented a robot selection model integrating quality function development (QFD) for the determination of criteria weight and the qualitative flexible multiple criteria method (QUALIFLEX) for generating the ranking of alternative robots. Tian et al. [22] used surrogate model for expensive optimization problems. Ghorabaee et al. [23] worked on developing a MCDM framework

where the VIKOR method with an interval type-2 fuzzy number was proposed for robot selection. Table 2 presents a comprehensive literature review of applications of MCDMs in robot selection in the last few years (2019–2023).

Table 2. Literature on application of MCDMs in robot selection (2019–2023).

Source	MCDM Method	Robot Application	Weight Used
Fu et al. [24]	Stochastic multicriteria acceptability analysis (SMAA)	-	Entropy, Criteria importance through intercriteria correlation (CRITIC)
Liu et al. [25]	QUALIFLEX	-	Extended QFD method
Mecheri and Christopher [26]	Analytical hierarchical process (AHP)	Collaborative robots	-
Narayanamoorthy et al. [27]	VIKOR	Industrial robots	Interval-valued intuitionistic hesitant fuzzy entropy
Yalçin and Nusin [28]	Evaluation based on distance from average solution (EDAS)	Industrial robot	-
Ahmad et al. [29]	Multi-attributive border approximation area comparison (MABAC)	Pick-and-place robot	CRITIC
Banerjee et al. [30]	De Novo approach	Material handling	Aggregate fiscal Terminal Value, Specific Benefit
Nasrollahi et al. [31]	Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE)	Industrial robots	Fuzzy Best–Worst Method
Agarwal et al. [32]	MABAC	Arc welding robots	Rough entropy method
Ali and Rashid [33]	-	Industrial robots	Objective weights, best–worst method
Goswami et al. [34]	TOPSIS- Additive Ratio Assessment (ARAS); Complex Proportional Assessment (COPRAS)-ARAS	-	CRITIC
Jagtap [35]	m-Polar fuzzy ELECTRE-I method	-	-
Rashid et al. [36]	EDAS	Industrial robot	Best–worst method
Rashid et al. [37]	TOPSIS; VIKOR	Industrial robots	Generalized interval-valued trapezoidal fuzzy weights
Singh et al. [38]	Fuzzy inference engine	Social robots	
Zhao et al. [39]	Multiple-criteria group decision making with individual preferences (MCGDM-IP)	Industrial robots	Entropy, CRITIC,
Bairagi [40]	TOPSIS	Industrial robot	-
Bairagi [41]	Technique of Accurate Ranking Order (TARO)	Material handling	Entropy
Chodha et al. [42]	TOPSIS	Arc welding robot	Entropy
Garg and Sharaf [43]	EDAS	Industrial robots	Spherical fuzzy
Kaya et al. [44]	DEMATEL, analytic network process (ANP), TOPSIS	Social robots	interval-valued Pythagorean fuzzy sets
Kumar et al. [45]	Combined compromise solution (CoCoSo)	Spray painting robot	Step wise weight assessment ratio analysis (SWARA)
Shanmugasundar et al. [46]	Combinative Distance based ASsesment (CODAS), COPRAS, CoCoSo, MABAC, VIKOR	Spray painting robot	Method based on the Removal Effects of Criteria (MEREC)
Dhumras and Bajaj [47]	EDAS	Robotic agrifarming	Dombi aggregation operators
Garg et al. [48]	CoCoSo	Automobile manufacturing	Bonferroni function; SWARA
Sampathkumar et al. [49]	COPRAS- Weighted Aggregates Sum Product Assessment (WASPAS)	Manufacturing robots	Intuitionistic dense fuzzy entropy
Soltan et al. [50]	Fuzzy–AHP–QFD–TOPSIS (FAQT-2)	Industrial robot (pharmaceutical)	-
Oyama et al. [51]	-	Pick-and-place robot	-
Kang et al. [52]	Multi-attribute utility theory (MAUT)	Medical service	Best–worst method
Dodevska et al. [53]	Hesitant intuitionistic fuzzy sets (HIFS)	-	Cross-entropy

The rapid expansion of industrial automation has witnessed an increased demand for the use of industrial robots. However, the challenge lies in the selection of the most appropriate robot for a specific task from a vast range of alternatives, each with varied specifications. The complexity of this selection process is the research problem that this study aims to address. In pursuit of solutions to this problem, the study intends to find the answers to the following research questions:

- How can multiple Multi-Criteria Decision-Making (MCDM) methods be effectively applied to industrial robot selection problems?
- What are the comparative results and performance metrics when these methods are applied to the selection problem?
- What is the potential impact of different weight allocation strategies on the robot selection outcome?

Guided by these research questions, this study develops the following hypotheses:

- Different MCDM methods, including Simple Additive Weighing (SAW), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), the Linear Programming Technique (LINMAP), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Elimination and Choice Translating Priority III (ELECTRE-III), and the Net Flow Method (NFM), can be effectively applied to solve industrial robot selection problems.
- A comprehensive comparison of these methods will reveal distinct patterns of results and performance.
- Different weight allocation strategies, including the mean weight method, standard deviation, and entropy method, significantly influence the selection outcome.

To test these hypotheses and answer the research questions, this study presents three case studies employing six different MCDM methods. Each method is analyzed in an objective weight scenario. Besides the commonly used mean weight method, the standard deviation and entropy method for determining the criteria weights are also utilized. Further, each of the six MCDM methods is hybridized with the Preference Selection Index (PSI) method. The results of this hybrid approach are then compared with those obtained from the other three objective weight allocation methods.

2. Methodology

2.1. Weight Allocation Methods

2.1.1. Mean Weight Method (MW)

Equal weights are assigned to each criterion in this approach to give equal importance to each criterion. For example, if n alternatives are evaluated based on m criteria, then the weight allocated to each criteria is $1/m$.

2.1.2. Standard Deviation Method (SDV)

The standard deviation allocates weights to each criterion in an unbiased manner. It is based on the standard deviation between performance ratings for criteria under consideration across all the alternatives. Since it is based on statistical analysis of the data, it significantly improves the decision-making process by minimizing the personal bias involved in decision making. Steps involved in this process are elucidated as follows:

Step 1: Normalization is carried out using Equation (1) before the calculation of weights by the SDV method.

$$B_{ij} = \frac{x_{ij} - \min(x)_{ij}}{\max(x)_{ij} - \min(x)_{ij}}$$

(1)

where B_j is the average of the values for the ith measure, where $j = 1, 2, 3$.

Step 2: The standard deviation across alternatives is calculated using Equation (2).

$$SDV_J = \sqrt{\frac{\sum_{i=1}^{m}\left(B_{ij} - B_j\right)^2}{m}} \tag{2}$$

Step 3: The weight of each criterion is then calculated as shown in Equation (3).

$$W_j = \frac{SDV_j}{\sum_{j=1}^{n} SDV_j} \tag{3}$$

2.1.3. Entropy Method

This is derived from the concept of entropy in information theory. The entropy function is based on the discrete probability distribution and measures the degree of uncertainty contained in the information being presented. Since the criterion with the highest uncertainty has the most significant influence on the decision-making process, the entropy concept has been used by numerous past researchers to determine the weight of criteria in the MCDM procedure. The objectivity of the weight calculated using the entropy method ensures that the weights are free from any biases of the decision maker. The following steps are followed to calculate the objective weights of criteria using the entropy method:

Step 1: The entropy of each criterion is calculated by using Equation (4) shown below.

$$e_j = \frac{-1}{\ln(m)} \sum_{i=1}^{m} n_{ij} \ln\left(n_{ij}\right) \tag{4}$$

Step 2: The degree of diversity (d) possessed by each criterion is evaluated:

$$d_j = 1 - e_j; \ j = 1, 2, 3 \ldots n \tag{5}$$

Step 3: The objective weight for each criterion is given by

$$W_j = \frac{d_i}{\sum_{i=1}^{n} d_i} \tag{6}$$

2.1.4. Preference Selection Index (PSI) Weights

The PSI method [15] begins by expressing the MCDM problem in terms of Equation (1). If the response is of benefit-type, i.e., larger values are desired, then the normalization is performed using Equation (7).

$$n_{ij} = \frac{x_{ij}}{x_j{}^{max}} \tag{7}$$

If the response is of cost-type, i.e., smaller values are anticipated, then the normalization is performed using Equation (8).

$$n_{ij} = \frac{x_j{}^{min}}{x_{ij}} \tag{8}$$

The mean value of each normalized value of each response is calculated as

$$N = \frac{\sum_{i=1}^{n} n_{ij}}{n} \tag{9}$$

Next, a preference variation value among each response is calculated as

$$\phi_j = \sum_{i=1}^{n} \left[n_{ij} - n\right]^2 \tag{10}$$

The variation in the preference value for each response is calculated as

$$\Omega_j = \left[1 - \phi_j\right] \tag{11}$$

Then, the overall preference value is obtained for individual responses by

$$\omega_j = \frac{\Omega_j}{\sum_{j=1}^m \Omega_j} \text{ such that } \sum_{j=1}^m \omega_j = 1 \tag{12}$$

2.2. Multi-Criteria Decision-Making Methods

This study employs six different MCDM methods, namely Simple Additive Weighing (SAW), the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), the Linear Programming Technique (LINMAP), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Elimination and Choice Translating Priority III (ELECTRE III), and the Net Flow Method (NFM). The rationale for the selection of these specific methods and their distinctive features are discussed below:

- The SAW method is chosen for this study because it is one of the most straightforward and widely used MCDM methods. This method is simple in its computation and can handle large datasets efficiently.
- The TOPSIS method is chosen for this study because it is a popular MCDM method known for its strength in identifying solutions that are closest to the ideal and farthest from the negative-ideal solution. It is particularly suited to problems where trade-offs between criteria must be considered.
- LINMAP is chosen for its ability to handle complex decision-making scenarios that involve linear trade-offs. It is especially useful when the relationship between criteria is linear.
- The VIKOR method is included due to its unique approach of ranking alternatives based on the concept of compromise solutions. It is well suited for decision problems with conflicting and non-commensurable (different units) criteria.
- ELECTRE III is chosen for its distinct ability to handle uncertainty and imprecision in decision-making problems. It is also known for its capability of capturing complex preference structures among alternatives.
- NFM is included for its application in decision-making problems where the ranking of alternatives is required. It provides a holistic ranking of options, making it suitable for our study.

Each of these methods is selected for their unique characteristics and applicability to the problem of industrial robot selection. The distinct features of each method, including their treatment of criteria weights and ranking mechanism, contribute to a more thorough analysis of the selection problem, thus leading to more robust conclusions.

2.2.1. Simple Additive Weighting (SAW)

Simple Additive Weighing is a simple but useful tool in MCDM problems when the nature of the problem is not very complicated. It was proposed by Hwang and Yoon in 1982 to solve decision-making problems. It combines the weighted normalized performance rating values across all criteria to assign a performance index to all alternatives. The procedural steps involved in SAW are listed below.

Step 1: Linear normalization of the decision matrix is performed using Equations (13) and (14) for benefit- and cost-type criteria, respectively.

$$F_{ij} = \frac{f_{ij}}{f_j^+} \text{ for maximization criterion, where } f_j^+ = Max_{i \in n} f_{ij} \tag{13}$$

$$F_{ij} = \frac{f_j^-}{f_{ij}} \text{ for minimization criterion, where } f_j^- = Min_{i \in n} f_{ij} \tag{14}$$

Step 2: The normalized decision matrix is transformed to a weighted matrix by multiplying criteria weights corresponding to each criterion using Equation (15).

$$v_{ij} = F_{ij} \times w_j \tag{15}$$

Step 3: The aggregate score for each alternative is calculated by summing up the weighted performance rating under all criteria using Equation (16).

$$A_i = \sum_{j=1}^{n} v_{ij} \tag{16}$$

Step 4: The alternatives are ranked from best to worst in decreasing order of aggregate score.

2.2.2. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is among the first few MCDM methodologies developed by Hwang and Yoon in 1981 to incorporate the scientific method in decision making. It is based on the principle that the alternative that is closest to the ideally best alternative and farthest from the ideally worst solution is preferred. The Euclidean distance is used as the measure of closeness and farness from the best and worst solution, respectively, in the TOPSIS methodology. The steps involved in the TOPSIS method are listed below:

Step 1: Normalization of the decision matrix is performed using Equation (17) shown below.

$$F_{ij} = \frac{f_{ij}}{\sqrt{\sum_{i=1}^{m} f_{ij}^2}} \tag{17}$$

Step 2: The weighted normalized decision matrix is calculated using Equation (18).

$$v_{ij} = F_{ij} \times w_j \tag{18}$$

Step 3: Positive and negative ideal solutions for each criterion are identified across all alternatives using Equations (19) and (20).

$$A^+ = \left\{ \left(Max_i(v_{ij}) \ \forall \ \mathrm{j} \in J \right), \left(Min_i(v_{ij}) \ \forall \ \mathrm{j} \in J' \right) I_i \in 1, 2, \ldots, m \right\} = \left\{ v_1^+, v_2^+, v_3^+, \ldots v_j^+, \ldots v_n^+ \right\} \tag{19}$$

$$A^- = \left\{ \left(Min_i(v_{ij}) \forall \ \mathrm{j} \in J \right), \left(Max_i(v_{ij}) \ \forall \ \mathrm{j} \in J' \right) I_i \in 1, 2, \ldots, m \right\} = \left\{ v_1^-, v_2^-, v_3^-, \ldots v_j^-, \ldots v_n^- \right\} \tag{20}$$

where J and J' are beneficial and cost criteria, respectively.

Step 4: The Euclidean distances from the positive and negative ideal solutions are calculated using Equations (19) and (20), respectively.

$$S_{i+} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+ \right)^2} \qquad i = 1, 2, 3 \ldots, m \tag{21}$$

$$S_{i-} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^- \right)^2} \qquad i = 1, 2, 3 \ldots, m \tag{22}$$

Step 5: The alternatives are ranked based on the closeness coefficient calculated using Equation (21). The ranking is performed from best to worst in increasing order of closeness coefficient.

$$C_i = \frac{S_{i-}}{S_{i-} + S_{i+}} \tag{23}$$

2.2.3. Linear Programming Technique (LINMAP)

The LINMAP technique was proposed by Srinivasan and Shocker as a tool to solve MCDM problems. In LINMAP, the decision matrix is represented as linear equations. The ideal solution is then calculated by solving those linear equations. The Euclidian distances from the positive ideal solution are then computed such as in case of TOPSIS and this score is used to rank the alternatives. The solution closest to the ideal positive will be ranked more preferable by this technique. The procedural steps involved in this method are stated as follows [54]:

Step 1: A hybrid decision matrix S is created using Equation (24).

$$S = \{(K,L)\} \; : K, L \, \epsilon \, A \tag{24}$$

Step 2: The following linear programming problem is solved within the given constraints to find the ideal solution.

$$\min \left(\sum_{(k,l) \epsilon S} Z_{kl} \right) \tag{25}$$

$$Subject\ to: \sum_{j=1}^{n} W_j \sum_{(k,l) \in S} \left(x_{Lj}^2 - x_{Kj}^2 \right) - 2 \sum_{j=1}^{n} V_j \sum_{(k,l) \in S} \left(x_{Lj} - x_{Kj} \right) = h$$

$$\sum_{j}^{n} W_j \left(x_{Lj}^2 - x_{Kj}^2 \right) - 2 \sum_{j}^{n} V_j (x_{Lj} - x_{Kj}) + Z_{kl} > 0; (k,l) \in S$$

$$\sum_{j} W_j = 1 \; Z_{kl} \geq 0 \; (k,l) \in S$$

The product of weight and r* is an appropriate representation of the jth index V_j, which is represented as Equation (26).

$$V_j = W_j r_j^* \tag{26}$$

Step 3: Euclidean distances from the ideal solution are calculated using the following equation and alternatives are ranked in descending order of S_i.

$$S_i \sum_{j}^{n} W_j \left(x_{ij} - r_j^* \right)^2 \tag{27}$$

2.2.4. VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR)

VIKOR was proposed by Opricovic and Tzeng to find a compromise optimal solution for decision-making problems. The method is based on finding a compromise solution by identifying an 'ideal' solution in the solution space and measuring the distances from the ideal solution in that space. Manhattan and Chebyshev distances are considered in the VIKOR technique for the evaluation of distances from ideal solutions. The procedural steps are as follows [55]:

Step 1: Calculate the Manhattan distance from the ideal solution using Equation (28), which is a sum of all the row elements (across all criteria) of the weighted normalized decision matrix, i.e.,

$$S_i = \sum_{j=1}^{n} w_j \left(\frac{F_j^+ - f_{ij}}{F_j^+ - F_j^-} \right) \tag{28}$$

Step 2: Calculate the Chebyshev distance from the ideal solution using Equation (29), which is the maximum element among all the row elements (across all criteria) of the weighted normalized decision matrix, i.e.,

$$R_{i-} = Max_{j \in n} \left[w_j \left(\frac{F_j^+ - f_{ij}}{F_j^+ - F_j^-} \right) \right] \tag{29}$$

Step 3: Rank the alternatives based on an aggregated Q value calculated using Equation (30). Alternatives are ranked in ascending order of Q values.

$$Q_i = \gamma \left(\frac{S_i - S^+}{S^- - S^+} \right) + (1 - \gamma) \left(\frac{R_i - R^+}{R^- - R^+} \right) \quad Q_i = 1, 2, 3, \ldots m \tag{30}$$

2.2.5. Elimination and Choice Translating Priority III (ELECTRE III)

ELECTRE-III works on the principle that one alternative is better than the other alternative by the degree to which the alternative outranks the other. While ELECTRE-II was proposed earlier with different equations to evaluate the concordance and discordance matrices, ELECTRE-III relies on a different and improved method to evaluate the same. ELECTRE-III begins by converting a minimization problem to a maximization problem for all cost criteria. Three indices, the indifference threshold (Q), preference threshold (P), and veto threshold (V), are decided by the decision maker. The procedural steps involved in ELECTRE-III are as follows:

Step 1: Performance ratings are converted to suit maximization criteria as discussed in Equation (31).

$$\begin{array}{l} \text{For Maximization; } F_{ij} = f_{ij} \\ \text{For Minimization; } F_{ij} = -f_{ij} \end{array} \tag{31}$$

Step 2: The three threshold values are chosen and a concordance matrix $C(a, b) = \sum_{j=1}^{n} w_j C_j(a, b)$ is formulated such that:

$$C_j(a, b) = \begin{cases} 1 & if\ F_j(b) - F_j(a) \leq Q_j \\ 0 & if\ F_j(b) - F_j(a) > P_j \\ \frac{P_j - [F_j(b) - F_j(a)]}{P_j - Q_j} & if\ Q_j < F_j(b) - F_j(a) \leq P_j \end{cases} \tag{32}$$

Step 3: A discordance matrix is also formulated using Equation (33) below

$$D_j(a, b) = \begin{cases} 1 & if\ F_j(b) - F_j(a) > V_j \\ 0 & if\ F_j(b) - F_j(a) \leq P_j \\ \frac{F_j(b) - F_j(a) - P_j}{V_j - P_j} & if\ P_j < F_j(b) - F_j(a) \leq V_j \end{cases} \tag{33}$$

Step 4: Credibility matrix Sij is formulated from the concordance and discordance matrices based on Equation (34).

$$S(a, b) = \begin{cases} C(a, b) & if\ D_j(a, b) \leq C(a, b) \forall\ j \\ C(a, b) \prod_{j \epsilon J(a, b)} \frac{1 - D_j(a, b)}{1 - C(a, b)} & otherwise \end{cases} \tag{34}$$

Step 5: An index calculated by subtracting the strength (sum of row) by the weakness (sum of column) is used to rank the alternatives in descending order.

2.2.6. Net Flow Method (NFM)

The Net Flow Method was derived from ELECTRE-III with the objective to broaden the scope of application and improve the decision-making process. The NFW is similar to the ELECTRE-III method up until the formulation of the concordance matrix and then the

discordance matrix is calculated using Equation (35). The following steps are discussed in continuation:

$$D(a,b) = \prod_{j=1}^{n}\left[1 - \left(D_j(a,b)\right)^3\right] \tag{35}$$

$$\text{Where; } D_j(a,b) = \begin{cases} 1 & if\ F_j(b) - F_j(a) > V_j \\ 0 & if\ F_j(b) - F_j(a) \le P_j \\ \frac{F_j(b) - F_j(a) - P_j}{V_j - P_j} & if\ P_j < F_j(b) - F_j(a) \le V_j \end{cases}$$

Step 2: The credibility matrix is then calculated by multiplying each element of the concordance matrix with the corresponding element of the discordance matrix using Equation (36):

$$\sigma(a,b) = C(a,b) \cdot D(a,b) \tag{36}$$

Step 3: The ranking score is calculated as follows using Equation (37) and alternatives are ranked in decreasing order of ranking score.

$$S_i = \sum_{k=1}^{m} \sigma(i,k) - \sum_{k=1}^{m} \sigma(k,i) \tag{37}$$

3. Results and Discussion

3.1. Case Study 1

3.1.1. Problem Description

In this case study, an industrial robot selection problem consisting of five different robots (i.e., alternatives) is tackled. The selection is based on four different criteria—three among which are beneficial while the last one is non-beneficial (i.e., cost). The beneficial criteria are load capacity (LC), vertical reach (VR), and kinematic structure, i.e., degrees of freedom (DF). The cost criterion is repeatability error (RE). The descriptions of each of these properties are given in Table 1. The objective is to select the best robot among those shown in Table A1 based on these criteria. Additionally, the effect that the weights of criteria have on the selection outcome is also studied. A comparison is made between ranks obtained using the MCDM techniques discussed earlier based on four different objective weights—mean weight, standard deviation, entropy weights, and PSI weights.

3.1.2. Optimal Robot Selection

A 5×4 decision matrix is formulated using the data shown in Table A1. The weight of each criterion is first calculated using the four methodologies discussed in earlier sections. For mean weight allocation, $1/4 = 0.25$ is considered as the weight of each criterion based on the method discussed in Section 2.1.1. The standard deviation weight allocation requires the user to calculate the standard deviation across alternatives using Equation (2) after normalizing the decision matrix using the linear normalization method following Equation (1). The standard deviations are then normalized to make the weights add up to unity using Equation (3). The entropy of information is calculated using Equation (4), which is then subtracted from unity to find the degree of diversity in the data. This is then normalized using Equation (6) to calculate the entropy weights. To calculate the PSI weights of the criteria, the decision matrix is first normalized using Equations (7) and (8) for benefit and cost criteria, respectively. The mean normalized value is calculated for each response using Equation (9) and this is used to calculate the preference value among the responses from the normalized decision matrix using Equation (11). This is subtracted from 1 to calculate the preference value of the criterion for each response using Equation (12). The scaling of preference values is performed using Equation (13) to calculate the PSI weights. These criterion weights are then used with six MCDM techniques for the selection of robots.

The detailed procedure for decision making using all the MCDM techniques used in this study is explained in Section 2.2. The ranking of alternatives using SAW involves

normalization of the decision matrix using Equations (14) and (15) for cost and benefit criteria, respectively, and formulating a weighted performance matrix using Equation (16). An aggregate performance rating of all the alternatives is calculated using Equation (16) and the ranks obtained using SAW are shown in Figure 1. It is worth noticing here that the third robot is identified as the best alternative by the SAW method followed by robot 2 that is ranked second. All weight allocation methodologies assign the same ranks to each robot, suggesting very little sensitivity of the method to criteria weights.
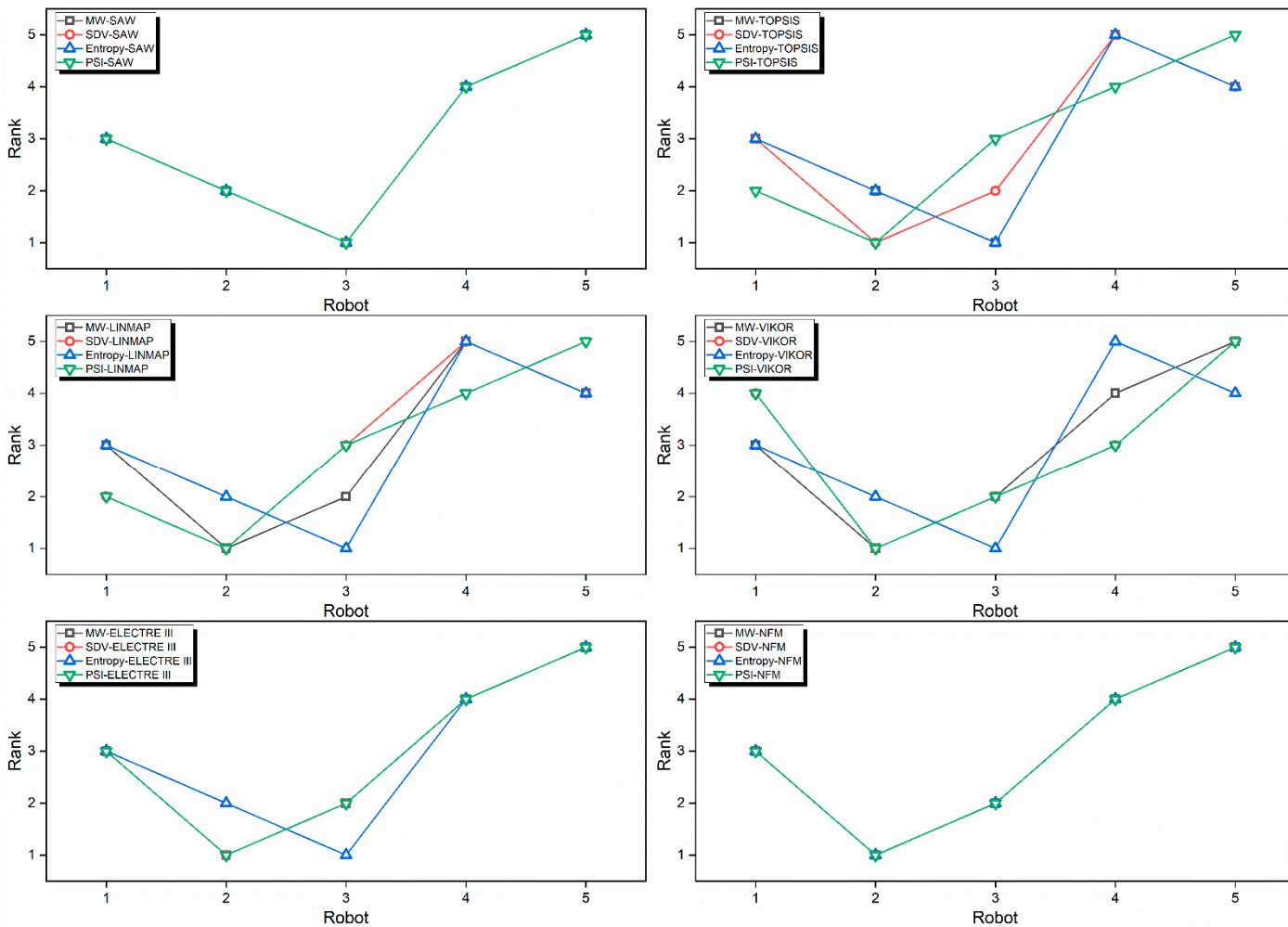
Figure 1. Rank of all alternatives obtained by various MCDM methods in Case Study 1.

While SAW is a simple technique that demands very little computational effort for decision making, TOPSIS is a slightly more elaborate method wherein the first step is to normalize the decision matrix using Equation (18). The normalized decision matrix is multiplied with the criteria weights to formulate a weighted normalized decision matrix. The positive ideal and negative ideal for all criteria are identified depending on the type of criteria following Equations (20) and (21). The Euclidean distances calculated using Equations (22) and (23) from the positive and negative ideal solution, respectively, are shown in Figure 2. This figure illustrates the differences in the robots' performances very nicely. While robots 1, 2, and 3 are very close to the positive ideal (hypothetically best-performing robot), robots 4 and 5 are closer to the negative ideal and are among the worst alternatives. We shall see in the discussions about other MCDM techniques that while all the techniques are not consistent with choosing the best robot, it is always robots 1, 2, and 3 that are closest to the positive ideal solution. A closeness coefficient calculated using Equation (24) is used to rank the best robot using the TOPSIS method.
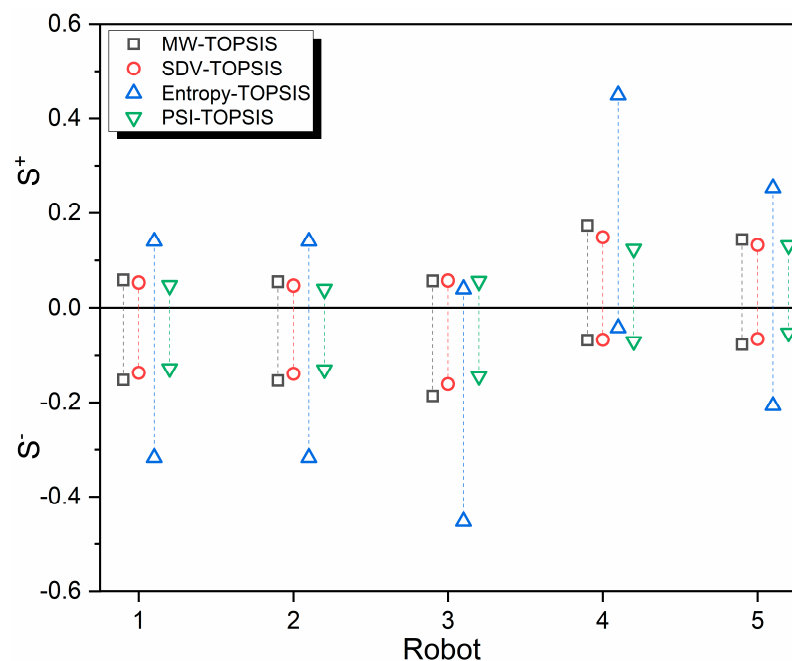
Figure 2. Positive and negative distance of each alterative from the ideal solution in Case Study 1.

The LINMAP technique relies on solving a linear programming problem for selecting the best alternative. A modified decision matrix formulated using Equation (24) is used to develop a linear programming model. The linear programming model shown as Equation (25) is solved to obtain the values of the ideal solution for each criterion. The Euclidean distance from the obtained ideal solution is calculated using Equation (27) and that is the criterion that is used to rank the alternatives from best to worst. The procedural resemblance with TOPSIS is also reflected in the high degree of correlation between ranks obtained by LINMAP and TOPSIS. Three of the four weight allocation methods suggest that the second robot is the best robot using the LINMAP procedure. The dominance of the second robot is understandable as the LINMAP procedure relies only on the distance from the positive ideal, while TOPSIS considers both negative and positive ideal solutions for calculating the Euclidean distance.

VIKOR is a three-step process that involves formulating a weighted normalized decision matrix before beginning the selection process. The calculations of Manhattan and Chebychev distances are performed using Equations (28) and (29). An aggregated Q score calculated using Equation (30) based on these distances is used for ranking the alternatives from best to worst. A graphical representation of ranks obtained using VIKOR can be seen in Figure 1. The VIKOR method seems to show inconsistencies only to very significant differences in weights, as seen from the rank plot for entropy. It predicts the second robot to be the best alternative 75% of the time. When entropy weights are considered, it loses only to the third robot possibly because of the high weighting to repeatability error criteria by the entropy method.

ELECTRE-III involves the conversion of all types of criteria to beneficial criteria by introducing a negative sign in front of cost-type criteria performance ratings. The concordance and discordance matrices are calculated using Equations (32) and (33), respectively. The Q_j, P_j, and V_j values are taken as 10%, 20%, and 80% of the ideal value for each criterion, respectively. Equation (34) is then used to formulate a credibility matrix. The difference between strengths and weaknesses of each alternative is calculated as discussed in step 5 of Section 2.2.5 to formulate a rating. Alternatives are then ranked based on these ratings. It is worth noting here that except for one of the weight allocation methods (entropy), all methods predict the second robot to be the best alternative. Entropy weights assign the first rank to robot 3, and robot 2 is placed second after that. Interestingly, all the MCDM techniques discussed so far rank the third robot as the best alternative when entropy weights are used.

NFM is very similar to the ELECTRE-III method where the difference is in calculating the discordance matrix and the steps thereafter. The discordance matrix is calculated using Equation (35). This discordance matrix is then multiplied with the concordance matrix using Equation (36) to construct the credibility matrix. It should be noted that the multiplication is element-to-element and not a matrix multiplication. The S_i calculated using Equation (37) from the credibility matrix is used to rank the robots from highly desirable to not desirable. The similarity between NFM and ELECTRE-III in procedural steps is reflected in the ranking obtained in the two. NFM seems to be very slightly sensitive to the criteria weights with a 100% overlap between all the weight allocation strategies. It ranks robot 2 as the most desirable alternative and robot 5 as the least desirable one among the five robots considered for this study.

The correlation matrix showing inter- and intra-weight comparisons among all the MCDM techniques employed in this study is shown in Figure 3. A very high correlation between most of the comparisons validates the process and results of this study. It can be safely concluded that robots 2 and 3 are the best alternatives among the robots compared, while robot 5 is the most poorly performing from the lot. The selection between robot 2 and 3 primarily depends on the weighting that the decision maker gives to each criteria and hence a subjective weight might be considered in the future for the current robot selection problem to include the interest of the decision maker.
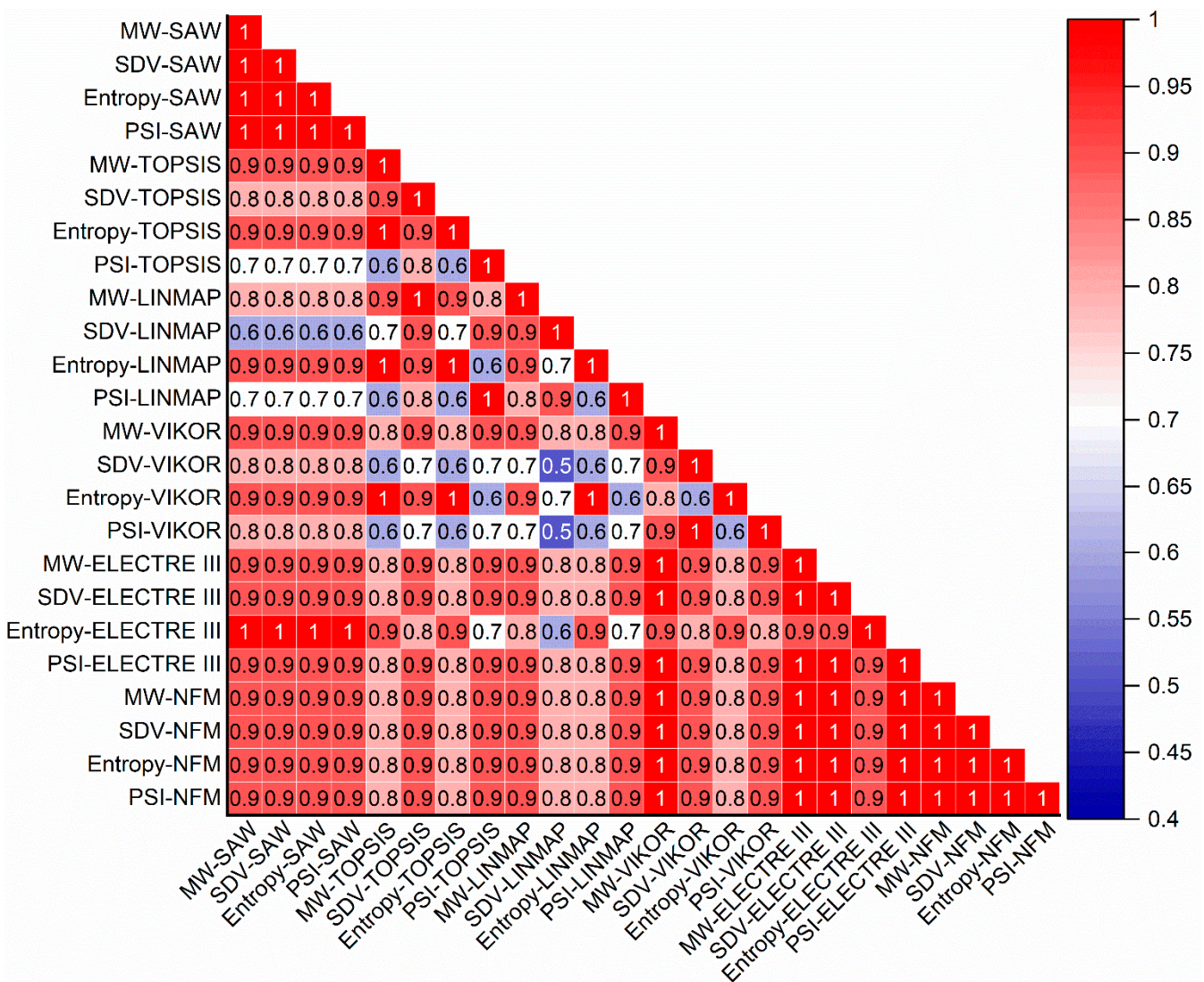

Figure 3. Correlation among various methods for Case Study 1.

3.2. Case Study 2

3.2.1. Problem Description

In this robot selection problem, we consider seven robots for simple pick-and-place applications in industries. The selection is based on five conflicting criteria out of which one of them—repeatability—is a cost criterion and the rest, i.e., Load Capacity, Tip Speed, Memory, and Reach, are beneficial criteria. The objective of the current work is to solve a robot selection problem using MCDM techniques discussed earlier and draw a comparison and correlation between the different methods used. Using multiple methods for decision making and weight allocation also helps to validate the study.

3.2.2. Optimal Robot Selection

A decision matrix for the current problem is formulated using Table A2 shown in the appendix section of the paper. The first step in solving the decision-making problem is to calculate the weights of criteria, and, for the current study, mean weights, standard deviation weights, entropy weights, and PSI weights are selected as four different weights for each criterion. Procedural steps as described in the methodology section of this paper are duly followed to calculate the criteria weights. These weights are used in combination with all six MCDM techniques for selection of the best robot.

The SAW method is implemented as discussed in case study 1 for the selection process and the ranks obtained are shown in Figure 4. The Cybotech V15 Electric robot is selected as the best robot 75% of the time by the SAW technique. While ASEA-IRB 60/2 is selected by the SAW method when entropy weights are used, the Cybotech V15 Electric robot is recommended as the second best among the robots considered for the study. The least desirable alternative is suggested to be fifth robot 75% of the time when the SAW method is used.
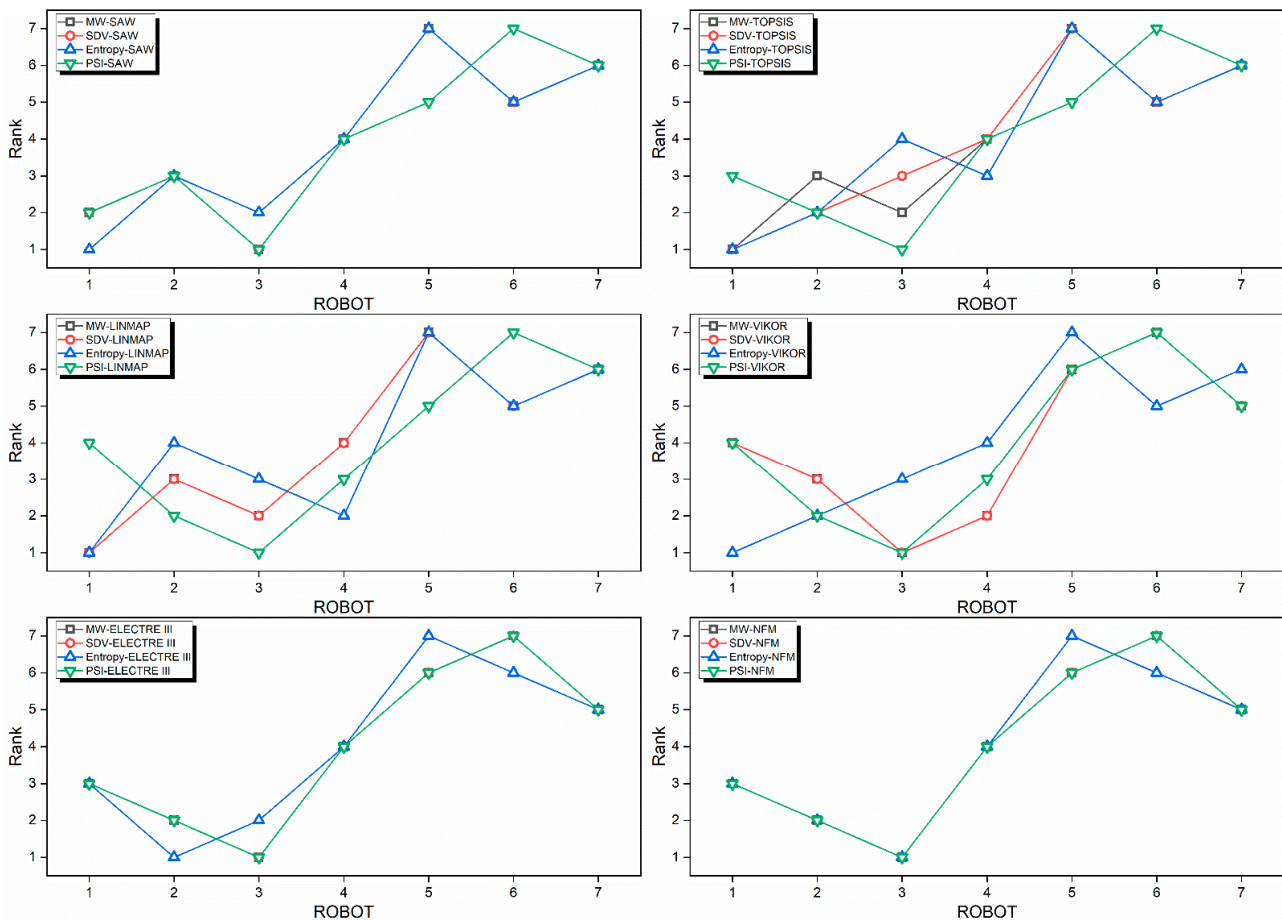

Figure 4. Rank of all alternatives obtained by various MCDM methods in Case Study 2.

Similarly, TOPSIS is also used to rank the best robot among the seven robots studied. Although the weights of criteria play a significant role in the ranks suggested by the TOPSIS method, the overall trend of first and third robots being the among the better alternatives while the fifth and sixth are the least desirable alternative is consistent among all the discussed methods. This can also be reflected in the closeness coefficient plot shown in Figure 5. While the difference among alternatives is not as prominent in case study 1, the plot can be carefully observed to identify that alternative 3 is closer to the ideal positive than all other alternatives. Alternative 1 seems to be farthest away from the negative ideal, resulting in a higher ranking among alternatives.
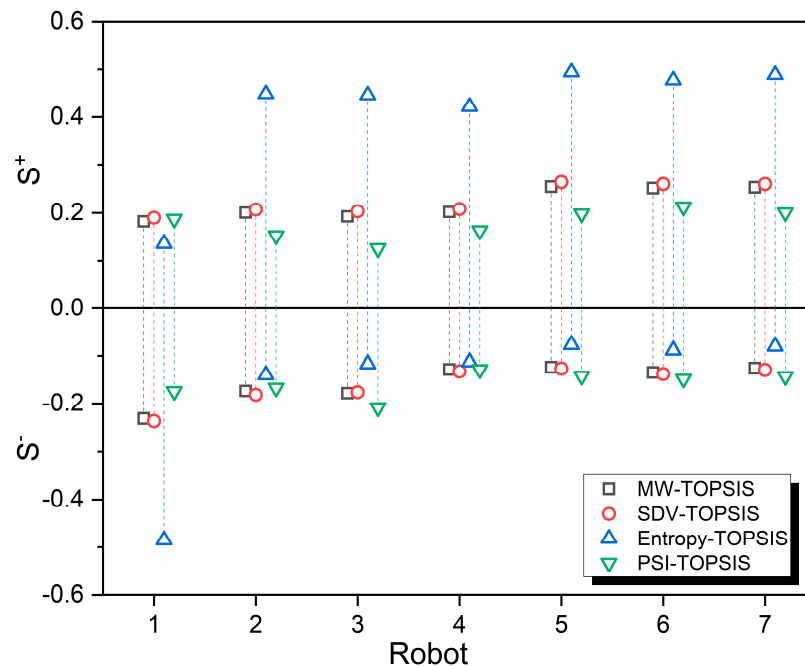

Figure 5. Positive and negative distance of each alterative from the ideal solution in Case Study 2.

Ranks obtained using LINMAP are similar to the ones obtained by TOPSIS except for a few weight allocation strategies as seen from the rank plots and correlation plot shown in Figures 4 and 6. The first robot, i.e., ASEA-IRB 60/2, is ranked as the best alternative 75% of the time except when the third robot is ranked as the best alternative using PSI weights. The close competition between the third and first robots reflects the importance of criteria weights in any MCDM study.

Similarly, VIKOR suggests that the third robot is the best alternative with the most weight allocation strategies. While entropy weights suggest that the first robot is the most desirable alternative, it is ranked fourth among the seven robots with all other weight allocation strategies. This suggests a slight skewing of the weight allocation strategy to favor selection under few specific criteria.

ELECTRE-III is not very sensitive to weight allocation strategies and is very consistent in assigning ranks to all the alternatives. The only inconsistency seen is in choosing the best and worst alternatives. While 75% of the time, ELECTRE-III chooses the third robot, i.e., the Cybotech V15 Electric robot, as the best robot, entropy weight allocation chooses the second robot as the best. A similar inconsistency can also be seen from Figure 4 regarding the selection of the worst robot wherein the highest weight allocation suggests the sixth robot to be the worst alternative, while entropy weight allocation suggests the fifth robot to be the least desirable.
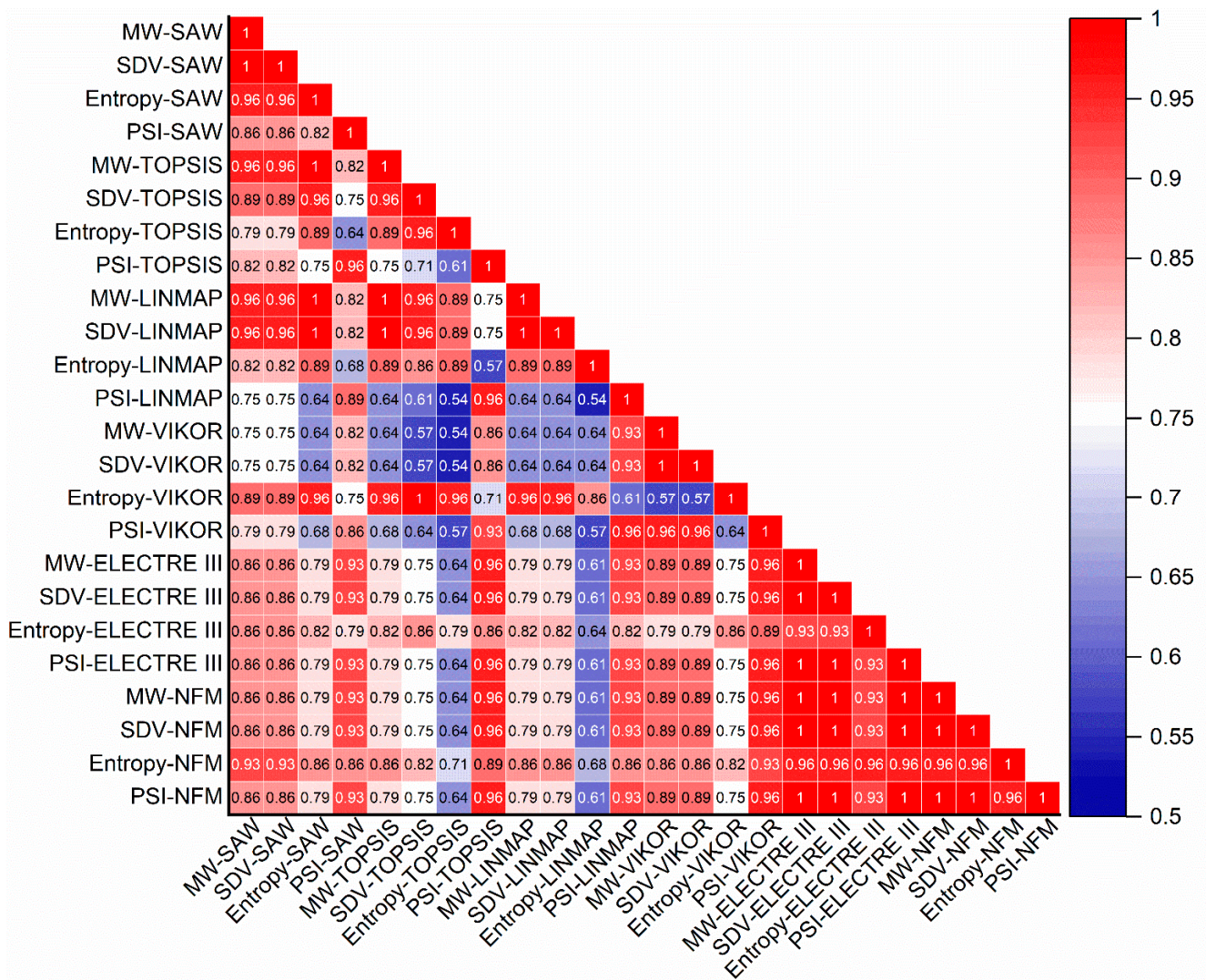
Figure 6. Correlation among various methods for Case Study 2.

NFM, like ELECTRE-III, shows very little sensitivity to criteria weights and an inconsistency is observed only in the selection of the worst alternative. The inconsistency is also similar in the worst alternative region, reflecting similarities in the methodologies between NFM and ELECTRE-III. The correlation plot shown in Figure 6 shows a high degree of correlation among most methods. A pattern between exceptions can be identified when one notices that a poor correlation with VIKOR is shown by techniques such as SAW, TOPSIS, and LINMAP, which shows a strong correlation among each other.

3.3. Case Study 3

3.3.1. Problem Description

One more case study is considered for the selection of robots among four alternatives based on six criteria—velocity, load capacity, vendor service quality, programming flexibility, repeatability error, and cost, among which the first four are the benefit-type criteria and the remaining two are the cost-type criteria. The details regarding each criterion are provided in Table 1 above. The effects of weights are also compared among the MCDM techniques used to rank the robots with a comprehensive correlation study within and among the techniques. Table A3 shows the decision matrix for this case study.

3.3.2. Optimal Robot Selection

As discussed in earlier sections, the weights of each criterion are first allotted based on the discussed methodologies. The weights obtained using all the weight allocation strategies are shown in Table 2. These weights are used with the discussed MCDM techniques for the selection of the best industrial robot. The individual techniques are discussed in earlier sections and hence a cumulative discussion is presented in this case study with a detailed discussion on the comparison between the techniques.

Ranks obtained for all the robots for all methods are shown in the graphical plot in Figure 7. The SAW technique is the only MCDM technique that selects the fourth robot as the best robot 75% of the time and hence shows the least correlation with other techniques. While TOPSIS does also suggest the same robot to be the best robot 25% of the time using entropy weights, the rest of the time, it suggests that the second robot is the best robot in the lot. The closeness coefficient plot for case study 3 is shown in Figure 8. The unique behavior of entropy weights can also be seen in this plot. It is also worth mentioning here that robot 2 with the distances closest to the ideal solution is identified to be the best alternative using all other methods. The rank plot such as LINMAP can be observed consistently across all MCDM techniques with at least one of the weight allocation strategies. Therefore, that can be taken as a reliable ranking of robots for the problem considered. The VIKOR process is seen to have the least internal correlation (Figure 9) across all the case studies, suggesting a high dependence on criteria weights in the VIKOR technique. ELECTRE-III also ranks the second robot as the best alternative and the first robot as the worst alternative, while the intermediate ranks vary depending upon the weights of criteria. For case study 3, it can be safely concluded that the second robot outperforms other robots and the first robot is the least desirable in the lot.
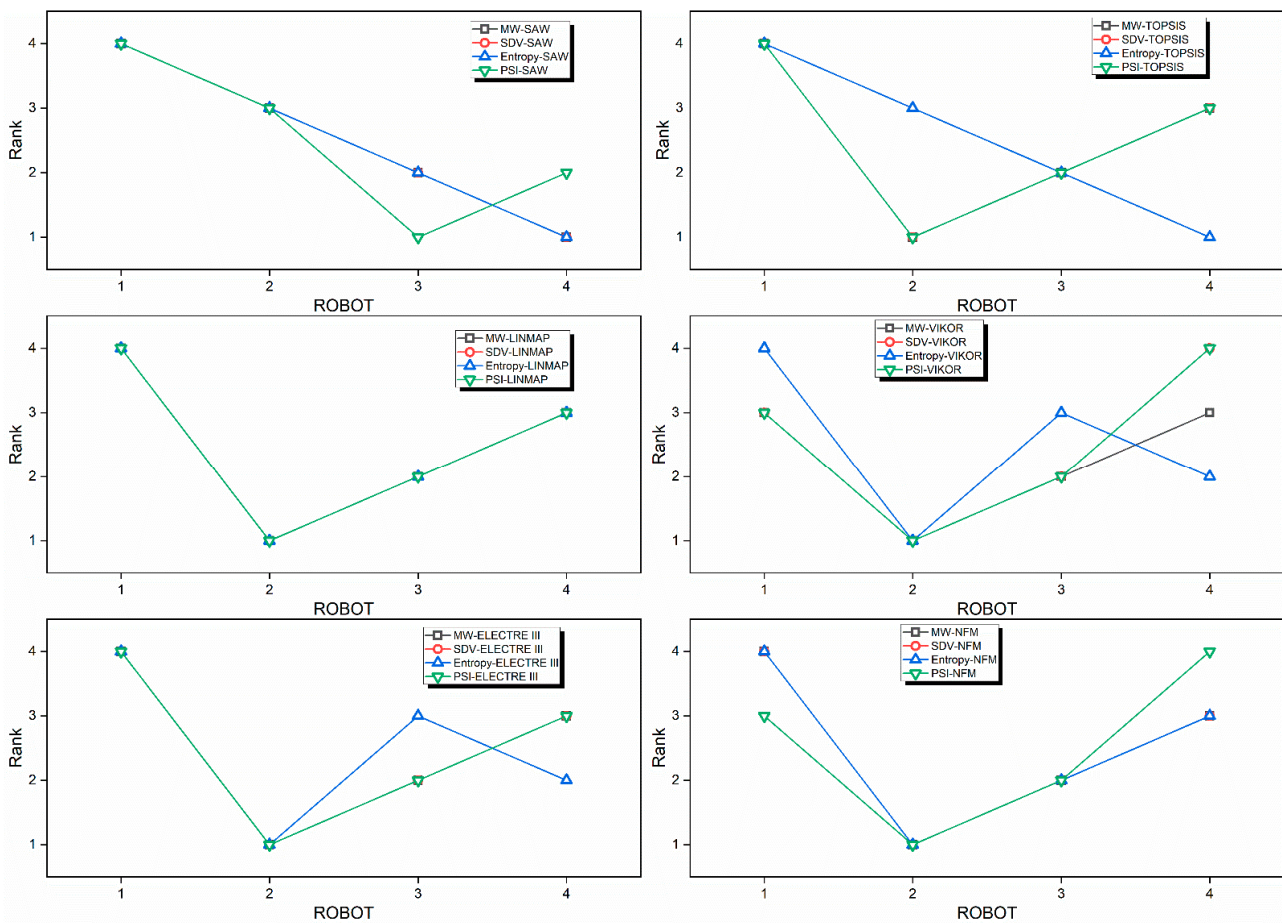

Figure 7. Rank of all alternatives obtained by various MCDM methods in Case Study 3.
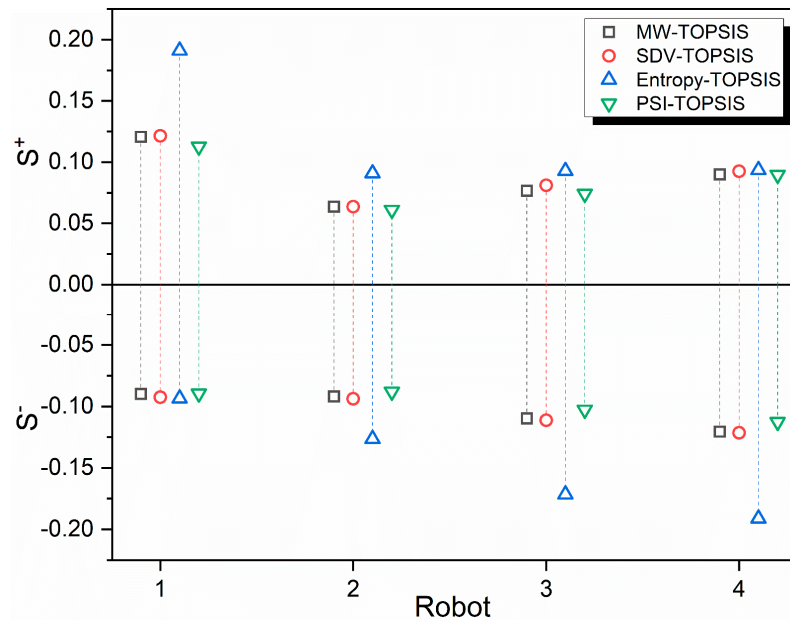
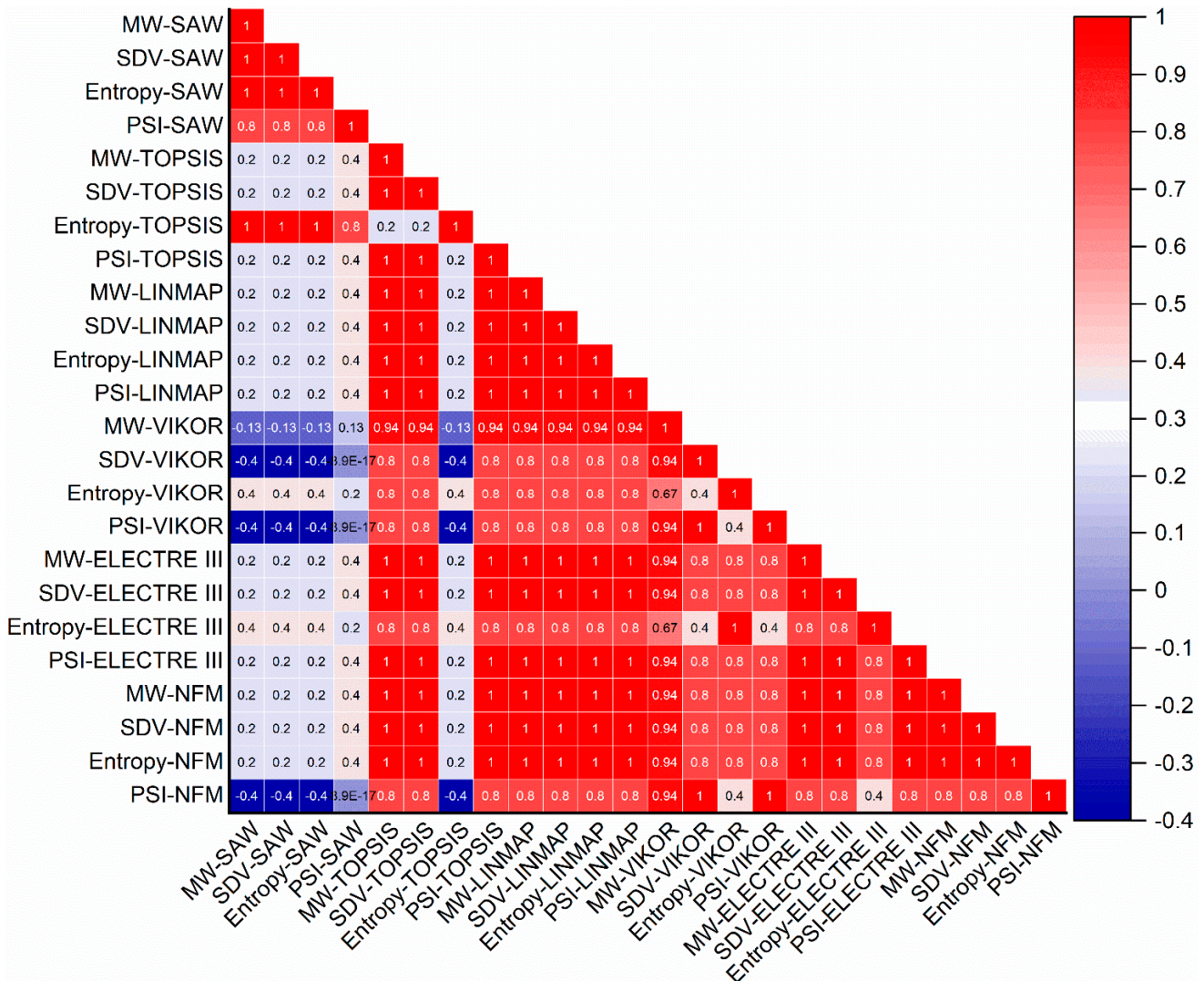**Figure 8.** Positive and negative distance of each alterative from the ideal solution in Case Study 3.

Figure 9. Correlation among various methods for Case Study 3.

4. Conclusions

The presented work deals with the comparison between six MCDM approaches for the selection of the optimum robot based on various conflicting criteria. Four different weight allocation methods are employed for deciding criteria weights and the effect of the weight allocation strategy is also studied. Three different case studies are considered to strengthen the comparative study. The following conclusions are made from the present study:

- For case study 1, robots 2 and 3 can be safely selected as the better alternatives for the desired pick-and-place jobs. Any further selection would require additional information on the most appropriate weight allocation depending on the application and expertise of the decision maker.
- Similarly, for case study 2, the first and third robots show the best rankings among the robots considered. A similar result is also observed in identifying the worst alternative between the fifth and the sixth robot considered in this case study.
- For the considered case study 3, most MCDM techniques choose the second robot to be the best alternative among the four robots considered. Although a few techniques do suggest the fourth robot to be the best alternative under a certain weight allocation strategy, the number of times that occurs is very few in the study.
- The entropy weight allocation strategy appears to be very unique among the methods considered because of its tendency to be skewed in favor of or against certain criteria.
- The observed correlation among the MCDM techniques considered and the consistency in identifying the best alternative suggest that the observations of this study are reliable. The current work safely validates itself.
- MCDM methods seem to greatly rely on the weight allocation strategy and it is absolutely crucial for weights to properly reflect the relative importance of individual criteria without biases.

As the application of industrial robots becomes more widespread, decision makers in manufacturing industries will need to understand the intricacies of robot selection. The decision models explored in this paper provide a comprehensive framework that decision makers can use to select an optimal robot for their specific applications, leading to improved efficiency and productivity in the short term. Mid-term impacts could include an increased focus on certain criteria in robot design and selection, informed by the findings of the MCDM methods. For instance, if reliability and precision are consistently found to be the most influential criteria in robot selection, manufacturers might prioritize these attributes in their design and production processes. In the long term, the MCDM methods could facilitate greater standardization in the industry's robot selection processes, leading to more reliable and comparable results across different settings. This could further promote the development and application of industrial robots in a variety of industries, contributing to increased automation and technological advancement.

The outcomes and findings of this work can lead to changes in industrial robot selection in the short-, mid-, and long-term. The different weight allocation strategies can impact the decision-making process and the importance of an unbiased reflection of the relative importance of individual criteria.

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

Appendix A

Table A1. Decision matrix for Case Study 1 (Reproduced with permission from) [56].

Alternative Freedom	Load Capacity (kg)	Repeatability Error (mm)	Vertical Reach (cm)	DF
Robot 1	60	0.4	125	5
Robot 2	60	0.4	125	6
Robot 3	68	0.13	75	6
Robot 4	50	1.0	100	6
Robot 5	30	0.6	55	5

Table A2. Decision matrix for Case Study 2 (Reproduced with permission from) [57].

Robot	Load Capacity (kg) LC	Reach (mm) R	Maximum Tip Speed (mm/s) MTS	Memory Capacity (MC)	Repeatability Error (mm) R
1	60	990	2540	500	0.4
2	6.35	1041	1016	3000	0.15
3	6.8	1676	1727.2	1500	0.1
4	10	965	1000	2000	0.2
5	2.5	915	560	500	0.1
6	4.5	508	1016	350	0.08
7	3	920	177	1000	0.1

Table A3. Decision matrix for Case Study 3 (Reproduced with permission from) [24].

Robot	Velocity (m/s) V	Load Capacity (kg) LC	Vendor's Service Quality VSQ	Robot's Programming Flexibility PF	Cost ($) C	Repeatability Error (mm) R
1	1.8	90	8	4	9500	0.45
2	1.4	80	7	5	5500	0.3
3	0.8	70	6	6	4000	0.2
4	0.8	60	4	7	4000	0.15

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