



# A Hybrid Multicriteria Decision Approach for Industrial Robot Selection

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## Abstract

Numerous manufacturing companies worldwide have widely adopted industrial robots due to their advantages, such as increased efficiency and profitability. Robots with numerous features and abilities are available for a wide variety of applications. They can handle numerous tasks in various industrial applications, including welding, assembly, material handling, loading, and painting. The selection of a robot for a particular application is a multifaceted task due to its complexity, advanced features, and facilities. The decision-maker needs to choose the most suitable robot, taking into account the various features, maximizing benefits, and minimizing costs. In this context, the main objective of this study is to present an integrated multiple criteria decision analysis (MCDA) approach for industrial robot selection. The selection of the optimal robot is conducted based on three weighting methods, namely standard deviation (SD), mean weight (MW), and Shannon entropy, and three MCDA methods, namely additive ratio assessment (ARAS), simple additive weighting (SAW), and weighted product method (WPM). The objective weighting methods, SD, MW, and Shannon entropy, are adopted to eliminate subjective evaluations while determining attribute weights. Using the output of each weighting method as the input of each MCDA method, nine different ranking models are developed. The correlation between all models is examined through Kendall's correlation coefficients. The results of all method pairs are integrated through the Borda method to reach a final consensus ranking. The results indicate that the proposed hybrid approach can be utilized successfully for the purpose of the present study, and ARAS is the most robust method.

**Keywords:** Industrial robots, Robot selection, Multi-attribute decision making, Borda, Additive ratio assessment.

## Endüstriyel Robot Seçiminde Hibrit Çok Kriterli Karar Yaklaşımı

### Öz

Dünya çapında çok sayıda imalat şirketi, artan verimlilik ve karlılık gibi avantajları nedeniyle endüstriyel robotları yaygın olarak benimsemiştir. Çok çeşitli uygulamalar için çok sayıda özellik ve beceriye sahip robotlar mevcuttur. Bunlar kaynak, montaj, malzeme taşıma, yükleme ve boyama dahil olmak üzere çeşitli endüstriyel uygulamalarda çok sayıda görevi yerine getirebilirler. Belirli bir uygulama için robot seçimi, karmaşıklık, gelişmiş özellikleri ve olanakları nedeniyle çok yönlü bir görevdir. Karar vericinin, çeşitli özellikleri dikkate alarak, faydaları en üst düzeye çıkararak ve maliyetleri en aza indirerek en uygun robotu seçmesi gerekir. Bu bağlamda, bu çalışmanın temel amacı, endüstriyel robot seçimi için bir hibrit çok kriterli karar analizi yaklaşımı sunmaktır. Optimal robot seçimi, standart sapma (SD), ortalama ağırlık (MW) ve Shannon entropisi olmak üzere üç ağırlıklandırma yöntemine ve üç çok kriterli karar verme yöntemine, yani ARAS (additive ratio assessment), SAW (simple additive weighting) ve WPM (weighted product method) dayalı olarak gerçekleştirilir. Kriter ağırlıklarını belirlerken öznal değerlendirmeleri ortadan kaldırmak için nesnel ağırlıklandırma yöntemleri, SD, MW ve Shannon entropisi benimsenmiştir. Her bir MCDA yönteminin girdisi olarak her ağırlıklandırma yönteminin çıktısını kullanarak, dokuz farklı sıralama modeli geliştirilmiştir. Tüm modeller arasındaki korelasyon, Kendall'ın korelasyon katsayıları ile incelenmektedir. Tüm yöntem çiftlerinin sonuçları, nihai bir fikir birliği sıralamasına ulaşmak için Borda yöntemiyle entegre edilir. Sonuçlar, önerilen hibrit yaklaşımın bu çalışmanın amacı için başarıyla kullanılabileceğini ve ARAS'ın en tutarlı yöntem olduğunu göstermektedir.

**Anahtar Kelimeler:** Endüstriyel robotlar, Robot seçimi, Çok kriterli karar verme, Borda, ARAS.

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## **1. Introduction**

The advancement of technology and the developments in engineering have been the triggering sources of the increasing use of industrial robots in different advanced manufacturing processes. Industrial robots are defined as programmable in three or more axes, automatically controlled, multipurpose machine, and reprogrammable (International Organization for Standardization, 2012). These flexible features enable industrial robots to perform a variety of dangerous, complex, and repetitious tasks with high precision. Therefore, they are preferred for numerous processes, such as welding, assembly, disassembly, machine loading, material handling, spray painting, and finishing (Kumar & Garg, 2010; Ravipudi Venkata Rao, 2007).

Choosing the most suitable for a particular application area from a wide variety of robots available on the market is a critical decision in the manufacturing environment (Boubekri, Sahoui, & Lakrib, 1991; Breaz, Bologa, & Racz, 2017). A poor selection decision can lead to various catastrophic consequences, such as high costs and low productivity. Therefore, the decision-maker needs to determine alternative robots and choose the most appropriate robot to avoid such consequences and achieve the expected output with minimum cost and high productivity. In this context, multiple criteria decision analysis (MCDA) methods, which have been proven to produce practical solutions to numerous problems in various areas and help decision-makers to make fast and correct decisions, can also be used in the solution of this problem.

The MCDA methods have been successfully implemented for solving industrial robot selection problems. Chatterjee, Manikrao Athawale, and Chakraborty (2010) presented the multicriteria decision-making (MCDM) approach, which was based on the elimination and choice translating reality (ELECTRE) and visekriterijumsko kompromisno rangiranje (VIKOR). Fu, Li, Luo, and Huang (2019) introduced a group decision-making approach that involved four weighting methods, namely CRITIC, distance-based, Shannon entropy, and ideal point, and two MCDA methods, namely ELECTRE II and VIKOR. Nasrollahi, Ramezani, and Sadraei (2020) applied a subjective weighting method, fuzzy Best-Worst Method (BWM), and an MCDA method, PROMETHEE. Ali and Rashid (2020) presented an approach that was based on the BWM and group best-worst method (GBWM) and compared the results with the analytic hierarchy process (AHP) and group analytic hierarchy process (GAHP) methods. Athawale and Chakraborty (2011) utilized ten MCDM methods, namely AHP, the technique for order preference by similarity to ideal solution (TOPSIS), WPM, SAW, VIKOR, ELECTRE II, graph theory and matrix approach, grey relational analysis, range of value method, and preference ranking organization method for enrichment evaluation (PROMETHEE) II to reveal a comparative analysis. Narayanamoorthy, Geetha, Rakkiyappan, and Joo (2019) integrated the fuzzy entropy method with fuzzy VIKOR. Keshavarz Ghorabae (2016) proposed an extended version of the VIKOR technique for group decision-making.

The literature review reveals that the decision problem of industrial robot selection has been an important issue studied for years. Due to the importance and criticality of the decision, MCDA methods have been extensively preferred. As can be seen, various MCDA methods have been utilized; however, most of the studies utilized one MCDA method. Relying on the result of one MCDA method can be misleading due to the fact that the result is mostly dependent on attribute weights. It can be inferred that there is still a need for a systematic, integrated approach that help decision-makers while making their decision. In this context, unlike other studies, in this study, three weighting methods and three MCDA methods are integrated. By pairing each weighting and MCDA methods, various models are obtained. Then, integrating the outcome of each model through the Borda method, a final consensus is obtained. Thus, it is believed that a more tangible and reliable selection is provided.

The main contributions of the present study can be summarized as follows. First, the ARAS method is used for the industrial robot selection problem for the first time. Second, three weighting and three MCDA methods are used, and their results are analyzed. Thus, unlike most other studies conducted for the same problem, different model pairs are generated. Considering the fact that the results of the MCDA methods are dependent on the attribute weights, relying on one weighting and one MCDA method can be misleading. To avoid such problems and increase the accuracy of the result, it is essential to use more than one weighting and MCDA method, consider and integrate their results. Some models, such as SD-based SAW, WPM, and ARAS models, are implemented to the problem selected for the first time. Last, a novel hybrid approach, including SD, MW, Shannon entropy, ARAS, SAW, WPM, Kendall, and Borda methods, is presented for the industrial robot selection problem. This approach considers the results of different models and presents a final consensus of these models as the selection decision.

The remainder of the study is structured as follows. The following section presents the algorithms of the methods used and the description and implementation of the proposed methodology. Section 3 then illustrates the results of the analyses and presents the discussion. In the last section, conclusions and recommendations for future studies are presented.

## **2. Material and Method**

The industrial robot selection problem is solved based on the integrated approach. In this context, three objective weighting methods, namely Shannon entropy, MW, and SD, three MCDA methods, namely ARAS, SAW, and WPM, and an integrating method, namely, Borda, are described in the following subsections. Then, the details of the proposed approach are presented.

### **2.1. Shannon Entropy**

The concept of entropy, presented by Shannon (1948), is a measure of the uncertainty in information expressed by probability theory. Low entropy value indicates that the degree of disorder in the system is low, and the weight is high (Mohsen & Fereshteh, 2017). The procedure of this approach is explained in the following steps.

Step 1: The performance matrix is normalized using the following equations for benefit and cost attributes.

$$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^m a_{ij}} \quad \text{for } i = 1, 2, \dots, m \quad (1)$$

$$r_{ij} = \frac{1/a_{ij}}{\sum_{i=1}^m (1/a_{ij})} \quad \text{for } i = 1, 2, \dots, m \quad (2)$$

Step 2: Entropy values are obtained using the following equation.

$$e_j = -(\ln m)^{-1} \sum_{i=1}^m r_{ij} \ln r_{ij} \quad \text{for } j = 1, 2, \dots, n \quad (3)$$

Step 3: The attribute weights are determined using the following equation.

$$w_j = \frac{1 - e_j}{(n - \sum_{j=1}^n e_j)} \quad \text{for } j = 1, 2, \dots, n \quad (4)$$

## 2.2. Mean Weight (MW)

MW is a simple weighting method in which all attributes are assumed to be equally important, so equal weights are assigned, as represented by the following equation.

$$w_j = \frac{1}{m}, \quad j = 1, 2, \dots, m \quad (5)$$

## 2.3. Standard Deviation (SD)

Attribute weights are determined based on their standard deviations through Eq. 6.

$$w_j = \frac{\sigma_j}{\sum_{k=1}^m \sigma_k}, \quad j = 1, 2, \dots, m \quad (6)$$

## 2.4. Additive Ratio Assessment (ARAS)

Zavadskas and Turskis (2010) introduced ARAS as an MCDA method. The algorithm of the approach is described in the following steps.

Step 1. The performance matrix is normalized through the following equations. Eq. 7 is implemented for beneficial and Eq. 8 is for non-beneficial attributes, respectively.

$$r_{ij}^* = \frac{r_{ij}}{\sum_{i=0}^m r_{ij}} \quad \text{for } j = 1, 2, \dots, n \quad (7)$$

$$r_{ij} = \frac{1}{r_{ij}^{**}}; r_{ij}^* = \frac{r_{ij}}{\sum_{i=0}^m r_{ij}} \quad \text{for } j = 1, 2, \dots, n \quad (8)$$

Step 2. Eq. 9 is implemented to obtain the weighted normalized decision matrix. The weights of criteria ( $w_1, w_2, \dots, w_n$ ) are obtained through weighting methods (SD and Shannon entropy).

$$\hat{r}_{ij} = r_{ij}^* * w_j \quad \text{for } i = 0, 1, 2, \dots, m \quad j = 1, 2, \dots, n \quad (9)$$

Step 3. The optimality function ( $S_i$ ) is obtained via Eq. 10.

$$S_i = \sum_{j=1}^n \hat{r}_{ij} \quad \text{for } i = 0, 1, 2, \dots, m \quad (10)$$

Step 4. Finally, to rank alternatives, the utility degree is obtained. The utility degree ( $k_i$ ) for the  $i$ th alternative is determined based on Eq. 11. The industrial robot with the highest utility degree is chosen as optimal.

$$k_i = \frac{S_i}{V_0} \quad \text{for } i = 0,1,2, \dots, m \quad (11)$$

where  $V_0$  is the optimality value of  $S_i$ .

### 2.5. Simple Additive Weighting (SAW)

SAW is one of the simplest and most commonly used MCDM methods. It is also frequently preferred in comparison with other methods. In this method, the best alternative is determined based on Eq. 12. In the equation, the numbers of attributes and alternatives are denoted by  $n$  and  $m$ . Also,  $A_i$  indicates the score of the  $i$ th alternative,  $r_{ij}$  represents the value of the  $i$ th alternative based on the  $j$ th decision attribute, and  $w_j$  denotes the weight of the  $j$ th attribute. Once the scores for all alternatives are obtained, the alternative with the maximum total value is determined as the best.

$$A_i = \sum_{j=1}^n r_{ij}w_j \quad \text{for } i = 1,2,3, \dots, m \quad (12)$$

### 2.6. Weighted Product Method (WPM)

The WPM is similar to the SAW method. The main difference is that the main mathematical operation is now multiplication instead of addition, as follows.  $w_j$  and  $r_{ij}$  were explained in the previous subsection.

$$WPM = \prod_{j=1}^n (r_{ij})^{w_j} \quad (13)$$

### 2.7. Application of the Proposed Approach

The proposed hybrid approach is summarized in Figure 1.

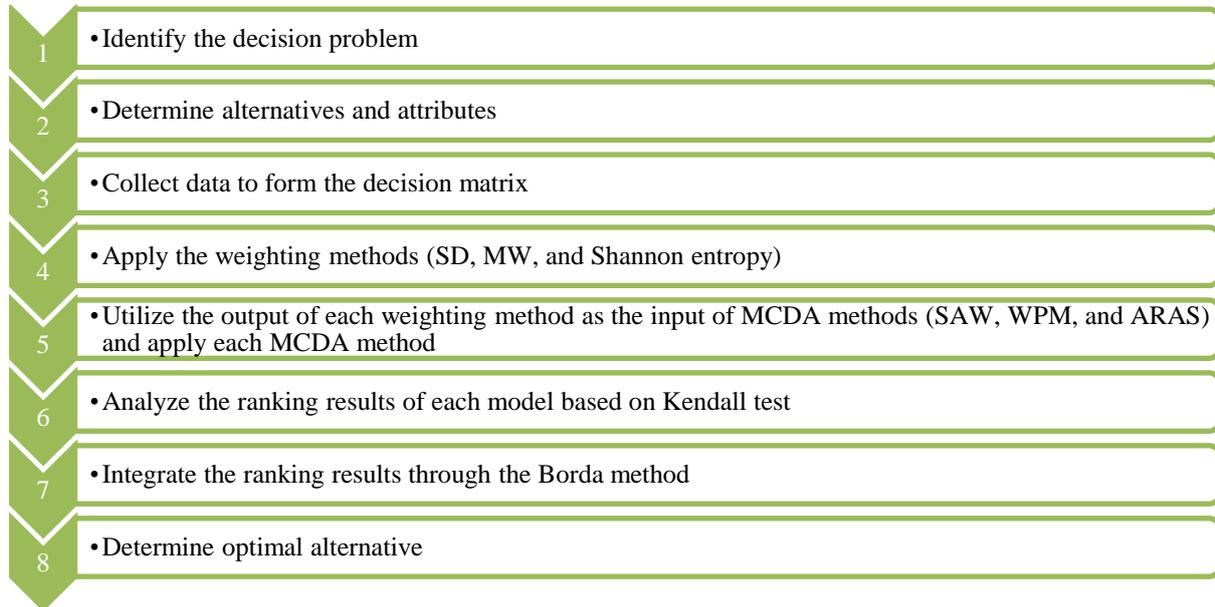


Figure 1. The steps of the proposed hybrid approach

The proposed integrated approach is implemented to solve the problem of industrial robot selection. First, the problem of the selection of the industrial robot is defined. Then, alternatives and attributes are identified. In this context, the evaluation of the industrial robot alternatives is made based on load capacity (kg), manipulator reach (mm), maximum tip speed (mm/sec), memory capacity (points or steps), and repeatability (mm). Load capacity (C1) refers to the maximum load that can be carried. Manipulator reach (C2) refers to the maximum distance traveled by the robotic manipulator to grip the object for a given pick and place operation. The maximum tip speed (C3) is the speed at which a robot can move in an inertial reference frame. The memory capacity (C4) of a robot is expressed in terms of the number of points or steps it can store in its memory as it moves along a predefined path. Repeatability (C5) is a measure of a robot's ability to return to the same position and orientation repeatedly. To be noted that load capacity, manipulator reach, memory capacity, and maximum tip speed are beneficial attributes, whereas repeatability is the cost attribute. Then, the data is collected to form

the decision matrix. In this study, the data drawn from the literature (Bhangale, Agrawal, & Saha, 2004) is included in implementing the proposed study (Table 1).

Table 1. The decision matrix data for the industrial robot selection problem (Bhangale et al., 2004)

| Industrial Robot (IR)                         | Load capacity (C1) | Manipulator reach (C2) | Maximum tip speed (C3) | Memory capacity (C4) | Repeatability (C5) |
|---|--------------------|------------------------|------------------------|----------------------|--------------------|
| ASEA-IRB 60/2 (IR1)                           | 60                 | 990                    | 2540                   | 500                  | 0.4                |
| Cincinnati Milacron T <sup>3</sup> -726 (IR2) | 6.35               | 1041                   | 1016                   | 3000                 | 0.15               |
| Cybotech V15 Electric Robot (IR3)             | 6.8                | 1676                   | 1727.2                 | 1500                 | 0.1                |
| Hitachi America Process Robot (IR4)           | 10                 | 965                    | 1000                   | 2000                 | 0.2                |
| Unimation PUMA 500/600 (IR5)                  | 2.5                | 915                    | 560                    | 500                  | 0.1                |
| United States Robots Maker 110 (IR6)          | 4.5                | 508                    | 1016                   | 350                  | 0.08               |
| Yaskawa Electric Motoman L3C (IR7)            | 3                  | 920                    | 1778                   | 1000                 | 0.1                |

The data is normalized, considering beneficial and cost attributes, as given in Table 2. The data in this table is an example of the normalization of the data since each method may require a different normalization method. Then, each weighting method is applied to determine the weights of the attributes. Using the weights provided by each method, each MCDA method is implemented. The ranking results of all models are examined through Kendall correlation coefficients. Then, the rankings provided by nine different models are integrated through the Borda method (Borda, 1784) to determine the final consensus ranking. In the Borda method, all models are considered to obtain Borda scores. In this context, to score an alternative, for all other alternatives that rank below the chosen alternative, a value of one is given; otherwise, a zero value is given to the corresponding matrix value (Şahin, 2020). Thus, the final consensus ranking reveals the optimal industrial robot.

Table 2. Normalized decision matrix data

| IR  | C1    | C2    | C3    | C4    | C5    |
|-----|-------|-------|-------|-------|-------|
| IR1 | 0.644 | 0.141 | 0.264 | 0.056 | 0.044 |
| IR2 | 0.068 | 0.148 | 0.105 | 0.339 | 0.118 |
| IR3 | 0.073 | 0.239 | 0.179 | 0.169 | 0.176 |
| IR4 | 0.107 | 0.138 | 0.104 | 0.226 | 0.088 |
| IR5 | 0.027 | 0.130 | 0.058 | 0.056 | 0.176 |
| IR6 | 0.048 | 0.072 | 0.105 | 0.040 | 0.221 |
| IR7 | 0.032 | 0.131 | 0.184 | 0.113 | 0.176 |

### 3. Results and Discussion

The attribute weights obtained from Shannon entropy and SD methods are presented in Table 3. According to the results of both methods, load capacity is the most important attribute, followed by memory capacity, maximum tip speed, repeatability, and manipulator reach. Also, the weights of all attributes are equal according to the MW method, as seen in Table 3. All weights provided by these weighting methods are illustrated in Figure 1 for better observation and comparison.

Table 3. Attribute weights obtained from Shannon entropy and SD methods

| Weighting Method | C1     | C2     | C3     | C4     | C5     |
|------------------|--------|--------|--------|--------|--------|
| Shannon entropy  | 0.5899 | 0.0419 | 0.0847 | 0.2067 | 0.0769 |
| SD               | 0.4339 | 0.0959 | 0.1358 | 0.2143 | 0.1201 |
| MW               | 0.2000 | 0.2000 | 0.2000 | 0.2000 | 0.2000 |

The importance given by Shannon entropy and the SD method to load capacity is seen in Figure 1. It is also seen that the SD method allocates more weight to attributes other than the load capacity compared to Shannon entropy.

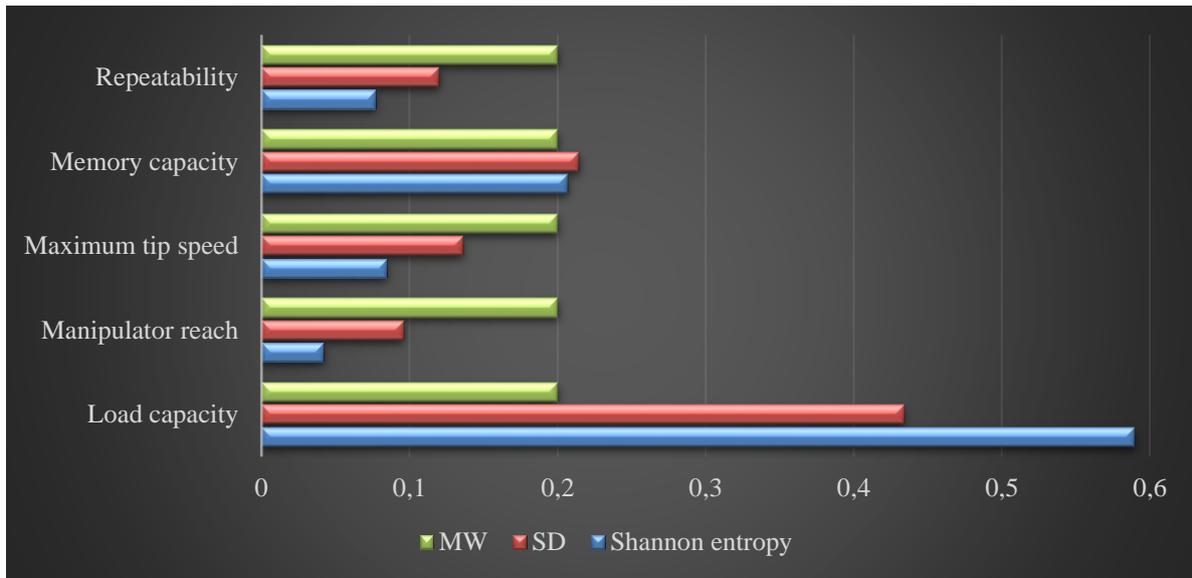


Figure 2. The comparison of attribute weights provided by MW, SD, and Shannon entropy

The weights provided by each weighting method are used as the input of each MCDA method. The utility values provided by each method pair (model) are presented in Table 4. The utility values determine the rank of alternatives. Based on the utility values, the ranking of each model is determined, as presented in Table 5.

Table 4. The utility values of models

|     | Utility Value |             |        |        |             |        |         |              |         |
|-----|---------------|-------------|--------|--------|-------------|--------|---------|--------------|---------|
|     | SD-WPM        | Entropy-WPM | MW-WPM | SD-SAW | Entropy-SAW | MW-SAW | SD-ARAS | Entropy-ARAS | MW-ARAS |
| IR1 | 0.2122        | 0.2758      | 0.1430 | 0.6214 | 0.7035      | 0.4939 | 0.9247  | 0.9154       | 0.9771  |
| IR2 | 0.1173        | 0.1062      | 0.1336 | 0.4122 | 0.3449      | 0.5070 | 0.3941  | 0.3131       | 0.5589  |
| IR3 | 0.1231        | 0.1054      | 0.1564 | 0.4140 | 0.2977      | 0.6071 | 0.3372  | 0.2507       | 0.5288  |
| IR4 | 0.1254        | 0.1243      | 0.1250 | 0.3328 | 0.2889      | 0.3983 | 0.3805  | 0.3109       | 0.5326  |
| IR5 | 0.0510        | 0.0413      | 0.0727 | 0.1581 | 0.0984      | 0.2685 | 0.1519  | 0.1050       | 0.2629  |
| IR6 | 0.0642        | 0.0566      | 0.0797 | 0.1665 | 0.1169      | 0.2530 | 0.1575  | 0.1210       | 0.2399  |
| IR7 | 0.0750        | 0.0585      | 0.1092 | 0.2863 | 0.1948      | 0.4319 | 0.2383  | 0.1659       | 0.3942  |

Table 5. The ranks of alternative robots provided by each method pair

| Model        | Ranking of Alternative Industrial Robot |     |     |     |     |     |     |
|--------------|---|-----|-----|-----|-----|-----|-----|
|              | IR1                                     | IR2 | IR3 | IR4 | IR5 | IR6 | IR7 |
| SD-WPM       | 1                                       | 4   | 3   | 2   | 7   | 6   | 5   |
| Entropy-WPM  | 1                                       | 3   | 4   | 2   | 7   | 6   | 5   |
| MW-WPM       | 2                                       | 3   | 1   | 4   | 7   | 6   | 5   |
| SD-SAW       | 1                                       | 3   | 2   | 4   | 7   | 6   | 5   |
| Entropy-SAW  | 1                                       | 2   | 3   | 4   | 7   | 6   | 5   |
| MW-SAW       | 3                                       | 2   | 1   | 5   | 6   | 7   | 4   |
| SD-ARAS      | 1                                       | 2   | 4   | 3   | 7   | 6   | 5   |
| Entropy-ARAS | 1                                       | 2   | 4   | 3   | 7   | 6   | 5   |
| MW-ARAS      | 1                                       | 2   | 4   | 3   | 6   | 7   | 5   |

According to the results, IR1 is the best alternative robot according to SD-based WPM, Shannon entropy-based WPM, SD-based SAW, Shannon entropy-based SAW, SD-based ARAS, Shannon entropy-based ARAS, and MW-based ARAS. Besides, IR3 is an optimal option based on the results of MW-based WPM and MW-based SAW. The results also indicate that the rankings of SD-based ARAS and Shannon entropy-based ARAS are identical, in which IR1 is the best alternative, followed by IR2, IR4, IR3, IR7, IR6, and IR5. These results reveal that the ranking provided by an MCDA method varies depending on the attribute weights. In other words, these

results prove that the outcome of MCDA methods is dependent on the attribute weights. Therefore, the choice of weighting method is very important. Also, these results prove that relying on the ranking of an MCDA method may be misleading. As seen from Table 5, the small changes in the attribute weights alter the rank of the MCDA. In addition, the ARAS method is observed as the most robust MCDA method for the problem chosen in the present study. The ranking provided by this method is less susceptible to the attribute weights. The rank of all robots remains the same except IR5 and IR6, according to the result of the MW-ARAS model.

To illustrate the results, Figure 3 is presented for better observation and comparison of the rankings. The figure demonstrates that seven models recommend the IR1 alternative as the best out of nine models. In addition, the impact of attribute weights on the ranking result can be observed well in this figure. For instance, the ranking of IR3 varies depending on the attribute weights. Although the same MCDA method is applied, the use of SD weights allows IR3 to be placed in the third place, the use of Shannon entropy weights to move it to the fourth place, and the use of equal weights provided by the MW method makes it the best alternative. However, the ranking of IR1 (first) provided by the ARAS method is not affected by the attribute weights. The ARAS method recommends the IR1 as the best alternative for the attribute weights provided by three different weighting methods. This situation provides some insight into the robustness of the method.

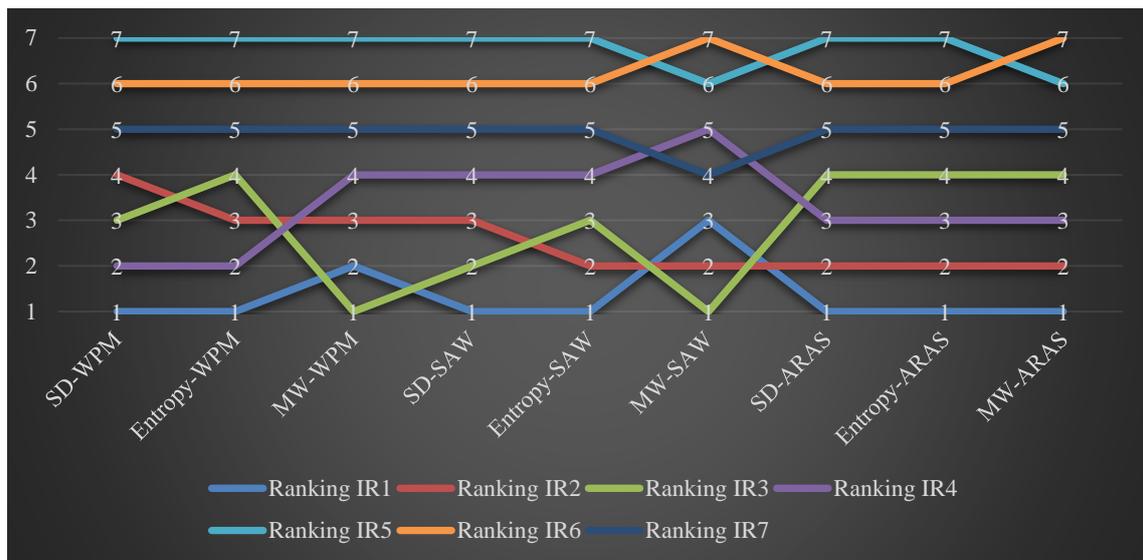


Figure 3. The comparison of rankings provided by the models

To see the correlation between the models, Kendall correlation coefficients are obtained, as given in Table 6. Kendall rank correlation coefficients are used to assess the correlations between the models. In other words, the Kendall rank correlation coefficient (Kendall, 1948) assesses the degree of similarity between two rank sets given to the same set of alternatives. The Kendall coefficients prove the perfect correlation between SD-based ARAS and Shannon entropy-based ARAS. In addition, there is a strong correlation between SD-based WPM and Shannon entropy-based WPM, Shannon entropy-based-WPM and SD-based ARAS, Shannon entropy-based WPM and Shannon entropy-based ARAS, MW-based WPM and SD-based SAW, SD-based SAW and Shannon entropy-based SAW, Shannon entropy-based SAW and SD-based ARAS, Shannon entropy-based SAW and Shannon entropy-based ARAS, SD-based ARAS, and MW-based ARAS, and Shannon entropy-based ARAS and MW-based ARAS. To sum up, the ranking of these models is similar to each other.

Table 6. Kendall rank correlation coefficients of models

|              | SD-WPM | Entropy-WPM | MW-WPM | SD-SAW  | Entropy-SAW | MW-SAW | SD-ARAS | Entropy-ARAS | MW-ARAS |
|--------------|--------|-------------|--------|---------|-------------|--------|---------|--------------|---------|
| SD-WPM       | 1      | 0.905**     | 0.714* | 0.810*  | 0.714*      | 0.429  | 0.810*  | 0.810*       | 0.714*  |
| Entropy-WPM  |        | 1           | 0.619  | 0.714*  | 0.810*      | 0.333  | 0.905** | 0.905**      | 0.810*  |
| MW-WPM       |        |             | 1      | 0.905** | 0.810*      | 0.714* | 0.714*  | 0.714*       | 0.619   |
| SD-SAW       |        |             |        | 1       | 0.905**     | 0.619  | 0.810*  | 0.810*       | 0.714*  |
| Entropy-SAW  |        |             |        |         | 1           | 0.524  | 0.905** | 0.905**      | 0.810*  |
| MW-SAW       |        |             |        |         |             | 1      | 0.429   | 0.429        | 0.524   |
| SD-ARAS      |        |             |        |         |             |        | 1       | 1.000**      | 0.905** |
| Entropy-ARAS |        |             |        |         |             |        |         | 1            | 0.905** |
| MW-ARAS      |        |             |        |         |             |        |         |              | 1       |

\*\* . Correlation is significant at the 0.01 level (2-tailed).

\* . Correlation is significant at the 0.05 level (2-tailed).

To integrate the results of all models, the Borda method is implemented. The final calculations of the method and final ranking based on Borda scores are presented in Table 7.

*Table 7. The calculations for the Borda method and final ranking based on Borda scores*

| Alternatives | IR1 | IR2 | IR3 | IR4 | IR5 | IR6 | IR7 | Row Sum | Final ranks based on Borda |
|--------------|-----|-----|-----|-----|-----|-----|-----|---------|----------------------------|
| IR1          | 0   | 1   | 1   | 1   | 1   | 1   | 1   | 6       | 1                          |
| IR2          | 0   | 0   | 1   | 1   | 1   | 1   | 1   | 5       | 2                          |
| IR3          | 0   | 0   | 0   | 0   | 1   | 1   | 1   | 3       | 4                          |
| IR4          | 0   | 0   | 1   | 0   | 1   | 1   | 1   | 4       | 3                          |
| IR5          | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0       | 7                          |
| IR6          | 0   | 0   | 0   | 0   | 1   | 0   | 0   | 1       | 6                          |
| IR7          | 0   | 0   | 0   | 0   | 1   | 1   | 0   | 2       | 5                          |

Based on the results provided by the Borda method, the final consensus ranking reveals that IR1 is the best alternative industrial robot, followed by IR2, IR4, IR3, IR7, IR6, and IR5. Based on this result, it can be inferred that adopting MW-based WPM or MW-based SAW would determine IR2 or IR3 as the best option that could be misleading. In addition, the other models, except SD-based ARAS and Shannon entropy-based ARAS, would provide different rankings that could also be misleading. However, SD-based ARAS and Shannon entropy-based ARAS provided the same ranking as the final consensus ranking. It can be inferred that either SD-based ARAS or Shannon entropy-based ARAS can be used for the problem considered in this study. However, it is difficult to say that these models will provide a guaranteed solution to such problems. Instead, a hybrid approach will increase the dependability of the solution. Therefore, the hybrid approach forms the basis of this study.

The final consensus ranking of the nine models is compared to previous studies. In the study conducted by Bhangale et al. (2004), IR4, IR1, and IR3 were recommended as the best industrial robots by three different models. In addition, some other studies used the same data, except the corresponding data of IR7 for maximum tip speed. This data was taken as 1778 by Bhangale et al. (2004) as in this study; however, it was taken as 177 in the following studies. Chatterjee et al. (2010) implemented VIKOR and ELECTRE II, and the results of both methods suggested IR3 as the best alternative. R. V. Rao, Patel, and Parnichkun (2011) found IR1 and IR3 as the best alternatives in different situations in their analysis. Fu et al. (2019) implemented VIKOR, ELECTRE II, and group decision making (GDM) methodology, and IR3 was the best alternative based on the results of VIKOR and ELECTRE II and IR1 was the best option based on the result of the GDM methodology. As can be seen, the rankings vary depending on the weights and the type of the MCDA method. In general, one weighting method and one, two, or three MCDA methods were adopted, and the results of the models were compared. This study differs from others in terms of integrating the ranking results of nine models. Hence, it is believed that the reliability of the model is increased compared to dependence on the result of one model.

To summarize, the results indicated that two models out of nine models provided the same ranking. Therefore, relying on one MCDA method may be deceptive. Also, the results revealed that the MCDA methods were highly dependent on the outcome of the weighting methods. Therefore, utilizing multiple weighting and MCDA methods helps to achieve a more reliable ranking. Besides, ARAS was the most robust method compared to the WPM and SAW. It provided the same ranking for SD and Shannon entropy weights. Also, for ARAS models, the ranking based on the weights provided by the MW was correlated with the rankings based on weights provided by SD and Shannon entropy. Last, the outcomes of SD and Shannon entropy were parallel. In other words, the order of importance of the attributes was the same.

## 4. Conclusions and Recommendations

The most suitable industrial robots must be carefully selected as incorrect selection can result in loss of productivity, time, and product quality, which means a significant negative impact on the overall performance of the manufacturing system. The availability of multiple alternatives and various evaluation criteria makes industrial robot selection a typical MCDA problem. In this context, considering the importance of the subject and the fact that it can be misleading to rely on the result of an MCDA method, a hybrid MCDA approach is presented in this study, unlike other studies. Three subjective weighting and three MCDA methods were adopted. The results of each method pair were integrated through the Borda method to reveal the final consensus for industrial robot selection. According to the results obtained, IR1 was the best alternative, followed by IR2, IR4, IR3, IR7, IR6, and IR5. Also, ARAS was found as the most robust MCDA method compared to SAW and the WPM. Last, the weights provided by SD and Shannon entropy methods were parallel.

Although the hybrid MCDA approach presented provides meaningful guidance for selecting the optimum industrial robots, it includes some limitations such as a limited number of evaluation attributes and a limited number of MCDA and weighting methods. In this context, future studies can concentrate on expanding the number of attributes. Also, more MCDA methods, such as VIKOR, ELECTRE, and PROMETHEE, can be included in the approach. Last, the subjective weighting methods, such as AHP and BWM, may extend the scope of analysis as they provide subjective evaluations of experts.

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