

Using Multi-Criteria Decision-Making Techniques for Industrial Robot Selection

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SUMMARY & CONCLUSIONS

The selection of industrial robots is crucial for enhancing manufacturing efficiency and overall output. This study evaluates the effectiveness of various Multi-Criteria Decision-Making (MCDM) techniques, including TOPSIS and VIKOR, in ranking robots based on a comprehensive set of criteria. A detailed dataset was utilized, incorporating factors such as availability, flexibility, performance indicators, and cost-effectiveness, to assess the competency of four MCDM methods. The analysis provides valuable insights into the comparative strengths and weaknesses of these MCDM techniques. By examining VIKOR and TOPSIS within the framework of industrial robot selection, the unique advantages and limitations of each method are identified. Additionally, the impact of different criteria weights on the rankings is explored, highlighting the sensitivity of MCDM methods to parameter adjustments. The findings offer practical knowledge for decision-makers facing challenges in robot selection, facilitating improved problem-solving and alignment of decision-making models with organizational goals and preferences. Understanding the performance characteristics of various MCDM techniques enhances institutions' ability to address industrial needs effectively. This comparative analysis is beneficial for professionals in industrial automation, robotics research, and policy development. It aids raw material manufacturers and other industries in achieving organizational objectives, improving efficiency, and enhancing

competitiveness. The study underscores the importance of selecting the appropriate MCDM technique to optimize the evaluation and decision-making processes for industrial robots.

1 INTRODUCTION

In today's flexible industrial environment, robotics is a key strategy for boosting productivity and precision, offering companies a competitive edge in a rapidly evolving market. Given that industrial robots can perform various tasks, from simple assembly to complex material handling, selecting the right robot is crucial due to its significant impact on operations and costs. Industrial robots are valued for their decision-making capabilities, machine communication, and responsiveness to sensory inputs [1]. They are used in diverse applications such as material handling, machine loading and unloading, painting, welding, and assembling. These robots feature multiple degrees of freedom, ease of programming, high flexibility, and substantial memory capacity. Choosing the appropriate robot involves evaluating both qualitative and quantitative attributes. Beneficial quantitative attributes include arm movement distance, load capacity, and programming flexibility, while non-beneficial attributes are cost and maintenance expenses. Since optimizing all attributes is often impractical, MCDM methods are employed to aid in decision-making. A comparative study by Athawale and Chakraborty (2011) examined ten MCDM methods, including SAW, WPM, AHP, TOPSIS, and VIKOR, to evaluate their effectiveness in selecting industrial pick-and-place robots. This research

highlighted the importance of accurately identifying evaluation criteria and weighting their importance based on specific applications [2]. Athawale *et al.* (2012) compared VIKOR, a compromise ranking method, with ELECTRE, an outranking method, for selecting industrial robots. Their research identified key attributes such as velocity and load capacity as advantageous, while cost and repeatability were considered non-beneficial [3]. Parameshwaran *et al.* (2015) introduced a fuzzy MCDM model incorporating the Fuzzy Delphi Method (FDM), Fuzzy Analytic Hierarchical Process (FAHP), and Fuzzy modified TOPSIS to account for both objective and subjective criteria. This model helps set priorities, determine weights, and rank alternatives effectively [4]. Zhou *et al.* (2018) developed a decision support model for selecting mobile robots in hospital pharmacies by integrating fuzzy reasoning with extended VIKOR. This model considers factors such as accuracy, cost, and adaptability to the hospital system [5]. Chodha *et al.* (2021) utilized TOPSIS and the Entropy method to select arc welding robots, prioritizing attributes such as mechanical weight, repeatability, and payload capacity [6]. Goswami *et al.* (2021) developed two hybrid systems by combining ARAS with TOPSIS and COPRAS for real-time robot selection, addressing five criteria and twelve robots [7]. Shanmugasundar *et al.* (2023) conducted a comprehensive comparison of MCDM methods, including SAW, TOPSIS, LINMAP, VIKOR, and ELECTRE-III, to address both subjective and objective attributes in robot selection. Their study emphasized the need to balance beneficial and non-beneficial elements, such as load capacity and economic cost [8]. Eisa *et al.* (2023) explored the significance of weighting in MCDM methods, comparing techniques like COCOSO, TOPSIS, VIKOR, and MOORA for optimal robot selection. Their study also compared AHP, entropy, and BWM with various weighting strategies [9]. The significance of this study lies in its potential to enhance decision-making in industrial robotics, resulting in improved efficiency, minimized downtime, and reduced production costs. Effective robot selection enhances product quality and shortens time-to-market, which is crucial in the highly competitive industrial landscape. By offering an in-depth analysis of various MCDM methods and their applications, this research supports industry professionals and academics in making well-informed decisions about industrial automation.

2 PROBLEM DESCRIPTION

To enhance productivity, reduce costs, and maintain a reliable work environment, industrial robots are widely used for repetitive production tasks, some of which are hazardous. Selecting the right robot is challenging due to diverse criteria such as cost, load capacity, precision, durability, energy consumption, and technological compatibility. These criteria often have conflicting features; for instance, a robot with high load capacity may consume more power and be less reliable. This selection process is critical as it involves significant investment in robot acquisition and installation, yet existing literature often lacks an integrated approach for comparing these diverse factors. Research objectives of this paper include: (1) Evaluate MCDM Methods: Assess the effectiveness of popular MCDM methods like VIKOR and TOPSIS in ranking industrial robots based on multiple criteria; (2) Compare

Ranking Consistency: Analyze ranking consistency in pick-and-place operations to identify which methods align better with practical requirements; (3) Assess Decision Impact: Examine the impact of MCDM methods on robot selection, highlighting which methods are best suited to specific needs; (4) Emphasize Proper Criteria Selection: Stress the importance of selecting and weighing decision criteria appropriately rather than solely relying on MCDM methods. This study aims to provide a comprehensive analysis of MCDM methods in industrial robot selection, helping businesses identify the most suitable robots for their operations. By considering various criteria and alternatives, the research offers a robust decision-making framework that balances conflicting factors, significantly impacting the economic viability and operational efficiency of industrial robots.

3 METHODOLOGY

Selecting the optimal industrial robot is crucial for enhancing operational efficiency, reducing costs, and improving product quality. To address this challenge, two advanced MCDM methods, TOPSIS and VIKOR, are often employed due to their flexibility and ability to assess multiple criteria. TOPSIS is particularly effective when identifying the best solution, as it selects the alternative closest to the ideal solution using geometric distance. Conversely, VIKOR excels in finding a balanced compromise, making it ideal for scenarios that aim to minimize the worst-case outcomes. The selection process begins with data collection and preparation, which are critical to ensuring credible results. In this study, data from seven industrial robots were analyzed based on five key criteria: load capacity (LC), repeatability (RE), maximum tip speed (MTS), memory capacity (MC), and manipulator reach (MR). These criteria are essential as they directly influence robot performance and suitability for various manufacturing tasks. Thus, the robot selection problem involves evaluating five criteria across seven alternatives, as outlined in Table 1. Each metric is weighted according to its strategic importance in industrial applications, as outlined in Table 2. These weights were determined through expert consultations and analysis of historical robot performance data. Utilizing the MCDM methodology in this research provides a comprehensive view of each robot's productivity and trade-offs. The results enhance clarity and objectivity in resource planning, aligning with the risk profile and operational goals of industrial companies using robotics.

4 DATA ANALYSIS AND RESULT

In this study, TOPSIS and VIKOR methodologies were applied to evaluate seven industrial robots based on five key criteria: load capacity, repeatability, maximum tip speed, memory capacity, and manipulator reach. Criteria weights were determined through expert consultations to reflect their strategic importance in industrial robotics.

4.1 TOPSIS method: Selecting the right industrial robot is crucial for optimizing manufacturing strategies, impacting efficiency and cost. TOPSIS provides a structured approach for comparing robots by evaluating their proximity to an ideal solution. The steps include [10, 11]: Normalizing data to a common scale.; Calculating ideal and negative-ideal solutions;

Measuring each alternative's distance from these solutions; Ranking alternatives based on their proximity to the ideal.

Table 1. Key features of industrial robots analyzed in this study

Alternative	Robot	Load capacity (kg)	Repeatability (mm)	Maximum tip speed (mm/s)	Memory capacity (GB)	Manipulator reach (mm)
A1	ASEA-IRB 60/2	60	0.4	2540	500	990.00
A2	Cincinnati Milacron T3-726	6.35	0.15	1016	3000	1041.00
A3	Cybotech V15 Electric Robot	6.8	0.1	1727.2	1500	1676.00
A4	Hitachi America Process Robot	10	0.2	1000	2000	965.00
A5	Unimation PUMA 500/600	2.5	0.1	560	500	915.00
A6	United States Robots Maker 110	4.5	0.08	1016	350	508.00
A7	Yaskawa Electric Motoman L3C	3	0.1	177	1000	92.00

Table 2. Criteria weights in TOPSIS method

Criteria Weights (TOPSIS)	
W _{LC}	0.1574
W _{RE}	0.1825
W _{MTS}	0.2138
W _{MC}	0.2172
W _{MR}	0.2043

This approach helps manufacturers make informed decisions, aligning robot capabilities with operational goals.

4.1.1 Step 1: Normalization: It ensures that criteria with different scales contribute uniformly to the final decision. Beneficial costs, like load capacity, maximum tip speed, memory capacity, and manipulator reach, favor higher values, while repeatability, a non-beneficial cost, favors lower values. This standardization allows consistent comparison, enhancing the accuracy of the robot selection process using the normalization formula shown by equation 1.

$$D_{ij} = \frac{x_{ij}}{\sqrt{x_{i1}^2 + \dots + x_{in}^2}} \quad (1)$$

Where D_{ij} is the normalized value, x_{ij} is the original value, and n is the number of alternatives

This process ensures that all criteria contribute equally, forming a normalized decision matrix that serves as the foundation for further analysis.

4.1.2 Step 2: Weighting and aggregation: Using the criteria weights from Table 2, the weighted normalized decision matrix is calculated by multiplying each element of the normalized matrix by its corresponding criterion weight (see equation (2)). This step ensures that more important criteria have a greater impact on the final ranking of alternatives. Weights are usually determined through expert opinion or methods like the Analytical Hierarchy Process (AHP). The resulting weighted normalized decision matrix is shown in Table 3.

$$V_{ij} = w_j D_{ij} \quad (2)$$

Where w_j is the weight of the j^{th} criterion and V_{ij} is the weighted normalized value

4.1.3 Step 3: Determination of Ideal and Negative-Ideal Solutions: The ideal solution maximizes benefit criteria and minimizes cost criteria, while the negative-ideal solution does the opposite. These are computed as follows and shown in Table 4. Positive ideal solution of $A^+ = (\max(v_{i1}), \max(v_{i2}), \dots, \min(v_{in}))$ for benefit and cost criteria respectively. Negative ideal solution of $A^- = (\min(v_{i1}), \min(v_{i2}), \dots, \max v_{in})$ for benefit and cost criteria respectively. The distance of each alternative from the

positive ideal and negative ideal solutions is calculated using the Euclidean distance formula via equations (2) and (3).

Table 3. Weighted normalized decision matrix in TOPSIS method

Robot	Load capacity (kg)	Repeatability (mm)	Maximum tip speed (mm/s)	Memory capacity (GB)	Manipulator reach (mm)
ASEA-IRB 60/2	0.1528	0.1435	0.1515	0.0264	0.0727
Cincinnati Milacron T3-726	0.0162	0.0538	0.0606	0.1586	0.0764
Cybotech V15 Electric Robot	0.0173	0.0359	0.1030	0.0793	0.1230
Hitachi America Process Robot	0.0255	0.0717	0.0597	0.1058	0.0708
Unimation PUMA 500/600	0.0064	0.0359	0.0334	0.0264	0.0672
United States Robots Maker 110	0.0115	0.0287	0.0606	0.0185	0.0373
Yaskawa Electric Motoman L3C	0.0076	0.0359	0.0106	0.0529	0.0675

Table 4. Ideal and negative ideal solutions

A^+	0.1528	0.0287	0.1515	0.1586	0.1230
A^-	0.0064	0.1435	0.0106	0.0185	0.0373

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2}, i = 1, 2, \dots, m \quad (1)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2}, i = 1, 2, \dots, m \quad (2)$$

Where S_i^+ and S_i^- are the distances of the i^{th} alternative from the positive and negative ideal solutions, respectively computed as given in Table 5.

Table 5. Calculated the positive and negative ideal solutions in TOPSIS method

S_i^+	0.1822	0.172413	0.164436	0.178935	0.236708	0.234986	0.235047
S_i^-	0.2064	0.178346	0.176916	0.129068	0.114261	0.125317	0.116943

4.1.4 Step 4: Ranking the alternatives based on their proximity to the positive ideal solution

The final step calculates relative closeness of each alternative to the positive ideal solution, determining their ranking:

$$C_i = \frac{S_i^-}{(S_i^+ + S_i^-)} \quad (3)$$

Where C_i is the relative closeness coefficient. The relative closeness values, which show how closely each robot aligns with the ideal solution, are listed in Table 6. The industrial robot with the highest C_i value is considered as the best choice.

Table 6. Calculated relative closeness coefficient

C1	0.531233538
C2	0.508457989
C3	0.518279388
C4	0.41904728
C5	0.325559573
C6	0.347810191
C7	0.332234072

This result reveals how closely each robot aligns with the ideal solution based on the criteria. The ASEA-IRB 60/2 emerges as the top choice, followed closely by the Cybotech V15 Electric Robot. This table is crucial for decision-makers as it highlights performance differences among robots, aiding in the selection of the robot that best balances benefits and costs.

4.1 VIKOR method: The choice of industrial robots impacts production efficiency and cost management. The VIKOR

method offers a structured approach to evaluate and compare robot options, helping decision-makers select the closest match to the ideal solution. The VIKOR process involves four main steps [12] of Determining the best and worst values for each criterion; Computing utility and regret measures; Calculating the VIKOR Index; and Ranking alternatives based on the VIKOR Index. This method allows for a comprehensive assessment by considering both utility and regret, ensuring that the selected robot aligns with operational goals. Our dataset evaluates seven robots across criteria such as load capacity, repeatability, maximum tip speed, memory capacity, and manipulator reach, with weights shown in the Table 2 (section 3).

4.2.1 Step 1: Determining the best and the worst values for each criterion: In this step, f^* and f^- values are determined for each criterion. This will help to assess performance of each criterion as it is a crucial step for evaluating the outcomes. The f^* is the maximum value among all the options for beneficial criteria while for non-beneficial criteria, minimum value is preferred. The f^- is the minimum value for the beneficial criteria while for non-beneficial criteria maximum value is considered among all the alternatives. For decision-making space, it is a crucial point because they represent the ideal and anti-ideal points. It will act as a reference point to analyze how far each alternative is from these values.

Table 7. Calculated values for f^* and f^-

Criteria	Best Value (f^*)	Worst Value (f^-)
Load capacity (kg)	60	2.5
Repeatability (mm)	0.08	0.4
Maximum tip speed (mm/s)	2540	177
Memory capacity (GB)	3000	350
Manipulator reach (mm)	1676	92

4.2.2 Step 2: Computing the utility and regret measures: In this step, utility and regret measures for each alternative are calculated based on the f^* and f^- values from Step 1. Utility measure (S_i): It represents the aggregated deviation from the best value for each criterion, calculated as a weighted sum of normalized deviations. This measure reflects the overall performance of each alternative across all criteria. Regret measure (R_i): This measure shows the maximum deviation from all the best values. VIKOR method provides a balanced evaluation of each alternative by considering both utility (overall deviation) and regret (maximum single-criterion deviation) described in step 3.

$$S_i = \sum_{j=1}^n w_j \cdot \left(\frac{|f_j^* - f_{ij}|}{|f_j^* - f_j^-|} \right) \quad (4)$$

Where f_j^* : the best value for criterion j
 f_{ij} : Value for criteria j and alternative i
 f_j^- : Worst value for criterion j
 w_j : weight of criterion j showing its importance

$$R_i = [w_j \cdot \left(\frac{|f_j^* - f_{ij}|}{|f_j^* - f_j^-|} \right)] \quad (5)$$

4.2.3 Step 3: Calculate the VIKOR index: The Q_i measure called VIKOR index is calculated by combining utility measure of S_i and regret measure of R_i and helps to identify a compromise solution.

$$Q_i = \vartheta \cdot \frac{(S_i - S^*)}{(S^- - S^*)} + (1 - \vartheta) \cdot \frac{(R_i - R^*)}{(R^- - R^*)} \quad (6)$$

Where S^* and S^- : Best and worst value of utility measures; R^* and R^- : Best and worst value of regret measures.

By assuming $\vartheta = 0.5$, equal weight is assigned to both utility and regret measures when calculating the Q_i measure value. Table 8 shows the calculated values of S_i , R_i , and Q_i for different industrial robots (alternatives).

Table 8. Calculated values for S_i , R_i , and Q_i

i	S_i	R_i	Q_i
1	0.475884069	0.20490566	0.57557512
2	0.406572272	0.14686104	0.11531466
3	0.353519549	0.14562922	0.04040902
4	0.518308607	0.13933644	0.20809719
5	0.651010462	0.20490566	0.79672639
6	0.657659457	0.21720000	0.88407077
7	0.749462083	0.21380000	0.97816694

4.2.4 Step 4: Ranking the alternative in VIKOR method: In the VIKOR technique, alternatives are ranked based on the Q_i measure. The VIKOR index of Q_i determined that the alternative with the lowest value is the best compromise solution. This approach provides decision-makers with balanced options that meet all criteria. The compromise solution, derived from the VIKOR index, ensures that no single criterion has significant drawbacks and is closest to the ideal solution. Table 9 presents the ranking, where the lowest value indicates the most balanced and optimal choice among the options. **DQ Calculation:** This calculation provides a threshold to ensure a significant distinction between the best and second-best alternatives. The difference between the Q values of the best alternative (A3) and the second-best (A2) should be greater than DQ to confirm Robot 3 (Cybotech V15 Electric Robot) as the final choice without ambiguity. Since $Q(A3) - Q(A2) = 0.0810$ is less than DQ , it indicates that while Robot 3 has the lowest Q, the decision isn't robust enough against the DQ threshold. Hence, both Robot 2 (Cincinnati Milacrone T3-726) and Robot 3 (Cybotech V15 Electric Robot) are concluded to be the best, implying a very close performance between these two robots.

Table 9. Ranking of industrial robots based on S_i , R_i , and Q_i measures in VIKOR method

	A1	A2	A3	A4	A5	A6	A7
S	4	1	2	3	6	5	7
R	4	2	1	3	4	6	6
Q	4	2	1	3	5	6	7

$$DQ = \frac{1}{(n-1)}, \quad (7)$$

Where n is the number of alternatives

In this study, $n=7$ and $DQ = 0.166667$. Using the TOPSIS method, the ASEA-IRB 60/2 industrial robot is ranked highest, reflecting its superior performance in most beneficial criteria. In contrast, the VIKOR method identifies the Cincinnati Milacrone T3-726 robot and Cybotech V15 electric robot as the optimal choices. These robots achieve the best balance across assessment categories, effectively minimizing major shortcomings and ensuring robust performance for industrial applications. The differing results highlight the influence of the decision-making framework on selection outcomes. TOPSIS emphasizes maximizing performance in chosen criteria, while VIKOR seeks to balance and minimize disadvantages, which is crucial when no single performance axis dominates. This

variation underscores the importance of selecting the most suitable MCDM method based on specific requirements and preferences. Understanding the mechanics of each MCDM approach is essential, as it significantly impacts the decision outcome. Additionally, the application of these methods enhances decision-making transparency. They provide a systematic approach that ensures fair and contextually informed choices, making complex decisions more justifiable and streamlining the selection process for optimal operational efficiency. In summary, the analysis showcases the effectiveness and flexibility of MCDM methods in industrial robot selection. Future research should focus on practical applications to further validate and refine the usefulness of these methods in real-world scenarios.

5 CONCLUSION AND FUTURE RESEARCH

The conducted analysis of this study revealed the effective application of MCDM methods, specifically TOPSIS and VIKOR, in the selection of industrial robots. TOPSIS demonstrated its utility in scenarios where the goal is to find the solution closest to the ideal, while VIKOR was adept at identifying the best compromise when dealing with conflicting criteria. Both methods substantially enhance decision-making in industrial automation by offering impartial, transparent insights that improve productivity, reduce costs, and provide a competitive advantage. Looking ahead, several research avenues could further develop the application of MCDM techniques such as exploring other MCDM approaches, such as ELECTRE, and PROMETHEE, to provide a more comprehensive understanding of their effectiveness across different industrial environments and combining traditional MCDM methods into hybrid models may address their limitations and offer a more robust and versatile decision-making framework.

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