



Decision-Making Model for Robot Selection Application using Neutrosophic Sets

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Abstract:

Robot selection is a crucial process that involves choosing the most suitable robot for a specific task or application. This work provides an overview of the critical criteria for selecting a robot. It emphasizes the importance of evaluating task requirements, payload capacity, workspace and reach, precision and accuracy, speed and cycle time, safety features, programming and control interface, maintenance and reliability, cost and return on investment, integration, and compatibility, and future scalability and flexibility. By carefully considering these criteria, stakeholders can make informed decisions and select a robot that meets their needs, optimizing productivity, efficiency, and safety in various industrial and commercial settings. We used the concept of multi-criteria decision-making to deal with multiple criteria in the robot section. We used the Weighted Euclidean distance-based Approach (WEDBA) to analyze the robot selection criteria and rank the alternatives. The WEDBA method integrated with the neutrosophic set environment. The neutrosophic set used for dealing with uncertainty information. We used the 11 criteria and 15 options in this study. The main results show the load capacity has the highest weight.

Keywords: The Weighted Euclidean Distance Based Approach Method (WEDBA); Robot Selection; MCDM; Decision Making; Neutrosophic Set; Uncertainty

1. Introduction

Robot selection is a critical process in industries and applications where automation is employed to enhance productivity, efficiency, and safety. Choosing the right robot for a specific task or application requires careful consideration of various factors to ensure optimal performance and cost-effectiveness. The process involves evaluating criteria such as task requirements, payload capacity, workspace and reach, precision and accuracy, speed and cycle time, safety features, programming and control interface, maintenance and reliability, cost and return on investment, integration and compatibility, and future scalability and flexibility[1]–[3]. Robots have become increasingly sophisticated and versatile in today's rapidly advancing technological landscape, offering a wide range of capabilities and applications. Robots are transforming industries and streamlining operations from manufacturing and assembly

lines to healthcare, logistics, and even household tasks. However, with many options available, selecting the most suitable robot can be complex and strategic[4]–[7].

Robot selection aims to identify the robot that best meets the specific requirements of the intended task or application. Each criterion plays a crucial role in determining the optimal choice. Task requirements encompass the functionalities and specifications necessary for the robot to perform the desired operations effectively. Payload capacity is essential for tasks involving the handling or manipulating of objects of varying weights. Workspace and reach determine the robot's ability to operate within the designated environment and access all necessary points[8]–[10]. Precision and accuracy are crucial when precision is required, such as in manufacturing or surgical procedures. Speed and cycle time influence productivity and throughput, making them significant considerations for high-volume operations. Safety features are paramount to ensure the well-being of human operators and equipment in the robot's vicinity[11]–[13]. The programming and control interface should be user-friendly and intuitive for seamless operation and maintenance. Maintenance and reliability are essential for long-term performance and minimize downtime. Cost and return on investment must be carefully evaluated to justify the investment and achieve cost-effectiveness[14]–[16].

Integration and compatibility with existing systems or equipment are critical for seamless integration into the workflow. Future scalability and flexibility are considerations to accommodate evolving needs and technological advancements[17]–[19]. By understanding and evaluating these criteria, stakeholders can make informed decisions about robot selection, aligning the capabilities of the chosen robot with the specific requirements of the task or application. Proper robot selection can optimize productivity, efficiency, and safety, leading to improved operational outcomes and a competitive edge in today's automated landscape[20]–[22]. Dynamical systems under potential uncertainties are suitably modelled using the neutrosophic environment. L. Zadeh was the first to suggest the idea of a fuzzy set, in which each element of the set was assigned a degree of membership. Later, K. T. Atanassov upgraded fuzzy sets to intuitionistic fuzzy sets (IFS), while F. Smarandache expanded them even further to neutrosophic sets (NS). In addition to membership level, the IFS has non-membership level. In contrast, fuzzy and intuitionistic fuzzy logic imports less information than NS, which raises the degree of indeterminacy[23]–[26].

Therefore, neutrosophic [27]adaptation of the diffusion equations' environment will result in improved performance in mathematical modelling of drug diffusion in human tissues with inaccurate or indeterminate flow parameters[28]. Fuzzy differential equations, often referred to as differential equations with inaccurate parameters, have been the focus of study in recent years[29]–[32].

The main contributions of this study are:

- Analyze the criteria in the robot section, rank the robots, and select the best one.
- The Weighted Euclidean distance-based Approach Method is used to rank the alternatives.
- This study used a large scale of problems, including 11 criteria and 15 robots.

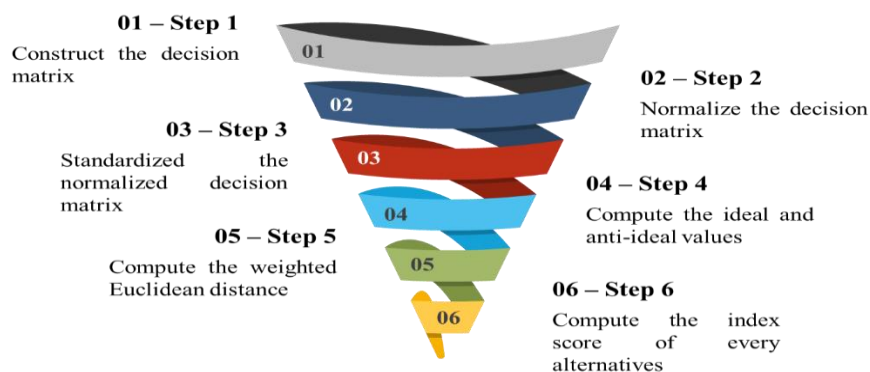


Figure 1. The process steps of the Weighted Euclidean Distance Based Approach Method

2. Preliminaries

Definition 1

The single valued neutrosophic set presented as:

$$X_{ne} = \left\{ \begin{array}{l} x: (\varepsilon_{x_{ne}}(x), \gamma_{x_{ne}}(x), \delta_{x_{ne}}(x)); x \in U \\ \varepsilon_{x_{ne}}(x): U \rightarrow [0,1], \\ \gamma_{x_{ne}}(x): U \rightarrow [0,1], \\ \delta_{x_{ne}}(x): U \rightarrow [0,1], \end{array} \right\}$$

$$0 \leq \varepsilon_{x_{ne}}(x) + \gamma_{x_{ne}}(x) + \delta_{x_{ne}}(x) \leq 3$$

Definition 2

α, β, γ – cut neutrosophic set $X_{ne(\alpha, \beta, \gamma)}$ presented as:

$$X_{ne(\alpha, \beta, \gamma)} = \left\{ \begin{array}{l} (\varepsilon_{x_{ne}}(x), \gamma_{x_{ne}}(x), \delta_{x_{ne}}(x)): x \in X, \\ \varepsilon_{x_{ne}}(x) \geq \alpha, \\ \gamma_{x_{ne}}(x) \leq \beta, \\ \delta_{x_{ne}}(x) \leq \gamma \end{array} \right\}$$

$$\alpha + \beta + \gamma \leq 3$$

Definition 3

Trapezoidal neutrosophic number (TNN) presented as:

$$T_{neu}(y) = \left\{ \begin{array}{ll} \left(\frac{y - e_1}{e_2 - e_1}\right) \beta & \text{for } e_1 \leq y \leq e_2 \\ \beta & \text{for } e_2 \leq y \leq e_3 \\ \left(\frac{e_4 - y}{e_4 - e_3}\right) \beta & \text{for } e_3 \leq y \leq e_4 \\ 0 & \text{otherwise} \end{array} \right\}$$

$$I_{neu}(y) = \left\{ \begin{array}{ll} \left(\frac{e_2 - y}{e_2 - e_1}\right) \gamma & \text{for } e_1 \leq y \leq e_2 \\ \gamma & \text{for } e_2 \leq y \leq e_3 \\ \left(\frac{e_4 - y}{e_4 - e_3}\right) \gamma & \text{for } e_3 \leq y \leq e_4 \\ 1 & \text{otherwise} \end{array} \right\}$$

$$F_{neu}(y) = \left\{ \begin{array}{ll} \left(\frac{e_2 - y}{e_2 - e_1}\right) \delta & \text{for } e_1 \leq y \leq e_2 \\ \delta & \text{for } e_2 \leq y \leq e_3 \\ \left(\frac{e_4 - y}{e_4 - e_3}\right) \delta & \text{for } e_3 \leq y \leq e_4 \\ 1 & \text{otherwise} \end{array} \right\}$$

$$0 \leq T_{neu}(y) + I_{neu}(y) + F_{neu}(y) \leq 3$$

3. The Weighted Euclidean Distance Based Approach Method (WEDBA)[33]–[38]

We used the MCDM methodology to deal with various criteria[39], [40].

1. Construct the decision matrix
2. Normalize the decision matrix

The normalized decision matrix is computed for cost and positive criteria as:

$$V_{ij} = \frac{\min_i r_{ij}}{r_{ij}} \tag{1}$$

$$V_{ij} = \frac{r_{ij}}{\max_i r_{ij}} \tag{2}$$

3. Standardized the normalized decision matrix

$$S_j = \frac{\sum_{i=1}^m V_{ij}^2}{m} \tag{3}$$

$$\phi_j = \sqrt{\frac{\sum_{i=1}^m (V_{ij} - S_j)^2}{m}} \tag{4}$$

$$\gamma_j = \frac{V_{ij} - S_j}{\phi_j} \tag{5}$$

4. Compute the ideal and anti-ideal values

$$\gamma_{ij}^+ = \max(\gamma_{ij}) \tag{6}$$

$$\gamma_{ij}^- = \min(\gamma_{ij}) \tag{7}$$

5. Compute the weighted Euclidean distance

$$EC_i^+ = \sqrt{\sum_{j=1}^n \{w_j (\gamma_{ij} - \gamma_{ij}^+)^2\}} \tag{8}$$

$$EC_i^- = \sqrt{\sum_{j=1}^n \{w_j (\gamma_{ij} - \gamma_{ij}^-)^2\}} \tag{9}$$

6. Compute the index score of every alternatives

$$E = \frac{EC_i^-}{EC_i^+ + EC_i^-} \tag{10}$$

4. Robot Selection Application

This section used the MCDM method to select the best robot based on several criteria. We let the experts and decision-makers evaluate the criteria and alternatives on a neutrosophic numbers.

There are 11 criteria for Robot Selection are used in this study and 15 robots as[41]–[44]:

- **Task Requirements:** The first and foremost criterion for robot selection is ensuring that the robot can perform the intended tasks effectively. The robot should possess the necessary features, capabilities, and specifications to meet the specific requirements of the task at hand.
- **Payload Capacity:** The payload capacity of the robot is an essential factor to consider, especially when the task involves handling or manipulating objects of varying weights. The robot should be able to handle the required payload without compromising its safety or performance.
- **Workspace and Reach:** The size and reach of the robot's workspace are crucial considerations. It is essential to ensure the robot can operate within the designated workspace and reach all the necessary points to perform the desired tasks efficiently.
- **Precision and Accuracy:** Precision and accuracy requirements may vary depending on the task. The robot should have the necessary control and sensing capabilities to achieve the desired level of precision and accuracy in its movements and operations.
- **Speed and Cycle Time:** The speed at which the robot can perform tasks and its cycle time (the time taken to complete one entire operation cycle) are essential, especially in high-throughput or time-sensitive operations. The robot should have the speed and cycle time capabilities to meet the production or operational requirements.
- **Safety Features:** Safety is a critical consideration in robot selection. The robot should have built-in safety features, such as collision detection and avoidance, emergency stop buttons, and protective barriers or sensors, to ensure the safety of human operators and other equipment in its vicinity.
- **Programming and Control Interface:** The ease of programming and control interface is essential for efficient operation and maintenance of the robot. The robot should have intuitive programming tools and a user-friendly control interface that enables easy integration, programming, and operation by human operators.
- **Maintenance and Reliability:** The maintenance requirements and reliability of the robot are crucial considerations for long-term operation. The robot should have a track record of reliability, and its maintenance requirements, including spare parts availability and service support, should be feasible and manageable.
- **Cost and Return on Investment (ROI):** Cost is a significant factor in robot selection. The robot's initial purchase cost, operational costs, and expected return on investment should be evaluated for its benefits and productivity gains.
- **Integration and Compatibility:** If the robot needs to be integrated into an existing system or work alongside other equipment, compatibility with the existing infrastructure should be considered. The robot's communication protocols, software compatibility, and integration capabilities should be evaluated.
- **Future Scalability and Flexibility:** Considering future needs and scalability is essential in robot selection. The robot should have the potential for expansion or reconfiguration to adapt to changing requirements or accommodate future growth and technological advancements.

We let experts evaluate the 11 criteria and 15 robots, then we used the average method to compute the weights of the criteria. The weights of criteria show that scalability has the lowest weight and payload capacity has the largest weight. The 11 criteria weights are organized in Figure 2.

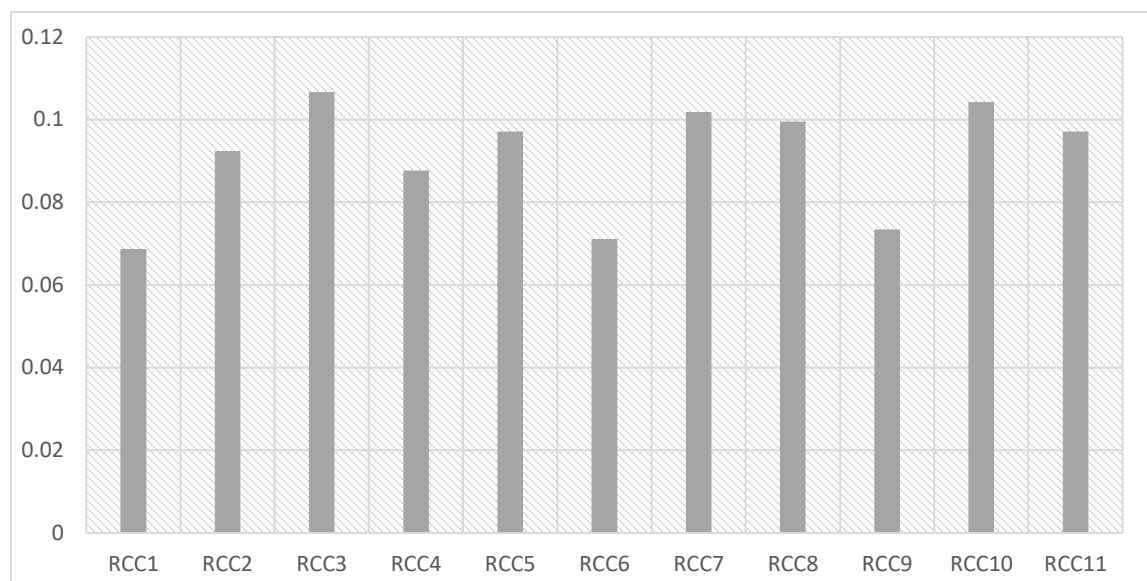


Figure 2. The robot selection criteria weights in this study

We discuss the results of the WEDBA method. There are 11 criteria and 15 robots are used in this study.

1. Construct the decision matrix between 11 criteria and 15 robots. The experts evaluate the criteria and robots.
2. Normalize the decision matrix by Eqs. (1 and 2) for positive and negative criteria are shown in Table 1.

Table 1. The normalization decision matrix.

	RCC ₁	RCC ₂	RCC ₃	RCC ₄	RCC ₅	RCC ₆	RCC ₇	RCC ₈	RCC ₉	RCC ₁₀	RCC ₁₁
RCA ₁	0.666667	1	0.888889	0.444444	0.555556	0.333333	0.666667	0.555556	0.666667	1	0.777778
RCA ₂	0.444444	0.666667	1	0.888889	0.777778	0.444444	0.555556	0.666667	0.333333	0.555556	0.555556
RCA ₃	0.555556	0.555556	0.666667	1	1	0.666667	0.888889	0.777778	0.555556	0.666667	0.666667

RCA ₁₃	RCA ₁₂	RCA ₁₁	RCA ₁₀	RCA ₉	RCA ₈	RCA ₇	RCA ₆	RCA ₅	RCA ₄
0.666667	0.777778	1	0.888889	0.777778	0.444444	0.555556	0.666667	0.555556	0.333333
1	0.888889	0.777778	0.444444	0.555556	0.666667	1	0.888889	0.777778	0.444444
0.666667	1	0.888889	0.777778	0.444444	0.555556	0.666667	0.555556	0.888889	1
0.555556	0.888889	0.888889	1	0.666667	0.555556	0.777778	0.444444	0.666667	0.666667
0.444444	0.777778	0.888889	0.777778	0.888889	1	0.555556	0.666667	1	0.555556
0.777778	0.444444	1	0.555556	0.555556	1	0.666667	0.555556	0.888889	0.444444
0.888889	0.555556	0.666667	0.555556	0.444444	0.777778	0.888889	1	0.777778	0.888889
1	0.666667	1	0.888889	0.777778	0.444444	0.555556	1	0.666667	1
0.222222	0.555556	0.888889	1	0.666667	0.333333	0.222222	0.555556	0.666667	0.666667
0.666667	0.333333	0.555556	0.333333	0.666667	0.555556	0.444444	0.777778	0.888889	1
0.666667	0.555556	0.333333	0.666667	0.555556	0.444444	0.777778	0.888889	1	0.666667

RCA ₁₄	0.888889	0.666667	0.333333	0.666667	0.555556	0.444444	0.777778	0.888889	1	1	1
RCA ₁₅	1	0.777778	0.444444	0.555556	0.666667	1	0.888889	0.777778	0.444444	0.555556	0.888889

3. Standardized the normalized decision matrix by using Eqs. (3-5) as shown in Table 2.

Table 2. The standardized decision matrix.

	RCA ₁	RCA ₂	RCA ₃	RCA ₄	RCA ₅	RCA ₆	RCC ₁	RCC ₂	RCC ₃	RCC ₄	RCC ₅	RCC ₆	RCC ₇	RCC ₈	RCC ₉	RCC ₁₀	RCC ₁₁
RCA ₁	-0.30289	-0.31243	-0.30766	-0.3172	-0.30766	-0.29334	-0.28857	-0.28857	-0.29334	-0.31243	-0.30766	-0.3172	-0.30289	-0.30766	-0.30289	-0.28857	-0.29811
RCA ₂	-0.31243	-0.30289	-0.30766	-0.31243	-0.29811	-0.30766	-0.30289	-0.30289	-0.28857	-0.29334	-0.30766	-0.31243	-0.30289	-0.30766	-0.3172	-0.30766	-0.30766
RCA ₃	-0.30766	-0.30289	-0.30766	-0.30766	-0.28857	-0.29334	-0.28857	-0.28857	-0.30289	-0.28857	-0.29334	-0.30289	-0.29334	-0.29811	-0.30766	-0.30289	-0.30289
RCA ₄	-0.3172	-0.31243	-0.30766	-0.28857	-0.30289	-0.30766	-0.31243	-0.30289	-0.28857	-0.30289	-0.29334	-0.31243	-0.29334	-0.28857	-0.30289	-0.28857	-0.30289
RCA ₅	-0.30766	-0.29811	-0.29334	-0.30289	-0.28857	-0.29334	-0.29334	-0.29811	-0.30289	-0.30289	-0.28857	-0.29334	-0.29811	-0.30289	-0.30289	-0.29334	-0.28857
RCA ₆	-0.30289	-0.29334	-0.30766	-0.31243	-0.30289	-0.30766	-0.28857	-0.28857	-0.30766	-0.31243	-0.30289	-0.30766	-0.28857	-0.28857	-0.30766	-0.29811	-0.29334

RCA ₇	-0.30766	-0.28857	-0.30289	-0.29811	-0.30766	-0.30289	-0.29334	-0.30766	-0.30766	-0.32198	-0.31243	-0.29811
RCA ₈	-0.31243	-0.30289	-0.30766	-0.30766	-0.28857	-0.28857	-0.29811	-0.29811	-0.31243	-0.3172	-0.30766	-0.31243
RCA ₉	-0.29811	-0.30766	-0.31243	-0.30289	-0.29334	-0.30766	-0.31243	-0.31243	-0.29811	-0.30289	-0.30289	-0.30766
RCA ₁₀	-0.29334	-0.31243	-0.29811	-0.28857	-0.29811	-0.30766	-0.30766	-0.30766	-0.29334	-0.28857	-0.3172	-0.30289
RCA ₁₁	-0.28857	-0.29811	-0.29334	-0.29334	-0.29334	-0.28857	-0.30289	-0.30289	-0.28857	-0.29334	-0.30766	-0.3172
RCA ₁₂	-0.29811	-0.29334	-0.28857	-0.29334	-0.29811	-0.31243	-0.30766	-0.30766	-0.30289	-0.30766	-0.3172	-0.30766
RCA ₁₃	-0.30289	-0.28857	-0.30289	-0.30766	-0.31243	-0.29811	-0.29334	-0.28857	-0.32198	-0.30289	-0.30289	-0.30289
RCA ₁₄	-0.29334	-0.30289	-0.3172	-0.30289	-0.30766	-0.31243	-0.29811	-0.29334	-0.28857	-0.28857	-0.28857	-0.28857
RCA ₁₅	-0.28857	-0.29811	-0.31243	-0.30766	-0.30289	-0.28857	-0.29334	-0.29811	-0.31243	-0.30766	-0.30766	-0.29334

4. Compute the ideal and anti-ideal values for positive and cost criteria by Eqs. (6 and 7).
5. Compute the weighted Euclidean distance by Eqs. (8 and 9) as shown in Table 3.

Table 3. The weighted Euclidean distance.

		RCC ₁	RCC ₂	RCC ₃	RCC ₄	RCC ₅	RCC ₆	RCC ₇	RCC ₈	RCC ₉	RCC ₁₀	RCC ₁₁
RCA ₁		-0.00098	0	-0.00051	-0.00209	-0.00185	-0.00204	-0.00146	-0.0019	-0.00105	0	-0.00093
RCA ₂		-0.00164	-0.00132	0	-0.00042	-0.00093	-0.0017	-0.00195	-0.00142	-0.0021	-0.00199	-0.00185
RCA ₃		-0.00131	-0.00176	-0.00153	0	0	-0.00102	-0.00049	-0.00095	-0.0014	-0.00149	-0.00139
RCA ₄		-0.00197	-0.00221	0	-0.00126	-0.00185	-0.0017	-0.00049	0	-0.00105	0	-0.00139
RCA ₅		-0.00131	-0.00088	-0.00051	-0.00126	0	-0.00034	-0.00097	-0.00142	-0.00105	-0.0005	0
RCA ₆		-0.00098	-0.00044	-0.00204	-0.00209	-0.00139	-0.00136	0	0	-0.0014	-0.001	-0.00046
RCA ₇		-0.00131	0	-0.00153	-0.00084	-0.00185	-0.00102	-0.00049	-0.0019	-0.00245	-0.00249	-0.00093
RCA ₈		-0.00164	-0.00132	-0.00204	-0.00167	0	0	-0.00097	-0.00237	-0.0021	-0.00199	-0.00232
RCA ₉		-0.00066	-0.00176	-0.00254	-0.00126	-0.00046	-0.00136	-0.00243	-0.00095	-0.00105	-0.00149	-0.00185

RCA ₁₀	-0.00033	-0.00221	-0.00102	0	-0.00093	-0.00136	-0.00195	-0.00047	0	-0.00299	-0.00139
RCA ₁₁	0	-0.00088	-0.00051	-0.00042	-0.00046	0	-0.00146	0	-0.00035	-0.00199	-0.00278
RCA ₁₂	-0.00066	-0.00044	0	-0.00042	-0.00093	-0.0017	-0.00195	-0.00142	-0.0014	-0.00299	-0.00185
RCA ₁₃	-0.00098	0	-0.00153	-0.00167	-0.00232	-0.00068	-0.00049	0	-0.00245	-0.00149	-0.00139
RCA ₁₄	-0.00033	-0.00132	-0.00305	-0.00126	-0.00185	-0.0017	-0.00097	-0.00047	0	0	0
RCA ₁₅	0	-0.00088	-0.00254	-0.00167	-0.00139	0	-0.00049	-0.00095	-0.00175	-0.00199	-0.00046

6. Compute the index score of every alternative by Eq. (10) as shown in Figure 3. Alternative 5 is the best and Alternative 8 is the worst.

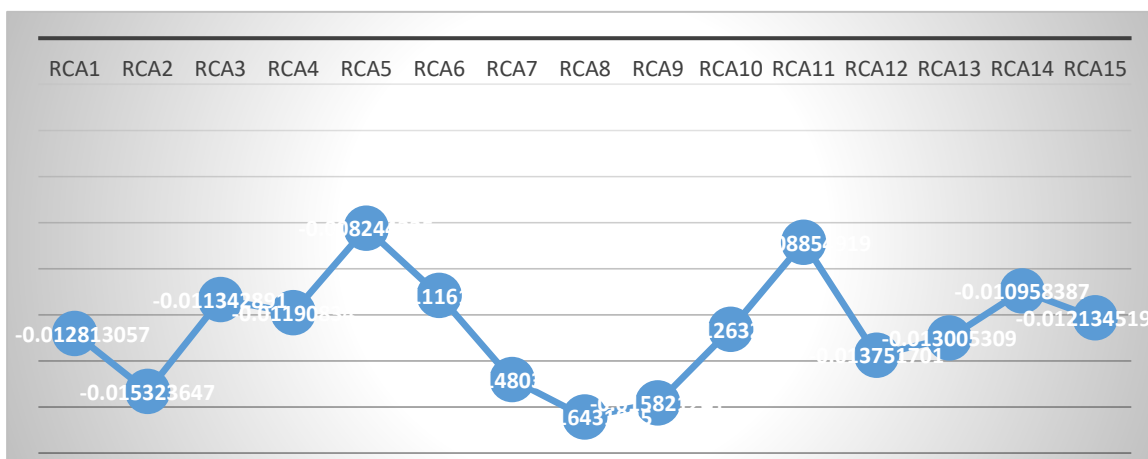


Figure 3. The index score of every alternative.

5. Conclusions

Robot selection is a significant decision that requires a thorough evaluation of various criteria to ensure the correct robot is chosen for the intended task or application. By considering task requirements, payload capacity, workspace and reach, precision and accuracy, speed and cycle time, safety features, programming and control interface, maintenance and reliability, cost and return on investment, integration, and compatibility, and future scalability and flexibility, stakeholders can make informed choices that align with their specific needs. The selection of a suitable robot directly impacts productivity, efficiency, and safety in industrial and commercial settings. A well-selected robot can perform tasks effectively, safely, and with the desired level of precision and accuracy. It can handle the required payload, operate within the designated workspace, and meet the speed and cycle time requirements. The robot's safety features ensure the well-being of human operators and other equipment nearby.

Furthermore, the ease of programming and control interface, along with reliable maintenance and service support, contribute to the selected robot's efficient operation and long-term reliability. Cost considerations, including the initial purchase cost, operational expenses, and expected return on investment, play a crucial role in determining the feasibility and viability of the selected robot. It is also essential to assess the compatibility and integration capabilities of the robot with existing systems or equipment. The selected robot should have the potential for future scalability and flexibility, allowing for adaptation to changing requirements or accommodating future growth and technological advancements. By carefully evaluating these criteria, stakeholders can make informed decisions and select a robot that aligns with their specific needs and optimizes productivity, efficiency, and safety in various industrial and commercial applications. Proper robot selection can improve operational outcomes, cost-effectiveness, and a competitive advantage in the ever-evolving landscape of automation and robotics. We used the MCDM concept to deal with various criteria. We used the WEDBA method to analyze the criteria for robot selection and select the best one. The WEDBA method used under neutrosophic set to deal with uncertainty in the evaluation process. We used 11 criteria and 15 robots to select the best one. The results show that alternative 5 is the best and alternative 8 is the worst.

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