**Data Analytics and Artificial Intelligence**

**Vol: 5(1), 2025**

**REST Publisher; ISBN: 978-81-948459-4-2**

**Website: http://restpublisher.com/book-series/daai/**

**DOI: https://doi.org/10.46632/daai/5/1/19**

# Identification of Evaluation Criteria in Industrial Robot Selection using GRA method

***Chinnasami Sivaji, M. Ramachandran, Nathiya Murali, Poonkodi Sathiyamoorthy**

*REST Labs, Kaveripattinam, Krishnagiri, Tamil Nadu, India.*

*Corresponding Author Email: chinnasami@restlabs.in

***Abstract****: The selection of an optimal industrial robot is a critical decision that can significantly impact the efficiency and productivity of manufacturing processes. In this context, the Grey Relational Analysis (GRA) method provides a systematic and objective approach to evaluate and rank different robot options based on multiple criteria. This paper explores the application of the GRA method in industrial robot selection. The GRA method allows decision-makers to consider various factors simultaneously, incorporating both quantitative and qualitative criteria. By assigning appropriate weights to each criterion and calculating the grey relational grade, the GRA method facilitates the identification of the most suitable industrial robot option for a specific application. Through the GRA method, organizations can effectively assess the performance of industrial robots based on criteria such as payload capacity, reach, speed, flexibility, safety features, maintenance requirements, and cost. The interrelationships and interactions among these criteria are also taken into account, providing a holistic understanding of the robots' performance relative to each other and their alignment with the specific application requirements. Furthermore, the GRA method enables decision-makers to rank the robot options based on their grey relational grades, allowing for a clear comparison of their performance. This ranking assists in identifying the most promising robot options that warrant further consideration and evaluation. The application of the GRA method in industrial robot selection provides decision-makers with a structured framework and quantitative analysis, facilitating informed decisions that lead to the selection of an optimal industrial robot. This, in turn, can enhance productivity, efficiency, and overall success in manufacturing processes. The rapid advancements in technology have led to the widespread adoption of automation in various industries. Industrial robots have emerged as a vital component of this automation revolution, offering increased productivity, precision, and efficiency in manufacturing processes. However, with a wide range of options available in the market, selecting the optimal industrial robot for a specific application can be a complex task. The process of industrial robot selection requires careful consideration of several factors to ensure that the chosen robot meets the unique requirements of the application and delivers the desired outcomes. This introduction aims to provide an overview of the importance of optimal industrial robot selection and the key factors that need to be taken into account during the decision-making process. we will use the GRA in this study, which is a research approach that gives decision making trial and evaluation laboratory to make conclusions based on their relative relevance in a data. Alternative parameters taken as R-robot selection r1, r2, r3, r4, r5, r6, r7. Evaluation parameters taken as load capacity (LC), maximum tip speed (MTS), memory capacity (MC), manipulator reach (MR), repeatability (RE), purchase cost (PC). From the result it is seen that robot selection 1 is got the first rank where as is the robot selection 6 is having the lowest rank. The Grey Relational Analysis (GRA) method offers a systematic and objective approach for selecting the optimal industrial robot. By considering multiple criteria and their interrelationships, decision-makers can evaluate and rank different robot options. The GRA method provides valuable insights into the performance and suitability of each option, aiding in informed decision-making. It allows for a comprehensive evaluation of factors such as payload capacity, reach, speed, flexibility, safety features, maintenance requirements, and cost. By applying the GRA method, organizations can make efficient and effective choices, ultimately selecting the industrial robot that best meets their specific application requirements.*

***Keywords:*** *load capacity (LC), maximum tip speed (MTS), memory capacity (MC), manipulator, reach (MR)*

## 1. INTRODUCTION

Robots represent the pinnacle of mechatronics, embodying the cutting-edge developments in various scientific and technological fields. Drawing from disciplines such as mechanical engineering, computer technology, electronics, artificial intelligence, and automatic control theory, robot technology has made significant progress over the years. The industrial automation revolution has propelled the widespread use of industrial robots in various aspects of our lives and work, with applications ranging from painting and welding to stacking materials [1]. An essential aspect of robot control is kinematic equation analysis, which forms the foundation for understanding and manipulating robot movements. By analyzing the position and orientation of each robot link and its corresponding mechanism parameters, kinematic analysis enables precise control over the robot's end device. This analysis encompasses both forward kinematics and inverse kinematics. Forward kinematics allows the determination of the robot's end device position and orientation based on the analyzed link and mechanism parameters. In contrast, inverse kinematics deals with finding the joint angles and positions required to achieve a specified position and orientation for the end device [2]. Forward kinematics analysis and inverse kinematics analysis are integral components of robot kinematics. In the realm of forward kinematics, researchers commonly employ methods such as the Denavit Hartenberg (D-H) coordinate transformation or quaternions to describe and calculate the robot's motion. Inverse kinematics, on the other hand, offers several solution methods, including analytical approaches, geometric methods, and intelligent algorithms, to determine the joint angles and positions needed for a given end device position and orientation [3]. This study focuses on investigating the PUMA560 industrial robot, employing the D-H coordinate transformation method to derive the forward kinematics equation expressed through position vectors and Euler angles. Additionally, the inverse kinematics problem is addressed using a separation method that distinguishes position and orientation, followed by the selection of the most suitable solution group based on the principle of the shortest path. The correctness of the kinematics solution is then verified using the MATLAB robot toolbox [4]. By paraphrasing the provided text, we can present the same information in a different way while maintaining the core concepts and ideas. The primary goal of selecting the right industrial robot is to maximize productivity while minimizing costs. A well-chosen robot can significantly improve production efficiency, reduce errors, and enhance the overall quality of manufactured products. On the other hand, selecting an inappropriate robot can lead to inefficient operations, excessive downtime, and increased maintenance costs. To ensure optimal industrial robot selection, several crucial factors must be considered. First and foremost, the specific application requirements must be thoroughly analyzed. This includes understanding the production process, the tasks the robot needs to perform, the desired cycle time, and the expected workload. Additionally, factors such as payload capacity, reach, and speed need to be evaluated to ensure that the robot can effectively handle the intended tasks. Another vital consideration is the robot's flexibility and adaptability. As industries evolve and production needs change, it is essential to select a robot that can be easily reprogrammed or reconfigured to accommodate new processes or tasks. The ease of programming, user-friendly interfaces, and compatibility with existing automation systems should be evaluated to determine the robot's suitability for long-term use. Safety is also a paramount concern when selecting an industrial robot. The robot's design and features, such as collision detection sensors, emergency stop systems, and protective barriers, must comply with established safety standards to prevent accidents and ensure the well-being of human operators working alongside the robot. Furthermore, the total cost of ownership (TCO) should be carefully assessed. Apart from the initial purchase cost, factors such as maintenance requirements, spare parts availability, energy consumption, and the robot's expected lifespan should be considered to evaluate the long-term economic viability of the chosen robot. In conclusion, selecting the optimal industrial robot is a crucial decision that can significantly impact the efficiency, productivity, and profitability of manufacturing processes. By considering factors such as application requirements, flexibility, safety, and total cost of ownership, organizations can make informed choices that align with their unique needs and goals. A well-selected industrial robot can empower businesses to stay competitive in the rapidly evolving landscape of industrial automation.

## 2. MATERIALS AND METHODS

Grey relational analysis (GRA) is recommended as a tool to utilise a number of criteria achievement plan, which is employed for choosing remedies from a finite set of choices, in the context of fuzzy multiple factors model (26). In order to choose an ERP package, investigators have used a variety of methods. We believe that this study is the first that combines the IFS and GRA approaches to choosing an ERP system. (27), the proposed method is only used for personnel selection. GRA. Deng (1982) first put forth the concept of the grey system. By integrating all of the operational attributes that are taken into account for all possibilities into one value, GRA is able to solve the issues related to MCDM. As a result, the original issue is reduced to a taking decisions issue involving a single attribute. Consequently, options with (28). In the process of identifying the best option after DM evaluations, GRA benefits. The fuzzing steps of the procedure require assessment of DMs with hesitancy and uncertainty. The purpose of this study aims to propose a comprehensive MCDM approach that utilises IFS and GRA for the selection of green vendors in light of the data that was provided (29). The multi-attribute decision-making (MADM) approach is presented as a modified grey analysis of relationships. A new logarithmic standardisation method is used for data preparatory processing or normalisation to address the weakness of the GRA method indicated in Section 2. Each of the M-GRA steps for resolving problems involving multiple attributes during choice-making (30). The GRA can be used to resolve issues involving intricate connections between many possible solutions and characteristics. The GRA technique has been extensively used to address uncertainty issues arising from separate data and incomplete knowledge. The optimal accessibility network is obtained using the GRA method, and the proportional importance of the requirements for various services are determined using the AHP method (32).Through the optimisation of grey relational grades, grey relational analysis (GRA), which has been shown to be into effect for dealing about poor, unfinished; and uncertain facts, can be used to handle a variety of inexact shortcomings that includes a variety of requirements and goals (33).Grey Relational Analysis (GRA) is a subset of Grey Although it Theory, which is appropriate for complicated interactions between numerous variables and contributing factors in making choices. Although GRA has been successfully used in network selection processes through, rank the reverse phenomenon still affects it (35). Another GRA technique that draws attribute value data using PFN, unidentified attribute pounds data, and builds a MADM approach to handle information conflict under PF conditions is presented. presented a longer version of the linguistic PF Topis methods before addressing the issues in a company's resource planning system. for choosing and evaluating sustainable suppliers (36). The procedure for choosing suppliers has been the subject of numerous attempts to use grey relational analysis (GRA), which relies on grey theory of systems. The disadvantage is that the GRA's choice of supplier’s simulation only takes into account the whitening principles of the grey number. Dealing with the characteristics of quality is challenging (37). Two sections of the literature have been reviewed. The first review addresses the current models that can be used to choose a supplier. The second part discusses various MCDM programmes for AHP and GRA (38). The previously discussed fuzzy readily apparent MADM issues cannot be resolved using the traditional GRA methods because there is inadequate pounds information. How to identify substantial items using data that is difficult to assign weight to and provided fuzzily easily understood (39). When performing an assessment of choosing suppliers, the GRA method is used to combine both quantitative and qualitative data while taking into account its "large-is-better" or "smaller-is-better" properties. It has been proposed for automatically performing the analysis of mathematics and get the results using an Excel programme called AHP-GRA model. Finally, a real-world example of a Taiwanese a notebook computer producer is given to highlight the viability of this integrated scheme (41). Grey relational analysis (GRA), which is a crucial component, can only reflect the trend that exists between a possible substitute and the perfect alternative. Several GRA steps have been amended altered to address this issue, including the normalised formula and the simultaneous consideration of both ideal and non-ideal alternatives (42). The study's enhanced GRA method is a potent tool for making decisions when dealing with unpredictability because it uses numbers that represent intervals. The fact that the enhanced GRA allows for distinct gathering and subsequent integration of expert opinions gives it an edge over other ways of making decisions. Comparatively to other models utilising, this makes our suggested model more flexible (46).

## 3. RESULTS AND DISCUSSIONS

**TABLE 1.** Industrial Robot Selection

| Robot | **load capacity (LC)** | **maximum tip speed (MTS)** | **memory capacity (MC)** | **manipulator reach (MR)** | **repeatability (RE)** | **purchase cost (PC)** |
|---|---|---|---|---|---|---|
| Robot Selection 1 | 60.0 | 2540.0 | 500 | 990 | 0.421 | 77.0 |
| Robot Selection 2 | 6.4 | 1016.0 | 3000 | 1041 | 0.151 | 8.2 |
| Robot Selection 3 | 6.8 | 1727.2 | 1500 | 1676 | 0.121 | 9.5 |
| Robot Selection 4 | 10.0 | 1000.0 | 2000 | 965 | 0.224 | 14.8 |
| Robot Selection 5 | 2.5 | 560.0 | 500 | 915 | 0.142 | 5.6 |
| Robot Selection 6 | 4.5 | 1016.0 | 350 | 508 | 0.084 | 7.1 |
| Robot Selection 7 | 3.0 | 1778.0 | 1000 | 920 | 0.124 | 7.4 |

Table 1. shows the Alternative parameters: Robot Selection 1, Robot Selection 2, Robot Selection 3, Robot Selection 4, Robot Selection 5, Robot Selection 6, Robot Selection 7. Evaluation parameters: load capacity (LC), maximum tip speed (MTS), memory capacity (MC), manipulator reach (MR), repeatability (RE), purchase cost (PC).

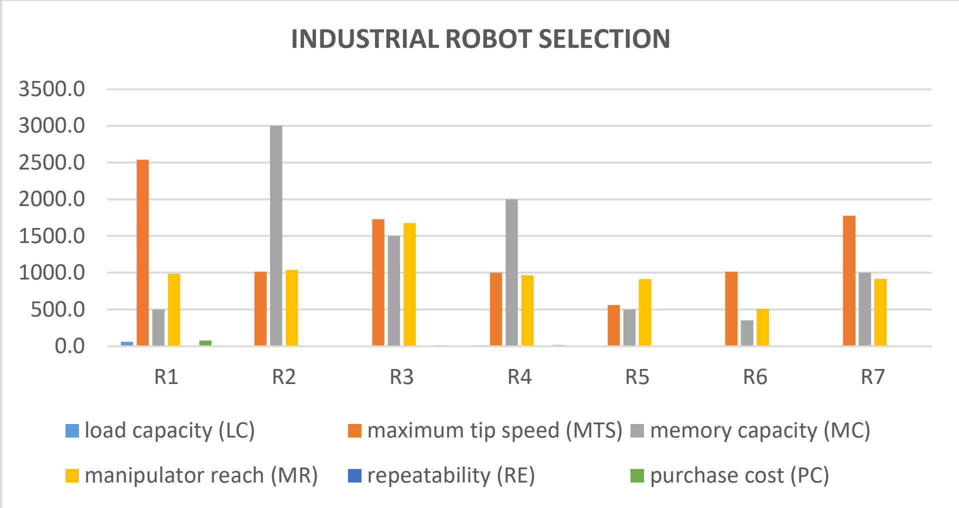


**FIGURE 1.**

Figure 1 shows the graphical representation in load capacity (LC) it is seen that Robot Selection 4 is showing the highest value for Robot Selection 5 is showing the lowest value. maximum tip speed (MTS) it is seen that Robot Selection 1 is showing the highest value for Robot Selection 5 is showing the lowest value. memory capacity (MC) it is seen that Robot Selection 2 is showing the highest value for Robot Selection 6 is showing the lowest value. manipulator reach (MR) it is seen that Robot Selection 3 is showing the highest value for Robot Selection 6 is showing the lowest value. repeatability (RE) it is seen that Robot Selection 4 is showing the highest value for Robot Selection 6 is showing the lowest value. purchase cost (PC) it is seen that Robot Selection 4 is showing the highest value for Robot Selection 5 is showing the lowest value.

**TABLE 2.** Deviation Sequence

| **Deviation sequence** | | | | | |
|---|---|---|---|---|---|
| 0 | 0 | 0.83333 | 0.4093 | 1 | 1 |
| 53.894 | 0.6 | 0 | 0.3789 | 0.198813 | 0.036 |
| 53.887 | 0.32 | 0.5 | 0 | 0.109792 | 0.055 |
| 53.833 | 0.606 | 0.33333 | 0.4242 | 0.41543 | 0.129 |
| 53.958 | 0.78 | 0.83333 | 0.4541 | 0.172107 | 0 |
| 53.925 | 0.6 | 0.88333 | 0.6969 | 0 | 0.021 |
| 53.95 | 0.3 | 0.66667 | 0.4511 | 0.118694 | 0.025 |

Table 2 shows the Normalized data for Alternative parameters: Robot Selection 1, Robot Selection 2, Robot Selection 3, Robot Selection 4, Robot Selection 5, Robot Selection 6,Robot Selection 7. Evaluation parameters: load capacity (LC), maximum tip speed (MTS), memory capacity (MC), manipulator reach (MR), repeatability (RE), purchase cost (PC) it is also the Normalized value.

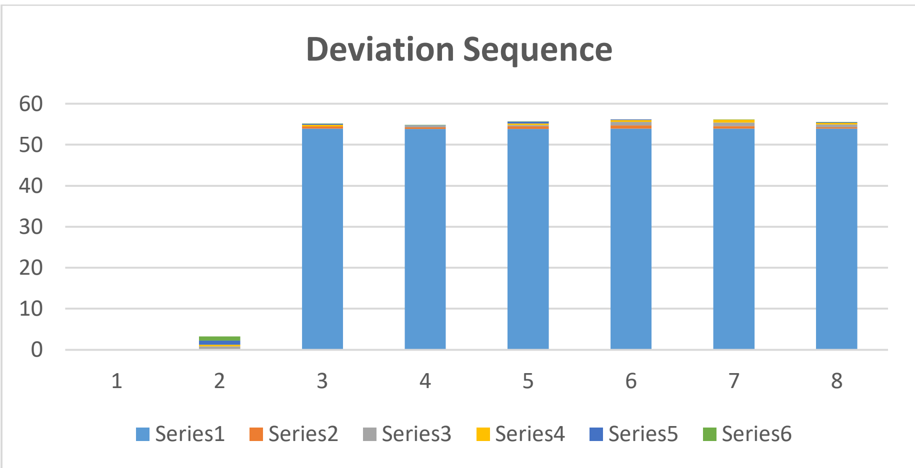


**FIGURE 2.** Deviation Sequence

Table 3 shows the Deviation sequence for Alternative parameters: Robot Selection 1, Robot Selection 2, Robot Selection 3, Robot Selection 4, Robot Selection 5, Robot Selection 6,Robot Selection 7. Evaluation parameters: load capacity (LC), maximum tip speed (MTS), memory capacity (MC), manipulator reach (MR), repeatability (RE), purchase cost (PC) it is also the Maximum or Deviation sequence value.

**TABLE 3.** Grey Relation Coefficient

| **Grey relation coefficient** | | | |
|---|---|---|---|
| 1 | 1 | 0.346405 | 0.459843 |
| 0.333598 | 0.393795 | 1 | 0.479081 |
| 0.333629 | 0.549146 | 0.469027 | 1 |
| 0.333849 | 0.391304 | 0.569892 | 0.450965 |
| 0.333333 | 0.333333 | 0.346405 | 0.434201 |
| 0.333471 | 0.393795 | 0.333333 | 0.333333 |
| 0.333368 | 0.565068 | 0.398496 | 0.435821 |

The given table represents the grey relation coefficients for different robot selections. Each row corresponds to a specific robot selection, and each column represents a different factor or criterion. The values in the table indicate the degree of similarity or relation between each robot selection and the factors.

Robot Selection 1:
- High similarity with itself (coefficient = 1)
- Moderate similarity with the third factor (coefficient = 0.346405)
- Moderate similarity with the fourth factor (coefficient = 0.459843)

Robot Selection 2:
- Moderate similarity with the first factor (coefficient = 0.333598)
- Moderate similarity with the second factor (coefficient = 0.393795)
- High similarity with itself (coefficient = 1)
- Moderate similarity with the fourth factor (coefficient = 0.479081)

Robot Selection 3:
- Moderate similarity with the first factor (coefficient = 0.333629)
- Moderate similarity with the second factor (coefficient = 0.549146)
- Moderate similarity with the third factor (coefficient = 0.469027)
- High similarity with itself (coefficient = 1)

Robot Selection 4:
- Moderate similarity with the first factor (coefficient = 0.333849)
- Moderate similarity with the second factor (coefficient = 0.391304)
- Moderate similarity with the third factor (coefficient = 0.569892)
- Moderate similarity with the fourth factor (coefficient = 0.450965)

Robot Selection 5:
- High similarity with itself (coefficient = 1)
- High similarity with the third factor (coefficient = 0.346405)
- Moderate similarity with the fourth factor (coefficient = 0.434201)

Robot Selection 6:
- Moderate similarity with the first factor (coefficient = 0.333471)
- Moderate similarity with the second factor (coefficient = 0.393795)
- High similarity with the fourth factor (coefficient = 0.333333)
- High similarity with itself (coefficient = 1)

Robot Selection 7:
- Moderate similarity with the first factor (coefficient = 0.333368)
- Moderate similarity with the second factor (coefficient = 0.565068)
- Moderate similarity with the third factor (coefficient = 0.398496)

- Moderate similarity with the fourth factor (coefficient = 0.435821)

These coefficients indicate the relative performance or compatibility of each robot selection with the given factors. Higher coefficients signify a higher degree of similarity or relation to the corresponding factor.

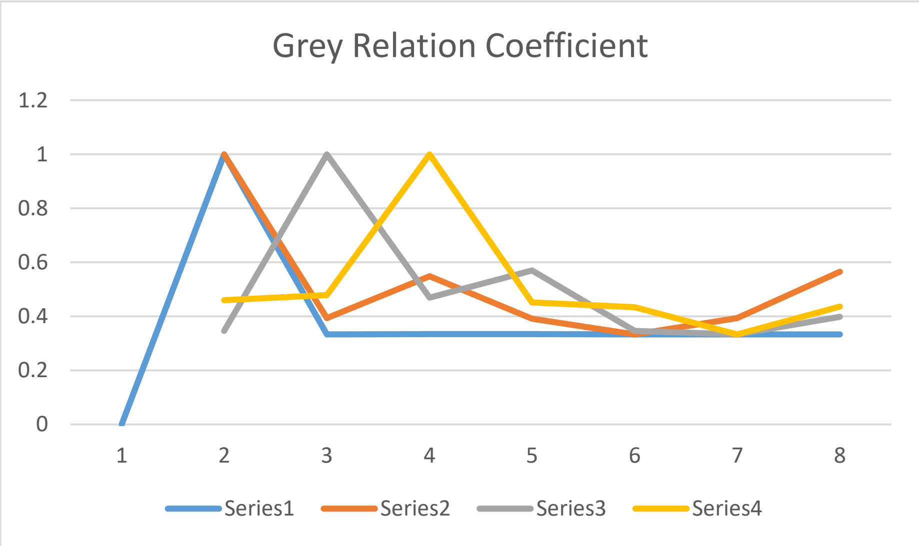


**FIGURE 3.** Grey Relation Coefficient

**TABLE 4.** GRG & Rank

| | GRG | Rank |
|---|---|---|
| Robot Selection 1 | 0.701562 | 1 |
| Robot Selection 2 | 0.551618 | 3 |
| Robot Selection 3 | 0.58795 | 2 |
| Robot Selection 4 | 0.436503 | 4 |
| Robot Selection 5 | 0.361818 | 6 |
| Robot Selection 6 | 0.348483 | 7 |
| Robot Selection 7 | 0.433188 | 5 |

The table lists seven different robot selections, each with their corresponding GRG (Global Rank Gain) and Rank values. The robot selections are ranked based on their GRG values, with Robot Selection 1 having the highest GRG value of 0.701562, followed by Robot Selection 3 with a GRG value of 0.58795. Robot Selection 2 is ranked third with a GRG value of 0.551618, and Robot Selection 4 is ranked fourth with a GRG value of 0.436503. The remaining robot selections have lower GRG values. Robot Selection 7 has a GRG value of 0.433188, placing it in the fifth rank. Robot Selection 5 has a GRG value of 0.361818, which ranks it sixth. Finally, Robot Selection 6 has the lowest GRG value of 0.348483 and is ranked seventh. In summary, Robot Selection 1 has the highest rank and the highest GRG value, while Robot Selection 6 has the lowest rank and the lowest GRG value.

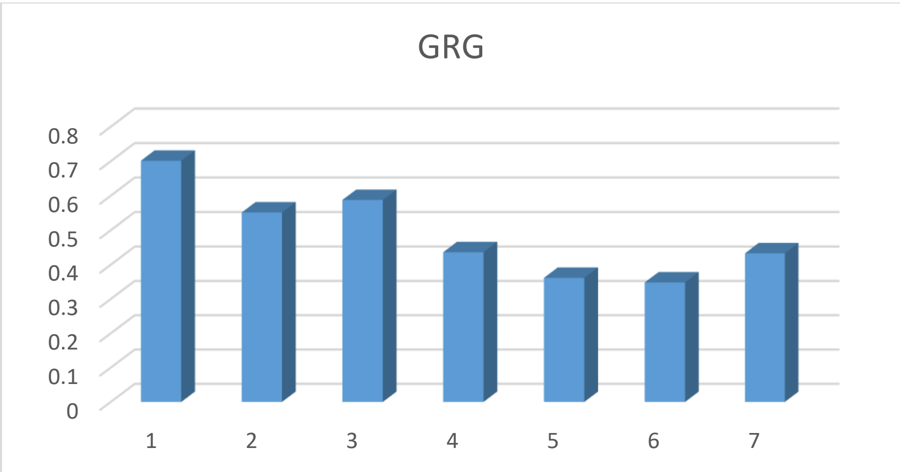


**FIGURE 4.** GRG

Figure 5 shows the Robot Selection 1 (0.701562), Robot Selection 2 (0.551618), Robot Selection 3 (0.58795), Robot Selection 4 (0.436503), Robot Selection 5 (0.361818), Robot Selection 6 (0.348483), Robot Selection 7 (0.433188).

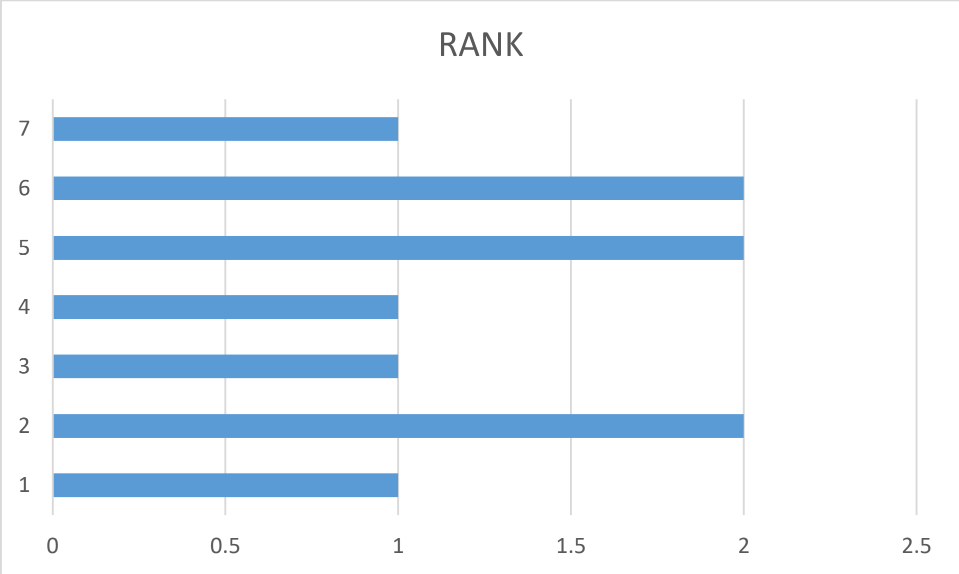


**FIGURE 5.** Rank

Figure 5 shows that Robot Selection 1 are in first place, Robot Selection 2 in third place, Robot Selection 3 in the second place, Robot Selection 4 in fourth place, Robot Selection 6 in sixth place, Robot Selection 7 in seventh place and Robot Selection 5 in fifth place. The final decision is made using the GRA method.

## 4. CONCLUSION

In conclusion, the selection of an optimal industrial robot is a crucial task that can greatly impact the efficiency, productivity, and overall success of manufacturing processes. The application of the Grey Relational Analysis (GRA) method in robot selection provides a systematic and effective approach to evaluate and rank the performance of different robot options based on multiple criteria. The GRA method allows decision-makers to consider various factors simultaneously and objectively, taking into account both quantitative and qualitative criteria. By assigning appropriate weights to each criterion and calculating the grey relational grade, the GRA method facilitates the identification of the most suitable industrial robot option for a specific application. Through the GRA method, organizations can effectively assess the performance of industrial robots based on criteria such as payload capacity, reach, speed, flexibility, safety features, maintenance requirements, and cost. These criteria play a vital role in determining the overall suitability and value of a robot for the intended application. The GRA method not only considers the individual performance of each criterion but also captures the interrelationships and interactions among them. This holistic approach enables decision-makers to gain a comprehensive understanding of how different robots perform relative to each other and how they align with the specific requirements of the application. Moreover, the GRA method allows decision-makers to rank the robot options based on their grey relational grades. This ranking provides valuable insights into which robot options are the most promising and deserving of further consideration. It enables decision-makers to make informed choices, selecting the industrial robot that offers the best overall performance and value for the specific application. It is worth noting that the GRA method is not a standalone solution but rather a tool to support decision-making. It should be used in conjunction with other evaluation methods, expert knowledge, and practical considerations. The GRA method provides a structured framework and quantitative analysis, but it should be complemented with qualitative assessments and real-world validation to ensure the selected robot can effectively meet the unique needs of the application. In conclusion, the application of the GRA method in industrial robot selection offers a systematic and objective approach to evaluate and rank different robot options based on multiple criteria. By considering various performance factors and their interrelationships, decision-makers can identify the most suitable robot option for a specific application. The GRA method empowers organizations to make informed decisions, ultimately leading to the selection of an optimal industrial robot that enhances productivity, efficiency, and overall success in manufacturing processes.

## REFERENCES


[1]. Xu, Peng, Yinghao Gao, Xiling Yao, Ye Han Ng, Kui Liu, and Guijun Bi. "Influence of process parameters and robot postures on surface quality in robotic machining." *The International Journal of Advanced Manufacturing Technology* 124, no. 7-8 (2023): 2545-2561.

[2]. Yalçin, Neşe, and U. N. C. U. Nuşin. "Applying EDAS as an applicable MCDM method for industrial robot selection." *Sigma Journal of Engineering and Natural Sciences* 37, no. 3 (2019): 779-796.

[3]. Omoniwa, Babatunji. "A solution to multi criteria robot selection problems using grey relational analysis." *International Journal of Computer and Information Technology* 3, no. 2 (2014): 328-332.

[4]. Meike, Davis, Marcello Pellicciari, and Giovanni Berselli. "Energy efficient use of multirobot production lines in the automotive industry: Detailed system modeling and optimization." *IEEE Transactions on Automation Science and Engineering* 11, no. 3 (2013): 798-809.

[5]. Gadaleta, Michele, Giovanni Berselli, and Marcello Pellicciari. "Energy-optimal layout design of robotic work cells: Potential assessment on an industrial case study." *Robotics and Computer-Integrated Manufacturing* 47 (2017): 102-111.

[6]. Meike, Davis, Marcello Pellicciari, and Giovanni Berselli. "Energy efficient use of multirobot production lines in the automotive industry: Detailed system modeling and optimization." *IEEE Transactions on Automation Science and Engineering* 11, no. 3 (2013): 798-809.

[7]. Saravanan, R., S. Ramabalan, and P. Dinesh Babu. "Optimum static balancing of an industrial robot mechanism." *Engineering Applications of Artificial Intelligence* 21, no. 6 (2008): 824-834.

[8]. Shanmugasundar, G., Gaurav Sapkota, Robert Čep, and Kanak Kalita. "Application of MEREC in Multi-Criteria Selection of Optimal Spray-Painting Robot." *Processes* 10, no. 6 (2022): 1172.

[9]. Yao, Cenglin, Yongzhou Li, Mohd Dilshad Ansari, Mohammed Ahmed Talab, and Amit Verma. "Optimization of industrial process parameter control using improved genetic algorithm for industrial robot." *Paladyn, Journal of Behavioral Robotics* 13, no. 1 (2022): 67-75.

[10]. Raja, SA Kalaiselvan R., P. Udayakumar, C. Murugamani, and M. Shanmukhi. "A Novel Framework for Evaluation of Trust in Mobile Adhoc Networks using Flower Pollination Algorithm." *Annals of the Romanian Society for Cell Biology, Volume25, Issue4, Pages17631* 17639 (2021).

[11]. Wu, Yier, Alexandr Klimchik, Stéphane Caro, Benoît Furet, and Anatol Pashkevich. "Geometric calibration of industrial robots using enhanced partial pose measurements and design of experiments." *Robotics and Computer-Integrated Manufacturing* 35 (2015): 151-168.

[12]. Deng, Kenan, Dong Gao, Shoudong Ma, Chang Zhao, and Yong Lu. "Elasto-geometrical error and gravity model calibration of an industrial robot using the same optimized configuration set." *Robotics and Computer-Integrated Manufacturing* 83 (2023): 102558.

[13]. Rambabu, Inaganti, and Yalavarthy Sreekanth. "FUSING CYBERSECURITY, AI, AND EMERGING TECHNOLOGIES IN MEDICAL DEVICES FOR IMPROVED HEALTHCARE." *INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS* 10, no. 4 (2023).

[14]. Ranjith Kumar, A., and A. Sivagami. "Security aware multipath routing protocol for WMSNs for minimizing effect of compromising attacks." *Journal of Network and Systems Management* 27, no. 3 (2019): 573-599.

[15]. Feifei, Liu, and Lin Fei. "Time-jerk optimal planning of industrial robot trajectories." *International Journal of Robotics and Automation* 31, no. 1 (2016): 1-7.

[16]. Yashaswi, Lambu, Sreenivas Mekala, and Maktala Durga Prasad. "Human anomaly detection using deep learning." *Asian Journal of Computer Science and Technology* 12, no. 1 (2023): 35-40.

[17]. Munasinghe, S. Rohan, Masatoshi Nakamura, Satoru Goto, and Nobuhiro Kyura. "Optimum contouring of industrial robot arms under assigned velocity and torque constraints." *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 31, no. 2 (2001): 159-167.

[18]. Şahin, Mehmet. "A Hybrid Multicriteria Decision Approach for Industrial Robot Selection." *Avrupa Bilim ve Teknoloji Dergisi* (2020): 1-9.

[19]. Varma, P. Bharat Siva, Prathap Adimoolam, Yamini Lahari Marna, Anantharamaiah Vengala, VS Divya Sundar, and MVT Ram Pavan Kumar. "Enhancing robust object detection in weather-impacted environments using deep learning techniques." In *2024 2nd International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS)*, pp. 599-604. IEEE, 2024.

[20]. von Stryk, Oskar, and Maximilian Schlemmer. "Optimal control of the industrial robot Manutec r3." *Computational optimal control, International series of Numerical Mathematics* 115 (1994): 367-382.

[21]. Li, Guohong, and Yuanliang Wang. "Industrial robot optimal time trajectory planning based on genetic algorithm." In *2019 IEEE International Conference on Mechatronics and Automation (ICMA)*, pp. 136-140. IEEE, 2019.

[22]. Saravanan, R., S. Ramabalan, and C. Balamurugan. "Evolutionary multi-criteria trajectory modeling of industrial robots in the presence of obstacles." *Engineering Applications of Artificial Intelligence* 22, no. 2 (2009): 329-342.


 

[23]. Kamali, Kaveh, Ahmed Joubair, Ilian A. Bonev, and Pascal Bigras. "Elasto-geometrical calibration of an industrial robot under multidirectional external loads using a laser tracker." In *2016 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 4320-4327. IEEE, 2016.
[24]. Priya, R. "Stress coping mechanisms adopted by banking sector employees for downsize the stress: A study." *IOSR J Busi Mgt* 19 (2017): 13-7.
[25]. Ge, LianZheng, Jian Chen, Ruifeng Li, and Peidong Liang. "Optimization design of drive system for industrial robots based on dynamic performance." *Industrial Robot: An International Journal* 44, no. 6 (2017): 765-775.
[26]. Athawale, Vijay Manikrao, and Shankar Chakraborty. "A comparative study on the ranking performance of some multi-criteria decision-making methods for industrial robot selection." *International journal of industrial engineering computations* 2, no. 4 (2011): 831-850.
[27]. Manikandan, G., D. Karunkuzhali, D. Geetha, and V. Kavitha. "Design of an IoT approach for security surveillance system for industrial process monitoring using Raspberry-Pi." In *AIP Conference Proceedings*, vol. 2519, no. 1, p. 030024. AIP Publishing LLC, 2022.
[28]. Raghunadha Reddy, T., M. Srilatha, M. Sreenivas, and N. Rajasekhar. "Author Profiles Prediction Using Syntactic and Content-Based Features." In *Data Engineering and Communication Technology: Proceedings of 3rd ICDECT-2K19*, pp. 265-273. Singapore: Springer Nature Singapore, 2020.
[29]. Inaganti, Rambabu, and Sreekanth Yalavarthi. "Securing Healthcare Innovations: Cybersecurity Frameworks for FDA-Regulated Medical Devices in the Age of AI." In *AI-Driven Healthcare Cybersecurity and Privacy*, pp. 343-364. IGI Global Scientific Publishing, 2025.
[30]. Mahendiran, A., and R. Priya. "Teachers' Attitude towards the Use of Information and Communication Technologies (ICT): Teachers Perspective in Rural Colleges." *Pacific Business Review International* 13, no. 7 (2021).
[31]. Ravuri, Ananda, R. Josphineleela, G. V. S. Kumar, and T. SathishKumar. "Machine learning-based distributed big data analytics framework for IoT applications." *J. Electr. Syst.* 20, no. 3 (2024): 1788-1802.
[32]. Ragavan, V. K., N. S. Nithya, Anantharamaiah Vengala, Balambigai Subramanian, and C. Ambhika. "Refractive Index Biosensor–Based Detection of Mycobacterium Tuberculosis Using Sea Lion Political Optimizer and Deep Learning." *Plasmonics* (2025): 1-19.
[33]. Panneerselvam, Karthick, K. Mahesh, V. L. Josephine, and A. Ranjith Kumar. "Effective and Efficient Video Compression by the Deep Learning Techniques." *Computer Systems Science & Engineering* 45, no. 2 (2023).
[34]. Arunadevi, R., and G. S. Subashini. "Virtual Teams Effectiveness In The Selected IT Companies In South India." *Journal of Namibian Studies* 38 (2023).
[35]. Kumar, KRN Kiran, and K. Bhavani. "Folded spined cube: new topology in interconnection networks." In *2022 6th International Conference on Computing Methodologies and Communication (ICCMC)*, pp. 314-319. IEEE, 2022.
[36]. Jyothi, P., and G. Pradeepini. "Correction to: Classification of normal/abnormal heart sound recording through convolution neural network through the integration of baseline and AdaBoost classifier." In *Proceedings of the 2nd International Conference on Computational and Bio Engineering: CBE 2020*, pp. C1-C1. Singapore: Springer Singapore, 2022.
[37]. Bogireddy, Srinivasa Rao, and Haritha Murari. "Machine learning for predictive telemarketing: Boosting campaign effectiveness in banking." In *2024 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS)*, pp. 1-6. IEEE, 2024.
[38]. Zhang, Shi-fang, and San-yang Liu. "A GRA-based intuitionistic fuzzy multi-criteria group decision making method for personnel selection." Expert Systems with Applications 38, no. 9 (2011): 11401-11405.
[39]. Ozturkoglu, Yucel, and Ebru Esendemir. "ERP software selection using IFS and GRA methods." Journal of Emerging Trends in Computing and Information Sciences 5, no. 5 (2014): 363-370.
[40]. Gangurde, Sanjaykumar R. "Benchmark the best factory data collection system (FDC) using AHP-GRA method." Benchmarking: An International Journal (2016).
[41]. Maithili, K., T. Sathish Kumar, R. Subha, PL Srinivasa Murthy, M. N. Sharath, Koppuravuri Gurnadha Gupta, Praseeda Ravuri, T. N. P. Madhuri, and Vikas Verma. "Development of an efficient machine learning algorithm for reliable credit card fraud identification and protection systems." In *MATEC Web of Conferences*, vol. 392, p. 01116. EDP Sciences, 2024.
[42]. Nayak, Namitha, Manasa Rayachoti, Ananya M. Gupta, G. P. Prerna, Sreenath MV, and D. Annapurna. "Learning future terrorist targets using attention based hybrid cnn and bilstm model." In *2023 IEEE International Conference on Integrated Circuits and Communication Systems (ICICACS)*, pp. 1-5. IEEE, 2023.
[43]. Bali, Ozkan, Erkan Kose, and Serkan Gumus. "Green supplier selection based on IFS and GRA." Grey Systems: Theory and Application (2013).
[44]. Rajendra Prasad, D., B. Kiran Kumar, and S. Indraneel. "Mobility in wireless sensor networks." In *International Conference on Innovative Data Communication Technologies and Application*, pp. 165-171. Cham: Springer International Publishing, 2019.
[45]. Murugamani, C., S. Shitharth, S. Hemalatha, Pravin R. Kshirsagar, K. Riyazuddin, Quadri Noorulhasan Naveed, Saiful Islam, Syed Parween Mazher Ali, and Areda Batu. "Machine Learning Technique for Precision Agriculture

Applications in 5G-Based Internet of Things." *Wireless Communications and Mobile Computing* 2022, no. 1 (2022): 6534238.
[46]. Maniya, K. D., and M. G. Bhatt. "A multi-attribute selection of automated guided vehicle using the AHP/M-GRA technique." International Journal of Production Research 49, no. 20 (2011): 6107-6124.
[47]. Verma, Rajiv, and Niraj Pratap Singh. "GRA based network selection in heterogeneous wireless networks." Wireless personal communications 72 (2013): 1437-1452.
[48]. Mohan, VakaMurali, MalliKarjuna Reddy, and KRN Kiron Kumar. "A New Approach to Optical Networks Security: Attack-Aware Routing and Wavelength Assignment." In *IJCA Special Issues on "2nd National Conference-Computing, Communication and Sensor Network" CCSN*. 2011.
[49]. Suhasini, S., J. M. SheelaLavanya, M. Parameswari, G. Manikandan, and S. Gracia Nissi. "Input Based Resource Allocation in Motion Estimation using Re-configurable Architecture." In *2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)*, pp. 1091-1095. IEEE, 2021.
[50]. Sreeram, Indraneel, and Venkata Praveen Kumar Vuppala. "HTTP flood attack detection in application layer using machine learning metrics and bio inspired bat algorithm." *Applied computing and informatics* 15, no. 1 (2019): 59-66.
[51]. Yang, Fu, Guang-Ming Zeng, Chunyan Du, Lin Tang, Jiangfei Zhou, and Zongwu Li. "Integrated Geographic Information Systems–Based Suitability Evaluation of Urban Land Expansion: A Combination of Analytic Hierarchy Process and Grey Relational Analysis." Environmental Engineering Science 26, no. 6 (2009): 1025-1032.
[52]. Huszak, A., and Sándor Imre. "Eliminating rank reversal phenomenon in GRA-based network selection method." In 2010 IEEE International Conference on Communications, pp. 1-6. IEEE, 2010.
[53]. Sathiyaraj Chinnasamy, Vimala Saravanan, Nathiya Murali, M. Ramachandran, "Optimization of Welding Process Parameters using the MOORA Method", Building Materials and Engineering Structures, 2(4), December 2024, 9-17.
[54]. Kumar, VV Praveen, Vutukuri Sai Mounika, Bandaru Gayathri, Yelchuri Venkata Sudheshna, Kaki Sandhya, and Gogulapati Glory. "IOT ENABLED REAL-TIME DIGITAL CAMPUS NOTICE BOARD." *International Journal of Engineering Research and Science & Technology* 21, no. 2 (2025): 1307-1316.
[55]. Ullah, Waheed, Muhammad Ibrar, Asghar Khan, and Musa Khan. "Multiple attribute decision making problem using GRA method with incomplete weight information based on picture hesitant fuzzy setting." International Journal of Intelligent Systems 36, no. 2 (2021): 866-889.
[56]. Giri, Animesh, and D. Annapurna. "RPL-Based Hybrid Hierarchical Topologies for Scalable IoT Applications." In *Evolutionary Computing and Mobile Sustainable Networks: Proceedings of ICECMSN 2020*, pp. 421-430. Singapore: Springer Singapore, 2020.
[57]. Agrawal, Vikash K., Srinivasa Rao Bogireddy, Lalit N. Patil, Mahesh Sonekar, Yashraj M. Patil, and Vikas Singh Panwar. "Optimizing Handwritten Character Recognition Systems: Neural Networks vs. Statistical Methods." In *2024 International Conference on Intelligent Systems and Advanced Applications (ICISAA)*, pp. 1-9. IEEE, 2024.
[58]. Koteeswaran, S., N. Malarvizhi, E. Kannan, S. Sasikala, and S. Geetha. "Data mining application on aviation accident data for predicting topmost causes for accidents." *Cluster computing* 22, no. Suppl 5 (2019): 11379-11399.
[59]. Li, Guo-Dong, Daisuke Yamaguchi, and Masatake Nagai. "A grey-based rough decision-making approach to supplier selection." The International Journal of Advanced Manufacturing Technology 36 (2008): 1032-1040.
[60]. JYOTHI, P., and G. PRADEEPINI. "AUTOMATIC CLASSIFICATION OF ECG AND PCG SIGNALS USING CONVOLUTION NEURAL NETWORK FOR DETECTING CARDIOVASCULAR DISEASE." *Journal of Theoretical and Applied Information Technology* 102, no. 21 (2024).
[61]. GS, Subashini, and P. Vijayalakshmi. "A Study on Gender Disparity and Female Agriculture Worker Participation in Decision Making at Thanjavur District." *Journal of the Gujarat Research Society* 21, no. 12 (2019): 1-9.
[62]. Rani, Dr V. Vasudha, D. Vasavi, and K. Kumar. "Significance of multilayer perceptron model for early detection of diabetes over ml methods." *J. Univ. Shanghai Sci. Technol* 23, no. 08 (2021): 148-160.
[63]. VUPPALA, VENKATA PRAVEEN KUMAR, PAZHANIRAJAN SAMBANDAM, and INDRANEEL SREERAM. "An efficient point-of-interest recommendation for LOcation-based social networks system with spatio-temporal model." (2022).
[64]. Malarvizhi, Nandagopal, and V. Rhymend Uthariaraj. "A minimum time to release job scheduling algorithm in computational grid environment." In *2009 Fifth International Joint Conference on INC, IMS and IDC*, pp. 13-18. IEEE, 2009.
[65]. Gogulamudi, Subbarao, V. Mahalakshmi, and Indraneel Sreeram. "A Hybrid Framework Using the Boosting Technique for Efficient Rain Streak Removal During Daylight." In *Inventive Communication and Computational Technologies: Proceedings of ICICCT 2021*, pp. 963-977. Singapore: Springer Nature Singapore, 2022.
[66]. Kumar, T. Sathish, N. P. Gopalan, and R. Rajesh. "Enhance the routing QoS for multimedia streaming using two-hop information in mobile ad hoc networks." *International Journal of Enterprise Network Management* 12, no. 2 (2021): 181-197.
[67]. Sridhar, P., S. Sri Nandhini Kowsalya, M. Venkatasudhahar, T. Sathish Kumar, Amit Gangopadhyay, Koppuravuri Gurnadha Gupta, and G. Manikandan. "Revolutionary building approach for maximal photovoltaic system results to

improve maximum power point tracking in solar inverter." In *MATEC Web of Conferences*, vol. 392, p. 01146. EDP Sciences, 2024.

[68]. Sreeram, Indraneel, and Venkata Praveen Kumar Vuppala. "Voice Enabled ATMS and Deployment of Wavelets for Recognition and Authentication of Voice Based Inputs." *i-Manager's Journal on Computer Science* 4, no. 4 (2016): 25.

[69]. Malarvizhi, N., J. Aswini, S. Sasikala, M. Hemanth Chakravarthy, and E. A. Neeba. "RETRACTED ARTICLE: Multi-parameter optimization for load balancing with effective task scheduling and resource sharing." *Journal of Ambient Intelligence and Humanized Computing* 13, no. Suppl 1 (2022): 75-75.

[70]. Manjula Selvam, Sathiyaraj Chinnasamy, M. Ramachandran, Chinnasami Sivaji, "Assessing the Growth and Challenges of Istanbul's Technology Sector: A Comparative Analysis of Key Industry Players", Journal on Innovations in Teaching and Learning3(4), December 2024, 21-29.

[71]. Cheekati, Venkateswararao, D. Natarajasivan, and S. Indraneel. "Ensemble approaches can aid in the early detection of coronary heart disease." (2021): 12224-12239.