



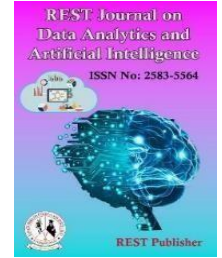
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Industrial Robot Selection: Key Considerations and Best Practices

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Abstract: Businesses looking to increase productivity and efficiency in their manufacturing processes must carefully consider their industrial robot choices. With so many alternatives available, selecting the best robot necessitates careful consideration of a number of variables. Examining factors including payload capacity, reach, precision, speed, and the range of programming possibilities are part of this process. Additionally, it is necessary to evaluate the cost-effectiveness of a solution and its suitability for the application in question. Manufacturers may choose industrial robots with confidence by carefully examining these factors and matching them with production objectives and integration capabilities. This guarantees that the robots selected will meet their special requirements, resulting in improved operational success. The potential for improving production processes and promoting operational excellence makes research on industrial robot selection important. Choosing the correct industrial robot is essential for maximizing productivity, efficiency, and overall business performance as automation becomes more widely adopted in various industries. Manufacturers can learn more about the numerous aspects that affect the choice of a robot through systematic research, including payload capacity, reach, accuracy, speed, programming possibilities, application requirements, workspace restrictions, safety considerations, and cost-effectiveness. Enterprises should strategically invest in industrial robots that meet their unique demands by being aware of the importance of these variables and taking well-informed decisions. This will improve production outcomes, lower costs, improve quality, and provide enterprises a competitive edge in the market. A methodical technique is used to find and assess the best robot for a given application as part of the industrial robot selection process. A detailed study of the application requirements, including the required activities, performance standards, and environmental considerations, usually comes first in the process. Following that, a list of potential robots is created based on how well they match the specified requirements. Each robot is evaluated based on a number of factors, including load capacity, maximum tip speed, memory capacity, manipulator reach, repeatability, and cost of purchase. The relative weight of these requirements can be determined. To rank and choose the best robot, a variety of multi-criteria decision-making (MCDM) strategies can be used, including the Weighted Sum Method (WSM), Weighted Product Model (WPM), and Analytic Hierarchy Process (AHP). To guarantee a thorough evaluation, input from experts, stakeholders, and end users is essential throughout the technique. Following examination and evaluation of the criteria, the process is completed by choosing the industrial robot that will provide the best performance and efficiency for the desired application. IR1, IR2, IR3, IR4, IR5, IR6, IR7 Maximum tip speed, memory capacity, manipulator reach, repeatability, and cost of procurement. From the result it is seen that IR2 stands on the top of the table by securing the 1st rank which was acquired by using TOPSIS method. The first ranking is obtained by having the highest C_i value.

Keywords: TOPSIS, robot, MCDM, VIKOR, Fuzzy relation

1. INTRODUCTION

The impact that industrial robot selection has on enhancing manufacturing procedures and businesses' overall competitiveness is what gives this topic study significance. Making the appropriate robot selection for their unique applications is essential for manufacturers as the use of robots in modern manufacturing systems increases. Robots are highly sought after for a variety of industrial jobs due to their precision capacity to do repetitive, challenging, and dangerous operations. However, given the large range of robot capabilities and specifications available, the choosing process can be difficult. The choice of a robot can have a negative impact on output and product quality. In light of aspects like product design, production system needs, and economic concerns, doing research in industrial robot

selection aids manufacturers in making wise judgements. Companies may increase productivity, improve product quality, and keep a competitive edge in the market by choosing the best robot.[1] In the context of selecting robots, this study aims to evaluate the robustness of six commonly used multi-criteria decision-making (MCDM) techniques. The methods chosen for the investigation include the weighted sum method (WSM), weighted product model (WPM), weighted aggregated sum product assessment (WASPAS), multi-objective optimization based on ratio analysis and reference point approach (MOORA), and the multiplicative form of MOORA method (MULTIMOORA). The main goal is to assess the performance and behavior of these techniques when the weights of the most important criteria are altered. The study calculates the local and global weight stability intervals for each approach by conducting both single-dimensional and high-dimensional weight sensitivity assessments. Finding the most sensitive and trustworthy MCDM approaches for real-time robot selection is the ultimate goal.[2] Extensive research in the field of industrial robot selection has led to the development of various procedures and methods for decision-making. Researchers have explored numerous techniques including TOPSIS, DEA, genetic algorithms, weighted sum models, AHP, dimensional analysis, fuzzy TOPSIS, QFD, common weight MCDM, digraph and matrix methods, hierarchical fuzzy TOPSIS, fuzzy digraph method, VIKOR, ELECTRE II, distance-based approaches, and hybrid decision-making techniques. These methods have focused on diverse aspects such as user requirements, technical specifications, robot performance factors, and the integration of subjective and objective criteria. The objective has been to optimize evaluation, selection, and ranking of robots, while considering priorities, visualization, uncertainty, changing demands, relative efficiency, and user preferences. This study contributes to the enhancement of knowledge and the development of effective strategies for industrial robot selection. These approaches provide valuable insights and practical tools to assist decision-makers in making informed choices based on specific needs, limitations, and objectives of their industrial applications. Manufacturers can benefit from employing a range of factors and decision-making approaches to select the most suitable robots, thereby enhancing productivity, competitiveness, and product quality.[3] The significance of considering various aspects such as payload capacity, reach, precision, speed, programming options, application requirements, workspace restrictions, safety considerations, and cost-effectiveness when selecting an industrial robot has been highlighted in previous research. Diverse strategies have been put forth by researchers to assist in the selection of robots. To find robots with the optimum mix of vendor specs, Agrawal et al. recommended utilising the TOPSIS approach and an expert system, whereas Khouja used data envelopment analysis (DEA) and a multi-attribute decision-making approach. The weighted sum decision model was improved by Goh et al. by including both objective and arbitrary attributes. Other academics have investigated methods for robot selection, taking into account a variety of characteristics and preferences, including fuzzy TOPSIS, analytic hierarchy process, quality function deployment, and genetic algorithms. The value of this research lies in its ability to simplify the robot selection process and empower manufacturers to make well-informed decisions based on their specific requirements and limitations. By utilizing these approaches, companies can optimize their manufacturing processes, increase productivity, and enhance product quality. Moreover, appropriate robot selection can lead to higher output, cost reduction, and enhanced competitiveness in the manufacturing sector. To address the limitations of earlier approaches, a recommended paradigm was proposed, which involved economic modeling to assess different robotic systems under uncertainty. This thorough analysis included estimations of the entire net present values of the cash flows from investments, labour components, and overheads, allowing for a more in-depth assessment of the options. Off Odile et al. used a coding and classification system to capture robot attributes in a database and created an efficient retrieval and selection system based on economic modelling. However, this method may be more suitable for the final selection phase rather than the initial selection phase when numerous potential robots need to be considered. Imang and Schlesinger provided robot selection choice models and compared linear goal programming and ordinary least squares approaches. These models offered decision-makers more options to consider and incorporated both objective and subjective aspects. However, Agrawal et al. focused primarily on objective aspects in their TOPSIS-based study, leaving room for future research to explore subjective elements. The proposed methodology aims to enhance robot selection by incorporating economic modeling, subjective aspects, and a broader range of criteria, enabling more informed and comprehensive decision-making in the face of ambiguity.[4] Industrial robots play a crucial role in various industrial applications due to their programmability and adaptability. Apart from their mechanical arm, they possess decision-making capabilities, environmental responsiveness, and the ability to communicate with other robots. They can now carry out jobs like material handling, assembly, finishing, loading, painting, and welding thanks to these developments. Several essential qualities should be taken into account when choosing an industrial robot for a particular application. The necessary attributes are control resolution, accuracy, repeatability, load capacity, degrees of freedom, man-machine interface, programming flexibility, tip speed, memory capacity, and supplier service level. These attributes can be classified as objective or subjective, advantageous or disadvantageous. Subjective features, such as service quality or programming flexibility, are qualitative, while objective attributes, like cost and load capacity, are quantitative. Desired attributes are those with higher values that provide benefits, while non-beneficial

attributes are preferred to have lower values. Decision-makers must strike a compromise between these qualities and the robot's performance indicators when choosing an industrial robot. Numerous selection methods for robots, including multi-criteria decision-making techniques, performance optimization models for production systems, computer-assisted models, and statistical models, have been developed by researchers. These methods aid in making well-informed decisions that align with the specific requirements of the application and enhance overall performance.[5] Significant improvements have been made in the field of precision-based robot selection methods, particularly in the use of multi-criteria decision-making (MCDM) models. Researchers have put forth a number of robot selection strategies, each giving distinctive procedures and methods. The ELECTRE and VIKOR techniques, for instance, were introduced by Chatterjee et al. (2010) and can be used to evaluate and rank robots based on a variety of factors. For robot selection, Kumar and Garg (2010) proposed a distance-based approach (DBA). A novel fuzzy-based decision-making strategy that takes into account both objective and subjective preferences was created by Rao et al. in 2011. Using the FAHP approach, Iç et al. (2013) developed the robot selection decision support system (ROBOSEL). For robot selection, Rashid et al. (2014) used TOPSIS and generalized interval-valued fuzzy numbers. For robot evaluation and selection, Liu et al. (2014) suggested an interval 2-tuple linguistic MCDM method. Fuzzy MCDM was used by Parameswaran et al. (2015), taking both objective and subjective elements into account. For robot evaluation and selection, Ghorabae (2016) used the VIKOR technique with Interval Type-2 Fuzzy sets. These are only a few instances of the different robot selection systems that have been developed, each of which offers its own procedures and ways for reaching judgement calls.[6] The main goal of this study is to provide the Evaluation based on Distance from Average Solution (EDAS) method as a useful multi-criteria decision-making (MCDM) approach for robot selection problems (RSPs). The EDAS approach has proven successful in a number of engineering applications since it was first created by Keshavarz Ghorabae et al. for multi-criteria inventory ABC categorization. The EDAS method analyses choices based on their divergence from the average solution, in contrast to other MCDM techniques like VIKOR and TOPSIS. It utilizes positive distance from average (PDA) and negative distance from average (NDA) metrics, where higher PDA values and lower NDA values indicate better solutions. The research aims to demonstrate the suitability of the EDAS method for selecting industrial robots by comparing its results with other MCDM and related approaches used in similar RSPs. The paper includes a literature overview in Section 2, discussing various MCDM techniques applied to industrial robot selection. Section 3 presents the EDAS method, its calculation procedures, and its application as an MCDM tool. Section 4 offers a comparison between the EDAS approach and other relevant methods through four robot selection examples.[7] In the context of robot selection decisions, it is common for a committee or group of specialists with diverse backgrounds and expertise to be involved. However, reaching a consensus among these specialists can be challenging due to their different technical knowledge and perspectives. Moreover, the selection of a robot can have significant implications for a company, as it involves a substantial investment and can impact productivity and product quality. To address the complexities of multiple criteria robot selection problems (MCRSP) and leverage the expertise of the group, the use of a Group Decision Support System (GDSS) is both reasonable and significant. A GDSS provides a structured framework and tools to support the decision-making process in MCRSP, specifically tailored to the unique characteristics of industrial robot selection decisions. It enables the team of experts to systematically evaluate and compare different robots based on various factors. Through a GDSS, experts can collaborate, exchange knowledge and ideas, and collectively select the best robot for the given context. The GDSS facilitates the integration of preferences and viewpoints from different specialists, helps resolve conflicts or disagreements, and enables the group to reach a consensus that represents the overall assessment of the experts. This approach enhances the decision-making process, increasing the likelihood of selecting a robot that meets the diverse needs and concerns of the experts while aligning with the financial and operational goals of the business. In summary, employing a GDSS for MCRSP enables efficient group decision making, taking into account the unique characteristics of industrial robot selection decisions and the importance of expert agreement. It provides a systematic and collaborative approach to address the multiple factors and significant implications associated with robot selection.[8] The study by Bhangale et al. (2004) sought to compile all pertinent data into a comprehensive database of robot manipulators. In an effort to standardize the robot selection process for particular processes, this database acted as a trustworthy resource for decision-makers. The authors concentrated on offering a reliable and standardised method to help decision-makers assess and select the best industrial robots for their unique requirements. To assess various industrial robots, Rao and Padmanabhan (2006) created a method based on digraphs and matrix techniques. They suggested an index that would allow for the ranking and assessment of different robots when choosing which ones to use in particular industrial applications. This strategy enabled logical comparisons and gave decision-makers a structure for the robot selection process. To evaluate and choose various robots, Kumar and Garg (2010) proposed a deterministic quantitative model based on a distance-based method in their work. To discriminate between critical and non-critical robot performance characteristics, they also carried out sensitivity analysis. Making educated decisions was made easier thanks to this study, which revealed how many

attributes affected the robot's overall performance. Athawale et al. (2010) used the VIKOR (Vise Kriterijumska Optimizacija Kompromisno Resenje) methodology, a compromise ranking system that takes a number of aspects into account, to address the robot selection challenge. Thanks to this study, which showed how many factors impacted the robot's overall performance, making informed judgements became simpler. The robot selection difficulty was addressed by Athawale et al. (2010) using the VIKOR (Vise Kriterijumska Optimizacija Kompromisno Resenje) technique, a compromise ranking system that takes a number of factors into account. To demonstrate and verify the suitability and efficacy of these MCDM strategies in the context of robot selection, authors provided real-world examples. These studies show how several MCDM strategies, such as VIKOR, ELECTRE, and distance-based methods, can be used to tackle the robot selection problem. Each method gives a unique way to evaluate and rate various robots, aiding decision-makers in choosing the best choice depending on their particular industrial needs. [9] The study project discussed in this context tries to address a topic left unaddressed by the previously stated studies: choosing a robot or robotic system in light of customer requirements. The objective is to create a reliable technique that takes into account both technical and customer needs during the selection process. The simplicity of the suggested method and its capacity to take into account technical needs, client requirements, and the financial elements of robot systems are its distinguishing features. The Analytic Hierarchy Process (AHP) and Quality Function Deployment (QFD) are combined in the integrated solution for the industrial robot-selection problem presented in this paper. By determining the degree of relative relevance for those needs, AHP is utilised to prioritise client requirements. Then, using QFD, these priorities are transformed to establish the relative and normalised priority levels for each technical requirement. This process assists in building the robot selection model. An overall score is calculated for each robot by taking into account a number of factors, some of which may be at odds. The decision-maker can choose the best robot or robotic system based on this score if it meets the specified standards. The combined strategy of AHP and QFD enables a thorough evaluation procedure that combines both technical The uniqueness of this research is in its capacity to offer a simple methodology that takes into account economic, consumer, and technological needs when choosing a robot. It provides a useful and efficient method for helping decision-makers make well-informed decisions based on various factors and competing priorities. The study also presents a straightforward and original method for incorporating economic considerations into the choice of robots. [10] Since the first robot, Unimate, was introduced in 1961, the field of industrial robotics has seen substantial changes. Industrial robots, which were first used by General Motors, have developed into reprogrammable multifunctional manipulators that are capable of carrying out a variety of activities like material handling, part assembly, and tool manipulation. Modern manufacturing organisations are increasingly using industrial robots as a result of ongoing technological developments, such as the introduction of artificial intelligence and new functionality. Robotics and other modern manufacturing technologies must now be implemented by manufacturing companies in order to remain competitive in today's high-tech world. Precision, cost-effectiveness, and the capacity to create high-quality goods are all benefits of industrial robots. However, incorporating industrial robots into a manufacturing system successfully is challenging. An in-depth knowledge of the available options and the identification of important features that are essential for robot selection are required for the selection, evaluation, and economic justification of an industrial robot for a particular application. The process of choosing an industrial robot has grown complicated and time-consuming as a result of manufacturers including numerous technological characteristics. It is crucial to take into account elements including the robot's capabilities, technological developments, compatibility with current systems, and affordability. Manufacturers and decision-makers must have a thorough understanding of the various robot alternatives and their individual features in order to address these issues. They must also determine the key criteria for choosing a robot based on the particular demands of their applications. To make educated decisions, this process requires carefully assessing, contrasting, and analysing the options. In conclusion, the use of industrial robots in modern manufacturing organisations has become crucial, and their selection and integration into manufacturing systems necessitate a full grasp of the options available and evaluation of numerous qualities. Despite the challenges, using industrial robots in production processes has many advantages that make the effort worthwhile. [11] You have provided a comprehensive overview of the challenges faced by modern manufacturing organizations in selecting the appropriate industrial robot. The complexity of available options and the integration of advanced features by diverse manufacturers make the decision-making process more difficult. The consequences of improper robot selection can have a negative impact on a company's competitiveness, affecting production efficiency and product quality. Decision-makers must take into account a variety of elements, such as subjective and objective considerations, cost-related concerns, and beneficial features, in order to meet these problems. The performance metrics of the robot must be balanced with these parameters. The use of optimization models, computer-aided models, statistical models, and multi-criteria decision-making (MCDM) methodologies are just a few of the techniques researchers have proposed to assist in robot selection. By taking into account several characteristics and performance indicators that are in line with the particular requirements of the industrial application, these strategies seek to assist decision-makers in making wise decisions. In the end, the strategy selected will depend on the

particular requirements and characteristics of the current robot selection challenge. Decision-makers may improve their decision-making process and choose the best industrial robot to optimise productivity and product quality by utilising the proper tactics and approaches.[13].

2. MATERIALS & METHODS

Industrial robot selection: To ensure optimum performance and efficiency in manufacturing operations, industrial robot selection is a crucial step that needs careful thought. There are several things to consider while choosing an industrial robot. These include the ability to meet different production demands and the payload capacity, reach, speed, precision, and flexibility. A robot's end-of-arm tooling alternatives, like as grippers or welding gear, must also work with the robot of choice. In addition, important considerations include cost, maintenance needs, and programming simplicity. It is crucial to assess the robot's dependability, safety features, and infrastructure compatibility. Increased productivity, better product quality, and higher operational success are all benefits of a well-informed choosing process.

Load capacity: Payload Capacity: The utmost weight that a robot can carry without jeopardizing its performance and safety is referred to as the payload capacity. The payload capacity of the robot must be matched by the weight of the components or things it will be operating. Selecting a robot with a lesser payload capacity could result in inefficiency or even harm to the robot or the objects it is handling, while selecting one with a higher payload capacity than necessary could result in excessive costs. Depending on whether the load is dynamic or static, industrial robots may have varied load capacity requirements. Static loads are motionless or move very little, whereas dynamic loads move continuously or accelerate.

Maximum tip speed: The fastest it can tip, or maximum tip speed, is a crucial factor to take into account when choosing an industrial robot. The linear velocity at the end of the robot's tool or end effector is referred to as the "tip speed." When dealing with applications that demand quick and accurate motions, like pick-and-place procedures or assembly jobs, it is a crucial aspect. A robot's capacity to complete tasks quickly and effectively depends on its maximum tip speed. For optimum efficiency and productivity, it is crucial to align the robot's maximum tip speed with the demands of the particular application. In manufacturing processes, selecting a robot with a higher maximum tip speed might result in shorter cycle times and higher throughput.

Memory capacity: Another crucial aspect to take into account when choosing an industrial robot is memory capacity. The quantity of internal storage that can be used to store programmer, instructions, and data is referred to as the memory capacity. A greater memory capacity enables the robot to accomplish a wider range of activities by storing more intricate and elaborate programs. It's critical to evaluate the memory needs of the individual applications and ascertain whether the robot's memory capacity can support the programming requirements. A robot's ability to handle complex jobs or various program me variants may be limited by a lack of memory, which can result in inefficiencies and the necessity for repeated programme transfers or adjustments. A sufficient amount of memory allows for flexible programming of the robot for various manufacturing processes and assures smoother operation.

Manipulator reach: When choosing an industrial robot, the manipulator reach is a key aspect to take into account. The robot's arm's reach is the furthest it can extend from its base to reach work locations. For the robot to successfully reach and control objects inside of its defined workspace, it must have a long enough reach. It is crucial to assess the particular application needs and take into account elements like the size and structure of the work area, the placement of the objects that must be handled, and any potential stumbling blocks or restrictions. By selecting a robot with an adequate reach, you can prevent the requirement for extra robot repositioning or productivity loss because of a robot's low reach.

Repeatability: When choosing an industrial robot, repeatability is an important factor to take into account. It describes the robot's capacity to precisely and repeatedly return to a given location or move along a predetermined path. The greatest positional variation a robot can obtain while repeating the same task is used to gauge its repeatability. For applications requiring accurate positioning, such as assembly, welding, or inspection operations, high repeatability is essential. A robot with good repeatability provides accurate and constant performance, eliminating errors, cutting down on waste, and raising product quality. It's critical to compare the repeatability needs of various robots and pick one that satisfies the application's precise requirements.

Purchase cost: When choosing an industrial robot, the cost of the purchase is a crucial aspect to take into account. The purchasing price includes the initial outlay needed to buy the robot and any extra parts or accessories. Analyzing the cost in light of the budget and the anticipated return on investment is crucial. Although it may be tempting to choose the choice with the lowest cost, it is important to take the long-term effects into account. Cheaper robots might not be as effective, dependable,

or future-proof as more expensive ones. Finding a robot that gives the required features, capabilities, and support while still falling within the budgetary limits requires striking a compromise between cost and quality

3. TOPSIS METHOD

The work expands on the original TOPSIS technique by introducing the M-TOPSIS modified synthetic assessment method. The "optimised ideal reference point" concept is incorporated into M-TOPSIS to calculate the separations between alternatives and the reference point in the D+ D- plane. M-TOPSIS offers enhancements by resolving some shortcomings of the original TOPSIS method, such as rank reversals and assessment failure. The introduction of the optimised ideal reference point, which tries to offer a more logical framework for assessing alternatives, is one important aspect of the M-TOPSIS technique. Another benefit of the M-TOPSIS technique is its simplicity. M-TOPSIS' computation method and underlying idea are simple to follow and comprehend. Because of its simplicity, the approach is usable and available to decision-makers. The proposed M-TOPSIS method offers a modified approach to synthetic assessment by variously altering the original TOPSIS method. It is a potentially useful tool for decision-making in a variety of sectors due to its simplicity and reasonable procedure.[1] Indeed, the TOPSIS approach is not without its limitations and criticisms. Some of the primary objections to the TOPSIS approach include: Rank reversal phenomenon: The TOPSIS method, like the Analytic Hierarchy Process (AHP), may exhibit rank reversal, where the order of alternatives changes when criteria or alternatives are added or removed. This suggests that the relative importance or weights of criteria may not be consistently maintained when modifications are made to the decision problem. Disregard for relative significance of distances: TOPSIS seeks to identify the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) as compromise ideal solutions. However, the ranking calculation in TOPSIS does not consider the relative weights or importance assigned to these two distances. This can introduce bias into the ranking results. Ignoring correlation between criteria: The TOPSIS approach calculates distances between alternatives and ideal solutions using the Euclidean distance, without considering the correlation between criteria. This oversight can lead to issues when there is information overlap or interdependence among criteria, potentially affecting the TOPSIS results. These criticisms highlight some weaknesses of the TOPSIS approach and indicate areas for improvement. Researchers have developed various modifications and variants of the TOPSIS technique, such as the mentioned M-TOPSIS, to address these drawbacks and provide more reliable decision-making frameworks.[2] Among MCDM techniques, the TOPSIS method has grown significantly in popularity, and many academics have used and adapted it to address a variety of issues in several fields. The TOPSIS method's growing applications and development patterns mirror the general development trends of MCDM approaches in dealing with both straightforward and challenging decision-making issues. A comprehensive assessment is required to compile recent advancements in this field given the growing corpus of research on the TOPSIS approach and its different variants. While earlier studies have used TOPSIS and fuzzy TOPSIS for criteria identification, ranking, and evaluation, they might not be up to date with the most recent developments. Consequently, it is crucial to undertake a thorough investigation that takes into account recent advancements and new changes. While the current inquiry focuses on specific articles proposing improvements and adjustments to the TOPSIS approach, it is important to keep in mind that there may be additional pertinent research that have used the TOPSIS technique but are not covered in this specific investigation. In order to contribute to the ongoing progression in the field of MCDM, the paper's goal is to present an overview of recent innovations and improvements in the TOPSIS technique.[3] The research proposes a novel direct approach to extend the TOPSIS method, enabling it to handle interval data. In this approach, the ratings of alternatives concerning criteria are expressed as intervals rather than precise values. Unlike alternative methods, this direct interval extension avoids making heuristic assumptions and imposing constraints.. The authors substantiate, through numerical examples, that the ranking of alternatives can exhibit significant differences compared to the results obtained using existing techniques. The direct interval extension proposed in the research offers a new perspective and evaluation of alternatives by eliminating heuristic assumptions and restrictions. Other interval extension methods often rely on heuristic approaches to determine the positive and negative ideal solutions, which may involve using real values or intervals that are unattainable within the decision matrix. However, this approach contradicts the fundamental principles of the traditional TOPSIS method. In conclusion, the research presents a new approach for incorporating interval data into the TOPSIS algorithm, offering a distinct perspective on evaluating alternatives without relying on heuristic assumptions and restrictions.[4] The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was first introduced by Hwang and Yoon in 1981 as a practical method for resolving multi-attribute decision-making problems with a constrained number of options. The fundamental idea of TOPSIS is to rank the alternatives according to how far away they are from the ideal and the undesirable answer, so determining the best option for making decisions. Because it is straightforward, simple to learn, and easy to incorporate with other approaches, TOPSIS has grown in popularity. It has been widely used in a variety of industries, including risk management, sustainable development, water resource management, and renewable energy. Numerous academics have recently expanded and improved the TOPSIS approach theoretically from various angles. In order to strengthen the theoretical basis of TOPSIS, some of these extensions entail combining fuzzy and grey number theory, swapping the Euclidean distance for vertical distance, or Mahalanobis distance. Choosing the attribute weights, which affects the final ranking of alternatives,

is a crucial stage in the TOPSIS technique.[5] The TOPSIS approach has been used in a variety of areas of life. It has been applied to the management and decision-making of energy [3–7]. For clinic selection, disease diagnosis, and identification in medicine, TOPSIS has been used [2, 8–10]. For process optimization and equipment selection, TOPSIS has been used in engineering and industrial systems [11–16]. Risk assessment and environmental impact assessments have benefited from TOPSIS in the safety and environmental areas [17–22]. For process design and selection, chemical engineering has used TOPSIS [5, 23, 24]. Studies on water resources have used TOPSIS to manage water and allocate resources [5, 19, 23, 25]. In order to solve particular issues and incorporate fuzzy or ambiguous data, researchers have additionally expanded upon and modified the TOPSIS approach. While Zulqarnain et al. created a graphical model for clinic selection, Chen and Hwang proposed a novel model for TOPSIS [26]. For collective decision-making in a fuzzy context, Chen extended TOPSIS [28]. Numerous other researchers have also improved TOPSIS for making decisions in ambiguous situations [3, 4, 18, 19, 25, 29–35, 6, 8, 11–15, 17, and many more].The application of TOPSIS in decision-making has been further improved by the use of interval numbers and generalised interval-valued fuzzy soft matrices (IVFSM) [36, 37, 38–40]. As an illustration, TOPSIS with fuzzy data has been used to project the likelihood of success for pancreatic transplantation [8]. In order to enhance decision-making processes and overcome numerous issues brought on by ambiguity and complexity, TOPSIS has generally been widely used and extended in several sectors.[6] The literature review indicates that the majority of existing TOPSIS algorithms, with the exception of Triantaphyllou and Lin's fuzzy TOPSIS technique, generate crisp relative closeness values. However, when working with fuzzy weights and fuzzy ratings, it is believed that the relative closeness should also be fuzzy to capture the entire range of potential outcomes in a fuzzy MCDM situation. Crisp relative closeness values provide only a single solution and do not represent the full spectrum of options. While Triantaphyllou and Lin's fuzzy TOPSIS approach does offer fuzzy relative closeness values, it is worth noting that these values can be exaggerated and distorted due to the inherent characteristics of fuzzy arithmetic operations. The study addresses this issue and provides a numerical example illustrating the problem in Section 5.. Therefore, there is a need to develop a precise fuzzy TOPSIS approach that can effectively handle fuzzy MCDM problems.To address this need, the study suggests a fuzzy TOPSIS technique based on alpha level sets and the concept of fuzzy extension. The problem is formulated as a nonlinear programming (NLP) problem using the proposed approach, which can be solved using software programs such as LINGO or Microsoft Excel Solver.In conclusion, the study proposes a novel fuzzy TOPSIS approach that incorporates fuzzy relative closeness values to better handle fuzzy MCDM problems. This approach provides a more comprehensive and accurate evaluation of alternatives compared to existing techniques.[7] TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a well-known technique for multiple attribute decision making (MADM) developed by Hwang and Yoon. The core concept of TOPSIS is to select the option that is closest to the ideal solution on the positive side and farthest from the ideal solution on the negative side. This technique has been extensively studied in the literature and applied in various fields. Researchers have expanded the TOPSIS approach to address different decision-making problems. For instance, Lai et al. utilized the TOPSIS idea to solve multiple-objective decision-making (MODM) problems. Abo-Sinna and Amer extended the TOPSIS approach to handle complex nonlinear programming problems with multiple objectives.Opricovic and Tzeng compared the VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) and TOPSIS methodologies. VIKOR is a ranking strategy that aims to balance the opponent's regret and the majority's utility by maximizing the former while minimizing the latter. They also introduced a multicriteria ranking index based on the concept of proximity to the perfect solution. Jahanshahloo et al. developed an algorithmic approach to extend TOPSIS for decision-making problems involving interval data. Yang and Hung investigated the application of TOPSIS and fuzzy TOPSIS in plant layout design. The main difference between TOPSIS and fuzzy TOPSIS lies in the rating approach.Overall, TOPSIS has been widely studied and applied in various decision-making contexts. Researchers have expanded and compared the TOPSIS approach, leading to the development of variations and adaptations to address different types of problems.[8] The authors of the paper emphasize the need for evaluation techniques that are appropriate for assessing the competitiveness of the Chinese high-tech industry, considering the mutual interference among evaluation indicators. While the TOPSIS approach is recognized as a valuable tool for multiple criteria decision making (MCDM), the authors point out a limitation in the conventional TOPSIS method.The conventional TOPSIS method treats the indicators as independent and uses the Euclidean measure of distance to make decisions, without considering their mutual disruption. This can lead to information overlap and potentially result in overestimated or underestimated indicators that take into account slack information.To address this limitation, the authors propose an improved method that considers the mutual interference among evaluation indicators. By incorporating this consideration, the authors aim to provide a more accurate and realistic assessment of the competitiveness of the Chinese high-tech industry.[9] The paragraph provides an overview of the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) approach in multi-attribute or multi-criteria decision making (MADM/MCDM). It highlights the advantages of TOPSIS, such as considering both positive and negative aspects, comparing alternatives based on multiple criteria, and emulating human decision-making.However, the paragraph also mentions two limitations of the TOPSIS approach. First, the normalization process in TOPSIS can lead to small differences in performance measurements, which may not adequately reflect the true dominance of alternatives and affect proper ranking. Second, TOPSIS does not incorporate risk assessment, failing to consider the decision-maker's risk tolerance or preferences.To address these limitations, the paragraph

suggests using fuzzy values or interval values to handle ambiguous data and incorporate subjective human judgments. It mentions the application of fuzzy TOPSIS or extended TOPSIS in various fields, including supply chain management, alternative ranking, and plant layout design.[10] The paragraph states that the primary focus of the study is to evaluate the reliability of the TOPSIS method for multi-criteria decision-making (MCDM). The effectiveness of the approach is assessed by comparing the results obtained from the TOPSIS method with the findings of Celen (2014). An example is provided as evidence to demonstrate the robustness of the assessment method. While the current study focuses on the TOPSIS method, the researchers plan to expand their investigation in the future. They aim to incorporate additional MCDM techniques such as the simple additive method, ELECTRE, and others. Simulations will be conducted to generalize the findings and determine the best normalization approach for each method. The ultimate goal is to provide a comprehensive understanding of the optimal normalization strategy for various decision-making approaches by extending the study to other MCDM methods and utilizing simulations.[11] The paragraph provides an overview of the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) technique, which is a well-known method in the field of Multiple Criteria Decision Analysis/Multiple Criteria Decision Making (MCDA/MCDM). The TOPSIS technique, developed by Hwang and Yoon, aims to identify the optimal option that achieves a balance between proximity to the positive ideal solution and distance from the negative ideal solution. In TOPSIS, the positive ideal solution represents values that maximize profit criteria and minimize cost criteria, while the negative ideal solution represents the opposite. These ideal solutions are determined based on the attainable values of the criteria. A decision matrix is constructed using the scores obtained for each alternative across all criteria, and then a normalized decision matrix is created. The preference order of the alternatives is determined by calculating the distances between each alternative and both the positive and negative ideal solutions. The option that is closest to the positive ideal solution and farthest from the negative ideal solution is considered the most preferable in TOPSIS. This technique is designed to handle real-world decision problems by taking into account multiple factors simultaneously. It provides a valuable tool for decision-making processes that require balancing different elements and making optimal choices [12]. The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) approach is applied in this work to evaluate the effectiveness of competing shopping websites. The Multiple Attribute Decision Making (MADM) problem with multiple choices is modeled as an n-dimensional geometric system with m points using the TOPSIS approach. The goal of the TOPSIS technique is to find the alternative that is both the furthest away from the negative-ideal solution and the closest to the positive-ideal solution. To aid in decision-making, the TOPSIS technique introduces two new indices: similarity to the positive-ideal solution and distance from the negative-ideal solution. The fuzzy TOPSIS technique is utilized to address the challenge of providing accurate performance evaluations for the attributes being considered. Instead of precise numbers, fuzzy numbers are employed in this method to represent relative values for the attributes. The fuzzy TOPSIS technique is particularly valuable for handling group decision-making problems in a fuzzy environment. Fuzzy theory is the foundation upon which fuzzy TOPSIS is based, with earlier research by Wang and Chang, Büyüközkan, Feyzioglu, and Nebol, as well as Ashtiani, Haghhighirad, Makui, and Montazer being drawn upon. The study's adaptation of the TOPSIS technique to a fuzzy environment enables decision-makers to rate and evaluate shopping website alternatives in scenarios including group decision-making. The fuzzy technique draws on theoretical underpinnings from earlier research in the subject and uses fuzzy numbers to represent the relative weights of qualities while accounting for the imprecision of performance ratings.[13].

4. RESULT AND DISCUSSION

TABLE 1. Industrial robot selection

Robot	DATA SET					
	Load capacity	Maximum tip speed	Memory capacity	Manipulator reach	repeatability	Purchase cost
IR1	60.000	2540.000	500.000	990.000	0.421	77.000
IR2	6.350	1016.000	3000.000	1041.000	0.151	8.200
IR3	6.800	1727.200	1500.000	1676.000	0.121	9.500
IR4	10.000	1000.000	2000.000	965.000	0.224	14.800
IR5	2.500	560.000	500.000	915.000	0.142	5.600
IR6	4.500	1016.000	350.000	508.000	0.084	7.100
IR7	3.000	1778.000	1000.000	920.000	0.124	7.400

Table 1 shows the Industrial robot selection using the Analysis Method Alternative: IR1, IR2, IR3, IR4, IR5, IR6, IR7 and Evaluation parameters load capacity, top tip speed, memory capacity, manipulator reach, repeatability, and cost of purchasing.

TABLE 2. Normalized Data

	Normalized					
robot	load capacity	maximum tip speed	memory capacity	manipulator reach	repeatability	purchase cost
IR1	0.9705	0.6355	0.1217	0.3557	0.7593	0.9594
IR2	0.1027	0.2542	0.7304	0.3740	0.2723	0.1022
IR3	0.1100	0.4321	0.3652	0.6022	0.2182	0.1184
IR4	0.1618	0.2502	0.4869	0.3467	0.4040	0.1844
IR5	0.0404	0.1401	0.1217	0.3288	0.2561	0.0698
IR6	0.0728	0.2542	0.0852	0.1825	0.1515	0.0885
IR7	0.0485	0.4449	0.2435	0.3306	0.2236	0.0922

Table 2 shows the Normalized Data for Alternative: IR1, IR2, IR3, IR4, IR5, IR6, IR7 and Evaluation parameters is loading capacity, top tip speed, memory capacity, manipulator reach, repeatability, and cost of purchasing.

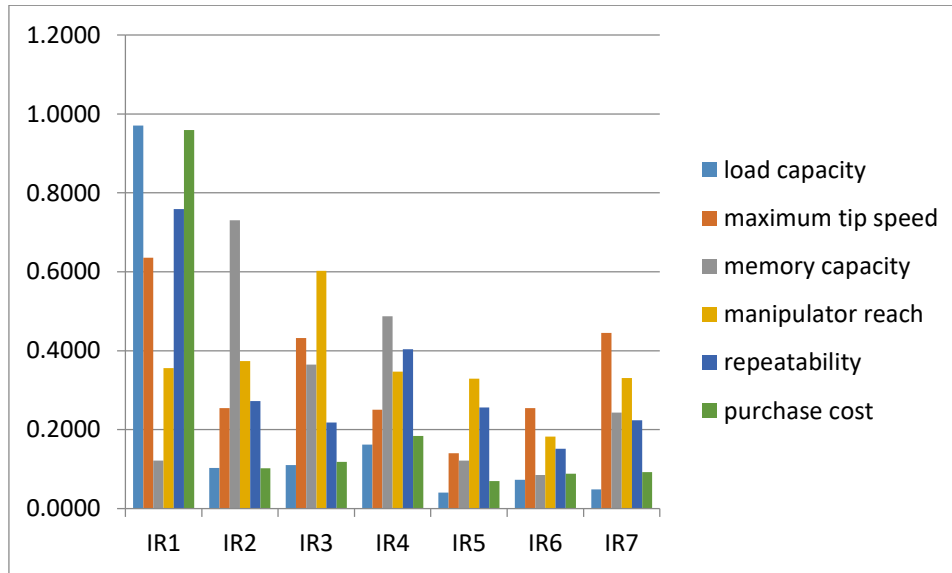


FIGURE 1. Normalized Data

Figure 1 shows the Normalized Data for Industrial robot selection Alternative: IR1, IR2, IR3, IR4, IR5, IR6, IR7 and Evaluation parameters is load capacity, top tip speed, memory capacity, manipulator reach, repeatability, and cost of purchasing.

TABLE 3. Weightages

	Weight					
Robot	load capacity	maximum tip speed	memory capacity	manipulator reach	repeatability	purchase cost
IR1	0.16	0.16	0.16	0.16	0.16	0.16
IR2	0.16	0.16	0.16	0.16	0.16	0.16
IR3	0.16	0.16	0.16	0.16	0.16	0.16
IR4	0.16	0.16	0.16	0.16	0.16	0.16
IR5	0.16	0.16	0.16	0.16	0.16	0.16
IR6	0.16	0.16	0.16	0.16	0.16	0.16
IR7	0.16	0.16	0.16	0.16	0.16	0.16

Table 3 lists the weights that were employed in the analysis. For the analysis, we use the same weights for all the parameters.

TABLE 4. Weighted normalized decision matrix

Weighted normalized decision matrix						
Robot	load capacity	maximum tip speed	memory capacity	manipulator reach	repeatability	purchase cost
IR1	0.1553	0.1017	0.0195	0.0569	0.1215	0.1535
IR2	0.0164	0.0407	0.1169	0.0598	0.0436	0.0163
IR3	0.0176	0.0691	0.0584	0.0964	0.0349	0.0189
IR4	0.0259	0.0400	0.0779	0.0555	0.0646	0.0295
IR5	0.0065	0.0224	0.0195	0.0526	0.0410	0.0112
IR6	0.0116	0.0407	0.0136	0.0292	0.0242	0.0142
IR7	0.0078	0.0712	0.0390	0.0529	0.0358	0.0148

Table 4 shows the Industrial robot selection using the Analysis Method Alternative: IR1, IR2, IR3, IR4, IR5, IR6, IR7 and Evaluation parameters is loading capacity, top tip speed, memory capacity, manipulator reach, repeatability, and cost of purchasing.

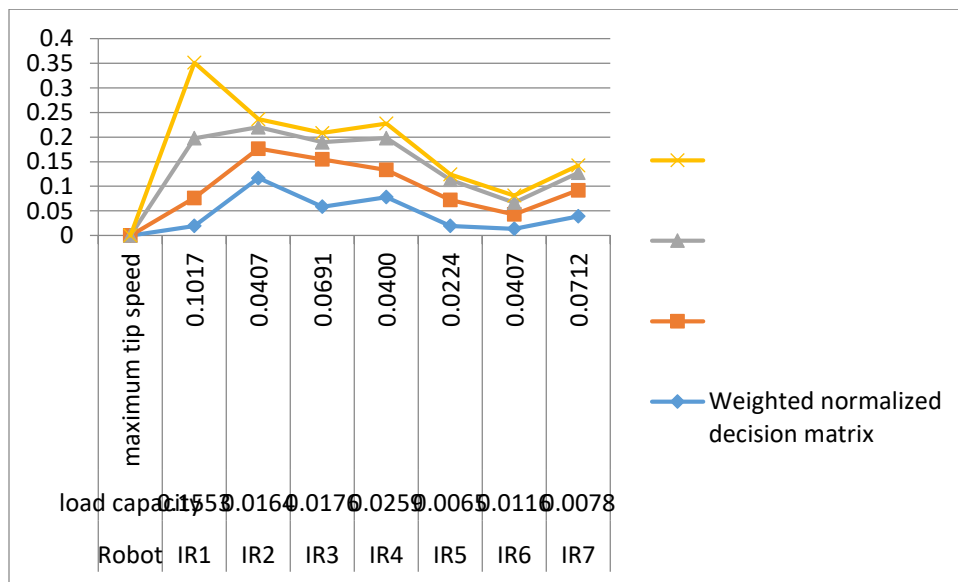


FIGURE 2. Weighted Normalized Decision matrix

The weighted normalized choice matrix is shown in Figure 2 along with the evaluation criteria for the load capacity, maximum tip speed, memory capacity, manipulator reach, repeatability, and purchase cost.

TABLE 5. Positive Matrix

Robot	load capacity	maximum tip speed	memory capacity	manipulator reach	repeatability	purchase cost
IR1	0.1553	0.1017	0.1169	0.0964	0.0242	0.0112
IR2	0.1553	0.1017	0.1169	0.0964	0.0242	0.0112
IR3	0.1553	0.1017	0.1169	0.0964	0.0242	0.0112
IR4	0.1553	0.1017	0.1169	0.0964	0.0242	0.0112
IR5	0.1553	0.1017	0.1169	0.0964	0.0242	0.0112
IR6	0.1553	0.1017	0.1169	0.0964	0.0242	0.0112
IR7	0.1553	0.1017	0.1169	0.0964	0.0242	0.0112

Table 5 shows the Positive Matrix of the Alternative: IR1, IR2, IR3, IR4, IR5, IR6, IR7 and Evaluation parameters is loading capacity, top tip speed, memory capacity, manipulator reach, repeatability, and cost of purchasing.

TABLE 6. Negative Matrix

Robot	load capacity	maximum tip speed	memory capacity	manipulator reach	repeatability	purchase cost
IR1	0.0065	0.0224	0.0136	0.0292	0.1215	0.1535
IR2	0.0065	0.0224	0.0136	0.0292	0.1215	0.1535
IR3	0.0065	0.0224	0.0136	0.0292	0.1215	0.1535
IR4	0.0065	0.0224	0.0136	0.0292	0.1215	0.1535
IR5	0.0065	0.0224	0.0136	0.0292	0.1215	0.1535
IR6	0.0065	0.0224	0.0136	0.0292	0.1215	0.1535
IR7	0.0065	0.0224	0.0136	0.0292	0.1215	0.1535

Table 6 shows the Negative Matrix of the Table 6 shows the Alternative: IR1, IR2, IR3, IR4, IR5, IR6, IR7 and Evaluation parameters is loading capacity, top tip speed, memory capacity, manipulator reach, repeatability, and cost of purchasing.

TABLE 7. Values of SI Plus, Si Negative and Ci

Robot	SI Plus	SI Negative	Ci
IR1	0.2019	0.1710	0.4586
IR2	0.1573	0.1921	0.5499
IR3	0.1536	0.1855	0.5470
IR4	0.1603	0.1553	0.4920
IR5	0.2003	0.1653	0.4522
IR6	0.1988	0.1710	0.4624
IR7	0.1755	0.1737	0.4975

Table 7 shows the values of SI plus, Si Negative and Ci of Alternative: IR1, IR2, IR3, IR4, IR5, IR6, IR7 by using the TOPSIS Method.

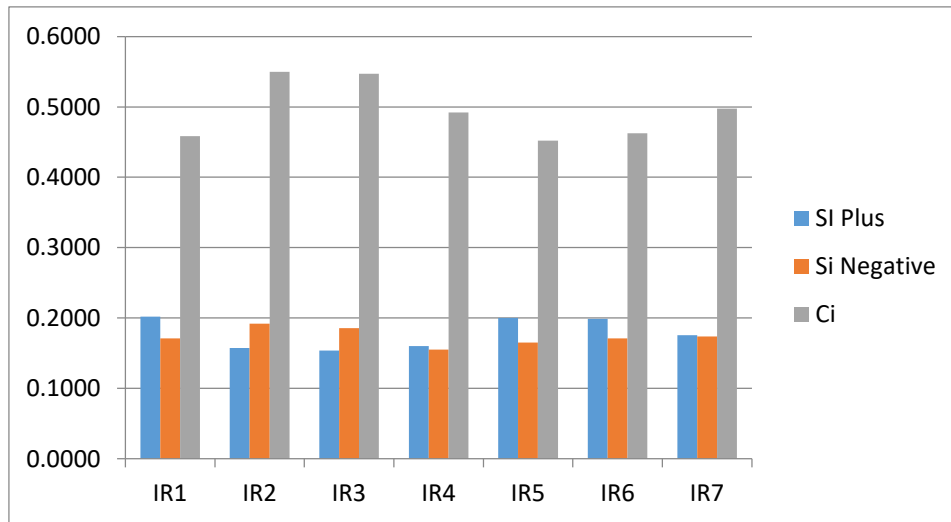


FIGURE 3. SI Plus, Si Negative and Ci.

TABLE 8. Rank

Robot	Rank
IR1	6
IR2	1
IR3	2
IR4	4
IR5	7
IR6	5

IR7	3
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Table 8 displays this paper's ultimate rank, with IR1 coming in at number six, IR2 at number one, IR3 at number two, IR4 at number four, IR5 at number seven, IR6 at number five, and IR7 at number three. The TOPSIS approach is used to produce the end result.

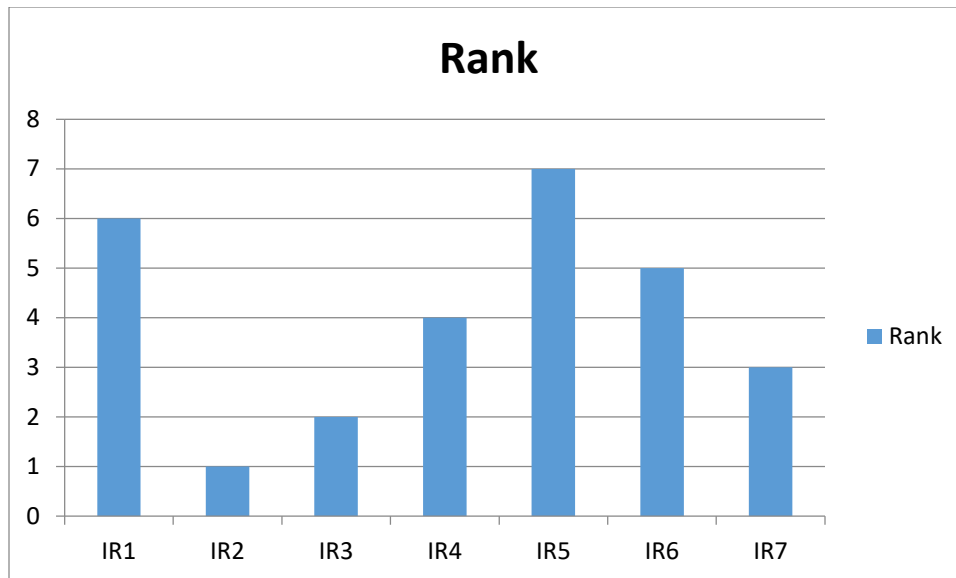


FIGURE 4. Ranking

Figure 4 shows the rank on the basis of my analysis and the result is obtained by using the TOPSIS method. IR2 stands on the top by securing 1st position on the table.

5. CONCLUSION

In conclusion, choosing industrial robots is a crucial choice that needs to carefully take into account a number of factors. We have examined the significance of using a systematic and thorough strategy throughout this study to guarantee the best selection of industrial robots for particular applications. Multiple parameters, including performance capabilities, cost effectiveness, flexibility, dependability, and safety, are evaluated during the selection of industrial robots. Numerous procedures and strategies, such as the TOPSIS technique, fuzzy logic, and the analytical hierarchy process (AHP), have been addressed in attempt to aid in this decision-making process. Utilizing these methods will enable decision-makers to evaluate the relative weight of each criterion and compare the performance of various robot solutions. As a result, they are able to make decisions that are in line with their unique needs and goals. In order to ensure a comprehensive grasp of the operational needs and challenges, it is also necessary to include key stakeholders in the selection process, such as engineers, production managers, and operators. Their knowledge and perceptions can provide significant value and raise the general effectiveness of the decision-making process. It is worth noting that the selection of industrial robots is not a one-size-fits-all approach. Each industry and application may have unique requirements, and therefore, customization and adaptation of evaluation methodologies may be necessary. Additionally, advancements in robotics technology and emerging trends, such as collaborative robots and artificial intelligence, should be taken into account when selecting industrial robots. In conclusion, a well-informed and systematic approach to industrial robot selection, considering various criteria and involving key stakeholders, is crucial for achieving optimal performance, productivity, and efficiency in industrial settings. Continuous evaluation and adaptation of selection methodologies will contribute to staying up-to-date with the evolving landscape of robotics technology.

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