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A MULTI-ATTRIBUTE DECISION-MAKING FRAMEWORK FOR INDUSTRIAL ROBOT SELECTION

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Abstract

The selection of an appropriate industrial robot has remained a significant challenge for manufacturers due to the increasing complexity of robotic systems and the wide range of available features and specifications. This study aims to develop and maintain a reliable, comprehensive database of robotic manipulators based on their relevant technical, operational, and performance attributes. The proposed database is intended to standardize the robot selection process and assist manufacturing industries in identifying the most suitable robotic system for specific applications. The developed selection framework minimizes the time and effort required for decision-making by systematically evaluating available alternatives against operational requirements. Initially, an elimination-based search strategy is employed to narrow down a large pool of candidate robots into a manageable shortlist using critical selection attributes. Subsequently, the shortlisted alternatives are evaluated and ranked through attribute-based specification, comparison, and selection techniques. The proposed methodology serves as a practical decision-support tool for robot users while providing valuable insights to manufacturers for improving existing products and developing new robotic systems that better satisfy customer requirements. Furthermore, the database can support various stages of robotic system design, operation, and maintenance by enabling maintenance personnel to formulate effective strategies for reducing equipment downtime and maintenance efforts. The study focuses on identifying and organizing an extensive range of robotic manipulator attributes to establish a structured and comprehensive information repository. The proposed attribute coding scheme and systematic selection procedure are presented through mathematical formulations, graphical representations, and illustrative examples to demonstrate their applicability and effectiveness in industrial robot selection.

Keywords: Unimation PUMA, Yaskawa electric motoman L3C, Hitachi robot, ASEA-IRA 60/2, Cybotech robot.

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1. INTRODUCTION

Industrial robot selection can be formulated as a multi-criteria decision-making (MCDM) problem with multiple alternatives and conflicting evaluation attributes. When decision makers need to evaluate many robotic systems with different technical specifications and units of measurement, traditional selection procedures can become insufficient. To overcome these limitations, various MCDM techniques have been developed to systematically evaluate alternatives based on their relative performance across multiple criteria. Among these approaches, the Preference Ranking Organization Method for Detailed Evaluation (PROMETHEE) has emerged as an effective dominance method for solving complex decision-making problems involving conflicting quantitative and qualitative characteristics. PROMETHEE II provides a comprehensive ranking of alternatives by evaluating their relative priorities through positive, negative, and net-out ranking flows. The PROMETHEE II method evaluates the performance of each alternative robot using predefined selection criteria, corresponding criterion weights, and appropriate priority functions. Selection attributes are ranked based on an optimization direction such as more is better or less is better and include categorical features using appropriate precedence rules or feasibility constraints. Perform pairwise comparisons to determine how much one robot is preferred over the other for each evaluation criterion. The aggregate preference indices are subsequently used to calculate positive and negative superiority flows, reflecting the relative strengths and weaknesses of the alternatives. The difference between these streams provides a

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net stream of superiority that serves as the basis for establishing the overall ranking of robotic arm candidates. This approach facilitates systematic comparison without requiring direct aggregation of attributes expressed in different physical units. Agrawal et al. (1919) presented an effective computational approach to solving the problem of selecting the “best robot” specifically designed to assist industry. This approach innovates by applying multi-attribute decision making (MADM) to hardware (robot) selection. This is important because selection is an implicit aspect of design. In fact, this approach can also be applied to robot design problems. The robot selection procedure quickly moves from many robots to a manageable shortlist of potentially suitable robots using a "search to exclude" procedure based on several relevant robot characteristics. Subsequently, the selection procedure proceeds to ranking the alternatives in a short list using a MADM method called TOPS1S (Method of Order Preference by Similarity to Ideal Solution). An expert system has been developed as part of the software package, which helps an inexperienced user set priorities and “control” the selection process at various stages. Braglia, M. and Petroni, A. (1999) propose an alternative method for selecting industrial robots using data envelopment analysis (DEA). The purpose is to measure the relative efficiency of each robot by solving a linear programming problem and identify the optimal robot in terms of cost and benefits. The adopted methodology is based on sequential dual DEA with limited weights. This approach improves the discriminatory power of the DEA standard and allows for a better balance of robot characteristics. A further advantage concerns the possibility of extending the use of this approach to a variety of multi-attribute decision problems, where each performance may depend on many factors. Empirical application of this methodology using data from 12 robot manufacturers validates the applicability of the revised DEA to the selection of advanced manufacturing technologies and strengthens its use as a tactical/operational tool in manufacturing/operations. A sensitivity analysis (with variable weight constraints) is also performed to assess the overall balance of the robot's performance. A comparison of the results with those obtained by applying cross-efficiency, another DEA-based methodology (Baker and Talluri, 1997 Computers and Industrial Engineering, 32, 101-108) is also reviewed and discussed. Finally, the dual DEA model helped provide useful economic and technological analysis of inefficient robots. Senkala et al. (2024) reported that industrial robots, like all machines, require energy to operate, which is why the energy efficiency of industrial robotics has become a topic of discussion in many scientific and industrial centers in recent years. Interest in this subject is particularly visible in Industry 4.0. Research in the field of energy efficiency is associated with the emergence of new opportunities in terms of making strategic decisions related to production processes. Energy-efficient production is an essential part of sustainable development, so the energy efficiency of industrial robots must be considered. The need to reduce costs while maintaining quality and increasing production efficiency requires the introduction of modern solutions aimed at reducing energy consumption. The rational use of electrical energy, especially in the industrial sector, significantly reduces production costs and contributes to the profits and competitiveness of enterprises. This article aims to provide an overview of energy efficiency issues based on recently published articles. This article describes selecting the right robot, programming the robot, planning energy-efficient trajectories, and monitoring the performance of robotic systems to minimize energy consumption. Typical industrial applications of robots are also mentioned and discussed. Berguggi and Sulimani (2026) use panel data for 50 countries over the period 2000–2024 to investigate the relationship between the adoption of industrial robots and environmental capacity as measured by biological production capacity. We investigate the transfer mechanisms, nonlinearities, spatial spillovers, and heterogeneities that characterize these relationships. Our empirical analysis yields five main conclusions. First, industrial robots have a positive effect on biological performance. Second, mechanism analysis reveals that robotics strengthens ecological capacity through two primary transmission channels: institutional flexibility via reduced transaction costs and accelerated green-biased technological progress, with the latter representing the dominant pathway. Third, threshold regression models identify a three-regime non-linear relationship: Robotics exhibits modest positive effects at low levels of industrial upgrading, counterintuitively adverse effects during the intermediate transition phase, and substantially amplified positive effects at advanced stages of industrial upgrading. Fourth, spillover analyzes show that ecological benefits from robotics are significantly greater in countries geographically close to Japan, the world's center of robotics innovation, while trade-based heterogeneity reveals significantly amplified effects in high-trade economies and significant effects only in countries with deeply integrated global value chains. Fifth, heterogeneity analysis shows that the environmental benefits of robotics are greater in high-income countries, countries with advanced digital infrastructure, and densely populated economies, while the effects are attenuated or negative in low-income countries and digitally limited settings. The results suggest that policy coherence, combining the introduction of robotics with structural improvements, institutional strengthening, investment in skills and infrastructure, and strategic trade integration, is essential to achieve sustainable improvements in environmental capacity.

In the present study, an attribute-based industrial robot selection framework is developed by integrating a comprehensive database of robotic manipulators with the PROMETHEE II ranking technique (Annamalai et al., 2025; Babu et al., 2026; Bakas et al., 2025; Hekmat et al., 2026; Lakshmanan et al., 2025; Triantaphyllou et al., 2025). Initially, technical characteristics and operational characteristics of available robotic systems are collected and

organized using a structured attribute coding scheme. An elimination-based selection procedure is then used to identify bots that meet the minimum requirements of the application, thereby reducing the initial set of alternatives to a manageable number of possible candidates. Subsequently, PROMETHEE II is applied to evaluate and rank the shortlisted robots based on their relevant performance attributes and assigned criterion weights. The effectiveness of the proposed framework is demonstrated through an illustrative pick-and-place application involving payload capacity, repeatability, maximum tip speed, actuator type, memory capacity, manipulator reach, and degrees of freedom. The main objective of this research is to establish a systematic and transparent decision support framework for attribute-based specification, comparison and selection of industrial robots using PROMETHEE II. The proposed methodology combines pre-elimination, attribute-specific preference assessment, and comprehensive superiority analysis to help decision makers determine the most appropriate robotic arm for a given industrial application. Furthermore, the developed framework aims to reduce the time and complexity associated with robot selection, improve consistency when evaluating competing robot alternatives, and provide useful information to robot manufacturers to improve product performance and meet application-specific requirements.

2. PREFERENCE RANKING ORGANISATION METHOD OF ENRICHMENT EVALUATION (PROMETHEE II) METHOD

Table 1, shows two types of criterion functions, the component D_α is the highest level of indifference designates the largest difference which is insignificant when measuring up the two alternatives in related to that criterion. The PROMETHEE II technique determines the preference of robot a over robot b through the aggregated preference index:

$$\pi(a,b) = \sum_{j=1}^{m} w_j \, P_j(a,b) \quad (1)$$

where (wj) denotes the normalized importance weight of criterion (j), and (Pj(a,b)) denotes the preference of robot (a) over robot (b).

The positive outranking flow is:

$$\phi^+(a) = \frac{1}{n-1} \sum_{b \neq a} \pi(a,b) \quad (2)$$

The negative outranking flow is:

$$\phi^-(a) = \frac{1}{n-1} \sum_{b \neq a} \pi(b,a) \quad (3)$$

The net outranking flow is:

$$\phi(a) = \phi^+(a) - \phi^-(a) \quad (4)$$

The robots are ranked in descending order of net outranking flow. The alternative with the highest net flow receives the first rank.

Table 1: Functions for criteria and appropriate preference values (Annamalai & Dhavamani 2023)

S. No.	Criterion functions	Values of choice
1	Normal criterion	$G(D_\alpha) = [0 \; if \; D_\alpha = 0 \; 1 \; if \; D_\alpha > 0]$

The current issue was adapted from (Bhangale et al. (2024), where it was solved using Graphical method-based ranking and TOPSIS method for ranking. Now, we're using the PROMETHEE II approach to examine the best robot and rank it against other robots with the same problem. Table 2 presents the adapted attributes.

Table 2: Attributes of the robots

	Load Capacity in Kg	Repeatability in mm	Maxi. Tip speed in mm/sec	Memory capacity in points	Manipulator reach in mm
ASEA-IRB 60/2	60	-0.4	2540	500	990
Cincinnati Milacrone T^3-726	6.35	-0.15	1016	3000	1041
Cybotech V15 Electric robot	6.8	-0.1	1727.2	1500	1676
Hitachi America Process robot	10	-0.2	1000	2000	965
Unimation PUMA 500/600	2.5	-0.1	560	500	915
United states robots maker 110	4.5	-0.08	1016	350	508
Yaskawa Electric motorman L3C	3	-0.1	1778	1000	920

Table 3: Classification of robot selection attributes

S. No.	Robot attribute	Minimum requirement	Selection criterion	Justification
1	Load capacity	≥ 2 kg	Larger-the-Better (LTB)	Higher payload capacity provides greater load-handling capability.
2	Repeatability	0.5 mm	Smaller-the-Better (STB)	Lower positional error indicates higher repeatability and precision.
3	Maximum tip speed	≥ 255 mm/s	Larger-the-Better (LTB)	Higher speed can reduce cycle time and improve productivity.
4	Memory capacity	≥ 250 points/steps	Larger-the-Better (LTB)	Higher memory capacity enables storage of more programmed positions and instructions.
5	Manipulator reach	500 mm	Larger-the-Better (LTB), subject to feasibility	Greater reach provides a larger working envelope, although excessive reach may not be beneficial.

Table 4: PROMETHEE II ranking of industrial robots

Robot alternative	Positive outranking flow (Φ^+)	Negative outranking flow (Φ^-)	Net outranking flow (Φ)	Rank
R1	0.5667	0.4000	0.1667	3
R2	0.6000	0.3667	0.2333	2
R3	0.7000	0.2333	**0.4667**	**1**
R4	0.5000	0.5000	0.0000	4 (Tie)
R5	0.1667	0.7333	−0.5667	7
R6	0.3333	0.6333	−0.3000	6
R7	0.4667	0.4667	0.0000	4 (Tie)

Note: Equal weights (0.20 for each of five criteria) and the usual preference function were used. Higher net outranking flow indicates a more preferred alternative.

3. ANALYSIS OF PROMETHEE-II

The PROMETHEE II method was employed to evaluate seven industrial robotic manipulators based on five selection attributes, namely load capacity, repeatability, maximum tip speed, memory capacity, and manipulator reach. Among these attributes, load capacity, maximum tip speed, memory capacity, and manipulator reach were considered benefit criteria (larger-the-better), whereas repeatability error was treated as a cost criterion (smaller-the-better) (Jagannathan et al., 2025; Mythili et al., 2025; Rajendran et al., 2026; Tamang et al., 2026; Viswanathan et al., 2025). Equal weights of 0.20 were assigned to the five criteria, and the usual preference function was adopted to establish pairwise preference relationships among the alternatives. The results revealed that robot R3 achieved the highest net outranking flow of 0.4667, followed by R2 (0.2333) and R1 (0.1667). Robots R4 and R7 exhibited equal net outranking flows of 0.0000, while R6 and R5 recorded negative net flows of −0.3000 and −0.5667, respectively. Based on the calculated net outranking flows, the ranking order was established as R3 > R2 > R1 > R4 = R7 > R6 > R5. The findings indicate that R3 is the most preferred alternative under the adopted preference function and equal weighting scheme, demonstrating the applicability of PROMETHEE II for the comparative assessment and selection of industrial robots with conflicting performance attributes (Table 4).

4. CONCLUSIONS

The present study developed a systematic multi-attribute decision-making framework for the evaluation and selection of industrial robots using the PROMETHEE II technique. Seven industrial robotic manipulators were evaluated based on five key performance attributes, namely load capacity, repeatability, maximum tip speed, memory capacity, and manipulator reach. Among these criteria, repeatability error was considered a smaller-the-better attribute, whereas the remaining four attributes were treated as larger-the-better criteria. Equal weights of 0.20 were assigned to all five attributes, and the usual preference function was employed to determine the relative preference of each robotic alternative.

The PROMETHEE II analysis revealed that the Cybotech V15 Electric Robot (R3) achieved the highest net outranking flow of 0.4667, followed by the Cincinnati Milacron T³-726 (R2) and ASEA-IRB 60/2 (R1), with net flows of 0.2333 and 0.1667, respectively. Robots R4 and R7 attained identical net outranking flows of 0.0000, whereas R6 and R5 recorded negative values of −0.3000 and −0.5667, respectively. The final ranking order was established as R3 > R2 > R1 > R4 = R7 > R6 > R5. These findings identify R3 as the most preferred robotic manipulator under the adopted weighting scheme and preference function.

The results demonstrate the applicability of PROMETHEE II as a structured decision-support technique for comparing industrial robots with conflicting technical

specifications. The proposed approach facilitates transparent evaluation and systematic ranking of robotic alternatives, thereby supporting manufacturing industries in making informed robot selection decisions. However, the findings are limited to the selected performance attributes, equal criterion weights, and the assumed preference function. Future research may incorporate additional criteria, including acquisition cost, energy consumption, maintenance requirements, and operational reliability, together with sensitivity analysis and alternative weighting schemes to enhance the robustness and practical applicability of the proposed framework.

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CONFLICT OF INTEREST

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