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A HYBRID MULTI-CRITERIA DECISION-MAKING TECHNIQUE COMBINING AHP AND GRA FOR INDUSTRIAL COLLABORATIVE ROBOT SELECTION

Summary

Technological progress in robotics has played a pivotal role in revolutionising manufacturing systems across industries. Collaborative robotics has become prominent among crucial innovations, where robotics finds extensive applications in production processes. Small and medium-sized enterprises are engaged in activities that include unsafe and repetitive jobs. The selection of an appropriate robot for an efficient industrial process has become complex due to the abundance of robot configurations and capabilities. A combination of objective and subjective elements determines the characteristics and operational accuracy of the best industrial collaborative robot (cobot). The proposed technique for selecting collaborative robots integrates analytic hierarchy process (AHP) and grey relational analysis (GRA) for determining criterion weights and ranking cobots, respectively. The combined methodology addresses decision-making uncertainties by evaluating robots based on parameters, such as reachability, repeatability, robot mass, power consumption, footprint, payload, and cobot price. The method, novel in the collaborative robot selection, aims to classify several robot models for flexible assembly stations comprehensively. The paper highlights the identification of critical criteria and the methodology for evaluating and selecting the most appropriate collaborative robots and standard industrial robots for an application.

Key words: *collaborative robot; analytic hierarchy process; multi-criteria decision making; grey relational analysis*

1. Introduction

Engineering and information technology advancements have led to an increased adoption of robots with diverse abilities, features, and specifications. Robots are often autonomous, adaptable, and reprogrammable. Due to these characteristics, they are also vital equipment for industrial applications. Additionally, deploying robots has helped businesses become more productive. Further, companies have raised productivity by utilising robots. Hence, improvements in production dependability, operational speed, and quality are benefits linked to the information technology of an organisation [1].

A robot's choice characteristic is a variable that influences the choice of a robot for a particular application in an industry. The beneficial and unbeneficial aspects can be used to

categorise the factors impacting the choice of a robot. In comparison, the unfavourable attributes are ideally expected to have lower values, including cost and repeatability. Simultaneously, the desirable characteristics, such as load-carrying capacity and programming flexibility are aimed at higher values. Prior focus has been on memory capacity, maximum tip speed, purchase cost, repeatability, supplier service quality, adaptability, and other essential strategic aspects. Selecting an industrial robot for a particular application and production environment can take time due to a wide range of available options. In addition, the selection of robots is still relatively challenging in the industry, in particular when a company acquires a robot for the first time. Considering the demands, a structured decision-making method for assessing and rating robots was recommended to choose the best robot [2].

2. Literature review

The integrated multiple-attribute decision-making strategy for selecting industrial robots, considering existing expert knowledge in the field is essential for industries to move towards sustainability. The decision support system blends both subjective and objective criteria to aid in a suitable decision-making process. The distance-based approach (DBA) has been employed in constructing a deterministic quantitative model to evaluate robot rank, an area of the problem domain where the DBA has yet to be extensively investigated [3]. The consequences of attribute significance were decided by hybrid procedures with the decision maker's subjective preferences as well as the precise weights allocated to the attribute significance [4]. A decision support system (ROBOSEL) is used in the fuzzy analytical hierarchical process (FAHP) to find and arrange different criteria and rank the most practical robots available to help decision-makers to select robots [5]. The technique for order of preference by similarity to ideal solution (TOPSIS) method was used to provide a practical approach for selecting robots using generalised interval-valued fuzzy numbers [6].

A fuzzy multi-criteria decision-making (MCDM) method was employed in selecting robots, considering both objective and subjective characteristics. The methodology for unclear definitions encompasses the fuzzy Delphi method (FDM) and the Brown-Gibson model. Additionally, fuzzy decision-making techniques, such as fuzzy VIKOR, fuzzy modified TOPSIS, and the FAHP were employed in the decision-making process [7,8]. In investigating mobile robot selection within the context of application domain, the problem was framed as a decision-making problem. An approach selected the best alternative (robot) based on the ideal and extreme solution without defuzzification [9]. The hybrid MCDM method combines simple additive weighting (SAW), TOPSIS, and GRA techniques. The method employs an experimental design technique to assign attribute weights and then combines different MCDM assessment methods to construct a hybrid decision-making model [10]. The ranking results were compared with widely employed MCDM techniques, including GRA, data envelopment analysis (DEA), AHP, preference selection index (PSI), analytic network process (ANP), SAW, preference ranking organisation method for enrichment of evaluations (PROMETHEE), elimination and choice translating reality (ELECTRE), multi-objective optimisation by ratio analysis (MOORA), TOPSIS, and graph-based approaches.

In every instance, the top-rated options correspond with those established in prior research. This finding illustrates how the proposed approach can effectively tackle real-world MCDM challenges by providing accurate evaluations of alternatives and facilitate a more informed selection of robots. The utilisation of the GRA methodology was found to be the optimal decision-making method, as it demonstrated effectiveness in ranking and optimising strategies for selecting superior options [11,12]. The criterion importance can be evaluated using the interval-valued intuitionistic hesitant fuzzy entropy. Furthermore, the interval-valued intuitionistic hesitant fuzzy VIKOR method can be utilised to rank available options [13]. The issue of real-time robot selection, which involved 12 alternatives, i.e. robots and

five selection criteria, was met by deploying two hybrid models: TOPSIS-additive ratio assessment (ARAS) and complex proportional assessment (COPRAS)-ARAS [14,15]. To assess the relevance of the parameters, these models used the criteria importance via inter criteria correlation (CRITIC) objective weighting estimation technique. To evaluate the performance of these hybrid models, comparisons were made against the robot alternative rankings produced by eight individual MCDM tools. The results from all the applied approaches are sufficiently consistent despite variations in their generated order. This consistency suggests that, among 12 alternatives, robot 12 is the better choice; after that robot 11 and robot 4 follow. In the fuzzy AHP, the weight of each subjective criterion as well as the weight of the objective criterion was determined. Alternatives were then ranked using either fuzzy modified TOPSIS or fuzzy VIKOR, taking into account both subjective and empirical factors.

Kumar et al. [16] used the stepwise weight assessment ratio analysis (SWARA) and the combined compromise solution (CoCoSo) based approach for the selection of a spray-painting robot used in the automobile industry. The selection process was based on seven evaluation criteria: payload, mass, speed, repeatability, reach, cost, and power consumption. In the context of two real-time industrial robot selection scenarios, a ranking system was introduced that incorporates six widely recognised and easily understandable MCDM methods: the weighted sum method (WSM), weighted product method (WPM), weighted aggregated sum product assessment (WASPAS), MOORA, and the multiplicative form of MOORA (MULTIMOORA) [17]. The study examines the assignment of variations in the weight to the criterion that affects the consistency of rankings across all six MCDM techniques. Additionally, it includes both single-dimensional and high-dimensional weight sensitivity experiments. Baig et al. [18] attempted to define and prioritise future research in robotics using MCDM with AHP. Subsequently, the results were analysed by the Expert Choice software. The MCDM models developed by integrating the AHP and GRA methods were found to be effective in determining the supply chain complexity [19]. Vijayaanand and Rao [20] implemented an artificial neural network model combined with hybrid multi-criteria decision-making approaches. The combined entropy and TOPSIS procedure were applied to rank lean tools in a foundry to improve efficiency and reduce waste. The results aligned well with expert assessments. Table 1 summarises important literature on the AHP and GRA MCDM methods relevant to robot selection and industrial functions.

Table 1 Literature on hybrid MCDM

S. No.	References	Year	MCDM Tool	Number of criteria and alternatives		Objectives
				Criteria	Alternatives	
1	[1]	2011	WPM, TOPSIS and GRA	5	7	In an industrial pick-and-place task, ranks and relative performance of alternative robots were compared.
2	[15]	2023	ARAS and COPRAS	5	3	A hybrid MCDM model combining COPRAS and ARAS was developed for the selection of an industrial robot.
3	[17]	2013	GRA and MULTIMOORA	12	4	Robot selection for a manufacturing process.
4	[20]	2024	ANN and TOPSIS	5	5	An artificial neural network model combined with hybrid multi-criteria decision-making approaches to rank lean tools to improve efficiency in a foundry.
5	[21]	2016	TODIM and GRA	6	4	Robot selection for a manufacturing process.

6	[22]	2019	GRA and RSM	15	3	Tests were conducted on the application of a robotic belt polishing aviation engine blades.
7	[23]	2016	AHP and MGRA	4	5	Integrated methodology based on AHP and modified gray rational analysis (MGRA) for the selection of a mobile robot for material handling.
8	[24]	2012	GRA and FUZZY LOGIC	10	5	Advanced manufacturing system selection and improvement of manufacturing

3. Problem statement

The literature review on MCDM approaches for selecting industrial robots revealed that the cost and safety criteria are not addressed suitably. Also, the hybrid MCDM based algorithm has been applied for mobile robots, whereas in the present study, a method for the cobot selection process is proposed. The combined method enables the determination of criterion weights using the AHP and the ranking of cobots using the GRA. The approach considers the principal parameters of cobots, such as payload, repeatability, reachability, cobot mass, power consumption, footprint, and price for the selection of a cobot for flexible assembly stations. The proposed study is intended to develop a hybrid decision-making method for identifying an appropriate collaborative robot for a filter assembly process by incorporating multiple parameters, which have not yet been reported for the process of selecting a collaborative robot.

4. Research methodology

The article proposes a hybrid strategy to rank cobots for industrial processes using the GRA and AHP techniques. Based on their characteristics, industrial cobots are chosen using an easy-to-use, dependable, and efficient MCDM approach. When comparing the AHP approach to alternative methods, the AHP offers several advantages, including easier identification of the most and least important criteria, decreased pairwise computations, and the generation of consistent results. Due to minimal processing requirements, the GRA approach was employed to rank the robots. Depending on the use of resources, parameters are categorised as beneficial or non-beneficial criteria. Table 2 lists different cobots and parameters for the selection of a suitable cobot for an assembly process.

Table 2 Parameters considered in selection of cobot for assembly process.

S. No.	Cobot model	Reachability /mm	Repeatability /mm	Robot mass /kg	Power consumption /W	Footprint /mm	Payload /kg	Estimated cobot price /INR
1	UR5 Robot	850	0.03	20.6	570	190	5	1800000
2	AUBO Robotics i5	887	0.05	24	200	142	3	1900000
3	Elephant Robotics Panda 5	850	0.05	24.5	260	135	5	1650000
4	Hanwha Collaborative Robot 5A	915	0.05	21	350	150	5	2200000
5	JAKA Zu5	954	0.02	23	350	129	3	1700000

Figure 1 shows different cobot models, i.e. the cobot alternatives selected for the present study. They were simulated to evaluate the dexterity of the cobot structure. The simulation was performed using computer automated machining (CAM) software, which is commercially accessible. 3D geometric and kinematic models of each cobot were used in the simulation process.

(a) UR5 Robot

(b) AUBO Robotics i5

(c) Elephant Robotics panda 5

(d) Hanwha Collaborative Robot 5A

(e) JAKA Zu5

Fig. 1 Models of cobots

5. GRA and AHP

The hierarchical framework for a decision-making module for the robot selection has seven essential characteristics to be considered while choosing the right robot for an application. Both positive characteristics and cost attributes are applied to the hierarchical model as cost qualities. The weighted relevance of measures/metrics was derived using the performance rating data collected from the expert group. The five collaborative robot models meet the requirements of the industrial assembly process. The objective was to choose the optimal collaborative robot based on total assembly performance among available options, i. e. UR5 Robot, AUBO Robotics i5, Elephant robotics panda 5, Hanwha Collaboration robot 5A, and Jaka Zu5. The interval-valued GRA with an AHP technique was selected for the study. The study is a cross-sectional study that employs the Delphi method. The robot databases were reviewed symmetrically, and the collected data were classified with the help of a robotic expert group survey. Table 3 lists the initial assessment values given by the experts on robot characteristics. Table 4 categorises the non-beneficial and beneficial cobot parameters.

Table 3 Initial assessment of expert values on robot characteristics

Expert	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7
Criterion 1	1	0.5	3	9	3	5	0.5
Criterion 2	2	1	3	0.5	2	5	0.5
Criterion 3	0.33	0.33	1	0.5	4	5	0.5
Criterion 4	0.11	2	2	1	2	5	9
Criterion 5	0.33	0.5	0.25	0.5	1	5	0.5
Criterion 6	2	2	2	0.11	2	5	1
Criterion 7	0.35	0.5	0.44	0.5	1	0.5	1

Table 4 Non-beneficial and beneficial cobot parameters

Cobot parameters	Non-beneficial (NB)	Beneficial (B)
Cobot price	✔	
Repeatability		✔
Reachability	✔	
Footprint		✔
Robot mass		✔
Power consumption	✔	
Payload		✔

5.1 Grey relational analysis theory and scheme

In MCDM techniques, the GRA is a frequently applied valuable assessment method, mostly when decision-making is ambiguous. Wang et al. evaluated the alliance of every component to create a suitable solution, and the link between each aspect was assessed to develop an appropriate solution [10].

Step 1: The initial assessment values were collected from experts and listed in Table 5.

Table 5 Scale of relative alternatives (Saaty scale)

Performance intensity value	Description
1	Identical significance
3	Greater significance
5	Much more crucial
7	Significantly more crucial
9	Unquestionably more crucial
2, 4, 6, 8	Values in the middle

Step 2: Normalisation and reference sequence: For the beneficial criterion, where "larger is better," and for the cost criterion, where "smaller is better," data normalisation is performed separately for each decision matrix:

$$x_i(k) = \frac{x_i^o(K) - \min_i^o(K)}{\max x_i^o(K) - \min x_i^o(K)} \quad (1)$$

(Order of alternatives: i = 1, 2... m, j = 1, 2... n.)

Non-beneficial attribute:

$$x_i(k) = \frac{\max x_i^o(K) - x_i^o(k)}{\max x_i^o(K) - \min x_i^o(K)} \quad (2)$$

(Sequence of alternatives i=1, 2… m, j=1, 2… n)

Step 3: The grey relational co-efficient is computed using equation 3:

$$\xi(K) = \frac{\Delta \min + \xi \Delta_{max}}{\Delta_{oi} + \xi \Delta_{max}} \quad (3)$$

The distinguishing coefficient ξ =0.5

Step 4: Evaluation of the grey relational grade and assignment of rank to the cobot, where W_k is the weight of j^{th} criterion.

$$\Upsilon_i = {}^1/_n \sum_{k=1}^{n} \omega_k(K)\, \xi_i(K) \quad (4)$$

The grey relational degree illustrates the association between the linked sequence and reference category. The grey relationship degree is the basis for prioritisation assessment; the highest grade of connection corresponds to the best parameter.

5.2 Analytical hierarchy process

The AHP, proposed by Satty (1987), is the primary approach in the MCDM process for establishing the relative significance of each studied criterion. The problems with cobot selection could be tackled using the MCDM technique [25]. Figure 2 shows a hierarchical structure with an objective at the highest level, the criteria at the second level, and alternatives at the third level.

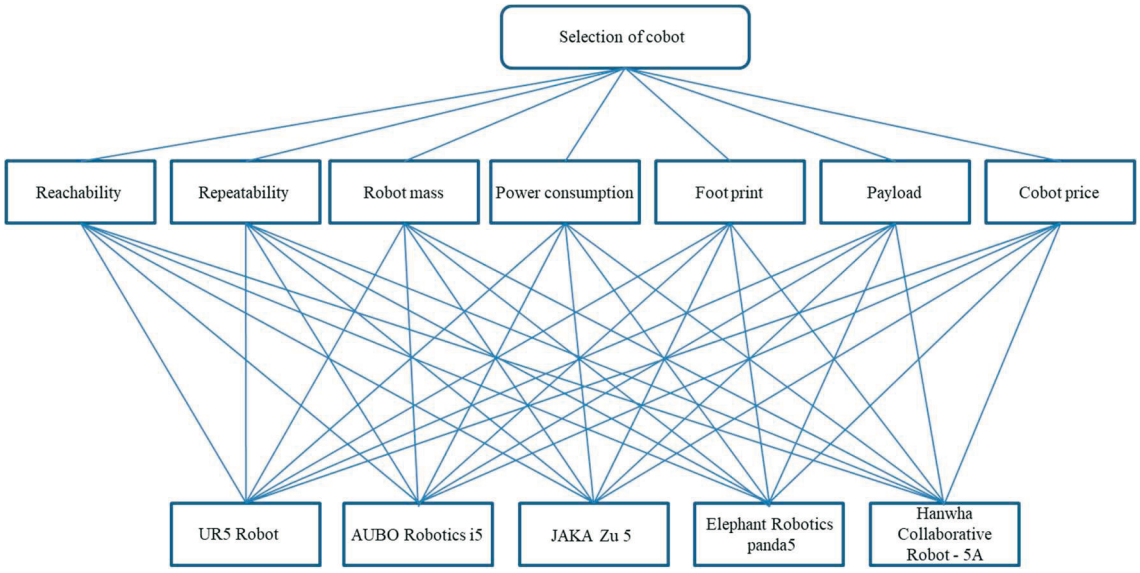

Fig. 2 Analytic hierarchy process

As suggested by Satty, the following step-by-step procedure was used to assign the relative weight factors to the criteria.

***Step 1*:** To construct the pairwise comparison matrix, a value between 1 and 9 was assigned to the comparative significance of each factor.

***Step 2*:** The relative significance of various criteria or features with respect to the goal was established to create a pairwise comparison matrix (PCM) under the direction of an expert.

$$A = \begin{bmatrix} 1 & x_{12} & \cdots & x_{1n} \\ 1/x_{12} & 1 & \cdots & x_{2n} \\ \vdots & \vdots & 1 & \cdots \\ 1/x_{1n} & 1/x_{2n} & \cdots & 1 \end{bmatrix} \quad (5)$$

Step 3: To compute the weight of each criterion, the total of each row was divided by the normalised pairwise comparison matrix**.**

Step 4: The normalisation and criterion weights of the pair-wise comparison matrix were computed.

***Step 5*:** Equation (6) was used to do a consistency check to determine whether the evaluation is consistent. The maximum eigenvalue of each criterion (λ_{max}) is the highest eigenvalue of the pairwise comparison matrix), consistency index (CI), consistency ratio (CR), random consistency index (RI), and the number of factors being compared in the matrix (n) were determined. RI is listed in Table 6.

$$\text{CI} = \frac{\lambda\text{max}-\text{n}}{n-1} \quad (6)$$

$$\text{CR} = \frac{CI}{RI} \quad (7)$$

Table 6 Random index (RI)

No. of criteria	1	2	3	4	5	6	7	8	9	10
Random consistency index	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

***Step 6*:** The procedure was iterated until these values reached a point within the permissible range if the calculated CR was less than 0.10 using equation (7). This indicates that the expert assessments are dependable, and the derived weight results are satisfactory.

6. Hybrid AHP-GRA technique

To create an effective decision support system, the AHP could be integrated with GRA to tackle the challenges in robot evaluation and selection. In such a case, both subjective and objective criterion weights need to be considered. The intended model comprises three essential phases:

(i) establishment of the assessments for the available robots,

(ii) evaluation of the implications linked to the evaluation criteria,

(iii) ranking of different proposed robots.

An integrated methodology based on the AHP and the modified GRA for the selection of a mobile robot for material handling in flexible manufacturing system (FMS) environment was reported. In this methodology, the AHP technique was used to assign the relative importance to the mobile robot selection attributes, and the MGRA technique was applied to determine the mobile robot selection utility index [24]. The hybrid mathematical models developed by integrating the AHP and the GRA methods were found to be effective to measure the level of the supply chain complexity [23]. In the present method, the AHP approach is used to determine the major weight of the selection criterion at the beginning of the process, and the possibilities are then ranked using the approach of the GRA method. Using a flowchart, Figure 3 illustrates a step-by-step procedure of the analysis. Table 7 consists of the cobot parameters for determining the criterion weights.

Table 7 Criterion definition

S. No.	Criterion	Definition
1	Repeatability	An evaluation of the robot's reliability in achieving a given goal.
2	Reachability	It is the maximum distance between the maximal extension of the end effector-holding component and the centre of the robotic base.
3	Cobot price	Cost relates to the overall cost spent on buying a collaborative robot for a particular assembly operation.
4	Power consumption	Total power required by the robotic structure.
5	Footprint	The total area a robot occupies at any moment.
6	Cobot payload	The total weight the cobot can lift.
7	Cobot mass	The mass of the robot system with end effector.

Figure 3 depicts the steps involved in the MCDM approach for cobot selection from the identification of objective and subjective factors to the grey relational rank.

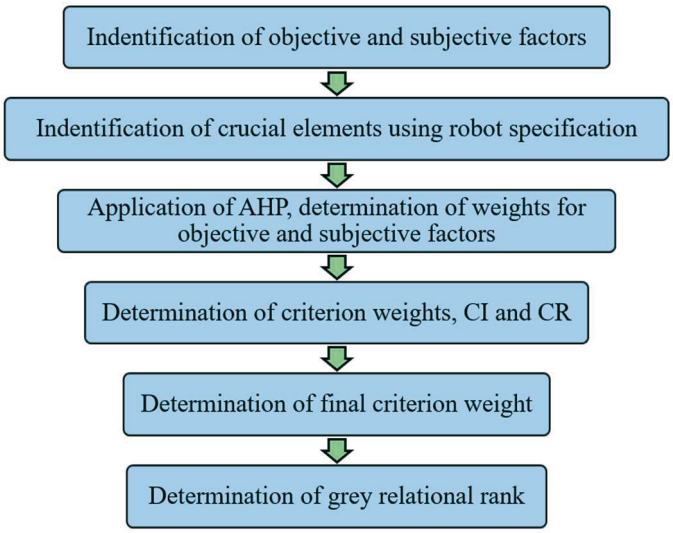

Fig. 3 MCDM approach for robot selection

The AHP pairwise comparisons are shown in Table 8. The normalised matrix rows were averaged to determine the respective weights of alternative preferences with each criterion and sub-criterion presented in Table 9.

Table 8 AHP pairwise comparisons

Input Data	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7
Criterion 1	1	0.9086	0.90856	2.6207	1.4422	1.3104	2.8844
Criterion 2	1.1006	1	2.28943	0.5	2.2894	0.5	2
Criterion 3	1.1006	0.4368	1	1.0772	1.1447	1.2599	2.2894
Criterion 4	0.3816	2	0.92832	1	1.1262	1.8899	2
Criterion 5	0.6934	0.4368	0.87358	0.8879	1	0.5	1
Criterion 6	0.7631	2	0.79370	0.5291	2	1	2
Criterion 7	0.3467	0.5	0.43679	0.5	1	0.5	1
Summation	5.3860	7.2821	7.23038	7.1149	10.0026	6.9602	13.1730

Table 9 Normalised decision matrix

Criteria	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7	Criterion weight
Criterion 1	0.19	0.12	0.13	0.37	0.14	0.19	0.22	0.19
Criterion 2	0.20	0.14	0.32	0.07	0.23	0.07	0.15	0.17
Criterion 3	0.20	0.06	0.14	0.15	0.11	0.18	0.17	0.15
Criterion 4	0.07	0.27	0.13	0.14	0.11	0.27	0.15	0.16
Criterion 5	0.13	0.06	0.12	0.12	0.10	0.07	0.08	0.10
Criterion 6	0.14	0.27	0.11	0.07	0.20	0.14	0.15	0.16
Criterion 7	0.06	0.07	0.06	0.07	0.10	0.07	0.08	0.07

The computation of the maximum eigenvalue (λ_{max}) for the comparison matrix followed the AHP procedure. Table 10 illustrates the outcomes obtained by multiplying each value in the column by the criterion weights. The criterion values from the rows in Table 11 are combined to provide the weighted sum value. Both the average ratio of the weighted sum value (WSV) to the criterion weight (CW) and the calculation of the ratio of each weighted sum value to its corresponding criterion weight are shown in Table 11.

Table 10 Consistency matrix

Criterion weight	0.193691	0.168732	0.146183	0.164338	0.097435	0.156559	0.073062
Criteria	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7
Criterion 1	1	0.908560	0.908560	2.620741	1.442250	1.310371	2.884499
Criterion 2	1.100642	1	2.289429	0.5	2.289429	0.5	2
Criterion 3	1.100642	0.436790	1	1.077217	1.144714	1.259921	2.289429
Criterion 4	0.381571	2	0.928318	1	1.126248	1.889882	2
Criterion 5	0.693361	0.436790	0.873581	0.88790	1	0.5	1
Criterion 6	0.763143	2	0.793701	0.529134	2	1	2
Criterion 7	0.346681	0.5	0.436790	0.5	1	0.5	1

Table 11 Ratio matrix

Criteria	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7	WSV	CW	Ratio
Criterion 1	0.193	0.153	0.132	0.431	0.140	0.205	0.211	1.4669	0.1937	7.57
Criterion 2	0.213	0.168	0.334	0.082	0.223	0.078	0.146	1.2462	0.1687	7.39
Criterion 3	0.213	0.073	0.146	0.177	0.111	0.197	0.167	1.0861	0.1462	7.43
Criterion 4	0.073	0.337	0.135	0.164	0.109	0.295	0.146	1.2631	0.1643	7.69
Criterion 5	0.134	0.073	0.127	0.146	0.097	0.078	0.073	0.7303	0.0974	7.50
Criterion 6	0.147	0.337	0.116	0.087	0.194	0.156	0.146	1.1858	0.1566	7.57
Criterion 7	0.067	0.084	0.063	0.082	0.097	0.078	0.073	0.5463	0.0731	7.48

The consistency of the comparison is confirmed by computing the CR. Table 12 shows the computed AHP results.

Table 12 AHP results

Parameter	Value
λmax	7.5180
Consistency index	0.0860
Consistency ratio = CI/RI	0.0654
CI = (λmax - n)/(n-1)	0.0863
No. of criteria	7
CI = Consistency index	0.0863
RI = Random consistency index	1.3200
λmax = average of the ratio	7.5180

7. Results and discussion

The grey relations, listed in Table 13, were determined by employing a suitable normalisation method. Table 13 contains the measurements of beneficial and non-beneficial values.

Table 13 Grey relations

Alternatives	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7
UR5 Robot	0.727	0.333	1	0	1	0	1
AUBO Robotics i5	0.545	1	0.644	0.786	0.128	1	0
Elephant Robotics Panda 5	1	1	1	0.901	0	0.837	1
Hanwha Collaborative Robot 5A	0	1	0.375	0.655	0.897	0.594	1
JAKA Zu 5	0.909	0	0	1	0.384	0.594	0

Concerning the j^{th} criterion for the i^{th} alternative, the i^{th} option is considered as the most preferable when the value of x_{ij} equals 1 or exceeds the values of the other alternatives. As a result, the choice of the best alternative is determined by comparing its performance values to the reference option, identified as 0 in Table 14.

Table 14 Deviation sequence

Alternatives	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7
UR5 Robot	0.272	0.666	0	1	0	1	0
AUBO Robotics i5	0.454	0	0.355	0.213	0.871	0	1
Elephant Robotics Panda 5	0	0	0	0.098	1	0.162	0
Hanwha Collaborative Robot 5A	1	0	0.625	0.344	0.102	0.405	0
JAKA Zu 5	0.090	1	1	0	0.615	0.405	1

The grey relation coefficient matrix for the problem of cobot selection is shown in Table 16. Equation 3 is used to obtain the value, and the zeta value is 0.5. The grey relation coefficient can be computed using the deviation sequence matrix presented in Table 15.

Table 15 Grey relational coefficient

Alternatives	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7
UR5 Robot	0.647	0.429	1	0.333	1	0.333	1
AUBO Robotics i5	0.523	1	0.584	0.701	0.364	1	0.333
Elephant Robotics Panda 5	1	1	1	0.835	0.333	0.755	1
Hanwha Collaborative Robot 5A	0.333	1	0.444	0.592	0.829	0.552	1
JAKA Zu 5	0.846	0.333	0.333	1	0.448	0.552	0.333

Considering the technical and operational parameters, the alternatives were ranked and listed in Table 16. It was observed that the Elephant Robotics Panda 5 cobot model was ranked 1 and selected as the best for the intended assembly process.

Table 16 Grey relation grade value

Alternatives	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7	Rank
UR5 Robot	0.125	0.072	0.146	0.054	0.097	0.052	0.0731	4
AUBO Robotics i5	0.101	0.168	0.085	0.115	0.035	0.156	0.0244	2
Elephant Robotics Panda 5	0.193	0.168	0.146	0.137	0.032	0.118	0.0731	1
Hanwha Collaborative Robot 5A	0.064	0.168	0.064	0.097	0.080	0.086	0.0731	3
JAKA Zu 5	0.163	0.056	0.048	0.164	0.043	0.086	0.0244	5

Fig. 4 Elephant Robotics Panda 5

8. Conclusion

Choosing cobot models within an exhaustive range of specifications becomes noticeably complicated. The hybrid AHP and GRA multi-criteria decision-making approach stands to decide on the most appropriate collaborative robot model for an industrial assembly process. The hybrid MCDM approach was evaluated by choosing a collaborative robot for an assembly process from six potential cobot models while considering seven factors. The GRA technique uses the criterion weight to rank the alternatives, and the AHP calculates the weight of the prospective criteria for subsequent processing. After the analysis, the Elephant Robotics Panda 5 cobot was found to be the optimal choice for the designated assembly workstation based on the grey relation grade value of 1, considering both operational and technological aspects. The proposed MCDM technique offers a genuine ranking order. With careful field testing and optimisation, the proposed method may be utilised in further studies to address discrete MCDM problems. The proposed selection criteria indeed apply to any serial industrial robot. However, the study dealt with industrial collaborative robots as alternatives. A criterion addressing the level of collaboration ought to be added, if conventional serial industrial robots are compared with several models of collaborative robots.

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