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A comparative study of preference dominance-based approaches for selection of industrial robots

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A B S T R A C T

In the modern era of highly mechanized technologies, manufacturing organizations are now extensively using different kinds of industrial robots for performing complicated and perilous tasks with superior levels of accuracy. The major role of robotic technology within manufacturing organizations is to amalgamate design, manufacturing and management planning activities into a flexible system for improving production lines with minimum manufacturing cost involvement. However, the pre-implementation, implementation, and post-implementation phases of robotic technologies are the foremost issues associated with the selection and rationalization of robotic investments, which is based on a thorough review and exploration of various alternative robots and their mutually conflicting performance measures. Evaluating alternative robots in the presence of multiple conflicting attributes often makes the selection task very complex. This paper focuses on the application feasibilities of two preference dominance-based multi-attribute decision-making (MADM) approaches, namely evaluation of mixed data (EVAMIX) and extended preference ranking organization method for enrichment evaluation II (EXPROM2) whilst selecting the best alternative robots within given manufacturing environments. Using these two methods, a list of all the feasible alternatives from the best to the worst suitable robot is obtained by taking into account different robot selection attributes. The ranking performances of these methods are also compared with those of the past researchers, using four performance tests.

A R T I C L E   I N F O

Keywords:
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1. Introduction

Advanced manufacturing technologies (AMTs) play a major role in improving quality and flexibility of small, medium and large scale manufacturing organizations. AMTs have an immense potential in enhancing manufacturing performance to compete in the global market. Today's highly competitive global market requirements can only be fulfilled by implementing computer integrated manufacturing (CIM) technologies, like robots. Recent growths in information technology and computer science have been the key reason for increased utilization of robots in different advanced manufacturing systems. The principal role of robotic technology in manufacturing organizations is to integrate design, manufacturing, management and planning functions into a flexible system. Proper decision-making in pre-implementation, implementation and post-implementation phases of robotic technology is one of major issues associated with the selection and justification of advanced manufacturing technologies which needs a thorough assessment and analysis of various performance measures based on a number of key decisive factors. An industrial robot is commonly defined as a mechanical device that sometimes resembles a human and is capable of performing a variety of complex human tasks on command or by being programmed in advance. In a wider perspective, robot is a reprogrammable multifunctional manipulator which is designed to move materials, parts, tool or other devices by means of variable programmed motions and perform a variety of other tasks. Robots can work under menial conditions, like excessive heat and noise, heavy load, toxic gases etc. The application domains of robots include welding, spray painting, material handling, component assembling, surface treatment etc. If robots are properly deployed, they can improve quality and productivity of a manufacturing organization radically. The important features, like its decision-making capability, capability of responding to various sensory inputs and communicating with other machines make it an essential tool for different industrial applications. Since, a huge amount of initial investment is required for robot acquisition and installation, the investment in robot systems needs a strong decision-making and evaluation process for the manufacturing organizations. Many organizations are now using robots as an integrated part of CIM technology. So, improper selection of robots may adversely affect an organization's competitiveness in terms of productivity of its facilities and quality of its products [1]. Robotic system selection is an important and a crucial task in today's highly competitive environment. Selecting robot technologies for specific industrial applications requires careful scrutiny and assessment of robot alternatives based on industry-specific requirements as well as characteristics of the alternative robots [2]. Different types and categories of robot technologies with diverse capabilities, features, facilities and specifications, as available in today's market, make it more difficult to select the best one among several alternatives. So the main objective of a robot selection process is to identify the predominant attributes and obtain the most appropriate combination of those attributes in combination with the real time requirements of the industrial application. A robot selection attribute is defined as a factor that influences the selection of an industrial robot. To properly evaluate and select a robot for a particular industrial application, several subjective and objective attributes, including accuracy, repeatability, degrees of freedom, control resolution, maximum tip speed, memory capacity, load carrying capacity, programming flexibility, man-machine interfacing ability and vendor's service quality are usually taken into consideration. Also manufacturing environment, product design, production system and cost involvement are some other influencing factors that directly affect the robot selection process. Cost and load capacity of a robot are objective attributes that can be numerically defined, on the other hand, programming flexibility, man-machine interfacing ability and vendor's service quality are subjective attributes. These attributes can be further classified as beneficial and non-beneficial. Beneficial attributes are those whose higher values are desirable (e.g., load carrying capacity, programming flexibility) and non-beneficial attributes are those whose lower values are preferable (e.g., cost, repeatability error). Many of these attributes are conflicting in nature and have different units, which cannot be unified and compared as they are. Thus, while selecting the most suitable robot for a given application, the decision makers (DMs) generally face difficulties due to involvement of such a huge number of conflicting and non-commensurate robot performance characteristics, making the selection process an MADM problem.

Several MADM-based approaches for robot selection have already been proposed and developed by the past investigators to help the manufacturing organizations for making good robot selection decisions. To provide an overview of these various approaches, the literature on robot selection is briefly reviewed here. Bhangale et al. [3] developed a three-stage robot selection procedure for some pick-n-place operation, including elimination stage, evaluation stage, and ranking and selection stage. TOPSIS and a graphical approach were used to rank and select the best robot alternative, and the relative rankings of the alternative robots were compared with those as obtained using the other methods. Rao and Padmanabhan [4] employed diagraph and matrix approach (GTMA) for evaluating and ranking a set of alternative robots for a given industrial application, using the similarity and dissimilarity coefficient values. A robot selection index was also proposed to evaluate and rank the alternative robots. Shih [5] suggested an incremental analysis method with group Technique for Order of Preference by Similarity to Ideal Solution

(TOPSIS) for selection of industrial robots. Chatterjee et al. [6] applied 'VIsekriterijumsko KOmpromisno Rangiranje' (VIKOR) and 'ELimination and Et Choice Translating Reality' (ELECTRE) methods for the selection of robots for some industrial applications. Kumar and Garg [7] developed a distance-based approach for evaluation, selection and ranking of robots, and compared its ranking performance with other techniques. Athawale and Chakraborty [8] compared the ranking performances of ten most popular MADM methods while selecting the best robot for some industrial pick-n-place operation. Rao et al. [9] proposed a novel decision-making method for optimal robot selection by integrating the objective weights of criteria and subjective preferences of the DM in conjunction with fuzzy logic which would convert the qualitative attributes into quantitative attributes. Koulouriotis and Ketipi [10] developed a digraph-based model for evaluation and selection of industrial robots from a feasible set of alternatives. Devi [11] extended VIKOR method in intuitionistic fuzzy environment for solving MADM problems in the area of robot selection. Athawale et al. [12] solved two industrial robot selection problems using solving VIKOR method and validated the results. İç [13] explored the applicability of an integrated TOPSIS and design of experiments (DoE) methodology to identify critical selection attributes and their interactions while solving different real time CIM selection problems, including industrial robots. İç et al. [14] developed a two-phase robot selection decision support system (DSS), i.e., ROBSEL, to help the DMs in robot selection. In that DSS, at first, the user would obtain a feasible set of robots by providing the values of 15 predefined requirements, and then it would use fuzzy analytic hieararchy process (FAHP) to rank the alternative robots. Bahadir and Satoglu [15] developed a DSS for robot selection based on axiomatic design principles (ADP). Datta et al. [16] explored the use of interval-valued grey numbers (IVGN) to tackle subjective evaluation information collected from a group of expert and multiplicative multi-objective optimization by ratio analysis (MULTIMOORA) method in order to aggregate individual criterion scores into an equivalent evaluation index towards evaluating feasible ranking order of candidate alternative robots. Liu et al. [17] proposed an interval 2-tuple linguistic TOPSIS (ITL-TOPSIS) method to handle the robot selection problem under uncertain and incomplete information environment. Ketipi and Koulouriotis [18] presented an extensive review of robot selection models with their advantages and disadvantages considering the flexibility and the other utility parameters. Ketipi et al. [19] presented an integrated comparative analysis of a representative sample of methodologies which have been implemented for two real-world problems and also used a generator of random example cases in conjunction with rank correlation coefficients along with dendrograms and bar graphs tools in order to detect similarities and differences between the selection methods as well as to evaluate qualitatively their overall behavior.

From the literature survey as presented above, it is understood that numerous research works have already been reported by the past researchers on solving the industrial robot selection problems using different mathematical and MADM-based approaches. But till date, very less effort has been made to compare the relative performances of several MADM methods employed simultaneously. In this paper, an effort is made to compare the relative performances of two almost unrevealed, yet very potential preference dominance-based MADM methods, namely EVAMIX and EXPROM2, while solving two industrial robot selection problems in discrete manufacturing environments. The illustrative examples are used to demonstrate the application aptness of the two MADM methods. It is observed that both the considered methods have huge potentials to deal with such complex decision-making problems in conflicting real time manufacturing environments. The computational details of these methods are presented in Section 2 and 3, respectively.

2. EVAMIX method

The EVAMIX method was primarily established by Voogd in 1983, and later advocated by Martel and Matarazzo [20]. This method is a generalization of concordance analysis for those decision matrices which consist of both ordinal and cardinal data. The basic concept of this method is based on the computation of the dominance score of an alternative over another alternatives on criterion-by-criterion basis. As an initial step, the ordinal and cardinal information is dealt separately through two separate overviews. Alternatives are compared two-by-two for each overview. The outcome is displayed in two dominance matrices, which display the respective dominance scores, thereby indicating to which extent one alternative is dominant over the other. Through standardization of these two matrices, a mutual comparison of quantitative and qualitative information becomes possible. Summation of the standardized dominance scores, including the weights of the quantitative and qualitative attributes results in a total score of each pair of alternatives. The attribute weights can be obtained applying AHP [21] or entropy method [22]. These standardized dominance scores are further utilized to compute the appraisal scores for each of the alternatives which are subsequently used to determine a complete ranking preorder of the alternatives. From a procedural point of view, EVAMIX method consists of the following steps as enlisted below [20, 23-25]:

Step 1: First separate the ordinal and cardinal criteria in the decision matrix.

Step 2: Normalize the beneficial attributes (where higher values are preferable) using the following equation:

$$r_{ij} = \left[x_{ij} - min(x_{ij})\right] / \left[max(x_{ij}) - min(x_{ij})\right] \; (i = 1,2, \dots, m \,;\; j = 1,2, \dots, n) \tag{1}$$

where x_{ij} is the performance measure of i^{th} alternative with respect to j^{th} criterion, r_{ij} is the normalized value of x_{ij}, m is the number of alternatives and n is the number of criteria. For non-beneficial attributes (where lower values are preferable), Eq. 1 can be rewritten as follows:

$$r_{ij} = \left[max(x_{ij}) - x_{ij}\right] / \left[max(x_{ij}) - min(x_{ij})\right] \tag{2}$$

Step 3: Calculate the evaluative differences of i^{th} alternative on each ordinal and cardinal attributes with respect to other alternatives. This step involves the calculation of differences in criteria values between different alternatives pair-wise.

Step 4: Compute the dominance scores of each alternative pair, (i, i') for all the ordinal and cardinal criteria using the following equations:

$$\alpha_{ii'} = \left[\sum_{j \epsilon O} \{w_j sgn(r_{ij} - r_{i'j})\} c\right]^{1/c} \tag{3}$$

where

$$sgn(r_{ij} - r_{i'j}) = \begin{cases} +1 \text{ if } r_{ij} > r_{i'j} \\ \;\;0 \text{ if } r_{ij} = r_{i'j} \\ -1 \text{ if } r_{ij} < r_{i'j} \end{cases}$$

$$\gamma_{ii'} = \left[\sum_{j \epsilon C} \{w_j sgn(r_{ij} - r_{i'j})\} c\right]^{1/c} \tag{4}$$

where the symbol c is a scaling parameter, for which any arbitrary positive odd number, like 1,3,5,... may be chosen, O and C are the sets of ordinal and cardinal criteria, respectively, $\alpha_{ii'}$ and $\gamma_{ii'}$ are the dominance scores for alternative pair, (i, i') with respect to ordinal and cardinal criteria, respectively, and w_j is the weight of j^{th} criterion.

Step 5: Calculate the standardized dominance scores. Martel and Matarazzo [20] proposed an additive interval method to derive the standardized ordinal dominance score $(\delta_{ii'})$ and cardinal dominance score $(d_{ii'})$ for the alternative pair, (i, i') as follows. Standardized ordinal dominance score:

$$(\delta_{ii'}) = \frac{(\alpha_{ii'} - \alpha^-)}{(\alpha^+ - \alpha^-)} \tag{5}$$

where α^+ (α^-) is the highest (lowest) ordinal dominance score for the alternative pair, (i, i'). Standardized cardinal dominance score:

$$(d_{ii'}) = \frac{(\gamma_{ii'} - \gamma^-)}{(\gamma^+ - \gamma^-)} \tag{6}$$

where γ^+ (γ^-) is the highest (lowest) cardinal dominance score for the alternative pair, *(i, i')*.

Step 6: Determine the overall dominance score. The overall dominance score, $D_{ii'}$ for each pair of alternatives, *(i, i')* is calculated to measure the degree by which alternative *i* dominates alternative *i'*.

$$D_{ii'} = w_O \delta_{ii'} + w_c d_{ii'} \tag{7}$$

where w_O is the sum of the weights for the ordinal criteria ($w_o = \sum_{j\epsilon o} w_j$) and w_C is the sum of the weights for the cardinal criteria ($w_c = \sum_{j\epsilon c} w_j$).

Step 7: Calculate the appraisal score.

$$(S_i) = \sum\nolimits_{i'} \left(\frac{D_{i'i}}{D_{ii'}}\right)^{-1} \tag{8}$$

The appraisal score for i^{th} alternative *(S_i)* is computed which gives the final preference of the alternatives. Higher the appraisal score, better is the performance of the alternative. The best alternative is the one which has the highest value of the appraisal score.

3. Extended PROMETHEE II method

The extended PROMETHEE II (EXPROM2) is a modifed version of PROMETHEE II method. Similar to PROMETHEE II, pair-wise comparison of alternatives considering the deviations with respect to each criterion is considered in EXPROM2 method. Basically, it is based on the concept of the ideal and anti-ideal solutions. The ideal and anti-ideal alternatives do not necessarily belong to the set of considered alternatives, although in most of situations, they are directly derived from the existing set of alternatives. Practically, the ideal and anti-ideal alternatives simply represent the extreme limits on the performances, set by the constraints of the problem under consideration. PROMETHEE II method derives a full ranking preorder of the alternatives by using a net flow value concept, but excludes the incomparability between two alternatives. This complete preorder expresses the preference of an alternative over another. This constitutes a limitation of the original PROMETHEE II method. To overcome this limitation, Diakoulaki and Koumoutsos [26] developed an extension of PROMETHEE II method which is popularly known as EXPROM2. In this method, the relative performance of one alternative over the other is defined by two preference indices. The first one is the weak preference index, based on the aggregated preference function considering the criteria weights, as determined in PROMETHEE II method. The second one is the strict preference index, based on the notion of the ideal and anti-ideal solutions. The ideal and anti-ideal values are directly derived from the decision matrix, and they reflect the extreme limits for a particular criterion. A total preference index is also computed by adding the strict and the weak preference indices which gives an accurate measure of the intensity of preference of one alternative over the other considering all the criteria. The procedural steps of EXPROM2 method are given as below [26-28]:

Step 1: Normalization of the decision matrix for beneficial and non-beneficial attributes using Eqs. 1 and 2, respectively.

Step 2: Calculation of the evaluative differences of i^{th} alternative with respect to other alternatives. This step involves the calculation of differences in criteria values *(d_j)* between different alternatives pair-wise.

Step 3: Determination of the preference function, $P_j(i, i')$. There are mainly six types of preference functions, e.g., usual criterion, U-shape criterion, *V*-shaped criterion, level criterion, *V*-shape with indifference criterion and Gaussian criterion. But most of these preference functions require the definition of some preferential parameters, like preference and indifference thresholds. However, in real time situations, it may be difficult for the DM to specify which specific form of preference function is suitable for each criterion and also to determine the parameters involved with them. To overcome these difficulties and make the related mathematical approach easier and faster, the simplest form of preference function (usual criterion) is adopted here, as given below:

$$P_j(i,i') = 0 \; if r_{ij} \leq r_{i'j} \tag{9}$$

$$P_j(i,i') = (r_{ij} - r_{i'j}) if \; r_{ij} > r_{i'j} \tag{10}$$

Step 4: Calculation the weak preference index considering the criteria weight values using the following equation:

$$WP(i,i') = \left[\sum\nolimits_{j=1}^{n} w_j \, x P_j(i,i')\right] \Big/ \sum\nolimits_{j=1}^{n} w_j \tag{11}$$

where w_j is the relative importance (weight) of j^{th} criterion.

Step 5: Defining the strict preference function, $SP_j(i, i')$. The strict preference function is based on the comparison of the difference values (dm_j) with the range of values as defined by the evaluation of the whole set of alternatives for a criterion.

$$SP_j(i,i') = \left[max(0, d_j - L_j)\right] / \left[dm_j - L_j\right] \tag{12}$$

where L_j is limit of preference (0 for usual criterion preference function, and indifference values for other five preference functions) and dm_j is difference between the ideal and anti-ideal values of j^{th} criterion.

Step 6: Computation of the strict preference index using the following equation:

$$SP(i,i') = \left[\sum_{j=1}^{n} w_j x SP_j(i,i')\right] \Big/ \sum_{j=1}^{n} w_j \tag{13}$$

Step 7: Calculation of the total preference index value as:

$$TP(i,i') = Min[1, WP(i,i') + SP(i,i')] \tag{14}$$

Step 8: Determination of the leaving and the entering outranking flows using the following equations. Leaving (positive) flow for i^{th} alternative:

$$\varphi^+(i) = \frac{1}{m-1} \sum_{i'=1}^{m} TP(i,i') \quad (i \neq i') \tag{15}$$

Entering (negative) flow for i^{th} alternative:

$$\varphi^-(i) = \frac{1}{m-1} \sum_{i'=1}^{m} TP(i',i) \quad (i \neq i') \tag{16}$$

The leaving flow expresses how much an alternative dominates the other alternatives, while the entering flow denotes how much an alternative is dominated by the other alternatives. Based on these flow values, EXPROM2 method can give the complete ranking preorder of the candidate alternatives by using a net flow.

Step 9: Computaion of the net outranking flow $\varphi(i)$ for each alternative as:

$$\varphi(i) = \varphi^+(i) - \varphi^-(i) \tag{17}$$

Step 10: Determination of the ranking of all the considered alternatives depending on the values of $\varphi(i)$. The higher the value of $\varphi(i)$, the better is the alternative. Thus, the best alternative is the one having the highest $\varphi(i)$ value.

The EXPROM2 is a preference dominance approach designed to handle quantitative as well as qualitative attributes with discrete alternatives. In this method, pair-wise comparison of the alternatives is performed to compute a preference function for each criterion. Based on this preference function, a preference index for alternative i over i' is determined. This preference index is the measure to support the hypothesis that alternative i is preferred to i'.

4. Performance comparison tests for preference dominance-based methods

In order to establish the application suitability of the two preference dominance-based methods for solving industrial robot selection problems, their relative ranking performances are compared using the following four tests [29]:

(a) Determination of overall ranking aggrement among all the considered methods using Kendall's coefficient of concordance (Z) value employing Eq. 18.

$$Z = \frac{\sum_{i=1}^{m}\left(S_i - \frac{\sum_{i=1}^{m} S_i}{m}\right)^2}{\frac{1}{12}k^2(m^3 - m)} \tag{18}$$

(b) Computation of pair-wise rank similarities among all the methods by Spearman's rank correlation coefficient (r_s) values accoprding to Eq. 19.

$$r_s = 1 - 6\frac{\sum_{i=1}^{m} D_i^2}{m(m^2 - 1)} \tag{19}$$

(c) Agreement between the top three ranked alternatives, and
(d) Number of ranks matched, as the percentage of the total number of considered alternatives.

5. Illustrative examples

In order to reveal the computational precision and expediency of the two considered preference dominance-based MADM methods for solving industrial robot selection problems, the following two real time examples are illustrated.

5.1 Industrial robot selection example 1

This example deals with the selection of the most appropriate industrial robot to be used for some pick-andn-place operations to avoid certain obstacles. In this example, Bhangale et al. [3] considered five different robot selection attributes, such as load capacity (LC), repeatability (R), maximum tip speed (MTS), memory capacity (MC) and manipulator reach (MR). The minimum requirements with respect to different robot selection attributes for this application are presented in Table 1. Load capacity is defined as the maximum operating payload capacity of a robot without affecting its performance. It is basically related to robot acceleration and speed, and is a function of manipulator acceleration and wrist torque. Repeatability is the measure of the ability of a robot to return to a programmed position. Accuracy is the measure of closeness between the robot end effectors and the target point, and can usually be defined as the distance between the target point and the center of all points to which the robot goes on repeated trials.

Maximum tip speed is the speed at which a robot can move in an inertial reference frame. Memory capacity of a robot is measured in terms of number of points or steps that it can store in its memory while traversing along its pre-defined path. Manipulator reach is the maximum distance that can be covered by the robotic manipulator so as to grasp an object for the given pick-n-place operation.

Table 1 Minimum criteria requirements for example 1 [3]

Sl. No.	Attribute	Minimum requirement
1	Load capacity	2 kg
2	Repeatability	0.5 mm
3	Maximum tip speed	255 mm/s
4	Type of drives (actuators)	electrical only
5	Memory capacity	250 points/steps
6	Manipulator reach	500 mm
7	Degree of freedom	5

Among these robot selection attributes as considered in this problem, load capacity, maximum tip speed, memory capacity and manipulator reach are beneficial criteria, requiring higher values, whereas, repeatability is a non-beneficial attribute, requiring lower value.

Based on the predefined attribute requirements as presented in Table 1, Bhangale et al. [3] listed seven alternative robots with their relevant attribute values, Table 2. Bhangale et al. [3] also calculated the criteria weights as w_{LC} = 0.1761, w_R = 0.2042, w_{MTS} = 0.2668, w_{MC} = 0.243 and w_{MR} = 0.2286 using an eigen vector-based approach, but did a mistake while calculating the weights, as the summation of all the criteria weights exceeds one. So, in this research work, the criteria weights, as estimated by Rao [30] using AHP method, are used for all the preference ranking-based analyses, and these weights are w_{LC} = 0.036, w_{RE} = 0.192, w_{MTS} = 0.326, w_{MC} = 0.326 and w_{MR} = 0.120. Rao [30] solved the same robot selection problem using AHP method and obtained a ranking of the alternative robots as 3 > 2 > 7 > 1 > 4 > 6 > 5.

Table 2 Quantitative data for robot selection problem 1 [3]

Sl. No.	Robot	LC [kg]	R [mm]	MTS [mm/s]	MC [points]	MR [mm]
1	ASEA-IRB 60/2	60	0.4	2540	500	990
2	Cincinnati Milacrone T3-726	6.35	0.15	1016	3000	1041
3	Cybotech V15 Electric Robot	6.8	0.1	1727.2	1500	1676
4	Hitachi America Process Robot	10	0.2	1000	2000	965
5	Unimation PUMA 500/600	2.5	0.1	560	500	915
6	United States Robots Maker 110	4.5	0.08	1016	350	508
7	Yaskawa Electric Motoman L3C	3	0.1	177	1000	920

5.1.1 EVAMIX method

The problem of selecting the best suited industrial robot for the given pick-n-place operation is first solved using EVAMIX method. It begins with the separation of ordinal and cardinal criteria values in the decision matrix. In this example, as there is no ordinal criterion, this step is omitted here. Now, the decision matrix of Table 2 is normalized using Eqs. 1 and 2, respectively for beneficial and non-beneficial attributes, as shown in Table 3. After normalizing the decision matrix, the evaluative differences for each criterion with respect to all pair of alternative robots are calculated. Now, the dominance scores of each pair of alternative robots (i, i') with respect to each attribute are computed applying Eq. 4. While calculating the dominance scores, the value of c is taken as 1. Based on the additive interval technique, the standardized dominance scores for all the robot pairs are determined using Eq. 6. As the pick-n-place robot selection matrix has no ordinal criteria, so the ordinal dominance scores and standardized ordinal dominance scores need not to be calculated.

The overall dominance score for each pair of alternative robots is estimated using Eq. 7 which exemplifies the degree by which one robot dominates the others. These overall dominance scores for all pairs of alternative robots are given in Table 4. The appraisal score for each alternative is then calculated using Eq. 8 and based on the descending values of these appraisal scores, the final ranking of the alternative robots is obtained, as shown in Table 5.

Table 3 Normalized decision matrix

Robot	LC	RE	MTS	MC	MR
1	1.0000	0	1.0000	0.0566	0.4127
2	0.0670	0.7813	0.3551	1.0000	0.4563
3	0.0748	0.9375	0.6560	0.4340	1.0000
4	0.1304	0.6250	0.3483	0.6226	0.3913
5	0	0.9375	0.1621	0.0566	0.3485
6	0.0348	1.0000	0.3551	0	0
7	0.0087	0.9375	0	0.2453	0.3527

Table 4 Overall dominance scores for each robot pair

Robot pair	$D_{ii'}$	Robot pair	$D_{ii'}$	Robot pair	$D_{ii'}$
(1, 2)	0.3513	(3, 4)	0.8707	(5, 6)	0.2974
(1, 3)	0.3513	(3, 5)	0.8631	(5, 7)	0.4881
(1, 4)	0.5582	(3, 6)	0.6875	(6, 1)	0.3125
(1, 5)	0.6228	(3, 7)	0.8631	(6, 2)	0.4881
(1, 6)	0.6875	(4, 1)	0.4418	(6, 3)	0.3125
(1, 7)	0.5582	(4, 2)	0.0000	(6, 4)	0.6638
(2, 1)	0.6487	(4, 3)	0.1293	(6, 5)	0.7026
(2, 3)	0.0905	(4, 5)	0.6875	(6, 7)	0.7026
(2, 4)	1.0000	(4, 6)	0.3362	(7, 1)	0.4418
(2, 5)	0.6875	(4, 7)	0.6875	(7, 2)	0.3125
(2, 6)	0.5119	(5, 1)	0.3772	(7, 3)	0.1369
(2, 7)	0.6875	(5, 2)	0.3125	(7, 4)	0.3125
(3, 1)	0.6487	(5, 3)	0.1369	(7, 5)	0.5119
(3, 2)	0.9095	(5, 4)	0.3125	(7, 6)	0.2974

Table 5 Appraisal score and rank of each robot alternative

Robot	S_i additive interval technique	Rank
1	0.1578	2
2	0.0803	5
3	0.6405	1
4	0.0919	4
5	0.0634	7
6	0.1470	3
7	0.0654	6

The ranking of the alternative robots is observed as 3 > 1 > 6 > 4 > 2 > 7 > 5 which signifies that Robot 3 (Cybotech V15 Electric Robot) is the best choice for this given pick-n-place operation. Robot 1 (ASEA-IRB 60/2) is the second best choice and Robot 5 (Unimation PUMA 500/600) is the worst chosen alternative.

5.1.2 EXPROM2 method

In this method, at first, the decision matrix of Table 2 is normalized using Eqs. 1 and 2, respectively for beneficial and non-beneficial attributes and is shown in Table 6. Then employing Eqs. 9, 10 and 12 the corresponding weak and strict preference functions are computed for all pairs of robot alternatives. Although there are six different types of preference functions that may be adopted, but as most of these preference functions require the definition of some preferential parameters, like preference and indifference thresholds to be specified by the DM in real time situations, the usual criterion is adopted here for computing the weak preference function. After specifying these preference functions, weak preference index, strong preference index and total preference index values for the alternative pairs of robots are computed using Eqs. 11, 13 and 14 respectively, as shown in Table 7. As in this computation, usual criterion is chosen as the preferred preference function, both the values of weak and strong preference indices are observed to be same here.

Table 6 Normalized decision matrix

Robot	LC	RE	MTS	MC	MR
1	1.0000	0	1.0000	0.0566	0.4127
2	0.0670	0.7813	0.3551	1.0000	0.4563
3	0.0748	0.9375	0.6560	0.4340	1.0000
4	0.1304	0.6250	0.3483	0.6226	0.3913
5	0	0.9375	0.1621	0.0566	0.3485
6	0.0348	1.0000	0.3551	0	0
7	0.0087	0.9375	0	0.2453	0.3527

Table 7 Weak, strong and total preference index values for robot pairs

Robot pair	$WP(i,i')$	$SP(i,i')$	$TP(i,i')$	Robot pair	$WP(i,i')$	$SP(i,i')$	$TP(i,i')$
(1, 2)	0.2438	0.2438	0.4877	(4, 5)	0.2551	0.2551	0.5101
(1, 3)	0.1454	0.1454	0.2909	(4, 6)	0.2534	0.2534	0.5068
(1, 4)	0.2463	0.2463	0.4927	(4, 7)	0.2456	0.2456	0.4911
(1, 5)	0.3169	0.3169	0.6337	(5, 1)	0.1800	0.1800	0.3600
(1, 6)	0.3130	0.3130	0.6259	(5, 2)	0.0300	0.0300	0.0600
(1, 7)	0.3689	0.3689	0.7378	(5, 3)	0	0	0
(2, 1)	0.4628	0.4628	0.9256	(5, 4)	0.0600	0.0600	0.1200
(2, 3)	0.1845	0.1845	0.3691	(5, 6)	0.0603	0.0603	0.1205
(2, 4)	0.1630	0.1630	0.3261	(5, 7)	0.0528	0.0528	0.1057
(2, 5)	0.3858	0.3858	0.7716	(6, 1)	0.1920	0.1920	0.3840
(2, 6)	0.3819	0.3819	0.7638	(6, 2)	0.0420	0.0420	0.0840
(2, 7)	0.3763	0.3763	0.7526	(6, 3)	0.0120	0.0120	0.0240
(3, 1)	0.3735	0.3735	0.7470	(6, 4)	0.0742	0.0742	0.1484
(3, 2)	0.1936	0.1936	0.3873	(6, 5)	0.0762	0.0762	0.1523
(3, 4)	0.2334	0.2334	0.4667	(6, 7)	0.1287	0.1287	0.2574
(3, 5)	0.3649	0.3649	0.7298	(7, 1)	0.2415	0.2415	0.4830
(3, 6)	0.3610	0.3610	0.7221	(7, 2)	0.0300	0.0300	0.0600
(3, 7)	0.3554	0.3554	0.7109	(7, 3)	0	0	0
(4, 1)	0.3045	0.3045	0.6091	(7, 4)	0.0600	0.0600	0.1200
(4, 2)	0.0023	0.0023	0.0046	(7, 5)	0.0623	0.0623	0.1247
(4, 3)	0.0635	0.0635	0.1270	(7, 6)	0.1223	0.1223	0.2446

Now, based on the leaving and entering outranking flows as given in Table 8 and computed using Eqs. 15 and 16, respectively, the related net outranking flows are estimated for all the alternatives using Eq. 17. After arranging these net outranking flows in descending order, the final ranking of the alternative robots is obtained, as shown in Table 8. This table depicts that Robot 3 (Cybotech V15 Electric Robot) is the best choice, followed by Robot 3 (Cincinnati Milacrone T3-726). Robot 5 (Unimation PUMA 500/600) is the worst chosen robot among the considered alternatives.

Table 8 Ranking of alternative robots with leaving, entering and net flow values

Robot	$\varphi^+(i)$	$\varphi^-(i)$	$\varphi(i)$	Rank
1	0.5448	0.5848	-0.0400	4
2	0.6515	0.1806	0.4709	2
3	0.6273	0.1352	0.4921	1
4	0.3748	0.2790	0.0958	3
5	0.1277	0.4871	-0.3594	7
6	0.1750	0.4973	-0.3223	5
7	0.1720	0.5092	-0.3372	6

5.2 Performance analysis of preference dominance-based methods for example 1

Now, to examine the suitability and judge the rank conformities among the two preference dominance-based methods while solving this pick-n-place industrial robot selection problem, their ranking performances are compared using four different performance tests.

These performance tests compare the ranking as provided by these two methods with respect to each other and also with respect to AHP method as applied by Rao [30] for solving this robot selection problem. Table 9 summarizes the ranking preorders of the robot alternatives, as obtained using these eight methods. The ranking performances of both the Evamix and EXPROM2 methods with respect to those derived by Rao [30] are exhibited in Fig. 1.

Table 9 Ranking preorders obtained using different methods

Robot	AHP [30]	EVAMIX	EXPROM2
1	4	2	4
2	2	5	2
3	1	1	1
4	5	4	3
5	7	7	7
6	6	3	5
7	3	6	6

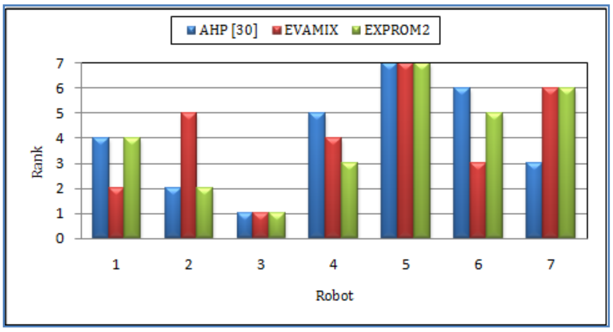

Fig. 1 Comparative rankings of alternative robots for example 1

a) Now, in order to determine the overall ranking agreement among all the considered methods, the Kendall's coefficient of concordance *(Z)* value is now computed. For this industrial robot selection problem, the *z* value is obtained as 0.7460, suggesting a high rank conformity among all these methods.
b) Table 10 shows the Spearman's rank correlation coefficient (r_s) values when the rankings of the robot alternatives as obtained using the two preference dominance-based methods are compared between themselves and also with respect to the rank ordering of Rao [30] as derived using AHP method. It is revealed that the r_s value ranges from 0.4285 to 0.7500. Table 10 also shows that there are good agreements between the two preference dominance-based methods and also with AHP method. The performances of EVAMIX in comparison to EXPROM2 method is relatively poor in terms of rank similarities.

c) Table 10 also shows the results of another test, performed to determine the agreement between the top three ranked robot alternatives as indicated by these methods. This table suggests that the ranks obtained applying EXPROM2 method perfectly match with those of Rao [30] for the best and the second best robot alternatives.
d) The last test is performed with respect to the number of total ranks matched, expressed as the percentage of the number of alternatives. These results are also shown in Table 10. It is again observed that EXPROM2 evolves out as the best method as compared to EVAMIX.

Table 10 Performance test table for preference dominance-based methods for robot selection problem 1

Method	EVAMIX	EXPROM2
AHP [30]	0.4285, (1,#,#), 28.57	0.7500, (1,2,#), 57.14
EVAMIX		0.6785, (1,#,#), 42.86

5.3 Industrial robot selection example 2

Now in order to further demonstrate and validate the efficiency of the two preference dominance-based methods while utilizing various robot selection attributes to achieve a comprehensive ranking of the alternative robots, another industrial example from Rao and Padmanabhan [4] is considered here.

In this example, four attributes were identified and five alternative robots were short-listed based on the threshold values set for those attributes. In the present research work, the considered attributes are load capacity (*LC*), repeatability error (*RE*), vertical reach (*VR*) in mm and degrees of freedom (*DF*). Among these attributes, *LC*, *VR* and *DF* are beneficial in nature requiring higher values. *RE* is a non-beneficial attribute where lower value is desirable. The relative normalized weights for the attributes were calculated by Rao and Padmanabhan [4] using AHP method as w_{LC} = 0.0963, w_{RE} = 0.5579, w_{VR} = 0.0963 and w_{DF} = 0.2495. The consistency ratio (*CR*) was computed as 0.0160, which is much less than its threshold value of 0.1 as used in AHP method, and hence, these weights are acceptable. Rao and Padmanabhan [4] solved this industrial robot selection problem using GTMA, and obtained a ranking of the alternative robots as 3 > 2 > 1 > 4 > 5, indicating robots 3 and 5 as the best and the worst choices for the given industrial application under the specified conditions. The decision matrix for this industrial robot selection problem is shown in Table 11.

Table 11 Quantitative data for robot selection problem 2 [4]

Robot	*LC*	*RE*	*VR*	*DF*
1	60	0.4	125	5
2	60	0.4	125	6
3	68	0.13	75	6
4	50	1	100	6
5	30	0.6	55	5

5.3.1 EVAMIX method

This robot selection problem is now solved using EVAMIX method. At first, the decision matrix of Table 11 is normalized, as shown in Table 12. After obtaining the normalized decision matrix, the evaluative differences of each robot for all the qualitative and quantitative criteria with respect to other robot alternatives are computed. Then, the dominance scores of each pair of alternative robots are calculated. Now, the standardized ordinal and cardinal dominance scores for all the robot pairs are determined using the additive interval technique. The overall dominance score for each pair of robots is calculated, representing the degree by which a particular robot dominates the others. These overall dominance scores for all the robot pairs are shown in Table 13. Finally, the appraisal score for each alternative robot is computed and based on the descending order of these appraisal scores, the final ranking is obtained, as shown in Table 14. The best choice of robot for this industrial example is Robot 3, followed by Robot 2 and the last choice is Robot 4.

Table 12 Normalized decision matrix

Robot	LC	RE	VR	DF
1	0.7895	0.6897	1.0000	0.0000
2	0.7895	0.6897	1.0000	1.0000
3	1.0000	1.0000	0.2857	1.0000
4	0.5263	0.0000	0.6429	1.0000
5	0.0000	0.4598	0.0000	0.0000

Table 13 Overall dominance scores for robot pairs

Robot pair	$D_{ii'}$	Robot pair	$D_{ii'}$
(1, 2)	0.3753	(3, 4)	0.7790
(1, 3)	0.0963	(3, 5)	1.0000
(1, 4)	0.7505	(4, 1)	0.2495
(1, 5)	0.8753	(4, 2)	0.1248
(2, 1)	0.6248	(4, 3)	0.2211
(2, 3)	0.2211	(4, 5)	0.4421
(2, 4)	0.8753	(5, 1)	0.1248
(2, 5)	1.0000	(5, 2)	0.0000
(3, 1)	0.9037	(5, 3)	0.0000
(3, 2)	0.7790	(5, 4)	0.5579

Table 14 Appraisal score and rank for each robot

Robot	S_i additive interval technique	Rank
1	0.0868	4
2	0.2344	2
3	1.4834	1
4	0.0675	5
5	0.1281	3

5.3.2. EXPROM2 method

In this method, first, the corresponding weak and strict preference functions are computed for all pairs of robot alternatives from the normalized decision matrix as shown in Table 12. After calculating these preference functions, weak preference index, strong preference index and total preference index are estimated, as shown in Table 15. After determining these three preference indices, the leaving and entering outranking flows for different robots are calculated, as given in Table 16. The related net outranking flows are then computed for all robots which are used to derive the final ranking order of the robot alternatives by arranging them in a descending order of preference, as also shown in Table 16. Robot 3 emerges out as the best choice, while Robot 5 becomes the last ranked alternative.

Table 15 Weak, strong and total preference index values for different robot pairs

Robot pair	$WP(i,i')$	$SP(i,i')$	$TP(i,i')$	Robot pair	$WP(i,i')$	$SP(i,i')$	$TP(i,i')$
(1, 2)	0	0	0	(3, 4)	0.6035	0.6035	1.0000
(1, 3)	0.0688	0.0688	0.1376	(3, 5)	0.6747	0.6747	1.0000
(1, 4)	0.4445	0.4445	0.8890	(4, 1)	0.2495	0.2495	0.4990
(1, 5)	0.3006	0.3006	0.6012	(4, 2)	0	0	0
(2, 1)	0.2495	0.2495	0.4990	(4, 3)	0.0344	0.0344	0.0688
(2, 3)	0.0688	0.0688	0.1376	(4, 5)	0.3621	0.3621	0.7242
(2, 4)	0.4445	0.4445	0.8890	(5, 1)	0	0	0
(2, 5)	0.5501	0.5501	1.0000	(5, 2)	0	0	0
(3, 1)	0.4429	0.4429	0.8858	(5, 3)	0	0	0
(3, 2)	0.1934	0.1934	0.3868	(5, 4)	0.2565	0.2565	0.5130

Table 16 Leaving, entering and net outranking flow values with robot ranks

Robot	$\varphi^{+}(i)$	$\varphi^{-}(i)$	$\varphi(i)$	Rank
1	0.4069	0.4710	-0.0640	3
2	0.6314	0.0967	0.5347	2
3	0.8182	0.0860	0.7322	1
4	0.3230	0.8227	-0.4998	4
5	0.1283	0.8313	-0.7031	5

5.4 Performance analysis of preference dominance-based methods for example 2

Now, to examine the rank similarities among the two preference dominance-based methods while solving this industrial robot selection problem, their ranking performances are compared using the four different performance tests. Table 17 summarizes the ranking preorders of the robot alternatives as obtained using different MADM methods. The ranking performances of both the Evamix and EXPROM2 methods with respect to those derived by Rao and Padmanabhan [4] are exhibited in Fig. 2.

Table 17 Ranking preorders of robot alternatives obtained using different methods

Robot	GTMA [4]	EVAMIX	EXPROM2
1	3	4	3
2	2	2	2
3	1	1	1
4	4	5	4
5	5	3	5

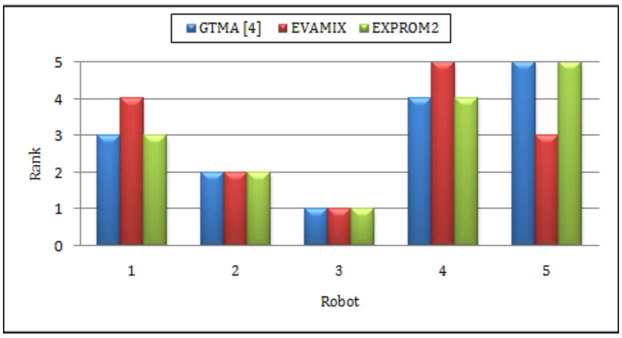

Fig. 2 Comparative rankings of alternative robots for example 2

a) At first for this industrial robot selection problem, the z value is computed as 0.8666, indicating a very strong rank similarities among these methods.
b) In the second test, the r_s values are calculated to compare the rankings of the alternative robots, as obtained using different preference dominance-based methods between themselves and also with respect to the rank ordering as derived by GTMA. It is revealed that the r_s value ranges from 0.7 to 1.0, and a perfect match exists for GTMA-EXPROM2 methods. Table 18 shows that the two preference dominance-based methods have very high rank agreement between themselves and also with respect to GTMA.
c) Table 18 shows the results of the next test, performed to evaluate the agreement between the top three ranked robot alternatives as indicated by these methods. This table confirms that EXPROM2 method produces the same rankings for the best, second best and third best robot alternatives with respect to GTMA.
d) The last test is conducted with respect to the number of total ranks matched, expressed as a percentage of the number of alternatives. These results are shown in Table 18. It is again observed that EXPROM2 method evolves out as the best performer as compared to EVAMIX method.

Table 18 Performance test table for preference dominance-based methods for robot selection problem 2

Method	EVAMIX	EXPROM2
GTMA [4]	0.70, (1,2,#), 40	1.00, (1,2,3), 100
EVAMIX		0.70, (1,2,#), 40

6. Conclusions

Although different MADM methods have already been proposed by the past researchers for economic evaluation and selection of industrial robots, it is not still clear which MADM method is the best for a given industrial robot selection problem. This paper considers two preference dominance-based methods and compares their relative ranking performances while selecting the best suited industrial robots for the given industrial applications. Four performance tests are also conducted. The cited industrial robot selection problems demonstrate the suitability and accuracy of EVAMIX and EXPROM2 methods which have very high prospects in solving complex robot selection decision-making problems. The rankings derived using these four preference ranking methods almost perfectly match with those as obtained by the past researchers. It is found that although EXPROM2 performs well, EVAMIX method can also be successfully applied for the robot selection problems as the change of the method does not produce any significant differences in the top-ranked robot alternatives. In EVAMIX method, a linear criteria transformation procedure converts all the criteria values into dimensionless numbers ranging from 0 to 1. The dominance scores for each pair of alternatives are calculated on the basis of criterion-by-criterion comparison and an additive interval model is then adopted. While in EXPROM2 method, alternatives are compared with respect to the deviations that the alternatives show to each other for each criterion. EXPROM2 method also allows the involvement of different preferential parameters set by the decision maker. The considered methods can give precise rankings of the considered alternatives irrespective of the complexity of the decision-making problem, which is validated by the performance comparison tests. For all the illustrative case studies, very high z and r_s values clearly justify the universal applicability of these methods for solving complex decision-making problems. As these two preference dominance-based methods can easily be implemented using EXCEL worksheet, any type of industrial robot selection problem can be solved employing these methods, thus reducing the cost, computational time and programming knowledge constraints as involved in most of the popular MADM tools like AHP, ELECTRE and GTMA methods. Both these methods can be efficiently applied to any type of real time robot selection problems involving any number of criteria, and any number of decision alternatives.

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