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INDUSTRIAL ROBOT SELECTION USING VIKOR AND TOPSIS TECHNIQUES

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ABSTRACT

Selection of a robot for a specific industrial application is one of the most challenging problems in real time manufacturing environment. It has become more and more complicated due to increase in complexity, advanced features and facilities that are continuously being incorporated into the robots by different manufacturers. At present, different types of industrial robots with diverse capabilities, features, facilities and specifications are available in the market. Manufacturing environment, product design, production system and cost involved are some of the most influencing factors that directly affect the robot selection decision. The decision maker needs to choose the most suitable and applicable industrial robot among five industrial robots in order to get the required output with minimum cost and having the specific abilities. Attributes selected for selection of industrial robots are load capacity, repeatability error, maximum tip speed, memory capacity, and manipulator reach. Five industrial robots selected for this study are Cybotech V15 Electric Robot, Yaskawa Electric Motoman L3C, Cincinnati Milacrone T3-726, Hitachi America Process Robot, and ASEA-IRB 60/2. This paper mainly focuses to compare the different multiple criteria decision making (MCDM) techniques/methods such as 'VIsekriterijumsko KOmpromisno Rangiranje' (VIKOR) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods for selection of alternative industrial robots. These the methods are based on an aggregating function that represents closeness to the ideal solution. VIKOR method is based on linear normalization whereas TOPSIS method used vector normalization to eliminate the units of criterion functions. A solution obtained by TOPSIS method has the shortest distance from the ideal one and farthest from the negative ideal solution. VIKOR method helps to determine a compromise solution that gives a maximum group utility for the majority and minimum for opponents. It is observed that the relative rankings of the alternative robots as obtained using these three MCDM methods match quite well with those as derived by the past researchers. It is observed that the relative rankings of the alternative robots as obtained using these two MCDM methods match quite well with those as derived by the past researchers. This industrial robots selection methodology can be adopted by any Ethiopian manufacturing company, if the criteria and alternatives are clearly known.

Keywords - Industrial Robot Selection, Multiple Criteria Decision Making, TOPSIS. VIKOR

I INTRODUCTION

Robots with vastly different capabilities and specifications are available for a wide range of applications. The selection of the robot to suit a particular application and production environment, from the large number of robots available in the market today has become a difficult task. Various considerations such as availability, management policies, production systems compatibility, and economics need to be considered before a suitable robot can be selected.

Control resolution, accuracy, repeatability, load carrying capacity, degrees of freedom, man-machine interfacing ability, programming flexibility, maximum tip speed, memory capacity and supplier’s service quality are the most important attributes to be taken into consideration while selecting an industrial robot for a particular application. These attributes affecting the robot selection decision can be classified as objective and subjective attributes or beneficial and non-beneficial attributes. Objective attributes can be numerically defined, such as the cost and load carrying capacity of a robot, etc. On the other hand, subjective attributes are qualitative in nature, e.g. vendor’s service quality, programming flexibility of a robot, etc. The beneficial attributes are those whose higher values are always desirable, e.g. load carrying capacity, programming flexibility and non-beneficial attributes are those whose lower values are preferable, e.g. cost, repeatability. While selecting an industrial robot for a given application, the decision maker needs to consider all these attributes, where a trade off between them and the robot performance measures is necessary. Several approaches for robot selection have already been proposed by the past researchers, which include the applications of multi-criteria decision-making (MCDM) methods, production system performance optimization models, computer-assisted models and statistical models.

Bhangale et al. (2004) presented a robot selection methodology using the technique for order performance by similarity to ideal solution (TOPSIS) and graphical methods, and compared the relative rankings of the alternative robots as obtained using these two methods [1]. Goh et al. (1996) proposed a revised weighted sum decision model that can take into account both the objective and subjective attributes while selecting an industrial robot [2]. Khouja and Booth (1995) applied a statistical procedure, known as robust fuzzy cluster analysis that can identify the robots with the best combination of specifications based on various performance parameters [3]. Khouja (1995) developed a two-phase decision model for solving the industrial robot selection problems. In the first phase, data envelopment analysis (DEA) is employed for identifying the robots with the best combination of vendor specifications based on the robot performance parameters. In second phase, a multi-attribute decision-making (MADM) method is applied to select the best robot from those as identified in the previous phase [4]. Baker and Talluri (1997) proposed an industrial robot selection methodology based on cross efficiencies in DEA without considering the criteria weights or the decision maker’s preferences [5]. Goh (1997) applied the analytic hierarchy process (AHP) for robot selection that can simultaneously consider both the objective and subjective attributes [6]. Parkan and Wu (1999) presented the applications and interrelationship of the operational competitiveness rating and TOPSIS methods in a robot selection problem and compared their performance with other approaches. It is observed that both these methods are strongly interrelated, and their performance measurements and decision-making processes involve the same mathematical treatment though they have their apparent structural differences [7]. Rao and Padmanabhan (2006) employed the diagraph and matrix methods for evaluating and ranking of the alternative robots for a given industrial application, using the similarity and dissimilarity coefficient values [8]. Kahraman et al. (2007) developed a hierarchical fuzzy TOPSIS method to solve the multi-attribute robot selection problems [9]. Karsak (2008) proposed a decision model for robot selection based on quality function deployment and fuzzy linear regression methods while integrating the user demands with the technical characteristics of the robots [10].

Taking decision in the presence of multiple conflicting attributes is known as the MCDM problem. A typical MCDM problem usually consists of three main components, i.e. (a) alternatives, (b) criteria/attributes and (c) relative importance (weight) for each criterion. All the elements of a MCDM problem are to be normalized to the same units so that all the possible criteria can be considered in the decision-making process. The main advantage of any MCDM method lies in its consideration of a large number of attributes and alternatives. In this paper, an attempt is made to discover the applicability and potentiality of another two yet to be popular MCDM methods while selecting the most suitable industrial robot for a given application. The first MCDM method is VIKOR (a compromise ranking method) and the other one is TOPSIS (technique for order performance by similarity to ideal solution). An example is cited to demonstrate and compare the performance of both these MCDM methods.

II RESEARCH METHODOLOGY

A MCDM problem can be concisely expressed in a matrix format, in which columns indicate criteria (attributes) considered in a given problem; and in which rows list the competing alternatives. Specifically, a MCDM problem with m alternatives (A_1, A_2, ..., A_m) that are evaluated by n criteria (C_1, C_2, ..., C_n) can be viewed as a geometric system with m points in n-dimensional space. An element xij of the matrix indicates the performance rating of the ith alternative Ai, with respect to the jth criterion C_j, as shown in Eq. (1).

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ . \\ . \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2n} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3n} \\ . & . & . & . & . \\ . & . & . & . & . \\ x_{m1} & x_{m2} & x_{m3} & \cdots & x_{mn} \end{bmatrix} \end{array} \quad (1)$$

The VIKOR method was introduced as an applicable technique to implement within MCDM [11]. It focuses on ranking and selecting from a set of alternatives in the presence of conflicting criteria. The compromise solution, whose foundation was established by Yu (1973) and Zeleny (1982) is a feasible solution, which is the closest to the ideal, and here compromise" means an agreement established by mutual concessions [12, 13].

2.1. Illustrative Example

Suppose we want to select a robot for some pick-n-place operation, where it has to avoid some obstacles. The minimum requirement for this application is Load capacity: Minimum 2 kg, Repeatability error:0.5mm, Maximum tip speed: At least 255mm/sec, Memory capacity: At least 250 points/steps, Manipulator reach:500mm. This example deals with the selection of the most appropriate industrial robot for some pick-n-place operations where it has to avoid certain obstacles. Performance of an industrial robot is often specified using different attributes. Repeatability, accuracy, load capacity and velocity are observed to be the most important attributes affecting the robot selection decision. Among these, repeatability and accuracy are the most confusing attributes. Repeatability is the measure of the ability of a robot to return to the same position and orientation over and over again, while 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. It is easier to correct poor accuracy than repeatability and thus, repeatability is generally assumed to be a more critical attribute. Load capacity is the maximum load that a manipulator can carry without affecting its performance. Load capacity of a robot is related to its acceleration and speed, and is a function of manipulator acceleration and wrist torque. 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 predefined path. Manipulator reach is the maximum distance that can be covered by the robotic manipulator so as to grasp the object for the given pick-n-place operation. Although it is usually assumed that the specified robot selection attributes are mutually independent, in general, performance parameters provided by different robot manufacturers are not simultaneously achievable. Furthermore, it is quite difficult to establish the functional relationship between those robot selection attributes. Hence, making this assumption introduces a risk of selecting a robot that may fail to provide the required performance.

In this example, five different robot selection attributes are considered as load capacity (LC), maximum tip speed (MTS), repeatability (RE), memory capacity (MC) and manipulator reach (MR), among which load capacity, maximum tip speed, memory capacity and manipulator reach are the beneficial attributes (where higher values are desirable), whereas repeatability is a non-beneficial attribute (where lower value is preferable) [1]. Thus, the industrial robot selection problem consists of five criteria and seven alternative robots, as given in Table 1.

Table 1. Criteria's (C)/Attributes for the Short-Listed Candidate Robots

Rn: Robots Types	**LC (C_1)**	**RE (C_2)**	**MTS (C_3)**	**MC (C_4)**	**MR (C_5)**
R_1: ASEA-IRB 60/2	60.00	0.40	2540.00	500	990
R_2: Cincinnati Milacrone T^3-726	6.35	0.15	1016.00	3000	1041
R_3: Cybotech V15 Electric Robot	6.80	0.10	1727.20	1500	1676
R_4: Hitachi America Process robot	10.00	0.20	1000.00	2000	965
R_5: Yaskawa Electric Motoman L3C	3.00	0.10	1778.00	1000	920
Note: C: Criteria, LC: Load Capacity (kg), RE: Repeatability (mm), MTS: Maximum Tip Speed/Steps (mm/sec), MC: Memory Capacity (points), MR: Manipulator Reach (mm)					

2.2. VIKOR Technique/Method

The VIKOR method determines the compromise ranking list and the compromise solution by introducing the multi-criteria ranking index based on the particular measure of "closeness" to the "ideal"solution. The following steps are involved in VIKOR method [14-16]. Formation of decision matrix, D, i.e., the matrix which will contain all the magnitudes of specifications. The rows of the matrix are the candidate robots, with their criteria (C) values listed in columns.

$$D = \begin{bmatrix} & C_1 & C_2 & C_3 & C_4 & C_5 \\ R_1 & 60.00 & 0.40 & 2540.00 & 500 & 990 \\ R_2 & 6.35 & 0.15 & 1016.00 & 3000 & 1041 \\ R_3 & 6.80 & 0.10 & 1727.20 & 1500 & 1676 \\ R_4 & 10.00 & 0.20 & 1000.00 & 2000 & 965 \\ R_5 & 3.00 & 0.10 & 1778.00 & 1000 & 920 \end{bmatrix}$$

Note that all attributes are the benefits except repeatability (C_2) which is the minimum magnitude is preferable.

Step 1: Construct the normalized decision matrix:

This process tries to transform the various attribute dimensions into non-dimensional attributes, which allows comparison across the attributes. One way is to take the outcome of each criterion divided by the norm of the total outcome vector of the criterion at hand. An element r_{ij} of the normalized decision matrix R can be calculated as

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \ i = 1,2,\ldots,m; \ j = 1,2,\ldots,n \qquad (2)$$

Consequently, each attribute has the same unit length of vector.

Step 1(a): Calculate $\sqrt{\sum x_{ij}^2}$ for each column.

From Table 1, for column C1: $\sqrt{60^2 + 6.35^2 + 6.80^2 + 10^2 + 3^2} = 61.6081$

Rest of calculations are done in same fashion and shown in Table 2.

Table 2. Square Roots of Sum of Squares

Alternatives (i)	**Criteria** (j)				
	C_1	**C_2**	**C_3**	**C_4**	**C_5**
R_1: ASEA-IRB 60/2	60.00	0.40	2540.00	500	990
R_2: Cincinnati Milacrone T^3-726	6.35	0.15	1016.00	3000	1041
R_3: Cybotech V15 Electric Robot	6.80	0.10	1727.20	1500	1676
R_4: Hitachi America Process robot	10.00	0.20	1000.00	2000	965

R_5: Yaskawa Electric Motoman L3C	3.00	0.10	1778.00	1000	920
$\sqrt{\sum x_{ij}^2}$	61.6081	0.4924	3824.6134	4034.2285	2578.8334

Step 1(b): Divide each column by the value obtained above to get r_{ij} as per eq. (2), $r_{ij} = \frac{60}{61.6081} = 0.9738$

Rest of calculations are done in same fashion and shown in Table 3.

Table 3. Normalized Decision Matrix

Alternatives (i)	**Criteria's (j)**				
	C_1	**C_2**	**C_3**	**C_4**	**C_5**
R_1: ASEA-IRB 60/2	0.9738	0.8123	0.6641	0.1239	0.3838
R_2: Cincinnati Milacrone T^3-726	0.1030	0.3046	0.2774	0.7436	0.4036
R_3: Cybotech V15 Electric Robot	0.1103	0.2030	0.4516	0.3718	0.6499
R_4: Hitachi America Process robot	0.1623	0.4061	0.2614	0.4957	0.3742
R_5: Yaskawa Electric Motoman L3C	0.0486	0.2030	0.4648	0.2478	0.3567

Step 2: Determination of positive ideal (A) and negative ideal (A^-) solutions:*

The ideal solution A* and the negative ideal solution A^- are determined as follows.

$$A^* = \left\{ \left(\max f_{ij} \mid j \in J \right) \text{ or } \left(\min j \in j' \right),\ i = 1, 2, \ldots, m \right\} = \left\{ f_1^*, f_2^*, \ldots, f_j^*, \ldots, f_n^* \right\} \tag{3}$$

$$A^- = \left\{ \left(\min f_{ij} \mid j \in J \right) \text{ or } \left(\max j \in j' \right),\ i = 1, 2, \ldots, m \right\} = \left\{ f_1^-, f_2^-, \ldots, f_j^-, \ldots, f_n^- \right\} \tag{4}$$

Where, $J = \left\{ j = 1, 2, \ldots, n \,\middle|\, f_{ij}, \text{desire response is large} \right\}$, $J' = \left\{ j = 1, 2, \ldots, n \,\middle|\, f_{ij}, \text{desire response is small} \right\}$

Then it is certain that the two created alternatives A^* and A^- indicate the most preferable alternative (negative-ideal solution), respectively. The positive ideal solution (*) is the largest number within the column of the decision matrix. The negative ideal solution (-) is the smallest from the column.

As per Table 3, eqs. (3) and (4),

$$f^* = \{0.9738,\ 0.8123,\ 0.6641,\ 0.7385,\ 0.6499\},\ f^- = \{0.0486,\ 0.2030,\ 0.2614,\ 0.1230,\ 0.3567\}$$

Step 3: Calculation of utility measure and regret measure:

The utility and the regret measure for each alternative are given as

$$S_i = \sum_{n=1}^{n} w_j \left(\frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \right) \tag{5}$$

$$R_i = \mathrm{Max}_j \left[w_j \left(\frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \right) \right] \tag{6}$$

Where, S_i and R_i represent the utility and the regret measure, respectively, and w_j is the weight of the j^{th} criterion Tables 4 and 5 shows the calculation of utility measure and regret measure.

As per eq. (5), Table 4 shows utility measure and as per eq. (6), Table 5 shows regret measure.

Table 4. Utility Measure

Robot No.	**1**	**2**	**3**	**4**	**5**
S_i	0.626889	0.489291	0.401260	0.664836	0.578106

Table 5. Regret Measure

Robot No.	**1**	**2**	**3**	**4**	**5**
R_i	0.326000	0.322613	0.195600	0.326000	0.260800

Step 4: Computation of VIKOR index:

The VIKOR index can be expressed as follows.

$$Q_i = v \left[\frac{S_i - S^*}{S^- - S^*} \right] + (1 - v) \left[\frac{R_i - R^*}{R^- - R^*} \right] \tag{7}$$

Where, Q_i, represents the i^{th} alternative VIKOR value, i=1, 2,...,m; $S^* = \mathrm{Min}_i (S_i)$, $S^- = \mathrm{Max}_i (S_i)$, $R^* = \mathrm{Min}_i (R_i)$, $R^- = \mathrm{Max}_i (R_i)$ and v is the weight of the maximum group utility (usually it is set 0.5 [11, 17, 18].

Table 6 shows the calculation of VIKOR index value as per eq. (7).

Step 5: Rank alternatives:

Rank of the alternatives is done by observing the minimum Q_i value. The alternative having smallest VIKOR value is determined to be the best solution. As per Table 6, the best choice of robot for the given pick-n-place operation is robot 3 (Cybotech V15 Electric Robot).

Table 6. VIKOR Index Value Q_i

Robot No.	1	2	3	4	5
Q_i	0.928015	0.654006	0.000000	1.000000	0.585475
Rank	4th	3rd	**1st**	5th	2nd

2.3. TOPSIS Technique/Method

TOPSIS assumes that each attributes in the decision matrix takes either monotonically increasing or monotonically decreasing utility [19]. In other words, the larger the attribute outcomes, the greater the preference for the "benefits" criteria and the less the preference for the "cost" criteria. Further, any outcome which is expressed in a non-numerical way should be quantified through the appropriate scaling technique. Since all criteria cannot be assumed to be of equal importance, the method receives a set of weights from the decision maker.

Step 1: Construct the normalized decision matrix:

This step is already covered in VIKOR method and is same.

Step 2: Construct the weighted normalized decision matrix:

A set of weights $w = (w_1, w_2, \ldots, w_j, \ldots, w_n)$, $\sum_{j=1}^{n} w_j = 1$, from the decision maker is accommodated to the decision matrix in this step. This matrix can be calculated by multiplying each column of the matrix r_{ij} with its associated weight w_j. Therefore, the weighted normalized decision matrix V is equal to

$$V = \begin{bmatrix} v_{11} & . & v_{1j} & . & v_{1n} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ v_{m1} & . & v_{mj} & . & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 r_{11} & . & w_j r_{1j} & . & w_n r_{1n} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ w_1 r_{m1} & . & w_j r_{mj} & . & w_n r_{mn} \end{bmatrix} \quad (8)$$

w_j for w_1 = 0.036, w_2= 0.192, w_3=0.326 w_4 =0.326, w_5=0.12

As per (8), V_{11}=0.9738 × 0.036=0.0350

Rest of calculations are done in same fashion and shown in Table 7.

Table 7. Weighted Decision Matrix

Alternatives (i)	**Criteria's (j)**				
	C_1	**C_2**	**C_3**	**C_4**	**C_5**
R_1: ASEA-IRB 60/2	0.0350	0.1559	0.2164	0.0403	0.0460
R_2: Cincinnati Milacrone T^3-726	0.0037	0.0584	0.0904	0.2424	0.0484

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R_3: Cybotech V15 Electric Robot	0.0039	0.0389	0.1472	0.1212	0.0779
R_4: Hitachi America Process robot	0.0058	0.0779	0.0852	0.1615	0.0449
R_5: Yaskawa Electric Motoman L3C	0.0017	0.0389	0.1515	0.0807	0.0428

Step 3: Determine positive ideal solution A^* *and negative ideal solution* A^- *:*

Let the two artificial alternatives A^* and A^- be defined as

$$A^* = \left\{ \left(\max_i v_{ij} \middle| j\varepsilon \right), \left(\min_i v_{ij} \middle| j\varepsilon J \right) \middle| i = 1,2,\ldots,m \right\}, \; A^* = \left\{ v_1^*, v_2^*, \ldots, v_j^*, \ldots, v_n^* \right\}$$

$$A^- = \left\{ \left(\min_i v_{ij} \middle| j\varepsilon J \right), \left(\max_i vij \middle| j\varepsilon J' \right) \middle| i = 1,2,\ldots,m \right\}, \; A^- = \left\{ v_1^-, v_2^-, \ldots, v_j^-, \ldots, v_n^- \right\}$$

Where, $J = \left\{ j = 1,2,\ldots,n \middle| j \text{ associated with benefit criteria} \right\}$, $J' = \left\{ j = 1,2,\ldots,n \middle| j \text{ associated with cost criteria} \right\}$

Then it is certain that the two created alternatives A^* and A^- indicate the most preferable alternative (negative-ideal solution), respectively. The positive ideal solution (*) is the largest number within the column of the weighted decision matrix. The negative ideal solution ($^-$) is the smallest from the column as shown in Table 8.

Table 8. Positive-Ideal and Negative-Ideal Solutions

Alternatives (i)	**Criteria's (j)**				
	C_1	**C_2**	**C_3**	**C_4**	**C_5**
R_1: ASEA-IRB 60/2	**0.0350***	**0.1559-**	**0.2164***	**0.0403-**	0.0460
R_2: Cincinnati Milacrone T^3-726	0.0037	0.0584	0.0904	**0.2424***	0.0484
R_3: Cybotech V15 Electric Robot	0.0039	**0.0389***	0.1472	0.1212	**0.0779***
R_4: Hitachi America Process robot	0.0058	0.0779	**0.0852-**	0.1615	0.0449
R_5: Yaskawa Electric Motoman L3C	**0.0017-**	0.0389	0.1515	0.0807	**0.0428-**

Therefore,

$$A^* = \left\{ \max_i v_{i1}, \min_i v_{i2}, \max_i v_{i3}, \max_i v_{i4}, \max_i v_{i5} \right\}$$

$$A^* = \{0.0350, 0.0389, 0.2164, 0.2424, 0.0779\} \tag{9}$$

$$A- = \left\{ \min_i v_{i1}, \max_i v_{i2}, \min_i v_{i3}, \min_i v_{i4}, \min_i v_{i5} \right\}$$

$$A^- = \{0.0017, 0.1559, 0.0852, 0.0403, 0.0428\} \tag{10}$$

Step 4: Determine separation measure from positive and negative ideal solution:

The separation between each alternative can be measured by the n-dimensional Euclidean distance. The separation of each alternative from the ideal one is then given by

$$S_i^* = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^*\right)^2} \tag{11}$$

Similarly, the separation from the negative-ideal one is given by

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2}, i = 1,2,\ldots,m \tag{12}$$

As per eqs. (11) and (12),

$$S_1^* = \sqrt{(0.0350-0.0350)^2 + (0.1559-0.0389)^2 + \ldots + (0.0460-0.0779)^2} = 0.2356$$

$$S_1^- = \sqrt{(0.0350-0.0017)^2 + (0.1559-0.1559)^2 + \ldots + (0.0460-0.0428)^2} = 0.1353$$

Rest of calculations is done in same fashion.

Therefore, $S_i^* = 0.2356,\ 0.11345,\ 0.1429,\ 0.1649,\ 0.1808$, $S_i^- = 0.1353,\ 0.2245,\ 0.1591,\ 0.1431,\ 0.1404$

Step 5: Calculate the relative closeness to the ideal solution:

The relative closeness of A_i with respect to A^* is defined as

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-},\ 0 \langle C_i \langle 1,\ i = 1,2,\ldots,m \tag{13}$$

It is clear that $C_i^* = 1$ if $A_i = A^*$ and $C_i^* = 0$ if $A_i = A^-$. An alternative A_i is closer to A^* as C_i^* approaches to 1.

As per eq. (13), $C_1^* = \frac{0.1353}{0.2356 + 0.1353} = 0.3647$

Rest of calculations is done in same fashion.

$C_i^* = 0.3647,\ 0.6642,\ 0.5268,\ 0.4646,\ 0.0437$

Step 6: Rank the preference order:

A set of alternatives can now be preference ranked according to the descending order of C_i^*, i.e. Robot 2=0.6642, Robot 3=0.5268, Robot 4=0.4646, Robot 5=0.0437, Robot 1=0.3647

As such, the best candidate is Robot 2 and will be selected for the production activities.

Table 9. Ranking of Preference Order

Robot No.	**1**	**2**	**3**	**4**	**5**
C_i^*	0.3647	0.6642	0.5268	0.4646	0.0437
Rank	5th	**1st**	2nd	3rd	4th

III CONCLUSION

The cited example demonstrates the potentiality, applicability and simplicity of both the VIKOR and TOPISIS methods in solving industrial robot selection decision making problems. Both these methods can incorporate the decision maker's preferences regarding the relative importance of different robot selection attributes. As the measures of the quantitative as well as qualitative attributes and their relative importance are used together to rank the alternatives, both these MCDM methods provide a better evaluation of the alternatives. Both these methods are computationally easy to implement and have sound logic, which helps the decision maker to choose the best industrial robot from a finite set of alternatives for a given robot selection problem. These methods can also be used for any type of decision-making problems, involving any number of quantitative and qualitative attributes, and any number of alternatives.

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