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Research Article

A HYBRID MULTI-CRITERIA DECISION MAKING METHOD FOR ROBOT SELECTION IN FLEXIBLE MANUFACTURING SYSTEM

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Abstract: *Advancement of the manufacturing system is governed by robots which improve the product quality and decrease market availability period. Different robots have been used for the pick and drop the operation of components in flexible manufacturing systems (FMS). Each robot have their advantages and disadvantages therefore, selection of the most suitable robot is significantly important. The selection of robots based on various criteria is a multi-decision making problem (MCDM). In this study seven robots (R1, R2, R3, R4, R5, R6, R7) are ranked using the proposed approach on the basis of five criteria viz. load capacity (L_C), memory capacity (M_C), manipulator reach (M_R), maximum tip speed (M_{TS}), and repeatability (R_E) by employing hybrid Criteria Importance Through Inter criteria Correlation (CRITIC) and Multi-attributive border approximation area comparison (MABAC) methods. Weights of criteria were obtained using correlation coefficient and standard deviation method whereas, the ranking of alternative was done using hybrid CRITIC and MABAC method. As a result of this study, robot R3 acquired the first rank whereas, R1 occupied the last rank which showed that R3 is the most suitable robot for the pick and place operation in FMS. Besides, Ranking comparison was also done with other MCDM methods.*

Keywords: *Robot Selection, MCDM model, CRITIC method, MABAC method, VIKOR*

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1. Introduction

An activated instrument with a level of independence, programmable in more than one axis used to execute deliberated operations is known as a robot. The term independence defines the capability of a robot to execute projected operations within the existing conditions and sensing, exclusive of human interference. In this regard, robots overpass the breach among mechanical instruments and human operators. They are considered to execute repetitious, complex, and dangerous operations in an accurate manner for eminence, production, and safety reasons [1], [2]. Due to which they have been expansively accepted to execute different operations. In the last decade, a hot-headed escalation of robot implementation in flexible manufacturing systems (FMS) and automatic storage and retrieval systems (AS/RS) have been observed. However, the use of a robot in manufacturing systems has a significant impact on the company. As the cost of these robots is generally high, using an inappropriate robot in the manufacturing system will unfavorably influence the productivity and efficiency of the system [1], [2].

Hence, in order to improve the efficiency and productivity of entire manufacturing systems, an appropriate selection of industrial robots is vital [3], [4]. With the advancement of information technology and computer science, there are a large number of robots with enormously diverse stipulations and potential for a variety of application fields [5]. In such conditions, the selection of a qualified robot among a variety of existing alternatives is a very difficult task for decision-makers [2].

Robot selection is reasonably complex because of the convolution, characteristics, quality, and capabilities of different robots that are constantly improved [6]. Additionally, the incompatible characteristics and capabilities of some robots complicate the decision-making process. It has been found that there exist a large number of criteria that should be reckoning while selecting a robot to perform desired operations [5]. However, it is very difficult to consider all the criteria simultaneously while selecting an appropriate robot for the desired output. This entails that multiple criteria decision making (MCDM) methods might be helpful to solve this kind of problem. The solution to the robot selection process starts with the identification of the appropriate evaluation criteria and thereby prioritizing these criteria using MCDM methods. Subsequently, the best amalgamation of these criteria is used to select a qualified robot among the available robots in the market [7].

Over the years researchers have used different MCDM methods to solve robot selection problems [13, 14]. This work put forward a hybrid MCDM model based on Criteria Importance Through Inter criteria Correlation (CRITIC) and Multi-attributive border approximation area comparison (MABAC) methods. The viability of the proposed approach is demonstrated by employing the proposed approach to select an appropriate robot for pick and place operation. Pick and drop operation in an FMS is usually performed by automated guided vehicles (AGVs) which are a specific type of robot used for picking and placing part at the desired location. Seven robots are ranked using the proposed approach on the basis of five criteria viz. load capacity (LC), memory capacity (MC), manipulator reach (MR), maximum tip speed (MTS), and repeatability (RE) [8]. The rest of the paper is organized as follows: Section 2 of the paper describes the proposed approach to solve the robot selection problem. The computations steps involved in CRITIC and MABAC methods are also discussed in this section. Section 3 of the paper depicts the results of the study. The comparison of the ranking results of the proposed method with previous methods is also shown in this section to validate the results of the study. Finally, Section 4 of the paper presents the conclusion of this study.

2. 2. Proposed MCDM model for robot selection

The proposed MCDM model to solve the robot selection problem has been depicted in the form of a flowchart in Figure 1.

At first, alternative robots for the desired application are identified. It is likely that each robot has different properties for the different attributes. Hence, significant attributes for the evaluation of the robots are identified. Further, CRITIC method which is a widely used MCDM tool for calculation of criteria weight is employed to calculate the weights of the criteria. Using the weights of the criteria and the properties of robots, the MABAC method is employed to rank the identified robots.

The Criteria Importance Through Inter criteria Correlation (CRITIC) method was proposed by [9]. This method computes the objective weight of the attributes on the basis of two fundamental notions of MCDM viz. Contrast intensity and conflict among the attributes. It has been established that the weight of the attributes obtained using CRITIC method is identical with PCA with simple computations steps [9]. The Multi-Attribute Border Approximation area Comparison (MABAC) method was developed in 2015 and is effectively employed to solve problems pertaining to different knowledge domains [10]–[12]. In this method, ranks to the alternatives are defined on the basis of their distance from the border approximation area. An alternative having the highest distance from the border approximation area is ranked first and subsequently ranks to other alternatives are defined in descending values of their distance from the border approximation area.

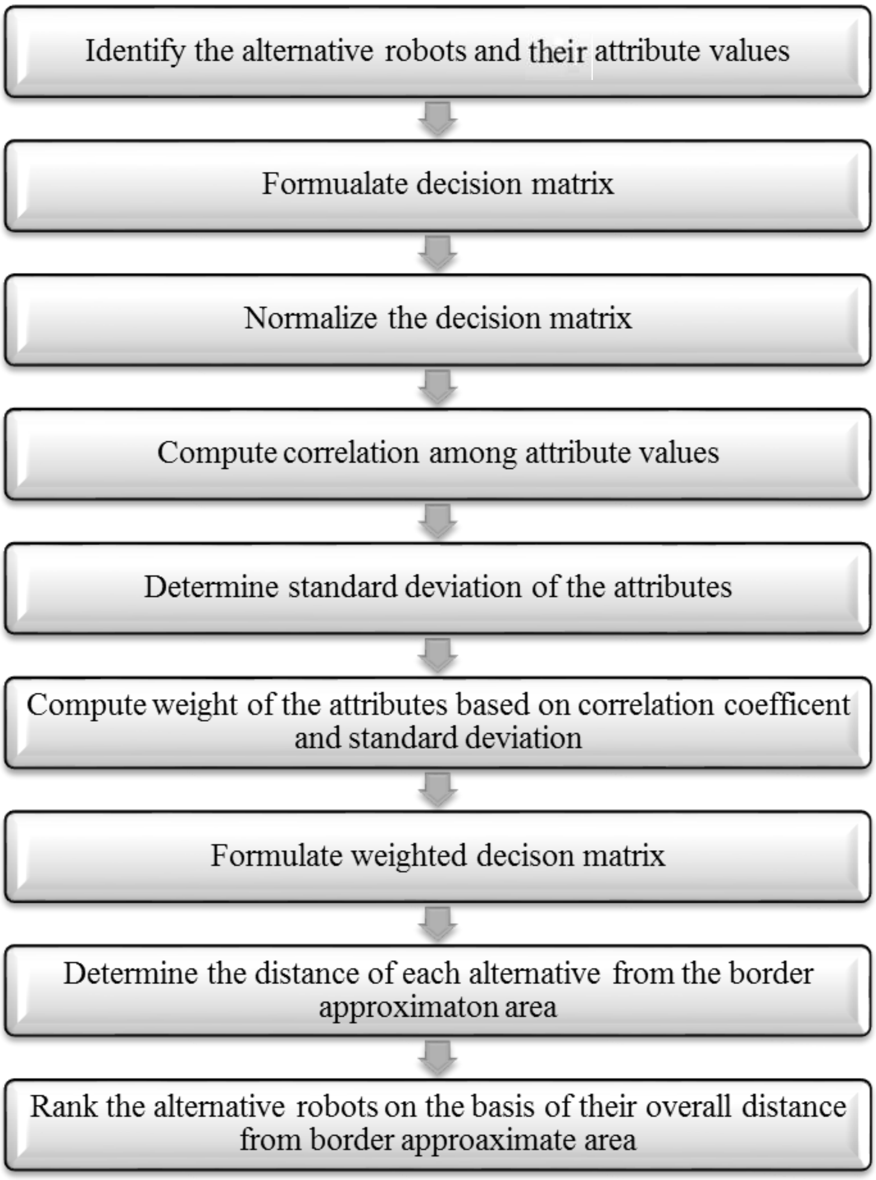

Figure 1. Proposed MCDM model for robot selection

The computational steps involved in the proposed MCDM model for robot selection are discussed as follows:

Step 1: Formulate decision matrix by arranging alternative robots and their attribute values in rows and columns. Assuming there are *"p"* alternative robots and *"q"* decision attributes. The decision matrix *(DM)* can be formulated as shown in Eq. (1):

$$DM = [a_{ij}]_{p\times q} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1j} & \cdots & a_{1q} \\ a_{21} & a_{22} & \cdots & \cdots & \cdots & a_{2q} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ a_{i1} & \cdots & \cdots & a_{ij} & \cdots & a_{iq} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ a_{p1} & \cdots & \cdots & a_{pj} & \cdots & a_{pq} \end{bmatrix}$$

where its elements a_{ij} represents the value of the jth decision attribute for ith alternative robot. i = 1,2,3,……..,p; j = 1,2,3,………….,q.

Step 2: Normalize the decision matrix to convert the distinct range of attribute values into a comparable range. Since attributes can be of different nature viz. beneficial and non-beneficial, they are normalized using Eq. (2) according to their nature.

$$n_{ij} = \left\{ \begin{array}{ll} \dfrac{a_{ij} - \min\limits_i (a_{ij})}{\max\limits_i (a_{ij}) - \min\limits_i (a_{ij})}; & if\ j \in beneficial\ attribute \\ \dfrac{\max\limits_i (a_{ij}) - a_{ij}}{\max\limits_i (a_{ij}) - \min\limits_i (a_{ij})}; & if\ j \in non\ beneficial\ attribute \end{array} \right\} \tag{2}$$

where nij indicates the normalized value of the ith alternative for jth attribute.

Step 3: Determine the Correlation Coefficient (ρ_{jk}) among all the attributes using Eq. (3).

$$\rho_{jk} = \frac{\sum_{i=1}^{p}(n_{ij} - \overline{n}_j)(n_{ik} - \overline{n}_k)}{\sqrt{\sum_{i=1}^{p}(n_{ij} - n_j)^2 * \sum_{i=1}^{p}(n_{ik} - \overline{n}_k)^2}} \tag{3}$$

Step 4: Determination of the standard deviation of the attributes (σ_j) as defined by Eq. (4)

$$\sigma_j = \sqrt{\frac{1}{q-1}\sum_{j=1}^{q}(n_{ij} - \overline{n}_j)^2} \tag{4}$$

Step 5: Compute the amount of information provided by each attribute (Aj) using Eqn. (5)

$$A_j = \sigma_j \sum_{j=1}^{q}(1 - \rho_{jk}) \tag{5}$$

Step 6: Compute the weight of the attributes using Eqn. (6).

$$w_j = \frac{A_j}{\sum_{j=1}^{n} A_j} \tag{6}$$

It must be ensured that all weights add up to 1.

Step 7: Determine weighted normalized decision matrix W = [vij]p×q.

$$W = [v_{ij}]_{p\times q} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1j} & \cdots & v_{1q} \\ v_{21} & v_{22} & \cdots & \cdots & \cdots & v_{2q} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ v_{i1} & \cdots & \cdots & v_{ij} & \cdots & v_{iq} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ v_{p1} & \cdots & \cdots & v_{pj} & \cdots & v_{pq} \end{bmatrix} \tag{7}$$

where, vij = (nij+1)×wj.

Step 8: Determine the border approximation area of each attribute as defined by Eqn. (8).

$$B_j = \left(\prod_{i=1}^{p} v_{ij}\right)^{1/p} \tag{8}$$

Step 9: Compute total distance of each alternative from the border approximation area as given by Eqn. (9).

$$S_i = \sum_{j=1}^{q} r_{ij} \tag{9}$$

where, rij = vij − Bj

Step 10: Rank the alternatives based on Si values in ascending order. An alternative with the minimum Si value is ranked first and an alternative with the highest value is ranked last.

3. Additional instructions

To demonstrate the potential application of the proposed MCDM model to solve the robot selection problem, it has been employed on a specific problem chosen from the literature [5]. Every manufacturing company requires a robot for picking parts and placing them in the right place. Hence, the selection of an appropriate robot for performing these operations is imperative. Five criteria are used for the selection of these types of robots i.e. load capacity (L_C), memory capacity (M_C), manipulator reach (M_R), maximum tip speed (M_{TS}), and repeatability (R_E). These criteria are defined as follows:

- Load capacity (L_C): It is the maximum load that a manipulator can carry without affecting the performance.
- Memory capacity (M_C),: It is the number of points or steps that a robot can store in its memory while traveling along its predetermined path.
- Manipulator reach (M_R): It is the maximum distance that can be covered by the robotic manipulator so as to grasp the object for the given pick-and-place operation.
- Maximum tip speed (M_{TS}): It is the speed at which a robot can move in an inertial reference frame
- Repeatability (R_E): It measures the ability of a robot to return to the same position and orientation over and over again.

Among these criteria, L_C, M_{TS}, $M_{C,}$ and M_R are benefit-type criteria, and R_E is a cost-type criterion. Seven robots have been identified which are widely used in the industry for pick and place operations. The criteria values of these robots are shown in Table 1.

Table 1. Attribute Values for different robots

Robot	L_C (kg)	M_C	M_R (mm)	M_{TS} (mm/s)	R_E (mm)
ROB_1	6	500	990	2540	0.4
ROB_2	6.35	3000	1041	1016	0.15
ROB_3	6.8	1500	1676	1727.2	0.1
ROB_4	10	2000	965	1000	0.2
ROB_5	2.5	500	915	560	0.1
ROB_6	4.5	350	508	1016	0.08
ROB_7	3	1000	920	177	0.1

Since the first step in the proposed MCDM model is to formulate a decision matrix. Table 1 acts as a decision matrix for this robot selection problem. The attribute values provided in Table 1 are normalized as per Eqn. (2) and the normalized values are depicted in Table 2:

Table 2. Normalized attribute

	LC	RE	MTS	MC	MR
R1	0.5333	1.0000	0.0000	0.9434	0.5873
R2	0.4867	0.2188	0.6449	0.0000	0.5437
R3	0.4267	0.0625	0.3440	0.5660	0.0000
R4	0.0000	0.3750	0.6517	0.3774	0.6087
R5	1.0000	0.0625	0.8379	0.9434	0.6515
R6	0.7333	0.0000	0.6449	1.0000	1.0000
R7	0.9333	0.0625	1.0000	0.7547	0.6473

Further, the correlation coefficient and standard deviation of the attributes are computed using Eqn. (3) and Eqn. (4) as per step 3 and step 4 of the proposed model. On the basis of the correlation coefficient and standard deviation, the amount of information and weights of the attributes are computed using Eqn. (5) and Eqn. (6) and are exhibited in Table 3.

Subsequently, the weighted normalized decision matrix is formulated as defined by Eqn. (7). Table 4 represents the weighted normalized decision matrix so formulated.

Correspondingly, the border approximation area for each attribute is determined as defined by Eqn. (8). Finally, the ranking of the alternative robot is done on the basis of the sum of the distance of each alternative from the border approximate area computed using Eqn. (9). Table 5 exhibit the Si values and the rank of the alterative robot so obtained.

Table 3. Amount of information and weight of the attributes.

Attribute	A	Weight
LC	1.0361	0.1679
RE	1.7854	0.2893
MTS	1.3411	0.2173
MC	1.1287	0.1829
MR	0.8790	0.1424

Table 4. Weighted normalized decision matrix

	LC	**RE**	**MTS**	**MC**	**MR**
R1	0.2575	0.5787	0.2173	0.3555	0.2261
R2	0.2496	0.3526	0.3575	0.1829	0.2199
R3	0.2396	0.3074	0.2921	0.2865	0.1425
R4	0.1679	0.3979	0.3590	0.2520	0.2292
R5	0.3358	0.3074	0.3995	0.3555	0.2353
R6	0.2910	0.2894	0.3575	0.3659	0.2849
R7	0.3246	0.3074	0.4347	0.3210	0.2347

Table 5. Si and rank of the alternative robots

	Si	Rank
R1	0.1671	7
R2	-0.1053	2
R3	-0.1999	1
R4	-0.0621	3
R5	0.1654	6
R6	0.1206	4
R7	0.1543	5

Further, the ranking results of the proposed MCDM model are compared with that of the ranking results given by other researchers [6]. Figure 2 shows the comparison of the ranking results for all the seven robots using VIKOR, ELECTREII, and the proposed model.

It can be observed from Figure 2 that the ranking results for the robots vary for all three methods. It is quite obvious as the approach adopted is different and it is difficult to suggest the best method among the available MCDM method. However, the proposed approach suggests ROB_3 is the best robot which is in line with the results of the other methods. Hence, the proposed method can be profitably used to solve the robot selection problem.

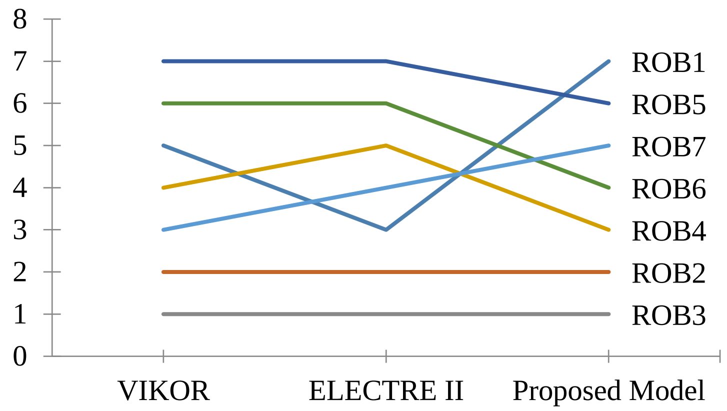

Figure 2. Comparison of the ranking results

4. Conclusions

The selection of appropriate robots for desired operations in manufacturing systems is very difficult for decision-makers as there exist a number of different robots with a variety of characteristics and features. The problem of robot selection can be solved using MCDM methods. In this study, a hybrid MCDM method combining CRITIC and MABAC method has been employed to rank the robots used in manufacturing facilities. Weights of all the criteria were calculated using correlation coefficient and standard deviation methods and then, the ranking of seven alternatives was done. Besides, ranking results were also compared with widely used methods such as VIKOR and ELECTRE II. Based on the results obtained in this study, the following major conclusions are made.

1. Most suitable robot ranking sequence obtained using the CRITIC and MABAC method is R3>R2>R4>R6>R7>R5>R1.
2. Robot 3 is the most suitable alternative for pick and drop mechanism as it has the highest manipulator reach, optimum load capacity along with higher maximum tip speed and lower repeatability. Whereas, Robot 7 is the least favorable choice.
3. Ranking obtained using the VIKOR and ELECTRE II methods were similar to the hybrid method applied in this study which supported the reliability and consistency of the CRITIC and MABAC methods.

The compliance to the Research and Publication Ethics: This study was carried out in accordance with the rules of research and publication ethics.

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