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AN INTEGRATED MULTI ATTRIBUTE DECISION MAKING METHODOLOGY FOR SELECTION OF INDUSTRIAL ROBOT

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ABSTRACT

The aim of the present work is to propose an integrated multi attribute decision making (MADM) methodology for selection of Industrial Robot for a given application. The proposed methodology is based on Grey relational analysis with considering integrated weight of every industrial robot selection attributes. The integrated weights are computed using Analytical hierarchy method and Entropy method. One numerical application is presented to demonstrate and validate the proposed industrial robots selection methodology. The study has concluded that the proposed methodology is an appropriate for selection of Industrial robot.

Keywords: *Industrial Robot, Grey Relational Analysis, Analytical Hierarchy Method and Entropy Method*

1. Introduction

Today development in manufacturing processes, CAM, FMS, CIM and Advance welding processes, are used in place of traditional manufacturing processes. Widely industrialists are extensively used robots to perform various difficult, precise, repetitious and hazardous tasks. That's why selection of proper industrial robot for a given application is an important task for decision makers.

Industrial robots improve quality, productivity, effectiveness if robot is selected properly. Selection of robot does not depend on only one factor or attribute but it depends on number of attributes like cost, load capacity, degree of freedom, repeatability, weight control mode, power drive system, flexibility etc.

Industrial robot selection is multi attribute decision making (MADM) problem and lot of work reported in the earlier period. Wang et al. [1] had used a decision support system for robot selection. Goh [2] used the analytic hierarchy process (AHP) method for robot selection.

Parkan and Wu [3] presented decision-making and performance measurement models with applications to robot selection using performance measurement procedure called operational competitiveness rating (OCRA) and a multiple attribute decision-making method, TOPSIS. Khouja and Kumar [4] used options theory and an investment evaluation procedure for selection of robots. Braglia and Petroni [5] carried out investment evaluation using DEA for robot selection. Chu and Lin [6] proposed a fuzzy TOPSIS method for robot selection. Bhangale et al. [7] listed a large number of robot selection attributes, and ranked the robots using TOPSIS and graphical methods.

Rao and Padmanabhan [8] proposed a methodology based on digraph and matrix methods for evaluation of alternative industrial robots. A robot selection index was proposed that evaluates and ranks robots for a given industrial application. Kahranan et al. [9] proposed fuzzy multi-criteria evolution of industrial robotic system.

The selection of robots to suit a particular application and production environment from the large number available in the market has become a difficult task for that a systematic, logical, and efficient tool is required to decision maker for selecting proper industrial robot for a given application. In addition, there are several MADM a major criticism of MADM is that different techniques may yield different results when applied to the same problem [10]. Hence, in this study an integrated multi attribute decision making methodology for selection of industrial robot is presented based on Grey relational Analysis (GRA) method in conjunction with AHP and Entropy method. A GRA method used for the evaluation and ranking of industrial robot while AHP and Entropy method are used to determine the subjective and objective weights of industrial robot selection attributes.

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2. Methodology Review

The selection of best alternative from the given set of pre determined alternatives according to established criteria or attributes is known as multi attribute decision making (MADM) process [11]. To treat industrial robot selection problems as a MADM problem, we utilize Grey relational analysis (GRA) method to select an appropriate alternative for the given application. The methodologies used for industrial robot selection is classified in three phases. Phase1: Definition of the problem, phase 2: Determine of integrated weight of attributes, and phase 3: GRA method for selection of industrial robot.

2.1 Phase-1: Problem definition and formulation

Define the goal of considered problem as selection or ranking of alternatives. Find out all possible alternatives, its attributes, and attributes measures. Let, A = {A_i for i = 1,2,3,…n} be a set of alternative, C = {C_j for j =1,2,3,…,m } be a set of decision criteria or attributes, W = {W_j for j =1,2,3,…,m } be a set of weight of criteria C_j, and x_{ij} = Performance of alternative A_i when it examined with criteria C_j

2.2 Phase-2: Determination of attributes weight

The estimation of attributes weight plays an important role in MADM approach due to complexity and uncertainty of real world decision making problems. Hence, calculation of weight is most important task in MADM. An integrated weight is the combination of subjective and objective weight of attribute. A subjective and objective weight of every attribute is computed using Analytical Hierarchy Process (AHP) method [12] and Entropy method [13] respectively. In present study integrated weight is used for FMS selection is calculated using following equation.

$$W_j = \frac{\alpha_j \beta_j}{\sum_{j=1}^{m} \alpha_j \beta_j} \quad (1)$$

2.2.1 AHP method

The Analytical Hierarchy Process (AHP) is a potential decision making tool developed by Saaty [12]. AHP is particularly useful for evaluating complex multi-attribute alternatives involving subjective or objective criteria [12]. In the present study AHP method is used only for the determination of relative normalized or subjective weight (α_j) of FMS selection attributes. A determination of subjective weight is started with the constructing the pair-wise decision matrix according to the judgments taken by decision maker for assigning relative importance between attributes using a scale of relative importance suggested by Saaty [12] as shown in Table 1. Now, a subjective weight of each selection criteria is computed using AHP is described in the following steps.

Step I: Generate pair wise matrices.

A pair wise comparison matrix is constructed using a scale of relative importance as given in Table 1. Assuming m attributes, the pair wise comparison of attribute i with attribute j yields a square matrix $A1_{m \times m} = [a_{ij}]_{m\times m}$, where a_{ij} denotes the comparative importance of attribute i with respect to attribute j. In the matrix, a_{ij} = 1 when i = j and $a_{ji} = 1/a_{ij}$.

$$A1_{mxm} = \begin{array}{c} C_1 \\ C_2 \\ C_3 \\ - \\ - \\ C_m \end{array} \begin{bmatrix} 1 & a_{12} & a_{13} & -- & -- & a_{1m} \\ a_{21} & 1 & a_{23} & -- & -- & a_{2m} \\ a_{31} & a_{32} & 1 & -- & -- & a_{3m} \\ -- & -- & -- & 1 & -- & -- \\ -- & -- & -- & -- & 1 & -- \\ a_{m1} & a_{m2} & a_{m3} & -- & -- & 1 \end{bmatrix}$$

Fig. 1 A Pair Wise Comparison Matrix

Table 1: Scale of Relative Importance [12]

Scale	Importance	Meaning for attributes
1	equal importance	Two attributes are equally important
3	moderate importance	One attribute is moderately important over the other
5	strong importance	One attribute is strongly important over the other
7	very importance	One attribute is very important over the other
9	absolute importance	One attribute is absolutely important over the other
2,4,6,8	compromise importance between 1,3,5,7 and 9	

Step II: Determination of relative normalized weight.

A relative normalized weight at each level of hierarchy structure is calculated using Eq. (2) and Eq. (3).

$$GM_j = \left[\prod_{j=1}^{m} a_{ij}\right]^{\frac{1}{m}} \quad (2)$$

.

$$W_j = \frac{GM_j}{\sum_{j=1}^{m} GM_j} \quad (3)$$

Step III: Consistency Test.

If the judgment matrix or pair-wise comparison matrix is inconsistent then judgment should be reviewed and it is improved to obtain consistent matrix. Hence,consistency test will be carried out using following steps.

- Calculate matrices
  A3 = A1 x A2 and A4 = A3 / A2
  Where; A1= $[a_{ij}]_{m\times m}$, A2 = $[W_1, W_2, \ldots, W_j]^T$
- Calculate Eigen value λ_{max} (average of matrix A4)
- Calculate the consistency index: CI = (λ_{max} - m) / (m - 1)
- Calculate the consistency ratio: CR = CI/RI, select value of random index (RI) according to number of attributes used in decision-making [12].

If CR < 0.1, considered as acceptable decision, otherwise judgment of the analyst about the problem under study.

2.2.2 Entropy method

In the present study Entropy method is used to determine objective weights of attributes. The detail steps of Entropy method are described as following [13]:

Step I: Formulate the normalized decision matrix as shown in Figure 2.

$$\bar{X} = \begin{array}{c} A_1 \\ A_2 \\ \ldots \\ A_m \end{array} \begin{bmatrix} \bar{x}_{11} & \bar{x}_{12} & \ldots & \bar{x}_{1n} \\ \bar{x}_{21} & \bar{x}_{22} & \ldots & \bar{x}_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ \bar{x}_{m1} & \bar{x}_{m2} & \ldots & \bar{x}_{mn} \end{bmatrix}$$

Fig. 2 Normalized Decision Matrix

In this normalized decision matrix, value of $\bar{x}_{ij}$ would be calculated using following equation.

If higher value of attribute is desirable,

$$\bar{x}_{ij} = \frac{x_{ij}}{x_{j,max}}; \forall i, j \qquad (4)$$

If smaller value of attribute is desirable,

$$\bar{x}_{ij} = \frac{x_{j,min}}{x_{ij}}; \forall i, j \qquad (5)$$

Step II: Determine Entropy level.

In this step Entropy level (E_j) of every attribute is calculated using following equation.

$$E_j = \frac{-1}{\ln(n)} \sum_{i=1}^{n} \left[\bar{x}_{ij} \bullet \ln \bar{x}_{ij} \right]; \forall i, j \qquad (6)$$

Step III: Compute the normalized objective weight of every attribute using following equation.

$$\beta_j = \frac{d_j}{\sum_{j=1}^{m} d_j}, j = 1, 2, \ldots, n \qquad (7)$$

In the above equation d_j represents degree of deviation. In addition, $d_j = 1 - E_j; \forall j$

2.3 Phase-3: Grey Relational Analysis method

Recently, Grey Relational Analysis **(**GRA) method has been employed to aid decision making in many fields. A Grey Relational Analysis is an important part of Grey system theory, which was developed by Deng [14] and its process is as follow:

Step-I Grey relation generating

In multi attribute decision-making problems, attributes have different performance measuring units. Hence, it is necessary to standardize all the data or performance value of attribute in comparability sequence using following formulas. This process is called grey relation generation.

If the expectancy is the- larger- the- better (e.g., the profit), then the original attribute performance can be normalized as follows:

$$R_{ij} = \frac{x_{ij} - \min_j x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}, \forall i, j \qquad (8)$$

If the expectancy is the- smaller- the- better (e.g., loss), then the original attribute performance can be normalized as follows:

$$R_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}}; \forall i, j \qquad (9)$$

Step-II Generate reference data series

After the data processing using for formula, mostly the reference sequence defines as R0 = (R01, R02, R03,...., R0l) = (1,1,1,.....,1). It indicates that performance value of alternative *i* with reference to attribute *j* is one.

Step-III Calculate the Grey relational coefficient (γ_{ij})

Grey relational coefficient is used for determining how close R_{ij} is to R_{0j}. The grey relational coefficient is calculated using following equation.

$$\gamma_{ij}(R_{0j}, R_{ij}) = \frac{\min_i \min_j \left| R_{0j} - R_{ij} \right| + \xi \max_i \max_j \left| R_{0j} - R_{ij} \right|}{\left| R_{0j} - R_{ij} \right| + \zeta \max_i \max_j \left| R_{0j} - R_{ij} \right|}; \forall i, j \qquad (10)$$

Where, ζ is the distinguishing coefficient, $\zeta \in [0, 1]$. In present study value of ζ is set 0.5.

Step-IV Grey relational grade calculation

In this step grey priority grade of each alternative is calculated using following equation.

$$\Gamma_i = \sum_{j=1}^{m} (W_j \times \gamma_{ij}); \forall i, j \qquad (11)$$

Where, Wj is integrated weight of attribute *j*.

Step-V Ranking and Selection of alternative

After calculation of the grey priority grade, alternatives are ranked according to descending or ascending order to facilitate the managerial interpretation of the results. Pick up alternatives with leading position in the ranking as potential candidates.

3. Proposed Methodology

Now, all the methods described above are integrated for industrial robot selection for a given application and named as industrial robot selection methodology and the main steps are as follow:

Step-1: Define and describe the industrial robot alternatives and its selection criteria.
Step-2: Evaluate the entire industrial robot alternative with respect to each selection criteria.
Step-3: Determine the subjective weight of every industrial robot selection attributes using AHP method.
Step-4: Determine the objective weight of every industrial robot selection attributes using Entropy method.
Step-5: Determine the integrated weight of every industrial robot selection attributes.
Step-6: Generate the Grey relation for every industrial robot selection attributes.
Step-7: Define the reference data series for every industrial robot selection attributes.
Step-8: Compute the Grey relational coefficient for every industrial robot selection attributes.
Step-9: Compute the Grey relational grade for every industrial robot alternative.
Step-10: Rank and select the appropriate industrial robot alternative with respect to grey relational grade.

4. Numerical Application

Now, a numerical application of industrial robot selection example is considered to demonstrate and validate the proposed integrated multi attribute decision making methodology based on GRA, AHP and Entropy method. The proposed procedural for selection of industrial robot are as follow.

Step-1: Let decision maker want to select an industrial robot for a given application. In present study we consider the industrial robot selection example as same of Bhangale et al. [7]. In this problem there are seven industrial robots and four beneficial selection criteria such as load capacity in Kg, Maximum tip speed in mm/sec, Memory capacity in points or steps, Manipulator reach in mm and one non-beneficial criteria such as repeatability error in mm are considered.

Step-2: These all industrial robots are evaluated with entire robot selection criteria and their performance measure or objective data are shown in Table 2.

Step-3: Determination of subjective weight

In this step subjective weight of every industrial robot selection attributes are computed using AHP method. In present study, we consider same pair-wise comparison matrix as of Rao[15] for validation of the proposed methodology. Rao [15] has prepared the following pair-wise comparison matrix as shown in Figure 3 for calculating the subjective weight of every industrial robot selection criteria.

$$
A1 = \begin{array}{c} \\ C1 \\ C2 \\ C3 \\ C4 \\ C5 \end{array}
\begin{array}{c}
\begin{array}{ccccc} C1 & C2 & C3 & C4 & C5 \end{array} \\
\begin{bmatrix}
1 & 1/6 & 1/7 & 1/7 & 1/5 \\
6 & 1 & 1/2 & 1/2 & 2 \\
7 & 2 & 1 & 1 & 3 \\
7 & 2 & 1 & 1 & 3 \\
5 & 1/2 & 1/3 & 1/3 & 1
\end{bmatrix}
\end{array}
$$

Fig. 3 A Pair Wise Comparison Matrix [15]

Rao[15] obtained the subjective weight of every industrial robot selection criteria such as α_{C1} = 0.3230, α_{C2} = 0.4000, α_{C3} = 0.1041, α_{C4} = 0.0687, α_{C5} = 0.1044, with good consistency in the judgments taken for the generating the pair-wise comparison matrix.

Table 2: Objective Data of Industrial Robot Selection Attributes [7]

Robots	C1	C2	C3	C4	C5
IR1	60	0.4	2540	500	990
IR2	6.35	0.15	1016	3000	1041
IR3	6.8	0.1	1727.2	1500	1676
IR4	10	0.2	1000	2000	965
IR5	2.5	0.1	560	500	915
IR6	4.5	0.08	1016	350	508
IR7	3	0.1	1778	1000	920

C1: load capacity in Kg, C2: Repeatability error in mm, C3: Maximum tip speed in mm/sec, C4: Memory capacity in points or steps, C5: Manipulator reach in mm

Step-4: Determination of the objective weight. In this step, objective weight of every industrial robot selection criteria using entropy method as described in previous section. Now, according to step-I of entropy method, a normalized decision matrix is formulated using Eq. (4) and Eq. (5) as shown in Table3. Finally, a normalized objective weight of every industrial robot selection criteria is calculated using Eq. (7) and its values are: β_{C1} = 0.3230, β_{C2} = 0.4000, β_{C3} = 0.1041, β_{C4} = 0.0687, β_{C5} = 0.1044.

Table 3: Normalized Decision Matrix of Entropy Method

Industrial Robots	Robot selection criteria or attributes				
	C1	C2	C3	C4	C5
IR1	1.000	0.200	1.000	0.167	0.591
IR2	0.106	0.533	0.400	1.000	0.621
IR3	0.113	0.800	0.680	0.500	1.000
IR4	0.167	0.400	0.394	0.667	0.576
IR5	0.042	0.800	0.221	0.167	0.546
IR6	0.075	1.000	0.400	0.117	0.303
IR7	0.050	0.800	0.700	0.333	0.549

Step-5: Now, the integrated normalized weight of every industrial robot selection attributes are calculated using Eq. (1) and its values are**:** W_{C1} = 0.0739, W_{C2} = 0.4880, W_{C3} = 0.2158, W_{C4} = 0.1424, and W_{C5} = 0.0796

Step-6: A comparability sequence is defined or grey relation is generated for every attribute of industrial robot selection criteria using Eq. (8) and Eq. (9). Results of grey relation generation are shown in the following Table 4.

Table 4: Results of Grey Relation Generation (R_{ij}) of Industrial Robots Selection Attribute

Robots	C1	C2	C3	C4	C5
IR1	1.0000	0.0000	1.0000	0.0566	0.4127
IR2	0.0670	0.7813	0.2303	1.0000	0.4564
IR3	0.0748	0.9375	0.5895	0.4340	1.0000
IR4	0.1304	0.6250	0.2222	0.6226	0.3913
IR5	0.0000	0.9375	0.0000	0.0566	0.3485
IR6	0.0348	1.0000	0.2303	0.0000	0.0000
IR7	0.0087	0.9375	0.6152	0.2453	0.3527

Step-7: A reference sequence for every industrial robot selection attribute is defines as:
$R_{0j} = (R_{01}, R_{02}, R_{03}, ..., R_{0n}) = (1,1,1,.....,1)$.

Step-8: In this step, grey relational coefficient is calculated using Eq. (10) as described GRA method. Here, a distinguishing coefficient value ζ is set at 0.5 to get the value of grey relational coefficient. Results of grey relational coefficient for every industrial robot selection attribute are shown in the Table 5.

Step-9: A grey priority grade for every industrial robot alternatives is calculated using Eq. (11) with considering integrated W_j of attributes, calculated in step-5. A result of grey priority grade for every industrial robot alternatives are: Γ_{IR1} = 0.5384, Γ_{IR2} = 0.6175, Γ_{IR3} = 0.7126, Γ_{IR4} = 0.8818, Γ_{IR5} = 0.6911, Γ_{IR6} = 0.6722, Γ_{IR7} = 0.7550.

Step-10: According to value of grey priority grade, industrial robot alternatives are ranked in descending order as: IR4 > IR7 > IR3 > IR5 > IR6 > IR2 > IR1.
This result shows that Robot 4 is an optimal choice for the given application and Robot 7 is the second choice

Table 5: Results of Grey Relation Coefficient of Industrial Robots Selection Attribute

Robots	C1	C2	C3	C4	C5
IR1	1	0.3333	1	0.3464	0.4598
IR2	0.3333	0.6808	0.3774	1	0.4618
IR3	0.3333	0.881	0.5298	0.4497	1
IR4	0.6208	1	0.6678	0.9971	0.776
IR5	0.375	1	0.375	0.3897	0.4885
IR6	0.3413	1	0.3938	0.3333	0.3333
IR7	0.3754	1	0.6339	0.4464	0.4884

5. Sensitivity Analysis

In the present study sensitivity analysis is performed to analyze the impact of distinguishing coefficient on the final ranking of Industrial Robot alternatives obtained using Proposed integrated MADM approach. The distinguishing coefficient value is set at 0.1, 0.3, 0.5, 0.7 and 0.9. The results are shown in the following Figure 4.

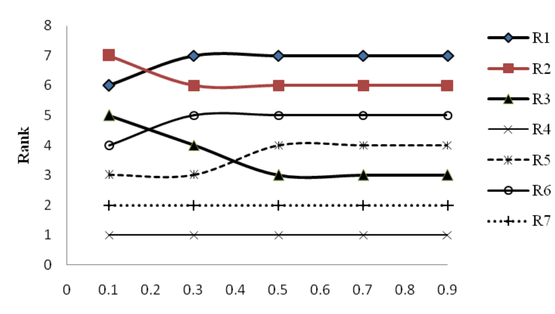

Fig. 4 Result of Sensitivity Analysis

The result of sensitivity analysis indicates that an effect of distinguishing coefficient on final ranking of industrial robot alternatives using the proposed method is minor or negligible. It means that for any value of distinguishing coefficient suggest same best industrial robot i.e. Industrial Robot 4. In addition, this sensitivity analysis indicates that if decision maker select value of distinguishing coefficient on higher side, then proposed method gives more stable results. If decision maker will select the smaller value of distinguishing coefficient then there is risk of obtaining incorrect ranking order of selection alternatives.

6. Result Comparison and Discussion

The results obtained using proposed methodology is compared with published results as shown in Table 6. To compare the results only ranking order is considered for industrial robot alternatives.

Table 6: Results Obtained using Proposed Methodology is Compared with Published Results

Industrial Robots	Proposed method	GTMA [15]	TOPSIS [7]
IR1	7	2	2
IR2	6	3	5
IR3	3	1	3
IR4	1	5	1
IR5	4	7	7
IR6	5	6	6
IR7	2	4	4

Bhangale et al. [7] used TOPSIS and graphical method and suggested Robot 4 as a first choice. In addition Rao [15] point out that the relative importance matrix prepared by Bhangale et al. [7] was completely inconsistent, and it is not possible to justify how the authors had calculated the weights of the relative importance of the attributes based on such a highly inconsistent judgement matrix and to overcome this difficulty Rao[15] examined the same problem using graph theory and matrix approach (GTMA) and Rao[15] computed the weights of industrial robot selection criteria using AHP method. Rao [15] suggest Robot 3 as a first choice. To get this solution Rao [15] prepare 5×5 industrial robot selection attributes matrix using 9-point scale for pair-wise comparison of industrial robot selection criteria. Rao [15] solved 5×5 industrial robot selection attributes matrix 7 times to find the industrial robot selection index. It indicates that if there are several alternatives and selection criteria are involved in the decision making problem then it is very difficult to solve the problem using GTMA. In both the method authors considered only subjective weight of selection criteria, but performance measure or data of every selection criteria contains the useful information that information is used in the present study as objective weight calculated by entropy method. In addition, it very difficult to conclude that which ranking order is more suitable which obtained using individual MADM methods. Hence, use of integrated approach is more comprehensive and gives effective results compare to individual approach.

7. Conclusion

The grey relational analysis model with integrated weight is an effective tool for the selection of appropriate industrial robots. The use of subjective weight and objective weight for determination of integrated weight gives effect group decision support. The proposed industrial robot selection methodology can be applied for any multi attribute decision making problems.

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