A NOVEL MULTIPLICATIVE MODEL OF MULTI CRITERIA ANALYSIS FOR ROBOT SELECTION

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ABSTRACT

Selection of an industrial robot for a specific purpose is one of the most challenging problems in modern manufacturing atmosphere. The selection decisions become more multifaceted due to continuous incorporation of advanced features and facilities as the decision makers in the manufacturing environment are to asses a wide varieties of alternatives based on a set of conflicting criteria. To assist the selection procedure various Multiple Criteria Decision Making (MCDM) approaches are available. The present investigation endeavours to mitigate and unravel the robot selection dilemma employing the newly proposed Multiplicative Model of Multiple Criteria Analysis (MMMCA) approach. MMMCA is a novel model in which all performance ratings are converted into numerical values greater than and equal to unity and converting all non-benefit rating into benefit category. Each normalized weight is used as the index of corresponding normalized ratings those are multiplied to obtain the resultant score. The best alternative is associated with the highest resultant score. A real life example is cited in order to demonstrate and validate the applicability, potentiality, suitability, flexibility and validity of the proposed model. At last sensitivity analysis is carried out for making dynamic decision.

KEYWORDS

Multiplicative Model of Multiple Criteria Analysis, Industrial Robot Selection, Sensitivity Analysis

1. INTRODUCTION

Last few decades' remarkable progresses in information technology, engineering and science are the major motivation for the augmented utilization of robots in industries in variety of application including advanced manufacturing technologies. Industrial robots can be programmed for constant speed and predetermined quality while performing a task repetitively. Robots are increasingly and extensively used in industries for performing repetitive, hard and hazardous job with improved precision, desired accuracy and enhanced rapidness in material handling, spot welding, arc welding, mechanical assembly, electronic assembly, material removal, inspection and testing, water jet cutting, loading and unloading, spray painting and finishing operation. There is large number of robot manufacturers; the specifications of the robots are different in many cases, the attributes of the robots are not same, also the same performance characteristic of manufacturers cannot be expected. On the contrary, the materials to be handled are versatile in nature, e.g. powdered, sticky, fragile, bulky etc. So it is hard to select a suitable robot as a material handling equipment for a particular material from a set of different robots. End-users face with many options in both economical and technical factors in the evaluation and selection procedure of the industrial robots and may easily be misled.

The right selection of robots to suit a particular application in manufacturing environment from a large set of feasible alternative robots is a difficult task for the decision makers. It becomes more complicated due to enhance in complexity, highly developed features and facilities those are continuously being incorporated into the robots by different designers and manufacturers. Robot selection attribute (criterion) is defined as a factor that directly influences the selection of a robot for a given industrial application. Robot selection criteria include: availability or assured supply, cost, configuration, drive system, load capacity, man-machine interface, management constraints, number of degrees of freedom, positioning accuracy, programming flexibility, reliability, repeatability, training delivery period, type of control, type of programming, work volume, velocity of movements, vendor's service quality etc. Decision makers need to identify and select the best suited robot in order to achieve the desired output with minimum cost and specific applicability.

2. LITERATURE SURVEY

In the past, several models have been suggested for robot selection. These models can be classified into five categories: (1) multi-criteria decision-making (MCDM) models, (2) production system performance optimization models, (3) computer assisted models, (4) statistical models, and (5) other approaches [1, 2].

Each MCDM process always contains at least two conflicting criteria and two alternatives [3] . MCDM problems share the following common characteristics.

- *Multiple objectives and attributes*: Each problem has multiple objectives/ attributes. A decision- maker must generate relevant objectives/ attributes.
- *Conflicting among criteria:* Multiple criteria usually conflict with each other.
- *Incommensurable units:* Each objective or attribute has a different unit of measurement.
- *Design/Selection:* Solutions to those problems are either to design the best alternative or to select the best one among the previously specified finite alternatives [4]. .

Several techniques for solving MCDM problem are Analytical Hierarchy Process (AHP), Analytical Network Process (ANP), Weighted Product Method (WPM), Weight and Score Method, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VIKOR (the Serbian name is 'VIsekriterijumsko KOmpromisno Rangiranje', which means multi-criteria optimization and compromise solution), MOORA, Simple Additive Weighting (SAW) method, ELECTRE (an outranking method), Utility functions model, Diagraph and matrix method, PROMETHEE (an outranking method), Quality function development (QFD), Delphi method, Distance based approach (DBA), Operational competitiveness rating (OCRA), Complex proportional assessment (COPRAS), Grey rational analysis (GRA) etc. Other useful optimization techniques are mathematical programming (Linear programming, Goal programming, Data envelopment analysis etc), Artificial intelligence (Neural Network, Case-based reasoning, expert system etc) and some hybrid and innovative approaches.

The features of MCDM process are

- It should have a set of quantitative objectives;
- It should posses a set of well defined constraints;
- It should have a process to obtain some trade-off information between the stated and unstated objectives.

MCDM models include multi-attribute decision-making (MADM) models [5, 6, 7, 8] multi-objective decision-making (MODM) models and other similar approaches. In MODM, the decision-maker's objective, such as optimal utilization of resources and improved quality, remain explicit and are assigned weights reflecting their relative importance [9,10] . In MADM, all objectives of decision maker are unified under a super function termed the decision-maker's utility, which depends on robot attributes. The main advantage of MCDM models is their ability to consider a large number of attributes. Afuzzy hierarchical TOPSIS model for selection of industrial robotic systems was proposed and an application was also presented with some sensitivity analysis by changing the critical parameters [11].

Using MCDM, the decision-maker can consider engineering, vendor-related, and cost attributes [12] . Optimization models related to performance of production system select a robot that optimizes some performance measures of the production system, such as quality or throughput, with robot attributes treated as decision variables. Computer assisted models have been advocated by many researchers to deal with the large number of robot attributes and available robots [13, 14] .

A robot selection procedure was proposed in which multiple criteria of robots were first recognized as two categories- benefits and costs [15]. The performance of robots were evaluated by incremental benefit-cost ratios and the robots were ranked by applying group TOPSIS. In this approach the incremental benefit-cost or the cut-off ratio is the key factor for selection of robot. The algorithm is complex, repetitive and tedious while robots are ranked. A fuzzy TOPSIS method was developed where the values of objective criteria were converted into dimensionless indices to ensure compatibility between the linguistic rating of subjective criteria and the values of objective criteria [16]. Through internal arithmetic of fuzzy numbers, the defuzzying of weighted rating into crisp values and determination of closeness coefficient, the robots were ranked.

A method was suggested that demonstrated the use and compared some of the current multi-attribute decision making (MADM) and performance measurement procedures through a robot selection problem [17]. But this paper is not adequately robust and effective for simultaneously handling both tangible and intangible factors. A new method based on TOPSIS concepts in grey theory was presented to deal with the selection problem [18]. An integration of TOPSIS approach and multi-objective mixed integer linear programming (MOMILP) was used to define the optimum quantities among the alternatives in order to maximize the total value and minimize the total cost. AHP and ANP were integrated to select alternatives [20].

So the detail literature survey shows that no attention has yet been given to employ MMMCA in robot selection though a lot of scopes are available for mitigating the complexity in the robot selection procedure. A detail step by step algorithm of MMMCA method is given in section 3, the applicability of which is demonstrated by solving the cited MCDM problems on industrial robot selection in section 4. Section 5 gives some concluding remarks.

3. ALGORITHM OF MULTIPLICATIVE MODEL OF MULTIPLE CRITERIA ANALYSIS

Step1. Identify the decision criteria as C_1,...C_j,..,C_n and preliminary list alternatives as A_1, …A_i, ...,A_m. *n* is number of criteria and *m* is number of alternatives under consideration.

Step 2. Construct decision matrix with performance score of alternative.

$$\begin{array}{c} \\ A_1 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array}\begin{array}{c} \begin{array}{ccccc} C_1 & \cdots & C_j & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \end{array}$$

Where x_{ij} is the performance rating (response) to the *i*th alternative (A_i) under *j*th criterion (C_j).

Step 3. Construct weight matrix with weights of criteria. $W = \lfloor w_j \rfloor_{1\times n}$. Where w_j is the weight of j[th] attribute (criterion).

Step 4. Normalize performance score and weight using following formulae.

$$z_{ij} = \frac{x_{ij}}{\min_i (x_{ij})}, \qquad z_{ij} \geq 1, \quad j \in B \tag{1}$$

$$z_{ij} = \frac{\max_i (x_{ij})}{x_{ij}}, \qquad z_{ij} \geq 1, \quad j \in NB \tag{2}$$

$$v_j = \frac{w_j}{\min (w_j)}, \qquad v_j \geq 1, \quad \forall j \tag{3}$$

In normalization of scores under benefit criteria, equation (1) is used. First, the minimum score under each benefit attribute is found. Then each score under a criterion is divided by its minimum score. In normalization of scores under non-benefit criteria, equation (2) is used. First, the maximum score under each non-benefit attribute is found. Then each score under the attribute is divided by the minimum score under the attribute. The normalized score z_{ij} is a dimensionless quantity such that $z_{ij} \geq 1,$ which represents normalized score of alternative i on attribute j. In normalization of attribute weight equation (3) is used. First, the minimum weight is found, and then each weight is divided by the minimum weight. The normalized weight v_j is a quantity such that $v_j \geq 1,$ which represents the normalized weight of attribute j.

Step 5. Compute weighted score

The proposed MMMCA approach assumes exponential relationship between normalized performance score and normalized weight. In maximization of benefit criteria and minimization of non-benefit criteria it is ensured that normalized value of both performance rating and weight are less than or equal to unity. The normalized value of performance rating under non-benefit criteria is inversely proportional to the rating. Thus by normalization technique non-benefit criteria are converted into benefit criteria which are to be maximized. The following equation is used in computation of weighted normalized rating.

$$IS_{ij} = z_{ij}^{v_j} \tag{4}$$

Step 6. Determine resultant score. Resultant score of each alternative is the geometric mean of the weighted score of alternatives. Resultant score is the factor which is the measure of benefit of alternatives. The higher the resultant score is the better the associated alternative is. The following equation (5) is used to calculate resultant score which is multiplicative in nature.

$$RS_i = \left[\prod_{i=1}^{n} WS_{ij} \right]^{1/n} = \left[\prod_{j=1}^{n} z_{ij}^{v_j} \right]^{1/n} \tag{5}$$

Step 7. Arrange the alternatives in descending order of their resultant scores. Select the best alternative with the highest resultant score. Figure 1 shows the flow diagram of the methodology.

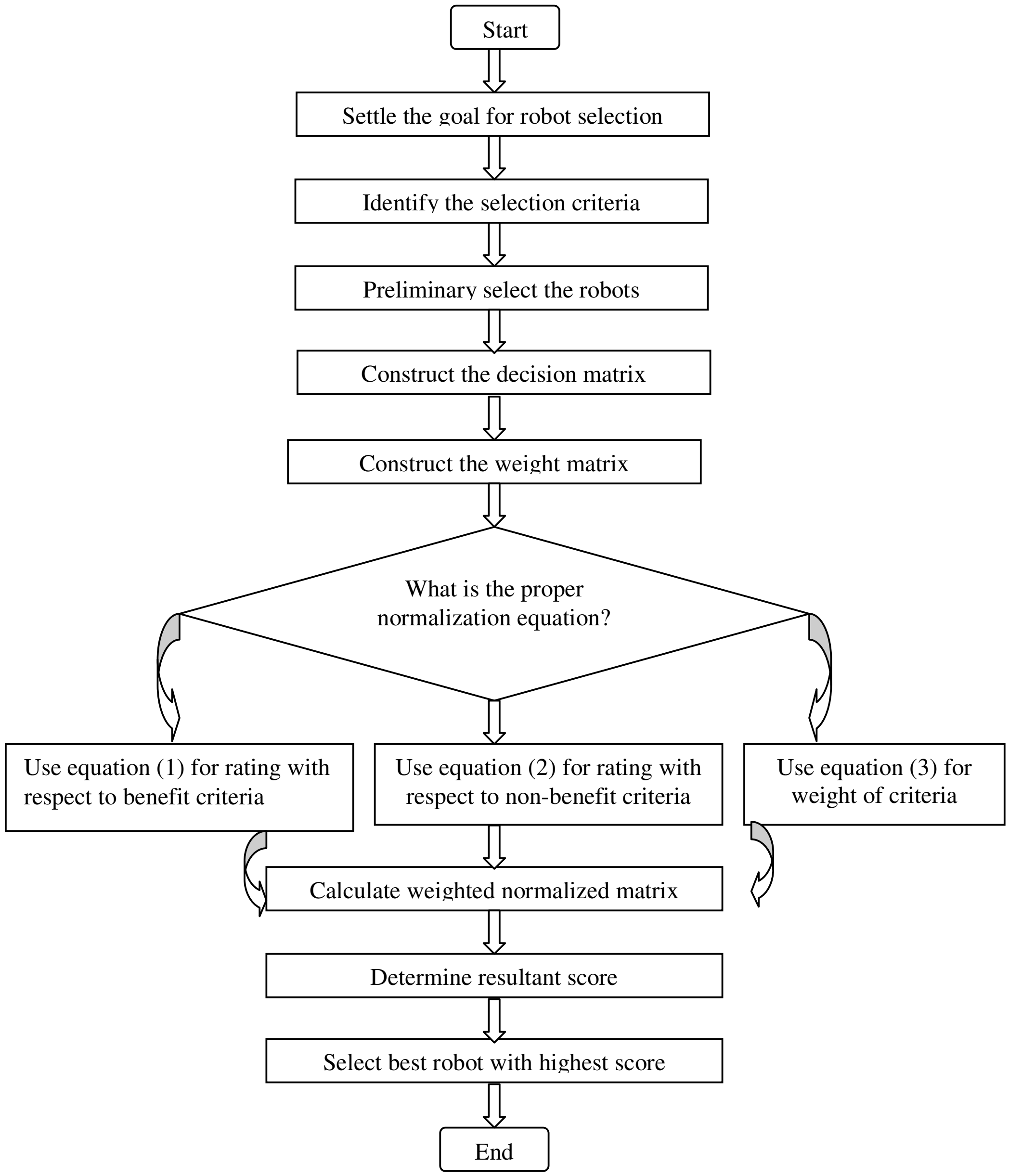

Figure 1. Flow diagram of the methodology

4. NUMERICAL ANALYSIS

Goh, Tung and Cheng, (1997) judged a robot selection problem with four robots and six criteria among those four criteria (velocity, load capacity, cost, and repeatability) are objective (quantitative) and two criteria (vendor's service quality and programming flexibility) are subjective (qualitative) [21]. Velocity (V) is the maximum speed that a manipulator arm can achieve. Load capacity (LC) is the maximum load that a manipulator can carry without affecting its performance. Robot's Cost (C) involves purchasing cost, installation cost and training cost. Repeatability (R) is the measure of ability of a robot to return to the same position and same orientation over and over again. Vendor's service quality (VSQ) refers to the level and varieties of service offered by a vendor. Programming flexibility (PF) refers to the ability of a robot to accept different programming codes. The subjective criteria are given subjective weights by a group of experts in 10 point scale. The objective and subjective data are illustrated in Table 1.

Goh *et al*. (1996) determined the criteria weights as shown in the decision matrix and these are modified using normalizing equation (3) and utilized in the current problem for subsequent analysis [22]. In the current example four criteria (velocity, load capacity, vendor's service quality and programming flexibility) being beneficial criteria (B) are to be maximized and the rest two criteria (cost and repeatability) being non beneficial criteria (NB) are to be minimized. Normalization of subjective and objective data is carried out using equation (1) and equation (2). The weighted normalized decision matrix is shown in Table 2. Each element in the matrix is the normalized response to the power corresponding normalized weight of the corresponding attribute. Product of weighted normalized scores is computed and is shown in Table 3. Finally the alternatives are ranked in descending order of their resultant scores (RI_i). The rank of the alternative robots in the current example is 3-1-2-4. Figure 2 shows the graphical representation of the resultant score of the robots.

Table1. Weight matrix and Decision matrix

Criteria →	Velocity (V)(m/s) (+)	Load Capacity (LC)(Kg) (+)	Vendors service Quality (VSQ) (+)	Programming Flexibility (PF) (+)	Cost (C) ($) (-)	Repeatability (R) (-)
weight →	0.1860	0.1860	0.1860	0.1628	0.1396	0.1396
R1	1.8	90	8	4	9500	0.45
R2	1.4	80	7	5	5500	0.30
R3	0.8	70	6	6	4000	0.20
R4	0.8	60	4	7	4000	0.15

Table 2. Normalized weight matrix and normalized decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6
Weight	1.33	1.33	1.33	1.16	1	1
A_1	2.25	1.5	2	1	1	1
A_2	1.75	1.3333	1.75	1.25	1.7273	1.5
A_3	1	1.1667	1.5	1.5	2.375	2.25
A_4	1	1	1	1.75	2.375	3

Table 3. Weighted score, resultant score and rank

	C_1	C_2	C_3	C_4	C_5	C_6	RS_i	Rank
A_1	2.9404	1.7148	2.5140	1	1	1	12.6757	3
A_2	2.1049	1.4661	2.1049	1.2954	1.7273	1.5	21.8031	1
A_3	1	1.2276	1.7147	1.6005	2.375	2.25	18.0033	2
A_4	1	1	1	1.75	2.375	3	12.4688	4

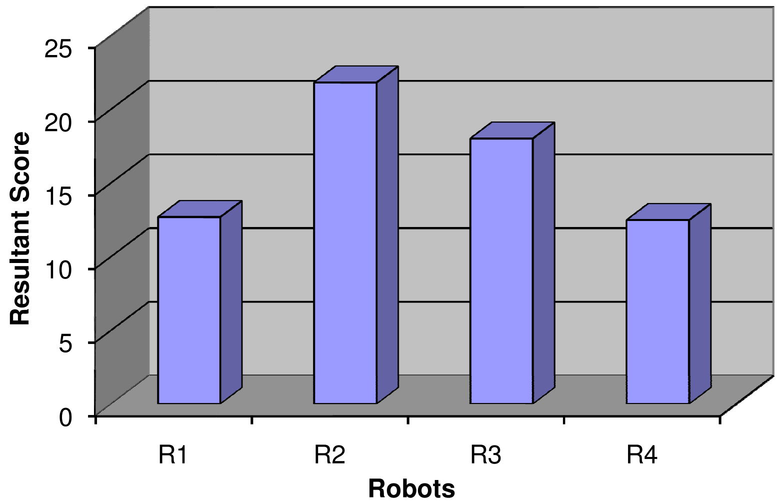

Figure 2. Resultant score of robots

5. CONCLUSION

The Multiplicative Model of Multiple Criteria Analysis MMMCA based approach is newly proposed, developed which helps in selecting the most suitable robot for a particular type of industrial application. The proposed methodology identifies and considers different robot selection attributes. This simple methodology can simultaneously take into account any number of quantitative and qualitative robot selection. The comparative study between the alternative robot aids in developing and deploying the available technologies by focusing into the robot characteristics that are not present in the robots. Another advantage of these expert systems is that it does not need any comprehensive technological knowledge regarding the applicability of the robots. Moreover, these expert systems alleviate the user from committing any error while taking the decision about selection of most suitable robot for a specific industrial application. This proposed methodology can be applied as a bench mark to select the robots for different industrial applications.

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