SELECTION OF ROBOT FOR WELDING OPERATION BY MULTIPLE ATTRIBUTE DECISION MAKING (MADM) APPROACH

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ABSTRACT *: It is difficult to select a robot for a particular operation according to our requirement because there are number of robots is available as alternative in the market from different companies. In this thesis an efficient approach for a solution of computer aided selection of robot using MADM approach. MADM is a multiple attribute decision making approach which is use to select a suitable robot according to customer requirement. With the help of this approach we can generate a database of robot manipulator on the basis of their attribute. And after assigning weights to each attribute, rank of the available alternative is determined with the help of TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method. This method has been illustrated with a mathematically solved example which can be used to compare the developed software compatibility among all parameter***.**

Keywords: Attribute, selection of robot, MADM approach, rank according to requirement .

INTRODUCTION

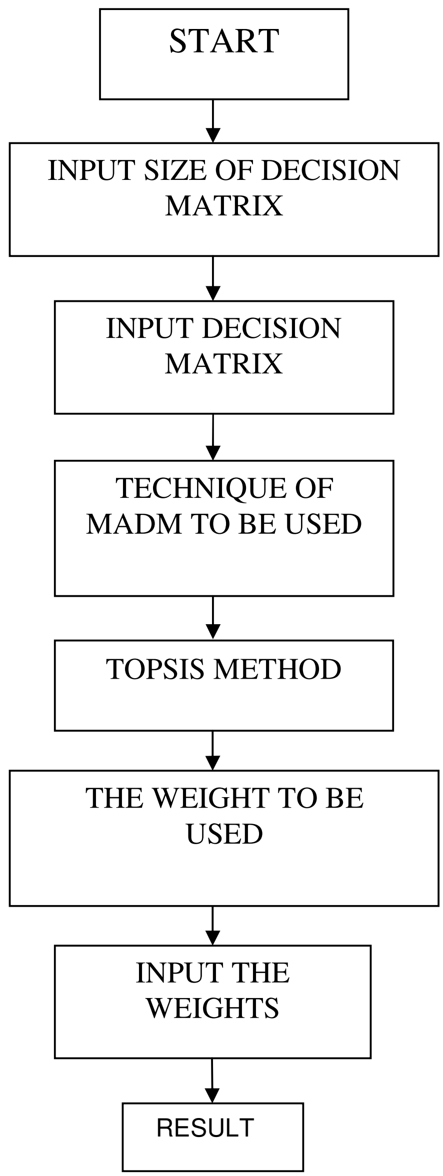
There has been rapid increase in the number of robot systems and robot manufacturers. Robots with vastly different capabilities and specifications are available for a wide range of applications. The selection of the robot to suit a particular application and production environment, from the large number 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. The complexity of problem can be better appreciated when one realizes that there are over 75 attributes that have to be considered in the selection of robot for particular application. Moreover, many of them are conflicting in nature and have different units, which cannot be unified and compared as they are. The quantification and monitoring of the attribute magnitudes will help the manufacturer to control them closely so that he can fulfil the demand of the user precisely. Moreover, he can find out the market trend by observing the attributes magnitudes. This will help the manufacturer to modify his product to suit the future needs of the robot user. He can use the database to produce optimum robots in the minimum possible time. The robot manufacturer can also use these attributes for the SWOT (Strength–Weakness–Opportunity–Threat) analysis of his product. This identification of the attributes will help the user for the database storage and its retrieval. This will generate the computerized database, which can be used in different formats for different purposes by different people in the organization. It also will help the user to select the best possible robot for the particular application whenever it is required. The user will know exactly what arethe physical characteristics and performance parameters of the robot. This will keep the user well informed about the capabilities of the robot while putting it to use.

LITERATURE REVIEW

A. P. Agalgaonkar, S. V. Kulkarni, and S. A. Khaparde [1] proposed a Multi-Attribute Decision Making Approach for Strategic Planning of DGs with the help of Analytical Hierarchy Process (AHP) to identify the relative significance of the chosen attributes. MADM technique is applied to three cases: conventional grid, hybrid DG operation and micro-grid. It is assumed that attributes are not related with each other. The proposed decision making technique has an ability to quantify the merits and justify new technology. Abhishek Kumar and V.P. Agrawal [2] proposed Attribute based specification, comparison and selection of electroplating system using MADM approach.The objective of this paper is to propose a methodology by which selection of electroplating product/ plant can be made easy. This selection procedure will help the user to select the system most suited for his operational needs. Moreover, the paper discusses how the electroplating suppliers, designers and maintenance personnel will also be benefited.A.S. Milani [3] evaluates the effect of different normalization norms within multiple attribute decision making (MADM) models. The application of the work is dedicated to gear material selection for power transmission. Technique for order preference by similarity to ideal solution (TOPSIS) is employed to weigh the selected failure criteria and to rank the selected material IDs, respectively. A simple multi-axial strategy is also recommended from which safer engineering decisions may be attained.Cengiz Kahraman&Selçuk Çebı [4] suggestsa new multi-attribute decision making method: Hierarchical fuzzy axiomatic design. In this paper, three important tolls are added Fuzziness in axiomatic design (FAD) method so as to supply its deficiency. The first one is the hierarchy which has the ability of taking the hierarchical structures into account. The second is the crisp toll which has the ability of taking the positive information into consideration under fuzzy environment. The last one is the ranking ability. As a matter of fact, FAD method is developed to be used for the solution of all manners of multi-attribute decision making problems. Moreover, an application to a teaching assistant selection problem is made to show the usability of the developed method.Christer Carlsson [5]states thatMultiple Criteria Decision Making (MCDM) shows signs of becoming a maturing field. There are four quite distinct families of methods: (i) the outranking, (ii) the value and utility theory based, (iii) the multiple objective programming, and (iv) group decision and negotiation theory based methods. Fuzzy MCDM has basically been developed along the same lines, although with the help of fuzzy set theory a number of innovations have been made possible; the most important methods are reviewed and a novel approach – interdependence in MCDM is introduced.Chen, Jason C.H. ,Ma, Jian [6] presented Multiple attribute decision making: approach integrating subjective and objective information to solve multiple attribute decision making (MADM) problems with preference information on alternatives. To reflect both the decision-makers' subjective preference information and the objective information from the decision matrix, the resulting social subjective fuzzy preference relation and the objective fuzzy preference relation derived from the decision matrix are integrated into a synthetic fuzzy preference relation. Based on the synthetic fuzzy preference relation, the fuzzy majority method is used to obtain the quantifier guided dominance degree (QGDD) and the quantifier guided non-dominance degree (QGNDD) of each alternative. According to the QGDD and QGNDD of the alternatives, the selection of them is done.Gin-Shuh Liang [7]presents a fuzzy multi-criteria decision making approach for robot selection. From combing the concepts of fuzzy set theory and hierarchical structure analysis, a robot selection algorithm is proposed. By utilizing this decision algorithm, the decision maker's fuzzy assessments with various rating attitudes and the trade off between various selection criteria can be taken into account in the aggregation process to ensure more convincing and accurate decision making.Hsu-Shih Shih [8] presents a paper on Incremental analysis for MCDM with an application to group TOPSIS. The study aims to exploit incremental analysis or marginal analysis to overcome the drawbacks of ratio scales utilized in various multi-criteria or multi-attribute decision making (MCDM/MADM) technique with the help of 11-step procedure.Haymwantee P. Singh & Wilfred V. Huang [9]presents a decision support robot selection system which applies the fuzzy set method to this multi-criteria decision making problem. The objective robot attributes are evaluated via marginal value functions while the subjective robot attributes are evaluated via fuzzy set membership function. Data from both evaluations are finally processed such that a fuzzy set decision making body are integrated. Sensitivity analysis has shown that final choices can be varied when the weight assignment are changed.K. L. Pok [10] developed a knowledge-based guidance system for multi-attribute decision making. That presents a microcomputer implementation of an intelligent system that provides an integrated environment for multiple attribute decision making. Incorporated into the system is a knowledge-based system that guides users in the selection of the most appropriate multiple attribute decision making methods given information about the problem characteristics by the users. An application of the system to the problem of selection an aircraft from a set of alternatives is presented. Muh-Cherng Wu & Wen-Jen Chang [11] presents a multiple criteria decision for trading capacity between two semiconductor fabs in order to further increase the two fabs' throughput. This research developed a method to find an optimal weighting vector for the three decision criteria: number of operations, number of layers, and number of wafers. The method firstly used NN + GA (neural network + genetic algorithm) to find an optimal trading decision in each week, and then used DOE + RSM (design of experiment + response surface method) to find an optimal weighting vector for a longer period, say 10 weeks.Moutaz Khouja [12]proposes a decision model for technology selection problems using a two-phase procedure. This model takes into consideration the fact that the performance of a technology, as specified by its vendor, is often unobtainable in reality. The proposed model is illustrated using robot selection and is tested on an actual robot data set.Piotr Jankowski, Natalia Andrienko and Gennady Andrienko [13] developed a Map-centred exploratory approach to multiple criteria spatial decision making Spatial decision support is one of the central functions ascribed to Geographical Information Systems (GIS). This approach presents a new prototype spatial decision support tools emphasising the role of maps as a source of structure in multiple criteria spatial decision problems. In these tools the role of map goes beyond the mere display of geographic decision space and multi-criterion evaluation results.Quan ZhangZhi-Ping Fan [14] proposed an approach to multiple attribute decision making based on fuzzy preference information on alternatives.S.K.Saha, V.P. Agrawal and P.P. Bhangale [15] gives the procedure of Attribute Based Specification, Comparision and Selection of robot with the objective to generate and maintain reliable and exhaustive database of robot manipulator based on their different pertinent attributes. This database can be used to standardize the robot selection procedure with the help of attribute based specification method and graphical method.Van Hop N.; Tabucanon M. T. [16] suggests Fuzzy multi-attribute decision-making for grouping of electronic components in process planning. This paper considers the grouping problem of electronic component families based on their multiple attributes. The difficulty lies with the conflict of criteria when selecting a certain component into a group.

METHODOLOGY

Flow chart for Multiple attribute decision making is given below-



THE 3-STAGE SELECTION PROCEDURE

Elimination search: -

Though all the attributes have been identified, all of them would not be important while selecting the robot for particular application. There will be few attributes, which will have direct effect on the selection procedure. This small number of attributes may be set-aside as pertinent attributes as necessitated by the particular application and/or the user. The threshold values to these pertinent attributes may be assigned by obtaining information from the user and the group of experts. On the basis of the threshold values of the pertinent attributes, a shortlist of robots is obtained. This may be achieved by scanning the database for pertinent attributes, one at a time, to eliminate the robot alternatives, which have one or more pertinent attribute values that fall short of the minimum required (threshold) values. To facilitate this search procedure an identification systemhas been made for all the robots in the data base.

3.2.2 Evaluation procedure: -

A mini-database is thus formed which comprises these satisfying solutions i.e., alternatives which have all attributes satisfying the acceptable levels of aspiration. The problem is now one of finding out the optimum or best out of these satisfying solutions. The selection procedure therefore needs to rank these solutions in order of merit. The first step here will be to represent all the information available from the database about these satisfying solutions in the matrix form. Such a matrix is called as decision matrix, **D**. Each row of this matrix is allocated to one candidate robot and each column to one attribute under consideration. Therefore an element d_{ij} of the decision matrix D, gives the value of jth attribute in the row (non-normalized) form and units, for the ith robot. Thus if the number of short-listed robots is m and the number of pertinent attributes is n, the decision matrix is an m * n matrix. This evaluation procedure completes in three steps

Step-1 Normalized specifications:

The next step is construction of the normalized specification matrix, N, from the decision matrix, D. Normalization is used to bring the data within particular range or scale, and moreover, it provides the dimensionless magnitudes. This phenomenon is used to calculate the normalized specification matrix. The normalized specification matrix will have the magnitudes of all the attributes of the robots on the common scale of 0 to 1. It is a sort of value, which indicates the standing of that particular attribute magnitude when compared to the whole range of the magnitudes for all candidate robots.

An element n_{ij} of the normalized matrix N can be calculated as

$$n_{ij} = d_{ij} \Big/ \sqrt{\sum_{i=1}^{m} d_{ij}^{2}}$$

Where d_{ij} is an element of the decision matrix D.

Step-2 Method for Assigning Weights:

Many methods for MADM problems require information about the relative importance of each attribute. It is usually given by a set of weights which is normalized to sum to 1. In case of n attributes, a set of weights is-

$$W^T = (W_1, W_2, W_3, ..., W_n)$$

$$\sum_{j=1}^{n} W_j = 1$$

Step-3 Weighted normalized specification: -

The weights obtained from the relative importance matrix have to be applied to the normalized specifications since all attributes have different importance while selecting the robot for particular application. The matrix, which combines the relative weights and normalized specification of the candidates, is weighted normalized matrix, V. It will give the true comparable values of the attributes. This can be obtained as follows:

$$\text{V} = \begin{pmatrix} w_1 n_{1,1} & w_2 n_{1,2} & \dots w_n n_{1,n} \\ w_1 n_{2,1} & \ddots & \vdots \\ w_1 n_{m,1} & w_2 n_{m,2} & \dots w_n n_{m,n} \end{pmatrix} = \begin{pmatrix} v_{1,1} & v_{1,2} & \cdots v_{1,n} \\ v_{2,1} & \ddots & \vdots \\ v_{m1} & v_{m,2} & \cdots v_{m,n} \end{pmatrix}$$

1.2 TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)

The weighted normalized matrix V is used to obtain the +ve and -ve benchmark robots, where the both benchmark robots are hypothetical robots, which supposed to have best and worst possible attribute magnitudes. Hwang and Yoon developed TOPSIS based upon the concept that the chosen option (optimum) should have the shortest distance from the +ve benchmark robot (best possible robot) and be farthest from the -ve benchmark robot (worst possible robot). The measure ensures that the top ranked robot is closest to +ve benchmark robot and farthest from -ve benchmark robot. Here, we calculate separation measures from +ve and -ve benchmark robots, respectively, as S_i^* and S_i^- as follows.

The separation from the +ve benchmark robot is given by

$$S_i^* = \left[\sum_{i=1}^{n}(v_{ij} - v_1^*)^2\right]^{1/2} \qquad (i = 1, 2, \ldots, m)$$

and separation from the -ve benchmark robot is given by

$$S_i^- = \left[\sum_{j=1}^{n}(v_{ij} - v_1^-)^2\right]^{1/2} \qquad (i = 1, 2, \ldots, m)$$

Then the relative closeness to the +ve benchmark robot, C*, which is a measure of the suitability of the robot for the chosen application on the basis of attributes considered, is calculated. A robot with the largest C* is preferable.

$$C^* = S_i^- / (S_i^* + S_i^-)$$

Ranking of the candidate robots in accordance with the decreasing values of indices C* indicating the most preferred and the least preferred feasible optional solutions is done.

Selection of ROBOT using Multiple Attribute Decision Making -

We take the example of robot selection for welding operation using MADM approach. The minimum requirement for this application is as follows Table 1:

Table.1

1. Load capacity	minimum 2 kg
2. Repeatability	0.5 mm
3. Maximum tip speed	at least 255 mm/s
4. Type of drives (actuators)	electrical only
5. Memory capacity	At least 250 points/steps
6. Manipulator reach	500 mm
7. Degree of freedom	at least 5

From the database generated, after 'elimination search' we can find out manageable number of candidate robots and their pertinent attributes.

Candidate robots are listed below: -

ABB–IRA1400M97 - (A_1)
Kawasaki F 545 N - (A_2)
Mitshubishi Melfa CR- E 356 - (A_3)
Yaskawa Electric Motoman - (A_4)
Fanuc Arcmate100 I - (A_5)
Panasonic VR 006 - (A_6)

Pertinent attributes are listed below: -

- Reach (mm) (X_1)
- Max. Tip Speed (mm/sec) (X_2)
- Memory Capacity (Points or Steps) (X_3)
- Load Capacity (kg) (X_4)
- Repeatability (mm) (X_5)
- Price (Rs.) (X_6)

Attributes for the short-listed candidate robots is show in table 2:

Table.2

Att - Alt	X_1	X_2	X_3	X_4	X_5	X_6
(A_1)	1.40	1200	500	6	0.30	375000
(A_2)	1.97	1450	3000	20	0.25	425000
(A_3)	1.00	1000	800	5	0.08	100000
(A_4)	0.92	850	1000	3	0.15	150000
(A_5)	1.36	1600	2000	5	0.16	225000
(A_6)	1.36	1740	1400	6	0.12	250000

Here repeatability and cost are the type of attribute of which is the minimum magnitude is preferable and hence the reciprocal of the values in column representing repeatability should be used to form the decision matrix.

Table 3

Att. Alter	(X_1)	(X_2)	(X_3)	(X_4)	(X_5)	(X_6)
(A_1)	1.40	1200	500	6	3.33	.00000266
(A_2)	6.8	10	1676	1727.2	1500	.000005
(A_3)	10	5	965	1000	2000	.00000307
(A_4)	2.5	10	915	560		

Att. Alter	(X1)	(X2)	(X3)	(X4)	(X5)	(X6)
					500	.00000666
(A5)	150	6.66	3500	1400	1200	.00000111
(A6)	300	2	1500	1600	1950	.00000114
(A7)	570	6.66	2826	1550	1600	.00000093

Data obtained from the above table is use in the procedure of selection of robot which is as follows:

Step 1

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 attribute values listed in columns.

$$\mathbf{D}=\begin{pmatrix} 1.40 & 1200 & 500 & 6 & 3.33 & .00000266 \\ 1.97 & 1450 & 3000 & 20 & 4.00 & .00000235 \\ 1.00 & 1000 & 800 & 5 & 12.5 & .000001 \\ 0.92 & 850 & 1000 & 3 & 6.66 & .00000666 \\ 1.36 & 1600 & 2000 & 5 & 6.25 & .00000444 \\ 1.36 & 1740 & 1400 & 6 & 8.33 & .000004 \end{pmatrix}$$

Step 2: -

Calculating the normalized specification matrix. This normalization helps to provide the dimensionless elements of the matrix.

$$r_{ij} = d_{ij} \Big/ \left(\sum_{i=1}^{m} d_{ij}^2 \right)^{1/2}$$

N=

$$\begin{pmatrix} 0.41489 & 0.364262 & 0.121806 & 0.260378 & 0.181627 & 0.274845 \\ 0.583809 & 0.44015 & 0.730838 & 0.867926 & 0.218171 & 0.242814 \\ 0.29635 & 0.303552 & 0.19487 & 0.216982 & 0.681783 & 0.103325 \\ 0.272642 & 0.258019 & 0.243631 & 0.130189 & 0.363254 & 0.688145 \\ 0.403036 & 0.485683 & 0.487226 & 0.216982 & 0.340891 & 0.458764 \\ 0.403036 & 0.52818 & 0.341056 & 0.260378 & 0.45434 & 0.413301 \end{pmatrix}$$

Step 3: -

Assign weights for each attribute such that their sum will be equal to one.

$$\sum_{i=1}^{n} w_i = 1$$

$w_1+w_2+w_3+w_4+w_5+w6 =1$

$w_1= 0.2 \quad w_2 = 0.15 \quad w_3= 0.10 \qquad w_4= 0.05$

$w_5= 0.10 \quad w_6 = 0.40$

Calculating the weighted normalized specification matrix. Here we incorporate the relative importance of the attributes with their normalized value to create unique parameter for the candidate robot.

$$V_{ij} = N_{ij}\, W_i$$

$$V_{ij} = \begin{pmatrix} 0.41489 & 0.364262 & 0.121806 & 0.260378 & 0.181627 & 0.274845 \\ 0.583809 & 0.44015 & 0.730838 & 0.867926 & 0.218171 & 0.242814 \\ 0.29635 & 0.303552 & 0.19487 & 0.216982 & 0.681783 & 0.103325 \\ 0.272642 & 0.258019 & 0.243631 & 0.130189 & 0.363254 & 0.688145 \\ 0.403036 & 0.485683 & 0.487226 & 0.216982 & 0.340891 & 0.458764 \\ 0.403036 & 0.52818 & 0.341056 & 0.260378 & 0.45434 & 0.413301 \end{pmatrix} \begin{pmatrix} 0.2 \\ 0.15 \\ 0.10 \\ 0.05 \\ 0.10 \\ 0.40 \end{pmatrix}$$

$$V_{ij} = \begin{pmatrix} 0.082978 & 0.054639 & 0.012181 & 0.013019 & 0.018163 & 0.109938 \\ 0.116762 & 0.066023 & 0.073084 & 0.0433396 & 0.021817 & 0.097126 \\ 0.05927 & 0.045533 & 0.019489 & 0.010849 & 0.068178 & 0.04133 \\ 0.054528 & 0.038703 & 0.024361 & 0.006509 & 0.036325 & 0.275258 \\ 0.080607 & 0.072852 & 0.048723 & 0.010849 & 0.034089 & 0.183505 \\ 0.080607 & 0.079227 & 0.034106 & 0.013019 & 0.045434 & 0.16532 \end{pmatrix}$$

TOPSIS method for ranking

This is the fifth step of the selection procedure. The weighted normalized attributes for the +ve and −ve benchmark robots can be obtained as:

v^* = (0.116762,0.079227,0.073480,0.043396,0.0524428)

v^- = (0.000753 0.013334 0.025945 0.013322 0.013107 0.019693)

Separation of the alternatives from the ideal and negative ideal solution is as follows:

$$S_1^+ = 0.19029 \quad S_1^- = 0.076242$$
$$S_2^+ = 0.18454 \quad S_2^- = 0.113207$$
$$S_3^+ = 0.251187 \quad S_3^- = 0.051409$$
$$S_4^+ = 0.101313 \quad S_4^- = 0.234948$$
$$S_5^+ = 0.112166 \quad S_5^- = 0.153844$$
$$S_6^+ = 0.127878 \quad S_6^- = 0.137705$$

RESULT AND DISCUSSION

Relative closeness to the ideal solution obtained as:

$$C_1^+ = 0.286051$$
$$C_2^+ = 0.380211$$
$$C_3^+ = 0.169895$$
$$C_4^+ = 0.698707$$
$$C_5^+ = 0.578339$$
$$C_6^+ = 0.5185$$

Result obtained with this model is shown below.

Table 3

Sr. No.	Alternatives	TOPSIS—closeness to the +ve benchmark robot C^*	Rank based on C^*
1	ABB –IRA 1400 M 97 A	0.286051	5
2	Kawasaki F 545 N	0.380211	4
3	Mitshubishi Melfa CR- E 356	0.169895	6
4	Yaskawa Electric Motoman	0.698707	1
5	Fanuc Arcmate	0.578339	2

Sr. No.	Alternatives	TOPSIS—closeness to the +ve benchmark robot C^*	Rank based on C^*
	100 I		
6	Panasonic VR 006	0.5185	3

Arrow shows the best alternative according to user requirement.

Thus the robots are ranked in order of preference based on the attributes selected. For the purchase of a new robot, the management can use the above ranking effectively to select the robot, which will be best suitable for the application and is based on this set together with other considerations

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