A REPORT
ON

‘MADM Methods’

BY

Name of the Student	ID Number
DEVEN PAUL	*2018A4PS0047G*
SWANAND KULKARNI	*2019A4PS0585G*
NITISHKUMAR SHUKLA	*2019A4PS0582G*
AKSHAY SHETH	*2019A4PS0797G*
AYUSH MISHRA	*2018B1A40601G*
LAKSHYA JAIN	*2019A4PS0472G*

Under
Ravindra Singh Saluja

BIRLA INSTITUTE OF TECHNOLOGY AND SCIENCE, PILANI,
K.K. BIRLA GOA CAMPUS

March 2022

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LAKSHYA JAIN	***2019A4PS0472G***

Prepared on completion of the
Laboratory Oriented Project (ME F366)
Under
Ravindra Singh Saluja

ACKNOWLEDGEMENTS

We would like to thank Ravindra Singh Saluja Sir for this excellent opportunity to pursue Laboratory Oriented Project under his excellent guidance.

His guidance and mentorship helped us throughout the project. Studying these methods and approaches to decision making processes would have never occurred to either of us were it not for his guidance and willingness to guide us when we needed help.

We are also grateful to our Administration for this opportunity to pursue this project.

Without the help and contribution of the people mentioned above, this project would not have been a success.

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ABSTRACT

The main aim of the project here involves studying carefully and analyzing the MULTIMOOSRAL method. The MULTIMOOSRAL method is a relatively new approach that has been formulated for supplier selection and it is special because it integrates all the major advantages of the three most prominent and well known methods that we know for making decisions involving many criterias.

These three methods are known as : MOOSRA, MOORA, and the MULTIMOORA methods respectively.

Other than using the traits from these three already existing previous methods, the Multimoosral method has many other upgrades over them as well, like for an instance : the Multimoosral method involves using a logarithmic scale unlike the usual standard. It also picks up a few of its key features from the pretty famous WASPAS and the CoCoSo methods.

In our project we aim to test the Multimoosral method's efficiency in our performed case studies using the Robot selection method so that we can possibly compare them onto each other.

INTRODUCTION

A robot is a machine that is reprogrammable consisting of anthropometric features and can be used for many different general purposes. They can complete repetitive, difficult and tedious tasks with accuracy and precision. There are many types of robots with different capabilities available to perform a wide range of industrial applications. Both the types of robots and the types of applications have been increasing a lot in recent years. As we are already aware that industrial robots are rather quite expensive, hence their selection process requires a good examination of their requirements. Many things such as load capacity, product design, cost etc need to be considered for this. We can classify these features into two categories broadly -

1. Objective attributes - They are usually defined in numerical terms, e.g. positioning accuracy, reliability, cost, repeatability, load capacity etc
2. Subjective attributes - They are usually found to be having qualitative definitions, e.g. training, vendor's service contract, programming flexibility, etc

In our project we aim to test the process of Robot Selection using the MULTIMOOSRAL method.

The MULTIMOOSRAL method has been formed from three prominent methods that are the MOORA, MOOSRA and the MULTIMOORA methods.

If we talk about what is different in the MULTIMOOSRAL method as compared to the previous methods then we must observe that in addition to the four arithmetic operations (addition, subtraction, multiplication and division) that have been incorporated in the model, there is also a fifth operation that is the logarithmic scale which has been included. The MOORA and MOOSRA methods only use two arithmetic operations, while the MULTIMOORA method uses three arithmetic operations. But the MULTIMOOSRAL method on the other hand uses four arithmetic operations in addition to a logarithmic scale as well. The MULTIMOOSRAL method was hence formulated to be a significant and strong upgrade on the previous methods and give us the best results in our operations.

METHODOLOGY

- The MOOSRA Method

Multi-Objective Optimization on the basis of Simple Ratio Analysis (MOOSRA) method uses the ratio approach to calculate the overall performance score(v) of each alternative and rank them accordingly in descending order. The alternative with the highest performance score is preferable.

To calculate the performance score (v), we take the ratio of the summation of a set of beneficial criteria to the summation of a set of non-beneficial criteria. To calculate the set of beneficial/non-beneficial criteria, we multiply the weightage of each alternative (w) with the normalized rating of the respective alternative(r). For normalized rating, the MOOSRA method uses a vector normalization procedure where the rating of each alternative(x) is divided by the square root of summation of the square of rating of all alternatives.
Mathematically, the formula comes out like this

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} (x_{ij})^2}}, \quad v_i = \frac{\sum_{j \in \theta_{\max}} w_j r_{ij}}{\sum_{j \in \theta_{\min}} w_j r_{ij}},$$

- The MOORA Method

Multi-Objective on the Basis of Ratio Analysis (MOORA) uses two approaches, namely RS (Ratio Approach) Approach and RP (Reference Point)

Approach to rank the alternatives. The MOORA method's final ranking of alternatives is based on dominance theory, which states that the alternative with the most occurrences in the first places on two ranking lists is the most acceptable alternative.

The RS Approach computes the difference in ratings between beneficial and non-beneficial criteria. The difference is denoted as “y” and the rating of beneficial/non-beneficial criteria is calculated in the same way as it was calculated in the MOOSRA Method. The alternative with the highest value of “y” is the most preferable choice. Mathematically, it comes out like this:

$$y_i = \sum_{j \in \theta_{\max}} w_j r_{ij} - \sum_{j \in \theta_{\min}} w_j r_{ij},$$

The RP Approach takes the difference between the rating of alternative and rating the reference point and multiplies it with the respective weight. The difference is denoted as “t”. Mathematically, it comes out like this:

$$t_i = \max_j \left(w_j \left| r_j^* - r_{ij} \right| \right),$$

The reference point is chosen as the maximum rating value of the beneficial criteria and the minimum rating value of the non-beneficial criteria. It’s mathematically denoted as:

$$r_j = \begin{cases} \max_i r_{ij}, & j \in \theta_{\max}, \\ \min_i r_{ij}, & j \in \theta_{\min}. \end{cases}$$

The lowest value of t is the most preferable in the RP Approach.

The final ranking is then evaluated by the dominance theory.

- The MULTIMOORA Method

The Multi-Objective Optimization by Ratio Analysis plus Full Multiplicative Form (MULTIMOORA) method uses three approaches, two of which are the one used in MOORA Method namely, RS and RP Approaches and the third method is the Full Multiplicative Form (FMF) which computes the ratio between ratings of beneficial and non-beneficial criteria. This ratio is called the overall utility of the respective alternative (u). The highest value of the “u” (the overall utility) is preferred. Similar to the MOORA Method, MULTIMOORA Method also uses dominance theory for the final ranking of all the alternatives.

The overall utility is calculated by taking the ratio of the product of all the normalized rating(r) and weightage(w) of beneficial criteria to the non-beneficial criteria of each alternative. Mathematically it’s computed as,

$$u_i = \frac{\prod_{j \in \theta_{\max}} w_j r_{ij}}{\prod_{j \in \theta_{\min}} w_j r_{ij}},$$

- The MULTIMOOSRAL Method

The MULTIMOOSRAL Method combines all the discussed approaches for ranking alternatives i.e. in the MOOSRA, MOORA, and MULTIMOORA, and additionally it adds one more approach which is the LA Approach.

The overall utility through LA Approach is calculated as follows and it's denoted by "k".

$$k_i = \sum_{j \in \theta_{\max}} \ln(1 + w_j r_{ij}) + \frac{1}{\sum_{j \in \theta_{\min}} \ln(1 + w_j r_{ij})}.$$

The main differentiating point of the MULTIMOOSRAL Method is that it doesn't use the Dominance Theory for computing the final ranking list. Instead of the Dominance Theory, MULTIMOOSRAL Method normalizes the overall utility obtained from each ranking approach and then adds them to compute a new utility factor to rank the alternatives. It's denoted by "S" and is computed as follows,

$$S_i = m'_i + t'_i + u'_i + v'_i + k'_i.$$

Here, m', t', u', v', k' represents normalized utility value obtained from the RS Approach, RP Approach, FMF Approach, AF Approach, and LA Approach respectively. Here, the highest value of "S" is the most preferable alternative. Normalization of the utility values obtained from the various approaches is done by taking the ratio of the difference between the respective utility values with the max/min utility value to the difference between the max and min utility value of the respective approach. The formulas of normalization of the 5 approaches are given below,

$$m_i' = \frac{m_i - \min(m_i)}{\max(m_i) - \min(m_i)}, \qquad t_i' = \frac{\max(t_i) - t_i}{\max(t_i) - \min(t_i)},$$

$$u_i' = \frac{u_i - \min(u_i)}{\max(u_i) - \min(u_i)}, \qquad v_i' = \frac{v_i - \min(v_i)}{\max(v_i) - \min(v_i)},$$

$$k_i' = \frac{k_i - \min(k_i)}{\max(k_i) - \min(k_i)},$$

EXAMPLES

In Example 1, the usability of the MULTIMOOSRAL method was demonstrated for the purpose of selection of the most appropriate industrial robot for some pick-n-place operations where it has to avoid certain obstacles. The method considers the objective weights of importance of the attributes as well as the subjective preferences of the decision maker to decide the integrated weights of importance of the attributes. Repeatability, accuracy, load capacity and velocity are observed to be the most important attributes affecting the robot selection decision.

Table 1: Evaluation criteria and their weights

	Load Capacity (kg)	Repeatability (mm)	Maximum Tip Speed (mm/s)	Memory capacity	Manipulator Reach (mm)
ASEA-IRB 60/2	60	0.4	2540	500	990
Cincinnati Milacrone T3-726 6.35	6.35	0.15	1016	3000	1041
Cybotech V15 Electric Robot 6.8	6.8	0.1	1727.2	1500	1676

Hitachi America Process Robot	10	0.2	1000	2000	965
Unimation PUMA 500/600 2.5	2.5	0.1	560	500	915
United States Robots Maker 110	4.5	0.08	1016	350	508
Yaskawa Electric Motoman L3C	3	0.1	177	1000	920

Weights	0.6282	0.1264	0.0615	0.1532	0.0307

Criteria	1	0	1	1	1

Table 2: Normalized Decision Matrix

Normalized Decision Matrix	Load Capacity (kg)	Repeatability (mm)	Maximum Tip Speed (mm/s)	Memory capacity	Manipulator Reach (mm)
ASEA-IRB 60/2	0.9705	0.7861	0.7087	0.1217	0.3557
Cincinnati Milacrone T3-726 6.35	0.1027	0.2948	0.2835	0.7304	0.3740
Cybotech V15 Electric Robot 6.8	0.1100	0.1965	0.4819	0.3652	0.6022
Hitachi America Process Robot	0.1618	0.3931	0.2790	0.4869	0.3467
Unimation PUMA 500/600 2.5	0.0404	0.1965	0.1563	0.1217	0.3288
United States Robots Maker 110	0.0728	0.1572	0.2835	0.0852	0.1825

Yaskawa Electric Motoman L3C	0.0485	0.1965	0.0494	0.2435	0.3306

Table 3: Computational details on the basis of RS Approach

RS Approach	Overall Importance	Overall Utility	Normalized Overall Utility
ASEA-IRB 60/2	0.5835	0.5835	1.0000
Cincinnati Milacrone T3-726 6.35	0.1681	0.1681	0.2372
Cybotech V15 Electric Robot 6.8	0.1483	0.1483	0.2009
Hitachi America Process Robot	0.1543	0.1543	0.2119
Unimation PUMA 500/600 2.5	0.0389	0.0389	0.0000
United States Robots Maker 110	0.0619	0.0619	0.0423

Yaskawa Electric Motoman L3C	0.0561	0.0561	0.0316

Table 4: Reference Point

	Load Capacity (kg)	Repeatability (mm)	Maximum Tip Speed (mm/s)	Memory capacity	Manipulator Reach (mm)
Reference Point	0.9705	0.1572	0.7087	0.7304	0.6022

Table 5: Computational details on the basis of RP Approach

RP	Maximal Distance	Normalized Maximal Distance
ASEA-IRB 60/2	0.0932	1.0000

Cincinnati Milacrone T3-726 6.35	0.5452	0.0797
Cybotech V15 Electric Robot 6.8	0.5406	0.0890
Hitachi America Process Robot	0.5081	0.1552
Unimation PUMA 500/600 2.5	0.5843	0.0000
United States Robots Maker 110	0.5640	0.0414
Yaskawa Electric Motoman L3C	0.5792	0.0103

Table 6: Computational details on the basis of FMF Approach

FMF	Overall Utility	Normalized Overall Utility
ASEA-IRB 60/2	5.45E-05	0.6326
Cincinnati Milacrone T3-726 6.35	3.88E-05	0.4457

Cybotech V15 Electric Robot 6.8	8.53E-05	1.0000
Hitachi America Process Robot	2.79E-05	0.3155
Unimation PUMA 500/600 2.5	1.85E-06	0.0052
United States Robots Maker 110	2.93E-06	0.0182
Yaskawa Electric Motoman L3C	1.41E-06	0.0000

Table 7: Computational details on the basis of AF Approach

AF	Maximal Distance	Normalized Maximal Distance
ASEA-IRB 60/2	6.8718	0.9775
Cincinnati Milacrone T3-726 6.35	5.5104	0.6684

Cybotech V15 Electric Robot 6.8	6.9709	1.0000
Hitachi America Process Robot	4.1062	0.3496
Unimation PUMA 500/600 2.5	2.5664	0.0000
United States Robots Maker 110	4.1170	0.3520
Yaskawa Electric Motoman L3C	3.2593	0.1573

Table 8: Computational details on the basis of LA approach

LP	Maximal Distance	Normalized Maximal Distance
ASEA-IRB 60/2	11.1039	0.0000

Cincinnati Milacrone T3-726 6.35	27.5309	0.4128
Cybotech V15 Electric Robot 6.8	40.9217	0.7493
Hitachi America Process Robot	20.8197	0.2442
Unimation PUMA 500/600 2.5	40.8160	0.7467
United States Robots Maker 110	50.8976	1.0000
Yaskawa Electric Motoman L3C	40.8326	0.7471

Table 9: Computational details on the basis of MULTIMOOSRAL approach

MULTIMOOSRAL	m_i'	t_i'	u_i'	v_i'	k_i'	S_i	Rank

ASEA-IRB 60/2	1.0000	1.0000	0.6326	0.9775	0.0000	3.6102	1
Cincinnati Milacrone T3-726 6.35	0.2372	0.0797	0.4457	0.6684	0.4128	1.8438	3
Cybotech V15 Electric Robot 6.8	0.2009	0.0890	1.0000	1.0000	0.7493	3.0392	2
Hitachi America Process Robot	0.2119	0.1552	0.3155	0.3496	0.2442	1.2764	5
Unimation PUMA 500/600 2.5	0.0000	0.0000	0.0052	0.0000	0.7467	0.7519	7
United States Robots Maker 110	0.0423	0.0414	0.0182	0.3520	1.0000	1.4539	4
Yaskawa Electric Motoman L3C	0.0316	0.0103	0.0000	0.1573	0.7471	0.9463	6

Table 10: Ranking of alternatives using MOOSRA method

MOOSRA	v_i	Normalized Overall Utility
ASEA-IRB 60/2	6.8718	0.9775
Cincinnati Milacrone T3-726 6.35	5.5104	0.6684
Cybotech V15 Electric Robot 6.8	6.9709	1.0000
Hitachi America Process Robot	4.1062	0.3496
Unimation PUMA 500/600 2.5	2.5664	0.0000
United States Robots Maker 110	4.1170	0.3520
Yaskawa Electric Motoman L3C	3.2593	0.1573

Table 11: Ranking of alternatives using MOORA method

MOORA	RS	RS Rank	RP	RP Rank
ASEA-IRB 60/2	0.5835	1	0.0932	7
Cincinnati Milacrone T3-726 6.35	0.1681	2	0.5452	4
Cybotech V15 Electric Robot 6.8	0.1483	4	0.5406	5
Hitachi America Process Robot	0.1543	3	0.5081	6
Unimation PUMA 500/600 2.5	0.0389	7	0.5843	1
United States Robots Maker 110	0.0619	5	0.5640	3
Yaskawa Electric Motoman L3C	0.0561	6	0.5792	2

Table 12: Ranking of alternatives using MULTIMOORA method

MULTIMOORA	RS	RS Rank	RP	RP Rank	FMF	FMF Rank	Rank
ASEA-IRB 60/2	0.5835	1	0.0932	7	5.45E-05	2	6
Cincinnati Milacrone T3-726 6.35	0.1681	2	0.5452	4	3.88E-05	3	5
Cybotech V15 Electric Robot 6.8	0.1483	4	0.5406	5	8.53E-05	1	7
Hitachi America Process Robot	0.1543	3	0.5081	6	2.79E-05	4	4
Unimation PUMA 500/600 2.5	0.0389	7	0.5843	1	1.85E-06	6	2

United States Robots Maker 110	0.0619	5	0.5640	3	2.93E-06	5	3
Yaskawa Electric Motoman L3C	0.0561	6	0.5792	2	1.41E-06	7	1

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Table 13: Comparative analysis of ranking orders using different MCDM methods

	MULTIMOORSAL	TOPSIS	MULTIMOORA	CoCoSo
ASEA-IRB 60/2	1	1	6	7
Cincinnati Milacrone T3-726 6.35	3	2	5	4

Cybotech V15 Electric Robot 6.8	2	4	7	5
Hitachi America Process Robot	5	3	4	6
Unimation PUMA 500/600 2.5	7	7	2	1
United States Robots Maker 110	4	5	3	3
Yaskawa Electric Motoman L3C	6	6	1	2

CONCLUSION

Manufacturers prefer to use robots in many industrial applications to perform repetitious, difficult and hazardous tasks with precision. Hence, to improve product quality and to increase productivity, robot selection has always been a vital concern for manufacturing companies. A novel multiple attribute decision making method is proposed in this paper to deal with the decision making situation of the robot selection in industrial environments considering both qualitative and quantitative attributes.

This work offers a new MCDM methodology called MULTIMOOSRAL, which is based on the MOOSRA, MOORA, and MULTIMOORA methodologies, as well as the LA approach for decision-making facilitation. The fundamental motivation for presenting the new method is from a desire to provide an approach that will help to improve the credibility of the findings achieved. The dependability and stability of the final ranking order are improved in this situation by using five techniques (RS, RP, FMF, AF, and LA). The numerical example is demonstrated to show the performance of the proposed approach.

Although this unique strategy improves the dependability of the executed choice process by including additional ways, the same could be said of its primary flaw. The computational process, in particular, may be regarded as too difficult for individuals unfamiliar with the MCDM discipline to use. This model might also be modified to include fuzzy, gray, or neutrosophic numbers in order to properly capture uncertainty. Despite these flaws, the MULTI-MOOSRAL technique has demonstrated its effectiveness in improving decision-making, and its potential should be explored further.

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