Developing an efficient decision support system for non-traditional machine selection: an application of MOORA and MOOSRA

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The purpose of this paper is to find out an efficient decision support method for non-traditional machine selection. It seeks to analyze potential non-traditional machine selection attributes with a relatively new MCDM approach of MOORA and MOOSRA method. The use of MOORA and MOOSRA method has been adopted to tackle subjective evaluation of information collected from an expert group. An example case study is shown here for better understanding of the said selection module which can be effectively applied to any other decision-making scenario. The method is not only computationally very simple, easily comprehensible, and robust, but also believed to have numerous subjective attributes. The rankings are expected to provide good guidance to the managers of an organization to select a feasible non-traditional machine. It shall also provide a good insight for the non-traditional machine manufacturer who might encourage research work concerning non-traditional machine selection.

Keywords: multicriteria decision-making; multiobjective optimization by ratio analysis; performance; non-traditional machining; selection

Introduction

Non-traditional machining processes is a group of processes that remove excess material by various techniques involving mechanical, thermal, electrical, or chemical energy or a combination of these energies, but do not use a sharp cutting tool as used in traditional machining processes. Conventional machining processes have been meeting the requirement of the industries over the decades. But new exotic work materials as well as innovative geometric designs of the products and components have been putting a lot of pressure on machine manufacturers to search for new machining processes to manufacture components with desired tolerance. This led to the development and establishment of non-conventional machining processes in the industry as efficient and economical alternatives to the conventional ones. In the present-day scenario, aerospace, nuclear plants, missile, turbine, automobile tool and dye-making industries often require newer and harder materials with higher strengths, hardness, toughness, and other diverse mechanical properties. In those industries, titanium, stainless steel, high-strength temperature-resistant alloys, fiber-reinforced composites, ceramic refractories, and other difficult-to-machine alloys are being utilized for generating complex and accurate shapes.
that may not be machined by the conventional machining processes, where the materials are removed from the work-piece surface in the form of chips.

In a manufacturing environment, the decision-makers need to select the most suitable advanced manufacturing method after assessing a wide range of alternate options based on a set of conflicting attributes/criteria. To help and guide the decision-makers, it is required to apply simple, systematic, and logical approaches or mathematical tools believed to have many number of selection attributes and candidate alternatives. The objective of any selection procedure is to identify the appropriate selection attributes and obtain the best selection in conjunction with real-time requirements. Although many multiobjective decision-making (MODM) methods are now available to deal with various evaluation and selection problems, this paper attempts to explore the applicability of an almost new MODM method, i.e. the multiobjective optimization on the basis of ratio analysis (multiobjective optimization by ratio analysis [MOORA] and multiobjective optimization on the basis of simple ratio analysis [MOOSRA]) method to solve the different non-traditional selection problems, in real-time manufacturing environment. The selection of a non-traditional machine for an organization for a given work material and shape feature combination is illustrated in this paper. This method is observed to be quite robust, comprehensible and computationally simple which helps the decision-makers to eliminate the unsuitable alternatives after selecting the most appropriate alternatives to strengthen the existing selection procedures. Multiobjective optimization (programming), also known as multicriteria or multiattribute optimization, is the process of simultaneously optimizing two or more conflicting attributes (objectives) subject to certain constraints. Multiobjective optimization problems may be found in various fields, such as product and process designs, finance, aircraft designs, oil and gas industry, manufacturing sector, automobile design or wherever optimal decisions need to be taken in the presence of take-offs among two or more conflicting objectives.

In real-time manufacturing environment, different decision-makers with various interest and values make a decision-making process with much more difficulty. In a decision-making problem, the objectives (attributes) must be measurable and their outcomes may be measured for every decision alternative. Objective outcomes provide the basis of comparison of choices and consequently facilitate the selection of the best (satisfactory) choice. Therefore, multiobjective optimization techniques seem to be an appropriate tool for ranking or selecting and must be used consistently: one or more alternatives from a set of available options based on multiple, conflicting attributes are problems of selection. The MOORA and MOOSRA method, first introduced by Brauers (2004), is such a multiobjective optimization technique that may be successfully applied to solve various types of complex decision-making problems in the manufacturing environment. The MOORA and MOOSRA method (Brauers, Zavadskas, 2006, 2009; Brauers, Zavadskas, Peldschus, & Turskis, 2008; Kalibatas & Turskis, 2008; Brauers & Zavadskas, 2006, 2009) starts with a decision matrix showing the performance of different alternatives about various attributes (objectives).

The different multicriteria decision-making tools are as follows: (1) the analytic hierarchy process (AHP), (2) technique for order of preference by similarity to ideal solution (TOPSIS), (3) analytic network process (ANP), (4) MOORA and MOOSRA, (5) ELECTRE, (6) complex proportional assessment of alternatives with gray relations (COPRAS-G), and (7) VIKOR.

The case study is taken as the selection of a non-traditional machine for the workshop of NIT, Agartala.
The case institute is one of the technical institutes in northeast region of India with the basic objective to impart world-class technical education and to prepare globally employable engineers. The institute had several branches of engineering, out of these branches manufacturing engineering is taught at the undergraduate level, postgraduate level and Ph.D. level. Basically manufacturing laboratory is part of the curriculum at all levels of engineering. The workshop had mostly earlier generation traditional machines. But there is a requirement for specialized machines, especially machines that meet the expectation of knowledge-hungry students of the institute.

An expert-level committee was formed with the HOD, two senior faculty and two manufacturing experts of the institute to look after the selection process. The committee visited several non-traditional machine-manufacturing facilities, and checked the log-books and daily registers maintained in the premises of manufacturers and consulted the manuals of different non-traditional machining processes and had brainstorming sessions. The committee had fixed the following parameters for the selection of the machine, (1) tolerance, (2) surface measurement, (3) power, (4) MRR, (5) tooling and fixtures (TF), (6) tool consumption (TC), (7) shape, (8) material, (9) cost, and (10) safety. Among these attributes, TSF (μm), PR (kW), C, [Cost in INR], and MRR (mm³/min) are quantitative having absolute numerical values, whereas TF, TC, S, M, and F have qualitative measures for which a ranked value judgment on a scale of 1–5 (1 - lowest, 3 - moderate, and 5 - highest) is suggested and points are allotted accordingly to these qualitative measures. MRR, E, S, M, and F are believed to be beneficial attributes, whereas TSF, PR, C, TF, and TC are believed to be non-beneficial attributes.

In reference to the selection of non-traditional machines, a novel decision-making method is proposed in this paper for the selection of non-traditional machine for the institute workshop. The aim of this paper is to propose a novel MOORA and MOOSRA method to deal with the manufacturing process selection problem that is believed to have both qualitative and quantitative attributes. A ranked value judgment on a beneficial and non-beneficial scale for the qualitative attributes is introduced. The proposed method helps the decision-maker to arrive at a decision based on either the objective weights of importance of the attributes or his/her subjective preferences, or believed to be both the objective weights and the subjective preferences.

**Related literature**

Decision-making may be regarded as the cognitive process resulting in the selection of a course of action between several alternate scenarios. Every decision-making process produces a final choice. The output can be an action or an opinion of choice. Past researchers have already solved the machine tool selection problem for different manufacturing facilities using various mathematical models as heuristics and MCDM techniques. It shall possibly improve the methods proposed in the literature, such as AHP, ANP, TOPSIS, PROMETHEE, VIKOR, ELECTRE, GREY, LINMAP, and conjoint analysis, to solve the multicriteria decision-making problems. For example, Kahraman, Cebeci, and Ulukan (2003) employed analytical hierarchy process (AHP) with fuzzy data in order to compare the catering service companies. Kull and Talluri (2008) used an integrated AHP–GP approach to evaluate and select suppliers about risk factors and product life cycle considerations. In the proposed model, AHP was used to assess suppliers along the risk criteria and to derive risk scores. The GP model was then constructed to evaluate alternate suppliers based on multiple risk goals and various hard constraints. Sarkis and Talluri (2002) believed that supplier-evaluating factors should
influence each other and the internal interdependency was needed, as believed, to be in
the evaluation process. They applied ANP to evaluate and select the best supplier about
organizational factors and strategic performance metrics, which consist of seven evaluat-
ing criteria. Talluri and Narasimhan (2005) developed a linear programming model to
evaluate and select potential suppliers about the strengths of existing suppliers and
exclude out-performing suppliers from a telecommunications company’s supply base.
The method of multiattribute complex proportional evaluation (COPRAS) is based on
the initial data normalization method. It assumes that the significance and priority of the
investigated alternatives depend directly on the proportional method of criterion ade-
quately describing the alternatives and to the values and weights of the attributes
(Kaklauskas et al., 2010). The process of attributes is determined and their values and
initial weights are calculated. The TOPSIS (technique for order preference by similarity
to an ideal solution) method was developed by Hwang and Yoon (1981). The basic rule
is that the chosen alternate should have the shortest distance from the ideal solution and
the farthest distance from the negative ideal solution. The MOORA method is applied
for the assessment of an indoor environment of dwelling houses. In this paper, the
experiment was chosen for research according to the related works and results presented
in Das, Sarkar, and Ray (2012). The MOORA (Brauers & Zavadskas, 2006, 2009;
Brauers et al., 2008) procedure is one of the simplest multicriteria methods in selecting
the corresponding decision attributes. Narender Singh, Raghukandan, and Pai (2004)
worked on optimization by gray relational analysis of machining parameters in electric
discharge machining (EDM) of (Al-10%Si-10% rest C) composite. Hocheng and Hsu
(1995) conducted an experimental study on ultrasonic drilling of carbon fiber-reinforced
plastic composites. Karthikeyan, Lakshmi Narayanan, and Naagarazan (1999) worked
on mathematical modeling for EDM of aluminum–silicon carbide metal matrix
composite. The earlier researchers have also employed various tools and techniques like
data envelopment analysis (DEA) (Sadhu & Chakraborty, 2011) and multiobjective
optimization using ratio analysis (MOORA) method (Chakraborty, 2011) for selecting
the best NTM processes for various machining applications, (TOPSIS-based methodol-
ogy for selecting the best non-traditional machine by Chakladar and Chakraborty
(2008), (ANP for selection of non-traditional machining processes by Das and
Chakraborty [2011]).

Thus, from the review of the past researches, it is observed that the MCDM methods
are quite suited and appropriate for solving the machine tool selection problem for a
given manufacturing application. In this paper, the exactly suitable non-traditional
machine is selected using MOORA and MOOSRA method that are efficient MCDM
tools for solving such kind of complex decision-making problems in non-traditional
manufacturing domain.

Decision-making problems

In order to demonstrate the applicability and potentiality of the MOORA and MOOSRA
method in solving multiobjective decision-making problems in real-time manufacturing
environment, the following problem is taken as a case study of selection of non-tradi-
tional machine for the institute workshop. For this non-traditional machine selection
problem, seven alternatives viz. ultrasonic machining (USM), abrasive jet machining
(AJM), electrochemical machining (ECM), EDM, wire electrical discharge machining
(WEDM), electron beam machining (EBM), and laser beam machining (LBM) are taken
into consideration in this study. The most influencing attributes for this problem are
tolerance (T), surface finish (SF), power requirement (PR), material removal rate (MRR), cost (C), tooling and fixtures (TF), tool consumption (TC), safety (S), work material (M), and shape feature (F). The weights of the attributes are assigned after working in AHP. An expert-level committee is formed with the HOD and other four senior-level professionals. The attributes T (mm), SF (μm), PR (kW), C, and MRR are collected from different available literatures and working registers of industrial plants and the corresponding values are assigned by the experts to the decision matrix. The value of other criteria such as TF, TC, S, M, and F are assigned after consultation with the expert committee (as stated earlier) and the final decision matrix with the relative weight of each criterion is presented in Table 1.

Methodology adopted

The methodology for selection of best non-traditional machine is shown in the following flowchart depicted here as Figure 1.

The methodology is divided into two sections viz A and B. Section A deals with the methodology of determination of weight-age of criteria by applying AHP and Section B deals with the methodology of non-traditional-machine selection.

Section A

Methodology of AHP is as follows: The pairwise comparison matrix is of size $n \times n$, where $n$ is the number of elements to be compared pairwise. The matrix will be filled up accordingly using the following procedures:

Step I: Each element compared with itself will get a value 1 i.e. $a(1,1)=a(2,2)=\ldots=a(n,n)=1$

Step II: If the $i$th element, when compared with $j$th element, has got a value $A(i,j)$, then the $j$th element being compared with $i$th element has got a value $a(j,i)=1/a(i,j)$ i.e. $a(2,1)=1/a(1,2)$, $a(3,1)=1/a(1,3)$, $\ldots$ $a(n,1)=1/a(1,n)$

Step III: Relative weight, $(RW) = \sqrt[n]{a(1,1)a(2,1)a(3,1)a(4,1)a(5,1)}$

Step IV: Normalized weight, $(NW) = RW/\sum RW$

Step V: Maximum Eigen value $(MAX)=\sum$ column $A \times$ NW value row $A + \sum$ column $B \times$ NW value row $B + \ldots + \sum$ Column $n \times$ NW value row $n$

Step VI: Consistency Index $(CI) = (MAX - n)/(n-1)$

Step VII: Random Index $(RI) = 1.98(n-2)/n$

Table 1. The decision matrix prepared after consultation with the experts constituted by NIT Agartala.

| Criteria | TSF | SF | PR | MRR | C | TF | TC | S | M | F |
|----------|-----|----|----|-----|---|----|----|---|---|---|
| Optimization direction | min | max | min | max | min | min | min | max | max | max |
| Alternative Performance score assigned by the Expert on different attributes/criteria |
| 1. USM | 1 | 4 | 10 | 500 | 2 | 2 | 3 | 1 | 5 | 5 |
| 2. AJM | 2.5 | 4 | 0.24 | 0.5 | 1 | 2 | 2 | 3 | 5 | 4 |
| 3. ECM | 3 | 2 | 100 | 400 | 5 | 3 | 1 | 3 | 1 | 1 |
| 4. EDM | 3.5 | 4 | 2.7 | 800 | 3 | 4 | 4 | 3 | 1 | 5 |
| 5. WEDM | 3.5 | 4 | 2.5 | 600 | 3 | 4 | 4 | 3 | 1 | 5 |
| 6. EBM | 2.5 | 5 | 0.2 | 1.6 | 4 | 2 | 1 | 3 | 5 | 5 |
| 7. LBM | 2 | 5 | 1.4 | 0.1 | 3 | 2 | 1 | 3 | 5 | 5 |
**Step VIII:** Consistency Ratio (CR) = CI/RI, should be within 10%.

The criteria are separated as beneficial criteria and non-beneficial criteria and are shown in Table 2.

The weights are determined by applying pairwise comparison between the criteria by quantifying the Saaty’s 1–9 scales (Table 3). After numbering and separating as beneficial and non-beneficial criteria [C1], the criteria are compared and points are allotted as per Satty’s scale. After that all criteria points are multiplied and put in the GM column. After that GM 0.1 (as 10 numbers of criteria are selected) is evaluated and the total score is obtained. Then individual score is divided by the total score and the corresponding weight-age of each criterion is determined. The consistency ratio is checked regardless of whether the assigned value allotted in the table as per Satty’s scale is right or wrong.
Now, we are generating the primary decision matrix from the AHP method introduced by T.L. Satty and his scale. The calculation of weight-age is shown in Table 4.

\[
\lambda_{\text{max}} = 7.28 \times 0.15 + 0.17 \times 6.24 + 7.91 \times 0.142 + 19.16 \times 0.069 + 15.5 \times 0.085 \\
+ 11.83 \times 0.09 + 12.08 \times 0.099 + 0.074 \times 14.5 + 18 \times 0.057 + 19 \times 0.057 \\
= 11.386
\]

Consistency Index (CI) = \((\lambda_{\text{max}} - n)/(n-1)\)

\[
CI = [11.386 - 10]/10 - 1 = 0.597 = 0.154
\]

Random Index (RI) = 1.98\((n-2)/n\) = 1.58

Consistency Ratio (CR) = CI/RI = 0.154/1.58 = 0.097 < 0.1 < 10%

The weight factors we are getting from the above matrix:

\[
[C_1]^W = 0.15, [C_2]^W = 0.170, [C_3]^W = 0.142, [C_4]^W = 0.069, [C_5]^W = 0.085, \\
[C_6]^W = 0.09, [C_7]^W = 0.099, [C_8]^W = 0.074, [C_9]^W = 0.057, [C_{10}]^W = 0.057
\]

**Section B**

The selection of non-traditional machine is carried out under the following steps:

**Step I:** formation of the decision matrix
Table 4. AHP matrix from the Satty’s scale.

| Criteria | C_1 | C_2 | C_3 | C_4 | C_5 | C_6 | C_7 | C_8 | C_9 | C_10 | GM   | GM^0.1 | Weight-age |
|----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|-------|---------|------------|
| C_1      | 1   | 1   | 1   | 3   | 5   | 1   | 1   | 1   | 2   | 4    | 120   | 1.61    | 0.15       |
| C_2      | 1   | 1   | 2   | 3   | 4   | 1   | 3   | 2   | 3   | 1    | 432   | 1.83    | 0.170      |
| C_3      | 1   | 1   | 2   | 4   | 1   | 2   | 1   | 3   | 2   | 3    | 72    | 1.53    | 0.142      |
| C_4      | 1/3 | 1/3 | 1/4 | 1   | 1/2 | 3   | 1/4 | 3   | 1   | 2    | 0.063 | 0.75    | 0.069      |
| C_5      | 1/5 | 1/4 | 1   | 2   | 1   | 1   | 2   | 1   | 3   | 1    | 0.4   | 0.912   | 0.085      |
| C_6      | 1   | 1   | 1/2 | 1/3 | 1   | 1   | 2   | 1   | 3   | 1    | 1     | 1       | 0.09       |
| C_7      | 1   | 1/3 | 1   | 4   | 1/2 | 1/2 | 1   | 1   | 2   | 3    | 2     | 1.071   | 0.099      |
| C_8      | 1   | 1   | 1/2 | 1/3 | 1/3 | 1   | 1   | 1   | 1   | 2    | 0.11  | 0.80    | 0.074      |
| C_9      | 1/2 | 1/3 | 1/2 | 1   | 1/2 | 1/3 | 1/2 | 1   | 1   | 1    | 0.007 | 0.61    | 0.057      |
| C_10     | 1/4 | 1   | 1/3 | 1/2 | 1   | 1   | 1/3 | 1/2 | 1   | 1    | 0.007 | 0.61    | 0.057      |
|          | 7.28| 6.24| 7.91| 19.16|15.5 |11.83|12.08|14.5 |18   |19    |10.72  |0.995    |            |
In this stage the variables or alternatives are defined and collected. After that the attributes on which the selection is to be based are defined. After that the weight-age of each criterion is determined by AHP method (stated earlier). Application of AHP method in selecting the weight-age of each criterion is shown separately (stated earlier). The performance of each alternate against each criterion is expressed in the following decision matrix.

\[
D = [x_{ij}]
\]

where \( A_i \) represents the alternatives, \( i = 1, 2, \ldots, m \); \( C_j \) represents \( j \)th criteria or attribute, \( j = 1, 2, \ldots, n \), relate to \( i \)th alternative. The attributes are classified as either beneficial criteria or non-beneficial criteria. The subjective weight of the \( j \)th attribute is denoted by \( W_j \); and \( x_{ij} \) indicates the performance of each alternate \( A_i \) about each criteria \( C_j \).

Step II: Normalization of decision matrix: The normalization of decision matrix is carried out by applying the following formula

\[
v_i = \frac{\sum_{j=1}^{g} W_j x_{ij}}{\sum_{j=g+1}^{n} W_j x_{ij}}
\]

with \( j = 1, 2, \ldots g \) indicate the beneficial criteria and \( j = g + 1, g + 2 \ldots n \) indicate the non-beneficial criteria. \( W_j \) is associated weight the \( j \)th attribute.

Step III: Application of MOORA method and determination of performance score of the alternatives by that method. The performance score (\( Y_i \)) of alternative is calculated by applying the following equation

\[
Y_i = \sum_{j=1}^{g} w_j x_{ij} - \sum_{j=g+1}^{n} w_j x_{ij} - [j = 1, 2, \ldots n]
\]

where \( w_j \) is the weight of \( j \)th attribute, which can be determined applying AHP or entropy method and \( \sum_{j=1}^{g} w_j x_{ij} \) is the sum of beneficial criteria and \( \sum_{j=g+1}^{n} w_j x_{ij} \) is the sum of non-beneficial criteria.

Step IV: The \( v_i \) value and \( Y_i \) value can be positive or negative depending of the totals of its maxima (beneficial attributes) and minima (non-beneficial attributes) in the decision matrix. An ordinal ranking of \( v_i \) and \( Y_i \) shows the final preference. Thus, the best alternative has the highest \( v_i \) and \( Y_i \) value, while the worst alternative has the lowest \( v_i \) and \( Y_i \) value.

Calculation

The calculation for selection of best non-traditional machine is shown in the flowchart depicted as in Figure 2
The calculations are done in the following steps:

**Step 1: Identification of decision matrix:** The decision matrix with the alternatives and criteria and permanence score are stated in Table 1.
Step II: Determination of weight-age value using Satty’s scale. The criterions are separated as beneficial criterion and non-beneficial criterion and are shown in Table 2. After that AHP method is applied to determine the weight-age of each criterion and is shown in Table 4.

Step III: The normalization of decision matrix is carried out using the formula. The sum of squares is calculated by adding all column elements. The sum of square value is obtained by square root of sum of square and is shown in Table 5.

The normalized matrix is formed using the following formula \( x'_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \) (for \( j = 1, 2, \ldots, n \)) and is presented in Table 6. For example, in column 3 and row 5 of Table 5, the tolerance value is designated as 1 and sum of square value is designated as 6.7. When 1 is divided by 6.7 it becomes 0.15 and is presented in Table 6. Similarly, other values of Table 5 are divided by the sum of square value and presented in Table 6.

The weighted normalized matrix is calculated using the following formula \( w_j \times x_{ij} \) and presented in Table 7. For example in column 2 and row 4 of Table 6, the value of tolerance is 0.15. When multiplied by weights 0.15 it becomes 0.0225 and is tabulated in Table 7. Similarly, other values of Table 6 are multiplied by corresponding weights and presented in Table 7.

Results

The case institute is one of the youngest NITs in India. The problem is to select the non-traditional machine for the case institute workshop. The Director wanted to procure the best machine for this purpose. For this an expert-level committee was formed by the Director to select the best machine under the criterion of tolerance, surface finish, tooling and fixture, cost, material removing rate, tool consumption, safety, etc[stated earlier]. The expert committee visited different factories of non-traditional machine and collected the data from the manufacturers and available literature and started the work that is shown in Table 1. The weighted normalized matrix is separated into beneficial criterion

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Table 5. The calculation of sum of square and \( \sqrt{\sum_{i=1}^{n} x_{ij}^2} \).

| Criteria Optimization direction | T | SF | PR | MRR | C | TF | TC | S | M | F |
|---------------------------------|---|----|----|-----|---|----|----|---|---|---|
| Weights                         | 0.15 | 0.17 | 0.142 | 0.069 | 0.085 | 0.09 | 0.099 | 0.074 | 0.057 | 0.057 |
| ALT Performance score of various attributes of non-traditional machining process |
| Sum of square                  | 45 | 118 | 10,121 | 1,410,005 | 64 | 45 | 33 | 50 | 66 | 106 |
| Sum of square root of square   | 6.7 | 10.9 | 100.6 | 1674.3 | 8 | 6.7 | 5.74 | 7.07 | 8.12 | 10.3 |

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For example, in column 3 and row 5 of Table 5, the tolerance value is designated as 1 and sum of square value is designated as 6.7. When 1 is divided by 6.7 it becomes 0.15 and is presented in Table 6. Similarly, other values of Table 5 are divided by the sum of square value and presented in Table 6.
Table 6. Normalized matrix.

| Alternative | T   | SF   | PR     | MRR    | C     | TF    | TC    | S     | M     | F     |
|-------------|-----|------|--------|--------|-------|-------|-------|-------|-------|-------|
|             | min | max  | min    | max    | min   | min   | min   | max   | max   | max   |
| USM         | 0.15| 0.17 | 0.142  | 0.069  | 0.085 | 0.09  | 0.099 | 0.074 | 0.057 | 0.057 |
| AJM         | 0.3 | 0.0367| 0.099  | 0.0006 | 0.125 | 0.3   | 0.52  | 0.14  | 0.246 | 0.019 |
| ECM         | 0.45| 0.183| 0.99   | 0.239  | 0.5   | 0.447 | 0.174 | 0.28  | 0.123 | 0.097 |
| EDM         | 0.45| 0.367| 0.03   | 0.4778 | 0.375 | 0.6   | 0.174 | 0.42  | 0.123 | 0.485 |
| WEDM        | 0.45| 0.183| 0.03   | 0.358  | 0.375 | 0.3   | 0.69  | 0.42  | 0.123 | 0.485 |
| EBM         | 0.45| 0.458| 0.009  | 0.0012 | 0.5   | 0.3   | 0.174 | 0.42  | 0.61  | 0.485 |
| LBM         | 0.3 | 0.458| 0.009  | 0.0006 | 0.375 | 0.3   | 0.174 | 0.42  | 0.61  | 0.485 |

Normalized performance score / square root of sum of square of performance score.
Table 7. Weighted normalized matrix.

| Criteria | Optimization direction | T       | SF      | PR     | MRR    | C       | TF      | TC      | S       | M       | F       | Weights |
|----------|-------------------------|---------|---------|--------|--------|---------|---------|---------|---------|---------|---------|---------|---------|
| ALT      | min                     | 0.15    | 0.17    | 0.142  | 0.069  | 0.085   | 0.09    | 0.099   | 0.074   | 0.057   | 0.057   | 0.099   |
| ALT      | max                     | 0.099   | 0.074   | 0.057  | 0.057  | 0.057   | 0.057   | 0.057   | 0.057   | 0.057   | 0.057   | 0.057   |

| ALT      | USM                     | 0.0225  | 0.014   | 0.003  | 0.02125| 0.027   | 0.05148 | 0.01036 | 0.014022| 0.01083 |
| ALT      | AJM                     | 0.045   | 0.013   | 0.00004| 0.010625| 0.027   | 0.03465 | 0.03108 | 0.021033| 0.005529|
| ALT      | ECM                     | 0.0675  | 0.140   | 0.0164 | 0.0425 | 0.04023 | 0.017226| 0.02072 | 0.007011| 0.005529|
| ALT      | EDM                     | 0.0675  | 0.0042  | 0.4778 | 0.031875| 0.054   | 0.017226| 0.03108 | 0.007011| 0.027645|
| ALT      | WEDM                    | 0.0675  | 0.0042  | 0.033  | 0.031875| 0.027   | 0.06831 | 0.03108 | 0.007011| 0.027645|
| ALT      | EBM                     | 0.0675  | 0.003   | 0.00008| 0.0425 | 0.027   | 0.017226| 0.03108 | 0.03477 | 0.027645|
| ALT      | LBM                     | 0.045   | 0.003   | 0.00004| 0.031875| 0.027   | 0.017226| 0.03108 | 0.03477 | 0.027645|
and non-beneficial criterion. The beneficial criterion of each alternate is separated and after that added and presented in Table 8. After that the non-beneficial criterion is separated and after that added and presented in Table 9. Then all the non-beneficial criteria are subtracted from beneficial criteria and beneficial criterion are divided by non-beneficial criteria and presented in Table 10. This is designated as performance score of particular alternative.

As for example, for alternative $A_1$ the beneficial criterion is $0.100612$ and non-beneficial criterion is $0.16323$. So ranking score by MOOSRA is $v_{d1} = \frac{0.100612}{0.16323} = 0.61637$ and ranking score by MOORA is equal to $Y_{d1} = \sum_{j=1}^{9} w_jx_{ij} - \sum_{j=g+1}^{n} w_jx_{ij} = 0.10062 - 0.16323 = -0.06261$.

For alternative $A_2$ the beneficial criterion is $0.120442$ and non-beneficial criterion is $0.18575$.

So ranking score by MOOSRA is $v_{d2} = \frac{0.120442}{0.18575} = 0.646957$ and ranking score by MOORA is equal to $Y_{d2} = \sum_{j=1}^{9} w_jx_{ij} - \sum_{j=g+1}^{n} w_jx_{ij} = 0.120442 - 0.18575 = -0.06531$.

For alternative $A_3$ the beneficial criterion is $0.08076$ and non-beneficial criterion is $0.307456$. So ranking score by MOOSRA is $v_{d3} = \frac{0.08076}{0.307456} = 0.261886$ and ranking

| Criteria Optimization direction Weight ALT | SF | MRR | S | M | F | Sum of weighted normalized benefit performance score |
|---------------------------------------------|----|-----|---|---|---|-----------------------------------------------------|
| Max                                         | 0.17 | 0.069 | 0.074 | 0.057 | 0.057 | 0.100612 |
| 1.                                           | 0.0624 | 0.003 | 0.01036 | 0.014022 | 0.01083 | 0.100612 |
| 2.                                           | 0.0624 | 0.00004 | 0.03108 | 0.021033 | 0.005529 | 0.120442 |
| 3.                                           | 0.0311 | 0.0164 | 0.02072 | 0.007011 | 0.005529 | 0.08076 |
| 4.                                           | 0.0624 | 0.4778 | 0.03108 | 0.007011 | 0.027645 | 0.605936 |
| 5.                                           | 0.0624 | 0.033 | 0.03108 | 0.007011 | 0.027645 | 0.161136 |
| 6.                                           | 0.078 | 0.00008 | 0.03108 | 0.03477 | 0.027645 | 0.172295 |
| 7.                                           | 0.078 | 0.00004 | 0.03108 | 0.03477 | 0.027645 | 0.171895 |

| Criteria Optimization direction Weight ALT | T | PR | C | TF | TC | Sum of weighted normalized non-benefit performance score |
|---------------------------------------------|---|----|---|---|---|------------------------------------------------------|
| Min                                         | 0.15 | 0.142 | 0.085 | 0.09 | 0.099 | 0.13523 |
| 1.                                           | 0.0225 | 0.014 | 0.02125 | 0.027 | 0.05148 | 0.13523 |
| 2.                                           | 0.045 | 0.0013 | 0.010625 | 0.027 | 0.03465 | 0.118575 |
| 3.                                           | 0.0675 | 0.140 | 0.0425 | 0.04023 | 0.017226 | 0.307456 |
| 4.                                           | 0.0675 | 0.0042 | 0.031875 | 0.054 | 0.017226 | 0.174801 |
| 5.                                           | 0.0675 | 0.0042 | 0.031875 | 0.027 | 0.06831 | 0.198885 |
| 6.                                           | 0.0675 | 0.003 | 0.0425 | 0.027 | 0.017226 | 0.157226 |
| 7.                                           | 0.045 | 0.003 | 0.031875 | 0.027 | 0.017226 | 0.124101 |
Table 10. Ranking by MOOSRA and MOORA method.

| ALT     | $\sum_{j=1}^{g} w_j x_{ij}^x$ | $\sum_{j=g+1}^{n} w_j x_{ij}^x$ | $v_i = \frac{\sum_{j=1}^{g} w_j x_{ij}^y}{\sum_{j=g+1}^{n} w_j x_{ij}^y}$ | Ranking by MOOSRA | $Y_i = \sum_{j=1}^{g} w_j x_{ij}^y - \sum_{j=g+1}^{n} w_j x_{ij}^y$ | Ranking by MOORA |
|---------|-------------------------------|---------------------------------|-------------------------------------------------|-----------------|---------------------------------------------|------------------|
| 1. USM  | 0.100612                      | 0.13623                         | 0.61637                                         | 6               | -0.06261                                    | 6                |
| 2. AJM  | 0.120442                      | 0.118575                        | 1.01574531                                      | 4               | 0.001867                                   | 4                |
| 3. ECM  | 0.08076                       | 0.307456                        | 0.262672                                        | 7               | -0.226696                                   | 7                |
| 4. EDM  | 0.605936                      | 0.174801                        | 3.46643                                         | 1               | 0.431135                                   | 1                |
| 5. WEDM | 0.161136                      | 0.19885                         | 0.8102                                          | 5               | -0.03775                                   | 5                |
| 6. EBM  | 0.172295                      | 0.157226                        | 1.095843                                        | 3               | 0.01507                                    | 3                |
| 7. LBM  | 0.171895                      | 0.124101                        | 1.3851218                                       | 2               | 0.04784                                   | 2                |
score by MOORA is equal to \( Y_{A3} = \sum_{j=1}^{g} w_j x_{ij}^* - \sum_{j=g+1}^{n} w_j x_{ij}^* = 0.08076 - 0.307456 = -0.226696 \).

For alternative \( A_4 \) the beneficial criterion is 0.605936 and non-beneficial criterion is 0.174801. So ranking score by MOOSRA is \( v_{A4} = \frac{0.605936}{0.174801} = 3.46643 \) and ranking score by MOORA is equal to \( Y_{A4} = \sum_{j=1}^{g} w_j x_{ij}^* - \sum_{j=g+1}^{n} w_j x_{ij}^* = 0.605936 - 0.174801 = 0.431135 \). For alternative \( A_5 \), the beneficial criterion is 0.161136 and non-beneficial criterion is 0.198885. So ranking score by MOOSRA is \( v_{A5} = \frac{0.161136}{0.198885} = 0.8102 \) and ranking score by MOORA is equal to \( Y_{A5} = \sum_{j=1}^{g} w_j x_{ij}^* - \sum_{j=g+1}^{n} w_j x_{ij}^* = 0.161136 - 0.198885 = 0.03775 \).

For alternative \( A_6 \), the beneficial criterion is 0.172295 and non-beneficial criterion is 0.157226. So ranking score by MOOSRA is \( v_{A6} = \frac{0.172295}{0.157226} = 1.095843 \) and ranking score by MOORA is equal to \( Y_{A6} = \sum_{j=1}^{g} w_j x_{ij}^* - \sum_{j=g+1}^{n} w_j x_{ij}^* = 0.172295 - 0.157226 = 0.01507 \).

For alternative \( A_7 \), the beneficial criterion is 0.171895 and non-beneficial criterion is 0.124101. So ranking score by MOOSRA is \( v_{A7} = \frac{0.171895}{0.124101} = 1.3851218 \) and ranking score by MOORA is equal to \( Y_{A7} = \sum_{j=1}^{g} w_j x_{ij}^* - \sum_{j=g+1}^{n} w_j x_{ij}^* = 0.171895 - 0.124101 = 0.04784 \). In this way all the performance scores are calculated and tabulated in Table 10.

Similarly, the non-beneficial criterion is separated from Table 7 and presented in Table 9. After that all the non-beneficial criteria are added for each alternative and are presented in the last column of Table 9.

The performance score of alternative is carried out in the following way: For performance score by MOOSRA, the following formula is applied \( v_i = \frac{\sum_{j=1}^{g} w_j x_{ij}^*}{\sum_{j=g+1}^{n} w_j x_{ij}^*} \), that is dividing the beneficial criteria by the non-beneficial criteria.

The performance score by MOORA method, is carried out by applying the following formula \( Y_i = \sum_{j=1}^{g} w_j x_{ij}^* - \sum_{j=g+1}^{n} w_j x_{ij}^* \), that is non-beneficial criteria is subtracted from beneficial criteria. The result is shown in Table 10.

Now in this particular example both the methods give the same ranking such as Alternative 4 > Alternative 7 > Alternative 6 > Alternative 2 > Alternative 5 > Alternative 1 > Alternative 3 which equals EDM > ECM > EBM > AJM > WEDM > USM > ECM. Which means that electro-discharge machining is the best non-conventional machine to procure.

Discussion

This generalized criterion is directly proportional to the relative effect of the values and weights of the considered criteria (Hajkowicz & Higgins, 2008). The COPRAS, TOPSIS, and VIKOR methods are more efficient in dealing with the tangible attributes but each one cannot deal extremely well if the criteria are expressed qualitatively, whereas AHP can also deal with tangible as well as non-tangible attributes, especially where the subjective judgments of different individuals constitute an important part of the decision-making process. As several alternatives increase, the amount of calculations
rises quite rapidly and computational procedures become quite elaborate. To use a highly complex MCDM method with lack of transparency (as of AHP), it is extremely difficult for the decision-maker to identify any mistake made during the calculation process that can often lead to an extremely high degree of risk involvement by misleading the entire selection process. Table 11 compares the performance of COPRAS, EVAMIX, TOPSIS, VIKOR, AHP, MOORA, SAW, and ELECTRE methods about computation time, simplicity, transparency, and Flexibility of the information (Torrez, 2007). If the first choice of a non-traditional manufacturing process as decided by the results of those MOORA methods that have a very significant positive rank correlation coefficient and cannot be believed due to certain constraints, then the user can opt for the second choice of the manufacturing system. A final decision may be taken keeping in view the practical considerations. All possible constraints likely to be experienced by the user have to be considered. If the most influencing attributes for this problem such as tolerance [T], surface finish (SF), power requirement (PR), material removal rate (MRR), cost (C), tooling and fixtures (TF), tool consumption (TC), safety (S), work material (M), and shape feature (F) cannot be believed because of certain constraints, then the user can opt for the third choice of the non-traditional manufacturing system.

In this paper, the decision-making problem is believed to be from a case study of the institute workshop. In solving this problem, the decision-makers had taken the well-recognized published works of the past researchers and that those have already been solved and validated using other mathematical approaches. The AHP method is used in selecting the criterion weight-age. The scale point is allotted by comparison, regardless of whether one criterion is more important than other criterion. Although developing the decision matrices, all the possible interrelations between objectives and candidate alternatives are also taken care of at the same time. The analysis of MOORA and MOOSRA method are quite stable. Again the work of the past researchers are quite recent, therefore, it can be assumed that the MOORA and MOOSRA method uses the latest available data as a base for the initial decision-making process. From the above discussion, it can be concluded that for the decision-making problem, the MOORA and MOOSRA method fulfils most all the conditions and hence the method is quite robust under diverse non-traditional manufacturing environment. If the denominator of this ratio is expressed in cost, then this ratio becomes equivalent with benefit-to-cost ratio that is a standard performance measure for an economic activity. Therefore, this MOORA and MOOSRA method conceptually conforms to other established performance measurement methods. This is understood with the help of Tables 8–10. The beneficial criteria are separated from Table 7 and are presented in Table 8. After that the entire beneficial criterion are added for each alternate and presented in the last column of Table 8. Similarly, the

| MCDM methods | Calculation time | Simplicity | Transparency | Flexibility |
|-------------|------------------|------------|--------------|-------------|
| MOORA       | Less             | Simple     | Good         | Very high   |
| EVAMIX      | Moderate         | Moderately | Critical      | Low         |
| ELECTRE     | Moderate         | Moderately | Critical      | Low         |
| TOPSIS & AHP| High             | Moderately | Good         | High        |
| VIKOR       | Less             | Simple     | Very good    | Moderate    |
| MADM        | Moderate         | Moderately | Critical      | High        |
| COPRAS      | Less             | Simple     | Very good    | High        |
| SAW         | Less             | Simple     | Good         | High        |
non-beneficial criteria are separated from Table 7 and are presented in Table 9. Then all the non-beneficial criteria are added for each alternate and presented in the last column of Table 9. The performance score of each alternate is calculated by applying appropriate formula of MOORA and MOOSRA method and presented in Table 10.

**Conclusions**

In order to see the efficacy of MOORA and MOOSRA method, a decision matrix in consultation with the experts is applied in solving the non-traditional machine selection process at the case institute workshop. By applying both the MOORA and MOOSRA method, it has been found that electro-discharge machining is the best non-conventional machine to procure for the case institute workshop. The case study is considered to demonstrate the application of this method. The decision-maker can easily apply MOORA and MOOSRA method to evaluate the alternatives and select the most suitable non-traditional manufacturing system, while being completely unaware of the physical meaning of the decision-making process. Moreover, this method allows for the formulation of a reduced performance criterion that is directly proportional to the relative effect of the compared criteria values. The application of the MOORA and MOOSRA method is suggested for decision-making in the non-traditional manufacturing environment that helps in selecting the most suitable choice between many candidate alternatives for a given problem. In this case, it is observed that the top-ranked alternatives exactly match with those derived by the past researchers. The MOORA and MOOSRA method can consider all the attributes along with their relative importance, and hence, it may provide a better accurate evaluation of the alternatives. This method is computationally and exceptionally simple and easily comprehensively robust and believed to have any number of quantitative and qualitative selection attributes but offering a more objective and logical selection approach. However, it is not efficient when the decision matrix contains many of the qualitative attributes. Application of this method in a wider range of selection problems in real-time manufacturing environment remains as a future research scope.

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