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ORIGINAL ARTICLE

Nontraditional machining processes selection using evaluation of mixed data method

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Abstract Traditional edged cutting tool-based machining processes are now being continuously replaced by nontraditional machining (NTM) processes so as to generate complex and intricate shapes on advanced and harder materials, like titanium, stainless steel, high-strength temperature-resistant alloys, fiber-reinforced composites, and engineering ceramics. These NTM processes, while using energy in its direct form for removing materials from the workpiece surfaces, have the capabilities of meeting some higher level requirements, such as low tolerance, high surface finish, higher production rate, automated data transmission, miniaturization, etc., and are also quite suitable in the areas of micro- and nano-machining. Selection of the most appropriate NTM process to generate a desired shape feature on a given work material is often a challenging task as it involves consideration of diverse machining characteristics and performance of the NTM processes. This paper explores in details the applicability, suitability, and potentiality of evaluation of mixed data method for solving the NTM process selection problems. Three illustrative examples are presented, which validate the usefulness of this method. The observed results exactly corroborate with those obtained by the past researchers.

Keywords Nontraditional machining process · Evaluation of mixed data method · Cardinal data · Ordinal data

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1 Introduction

Present-day aerospace, nuclear, missile, turbine, automobile, tool, and die-making industries often require newer and harder materials with higher strength, hardness, toughness, and other diverse mechanical properties. In those industries, titanium, stainless steel, high-strength-temperature-resistant alloys, fiber-reinforced composites, ceramics, refractories, and other difficult-to-machine alloys are being used for generating complex and accurate shapes, which cannot be machined by the conventional machining processes where the materials are removed from the workpiece surface in the form of chips. Traditional edged cutting tool-based machining processes are not suitable for those materials as the desired level of accuracy and surface finish cannot be easily achieved. For these reasons, the conventional machining processes are now being replaced by the nontraditional machining (NTM) processes, which have the capabilities to be implemented in the areas of micro- and nano-machining. Some of these NTM processes can also machine workpieces in the areas, which are inaccessible for the conventional machining processes. In these NTM processes, as the material is removed from the workpiece surface in the form of atoms or molecules individually or in groups, accurate and intricate shapes can easily be machined with high level of surface finish [1, 2].

Selecting the most appropriate NTM process for a given shape feature and work material combination is often a time-consuming and challenging task as it requires consideration of several conflicting criteria (like maximization of material removal rate and minimization of surface finish, maximization of efficiency and minimization of power requirement, etc.), and a vast array of machining capabilities and characteristics of NTM processes. For effective utilization of the capabilities of different NTM processes and also for maximized machining performance, careful selection of the most suitable process for a given machining application is often required. As the NTM process selection is quite difficult requiring human expertise and being affected by several criteria, there is always a need for a structured approach for appropriate NTM process selection for a given machining application. It has been observed that the criteria influencing the NTM process selection decision are quantitative as well as qualitative in nature, and it is also quite difficult to take into account both these types of attributes in a single decision-making framework. This paper mainly focuses on the application of an almost unexplored multicriteria decision-making (MCDM) technique, i.e., evaluation of mixed data (EVAMIX) method for soving the NTM process selection problems. It helps select the most appropriate NTM process for a given machining application based on some parametric requirements, such as material type, shape feature, process economy, and other process capabilities, like material removal rate, surface finish, surface damage depth, tolerance, machining medium contamination, efficiency, etc. This method has the advantage of treating the quantitative (cardinal) and qualitative (ordinal) criteria separately, which helps the decision makers not to lose information during the decision-making process. The derived results show promise for the adopted methodology for NTM process selection.

2 Review of past researches

Cogun [3, 4] developed computer-aided procedures to select NTM processes for the given parts, using an interactively generated 16-digit classification code to rank the acceptable processes. Yurdakul and Cogun [5] applied a multiattribute-based selection procedure to help the user to shortlist the NTM processes containing only the feasible ones. Two multiattribute decision-making (MADM) methods, e.g., analytic hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS) were employed to rank the feasible NTM processes according to their suitability for a specific machining application. Chakraborty and Dey [6] developed an AHP-based expert system to aid the NTM process selection decision based on the priority values for different criteria and subcriteria, as related to a specific NTM process selection problem. The feasible processes were observed to usually lie in the acceptability zone and the NTM process with the highest acceptability index value would be the best choice. Chakraborty and Dey [7] designed a quality function deployment-based expert system for NTM process selection where various product and process characteristics, and the corresponding weights obtained for the process characteristics were adopted to estimate the overall scores for the NTM processes to select the most appropriate one. Chakrabarti et al. [8] considered the typical problems of parameter selection and optimization in NTM processes to bring out the related design ideas that would form the foundation of an *n*-tier management information system (MIS). All the parametric data for some of the NTM processes, like abrasive water jet machining, wire electric discharge machining, and electric discharge machining, were conglomerated to facilitate extraction of the relevant information using a distinct architecture of MIS, having three scalable layers. Das Chakladar and Chakraborty [9] employed a combination of TOPSIS and AHP methods, and Das Chakladar et al. [10] applied a digraph method to select the best suited NTM processes for some given machining applications. Edison Chandrasselan et al. [11] developed a web-based, knowledge-based system for identifying the most appropriate NTM process to suit specific circumstances based on some input parameter requirements, such as material type, shape applications, process economy, and process capabilities. It was observed that the system, employing a three-tier web architecture for implementing user module to do the selection and expert module to update the knowledge base, could cut down the product cost, enhance the product quality, and decrease the product lead time. Edison Chandrasselan et al. [12] described the development of a knowledge-based system which could identify the most suitable NTM process from 20 alternatives of industrial importance. Only material type and some of the process capabilities, like surface finish, tolerance, surface damage, corner radii, taper, hole diameter, width of cut, depth/diameter ratio (for cylindrical holes), and depth/width ratio (for blind cavities), were used to obtain the best choice to suit a specific machining application. Sadhu and Chakraborty [13] applied a two-phase decision model for NTM process selection. In the first phase, the most efficient NTM processes were chosen for a given shape feature and work material combination using Charnes, Cooper, and Rhodes model of data envelopment analysis. In the second phase, the efficient NTM processes were ranked in descending order of priority using the weighted-overall efficiency ranking method of MADM theory. Das and Chakraborty [14] proposed an analytic network process (ANP)-based approach to select the most appropriate NTM process taking into account the interdependency and feedback relationships among various criteria affecting the NTM process selection decision. An ANP solver with graphical user interface was also developed to automate the entire NTM process selection decision procedure. Chakraborty [15] applied multiobjective optimization on the basis of ratio analysis (MOORA) method to choose NTM processes for various machining applications. Temuçin et al. [16] provided distinct systematic approaches both in fuzzy and crisp environments to deal with the NTM process selection problem and proposed a decision support model helping the decision makers to assess potentials of distinct NTM processes.

Karande and Chakraborty [17] solved four NTM process selection problems using an integrated preference ranking organization method for enrichment evaluation (PROMETHEE) and geometrical analysis for interactive aid (GAIA) method, which would act as a visual decision aid to the process engineers.

To select an appropriate MCDM method for any process selection decision, it is necessary to search out the important characteristics of the available methods. Then, it becomes easier to design or choose a method with respect to the problem's conditions. In MCDM problems, input parameters (criteria) often include both the quantitative and qualitative information, which compel the adoption of a suitable method that can tackle both these types of data.

Most of the qualitative methods use ordinal scales and are best suited when all the criteria values are expressed qualitatively. In quantitative methods, there is a possibility of losing information due to different normalization procedures adopted. Moreover, some methods are not flexible enough to model the decision makers' preferences. Some MCDM methods are based on the concept that the best alternative should have the shortest distance from the "ideal solution" and the farthest distance from the "negative ideal" solution. Such methods do not consider the relative importance of the distances from these points. It means that the best alternative in these methods may not always mean that it is the closest to the ideal solution. On the other hand, some methods have complex mathematical computations and require extensive knowledge on graph theory, linear programming, etc. Hence, after careful and in-depth studies about different characteristics of the available methods, EVAMIX appears to be the most suited one for solving the NTM process selection problems. The main motivation behind adoption of EVAMIX method is that while studying different methods for dealing with NTM process selection problems, it has been found that, in most of the qualitative methods, the available quantitative information is used partially (i.e., only ordinal rank characteristics). In EVAMIX method, the set of criteria in the decision matrix is divided into ordinal and cardinal criteria values. The ordinal variant of EVAMIX constructs an outranking flow, based on the quantitative weights assigned to the criteria and the information generated by the purely ordinal comparison of levels of alternative pairs. This method treats ordinal evaluations in a more consistent way, and it is also capable of dealing with ordinal values without converting them into cardinal values. It requires quantitative weights but can be used in combination with any of the methods dealing with ordinal priority information. Thus, EVAMIX can be treated as an efficient MCDM approach, as there is no ideal value and the final appraisal scores of the alternatives do not provide the absolute choice possibility of any alternative. It only shows how different a certain alternative is with respect to the others.

3 Evaluation of mixed data method

The EVAMIX method was mainly established by Voogd in 1983, and later advocated by Martel and Matarazzo [18]. It is based on the determination of the dominance score of an alternative on criterion-by-criterion basis. This method is especially designed to deal with the mixed (quantitative and qualitative) data. The main difference between EVAMIX and other MCDM methods is that it can treat the qualitative (ordinal) criteria and quantitative (cardinal) criteria separately. Both the ordinal and cardinal data are separately normalized in the range of 0–1 using linear normalization procedure [19]. In this method, the degree of pairwise dominance for each pair of alternatives is calculated, as the difference in score received by the higher performing alternative compared to the poorer performing alternative. The weighted sum of the dominance scores is then assigned to each alternative. These criteria weights can be obtained applying any of the weighting techniques, e.g., AHP and entropy method. The outcome of this aggregation procedure is similar to the outcome of the weighted sum method; the relative performance of the alternatives is the same, but there is difference in the scale of the measure of performance [20]. In this method, for both the cardinal and ordinal criteria, dominance scores are calculated. By applying separate standardization and aggregation techniques for ordinal and cardinal sets of data, they are finally combined to determine an overall weighted appraisal score, which determines the position of an alternative in the ranking preorder. It offers the advantage that quantitative scores are being processed in a quantitative way and also qualitative scores in a qualitative way before being combined to determine the overall dominance scores. In addition, it offers the possibility to assign weights to the criteria, standardize the criteria, and carry out sensitivity and uncertainty analyses on the results achieved. It is a generalized form of concordance analysis technique, except that separate indices are computed for ordinal and cardinal criteria.

The EVAMIX method consists of the following seven procedural steps presented as below [18, 20]:

Step 1: In the decision matrix, at first, differentiate between the ordinal and cardinal criteria.

Step 2: For beneficial attributes (where higher values are desired), normalize the decision matrix using the following equation:

$$r_{ij} = \left[x_{ij} - min(x_{ij})\right] / \left[max(x_{ij}) - min(x_{ij})\right] \quad (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n) \tag{1}$$

where x_{ij} is the performance of ith alternative on jth criterion, r_{ij} is the normalized value of x_{ij}, m is the number of alternatives, and n is the number of criteria.

For nonbeneficial attributes (where lower values are preferred), Eq. (1) can be rewritten as follows:

$$r_{ij} = \left[max\left(x_{ij}\right) - x_{ij}\right] / \left[max\left(x_{ij}\right) - min\left(x_{ij}\right)\right] \quad (2)$$

Step 3: Calculate the evaluative differences of ith alternative on each ordinal and cardinal criteria with respect to other alternatives. This step involves the calculation of differences in criteria values between different alternatives pairwise.

Step 4: Compute the dominance scores of each alternative pair, $(i, i')$for all the ordinal and cardinal criteria using the following equations:

$$\alpha_{ii'} = \left[\sum_{j \in O} \left\{w_j sgn\left(r_{ij} - r_{i'j}\right)\right\}^c\right]^{1/c} \quad (3)$$

where $sgn\left(r_{ij} - r_{i'j}\right) = \begin{cases} +1 \; if \; r_{ij} > r_{i'j} \\ 0 \; if \; r_{ij} = r_{i'j} \\ -1 \; if \; r_{ij} < r_{i'j} \end{cases}$

$$\gamma_{ii'} = \left[\sum_{j \in C} \left\{w_j sgn\left(r_{ij} - r_{i'j}\right)\right\}^c\right]^{1/c} \quad (4)$$

where the symbol c is a scaling parameter, for which any arbitrary positive odd number, like 1, 3, 5, … may be chosen, O and C are the sets of ordinal and cardinal criteria respectively, and $\alpha_{ii'}$ and $\gamma_{ii'}$ are the dominance scores for alternative pair, (i,i') with respect to ordinal and cardinal criteria, respectively, and w_j is the importance (weight) of jth criterion.

Step 5: Calculate the standardized dominance scores, which can be obtained using three different approaches, i.e., (a) subtractive summation technique, (b) subtracted shifted interval technique, and (c) additive interval technique. Martel and Matarazzo [18] proposed a systematic additive interval approach to derive the standardized ordinal dominance score $(\delta_{ii'})$ and cardinal dominance score $(d_{ii'})$ for the alternative pair, (i,i')as follows:

Standardized ordinal dominance score

$$(\delta_{ii'}) = \frac{(\alpha_{ii'} - \alpha^-)}{(\alpha^+ - \alpha^-)} \quad (5)$$

where α^+ (α^-) is the highest (lowest) ordinal dominance score for the alternative pair, (i,i').

Standardized cardinal dominance score

$$(d_{ii'}) = \frac{(\gamma_{ii'} - \gamma^-)}{(\gamma^+ - \gamma^-)} \quad (6)$$

where γ^+ (γ^-) is the highest (lowest) cardinal dominance score for the alternative pair, (i,i').

If the subtractive summation technique is used for calculating the standardized dominance scores, then Eqs. (5) and (6) become as follows [20]:

$$\delta_{ii'} = \alpha_{ii'} \left(\sum_{i=1}^{m} \sum_{i'=1}^{m} |\alpha_{ii'}|\right)^{-1} \quad (7)$$

$$d_{ii'} = \gamma_{ii'} \left(\sum_{i=1}^{m} \sum_{i'=1}^{m} |\gamma_{ii'}|\right)^{-1} \quad (8)$$

Step 6: Determine the overall dominance score.

The overall dominance score, $(D_{ii'})$ for each pair of alternatives, $(i,i')$is calculated, which gives the degree by which alternative i dominates alternative i'.

$$D_{ii'} = w_O \delta_{ii'} + w_C d_{ii'} \quad (9)$$

where w_O is the sum of the weights for the ordinal criteria $\left(w_o = \sum_{j \in O} w_j\right)$, and w_C is the sum of the weights for the cardinal criteria $\left(w_C = \sum_{j \in C} w_j\right)$.

Step 7: Calculate the appraisal score.

The appraisal score for ith alternative (S_i) is computed which gives the final preference of the candidate alternatives. The higher the appraisal score, the better is the performance of the alternative. The best alternative is the one that has the highest value of the appraisal score. It can be calculated using the following equation:

$$\text{Appraisal score } (S_i) = \sum_{i'} \left(\frac{D_{i'i}}{D_{ii'}}\right)^{-1} \quad (10)$$

If the above-mentioned three different approaches, i.e., subtractive summation technique, subtracted shifted interval technique, and additive interval technique, are simultaneously used or if more than one technique are used for calculating the standardized dominance score for ith alternative with respect to other alternatives, then a standardized "average appraisal score" (S_{ai}) for ith alternative can be obtained as follows [18]:

$$S_{ai} = \sum_{t=1}^{p} \left(\frac{S_{ti} - S_{ti\ min}}{S_{ti\ max} - S_{ti\ min}}\right) \; (\text{for } p = 1, 2, 3) \quad (11)$$

where S_{ti} is the appraisal score of ith alternative for tth adopted technique, and $S_{ti\ \min}$ and $S_{ti\ \max}$ are the lowest and the highest appraisal scores for tth technique respectively. In Eq. (11), p can take any value

Table 1 Data for example 1 [9]

NTM	TSF	PR	MRR	C	E	TF	TC	S	M	F
USM	1	10	500	2	4	2	3	1	4	1
WJM	2.5	0.22	0.8	1	4	2	2	3	4	1
AJM	2.5	0.24	0.5	1	4	2	2	3	4	1
ECM	3	100	400	5	2	3	1	3	5	4
CHM	3	0.4	15	3	3	2	1	3	5	1
EDM	3.5	2.7	800	3	4	4	4	3	5	1
WEDM	3.5	2.5	600	3	4	4	4	3	5	1
EBM	2.5	0.2	1.6	4	5	2	1	3	4	1
LBM	2	1.4	0.1	3	5	2	1	1	4	1

between 1 and 3 depending upon the number of methods adopted from subtractive summation technique, subtracted shifted interval technique, and additive interval technique for a given MCDM problem to evaluate the "average appraisal score" for a particular alternative. Based on the standardized "average appraisal scores," a complete ranking of the candidate alternatives can be derived and the best alternative is the one having the highest "average appraisal score."

In EVAMIX method, the difference between two alternatives is expressed in a condensed way by means of two dominance scores, i.e., ordinal dominance score and cardinal dominance score. While computing these dominance scores, the ordinal and metric characteristics of the variables are separately taken into consideration. After computing these dominance scores, the highest and lowest ordinal dominance scores, α^+ and α^- among all the alternative pairs are determined to standardize the dominance scores into the same measurement unit in order to make them comparable. α^+ and α^- indicate the maximum and minimum level by which one alternative dominates other alternatives among all the alternative pairs. Similarly, γ^+ and γ^- are respectively the highest and lowest cardinal dominance scores among the alternative pairs, which indicate the maximum and minimum level by which one alternative dominates the others with respect to all alternative pairs. The overall dominance scores are calculated as the weighted sum of the ordinal and cardinal dominance scores, indicating the degree by which one alternative dominates another alternative by taking into account all the attributes and their relative importance.

4 Selection of the NTM processes

In order to select the most appropriate NTM process for generating a desired shape feature on a given work material using EVAMIX method, the following NTM processes of industrial importance are considered:

(a) Ultrasonic machining (USM)
(b) Water jet machining (WJM)
(c) Abrasive jet machining (AJM)
(d) Electrochemical machining (ECM)
(e) Chemical machining (CHM)
(f) Electrical discharge machining (EDM)
(g) Wire electrical discharge machining (WEDM)
(h) Electron beam machining (EBM)
(i) Laser beam machining (LBM).

Table 2 Normalized decision matrix for example 1

NTM	TSF	PR	MRR	C	E	TF	TC	S	M	F
USM	1.0000	0.9018	0.6250	0.7500	0.6667	1.0000	0.3333	0	0	0
WJM	0.4000	0.9998	0.0009	1.0000	0.6667	1.0000	0.6667	1.0000	0	0
AJM	0.4000	0.9996	0.0005	1.0000	0.6667	1.0000	0.6667	1.0000	0	0
ECM	0.2000	0	0.4999	0	0	0.5000	1.0000	1.0000	1.0000	1.0000
CHM	0.2000	0.9980	0.0186	0.5000	0.3333	1.0000	1.0000	1.0000	1.0000	0
EDM	0	0.9749	1.0000	0.5000	0.6667	0	0	1.0000	1.0000	0
WEDM	0	0.9770	0.7500	0.5000	0.6667	0	0	1.0000	1.0000	0
EBM	0.4000	1.0000	0.0019	0.2500	1.0000	1.0000	1.0000	1.0000	0	0
LBM	0.6000	0.9880	0	0.5000	1.0000	1.0000	1.0000	0	0	0

Table 3 Dominance scores for NTM process pairs for example 1

NTM process	$a_{ii'}$	$\gamma_{ii'}$	NTM process	$a_{ii'}$	$\gamma_{ii'}$	NTM process	$a_{ii'}$	$\gamma_{ii'}$
(1,2)	−0.1414	0.1707	(4,1)	0.1380	−0.0692	(7,1)	0.1373	0.1363
(1,3)	−0.1414	0.1707	(4,2)	0.1234	0.2378	(7,2)	0.1227	0.0141
(1,4)	−0.1380	0.0692	(4,3)	0.1234	0.2378	(7,3)	0.1227	0.0141
(1,5)	−0.1651	0.1707	(4,5)	−0.1727	0.3161	(7,4)	0.0990	−0.0874
(1,6)	−0.1373	−0.1363	(4,6)	−0.0990	0.0874	(7,5)	−0.0083	0.0141
(1,7)	−0.1373	−0.1363	(4,7)	−0.0990	0.0874	(7,6)	0	−0.0924
(1,8)	0.1024	−0.0141	(4,8)	−0.4110	−0.1707	(7,8)	−0.2159	−0.1707
(1,9)	0.0878	−0.0141	(4,9)	−0.4256	−0.1707	(7,9)	−0.3378	−0.1707
(2,1)	0.1414	−0.1707	(5,1)	−0.1707	0.0530	(8,1)	−0.0349	−0.1707
(2,3)	0	0.2146	(5,2)	0.0141	0.2989	(8,2)	−0.0885	0.2146
(2,4)	−0.1234	−0.2378	(5,3)	0.0141	0.2989	(8,3)	−0.0495	0.2146
(2,5)	−0.1505	−0.0141	(5,4)	−0.3161	−0.0924	(8,4)	−0.1039	−0.2378
(2,6)	−0.1227	−0.0141	(5,6)	−0.0141	−0.2378	(8,5)	−0.3456	−0.0141
(2,7)	−0.1227	−0.0141	(5,7)	−0.0141	−0.2378	(8,6)	−0.2990	−0.0141
(2,8)	0.0878	0.2146	(5,8)	−0.1707	−0.4555	(8,7)	−0.2990	−0.0141
(2,9)	0.0732	−0.2929	(5,9)	−0.2929	−0.5166	(8,9)	−0.0927	0.1363
(3,1)	0.1414	−0.1707	(6,1)	0.1373	0.1363	(9,1)	−0.0495	−0.1707
(3,2)	0	−0.2146	(6,2)	0.1227	0.0141	(9,2)	−0.0641	−0.1363
(3,4)	−0.1234	−0.2378	(6,3)	0.1227	0.0141	(9,3)	−0.0641	−0.1363
(3,5)	−0.1505	−0.0141	(6,4)	0.0990	−0.0874	(9,4)	−0.1185	−0.2378
(3,6)	−0.1227	−0.0141	(6,5)	−0.0083	0.0141	(9,5)	−0.2529	−0.1363
(3,7)	−0.1227	−0.0141	(6,7)	0	0.0924	(9,6)	−0.2063	−0.0141
(3,8)	0.0878	0.2146	(6,8)	−0.2159	−0.1707	(9,7)	−0.2063	−0.0141
(3,9)	0.0732	−0.2929	(6,9)	−0.3378	−0.1707	(9,8)	0.0927	−0.1363

In this paper, the following work materials, which are now being widely used in the manufacturing industries and can be machined using the considered NTM processes, are taken into account:

(a) Aluminium
(b) Stainless steel
(c) Super alloys
(d) Titanium
(e) Refractories
(f) Plastics
(g) Ceramics
(h) Glass
(i) Duralumin (aluminium alloy).

It is also considered that the following shape features can be machined by the available NTM processes on the above-cited work materials:

(a) Holes:

1. Precision
2. Standard with slenderness ratio $(L/D) \leq 20$
3. Standard with slenderness ratio $(L/D) > 20$

(b) Through cavities:

1. Precision
2. Standard

(c) Surfacing:

1. Double contouring
2. Surface of revolution

(d) Through cutting:

1. Shallow
2. Deep.

4.1 Example 1

In this example, surface of revolution feature is to be generated on stainless steel work material. To select the most appropriate NTM process for generating surface of revolution feature on stainless steel, at first, various important criteria affecting the NTM process selection decision are identified. These criteria are tolerance and surface finish (TSF), power requirement (PR), material removal rate (MRR), cost (C), efficiency (E), tooling and fixtures (TF), tool consumption (TC), safety (S), work material (M), and

Table 4 Standardized dominance scores for NTM process pairs for example 1

NTM process	$\delta_{ii'}$	$d_{ii'}$	NTM process	$\delta_{ii'}$	$d_{ii'}$	NTM process	$\delta_{ii'}$	$d_{ii'}$
(1,2)	0.4750	0.7700	(4,1)	0.9420	0.3905	(7,1)	0.9408	0.7156
(1,3)	0.4750	0.7700	(4,2)	0.9176	0.8761	(7,2)	0.9164	0.5223
(1,4)	0.4807	0.6095	(4,3)	0.9176	0.8761	(7,3)	0.9164	0.5223
(1,5)	0.4354	0.7700	(4,5)	0.4227	1.0000	(7,4)	0.8768	0.3618
(1,6)	0.4819	0.2844	(4,6)	0.5459	0.6382	(7,5)	0.6975	0.5223
(1,7)	0.4819	0.2844	(4,7)	0.5459	0.6382	(7,6)	0.7113	0.3538
(1,8)	0.8825	0.4777	(4,8)	0.0244	0.2300	(7,8)	0.3505	0.2300
(1,9)	0.8581	0.4777	(4,9)	0	0.2300	(7,9)	0.1467	0.2300
(2,1)	0.9477	0.2300	(5,1)	0.9221	0.2300	(8,1)	0.6530	0.2300
(2,3)	0.7113	0.8394	(5,2)	0.9629	0.5223	(8,2)	0.5634	0.8394
(2,4)	0.5051	0.1239	(5,3)	0.9629	0.5223	(8,3)	0.6286	0.8394
(2,5)	0.4598	0.4777	(5,4)	1.0000	0	(8,4)	0.5377	0.1239
(2,6)	0.5063	0.4777	(5,6)	0.7252	0.4777	(8,5)	0.1337	0.4777
(2,7)	0.5063	0.4777	(5,7)	0.7252	0.4777	(8,6)	0.2116	0.4777
(2,8)	0.8581	0.8394	(5,8)	0.4284	0.2300	(8,7)	0.2116	0.4777
(2,9)	0.8337	0.0367	(5,9)	0.2246	0.0367	(8,9)	0.5564	0.7156
(3,1)	0.9477	0.2300	(6,1)	0.9408	0.7156	(9,1)	0.6286	0.2300
(3,2)	0.7113	0.1606	(6,2)	0.9164	0.5223	(9,2)	0.6042	0.2844
(3,4)	0.5051	0.1239	(6,3)	0.9164	0.5223	(9,3)	0.6042	0.2844
(3,5)	0.4598	0.4777	(6,4)	0.8768	0.3618	(9,4)	0.5133	0.1239
(3,6)	0.5063	0.4777	(6,5)	0.6975	0.5223	(9,5)	0.2887	0.2844
(3,7)	0.5063	0.4777	(6,7)	0.7113	0.6462	(9,6)	0.3665	0.4777
(3,8)	0.8581	0.8394	(6,8)	0.3505	0.2300	(9,7)	0.3665	0.4777
(3,9)	0.8337	0.0367	(6,9)	0.1467	0.2300	(9,8)	0.8663	0.2844

Table 5 Overall dominance scores for example 1

NTM process	$D_{ii'}$	NTM process	$D_{ii'}$	NTM process	$D_{ii'}$	NTM process	$D_{ii'}$
(1,2)	0.7090	(3,4)	0.2027	(5,6)	0.5289	(7,8)	0.2549
(1,3)	0.7090	(3,5)	0.4740	(5,7)	0.5289	(7,9)	0.2128
(1,4)	0.5828	(3,6)	0.4836	(5,8)	0.2710	(8,1)	0.3175
(1,5)	0.7008	(3,7)	0.4836	(5,9)	0.0756	(8,2)	0.7824
(1,6)	0.3252	(3,8)	0.8433	(6,1)	0.7622	(8,3)	0.7958
(1,7)	0.3252	(3,9)	0.2015	(6,2)	0.6038	(8,4)	0.2094
(1,8)	0.5614	(4,1)	0.5046	(6,3)	0.6038	(8,5)	0.4066
(1,9)	0.5564	(4,2)	0.8847	(6,4)	0.4683	(8,6)	0.4227
(2,1)	0.3784	(4,3)	0.8847	(6,5)	0.5585	(8,7)	0.4227
(2,3)	0.8130	(4,5)	0.8806	(6,7)	0.6596	(8,9)	0.6827
(2,4)	0.2027	(4,6)	0.6191	(6,8)	0.2549	(9,1)	0.3124
(2,5)	0.4740	(4,7)	0.6191	(6,9)	0.2128	(9,2)	0.3505
(2,6)	0.4836	(4,8)	0.1875	(7,1)	0.7622	(9,3)	0.3505
(2,7)	0.4836	(4,9)	0.1824	(7,2)	0.6038	(9,4)	0.2044
(2,8)	0.8433	(5,1)	0.3731	(7,3)	0.6038	(9,5)	0.2853
(2,9)	0.2015	(5,2)	0.6134	(7,4)	0.4683	(9,6)	0.4547
(3,1)	0.3784	(5,3)	0.6134	(7,5)	0.5585	(9,7)	0.4547
(3,2)	0.2745	(5,4)	0.2068	(7,6)	0.4278	(9,8)	0.4047

Table 6 Appraisal scores for NTM processes for example 1

NTM process	Appraisal score	Rank
USM	6.97	3
WJM	7.17	7
AJM	6.25	9
ECM	14.49	1
CHM	8.75	8
EDM	9.71	5
WEDM	9.36	6
EBM	9.04	4
LBM	12.82	2

shape feature (F). Tolerance and surface finish are the two important product quality attributes used to measure the performance of a NTM process for a particular application. Tolerance is the difference between maximum and minimum dimensions of a component. Depending on the type of application, the permissible variation of dimension is set according to the available standard grades. It also relates to the capability of a NTM process stating how closely the process can achieve the required surface finish on the work material. Power requirement deals with the power rating of the machine/equipment for a particular NTM process. Material removal rate is the most important criterion, leading to the fact that higher MRR leads to lower machining time, and the effectiveness of a NTM process is usually measured in terms of MRR. Cost is concerned with the initial investment and acquisition cost required to install a NTM process-based machining system for a given application. Sometimes, it may also indicate the cost of machining. Efficiency of a NTM process can be defined as the ratio of the quantity of output energy available for material removal to the input energy. Tooling and fixtures are associated with the cost of tooling and work fixtures that need to be replaced from time to time during the NTM operation. Some of the NTM processes require frequent changing of tools and for this reason, tool consumption criterion is taken into consideration to account for the cost related to tool changes. Safety is an important characteristic of a NTM process with respect to emission of toxic gases/fumes, contamination effects, secured environment, and less hazardous effects on the operators. Work material mainly relates to the fact that how often a particular NTM process can be used on a given material for machining operation. It basically shows the easiness of a NTM process to machine a given material. Shape feature corresponds to the capability of a NTM process to generate a specific shape feature on a given material to be machined. Among all these criteria, TSF (micrometers), PR (kilowatts), and MRR (cubic millimeters per minute) are quantitative in nature, having absolute numerical values [2], whereas, C, E, 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 [2]. MRR, E, S, M, and F are beneficial attributes where higher values are desired; on the other hand, TSF, PR, C, TF, and TC are nonbeneficial attributes for which lower values are always preferred. The data for TSF, PR, and MRR are cardinal in nature, whereas the data for other criteria, such as C, E, etc., are ordinal, so the relatedness is ensured using a five-point scale. Das Chakladar and Chakraborty [9] determined the criteria weights as $w_{TSF}=0.0783$, $w_{PR}=0.0611$, $w_{MRR}=0.1535$, $w_C=0.1073$, $w_E=0.0383$, $w_{TF}=0.0271$, $w_{TC}=0.0195$, $w_S=0.0146$, $w_M=0.2766$, and $w_F=0.2237$ using AHP method. These same criteria weights are used here for further analyses. As the NTM process selection problems contain a mixture of both ordinal and cardinal data, EVAMIX is the most suitable MCDM approach to tackle such types of problems.

While solving this NTM process selection problem, the original decision matrix, as shown in Table 1, is developed, and the corresponding ordinal and cardinal data are then separated. Applying Eq. (1) or (2), the decision matrix is normalized, as given in Table 2.

From the normalized decision matrix, the evaluative differences of an NTM alternative for each ordinal and cardinal criteria with respect to all other alternatives are calculated. Now, the dominance scores of each pair of NTM alternatives for all the ordinal and cardinal criteria are computed using

Table 7 Data for example 2

NTM	TSF	PR	MRR	C	E	TF	TC	S	M	F
USM	1	10	500	2	4	2	3	1	4	1
WJM	2.5	0.22	0.8	1	4	2	2	3	3	1
AJM	2.5	0.24	0.5	1	4	2	2	3	3	1
ECM	3	100	400	5	2	3	1	3	5	4
CHM	3	0.4	15	3	3	2	1	3	5	4
EDM	3.5	2.7	800	3	4	4	4	3	4	5
WEDM	3.5	2.5	600	3	4	4	4	3	4	5
EBM	2.5	0.2	1.6	4	5	2	1	3	4	1
LBM	2	1.4	0.1	3	5	2	1	1	4	1

Table 8 Normalized decision matrix for example 2

NTM	TSF	PR	MRR	C	E	TF	TC	S	M	F
USM	1.0000	0.9018	0.6250	0.7500	0.6667	1.0000	0.3333	0	0.5000	0
WJM	0.4000	0.9998	0.0009	1.0000	0.6667	1.0000	0.6667	1.0000	0	0
AJM	0.4000	0.9996	0.0005	1.0000	0.6667	1.0000	0.6667	1.0000	0	0
ECM	0.2000	0	0.4999	0	0	0.5000	1.0000	1.0000	1.0000	0.7500
CHM	0.2000	0.9980	0.0186	0.5000	0.3333	1.0000	1.0000	1.0000	1.0000	0.7500
EDM	0	0.9749	1.0000	0.5000	0.6667	0	0	1.0000	0.5000	1.0000
WEDM	0	0.9770	0.7500	0.5000	0.6667	0	0	1.0000	0.5000	1.0000
EBM	0.4000	1.0000	0.0019	0.2500	1.0000	1.0000	1.0000	1.0000	0.5000	0
LBM	0.6000	0.9880	0	0.5000	1.0000	1.0000	1.0000	0	0.5000	0

Eqs. (3) and (4), respectively, and are given in Table 3. While calculating the dominance scores, the value of c is taken as 1.

Now, based on the additive interval technique, the standardized dominance scores for all the pairs of NTM alternatives are determined using Eqs. (5) and (6), respectively, for both the ordinal and cardinal criteria, as given in Table 4.

The overall dominance score for each pair of NTM alternatives is calculated using Eq. (9), which shows the degree by which a NTM alternative dominates the other. These overall dominance scores for all the pairs of NTM processes are shown in Table 5.

The appraisal score for each NTM process is then calculated using Eq. (10) and based on the descending values of this appraisal score, the final ranking of NTM alternatives is obtained, as shown in Table 6. The best choice for generating surface of revolution feature on stainless steel material is observed to be the electrochemical machining process. Laser beam machining is the second best process, and abrasive

Table 9 Dominance scores for NTM process pairs for example 2

NTM process	$\alpha_{ii'}$	$\gamma_{ii'}$	NTM process	$\alpha_{ii'}$	$\gamma_{ii'}$	NTM process	$\alpha_{ii'}$	$\gamma_{ii'}$
(1,2)	0.1352	0.1707	(4,1)	0.3617	−0.2929	(7,1)	0.0844	0.1363
(1,3)	0.1352	0.1707	(4,2)	0.3471	0.0141	(7,2)	0.3464	0.0141
(1,4)	−0.3617	0.2929	(4,3)	0.3471	0.0141	(7,3)	0.3464	0.0141
(1,5)	−0.3888	0.1707	(4,5)	−0.1727	0.0924	(7,4)	0.0461	0.1363
(1,6)	−0.0844	−0.1363	(4,6)	−0.0461	−0.1363	(7,5)	−0.0612	0.0141
(1,7)	−0.0844	−0.1363	(4,7)	−0.0461	−0.1363	(7,6)	0	−0.0924
(1,8)	0.1024	−0.0141	(4,8)	−0.3581	−0.1707	(7,8)	−0.1630	−0.1707
(1,9)	0.0878	−0.0141	(4,9)	−0.3727	−0.1707	(7,9)	−0.2849	−0.1394
(2,1)	−0.1352	−0.1707	(5,1)	0.3888	−0.1707	(8,1)	−0.0349	−0.1707
(2,3)	0	0.2146	(5,2)	0.3742	0.0141	(8,2)	0.2271	0.2146
(2,4)	−0.3471	−0.0141	(5,3)	0.3742	0.0141	(8,3)	0.2271	0.2146
(2,5)	−0.3742	−0.0141	(5,4)	0.1727	−0.0924	(8,4)	−0.3276	−0.0141
(2,6)	−0.3464	−0.0141	(5,6)	0.0612	−0.0141	(8,5)	−0.5693	−0.0141
(2,7)	−0.3464	−0.0141	(5,7)	0.0612	−0.0141	(8,6)	−0.2461	−0.0141
(2,8)	0.0878	0.2146	(5,8)	−0.1164	−0.1707	(8,7)	−0.2461	−0.0141
(2,9)	0.0732	−0.2929	(5,9)	−0.2383	−0.2929	(8,9)	−0.0927	0.1363
(3,1)	−0.1352	−0.1707	(6,1)	0.0844	0.1363	(9,1)	−0.0495	−0.1707
(3,2)	0	−0.2146	(6,2)	0.3464	0.0141	(9,2)	0.2125	−0.1363
(3,4)	−0.3471	−0.0141	(6,3)	0.3464	0.0141	(9,3)	0.2125	−0.1363
(3,5)	−0.3742	−0.0141	(6,4)	0.0461	0.1363	(9,4)	−0.3422	−0.0141
(3,6)	−0.3464	−0.0141	(6,5)	−0.1378	0.0141	(9,5)	−0.4766	−0.1363
(3,7)	−0.3464	−0.0141	(6,7)	0	0.1707	(9,6)	−0.1534	−0.0141
(3,8)	0.0878	0.2146	(6,8)	−0.1630	−0.1707	(9,7)	−0.1534	−0.0141
(3,9)	0.0732	−0.2929	(6,9)	−0.2849	−0.1707	(9,8)	0.0927	−0.1363

Table 10 Standardized dominance scores for NTM process pairs for example 2

NTM process	$\delta_{ii'}$	$d_{ii'}$	NTM process	$\delta_{ii'}$	$d_{ii'}$	NTM process	$\delta_{ii'}$	$d_{ii'}$
(1,2)	0.7353	0.7914	(4,1)	0.9717	0	(7,1)	0.6823	0.7327
(1,3)	0.7353	0.7914	(4,2)	0.9565	0.5241	(7,2)	0.9557	0.5241
(1,4)	0.2167	1.0000	(4,3)	0.9565	0.5241	(7,3)	0.9557	0.5241
(1,5)	0.1884	0.7914	(4,5)	0.4139	0.6577	(7,4)	0.6423	0.7327
(1,6)	0.5061	0.2673	(4,6)	0.5461	0.2673	(7,5)	0.5303	0.5241
(1,7)	0.5061	0.2673	(4,7)	0.5461	0.2673	(7,6)	0.5942	0.3423
(1,8)	0.7011	0.4759	(4,8)	0.2204	0.2086	(7,8)	0.4241	0.2086
(1,9)	0.6858	0.4759	(4,9)	0.2052	0.2086	(7,9)	0.2968	0.2621
(2,1)	0.4531	0.2086	(5,1)	1.0000	0.2086	(8,1)	0.5578	0.2086
(2,3)	0.5942	0.8663	(5,2)	0.9848	0.5241	(8,2)	0.8312	0.8663
(2,4)	0.2319	0.4759	(5,3)	0.9848	0.5241	(8,3)	0.8312	0.8663
(2,5)	0.2036	0.4759	(5,4)	0.7744	0.3423	(8,4)	0.2523	0.4759
(2,6)	0.2326	0.4759	(5,6)	0.6581	0.4759	(8,5)	0	0.4759
(2,7)	0.2326	0.4759	(5,7)	0.6581	0.4759	(8,6)	0.3373	0.4759
(2,8)	0.6858	0.8663	(5,8)	0.4727	0.2086	(8,7)	0.3373	0.4759
(2,9)	0.6706	0	(5,9)	0.3455	0	(8,9)	0.4974	0.7327
(3,1)	0.4531	0.2086	(6,1)	0.6823	0.7327	(9,1)	0.5425	0.2086
(3,2)	0.5942	0.1337	(6,2)	0.9557	0.5241	(9,2)	0.8160	0.2673
(3,4)	0.2319	0.4759	(6,3)	0.9557	0.5241	(9,3)	0.8160	0.2673
(3,5)	0.2036	0.4759	(6,4)	0.6423	0.7327	(9,4)	0.2370	0.4759
(3,6)	0.2326	0.4759	(6,5)	0.4504	0.5241	(9,5)	0.0968	0.2673
(3,7)	0.2326	0.4759	(6,7)	0.5942	0.7914	(9,6)	0.4341	0.4759
(3,8)	0.6858	0.8663	(6,8)	0.4241	0.2086	(9,7)	0.4341	0.4759
(3,9)	0.6706	0	(6,9)	0.2968	0.2086	(9,8)	0.6910	0.2673

Table 11 Overall dominance scores for example 2

NTM process	$D_{ii'}$	NTM process	$D_{ii'}$	NTM process	$D_{ii'}$	NTM process	$D_{ii'}$
(1,2)	0.7517	(3,4)	0.3034	(5,6)	0.6047	(7,8)	0.3610
(1,3)	0.7517	(3,5)	0.2834	(5,7)	0.6047	(7,9)	0.2867
(1,4)	0.4461	(3,6)	0.3039	(5,8)	0.3954	(8,1)	0.4555
(1,5)	0.3650	(3,7)	0.3039	(5,9)	0.2443	(8,2)	0.8415
(1,6)	0.4362	(3,8)	0.7387	(6,1)	0.6970	(8,3)	0.8415
(1,7)	0.4362	(3,9)	0.4742	(6,2)	0.8293	(8,4)	0.3178
(1,8)	0.6351	(4,1)	0.6871	(6,3)	0.8293	(8,5)	0.1394
(1,9)	0.6244	(4,2)	0.8298	(6,4)	0.6688	(8,6)	0.3779
(2,1)	0.3815	(4,3)	0.8298	(6,5)	0.4720	(8,7)	0.3779
(2,3)	0.6739	(4,5)	0.4853	(6,7)	0.6520	(8,9)	0.5663
(2,4)	0.3034	(4,6)	0.4644	(6,8)	0.3610	(9,1)	0.4447
(2,5)	0.2834	(4,7)	0.4644	(6,9)	0.2710	(9,2)	0.6553
(2,6)	0.3039	(4,8)	0.2170	(7,1)	0.6970	(9,3)	0.6553
(2,7)	0.3039	(4,9)	0.2062	(7,2)	0.8293	(9,4)	0.3070
(2,8)	0.7387	(5,1)	0.7682	(7,3)	0.8293	(9,5)	0.1467
(2,9)	0.4742	(5,2)	0.8498	(7,4)	0.6688	(9,6)	0.4463
(3,1)	0.3815	(5,3)	0.8498	(7,5)	0.5285	(9,7)	0.4463
(3,2)	0.4593	(5,4)	0.6479	(7,6)	0.5204	(9,8)	0.5669

Table 12 Appraisal scores for NTM processes for example 2

NTM process	Appraisal score	Rank
USM	9.1154	6
WJM	5.0081	8
AJM	4.2225	9
ECM	10.5030	4
CHM	11.6504	3
EDM	12.0912	1
WEDM	11.7653	2
EBM	7.9058	7
LBM	9.7284	5

jet machining is the worst chosen process. Das Chakladar and Chakraborty [9] derived the ranking of NTM processes as ECM–EDM–WEDM–USM–EBM–CHM–LBM–WJM–AJM while solving the same problem applying a combined AHP and TOPSIS approach. It is observed that, in both the cases, the best and the worst choices of NTM processes remain the same.

4.2 Example 2

In this example, the most appropriate NTM process that can efficiently machine precision holes on Duralumin (aluminium alloy) needs to be selected. From the available information regarding the machining characteristics of different NTM processes [2], the decision matrix of Table 7 is developed. Table 8 exhibits the normalized decision matrix. Then, the evaluative differences of a NTM process for each ordinal and cardinal criteria with respect to other NTM alternatives are estimated. Now, for all the ordinal and cardinal criteria, the dominance scores of each pair of NTM alternatives are computed (taking $c=1$), as shown in Table 9.

Table 10 gives the standardized dominance scores for all the pairs of NTM processes for both the ordinal and cardinal criteria. The overall dominance score for each pair of NTM processes is computed to evaluate the degree of dominance of a NTM process over the others. These overall dominance scores for all the pairs of NTM processes are depicted in Table 11. Based on the descending values of this appraisal score, as shown in Table 12, the final ranking of NTM alternatives is observed as EDM–WEDM–CHM–ECM–LBM–USM–EBM–WJM–AJM. Electrical discharge machining and wire electrical discharge machining are the two most efficient NTM processes, which can be used for generating precision holes on Duralumin alloy. It is also found out that abrasive jet machining and water jet machining processes are not at all capable to machine precision holes on that alloy. For this shape feature and work material combination, Das Chakladar and Chakraborty [9] ranked the NTM processes as EDM–ECM–WEDM–CHM–USM–EBM–LBM–WJM–AJM in descending order of preference. It is observed that while solving this NTM process selection problem employing EVAMIX method, the rankings of the most feasible as well as the most infeasible NTM processes remain unaltered.

4.3 Example 3

This illustrative example is taken from Yurdakul and Cogun [5] where cylindrical through holes [hole diameter= 0.64 mm and slenderness ratio (L/D)=5.7] are to be machined on ceramic (nonconductive) materials. Yurdakul and Cogun [5] solved this NTM process selection problem applying a combined TOPSIS and AHP method and observed the ranking of NTM processes as USM–LBM–EBM–CHM–AJM. Now, the same selection problem is solved using EVAMIX method. Tables 13 and 14, respectively, show the original decision matrix and the normalized decision matrix for the problem. Now, taking the value of c as 1, the dominance scores of each pair of NTM processes are computed, as given in Table 15. The standardized dominance scores for all the pairs of NTM processes for both the ordinal and cardinal criteria, and the overall dominance scores for each pair of NTM processes are then estimated, as exhibited in Tables 16 and 17, respectively. Table 18

Table 13 Data for example 3

NTM	TSF	PR	MRR	C	E	TF	TC	S	M	F
USM	1	10	500	2	4	2	3	1	5	5
WJM	2.5	0.22	0.8	1	4	2	2	3	3	1
AJM	2.5	0.24	0.5	1	4	2	2	3	3	1
ECM	3	100	400	5	2	3	1	3	3	1
CHM	3	0.4	15	3	3	2	1	3	3	1
EDM	3.5	2.7	800	3	4	4	4	3	4	3
WEDM	3.5	2.5	600	3	4	4	4	3	3	1
EBM	2.5	0.2	1.6	4	5	2	1	3	3	1
LBM	2	1.4	0.1	3	5	2	1	1	4	3

Table 14 Normalized decision matrix for example 3

NTM	TSF	PR	MRR	C	E	TF	TC	S	M	F
USM	1.0000	0.9018	0.6250	0.7500	0.6667	1.0000	0.3333	0	1.0000	1.0000
WJM	0.4000	0.9998	0.0009	1.0000	0.6667	1.0000	0.6667	1.0000	0	0
AJM	0.4000	0.9996	0.0005	1.0000	0.6667	1.0000	0.6667	1.0000	0	0
ECM	0.2000	0	0.4999	0	0	0.5000	1.0000	1.0000	0	0
CHM	0.2000	0.9980	0.0186	0.5000	0.3333	1.0000	1.0000	1.0000	0	0
EDM	0	0.9749	1.0000	0.5000	0.6667	0	0	1.0000	0.5000	0.5000
WEDM	0	0.9770	0.7500	0.5000	0.6667	0	0	1.0000	0	0
EBM	0.4000	1.0000	0.0019	0.2500	1.0000	1.0000	1.0000	1.0000	0	0
LBM	0.6000	0.9880	0	0.5000	1.0000	1.0000	1.0000	0	0.5000	0.5000

gives the appraisal scores for all the considered NTM processes, which, when arranged in descending order, suggest that the ranking of NTM processes for generating through holes on ceramics is USM–LBM–EDM–WJM–AJM–EBM–WEDM–CHM–ECM. Ultrasonic machining is the most suitable process for this machining application, and it is quite impossible to generate through holes on ceramics using electrochemical machining process. Das Chakladar and Chakraborty [9] also found USM as the most appropriate NTM process for this same machining application. For this problem, applying MOORA method, Chakraborty [15] derived the ranking of the alternative NTM processes as USM–LBM–WJM–AJM–EBM–EDM–WEDM–CHM–ECM. Excellent Spearman's rank correlation coefficients of 0.75 and 0.90, respectively, exist between the rankings obtained by Das Chakladar and Chakraborty [9] and Chakraborty [15], and those achieved using EVAMIX method.

Table 15 Dominance scores for NTM process pairs for example 3

NTM process	$\alpha_{ii'}$	$\gamma_{ii'}$	NTM process	$\alpha_{ii'}$	$\gamma_{ii'}$	NTM process	$\alpha_{ii'}$	$\gamma_{ii'}$
(1,2)	0.3589	0.1707	(4,1)	−0.6389	−0.2929	(7,1)	−0.6396	0.1363
(1,3)	0.3589	0.1707	(4,2)	−0.1532	0.0141	(7,2)	−0.1539	0.0141
(1,4)	0.6389	0.2929	(4,3)	−0.1532	0.0141	(7,3)	−0.1539	0.0141
(1,5)	0.6118	0.1707	(4,5)	−0.1727	0.0924	(7,4)	0.0990	0.1363
(1,6)	0.6396	−0.1363	(4,6)	−0.5993	−0.1363	(7,5)	−0.0083	0.0141
(1,7)	0.6396	−0.1363	(4,7)	−0.0990	−0.1363	(7,6)	−0.5003	−0.0924
(1,8)	0.6027	−0.0141	(4,8)	−0.1344	−0.1707	(7,8)	0.0607	−0.1707
(1,9)	0.5881	−0.0141	(4,9)	−0.6493	−0.1707	(7,9)	−0.5615	−0.1707
(2,1)	−0.3589	−0.1707	(5,1)	−0.6118	−0.1707	(8,1)	−0.5352	−0.1707
(2,3)	0	0.2146	(5,2)	−0.1261	0.0141	(8,2)	−0.0495	0.2146
(2,4)	0.1532	−0.0141	(5,3)	−0.1261	0.0141	(8,3)	−0.0495	0.2146
(2,5)	0.1261	−0.0141	(5,4)	0.1727	−0.0924	(8,4)	0.1727	−0.0141
(2,6)	−0.3464	−0.0141	(5,6)	−0.4920	−0.0141	(8,5)	−0.0690	−0.0141
(2,7)	0.1539	−0.0141	(5,7)	0.0083	−0.0141	(8,6)	−0.5227	−0.0141
(2,8)	0.0878	0.2146	(5,8)	0.1073	−0.1707	(8,7)	−0.0224	−0.0141
(2,9)	−0.4271	−0.2929	(5,9)	−0.5149	−0.2929	(8,9)	−0.5930	0.1363
(3,1)	−0.3589	−0.1707	(6,1)	−0.6396	0.1363	(9,1)	−0.5498	−0.1707
(3,2)	0	−0.2146	(6,2)	0.3464	0.0141	(9,2)	0.4362	−0.1363
(3,4)	0.1532	−0.0141	(6,3)	0.3464	0.0141	(9,3)	0.4362	−0.1363
(3,5)	0.1261	−0.0141	(6,4)	0.5993	0.1363	(9,4)	0.6584	−0.0141
(3,6)	−0.3464	−0.0141	(6,5)	0.4920	0.0141	(9,5)	0.5240	−0.1363
(3,7)	0.1539	−0.0141	(6,7)	0.5003	0.0924	(9,6)	0.0703	−0.0141
(3,8)	0.0878	0.2146	(6,8)	0.5610	−0.1707	(9,7)	0.5706	−0.0141
(3,9)	−0.4271	−0.2929	(6,9)	−0.0612	−0.1707	(9,8)	0.5930	−0.1363

Table 16 Standardized dominance scores for NTM process pairs for example 3

NTM process	$\delta_{ii'}$	$d_{ii'}$	NTM process	$\delta_{ii'}$	$d_{ii'}$	NTM process	$\delta_{ii'}$	$d_{ii'}$
(1,2)	0.7710	0.7914	(4,1)	0.0080	0	(7,1)	0.0074	0.7327
(1,3)	0.7710	0.7914	(4,2)	0.3794	0.5241	(7,2)	0.3788	0.5241
(1,4)	0.9851	1.0000	(4,3)	0.3794	0.5241	(7,3)	0.3788	0.5241
(1,5)	0.9644	0.7914	(4,5)	0.3645	0.6577	(7,4)	0.5722	0.7327
(1,6)	0.9856	0.2673	(4,6)	0.0382	0.2673	(7,5)	0.4902	0.5241
(1,7)	0.9856	0.2673	(4,7)	0.4208	0.2673	(7,6)	0.1139	0.3423
(1,8)	0.9574	0.4759	(4,8)	0.3937	0.2086	(7,8)	0.5429	0.2086
(1,9)	0.9462	0.4759	(4,9)	0	0.2086	(7,9)	0.0671	0.2086
(2,1)	0.2221	0.2086	(5,1)	0.0287	0.2086	(8,1)	0.0873	0.2086
(2,3)	0.4965	0.8663	(5,2)	0.4001	0.5241	(8,2)	0.4587	0.8663
(2,4)	0.6137	0.4759	(5,3)	0.4001	0.5241	(8,3)	0.4587	0.8663
(2,5)	0.5929	0.4759	(5,4)	0.6286	0.3423	(8,4)	0.6286	0.4759
(2,6)	0.2316	0.4759	(5,6)	0.1203	0.4759	(8,5)	0.4438	0.4759
(2,7)	0.6142	0.4759	(5,7)	0.5029	0.4759	(8,6)	0.0968	0.4759
(2,8)	0.5637	0.8663	(5,8)	0.5786	0.2086	(8,7)	0.4794	0.4759
(2,9)	0.1699	0	(5,9)	0.1028	0	(8,9)	0.0431	0.7327
(3,1)	0.2221	0.2086	(6,1)	0.0074	0.7327	(9,1)	0.0761	0.2086
(3,2)	0.4965	0.1337	(6,2)	0.7614	0.5241	(9,2)	0.8301	0.2673
(3,4)	0.6137	0.4759	(6,3)	0.7614	0.5241	(9,3)	0.8301	0.2673
(3,5)	0.5929	0.4759	(6,4)	0.9548	0.7327	(9,4)	1.0000	0.4759
(3,6)	0.2316	0.4759	(6,5)	0.8728	0.5241	(9,5)	0.8972	0.2673
(3,7)	0.6142	0.4759	(6,7)	0.8791	0.6577	(9,6)	0.5503	0.4759
(3,8)	0.5637	0.8663	(6,8)	0.9255	0.2086	(9,7)	0.9329	0.4759
(3,9)	0.1699	0	(6,9)	0.4497	0.2086	(9,8)	0.9500	0.2673

Table 17 Overall dominance scores for example 3

NTM process	$D_{ii'}$	NTM process	$D_{ii'}$	NTM process	$D_{ii'}$	NTM process	$D_{ii'}$
(1,2)	0.7770	(3,4)	0.5733	(5,6)	0.2245	(7,8)	0.4450
(1,3)	0.7770	(3,5)	0.5587	(5,7)	0.4950	(7,9)	0.1086
(1,4)	0.9895	(3,6)	0.3032	(5,8)	0.4702	(8,1)	0.1228
(1,5)	0.9137	(3,7)	0.5737	(5,9)	0.0727	(8,2)	0.5781
(1,6)	0.7752	(3,8)	0.6523	(6,1)	0.2198	(8,3)	0.5781
(1,7)	0.7752	(3,9)	0.1201	(6,2)	0.6919	(8,4)	0.5839
(1,8)	0.8164	(4,1)	0.0056	(6,3)	0.6919	(8,5)	0.4532
(1,9)	0.8085	(4,2)	0.4218	(6,4)	0.8897	(8,6)	0.2079
(2,1)	0.2181	(4,3)	0.4218	(6,5)	0.7706	(8,7)	0.4784
(2,3)	0.6048	(4,5)	0.4504	(6,7)	0.8143	(8,9)	0.2450
(2,4)	0.5733	(4,6)	0.1053	(6,8)	0.7155	(9,1)	0.1149
(2,5)	0.5587	(4,7)	0.3759	(6,9)	0.3791	(9,2)	0.6653
(2,6)	0.3032	(4,8)	0.3395	(7,1)	0.2198	(9,3)	0.6653
(2,7)	0.5737	(4,9)	0.0611	(7,2)	0.4214	(9,4)	0.8465
(2,8)	0.6523	(5,1)	0.0814	(7,3)	0.4214	(9,5)	0.7127
(2,9)	0.1201	(5,2)	0.4364	(7,4)	0.6192	(9,6)	0.5285
(3,1)	0.2181	(5,3)	0.4364	(7,5)	0.5001	(9,7)	0.7990
(3,2)	0.3902	(5,4)	0.5447	(7,6)	0.1808	(9,8)	0.7500

Table 18 Appraisal scores for NTM processes for example 3

NTM process	Appraisal score	Rank
USM	215.0396	1
WJM	7.5790	4
AJM	6.6743	5
ECM	3.6827	9
CHM	5.1795	8
EDM	25.3908	3
WEDM	5.6986	7
EBM	6.2985	6
LBM	46.6918	2

5 Conclusions

An EVAMIX method-based approach is proposed, which helps the decision makers in selecting the most appropriate NTM process from a large number of candidate alternatives for generating a desired shape feature on a given work material. As the NTM process selection problems generally consist of both the quantitative (cardinal) and qualitative (ordinal) criteria, EVAMIX method is quite suitable to tackle these types of decision-making problems, giving satisfactory results. The algorithm of EVAMIX method combines the characteristics of cardinal and ordinal data, designed to combine the output in a single appraisal score, which gives it much greater flexibility over the other MCDM methods, allowing the decision makers to use all the available data in its original form. In this method, the chance of loss of information is minimum, as it employs separate mathematical models to deal with the ordinal and cardinal criteria in the decision matrix. It is quite flexible, easily comprehendible, and segregates the subjective part of the evaluation process into criteria weights including decision makers' preferences. Furthermore, an additional advantage of this method is that it allows for different priorities among the criteria, a useful property since quite different criteria are more important than the others reflecting the different needs and objectives of the decision makers. Three illustrative examples prove the applicability, usefulness, and accuracy of this mixed data method while solving complex MTM process selection problems. It can simultaneously take into account any number of quantitative and qualitative NTM process selection criteria and offer a more objective and simple NTM process selection approach. It can be made more versatile and exhaustive by including all the NTM processes, shape features, and materials, yet to come in near future.

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