Int J Adv Manuf Technol (2011) 54:1155–1166
DOI 10.1007/s00170-010-2972-0

ORIGINAL ARTICLE

Applications of the MOORA method for decision making in manufacturing environment

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Received: 13 March 2010 / Accepted: 29 September 2010 / Published online: 13 October 2010
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Abstract To meet the challenges of global competitiveness, manufacturing organizations are now facing the problems of selecting appropriate manufacturing strategies, product and process designs, manufacturing processes and technologies, and machinery and equipment. The selection decisions become more complex as the decision makers in the manufacturing environment have to assess a wide range of alternatives based on a set of conflicting criteria. To aid these selection processes, various multi-objective decision-making (MODM) methods are now available. This paper explores the application of an almost new MODM method, i.e., the multi-objective optimization on the basis of ratio analysis (MOORA) method to solve different decision-making problems as frequently encountered in the real-time manufacturing environment. Six decision-making problems which include selection of (a) an industrial robot, (b) a flexible manufacturing system, (c) a computerized numerical control machine, (d) the most suitable non-traditional machining process for a given work material and shape feature combination, (e) a rapid prototyping process, and (f) an automated inspection system are considered in this paper. In all these cases, the results obtained using the MOORA method almost corroborate with those derived by the past researchers which prove the applicability, potentiality, and flexibility of this method while solving various complex decision-making problems in present day manufacturing environment.

Keywords Decision making · MOORA method · Industrial robot · Flexible manufacturing system · Machine tool · Non-traditional machining process · Rapid prototyping · Automated inspection system

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1 Introduction

Decision making is the study of identifying and choosing alternatives based on the values and preferences of the decision maker. Making a decision implies that there are alternative choices to be considered, and in such a case, not only as many of these alternatives as possible are identified but also the best one is chosen to meet the decision maker's goals, objectives, desires, and values. Thus, every decision-making process produces a final choice. Problem solving and decision making are important skills for business and life. Problem solving often involves decision making, and decision making is especially important for management and leadership. Decision making is more natural to certain personalities, so these people should focus more on improving the quality of their decisions. People who are less natural decision makers are often able to make quality assessments, but then need to be more decisive in acting upon the assessments made. Good decision making requires a mixture of skills, like creative development and identification of options, clarity of judgment, firmness of decision, and effective implementation.

High competition, rapid technological advancements, and continuous change in customers' demands have made the manufacturing organizations realize the importance of available advanced manufacturing systems (AMS) having wider range of performance capabilities. Industrial robots, flexible manufacturing systems (FMS), computerized numerical control (CNC) machines, automated material handling systems, rapid prototyping (RP) processes, automated inspection systems, various types of non-traditional machining (NTM) processes etc. are a few examples of available options where the manufacturing organizations are presently concentrating on. Adoption of these AMSs is not only labor saving, but also provides improved product quality, faster production rate and delivery, and increased product flexibility with enhanced manufacturing effectiveness. However, implementation of these systems is extremely capital-intensive and as this investment tends to be irreversible, serious consideration is required before a decision has been made. Therefore, the investment justification problems for AMSs have become a major global concern to the manufacturing organizations. Thus, evaluation and selection of an AMS tends to be a complex decision-making problem involving consideration of various issues at the strategic, tactical, and operational levels.

In a manufacturing environment, the decision makers need to select the most suitable AMS while assessing a wide range of alternative options based on a set of conflicting attributes/criteria. To help and guide the decision makers, there is a need for simple, systematic, and logical approaches or mathematical tools that can consider a large number of selection attributes and candidate alternatives. The objective of any selection procedure is to identify the appropriate selection attributes and obtain the best decision in conjunction with the real-time requirements. Although, a lot of multi-objective decision-making (MODM) methods is now available to deal with varying evaluation and selection problems, this paper attempts to explore the applicability of an almost new MODM method, i.e. the multi-objective optimization on the basis of ratio analysis (MOORA) method to solve different AMS selection problems in real-time manufacturing environment. Six illustrative examples consisting of selection of (a) an industrial robot, (b) a flexible manufacturing system, (c) a computerized numerical control machine, (d) the most suitable non-traditional machining process for a given work material and shape feature combination, (e) a rapid prototyping process, and (f) an automated inspection system are considered in this paper. This method is observed to be quite robust, comprehendible, and computationally easy which helps the decision makers to eliminate the unsuitable alternatives, while selecting the most appropriate alternative to strengthen the existing selection procedures.

2 The MOORA method

Multi-objective optimization (or programming), also known as multi-criteria or multi-attribute optimization, is the process of simultaneously optimizing two or more conflicting attributes (objectives) subject to certain constraints. Multi-objective optimization problems can be found in various fields, like product and process design, finance, aircraft design, oil and gas industry, manufacturing sector, automobile design, or wherever optimal decisions need to be taken in presence of trade-offs between two or more conflicting objectives. Maximizing profit and minimizing the cost of a product; maximizing performance and minimizing fuel consumption of a vehicle; and minimizing weight while maximizing the strength of a particular engineering component are the typical examples of multi-objective optimization problems.

In a real-time manufacturing environment, different decision makers with varying interests and values, make a decision-making process much more difficult. In a decision-making problem, the objectives (attributes) must be measureable and their outcomes can 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, multi-objective optimization techniques seem to be an appropriate tool for ranking or selecting one or more alternatives from a set of available options based on multiple, usually conflicting attributes. The MOORA method, first introduced by Brauers [1], is such a multi-objective optimization technique that can be successfully applied to solve various types of complex decision-making problems in the manufacturing environment.

The MOORA method [2–8] starts with a decision matrix showing the performance of different alternatives with respect to various attributes (objectives).

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & \dots & x_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & \dots & x_{mn} \end{bmatrix} \quad (1)$$

where x_{ij} is the performance measure of ith alternative on jth attribute, m is the number of alternatives, and n is the number of attributes.

Then a ratio system is developed in which each performance of an alternative on an attribute is compared to a denominator which is a representative for all the alternatives concerning that attribute. Brauers et al. [2] considered various ratio systems, such as total ratio, Schärlig ratio, Weitendorf ratio, Jüttler ratio, Stopp ratio, Körth ratio etc. and concluded that for this denominator, the best choice is the square root of the sum of squares of each alternative per attribute. This ratio can be expressed as below:

$$x^*_{ij} = x_{ij} / \left[\sum_{i=1}^{m} x_{ij}^2 \right]^{1/2} (j = 1, 2, \dots, n) \quad (2)$$

where x^*_{ij} is a dimensionless number which belongs to the interval [0,1] representing the normalized performance of ith alternative on jth attribute.

For multi-objective optimization, these normalized performances are added in case of maximization (for beneficial attributes) and subtracted in case of minimization (for non-beneficial attributes). Then the optimization problem becomes:

$$y_i = \sum_{j=1}^{g} x_{ij}^{*} - \sum_{j=g+1}^{n} x_{ij}^{*} \tag{3}$$

where g is the number of attributes to be maximized, $(n-g)$ is the number of attributes to be minimized, and y_i is the normalized assessment value of ith alternative with respect to all the attributes.

In some cases, it is often observed that some attributes are more important than the others. In order to give more importance to an attribute, it could be multiplied with its corresponding weight (significance coefficient) [3]. When these attribute weights are taken into consideration, Eq. 3 becomes as follows:

$$y_i = \sum_{j=1}^{g} w_j x_{ij}^{*} - \sum_{j=g+1}^{n} w_j x_{ij}^{*} (j = 1, 2, \ldots, n) \tag{4}$$

where w_j is the weight of jth attribute, which can be determined applying analytic hierarchy process (AHP) or entropy method.

The 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 y_i shows the final preference. Thus, the best alternative has the highest y_i value, while the worst alternative has the lowest y_i value.

3 Decision-making problems

In order to demonstrate the applicability and potentiality of the MOORA method in solving multi-objective decision-making problems in real-time manufacturing environment, the following six illustrative examples are considered.

3.1 Industrial robot selection

An industrial robot is a general purpose, reprogrammable machine with certain anthropometrical characteristics. Its mechanical arm is the most important and vital anthropometrical component. Other less but still important features, like its decision-making capability, capacity of responding to various sensory inputs, and communicating with other machines make it an important tool for diverse industrial applications, including material handling, assembly, finishing, machine loading, spray painting, and welding. Control resolution, accuracy, repeatability, load carrying capacity, degrees of freedom, man-machine interfacing ability, programming flexibility, maximum tip speed, memory capacity, and vendor's service quality are the most important attributes to be taken into consideration while selecting an industrial robot for a particular application.

Bhangale et al. [9] considered the selection problem of the most suitable industrial robot for some pick-n-place operations where it has to avoid certain obstacles. In this problem, load carrying capacity, repeatability, maximum tip speed, memory capacity, and manipulator reach are observed to be the most critical attributes affecting the robot selection decision. Load capacity (LC) is the maximum load that a manipulator can carry without affecting its performance. Repeatability (RE) is the measure of the ability of a robot to return to the same position and orientation over and over again. Maximum tip speed (MTS) is the speed at which a robot can move in an inertial reference frame. Memory capacity (MC) of a robot is measured in terms of number of points or steps that it can store in its memory while traversing along a predefined path. Manipulator reach (MR) is the maximum distance that can be covered by the robotic manipulator so as to grasp objects for the given pick-n-place operation. Among these five attributes, load capacity, maximum tip speed, memory capacity, and manipulator reach are beneficial in nature (where higher values are desirable), whereas, repeatability is a non-beneficial attribute (where lower value is preferable). Thus, the industrial robot selection problem consists of five performance attributes and seven alternative robots, as shown in Table 1.

Bhangale et al. [9] determined the criteria weights as w_{LC}=0.1761, w_{RE}=0.2042, w_{MTS}=0.2668, w_{MC}=0.2430, and w_{MR}=0.2286 using AHP method. But the sum of these criteria weights exceeds one. Hence, these are re-normalized as w_{LC}=0.1574, w_{RE}=0.1825, w_{MTS}=0.2385, w_{MC}=0.2172, and w_{MR}=0.2043, and used here for subsequent analysis. Bhangale et al. [9] obtained a ranking of the industrial robots as 2-3-1-5-7-6-4 while solving this problem using similarity coefficient values of technique for order preference by similarity to ideal solution (TOPSIS) method. Rao [10] solved the same robot selection problem using AHP method and observed the ranking of the alternatives as 4-2-1-5-7-6-3 which reveals that Cybotech V15 electric robot is the best choice. Table 2 shows the normalized performance scores of the alternatives with respect to the considered attributes, as obtained using Eq. 2. Then applying Eq. 4, the normalized assessment values (y_i) of all the alternatives with respect to the considered attributes are computed. Table 2 also exhibits these results of the MOORA method-based analysis which gives a comparative ranking of the alternative robots as 2-3-1-4-7-5-6 when arranged according to the descending order of their assessment values. Here, Cybotech V15 electric robot

Table 1 Quantitative data for robot selection problem [9]

Sl. no.	Robot	Load capacity (LC) (kg)	Repeatability (RE) (mm)	Maximum tip speed (MTS) (mm/s)	Memory capacity (MC)	Manipulator reach (MR) (mm)
1	ASEA-IRB 60/2	60	0.40	2,540	500	990
2	Cincinnati Milacrone T3-726	6.35	0.15	1,016	3,000	1,041
3	Cybotech V15 Electric Robot	6.8	0.10	1,727.2	1,500	1,676
4	Hitachi America Process Robot	10	0.20	1,000	2,000	965
5	Unimation PUMA 500/600	2.5	0.10	560	500	915
6	United States Robots Maker 110	4.5	0.08	1,016	350	508
7	Yaskawa Electric Motoman L3C	3	0.10	177	1,000	920

is also observed to be the best-suited alternative and the first three top ranks exactly match with those derived by Bhangale et al. [9]. In all these cases, the worst choice remains to be Unimation PUMA 500/600 robot. The nature of this robot selection problem involves that the total number of the maxima (beneficial attributes) is larger than the total number of the minima (non-beneficial attributes) for which all the assessment values become positive.

3.2 FMS selection

A flexible manufacturing system consists of computerized numerical control machines and/or robots, physically linked by a conveyance network to move parts and/or tools, and an overall effective computer control to create an integrated system. The reason the FMS is called “flexible” is that it is capable of processing a variety of different part styles simultaneously at various workstations, and the mix of part styles and production quantities can be easily adjusted in response to changing demand patterns. Potential benefits of an FMS implementation include reduced inventory levels, manufacturing lead times, floor space, and setup and labor costs, in addition to higher flexibility, quality, speed of response, and a longer useful life of the equipment over successive generations of products. An FMS can manufacture a wide range of products in batch sizes from one to thousands. An FMS has the advantage that it can combine the efficiency of a mass production system and the flexibility of a job shop production system to produce high-quality products. As an FMS implementation involves a huge capital investment, the selection of the most appropriate FMS design from a set of candidate configurations requires extensive analysis and evaluation.

Karsak and Kuzgunkaya [11], while employing a fuzzy multi-objective programming approach for selection of an FMS, considered eight alternative flexible manufacturing systems and seven attributes affecting the FMS selection decision. These attributes are reduction in labor cost (RLC), reduction in WIP (RWP), reduction in setup cost (RSC), increase in market response (IMR), improvement in quality (IQ), capital and maintenance cost (CMC), and floor space used (FSU). Among these, five attributes are quantitative in nature and the remaining two are qualitative. Table 3 represents the performance characteristics of the considered flexible manufacturing systems with respect to all the attributes. The qualitative information of the two attributes, i.e., IMR and IQ are converted into appropriate quantitative data using a fuzzy conversion scale [10]. RLC, RWP, RSC, IMR, and IQ are beneficial attributes; on the other hand, CMC and FSU are non-beneficial attributes. Karsak and Kuzgunkaya [11] observed that the FMS alternatives 7 and 4 are the best choices for the given problem. Rao and

Table 2 Assessment values for robot selection problem

Sl. no.	LC	RE	MTS	MC	MR	y_i	Rank
1	0.9705	0.7861	0.7087	0.1217	0.3557	0.3104	2
2	0.1027	0.2948	0.2835	0.7303	0.3740	0.2965	3
3	0.1110	0.1965	0.4820	0.3652	0.6022	0.3342	1
4	0.1617	0.3931	0.2790	0.4869	0.3467	0.2202	4
5	0.0404	0.1965	0.1562	0.1217	0.3288	0.1134	7
6	0.0728	0.1572	0.2835	0.0852	0.1825	0.1188	5
7	0.0485	0.1965	0.0494	0.2434	0.3306	0.1163	6

Table 3 Quantitative data for FMS selection problem [11]

Alternative FMS	Reduction in labor cost (RLC) (%)	Reduction in WIP (RWP) (%)	Reduction in setup cost (RSC) (%)	Increase in market response (IMR)	Improvement in quality (IQ)	Capital and maintenance cost (CMC) ($ 000)	Floor space used (FSU) (ft^2)
1	30	23	5	0.745	0.745	1,500	5,000
2	18	13	15	0.745	0.745	1,300	6,000
3	15	12	10	0.500	0.500	950	7,000
4	25	20	13	0.745	0.745	1,200	4,000
5	14	18	14	0.255	0.745	950	3,500
6	17	15	9	0.745	0.500	1,250	5,250
7	23	18	20	0.500	0.745	1,100	3,000
8	16	8	14	0.255	0.500	1,500	3,000

Parnichkun [12] determined the relative importance (weight) of these attributes as w_{RLC}=0.1129, w_{RWP}= 0.1129, w_{RSC}=0.0445, w_{IMR}=0.1129, w_{IQ}=0.2861, w_{CMC}=0.2861, and w_{FSU}=0.0445 using AHP method, and obtained a ranking of the FMS alternatives as 3-4-7-2-5-6-1-8 using graph theory and matrix approach. Based on these criteria weights, the results of the MOORA-method-based analysis, as shown in Table 4, reveal the FMS rankings as 3-5-7-2-4-6-1-8. In both these cases, the first (FMS 7), second (FMS 4), third (FMS 1), and last (FMS 8) rankings are exactly similar. In Table 4, all the assessment values are positive in nature because the total number of beneficial attributes is larger than that of non-beneficial attributes.

3.3 Machine tool selection

Sun [13] applied data envelopment analysis (DEA) to evaluate 21 CNC machines (lathes) in terms of system specifications and cost at the operational level. The evaluation of CNC machines is based on the combination of the Banker, Charnes, and Cooper (BCC) model and cross-efficiency method of DEA. It aims at identifying a homogenous set of good systems, by measuring, for each machine, the pure technical efficiency through the BCC model. The use of cross-efficiency evaluation is to discriminate better between the good systems and bad systems. These good systems can be further evaluated for the selection of the best system in the decision-making process. The main input and output measures for assessing the CNC machines are considered to be the purchase cost and technical specifications. The capital cost of a CNC machine, quoted in New Taiwanese Dollar (NT$), is the only input parameter. The technical features (output) on which the performance of a CNC machine depends are work capacity, machine body, spindle, and tool turret. Work capacity is measured by the maximum machining diameter (mm) and machining length (mm). The machine body is measured by rapid traverse rates (m/min) of the *X*- and *Z*-axes. Rapid traverse rates of the *X* and *Z*-axes reflect the positioning capability of a turning center. The spindle characteristic is measured by spindle speed range (rpm). Spindle speed is the number of revolutions that a spindle can make in 1 min and it allows a machine to maintain a constant cutting speed regardless of the part diameter. The tool turret is characterized by tool capacity. The fewer is the number of tools in the turret, the more is the time required to change the tools as selected for use in a particular program. Thus, seven criteria, i.e., capital cost (CC), spindle speed range (SS), tool capacity (TC), rapid traverse rate of *X*-axis (TX), rapid traverse rate of *Z*-axis (TZ), maximum machining diameter (MD), and maximum machining length (ML) are considered that affect the ability of a CNC machine to perform various machining operations.

Table 4 Assessment values for FMS selection problem

FMS	RLC	RWP	RSC	IMR	IQ	CMC	FSU	y_i	Rank
1	0.5188	0.4927	0.1340	0.4413	0.3968	0.4293	0.3688	0.1443	3
2	0.3113	0.2785	0.4020	0.4413	0.3968	0.3721	0.4425	0.1217	5
3	0.2594	0.2571	0.2680	0.2962	0.2663	0.2719	0.5163	0.0791	7
4	0.4323	0.4284	0.3484	0.4413	0.3968	0.3434	0.2950	0.1593	2
5	0.2421	0.3856	0.3752	0.1510	0.3968	0.2719	0.2581	0.1289	4
6	0.2940	0.3213	0.2412	0.4413	0.2663	0.3578	0.3872	0.0867	6
7	0.3977	0.3856	0.5360	0.2962	0.3968	0.3148	0.2213	0.1646	1
8	0.2767	0.1714	0.3752	0.1510	0.2663	0.4293	0.2213	0.0278	8

Table 5 shows the attribute values for 21 alternative CNC machines (lathes), where CC, TX, and TZ are the non-beneficial attributes, and SS, TC, MD, and ML are the beneficial attributes. According to their higher cross-efficiency mean scores, lower false positive indices, and maverick index values, Sun [13] short-listed the CNC lathes 3, 4, 12, 14, 15, and 16 as the possible systems for further consideration and finally, observed that CNC lathe 4 (VTURN 16) is the best alternative for the present situation.

For the MOORA method, the weight values for the considered seven attributes are estimated as w_{CC}=0.1148, w_{SS}=0.1808, w_{TC}=0.1884, w_{TX}=0.1197, w_{TZ}=0.1148, w_{MD}=0.1546, and w_{ML}=0.1268 using AHP method. Table 6 shows the results of this CNC machine tool selection problem using the MOORA method where alternative 4 (VTURN 16) also becomes the right choice. In this problem, as the total number of beneficial attributes is greater than the total number of non-beneficial attributes, all the assessment values become positive.

3.4 NTM process selection

The difficulty in machining caused by the advanced engineering materials, such as titanium, stainless steel, high-strength temperature-resistant alloys, ceramics, refractories, fiber-reinforced composites, and other difficult-to-machine alloys having higher strength, hardness, toughness, low machinability, and other diverse mechanical properties has placed a demand for the development of non-traditional machining processes due to lack of availability of sufficiently hard and strong cutting tool materials for the generation of complex and accurate shape features on those new work materials. In conventional machining operations, materials are removed from the workpiece surface in the form of chips and hence, high degree of precision and accuracy cannot be achieved. Whereas, the NTM processes use energy (mechanical, thermoelectric, electrochemical, chemical, sound etc.) in its direct form to remove materials in the form of atoms or molecules to obtain the desired accuracy and burr-free machined surface. Low applied forces can prevent damage to the workpiece surface that may occur during conventional machining operations. Because the NTM processes can provide new ways of satisfying the demands of nascent technological advances in many areas, like automated data transmission and miniaturization, the design engineers need not only limit their ideas to the traditional machining processes, but also venture for the application of different NTM processes to fulfill the machining and surface quality requirements. A new horizon of choices from a pool of NTM processes has been opened up for the design and machining of products. But, for effective utilization of the capabilities of different NTM processes, an in-depth knowledge about various machining characteristics of those processes is of utmost importance.

Table 5 Quantitative data for machine tool selection problem [13]

Sl. no.	CNC lathe	CC	SS	TC	TX	TZ	MD	ML
1	YANG ML-5A	1,200,000	5,590	8	24	24	205	350
2	YANG ML-25A	1,550,000	3,465	8	20	20	280	520
3	YCM TC-15	1,400,000	5,950	12	15	20	250	469
4	VTURN 16	1,100,000	5,940	12	12	15	230	600
5	FEMCO HL-15	1,200,000	5,940	12	12	16	150	330
6	FEMCO WNCL-20	1,500,000	3,465	12	6	12	260	420
7	FEMCO WNCL-30	2,600,000	3,960	12	12	16	300	625
8	EX-106	1,320,000	4,950	12	24	30	240	340
9	ECOCA SJ20	1,180,000	4,480	8	24	24	250	330
10	ECOCA SJ25	1,550,000	3,950	12	15	20	280	460
11	ECCOA SJ30	1,600,000	3,450	12	15	20	280	460
12	TOPPER TNL-85A	1,200,000	3,465	8	20	24	264	400
13	TOPPER TNL-100A	1,350,000	2,970	8	20	24	264	400
14	TOPPER TNL-100AL	1,400,000	2,970	12	24	30	300	600
15	TOPPER TNL-85T	1,350,000	3,465	12	30	30	264	350
16	TOPPER TNL-100T	1,450,000	2,970	12	20	24	300	400
17	TOPPERTNL-120T	1,520,000	2,475	12	20	24	300	400
18	ATECH MT-52S	1,376,000	4,752	12	20	24	235	350
19	ATECH MT-52L	1,440,000	4,752	12	20	24	235	600
20	ATECH MT-75S	1,824,000	3,790	10	12	20	300	530
21	ATECH MT-75L	1,920,000	3,790	10	12	20	300	1,030

Table 6 Assessment values for machine tool selection problem

Sl. no.	CC	SS	TC	TX	TZ	MD	ML	y_i	Rank
1	0.1732	0.2869	0.1589	0.2783	0.2332	0.1695	0.1528	0.0474	17
2	0.2237	0.1779	0.1589	0.2319	0.1943	0.2315	0.2271	0.0509	15
3	0.2021	0.3054	0.2383	0.1739	0.1943	0.2067	0.2042	0.0917	3
4	0.1588	0.3049	0.2383	0.1392	0.1458	0.1902	0.2620	0.1110	1
5	0.1732	0.3049	0.2383	0.1392	0.1555	0.1240	0.1441	0.0831	5
6	0.2165	0.1779	0.2383	0.0696	0.1166	0.2150	0.1834	0.0869	4
7	0.3753	0.2033	0.2383	0.1392	0.1555	0.2481	0.2729	0.0770	6
8	0.1905	0.2541	0.2383	0.2783	0.2915	0.1985	0.1485	0.0517	14
9	0.1703	0.2299	0.1589	0.2783	0.2332	0.2067	0.1441	0.0421	19
10	0.2237	0.2028	0.2383	0.1739	0.1943	0.2315	0.2009	0.0740	7
11	0.2309	0.1771	0.2383	0.1739	0.1943	0.2315	0.2009	0.0685	10
12	0.1732	0.1779	0.1589	0.2319	0.2332	0.2183	0.1747	0.0436	18
13	0.1948	0.1525	0.1589	0.2319	0.2332	0.2183	0.1747	0.0365	20
14	0.2021	0.1525	0.2383	0.2783	0.2915	0.2481	0.2620	0.0540	13
15	0.1948	0.1779	0.2383	0.3479	0.2915	0.2183	0.1528	0.0327	21
16	0.2093	0.1525	0.2383	0.2319	0.2332	0.2481	0.1747	0.0544	12
17	0.2194	0.1270	0.2383	0.2319	0.2332	0.2481	0.1747	0.0486	16
18	0.1986	0.2439	0.2383	0.2319	0.2332	0.1943	0.1528	0.0611	11
19	0.2078	0.2439	0.2383	0.2319	0.2332	0.1943	0.2620	0.0739	8
20	0.2633	0.1945	0.1986	0.1392	0.1943	0.2481	0.2314	0.0711	9
21	0.2771	0.1945	0.1986	0.1392	0.1943	0.2481	0.4498	0.0972	2

Yurdakul and Cogun [14] considered the generation of cylindrical standard through holes on ceramic (non-conductive) materials, where the hole diameter and slenderness ratio (length/diameter) are 0.64 mm and 5.7, respectively. This work material and shape feature combination is taken here as the illustrative example. Das Chakladar and Chakraborty [15] identified 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 shape feature (F) as the most influencing attributes affecting the NTM process selection decision. Among these attributes, TSF (μm), PR (kW), and MRR (mm^3/min) are quantitative in nature having absolute numerical values, 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. MRR, E, S, M, and F are the beneficial attributes, and TSF, PR, C, TF, and TC are the non-beneficial attributes. Nine alternative NTM processes, i.e., ultrasonic machining (USM), water jet machining (WJM), abrasive jet machining (AJM), electrochemical machining (ECM), chemical machining (CHM), electric discharge machining (EDM), wire electrical discharge machining (WEDM), electron beam machining (EBM), and laser beam machining (LBM) are taken into consideration. Table 7 shows the performance of these NTM processes with respect to the considered attributes when cylindrical standard through holes are generated on ceramic materials. Das Chakladar and Chakraborty [15] also determined various criteria

Table 7 Quantitative data for NTM process selection problem

NTM process	TSF	PR	MRR	*C*	*E*	TF	TC	*S*	*M*	*F*
USM	1.0	10.00	500.0	2	4	2	3	1	5	5
WJM	2.5	0.22	0.8	1	4	2	2	3	5	4
AJM	2.5	0.24	0.5	1	4	2	2	3	5	4
ECM	3.0	100.00	400.0	5	2	3	1	3	1	1
CHM	3.0	0.40	15.0	3	3	2	1	3	3	1
EDM	3.5	2.70	800.0	3	4	4	4	3	1	5
WEDM	3.5	2.50	600.0	3	4	4	4	3	1	5
EBM	2.5	0.20	1.6	4	5	2	1	3	5	5
LBM	2	1.4	0.1	3	5	2	1	3	5	5

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 which are used here for the MOORA-method-based analysis.

When this NTM process selection problem is solved using the MOORA method, ultrasonic machining is observed to be the most suitable NTM process for generating cylindrical standard through holes on ceramic materials. The detailed calculations are shown in Table 8 where as the total number of beneficial attributes is exactly equal to that of non-beneficial attributes, some of the assessment values are positive and some are negative. From this table, it is revealed that laser beam machining process is the second best choice, and the performance of water jet machining and abrasive jet machining processes are almost similar. Electrochemical machining is the worst process. For the same work material and shape feature combination, Yurdakul and Cogun [14] observed the ranking of the NTM processes as USM-LBM-EBM-CHM-AJM. On the other hand, Das Chakladar et al. [16] obtained a ranking of NTM processes as USM-AJM-EBM while employing a digraph-based expert system. In all these cases, the best choice of the NTM process for generating cylindrical standard through holes on ceramics is ultrasonic machining process.

3.5 RP process selection

Rapid prototyping process can be defined as a group of techniques used to quickly fabricate a scale model of a part or assembly using three-dimensional computer-aided design data. RP is also referred to as solid free-form manufacturing, computer automated manufacturing, and layered manufacturing. It has obvious use as a vehicle for visualization. In addition, RP models can be used for testing, such as when an airfoil shape is put into a wind tunnel. RP models can be used to create male models for tooling, such as silicone rubber molds and investment casts. In some cases, the RP part can be the final part, but typically, the RP material is not strong or accurate enough.

Due to rapid development of RP technology, the selection of the most suitable RP process to satisfy customers' requirements from a number of alternative processes has become increasingly important. However, it becomes difficult for the RP users to select an appropriate process due to the existence of a large number of alternatives where the best selection decision depends on many conflicting criteria. Furthermore, each RP process has its own strengths, weaknesses, applications, utilities, and limitations. Byun and Lee [17] developed a decision support system for selection of a RP process using the modified TOPSIS method. They identified six attributes, such as accuracy (A), surface roughness (R), tensile strength (S), elongation (E), cost of the part (C), and build time (B) as the most dominant criteria for evaluation and selection of the RP process. Cost of the part and build time are expressed in linguistic terms, and hence, equivalent ranked value judgments on a fuzzy conversion scale are made [18], as given in Table 9. The quantitative and qualitative data of this RP process selection problem are shown in Table 9. For the given problem, S and E are the beneficial attributes, and A, R, C, and B are the non-beneficial attributes. Rao and Patel [18] obtained the normalized weights of the attributes as w_A=0.3185, w_R= 0.3185, w_S=0.1291, w_E=0.1291, w_C=0.0524, and w_B= 0.0524 using AHP method which are subsequently used here for the MOORA-method-based analysis.

Table 10 shows the MOORA-method-based solution for this RP process selection problem which suggests that Quadra and SLA3500 are the first and second choices, respectively. Z402 is observed to be the last choice. In Table 10, all the assessment values are negative because the problem has four non-beneficial attributes against two beneficial attributes. Both Byun and Lee [17] and Rao and

Table 8 Assessment values for NTM process selection problem

NTM process	TSF	PR	MRR	*C*	*E*	TF	TC	*S*	*M*	*F*	y_i	Rank
USM	0.0994	0.4210	0.2195	0.3345	0.2481	0.4121	0.1170	0.4272	0.3965	0.0994	0.2320	1
WJM	0.0022	0.0007	0.1098	0.3345	0.2481	0.2747	0.3511	0.4272	0.3172	0.0022	0.1591	3
AJM	0.0024	0.0004	0.1098	0.3345	0.2481	0.2747	0.3511	0.4272	0.3172	0.0024	0.1590	4
ECM	0.9943	0.3368	0.5488	0.1672	0.3721	0.1374	0.3511	0.0854	0.0793	0.9943	−0.0566	9
CHM	0.0039	0.0126	0.3293	0.2509	0.2481	0.1374	0.3511	0.2563	0.0793	0.0039	0.0315	8
EDM	0.0268	0.6737	0.3293	0.3345	0.4961	0.5494	0.3511	0.0854	0.3965	0.0268	0.1389	6
WEDM	0.0248	0.5052	0.3293	0.3345	0.4961	0.5494	0.3511	0.0854	0.3965	0.0248	0.1131	7
EBM	0.0019	0.0013	0.4391	0.4185	0.2481	0.1374	0.3511	0.4272	0.3965	0.0019	0.1475	5
LBM	0.2457	0.0139	0.0008	0.3293	0.4181	0.2481	0.1374	0.3511	0.4272	0.3965	0.1632	2

Table 9 Data for RP process selection problem [17]

RP system	Accuracy (A)	Surface roughness (R)	Tensile strength (S)	Elongation (E)	Cost of the part (C)	Build time (B)
SLA3500	120	6.5	65	5.0	VH (0.745)	M (0.500)
SLS2500	150	12.5	40	8.5	VH (0.745)	M (0.500)
FDM8000	125	21.0	30	10.0	H (0.665)	VH (0.745)
LOM1015	185	20.0	25	10.0	SH (0.590)	SL (0.410)
Quadra	95	3.5	30	6.0	VH (0.745)	SL (0.410)
Z402	600	15.5	5	1.0	VVL (0.135)	VL (0.255)

Patel [18] obtained these same observations while solving this RP process selection problem using modified TOPSIS and preference ranking organization method for enrichment evaluation (PROMETHEE) methods, respectively.

3.6 Automated inspection system selection

Pandey and Kengpol [19] considered a problem of selecting the best possible automated inspection device for use in flexible manufacturing systems and solved the problem using PROMETHEE method. It is usually observed that the automated inspection systems used for mass production transfer lines cannot be successfully used for FMS in view of their limited programming capability and inability to accommodate different part/product types. Increasing demand for large variety of products with higher quality and at lower cost has entrusted new responsibilities to the quality control personnel to augment various automated inspection systems, like coordinate measuring machines (CMM), universal measuring machines, automated vision inspection (AVI) systems, and laser-assisted inspection systems for the flexible manufacturing cell. Choosing an appropriate automated inspection system mainly depends on the characteristics of the manufacturing system as well as the quality control functions to be integrated. This requires detailed consideration and evaluation of a number of feasible alternatives and criteria modeled as an MODM problem. Pandey and Kengpol [19] took into account four alternative automated inspection systems and 11 selection criteria among which accuracy (A), volumetric performance (V), repeatability (R), resolution (S), maintainability (M), reliability (L), throughput rate (T), and flexibility in software interface (F) are the beneficial attributes; on the other hand, initial cost (I), operation cost (O), and environmental factor requirement (E) are non-beneficial in nature. Table 11 shows the quantitative information of this automated inspection system selection problem. The nature of the problem is such that the total number of beneficial attributes is greater than that of non-beneficial attributes for which all the assessment values become positive. Pandey and Kengpol [19] suggested CMM (USA) as the first choice, Laser Scan (Japan) as the second choice, AVI (USA) as the third choice, and CMM (Japan) as the last choice. Using AHP method, Rao [10] determined the criteria weights as w_A=0.2071, w_V=0.0858, w_R=0.2071, w_S=0.0518, w_M=0.0325, w_L=0.0518, w_I=0.0858, w_O= 0.0325, w_T=0.1376, w_E=0.0219, and w_F=0.0858 which are subsequently used for the MOORA-method-based analysis. Table 12 gives assessment values for this automated inspection system selection problem which exhibit that the first choice is CMM (USA), followed by Laser Scan (Japan) proving the acceptability of the MOORA method in solving these types of complex decision-making problems.

4 Results and discussion

It is observed that in comparison to other MODM methods, like AHP, TOPSIS, ELECTRE (ELimination and Et Choice

Table 10 Assessment values for RP process selection problem

RP system	A	R	S	E	C	B	y_i	Rank
SLA3500	0.1777	0.1808	0.7145	0.2735	0.4737	0.4144	−0.0335	2
SLS2500	0.2222	0.3477	0.4397	0.4650	0.4737	0.4144	−0.1113	3
FDM8000	0.1851	0.5842	0.3298	0.5470	0.42287	0.6174	−0.1864	4
LOM1015	0.2740	0.5564	0.2748	0.5470	0.3752	0.3398	−0.1959	5
Quadra	0.1407	0.0974	0.3298	0.3282	0.4737	0.3398	−0.0332	1
Z402	0.8887	0.4312	0.0549	0.0547	0.0859	0.2114	−0.4218	6

Table 11 Quantitative data for automated inspection system selection problem [19]

Criteria	Alternatives			
	CMM (USA)	CMM (Japan)	AVI (USA)	Laser scan (Japan)
Accuracy	90	80	60	75
Volumetric performance	80	70	50	70
Repeatability	80	80	50	70
Resolution	70	70	80	60
Maintainability	60	60	80	70
Reliability	85	80	70	70
Initial cost	40	30	20	25
Operation cost	2	7	1	4
Throughput rate	70	70	80	80
Environmental factor requirement	80	80	60	70
Flexibility in software interface	80	60	60	70

Translating Reality), VIKOR (Vlse Kriterijumska Optimizacija Kompromisno Resenje), PROMETHEE, GRA (gray relational analysis) etc., the MOORA method is very simple to comprehend and easy to implement. As this method is based only on simple ratio analysis, it involves the least amount of mathematical calculations, which may be quite useful and helpful to the decision makers who may not have a strong background in mathematics. Again, because of its minimum computational requirements, the computation time of the MOORA method would obviously be less. Another major advantage of this method is that its calculation procedure is not affected by the introduction of any extra parameter (e.g., v in VIKOR method and ξ is GRA method) as it happens in case of other MODM methods. For this reason, the MOORA method is highly stable for varying decision-making problems.

Table 13 depicts the comparative performance of some of the most widely used MODM methods with respect to their computational time, simplicity, mathematical calculations involved, stability, and type of the information [20]. From this table, it is revealed that in all aspects, the MOORA method clearly outperforms the other MODM methods which proves its universal applicability and flexibility as an effective MODM tool in solving complex decision-making problems in diverse manufacturing environment.

Brauers and Zavadskas [3] identified the following seven conditions to justify the robustness of an MODM method:

1. The MODM method in which all the decision makers are included is more robust than that method in which only one decision maker is involved.

Table 12 Assessment values for automated inspection system selection problem

Criteria	Alternative			
	CMM (USA)	CMM (Japan)	AVI (USA)	Laser scan (Japan)
A	0.5843	0.5194	0.3895	0.4869
V	0.5850	0.5119	0.3656	0.5119
R	0.5629	0.5629	0.3518	0.4925
S	0.4975	0.4975	0.5685	0.4264
M	0.4411	0.4411	0.5882	0.5146
L	0.5554	0.5227	0.4574	0.4574
I	0.6737	0.5053	0.3369	0.4211
O	0.2390	0.8367	0.1195	0.4789
T	0.4656	0.4656	0.5321	0.5321
E	0.5481	0.5481	0.4111	0.4796
F	0.5882	0.4411	0.4411	0.5146
y_i	0.3936	0.3546	0.3264	0.3645
Rank	1	3	4	2

Table 13 Comparative performance of some popular MODM methods

MODM method	Computational time	Simplicity	Mathematical calculations involved	Stability	Information type
MOORA	Very less	Very simple	Minimum	Good	Quantitative
AHP	Very high	Very critical	Maximum	Poor	Mixed
TOPSIS	Moderate	Moderately critical	Moderate	Medium	Quantitative
VIKOR	Less	Simple	Moderate	Medium	Quantitative
ELECTRE	High	Moderately critical	Moderate	Medium	Mixed
PROMETHEE	High	Moderately critical	Moderate	Medium	Mixed

2. The MODM method in which all the non-correlated objectives are considered is more robust than that one in which only a limited number of objectives is taken into consideration.
3. The MODM method in which all the interrelations between objectives and alternatives are taken into account at the same time is more robust than that method in which the interrelations are only examined two by two.
4. The MODM method which is non-subjective is more robust than that one which uses subjective approaches. The normalization procedure affords a subjective solution for comparing different units of various objectives. Consequently, the MODM method which uses non-subjective dimensionless measures, meaning that normalization is not needed, like the MOORA method, is more robust than that method which uses subjective weights.
5. The MODM method based on cardinal numbers is more robust than that one based on ordinal numbers.
6. The MODM method which uses the last recent available data as a base in the decision matrix is more robust than that one based on earlier data.
7. The MOORA method satisfies the first six conditions if non-subjectivity in the choice of the objectives and non-subjectivity in the attribution of importance to an objective are solved.

In this paper, six decision-making problems are considered from real-time manufacturing environment. In all these six problems, the decision matrices are taken from the well-recognized published works of the past researchers, and those have already been solved and validated using other mathematical approaches. These decision matrices also take into account all the possible non-correlated objectives (attributes) that may exist for the given problems. While developing the decision matrices, all the possible interrelations between objectives and candidate alternatives are also taken care of at the same time. All the six decision-making problems (except the NTM process selection problem) mainly deal with non-subjective data which subsequently help to achieve a good ranking performance of the MOORA method. As the given problems (except the NTM process selection problem) have a good amount of cardinal numbers in their decision matrices, the analysis of the MOORA method is also quite stable. Again, as the considered works of the past researchers are quite recent, it can be assumed that the MOORA method uses the latest available data as a base for the initial decision matrices. From the above discussions, it can be concluded that for the six considered decision-making problems, the MOORA method fulfills almost all the conditions as cited by Brauers and Zavadskas [3], and hence, this method would be quite robust under diverse manufacturing environment.

5 Conclusions

The application of the MOORA method is suggested for decision making in the manufacturing environment which helps in selecting the most suitable choice from among a large number of candidate alternatives for a given problem. Six illustrative examples are considered to demonstrate the application of this method. In all the cases, it is observed that the top-ranked alternatives exactly match with those derived by the past researchers. There are slight discrepancies between the intermediate rankings of the alternatives which may be attributed due to the subjective judgments taken by the decision makers. The MOORA method can consider all the attributes along with their relative importance, and hence, it can provide a better accurate evaluation of the alternatives. This method is computationally very simple, easily comprehendible, and robust which can simultaneously consider any number of quantitative and qualitative selection attributes, while offering a more objective and logical selection approach. But it is not so efficient when the decision matrix contains a large number of qualitative attributes. Application of this method in a wider range of selection problems in real-time manufacturing environment remains as a future research scope of this paper.

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