RANKING OF SOME MOST COMMONLY USED NON-TRADITIONAL MACHINING PROCESSES USING ROV AND CRITIC METHODS

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The increased usage of advanced materials in the modern industry has resulted in a wider application of non-traditional machining processes (NTMPs). The right choice of the most appropriate NTMP is critical to the success and competitiveness of a manufacturing company. Selection of the most appropriate NTMP for a given machining application can be viewed as a multi-criteria decision making (MCDM) problem which involves many conflicting criteria. This paper introduces the use of an almost unexplored MCDM method, i.e. range of value (ROV) method for solving the NTMPs selection problems. MCDM model for ranking four NTMPs such as laser beam cutting, plasma arc cutting, abrasive water-jet cutting and oxy-fuel cutting was developed considering nine different techno-economical criteria. In order to determine the relative significance of considered criteria the CRITIC (Criteria Importance through Inter criteria Correlation) method was used. The proposed approach offers objective approach and systematical and relatively simple computational procedure for determination of complete ranking of competitive NTMPs.

Keywords: Non-traditional machining processes, multi-criteria decision making, ROV, CRITIC, ranking.

1. Introduction

In today's industry, a number of non-traditional machining processes (NTMPs) are increasingly being used for machining of a wide spectrum of materials. The NTMPs were developed in response to new and unusual machining requirements that could not be satisfied by conventional machining methods. These requirements and the resulting commercial and technological importance of NTMPs include [1]: (*i*) the need to machine newly developed metals and non-metals (having improved technological properties such as high strength, high hardness, high toughness, etc.), (*ii*) the need for unusual and/or complex part geometries that cannot be easily accomplished and in some cases are impossible to achieve by conventional machining methods, and (*iii*) the need to avoid surface damage that often accompanies the stresses created by conventional machining methods.

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Each NTMP is a complex multi-input/multi-output machining process characterized by its unique process capabilities, advantages and limitations. Although majority of NTMPs can fulfill the requirements of high surface quality, low tolerance, low surface damage, automation, flexibility, productivity etc., the best one for a given machining application may not be equally efficient under other conditions and requirements. Therefore, NTMPs users must assess different, and in some cases opposite criteria, which characterize NTMPs such as material removal rate, accuracy, environmental operating characteristics, material properties, cost, and the existing constraints to select the most appropriate process [2-5]. Moreover, as the price of machine tools for NTMPs is very high it has become more and more important to make proper selection since inadequate selection has long-term consequences on the business of the entire company.

To consistently support the above-mentioned selection and deal with a number of technical and economic criteria different methodologies were proposed in literature. Mourão et al. [2] proposed the use of axiomatic design theory for comprehensive analysis of different NTMPs. However, it was observed from the literature that different multi-criteria decision making (MCDM) methods were predominantly applied to this purpose. Integrated preference ranking organization method for enrichment evaluation (PROMETHEE) and geometrical analysis for interactive aid (GAIA) method [3], analytic hierarchy process (AHP) and technique for order preference by similarity to ideal solution (TOPSIS) methods [4, 6], evaluation of mixed data (EVAMIX) method [5], digraph-based approach [7], analytic network process (ANP) [8], data envelopment analysis (DEA) method [9], fuzzy TOPSIS method [10] and multi-objective optimization on the basis of ratio analysis (MOORA) method [11] were previously applied by past researchers for solving NTMPs selection problems.

Although a good amount of research work was already been carried out by the past researchers on NTMPs selection and ranking, this paper introduces the use of an almost unexplored MCDM method, i.e. the range of value (ROV) method. Till date, this method has very limited applications in the machining domain.

In this paper, firstly a MCDM model for ranking four NTMPs such as laser beam cutting (LBC), plasma arc cutting (PAC), abrasive water-jet cutting (AWJC) and oxy-fuel cutting (OFC) was defined. Nine different techno-economical criteria were included in the MCDM model. In order to determine relative significance of the considered criteria the CRITIC method was used. The proposed approach based on the combination of ROV and CRITIC methods has the advantage of determination of relative significance of criteria i.e. criteria weights using objective approach and systematical and relatively simple computational procedure.

2. Competing methods of cutting

In today's industry LBC, PAC, AWJC and OFC are one of the most commonly used NTMPs. These processes are widely used for cutting flat sheet and plate material as well as to trim formed parts. They are particularly used for processing difficult-to-machine materials such as titanium, stainless steel, high-strength temperature-resistant alloys, ceramics, composites, super alloys, etc.

From the technological point of view, each of these NTMPs is a very complex machining process governed by a large number of machining parameters (input variables). A unique characteristic of these processes is that there is no direct contact between the tool and the workpiece, as well as the ability to concentrate large amounts of energy per unit area. The non-contact nature of NTMPs means that there is no tool wear, no tool storage costs, no tool setup time, no deformation of the cut surface and no slippage with only light fixturing [12].

Although these cutting technologies offer many advantages, there are some drawbacks and limitations. For instance, AWJC can produce tapered edges on the kerfs of workpiece being cut. Similarly, inadequate selection of processing parameters may result in burr and heat affected zone (HAZ) formation in LBC. These and other examples can limit the potential applications of NTMPs particularly if post-processing is needed in order to achieve the requirements of the finished part.

2.1. Plasma arc cutting

The objective of the PAC is to concentrate a large amount of energy on a small surface of a workpiece which leads to intensive heating of the material surface. The source of energy is high temperature and high speed ionized gas. The gas is ionized using a direct current passing between the cathode (inside the nozzle) and anode (workpiece). The plasma jet cuts the material by releasing the energy spent for the plasma gas ionization upon hitting the workpiece surface. The removal of the melted material from the cutting zone is done by the action of plasma jet kinetic energy [13]. PAC is used for electrically conductive materials, and is particularly useful for metals with high thermal conductivity because of the concentrated energy input [12].

2.2. Abrasive water jet cutting

AWJC uses a jet of high pressure and velocity water and abrasive particles to cut the material by means of erosion. High-pressure water starts at the pump, and is delivered through special high-pressure plumbing to the orifice in cutting head. The water jet exits an orifice at a very high speed. In the mixing chamber of the cutting head, the abrasive particles are introduced and injected into the jet stream. The jet stream of water and abrasive particles, focused by focusing tube, exits the cutting head, impinges onto the material and does the required action of cutting [14]. The top of the cut is smooth because of the high energy of the jet, but becomes rougher and striated lower in the workpiece because abrasive particles are scattered [12].

2.3. Laser beam cutting

LBC is the process of melting or vaporizing material in a very small, well-defined area. The processes of heating, melting, and evaporation are produced by the laser beam, affecting a workpiece surface. Laser beam is a cutting tool able to cut almost all materials, focused into a very small spot of 0.1…0.2 mm in diameter concentrating thousands of watts. The power density for cutting steels is typically 10^5-10^6 MW/m^2 [15]. The high power density of the focused laser beam in the spot melts or evaporates material in a fraction of a second, and coaxial jet of an assist gas removes the evaporated and molten material from the cutting zone. Depending on the workpiece material, the assisting gas can be inert (helium, argon, etc.) or reactive (oxygen). Inert gas is used when cutting plastics, wood, etc., whilst oxygen is employed when cutting metals, those metals where oxidation of the metal can provide extra heat [16].

2.4. Oxy-fuel cutting

OFC or flame cutting is an economical method for cutting steel that provides good dimensional tolerances. Using gases, acetylene and oxygen, to produce a controlled flame, this technology cheaply burns through carbon steel and most alloys, producing near-net shapes with relative ease. OFC is a chemical reaction between pure oxygen and steel to form iron oxide. The commonly used cutting torch provides a hot flame to preheat the steel (to its “kindling temperature” of around 480º C), but this flame does not do the actual cutting. This is done by a high pressure jet of pure oxygen, which is delivered at the center of the preheat flame. As a result of rapid combustion process, burning steel leaves behind molten material called slag, which is basically iron oxide. Steel is unique because the slag it creates melts at a slightly lower temperature than the parent metal. The slag is formed as a liquid in the heat of combustion and is easily blown away as a fine spray when aided by the flow of more oxygen. This is a key factor, which allows the uncut metal to remain intact, with a smooth, square cut face, while letting the cut continue and burn adjacent material [17]. Only metals whose oxides have a lower melting point than the base metal itself can be cut with this process. Otherwise as soon as the metal oxidizes it terminates the oxidation by forming a protective crust. Only low carbon steel and some low alloys meet the above condition and can be cut effectively with the OFC [18].

2.5. Comparison of competitive NTMPs

Comparing the above-mentioned NTMPs, Ion [12] highlighted a few rules of thumb that can be applied when considering process selection:

- LBC normally provides the best combination of quality and productivity with homogeneous materials less than about 3 mm in thickness, when the equipment is in use for at least 16 hours per day.
- Thicker materials may be cut more quickly with PAC at the expense of edge quality.
- OFC is preferred for one-off jobs or short production runs in which quality is not of prime importance.
- Non-thermal cutting methods such as AWJC are more suitable for composite and inhomogeneous materials, but they are relatively slow.

A comparison of NTMPs requires both technical and economic criteria to be considered. Naturally, if the required technical quality can be achieved by using several processes, then the one with the lowest cost is chosen. Similarly, if the cost of using different processes is similar, then the one providing the highest quality is the preferred option. The techno-economical features of PAC, AWJC, LBC and OFC are given in Table 1 [12].

Table 1

Typical techno-economical features of cutting processes [12]

	M	MT (steel, mm)	MKW (mm)	HAZ (mm)	EQ (relative)	SHD (mm)	EI (relative)	CS (relative)	P (relative)
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
LBC	all homogenous	30	0.1	0.05	square, smooth	0.5	low	1	high
AWJC	all homogenous	100	0.7	0	square, smooth	1.5	low	1	medium-low
PAC	metallic	50	1	0.4	beveled	1.5	high	0.1	medium
OFC	metallic	300	2	0.6	square, rough	20	medium	0.01	low

M – materials, Max thickness – MT, Minimal kerfs width – MKW, Heat affected zone – HAZ, Edge quality – EQ, Smallest hole diameter – SHD, Energy input – EI, Capital cost – CS, Productivity – P

3. Range of value method

The ROV method was proposed by Yakowitz et al. [19]. The procedure of the application of the ROV method is simple and consists of the following steps:

Step 1: The ROV method starts with setting the goals and identification of the relevant criteria for evaluating available alternatives.

Step 2: In this step, based on the available information about the alternatives, decision-making matrix or decision table is set. Each row refers to one alternative, and each column to one criterion. The initial decision matrix, X, is:

$$X = \left[x_{ij} \right] = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \tag{1}$$

where x_{ij} is the performance measure of i-th alternative with respect to j-th criterion, m is the number of alternatives and n is the number of criteria.

Step 3: In this step performance measures of alternatives are normalized – defining values $\bar{x}_{ij}$ of normalized decision-making matrix $\bar{X}$.

$$\bar{X} = \left[\bar{x}_{ij} \right]_{m \times n} = \begin{bmatrix} \bar{x}_{11} & \bar{x}_{12} & \dots & \bar{x}_{1n} \\ \bar{x}_{21} & \bar{x}_{22} & \dots & \bar{x}_{2n} \\ \dots & \dots & \dots & \dots \\ \bar{x}_{m1} & \bar{x}_{m2} & \dots & \bar{x}_{mn} \end{bmatrix} \tag{2}$$

For beneficial criteria, whose preferable values are maximal, normalization is done by using linear transformation [20]:

$$\bar{x}_{ij} = \frac{x_{ij} - \min_{i=1}^{m}\left(x_{ij}\right)}{\max_{i=1}^{m}\left(x_{ij}\right) - \min_{i=1}^{m}\left(x_{ij}\right)} \tag{3}$$

For non-beneficial criteria, whose preferable values are minimal, normalization is done by:

$$\bar{x}_{ij} = \frac{\max_{i=1}^{m}\left(x_{ij}\right) - x_{ij}}{\max_{i=1}^{m}\left(x_{ij}\right) - \min_{i=1}^{m}\left(x_{ij}\right)} \tag{4}$$

Step 4: The application of the ROV method involves the calculation of the best and worst utility for each alternative. This is achieved by maximizing and minimizing a utility function. For a linear additive model, the best utility (u_i^+) and the worst utility (u_i^-) of i-th alternative are obtained using the following equations [20]:

$$\text{Maximize}: u_i^+ = \sum_{j=1}^{n} \bar{x}_{ij} \cdot w_j \tag{5}$$

$$\text{Minimize}: u_i^- = \sum_{j=1}^{n} \bar{x}_{ij} \cdot w_j \tag{6}$$

where w_j (j=1,...,n) are criteria weights which satisfy $\sum_{j=1}^{n} w_j = 1$ and $w_j \geq 0$.

If $u_i^- > u_{i'}^+$, then alternative i outperforms alternative i' regardless of the actual quantitative weights. If it is not possible to differentiate the alternatives on this basis then a scoring (enabling subsequent ranking) can be attained from the midpoint, which can be calculated as [20]:

$$u_i = \frac{u_i^- + u_i^+}{2} \tag{7}$$

Step 5: In this final step the complete ranking of the alternatives is obtained on the basis of u_i values. Thus, the best alternative has the highest u_i value and the worst alternative has the lowest u_i value.

4. CRITIC method

Criteria weights are affected as much from characteristics of the criteria as from subjective point of view of the decision makers. Such subjective weighting of the criteria is usually shaped by the decision makers experience, knowledge and perception of the problem. However this leads to doubt about reliability of the results. To overcome such problems, objective weighting approaches are used [21].

CRITIC method, which was proposed by Diakoulaki et al. in 1995 [22], is objective method for determination of criteria weights which includes the intensity of the contrast and the conflict that is contained in the structure of the decision making problem. It belongs to the class of correlation methods and is based on the analytical examination of decision matrix to determine the information contained in the criteria by which the alternatives are evaluated. To determine the criteria contrast the standard deviation of normalized criterion values by columns and the correlation coefficients of all pairs of columns are used [23].

Consider a initial decision matrix, $X = \left[x_{ij}\right]_{m \times n}$, where x_{ij} is the performance measure of i-th alternative with respect to j-th criterion, m is the number of alternatives and n is the number of criteria. The first step in the application of the CRITIC method is to normalize the initial decision matrix using the following equation:

$$r_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \tag{8}$$

where: $x_j^{\max} = \max\left(x_{ij}, i = 1,...,m\right)$ and $x_j^{\min} = \min\left(x_{ij}, i = 1,...,m\right)$.

In the process of criteria weights determination both standard deviation of the criterion and its correlation between other criteria are included. In this regard, the weight of the j-th criterion w_j is obtained as [21, 23]:

$$w_j = \frac{C_j}{\sum_{i=1}^{m} C_i} \tag{9}$$

where C_j is the quantity of information contained in j-th criterion determined as:

$$C_j = \sigma_j \sum_{i=1}^{m} \left(1 - r_{ij}\right) \tag{10}$$

where σ_j is standard deviation of the j-th criterion and r_{ij} is the correlation coefficient between the j-th and i-th criteria.

Based on the above analysis, it can be concluded that higher value of C_j implies a greater amount of information that is obtained from the given criterion, and thus the relative significance of the criterion for a given decision making problem is higher [23].

5. Results and discussion

In this section the application of the combined ROV-CRITIC approach for ranking NTMPs considering nine different techno-economical criteria was discussed.

It could be seen that four techno-economical features of NTMPs i.e. materials, edge quality, energy input and productivity are expressed in linguistic terms. Therefore, prior to the application of the ROV and CRITIC methods one need to convert these linguistic terms into crisp (real) values. In this paper this was performed in the range [0, 1] using the 11 point fuzzy scale [24]. Also, it has to be noted that among the techno-economical features i.e. selected criteria, materials, maximal thickness, edge quality and productivity are beneficial criteria where higher performance values are preferred. On the other hand, minimal kerf width, HAZ, smallest hole diameter, energy input and capital cost belong to the category of non-beneficial attributes where smaller performance values are preferred.

5.1. Criteria weights determination

In this section the application of the CRITIC method for criteria weights determination is discussed. First, the normalized decision matrix (Table 2), created by means of r_{ij} values, was developed according to Eq. 8. Here it should be noted that normalization does not take into account the type of criteria (beneficial or non-beneficial).

Then for all criteria, values of standard deviations were obtained as: σ_j=(0.474; 0.458; 0.418; 0.478; 0.491; 0.484; 0.479; 0.471; 0.449). The values of correlation coefficient are then calculated (Table 3).

Finally, using Eqs. 9 and 10, criteria weights are determined as: **w**=(0.123; 0.094; 0.087; 0.103; 0.125; 0.099; 0.114; 0.132; 0.124).

Table 2

Normalized decision matrix by CRITIC method

	M	MT (steel, mm)	MKW (mm)	HAZ (mm)	EQ (relative)	SHD (mm)	EI (relative)	CS (relative)	P (relative)
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
LBC	0.425	0	0	0.083	1	0	0	1	1
AWJC	1	0.259	0.316	0	1	0.051	0	1	0.183
PAC	0	0.074	0.474	0.667	0	0.051	1	0.684	0.622
OFC	0	1	1	1	0.396	1	0.5	0	0
M – materials, Max thickness – MT, Minimal kerfs width – MKW, Edge quality – EQ, Smallest hole diameter – SHD, Energy input – EI, Capital cost – CS, Productivity - P									

Table 3

Correlation coefficient values of criteria

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	1	-0.332	-0.542	-0.865	0.820	-0.497	-0.785	0.700	-0.055
C_2	-0.332	1	0.908	0.710	-0.213	0.979	0.113	-0.903	-0.824
C_3	-0.542	0.908	1	0.889	-0.586	0.903	0.504	-0.949	-0.808
C_4	-0.865	0.710	0.889	1	-0.809	0.796	0.743	-0.939	-0.452
C_5	0.820	-0.213	-0.586	-0.809	1	-0.300	-0.994	0.566	0.154
C_6	-0.497	0.979	0.903	0.796	-0.300	1	0.198	-0.955	-0.700
C_7	-0.785	0.113	0.504	0.743	-0.994	0.198	1	-0.477	-0.085
C_8	0.700	-0.903	-0.949	-0.939	0.566	-0.955	-0.477	1	0.625
C_9	-0.055	-0.824	-0.808	-0.452	0.154	-0.700	-0.085	0.625	1

5.2. Application of the ROV method

Now the step by step application procedure of the ROV method for ranking of the most commonly used NTMPs is as follows. Firstly, by using Eqs. 3 and 4 for beneficial and non-beneficial criteria, respectively, the normalized decision-making matrix is obtained (Table 4). Subsequently, by using Eqs. 5 and 6 the best and the worst utility functions for each NTMP were calculated. Finally, the u_i values of all NTMPs with respect to the considered criteria were estimated by using Eq. 7. Table 5 exhibits results of the ROV method upon which complete ranking of the NTMPs was obtained.

Table 4

Normalized decision matrix by the ROV method

	M	MT (steel, mm)	MKW (mm)	HAZ (mm)	EQ (relative)	SHD (mm)	EI (relative)	CS (relative)	P (relative)
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
LBC	0.425	0	1	0.917	1	1	1	0	1
AWJC	1	0.259	0.684	1	1	0.949	1	0	0.183
PAC	0	0.074	0.526	0.333	0	0.949	0	0.316327	0.622
OFC	0	1	0	0	0.396	0	0.5	1	0
M – materials, Max thickness – MT, Minimal kerfs width – MKW, Edge quality – EQ, Smallest hole diameter – SHD, Energy input – EI, Capital cost – CS, Productivity - P									

Table 5

Computational details of the ROV method and NTMPs rankings

NTMPs	u_i^+	u_i^-	u_i	Rank
LBC	0.3003	0.3946	0.3474	1
AWJC	0.2942	0.3706	0.3324	2
PAC	0.0838	0.2161	0.1500	4
OFC	0.1431	0.1891	0.1661	3

As could be seen from Table 5 by applying ROV and CRITIC methods, the ranking of the most commonly used NTMPs is obtained as LBC-AWJC-OFC-PAC. LBC is observed to be the best NTMP as it provides a unique solution to a manufacturing requirement considering the techno-economical features. AWJC has the second preference and based on the utility function it is observed that this NTMP, considering selected techno-economical features, is similar to LBC. PAC and OFC are observed as the least favored NTMPs having much smaller utility values.

6. Conclusions

Selection of the most appropriate NTMP for a given machining application is complex MCDM problem involving a set of different and opposite criteria. A large number of mathematical methods and procedures were proposed previously to assist in systematical selection and ranking of competitive NTMPs. In this paper, an approach based on the combination of ROV and CRITIC methods was proposed for solving NTMPs selection and ranking problems. Firstly a MCDM model for ranking four NTMPs considering nine different techno-economical criteria was defined. The CRITIC method was applied in order to determine relative significance of criteria in an objective manner. Subsequently, the ROV method was applied in order to obtain complete ranking of the competitive NTMPs which in descending order was obtained as LBC-AWJC-OFC-PAC.

The ROV method can simultaneously take into account any number of criteria and offer a very simple computational procedure. In combination with fuzzy scales it can also deal with qualitative criteria. Moreover, this method requires least amount of mathematical computations. On the other hand CRITIC method ensures objective determination of criteria weights which eliminates subjective point of view of the decision maker, its experience, knowledge and perception of the decision making problem.

All mathematical calculations of the combined approach can be easily implemented in MS Excel thus eliminating the need of using specialized MCDM software packages. Also it has to be noted that the calculation procedure is not affected by the introduction of any additional parameters as it happens in the case of some other MCDM methods.

Different problems in manufacturing environment such as selection of machining center, selection of design, selection of cutting tools, cutting strategies etc. are just some typical examples in which the proposed approach as well as other MCDM methods and approaches can be effectively applied.

Application of this combined approach in a wider range of MCDM problems in real-time manufacturing environment and development of decision support systems are future research scopes. Also, for further research, the results of this study can be compared with that of other MCDM methods.

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