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A FUZZY BASED DECISION SUPPORT MODEL FOR NON-TRADITIONAL MACHINING PROCESS SELECTION

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Original scientific paper
Usages of non-traditional machining processes are rapidly increasing together with increases in demand and usage of high strength, temperature resistant and complex materials. Due to their advantages such as cutting speed, surface quality and economizing, they became a vital process of manufacturing. Because of the conflicting criteria, the selections of appropriate non-traditional machining process highly require usage of multi criteria decision making methods. This study provides distinct systematic approaches both in fuzzy and crisp domain to deal with the selection problem of appropriate non-traditional machining process and proposes a decision support model for forth leading decision makers to assess potentials of distinct non-traditional machining processes. The required data for decision matrices is obtained via a questionnaire to specialists as well as deep discussions with experts, making use of past studies, and experimentally. An application of the proposed model is also performed to show the applicability of the model.

Keywords: *fuzzy logic, non-traditional machining processes, multi-criteria decision making, TOPSIS*

Model za pomoć kod donošenja odluka, zasnovan na neizrazitoj logici, u primjeni pri odabiru ne-tradicionalog postupka strojne obrade

Izvorni znanstveni članak
Primjena ne-tradicionalnih procesa obrade naglo se povećava, zajedno s povećanjem potražnje i korištenja složenih materijala visoke čvrstoće, otpornih na temperaturu. Zbog svojih prednosti, kao što su brzina rezanja, kvaliteta površine i ekonomičnosti, oni su postali vitalni proces proizvodnje. Zbog sukobljenih kriterija, izbor odgovarajuće ne-tradicionalne strojne obrade uveliko zahtijeva korištenje metoda višekriterijskog odlučivanja. Ovaj rad pruža različite sustavne pristupe kako u području neizrazite tako i čvrste logike kod odabira odgovarajućeg ne-tradicionalnog postupka strojne obrade i predlaže model za podršku odlučivanju vodećih donositelja odluka u procjeni potencijala različitih ne-tradicionalnih procesa obrade. Potrebni podaci za matrice u odlučivanju dobivaju se putem upitnika za stručnjake, temeljitim raspravama sa ekspertima, korištenjem postojećih radova i eksperimentalno. Primjena predloženog modela također je izvedena kako bi se pokazala njegova primjenljivost.

Ključne riječi: *multi-kriteriji za donošenje odluka, neizrazita logika, ne-tradicionalni obradni postupci, TOPSIS*

1 Introduction

Decision making, which is defined as the procedure to find the best alternative among a set of feasible ones [1], is one of the vital activities of mankind. As this complex process includes many parameters the complexity of the process rises as the number of inputs needed for the process increases. According to the concept of restricted rationalism, the capacity of a human is limited in the solution and formulation of complex problems. As a result, requirements let multi criteria decision making (MCDM) methods appear. These methods help decision makers in improving the quality of decisions by making the process more explicit, rational, and efficient. They are powerful tools used for problems featuring high uncertainty, conflicting objectives, multi interests, and perspectives [2].

Advances in industries like nuclear reactors, automobiles, missiles, and turbines require high strength and temperature resistant alloys. This requirement forced scientists in the field of material science to develop higher strength materials. However, in the course of time traditional machining processes began to become insufficient to produce complex shapes while working on strengthened materials such as titanium and stainless steel. Consequently, increase in the strength of work material triggered the requirement for cutting tools to be harder. In the course of time, this process let non-traditional machining (NTM) processes appear. NTM processes are characterized by the presence of a large number of viable alternatives, uncertainties concerning the process capabilities, and shortage of the experienced planners [3]. In this context, the ill-structured and multi criteria nature of the NTM process selection problems concluded MCDM methods to be used widely [3 ÷ 7].

The purpose of this study is to propose a decision support model which may be used for selecting the best NTM process option for cutting operations of a specific material. Criteria for the proposed model and weights representing the importance of each criterion were identified via questionnaires to specialists, deep discussions with experts, and making use of past studies. The rest of the study is as follows. In the second section, research methods are introduced. In the third section the proposed decision support model is introduced and an application is performed. Finally, conclusions and further recommendations are highlighted in the last section.

2 Research methods: TOPSIS and fuzzy TOPSIS

In this study, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is used as a decision support tool both in crisp and fuzzy domain. In this section, TOPSIS, fuzzy set theory, and Fuzzy TOPSIS methods are explained briefly.

2.1 TOPSIS

TOPSIS is developed by Yoon and Hwang in 1980. This method is preferable due to its following specifications [8, 9]:

- simple computation procedure
- its easily understandable logic
- weights illustrating the importance are incorporated into the procedure.

Ideal solution is the choice of the best performances in each criterion so that the alternative nearest to the ideal solution is to be preferred. TOPSIS uses the concepts of Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) to determine the best alternative that is nearest to the ideal solution. While PIS maximizes the benefit and minimizes the cost criteria, NIS maximizes the cost and minimizes the benefit criteria [8]. So, the method emphasizes that the best alternative is the one nearest to the PIS and furthermost to the NIS [10]. The algorithm of TOPSIS can basically be described as follow:

Step 1: Create Decision (*A*) and Weight (*W*) Matrices: At the beginning, the decision matrix which consists of three components has to be determined. These components are alternatives defined by $a_1, a_2, ..., a_i, a_m$; criteria defined by $c_1, c_2, ..., c_j, c_n$ and performance values defined by a_{ij} (i = 1, 2, ..., m) (j = 1, 2, ..., n). Additionally, weight matrix which has the weights defined for each criterion, $w_1, w_2, \ldots, w_j, w_n$, has to be created. The sum of the weights must be 1 after normalization process.

Step 2: Convert Criteria to the Same Type: Conversion of the predetermined criterion can be provided by computing the inverse of each performance value found in that criterion's column.

Step 3: Create Normalized Decision Matrix (*X*): The normalized decision matrix can be created according to Eq. (1) to make the data dimensionless.

$$x_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}}. \tag{1}$$

Step 4: Create Weighted Normalized Decision Matrix: The weighted normalized decision matrix can be created according to Eq. (2).

$$y_{ij} = x_{ij} \cdot w_j. \tag{2}$$

Step 5: Determine Positive and Negative Ideal Solutions: If c_1 and c_2 are benefit and cost criteria respectively, positive and negative ideal solutions can be determined with Eqs. (3) and (4).

$$P_j^+ (\max p_{ij}, J \in c_1; \min p_{ij}, J \in c_2), \tag{3}$$

$$P_j^- (\min p_{ij}, J \in c_1; \max p_{ij}, J \in c_2), \tag{4}$$

Step 6: Calculate Separation Measures: The positive and negative ideal separation measures, S_i^* and S_i^- respectively, can be calculated with Eqs. (5) and (6).

$$S_i^* = \sqrt{\sum_{j=1}^{n} (y_{ij} - y_j^*)^2}, \tag{5}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (y_{ij} - y_j^-)^2}. \tag{6}$$

Step 7: Calculate Relative Closeness to the Ideal Solution: The relative closeness to the ideal solution, C_i^*, for each alternative can be calculated according to Eq. (7).

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*}, \tag{7}$$

where $0 \le C_i^* \le 1$ and $i = (1, 2, 3, ..., m)$.

Step 8: Rank Preference Order: Finally, the alternative with the highest C_i^* represents the best choice.

2.2 Fuzzy Sets Theory in MCDM

Fuzzy set theory, which provides the basis for the fuzzy logic (FL), is introduced by L. A. Zadeh and can be defined as "a class of objects with a continuum of grades of membership" [11]. FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information [3]. In MCDM data is often imprecise and due to its ability arising from the fuzzy sets, the fuzzy set theory easily copes with these kinds of indefiniteness [3, 12].

2.3 Fuzzy TOPSIS

Principal steps of fuzzy TOPSIS method can be described as follows:

Step 1: Create Decision (*A*) and Weight (*W*) Matrices

Step 2: Convert Criteria to the Same Type

Step 3: Create Fuzzy Decision ($\widetilde{A}$) and Weight ($\widetilde{W}$) Matrices: Criteria are divided into two groups as objective and subjective criteria [13]. "Error rate" term is defined to fuzzify the crisp terms into triangular fuzzy numbers (TFNs) in decision and weight matrices. Considering a TFN is formed by a triplet $\{\tilde{a} = (a_1, a_2, a_3)\}$, the most extreme values and the middle one can be computed according to Eq. (8).

$$\begin{aligned} a_1 &= (crisp\ \ data) - (crisp\ \ data) * (error\ \ rate/100) \\ a_2 &= (crisp\ \ data) \\ a_3 &= (crisp\ \ data) + (crisp\ \ data) * (error\ \ rate/100) \end{aligned} \tag{8}$$

Step 4: Create Normalized Fuzzy Decision Matrix ($\widetilde{X}$) : The normalized fuzzy decision matrix is created as follows:

For benefit criteria:

- Determine the highest value of a_3's in that column and equalize it to x^*.
- The normalized value of $\tilde{a} = \left(\frac{a_1}{x^*}, \frac{a_2}{x^*}, \frac{a_3}{x^*} \right)$.

For cost criteria:

- Determine the smallest value of a_1's in that column and equalize it to x^*.

- The normalized value of $\tilde{a}=\left(\frac{x^*}{a_3},\frac{x^*}{a_2},\frac{x^*}{a_1}\right)$.

Step 5: Create Weighted Normalized Fuzzy Decision Matrix ($\tilde{Y}$): Each fuzzy performance value, $\{\tilde{a}_{ij}(i=1,2,3,...,m)(j=1,2,3,...,n)\}$, has to be multiplied with fuzzy weight, $\{\tilde{w}_j(j=1,2,3,...,n)\}$, to obtain weighted normalized fuzzy decision matrix.

Step 6: Determine Fuzzy Positive and Fuzzy Negative Ideal Solution Sets: Fuzzy positive ideal reference point, A^+ and fuzzy negative ideal reference point, A^- are defined with Eqs. (9) and (10).

$$A^+=\left(\tilde{v}_1^+,\tilde{v}_2^+,...,\tilde{v}_n^+\right) \tag{9}$$

$$A^-=\left(\tilde{v}_1^-,\tilde{v}_2^-,...,\tilde{v}_n^-\right), \tag{10}$$

where $\tilde{v}_j^+=(1,1,1)$ and $\tilde{v}_j^-=(0,0,0)$; $j=1,2,...,n$.

Step 7: Calculate Separation Measures: Vertex method can be used to compute the distance between fuzzy numbers [14]. If $\tilde{n}=(n_1,n_2,n_3)$ and $\tilde{m}=(m_1,m_2,m_3)$ are two TFNs then the distance between them is calculated according to Eq. (11).

$$d(\tilde{n},\tilde{m})=\sqrt{\frac{1}{3}\left[(n_1-m_1)^2+(n_2-m_2)^2+(n_3-m_3)^2\right]}. \tag{11}$$

Step 8: Calculate Relative Closeness to the Ideal Solution

Step 9: Rank Preference Order

3 Proposed decision support model and an application to machining process selection

3.1 Proposed Decision Support Model

Oxy-fuel, laser, and plasma machining processes are the most common NTM processes. Additionally, water jet and abrasive water jet are the most rapidly improving technological methods of machining materials [15, 16, 17]. Therefore, in this study concern is focused on these five alternatives. Determination of criteria for the proposed decision support model was done via questionnaires filled by specialists as well as deep discussions with experts studying at the Faculty of Manufacturing Technologies of The Technical University of Kosice, and making use of the past studies. This study considers the following seventeen criteria that usually influence the appropriate machining process selection decision.

Operational Cost (OC): Expenses related to the operation of the machining process or to the operation of the machining device, equipment, facility, or etc.

Initial Cost (IC): Expenses incurred on the purchase of facility and equipment to be used in the production of goods.

Technology Set Up (TSU): It is related to the space needed to operate the machining technology.

Depth of Thermal Effect (DTE): Field in mm. where heat comes out after the machining process.

Waviness (W): It corresponds to the rough cutting zone of the work piece created by the machining technology as a result of the lost kinetic energy.

Surface Roughness (SR): It is the texture of created surface.

Vibration (V): It refers to mechanical oscillations about an equilibrium point which is undesirable because it wastes energy and creates unwanted sound-noise.

Noise (N), Air Pollutants (AP), Radiation (R), Safety (S), Human Health (HH): It is related to the safety of the machine operators. It also considers the toxicity, machining medium contamination, and other adverse and hazardous effects of the machining process [3, 5].

Cutting Speed (CS): It is related to the measurement of the cutting speed in m/min. for the machining technology.

Simplicity of Operation (SO): It corresponds to the simplicity of the machining technology measured by required materials, number of personnel, education level and etc.

Cut on Any Spot (ESCAS): This criterion considers the ability of the machining technology if it can start or end the process in any point of the work piece.

Process Control (PC): This criterion considers the possibility of process control of machining technology such as manual mode, auto mode, programmable mode, on-line programmable mode and etc.

Usability/Flexibility (UF): This criterion considers the flexibility of cutting equipment in various conditions such as space, temperature, mobility etc.

Fig. 1 illustrates the proposed model including criteria and alternatives. Among these criteria, DTE (mm), SR (μm), and CS (m/min) are objective criteria which are obtained experimentally with the contribution of Assoc. Prof. Sergej Hloch, a colleague working at the Faculty of Manufacturing Technologies of Technical University of Kosice while OC, IC, TSU, W, V, N, AP, R, S, HH, SO, ESCAS, PC, and UF are subjective criteria which are evaluated on a scale of 1-10 by specialists and experts in this field. Additionally; S, HH, CS, SO, ESCAS, PC, and UF are benefit criteria while OC, IC, TSU, DTE, W, SR, V, N, AP, and R are cost criteria.

3.2 Application

AISI 309 stainless steel is chosen for evaluation of each alternative in terms of each criterion. AISI 309 is a heat resistant alloy with oxidation resistance to 19000 F. The high chromium and relatively low nickel content of the material provides good resistance to high temperature. Some features of this material are moderate strength at high temperature, ease of fabrication, and good weldability. The chemical composition of AISI 309 is given in Tab. 1 [18, 19]. Determination of the weights concerning each criterion, error rate, and performances of alternatives in terms of each criterion except DTE, SR, and CS was done via a questionnaire filled by specialists as well as deep discussions with experts working at the Faculty of Manufacturing Technologies of Technical University of Kosice. On the other hand, performances of alternatives in terms of DTE, SR, and CS criteria were obtained experimentally with the contribution of Assoc. Prof. Sergej Hloch. Error rate in this study is assumed as 10 %. The developed decision matrix is illustrated in Tab. 2.

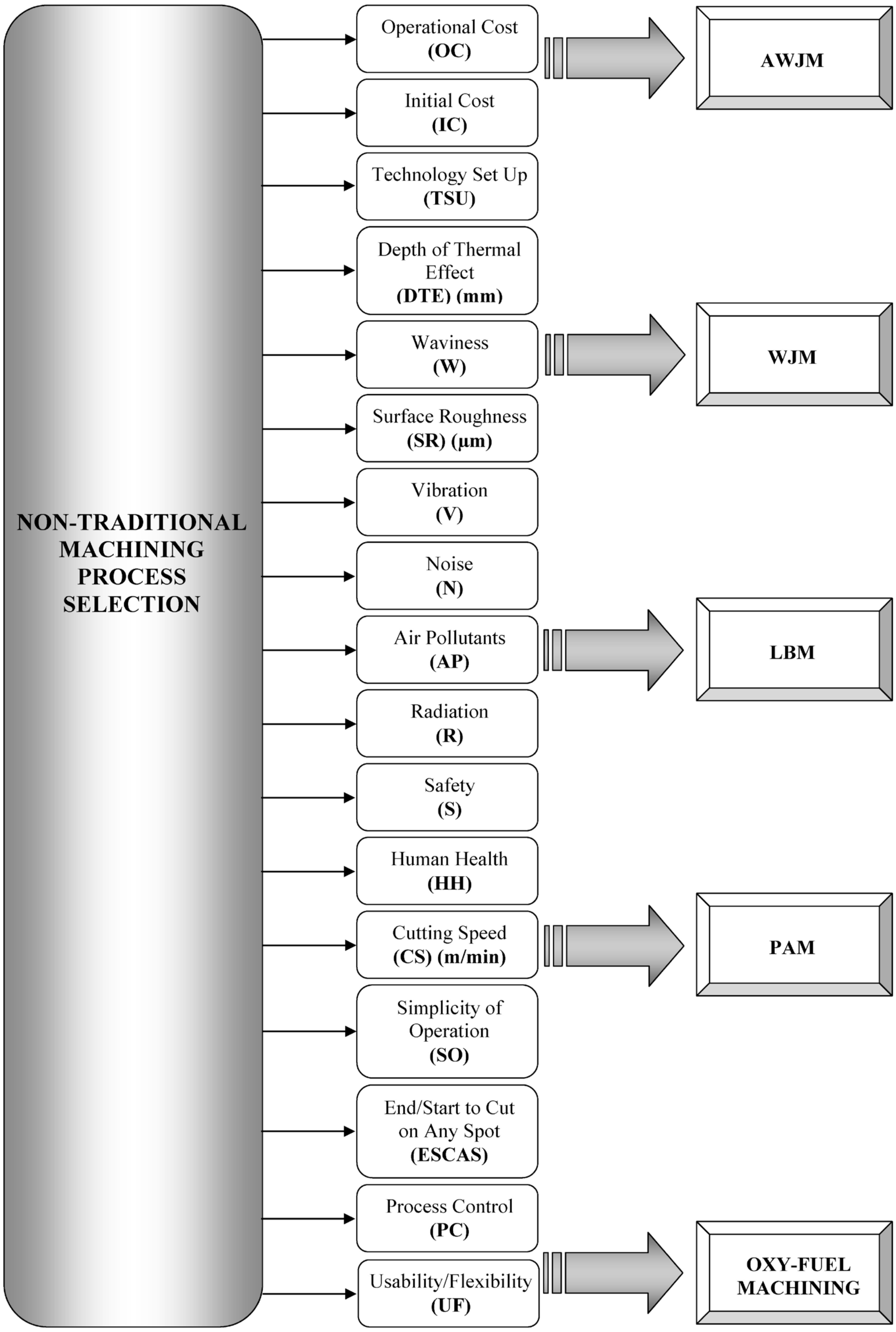

Figure 1 Proposed decision support model

Table 1 Chemical composition of AISI 309 [19] (in wt. %)

	Cr	Ni	C	P	S	Mn	Si
MIN	22	12	-	-	-	-	-
MAX	24	15	0,200	0,045	0,030	2	1

Table 2 Decision matrix

ALT./CRI.	S	HH	CS	SO	ESCAS	PC	UF	OC	IC	TSU	DTE	W	SR	V	N	AP	R
LBM	4	5	0,375	9	9	9	3	5	4	5	0,600	4	0,125	2	1	8	8
AWJM	6	7	1,500	9	10	9	4	3	2	3	10^{-5}	3	6,500	6	8	4	1
WJM	6	7	0,050	9	9	9	5	3	2	3	10^{-5}	4	0,500	6	7	3	2
PAM	2	2	5	8	8	8	1	2	2	4	0,500	8	300	7	9	9	6
O-FUEL	5	5	1	8	8	8	7	5	4	5	5	8	500	3	7	6	4
WEIGHTS	10	10	10	10	8	8	1	10	8	7	10	10	10	8	8	8	9

Machining Process Selection with TOPSIS: Cost criteria in the decision matrix shown in Tab. 2 are converted to benefit criteria. The reconstructed decision matrix is presented in Tab. 3. Determined weights shown in Tab. 2 are normalized and presented in Tab. 4 within the normalized decision matrix which is constructed according to Eq. (1). The weighted normalized decision matrix shown in Tab. 5 is constructed according to Eq. (2). Equations (5), (6) and (7) are used to determine positive ideal solution, negative ideal solution, and relative closeness to the ideal solution for each alternative shown in Tab. 6.

Machining Process Selection with Fuzzy TOPSIS: The decision matrix shown in Tab. 2 and the weight matrix shown in Tab. 4 (last row of the table) are fuzzified according to Eq. (8). The fuzzy decision matrix and fuzzy weight matrix are presented in Tab. 7. The normalized fuzzy decision matrix and the weighted normalized fuzzy decision matrix are presented in Tab. 8 and Tab. 9, respectively. Finally, Equations (11) and (7) are used to determine positive ideal solution, negative ideal solution, and relative closeness to the ideal solution for each alternative shown in Tab. 10.

Table 3 Reconstructed decision matrix

ALT./CRI.	S	HH	CS	SO	ESCAS	PC	UF	OC	IC	TSU	DTE	W	SR	V	N	AP	R
LBM	4	5	0,375	9	9	9	3	0,200	0,250	0,200	1,667	0,250	8	0,500	1	0,125	0,125
AWJM	6	7	1,500	9	10	9	4	0,333	0,500	0,333	10^5	0,333	0,154	0,167	0,125	0,250	1
WJM	6	7	0,050	9	9	9	5	0,333	0,500	0,333	10^5	0,250	2	0,167	0,143	0,333	0,500
PAM	2	2	5	8	8	8	1	0,500	0,500	0,250	2	0,125	0,003	0,143	0,111	0,111	0,167
OXY-FUEL	5	5	1	8	8	8	7	0,200	0,250	0,200	0,200	0,125	0,002	0,333	0,143	0,167	0,250

Table 4 Normalized decision matrix

ALT./CRI.	S	HH	CS	SO	ESCAS	PC	UF	OC	IC	TSU	DTE	W	SR	V	N	AP	R
LBM	0,370	0,406	0,070	0,467	0,456	0,467	0,300	0,269	0,267	0,331	$1,2\times10^{-5}$	0,483	0,970	0,756	0,967	0,261	0,107
AWJM	0,555	0,568	0,282	0,467	0,506	0,467	0,400	0,449	0,535	0,552	0,707	0,645	0,019	0,252	0,121	0,522	0,859
WJM	0,555	0,568	0,009	0,467	0,456	0,467	0,500	0,449	0,535	0,552	0,707	0,483	0,242	0,252	0,138	0,696	0,429
PAM	0,185	0,162	0,938	0,415	0,405	0,415	0,100	0,673	0,535	0,414	$1,4\times10^{-5}$	0,242	4×10^{-4}	0,216	0,107	0,232	0,143
OXY-FUEL	0,462	0,406	0,188	0,415	0,405	0,415	0,700	0,269	0,267	0,331	10^{-6}	0,242	2×10^{-4}	0,504	0,138	0,348	0,215
WEIGHTS	0,069	0,069	0,069	0,069	0,055	0,055	0,007	0,069	0,055	0,048	0,069	0,069	0,069	0,055	0,055	0,055	0,062

Table 5 Weighted normalized decision matrix

ALT./CRI.	S	HH	CS	SO	ESCAS	PC	UF	OC	IC	TSU	DTE	W	SR	V	N	AP	R
LBM	0,026	0,028	0,005	0,032	0,025	0,026	0,002	0,019	0,015	0,016	10^{-6}	0,033	0,067	0,042	0,053	0,014	0,007
AWJM	0,038	0,039	0,019	0,032	0,028	0,026	0,003	0,031	0,029	0,027	0,049	0,044	0,001	0,014	0,007	0,029	0,053
WJM	0,038	0,039	6×10^{-4}	0,032	0,025	0,026	0,003	0,031	0,029	0,027	0,049	0,033	0,017	0,014	0,008	0,038	0,027
PAM	0,013	0,011	0,065	0,029	0,022	0,023	7×10^{-4}	0,046	0,029	0,020	10^{-6}	0,017	$2,8\times10^{-5}$	0,012	0,006	0,013	0,009
OXY-FUEL	0,032	0,028	0,013	0,029	0,022	0,023	0,005	0,019	0,015	0,016	0	0,017	$1,7\times10^{-5}$	0,028	0,008	0,019	0,013

Table 6 Positive and negative ideal solutions, relative closeness to the ideal solution and preference orders

	Positive Ideal Solution	Negative Ideal Solution	Relative Closeness to the Ideal Solution	Preference Orders
LBM	0,101	0,092	0,474	2
AWJM	0,098	0,089	0,475	1
WJM	0,103	0,077	0,429	3
PAM	0,122	0,072	0,369	4
OXY-FUEL	0,126	0,034	0,213	5

Table 7 Fuzzy decision matrix and fuzzy weight matrix

CRI. /ALT.	LBM	AWJM	WJM	PAM	OXY-FUEL	WEIGHTS
S	(3,600;4,000;4,400)	(5,400;6,000;6,600)	(5,400;6,000;6,600)	(1,800;2,000;2,200)	(4,500;5,000;5,500)	(0,062;0,069;0,076)
H	(4,500;5,000;5,500)	(6,300;7,000;7,700)	(6,300;7,000;7,700)	(1,800;2,000;2,200)	(4,500;5,000;5,500)	(0,062;0,069;0,076)
CS	(0,338;0,375;0,413)	(1,350;1,500;1,650)	(0,045;0,050;0,055)	(4,500;5,000;5,500)	(0,900;1,000;1,100)	(0,062;0,069;0,076)
SO	(8,100;9,000;9,900)	(8,100;9,000;9,900)	(8,100;9,000;9,900)	(7,200;8,000;8,800)	(7,200;8,000;8,800)	(0,062;0,069;0,076)
ESCAS	(8,100;9,000;9,900)	(9,000;10,00;11,00)	(8,100;9,000;9,900)	(7,200;8,000;8,800)	(7,200;8,000;8,800)	(0,050;0,055;0,061)
PC	(8,100;9,000;9,900)	(8,100;9,000;9,900)	(8,100;9,000;9,900)	(7,200;8,000;8,800)	(7,200;8,000;8,800)	(0,050;0,055;0,061)
UF	(2,700;3,000;3,300)	(3,600;4,000;4,400)	(4,500;5,000;5,500)	(0,900;1,000;1,100)	(6,300;7,000;7,700)	(0,006;0,007;0,008)
OC	(0,180;0,200;0,220)	(0,300;0,333;0,367)	(0,300;0,333;0,367)	(0,450;0,500;0,550)	(0,180;0,200;0,220)	(0,062;0,069;0,076)
IC	(0,225;0,250;0,275)	(0,450;0,500;0,550)	(0,450;0,500;0,550)	(0,450;0,500;0,550)	(0,225;0,250;0,275)	(0,050;0,055;0,061)
TSU	(0,180;0,200;0,220)	(0,300;0,333;0,367)	(0,300;0,333;0,367)	(0,225;0,250;0,275)	(0,180;0,200;0,220)	(0,043;0,048;0,053)
DTE	(1,500;1,667;1,833)	$(9\times10^4 ; 10^5;11\times10^4)$	$(9\times10^4; 10^5 ;11\times10^4)$	(1,800;2,000;2,200)	(0,180;0,200;0,220)	(0,062;0,069;0,076)
W	(0,225;0,250;0,275)	(0,300;0,333;0,367)	(0,225;0,250;0,275)	(0,113;0,125;0,138)	(0,113;0,125;0,138)	(0,062;0,069;0,076)
SR	(7,200;8,000;8,800)	(0,138;0,154;0,169)	(1,800;2,000;2,200)	(0,003;0,003;0,004)	(0,002;0,002;0,002)	(0,062;0,069;0,076)
V	(0,450;0,500;0,550)	(0,150;0,167;0,183)	(0,150;0,167;0,183)	(0,129;0,143;0,157)	(0,300;0,333;0,367)	(0,050;0,055;0,061)
N	(0,900;1,000;1,100)	(0,113;0,125;0,138)	(0,129;0,143;0,157)	(0,100;0,111;0,122)	(0,129;0,143;0,157)	(0,050;0,055;0,061)
AP	(0,113;0,125;0,138)	(0,225;0,250;0,275)	(0,300;0,333;0,367)	(0,100;0,111;0,122)	(0,150;0,167;0,183)	(0,050;0,055;0,061)
R	(0,113;0,125;0,138)	(0,900;1,000;1,100)	(0,450;0,500;0,550)	(0,150;0,167;0,183)	(0,225;0,250;0,275)	(0,056;0,062;0,068)

Table 8 Normalized fuzzy decision matrix

CRI./ALT.	LBM	AWJM	WJM	PAM	OXY-FUEL
S	(0,545;0,606;0,667)	(0,818;0,909;1,000)	(0,818;0,909;1,000)	(0,273;0,303;0,333)	(0,682;0,758;0,833)
HH	(0,584;0,649;0,714)	(0,818;0,909;1,000)	(0,818;0,909;1,000)	(0,234;0,260;0,286)	(0,584;0,649;0,714)
CS	(0,061;0,068;0,075)	(0,245;0,273;0,300)	(0,008;0,009;0,010)	(0,818;0,909;1,000)	(0,164;0,182;0,200)
SO	(0,818;0,909;1,000)	(0,818;0,909;1,000)	(0,818;0,909;1,000)	(0,727;0,808;0,889)	(0,727;0,808;0,889)
ESCAS	(0,736;0,818;0,900)	(0,818;0,909;1,000)	(0,736;0,818;0,900)	(0,655;0,727;0,800)	(0,655;0,727;0,800)
PC	(0,818;0,909;1,000)	(0,818;0,909;1,000)	(0,818;0,909;1,000)	(0,727;0,808;0,889)	(0,727;0,808;0,889)
UF	(0,351;0,390;0,429)	(0,468;0,519;0,571)	(0,584;0,649;0,714)	(0,117;0,130;0,143)	(0,818;0,909;1,000)

OC	(0,327;0,364;0,400)	(0,545;0,606;0,667)	(0,545;0,606;0,667)	(0,818;0,909;1,000)	(0,327;0,364;0,400)
IC	(0,409;0,455;0,500)	(0,818;0,909;1,000)	(0,818;0,909;1,000)	(0,818;0,909;1,000)	(0,409;0,455;0,500)
TSU	(0,491;0,545;0,600)	(0,818;0,909;1,000)	(0,818;0,909;1,000)	(0,614;0,682;0,750)	(0,491;0,545;0,600)
DTE	(14×10^{-6}; 15×10^{-6};17×10^{-6})	(0,818;0,909;1,000)	(0,818;0,909;1,000)	(16×10^{-6}; 18×10^{-6}; 20×10^{-6})	(16×10^{-7};18×10^{-7};20×10^{-7})
W	(0,614;0,682;0,750)	(0,818;0,909;1,000)	(0,614;0,682;0,750)	(0,307;0,341;0,375)	(0,307;0,341;0,375)
SR	(0,818;0,909;1,000)	(0,016;0,017;0,019)	(0,205;0,227;0,250)	(34×10^{-5}; 38×10^{-5}; 42×10^{-5})	(20×10^{-5};23×10^{-5};25×10^{-5})
V	(0,818;0,909;1,000)	(0,273;0,303;0,333)	(0,273;0,303;0,333)	(0,234;0,260;0,286)	(0,545;0,606;0,667)
N	(0,818;0,909;1,000)	(0,102;0,114;0,125)	(0,117;0,130;0,143)	(0,091;0,101;0,111)	(0,117;0,130;0,143)
AP	(0,307;0,341;0,375)	(0,614;0,682;0,750)	(0,818;0,909;1,000)	(0,273;0,303;0,333)	(0,409;0,455;0,500)
R	(0,102;0,114;0,125)	(0,818;0,909;1,000)	(0,409;0,455;0,500)	(0,136;0,152;0,167)	(0,205;0,227;0,250)

Table 9 Weighted normalized fuzzy decision matrix

CRI./ALT.	LBM	AWJM	WJM	PAM	OXY-FUEL
S	(0,034;0,042;0,051)	(0,051;0,063;0,076)	(0,051;0,063;0,076)	(0,017;0,021;0,025)	(0,042;0,052;0,063)
HH	(0,036;0,045;0,054)	(0,051;0,063;0,076)	(0,051;0,063;0,076)	(0,015;0,018;0,022)	(0,036;0,045;0,054)
CS	(0,004;0,005;0,006)	(0,015;0,019;0,023)	(51×10^{-5};63×10^{-5};76×10^{-5})	(0,051;0,063;0,076)	(0,010;0,013;0,015)
SO	(0,051;0,063;0,076)	(0,051;0,063;0,076)	(0,051;0,063;0,076)	(0,045;0,056;0,067)	(0,045;0,056;0,067)
ESCAS	(0,037;0,045;0,055)	(0,041;0,050;0,061)	(0,037;0,045;0,055)	(0,033;0,040;0,049)	(0,033;0,040;0,049)
PC	(0,041;0,050;0,061)	(0,041;0,050;0,061)	(0,041;0,050;0,061)	(0,036;0,045;0,054)	(0,036;0,045;0,054)
UF	(0,002;0,002;0,003)	(0,003;0,004;0,004)	(0,004;0,004;0,005)	(73×10^{-5};90×10^{-5};108×10^{-5})	(0,005;0,006;0,008)
OC	(0,020;0,025;0,030)	(0,034;0,042;0,051)	(0,034;0,042;0,051)	(0,051;0,063;0,076)	(0,020;0,025;0,030)
IC	(0,020;0,025;0,030)	(0,041;0,050;0,061)	(0,041;0,050;0,061)	(0,041;0,050;0,061)	(0,020;0,025;0,030)
TSU	(0,021;0,026;0,032)	(0,036;0,044;0,053)	(0,036;0,044;0,053)	(0,027;0,033;0,040)	(0,021;0,026;0,032)
DTE	(8×10^{-7};10×10^{-7};13×10^{-7})	(0,051;0,063;0,076)	(0,051;0,063;0,076)	(10×10^{-7};13×10^{-7};15×10^{-7})	(10×10^{-7};13×10^{-7};15×10^{-7})
W	(0,038;0,047;0,057)	(0,051;0,063;0,076)	(0,038;0,047;0,057)	(0,019;0,024;0,028)	(0,019;0,024;0,028)
SR	(0,051;0,063;0,076)	(97×10^{-5};12×10^{-4};15×10^{-4})	(0,013;0,016;0,019)	(21×10^{-6};26×10^{-6};32×10^{-6})	(13×10^{-6};16×10^{-6};19×10^{-6})
V	(0,041;0,050;0,061)	(0,014;0,017;0,020)	(0,014;0,017;0,020)	(0,012;0,014;0,017)	(0,027;0,033;0,040)
N	(0,041;0,050;0,061)	(0,005;0,006;0,008)	(0,006;0,007;0,009)	(0,005;0,006;0,007)	(0,006;0,007;0,009)
AP	(0,015;0,019;0,023)	(0,030;0,038;0,046)	(0,041;0,050;0,061)	(0,014;0,017;0,020)	(0,020;0,025;0,030)
R	(0,006;0,007;0,009)	(0,046;0,056;0,068)	(0,023;0,028;0,034)	(0,008;0,009;0,011)	(0,011;0,014;0,017)

Table 10 Positive and negative ideal solutions, relative closeness to the ideal solution and preference orders

	Positive Ideal Solution	Negative Ideal Solution	Relative Closeness to the Ideal Solution	Preference Orders
LBM	16,432	0,576	0,034	3
AWJM	16,306	0,704	0,041	1
WJM	16,344	0,665	0,039	2
PAM	16,539	0,467	0,027	4
OXY-FUEL	16,561	0,445	0,026	5

4 Conclusion

In this study, a comprehensive decision support model is proposed to assist decision makers in the selection of the appropriate machining process. A case study is also performed for AISI 309 stainless steel. Most of the required data for the study is obtained via questionnaires given to experts and making use of the past studies. The remaining data is obtained experimentally. The results gathered from the application of TOPSIS and fuzzy TOPSIS methods illustrated that AWJM is the most appropriate alternative while WJM and LBM are second and third respectively due to determined criteria in the study. On the other hand, PAM and oxy-fuel have the lowest grades but negligible ranking due to their close values.

Further researches can be performed using other fuzzy MCDM methods such as fuzzy ELECTRE, fuzzy PROMETHEE and also using methods that have the ability to take the influences between alternatives and criteria into consideration such as fuzzy Analytic Network Process (FANP).

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