Operational Research in Engineering Sciences: Theory and Applications
Vol. 5, Issue 3, 2022, pp. 131-152
ISSN: 2620-1607
eISSN: 2620-1747
DOI: https:// https://doi.org/10.31181/oresta051022061d

APPLICATION OF FUCA METHOD FOR MULTI-CRITERIA DECISION MAKING IN MECHANICAL MACHINING PROCESSES

Duc Trung Do

Hanoi University of Industry, Vietnam

Received: 12 August 2022
Accepted: 29 September 2022
First online: 05 October 2022

Research paper

Abstract: *Multi-criteria decision making (MCDM) is a very useful tool to find the best solution among many solutions. For most MCDM methods, the data must be normalized. However, the data normalization method has a significant influence on the results of ranking solutions. Choosing the right data normalization method is sometimes complicated. In many MCDM methods, FUCA is known as the method without using normalize the data. However, the FUCA method has a small limitation. All publications that were applied this method have not mentioned this limitation. In this study, this limitation was overcome and then used for multi-criteria decision making in some cases in the mechanical processing field. The ranked results of the solutions when determined by the FUCA method are compared with those ones when using other MCDM methods. The sensitivity analysis was also performed. The results show that the FUCA method can be used for multi-criteria decision making in mechanical machining. It is also expected to be successful when applying in other fields. The works in the future were mentioned in the last section of this article as well.*

Keywords: MCDM, FUCA method, Mechanical machining

1. Introduction

The decision to choose one of many solutions always happens in many situations in many different fields. Each solution is described by different criteria, in which, there are criteria as the larger the better such as machining productivity, tool life, and product quality, etc. Conversely, there are also criteria as the smaller the better such as cost, energy consumption, etc. In these cases, the decision making to select a solution is known as "*multi-criteria decision making*" (Zopounidis & Doumpos, 2017).

Over the years, *MCDM* methods have received more and more attention from many scholars. A common feature of most *MCDM* methods is the need to perform the data normalization (Zopounidis & Doumpos, 2017). The criteria with different dimensions

* Corresponding author.
doductrung@haui.edu.vn (D. T. Do)

are converted to the same dimensionless form as the basis for ranking options, which is the goal of data normalization (Wen et al. 2020; Krishnan, 2022). However, the data normalization method in each *MCDM* method is not exactly the same, which leads to different ranking results of the *MCDM* methods (Aytekin, 2021; Ersoy, 2021; Palczewski & Sałabun, 2019; Lakshmi & Venkatesan, 2014). The rank inversion phenomenon can also occur if the selected data normalization method is not suitable with the MCDM method (Trung, 2022). Currently, many *MCDM* methods have been proposed by reseachers, it is quite difficult for decision makers to choose one of them in ranking process. *FUCA* is known as a multi-criteria decision making method without using data normalization (Fernando et al., 2011). Simple steps to implement decision making using this method, its limitations as well as improvements to overcome those limitations will be presented in the next sections of this paper.

Baydas (2022) simultaneously used three methods including *MOORA*, *MABAC*, and *FUCA* to assess the rankings of companies in the period before and after the Covid 19 pandemic. The author showed that the *FUCA* method gives more effective than the other two methods. In another study, Baydas (2022) used two methods F*UCA* and *WSA* to evaluate the financial performance of companies. The results of this study show that the *FUCA* method is better than the *WSA* method in finding the best solution. In another study, Baydas & Pamucar (2022) also used the *FUCA* method to evaluate the financial performance of companies. In addition to the *FUCA* method, in this study, six other methods were used simultaneously including *PROMETHEE*, *COPRAS*, *TOPSIS*, *SAW*, *CODAS*, and *MOORA*. Their results showed that *FUCA* and *PROMETHEE* were equally effective in finding the best solution, and that these two methods were better than the other five ones. Baydas et al. (2022) one time again used simultaneously ten multi-criteria decision making methods including *FUCA*, *PROMETHEE*, *TOPSIS*, *GRA*, *S*-, *WSA*, *SAW*, *COPRAS*, *MOORA*, and *LINMAP* to evaluate the financial performance of twenty-three companies. The authors concluded that the two methods *FUCA* and *PROMETHEE* were equally effective and better than other eight methods. Ouattara et al. (2022) used two methods *TOPSIS* and *FUCA* to make multi-criteria decisions in the selection of chemical manufacturing processes. They confirmed that the *FUCA* method is better than the *TOPSIS* method. The analysis results from some of the above studies show that the *FUCA* method has been successful in ranking the solutions in the economic and chemical manufacturing fields. It has also been determined to be better or equivalent to other *MCDM* methods. However, the number of studies that have applied this method is very limited. This method has never been applied to multi-criteria decision making in the field of mechanical processing. The application of *FUCA* method in multi-criteria decision-making in mechanical processing is a novelty and is also the first reason to conduct this study.

It is important to note that the *FUCA* method has a small limitation. This limitation has not been considered in any published studies. That limitation occurs when a certain criterion has equal value in two or more solutions. The detailed analysis of this limitation of the *FUCA* method as well as the improvement to overcome this limitation will be presented in section 2 of this paper. This is also the second reason for doing this study.

From the above analysis, the structure of the next sections of this paper includes: *(1)* Discovering the limitation of the *FUCA* method and improving this method to overcome the limitation; *(2)* Apply *FUCA* method for multi-criteria decision making for some common mechanical machining processes. In each example, the data were referenced from published studies. The ranking results of the solutions when using *FUCA* method were compared to that ones when using other *MCDM* methods. The sensitivity analysis in each case was also performed for different scenarios; *(3)* discussing about the achieved results; and *(4)* conclusion of this study and proposal of the further studies are the closing content of this paper.

2. FUCA Method

The *FUCA* method performs the ranking of solutions in just three simple steps as follows (Fernando et al. 2021):

Step 1. Rank the solutions for each criterion (r_{ij}). Suppose there are *m* solutions, the best value will be ranked 1, otherwise the worst value will be ranked *m*. If there are *n* criteria, perform *n* ranking times for each criterion.

However, at this step, we have noticed a limitation of the *FUCA* method that when a certain criterion has the same value in two or more solutions, how will the ranking of the solutions (for each criterion) be implemented? To clarify this issue, a simple example is presented as below.

Suppose there are four solutions including *A1*, *A2*, *A3*, and *A4*, each of which is described by three criteria *C1*, *C2*, and *C3*, where *C1* and *C2* are the criteria as the larger the bettere, and *C3* is the criterion as the smaller the better as shown in Table 1.

Table 1. Example of a certain criterion having equal value in several solutions

No.	Criteria		
	C1	*C2*	*C3*
A1	4	3	4
A2	6	5	2
A3	2	5	4
A4	8	7	4

The ranking of alternatives for each criterion will be conducted as follows.

For criterion *C1* (the larger the better): *A4* ranked 1, *A2* ranked 2, *A1* ranked 3, and *A2* ranked 4. For this criterion, its values in the four solutions are different. So the ranking process is performed easy.

For criterion *C2* (the larger the better): Because *C2* at *A4* is the largest, so *A4* ranked 1, *C2* at *A1* is the smallest, so *A1* ranked 4. However, *C2* at *A2* and *A3* are equal. So, what is the ranking order of *A2* and *A3*? A simple proposal that *A2* and *A3* should have the same rank, and equal to 2.5 (the average of 2 and 3).

For criterion *C3* (the smaller the better): because C3 at A2 is the smallest, so A2 is ranked 1. C3 has the same value in three solutions A1, A3, and A4, so all three solutions ranked 3 (the average of 2, 3, and 4).

From above analyzed results, a table of the ranking results of the solutions for the data in Table 1 was presented in Table 2.

Table 2. The ranked results of the solutions according to the data in table 1

No.	Rank		
	C1	*C2*	*C3*
A1	3	4	3
A2	2	2.5	1
A3	4	2.5	3
A4	1	1	3

Step 2. Calculate the score of each solution according to the Eq. (1).

$$v_i = \sum_{j=1}^{n} r_{ij}.w_j \quad (1)$$

where w_j is the weight of the criterion *j*.

Step 3. Rank the solutions by the value of v_i. The solution with the smallest v_i is the best one, and vice versa.

The discovery of the limitation of the *FUCA* method as well as the proposed method to overcome that limitation were performed. To evaluate the effectiveness of this remedial method, in the next sections of this study, the proposed method will be applied to multi-criteria decision making in some cases in the mechanical processing field.

Because the main purpose of this study is the application of the *FUCA* method for multi-criteria decision making in mechanical machining processes, the data are therefore all referenced from the published studies, the number of criteria in each case is not the same. Two main reasons for performing this content include: *first*, not spending too much effort on conducting the experiments; and *second*, published studies have used other *MCDM* methods to rank solutions. The ranking results of the solutions when using those *MCDM* methods are used to compare to those ones when using the *FUCA* method. In each case, first, the weight of the criteria that was used was the value in the published studies. Then, in each case, the sensitivity analysis was also performed for different scenarios by varying the weights of the criteria. The number of the generated scenarios in each case also varies. The implementation of examples in different mechanical processing processes, the number of criteria in different situations, the number of different scenarios aim to draw the most general conclusions.

3. Applying the FUCA method for Multi-Criteria Decision Making in Several Cases

3.1. Multi-Criteria Decision Making in Milling Process (example 1)

This case used the experimental data of the milling process of Ti-6Al-4V alloy by Nguyen et al. (2021). In that study, they conducted nine experiments, each of which changed three parameters including cutting speed, feed rate, and depth of cut. Two criteria were measured in each experiment including surface roughness (*C1*) and material removal rate (*C2*). The experimental data are presented in Table 3. In which

C1 is the smaller the better criterion, *C2* is the larger the better criterion. In addition, in that study, they used the Entropy method to determine the weights for the criteria, and the determined weights of *C1* and *C2* were 0.2906 and 0.7094, respectively. That study also used the *TOPSIS* method for multi-criteria decision making with the aim of determining the solution *Ai* (with $i = 1 \div 9$) with simultaneously ensuring the smallest *C1* and the largest *C2*.

Table 3. Experimental data when milling process of alloy Ti-6Al-4V (Nguyen et al. 2021).

No.	*Criteria*	
	C1 (μm)	*C2* (cm^3/min)
A_1	0.281	5.42
A_2	0.337	1.08
A_3	0.737	16.25
A_4	0.328	21.67
A_5	0.321	10.83
A_6	0.507	2.17
A_7	0.359	32.5
A_8	0.412	43.33
A_9	0.636	16.52

The ranking of the solutions according to the FUCA method will be performed as follows.

Step 1. Rank the solutions for each criterion. In this case, both criteria *C1* and *C2* have different values for all solutions, so the ranking of solutions according to the *FUCA* method is conducted normally. The results are presented in the Table 4.

Table 4. Ranking the solutions for each criterion (example 1)

No.	*Rank* (r_{ij})	
	C1	*C2*
A_1	1	7
A_2	4	9
A_3	9	4
A_4	3	3
A_5	2	6
A_6	7	8
A_7	5	2
A_8	6	1
A_9	8	5

Step 2. Calculate the score of each solution according to Eq (1). First of all, the weights of the selected criteria are the same as their values in the referenced literature, i.e., the weights of *C1* and *C2* are 0.2906 and 0.7094, respectively (Nguyen et al. 2021). The calculated results are presented in Table 5.

Table 5. The v_i score of each solution (example 1)

No.	$r_{ij}.\ w_j$		v_i
	C1	*C2*	
A_1	1	7	5.2564
A_2	4	9	7.5470
A_3	9	4	5.4530
A_4	3	3	3.0000
A_5	2	6	4.8376
A_6	7	8	7.7094
A_7	5	2	2.8718
A_8	6	1	2.4530
A_9	8	5	5.8718

Step 3. Ranking the solutions according to the value of v_i, the calculated results are presented in Table 6. The ranking results of the solutions when using the *TOPSIS* method are also presented in this table.

Table 6. Ranking the solutions for example 1

No.	Rank	
	FUCA	*TOPSIS*
A_1	5	*7*
A_2	8	*9*
A_3	6	*4*
A_4	3	*3*
A_5	4	*6*
A_6	9	*8*
A_7	2	*2*
A_8	1	*1*
A_9	7	*5*

The calculated results from Table 6 show that when using the improved *FUCA* method, it was determined that *A8* is the best solution. This result is also similar to the result when ranking solutions by *TOPSIS* method (Nguyen et al. 2021). In addition, the second ranked solution (*A7*) and the third ranked solution (*A4*) also coincide when using both improved *FUCA* and *TOPSIS* methods. Thus, in this case, it is seen that when using the same set of weight values, two methods including improved *FUCA* and *TOPSIS* are considered to be equally effectiveness.

However, in order to evaluate the effectiveness of a certain *MCDM* method in each case, the last work that needs to be done is the sensitivity analysis (Bozanic et al. 2021; Muhammad et al. 2021). Many studies have performed the sensitivity analysis by changing the weighted values of the criteria and using Sperman's rank correlation coefficient (Bobar et al. 2020; Pamucar et al. 2021; Dimic et al. 2019; Le et al. 2022; Lamba et al. 2019). In this study, the sensitivity analysis was also performed in the same way. The Sperman's rank correlation coefficient is determined according to Eq. (2).

$$S = 1 - \frac{6\sum_{i=1}^{n} D_i^2}{n(n^2-1)} \tag{2}$$

where *Di* presents the difference of the rank according to the given scenario and the rank in the corresponding scenario, and *n* is the number of ranked elements.

Six different scenarios were created by randomly changing the weights of the criteria as presented in Table 7. In which, *S4* is the scenario just implemented above.

Table 7. Weight of criteria in different scenarios (example 1)

Criteria	Scenarios					
	S1	*S2*	*S2*	*S4*	*S5*	*S6*
C1	0.2	0.22	0.25	0.2906	0.3	0.35
C2	0.8	0.78	0.75	0.7094	0.7	0.65

The ranked results solutions according to six different scenarios are presented in Table 8. We see that in all six given scenarios, *A8* is still the best solution.

Table 8. Ranking the solutions in different scenarios (example 1)

No.	Scenarios					
	S1	S2	S3	S4	S5	S6
A_1	7	7	6	5	5	5
A_2	9	9	9	8	8	8
A_3	4	4	5	6	6	6
A_4	3	3	3	3	3	2
A_5	5	5	4	4	4	4
A_6	8	8	9	9	9	9
A_7	2	2	2	2	2	3
A_8	1	1	1	1	1	1
A_9	6	6	7	7	7	7

Table 9 presents the values of the Spearman coefficients calculated according to formula (2) for comparison between scenarios as well as comparison of the initial ranking S_i.

Table 9. The values of Sperman's rank correlation *coefficients (example 1)*

	Si	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*
Si	1	1	1.000	0.958	0.900	0.900	0.883
S1		1	1.000	0.958	0.900	0.900	0.883
S2			1	0.958	0.900	0.900	0.883
S3				1	0.975	0.975	0.958
S4					1	1.000	0.983
S5						1	0.983
S6							1

The calculed results in Table 9 show that the Sperman's rank correlation coefficient of the solution is in the range S ∈ [0.883, 1]. It means the degree of correlation is very high. This shows that the change in rankings is not significant even though the weight of the criteria changed with a relatively large degree (the weight of *C1* changed from 0.2 to 0.35, the weight of *C2* changed from 0.8 to 0.65). One great thing that was achieved is that solution *A8* is always determined to be the best one of all scenarios.

Thus, a solid conclusion is drawn that the *FUCA* method was successful in solving the problem in this example.

3.2. Multi-Criteria Decision Making in Turning Process (example 2)

Singh et al. (2019) conducted twenty-seven experiments when turning Ti-6Al-4V steel. In each experiment, the input parameters were adjusted in each experiment including cutting speed, feed rate, and depth of cut. The criteria that were used to evaluate each solution included tool wear (*C1*), surface roughness (*C2*), cutting heat (*C3*), and cutting force (*C4*). All four of these criteria are the smaller tha better criteria. The values of the criteria at the solutions are as presented in Table 10.

Table 10. Experimental data when turning process of steel (Singh et al. 2019)

No.	Criteria			
	C1 (μm)	*C2* (μm)	*C3* (^{0}C)	*C4* (N)
A1	70	0.5	405	310
A2	85	0.53	410	315
A3	95	0.55	420	323
A4	110	0.62	440	295
A5	135	0.68	445	300
A6	120	0.6	435	298
A7	195	0.76	503	290
A8	180	0.72	490	280
A9	190	0.74	495	285
A10	118	0.62	438	296
A11	125	0.66	443	295
A12	132	0.69	455	305
A13	175	0.75	485	283
A14	180	0.73	490	289
A15	190	0.75	500	292
A16	65	0.52	410	314
A17	90	0.56	415	321
A18	98	0.57	425	325
A19	168	0.73	485	288
A20	175	0.74	497	284
A21	188	0.78	501	290
A22	92	0.54	415	328
A23	100	0.55	420	320
A24	105	0.57	425	332
A25	115	0.62	448	302
A26	130	0.63	450	308
A27	140	0.65	447	310

In that study, the ranking of the solutions by *TOPSIS* and *SAW* methods was also performed. In which, the weights of *C1*, *C2*, *C3*, and *C4* were determined by the *AHP* method, and those values were 0.5846, 0.2570, 0.1088, and 0.0556, respectively.

The application of the *FUCA* method to ranking solutions is similar to the example in section 3.1. However, in this case, the value of each criterion is equal in some solutions. Therefore, the ranking of the solutions for each criterion will have to consider the proposed solution. The specific steps are as follows.

For criterion C1, the ranks from rank 1 to rank 19 are ranked normally. Because *C1* at *A13* and *A20* are equal to each other, both *A13* and *A20* ranked 20.5 (average of 20 and 21); *C1* at *A8* and *A14* are equal each other, both *A8* and *A14* ranked 22.5 (average of 22 and 23); *C1* at *A9* and *A15* are equal each other, both *A9* and *A15* ranked 25.5 (average of 25 and 26).

For criterion *C2*, the ranks from rank 1 to rank 4 are ranked normally. Because *C2* at *A3* and *A23* are equal, both *A3* and *A23* ranked 5.5 (average of 5 and 6); *C2* at *A18* and *A24* are equal each other, both *A18* and *A24* ranked 8.5 (average of 8 and 9); ect.

For the remaining criteria (*C3* and *C4*), the ranking of solutions was performed similarly to this method. The ranking results of the solutions for each criterion are presented in Table 11.

Table 11. Ranking the solutions for each criterion in example 2

No.	Criteria				Rank (r_{ij})			
	C1	*C2*	*C3*	*C4*	*C1*	*C2*	*C3*	*C4*
A1	70	0.5	405	310	2	1	1	18.5
A2	85	0.53	410	315	3	3	2.5	21
A3	95	0.55	420	323	6	5.5	6.5	24
A4	110	0.62	440	295	10	12	12	10.5
A5	135	0.68	445	300	17	17	14	14
A6	120	0.6	435	298	13	10	10	13
A7	195	0.76	503	290	27	26	27	7.5
A8	180	0.72	490	280	22.5	19	21.5	1
A9	190	0.74	495	285	25.5	22.5	23	4
A10	118	0.62	438	296	12	12	11	12
A11	125	0.66	443	295	14	16	13	10.5
A12	132	0.69	455	305	16	18	18	16
A13	175	0.75	485	283	20.5	24.5	19.5	2
A14	180	0.73	490	289	22.5	20.5	21.5	6
A15	190	0.75	500	292	25.5	24.5	25	9
A16	65	0.52	410	314	1	2	2.5	20
A17	90	0.56	415	321	4	7	4.5	23
A18	98	0.57	425	325	7	8.5	8.5	25
A19	168	0.73	485	288	19	20.5	19.5	5
A20	175	0.74	497	284	20.5	22.5	24	3
A21	188	0.78	501	290	24	27	26	7.5
A22	92	0.54	415	328	5	4	4.5	26
A23	100	0.55	420	320	8	5.5	6.5	22
A24	105	0.57	425	332	9	8.5	8.5	27
A25	115	0.62	448	302	11	12	16	15
A26	130	0.63	450	308	15	14	17	17
A27	140	0.65	447	310	18	15	15	18.5

After ranking the solutions for each criterion, apply Eq. (1) to calculate the value of ν_i. First, the weights of the selected criteria are the same as their values in the references, i.e., the weights of *C1*, *C2*, *C3*, and *C4* are 0.5846, 0.2570, 0.1088, and 0.0556, respectively (Singh et al. 2019). The ranked results of the solutions by *FUCA* method and two other methods (including *TOPSIS* and *SAW*) are presented in Table 12.

Table 12. Ranking the solutions for example 2

No.	*FUCA*	TOPSIS	SAW
A_1	1	1	1
A_2	3	3	3
A_3	6	5	6
A_4	10	11	11
A_5	16	17	17
A_6	12	10	10
A_7	27	26	26
A_8	20	19	20
A_9	24	23	24
A_{10}	11	13	12
A_{11}	14	16	15
A_{12}	17	18	18
A_{13}	21	24	23
A_{14}	23	21	21
A_{15}	26	25	25
A_{16}	2	2	2
A17	5	7	5
A18	8	8	8
A19	19	20	19
A20	22	22	22
A21	25	27	27
A22	4	4	4
A23	7	6	7
A24	9	9	9
A25	13	12	13
A26	15	14	14
A27	18	15	16

The calculated results in Table 12 show that using the *FUCA* method, *A1* was identified as the best solution. This result is also consistent with cases using two methods including *TOPSIS* and *SAW*. In addition, all three methods jointly identify that *A16* solution ranked 2, and *A2* solution ranked 3.

Seven different scenarios were generated by randomly varying the weights of the criteria as presented in Table 13. Where *S7* is the scenario that was performed above.

Table 13. Weight of criteria in different scenarios (example 2)

Criteria	Scenarios						
	S1	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*
C1	0.1	0.2	0.3	0.3	0.3	0.4	0.5846
C2	0.2	0.1	0.2	0.1	0.3	0.4	0.2570
C3	0.3	0.4	0.1	0.3	0.1	0.1	0.1088
C4	0.4	0.3	0.4	0.3	0.3	0.1	0.0556

The ranking results of the solutions according to different scenarios are presented in Table 14. The calculated results show that in all 7 scenarios, it is always determined that *A1* is the best solution, *A16* ranked 2, *A2* ranked 3, and *A7* ranked 27.

Table 14. Ranking the solutions in different scenarios (example 2)

No.	Scenarios						
	S1	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*
A1	1	1	1	1	1	1	1
A2	3	3	3	3	3	3	3
A3	12	9	11	7	7	6	6
A4	4	6	4	5	5	10	10
A5	16	15	19	17	18	16	16
A6	5	8	6	10	9	11	12
A7	27	27	27	27	27	27	27
A8	10	18	10	18	15	20	20
A9	20	24	21	24	24	24	24
A10	6	10	5	9	10	12	11
A11	9	11	8	11	13	14	14
A12	24	23	23	21	21	18	17
A13	13	16	15	15	19	21	21
A14	19	22	18	23	22	22	23
A15	25	26	26	26	26	25	26
A16	2	2	2	2	2	2	2
A17	7	4	7	4	4	5	5
A18	17	12	17	12	11	8	8
A19	14	17	14	16	16	19	19
A20	18	21	16	20	20	23	22
A21	26	25	25	25	25	26	25
A22	11	5	12	6	6	4	4
A23	8	7	9	8	8	7	7
A24	21	13	22	14	14	9	9
A25	15	14	13	13	12	13	13
A26	22	19	20	19	17	15	15
A27	23	20	24	22	23	17	18

Eq. (2) is used to calculate the Spearman's rank correlation coefficients. Table 15 presents the values of the Spearman coefficients when comparing between scenarios as well as the initial rank S_i.

Table 15. The values of Sperman coefficients (example 2)

	Si	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*
Si	1	1	0.904	0.988	0.907	0.897	0.752	0.751
S1		1	0.904	0.988	0.907	0.897	0.752	0.751
S2			1	0.886	0.991	0.980	0.947	0.946
S3				1	0.901	0.901	0.744	0.747
S4					1	0.988	0.938	0.941
S5						1	0.946	0.948
S6							1	0.998
S7								1

The calculated data in Table 15 show that the Sperman's rank correlation coefficients of the solutions is in the range S ∊ [0.747, 1], this value represents a very high degree of correlation. This shows that the change in rankings is not significant even though the weight of the criteria changed with a relatively large degree. Specifically, although *C1* changed 5.846 times, *C2* and *C3* changed 4 times, and *C4* changed 7.19 times, the solutions ranked 1^{st}, 2^{nd}, 3^{rd}, and 27^{th} are all same to each other in all seven scenarios. Thus, for each criterion, when ranking solutions with equal value in several solutions was implemented according to the proposed method, the *FUCA* method was also successful in solving the problem of this example.

3.3. Multi-Criteria Decision Making in Drill Process of Magnesium AZ91 Material (example 3)

Varatharajulu et al. (2021) performed the drilling process of magnesium AZ91 in seventeen different experiments. In each experiment the input parameters are changed including spindle speed and feed rate. Six criteria that were used to evaluate each experiment included drilling time (*C1*), entry burr height (*C2*), exit burr height (*C3*), entry burr thickness (*C4*), exit burr thickness (*C5*), and surface roughness (*C6*). All six of these criteria are the smaller the better criteria. The data on the criteria for the seventeen experiments is presented in Table 16.

The multi-criteria decision-making that was performed to find a solution that ensures simultaneously all six criteria to be the same minimum values using *TOPSIS* and *COPRAS* methods (Varatharajulu et al. 2021). In which, the weights of *C1* and *C6* were chosen to be 0.3 and the weights of all the remaining four criteria were chosen to be 0.1. The application of the *FUCA* method to rank solutions was performed similarly to the example in section 3.1. It is note with the cases that one certain criterion is equally valid in several solutions. This process was presented follows.

The values of criterion *C1* are different in all seventeen solutions, so ranking of the solutions for this criterion is performed normally.

For criterion *C2*: *C2* at *A15* is the smallest, so *A15* ranked 1st; *C2* at *A8*, *A9*, and *A12* are equal to each other, so all three solutions are ranked 3 (the average of 2, 3, and 4); C2 at *A4* is equal to C2 at *A7*, so both solutions ranked 5.5 (average of 5 and 6); *C2* at *A10*, A11, and *A16* are equal to each other, so all three solutions ranked 11 (average of 10, 11, and 12), ect.

Table 16. Experimental data when drilling process of magnesium material (Varatharajulu et al. 2021)

No.	Criteria					
	C1 (s)	*C2* (mm)	*C3* (mm)	*C4* (mm)	*C5* (mm)	*C6* (μm)
A1	14.03	0.051	0.058	0.105	0.21	0.479
A2	7.59	0.053	0.058	0.155	0.245	1.211
A3	7.34	0.035	0.06	0.165	0.215	0.916
A4	4.06	0.033	0.075	0.18	0.215	0.535
A5	5.4	0.048	0.078	0.25	0.195	0.601
A6	5.5	0.05	0.084	0.185	0.185	0.703
A7	2.81	0.033	0.058	0.185	0.185	0.466
A8	2.62	0.028	0.048	0.2	0.19	0.577
A9	2.88	0.028	0.05	0.18	0.15	0.417
A10	2.75	0.043	0.051	0.23	0.195	0.675
A11	2.84	0.043	0.055	0.165	0.205	0.418
A12	1.59	0.028	0.074	0.145	0.17	0.601
A13	1.88	0.038	0.064	0.185	0.175	0.563
A14	3.44	0.049	0.066	0.19	0.185	0.391
A15	2.04	0.023	0.059	0.16	0.18	0.493
A16	2.1	0.043	0.05	0.235	0.185	0.675
A17	1.25	0.04	0.049	0.44	0.19	0.65

Table 17. Ranking the solutions when drilling process of magnesium material

No.	Rank (r_{ij})						Rank		
	C1	*C2*	*C3*	*C4*	*C5*	*C6*	*FUCA*	*TOPSIS*	*COPRAS*
A1	17	16	8	1	14	5	13	17	17
A2	16	17	8	3	17	17	17	16	16
A3	15	7	11	5.5	15.5	16	15	15	15
A4	12	5.5	15	7.5	15.5	7	11	12	12
A5	13	13	16	16	11.5	10.5	14	13	13
A6	14	15	17	10	6.5	15	16	14	14
A7	8	5.5	8	10	6.5	4	4	5	6
A8	6	3	1	13	9.5	9	6	7	7
A9	10	3	3.5	7.5	1	2	2	2	2
A10	7	11	5	14	11.5	13.5	12	10	11
A11	9	11	6	5.5	13	3	7	6	5
A12	2	3	14	2	2	10.5	3	4	3
A13	3	8	12	10	3	8	5	3	4
A14	11	14	13	12	6.5	1	9	8	8
A15	4	1	10	4	4	6	1	1	1
A16	5	11	3.5	15	6.5	13.5	10	9	9
A17	1	9	2	17	9.5	12	8	11	10

The ranking of the remaining criteria (*C3*, *C4*, *C5*, *C6*) was also conducted in a similar way. The ranked results of the solutions for each criterion are presented in Table 17. The data in Table 17 show that the *FUCA* method indicates that *A15* is the best solution. This result is also similar to the results when using *TOPSIS* and *COPRAS* methods. In addition, all three methods *FUCA, TOPSIS*, and *COPRAS* identified that *A9* ranked 2.

Eight different scenarios were also generated by randomly varying the weights of the criteria as shown in Table 18, where *S5* scenario was the just analyzed above.

Table 18. Weight of criteria in different scenarios (example 3)

Criteria	Scenarios							
	S1	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*
C1	0.2	0.2	0.25	0.28	0.3	0.32	0.33	0.35
C2	0.15	0.1	0.15	0.2	0.1	0.1	0.15	0.15
C3	0.2	0.1	0.15	0.2	0.1	0.1	0.1	0.1
C4	0.2	0.2	0.15	0.2	0.1	0.1	0.15	0.1
C5	0.15	0.15	0.2	0.1	0.1	0.1	0.1	0.15
C6	0.1	0.25	0.1	0.02	0.3	0.28	0.17	0.15

The ranking results of the solutions according to the different scenarios are presented in Table 19. It is seen that in all eight scenarios, *A15* is always determined to be the best solution.

Table 19. Ranking the solutions in different scenarios (example 3)

No.	Scenarios							
	S1	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*
A1	11	10	13	13	13	13	13	13
A2	15	17	16	15	17	17	15	17
A3	14	14	14	12	15	15	14	14
A4	13	12	12	11	11	11	12	12
A5	17	16	17	17	14	14	16	15
A6	16	15	15	16	16	16	17	16
A7	5	4	6	7	4	5	7	7
A8	4	7	5	4	6	6	5	5
A9	2	2	3	3	2	2	3	3
A10	10	13	10	10	12	12	11	11
A11	8	6	9	9	7	7	8	9
A12	3	3	2	2	3	3	2	2
A13	6	5	4	6	5	4	4	4
A14	12	8	11	14	9	9	10	10
A15	1	1	1	1	1	1	1	1
A16	9	11	8	8	10	10	9	8
A17	7	9	7	5	8	8	6	6

Eq. (2) is again used to calculate the Sperman coefficients. Table 20 presents the values of the Sperman coefficients when comparing between scenarios as well as the initial rank S_i.

The data in Table 20 show that the Sperman's rank correlation coefficients of the solutions is in the range S ∈ [0.853, 1], which means that the correlation level in this case is very high. This shows that the change in rankings is not significant even though the weight of the criteria changed with a relatively large degree. Specifically, the weight of *C1* changed from 0.2 to 0.35, the weight of four criteria *C2*, *C3*, *C4*, and *C5* all changed from 0.1 to 0.2. In particular, the weight of *C6* changed from 0.02 to 0.3. In all scenarios, *A15* is always determined to be the best solution. One time again, the *FUCA* method was confirmed as a successful applied method in this example.

Table 20. The values of Sperman's rank correlation coefficients (example 3)

	Si	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*
Si	1	1	0.931	0.978	0.966	0.946	0.944	0.971	0.961
S1		1	0.931	0.978	0.966	0.946	0.944	0.971	0.961
S2			1	0.924	0.853	0.973	0.971	0.929	0.924
S3				1	0.968	0.953	0.958	0.985	0.988
S4					1	0.897	0.900	0.961	0.956
S5						1	0.998	0.961	0.963
S6							1	0.968	0.971
S7								1	0.990
S8									1

3.4. Multi-Criteria Decision Making with the Qualitative Criteria (example 4)

The analyzed results in the three examples that were performed above confirmed that the *FUCA* method was successfully applied when used in each example. However, in all those examples, the the criteria are the quantitative ones. In this example, both qualitative and quantitative criteria will be considered. To implement the content of these cases, the authors of this paper were conducted the surface grinding process of SUJ2 steel with some basic parameters of the experimental system and the experimental conditions as summarized follows: The grinding machine was the APSG-820/2A machine, grinding wheel was the WA46J7V1A-180-13-31.5, workpiece material was SUJ2 steel; workpiece dimensions (length x width x height) were 60 mm x 40 mm x 10 mm, respectively. The workpiece was heat treated to reach a hardness of 62 HRC, the coolant was 10% emulsion oil with the flow of 4.6 l/min.

Eight experiments were carried out with the values of the changed cutting conditions in each experiment as listed in Table 21. Two quantitative criteria include the surface roughness (*C1*) and material remove rate (*C2*). The values of *C1* and *C2* at each experiment are also summarized in Table 21. In addition, in this study, another criterion is used which is the number of the grinding grains adhered in the surface of the part (*C3*). The number of grinding grains adhered in the surface of the part after grinding has a great influence on the workability of the part. If there are a large number of the grinding grains adhered in the surface of the part of the part, these grinding grains will scratch the surfaces when they contact with each other. It makes the level of wear happening quickly, especially in the initially wear stage. Thereby it will rapidly reduce the life of the product (Malkin & Guo, 2018; Marinescu et al. 2006). Therefore, creating a surface after grinding with a small number of the grinding grains adhered in the surface of the part is always desirable. However, it is very difficult to determine the exact number of the grinding grains adhered in the surface of the part. Instead, we can only evaluate them at the qualitative level, i.e., through the observation (using specialized equipment) to evaluate the number of the grinding grains adhered more or less in the surface of the part. It means that according to this measurement method, *C3* is in the form of a qualitative criterion. The evaluation of *C3* in this study was performed through the observation of workpiece surface micrographs after grinding (Figure 1).

Table 21. Experimental data when surface grinding process of SUJ2 steel

No.	Criteria		
	C1 (μm)	*C2* (mm^3/min)	*C3* (in Fig. 1)
A1	0.278	325	(1)
A2	0.844	1625	(2)
A3	1.041	975	(3)
A4	1.548	1300	(4)
A5	0.502	1950	(5)
A6	0.225	650	(6)
A7	1.059	2925	(7)
A8	1.542	3900	(8)

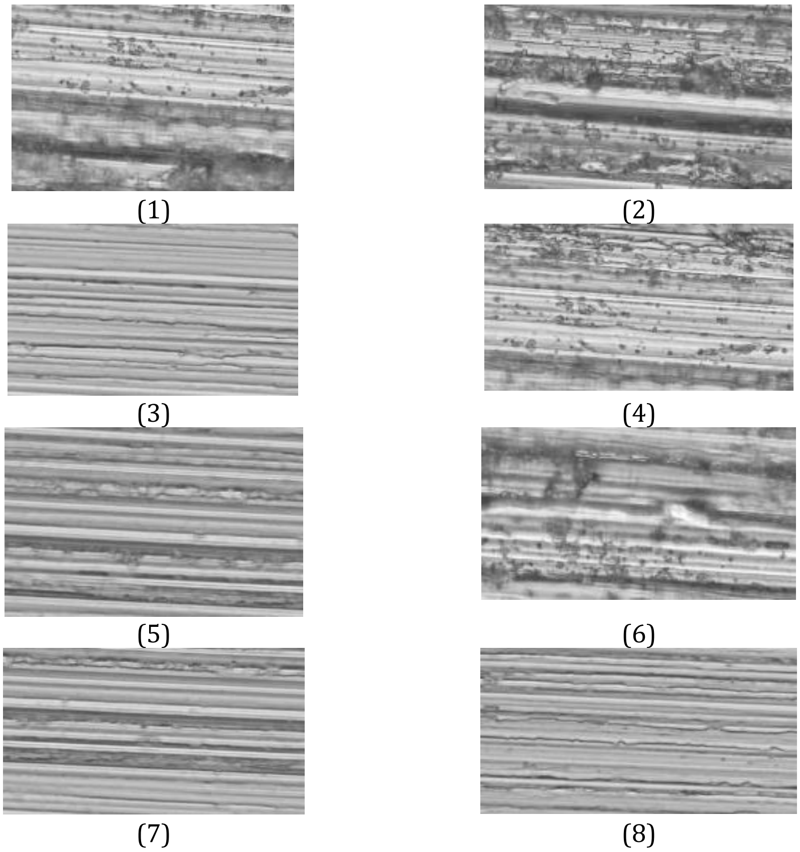

Figure 1. The surface of workpiece in surface grinding process of SUJ2 steel

Observation of Figure 1 shows that: In the photo (8) corresponding to the *A8*, the number of the grinding grains adhered in the surface of the part is the least, thus, *C3* at *A8* ranked 1. As observed the *C3* at *A3* and *A7* is quite the same and only more that that one at *A8*, so, both *A3* and *A7* rated *2.5* (the average of 2 and 3). For the remaining solutions, *C3* decrease in order *A5*, *A6*, *A4*, *A1*, and *A2*. Therefore, the ranks of *A5*, *A6*, *A4*, *A1*, and *A2* are rank 4, rank 5, rank 6, rank 7, and rank 8, respectively. The ranked results of the solutions for all three criteria are listed in Table 22.

Table 22. Ranking the solutions for each criterion when surface grinding of SUJ2 steel

No.	*Criteria*			*Rank (r_{ij})*		
	C1 (μm)	*C2* (mm^3/min)	*C3* (in Figure 1)	*C1*	*C2*	*C3*
A1	0.278	325	(1)	2	8	7
A2	0.844	650	(2)	4	4	8
A3	1.041	975	(3)	5	6	2.5
A4	1.548	1300	(4)	8	5	6
A5	0.502	1950	(5)	3	3	4
A6	0.225	650	(6)	1	7	5
A7	1.059	2925	(7)	6	2	2.5
A8	1.542	3900	(8)	7	1	1

The score of each solution was calculated according to Eq. (1) with six randomly selected different weight sets of the criteria (Table 23). The calculated results are presented in Table 24. The ranked results of the solutions according to the *FUCA* method as presented in Table 25.

Table 23. Weight of criteria in different scenarios (example 4)

Criteria	Scenarios							
	S1	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*
C1	0.2	0.25	0.28	0.3	0.32	1/3	0.35	0.38
C2	0.3	0.25	0.37	0.4	0.42	1/3	0.35	0.32
C3	0.5	0.4	0.35	0.3	0.26	1/3	0.3	0.3

Table 24. The v_i score of each solution (example 4)

No.	Scenarios							
	S1	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*
A1	6.300	6.100	5.970	5.900	5.820	5.667	5.600	5.420
A2	6.000	5.600	5.400	5.200	5.040	5.333	5.200	5.200
A3	4.050	4.350	4.495	4.650	4.770	4.500	4.600	4.570
A4	6.100	6.150	6.190	6.200	6.220	6.333	6.350	6.440
A5	3.500	3.400	3.350	3.300	3.260	3.333	3.300	3.300
A6	4.800	4.700	4.620	4.600	4.560	4.333	4.300	4.120
A7	3.050	3.200	3.295	3.350	3.410	3.500	3.550	3.670
A8	2.200	2.500	2.680	2.800	2.920	3.000	3.100	3.280

Table 25. Ranking the solutions according to the improved FUCA (example 4)

No.	Scenarios							
	S1	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*
A1	8	7	7	7	7	7	7	7
A2	6	6	6	6	6	6	6	6
A3	4	4	4	5	5	5	5	5
A4	7	8	8	8	8	8	8	8
A5	3	3	3	2	2	2	2	2
A6	5	5	5	4	4	4	4	4
A7	2	2	2	3	3	3	3	3
A8	1	1	1	1	1	1	1	1

The data in Table 25 shows that solution *A8* is always determined to be the best solution for all scenarios. Seven of the eight scenarios identified *A4* as the worst solution (except for *S1*). The ranking results for all solution are the same in the five scenarios *S4*, *S5*, *S6*, *S7*, and *S8*. The two scenarios *S2* and *S3* also give the same ranking results. In addition, there is only a small difference in ranking results between scenario *S1* and the rest.

Eq. (2) is again used to calculate the Sperman coefficients. Table 26 presents the value of the Sperman coefficients when comparing between scenarios as well as the initial rank Si.

Table 26. The values of Sperman's rank correlation *coefficients (example 4)*

	Si	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*
Si	1	1	0.943	0.943	0.829	0.829	0.829	0.829	0.829
S1		1	0.943	0.943	0.829	0.829	0.829	0.829	0.829
S2			1	1	0.886	0.886	0.886	0.886	0.886
S3				1	0.886	0.886	0.886	0.886	0.886
S4					1	1	1	1	1
S5						1	1	1	1
S6							1	1	1
S7								1	1
S8									1

The calculated results in Table 26 show that the Sperman's rank correlation coefficients of the solutions are in the range S ∈ [0.886, 1]. This represents a very high degree of correlation in this case. Thus, in this example, once again the *FUCA* method was successfully applied.

Although the four examples that were performed belonging to different machining processes (milling, turning, drilling, and grinding). The number of solutions, number of criteria, and number of scenarios that used in each case also were different. However, in each case, the obtained results confirmed the successful application of the *FUCA* method in multi-criteria decision making. From the obtained results, it can be concluded that the proposed method to overcome the limitations of the *FUCA* method is an accurate one. So, the application of *FUCA* method completely ensures the reliability when using for multi-criteria decision making, firstly in the mechanical processing field.

4. Conclusion

Having to choose a certain *MCDM* method to combine with a certain data normalization method to ensure the accuracy of multi-criteria decision making is a relatively complicated work with a lot of time consumption of decision makers. *FUCA* is a multi-criteria decision making method without requirement of data normalization. When using this method, the first mission is ranking the solutions for each criterion. However, the case with a certain criterion having equal value in several solutions has not considered in any published studies. In that case, the decision maker will not be able to rank the solutions. This is the first study to discover that limitation and to propose a method to overcome that one. With the additional use of the proposed method, the *FUCA* one was used for multi-criteria decision making for four different cases in the mechanical processing field. In each of those cases, the number of solutions, the number of criteria, and the type of criteria (qualitative, quantitative) are also not the same. The sensitivity analysis in ranking process was also performed with different scenarios for each case. Although there are many differences in the examples, the obtained results confirm that the *FUCA* method was successfully applied in the mentined cases. The discovery of the limitation of the *FUCA* method and the improvement of this method to overcome its limitation extends the application scope of this method. It was not only successful applied in multi-criteria decision making in the field of mechanical machining as done in this study, but it also promises to be successful applied in other fields as well.

The method to overcome the limitation of the *FUCA* one that was proposed in this study has not been presented in the form of a general mathematical formula. This limitation needs to be implemented in the next time. In addition, this study as well as the published studies that applied the *FUCA* method only considered the case the values of each criterion at each solution as a unique quantity. The case these values as a fuzzy set have been not considered in any studies. This gap also needs to be filled in the further studies.

In this study, the weighted values of the criteria were selected according to the studies that this study references (in those references, the weights were determined by the Entropy, AHP method, ect.), or were selected according to random values without considering the importance of the criteria. The use of weighting methods considering the importance of criteria, such as the *PIPRECIA* method (Stanujkic et al. 2017) in combination with the *FUCA* method are also the contents of works to be done in the future.

Refercences

Aytekin, A. (2021). Comparative Analysis of the Normalization Techniques in the Context of MCDM Problems. Decision Making: Applications in Management and Engineering, 4(2), 1-25. https://doi.org/10.31181/dmame210402001a

Baydas, M. (2022). The effect of pandemic conditions on financial success rankings of BIST SME industrial companies: a different evaluation with the help of comparison of special capabilities of MOORA, MABAC and FUCA methods. Business & Management Studies: An International Journal, 10(1), 245-260. https://doi.org/10.15295/bmij.v10i1.1997

Baydas, M. (2022). Comparison of the Performances of MCDM Methods under Uncertainty: An Analysis on Bist SME Industry Index. OPUS – Journal of Society Research, 19(46), 308-326. https://doi.org/10.26466/opusjsr.1064280

Baydas, M., Elma, O.E., & Pamucar, D. (2022). Exploring the specific capacity of different multi criteria decision making approaches under uncertainty using data from financial markets. Expert Systems with Applications, 197, 116775. https://doi.org/10.1016/j.eswa.2022.116755

Baydas, M., & Pamucar, D. (2022). Determining Objective Characteristics of MCDM Methods under Uncertainty: An Exploration Study with Financial Data. Mathematics, 10(7), 1115. https://doi.org/10.3390/math10071115

Bobar, Z., Bozanic, D., Djuric, K., & Pamucar, D. (2020). Ranking and Assessment of the Efficiency of Social Media using the Fuzzy AHP-Z Number Model - Fuzzy MABAC. Acta Polytechnica Hungarica, 17(3), 43-70.

Bozanic, D., Milic, A., Tesic, D., Sałabun, W., & Pamucar, D. (2021). D numbers – fucom – fuzzy rafsi model for selecting the group of construction machines for enabling mobility. FACTA UNIVERSITATIS - Mechanical Engineering, 19(3), 447 – 471. https://doi.org/10.22190/FUME210318047B

Dimic Srđan, H., & Ljubojevic Srđan, D. (2019). Decision making model in forest road network management. Military Technical Courier, 67(1), 93-115. https://doi.org/10.5937/vojtehg67-18446

Ersoy, N. (2021). Selecting the Best Normalization Technique for ROV Method: Towards a Real Life Application. Gazi University Journal of Science, 34(2) 592-609. https://doi.org/10.35378/gujs.767525

Fernando, M.M.L, Escobedo, J.L.P., Azzaro-Pantel, C., Pibouleau, L., Domenech, S., & Aguilar-Lasserre, A. (2011). Selecting the best alternative based on a hybrid multiobjective GA-MCDM approach for new product development in the pharmaceutical industry. IEEE Symposium on Computational Intelligence in Multicriteria Decision-Making (MDCM), https://ieeexplore.ieee.org/document/5949271

Krishnan, A.R. (2022). Past efforts in determining suitable normalization methods for multi-criteria decision-making: A short survey. Frontiers in Big Data, 5, 990699. https://doi.org/10.3389/fdata.2022.990699

Lakshmi, T.M, & Venkatesan, V.P. (2014). A Comparison of Various Normalization in Techniques for Order Performance by Similarity to Ideal Solution (TOPSIS). International Journal of Computing Algorithm, 3(3), 255-259.

Lamba, M., Munjal, G., & Gigras, Y. (2022). A MCDM-based performance of classification algorithms in breast cancer prediction for imbalanced datasets. International Journal of Intelligent Engineering Informatics, 9(5), 425-454. https://doi.org/10.1504/IJIEI.2021.10044779

Le, H.A., Hoang, X.T., Trieu, Q.H., Pham, D.L., & Le, X. H. (2020). Determining the Best Dressing Parameters for External Cylindrical Grinding Using MABAC Method. Applied scicences, 12(16), 8287. https://doi.org/10.3390/app12168287

Malkin, S. & Guo, C. (2008). Grinding technology: Theory and Applications of Machining with Abrasives (2nd Edition). New York: Industrial Press.

Marinescu, I.D., Hitchiner, M.P., Uhlmann, E., Rowe, W.B., & Inasaki, I. (2006). Handbook of machining with grinding wheels. CRC Press. https://doi.org/10.1201/b19462

Muhammad, L.J., Badi, I., Haruna, A.A., & Mohammed, I.A. (2021). Selecting the Best Municipal Solid Waste Management Techniques in Nigeria Using Multi Criteria Decision Making Techniques. Reports in Mechanical Engineering, 2(1), 180-189. https://doi.org/10.31181/rme2001021801b

Nguyen, V.C, Nguyen, T.D, & Tien, D.H. (2021). Cutting Parameter Optimization in Finishing Milling of Ti-6Al-4V Titanium Alloy under MQL Condition using TOPSIS and ANOVA Analysis. Engineering, Technology & Applied Science Research, 11(1), 6775-6780. https://doi.org/10.48084/etasr.4015

Ouattara, A., Pibouleau, L., Azzaro-Pantel, C., Domenech, S., Baudet, P., & Yao, B. (2022). Economic and environmental strategies for process design. Computers & Chemical Engineering, 36, 174-188. https://doi.org/10.1016/j.compchemeng.2011.09.016

Palczewski, K., & Sałabun, W. (2019). Influence of various normalization methods in PROMETHEE II: an empirical study on the selection of the airport location. Procedia Computer Science, 159, 2051-2060. https://doi.org/10.1016/j.procs.2019.09.378

Pamucar, D., Behzad, M., Bozanic, D., & Behzad, M. (2021). Decision making to support sustainable energy policies corresponding to agriculture sector: Case study in Iran's Caspian Sea coastline. Journal of Cleaner Production, 292, 125302. https://doi.org/10.1016/j.jclepro.2020.125302

Singh, R., Dureja, J.S, Dogra, M., & Randhawa, J.S. (2019). Optimization of machining parameters under MQL turning of Ti-6Al-4V alloy with textured tool using multi-attribute decision-making methods. World Journal of Engineering, 16(5), 648–659. https://doi.org/10.1108/WJE-06-2019-0170

Stanujkic, D., Zavadskas, E.K., Karbasevic, D., Smarandache, F., Turskis, Z. (2017). The use of the PIvot Pairwise RElative Criteria Importance Assessment method for determining the weights of criteria. Romanian Journal of Economic Forecasting, 20(4), 116-133.

Trung, D.D. (2022). Development of data normalization methods for multi-criteria decision making: applying for MARCOS method. Manufacturing review, 9, 22. https://doi.org/10.1051/mfreview/2022019

Varatharajulu, M., Duraiselvam, M., Bhuvanesh Kumar, M., Jayaprakash, G., & Baskar, N. (2021). Multi criteria decision making through TOPSIS and COPRAS on drilling parameters of magnesium AZ91. Journal of Magnesium and Alloys, 8(38), 1-18. https://doi.org/10.1016/j.jma.2021.05.006

Wen, Z., Liao, H., & Zavadskas, E.K. (2020). MACONT: Mixed Aggregation by Comprehensive Normalization Technique for Multi-Criteria Analysis. Informatica, 31(4), 857-880. https://doi.org/10.15388/20-INFOR417

Zopounidis, C., & Doumpos, M. (2017). Multiple Criteria Decision Making - Applications in Management and Engineering. Springer. https://doi.org/10.1007/978-3-319-39292-9

Abbreviations

MCDM: Multi-Criteria Decision Making

FUCA: Faire Un Choix Adéquat (in French) - Make an Adequate Choice

MOORA: Multiobjective Optimization On the basis of Ratio Analysis

MABAC: Multi-Attributive Border Approximation area Comparison

WSA: Weighted Sum Approach

PROMETHEE: Preference Ranking Organization METHod for Enrichment of Evaluations

COPRAS: COmplex PRroportional Assessment

TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution

S-: Negative Ideal Separation

SAW: Simple Additive Weighting

CODAS: COmbinative Distance-based Assessment

GRA: Grey Relational Analysis

LINMAP: LINear programming technique for Multidimensional Analysis of Preference

AHP: Analytic Hierarchy Process

COPRAS: COmplex PRoportional ASsessment

PIPRECIA: PIvot Pairwise RElative Criteria Importance Assessment