ISSN 2683-345X
journal homepage: http://ijiemjournal.uns.ac.rs/

International Journal of Industrial Engineering and Management

Volume 15 / No 2 / June 2024 / 156 - 168

Original research article

Data Normalization for Root Assessment Methodology

D. D. Trung[a] 0000-0002-3190-1026, B. Dudić[b,d,*] 0000-0002-4647-6026, N.-T. Nguyen[c] 0000-0002-2618-8713, A. Ašonja[d] 0000-0001-6667-1024

[a] *Hanoi University of Industry, School of Mechanical and Automotive Engineering, Vietnam;*
[b] *Comenius University Bratislava, Faculty of Management, Bratislava, Slovakia;*
[c] *Vietnam National University Hanoi, International School, Vietnam;*
[d] *University Business Academy, Faculty of Economics and Engineering Management, Novi Sad, Serbia*

ABSTRACT

Data standardization is considered as mandatory work when applying most Multi-Criteria Decision Making (MCDM) methods. This study was conducted to identify the appropriate data standardization methods in combining with the RAM (Root Assessment Method) method. Thirteen different data normalization methods were applied in combining with the RAM method to solve the different problems. Among the thirteen tested data normalization methods, there is an available data normalization method from RAM method. In addition to this one, this study proposed another data normalization method that is determined to be suitable when combining with the RAM method.

ARTICLE INFO

Article history:

Received November 6, 2023
Revised May 4, 2024
Accepted May 21, 2024
Published online May 31, 2024

Keywords:
MCDM;
RAM method;
Normalization method

*Corresponding author:
Branislav Dudić
branislav.dudic@fm.uniba.sk

1. Introduction

Determining the best solution among many solutions while considering many criteria of each solution is always the set goal in all situations, in all different fields. This is a multi-criteria decision making (MCDM) action [1], [2]. The number of MCDM methods proposed by scholars is increasing rapidly, currently, this number has exceeded 200 [3]. RAM is a very young method, it first appeared on September 7, 2023 [4]. According to the proponent of the RAM method, this method has the advantage of overcoming the shortcomings of existing MCDM methods. The advantage is the ability to compensate between beneficial criteria and non-beneficial criteria. Limiting the rank reversal phenomenon is also an advantage of RAM method [4]. It is also necessary to mention again the rank inversion phenomenon. This is the phenomenon that the ranks of solutions change when the number of ranked solutions increases or decreases. For example, when there is a ranking for

Published by the University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia.

http://doi.org/10.24867/IJIEM-2024-2-354

a set of solutions, but adding a solution that is worse than the previous solutions causes the ranks of the previous solutions to change. This often causes the confusion and difficulty in decision making, especially in situations that require multidimensionality and carefully analysis from many factors [5], [6].

Although the RAM method has been mentioned with its above advantages, this method has only appeared for a short time, so, only a few studies have applied this one. These can be mentioned as applying RAM method to choose the optimal solution about fertilizers and planting mixtures in mushroom care [7], applying to choosing the best lubricant for two-stroke engines, choosing the best materials for manufacturing gears [8], applied to select the best fireproof materials [9], applied to determine the most efficient production method for fuel cell vehicles [10].

When using the RAM method as well as most other MCDM methods, an important mission is the data normalization. Data normalization is the converting process of criteria with different dimensions into criteria without dimensions [11]. In this way, the decision making only focuses on the nature of the data and eliminates the influence of different dimensions on the decision [11]. However, when looking closely at the RAM method, a limitation of this method was found. This limitation of the RAM method is that the data normalization method available in it cannot be used in certain cases. Details about this issue will be discussed in section 3 of this paper. When a certain data standardization method cannot be used, it is necessary to find an alternative data standardization method [12], [13]. This study was conducted to search for data normalization methods that were determined to be suitable for combination with RAM method. In order to accomplish this task, an overview of some combinations of data normalization methods and the MCDM methods is necessary. This content is presented in section 2 of this paper.

2. Overview

As mentioned above, it is necessary to identify the data normalization methods that are suitable when combined with MCDM methods. Table 1 presents the names and calculation formulas of some commonly used data normalization methods [14]. In which, B and C represent the larger the better criterion and the smaller the better criterion, respectively. Also in Table 1, x_{ij} represents the value of criterion j at solution i, m is the number of solutions, with $i=1 \div m$.

The summarized information in Table 1 shows that not all data normalization methods can be used in all cases. Consider a few situations to clarify this statement. In the first situation, if a certain criterion is of type B (the bigger the better) and its maximum value is zero, the methods N1, N5, N6, N8, N9, N10 cannot be used. Consider another situation, if a certain criterion is of type C (the smaller the better) and its value in a certain solution is zero, then methods N1, N3, N5, N7, N10 also cannot be used. If these cases occur, choosing another data standardization method to instead is necessary.

However, many studies have shown that the choice of data normalization method has a significant impact on the results of ranking solutions [15, 16]. Therefore, before using a certain data normalization method to combine with an MCDM method, it is necessary to investigate the appropriateness of combining them together. This work has also been found in many studies, in many different fields. The Information about some investigations on this topic was summarized in Table 2. in which, the cells colored green show the compatibility when combining the data normalization methods and the MCDM methods. The cells highlighted in yellow represent the nonconformities when combining the data normalization methods and the MCDM methods. The uncolored cells show that the investigations about the combinations of the data normalization methods and the MCDM methods has not been mentioned (considered in the references that this work used).

The summarized results in Table 2 show that for each MCDM method, only one or a few data normalization methods are determined to be suitable to combine with it. Even with an MCDM method, the suitability of data normalization methods when combined with it will change when applied to specific problems. Reviewing Table 2 shows that N5 is determined to be suitable to combine with the CODAS method when ranking smartphones, but it is not suitable to combine with the CODAS method when ranking robots, ranking the atmosphere in the office, and rank turning processes. In another case, the VIKOR method was determined to be suitable in combining with N2 method to rank the wireless internet systems, but N2 method was determined to be unsuitable in combining with VIKOR when ranking the products through customer feedback. Similarly, with the N4 method, this problem also occurs when combining it with the VIKOR method. These issues show that determining the suitability of data normalization methods with each MCDM method needs to be carried out in each specific application case.

Table 1. The data normalization method [14]

Method	$if\, j \in B$	$if\, j \in C$	Sign
Linear normalization	$\frac{x_{ij}}{max\, x_{ij}}$	$\frac{min\, x_{ij}}{x_{ij}}$	N1
Weitendorf normalization	$\frac{x_{ij} - min\, x_{ij}}{max\, x_{ij} - min\, x_{ij}}$	$\frac{max\, x_{ij} - x_{ij}}{max\, x_{ij} - min\, x_{ij}}$	N2
Sum linear normalization	$\frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$	$\frac{1/x_{ij}}{\sum_{i=1}^{m} 1/x_{ij}}$	N3
Vector normalization	$\frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}(x_{ij})^2}}$	$1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}(x_{ij})^2}}$	N4
Logarithmic normalization	$\frac{ln x_{ij}}{ln(\prod_{i=1}^{m} x_{ij})}$	$1 - \frac{ln x_{ij}}{ln(\prod_{i=1}^{m} x_{ij})}$	N5
Max linear normalization	$\frac{x_{ij}}{max\, x_{ij}}$	$1 - \frac{x_{ij}}{max\, x_{ij}}$	N6
Min linear normalization	$1 - \frac{min\, x_{ij}}{x_{ij}}$	$\frac{min\, x_{ij}}{x_{ij}}$	N7
Jüttler-Körth normalization	$1 - \left\lvert\frac{max\, x_{ij} - x_{ij}}{max\, x_{ij}}\right\rvert$	$1 - \left\lvert\frac{min\, x_{ij} - x_{ij}}{max\, x_{ij}}\right\rvert$	N8
Peldschus normalization	$\left(\frac{x_{ij}}{max\, x_{ij}}\right)^2$	$\left(\frac{x_{ij}}{max\, x_{ij}}\right)^3$	N9
Stop normalization	$\frac{100 x_{ij}}{max\, x_{ij}}$	$\frac{100 min\, x_{ij}}{x_{ij}}$	N10
Z-score normalization	$\frac{x_{ij} - \frac{\sum_{i=1}^{m} x_{ij}}{m}}{\sqrt{\frac{\sum_{i=1}^{m}(x_{ij} - \mu_j)^2}{m}}}$	$-\frac{x_{ij} - \frac{\sum_{i=1}^{m} x_{ij}}{m}}{\sqrt{\frac{\sum_{i=1}^{m}(x_{ij} - \mu_j)^2}{m}}}$	N11
Enhanced accuracy normalization	$1 - \frac{max x_{ij} - x_{ij}}{\sum_{i=1}^{m}(max x_{ij} - x_{ij})}$	$1 - \frac{x_{ij} - min x_{ij}}{\sum_{i=1}^{m}(x_{ij} - \mathrm{x})}$	N12

The standardization method available in the RAM method cannot be used if the total value of a certain criterion in all solutions is zero. When observing the data normalization formula available in the RAM method in section 3 of this study, you will see that this comment is completely accurate. This issue prompted an investigation to find other data normalization methods that were identified as suitable methods in combining with RAM method.

3. RAM Method

In order to rank the solutions using RAM method, the performing process is presented by the steps as follows [4].

Step 1: Build a decision-making matrix with m rows and n columns, in which m is the number of the solutions that need to be ranked, n is the number of criteria for each solution. Let y_{ij} to be the value of criterion j at solution i, with $j = 1 \div n$, $i = 1 \div m$.

Step 2: Normalize the data by Eq. (1). This method of data normalization is denoted N13.

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{1}$$

Step 3: Calculate the standardized values when considering the weights of the criteria by Eq. (2).

$$y_{ij} = w_j \cdot r_{ij} \tag{2}$$

where, w_j is the weight of criterion number j.

Step 4: Calculate the total standardized score when considering the weights of the criteria by Eq. (3) and Eq. (4). In which, Eq. (3) applies to criteria of type B and Eq. (4) applies to criteria of type C.

$$S_{+i} = \sum_{j=1}^{n} y_{+ij} \tag{3}$$

Table 2. The combination of data normalization methods and MCDM methods

MCDM method	Normalization method												Application cases	Sources
	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12		
CODAS													Rank the smartphones	[17]
CODAS													Rank the robot types, rank the working room atmosphere, and rank the turning processes	[18]
SAW													Rank the participating candidates as PhD students	[19]
PIV													Rank the financial situation of companies	[20]
ROV													Rank the financial situation of companies	[21]
AHP													Rank the smart parking locations	[22]
WASPAS													Rank the food processing methods	[23]
TOPSIS													Rank the food processing methods	[23]
TOPSIS													Rank the drone landing solutions	[24]
TOPSIS													Rank the car types	[25]
Simple WISP													Rank the solutions for a set of random numbers	[26]
VIKOR													Rank the wireless internet network systems	[27]
VIKOR													Rank the products based on the customer feedback	[28]
WASPAS													Rank the robot types	[29]
PSI													Rank the personnel for a company, rank the types of robots, rank the turning processes, rank the air condition in the offices	[30]
CRADIS													Rank the metal drilling methods, rank the personnel for a garment company, rank the medical waste incinerators, rank the air quality in offices	[31]
MACONT													Rank the logistics service provider, rank the robots, rank the turning processes	[32]
MARCOS													Rank the turning processes, rank the milling processes, rank the grinding processes	[33]

$$S_{-i} = \sum_{j=1}^{n} y_{-ij} \tag{4}$$

Step 5: Calculate the score of each solution by Eq. (5).

$$RI_i = \sqrt[2+S_{-i}]{2 + S_{+i}} \tag{5}$$

Step 6: Rank the solutions in descending order of their *RIi* scores.

It seems that applying the six above steps to rank the solutions is very simple and straightforward. This was also confirmed by the proponent of this method [4]. However, if for a certain criterion the total of their values of the solutions is zero, then Eq. (1) will be meaningless. It means N13 cannot be used. In this case, applying the RAM method is impossible. This situation motivated the studies to identify other data normalization methods that could replace N13. This study will investigate the suitability of all thirteen data normalization methods that were mentioned above in combining with the RAM method. Thirteen data normalization methods are mentioned, including the twelve methods in Table 1, and N13 to be the method available of the RAM method. The main objective of this study is to determine the data normalization methods that are validated as suitable when combining with the RAM method. In order to save time and costs, the surveys were conducted based on the referenced datasets from published references. In previously published studies, the ranks of solutions were determined using other MCDM methods. The ranked results using other MCDM methods in those studies will be used as answers to evaluate the suitability of data normalization methods when combining with the RAM method. In the next section of this study, the surveys will be carried out in some specific cases.

4. Results and Discussion

4.1 Application Cases

4.1.1 Case 1

Nine experiments of a milling process were performed. Two objectives including surface roughness (Ra) and material removal rate (MRR) were measured in each experiment. The data of the experimental process was summarized in Table 3. The units and weights of each criterion are also clearly shown in this table [34]. Ra is a C-type criterion, MRR is a B-type criterion. The selection of the best experiment was also performed previously using five different methods including EDAS, MARCOS, PIV, MOORA, and TOPSIS methods [34].

Table 3. The experimental results of milling processes [34]

Exp.	Ra	MRR
	μm	mm^3/min
#1	0.571	1120
#2	0.818	2400
#3	0.493	4160
#4	0.426	1680
#5	0.47	3200
#6	0.851	2080
#7	0.437	2240
#8	0.694	1600
#9	0.717	3120
Weight	0.6641	0.3359

Ranking the experiments in Table 1 using the RAM method is conducted as follows:

Standardization of data according to the N13 method was performed, and the normalization results are summarized in Table 4.

The standardized values when considering the weights of the criteria were calculated according to Eq. (2). The results are summarized in Table 5.

Table 4. The normalized values using N13 method

Exp.	Ra	MRR
#1	0.1043	0.0519
#2	0.1494	0.1111
#3	0.0900	0.1926
#4	0.0778	0.0778
#5	0.0858	0.1481
#6	0.1554	0.0963
#7	0.0798	0.1037
#8	0.1267	0.0741
#9	0.1309	0.1444

Table 5. The normalized values using N13 method with the weights of criteria

Exp.	Ra	MRR
#1	0.0692	0.0174
#2	0.0992	0.0373
#3	0.0598	0.0647
#4	0.0517	0.0261
#5	0.0570	0.0498
#6	0.1032	0.0323
#7	0.0530	0.0348
#8	0.0841	0.0249
#9	0.0869	0.0485

The Eq. (3), (4), and (5) were applied respectively to calculate the values of some parameters in the RAM method. The calculated results were summarized in Table 6. The rankings of the experiments were also determined and summarized in this table.

Table 6. Several parameters in RAM method and the rank of the experiments

Exp.	S_{+i}	S_{-i}	RI_i	Rank
#1	0.0174	0.0692	1.4038	6
#2	0.0373	0.0992	1.4036	7
#3	0.0647	0.0598	1.4219	1
#4	0.0261	0.0517	1.4108	4
#5	0.0498	0.0570	1.4175	2
#6	0.0323	0.1032	1.4010	9
#7	0.0348	0.0530	1.4135	3
#8	0.0249	0.0841	1.4029	8
#9	0.0485	0.0869	1.4100	5

The ranking of milling experiments using N13 to normalize data has been completed. For twelve different data normalization methods (N1 to N12), the same processes were applied. Figure 1 shows a histogram of the ranking results of milling experiments when using the RAM method in combining

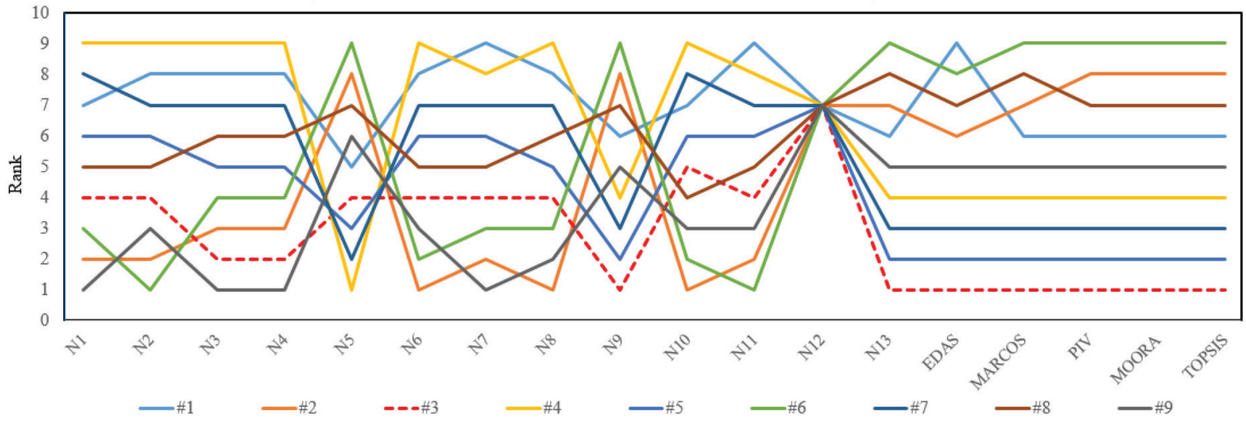

Figure 1. Ranking the experiments of milling processes using different methods

with thirteen different data normalization methods and when using five other MCDM methods (EDAS, MARCOS, PIV, MOORA, TOPSIS).

The results from Figure 1 show that, when using 13 different data normalization methods, only N9 and N13 were able to identify experiment #3 as the best experiment like when using the remaining five MCDM methods. In addition, the rankings of the experiments using the RAM method (combined with N13) are completely identical to those when using the MARCOS method. The rankings of the experiments when using N9 to combine with RAM also overlap in 7/9 experiments compared to the case using N13 to combine with RAM and compared to the case using the MARCOS method. This confirms that in this case, the N9 is suitable to combine with RAM. Additionally, the worst experiment that was found when using N9 combined with RAM (experiment #6) was the same as the case using N13 combined with RAM and the same the cases using the MARCOS, PIV, MOORA, and TOPSIS methods.

4.1.2 Case 2

Sixteen experiments of a turning process were performed. In each experiment, four criteria including surface roughness (Ra), roundness deviation (RE), tool wear (VB), and material removal rate (MRR) were measured and summarized in the Table. 7. Ra, RE, and VB are three criteria of type C, only one criterion of type B is MRR [35].

Determining the best experiment among sixteen experiments was also performed using the COCOSO, MABAC, MAIRCA, EAMR, and TOPSIS methods [35]. The ranking of turning experiments using the RAM method in combining with thirteen different data normalization methods was also performed similarly to case 1.

Table 7. The experimental results of turning processes [35]

Exp.	Ra	RE	VB	MRR
	μm	μm	μm	mm^3/min
	min	min	min	max
#1	0.238	1.500	2.898	21.333
#2	0.755	3.467	0.663	53.333
#3	1.271	6.233	3.941	96.000
#4	0.146	2.250	2.358	149.333
#5	0.442	5.200	2.874	53.333
#6	0.958	7.466	3.393	33.333
#7	0.389	3.000	1.812	160.000
#8	0.128	6.934	2.328	140.000
#9	0.644	8.527	2.848	96.000
#10	0.322	4.800	2.534	160.000
11	0.838	7.654	3.048	48.000
12	1.073	5.666	3.244	112.000
13	0.224	2.400	0.976	149.333
14	0.285	4.766	1.486	140.000
15	0.520	2.833	1.678	112.000
16	0.308	3.600	2.463	65.333
Weight	0.315	0.291	0.233	0.161

The results from Figure 2 show that when using the RAM method to rank the experiments, the experiments that were ranked 1st, 4th, 5th, 6th, 7th, 11th, 14th, 15th, and 16th were completely identical when using two data normalization methods (N9 and N13). The special thing is that the best experiment (experiment #13) is completely identical to that one when using RAM methods (combined with two methods N9 and N13) and other multi-criteria decision making methods including COCOSO, MABAC, MAIRCA, EAMR, and TOPSIS methods. In other words, in this case, N9 was also determined to be suitable to combine with the RAM method. Additionally, the worst experiment that was found using N9 combined

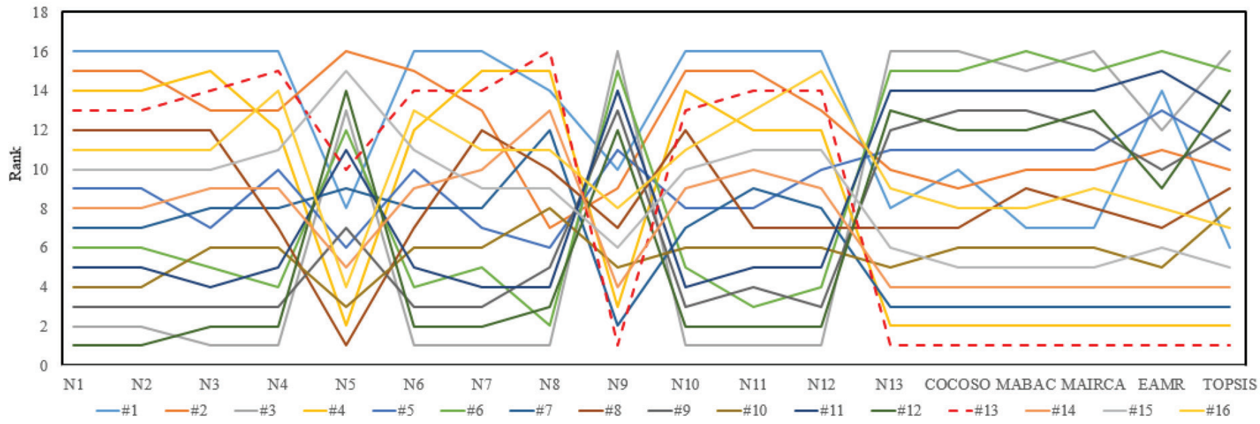

Figure 2. Ranking the experiments of turning processes using different methods

with the RAM method (experiment #3) is also the worst experiment when using N13 combining with the RAM method and also the worst one when using other multi-criteria decision-making methods including COCOSO, MAIRCA, and TOPSIS methods.

4.1.3 Case 3

In this case, ranking of drilling experiments was performed. The data of seventeen drilling experiments are listed in Table 8 [30, 36]. In each experiment, the six criteria include drilling time (T), entry burr height (enH), exit burr height (exH), entry burr thickness (enT), exit burr thickness (exT), and surface roughness (Ra) were measured and stored. All six of these criteria are B-type criteria. Determining the best drilling experiment among seventeen experiments was also conducted previously using the FUCA method [30] and using the two other methods (TOPSIS and COPRAS) [36].

The ranking of drilling experiments using the RAM method in combining with thirteen data normalization methods was also performed similarly to the two above cases.

Figure 3 presents the ranked results of drilling experiments using different methods.

Table 8. The experimental results of drilling processes [30, 36]

Exp.	T	enH	exH	enT	exT	Ra
	s	mm	mm	mm	mm	µm
	min	min	min	min	min	min
#1	14.03	0.051	0.058	0.105	0.21	0.479
#2	7.59	0.053	0.058	0.155	0.245	1.211
#3	7.34	0.035	0.06	0.165	0.215	0.916
#4	4.06	0.033	0.075	0.18	0.215	0.535
#5	5.4	0.048	0.078	0.25	0.195	0.601
#6	5.5	0.05	0.084	0.185	0.185	0.703
#7	2.81	0.033	0.058	0.185	0.185	0.466
#8	2.62	0.028	0.048	0.2	0.19	0.577
#9	2.88	0.028	0.05	0.18	0.15	0.417
#10	2.75	0.043	0.051	0.23	0.195	0.675
#11	2.84	0.043	0.055	0.165	0.205	0.418
#12	1.59	0.028	0.074	0.145	0.17	0.601
#13	1.88	0.038	0.064	0.185	0.175	0.563
#14	3.44	0.049	0.066	0.19	0.185	0.391
#15	2.04	0.023	0.059	0.16	0.18	0.493
#16	2.1	0.043	0.05	0.235	0.185	0.675
#17	1.25	0.04	0.049	0.44	0.19	0.65
Weight	0.3	0.1	0.1	0.1	0.1	0.3

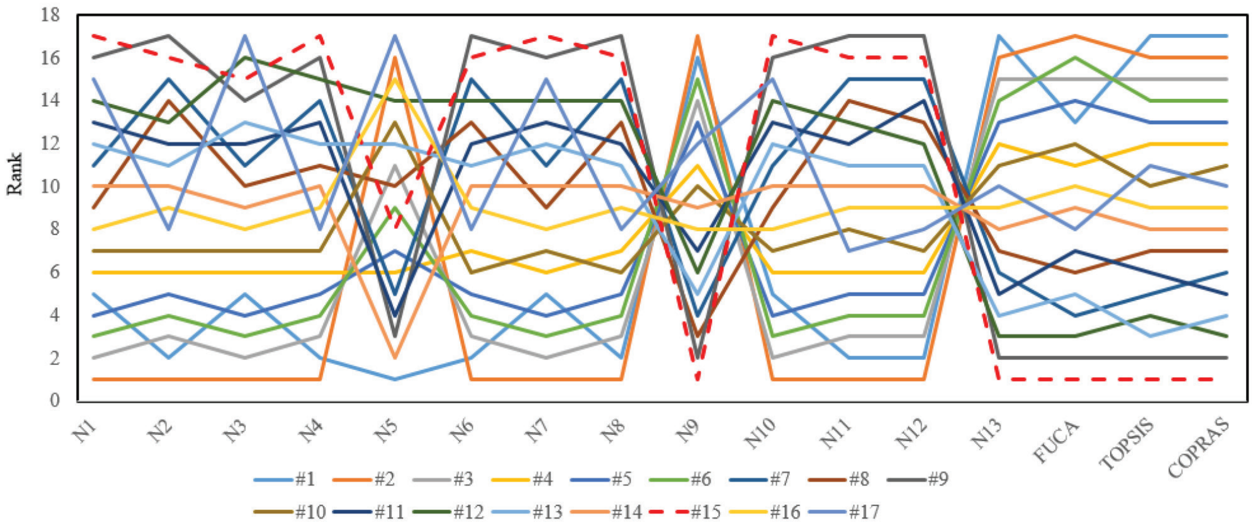

Figure 3. Ranking the experiments of drilling processes using different methods

The results in Figure 3 show that the experiments ranked 1 (experiment #15), ranked 2 (experiment #9) are completely identical when using RAM methods (combined with N9 and N13), FUCA method, TOPSIS method, and COPRAS method. Thus, in this case, we can also confirm that N9 is suitable to combine with RAM method.

The three cases performed above have differences in the number of solutions, differences in the number of B-type criteria, and differences in the number of C-type criteria. However, in all three cases, it has been confirmed that the combination of N9 with RAM always determines the best solution like when combining N13 with RAM method and also like when using other MCDM methods. This allows us to confirm that the N9 is suitable for combination with RAM method. However, can this compatibility still be maintained if other scenarios arise in each case? To answer this question, sensitivity analysis when ranking solutions is necessary and this content is presented in the next section of this study.

4.2 Sensitivity Analysis

Changing the determining weight method for criteria, changing the types of criteria, removing a solution from the list of solutions are three commonly used methods to create different scenarios when conducting the sensitivity analysis [37, 38, 39]. Removing a solution from the list of solutions that was the creating different scenarios method applied in this study. This method has also been used in several recent studies [14, 40].

To ensure the objectivity of the sensitivity analysis results, the elimination of a certain solution is also chosen objectively. In the case of ranking the milling experiments, the last experiment (experiment #9) was removed from the list. In the case of ranking the turning experiments, the first experiment (experiment #1) was removed from the list. In the case of ranking the drilling experiments, the best experiment (experiment #15) was removed from the list. The ranking of experiments (in each specific problem) is performed using the RAM method with two data normalization methods including N9 and N13 methods. Figures 4, 5 and 6 are the graphs presenting the ranked results of the experiments in the three cases as above mentioned.

The results from Figure 4 show that after removing #9, the rankings of 6/8 solutions are completely the same when using N9 and N13. The special thing is that #3 is still determined to be the best experiment, #6 is still determined to be the worst experiment like in the case when #9 was not removed from the list. This confirms that removing #9 from the list of solutions does not influence on the identified results of the best and worst experiments. Therefore, a definite conclusion is drawn that the N9 is suitable for combination with RAM.

The results from Figure 5 show that after removing #1 from the list, the best experiment that was found when using the combination of N9 with the RAM methods (experiment #13) is also the best one when using a combination of N13 and RAM methods. The worst experiment (experiment #13) was found to be the same when using both N9 and N13 methods. Interestingly, both the best and the worst experiments that were found after removing #1 from the list were still the best and the worst ones before removing #1 from the list. These things further rein-

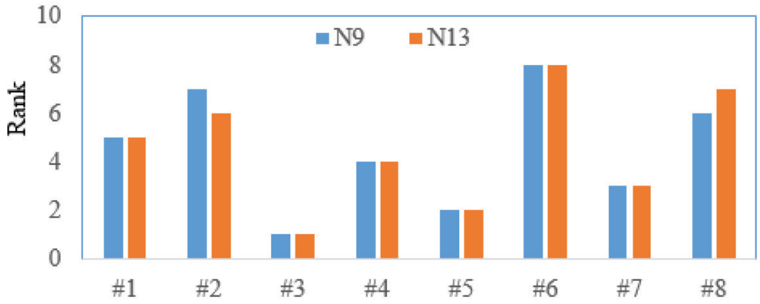

Figure 4. Ranking the milling experiments after removing #9 experiment from the list of experiments

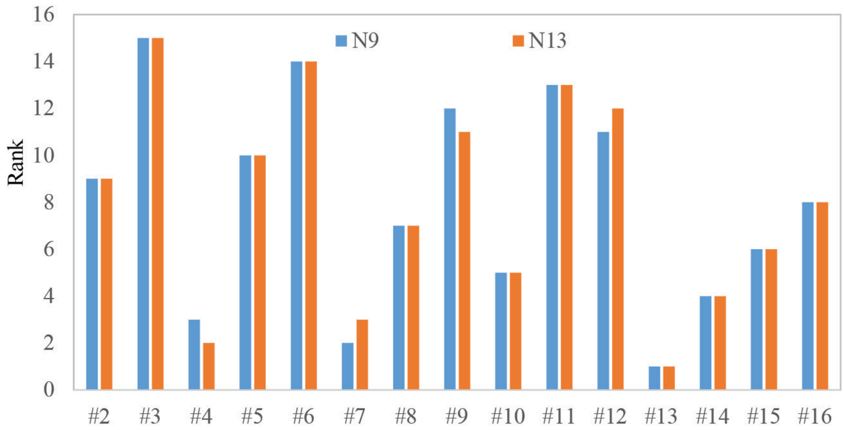

Figure 5. Ranking the turning experiments after removing #1 experiment from the list of experiments

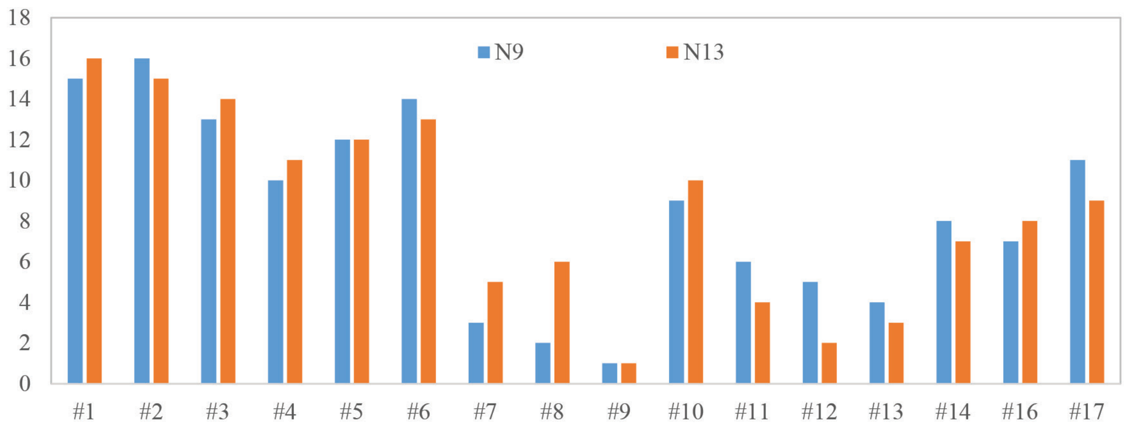

Figure 6. Ranking the drilling experiments after removing #15 experiment from the list of experiments

force the opinion that N9 is suitable to combine with RAM method.

The results from Figure 6 show that after removing the best experiment from the list (experiment #15), #9 is determined to be the best experiment in both cases using N9 combining with RAM and using N13 combining with RAM. The special thing is that before removing #15 from the list, #9 was ranked 2nd in all cases (combining N9 with RAM, combining N13 with RAM, and when using other MCDM methods including FUCA, TOPSIS, and COPRAS). This confirms that N9 is very suitable to combine with RAM method.

Through the three surveyed cases, it shows that when combining N9 with the RAM method, it always finds the best experiment like when combining N13 with the RAM method. It is also important to recall that N13 is a data normalization method available in

RAM method. In particular, the combination of N9 with RAM method always finds the best experiments like when using other MCDM methods. Different scenarios were also created for sensitivity analysis. The analytical results still confirm that N9 is very suitable for combination with the RAM method. The discovery that N9 was determined to be suitable for combination with RAM method is very important in cases when the data normalization method available in RAM method (N13) cannot be applied. In this case, we can use N9 to replace N13. A hypothetical case that follows will highlight this conclusion.

4.3 Using N9 in combining with RAM method in cases N13 cannot be used

Suppose there are five solutions including A1, A2, A3, A4, and A5. Each solution includes four criteria C1, C2, C3, and C4 as listed in Table 9. C1 and C3 are two criteria of type B, whereas the remaining two criteria (C2 and C4) are both of type C. This case is called case 4. The task of multi-criteria decision making is to find a solution (among five solutions) that ensures C1 and C3 are considered the smallest, and C2 and C4 are considered the largest.

Table 9. The data of case number 4

Alt.	C1	C2	C3	C4
A1	5	12	108	0.55
A2	2	27	98	0.34
A3	-6	32	72	0.34
A4	-1	33	100	0.18
A5	0	15	110	0.24
Weight	0.25	0.25	0.25	0.25

In Table 9, the authors tried to make the data special so that N13 could not be applied. The special thing is that the total value of criterion C1 in the five solutions is 0. In this case, N9 was selected to combine with the RAM method. For simplicity, the weights of criteria were chosen to be equal, i.e., equal to 0.25. The FUCA, TOPSIS, and CURLI methods were also used in this case. This work aims to evaluate the accuracy in finding the best solution when using a combination of N9 with RAM methods. The FUCA, TOPSIS, and CURLI were used to compare to the combination of N9 and RAM method because these three methods have differences in the ways to apply. FUCA that is a method, does not require the data normalization method [30, 41]. TOPSIS that is a well-known method is considered the most used among MCDM methods [42, 43]. In addition, CURLI that is the only one method can be used without data normalization method and without calculating method of the weights of the criteria [44, 45].

Figure 7 presents a graph showing the ranked results of solutions using different methods.

The results from Figure 7 show that the ranked 1 and 2 of solutions are completely coincident when using the FUCA, TOPSIS, CURLI methods and when combining N9 with RAM method. This further reinforces the assertion that N9 is suitable for combination with RAM. The sensitivity analysis was also performed in this case. A scenario that was created by removing the best solution (A3) from the list of solutions. Figure 8 presents a graph representing the results of ranking the solutions after removing A3 from the list of solutions.

After withdrawing the best solution (A3) from the list of solutions, A4 is determined to be the best solution in all four cases (including the combination of N9 and RAM method, and when using the three MCDM methods including FUCA, TOPSIS, and CURLI method). In which, A4 is the 2nd ranked solution when A3 has not been removed from the list of solutions. This helps us firmly confirm that N9 is suitable to combine with the RAM method, and N9 can completely be used to replace N13 in this case.

5. Conclusions

RAM is a recently proposed MCDM method. In order to apply this method, users only need to use simple mathematical formulas, so this method is expected to attract a large amount of attention from scholars. However, the data normalization method available in RAM (method N13) cannot be used in the cases where the total values of a certain criterion in all solutions is zero. Twelve other data normalization methods (from N1 to N12) were used to investigate the level of agreement when combined with the RAM method.

The investigation was conducted in four different cases. In the first three cases, the selected problems have differences in the number of solutions, the number of criteria, and the type of criteria. In all those cases, this study identified that N9 is the suitable method for combination with the RAM method. In the fourth case, the evaluation of the suitability when combining N9 with the RAM method was performed. In this case, N13 cannot be applied. The analyzed results still confirm that N9 is suitable for combination with the RAM method. Therefore, the

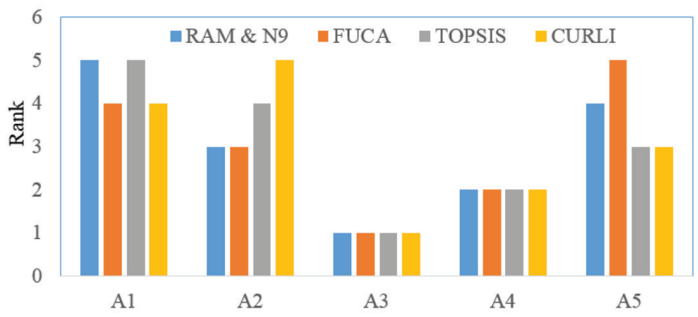

Figure 7. Ranking the solutions of case number 4 using different methods

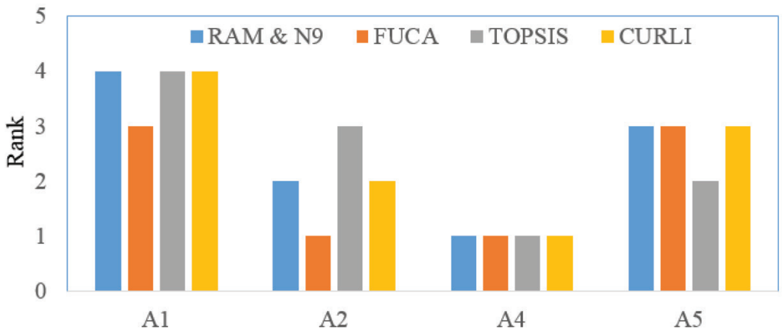

Figure 8. Ranking the solutions of case number 4 using different methods after removing A3 from the list of solutions

application range of the RAM method is expected to be much larger than its current version based on this new discovery.

In this study, N9 was determined to be suitable for combination with the RAM method in MCDM problems in three different mechanical machining processes (milling, turning, and drilling) and in one assumption case (case 4). However, has the N9 been determined to be suitable for combination with RAM in other fields? To answer this question, the investigation of combining the N9 with RAM method needs to continue to be carried out in each specific application.

In addition, this study has not considered the situation where the components in the decision-making matrix are sets of fuzzy numbers. In that context, whether the N9 method could still be determined to be suitable for combination with RAM method is a question that needs to be answered through the further development of fuzzy-RAM method in further studies.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

[1] V. H. Tran, Q. Q. N. Nguyen, H. B. Vu, M. H. Tran, T. T. T. Nguyen, T. N. Dao, Q. D. Nguyen, H. T. Pham, and D. T. Do, "Multi-criteria decision-making for electric bicycle selection," Adv Eng Lett, vol. 4, no. 1, pp. 126-135, 2022, doi: 10.46793/adeletters.2022.1.4.2.

[2] M. Žižović, D. Pamučar, M. Albijanić, P. Chatterjee, and I. Pribićević, "Eliminating rank reversal problem using a new multi-attribute model—The RAFSI method," Mathematics, vol. 8, no. 1015, 2020, doi: 10.3390/math8061015.

[3] M. Baydaş, T. Eren, Z. Stević, V. Starčević, and R. Parlakkaya, "Proposal for an objective binary benchmarking framework that validates each other for comparing MCDM methods through data analytics," Peer J, vol. 9, no. e1350–e1350, 2023, doi: 10.7717/peerj-cs.1350.

[4] A. Sotoudeh-Anvari, "Root Assessment Method (RAM): A novel multi-criteria decision making method and its applications in sustainability challenges," J Clean Prod, vol. 423, no. 138695, 2023, doi: 10.1016/j.jclepro.2023.138695

[5] N. Munier, "A new approach to the rank reversal phenomenon in MCDM with the SIMUS method,", Multiple criteria decision making, vol. 11, pp. 137-152, 2016, doi: 10.22367/mcdm.2016.11.09

[6] S. Mufazzal, and S. Muzakkir, "A New Multi-Criterion Decision Making (MCDM) Method Based on Proximity Indexed Value for Minimizing Rank Reversals,", Computers & Industrial Engineering", 2018, doi: 10.1016/j.cie.2018.03.045

[7] D. D. Trung, D. V. Duc, N. C. Bao, and D. T. T. Thuy, "Using the root assessment method to choose the optimal solution for mushroom cultivation,", Yugoslav Journal of Operations Research, 2024, doi: 10.2298/YJOR240115007T

[8] T. V. Dua, D. V. Duc, N. C. Bao, and D. D. Trung, "Integration of objective weighting methods for criteria and MCDM methods: Application in material selection,", EUREKA: Physics and Engineering, vol. 2024, no. 2, pp. 131–148, 2024, doi: 10.21303/2461-4262.2024.003171

[9] D. D. Trung, "Using RAM method for optimal selection of flame retardant nanocomposite material fabrication solution,", EPJ Applied Metamaterials, vol. 11, no. 4, 2024, doi: 10.1051/epjam/2024005

[10] A. Elsayed, "TrS-RAM:Leveraging Novel MCDM Techniques for Evaluating Sustainability of Fuel Cell Vehicles Based on Tree Soft Technique,", HyperSoft Set Methods in Engineering, vol. 1, pp. 46–58, 2024, doi: 10.61356/j.hsse.2024.18450

[11] A. Puska, A. Stilic, D. Pamucar, D. Bozanic, and M.Nedeljkovic, "Introducing a Novel Multi-Criteria Ranking of Alternatives with Weights of Criterion (RAWEC) Model,", MethodsX, 2024, doi: 10.1016/j.mex.2024.102628

[12] S. T. Mhlanga, M. Lall, "Influence of normalization techniques on multi-criteria decision-making methods," J. Phys.: Conf. Ser., vol. 2224, no. 012076, 2022, doi: 10.1088/1742-6596/2224/1/012076

[13] A. B. M. Pereira, J. A. B. Montevechi, W. G. M. Pinto, and C. H. Santos, "Simulation and digital twins to support reverse logistics decisions: A review," Int J Simul Model, vol. 22, no. 3, pp. 381–391, 2023, doi: 10.2507/IJSIMM22-3-640.

[14] D. D. Trung, V. D. Tran, V. D. Duong, and N. –T. Nguyen, "Investigation of the appropriate data normalization method for combination with preference selection index method in MCDM," Oper Res Eng Sci Theor Appl, vol. 6, pp. 44-64, 2023, doi: 10.31181/oresta/060103.

[15] M. Yazdani, P. Zaraté, E. Kazimieras Zavadskas, and Z. Turskis, "A Combined Compromise Solution (CoCoSo) method for multi-criteria decision-making problems," Manag Decis, vol. 57, pp. 2501-2519, 2019, doi: 10.1108/MD-05-2017-0458.

[16] Z. Wen, H. Liao, and E. Kazimieras Zavadskas, "MACONT: Mixed aggregation by comprehensive normalization technique for multi-criteria analysis," Informatica, vol. 31, pp. 857–880, 2020, doi: 10.15388/20-INFOR417.

[17] S. Biswas, and D. Pamucar, "Combinative distance based assessment (CODAS) framework using logarithmic normalization for multi-criteria decision making," Serb J Manag, vol 16, pp. 321-340, 2021, doi: 10.5937/sjm16-27758.

[18] D. D. Trung, "Expanding data normalization method to CODAS method for multi-criteria decision making," Appl Eng Lett, vol. 7, no. 2, pp. 54-66, 2022, doi: 10.18485/aeletters.2022.7.2.2.

[19] N. Vafaei, R. A. Ribeir, and L. M. Camarinha-Matos, "Assessing normalization techniques for simple additive weighting method," Procedia Comput Sci, vol. 199, pp. 1229-1236, 2022, doi: 10.1016/j.procs.2022.01.156

[20] N. Ersoy, "Application of the PIV method in the presence of negative data: an empirical example from a real-world case," Hitit Journal of Social Sciences, vol. 14, pp. 318-337, 2021, doi: 10.17218/hititsbd.974522.

[21] N. Ersoy, "Selecting the best normalization technique for ROV method: towards a real life application," Gazi Univ J Sci, vol. 34, pp. 592-609, 2021, doi: 10.35378/gujs.767525.

[22] N. Vafaei, R. A. Ribeiro, and L. M. Camarinha-Matos, "Normalization techniques for multi-criteria decision making: analytical hierarchy process case study," Technological Innovation for Cyber-Physical Systems, no. 470, 2016, doi: 10.1007/978-3-319-31165-4_26.

[23] A. Pacana and K. Czerwińska, "Universal Model for the Quality Analysis of Aluminium Alloys Castings," Tehnicki Vjesnik, vol. 30, no. 5, pp. 1635–1639, 2023, doi: 10.17559/TV-20230128000283.

[24] N. Vafaei, R. A. Ribeiro, and L. M. Camarinha-Matos, "Data normalisation techniques in decision making: case study with TOPSIS method," Int J Inform Dec Sci, vol. 10, pp. 19-38, 2018.

[25] N. Vafaei, R. A. Ribeiro, and L. M. Camarinha-Matos, "Assessing normalization techniques for TOPSIS Method," Technological Innovation for Applied AI Systems, no. 626, 2021, doi: 10.1007/978-3-030-78288-7_13.

[26] E. Kazimieras Zavadskas, D. Stanujkic, D. Karabasevic, and Z. Turskis, "Analysis of the simple WISP method results using different normalization procedures," Stud Inform Control, vol. 31, pp. 5-12, 2022, doi: 10.24846/v31i1y202201

[27] S. Baghla, and S. Bansal, "Effect of normalization techniques in VIKOR method for network selection in heterogeneous networks," in IEEE International Conference on Computational Intelligence and Computing Research, Coimbatore, India, 2014, pp.335-340, doi: 10.1109/ICCIC.2014.7238357

[28] F. Wang, J. Zhang, and P. Zhang, "Influencing Factors of Smart Government Information Security: Experience from China," Tehnicki Vjesnik, vol. 29, no. 2, pp. 572-579, 2022, doi: 10.17559/TV-20210816043215.

[29] S. K. Thomas, A. Ali, A. Alarjani, and E.-A. Attia, "Simulation based performance improvement: A case study on automotive industries," Int J Simul Model, vol. 21, no. 3, pp. 405–416, 2022, doi: 10.2507/IJSIMM21-3-606.

[30] D. D. Trung, "Application of FUCA method for multi-criteria decision making in mechanical machining processes," Oper Res Eng Sci Theor Appl, vol. 5, pp.131-152, 2022, doi: 10.31181/oresta051022061d.

[31] L. D. Ha, "Selection of suitable data normalization method to combine with the CRADIS method for making multi-criteria decision," Appl Eng Lett, vol. 8, no. 1,pp. 24-35, 2023, doi: 10.18485/aeletters.2023.8.1.4.

[32] A. –T. Nguyen, "Expanding the data normalization strategy to the MACONT method for multi-criteria decision making," Eng Technol Appl Sci Res, vol. 13, pp. 10489-10495, 2023, doi: 10.48084/etasr.5672.

[33] D. D. Trung, "Development of data normalization methods for multi-criteria decision making: applying for MARCOS method," Manufacturing Rev, vol. 9, no. 22, 2022, doi: 10.1051/mfreview/2022019.

[34] D. D. Trung, "Application of EDAS, MARCOS, TOPSIS, MOORA and PIV methods for multi-criteria decision making in milling process," Stroj čas, vol. 71, no. 2, pp. 69-84, 2021, doi: 10.2478/scjme-2021-0019.

[35] D. D. Trung, and N. -T. Nguyen, "Applying COCOSO, MABAC, MAIRCA, EAMR, TOPSIS and weight determination methods for multi-criteria decision making in hole turning process," Stroj čas, vol. 72, no. 2, pp. 15-40, 2022, doi: 10.2478/scjme-2022-0014.

[36] M. Varatharajulu, M. Duraiselvam,M. Bhuvanesh Kumar, G. Jayaprakash, and N. Baskar, "Multi criteria decision making through TOPSIS and COPRAS on drilling parameters of magnesium AZ91," J Magnes Alloy, vol. 10, pp. 2857-2874, 2022, doi: 10.1016/j.jma.2021.05.006.

[37] D. Bozanic, A. Milic, D. Tesic, W. Sałabun, and D. Pamucar, "D numbers – fucom – fuzzy rafsi model for selecting the group of construction machines for enabling mobility," Facta Univ Ser: Mech Eng, vol. 19, no. 3, 447-471, 2021, doi: 10.22190/FUME210318047B.

[38] L. J. Muhammad, I. Badi, A. A. Haruna, and I. A. Mohammed, "Selecting the best municipal solid waste management techniques in nigeria using multi criteria decision making techniques," Rep Mech Eng, vol 2, pp. 180-189, 2021, doi: 10.31181/rme2001021801b.

[39] M. Baydas, "Comparison of the performances of MCDM methods under uncertainty: an analysis on bist SME industry index," OPUS Journal of Society Research, vol. 19, pp. 308-326, 2021, doi: 10.26466/opusjsr.1064280.

[40] T. V. Dua, "Application of the collaborative unbiased rank list integration method to select the materials," Applied Engineering Letters, vol. 7, no. 4, pp. 133-142, 2022, doi: 10.18485/aeletters.2022.7.4.1

[41] X. T. Hoang, "Multi-objective optimization of turning process by fuca method,". Stroj. čas., vol. 73, no. 1, pp. 55-66, 2023, doi: 10.2478/scjme-2023-0005.

[42] L. Lamrini, M. C. Abounaima, and M. Talibi Alaoui, "New distributed-topsis approach for multi-criteria decision-making problems in a big data context," J Big Data, vol. 10, pp. 97, 2023, doi: 10.1186/s40537-023-00788-3

[43] F. Ciardiello, and A. Genovese, "A comparison between TOPSIS and SAW methods," Ann. Oper. Res., vol. 325, pp. 967–994, 2023, doi: 10.1007/s10479-023-05339-w.

[44] J. R. Kiger, and J. A. Annibale, "A new method for group decision making and its application in medical trainee selection,". Med Educ, vol. 50, pp. 1045-1053, 2016, doi: 10.1111/medu.13112

[45] T. V. Dua, "Development of a new multi-criteria decision making method,". East -Eur J Enterp Technol,vol. 3, pp. 33–38, 2023, doi: 10.15587/1729-4061.2023.279622.