International Journal of Advanced Technology and Engineering Exploration, Vol 11(116)
ISSN (Print): 2394-5443 ISSN (Online): 2394-7454
http://dx.doi.org/10.19101/IJATEE.2024.111100386

Research Article

Comparison of SRP and FUCA methods in selecting industrial tools and equipment

Do Duc Trung[1], Branislav Dudić[2*], Aleksandar Ašonja[3], Nguyen Chi Bao[1], Duong Van Duc[1] and Duong Thi Thanh Thuy[2]
School of Mechanical and Automotive Engineering, Hanoi University of Industry, Hanoi City, Vietnam[1]
Faculty of Management, Comenius University, Slovakia[2]
Faculty of Economics and Engineering Management, University Business Academy, Novi Sad, Serbia[3]

Received: 27-March-2024; Revised: 21-July-2024; Accepted: 24-July-2024

Abstract
In the context of selecting industrial tools and equipment, multi criteria decision making (MCDM) plays a crucial role in ensuring optimal and efficient choices. This study focuses on comparing two multi-criteria decision-making methods, simple ranking process (SRP) and faire un choix adéquat (FUCA), in ranking alternatives based on internal rankings for each criterion. Both methods share the common goal of evaluating and ranking alternatives; however, they differ in their implementation. The SRP method uses only natural numbers for internal ranking, while FUCA employs both natural numbers and decimals, allowing for more detailed and flexible rankings. The study was conducted in five specific cases of selecting industrial tools and equipment to compare the differences between these two methods. These cases provide a diverse range of criteria and real-world conditions, helping to test the applicability and effectiveness of each method. In all five cases conducted, the FUCA method consistently identified the best alternative similar to other MCDM methods. In contrast, when using the SRP method, there were 2 out of 5 cases where the best alternative found using this method did not match the best alternatives identified by other MCDM methods. The results show that the FUCA method has a clear advantage over SRP, demonstrated by its ability to provide more detailed assessments and accurate rankings. This study confirms that FUCA is the more effective method in the studied situations, recommending its use in decision making related to the selection of industrial tools and equipment.

Keywords
MCDM, SRP method, FUCA method, Industrial, Comparison.

1.Introduction
The selection of tools and industrial equipment plays an extremely important role in any production process, as it not only directly affects labor productivity but also has a significant impact on the economic aspects of the business. This decision is often very complex because each option is characterized by many criteria, including quality, cost, durability, technical features, and safety. These criteria sometimes conflict with each other; for instance, a high-quality piece of equipment with superior features usually comes with a high initial investment cost, while cost-saving options may not ensure long-term performance. An incorrect choice can lead to reduced productivity, increased downtime for maintenance, and higher operational costs. Conversely, a smart and reasonable choice optimizes the production process, minimizes waste, and increases profitability. Therefore, thorough evaluation and careful comparison of options are crucial to ensure the sustainable success of the business [1–3].

To select the best option among many alternatives while considering multiple criteria for each, the use of multi-criteria decision-making methods has become very common [4, 5]. However, there are over 200 available multi criteria decision making (MCDM) methods today, and rankings of alternative options may vary significantly when using different MCDM methods [6], making the decision to choose a method complex [7]. One of the reasons for the differences in ranking options using different methods is the need to normalize data when using MCDM methods. The essence of data normalization in MCDM is to convert parameters with different orders of magnitude into a consistent form. Therefore, if a certain MCDM method eliminates the need for data normalization, it somewhat reduces inaccuracies in ranking options [8,

*Author for correspondence

9]. Simple ranking process (SRP) [10] and Faire Un Choix Adéquat (FUCA) [11] are two MCDM methods that do not require data normalization. This is the similarity between SRP and FUCA, and also the difference between them and other methods. These methods share the common feature of ranking internal options for each criterion. However, the internal ranking of options for each criterion in these two methods differs. SRP uses only natural numbers for ranking options, while FUCA uses both natural and decimal numbers for ranking options. Since SRP and FUCA have similarities and differences, choosing which method to use is a challenge for users. This necessitates a comparison between these two methods.

The goal of this comparison is not to criticize or criticize any method but to provide additional insights for users in choosing which method to use. The structure of the following sections of the article is as follows. Section 2 provides an overview of the results of comparing MCDM methods in published literature. Section 3 is the theoretical basis of the SRP and FUCA methods. This section clarifies the similarities and differences between them. The comparison of these two methods is carried out in different cases for selecting industrial tools and equipment in section 4. A brief discussion is presented in section 5. Finally, it is concluded in Section 6.

2.Literature review

As mentioned above, to find the best option among available alternatives in various fields, one can utilize over 200 different MCDM methods. However, in each specific field, the best option identified using different MCDM methods may not be the same. This leads to the complexity of choosing a particular MCDM method to use, which itself is a complicated decision-making process. This complexity has prompted comparisons of various MCDM methods when applied to specific cases [12, 13]. Some studies have shown that different MCDM methods can be equally effective. For instance, the collaborative unbiased rank list integration (CURLI), preference ranking organization method for enrichment evaluation (PROMETHEE), and evaluation based on distance from average solution (EDAS) methods have shown equal effectiveness in selecting the best material for manufacturing car protective panels [14]. Two methods, measurement alternatives and ranking according to compromise solution (MARCOS), and preference selection index (PSI), have been confirmed to be equally effective in ranking welding robot [15]. The CURLI and proximity indexed value (PIV) methods have shown equal effectiveness in selecting the best cutting oil [16]. When used to evaluate the performance of house design methods, the analytic hierarchy process (AHP) method proves to be more effective than the complex prroportional assessment (COPRAS), technique for order preference by similarity to ideal solution (TOPSIS), vlsekriterijumska optimizacijai kompromisno resenje (VIKOR), and weighted sum method (WSM) methods [17]. When used to evaluate the quality of life at different spatial levels, the simple additive weighting (SAW) method is found to be more effective than the TOPSIS, VIKOR, and Elimination Et Choix Traduisant La Realite (ELECTRE) methods [18], etc.

For the FUCA method, it has attracted the interest of many scientists from various fields such as machine tool selection, material selection, finance, and more. When used to rank four types of saws with fourteen criteria for each option, the FUCA method also demonstrated equivalent effectiveness to the combined compromise solution (COCOSO), MARCOS, combinative distance-based assessment (CODAS), additive ratio assessment (ARAS), and TOPSIS methods [19]. When used to rank nine types of air conditioners with ten criteria specified for each option, rank eight types of washing machines with twelve criteria specified for each option, and rank seven types of drones in agricultural production with nine criteria specified for each option, the FUCA method consistently showed performance equivalent to the CURLI method [20]. When ranking materials used in electrical discharge machining, including ten types of powders with five criteria specified for each option, three types of dielectrics with four parameters used to describe each option, and nine types of electrodes with seven different criteria, the FUCA method also demonstrated equivalent effectiveness to the MARCOS method [21]. This method was also found to be as effective as the PIV method when used to rank seven types of materials for manufacturing connecting rods with nine criteria used to describe each material [22]. When used to rank equipment in university lecture halls, including ranking four types of desks and chairs for lecturers, each specified by five criteria, ranking twelve types of projectors, each specified by twelve criteria, and ranking five different types of amplifiers with ten criteria used to describe each option, the FUCA method also demonstrated equivalent effectiveness to the CURLI method [23]. In some studies, when used to rank sets of random numbers, such as ranking three sets of natural numbers, each set with four components (four criteria), the FUCA method also showed performance equivalent to the magnitude of the area for the ranking of alternatives (MARA) and CURLI methods [24].

Thus, it can be seen that many studies have shown that several MCDM methods are considered to be equivalently effective when used to solve the same problem. The FUCA method has also shown equivalent performance to many other methods regardless of the application scope, the number of options, and the number of criteria in each option in the problems where it has been applied. This information partly creates a certain reliability for users to use the FUCA method in ranking options in various fields.

Another noteworthy point is that in some studies, applying the FUCA method always identified the best option when the weights of the criteria were calculated by different methods, such as when selecting rice harvesters with the criteria weights calculated by two methods: equal weights and the pivot pairwise relative criteria importance assessment (PIPRECIA) method [25]; when selecting metal turning methods with the criteria weights calculated by four different methods: equal, rank sum (RS), rank order centroid (ROC), and method based on the removal effects of criteria (MEREC) [8]; when selecting materials for the electrical discharge machining process with the criteria weights calculated by two methods ROC and RS [21]. All of the above further increases user confidence in using the FUCA method in their tasks.

However, some studies have shown that MCDM methods are not equally effective. The weighted product method (WPM) and the VIKOR method have been identified as more effective than the SAW, AHP, TOPSIS, and ELECTRE methods when used to rank wastewater discharge alternatives from small hydroelectric plants in highland areas [26]. Both the VIKOR and TOPSIS methods are found to be more effective than the MOORA method in selecting 2 out of 26 researchers [27], etc.

For the FUCA method, several studies have also shown that its effectiveness differs from other methods. This method has been confirmed to be more effective than the weighted sum approach (WSA) method in ranking 31 companies based on financial efficiency using five different criteria [28]. In another study on ranking the financial efficiency of 24 companies with six different criteria, the FUCA method was also confirmed to be better than the multi-objective optimization on the basis of ratio analysis (MOORA) and multi attributive border approximation area comparison (MABAC) methods [29]. In yet another study, also tasked with ranking 24 companies based on financial performance with six different criteria, the FUCA method was found to be more effective than five methods CODAS, SAW, TOPSIS, MOORA, and COPRAS [30].

Thus, it can be seen that the effectiveness of MCDM methods varies significantly when used in different problems. Even for the FUCA method, it is noted that it is evaluated to be as good as a certain MCDM method in a specific problem, but other studies have confirmed it to be better than other MCDM methods when used in a different problem. These findings indicate that comparing FUCA with other methods is necessary in specific applications. The selection of industrial tools and equipment is no exception, and it is also necessary to compare FUCA with other methods.

Regarding the SRP method, since its recent introduction in May 2023, only a few studies have applied this method in their research, such as to select regression models for surface roughness in grinding [31] and to rank companies based on their readiness for Industry 4.0 [32]. Recently, this method has shown better performance than the MARCOS, MOORA, and TOPSIS methods when used to select materials in additive manufacturing technology [33].

FUCA and SRP are two methods with clearly defined similarities and differences, as mentioned in the introduction, and the details of these characteristics will be clarified in the next section of this article. While FUCA has been widely applied in various fields and has proven to be consistently as good as or better than other methods, the number of studies applying the SRP method remains very modest. This motivates the need for a comparison of these two methods, with the scope of application being the selection of industrial tools and equipment.

3.Methods

Assuming there are m options to be ranked, n is the number of criteria for each option. Let y_{ij} be the value of criterion j for option i, with $i = 1$ to m, $j = 1$ to n.
Both *SRP* [10] and *FUCA* [11] use the following three steps to rank options.

Step 1: Rank internal options, i.e., rank options for each criterion. For *SRP*, only natural numbers are used, while *FUCA* uses both natural and decimal numbers. According to studies employing the FUCA method, the decimal representation for ranking options requires retaining only one digit after the decimal point [24, 25]. Let r_{ij} be the rank of option *i* for criterion *j*. This means $r_{ij} \in N$ when using *SRP* and $r_{ij} \in R^{+}$ when using *FUCA*. To illustrate this, an example is provided:

Assuming there are five ranking options, namely *A1*, *A2*, *A3*, *A4*, and *A5*. Each option has three criteria, namely *C1*, *C2*, and *C3* as shown in *Table 1*. Among these, *C1* and *C2* are criteria where higher values are considered better, whereas *C3* is a criterion where lower values are considered better.

Table 1 Example of internal ranking of options using SRP and FUCA methods

Alt.	**C1**	**C2**	**C3**
	max	max	min
A1	7	4	6
A2	12	5	5
A3	6	6	8
A4	8	4	5
A5	10	5	5

Due to the different values of *C1* for each option, the rankings of the options using the *SRP* and FUCA methods are natural numbers. Specifically, for *C1*, *A2* has the highest value, so $r_{21} = 1$. *A5* is the second highest, so $r_{51} = 2$. *A4* is the third highest, so $r_{41} = 3$. *A1* is the fourth highest, so $r11 = 4$. Lastly, *A3* is the fifth highest, so $r_{31} = 5$.

Since *C2* at *A3* has the highest value, both *SRP* and *FUCA* methods yield $r_{32} = 1$. As *C2* at *A2* and *A5* are equal, using the *SRP* method, $r_{22} = r_{52} = 2$ (both ranked 2). If the *FUCA* method is used, $r_{22} = r_{52} = 2.5$ (averaged between 2 and 3).

As *C3* values at *A2*, *A4*, and *A5* are equal, using the *SRP* method, $r_{23} = r_{43} = r_{53} = 1$ (all ranked 1). Meanwhile, if the *FUCA* method is applied, $r_{23} = r_{43} = r_{53} = 2$ (average of 1, 2, and 3). This leads to the conclusion that using *SRP* results in $r_{13} = 2$ and $r_{33} = 3$, whereas using *FUCA* results in $r_{13} = 4$ and $r_{33} = 5$.

The results of internal ranking of options for each criterion are synthesized in *Table 2*.

Table 2 Internal ranking results of options using SRP and FUCA methods

Alt.	**SRP method**			**FUCA method**		
	C1	C2	C3	C1	C2	C3
A1	4	3	2	4	4.5	4
A2	1	2	1	1	2.5	2
A3	5	1	3	5	1	5
A4	3	3	1	3	4.5	2
A5	2	2	1	2	2.5	2
SUM	15	11	8	15	15	15

It is also observed that using the *FUCA* method, the total internal ranking of options is always the same for all criteria. Specifically, in this example, the total internal ranking for three criteria *C1*, *C2*, and *C3* is always 15. Whereas this is not guaranteed when using the *SRP* method. In this case, the total internal ranking for options for three criteria *C1*, *C2*, and *C3* is 15, 11, and 8, respectively. Analyzing the internal ranking of options, as in the example just performed, clearly shows the difference between the *SRP* and *FUCA* methods.

The difference between *SRP* and *FUCA* lies only in Step 1, as explained above. The remaining steps of these two methods are entirely the same.
Step 2: Calculate scores for each option according to Equation 1, where w_j is the weight of criterion *j*.

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

Step 3: Rank options in increasing order of their scores.
The sequence of applying each of the three steps of the FUCA and SRP methods is illustrated in *Figure 1*.

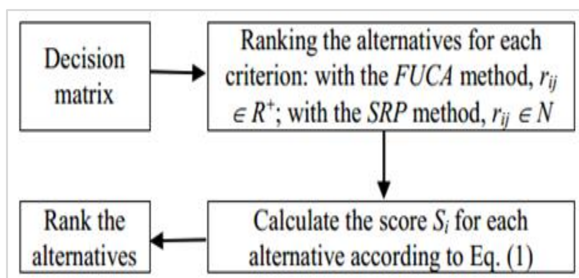

Figure 1 Block diagrams of FUCA and SRP

Comparing the rankings of options using the SRP and FUCA methods will be conducted in five different cases, with different numbers of options and criteria in each case. The data in each case are quoted from recent studies. The reason for doing this is that in those documents, the ranking of options has been done using different MCDM methods, and those results are considered answers to compare with the ranking results of options using the SRP and FUCA methods in this article.

4.Results

In this section, the methods FUCA and SRP are compared in five different cases. The number of options to be ranked in each case has been chosen progressively. Specifically, in the first two cases, the number of options to be ranked is 4. The number of options in the remaining three cases corresponds to 5, 6, and 12, respectively.

4.1Case 1

In this case, the comparison of FUCA and SRP methods was performed in ranking various types of wood milling machines (WMM). The data for four types of machines are presented in *Table 3* [34]. Each WMM is described by nine criteria from C1 to C9. These criteria include C1 as the working range along the X-axis (mm), C2 as the working range along the Y-axis (mm), C3 as the working range along the Z-axis (mm), C4 as the maximum speed of the main axis (m/min), C5 as the maximum travel speed (m/min), C6 as the maximum working speed (m/min), C7 as the maximum allowable wood moisture (0C), C8 as flash memory (Mb), and C9 as the price (million Vietnamese dong). The type of each criterion (min or max) is listed in the second row of *Table 3*. Only C9 is a criterion where smaller values are better, while the other eight criteria are larger is better. The weights of these nine criteria were also calculated using the symmetry point of criterion (SPC) method and are synthesized in the last row of *Table 3*.

Table 3 Types of WMM [34]

Type	C1	C2	C3	C4	C5	C6	C7	C8	C9
	max	max	max	max	max	max	max	max	min
WMM1	1800	2500	180	24000	50	25	75	128	164
WMM2	1500	1300	180	23000	42	22	70	100	149
WMM3	1500	1000	150	20000	50	25	50	120	129
WMM4	1800	2000	160	21500	50	25	50	120	154.56
Weight	0.0837	0.3350	0.0685	0.0570	0.0765	0.0566	0.1736	0.0787	0.0703

First, the SRP method is used to perform the internal ranking of WMMs. A brief explanation for the internal ranking of the options in this case is as follows. First, the internal ranking of the options for C1 (the criterion where the larger value is better) is determined. Since both WMM1 and WMM4 have a C1 value of 1800, which is the highest, they are both ranked 1. Next, since WMM2 and WMM3 both have a C1 value of 1500, they are both ranked 2. Following that, the internal ranking of the options for C2, which is also a criterion where the larger value is better, is determined. Since WMM1 has a C2 value of 2500, the highest among all options, it is ranked 1. WMM4, with a C2 value of 2000, is ranked 2. WMM2, with a C2 value of 1300, is ranked 3. Lastly, WMM3 is ranked 4 because its C2 value is the smallest compared to the other options. The internal ranking of the options for the remaining criteria is performed in a similar manner. The results of the internal ranking of WMMs (ranking for each criterion) are synthesized in *Table 4*.

Once again, the internal rankings of the scenarios are not entirely equal for all criteria. Proceed to multiply the internal ranking values of the options for each criterion by the weight of that criterion. For example, for criterion C1, multiply the internal ranking of WMM1 by the weight of C1, which is 1 x 0.0837 = 0.0837; multiply the internal ranking of WMM2 by the weight of C1, which is 2 x 0.0837 = 0.1674, and so on. This procedure is carried out for all criteria, resulting in the outcomes shown in *Table 5*.

Table 4 Internal rankings of WMMs using the SRP method

Type	r_{ij}								
	C1	C2	C3	C4	C5	C6	C7	C8	C9
WMM1	1	1	1	1	1	1	1	1	4
WMM2	2	3	1	2	2	2	2	3	2
WMM3	2	4	3	4	1	1	3	2	1
WMM4	1	2	2	3	1	1	3	2	3
SUM	6	10	7	10	5	5	9	8	10

Table 5 Internal ranking matrix of scenarios integrated with weights

Type	$r_{ij} \cdot w_j$								
	C1	C2	C3	C4	C5	C6	C7	C8	C9
WMM1	0.0837	0.3350	0.0685	0.0570	0.0765	0.0566	0.1736	0.0787	0.2812
WMM2	0.1674	1.0050	0.0685	0.1140	0.1530	0.1132	0.3472	0.2361	0.1406

Type	$r_{ij} \cdot w_j$								
	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
WMM3	0.1674	1.3400	0.2055	0.2280	0.0765	0.0566	0.5208	0.1574	0.0703
WMM4	0.0837	0.6700	0.1370	0.1710	0.0765	0.0566	0.5208	0.1574	0.2109

Scores for each WMM are calculated using Equation 1. For example, the score of WMM1 is the sum of the quantities 0.0837, 0.3350, 0.0685, 0.0570, 0.0765, 0.0566, 0.1736, 0.0787, 0.2812, and is calculated to be 1.2108. The scores and rankings of the WMMs are then synthesized in *Table 6*.

Table 6 Scores and rankings of WMMs when ranked using the SRP method

Type	S_i	Rank
WMM1	1.2108	1
WMM2	2.3450	3
WMM3	2.8225	4
WMM4	2.0839	2

Next, the ranking of WMMs using the FUCA method is carried out. The results of the internal ranking of WMMs using the FUCA method are summarized in *Table 7*. In this case, once again, we observe that the total internal rankings of the scenarios for all criteria are always equal (equal to 10).

Multiplying the internal ranking values of each scenario by the weight of the corresponding criterion leads to the results as shown in *Table 8*.

Scores for each WMM are calculated using Equation 1. The scores Si of the WMMs and their rankings are then synthesized in *Table 9*.

Table 7 Internal rankings of *WMM*s using the FUCA method

Type	C1	C2	C3	C4	C5	C6	C7	C8	C9
WMM1	1.5	1	1.5	1	2	2	1	1	4
WMM2	3.5	3	1.5	2	4	4	2	4	2
WMM3	3.5	4	4	4	2	2	3.5	2.5	1
WMM4	1.5	2	3	3	2	2	3.5	2.5	3
SUM	10	10	10	10	10	10	10	10	10

Table 8 Internal ranking matrix of scenarios integrated with weights

Type	C1	C2	C3	C4	C5	C6	C7	C8	C9
WMM1	0.1256	0.3350	0.1028	0.0570	0.1530	0.1132	0.1736	0.0787	0.2812
WMM2	0.2930	1.0050	0.1028	0.1140	0.3060	0.2264	0.3472	0.3148	0.1406
WMM3	0.2930	1.3400	0.2740	0.2280	0.1530	0.1132	0.6076	0.1968	0.0703
WMM4	0.1256	0.6700	0.2055	0.1710	0.1530	0.1132	0.6076	0.1968	0.2109

Thus, the ranking of WMMs using both the SRP and FUCA methods has been completed. In *Table 10*, the results of ranking WMMs using the two methods discussed in this article (SRP and FUCA) are summarized, along with two methods, compromise ranking of alternatives from distance to ideal solution (CRADIS) and CURLI, from [34].

The rankings of the WMMs are completely identical when ranked using the three methods SRP, FUCA, and CRADIS. The best type of WMM is found to be entirely the same when using four different methods. Therefore, in this case, no differences in rankings of scenarios are found when ranked using SRP and FUCA. However, as this is a new example, further investigation is needed to draw clearer conclusions.

Table 9 Scores and rankings of WMMs when ranked using the FUCA method

TYPE	S_I	RANK
WMM1	1.4200	1
WMM2	2.8497	3
WMM3	3.2758	4
WMM4	2.4535	2

4.2Case 2

Ranking of different types of saw machines (SM) is used to compare the SRP and FUCA methods in this case. *Table 11* provides information about four different types of SM, denoted as SM1, SM2, SM3, and SM4. Fourteen criteria were used, including C1 as the maximum diameter of a round workpiece that can be cut (mm), C2 as the maximum width of a rectangular workpiece that can be cut (mm), C3 as the maximum height of a rectangular workpiece that can be cut (mm), C4 as the minimum diameter of a round workpiece that can be cut (mm), C5 as the minimum width of a rectangular workpiece that can be cut (mm), C6 as the minimum height of a rectangular workpiece that can be cut (mm), C7 as the length of the saw blade (mm), C8 as the width of the saw blade (mm), C9 as the thickness of the saw blade (mm), C10 as the power of the machine (kW), C11 as the minimum speed (m/min), C12 as the maximum speed (m/min), C13 as the weight of the machine (kg), and C14 as the price (million VND) [35]. The forms of criteria (max, min) are clarified in row 2 of *Table 11*. The weights of the fourteen criteria were calculated using the criteria importance through intercriteria correlation (CRITIC) method, as shown in the last row of this table. Ranking of SMs using the SRP and FUCA methods was carried out similarly to how it was done in case 1. *Table 12* summarizes the results of ranking SMs using the SRP and FUCA methods, along with three methods implemented in [35], including COCOSO, MARCOS, and ARAS.

Table 10 Rankings of WMM types using different methods

Type	SRP	FUCA	CRADIS [34]	CURLI [34]
WMM1	1	1	1	1
WMM2	3	3	3	2
WMM3	4	4	4	3
WMM4	2	2	2	4

Table 11 Types of SM [35]

Type	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
	max	max	max	min	min	min	max	max	min	max	min	max	max	min
SM1	320	350	320	10	10	8	4440	34	1.1	2.6	15	110	1900	990
SM2	500	560	500	10	10	10	5450	41	1.3	1.5	16	85	3000	640
SM3	460	460	500	25	20	25	5450	41	1.3	1.5	25	75	2300	495
SM4	460	460	500	20	20	20	5450	41	1.3	2	25	75	3090	610
weight	0.05	0.0543	0.0528	0.0631	0.0699	0.0574	0.0528	0.0528	0.0528	0.1214	0.0645	0.1307	0.0599	0.1175

Table 12 Rankings of SM types

Type	SRP	FUCA	COCOSO [35]	MARCOS [35]	ARAS [35]
SM1	2	2	3	2	2
SM2	1	1	1	1	1
SM3	4	4	4	4	4
SM4	3	3	2	3	3

It is observed that the rankings of SMs are entirely identical when using the SRP, FUCA, MARCOS, and ARAS methods. The best and worst SMs are found to be entirely the same when using five different methods. Thus, in this case, no differences are observed in the rankings of scenarios when using the SRP and FUCA methods. In the two cases presented above, we ranked the scenarios with a total of four alternatives and found no differences in the rankings when using the SRP and FUCA methods. However, due to the small number of alternatives in each case, we refrain from hastily concluding the comparison results between SRP and FUCA. Instead, we proceed to further investigate additional cases with an increased number of alternatives to be ranked.

4.3 Case 3

Five types of milling machines (MM) have been selected for ranking in this case. Six criteria, C1 to C6, have been used to describe each MM. Specifically, C1 represents the price ($), C2 is the weight of the machine (kg), C3 is the power of the machine (watt), C4 is the speed of the main axis (rev/min), C5 is the maximum diameter of the tool that can be mounted on the machine (mm), and C6 is the range of movement of the cutting tool (mm). The weights of the criteria were calculated using the AHP. The weight values and the type of criteria for all six parameters have been predetermined. A summary of information about the five types of MM is presented in *Table 13* [35]. In *Table 14*, the results of ranking MM using two methods in this article (SRP and FUCA) are compiled, along with the methods PROMETHEE, AHP, TOPSIS, and ELECTRE used in [35].

In this case, the best type of MM identified using both SRP and FUCA methods is the same, and it aligns with the results obtained using other methods. However, unlike the two cases above, the rankings of MM in this case are not entirely identical when using SRP and FUCA. It's important to note that in the two cases above, the rankings of scenarios were entirely identical when using SRP and FUCA. This gives us the impression that differences in the rankings of scenarios when ranked using SRP and FUCA start to appear as the number of scenarios increases. However, this is still a subjective observation. To draw firm conclusions, further investigation is needed by examining additional cases.

Table 13 Types of MMs [35]

Type	C1	C2	C3	C4	C5	C6
	min	min	max	max	max	max
MM1	936	4.8	1300	24000	12.7	58
MM2	1265	6	2000	21000	12.7	65
MM3	680	3.5	900	24000	8	50
MM4	650	5.2	1600	22000	12	62
MM5	580	3.5	1050	25000	12	62
Weight	0.09	0.244	0.113	0.266	0.186	0.101

Table 14 Rankings of MM types

Type	SRP	FUCA	PROMETHEE [35]	AHP [35]	TOPSIS [35]	ELECTRE [35]
MM1	2	2	4	2	3	2
MM2	5	5	3	5	5	4
MM3	4	3	5	3	2	4
MM4	3	4	2	3	4	3
MM5	1	1	1	1	1	1

4.4Case 4

In this case, the comparison between the two methods SRP and FUCA is carried out to rank six types of forklifts (FOR). Each type of forklift has been described using six criteria: C1 is the lifting capacity (kg), C2 is the maximum lifting height (mm), C3 is the minimum lifting height (mm), C4 is the length of the FOR (mm), C5 is the width of the FOR (mm), and C6 is the price (million VND) [36]. The values, types, and weights of each criterion (calculated using the Entropy method) have been summarized in *Table 15*.

Table 15 Types of FOR [36]

Type	C1	C2	C3	C4	C5	C6
	max	max	min	max	max	min
FOR1	2000	200	80	1150	550	4.75
FOR2	2000	200	80	1220	685	4.95
FOR3	2500	200	80	1150	550	4.95
FOR4	2500	200	80	1220	685	5.15
FOR5	3000	200	80	1150	550	5.35
FOR6	3000	220	60	1220	685	5.5
Weight	0.1520	0.1561	0.1616	0.1525	0.1533	0.2245

Ranking of FOR using the two methods SRP and FUCA has been performed similarly to the approach in Case 1. In *Table 16*, the consolidated ranking results of FOR using SRP and FUCA are presented, along with rankings using other MCDM methods.

Table 16 Ranking of for types

Type	SRP	FUCA	COCOSO [36]	PIV [36]
FOR1	3	4	6	6
FOR2	6	2	3	4
FOR3	2	5	4	5
FOR4	4	3	2	2
FOR5	1	6	5	3
FOR6	5	1	1	1

A surprising finding in this case is that while the FOR type is determined as the best when using the SRP method, it turns out to be the worst when using the FUCA method. However, the best FOR type identified using the FUCA method is also the best type found when using the COCOSO and PIV methods. This implies that SRP does not ensure accuracy in ranking the FOR types in this case. However, drawing an immediate conclusion would be inappropriate, and further investigation is needed by examining additional cases.

4.5Case 5

In this case, the number of alternatives to be ranked has significantly increased compared to the four previously conducted cases. Specifically, twelve types of grinding machines (GM) were selected for ranking. Eight criteria from C1 to C8 were used, including C1, C2, C3 representing the maximum travel of the machine table along the X, Y, and Z axes. C4 is the maximum diameter of the grinding wheel that can be installed on the machine, C5 is the maximum speed of the grinding wheel, C6 is the machine's power, C7 is the achievable precision of the machine. For example, C7 = 0.002 means that the precision of machining dimensions can achieve two parts per ten thousand, and finally, C8 is the year the machine was manufactured. The types and weights (calculated using the equal method) of the criteria, as well as their values for each GM, have been synthesized in *Table 17* [37].

Table 17 Types of GM [37]

Type	C1	C2	C3	C4	C5	C6	C7	C8
	max	max	max	max	max	max	min	max
GM1	315	110	300	205	38.5	2.2	0.005	2016
GM2	600	300	350	305	28	3.7	0.005	2016
GM 3	600	300	350	305	28	3.7	0.005	1998
GM 4	600	400	380	305	28	3.7	0.005	1992
GM 5	315	110	300	205	38.5	2.2	0.005	2002
GM 6	315	110	300	205	38.5	2.2	0.002	2009
GM 7	500	200	350	205	31.5	3.7	0.005	2009
GM 8	510	205	355	205	31.5	3.7	0.005	2014
GM 9	1280	550	600	510	53.5	3.4	0.002	2017
GM 10	600	500	400	355	37	3.7	0.002	2018
GM 11	1600	720	650	510	53.5	4.2	0.002	2014
GM 12	510	205	355	205	31.5	3.7	0.005	2016
weight	1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8

Ranking of GM using the two methods SRP and FUCA was carried out similarly to the approach in Cases 1, 2, 3, and 4. In *Table 18*, the consolidated ranking results of GM using these two methods and using the CURLI method from [37] are presented.

In this case, the ranking of all GMs is the same when using FUCA and CURLI. Conversely, when using the SRP method, the GM considered the best is determined as the worst when using both FUCA and CURLI methods. On the other hand, the GM identified as the best when using FUCA and CURLI is determined as the worst when using the SRP method. This means that SRP is also verified as inappropriate for use in this case.

Through the first three cases, it was noticed that when the number of alternatives is small, the rankings do not differ significantly when using SRP and FUCA. Specifically, in the first two cases, when the number of alternatives was four, the rankings were completely identical (refer to *Table 10* and *Table 12*). When the number of alternatives increased to five (refer to *Table 14* in Case 3), the rankings began to differ when using SRP and FUCA. However, in all three cases, the best alternative was found to be the same when using SRP and FUCA, and it was also identified as the best alternative using other MCDM methods. This means that both SRP and FUCA show comparable performance.

However, as the number of alternatives to be ranked increases, while the best alternative is still found when using FUCA and matches with other MCDM methods, if SRP is used, this is not achieved. In Case 4, using SRP determined that FOR5 is the best, but it was identified as the worst when using FUCA. FOR5 was also identified as the fifth-ranked alternative using the PIV method. In Case 5, with twelve alternatives, while GM11 was determined as the best using FUCA and CURLI, it was identified as the worst using SRP. Conversely, when using FUCA and CURLI and identifying GM5 as the worst, SRP considered GM5 as the best. All these observations lead to the conclusion that SRP is not suitable for ranking a large number of alternatives.

Table 18 Ranking of GM types

Type	SRP	FUCA	CURLI [37]
GM1	2	11	11
GM2	8	4	4
GM 3	5	8	8
GM 4	8	5	5
GM 5	1	12	12
GM 6	3	10	10
GM 7	4	9	9
GM 8	5	7	7
GM 9	11	2	2
GM 10	10	3	3
GM 11	12	1	1
GM 12	7	6	6

5.Discussion

The comparison results between the FUCA and SRP methods across five different scenarios show that when the number of alternatives is small, these two methods yield similar outcomes. However, as the number of alternatives increases, SRP proves to be less effective in ranking, while FUCA maintains accuracy. The differences in the rankings of the options when using SRP and FUCA are explained by the differences in the total internal rankings of the options. The FUCA method uses both integer and decimal scales, ensuring that the total internal rankings of the options are always equal across all criteria. In contrast, using only an integer scale as in the SRP method does not guarantee this. Utilizing only integers in the ranking process can create a stepped scale with integer values. Meanwhile, the combination of integers and decimals results in a more flexible evaluation system. These findings suggest that the FUCA method may outperform the SRP method as the number of alternatives to be ranked increases. It should also be noted that in many published documents, the FUCA method has been shown to have superior performance compared to some other MCDM methods as the number of alternatives to be ranked increases, such as when the number of alternatives to be ranked is 24 [29, 30, 31,28].

Our results show that the FUCA method provides a more flexible and accurate ranking system compared to the SRP method, especially when the number of alternatives is large. This is because the FUCA method uses both integer and decimal scales, ensuring consistency in the total internal rankings of the options. Meanwhile, the SRP method only uses an integer scale, leading to a lack of flexibility and accuracy as the number of alternatives increases. These findings are significant in the selection of ranking methods for decisions with many alternatives. The FUCA method may be preferred in cases with a large number of alternatives due to its ability to maintain accuracy and flexibility. This also supports researchers and practitioners in choosing the appropriate ranking method for the specific characteristics of each situation.

In all five surveyed cases, the comparison between the FUCA and SRP methods was conducted only when the criteria weights were a fixed set of numbers, without considering the possibility of the criteria weights varying based on the decision makers' perspectives. This limitation constitutes a weakness of the study. Based on the research results, it is proposed that future studies should consider the possibility of changing the criteria weights based on the decision makers' perspectives to gain a more comprehensive understanding of the effectiveness of the ranking methods. Additionally, there should be comparative studies between FUCA and other MCDM methods in various contexts to affirm the superiority of FUCA. A complete list of abbreviations is listed in *Appendix I.*

6.Conclusion and future work

In this paper, a detailed comparison is conducted between two multi-criteria decision-making methods, SRP and FUCA, focusing on the characteristics of internal rankings of options for each criterion. The results indicate that, when the number of options to be ranked is less than or equal to 5, the effectiveness of SRP and FUCA is equivalent and similar to other MCMD methods. However, as the number of options increases, we observed a significant difference in the effectiveness of SRP and FUCA. While FUCA maintains relatively stable effectiveness compared to other methods, SRP faces difficulties and may even become less effective. Particularly noteworthy is the fact that the best solution identified by SRP can become the worst when using FUCA and other MCDM methods, highlighting a significant difference between the two approaches.

Based on the observations and analysis in this study, some directions for further research are proposed to optimize and expand the applications of SRP and FUCA in more complex situations. Specifically, research could explore ways to improve the performance of SRP with a large number of options, or optimize parameters in FUCA to ensure flexibility and effectiveness in various application contexts. The comparison of SRP and FUCA when using different methods to calculate the weights for the criteria is also a task to be carried out in the near future. Additionally, further exploration of alternative methods in the field of MCDM for comparison and development of advanced solutions is also warranted. These efforts could lead to significant improvements in the multi-criteria decision-making field, providing researchers and decision-makers with powerful and flexible tools to address real-world challenges.

Acknowledgment
None.

Conflicts of interest
The authors have no conflicts of interest to declare.

Data availability
Data sets generated during the current study are available from the corresponding author on reasonable request.

Author's contribution statement
Do Duc Trung: Conceptualization, investigation, writing – original draft, writing – review and editing. **Aleksandar Ašonja:** Conceptualization, investigation, writing – review and editing. **Branislav Dudić:** Data curation, writing – original draft. **Duong Van Duc:** Data curation, Writing – original draft. **Nguyen Chi Bao:** Writing – review and editing, Feedback provision. **Duong Thi Thanh Thuy:** Writing – review and editing, feedback provision.

References
[1] Temiz I, Calis G. Selection of construction equipment by using multi-criteria decision making methods. Procedia Engineering. 2017; 196:286-93.
[2] Hamasha MM, Bani-irshid AH, Al MS, Shwaheen G, Al QL, Shbool M, et al. Strategical selection of maintenance type under different conditions. Scientific Reports. 2023; 13(1):15560.
[3] Hagag AM, Yousef LS, Abdelmaguid TF. Multi-criteria decision-making for machine selection in manufacturing and construction: recent trends. Mathematics. 2023; 11(3):1-21.
[4] Stević Ž, Pamučar D, Puška A, Chatterjee P. Sustainable supplier selection in healthcare industries using a new MCDM method: measurement of alternatives and ranking according to compromise solution (MARCOS). Computers & Industrial Engineering. 2020; 140:106231.
[5] Wen Z, Liao H, Zavadskas EK. MACONT: mixed aggregation by comprehensive normalization technique for multi-criteria analysis. Informatica. 2020; 31(4):857-80.
[6] Baydaş M, Eren T, Stević Ž, Starčević V, Parlakkaya R. Proposal for an objective binary benchmarking framework that validates each other for comparing MCDM methods through data analytics. Peer Journal Computer Science. 2023; 9:e1350.
[7] Sotoudeh-anvari A. Root assessment method (RAM): a novel multi-criteria decision making method and its applications in sustainability challenges. Journal of Cleaner Production. 2023; 423:138695.
[8] Hoang XT. Multi-objective optimization of turning process by FUCA method. Strojnícky Časopis-Journal of Mechanical Engineering. 2023; 73(1):55-66.
[9] Ha LD. Selection of suitable data normalization method to combine with the CRADIS method for making multi-criteria decision. Applied Engineering Letters. 2023; 8(1):24-35.
[10] Zakeri S, Chatterjee P, Konstantas D, Ecer F. A decision analysis model for material selection using simple ranking process. Scientific Reports. 2023; 13(1):8631.
[11] Ouattara A, Pibouleau L, Azzaro-pantel C, Domenech S, Baudet P, Yao B. Economic and environmental strategies for process design. Computers & Chemical Engineering. 2012; 36:174-88.
[12] Paradowski B, Szyjewski Z. Comparative analyses of multi-criteria methods in supplier selection problem. Procedia Computer Science. 2022; 207:4593-602.
[13] Güçlü P. Comparative analysis of the MCDM methods with multiple normalization techniques: three hybrid models combine MPSI with DNMARCOS, AROMAN, and MACONT methods. Business and Economics Research Journal. 2024; 15(2):129-54.
[14] Dua TV. Development of a new multi-criteria decision-making method. Eastern-European Journal of Enterprise Technologies. 2023; 3(4):123.
[15] Hong SN, Hieu TT. Selection of welding robot by multi-criteria decision making method. Eastern-European Journal of Enterprise Technologies. 2023; 121(3):66-72.
[16] Thinh HX, Mai NT, Giang NT, Van KV. Applying multi-criteria decision making methods for cutting oil selection. Eastern-European Journal of Enterprise Technologies. 2023; 123(1).
[17] Rachman AP, Ichwania C, Mangkuto RA, Pradipta J, Koerniawan MD, Sarwono J. Comparison of multi-criteria decision-making methods for selection of optimum passive design strategy. Energy and Buildings. 2024; 314:114285.
[18] Vakilipour S, Sadeghi-niaraki A, Ghodousi M, Choi SM. Comparison between multi-criteria decision-making methods and evaluating the quality of life at different spatial levels. Sustainability. 2021; 13(7):4067.
[19] Tu NA, Anh BH. A novel multi-criteria decision making procedure for saw machine selection in the

mechanical machining. Journal of Science and Technology. 2023; 59(3):100-7.
[20] Nguyen AT. Combining FUCA, CURLI, and weighting methods in the decision-making of selecting technical products. Engineering, Technology & Applied Science Research. 2023; 13(4):11222-9.
[21] Van TN, Son NH. Material selection for PMEDM process. International Journal of Mechanical Engineering and Robotics Research. 2024; 13(3):315-24.
[22] Thinh HX, Mai NT. Comparison of two methods in multi-criteria decision-making: application in transmission rod material selection. EUREKA: Physics and Engineering. 2023 :59-68.
[23] Uyen VT, Thu PX. The multi-criteria decision-making method: selection of support equipment for classroom instructors. Applied Engineering Letters. 2023; 8(4):148-57.
[24] Thinh HX, Van DT. Research on expanding the scope of application of the MARA method. EUREKA: Physics and Engineering. 2024; 2024(3):90-9.
[25] Van DT. Application of multi-criteria decision-making method to choose rice harvester in Vietnam. EUREKA: Physics and Engineering. 2023; 2023(6):173-82.
[26] Vassoney E, Mammoliti MA, Desiderio E, Negro G, Pilloni MG, Comoglio C. Comparing multi-criteria decision-making methods for the assessment of flow release scenarios from small hydropower plants in the alpine area. Frontiers in Environmental Science. 2021; 9:635100.
[27] Kaya GK, Ozturk F. A comparison of the multi-criteria decision-making methods for the selection of researchers. In industrial engineering in the internet-of-things world: selected papers from the virtual global joint conference on industrial engineering and its application Areas, GJCIE. 2022 (pp. 147-59). Springer International Publishing.
[28] Baydaş M. Comparison of the performances of MCDM methods under uncertainty: an analysis on bist SME industry index. OPUS Journal of Society Research. 2022; 19(46):308-26.
[29] Baydaş M. 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. 2022; 10(1):245-60.
[30] Baydaş M, Pamučar D. Determining objective characteristics of MCDM methods under uncertainty: an exploration study with financial data. Mathematics. 2022; 10(7):1115.
[31] Thinh HX, Van DT. Optimal surface grinding regression model determination with the SRP method. Engineering, Technology & Applied Science Research. 2024; 14(3):14713-8.
[32] Biswas S, Božanić D, Pamučar D, Marinković D. A spherical fuzzy based decision making framework with einstein aggregation for comparing preparedness of SMES in quality 4.0. Facta Universitatis, Series: Mechanical Engineering. 2023; 21(3):453-78.
[33] Mian SH, Nasr EA, Moiduddin K, Saleh M, Abidi MH, Alkhalefah H. Assessment of consolidative multi-criteria decision making (C-MCDM) algorithms for optimal mapping of polymer materials in additive manufacturing: a case study of orthotic application. Heliyon. 2024; 10(10).
[34] Dua TV. Combination of symmetry point of criterion, compromise ranking of alternatives from distance to ideal solution and collaborative unbiased rank list integration methods for woodworking machinery selection for small business in Vietnam. EUREKA: Physics and Engineering. 2023; 2023(2):83-96.
[35] Dağdeviren M. Decision making in equipment selection: an integrated approach with AHP and PROMETHEE. Journal of Intelligent Manufacturing. 2008; 19:397-406.
[36] Van DT. Forklift selection by multi-criteria decision making methods. Eastern-European Journal of Enterprise Technologies. 2023; 125(3).
[37] Son NH, Hieu TT, Thang NM, Tan HN, Can NT, Thao PT, et al. Choosing the best machine tool in mechanical manufacturing. EUREKA: Physics and Engineering 2023; 2023(2):97-109.

Do Duc Trung, born in 1982, received his engineering degree in 2005, his master's degree in 2010, and his Ph.D. in 2017 from Thai Nguyen University of Technology (TNUT). His main research areas include optimization in mechanical machining, multi-criteria decision making, and modeling.
Email: doductrung@haui.edu.vn

Branislav Dudić, born in 1984, focuses his research on cooperation in international economics, industrial engineering, and international trade and investment between the EU and the Western Balkans.
Email: branislav.dudic@fm.uniba.sk

Aleksandar Ašonja, born in 1976, is currently a Full Professor at the Faculty of Economics and Engineering Management in Novi Sad. His research focuses on reliability problems of technical systems in mechanical engineering.

Email: asonja.aleksandar@fimek.edu.rs

Nguyen Chi Bao, born in 1962, is currently a lecturer at Hanoi University of Industry. His research focuses on optimization in mechanical machining, process modeling, and smart manufacturing.
Email: baonc@haui.edu.vn

Duong Van Duc, born in 1967, focuses his research on traditional machining methods in mechanical manufacturing, process optimization, and surface forming technology. He is currently a lecturer at Hanoi University of Industry.
Email: duongduc67@gmail.com

Duong Thi Thanh Thuy, born in 1986, focuses her research on the field of optimization. Currently, she is a researcher at Hanoi University of Industry.
Email: thuy_ck@haui.edu.vn

Appendix I

S. No.	Abbreviation	Description
1	AHP	Analytic Hierarchy Process
2	ARAS	Additive Ratio Assessment
3	COCOSO	Combined Compromise Solution
4	CODAS	Combinative Distance-based Assessment
5	COPRAS	Complex Proportional Assessment
6	CRADIS	Compromise Ranking of Alternatives from Distance to Ideal Solution
7	CRITIC	Criteria Importance Through Intercriteria Correlation
8	CURLI	Collaborative Unbiased Rank List Integration
9	ELECTRE	Elimination Et Choix Traduisant la Realite
10	FOR	Forklifts
11	FUCA	Faire Un Choix Adéquat
12	GM	Grinding Machines
13	MABAC	Multi Attributive Border Approximation Area Comparison
14	MARA	Magnitude of the Area for the Ranking of Alternatives
15	MARCOS	Measurement Alternatives and Ranking According to Compromise Solution
16	MCDM	Multi Criteria Decision Making
17	MEREC	Method based on the Removal Effects of Criteria
18	MM	Milling Machines
19	MOORA	Multi-objective Optimization On the basis of Ratio Analysis
20	PIPRECIA	Pivot Pairwise Relative Criteria Importance Assessment
21	PIV	Proximity Indexed Value
22	PROMETHE E	Preference Ranking Organization Method for Enrichment Evaluation
23	PSI	Preference Selection Index
24	ROC	Rank Order Centroid
25	RS	Rank Sum
26	SAW	Simple Additive Weighting
27	SM	Saw Machines
28	SPC	Symmetry Point of Criterion
29	SRP	Simple Ranking Process
30	TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
31	VIKOR	VlsekrIterijumska Optimizacijai Kompromisno Resenje
32	WMM	Wood Milling Machines
33	WSA	Weighted Sum Approach