

Comparison of MCDM methods effectiveness in the selection of plastic injection molding machines

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Abstract: In each specific problem of finding the best solution among many available options, where each option has multiple criteria, multi criteria decision making methods are considered equally effective when they converge to the same optimal solution. Proximity Indexed Value, Preference Selection Index, Faire Un Choix Adéquat (in French), and Collaborative Unbiased Rank List Integration are four Multi Criteria Decision Making methods with very different characteristics. All these four methods have been used a lot in recent times. The effectiveness of these four methods have been confirmed to be comparable to other multi criteria decision making methods in many applications. However, the comparison of these four methods with each other has never been performed in any studies. This article is performed to fill that gap. These four methods have been used to find to the best option among five types of plastic injection molding machine. Ten criteria have been chosen to describe each alternative. Two different methods that have been used to calculate the weights for the criteria are the MEAN weight method and the CRiteria Importance Through Intercriteria Correlation weight method. Different scenarios have been created to compare the effectiveness of these four methods. The results have shown that the four multi criteria decision making methods mentioned above are equally effective in the selection of plastic injection molding machines. Among the five types of plastic injection molding machines, namely JSW J350EII-SPA ANBE-002-02, Meiki M-200B-SJ, Meiki M-350C-DF-SJ, JSW J350E II, and JSW J550E-C5, the JSW J550E-C5 is the best type.

Keywords: MCDM; PIV Method; PSI Method; FUCA Method; CURLI Method.

1. Introduction

Nowadays, the number of MCDM (Multi Criteria Decision Making) methods has exceeded 200, and they are used a lot to find the best option among available options in many different fields [1]. The purpose of applying MCDM methods is to find the best option among available options. Therefore, the methods are considered to be equally effective when they find the same best option [2], [3], [4]. MCDM methods are divided into four main groups, the first group is the methods that need to normalize data and determine the weights for criteria (called group I), the second group is the methods that need to normalize data but do not need to determine the weights for criteria (group II), the third group is the methods that do not need to normalize data but need to determine the weights for criteria (group III), the fourth group is the methods that need neither data normalization nor determining the weights for criteria (group IV).

PIV (Proximity Indexed Value) is a method that belongs to group I, this method has an advantage of minimizing rank reversal [5], [6], [7], [8]. PSI (Preference Selection Index) is a method that belongs to group II, this method is known to be the method that can be combined with many data normalization methods. Which means when using many data normalization methods to combine with it, it still find the same best option [9]. Another advantage of the PSI method is that because it does not need to determine the weights for criteria so this method is very useful in solving problems where there is a conflict about the importance of criteria [10], [11]. FUCA (Faire Un Choix Adéquat) is a method that belongs to group III and is known to have a simpler algorithm than other methods [12]. In some studies, it was found that the best option determined by the FUCA method does not depend on the weights of criteria [13]. CURLI (CRiteria Importance Through Intercriteria Correlation) is the only method that belongs to group IV. The significant advantage of this method is when using it, it is not necessary to normalize data and determine the weights for criteria [14], [15], [16], [17], [18]. These four methods are confirmed to be equally effective as other methods in many different cases. In table 1, a summary of some contents related to this statement is presented.

Table 1. Some MCDM methods that were confirmed to be equally effective in each case

MCDM methods	Cases for application	Ref.
PIV, ARAS (Additive Ratio ASsessment), MOORA (Multi Objective Optimization on the basis of Ratio Analysis), MABAC (Multi-Attributive Border Approximation area Comparison)	Choosing location to build garment factory in Türkiye	[19]
PIV, AHP (Analytic Hierarchy Process), COPRAS (COMplex PRoportional ASsessment), WEDBA (Weighted Euclidean Distance Based Approach)	Choosing online learning website	[20]
PIV, SAW, MAUT (Multi Attribute Utility Theory)	Identify the Country worst affected by the Covid 19 pandemic	[21]
PIV, TOPSIS, WASPAS, COPRAS	Choosing location to build warehouse	[22]
PSI, SAW	Choosing personnel for manager position	[23]
PSI, CODAS (COMbinative Distance-based Assessment)	Choosing personnel of textile company in Denizli	[24]
PSI, EDAS	Choosing the Country with the best tourism potential	[25]
FUCA, CURLI	Choosing air conditioner, washing machine, drone	[14]
FUCA, CURLI	Choosing metal grinder, metal drilling machine, metal milling machine	[15]
CURLI, PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation), EDAS	Choosing material to manufacture protective panel on car	[16]
CURLI, EDAS, TOPSIS, PROMETHEE	Choosing material to manufacture gear	
CURLI, VIKOR	Choosing material for cutting tool	
CURLI, CRADIS (Compromise Ranking of Alternatives from Distance to Ideal Solution)	Choosing wood milling machine, wood sawing machine, wood planer	[17]
CURLI, VIKOR, TOPSIS	Choosing grinding wheel	[18]
CURLI, TOPSIS	Choosing supplier	

Thus, it can be seen that the four methods PIV, PSI, FUCA, and CURLI have been confirmed to be as effective as other MCDM methods in many different cases. However, there was no document that has been proceeded to compare these four methods. This study has been performed to fill this gap.

When using two methods PIV and FUCA, the determination of the weights for criteria is necessary. However, the weights for criteria also have a great influence on the ranks of alternatives [26], [27]. For the comparison between PIV method and FUCA method to be general, two different weighting methods have been used. MEAN weight is the first method to be used. According to this method, all criteria have the same weight. It is the simplest method among weighting methods [13], [15], [28]. PSI and CURLI are two methods that do not need to calculate the weights for criteria, so the combination of the MEAN weight method with two methods PIV and FUCA to compare with PSI and CURLI is considered a suitable approach. The second weighting method that has been used is the CRITIC (CRiteria Importance Through Intercriteria Correlation) method. This is the weighting method for criteria that consider the correlation between criteria [29], [30], [31], [32], [33].

For plastic injection molding machine, many parameters have correlation with each other. For example, the diameter size of screw is related to the maximum pressing force, or spindle motor power is related to maximum pressing force, or the diameter size of screw is related to spindle moter power, etc. Therefore, the application of the CRITIC method is considered to be suitable to calculate the weights for criteria that are correlated with each other of plastic injection molding machine. The plastic injection molding machine has been chosen as the subject of this study because selecting an appropriate plastic injection molding machine is crucial for plastic manufacturing businesses. A precise injection molding machine not only enhances productivity but also ensures the quality of the final products. This is because a suitable plastic injection molding machine can optimize the manufacturing process, minimize material waste, and maximize operational efficiency. Additionally, plastic injection molding machine can be utilized in various applications such as plastic packaging production, shaping industrial products, and even in the medical field. Therefore, searching for and selecting the right plastic injection molding machine is a crucial step for the success of a plastic manufacturing business. This study aims to achieve two goals. The first objective is to compare the effectiveness of four methods: PIV, PSI, FUCA and CURLI, when used to select plastic molding machines. The second objective is to identify the best plastic injection molding machine among the five available types. The motivation of this research is to broaden the understanding of the effectiveness of MCDM methods. The results of the study will provide a solid foundation for users when deciding to employ a specific MCDM method to solve a particular problem.

2. Material dan methods

2.1 Block diagram of the process

Determining the best type of plastic injection molding machine is conducted as illustrated in Figure 1. From the information about various types of molding machines, two *MCDM* methods without using criteria weights (including *PSI* and *CURLI*) will be employed to rank the alternatives. Also, from the information about the machines, weighting criteria using two methods, MEAN and *CRITIC*, will be performed. Subsequently, two *MCDM* methods requiring criteria weighting (including *PIV* and *FUCA*) will be utilized to rank the alternatives. A summary of the steps applying each method is presented in subsections 2.2 through 2.6.

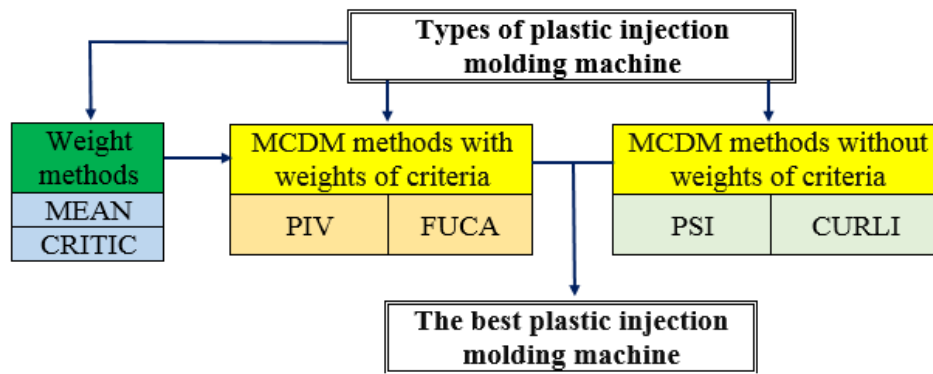


Figure 1. Block diagram of the process for determining the best type of plastic injection molding machine

2.2 The PIV method

Let m be the number of alternatives to be ranked, n is the number of criteria of each alternative, y_{ij} is the value of criterion j of alternative i , with $i = 1 \div m, j = 1 \div n$, ranking the alternatives when using the *PIV* method is performed in the following sequence [5].

Step 1: Calculate the normalized values according to equation (1).

$$n_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^m y_{ij}^2}} \quad (1)$$

Step 2: Calculate the weighted normalized values of the criteria according to equation (2).

$$V_{ij} = w_j \times n_{ij} \quad (2)$$

Step 3: Calculate the quantities u_i according to two equations (3) and (4). For the larger the better criteria, the formula (3) will be used. The equation (4) will be used for the smaller the better criteria.

$$u_i = v_{\max} - v_i \quad (3)$$

$$u_i = v_i - v_{\min} \quad (4)$$

Step 4: Equation (5) is used to calculate the scores of alternatives.

$$d_i = \sum_{j=1}^n u_i \quad (5)$$

Step 5: Alternatives are ranked in ascending order of their score.

2.3 The PSI method

The order of ranking alternatives when using the *PSI* method is as follows [9].

Step 1: Normalize data according to two equations (6) and (7). The equations (6) and (7) are applied respectively when criteria are the larger the better and the smaller the better.

$$n_{ij} = \frac{y_{ij}}{y_j^{max}} \tag{6}$$

$$n_{ij} = \frac{y_j^{min}}{y_{ij}} \tag{7}$$

Step 2: The average of normalized data is calculated according to equation (8).

$$n = \frac{1}{n} \sum_{i=1}^n n_{ij} \tag{8}$$

Step 3: The quantities $\varphi_j, \emptyset_j, \beta_j$ are calculated according to equations (9), (10) and (11).

$$\varphi_j = \sum_{i=1}^n [n_{ij} - n]^2 \tag{9}$$

$$\emptyset_j = [1 - \varphi_j] \tag{10}$$

$$\beta_j = \frac{\emptyset_j}{\sum_{j=1}^m \emptyset_j} \tag{11}$$

Step 4: Equation (12) is used to calculate the scores for alternatives.

$$PSI_j = \sum_{j=1}^m n_{ij} \cdot \beta_j \tag{12}$$

Step 5: The descending order of the scores of alternatives is the ranks of the alternatives.

2.4 The FUCA method

To rank the alternatives when using the *FUCA* method, the following sequence must be followed [34]:

Step 1: Rank the alternatives for each criterion. Let r_{ij} be the rank of the alternatives, $r_{ij} = 1$ if the criterion j of the alternative i is the best. Otherwise, $r_{ij} = m$ if the criterion j of the alternative i is the worst.

Step 2: Equation (13) is used to calculate the score of each alternative.

$$v_i = \sum_{j=1}^n r_{ij} \cdot w_j \tag{13}$$

Step 3: The ranks of alternatives are determined in ascending order of their scores.

2.5 The CURLI method

The sequence to apply the *CURLI* method is as follows [35].

Step 1: For each criterion, construct a square matrix of level m and score the alternatives. The scoring of alternatives (for each criterion) is performed as follows. For example, in the cell corresponding to column 1 and row 2, the value of the alternative 1 is better than that of the alternative 2, then score 1 in that cell. Another example, if in the cell corresponding to column 2 and row 1, the value of the alternative 2 is worse than that of the alternative 1, then score -1 in that cell. As another example, if in the cell corresponding to column 2 and row m , the value of the alternative 2 is equal to that of the alternative m , then score 0 in that cell, etc. 0 score will also be filled in the cells that lie in the main diagonal of matrix. The scoring matrix for criterion j is denoted by the matrix Q_j .

Step 2: The scoring matrix of the alternatives for all the criteria will be formed by adding all the matrices Q_j together. This matrix is called matrix Q , which means $Q = Q_1 + Q_2 + \dots + Q_j + \dots + Q_m$.

Step 3: Arrange the matrix Q by repositioning the rows and columns so that the part above the main diagonal has no cells with positive score. After rearranging, the alternative that is positioned in row 1 is considered the best alternative.

2.6 The weighting methods

The *MEAN* weight method is the method where the weights of criteria are equal [14, 17, 36]. The *CRITIC* method is used to calculate the weights of criteria according to equations (14) and (15) [29], [30], [31], [32], [33].

$$C_j = \sigma_j \sum_{j=1}^n (1 - r_{ij}) \tag{14}$$

$$W_j = \frac{C_j}{\sum_{j=1}^n C_j} \tag{15}$$

Where: σ_j and r_{ij} are the standard deviation of criterion j and the correlation coefficient between the two criteria, respectively.

2.7 Types of plastic injection molding machine

Five types of plastic injection molding machine have been chosen for ranking with product codes JSW J350EII-SPA ANBE-002-02, Meiki M-200B-SJ, Meiki M-350C-DF-Sj, JSW J350E II, and JSW J550E-C5. These five types of machine have been denoted by the letters A, B, C, D and E, respectively. To rank the machine types, ten criteria have been used to describe each product type including the minimum height of the mold that can be mounted on the machine (mm), the maximum height of the mold that can be mounted on the machine (mm), the screw diameter (mm), the mold pressing force (tons), the pressing stroke (mm), the width of the base plate (mm), the length of the base plate (mm), the spindle motor (kW), the maximum mold opening (mm), and selling price (million Vietnam dong). These ten criteria are denoted by the symbols from C1 to C10, respectively. C1 and C10 are the smaller the better criteria, the remaining eight criteria are the larger the better criteria. The minimum and maximum mold heights that the machine can accommodate determine its capability to work with molds of varying sizes. The diameter of the screw directly impacts the plastic molding efficiency, while the mold clamping force dictates the machine's ability to precisely inject plastic into the mold. The stroke length needs to be determined to ensure the machine can effectively handle different sizes and shapes of products. The size of the mold base plate must be compatible with both the mold and the machine to avoid mismatch or

constraints during production. The main axis motor needs to be sufficiently powerful to ensure stable and efficient machine operation, especially when dealing with large-sized molds or high-pressure plastic molding requirements. The maximum mold opening distance needs to be determined to ensure the machine can accommodate large-sized molds and adjust the opening distance flexibly. Finally, the cost is crucial for evaluating the feasibility and economic viability of investing in an injection molding machine. In table 2, the information of five types of plastic injection molding machine has been presented.

Table 2. Types of plastic injection molding machine

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A	250	530	53	350	570	630	630	55	1100	750
B	120	400	55	200	770	590	590	37	1000	300
C	600	600	50	350	745	1300	1300	55	1300	575
D	320	670	66	350	700	730	730	45	1370	1090
E	400	800	83	550	900	900	900	75	1700	1040

We can see that machine B has two criteria *C1* and *C10* are the best; machine C has two criteria *C6* and *C7* are the best; machine E has six criteria *C2*, *C3*, *C4*, *C5*, *C8*, *C9* are the best. Two machines A and D do not have any best criteria. Thus, the best machine type will not be found only base on observing the data in table 2. The best machine type can only be found when using multi-criteria decision-making methods to rank the machine types. Four methods *PIV*, *PSI*, *FUCA* and *CURLI* will be used to perform this task, respectively. To apply both *PIV* and *FUCA* methods, it is necessary to calculate the weights for the criteria first.

3. Results and discussion

3.1 Determination of the wights for criteria

According to the *MEAN* weight method, each criterion will have a weight of 0.1. To calculate the weights of the criteria according to the *CRITIC* method, the determination of the correlation coefficients between two criteria have been calculated online, the results are summarized in table 3.

Table 3. Correlation coefficients between the criteria

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	1	0.5678	0.0418	0.0561	0.2384	0.9639	0.9639	0.5242	0.5483	0.2722
C2	0.5678	1	0.1060	0.9381	0.4906	0.3987	0.3987	0.8084	0.9767	0.8714
C3	0.0418	0.1060	1	0.7852	0.7647	-0.0699	-0.0699	0.6516	0.8569	0.7150
C4	0.0561	0.9381	0.7852	1	0.4975	0.3477	0.3477	0.9560	0.9269	0.7658
C5	0.2384	0.4906	0.7647	0.4975	1	0.3217	0.3217	0.4465	0.6644	0.1174
C6	0.9639	0.3987	-0.0699	0.3477	0.3217	1	1.0000	0.4465	0.6644	0.1174
C7	0.9639	0.3987	-0.0699	0.3477	0.3217	1.0000	1	0.4086	0.4242	0.0317
C8	0.5242	0.8084	0.6516	0.9560	0.4465	0.4465	0.4086	1	0.8182	0.5607
C9	0.5483	0.9767	0.8569	0.9269	0.6644	0.6644	0.4242	0.8182	1	0.7694
C10	0.2722	0.8714	0.7150	0.7658	0.1174	0.1174	0.0317	0.5607	0.7694	1

The standard deviations of the criteria have also been calculated. The C_i values and w_j weights have also been calculated according to the formulas (14) and (15). All the data have been summarized in table 4.

Table 4. Some parameters in the CRITIC method

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
σ_j	0.3728	0.3746	0.4091	0.3557	0.3617	0.4066	0.4066	0.3748	0.3878	0.4164
C_j	1.798	1.28991	2.13517	1.20195	1.85796	1.95571	2.10364	1.2664	0.9115	1.98991
w_j	0.1089	0.0781	0.1293	0.0728	0.1125	0.1185	0.1274	0.0767	0.0552	0.1205

3.2 Application of the PIV method

Apply the formula (1), the normalized data have been calculated as shown in table 5.

Table 5. Normalized values in the PIV method

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A	0.2990	0.3855	0.3788	0.4154	0.3423	0.3241	0.3241	0.4480	0.3736	0.4158
B	0.1435	0.2910	0.3931	0.2374	0.4624	0.3035	0.3035	0.3014	0.3397	0.1663
C	0.7175	0.4365	0.3573	0.4154	0.4474	0.6688	0.6688	0.4480	0.4416	0.3188
D	0.3827	0.4874	0.4717	0.4154	0.4204	0.3756	0.3756	0.3666	0.4654	0.6044
E	0.4783	0.5819	0.5932	0.6527	0.5405	0.4630	0.4630	0.6110	0.5775	0.5766

The formula (2) has been applied to calculate the weighted normalized values of the criteria. First, the weight set of the criteria which was calculated by the *MEAN* weight method will be used, the results are summarized in table 6.

Table 6. The weighted normalized values of the criteria

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A	0.0299	0.0386	0.0379	0.0415	0.0342	0.0324	0.0324	0.0448	0.0374	0.0416
B	0.0143	0.0291	0.0393	0.0237	0.0462	0.0304	0.0304	0.0301	0.0340	0.0166
C	0.0717	0.0436	0.0357	0.0415	0.0447	0.0669	0.0669	0.0448	0.0442	0.0319
D	0.0383	0.0487	0.0472	0.0415	0.0420	0.0376	0.0376	0.0367	0.0465	0.0604
E	0.0478	0.0582	0.0593	0.0653	0.0540	0.0463	0.0463	0.0611	0.0577	0.0577

Two formulas (3) and (4) have been applied to calculate the values of u_{ij} . The scores of the alternatives have been calculated according to the formula (5). All the values that were calculated and the ranks of the alternatives have been summarized in table 7.

Table 7. Values of u_{ij} , scores d_i and ranking the alternatives by the PIV method when the weights of the criteria have been calculated by the *MEAN* weight method

Alt.	u_{ij}										d_i	Rank
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10		
A	0.0155	0.0196	0.0214	0.0237	0.0198	0.0345	0.0345	0.0163	0.0204	0.0250	0.2307	5
B	0.0000	0.0291	0.0200	0.0415	0.0078	0.0365	0.0365	0.0310	0.0238	0.0000	0.2262	4
C	0.0574	0.0145	0.0236	0.0237	0.0093	0.0000	0.0000	0.0163	0.0136	0.0152	0.1737	2
D	0.0239	0.0095	0.0121	0.0237	0.0120	0.0293	0.0293	0.0244	0.0112	0.0438	0.2194	3
E	0.0335	0.0000	0.0000	0.0000	0.0000	0.0206	0.0206	0.0000	0.0000	0.0410	0.1157	1

Following the same procedure, the scores have been calculated and the alternatives have been ranked when the weights of the criteria have been calculated by the *CRITIC* weight method, as shown in table 8.

Table 8. Values of u_{ij} , scores d_i and ranking the alternatives by the PIV method when the weights of the criteria have been calculated by the CRITIC weight method

Alt.	u_{ij}										d_i	Rank
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10		
A	0.0169	0.0153	0.0277	0.0173	0.0223	0.0408	0.0439	0.0125	0.0113	0.0301	0.2382	5
B	0.0000	0.0227	0.0259	0.0302	0.0088	0.0433	0.0465	0.0237	0.0131	0.0000	0.2143	3
C	0.0625	0.0114	0.0305	0.0173	0.0105	0.0000	0.0000	0.0125	0.0075	0.0184	0.1705	2
D	0.0260	0.0074	0.0157	0.0173	0.0135	0.0347	0.0374	0.0187	0.0062	0.0528	0.2298	4
E	0.0365	0.0000	0.0000	0.0000	0.0000	0.0244	0.0262	0.0000	0.0000	0.0495	0.1365	1

3.3 Application of the PSI method

The two formulas (6) and (7) have been applied to calculate the normalized data. The data has been summarized in table 9.

Table 9. Normalized values in the PSI method

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A	0.4800	0.6625	0.6386	0.6364	0.6333	0.4846	0.4846	0.7333	0.6471	0.4000
B	1.0000	0.5000	0.6627	0.3636	0.8556	0.4538	0.4538	0.4933	0.5882	1.0000
C	0.2000	0.7500	0.6024	0.6364	0.8278	1.0000	1.0000	0.7333	0.7647	0.5217
D	0.3750	0.8375	0.7952	0.6364	0.7778	0.5615	0.5615	0.6000	0.8059	0.2752
E	0.3000	1.0000	1.0000	1.0000	1.0000	0.6923	0.6923	1.0000	1.0000	0.2885

The formulas (8), (9), (10) and (11) have been applied to calculate the values of φ_j , \varnothing_j and β_j . The results have been summarized in table 10.

Table 10. Some parameters in PSI

Parameters	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
φ_j	0.3918	0.1403	0.1058	0.2050	0.0703	0.1973	0.1973	0.1442	0.1020	0.3557
\varnothing_j	0.6082	0.8597	0.8942	0.7950	0.9297	0.8027	0.8027	0.8558	0.8980	0.6443
β_j	0.0752	0.1063	0.1105	0.0983	0.1149	0.0992	0.0992	0.1058	0.1110	0.0796

The scores of the alternatives have been calculated according to the formula (12). The scores of PSI_i and the ranks of the alternatives have been presented in table 11.

Table 11. Scores and ranks of the alternatives

Alt.	$\beta_j * n_{ij}$										PSI_i	Rank
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10		
A	0.0361	0.0704	0.0706	0.0625	0.0728	0.0481	0.0481	0.0776	0.0718	0.0319	0.5898	5
B	0.0752	0.0531	0.0732	0.0357	0.0983	0.0450	0.0450	0.0522	0.0653	0.0796	0.6228	4
C	0.0150	0.0797	0.0666	0.0625	0.0951	0.0992	0.0992	0.0776	0.0849	0.0416	0.7214	2
D	0.0282	0.0890	0.0879	0.0625	0.0894	0.0557	0.0557	0.0635	0.0895	0.0219	0.6433	3
E	0.0226	0.1063	0.1105	0.0983	0.1149	0.0687	0.0687	0.1058	0.1110	0.0230	0.8297	1

3.4 Application of the FUCA method

The results of ranking the alternatives for each criterion are in table 12.

Table 12. Ranking the alternatives for each criterion

Alt.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A	2	4	4	3	5	4	4	2.5	4	3
B	1	5	3	5	2	5	5	5	5	5
C	5	3	5	3	3	1	1	2.5	3	4
D	3	2	2	3	4	3	3	4	2	1
E	4	1	1	1	1	2	2	1	1	2

Apply the formula (13) to calculate the score of each alternative. In two tables 13 and 14, the scores and ranks of the alternatives when the weights of the criteria are calculated according to two different methods are presented, respectively.

Table 13. Ranking the alternatives when the weights of the criteria are calculated according to the MEAN weight method

Alt.	r_{ij}										V_i	Rank
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10		
A	0.2	0.4	0.4	0.3	0.5	0.4	0.4	0.25	0.4	0.3	3.5500	4
B	0.1	0.5	0.3	0.5	0.2	0.5	0.5	0.5	0.5	0.5	4.1000	5
C	0.5	0.3	0.5	0.3	0.3	0.1	0.1	0.25	0.3	0.4	3.0500	3
D	0.3	0.2	0.2	0.3	0.4	0.3	0.3	0.4	0.2	0.1	2.7000	2
E	0.4	0.1	0.1	0.1	0.1	0.2	0.2	0.1	0.1	0.2	1.6000	1

Table 14. Ranking the alternatives when the weights of the criteria are calculated according to the CRITIC method

Alt.	r_{ij}										V_i	Rank
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10		
A	0.2178	0.3125	0.5173	0.2184	0.5627	0.4738	0.5097	0.1918	0.2208	0.3616	3.5863	4
B	0.1089	0.3906	0.3880	0.3640	0.2251	0.5923	0.6371	0.3835	0.2760	0.6026	3.9681	5
C	0.5446	0.2344	0.6466	0.2184	0.3376	0.1185	0.1274	0.1918	0.1656	0.4821	3.0669	3
D	0.3267	0.1563	0.2586	0.2184	0.4501	0.3554	0.3822	0.3068	0.1104	0.1205	2.6855	2
E	0.4356	0.0781	0.1293	0.0728	0.1125	0.2369	0.2548	0.0767	0.0552	0.2411	1.6931	1

3.5 Application of the CURLI method

The ten tables in the appendix section, from Table A1 to Table A10, represent the scoring results of the options based on each criterion. Add the matrices Q_1, Q_2, \dots, Q_{10} together, we get the matrix Q as shown in table 15.

Table 15. Matrix Q

Alt.	P1	P2	P3	P4	P5
A	0	-2	4	3	6
B	2	0	2	4	6
C	-4	-2	0	-1	4
D	-3	-4	1	0	8
E	-6	-6	-4	-8	0

Change the positions of the rows and change the positions of the columns in matrix Q so that the number of cells with negative values lies above the main diagonal is the maximum. The results are presented in table 16. We notice that all cells with negative values lie above the main diagonal of the matrix. In contrast, all the cells with positive values lie below the main diagonal of the matrix. Thus, the swapping of rows and columns has ended. The results of ranking the alternative have also been presented in the last column of table 16.

Table 16. Matrix Q after rearranging

Alt.	P5	P3	P4	P1	P2	Rank
E	0	-4	-8	-6	-6	1
C	4	0	-1	-4	-2	2
D	8	1	0	-3	-4	3
A	6	4	3	0	-2	4
B	6	2	4	2	0	5

Summary of the results of ranking the plastic injection molding machine when using different methods have been presented in the chart in figure 2.

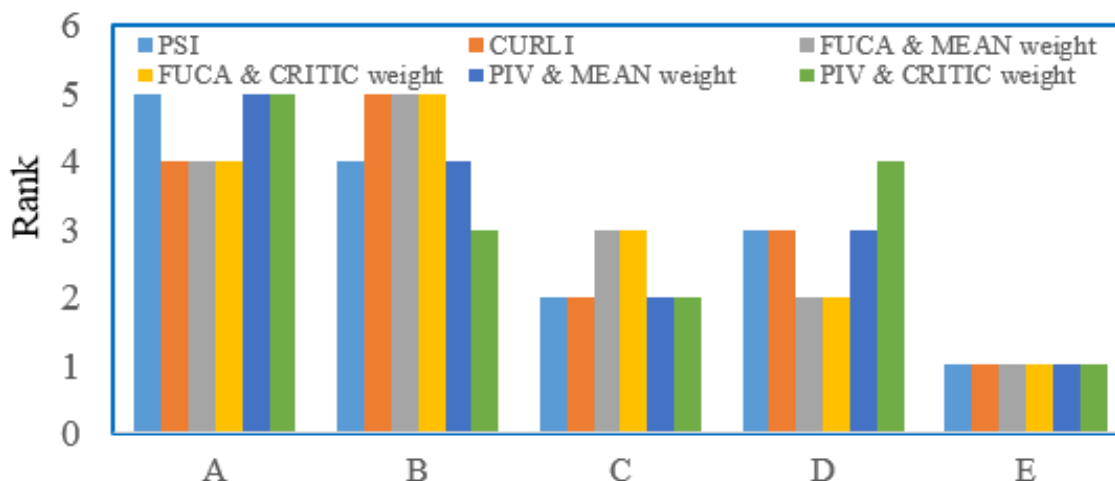


Figure 2. Ranking the plastic injection molding machines

It can be seen that in every cases, E is always determined to be the best alternative. Which means the four methods *PIV*, *PSI*, *FUCA*, and *CURLI* are equally effective. To reinforce this statement, the ranking of plastic injection molding is further performed with different scenarios. Generating various scenarios to assess the stability of ranking options is necessary because multiple studies have shown that when the number of options to be ranked changes, the rankings of the options may change as well. Even an option considered the best can become the worst if any option is removed from the list of options to be ranked [36], [37], [38]. Four scenarios have been performed, each scenario will remove one option from the list of alternatives to be ranked. This is how to create different scenarios that have been used in many studies [39]. In figure 3 to 6, the results of ranking plastic injection molding machines in four different scenarios are presented.

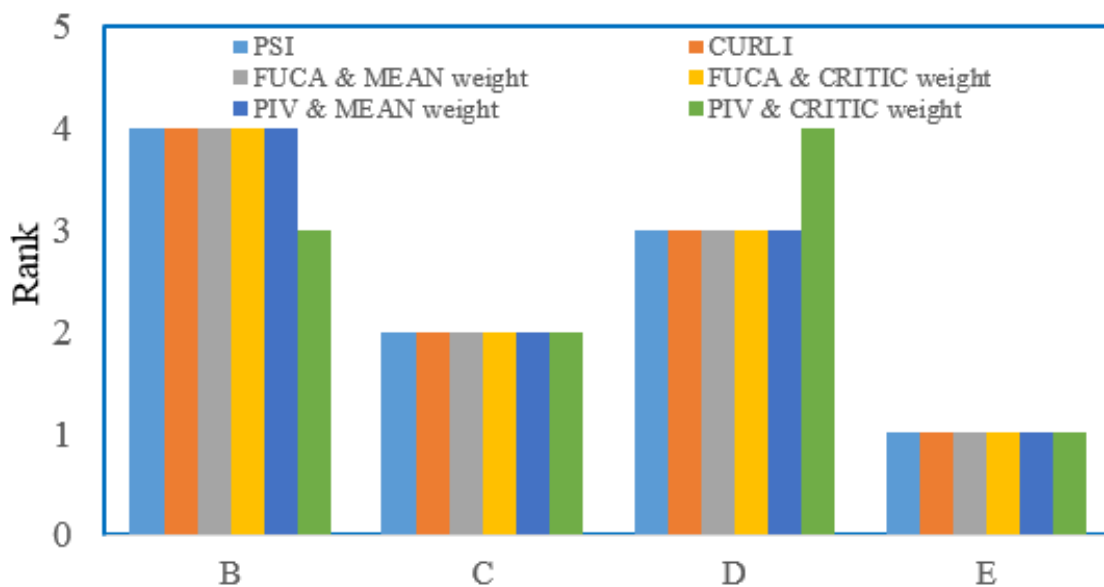


Figure 3. Ranking the plastic injection molding machines after removing alternative A from the list

After removing A from the list of alternatives, we see that there is only one exchange in the ranks of two alternatives B and D when using the *PIV* method (figure 3). Thus, in this case, we also notice that the four methods *PIV*, *PSI*, *FUCA*, and *CURLI* are equally effective because all of them determine E to be the best alternative.

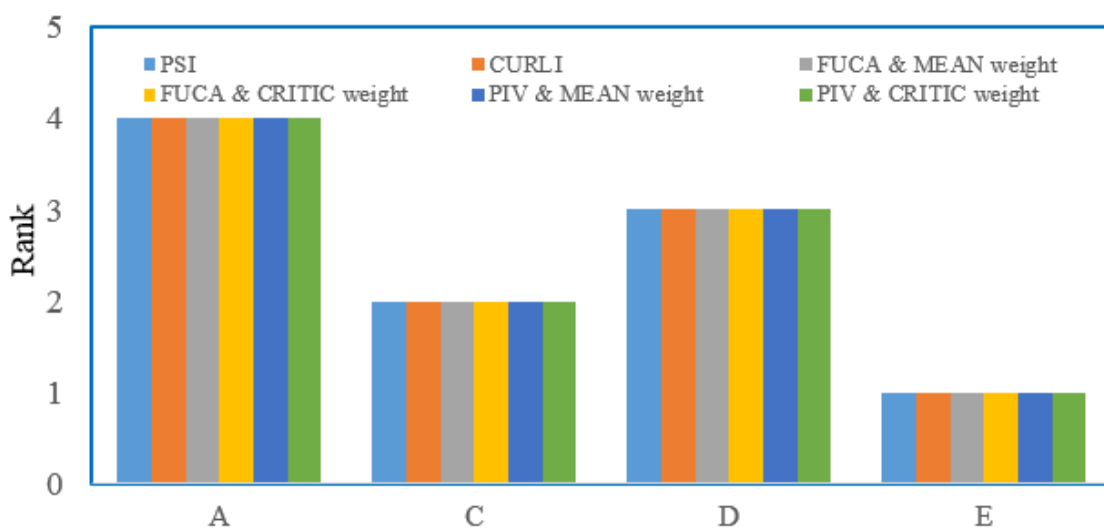


Figure 4. Ranking the plastic injection molding machines after removing alternative B from the list

For the scenario where B is removed from the list of alternatives, an extremely perfect result has occurred, that is the ranks of the alternatives are completely the same when using different methods (figure 4). Of course, in this case, we also find that the four methods *PIV*, *PSI*, *FUCA* and *CURLI* are equally effective.

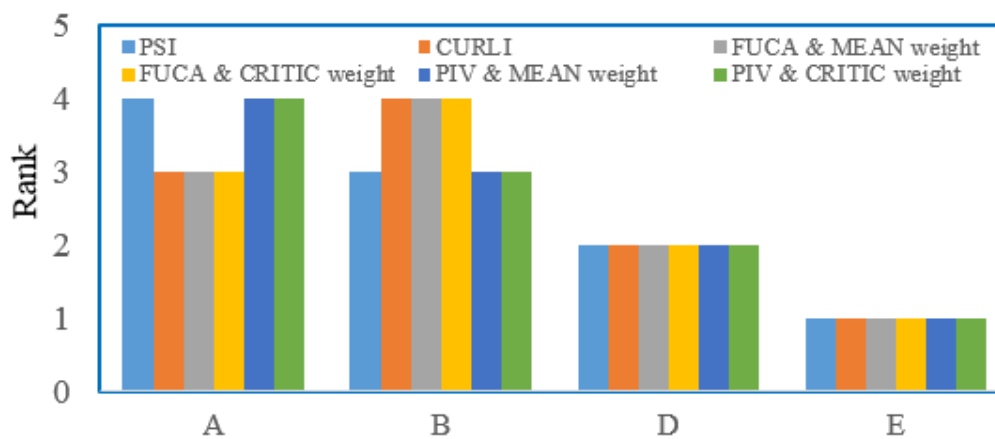


Figure 5. Ranking the plastic injection molding machines after removing alternative C from the list

In the scenario where C is removed from the list of alternatives, the alternatives that is ranked the 1st is completely the same when using different methods (figure 5). In this scenario, we also find that the four methods *PIV*, *PSI*, *FUCA* and *CURLI* are equally effective.

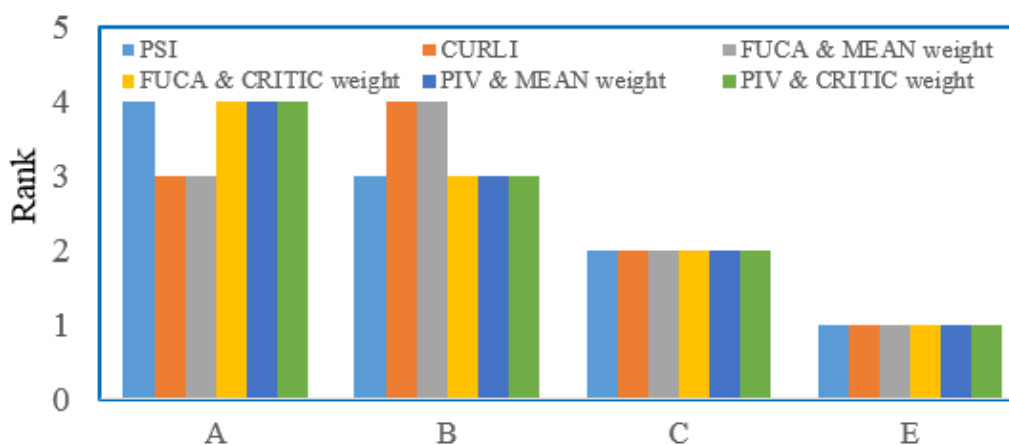


Figure 6. Ranking the plastic injection molding machines after removing alternative D from the list

After removing D from the list of alternatives, the ranks of the remaining alternatives are also quite similar when using different methods (figure 6). In particular, the alternatives that are ranked the 1st and the 2nd are completely the same. Thus, in this case, once again, we see that the four methods *PIV*, *PSI*, *FUCA* and *CURLI* are equally effective. All the statements above are enough for us to have a solid conclusion that the four methods *PIV*, *PSI*, *FUCA* and *CURLI* are equally effective in the selection of the best plastic injection molding machine. In addition, by observing five figures above, we can also make the following comments:

- The combination of the *PIV* method and the *MEAN* weight method shows that the ranking results are completely the same with when using the *PSI* method.
- The best alternative determined when using the *PIV* method does not depend on the weights of the criteria. This is also found in some previous studies [6], [7].
- When using the *FUCA* method to rank the alternatives, the best alternative does not depend on the weights of the criteria. This is also confirmed in some previous studies [13].

4. Conclusion

Four *MCDM* methods with different characteristics are used simultaneously for the first time in this study which are the *PIV* method, the *PSI* method, the *FUCA* method and the *CURLI* method. All these four methods are used to rank the plastic injection molding machines. In which the *PIV* method and the *FUCA* method are used to combine with two different weighting methods. Some conclusion are drawn as follows:

- Four methods including *PIV*, *PSI*, *FUCA* and *CURLI* are confirmed to be equally effective in making multi criteria decision to select plastic injection molding machine.
- When using the two methods *PIV* and *FUCA* to rank the alternatives, the best alternative to be found does not depend on the weights of the criteria.
- JSW J550E-C5 is confirmed to be the best type of plastic injection molding machine among five types of machines including JSW J350EII-SPA ANBE-002-02, Meiki M-200B-SJ, Meiki M-350C-DF-Sj, JSW J350E II, and JSW J550E-C5.
- Two methods have been used to calculate the weights for the criteria in this study, both of which are objective methods (*MEAN* and *CRITIC*). This means that the opinions of decision-makers (plastic buyers) regarding the importance of the criteria have not been taken into account. If one wants to consider the opinions of decision-makers on the importance of the criteria while still ensuring objectivity, it is necessary to use combined weighting methods. Combined weighting methods are methods that combine both objective and subjective factors. This means that weighting the criteria takes into account the opinions of decision-makers while still ensuring objectivity. Some methods of this type include *PIPRECIA* [40] and *CIMAS* [41].
- To be able to conclude whether these four methods are equally effective when they are applied in other cases, other surveys must be conducted. Other cases can be understood as determining the weights when using other methods, or ranking other types of product (service), or the number of criteria is changed, etc. Of course, the ways that have been used in this article can also be repeated.

Author contribution

Do Duc Trung conceived the idea, Branislav Dudić and Duong Van Duc performed calculations and analysis, Nguyen Hoai Son drafted the initial version of the paper, Aleksandar Ašonja and Do Duc Trung provided feedback on the article. All authors approved the final version.

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Competing interest

The authors declare no competing interest.

References

- [1] M. Baydaş, T. Eren, Ž. Stević, V. Starčević, and R. Parlakkaya, "Proposal for an objective binary benchmarking framework that validates each other for comparing MCDM methods

- through data analytics,” *PeerJ Comput Sci*, vol. 9, p. e1350, Apr. 2023, <https://doi.org/10.7717/peerj-cs.1350>
- [2] H.-Q. Nguyen, V.-T. Nguyen, D.-P. Phan, Q.-H. Tran, and N.-P. Vu, “Multi-Criteria Decision Making in the PMEDM Process by Using MARCOS, TOPSIS, and MAIRCA Methods,” *Applied Sciences*, vol. 12, no. 8, p. 3720, Apr. 2022, <https://doi.org/10.3390/app12083720>
- [3] T. H. Danh, T. Q. Huy, P. D. Lam, N. M. Cuong, H. X. Tu, and V. N. Pi, “A study on multi-criteria decision-making in powder mixed electric discharge machining cylindrical shaped parts,” *EUREKA: Physics and Engineering*, no. 5, pp. 123–129, Sep. 2022, <https://doi.org/10.21303/2461-4262.2022.002367>
- [4] H.-Q. Nguyen, X.-H. Le, T.-T. Nguyen, Q.-H. Tran, and N.-P. Vu, “A Comparative Study on Multi-Criteria Decision-Making in Dressing Process for Internal Grinding,” *Machines*, vol. 10, no. 5, p. 303, Apr. 2022, <https://doi.org/10.3390/machines10050303>
- [5] S. Mufazzal and S. M. Muzakkir, “A new multi-criterion decision making (MCDM) method based on proximity indexed value for minimizing rank reversals,” *Comput Ind Eng*, vol. 119, pp. 427–438, May 2018, <https://doi.org/10.1016/j.cie.2018.03.045>
- [6] S. Wakeel, S. Bingol, M. N. Bashir, and S. Ahmad, “Selection of sustainable material for the manufacturing of complex automotive products using a new hybrid Goal Programming Model for Best Worst Method–Proximity Indexed Value method,” *Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications*, vol. 235, no. 2, pp. 385–399, Feb. 2021, <https://doi.org/10.1177/1464420720966347>
- [7] S. Wakeel *et al.*, “A New Hybrid LGPMBWM-PIV Method for Automotive Material Selection,” *Informatica*, vol. 45, no. 1, Mar. 2021, <https://doi.org/10.31449/inf.v45i1.3246>
- [8] F. Jahan, M. Soni, S. Wakeel, S. Ahmad, and S. Bingol, “Selection of Automotive Brake Material Using Different MCDM Techniques and Their Comparisons,” *Journal of Engineering Science and Technology Review*, vol. 15, no. 1, pp. 24–33, 2022, <https://doi.org/10.25103/jestr.151.04>
- [9] K. Maniya and M. G. Bhatt, “A selection of material using a novel type decision-making method: Preference selection index method,” *Mater Des*, vol. 31, no. 4, pp. 1785–1789, Apr. 2010, <https://doi.org/10.1016/j.matdes.2009.11.020>
- [10] R. Attri and S. Grover, “Application of preference selection index method for decision making over the design stage of production system life cycle,” *Journal of King Saud University - Engineering Sciences*, vol. 27, no. 2, pp. 207–216, Jul. 2015, <https://doi.org/10.1016/j.jksues.2013.06.003>
- [11] A. DEMİRCİ, “LOJİSTİK SEKTÖRÜNDE PERSONEL SEÇİMİ İÇİN ÇOK KRİTERLİ KARAR VERME TEKNİĞİ YAKLAŞIMI: PSI ÖRNEĞİ,” *Toros Üniversitesi İİSBF Sosyal Bilimler Dergisi*, Oct. 2022, <https://doi.org/10.54709/iisbf.1167228>
- [12] M. Baydaş and D. Pamučar, “Determining Objective Characteristics of MCDM Methods under Uncertainty: An Exploration Study with Financial Data,” *Mathematics*, vol. 10, no. 7, p. 1115, Mar. 2022, <https://doi.org/10.3390/math10071115>
- [13] X. T. Hoang, “Multi-Objective Optimization of Turning Process by Fuca Method,” *Strojnícky Časopis - Journal of Mechanical Engineering*, vol. 73, no. 1, pp. 55–66, May 2023, <https://doi.org/10.2478/scjme-2023-0005>
- [14] A.-T. Nguyen, “Combining FUCA, CURLI, and Weighting Methods in the Decision-Making of Selecting Technical Products,” *Engineering, Technology & Applied Science Research*, vol. 13, no. 4, pp. 11222–11229, Aug. 2023, <https://doi.org/10.48084/etasr.6015>
- [15] N. H. Son *et al.*, “Choosing the best machine tool in mechanical manufacturing,” *EUREKA: Physics and Engineering*, no. 2, pp. 97–109, Mar. 2023, <https://doi.org/10.21303/2461-4262.2023.002771>

- [16] D. Van Tran, "Application of the Collaborative Unbiased Rank List Integration Method to Select the Materials," *Applied Engineering Letters: Journal of Engineering and Applied Sciences*, vol. 7, no. 4, pp. 133–142, 2022, <https://doi.org/10.18485/aeletters.2022.7.4.1>
- [17] T. Van Dua, "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*, no. 2, pp. 83–96, Mar. 2023, <https://doi.org/10.21303/2461-4262.2023.002763>
- [18] A.-T. Nguyen, "The Improved CURLI Method for Multi-Criteria Decision Making," *Engineering, Technology & Applied Science Research*, vol. 13, no. 1, pp. 10121–10127, Feb. 2023, <https://doi.org/10.48084/etasr.5538>
- [19] A. ULUTAŞ and C. B. KARAKUŞ, "Location selection for a textile manufacturing facility with GIS based on hybrid MCDM approach," *Industria Textila*, vol. 72, no. 02, pp. 126–132, Apr. 2021, <https://doi.org/10.35530/IT.072.02.1736>
- [20] N. Z. Khan, T. S. A. Ansari, A. N. Siddiquee, and Z. A. Khan, "Selection of E-learning websites using a novel Proximity Indexed Value (PIV) MCDM method," *Journal of Computers in Education*, vol. 6, no. 2, pp. 241–256, Jun. 2019, <https://doi.org/10.1007/s40692-019-00135-7>
- [21] S. E. Tuzcu and S. P. Türkoğlu, "How vulnerable are high-income countries to the covid-19 pandemic? An MCDM approach," *Decision Making: Applications in Management and Engineering*, vol. 5, no. 2, pp. 372–395, Oct. 2022, <https://doi.org/10.31181/dmame0318062022t>
- [22] A. Ulutaş, F. Balo, L. Sua, E. Demir, A. Topal, and V. Jakovljević, "A new integrated grey MCDM model: Case of warehouse location selection," *Facta Universitatis, Series: Mechanical Engineering*, vol. 19, no. 3, p. 515, Oct. 2021, <https://doi.org/10.22190/FUME210424060U>
- [23] N. Husna, Y. Yudianti, and R. Supardi, "Comparison of the Preference Selection Index (PSI) Method with the Simple Additive Weight (SAW) Method in The Selection of the Best Foreman at PT. Agro Muko," *Jurnal Komputer, Informasi dan Teknologi*, vol. 1, no. 2, Dec. 2021, <https://doi.org/10.53697/jkomitek.v1i2.294>
- [24] A. TUŞ and E. AYTAÇ ADALI, "CODAS ve PSI Yöntemleri İle Personel Değerlendirmesi," *Alphanumeric Journal*, vol. 6, no. 2, pp. 243–256, Dec. 2018, <https://doi.org/10.17093/alphanumeric.432843>
- [25] M. Stanujkic, D. Stanujkic, D. Karabasevic, C. Sava, and G. Popovic, "Comparison of Tourism Potentials Using Preference Selection Index Method," *Quaestus Multidisciplinary Research Journal*, vol. 16, no. April, 2020.
- [26] D. Stanujkic, E. K. Zavadskas, D. Karabasevic, F. Smarandache, and Z. Turskis, "The use of the pivot pairwise relative criteria importance assessment method for determining the weights of criteria," *Romanian Journal of Economic Forecasting*, vol. 20, no. 4, 2017.
- [27] Z. Gligorić, M. Gligorić, I. Miljanović, S. Lutovac, and A. Milutinović, "Assessing Criteria Weights by the Symmetry Point of Criterion (Novel SPC Method)—Application in the Efficiency Evaluation of the Mineral Deposit Multi-Criteria Partitioning Algorithm," *Computer Modeling in Engineering & Sciences*, vol. 136, no. 1, pp. 955–979, 2023, <https://doi.org/10.32604/cmescs.2023.025021>
- [28] H. X. Thinh, N. T. Mai, N. T. Giang, and V. Van Khiem, "Applying multi-criteria decision-making methods for cutting oil selection," *Eastern-European Journal of Enterprise Technologies*, vol. 3, no. 1 (123), pp. 52–58, Jun. 2023, <https://doi.org/10.15587/1729-4061.2023.275717>
- [29] E. A. Adalı and A. T. Işık, "Critic and Maut Methods for the Contract Manufacturer Selection Problem," *European Journal of Multidisciplinary Studies*, vol. 5, no. 1, p. 93, May 2017, <https://doi.org/10.26417/ejms.v5i1.p93-101>

- [30] A. R. Krishnan, M. M. Kasim, R. Hamid, and M. F. Ghazali, "A Modified CRITIC Method to Estimate the Objective Weights of Decision Criteria," *Symmetry (Basel)*, vol. 13, no. 6, p. 973, May 2021, <https://doi.org/10.3390/sym13060973>
- [31] S. Jovčić and P. Průša, "A Hybrid MCDM Approach in Third-Party Logistics (3PL) Provider Selection," *Mathematics*, vol. 9, no. 21, p. 2729, Oct. 2021, <https://doi.org/10.3390/math9212729>
- [32] S. Salimian, S. M. Mousavi, and Z. Turskis, "Transportation Mode Selection for Organ Transplant Networks by a New Multi-Criteria Group Decision Model Under Interval-Valued Intuitionistic Fuzzy Uncertainty," *Informatica*, pp. 337–355, Mar. 2023, <https://doi.org/10.15388/23-INFOR513>
- [33] A. Kumari and B. Acherjee, "Selection of non-conventional machining process using CRITIC-CODAS method," *Mater Today Proc*, vol. 56, pp. 66–71, 2022, <https://doi.org/10.1016/j.matpr.2021.12.152>
- [34] M. Mendoza Luis Fernando, J. L. Perez Escobedo, C. Azzaro-Pantel, L. Pibouleau, S. Domenech, and A. Aguilar-Lasserre, "Selecting the best portfolio alternative from a hybrid multiobjective GA-MCDM approach for New Product Development in the pharmaceutical industry," in *2011 IEEE Symposium on Computational Intelligence in Multicriteria Decision-Making (MDCM)*, IEEE, Apr. 2011, pp. 159–166. <https://doi.org/10.1109/SMDCM.2011.5949271>
- [35] J. R. Kiger and D. J. Annibale, "A new method for group decision making and its application in medical trainee selection," *Med Educ*, vol. 50, no. 10, pp. 1045–1053, Oct. 2016, <https://doi.org/10.1111/medu.13112>
- [36] X. T. Nguyen, A. Ašonja, and D. T. Do, "Enhancing Handheld Polishing Machine Selection: An Integrated Approach of Marcos Methods and Weight Determination Techniques," *Applied Engineering Letters : Journal of Engineering and Applied Sciences*, vol. 8, no. 3, pp. 131–138, 2023, <https://doi.org/10.18485/aeletters.2023.8.3.5>
- [37] L. D. Ha, "Selection of Suitable Data Normalization Method to Combine with the CRADIS Method for Making Multi-Criteria Decision," *Applied Engineering Letters : Journal of Engineering and Applied Sciences*, vol. 8, no. 1, pp. 24–35, 2023, <https://doi.org/10.18485/aeletters.2023.8.1.4>
- [38] D. D. Trung, N. X. Truong, H. T. Dung, and A. Ašonja, "Combining DOE and EDAS Methods for Multi-criteria Decision Making," 2024, pp. 210–227. https://doi.org/10.1007/978-3-031-51494-4_19
- [39] D. Božanić, A. Milić, D. Tešić, W. Salabun, and D. Pamučar, "D numbers–FUCOM–fuzzy RAFSI model for selecting the group of construction machines for enabling mobility," *Facta Universitatis, Series: Mechanical Engineering*, vol. 19, no. 3, p. 447, Oct. 2021, <https://doi.org/10.22190/FUME210318047B>
- [40] D. Stanujkić, D. Karabašević, and G. Popović, "Ranking alternatives using PIPRECIA method: A case of hotels' website evaluation," *Journal of Process Management. New Technologies*, vol. 9, no. 3–4, pp. 62–68, 2021, <https://doi.org/10.5937/jouproman2103062S>
- [41] S. Bošković, S. Jovčić, V. Simic, L. Švadlenka, M. Dobrodolac, and N. Bacanin, "A new criteria importance assessment (Cimas) method in multi-criteria group decision-making: Criteria evaluation for supplier selection," *Facta Universitatis, Series: Mechanical Engineering*, pp. 11–16, 2024. <https://doi.org/10.22190/FUME230730050B>

Appendix

Table A1. Matrix Q_1

Alt.	P1	P2	P3	P4	P5
A	0	1	-1	-1	-1
B	-1	0	-1	-1	-1
C	1	1	0	1	1
D	1	1	-1	0	-1
E	1	1	-1	1	0

Table A2. Matrix Q_2

Alt.	P1	P2	P3	P4	P5
A	0	-1	1	1	1
B	1	0	1	1	1
C	-1	-1	0	1	1
D	-1	-1	-1	0	1
E	-1	-1	-1	-1	0

Table A3. Matrix Q_3

Alt.	P1	P2	P3	P4	P5
A	0	1	-1	1	1
B	-1	0	-1	1	1
C	1	1	0	1	1
D	-1	-1	-1	0	1
E	-1	-1	-1	-1	0

Table A4. Matrix Q_4

Alt.	P1	P2	P3	P4	P5
A	0	-1	0	0	1
B	1	0	1	1	1
C	0	-1	0	0	1
D	0	-1	0	0	1
E	-1	-1	-1	-1	0

Table A5. Matrix Q_5

Alt.	P1	P2	P3	P4	P5
A	0	1	1	1	1
B	-1	0	-1	-1	1
C	-1	1	0	-1	1
D	-1	1	1	0	1
E	-1	-1	-1	-1	0

Table A6. Matrix Q_6

Alt.	P1	P2	P3	P4	P5
A	0	-1	1	1	1
B	1	0	1	1	1
C	-1	-1	0	-1	-1
D	-1	-1	1	0	1
E	-1	-1	1	-1	0

Table A7. Matrix Q_7

Alt.	P1	P2	P3	P4	P5
A	0	-1	1	1	1
B	1	0	1	1	1
C	-1	-1	0	-1	-1
D	-1	-1	1	0	1
E	-1	-1	1	-1	0

Table A8. Matrix Q_8

Alt.	P1	P2	P3	P4	P5
A	0	-1	0	-1	1
B	1	0	1	1	1
C	0	-1	0	-1	1
D	1	-1	1	0	1
E	-1	-1	-1	-1	0

Table A9. Matrix Q_9

Alt.	P1	P2	P3	P4	P5
A	0	-1	1	1	1
B	1	0	1	1	1
C	-1	-1	0	1	1
D	-1	-1	-1	0	1
E	-1	-1	-1	-1	0

Table A10. Matrix Q_{10}

Alt.	P1	P2	P3	P4	P5
A	0	1	1	-1	-1
B	-1	0	-1	-1	-1
C	-1	1	0	-1	-1
D	1	1	1	0	1
E	1	1	1	-1	0