A NOVEL MULTI-CRITERIA DECISION MAKING PROCEDURE FOR SAW MACHINE SELECTION IN THE MECHANICAL MACHINING

ĐỀ XUẤT QUY TRÌNH RA QUYẾT ĐỊNH ĐA TIÊU CHÍ ĐIỂN HÌNH ĐỂ LỰA CHỌN MÁY CƯA TRONG GIA CÔNG CƠ KHÍ

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ABSTRACT

Steel sawing machines are crucial pieces of machinery in the mechanical manufacturing process. This kind of machine is designed to produce steel billets that meet the specifications. In the subsequent phases of the technological procedure, these billets will be used to manufacture products. Thus, it is obvious that the selection of a steel sawing machine plays an important role in the manufacturing process. However, there are currently a variety of steel sawing machines available on the market that vary based on criteria such as cost, workpiece size, table size, saw blade thickness, etc. The aforementioned criteria are divided into two categories: cost criteria and benefit criteria. Hence, it is difficult for the purchaser to determine the optimal alternative among the various saw machine options. This task can only be accomplished through the implementation of multi-criteria decision-making (MCDM) methodologies. In this study, the rating of sawing machines is determined via two MCDM approaches with distinct characteristics: the Combined Compromise Solution (COCOSO) method and the Measurement of Alternatives and Ranking according to the Compromise Solution (MARCOS) method. These proposed methods are then combined, in turn, with different criteria weight calculation techniques to perform both the data normalization and ranking processes. Four circular sawing machines are evaluated, and seventeen criteria are used to describe each one. The results are also compared to those of other MCDM methods to analyze in depth the efficacy and reliability of the designed MCDM procedure.

Keywords: *MCDM method, saw machine, COCOSO, MARCOS.*

TÓM TẮT

Máy cưa thép là thiết bị quan trọng trong gia công cơ khí. Máy cưa thép thường được dung để sản xuất phôi thép đáp ứng các thông số kỹ thuật cho trước. Trong các giai đoạn tiếp theo của quy trình công nghệ, các phôi này sẽ được sử dụng để sản xuất hàng hóa. Như vậy, có thể nói việc lựa chọn ra máy cưa thép phù hợp đóng vai trò quan trọng trong quy trình sản xuất. Tuy nhiên, hiện nay trên thị trường có rất nhiều loại máy cưa thép với các thông số khác nhau về giá thành, kích thước phôi, kích thước bàn, độ dày lưỡi cưa,… Các tiêu chí đề cập trên có thể được chia thành hai nhóm: tiêu chí chi phí và tiêu chí lợi ích. Do đó rất khó để người mua xác định phương án tối ưu trong các vô vàn tùy chọn máy cưa thép khác nhau. Điều này chỉ có thể được thực hiện thông qua việc áp dụng phương pháp ra quyết định đa tiêu chí (MCDM). Bài báo này đề xuất quá trình xếp hạng máy cưa thép thông qua hai phương pháp MCDM với các đặc điểm riêng biệt: phương pháp COCOSO và phương pháp MARCOS. Các phương pháp được đề xuất sẽ kết hợp lần lượt với các kỹ thuật tính trọng số khác nhau để thực hiện quá trình chuẩn hóa dữ liệu và xếp hạng phương án. Dữ liệu đầu vào gồm bốn dòng máy cưa với thống số kỹ thuật cụ thể dựa trên mười bảy tiêu chí. Kết quả xếp hạng được so sánh với các phương pháp MCDM khác để đánh giá hiệu quả và độ tin cậy của quy trình MCDM được thiết kế.

Từ khóa: *Phương pháp ra quyết định đa tiêu chí, máy cưa, COCOSO, MARCOS.*

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1. INTRODUCTION

For any mechanical processing process, the first step is to create workpieces with the required shape and size. Various methods for creating workpieces can be used such as casting, pressure machining (punching, bending, etc.), and sawing. In which, sawing is the most popular used method due to its versatility. Steel sawing machines are used to create workpieces that meet the shape and size requirements of large metal raw. Productivity and precision of sawing workpieces have a direct impact on the productivity and accuracy of further machining processes in the production line. Therefore, the selection of a suitable steel sawing machine plays an important role in workshops. To choose the right type of sawing machine, it is necessary to consider various parameters such as the size of the workpiece that can be sawed (the largest and the smallest), the ability to saw angles, the saw speed, the size of the workpiece, the size of the workpiece, machine capacity, price, and so on. Therefore, choosing the right steel sawing machine means it needs to take multi-criteria decision making (MCDM) action. However, there are different MCDM methods, and the results of ranking alternatives may not be the same when using different MCDM methods. Hence, choosing a suitable method is a challenge for decision makers. It is therefore necessary to compare MCDM methods in the classification of steel saws.

2. LITERATURE REVIEW AND PROBLEM STATEMENT

Machine tools have a direct influence on both the economic and technical efficiency of machine processes. Therefore, the ranking of machine types to choose the best machine tool among the available options plays a very important role. Numerous MCDM methods have been proposed for solving this problem. In [1], the TOPSIS method was used to rank CNC lathe machines. In this study, the determination of the weights of the criteria was performed using the AHP method. In [2], the ranking of CNC lathe machines was also performed using the Fuzzy TOPSIS method. However, in this study the Entropy method was used to determine the weights for the criteria. In [3], FUCA and CURLI methods were used to rank universal lathe machines. The weights of the criteria were determined by the PIPRECIA method. The ranking results point out that both FUCA and CURLI methods can be applied effectively for solving the problem. In another study [4], FUCA and CURLI methods were also used to rank flat grinders, milling machines, and drills. In this study, the weights of the criteria were chosen equally for all criteria. The results show that both methods provided the same best machine for all three different machine groups. In [5], two methods CRADIS and CURLI were used to rank three types of machines in the woodworking industry, namely, wood milling machine, wood sawing machine, and wood planer. The weights of the criteria of each machine type were determined by the SPC method. In all considered cases study, the CRADIS and CURLI methods also produced the same best solution. In [6], two fuzzy methods, DEMATEL and VIKOR were used to rank CNC machining centers. The Entropy method was applied for determining the weights of the criteria. The results show that both methods produce the same best type of machine. In [7] a study to choose the provider of raw materials for a milk company in Turkey, the authors proposed an approach by combining DELPHI, PROMETHEE, and AHP methods. In which, AHP method was used to determine the weights for the criteria, and the other two methods were used to rank the machines. This study has confirmed that both DELPHI and PROMETHEE methods had the same result of the best provider. In [8], GRA, COPRAS, and MULTIMOORA methods were used to rank five-axis machining centers. The Best-Worst method was used to determine the weights the of criteria. The results confirmed that all three methods provided the same best alternative to a machining center.

It is obvious that MCDM methods have been widely used for multi-criteria decision making in machine tool selection [9]. The comparison of the effectiveness of MCDM methods in ranking machine tools has also been carried out in a number of studies. However, the study in ranking the steel sawing machine is very rare. Therefore, this paper focuses on the selection of sawing machines.

COCOSO and MARCOS are the MCDM methods that require both data normalization and weight distribution for criteria, but they are different in implementation. The COCOSO method utilizes the appraisal score strategies to identify the relative weights and then conducts the ranking process [10]. In contrast, the MARCOS method has recently been found. This method initially requires expanding the input matrix with the ideal option and the anti-ideal option to implement the ranking procedure [11]. Since the difference in characteristics of these methods prompts a comparison between them when applied to rank alternatives in a particular problem and is also the reason that these methods are used to rank steel sawing machines in this study.

As mentioned above, both COCOSO and MARCOS methods require determining the weights for the criteria. However, determining the weights of the criteria is also a difficult duty for decision makers. Numerous studies have pointed out that the ranking results of the alternatives are strongly affected by the method for determining the weight of the criteria [12]. If the weighting of criteria is based solely on the subjective opinion of the decision-maker, the optimal solution cannot be identified [13]. Also, the optimal solution cannot be determined if the weighting of criteria is based exclusively on calculated numbers [14]. This study designs the combinations between the MARCOS and COCOSO with different calculation techniques for criteria weights (including the CRiteria Importance Through Intercriteria Correlation (CRITIC) technique [15] and the Integrated Determination of Objective CRIteria Weights (IDOCRIW) technique [16]). The ranking results are then compared to inspect the effectiveness of the proposed procedures.

3. THE AIM AND OBJECTIVES OF THE STUDY

The objective of this study is to compare MCDM methods in sawing machine selection. To achieve this aim, the following objectives are accomplished:

– To determine the weight of the criteria of the steel saw machine using two techniques (the CRITIC and the IDOCRIW).

– To apply COCOSO and MARCOS methods to investigate the best sawing machine.

– In contrast to previous studies, the calculation procedures are now carried out automatically by programming in Python rather than Excel functions.

4. MATERIALS AND METHODS

4.1. CRiteria Importance Through Intercriteria Correlation (CRITIC) technique

Supposing there are m alternatives, each alternative includes n criteria, the order of weighting for the criteria by the CRITIC method is as follows [15]:

Step 1: Establishing decision making matrix using (1).

$$X=\left[x_{ij}\right]_{m\times n}=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}, \quad (1)$$

where: i=1, 2, …, m; j = 1, 2, …, n, and x_{ij} is the value of criteria j in the alternative i.

Step 2: Normalizing data using (2).

$$x_{ij}^{*}=\frac{x_{ij}-\min\left(x_{ij}\right)}{\max\left(x_{ij}\right)-\min\left(x_{ij}\right)}. \quad (2)$$

Step 3: Determining the weight of j^{th} criteria using (3) and (4).

$$\varpi_j=\frac{C_j}{\sum_{j=1}^{n}C_j} \quad (3)$$

$$C_j=\sigma_j\sum_{j=1}^{n}\left(1-r_{ij}\right), \quad (4)$$

In which σ_j is the standard deviation of the j^{th} criteria and r_{ij} is the correlation coefficient between the two criteria.

4.2. Integrated Determination of Objective CRIteria Weights (IDOCRIW) technique

The IDOCRIW technique is conducted as follows:

Step 1: Similar to the CRITIC technique

Step 2: The normalized values of the decision matrix are given by:

$$d_{ij}=\frac{x_{ij}}{\sum_{i=1}^{m}x_{ij}};\ i\in\{1,2,...,m\}\ \forall j\in\{1,2,...,n\} \quad (5)$$

Step 3: Calculating the degree of entropy by using the equation (6):

$$\varepsilon_j=-\frac{\sum_{i=1}^{m}d_{ij}\ln d_{ij}}{\ln m};(j=1,2,...,m) \quad (6)$$

Step 4: Determining the entropy weight by using the equation (7):

$$w_j=\frac{1-\varepsilon_j}{\sum_{j=1}^{n}(1-\varepsilon_j)} \quad (7)$$

Step 5: The positive or the negative attributes of the decision matrix are built based on equation (8) as follows:

$$\hat{d}_{ij}=\frac{\min_i x_{ij}}{x_{ij}};\ i\in\{1,2,...,m\}\ \forall j\in\{1,2,...,n\} \quad (8)$$

After that, the normalized values of the decision matrix is used to determine the square matrix values:

$$a_j=\max_i \hat{d}_{ij}=a_{k_j j} \quad (9)$$

Which $a_{k_j j}$ are the maximum values of j^{th} criteria.

Step 6: Regarding to the values from the previous step, the relative impact loss matrix is calculated by aiding the formulas (10) and (11):

$$\rho_{ij}=\frac{a_{jj}-a_{ij}}{a_{jj}}\ i\in\{1,2,...,m\}\ \forall j\in\{1,2,...,n\} \quad (10)$$

$$\rho_{jj}=0;\ j\in\{1,2,...,n\} \quad (11)$$

P_{ij} is the relative impact loss of j^{th} criteria in case of being selected as the best value.

Step 7: The weight system matrix is constructed as follows:

$$\mathbf{F}=\begin{pmatrix} -\sum_{i=1}^{m}P_{1i} & P_{12} & \cdots & P_{1n} \\ P_{21} & -\sum_{i=1}^{m}P_{i2} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & \cdots & -\sum_{i=1}^{m}P_{in} \end{pmatrix} \quad (12)$$

Step 8: The weights of attributes $\mathbf{h}=\left[h_1,h_2,...,h_n\right]$ by solving the equation (13):

$$\mathbf{F}\mathbf{h}^{T}=0 \quad (13)$$

Step 9: The formula (14) considers both the CILOS weight (h_j) and the entropy weight (w_j) to compute the total weight value of the attributes:

$$\varpi_j=\frac{h_j w_j}{\sum_{j=1}^{n}h_j w_j} \quad (14)$$

4.3. COCOSO method

The COCOSO method is implemented based on the following steps:

Step 1: Similar to the CRITIC technique.

Step 2: Conducting the data normalization based on the equations below:

$$d_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}; \text{with beneficial criteria} \quad (15)$$

$$d_{ij} = \frac{-x_{ij} + \max x_{ij}}{\max x_{ij} - \min x_{ij}}; \text{with non-beneficial criteria} \quad (16)$$

Step 3: Calculating the P_i and S_i values by the equations as follows:

$$P_i = \sum_{j=1}^{n} (d_{ij})^{\varpi_j} \quad (17)$$

$$S_i = \sum_{j=1}^{n} (\varpi_j d_{ij}) \quad (18)$$

where ϖ_j is the weight of the j^{th} criteria.

Step 4: Computing three appraisal score strategies to identify the relative weights of the remaining alternatives as:

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)} \quad (19)$$

$$k_{ib} = \frac{P_i}{\min_i P_i} + \frac{S_i}{\min_i S_i} \quad (20)$$

$$k_{ic} = \frac{(1-\tau) \times P_i + \tau \times S_i}{(1-\tau) \times \max_i P_i + \tau \times \max_i S_i}; 0 \le \tau \le 1 \quad (21)$$

Step 5: The general parameter k_i is then computed by using the formula:

$$k_i = \frac{k_{ia} + k_{ib} + k_{ic}}{3} + (k_{ia} \times k_{ib} \times k_{ic})^{\frac{1}{3}} \quad (22)$$

Step 6: Ranking the alternatives based on the values k_i. The alternative with the highest k_i is chosen as the best.

4.4. MARCOS method

The MARCOS method is implemented based on the following steps:

Step 1: Similar to the CRITIC technique.

Step 2: Expanding the input matrix with an ideal solution (AI) and its opposite (AAI).

$$\mathbf{E} = \begin{array}{c} AAI \\ A_1 \\ A_2 \\ \vdots \\ A_m \\ AI \end{array} \begin{bmatrix} x_{aa1} & \cdots & x_{aan} \\ x_{11} & \cdots & x_{1n} \\ x_{21} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots \\ x_{m1} & \cdots & x_{mn} \\ x_{ai1} & \cdots & x_{ain} \end{bmatrix} \quad (23)$$

For the beneficial criteria:

$$\begin{cases} AAI = \min_i x_{ij} \\ AI = \max_i x_{ij} \end{cases}; \forall j = 1,2,...,m \quad (24)$$

For the non-beneficial criteria:

$$\begin{cases} AAI = \max_i x_{ij} \\ AI = \min_i x_{ij} \end{cases}; \forall j = 1,2,...,m \quad (25)$$

Step 3: The expanded matrix **E** is then normalized based on the formulas (26) and (27).

$$d_{ij} = \frac{x_{ij}}{x_{ai}}; \text{with beneficial criteria} \quad (26)$$

$$d_{ij} = \frac{x_{ai}}{x_{ij}}; \text{with non-beneficial criteria} \quad (27)$$

Step 4: The weighted normalization matrix is calculated based on the weight distribution and the normalized matrix as follows:

$$W_{m\times n} = \left[w_{ij}\right]_{m\times n} = \left[d_{ij}\varpi_j\right]_{m\times n} \quad (28)$$

where ϖ_j is the weight of the j^{th} criteria.

Step 5: Calculating the relation parameters S_i, S_{aai}, and S_{ai} by using the equation (29):

$$\begin{cases} S_i = \sum_{i=1}^{m} v_{ij} \\ S_{aai} = \sum_{i=1}^{m} x_{aai} \\ S_{ai} = \sum_{i=1}^{m} x_{ai} \end{cases} \quad (29)$$

Step 6: Calculating the parameters k_i^- and k_i^+ by utilizing the given formula below:

$$\begin{cases} k_i^- = \frac{S_i}{S_{aai}} \\ k_i^+ = \frac{S_i}{S_{ai}} \end{cases} \quad (30)$$

Step 7: Calculating the utility function of alternatives $f(k_i)$ as:

$$f(k_i) = (k_i^+ + k_i^-) \times \left[1 + \frac{1 - f(k_i^+)}{f(k_i^+)} + \frac{1 - f(k_i^-)}{f(k_i^-)}\right]^{-1} \quad (31)$$

which k_i^+ and k_i^- are the utility functions with respect to the ideal solution and the anti-ideal solution, respectively.

$$\begin{cases} f(k_i^+) = \frac{k_i^-}{k_i^+ + k_i^-} \\ f(k_i^-) = \frac{k_i^+}{k_i^+ + k_i^-} \end{cases} \quad (32)$$

Step 8: Ranking the alternatives based on the values $f(k_i)$. The alternative with the highest $f(k_i)$ is chosen as the best.

5. NUMERICAL RESULTS

5.1. Calculating the weight for each criterion

The industrial provider in [17] introduces four types of circular saw machines with different specifications. There are 14 criteria in total that are applied to evaluate these saw machines. The meaning of each criterion is explained in Table 1. In which case, the unit of criterion C14 is "million VND", which represents the currency of Vietnam.

Table 1. The list of criteria

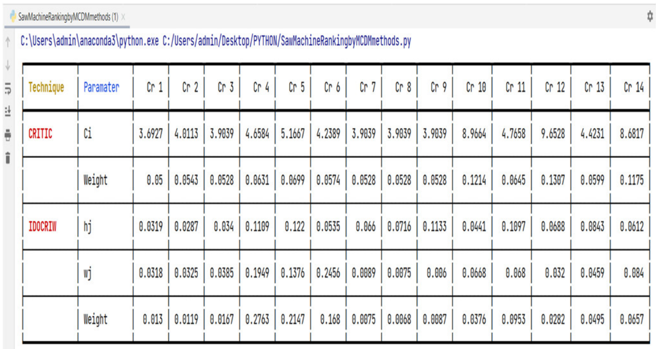
Criteria	Description	Unit	Type
C1	Maximum diameter of a circular workpiece that can be sawed	mm	Benefit Criteria
C2	Maximum width of a rectangular workpiece that can be sawed	mm	Benefit Criteria
C3	Maximum height of a rectangular workpiece that can be sawed	mm	Benefit Criteria
C4	Minimum diameter of a circular workpiece that can be sawed	mm	Cost Criteria
C5	Minimum width of a rectangular workpiece that can be sawed	mm	Cost Criteria
C6	Minimum height of a rectangular workpiece that can be sawed	mm	Cost Criteria
C7	Length of the saw blade	mm	Benefit Criteria
C8	Width of the saw blade	mm	Benefit Criteria
C9	Thickness of the saw blade	mm	Cost Criteria
C10	Power	kW	Benefit Criteria
C11	Minimum speed rate	m/min	Cost Criteria
C12	Maximum speed rate	m/min	Benefit Criteria
C13	Weight of the saw machine	kg	Benefit Criteria
C14	Price	trieu	Cost Criteria

It is evident that of the seventeen criteria mentioned above, C4, C5, C6, C9, C11, and C14 belong to the cost group. While the rest of the criteria belong to the benefit group. This case study seeks to identify the circular saw machine that minimizes the values of the cost criteria and maximizes the values of the benefit criteria by applying different MCDM methods. The detailed parameters of the proposed alternatives are presented in Table 2.

Table 2. Parameters of circular saw machines [18]

No.	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
A1	320	350	320	10	10	8	4440	34	1.1	2.6	15	110	1900	990
A2	500	560	500	10	10	10	5450	41	1.3	1.5	16	85	3000	640
A3	460	460	500	25	20	25	5450	41	1.3	1.5	25	75	2300	495
A4	460	460	500	20	20	20	5450	41	1.3	2	25	75	3090	610

Based on the input decision matrix in Table 2, the normalization matrix is established. Since then, the weight for each criterion is computed by applying the CRITIC technique and the IDOCRIW technique. The values of each criterion are calculated and shown in Figure 1. The summary weight distribution based on each technique is presented in Tables 3 and 4. These weighted values of the criteria are then used to rank the alternatives in the next sub-section.



SawMachineRankingbyMCDMmethods (1)

C:\Users\admin\anaconda3\python.exe C:/Users/admin/Desktop/PYTHON/SawMachineRankingbyMCDMmethods.py

Technique	Paramater	Cr 1	Cr 2	Cr 3	Cr 4	Cr 5	Cr 6	Cr 7	Cr 8	Cr 9	Cr 10	Cr 11	Cr 12	Cr 13	Cr 14
CRITIC	Ci	3.6927	4.0113	3.9039	4.6584	5.1667	4.2389	3.9039	3.9039	3.9039	8.9664	4.7658	9.6528	4.4231	8.6817
	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
IDOCRIW	hj	0.0319	0.0287	0.034	0.1109	0.122	0.0535	0.066	0.0716	0.1133	0.0441	0.1097	0.0688	0.0843	0.0612
	wj	0.0318	0.0325	0.0385	0.1949	0.1376	0.2456	0.0089	0.0075	0.006	0.0668	0.068	0.032	0.0459	0.084
	Weight	0.013	0.0119	0.0167	0.2763	0.2147	0.168	0.0075	0.0068	0.0087	0.0376	0.0953	0.0282	0.0495	0.0657

Figure 1. The criteria weight distribution by using two mentioned techniques

5.2. Multi-criteria decision-making for selecting circular saw machines

In this sub-section, two proposed MCDM methods (COCOSO and MARCOS) are applied in turn to rank the alternatives.

Table 3. The weights of the criteria based on the CRITIC technique

	Criteria													
Parameter	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
C_j	3.693	4.011	3.904	4.658	5.167	4.239	3.904	3.904	3.904	8.966	4.766	9.653	4.423	8.682
$\varpi_{j\text{-CRITIC}}$	0.050	0.054	0.053	0.063	0.070	0.057	0.053	0.053	0.053	0.121	0.065	0.131	0.060	0.118

Table 4. The weights of the criteria based on the IDOCRIW technique

	Criteria													
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
h_j	0.032	0.029	0.034	0.111	0.122	0.054	0.066	0.072	0.113	0.044	0.110	0.069	0.084	0.061
w_j	0.032	0.033	0.039	0.195	0.138	0.246	0.009	0.008	0.006	0.067	0.068	0.032	0.046	0.084
$\varpi_{j\text{-IDOCRIW}}$	0.013	0.012	0.017	0.276	0.215	0.168	0.008	0.007	0.009	0.038	0.095	0.028	0.050	0.066

Ranking the options based on the Combined Compromise Solution (COCOSO) method:

The normalization matrix of the input data is computed based on the equations (15) and (16). At the next step, three appraisal score strategies k_{ia}, k_{ib}, and k_{ic} is established to calculate the general parameter k_i. The ranking results are presented as in Table 5 and Figure 2. The most striking result to emerge from the obtained data is that A2 is always chosen as the best option and A3 picked up the last position in all cases.

MCDM Method	Technique	A1	A2	A3	A4
COCOSO	Ki (Critic)	1.8001	2.6992	1.5336	2.1034
	Rank	3	1	4	2
	Ki (Idocriw)	3.7201	4.709	1.5065	2.4919
	Rank	2	1	4	3

Figure 2. Exporting the ranking results by using the COCOSO method on Python idle

Table 5. The weights of the criteria based on the CRITIC technique

Alternative	MCDM procedure			
	COCOSO - CRITIC		COCSO - IDOCRIW	
	k_i	Rank	k_i	Rank
A1	1.8001	3	3.7201	2
A2	2.6992	1	4.709	1
A3	1.5336	4	1.5065	4
A4	2.1034	2	2.4919	3

Ranking the options based on the Ranking according to the Compromise Solution (MARCOS) method:

The normalization matrix of the input data is computed based on the equations from (23) and (24). After that, the relation parameters S_i, S_{aai}, and S_{ai} are computed. The final ranking results are indicated as in Table 6 and Figure 3.

MCDM Method	Technique	A1	A2	A3	A4
MARCOS	fk (Critic)	0.6862	0.7065	0.5968	0.6191
	Rank	2	1	4	3
	fk (Idocriw)	0.8055	0.797	0.461	0.5031
	Rank	1	2	4	3

Figure 3. Exporting the ranking results by using the MARCOS method on Python idle

Table 6. The weights of the criteria based on the CRITIC technique

Alternative	MCDM procedure			
	MARCOS - CRITIC		MARCOS - IDOCRIW	
	$f(k_i)$	Rank	$f(k_i)$	Rank
A1	0.6862	2	0.8055	1
A2	0.7065	1	0.797	2
A3	0.5968	4	0.461	4
A4	0.6191	3	0.5031	3

It is noticeable that there has been a reversal phenomenon when combining the MARCOS method with different techniques of weight calculation. To be more detailed, in the case of combining the MARCOS method and the CRITIC technique, the alternative A2 is selected as the best and the alternative A3 is chosen as the worst. Whereas the combination between MARCOS and IDOCRIW indicates that the optimal option is A1, and the worst option is A3.

6. RELIABILITY ANALYSIS

The analysis of reliability is performed by comparing the ranking results obtained by coupling various MCDM methods with two proposed techniques (CRITIC and IDOCRIW). The list of MCDM methods included COCOSO, MARCOS, CODAS, ARAS, and TOPSIS. Figure 4 and Table 7 depict the comparison's outcomes. In addtion, the correlation values between the MCDM procedures are also computed and investigated based on the Kendall's τ coefficient [18] and presented in Figure 5.

MCDM Method	Technique	A1	A2	A3	A4
COCOSO	CRITIC	1.8001	2.6992	1.5336	2.1034
	Rank	3	1	4	2
	IDOCRIW	3.7201	4.709	1.5065	2.4919
	Rank	2	1	4	3

MCDM Method	Technique	A1	A2	A3	A4
MARCOS	CRITIC	0.6862	0.7065	0.5968	0.6191
	Rank	2	1	4	3
	IDOCRIW	0.8055	0.797	0.461	0.5031
	Rank	1	2	4	3

MCDM Method	Technique	A1	A2	A3	A4
CODAS	CRITIC	0.2747	0.1345	-0.1479	-0.2613
	Rank	1	2	3	4
	IDOCRIW	1.1488	1.0704	-1.1752	-1.044
	Rank	1	2	4	3

MCDM Method	Technique	A1	A2	A3	A4
ARAS	CRITIC	0.8476	0.8613	0.7186	0.7477
	Rank	2	1	4	3
	IDOCRIW	0.9354	0.9177	0.5217	0.5716
	Rank	1	2	4	3

MCDM Method	Technique	A1	A2	A3	A4
TOPSIS	CRITIC	0.5608	0.5465	0.4061	0.4528
	Rank	1	2	4	3
	IDOCRIW	0.8233	0.8828	0.1505	0.2856
	Rank	2	1	4	3

Figure 4. Exporting the ranking results by using different MCDM methods on Python idle

Table 7. Comparing the ranking results of different MCDM methods

Al.	MCDM method									
	COCOSO		MARCOS		CODAS		ARAS		TOPSIS	
	CRITIC	IDOCRIW	CRITIC	IDOCRIW	CRITIC	IDOCRIW	CRITIC	IDOCRIW	CRITIC	IDOCRIW
	Rank	Rank	Rank	Rank	Rank	Rank	Rank	Rank	Rank	Rank
A1	3	2	2	1	1	1	2	1	1	2
A2	1	1	1	2	2	2	1	2	2	1
A3	4	4	4	4	3	4	4	4	4	4
A4	2	3	3	3	4	3	3	3	3	3

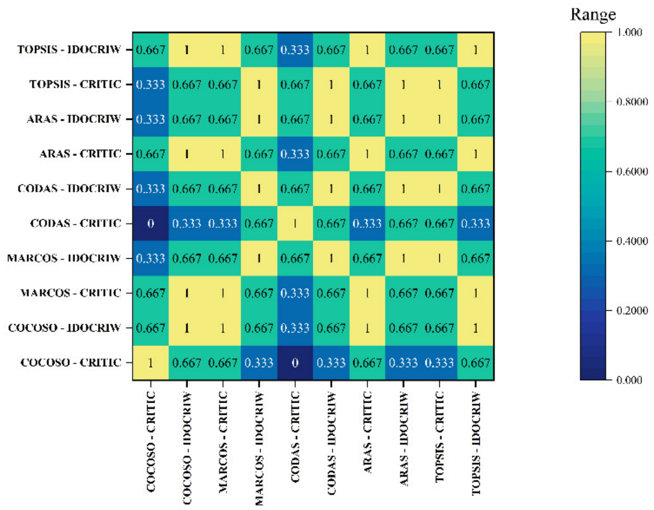


Figure 5. The Kendall rank correlation coefficient of the experimental MCDM procedures

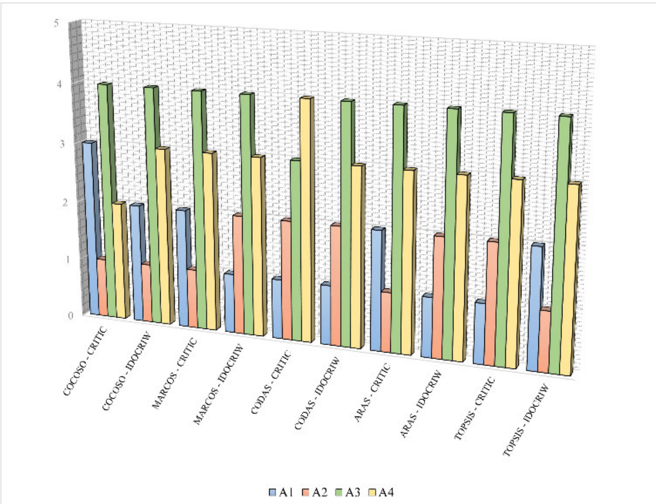


Figure 6. The 3D chart of the ranking comparisons

As shown in Figure 6, there are noticeable differences when ranking the saw machine alternatives based on experimental MCDM procedures. To be more specific, the best and worst alternatives chosen by the COCOSO method maintain the same values for A2 and A3, respectively. Meanwhile, the others (such as MARCOS, ARAS, and TOPSIS) generate the rank inversion. For instance, the combination of ARAS and CRITIC selects A2 as the optimal alternative, but the result for the combination of ARAS and IDOCRIW is A3. In contrast, the CODAS method reveals that the alternative A1 is the best, but the disturbance phenomenon occurs when ranking the worst option. Hence, the most striking summarization to emerge from the data comparison is that the COCOSO method is independent of the weight distribution techniques employed and suitable for ranking the steel saw machine.

7. CONCLUSION

1. For circular saws, the weights of criteria when determined by the CRITIC technique are 0.050, 0.054, 0.053, 0.063, 0.070, 0.057, 0.053, 0.053, 0.053, 0.121, 0.065, 0.131, 0.060, 0.118, respectively. Meanwhile, the values in case of determining by the IDOCRIW technique are 0.013, 0.012, 0.017, 0.276, 0.215, 0.168, 0.008, 0.007, 0.009, 0.038, 0.095, 0.028, 0.050, 0.066. It is evident that there are significant variances in the criteria weight distribution between the CRITIC technique and the IDOCRIW technique. This could lead to the reversion phenomenon when ranking the alternatives by different MCDM methods.

2. The proposed MCDM methods (MARCOS and COCOSO) determined the same best alternative in the case of combining with the CRITIC weight. However, the COCOSO method can be fully integrated with various weighting calculation techniques (CRITIC and IDOCRIW) while maintaining the accuracy of ranking results.

3. The best machine is the one with the value of fourteen criteria (from C1 to C14) are 500 (mm), 560 (mm), 500 (mm), 10 (mm), 10 (mm), 10 (mm), 5450 (mm), 41(mm), 1.3 (mm) 1.5 (kW), 16 (m/min), 85 (m/min), 3000(kg), and 640 (trieu), respectively.

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THÔNG TIN TÁC GIẢ

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