

# Multi-criteria decision making of turning operation based on PEG, PSI and CURLI methods

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**Abstract.** Multi-criteria decision-making (*MCDM*) is the methods identify an alternative that is considered the best among the implemented alternatives. This issue is probably more significant since each alternative is evaluated based on many criteria that may be contrary. This paper presents the multi-criteria decision-making of a turning process. Turning experiments were carried out with a total of sixteen alternatives. A test material used is SB410 steel. Cutting tools are coated with TiN. The aim of this study is to determine the experiment where the minimum surface roughness and the maximum material removal rate (*MRR*) are simultaneously obtained. Three multi-criteria decision-making methods were used include: Pareto-Edgeworth Grierson (*PEG*), Preference Selection Index (*PSI*) and Collaborative Unbiased Rank List Integration (*CURLI*). In each case of the application, it is not necessary to define weights for the criteria. The stability of ranking the alternatives on the basis of different MCDM methods is also identified according to the value Gini index. The results demonstrate that the *PEG* and *CURLI* methods both determine the best option. The cutting velocity of 1700 rev/min, feed rate 0.192 mm/rev and depth of cut of 0.6 mm are the options where the surface roughness and *MRR* are minimum and maximum respectively.

**Keywords:** *MCDM* / *PEG* / *PSI* / *CURLI* / TURNING / GINI INDEX

## 1 Introduction

Turning is the most common of the cutting machining methods. This method can be used on many types of machines, such as lathes, milling machines, drilling machines and boring machines. In a mechanical workshop, the lathes account for about 40% of the machine and around 25–35% of the mechanical processing volume is composed of the turning workload [1].

To evaluate effectiveness of a machining process in general or a turning process in particular, it is necessary to consider many criteria at the same time, such as surface quality, dimensional accuracy, machining productivity and costs. There are certain expectations for each of these criteria, for example, minimum surface roughness, highest accuracy, highest productivity, minimum machining cost, etc. In fact, however, the expectations are sometimes not satisfied simultaneously. For instance, in turning operation with high speed for improving machining productivity, the tool wear rate is high, reducing the tool life [2]; increasing the feed rate and depth of cut for higher *MRR* raise the surface roughness [3]; the flow rate and concentration of the

cooling fluid increased for reducing tool wear and cutting heat lead to pushing up the costs and affecting environment as well; and in the case of improving the cutting parameters for machining productivity, it also increases the vibration level of the cutting tool, thereby reducing the tool life and increasing surface roughness [4], etc. In this case, the decisions made should ensure that desires are simultaneously satisfied. Many multi-criteria decision-making methods are used during turning processes in many different cases.

The *TOPSIS* method was used for decision making in the selection of: cutting velocity, feed rate and depth of cut to have the minimum surface roughness and maximum *MRR* in turning EN8 steel [5]; cutting tool material, cutting velocity, feed rate and depth of cut to obtain both the minimum surface roughness and maximum *MRR* during turning process of EN25 steel [6]; cutting velocity, feed rate, depth of cut, tool nose radius and negative rake angle to reach the minimum surface roughness and minimum cutting force in the turning operation of AISI 52100 steel [7]; cutting velocity, feed rate and depth of cut to attain the minimum surface roughness (*Ra* and *Rz*) and maximum *MRR* in the experiments of turning EN19 steel [8]; cutting velocity, feed rate and depth of cut in order to acquire simultaneously minimum surface roughness and maximum

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*MRR* during turning AISI D2 steel [9]; cutting velocity, feed rate and depth of cut to have the minimum cutting force and surface roughness, maximum tool life and *MRR* in turning the material Pure Titanium [10], etc.

The *VIKOR* method was applied to multi-criteria decision-making in turning process in several studies so as to determine: spindle speed, feed rate and depth of cut for minimum surface roughness, minimum three shear force and three vibration components, and maximum *MRR* when steel EN 10503 workpiece was turned [11]; cutting velocity, feed rate and depth of cut for minimum surface roughness, maximum *MRR*, and minimum cutting force in turning CP-Titanium Grade 2 material [12]; workpiece speed, feed rate and depth of cut to reach simultaneously minimum surface roughness and tool wear rate, and maximum *MRR* during a turning process of AISI 316L part [13]; cutting velocity, feed rate, depth of cut and flow rate of cooling fluid to have minimum surface roughness and energy consumption, and maximum *MRR* in turning mild steel [14]; cutting velocity, feed rate and depth of cut to gain the maximum *MRR* and minimum surface roughness ( $R_a$ ,  $R_q$  and  $R_z$ ) turning AA7075 aluminum alloy [15], etc.

The *MOORA* method was used to multi-criteria decision-making in turning operation in several studies so as to identify: cutting velocity, feed rate, depth of cut and tool nose radius to have the minimum surface roughness, minimum three component cutting forces and maximum *MRR* in turning steel EN 10503 [16]; tool nose radius, cutting velocity, feed rate and depth of cut for minimum surface roughness and surface hardness, and maximum *MRR* during the process of turning EN25 steel [17]; cutting velocity, feed rate, depth of cut, positive rake angle, and cutting conditions (Dry and MQL) to achieve all parameters feed force, tangential force, radial force, resultant cutting force, and shape deviations which are minimum in the case of turning Al6026-T9 aluminum alloy [18]; cutting velocity, feed rate and depth of cut for minimum cutting force, surface roughness and tool wear rate in turning Commercially Pure Titanium material [19], etc.

The *COPRAS* method was used to define the spindle speed, feed rate and depth of cut to ensure that the cutting capacity, tool vibration and surface roughness were simultaneously minimized when in turning steel ASTM A36 [20]; cutting velocity, feed rate and depth of cut for minimum surface roughness and maximum *MRR* when SCM440 steel was turned [21]; cutting velocity, feed rate, depth of cut, cutting tool and machining environment (dry or wet) to reach the minimum surface roughness, machining time, tool wear rate, and maximum *MRR* during turning process of SU304 stainless steel [22], etc.

The use of multiple methods for multi-criteria decision-making was also carried out in a number of studies: The *MOORA* and *WASPAS* methods were applied so as to determine the cutting velocity, feed rate, depth of cut and percentage of TiC (additive) in order to have minimum cutting force and surface roughness and the largest *MRR* during the turning process of aluminum alloy Al 6063 [23]; the *TOPSIS* and *MOORA* were used to find the value of spindle speed, feed rate and depth of cut in order to ensure that all three parameters of cutting capacity, surface roughness and vibration frequency of the tool are smallest

in the case of turning steel ASTM A558 [24]; the *TOPSIS* and *SAW* were applied to identify the cutting velocity, feed rate and depth of cut for the minimum surface roughness, tool wear rate, cutting heat and cutting force in turning steel Ti-6Al-4V [25]; the *TOPSIS* and *PIV* were blended to define the cooling fluid concentration and flow rate, tool nose radius, cutting velocity, feed rate and depth of cut to gain minimum surface roughness, tool wear rate and roundness error during the process of turning 9XC steel [26]; another study applied eight methods *TOPSIS*, *VIKOR*, *MOORA*, *COPRAS*, *SAW*, *WASPAS*, *PIV* and *PSI* to determine spindle speed, feed rate, depth of cut and tool nose radius to have the minimum three component cutting forces have and highest *MRR* in turning operation of 150Cr14 steel [27], etc.

The importance of applying multi-criteria decision-making methods in turning processes is likely confirmed by the numerous studies related to this topic, some of which are mentioned above. However, it is necessary to define the weights of the criteria for application. This determination is relatively difficult for decision makers because of the fact that there are many dissimilar methods of weight determination and the weight of each criterion is different in each method. The number of criteria is also not the same. Since the weights of the criteria are different, the ranking of the alternatives is distinct as well [28]. Thus, if an application of a certain multi-criteria decision-making method does not require determining the weights of the criteria, this obstacle will be eliminated.

Pareto-Edgeworth Grierson (*PEG*) [29], Preference selection index (*PSI*) [30], and Collaborative Unbiased Rank List Integration (*CURLI*) [31] are known as multi-criteria decision making methods that do not need to define the weights of criteria. These three methods have been applied to multi-criteria decision making in several studies.

The *PEG* method was used for multi-criteria decision-making in several studies such as: polyethylene pipe design [32]; Flexural plate design, and in Seismic structural retrofitting. In both of these cases, the best option is the same as cases using the methods *ELECTRE III*, *PROMETHEE I* and *II*, and *AHP* [33]. The *PEG* is also applied in the design of building [34] and machine [35], the estimation of construction costs [36], etc. However, it can be confirmed that there has not been a study using the *PEG* to make multi-criteria decisions in the turning process to date.

Some researchers applied the *PSI* method in multi-criteria decision making: in the design of production systems [37]; in the selection of computer software for human resource management [38]; in finding a business location [39], etc. However, the application of this method to multi-criteria decision making during the turning processes is still limited.

The *CURLI* method was proposed in 2016 [31]. Apart from the application in the study itself, so far, this method has not been found to be used in any research in any area for some unknown reason. Perhaps, specific steps for implementation are not presented, leading to the lack of attention. This issue is further clarified in the next section of this article.

The two methods *PEG* and *CURLI* have never been applied to make multi-criteria decisions on the turning processes, while the *PSI* has only been used for multi-criteria decision making in the turning processes in several

studies. It can be said that applying all three of these methods at the same time to multi-criteria decision-making in the turning process has never been done before. This is the reason that motivates this study.

A turning test process took place in this research with the sixteen experiments. These were designed according to the Taguchi method. At each trial, the cutting velocity, feed rate and depth of cut were varied. They are parameters that can be easily changed by the operator of the machine [40]. The surface roughness and *MRR* were calculated. The reason these two parameters are chosen as output parameters is the surface roughness has a direct influence on the workability and lifetime of the product, while the *MRR* is an important measure to evaluate the productivity of the machining [41,42]. Three methods *PEG*, *PSI* and *CURLI* were used to solve the multi-objective decision problem. The aim of this study is to determine the experiment where the minimum surface roughness and the maximum *MRR* are simultaneously obtained.

## 2 Several methods of multi-criteria decision making

### 2.1 PEG method

The steps for implementation of multi-criteria decision making according to the *PEG* approach are as follows [29]:

**Step 1:** Determination of criteria vectors.

$$X_{i,j} = \min\left(\frac{y_{i,j} - \min(y_i)}{\max(y_i) - \min(y_i)}\right). \quad (1)$$

$$X_{i,j} = \min\left(\frac{\max(y_{i,j}) - y_i}{\max(y_i) - \min(y_i)}\right). \quad (2)$$

where function (1) is used for the criterion as high as possible, function (2) is used for the criterion as low as possible,  $i = 1, \dots, n$ ;  $j = 1, \dots, m$ .

**Step 2:** Arrangement of the criteria vector values in ascending order.

$$x_i = [X_i^{\min}, \dots, X_i^{\max}]^T = [0, \dots, 1]^T. \quad (3)$$

**Step 3:** Determination of aggregate vectors for each criterion.

$$Y_i = \frac{\sum_{k=1}^n x_k - x_i}{n - 1}. \quad (4)$$

**Step 4:** Arrangement of the aggregate vector values in descending order.

$$y_i = [Y_i^{\max}, \dots, Y_i^{\min}]^T = [1, \dots, 0]^T. \quad (5)$$

**Step 5:** Calculation of shifted vectors.

$$x^* = \frac{x + \delta x}{1 + \delta x} \quad (6)$$

$$y^* = \frac{y + \delta y}{1 + \delta y} \quad (7)$$

where  $\delta x = \delta y = \sqrt{2} - 1$ .

**Step 6:** Calculation of radial shift.

$$\Delta r_i = \sqrt{2}\Delta x_i = \sqrt{2}\Delta y_i \quad (8)$$

where

$$\Delta x_i = \Delta y_i = 0.5 - \frac{(x_j^* + x_{j+1}^*)(y_j^* + y_{j+1}^*)}{x_j^* + x_{j+1}^* + y_j^* + y_{j+1}^*}. \quad (9)$$

**Step 7:** Calculation of the functions Pareto–Edgeworth–Grierson (*PEG*).

$$f_i^0 = f_i^{\max} - (f_i^{\max} - f_i^{\min})(\Delta r_i + \sqrt{2}/2). \quad (10)$$

**Step 8:** Calculation of the mean square error (MSE) for each alternative.

$$MSE_i = \frac{1}{n} \sum \left( \frac{1 - f_i^*}{f_i^0} \right)^2. \quad (11)$$

**Step 9:** Ranking the alternatives according to the rule that the alternative with the highest is considered the best

### 2.2 PSI method

The steps for implementation of multi-criteria decision making according to the *PSI* approach are as follows [30]:

**Step 1:** Formation of decision matrix.

**Step 2:** Normalization of attributes.

$$N_{ij} = \frac{y_{ij}}{y_j^{\max}}. \quad (12)$$

$$N_{ij} = \frac{y_j^{\min}}{y_{ij}}. \quad (13)$$

where: function (12) is used for the criterion as high as possible, function (13) is used for the criterion as low as possible.

**Step 3:** Calculation of mean values of normalized data.

$$N = \frac{1}{n} \sum_{i=1}^n N_{ij} \quad (14)$$

**Step 4:** Identification of preference value from the mean value.

$$\varphi_\xi = \sum_{i=1}^n [N_{ij} - N]^2. \quad (15)$$

**Table 1.** Decision matrix.

Solution	$C_1$	$C_2$	$C_j$	$C_n$
$A_1$	$x_{11}$	$x_{12}$	$x_{1j}$	$x_{1n}$
$A_2$	$x_{21}$	$x_{22}$	$x_{2j}$	$x_{2n}$
$A_i$	$x_{i1}$	$x_{i2}$	$x_{ij}$	$x_{in}$
$A_m$	$x_{m1}$	$x_{m2}$	$x_{mj}$	$x_{mn}$

**Table 2.** Example of scoring matrix for each criterion.

Solution	$P_1$	$P_2$	...	$P_m$
$A_1$		-1	...	...
$A_2$	1		...	...
...	...	...	...	...
$A_m$	...	0	...	...

**Step 5:** Identification of deviation in the preference value.

$$\theta_j = [1 - \varphi_j]. \tag{16}$$

**Step 6:** Determination of the overall preference value for the attributes.

$$w_j = \frac{\theta_j}{\sum_{j=1}^m \theta_j}. \tag{17}$$

**Step 7:** Calculation of preference selection index for each alternative.

$$\theta_j = \sum_{j=1}^m x_{ij} \cdot w_j. \tag{18}$$

**Step 8:** Ranking the alternatives. The best alternative is the one with maximum value of  $\theta_i$ .

### 2.3 CURLI method

The CURLI method was first proposed in 2016 [31]. In that study, the authors selected candidates for a school of medicine. The candidates' abilities were in turn commented on by the interviewers. Instead of scoring the candidates in the traditional way, the interviewers only assessed whether a candidate is better or worse than another based on a certain criterion. However, in that study, they applied directly to the case of using four interviewers to evaluate four candidates without presenting the general steps. This may be explained that some of the candidates were interviewed by all the interviewers and some of them were not. As a result, formulating the generalized steps for implementation may be difficult for the authors of that study. Regarding machining processes in general and turning processes in particular, however, the results of each test (surface roughness, flatness error, dimensional accuracy, etc.) are all numbers that need to be

measured during the experiment. Therefore, the values of all those parameters must be examined equally. In other words, if each experimental alternative is considered as a candidate, then all those candidates must be considered by experiment analysts. Hence, it is necessary to develop a specific sequence of steps to rank the alternatives according to the CURLI method. In this study, the implementation steps are generalized to make multi-criteria decisions based on the CURLI method.

The steps are presented as follows:

**Step 1:** Building a matrix with  $m$  rows and  $n$  columns, where  $m$  is the number of alternatives,  $n$  is the number of criteria. The matrix is called the decision matrix, as shown in Table 1. In which, the criteria can be opposite, namely, some criteria should be as small as possible and some criteria should be as high as possible. The goal of building the matrix is to determine the alternative  $A_i$  ( $i = 1 \dots m$ ) to be considered the best.

**Step 2:** For each criterion, a square matrix of order  $m$  (with  $m$  rows and  $m$  columns) is established, as shown in Table 2. Scoring is carried out in each cell of the matrix in the following way, for example: scoring 1 at the cell of column 1 and row 2 if the value of  $C_j$  of  $A_1$  is better than of  $A_2$ ; scoring -1 at the cell of column 2 and row 1 if the value of  $C_j$  of  $A_2$  is worse than of  $A_1$ ; scoring 0 at the cell of column 2 and row  $m$  if the value of  $C_j$  of  $A_2$  is equal to of  $A_m$ ; no scoring at the cells that their order of the columns and rows are the same (the cells on the main diagonal of the matrix). This matrix is called the scoring matrix for each criterion. In short, there is  $n$  scoring matrices corresponding to  $n$  criteria.

**Step 3:** Adding all the scoring matrices for each criterion together for a new matrix, which is called the processing scoring matrix.

**Step 4:** Restructuring the processing scoring matrix by changing the positions of the rows and columns so as to form a matrix where the upper area of the main diagonal has no cells with a positive score (the highest is zero). The ideal case is that all negative scores are above the main diagonal of the matrix. After restructuring, the alternative ranked in row 1 is considered the best.



Fig. 1. ECOCA Lathe.

Table 3. Cutting parameters.

Cutting parameter	Unit	Symbol	Value at level			
			1	2	3	4
Cutting speed	rev/min	$n_w$	530	680	1350	1700
Feed rate	mm/rev	$f_d$	0.080	0.192	0.204	0.302
Depth of cut	mm	$a_p$	0.2	0.4	0.6	0.8

### 3 Turning experiment

The turning tests were implemented on a conventional lathe ECOCA (Fig. 1). SB410 steel (conforming to JIS – Japanese standard) was used in the experiments. This steel has good machinability, low cost and is the most popular steel for manufacturing common machining parts made of silver, shafts, gears, levers.

The cutting tool is coated with TiN. This type of cutting tool has high hardness, high oxidation resistance and is widely used in cutting technology [43,44].

Before the experiment, the specimens were roughly turned. The length and diameter of the test specimens were 320 mm and 28 mm, respectively. Three parameters were changed at each trial, including cutting velocity, feed rate and depth of cut. The values of the cutting parameters were chosen according to the machine's ability, workpiece material, and some studies [45,46], as shown in Table 3. Sixteen tests were performed as shown in Table 4.

MRR is defined as (19): Where  $n_w$  is the cutting velocity (rev/min),  $d$  is the diameter of the workpiece,  $f_d$  is the feed rate (mm/rev), and  $a_p$  is the depth of cut (mm).

$$MRR = n_w \cdot \pi \cdot d \cdot f_d \cdot a_p. \quad (19)$$

Surface roughness is measured by SJ-201 (Mitutoyo – Japan) machine. During the measurement, the part is mounted on two V-blocks, the measuring head of the machine moves parallel to the center shaft of the part, in

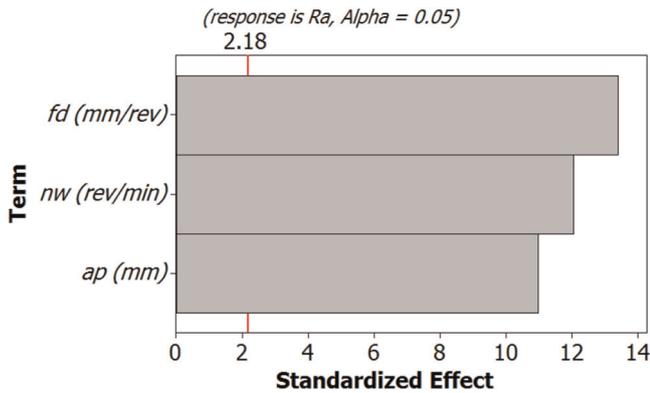
other words, perpendicular to the cutting velocity vector. Each steel specimen was measured at least three times, the surface roughness at each test was calculated as the average of successive measurements. The surface roughness and *MRR* results are also included in Table 4.

The Minitab software was used to analyze the experimental results. With the significance level to be 0.05 [47], the Pareto chart represents the influence of the cutting parameters on the surface roughness, shown in Figure 2. The Pareto software found a limit that a certain parameter is considered affecting the surface roughness to be 2.18. The gray rectangles representing the cutting parameters all show that this limit is exceeded, as a consequence, all three cutting parameters have a great influence on the surface roughness. In which, the feed rate is the most influential, followed by the cutting velocity and the depth of cut. These results are consistent with many published studies [3,48].

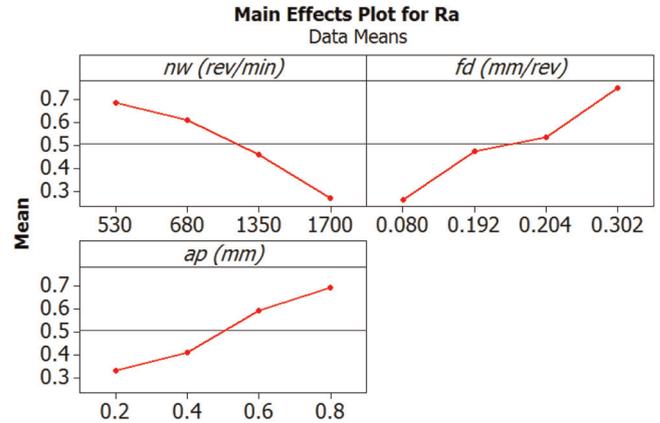
Figure 3 is another type of graph showing the impact of the cutting parameters on the surface roughness. Accordingly, the surface roughness decreases rapidly if the cutting velocity increases, while the surface roughness increases quickly if the feed rate and depth of cut both increase. This result is also consistent with the conclusions from some research [3,48]. It can be said that: in order to have a small surface roughness, it is necessary to choose a high cutting velocity and the low feed rate and depth of cut. However, the low feed rate and depth of cut lead to the low *MRR* as well (based on formula (19)). Thus, it is probably difficult

**Table 4.** Experiment matrix and result.

Trial.	Code value			Real value			Response	
	$n_w$	$f_d$	$a_p$	$n_w$ (rev/min)	$f_d$ (mm/rev)	$a_p$ (mm)	$Ra$ ( $\mu\text{m}$ )	$MRR$ ( $\text{mm}^3/\text{min}$ )
A1	1	1	1	530	0.08	0.2	0.264	799.221
A2	1	2	2	530	0.192	0.4	0.584	3836.262
A3	1	3	3	530	0.204	0.6	0.752	6114.042
A4	1	4	4	530	0.302	0.8	1.139	12068.240
A5	2	1	2	680	0.08	0.4	0.249	2050.832
A6	2	2	1	680	0.192	0.2	0.396	2460.998
A7	2	3	4	680	0.204	0.8	0.840	10459.242
A8	2	4	3	680	0.302	0.6	0.951	11612.834
A9	3	1	3	1350	0.08	0.6	0.336	6107.256
A10	3	2	4	1350	0.192	0.8	0.583	19543.220
A11	3	3	1	1350	0.204	0.2	0.326	5191.168
A12	3	4	2	1350	0.302	0.4	0.587	15369.928
A13	4	1	4	1700	0.08	0.8	0.203	10254.158
A14	4	2	3	1700	0.192	0.6	0.327	18457.485
A15	4	3	2	1700	0.204	0.4	0.220	13074.052
A16	4	4	1	1700	0.302	0.2	0.329	9677.362



**Fig. 2.** Pareto chart of the standardized effects.



**Fig. 3.** Main effect of cutting parameter on surface roughness.

to find the value of the cutting parameters for the small surface roughness and high  $MRR$  if only the graphs in Figures 2 and 3 are observed. On the other hand, the data in Table 4 shows that the minimum surface roughness is in  $A_{13}$ , while the maximum  $MRR$  is in  $A_{10}$ . Therefore, it is likely difficult to see which alternative is the best for obtaining the minimum surface roughness and maximum  $MRR$  at the same time. So as to cope with this issue, multi-criteria decision making should be considered. It is further clarified in the next section of this article.

## 4 Multi-criteria decision making of turning operation

### 4.1 Application of PEG method

Formulas (1) and (2) are applied to calculate  $X_{i,j}$ . Formula (3) is used to define  $x_i$ ;  $Y_{i,j}$  are calculated based on formula (4) and  $y_i$  are computed according to the formula (5).  $x^*$ ,  $y^*$  are identified on the basis of the formulas (6) and (7), respectively; Formula (8) is used for  $\Delta r_i$  determination.  $f_i^0$  are calculated based on formula (9). Table 5 presents the values of some parameters in PEG and rank of the alternatives.

**Table 5.** Some parameters in PEG and rank.

Trial.	$x_i$		$y_i$		$x^*$		$y^*$		$\Delta r_i$	$f_i^0$	MSE	Rank
	Ra	MRR	Ra	MRR	Ra	MRR	Ra	MRR				
A1	0	0	1	1	0.2929	0.2929	1	1	0.0664	0.4150	1849405	16
A2	0.079	0.0988	0.8348	0.9685	0.3488	0.3628	0.8832	0.9777	-0.0208	0.4966	29819924	13
A3	0.0962	0.1429	0.8082	0.9644	0.3609	0.3939	0.8644	0.9748	-0.0498	0.5237	68116971	10
A4	0.1208	0.1917	0.802	0.9521	0.3783	0.4284	0.8600	0.9661	-0.0842	0.5560	235541972	6
A5	0.1618	0.204	0.665	0.7432	0.4073	0.4371	0.7631	0.8184	-0.0714	0.5440	7099058	15
A6	0.2441	0.3855	0.6102	0.7088	0.4655	0.5655	0.7244	0.7941	-0.1613	0.6281	7669118	14
A7	0.2768	0.3891	0.6042	0.6245	0.4886	0.5680	0.7201	0.7345	-0.1585	0.6255	139790964	9
A8	0.2809	0.541	0.5951	0.6151	0.4915	0.6754	0.7137	0.7278	-0.2049	0.6689	150656518	8
A9	0.6151	0.5951	0.541	0.2809	0.7278	0.7137	0.6754	0.4915	-0.2049	0.6689	41661635	11
A10	0.6245	0.6042	0.3891	0.2768	0.7345	0.7201	0.5680	0.4886	-0.1585	0.6255	488100803	2
A11	0.7088	0.6102	0.3855	0.2441	0.7941	0.7244	0.5655	0.4655	-0.1613	0.6281	34138050	12
A12	0.7432	0.665	0.204	0.1618	0.8184	0.7631	0.4371	0.4073	-0.0714	0.5440	399072037	3
A13	0.9521	0.802	0.1917	0.1208	0.9661	0.8600	0.4284	0.3783	-0.0842	0.5560	170046504	7
A14	0.9644	0.8082	0.1429	0.0962	0.9748	0.8644	0.3939	0.3609	-0.0498	0.5237	620924159	1
A15	0.9685	0.8348	0.0988	0.079	0.9777	0.8832	0.3628	0.3488	-0.0208	0.4966	346473828	4
A16	1	1	0	0	1	1	0.2929	0.2929	0.0664	0.4150	271774995	5

**Table 6.** Some parameters in PSI and rank.

Trial.	N		$\theta_i$	Ranking
	Ra	MRR		
A1	0.769	0.041	607.254	16
A2	0.348	0.196	2914.654	13
A3	0.270	0.313	4645.186	10
A4	0.178	0.618	9168.846	5
A5	0.815	0.105	1558.133	15
A6	0.513	0.126	1869.783	14
A7	0.242	0.535	7946.374	7
A8	0.213	0.594	8822.817	6
A9	0.604	0.312	4639.930	11
A10	0.348	1.000	14847.660	1
A11	0.623	0.266	3943.951	12
A12	0.346	0.786	11677.096	3
A13	1.000	0.525	7790.414	8
A14	0.621	0.944	14022.736	2
A15	0.923	0.669	9932.768	4
A16	0.617	0.495	7352.236	9

**4.2 Application of PSI method**

Formation of decision matrix. It consists of the last two columns in Table 4.

The normalized values of the attributes are defined according to the formulas (12), (13). The result is presented in Table 6.

The mean of the normalized value is calculated according to formula (14). Accordingly, the mean of the

normalization of the surface roughness and the MRR correspondingly 0.527 and 0.407.

The preference value from the mean value is calculated based on (15):  $\varphi_{Ra} = 1.114$ ;  $\varphi_{MRR} = 1.360$ .

The deviation in the preference value is identified as (16):  $\dot{u}_{Ra} = -0.114$ ;  $\dot{u}_{MRR} = -0.360$ .

Determination of the overall preference value for the attributes is according to (17):  $w_{Ra} = 0.240$ ;  $w_{MRR} = 0.760$ .

**Table 7.** Scoring matrix of *Ra*.

	<i>P1</i>	<i>P2</i>	<i>P3</i>	<i>P4</i>	<i>P5</i>	<i>P6</i>	<i>P7</i>	<i>P8</i>	<i>P9</i>	<i>P10</i>	<i>P11</i>	<i>P12</i>	<i>P13</i>	<i>P14</i>	<i>P15</i>	<i>P16</i>
<i>A1</i>		-1	-1	-1	1	-1	-1	-1	-1	-1	-1	-1	1	-1	1	-1
<i>A2</i>	1		-1	-1	1	1	-1	-1	1	1	1	-1	1	1	1	1
<i>A3</i>	1	1		-1	1	1	-1	-1	1	1	1	1	1	1	1	1
<i>A4</i>	1	1	1		1	1	1	1	1	-1	1	1	1	1	1	1
<i>A5</i>	-1	-1	-1	-1		-1	-1	-1	-1	-1	-1	-1	1	-1	1	-1
<i>A6</i>	1	-1	-1	-1	1		-1	-1	1	-1	1	-1	1	1	1	1
<i>A7</i>	1	1	1	-1	1	1		-1	1	1	1	1	1	1	1	1
<i>A8</i>	1	1	1	-1	1	1	1		1	1	1	1	1	1	1	1
<i>A9</i>	1	-1	-1	-1	1	-1	-1	-1		-1	1	-1	1	1	1	1
<i>A10</i>	1	-1	-1	-1	1	1	-1	-1	1		1	-1	1	1	1	1
<i>A11</i>	1	-1	-1	-1	1	-1	-1	-1	-1	-1		-1	1	-1	1	-1
<i>A12</i>	1	1	-1	-1	1	1	-1	-1	1	1	1		1	1	1	1
<i>A13</i>	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1		-1	1	-1
<i>A14</i>	1	-1	-1	-1	1	-1	-1	-1	-1	-1	1	-1	1		1	-1
<i>A15</i>	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	-1		-1
<i>A16</i>	1	-1	-1	-1	1	-1	-1	-1	-1	-1	1	-1	1	1	1	

**Table 8.** Scoring matrix of *MRR*.

	<i>P1</i>	<i>P2</i>	<i>P3</i>	<i>P4</i>	<i>P5</i>	<i>P6</i>	<i>P7</i>	<i>P8</i>	<i>P9</i>	<i>P10</i>	<i>P11</i>	<i>P12</i>	<i>P13</i>	<i>P14</i>	<i>P15</i>	<i>P16</i>
<i>A1</i>		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
<i>A2</i>	-1		1	1	-1	-1	1	1	1	1	1	1	1	1	1	1
<i>A3</i>	-1	-1		1	-1	-1	1	1	-1	1	-1	1	1	1	1	1
<i>A4</i>	-1	-1	-1		-1	-1	-1	-1	-1	1	-1	1	-1	1	1	-1
<i>A5</i>	-1	1	1	1		1	1	1	1	1	1	1	1	1	1	1
<i>A6</i>	-1	1	1	1	-1		1	1	1	1	1	1	1	1	1	1
<i>A7</i>	-1	-1	-1	1	-1	-1		1	-1	1	-1	1	-1	1	1	-1
<i>A8</i>	-1	-1	-1	1	-1	-1	-1		-1	1	-1	1	-1	1	1	-1
<i>A9</i>	-1	-1	1	1	-1	-1	1	1		1	-1	1	1	1	1	1
<i>A10</i>	-1	-1	-1	-1	-1	-1	-1	-1	-1		-1	-1	-1	-1	-1	-1
<i>A11</i>	-1	-1	1	1	-1	-1	1	1	1	1		1	1	1	1	1
<i>A12</i>	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	-1		-1	1	-1	-1
<i>A13</i>	-1	-1	-1	1	-1	-1	1	1	-1	1	-1	1		1	1	-1
<i>A14</i>	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	-1	-1	-1		-1	-1
<i>A15</i>	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	-1	1	-1	1		-1
<i>A16</i>	-1	-1	-1	1	-1	-1	1	1	1	1	-1	1	1	1	1	

The preference selection index  $\theta$  for each alternative is defined as (18), shown in Table 6.

The alternatives are ranked based on the value of  $\theta_i$ . The result is also presented in Table 6.

**4.3 Application of CURLI method**

The steps under the *CURLI* method are applied for multi-criteria decision making.

Building a decision matrix. It consists of the last two columns in Table 4.

Scoring the alternatives for each criterion. Scoring results for the *Ra* and *MRR* are presented in Tables 7 and 8, respectively.

The processing scoring matrix is determined and the results are as shown in Table 9.

The rows and columns are repositioned in the way that the cells in the upper part of the main diagonal no longer have a positive score. This process can be executed manually or under programming methods with a computer. In this study, it was done manually. The results of sorting

**Table 9.** Processing scoring matrix.

	<i>P1</i>	<i>P2</i>	<i>P3</i>	<i>P4</i>	<i>P5</i>	<i>P6</i>	<i>P7</i>	<i>P8</i>	<i>P9</i>	<i>P10</i>	<i>P11</i>	<i>P12</i>	<i>P13</i>	<i>P14</i>	<i>P15</i>	<i>P16</i>
<i>A1</i>		0	0	0	2	0	0	0	0	0	0	0	2	0	2	0
<i>A2</i>	0		0	0	0	0	0	0	2	2	2	0	2	2	2	2
<i>A3</i>	0	0		0	0	0	0	0	0	2	0	2	2	2	2	2
<i>A4</i>	0	0	0		0	0	0	0	0	0	0	2	0	2	2	0
<i>A5</i>	-2	0	0	0		0	0	0	0	0	0	0	2	0	2	0
<i>A6</i>	0	0	0	0	0		0	0	2	0	2	0	2	2	2	2
<i>A7</i>	0	0	0	0	0	0		0	0	2	0	2	0	2	2	0
<i>A8</i>	0	0	0	0	0	0	0		0	2	0	2	0	2	2	0
<i>A9</i>	0	-2	0	0	0	-2	0	0		0	0	0	2	2	2	2
<i>A10</i>	0	-2	-2	-2	0	0	-2	-2	0		0	-2	0	0	0	0
<i>A11</i>	0	-2	0	0	0	-2	0	0	0	0		0	2	0	2	0
<i>A12</i>	0	0	-2	-2	0	0	-2	-2	0	2	0		0	2	0	0
<i>A13</i>	-2	-2	-2	0	-2	-2	0	0	-2	0	-2	0		0	2	-2
<i>A14</i>	0	-2	-2	-2	0	-2	-2	-2	-2	0	0	-2	0		0	-2
<i>A15</i>	-2	-2	-2	-2	-2	-2	-2	-2	-2	0	-2	0	0	0		-2
<i>A16</i>	0	-2	-2	0	0	-2	0	0	0	0	0	0	2	2	2	

**Table 10.** Processing scoring matrix arrangement.

	<i>A14</i>	<i>A12</i>	<i>A10</i>	<i>A8</i>	<i>A15</i>	<i>A16</i>	<i>A7</i>	<i>A13</i>	<i>A4</i>	<i>A9</i>	<i>A11</i>	<i>A3</i>	<i>A6</i>	<i>A2</i>	<i>A5</i>	<i>A1</i>
<i>A14</i>		-2	0	-2	0	-2	-2	0	-2	-2	0	-2	-2	-2	0	0
<i>A12</i>	2		-2	-2	0	0	-2	0	-2	0	0	-2	0	0	0	0
<i>A10</i>	0	2		-2	0	0	-2	0	-2	0	0	-2	0	-2	0	0
<i>A8</i>	2	2	2		-2	0	0	0	0	0	0	0	0	0	0	0
<i>A15</i>	0	0	0	2		-2	-2	0	-2	-2	-2	-2	-2	-2	-2	-2
<i>A16</i>	2	0	0	0	2		0	-2	0	0	0	-2	-2	-2	0	0
<i>A7</i>	2	2	2	0	2	0		0	0	0	0	0	0	0	0	0
<i>A13</i>	0	0	0	0	2	2	0		0	-2	-2	-2	-2	-2	-2	-2
<i>A4</i>	2	2	0	0	2	0	0	0		0	0	0	0	0	0	0
<i>A9</i>	2	0	0	0	2	2	0	2	0		0	0	-2	-2	0	0
<i>A11</i>	0	0	0	0	2	0	0	2	0	0		0	-2	-2	0	0
<i>A3</i>	2	2	2	0	2	2	0	2	0	0	0		0	0	0	0
<i>A6</i>	2	0	0	0	2	2	0	2	0	2	2	0		0	0	0
<i>A2</i>	2	0	2	0	2	2	0	2	0	2	2	0	0		0	0
<i>A5</i>	0	0	0	0	2	0	0	2	0	0	0	0	0	0		-2
<i>A1</i>	0	0	0	0	2	0	0	2	0	0	0	0	0	0	2	

for the processing scoring matrix are presented in Table 10. According to the data in Table 10, *A14* is the best alternative and *A1* is the worst.

The ranking results of the alternative under three approaches are shown in Table 11.

The data in Table 11 revealed that:

- All three methods found that *A1* is the worst alternative. The data in Table 4 show that the *MRR* at *A1* is considerably smaller than other fifteen alternatives. Consequently, *A1* to be the worst is reasonable.

- The *PEG* and *CURLI* both found *A14* to be the best alternative, while the *PSI* identified *A10* as the best option. The best and second best alternatives were opposite when using the *PEG* and *PSI* method. At the moment, this difference is not explained yet. However, due to this difference, the data in Table 4 should be looked at again. At *A10*, the *MRR* was highest among all sixteen alternatives, while the surface roughness was ranked at number 10. Meanwhile, *MRR* was ranked at number two, and surface roughness was ranked at

**Table 11.** Ranking results of the alternatives based on the three methods.

	<i>A1</i>	<i>A2</i>	<i>A3</i>	<i>A4</i>	<i>A5</i>	<i>A6</i>	<i>A7</i>	<i>A8</i>	<i>A9</i>	<i>A10</i>	<i>A11</i>	<i>A12</i>	<i>A13</i>	<i>A14</i>	<i>A15</i>	<i>A16</i>
<i>PEG</i>	16	13	10	6	15	14	9	8	11	2	12	3	7	1	4	5
<i>PSI</i>	16	13	10	5	15	14	7	6	11	1	12	3	8	2	4	9
<i>CURLI</i>	16	14	12	9	15	13	7	4	10	3	11	2	8	1	5	6

**Table 12.** Gini index value.

<i>Alternative</i>	<i>A1</i>	<i>A2</i>	<i>A3</i>	<i>A4</i>	<i>A5</i>	<i>A6</i>	<i>A7</i>	<i>A8</i>
<i>Gini index</i>	0.000000	0.062195	0.124389	0.310973	0.000000	0.062195	0.124389	0.248779
<i>Alternative</i>	<i>A9</i>	<i>A10</i>	<i>A11</i>	<i>A12</i>	<i>A13</i>	<i>A14</i>	<i>A15</i>	<i>A16</i>
<i>Gini index</i>	0.062195	0.186584	0.062195	0.062195	0.062195	0.124389	0.062195	0.435363

number six in *A14*. Under this circumstance, the decision maker must consider whether *A10* or *A14* is the best alternative. In this research, the calculation of the value Gini index was executed for reaching this task.

The value Gini index is used to determine the stability of ranking criteria when using different multi-criteria decision-making methods [49].

The value Gini index is defined according to the following formula [49].

$$D(R) = \frac{4}{(m - 1)(z^2 - |\sin(z \cdot \frac{\pi}{2})|)} \sum_{h=1}^{z-1} \sum_{l=h+1}^z |R_h - R_l| \quad (20)$$

where *m* is the number of alternatives, *z* is the number of multi-criteria decision-making methods used, *R<sub>h</sub>* and *R<sub>l</sub>* are the ranking values of the alternatives of the decision-making method *h* and *l*. *D(R)* ∈ [0,1]. *D(R)* = 0 means that the rank of an alternative is exactly the same under different methods. In contrast, *D(R)* = 1 means that the rank of the alternatives are the most different under the distinct *MCDM* methods. Upon comparing two alternatives, the one with the smaller value Gini index is the better. Formula (20) was applied to calculate the values Gini index in Table 11 and the results are presented in Table 12.

The alternatives of *A1* and *A5* have the same ranking results under all three *MCDM* methods, hence, their values Gini index are equal to 0. *A16* has the highest value Gini index, equal to 0.435363, its stability is lowest when using the three *MCDM* methods. Namely, *A16* was ranked No.5 when using the *PEG* method, No.9 when using the *PSI* method and No.6 when using the *CURLI* method. Comparison of *A10* and *A14* shows that: *A10* has a value Gini index of 0.186584 and *A14* has a value Gini index of 0.124389. Thus, the ranking stability of *A14* is smaller than *A10*. Hence, this proves that *A14* is better than *A10*, and at the same time *A14* is the best alternative among sixteen options. This result also demonstrates that the *PSI* method is not as good as the *PEG* and *CURLI* in determining the best alternative. A nearest published study indicated the

same: the *PSI* method is not as good as the *TOPSIS*, *VIKOR*, *MOORA*, *COPRAS*, *SAW*, *WASPAS*, và *PIV* [27].

## 5 Conclusion

In this paper, the experiments of turning SB410 steel with a TiN-coated cutting tool are performed. Three parameters were changed at each trial, including cutting velocity, feed rate and depth of cut. The surface roughness and *MRR* were identified in each test. Three multi-criteria decision making methods including *PEG*, *PSI* and *CURLI* were applied for selecting the solution so as to reach the minimum surface roughness and maximum *MRR*. Some conclusions are drawn as follows:

- For the first time, the two methods *PEG* and *CURLI* are used for multi-criteria decision making. These methods have the common feature that both do not need to determine the weights of the criteria when making multi-criteria decisions. Fortunately, both of these methods identified the same best and worst solution.
- The *PSI* are also known as multi-criteria decision making methods that do not need to define the weights of criteria. The worst alternative was pointed out when applying this method and it is similar to the *PEG* and *CURLI*.
- The stability of ranking the alternatives using the different *MCDM* methods is determined through the value Gini index and on the basis of it, the best solution is identified.
- The *PEG* and *CURLI* methods are likely better than the *PSI* in finding the best alternative.
- The use of multi-criteria decision-making methods without determining the weights of the criteria may be easier in decision-making. In which, *PEG* and *CURLI* methods are recommended to be used. Especially, while applying, most of the multi-criteria decision making methods (such as: *TOPSIS*, *VIKOR*, *MOORA*, etc.) require the value of the criteria to be a quantitative criterion, the *CURLI* method can rank the solutions with the criteria values in both qualitative and quantitative forms.

– To obtain the “minimum” surface roughness and “maximum” *MRR* at the same time, it is necessary to select the cutting velocity, feed rate and depth of cut respectively are 1700 rev/min, 0.192 mm/rev, and 0.6 mm.

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