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APPLICATION OF THE CURLI METHOD FOR MULTI-CRITICAL DECISION OF GRINDING PROCESS

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In the case of highly precise flat surfaces, surface roughness and flatness tolerance (FL) play virtual roles and directly cause the performance of the parts. In general, both surface roughness and FL are required at the minimum value. Grinding is needed in order to finish the surface. However, sometimes in specific grinding conditions, this could not be achieved. Hence, it is imperative to select the grinding conditions that satisfy both parameters to be considered "minimum". This problem is commonly known as multi-criteria decision making (MCDM). However, choose a method to determine the weights for the criteria sometimes makes the decision-makers confused because each method of determining the weights finds different sets of the weight values. Along with that, for each method of determining the weight, the ranking results of the alternatives may also be changed. Using an MCDM method without specifying weights for the criteria eliminates this problem. Collaborative Unbiased Rank List integration (CURLI) is one of the multi-criteria decision making methods that do not need to determine the weights for the criteria. In this research, we not only applying CURLI method to multi-criteria decision making, but also developing detailed steps to apply. This work has not been done before even for the authors who proposed it. Using this method for multi-criteria decision-making, the grinding process has determined the abrasive grain size, workpiece velocity, feed rate and depth of cut to ensure that the surface roughness and FL are kept to a minimum.

Key words: MCDM, Curli method, grinding, Surface roughness, Flatness tolerance

1 INTRODUCTION

In mechanical manufacturing processes in general, the research to find solutions to ensure the same criteria is always concerned because they directly affect product quality and manufacturing costs. In other words, the simultaneous assurance required for multiple criteria will improve both the machining process's economic and technical efficiency. However, for a machining process, the criteria are not guaranteed simultaneously sometimes, even conflicting. For example, the quality of the machined surface often conflicts with the machining productivity [1, 2]. Even with two surface texture parameters (Ra and Rz), the minimum value is not always reached [3], or the three vibration components of the grinding machine spindle will not be simultaneous. Minimum value at an experimental condition [4], etc. In this case, for the indicators to be achieved those "best" values, it is necessary to make decisions based on the harmonization of the criteria. Various mathematical methods have been proposed for multi-criteria decision making and have been used in many studies in distinct fields. SAW (Simple Additive Weighting) method is performed on the basis of weighted average, and normalizes the values of the criteria. The score for each criterion in each solution is calculated by multiplying the scaled value by the normalized value. The results of ranking solutions are based on the sum of the calculated products of all criteria [5]. The WASPAS (Weighted Aggregated Sum Product Assessment) method is a combination of the WSM (Weighted Sum Model) and the WPM (Weighted Product Model). First, the values of the criteria must be normalized, and then the score for each criterion of each solution is calculated by multiplying the normalized value by the corresponding weight. The score of each solution will be calculated by the total score of the criteria in that solution [6]. The TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method is based on the assumption that the distance from the considered best solution to the ideal solution is the shortest, and to the opposite to the ideal solution is the longest. The distance between two solutions is determined by the Euclidean function [7]. The VIKOR (Vlsekriterijumska optimizacija I Kompromisno Resenje in Serbian) method ranks solutions based on the assumption that compromise is acceptable to resolve the conflict. The decision maker wants a solution that is closest to the ideal and alternatives are evaluated against all established criteria [8]. MOORA (Multi-Objective Optimization based on Ratio Analysis) method is used to sort the solutions based on three assumptions, namely: the assumption of the numbers, the assumption of discrete choices, and the assumption of attributes [9]. The COPRAS (COmplex PRoportional ASsessment) method compares alternatives and determines their priority according to conflicting criteria by taking into account the weight of the criteria. This method performs the selection of the best alternative, which considers both the ideal solution and the opposite solution to the ideal solution [10]. The PIV (Proximity Indexed Value) method ranks the solutions by calculating the weighted asymptote values of all the criteria, thereby determining the distance from each solution to the ideal solution. This distance is calculated as the sum of all weighted asymptote values [11]. The RIM (Reference Ideal Method) method ranks the solutions considering the distribution range of the criteria, and the reference point. The reference point can be any point within the distribution range of the criteria [12]. The MARCOS (Measurement of Alternatives and Ranking according to Compromise Solution) method performs the ranking of solutions starting from building an expanded initial matrix. That is, from the decision matrix, the ideal solution and the opposite ideal solution will be added. This is followed by calculating the utility function values of all the solutions against both the ideal and the opposite ideal solution. The ranking results of the solutions will be performed according to the value of this useful function [13], etc.

Although there are differences between the steps performed in each of the above methods, there are two similarities between them: the solutions can only be ranked when the criteria values are in quantitative form, and determined the weights for the criteria. An obvious obstacle is posed as to which method to choose to determine the weights, because, for each method of determining the different weights, the weights of the criteria are different [14]. These obstacles will be eliminated if some multi-criteria decision-making method is available that does not need to assign weights to the criteria. According to the author of this study, CURLI is one of the few options for multi-criteria decision making without determining the weights for the criteria [15]. This method was proposed in 2016, in addition to being applied in the same study, so far for some reason, this method has not been found to be applied in any research in any one field. In our opinion, perhaps the authors who proposed this method have not presented its specific implementation steps. This method has not been interesting and referenced. We will elaborate more on this in the next part of this article.

X12M steel has high tensile strength, good wear resistance and excellent quenching permeability. This is a steel sign according to GOST (Russia) standards. This steel is equivalent to the steel of some countries, such as. X165CrMoV12/ 1.2601/ 1.2379 (DIN – Germany), SKD11 (JIS – Japan), Cr12MoV (GB – China), D2 (AISI – USA), 2310 (SS – Sweden). Machine parts that require high hardness and high wear resistance, such as stamping dies, rolling pins, gears, rollers, transmission shafts, and steel cutters, are often made from this steel. Obviously, the grinding method is almost indispensable when machining the important surfaces of these products.

In general, for machining methods machining flat surfaces, surface roughness and FL are always concerned, and for grinding in particular, these factors are considered even more. The reason is that roughness directly affects the workability and durability of the part surface [16]. Meanwhile, FL determines the tightness of the joint when that plane is assembled with another plane [17]. In another case, if the surface is to be machined in the plane on the cutting tool, the flatness tolerance will directly make the product surface, when cut with that tool will not be flat, even distorting the size [18]. Therefore, flatness tolerance also greatly affects the working conditions and durability of the product.

Research to find a solution to ensure one/several criteria when grinding flat steels equivalent to X12M steel has been carried out, such as: determining the value of wheel repair parameters (including feed rate, depth of rough dressing cut, rough dressing times, depth of finish dressing cut, finish dressing times, and non-feeding dressing) to minimize flatness error when grinding SKD11 steel [19]; multi-criteria decision-making in the selection of cutting parameters to ensure simultaneously small surface roughness, three small wheel shaft vibration components, and large material removal yield when grinding DIN 1.2379 steel [20]; multi-criteria decision making in the selection of cutting parameters to ensure simultaneously acceptable surface roughness and large material removal capacity when grinding SKD11 steel [2]. However, according to the authors, up to now, there have been no published studies on multi-criteria decision making to simultaneously ensure surface roughness and FL at acceptable value.

In this study, the X12M steel grinding experiment will be conducted with the parameters changing in each experiment, including wheel grain, workpiece velocity, feed rate, and depth of cut. At each experiment, the surface roughness and FL will be measured. The CURLI method will be applied for multi-criteria decision making. The objective of this study is to determine the wheel grain and cutting parameters to ensure that the surface roughness and the FL have the same minimum value.

2 CURLI METHOD

The CURLI method was first proposed in 2016 [15]. This study was conducted with the intention of selecting candidates for medical school. In order to accomplish that task, the candidates are in turn commented on by the interviewers. Instead of evaluating the scores of the candidates the traditional way, the interviewers will only judge whether a candidate is better or worse than another candidate based on certain criteria. Therefore, it can be seen that, according to this approach, when applying the CURLI method, it is possible to rank the alternatives when the values of the criteria are in both qualitative and quantitative form. This is a highlight of the CURLI method compared to other methods that can only rank solutions when the values of the criteria are in quantitative form. This study, however, focused on using it directly for a specific problem without presenting the steps in general terms. This is also understandable since, in that study, there are candidates who were interviewed by all of the interviewers; however, some candidates were not evaluated by all of them. Therefore, it could have been quite challenging for the authors of that study to formulate the implementation steps in general. However, when it comes to mechanical machining processes in general, particularly grinding, the responses of each experiment (surface roughness, FL, dimension tolerance, etc.) need to be evaluated during the experiment. Because of that, it is imperative to consider all those parameters equally. In other words, if each experimental is considered as a

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candidate, all of those candidates must be considered by the person who analyzes the experimental results. Therefore, it is necessary to develop a specific sequence of steps to rank alternatives according to the CURLI method. In this study, the authors will generalize the steps taken for multi-criteria decision-making by the CURLI method.

Accordingly, the proposed CURLI method involves the following steps:

Step 1. Build a matrix with m rows and n columns, where m is the number of options, n is the number of criteria. This is called the decision-making matrix, as shown in Table 1. In which, the criteria can be opposite, that is, some of that can be smaller is better, or bigger is better. Identifying the ideal plan A_i (with i = 1...m) is the objective of this study.

Table 1. Matrix of decision-making

Solution	C_1	C_2	C_i	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_{im}
A_m	x_{m1}	x_{m2}	x_{mj}	x_{mn}

Step 2. Each criterion will create a square matrix of level *m* (including *m* rows and *m* columns), as shown in Table 2. Score each cell of the matrix in the following way, for example, in the cell corresponding to column 1 and row 2, where the value of the indicator *Cj* of A_1 is better than that of A_2, then that cell will score 1; or in the cell corresponding to column 2 and row 1 where the value of indicator *Cj* of A_2 is worse than that of A_1, then score -1; or in the cell corresponding to column 2 and row *m* where the value of criterion *Cj* of A_2 is equal to that of A_m, then score 0; in cells where the number of rows matches the number of columns, for example, cells 1-1, cells 2-2, etc., cell *m*-*m* (cells on the main diagonal of the matrix) are left blank. This matrix is called the scoring matrix for each criterion. As we perform these calculations individually for each indicator, i.e., if there are n indicators, then we must perform *n* scoring matrices.

Table 2. Example of the scoring matrix for each criterion

Solution	P_1	P_2	…	P_m
A_1		-1	…	…
A_2	1		…	…
…	…	…		…
A_m	…	0	…	

Step 3. Combining (adding) all the scoring matrices for each criterion into a single matrix and naming it the process scoring matrix.

Step 4. The process scoring matrix can be rearranged by moving the rows and columns so that the portion above the main diagonal has the highest proportion of cells with negative scores. Ideally, all points with negative values should lie above the main diagonal of the matrix. At the end of the sorting process, the option ranked in row 1 is considered to be the best choice.

3 GRINDING PROCESS EXPERIMENTS

Experiments were conducted with X12M steel samples. Those are milled to a length of 60 mm, a width of 40 mm and a height of 10 mm. After heat treatment, the hardness of the test sample reaches up to 59 □0.3HRC percentage of chemical components of some major elements of workpiece steel is determined by analysis on a spectrophotometer and presented in Table 3.

Table 3. Compositions of X12M steel

Element	%
C	1.52
Mn	0.32
Si	0.28
Cr	11.12
V	0.36
Mo	0.98
P	0.01
S	0.01

Experiments were carried out on a conventional surface grinding machine (Figure 1). An aluminium oxide grinding wheel was used during the experiment, with four grades of the grain of 46, 60, 80 and 100. The outer diameter, thickness and inner diameter of the grinding wheel are 180 (mm), 13 (mm) and 31.75 (mm), respectively. As shown in Table 4, the cutting velocity, feed rate, and depth of cut will also be varied in addition to the wheel's grain in each experiment. In selecting the cutting parameters, factoring in the size of the grinding wheel, the type of material to be ground, and the references to myriad studies [20-22] have been taken into consideration.

Fig. 1. Experimental grinder

The most important feature of the Taguchi Method is that it allows designing an experimental matrix with a large number of input parameters as well as for each input parameter with many levels of values. The variables when designing according to the Taguchi method can be qualitative parameters, and this is the outstanding advantage of the Taguchi method compared to other methods of experimental design. Moreover, the values of variables at each level can also be selected arbitrarily when using the Taguchi method, and this is another advantage that only this approach offers [23]. For example, in this case, the four-level grain sizes are 46, 60, 80, 100 and obviously 60 ≠ (46 +80)/2. A good example of why the Taguchi method should be used in this instance. Accordingly, for each input parameter selected, as shown in Table 4, the Taguchi method was applied to design an orthogonal matrix of 16 experiments, as shown in Table 5.

Table 4. Input parameters

Parameters	**Unit**	**Code**	**Symbol**	**Value at levels**			
				1	**2**	**3**	**4**
Grain size	-	x_1	G_s	46	60	80	100
Workpiece velocity	m/min	x_2	v_w	5	10	15	20
Feed rate	mm/stroke	x_3	f_r	2	4	6	8
Depth of cut	mm	x_4	a_p	0.005	0.01	0.015	0.02

Table 5. Orthogonal matrix L16 and experimental results

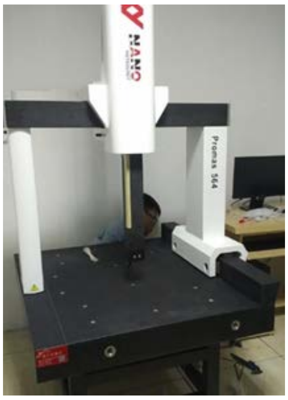
Trial.	**Code value**				**Real value**				**Response**	
	x_1	x_2	x_3	x_4	G_s	v_w (m/min)	f_r (mm/stroke)	a_p (mm)	*Ra* (μm)	*FL* (μm)
A1	1	1	1	1	46	5	2	0.005	0.333	6.365
A2	1	2	2	2	46	10	4	0.01	1.013	12.662
A3	1	3	3	3	46	15	6	0.015	1.249	9.222
A4	1	4	4	4	46	20	8	0.020	1.858	11.806
A5	2	1	2	3	60	5	4	0.015	0.602	6.012
A6	2	2	1	4	60	10	2	0.020	0.270	11.524
A7	2	3	4	2	60	15	8	0.005	1.271	11.553
A8	2	4	3	1	60	20	6	0.01	1.850	17.024
A9	3	1	3	4	80	5	6	0.020	0.256	9.824
A10	3	2	4	3	80	10	8	0.015	0.618	9.493
A11	3	3	1	2	80	15	2	0.01	0.794	13.500

Trial.	Code value				Real value				Response	
	x_1	x_2	x_3	x_4	G_s	v_w (m/min)	f_r (mm/stroke)	a_p (mm)	*Ra* (μm)	*FL* (μm)
A12	3	4	2	1	80	20	4	0.005	1.027	10.031
A13	4	1	4	2	100	5	8	0.01	0.331	14.500
A14	4	2	3	1	100	10	6	0.005	0.164	9.222
A15	4	3	2	4	100	15	4	0.020	0.376	9.024
A16	4	4	1	3	100	20	2	0.015	0.581	9.293

Before each experiment, the grinding wheel was dressed with a depth of 0.01 (mm), the feed rate of the dressing process was 100 (mm/min) [22]. A 10% emulsion cooling fluid was irrigated into the grinding area at a flow rate of 4.6 (l/min).

After each experiment, before measuring surface roughness and FL, the surface of the steel samples was cleaned by washing in alcohol and drying at room temperature. Surface roughness has been measured with the SJ-201 (Figure 2a), which has an accuracy of 0.001 (μm). The Promas 564-3D coordinate measuring machine was used to measure the flatness deviation (Figure 2b). Both surface roughness and FL were measured on each sample surface three times, then the average of those was taken. The results are also included in Table 5.

a. SJ201 surface roughness tester



b. The Promas 564-3D coordinate measuring machine

Fig. 2. Measurement system

In option *A6*, the minimum surface roughness is measured, but there is also a substantial flatness deviation (*FL* = *11.524* μm); while the flatness deviation in plan *A5* is the smallest, the surface roughness in this plan is larger than the surface roughness in plans *A1*, *A9*, *A13*, *A14*, *A15*, *A16*. It is clearly visible that the surface roughness of *A5* is almost twice times rougher than that of *A1*, *A13*, and *A15*, and almost four times that of *A14*. Thus, both *A5* and *A6* cannot be considered the best option. It is also practically impossible to have a solution where both the surface roughness and the flatness deviation are minimal, so the problem is solved only by giving a solution in which both the surface roughness and the flatness deviation are considered to be the "minimum".

4 MULTI-CRITERIA DECISION MAKING

Apply the steps described above of the CURLI method for multi-criteria decision making.

Step 1: Building a matrix requires decision making. This matrix is the last two columns in Table 5.

Step 2: Scoring solutions for each parameter. This work was done using a computer program written in Java language with pseudocode, as shown in Figure 3. The algorithm gets input from the text file with the first line is evaluation criteria (min is 0 and max is 1), following lines are value of the parameter. The output of the algorithm is the scoring matrix for this parameter. To produce the output, firstly the algorithm read data from text file to store in a variable for evaluation criteria and a vector for value of the parameter denoted by a. Next step, two nested loops are performed to scan all rows and columns of scoring matrix of this parameter denoted by b. For each iteration one element of the matrix is created as flowing rule:

Case 1: The evaluation criteria is min.

$$b[i][j] = \begin{cases} 0 & if i = j \\ 1 & if a[i] < a[j] \\ -1 & if a[i] \geq a[j] \end{cases} \quad (1)$$

Case 2: The valuation criteria is max.

$$[i][j] = \begin{cases} 0 & if i = j \\ 1 & if a[i] > a[j] \\ -1 & if a[i] \leq a[j] \end{cases} \quad (2)$$

where, b[i][j] is the element at ith rows and jth columns of the scoring matrix, a[i], a[j] are element at position ith and jth of the vector.

Final, we return calculated scoring matrix b.

The two scoring tables for the Ra and FL parameters are presented in Tables 6 and 7.

Step 3: The results from calculating the score matrix for process were shown in Table 8. This was done by summing of all scoring matrix for each parameter. In our case it is sum of the matrices Scoring matrix for the Ra criterion and Scoring matrix for the FL criterion.

Step 4: Changing rows and columns so that the number of cells with negative scores above the main diagonal of the matrix has the greatest number. This work can be done by computer programming method or done manually (by hand). In the research, the Java language was once used again. A summary of how to do the programming to change the position of rows and columns is as follows: Initialize an unsorted list of solutions, each solution will be compared with its immediate below on the rank list by checking the corresponding value of these two solutions in the process score matrix. If this value is negative, the two solutions are swapped in the rank list. For example, comparing solutions P4 and P5, from the process scoring matrix, the cell with column P4 and row A5 has a value of -2, so these two solutions are interchanged in the rank list. The above process is repeated until no pair of solutions are swapped. Figure 4 shows the pseudocode of the algorithm. This algorithm takes as input a process score matrix and to produce the output is a rank list of solution. To produce the output, firstly, we initialize an unsorted list contains all solutions. Next, we perform two nested loops (outside is do while loop and inside is for loop) to implement to change the position of rows and column. Final, we return the ranking list of solution with the best at the first and the worst at the last of the list. After obtaining the ranking list, the process scoring matrix has allnegative elements above the main diagonal and all positive elements below by changing the order of rows and columns according to the order of the element in the ranking list. The results of the process score matrix arrangement is presented in Table 9.

```
MODULE calcScoreMatrix
INPUT: Text File contains data of parameter to be scored and evaluation criteria (min or max)
OUTPUT: Scoring matrix for the parameter (b)
Read data from text file to store in the vector a.
FOR i = 1 TO N DO
        FOR j = 1 TO N DO
                IF i = j THEN
                        b[i][j] = 0
                ELSE IF a[i]<a[j] THEN
                        IF evaluation criteria is min THEN
                                b[i][j] = 1
                        ELSE
                                b[i][j] = -1
                        END IF
                ELSE
                        IF evaluation criteria is min THEN
                                b[i][j] = -1
                        ELSE
                                b[i][j] = 1
                        END IF
                END IF
                END IF
        END FOR
        END FOR
        RETURN b
```

Fig. 3. Pseudocode to score for each parameter

Table 6. Scoring matrix for the Ra criterion

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

Table 7. Scoring matrix for the FL criterion

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
A1		-1	-1	-1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
A2	1		1	1	1	1	1	-1	1	1	-1	1	-1	1	1	1
A3	1	-1		-1	1	-1	-1	-1	-1	-1	-1	-1	-1	0	1	-1
A4	1	-1	1		1	1	1	-1	1	1	-1	1	-1	1	1	1
A5	-1	-1	-1	-1		-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
A6	1	-1	1	-1	1		-1	-1	1	1	-1	1	-1	1	1	1
A7	1	-1	1	-1	1	1		-1	1	1	-1	1	-1	1	1	1
A8	1	1	1	1	1	1	1		1	1	1	1	1	1	1	1
A9	1	-1	1	-1	1	-1	-1	-1		1	-1	-1	-1	1	1	1
A10	1	-1	1	-1	1	-1	-1	-1	-1		-1	-1	-1	1	1	1
A11	1	1	1	1	1	1	1	-1	1	1		1	-1	1	1	1
A12	1	-1	1	-1	1	-1	-1	-1	1	1	-1		-1	1	1	1
A13	1	1	1	1	1	1	1	-1	1	1	1	1		1	1	1
A14	1	-1	0	-1	1	-1	-1	-1	-1	-1	-1	-1	-1		1	-1
A15	1	-1	-1	-1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1		-1
A16	1	-1	1	-1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	

Table 8: The process scoring matrix

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
A1		-2	-2	-2	0	0	-2	-2	0	-2	-2	-2	0	0	-2	-2
A2	2		0	0	2	2	0	-2	2	2	0	0	0	2	2	2
A3	2	0		-2	2	0	-2	-2	0	0	0	0	0	1	2	0
A4	2	0	2		2	2	2	0	2	2	0	2	0	2	2	2
A5	0	-2	-2	-2		0	-2	-2	0	-2	-2	-2	0	0	0	0
A6	0	-2	0	-2	0		-2	-2	2	0	-2	0	-2	0	0	0
A7	2	0	2	-2	2	2		-2	2	2	0	2	0	2	2	2
A8	2	2	2	0	2	2	2		2	2	2	2	2	2	2	2
A9	0	-2	0	-2	0	-2	-2	-2		0	-2	-2	-2	0	0	0
A10	2	-2	0	-2	2	0	-2	-2	0		-2	-2	0	2	2	2
A11	2	0	0	0	2	2	0	-2	2	2		0	0	2	2	2
A12	2	0	0	-2	2	0	-2	-2	2	2	0		0	2	2	2
A13	0	0	0	0	2	2	0	-2	2	0	0	0		0	0	0
A14	0	-2	-1	-2	0	-2	-2	-2	-2	-2	-2	-2	-2		0	-2
A15	2	-2	-2	-2	0	0	-2	-2	0	-2	-2	-2	0	0		-2
A16	2	-2	0	-2	0	0	-2	-2	0	-2	-2	-2	0	0	2	

Table 9. The process grading matrix arrangement

	P1	P5	P14	P15	P16	P9	P10	P3	P12	P6	P7	P2	P4	P11	P13	P8
A1		0	0	-2	-2	0	-2	-2	-2	0	-2	-2	-2	-2	0	-2
A5	0		0	0	0	0	-2	-2	-2	0	-2	-2	-2	-2	0	-2
A14	0	0		0	-2	-2	-2	-1	-2	-2	-2	-2	-2	-2	-2	-2
A15	2	0	0		-2	0	-2	-2	-2	0	-2	-2	-2	-2	0	-2
A16	2	0	0	2		0	-2	0	-2	0	-2	-2	-2	-2	0	-2
A9	0	0	0	0	0		0	0	-2	-2	-2	-2	-2	-2	-2	-2
A10	2	2	2	2	2	0		0	-2	0	-2	-2	-2	-2	0	-2
A3	2	2	1	2	0	0	0		0	0	-2	0	-2	0	0	-2
A12	2	2	2	2	2	2	2	0		0	-2	0	-2	0	0	-2
A6	0	0	0	0	0	2	0	0	0		-2	-2	-2	-2	-2	-2
A7	2	2	2	2	2	2	2	2	2	2		0	-2	0	0	-2
A2	2	2	2	2	2	2	2	0	0	2	0		0	0	0	-2
A4	2	2	2	2	2	2	2	2	2	2	2	0		0	0	0
A11	2	2	2	2	2	2	2	0	0	2	0	0	0		0	-2
A13	0	2	0	0	0	2	0	0	0	2	0	0	0	0		-2
A8	2	2	2	2	2	2	2	2	2	2	2	2	0	2	2	

Observing Table 9 shows that all points with negative values lie above the main diagonal. Thus, this is considered a perfect result when sorting the options according to the *CURLI* method. It shows that option *A1* is considered the best option, and *A8* is considered the worst option. Looking back at the experimental data in Table 5 (experimental data), we see that option *A8* has *FL = 17,024* (μm), which is the largest value in the total of sixteen options; *Ra = 1,850* (μm), which is the second largest of the sixteen alternatives (smaller only in option *A4*). Therefore, it can be seen that it is entirely correct to decide that *A8* is the worst option.

```
MODULE sortRankList
INPUT: Process score matrix
OUTPUT: Rank list
Initialize an unsorted list of solutions p.
REPEAT
        stop = true
        FOR i = 1 TO n-1 DO
                IF a[i][i+1]<0 THEN
                        Swapping the i and i+1th solutions in the list p.
                        stop = false
                END IF
        END FOR
ULTIL stop = true
RETURN p
```

Fig. 4. Pseudocode of algorithm to sort the rank list

For option *A1*, there is *Ra = 0.333* (μm). Although this is not the minimum value of the surface texture among the sixteen alternatives, it is larger than the surface roughness value of four variants *A6*, *A9*, *A13* and *A14*. On the other hand, the difference between the surface texture at option *A1* and options *A6*, *A9*, *A13* and *A14* is minimal. Also, at option *A1*, *FL = 6,365* (μm), ranked second among sixteen alternatives, and only a minimal amount greater than the *FL* value of alternative *A5*. It can confirm that *A1* is considered the best solution out of the total number of options implemented.

5 CONCLUSION

The process of grinding X12M steel was performed in this study. The experimental matrix of sixteen experiments was designed according to the Taguchi method. At each test will change the size of the abrasive grain, the workpiece velocity, the feed rate, and the depth of cut. Surface roughness and FL were measured at each experiment. The CURLI method was applied for multi-criteria decision making. Some conclusions are drawn as follows:

- Suggested steps to follow the CURLI method. Applying the CURLI method will be very simple to the steps suggested. Except for the authors who proposed the CURLI method, this study is the first to apply this method in multi-criteria decision making.
- For previously used decision making methods (such as: TOPSIS, MOORA, VIKOR, etc.) it is only possible when the values of the criteria are in quantitative form. Meanwhile, the CURLI method applies comparison of solutions in each criterion. Thus, this method can rank the solutions when the values of the criteria are in both qualitative and quantitative form. This is a difference of the CURLI method compared to other methods. Therefore, the CURLI method is recommended to be used, especially when the criteria values are in qualitative form.
- Comparing the effectiveness of the CURLI method with one (several) multi-criteria decision making methods is our future work.
- To minimize surface roughness and FL, it is necessary to choose the size of the abrasive grain, the workpiece velocity, the feed rate and the depth of cut to be respectively 46, 5 (m/min) and 2 (mm/stroke) and 0.005 (mm).

6 REFERENCES

[1] Trung, D. D. (2021). Application of TOPSIS an PIV methods for Multi - Criteria Decision Making in hard turning process. Journal of Machine Engineering, vol. 21, no. 4, 57-71, DOI: 10.36897/jme/142599

[2] Nguyen, N. T., Trung, D. D. (2021). Combination of taguchi method, moora and copras techniques in multi-objective optimization of surface grinding process. Journal of Applied Engineering Science, vol. 19, no. 2, 390 – 398, DOI: 10.5937/jaes0-28702

[3] Tien, D. H., Trung, D. D., Thien, N. V., Nguyen, N. T. Nguyen. Multi-Objective Optimization of the Cylindrical Grinding Process of SCM440 Steel Using Preference Selection Index Method. Journal of Machine Engineering, vol. 21, no. 3, 110-123,DOI: 10.36897/jme/141607

[4] Trung, D. D., Thien, N. V., Nguyen N. T. (2021). Application of TOPSIS Method in Multi-Objective Optimization of the Grinding Process Using Segmented Grinding Wheel. Tribology in Industry, vol. 43, no. 1, 12-22, DOI: 10.24874/ti.998.11.20.12

[5] Kusumadewi, S., Hartati, S., Harjoko, A., Wardoyo, R. (2006). Fuzzy Multi-Attribute Decision Making (FUZZY MADM). Yogyakarta: PenerbitGrahaIlmu.

[6] Zavadskas, E. K., Turskis, Z., Antucheviciene, J., Zakarevicius, A. (2012). Optimization of weighted aggregated sum product assessment. Elektronirelektrotechnika, vol. 122, no. 2012, 3-6

[7] Hwang, C. L., Lai, Y. J. Ting,_Y. L. (1993). A new approach for multiple objective decision making. Computers & Operations Research, vol. 20, 889–899

[8] Opricovic, S., Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Research, vol. 156, 445-455.

[9] Brauers, W. (2004). Optimization methods for a stakeholder society. A revolution in economic thinking by multi-objective optimization. Publisher: springer before Kluwer.

[10] riantaphyllou, Evangelos. (2020). Multi-criteria Decision Making Methods: A Comparative Study, Springer – Science + Busines media.

[11] Mufazzal, S., Muzakkir, S. M. (2008). A New Multi-Criterion Decision Making (MCDM) Method Based on Proximity Indexed Value for Minimizing Rank Reversals. Computers & Industrial Engineering, vol. 2008, 1-38.

[12] Cables Perez, E., Lamata, M.T., Verdegay, J.L. (2016). RIM-Reference Ideal Method in Multicriteria Decision Making. Information Sciences, vol. 337, no. 10, 1-10, DOI: 10.1016/j.ins.2015.12.011

[13] Stevic, Z., Pamucar, D., Puska, A., Chatterjee, P. (2020). Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement Alternatives and Ranking according to COmpromise Solution (MARCOS). Computers & Industrial Engineering, vol. 140, 1-33.

[14] Ewa, R. (2013). Rank Ordering Criteria Weighting Methods – A Comparative Overview. Journal Dedicated to the Needs of Science and Practice, vol. 5, no. 65, 1–168, DOI: 10.15290/ose.2013.05.65.02

[15] James, R. K., David, J. A. (2016). A new method for group decision making and its application in medical trainee selection. Medical Education, vol. 50, 1045–1053, DOI: 10.1111/medu.13112

[16] Huang Y., Wang L., Steven, Y. L. (2019). Hanbook of manufacturing, World Scientific, 2019, DOI: 10.1142/11006

[17] Varga, J., Teodor, T., Peter, F., Dulebov, L., Emil, S., Ivan, Z., Jozef, Z. (2011). The Influence of Automated Machining Strategy on Geometric Deviations of Machined Surfaces. Applied sciences, vol. 11, no. 2353, 1-15, DOI:.10.3390/app11052353

[18] Drake, P. J. (1999). Dimensioning and Tolerancing Handbook, McGraw-Hill.

[19] Hong, T. T., Giang, T. N., Vu. N. N., Danh, B. T., Tu, D, N., Dung, N. T. Q., Pi, V. N., Tung, L. A. (2021. Optimizing Dressing Conditions for Minimum Flatness Tolerance when Grinding SKD11 Tool Steel. Materials Science Forum, vol. 1020, 83-90, DOI: 10.4028/www.scientific.net/MSF.1020.83

[20] Trung, D. D., Nguyen, N. T., Thien, N. V. (2021). Application of TOPSIS Method in Multi-Objective Optimization of the Grinding Process Using Segmented Grinding Wheel. Tribology in Industry, vol. 43, no. 1, 12-22, DOI: 10.24874/ti.998.11.20.12

[21] Malkin, S., Guo, C. (2008). Grinding technology: Theory and Applications of Machining with Abrasives (2nd Edition). New York: Industrial Press.

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