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THE COMBINATION OF TAGUCHI – ENTROPY – WASPAS - PIV METHODS FOR MULTI-CRITERIA DECISION MAKING WHEN EXTERNAL CYLINDRICAL GRINDING OF 65G STEEL

This paper presents a study on the multi-creteria decision making in the external cylindrical grinding process of 65G steel. An aluminum oxide grinding wheel was used in the experimental process. The experimental matrix was designed according to the Taguchi method with twenty-seven experiments. Five parameters were used to design the experimental matrix including workpiece velocity, feed rate, depth of cut, dressing feed rate, and dressing depth of cut. The surface roughness and Material Removal Rate (*MRR*) were determined for each experiment. This is the first time that the Weighted Aggregates Sum Product ASsessment *(WASPAS)* and Proximity Indexed Value (*PIV)* methods were used to make the multi-criteria decision for grinding process. The weighs of ouput criteria (surface roughness and *MRR*) were determined by Entropy method. Both *WASPAS* and *PIV* methods determined an experiment that simultaneously ensured the “minimum value” of surface roughness and “maximum value” of *MRR*.

Nomenclature

Ra: The arithmetical mean deviation of the assessed profile
MRR: Material removal rate
TOPSIS: Technique for order preference by similarity to ideal solution
VIKOR: Vlsekriterijumska optimizacija i kompromisno resenje in Serbian
MOORA: Multi objective optimization on the basis of ratio analysis
COPRAS: Complex proportional assessment
RIM: Reference ideal method
WASPAS: Weighted aggregates sum product assessment
PIV: Proximity indexed value
S/N: Signal-to-noise ratio
NN: Neural network
GA: Genetic algorithm
RSM: Response surface methodology
GRA: Gray relational analysis

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1. INTRODUCTION

The goal of most machining methods is to be able to manufacture machine parts with small surface roughness and high *MRR*. Because the surface roughness directly affects on the workability of machine parts through the wear resistance, fatigue strength, and chemical corrosion resistance, and *MRR* is an important parameter to evaluate the machining productivity [1, 2].

This problem is even more significant when applying to grinding methods because grinding is known to be the final finishing method for surfaces with small roughness requirement [3]. The productivity when machining by grinding methods is limited because the depth of cut when grinding is often very small [4]. Machining productivity is directly depended on the parameters of the cutting process. But these parameters of the cutting process also have a direct influence on the surface roughness. In addition, surface roughness also depends on many other factors such as parameters of the dressing process, cooling parameters, machining material, conditions of experimental equipment, etc., [5]. Therefore, to ensure the machining process with small surface roughness and high *MRR*, it is required to conduct a case-by-case study. However, within a research process corresponding to a certain experimental system, it is impossible to survey all the above parameters (the parameters that affect on the surface roughness and *MRR*). Therefore, in each specific case, only a few parameters can be selected to survey and determine the values of these parameters to ensure small surface roughness and/or large *MRR*. Stemming from this feature, many experimental studies have been carried out to solve this problem.

The Taguchi method was used to design the experimental matrix, and then the *S/N* analysis method was used in many cases to determine the values of parameters of the machining process to ensure the minimum surface roughness.

When grinding the EN19 steel [6], the authors applied the Taguchi method to design the experimental matrix and applied S/N method to analyze the experimental results. They determined that to ensure the minimum value of surface roughness, the workpiece velocity, feed rate, and depth of cut were 410 rev/min, 0.18 mm/rev, and 0.02 mm, respectively. Taguchi and S/N method were also applied to optimize the grinding process of AISI 4140. The results showed that to obtain the minimum value of surface roughnes, the grinding wheel speed was 2640 rev/min, workpiece speed was 710 rev/min, grain size was 46 mesh/inch, depth of cut was 0.015 mm, concentration of the coolant was 5%, and number of passes was 3 [7]. Study on determination of cutting parameters to ensure the minimum value of surface roughness when grinding the AISI D3 steel was also performed according to matrix using Taguchi method. *S/N* method was also applied to analyze the experimental results [8]. The analyzed results showed that to obtain the smallest surface roughness, the grinding wheel speed was 2000 rev/min, workpiece speed 220 rev/min, feed rate was 3.2 mm/rev, and depth of cut was 0.005 mm. The grinding process of AISI 1045 was performed according to a matrix using Taguchi method. And then, *S/N* method was also applied to analyze the experimental results. The results showed that with the grinding wheel speed of 2100 rev/min, workpiece speed of 500 rev/min, grinding grain material of silicon carbide, grain size of 60, coolant concentration of 3%, and pass number of 4, the value of surface roughness was smallest [9]. When grinding the 9XC steel, to ensure the minimum of surface roughness, the coarse dressing depth of 0.07 (mm), the fine dressing depth of 0.02 (mm), the number of non-feeding dressing times is 3 [10]. In this study, Taguchi method was also used to design the experimental matrix, and then, *S/N* method was also used to analyze the experimental results. For EN19 steel, to ensure the minimum value of surface roughness, the dressing depth of cut was 0.02 mm, dressing feed rate was 80 mm/min, drag angle was 50^0, and the number of passes was 4 [11]. Taguchi and *S/N* methods were also used to design the experimental matrix and analyze the experimental results. The authors performed the grinding process of EN8 steel using four different grinding wheels including Al_2O_3 of grades K and L, and white alumina of grades J and K. Taguchi and *S/N* methods were also used to design the experimental matrix and analyze the experimental results. The analyzed results showed that the surface roughness was smallest when using the Al_2O_3 of grade L grinding wheel and with the grinding wheel speed was 1300 rev/min, workpiece speed was 278 rev/min, and depth of cut was 0.03 mm [12].

Taguchi method was also applied to design an experimental matrix, and then the *S/N* ratio analysis method was also applied to determine the values of machining parameters to ensure the maximum *MRR*.

When grinding the AISI 31 steel, Taguchi and S/N methods were also used to design the experimental matrix and analyze the experimental results. The results showed that to obtain the maximum value of *MRR*, the grinding speed, feed rate, and depth of cut were 1000 rev/min, 0.095 mm/min, and 0.03 mm, respectively [13]. When grinding the AISI 316 steel, to obtain maximum value of *MRR*, the cutting velocity was 560 m/min, feed rate was 0.13 mm/rev, and depth of cut was 0.005 mm [14]. In this study, Taguchi and *S/N* methods were also used to design the experimental matrix and analyze the experimental results. Taguchi and *S/N* methods were also used to design the experimental matrix and analyze the experimental results when grinding the 9CrSi steel [15]. This study showed that to obtain the maximum value of *MRR*, the dressing feed rate was 3 m/min, coarse dressing depth was 2 mm, coarse dressing times was 1, fine dressing depth was 1 mm, fine dressing times was 3, and non-feeding dressing times was 6.

Through some of the above studies, it can be found that the Taguchi method has been successfully applied in many different cylindrical grinding processes. This is also easily explained because the Taguchi method is known as an experimental design method enabling the performance of few experiments with many input parameters, and the input parameters with many levels. Another outstanding advantage of the Taguchi method is that it allows designing an experimental matrix with the input parameters being qualitative ones (such as type of grinding wheel). This is the exclusive advantage of the the matrix design method according to the Taguchi method [16]. However, if only the Taguchi method is applied to design the experimental matrix and then the *S/N* ratio analysis method is applied, only the values of parameters of the machining process can be determined to ensure only one criterion, such as ensure the integer minimum surface roughness or ensure the integer maximum *MRR*.

In order to overcome this limitation of the Taguchi method, a number of studies were also conducted by combining the matrix design according to the Taguchi method with a certain algorithm. When grinding AISI 316 steel, to simultaneously ensure the minimum value of surface roughness and maximum value of *MRR*, the workpiece velocity was 13 m/min, feed rate was 17 mm/min, and depth of cut was 0.01 mm [17]. To determine these velues of cutting parameters, the authors combine the Taguchi method and meta-heuristic algorithm. The Taguchi and *GRA* were combined when study on the grinding process of 9CrSi [18]. The results showed that to simultaneously ensure the minimum value of surface roughness and maximum value of *MRR*, the dressing feed rate was 1.4 mm/min, coarse dressing depth was 0.02 mm, coarse dressing time was 1, fine dressing depth was 0.005 mm, fine dressing times was 1, and non-feeding dressing was 5. The authors combined the Taguchi, RSM, and GA method when study on the grinding process of 6061-T4 aluminum alloy [19]. The results showed that to simultaneously ensure the minimum values of surface roughness and vibrations, the values of infeed, longitudinal feed, and work speed were 0.04 mm/cycle, 70 mm/s, and 80 rev/min, respectively.

In addition to combining the Taguchi method with a number of algorithms as presented above, to simultaneously ensure the multiple criteria of a machining process or of a certain operation, a concept that is known as "*multi-criteria decision making – MCDM*" is created. In order to realize multi-criteria decision making, the combination of the Taguchi method and mathematical methods has been carried out in many studies under many different fields. Some commonly used techniques, such as: *TOPSIS* [20], *VIKOR* [21], *MOORA* [22], *COPRAS* [23], *RIM* [24], *WASPAS* [25], *PIV* [26], etc.

However, when using methods such as *TOPSIS, VIKOR, MOORA, COPRAS, RIM* to rank the alternatives, it is very easy to occur the reversal to solutions. That is, if we add or subtract a certain solution, the order of the previously ranked solutions will not be maintained, sometimes even creating an opposite ranking compared to the original ranking [26]. The *PIV* method is known as a multi-criteria decision making method which enables to minimize the possibility of reversibility to solutions [26]. This method has been successfully applied in *MCDM* when ranking and selecting E-learning sites [27], for the selection of materials for manufacturing some parts of automobiles [28], for the selection of elements for logistics activities of the EU countries [29], for the selection of additives in a production process [30], etc. The *WASPAS* method has also been successful in *MCDM* in some studies, such as: in recovering used mobile phones [31], in human resource management to ensure the continuous development and satisfaction of employees [32], in selection of materials of a production process [33], in multi-criteria decision making when turning aluminum [34], in development of Klaipeda sea port [35], etc. However, until now, there have been no studies that apply such two methods (*WASPAS* and *PIV*) for *MCDM* in external cylindrical grinding.

It is also important to note that when *MCDM*, it is required to determine the weight of each criterion. However, if the weighting of the criteria is done according to the subjective opinion of the decision maker, it is a lack of necessary reliability. The weighting of each criterion which is done by expert opinions also depends a lot on the knowledge of the experts, and sometimes also greatly influenced by the design of questionnaires. Determining weights for criteria by Entropy method which is a well-known method, has been applied in many cases. However, unfortunately, to date, there have been no studies that apply the Entropy method to determine the weight of criteria in the external cylindrical grinding process.

To machine parts with high requirements for hardness and wear resistance such as those in the cement, thermal power, and sugar industries, 65G steel is one of the first selected materials. When machining surfaces with requirements for high precision of these parts, the cylindrical grinding method is often chosen as the final machining method. Several studies on grinding this steel (or equivalent steels) have been published, such as the study on changes in hardness after grinding [36], the study on the cutting force when grinding [37], the study on the effect of cutting parameters on surface roughness when face grinding [38]. However, a surprising thing has been discovered that up to now, there has been no published research on determining the value of technological parameters to simultaneously ensure the minimum surface roughness and the maximum *MRR* when circular grinding this type of steel.

From the above analysis and comments, it is shown that: ***Firstly***, the Taguchi method shows many advantages in designing an experimental matrix, but the combination of Taguchi method and the two methods (*WASPAS* and *PIV*) has not been implemented in any studies on grinding in general as well as the external cylindrical grinding method in particular; **Secondly,** the application of the Entropy method to determine the weights of criteria has not been applied to the external cylindrical grinding method; ***Thirdly***, No published research has been found on the simultaneous survey of two parameters (surface roughness and *MRR)* when cylindrical grinding 65G steel. These gaps will be covered in this study. Specifically, the experiments of cylindrical grinding 65G steel will be carried out according to the designing matrix by Taguchi method, Entropy method will be applied to determine the weights of surface roughness and *MRR*, *WASPAS* and *PIV* methods will be applied for multi-criteria decision making.

2. DETERMINATION OF THE WEIGHT USING ENTROPY METHOD

Determining the weights of criteria using Entropy method is done according to the following steps [39].

Step 1. Determine the normalized values for criteria

$$p_{\mathrm{ij}} = \frac{x_{\mathrm{ij}}}{m + \sum_{i=1}^{m} x_{\mathrm{ij}}^{2}} \tag{1}$$

where: x_{ij} is the value of criterion *j* corresponding to option *i*; *m* is the number of options.

Step 2. Calculate the value of the Entropy measure for each criterion.

$$e_{\mathrm{j}} = -\sum_{i=1}^{m}\left[p_{\mathrm{ij}} \times \ln(\mathrm{p_{ij}})\right] - \left(1 - \sum_{i=1}^{m} p_{\mathrm{ij}}\right) \times \ln\left(1 - \sum_{i=1}^{m} p_{\mathrm{ij}}\right) \tag{2}$$

Step 3. Calculate the weight for each criterion.

$$\mathrm{w_j} = \frac{1 - \mathrm{ej}}{\sum_{j=1}^{n}(1 - \mathrm{ej})} \tag{3}$$

3. MULTI-CRITERIA DECISION MAKING METHODS

3.1. WASPAS METHOD

The *WASPAS* method was first recommended in 2012 [25], the implementation steps of this method are as follows:

Step 1. Establish the initial decision-making matrix (*X*) as shown in formula (4)

$$X = \begin{array}{c} \\ S_1 \\ S_2 \\ \cdots \\ S_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{4}$$

where: *m* is the number of options (S_1, S_2, ..., S_m), *n* is the number of criteria (C_1, C_2, ..., C_n).
Step 2. Determine the normalized matrix using the following equations.

$$n_{\mathrm{ij}} = \frac{x_{\mathrm{ij}}}{max\, x_{ij}} \quad \text{for} \quad C_1, C_2, \ldots, C_n \in B \tag{5}$$

$$n_{\mathrm{ij}} = \frac{min\, x_{\mathrm{ij}}}{x_{ij}} \quad \text{for} \quad C_1, C_2, \ldots, C_n \in C \tag{6}$$

Of which *B* represents the benefit criteria, *C* represents the cost criteria.
Step 3. Develop a weight matrix by multiplying the initial matrix by the weight of the criteria, of which w_j is the weight of the criterion *j*.

$$v_n = \left[v_{\mathrm{ij}} \right]_{m \times n} \tag{7}$$

$$v_{ij} = w_j \times n_{ij}, \quad i = 1, 2, \ldots, m \quad j = 1, 2, \ldots, n \tag{8}$$

Step 4. Add up all values of the criteria in each option (sum by rows).

$$Q_i = \left[q_{\mathrm{ij}} \right]_{1 \times m} \tag{9}$$

$$q_{\mathrm{ij}} = \sum\nolimits_{j=1}^{n} v_{\mathrm{ij}} \tag{10}$$

Step 5. Determine the weighted product model according to the following formulas.

$$P_i = \left[p_{\mathrm{ij}} \right]_{1 \times m} \tag{11}$$

$$p_{\mathrm{ij}} = \prod\nolimits_{j=1}^{n} \left(v_{\mathrm{ij}} \right)^{\mathrm{w}_j} \tag{12}$$

Step 6. Determine the relative values of the options A_i according to the formulas.

$$A_i = \left[a_{\mathrm{ij}} \right]_{1 \times m} \tag{13}$$

$$A_1 = \lambda \times Q_i + (1 - \lambda) \times P_i \tag{14}$$

Of which the coefficient λ can choose one of the following values: 0; 0.1; 0.2; ...; 1.0
Step 7. Rank the options according to the principle, the one with the maximum A_i is the best, whereas the worst one obtains the minimum A_i.

3.2. PIV METHOD

PIV is a method for multi-criteria decision making, first introduced in 2018 [26]. The steps to implement multi-criteria decision making according to this method are as follows.
Step 1. Describe solutions S_i (with *j = 1, 2, ..., m)* and criteria C_i (with *j = 1, 2,...., n*).

Step 2. Develop a decision matrix *X* by arranging the solutions by rows and the criteria by columns as shown in the formula (4).

Step 3. Determine the normalized decision matrix using the formula (15).

$$R_j = \frac{x_j}{\sqrt{\sum_{i=1}^{m} x_j^{\;2}}} \tag{15}$$

Of which x_i is the actual decision value of the option *i*.

Step 4. Determine the weighted normalized decision matrix according to the formula (16)

$$v_j = \mathrm{w_j} \times R_j \tag{16}$$

Of which w_j is the weight of the criterion *j*.

Step 5. Evaluate the weighted proximity index according to the formula (17).

$$u_i = \begin{cases} vi_{max} & \text{for beneficial attributes} \\ v_i - v_{min} & \text{for cost attributes} \end{cases} \tag{17}$$

Step 6. Determine the overall proximity value according to the formula (18).

$$d_i = \sum_{j=1}^{n} u_i \tag{18}$$

Step 7. Rank the solutions according to the principle that the solution with the minimum d_i is the best.

4. GRINDING PROCESS EXPERIMENT

The 65G steel samples used in this study have been heat treated to a hardness of 62 HRC. The workpiece has diameter and length of 30mm and 320mm, respectively, but only performs the grinding process on the 250 length of the workpiece, the rest is for mounting parts (position for clamping buckles).

Fig. 1. Cylindrical grinder

The experiments were carried out on a traditional external cylindrical grinding machine (GU32x100S of Palmary Brand, Taiwan) as described in Fig. 1. The grinding wheel that was produced by Vietnam's Hai Duong grinding wheel company was used in this study. This grinding wheel is aluminum oxide wheel (*Cn*), grain size 80, ceramic binder (*G*), average hardness of 1 (TB_1), cylindrical wheel type (*V*), the maximum allowable velocity recommended by the wheel manufacturer of 35 m/s. The full symbol of the grinding wheel is $Cn80.TB_1.G.V.35m/s$. The external diameter, thickness and internal diameter of grinding wheels are 280 mm, 40 mm and 115 mm, respectively. Dressing by a multi-point diamond dresser with the symbol 3908-0088C (Russian Federation).

The experimental matrix was designed according to the Taguchi method with a total twenty-seven experiments. Parameters including workpiece speed, feed rate, depth of cut, dressing feed rate, and dressing depth were selected as the input ones. The reason these parameters are selected is because the adjustment to such parameters' values is done more quickly by the machine operator than the adjustment to other parameters (type of grinding wheels, type of coolants, parameters of the grinding machine, etc). Each input parameter has selected three levels of values as shown in Table 1, the experimental matrix is presented in Table 2.

Table 1. Value of input parameters at levels

Parameter	Symbol	Unit	Value at level		
			1	2	3
Workpiece speed	n	rev/min	400	600	800
Feed rate	f_w	mm/rev	0.05	0.075	0.09
Depth of cut	a_r	mm	0.01	0.015	0.02
Dressing feed rate	f_d	mm/min	100	150	200
Dressing depth	a_d	mm	0.005	0.01	0.015

Table 2. Experimental matrix and responses

Trial	Code value of input parameters					Actual value of input parameters					Responses	
	n	f_w	a_r	f_d	a_d	n (rev/min)	f_w (mm/rev)	a_r (mm)	f_d (mm/min)	a_d (mm)	R_a (μm)	*MRR* (mm^3/min)
1	1	1	1	1	1	400	0.05	0.01	100	0.005	0.295	18.843
2	1	1	1	1	2	400	0.05	0.01	100	0.01	0.332	18.843
3	1	1	1	1	3	400	0.05	0.01	100	0.015	0.370	18.843
4	1	2	2	2	1	400	0.075	0.015	150	0.005	0.399	42.39
5	1	2	2	2	2	400	0.075	0.015	150	0.01	0.436	42.39
6	1	2	2	2	3	400	0.075	0.015	150	0.015	0.474	42.39
7	1	3	3	3	1	400	0.09	0.02	200	0.005	0.489	67.813
8	1	3	3	3	2	400	0.09	0.02	200	0.01	0.527	67.813
9	1	3	3	3	3	400	0.09	0.02	200	0.015	0.564	67.813
10	2	1	2	3	1	600	0.05	0.015	200	0.005	0.425	42.39
11	2	1	2	3	2	600	0.05	0.015	200	0.01	0.460	42.39
12	2	1	2	3	3	600	0.05	0.015	200	0.015	0.495	42.39
13	2	2	3	1	1	600	0.075	0.02	100	0.005	0.312	84.766
14	2	2	3	1	2	600	0.075	0.02	100	0.01	0.347	84.766
15	2	2	3	1	3	600	0.075	0.02	100	0.015	0.382	84.766
16	2	3	1	2	1	600	0.09	0.01	150	0.005	0.408	50.877

17	2	3	1	2	2	600	0.09	0.01	150	0.01	0.443	50.877
18	2	3	1	2	3	600	0.09	0.01	150	0.015	0.478	50.877
19	3	1	3	2	1	800	0.05	0.02	150	0.005	0.417	75.348
20	3	1	3	2	2	800	0.05	0.02	150	0.01	0.457	75.348
21	3	1	3	2	3	800	0.05	0.02	150	0.015	0.497	75.348
22	3	2	1	3	1	800	0.075	0.01	200	0.005	0.542	56.53
23	3	2	1	3	2	800	0.075	0.01	200	0.01	0.582	56.53
24	3	2	1	3	3	800	0.075	0.01	200	0.015	0.622	56.53
25	3	3	2	1	1	800	0.09	0.015	100	0.005	0.398	101.737
26	3	3	2	1	2	800	0.09	0.015	100	0.01	0.438	101.737
27	3	3	2	1	3	800	0.09	0.015	100	0.015	0.478	101.737

Each experimental sample was measured for its surface roughness (*Ra*) using a SJ-201 meter of Mitutoyo (Japan). The standard length of the measurement has been set to 0.8 mm. Each experimental sample is measured at least three times, the measurement direction is parallel to the sample centerline (perpendicular to the cutting velocity vector). Surface roughness at each experiment was calculated as the average of successive measurements.

MRR is calculated as the amount of material takeoff in one minute. This quantity is calculated by subtracting the volume of the workpiece after grinding from the volume of the workpiece before grinding and then dividing it by the grinding time, of which the grinding time is calculated by the grinding length divided by the displacement velocity of the grinding wheel head (the feed rate).

The experiments were carried out under the following conditions: the speed of grinding wheel spindle 1750 rev/min; using N-600 industrial oil (made in Vietnam) with a concentration of 12%, flow rate 16 liters/min. These values have been selected according to the recommenddations of the coolant factory and the grinding wheel manufacturer.

5. RESULTS AND DISCUSSION

5.1. ANALYZING THE EXPERIMENTAL RESULTS

With the selected significance level of 0.05 [40], to investigate the influence of the input parameters on the surface roughness, the analysis of variance (*ANOVA*) was performed, the analyzed results are presented in Table 3. From the data in Table 3 showed that the probability *P-value* of the workpiece speed, dressing feed rate, and dressing depth of cut are all much smaller than the significance level. Thus, we conclude that these four parameters all significantly affect on the surface roughness. The dressing feed rate and dressing depth of cut are two parameters that have a great influence on the topography of the grinding wheel, thereby greatly influencing on the shape, size, and number of scratches of the grinding grains left on the workpiec surface, so they greatly affect on the surface roughness [41]. The change of the workpiece speed and the feed rate will change the contact time between the grinding wheel surface and the workpiece surface, thereby also changing the number of grinding grain scratches left on the workpiece surface as well as the changing the amount of heat transferred to the workpiece surface, thereby changing the surface roughness [42].

Table 3. The ANOVA results

Factors	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	–0.0275	0.0386	–0.7118	0.4844	–0.1077	0.0528	–0.1077	0.0528
n	0.0002	0.0000	5.2199	0.0000	0.0001	0.0002	0.0001	0.0002
f_w	1.3426	0.2870	4.6774	0.0001	0.7457	1.9396	0.7457	1.9396
a_r	–0.8889	1.1601	–0.7662	0.4521	–3.3014	1.5237	–3.3014	1.5237
f_d	0.0015	0.0001	12.9683	0.0000	0.0013	0.0017	0.0013	0.0017
a_d	7.5000	1.1601	6.4650	0.0000	5.0875	9.9125	5.0875	9.9125

The probability *P-value* of the depth of cut equals to 0.4521, this value is much larger than the significance level, so this parameter does not significantly affect on the surface roughness. When using aluminum oxide grinding wheel, cutting heat is transferred to the workpiece surface a large amount (about 60 to 90% of the total heat that is generated during grinding). This amount of heat can cause the metal layer at the machined surface to reach a molten state [43]. And so, the change in the depth of cut may having a negligible influence on the tangential cutting force component with the machining surface. Therefore, depth of cut has no significant effect on the surface roughness.

The data in Table 3 also showed that when increasing the value of the workpiece speed, feed rate, dressing feed rate, and dressing depth of cut, the surface roughness will increase (because the coefficients correspond to these parameters are the positive values). In contrast, when increasing the depth of cut, the surface roughness decreases (because the coefficient corresponding to this parameter is negative value). From there, it is shown that, in order to reduce surface roughness, it is necessary to reduce the workpiece speed, feed rate, dressing feed rate, and dressing depth of cut, and to increase the cutting depth. However, it is also easy to see that reducing the cutting speed and feed rate causes the *MRR* to decrease. From that, it can be seen that it is difficult to determine the value of the input parameters to simultaneously ensure the minimum value of surface roughness and the maximum value of *MRR*.

On the other hand, observing the data in Table 2 shows that: the experiment No. 1 has the minimum surface roughness, but also in this experiment, the *MRR* is also the minimum; Experiments No. 25, No. 26 and No. 27 have the maximum *MRR*, but also in such three experiments, the surface roughness is not the minimum. From there, it can be seen that if we only observe the data in Table 2, we will also fail in selecting the experiment (out of a total of twenty-seven experiments) to simultaneously ensure the minimum surface roughness and the maximum *MRR*. The fact also confirms that there is no experiment out of the total of twenty-seven experiments in Table 2 that guarantees absolute minimum surface roughness and absolute maximum *MRR*. Therefore, we can only determine the experiment where the surface roughness is considered to be the *"minimum"* and the *MRR* is considered the *"maximum"*. And of course, to do this, it is required to perform *MCDM* when considering the weight of each criterion.

5.2. MULTI-CRITERIA DECISION MAKING USING THE WASPAS METHOD

Applying the formulas (1), (2) and (3) to determine the weighs for the criteria as follows: $w_{Ra} = 0.1598$; $w_{MRR} = 0.8402$.

Applying the formula (4) to form the initial decision making matrix (*X*). This matrix is the last two columns in Table 2. Applying formulas (5), (6) to calculate n_i value. Applying formulas (7), (8) to calculate v_i value. The results are presented in Table 4.

Table 4. Values of n_i and v_i in *WASPAS*

Solutions	n_i		v_i	
	Ra	*MRR*	*Ra*	*MRR*
S_1	1.0000	0.1852	0.1598	0.1556
S_2	0.8886	0.1852	0.1420	0.1556
S_3	0.7973	0.1852	0.1274	0.1556
S_4	0.7393	0.4167	0.1181	0.3501
S_5	0.6766	0.4167	0.1081	0.3501
S_6	0.6224	0.4167	0.0995	0.3501
S_7	0.6033	0.6666	0.0964	0.5600
S_8	0.5598	0.6666	0.0895	0.5600
S_9	0.5230	0.6666	0.0836	0.5600
S_{10}	0.6941	0.4167	0.1109	0.3501
S_{11}	0.6413	0.4167	0.1025	0.3501
S_{12}	0.5960	0.4167	0.0952	0.3501
S_{13}	0.9455	0.8332	0.1511	0.7000
S_{14}	0.8501	0.8332	0.1359	0.7000
S_{15}	0.7723	0.8332	0.1234	0.7000
S_{16}	0.7230	0.5001	0.1155	0.4202
S_{17}	0.6659	0.5001	0.1064	0.4202
S_{18}	0.6172	0.5001	0.0986	0.4202
S_{19}	0.7074	0.7406	0.1130	0.6223
S_{20}	0.6455	0.7406	0.1032	0.6223
S_{21}	0.5936	0.7406	0.0949	0.6223
S_{22}	0.5443	0.5556	0.0870	0.4669
S_{23}	0.5069	0.5556	0.0810	0.4669
S_{24}	0.4743	0.5556	0.0758	0.4669
S_{25}	0.7412	1.0000	0.1184	0.8402
S_{26}	0.6735	1.0000	0.1076	0.8402
S_{27}	0.6172	1.0000	0.0986	0.8402

Applying formulas (9), (10) we can obtain the value of Q_i. Applying formulas (11), (12) we can obtain the value of P_i. Applying formulas (13), (14) we can obtain the value of A_i. These values were included in Table 5. The ranking of options according to the values of A_i were performed and included in Table 5.

Table 5. Several parameters in *WASPAS*

Solutions	Q_i	P_i	A_i	*Rank*
S_1	0.3154	0.1577	0.2366	25
S_2	0.2976	0.1486	0.2231	26
S_3	0.2830	0.1408	0.2119	27
S_4	0.4682	0.2034	0.3358	19
S_5	0.4582	0.1946	0.3264	21
S_6	0.4495	0.1866	0.3181	23
S_7	0.6564	0.2324	0.4444	10
S_8	0.6495	0.2238	0.4367	11

S_{9}	0.6436	0.2164	0.4300	12
S_{10}	0.4610	0.1971	0.3290	20
S_{11}	0.4526	0.1894	0.3210	22
S_{12}	0.4453	0.1826	0.3140	24
S_{13}	0.8511	0.3252	0.5882	4
S_{14}	0.8359	0.3084	0.5721	5
S_{15}	0.8234	0.2939	0.5587	6
S_{16}	0.5357	0.2203	0.3780	13
S_{17}	0.5266	0.2115	0.3690	16
S_{18}	0.5188	0.2036	0.3612	18
S_{19}	0.7353	0.2652	0.5003	7
S_{20}	0.7254	0.2534	0.4894	8
S_{21}	0.7171	0.2429	0.4800	9
S_{22}	0.5538	0.2015	0.3777	14
S_{23}	0.5479	0.1945	0.3712	15
S_{24}	0.5426	0.1881	0.3654	17
S_{25}	0.9586	0.3155	0.6371	1
S_{26}	0.9478	0.3007	0.6243	2
S_{27}	0.9388	0.2879	0.6133	3

5.3. MULTI-CRITERIA DECISION MAKING USING THE PIV METHOD

The main decision making matrix is the matrix produced by the last two columns of Table 2. Applying the formula (15) to calculate R_i values, apply the formula (16) to calculate v_i values, as shown in Table 6.

Table 6. Value of R_i and v_i in *PIV*

Solutions	R_i		*vi*	
	Ra	*MRR*	*Ra*	*MRR*
S_{1}	0.0369	1.0580	0.0059	0.8889
S_{2}	0.0467	1.0580	0.0075	0.8889
S_{3}	0.0580	1.0580	0.0093	0.8889
S_{4}	0.0675	5.3542	0.0108	4.4986
S_{5}	0.0806	5.3542	0.0129	4.4986
S_{6}	0.0953	5.3542	0.0152	4.4986
S_{7}	0.1014	13.7022	0.0162	11.5126
S_{8}	0.1178	13.7022	0.0188	11.5126
S_{9}	0.1349	13.7022	0.0216	11.5126
S_{10}	0.0766	5.3542	0.0122	4.4986
S_{11}	0.0897	5.3542	0.0143	4.4986
S_{12}	0.1039	5.3542	0.0166	4.4986
S_{13}	0.0413	21.4096	0.0066	17.9884
S_{14}	0.0511	21.4096	0.0082	17.9884
S_{15}	0.0619	21.4096	0.0099	17.9884
S_{16}	0.0706	7.7127	0.0113	6.4802
S_{17}	0.0832	7.7127	0.0133	6.4802
S_{18}	0.0969	7.7127	0.0155	6.4802
S_{19}	0.0737	16.9165	0.0118	14.2132
S_{20}	0.0885	16.9165	0.0141	14.2132
S_{21}	0.1047	16.9165	0.0167	14.2132
S_{22}	0.1245	9.5219	0.0199	8.0003
S_{23}	0.1436	9.5219	0.0229	8.0003

S_{24}	0.1640	9.5219	0.0262	8.0003
S_{25}	0.0672	30.8407	0.0107	25.9123
S_{26}	0.0813	30.8407	0.0130	25.9123
S_{27}	0.0969	30.8407	0.0155	25.9123

Applying the formula (17) to evaluate the weighted proximity index u_i, applying the formula (18) to calculate d_i. The ranking of options based on the value of d_i were implemented. The results are as shown in Table 7.

Table 7. Several parameters in *PIV*

Solutions	u_i		d_i	*Rank*
	Ra	*MRR*		
S_1	0.0000	25.0234	25.0234	25
S_2	0.0016	25.0234	25.0250	26
S_3	0.0034	25.0234	25.0268	27
S_4	0.0049	21.4138	21.4186	19
S_5	0.0070	21.4138	21.4207	21
S_6	0.0093	21.4138	21.4231	23
S_7	0.0103	14.3997	14.4100	10
S_8	0.0129	14.3997	14.4126	11
S_9	0.0157	14.3997	14.4154	12
S_{10}	0.0063	21.4138	21.4201	20
S_{11}	0.0084	21.4138	21.4222	22
S_{12}	0.0107	21.4138	21.4245	24
S_{13}	0.0007	7.9240	7.9247	4
S_{14}	0.0023	7.9240	7.9262	5
S_{15}	0.0040	7.9240	7.9279	6
S_{16}	0.0054	19.4321	19.4375	16
S_{17}	0.0074	19.4321	19.4395	17
S_{18}	0.0096	19.4321	19.4417	18
S_{19}	0.0059	11.6991	11.7050	7
S_{20}	0.0083	11.6991	11.7074	8
S_{21}	0.0108	11.6991	11.7100	9
S_{22}	0.0140	17.9120	17.9260	13
S_{23}	0.0171	17.9120	17.9291	14
S_{24}	0.0203	17.9120	17.9323	15
S_{25}	0.0048	0.0000	0.0048	1
S_{26}	0.0071	0.0000	0.0071	2
S_{27}	0.0096	0.0000	0.0096	3

After ranking the options according to the *WASPAS* and *PIV* methods as above, we find that two multi-criteria decision-making methods provide same results in twenty-two out of twenty-seven implemented options. Importantly, both methods indicate that the best option is the option S_{25}, and the worst one is the option S_3. In addition, the almost best options (rank: 2, 3, 4, ...) when ranked by the two methods also coincide; the almost worst options (rank: 25, 26) when ranked by the two methods also coincide. This affirms that the combination of the Entropy method with *WASPAS* and *PIV* methods has succeeded in *MCDM* in this study. Using the Entropy method to determine the weights for the criteria has helped the application of different *MCDM* methods all to indicate the best solution. This was also recommended in a recent study by the authors of this study [44].

The differences in the ranking order of options (S_{16}, S_{17}, S_{22}, S_{23}, S_{24}) have not been explained by the author of this paper at the present time. The most desired result of this study was achieved that both *WASPAS* and *PIV* methods show that for minimum surface roughness and maximum *MRR*, the values of workpiece speed, feed rate, depth of cut, dressing feed rate and dressing depth are 800 rev/min, 0.09 mm/rev, 0.015 mm, 100 mm/min and 0.05 mm, respectively.

6. CONCLUSION

In this paper, the experimental process of cylindrical grinding 65G steel using aluminum oxide grinding wheel was presented. The Taguchi method was applied to design the experimental matrix with a total of twenty-seven experiments. Workpiece speed, feed rate, depth of cut, dressing feed rate, and dressing depth were variables in each experiment. Surface roughness and *MRR* were selected as output parameters. The Entropy method was applied to determine the weight for each criterion. The *WASPAS* and *PIV* methods were applied for *MCDM*. Some conclusions are drawn as follows:

- With five surveyed parameters, dressing feed rate, dressing depth, workpiece speed, and feed rate has the greatest influence on the surface roughness. Meanwhile, the depth of cut has no significant influence on surface roughness.
- This is the first time that the Taguchi, Entropy, *WASPAS*, and *PIV* methods were combined to make the multi-criteria decision for grinding process. Both *WASPAS* and *PIV* method all determined same best solution.
- When making multi-criteria decisions by different methods, the Entropy method should be used to determine the weights for the criteria.
- The ranking order of options according to the *WASPAS* and *PIV* methods coincides with 22/27 options, equivalent to 81.5%.
- To ensure the minimum surface roughness and the maximum *MRR* simultaneously, the value of the workpiece speed, feed rate, depth of cut, dressing feed rate and dressing depth are 800 rev/min, 0.09 mm /rev, 0.015 mm, 100 mm/rev and 0.005 mm, respectively.
- In the futher work is the application of Taguchi, Entropy, *WASPAS*, and *PIV* methods to make multi-criteria decision of grinding process considering many criteria such as surface roughness, *MRR*, roundness deviation, dimensional accuracy, etc.

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