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APPLICATION OF TOPSIS AND PIV METHODS FOR MULTI-CRITERIA DECISION MAKING IN HARD TURNING PROCESS

In this study, *TOPSIS* and *PIV* methods were applied for multi-criteria decision making in hard turning process. Experiments have been conducted in accordance with an experimental matrix designed by the Taguchi method with a total of twenty-seven experiments. At each experiment, the values of coolant concentration, nose radius, coolant flow, cutting velocity, feed rate and depth of cut have been changed. Surface roughness, flank wear and roundness error have been selected as output criteria. The weights of criteria have been determined by three methods, inclusive of Equal weight, *ROC* weight and Entropy weight. The combination of multi-criteria decision-making methods with three weighting methods gives six ranking options of the experiments. The purpose of ranking the experiments is to find the experiment at which the three output parameters are ensured to have the minimum value simultaneously.

1. INTRODUCTION

Turning is the most common machining method among cutting and machining methods [1]. There are many criteria to evaluate turning process such as surface roughness, roundness error, cylindrical error, cutting force, tool wear, cutting power, etc. [2]. However, for a certain technology system, sometimes it is impossible to achieve the set objectives for all the criteria to be evaluated. In this case, consideration must be given to choosing a solution to harmonize the criteria simultaneously. This problem is known as multi-criteria decision-making.

There are many multi-criteria decision-making methods such as *VIKOR* [3], *TOPSIS* [4], *PIV* [5], etc. Among the decision-making methods having been just listed, *TOPSIS* is one of the most used methods, which has been used by many scientists to solve criteria-making in many different fields [6]. Several studies were performed using the *TOPSIS* method for multi-criteria decision making to select the machining parameters with simultaneously ensuring several criteria of machining processes. A study with aim is to select the cutting parameters (cutting speed, feed rate, and depth of cut) to simultaneously ensure that the six surface roughness parameters (including R_q, R_a, R_t, R_{ku}, R_z, and R_{sm}) having the smallest

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values. In this study, the weights of the criteria were determined by the Standard deviation method (*SDM*) [7]. Selecting the cutting parameters to simultaneously ensure the minimum surface roughness and the maximum material removal rate (*MRR*), where the weights of the parameters have been chosen by the decision-maker [8]. Selecting the cutting parameters to simultaneously ensure that the two parameters of the minimum values of the surface roughness (R_a and R_z) and maximum value of *MRR*, where the weights of the criteria were determined by the entropy method [9]. Study [10] determined the cutting parameters to simultaneously ensure the minimum value of surface roughness, the minimum values of flank wear, and the maximum value of *MRR*, where the weights of the criteria were determined by the Analytic hierarchy process method (*AHP*).

Selecting the cutting parameters to simultaneously ensure the minimum values of surface roughness, cutting force, flank wear, and heat of shear, and the maximum value of *MRR*, where weights of parameters were chosen by decision-makers [11]. Selecting the cutting parameters to simultaneously ensure the minimum values of surface roughness, cutting forces, flank wear, where weights of parameters were determined by decision-makers [12].

Study [13] was performed to determine the cutting parameters to simultaneously ensure the minimum values of surface roughness, cutting forces, flank wear, and cutting temperature, where the weights of the criteria were determined by the *AHP* method. Selecting the cutting parameters to simultaneously ensure the minimum value of surface roughness and maximum value of *MRR*, where weights of parameters were determined by decision-makers [12]. The decision of the cutting parameters to simultaneously ensure the minimum value of surface roughness and maximum value of MRR, where weights of parameters were determined by the Entropy method [15], and so on. From the above studies, some problems were drawn as follows:

Firstly, surface roughness and flank wear are often selected as criteria for evaluation of turning process. This is also easily explained because surface roughness directly affects workability and service life of the product, and flank wear affects not only tool durability but also machining accuracy (especially diameter error). However, there have not been any published studies having selected roundness error as a criterion for evaluation of turning process, while it is an important parameter to evaluate the workpiece surface of round cylinder. This parameter has a great effect on workability of machine parts [16].

Secondly, cutting velocity, feed rate, and depth of cut are often selected as input parameters during the experiment. This is also understandable because the adjustment of these parameters can be done easily by machine operator. However, the parameters of cooling and lubrication modes have not been mentioned in the above studies, while these parameters have a great effect on durability of cutting tool [17].

Thirdly, the analysed results from the above references showed that the Taguchi method is used to design the experimental matrix in most of the studies. This problem is also understandable because Taguchi is a method enabling to design a matrix with many input parameters, but the number of experiments is minimal (compared to other experimental design methods). Moreover, when designing the experimental matrix by the Taguchi method, it is unnecessary for the input parameter values to follow any certain rules, even the input parameters can be qualitative parameters [18].

Fourthly, many weighting methods for criteria have been. However, it must also be said that the determination of weights made by the decision of decision maker is an unreliable work, because then the weight of criteria depends heavily on the knowledge of decision maker. Even if the weights are determined by expert opinion, those weights depend on the design of questionnaire, the knowledge of expert and the number of asked experts. And this is a very time-consuming, even cost-intensive work [19].

Fifthly, in each published study, only one weighting method has been used, so the ranking results of options will depend heavily on the weighting method [19]. In order to ensure the reliability of the ranking results of options, it is necessary to rank the options in a number of ways, in each of which several different weighting methods should be used. Then, compare the raking of options by such methods, so that the ranking results of options have the necessary reliability.

The two simple weighting methods including Equal-weight method and Rank Order Centroid (*ROC*) weight method are considered to be the simplest methods, each using only one formula. Details on these two methods will be described in detail in the next part of this article. However, so far, there have been no studies applying these two methods to determine the weights for multi-criteria decision-making in turning process.

Multi-criteria ranking by the *PIV* method was first proposed in 2018 [5]. This method has been applied for multi-criteria decision-making in some cases such as in the ranking and selection of e-learning websites [20], in the selection of materials for the manufacture of several automotive parts [21], in the selection of elements of freight operations between EU countries [22], in the selection of additives for a manufacturing process [23]. However, so far, there have not been any studies applying this method to make multi-criteria decision for turning process.

From the detailed analysis above, on the basis of inheriting the previous studies as well as adding to the gap of problems that the previous studies have not carried out, both methods of *TOPSIS* and *PIV* for multi-criteria decision-making in turning process will be applied in this study. The criteria include surface roughness, flank wear and roundness error. The weights of criteria are determined by the three methods including Equal weight, *ROC* weight and Entropy weight. The experimental matrix has been designed by the Taguchi method with six input parameters including coolant concentration, nose radius, coolant flow, cutting velocity, feed rate and depth of cut. The purpose of this study is to simultaneously ensure that all the criteria are of small value.

2. WEIGHT METHODS

2.1. EQUAL WEIGHT METHOD

Equal weight is a method of selecting weights for equal criteria [24].

$$w_j = \frac{1}{n} \tag{1}$$

In which, n is the number of criteria.

2.2. RANH ORDER CENTROID WEIGHT METHOD (*ROC* WEIGHT METHOD)

ROC weight method is used to calculate the weight in accordance with the following formula [25].

$$w_j = \frac{1}{n}\sum_{k=i}^{n}\frac{1}{k} \tag{2}$$

In which, n is the number of criteria.

2.3. ENTROPY WEIGHT METHOD

The determination of the weights of criteria by Entropy weight method shall be conducted in accordance with the following steps [26].

Step 1. Determine the normalized value for the criteria.

$$p_{\mathrm{ij}} = \frac{y_{\mathrm{ij}}}{m + \sum_{i=1}^{m} y_{\mathrm{ij}}^2} \tag{3}$$

Where y_{ij} is the value of criterion j corresponding to option i; m is the number of options (number of experiments).

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

$$e_{\mathrm{j}} = -\sum_{i=1}^{m}\left[p_{\mathrm{ij}} \times \ln(\mathrm{p_{ij}})\right] - \left(1-\sum_{i=1}^{m} p_{\mathrm{ij}}\right) \times \ln\left(1-\sum_{i=1}^{m} p_{\mathrm{ij}}\right) \tag{4}$$

Step 3. Calculate the weight for each criterion.

$$w_j = \frac{1-e_j}{\sum_{j=1}^{m}\left(1-e_j\right)} \tag{5}$$

3. TWO MULTI CRITERIA DECISION MAKING METHODS

3.1. TOPSIS METHOD

The steps to follow the *TOPSIS* method are described as follows [4].

Step 1: Determine the conversion values in accordance with the formula.

$$y'_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{n} y_{ij}^2}} \tag{6}$$

Step 2: Calculate the normalized value in accordance with the formula.

$$Y = w_j . y'_{ij} \tag{7}$$

In which wj is the weight of the criterion j.

Step 3: Determine the best solution A^+ and the worst solution A^- for the criteria in accordance with the following two formulas.

$$A^+ = \{y_1^+, y_2^+, \dots, y_j^+, \dots, y_n^+\} \tag{8}$$

$$A^- = \{y_1^-, y_2^-, \dots, y_j^-, \dots, y_n^-\} \tag{9}$$

Where y_j^+ and y_j^- are the best and the worst values of criterion *j*, respectively.

Step 4: Determine the values of S_i^+ and S_i^- in accordance with the following two formulas.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_j^+\right)^2} \qquad i = 1, 2, \dots, m \tag{10}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_j^-\right)^2} \qquad i = 1, 2, \dots, m \tag{11}$$

Step 5: Determine the values of C_i^* in accordance with the formula.

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-} \qquad i = 1, 2, \dots, m; \ 0 \le C_i^* \le 1 \tag{12}$$

Step 6: Rank the options based on the principle that the option with the largest C_i^* is the best one.

3.2. PIV METHOD

The steps to follow the *PIV* method are as follows [5]:

Step 1, 2: Same as steps 1 & 2 of the *TOPSIS* method.

Step 3: Evaluate the weighted proximity index in accordance with the following formula.

$$u_i = \begin{cases} Y_{\max} - Y_i & \text{for } C_1, C_2, \dots, C_n \in B \\ Y_i - Y_{\min} & \text{for } C_1, C_2, \dots, C_n \in C \end{cases} \tag{13}$$

Where, *B* represents the criterion as large as possible, and *C* represents the criterion as small as possible.

Step 4. Determine the overall proximity value in accordance with the formula.

$$d_i = \sum_{j=1}^{n} u_i \tag{14}$$

Step 5. Rank the options based on the principle that the option with the smallest d_i is the best one.

4. TURNING PROCESS EXPERIMENT

In recent years, when cutting tools with high hardness and high heat resistance are manufactured more and more, hard turning is a fairly popular machining method for processing heat-treated parts with high hardness such as bearings, pins, shafts, mounting surfaces with bearings, etc. Hard turning is used not only for machining new products of these parts but also in the process of repairing (restoring) these ones. In the past, the grinding method was often used to machine the surfaces with high hardness. However, the grinding method has the disadvantage of limited machining productivity, on the other hand, the treatment of generated wastes by the grinding method is often quite expensive. Application of the hard turning method in this case not only overcomes the above limitations of the grinding method, but the surface roughness when turning hard is also equivalent, even smaller than that one by grinding method [27]. Besides, the residual stress on the surface layer of the part after turning is the compressive residual stress, which is especially better than that one by grinding, because when grinding, the residual stress on the surface layer is usually tensile residual stress [28].

In this study, the hard turning process of 9XC steel was conducted. This is a low alloy steel, but this steel has high hardness, while retaining good toughness, and being less deformed during heat treatment, thanks to the silicon and chromium content. This type of steel is often used to manufacture parts such as drill bits, reamers, forging dies, gears, and threading toolds. The steel stample has a diameter of 30 mm and a length of 280 mm. The preparation of the experimental workpieces was carried out in a sequence of steps including rough turning, center hole drilling, and heat treatment to reach a hardness of 61±0.5 HRC).

A CNC lather of DOOSAN (Korea) has been used to conduct the experiments. The Taguchi method has been used to design the experimental matrix with six parameters having been selected as input parameters for each experiment including coolant concentration, nose radius, coolant flow, cutting velocity, feed rate and depth of cut. Each parameter has been selected with three values corresponding to three encoding levels 1, 2 and 3. The type of cooling oil used in this study is the N60 industrial oil made in Vietnam. The flow rate and concentration of this oil have been selected in accordance with the instructtions of manufacturer [29].

The used insert is the TiN coated type, with the three different radius values of 0.3 mm, 0.5 mm and 0.8 mm respectively. This type of insert is very suitable for machining steels with high hardness and high heat resistance [30]. Each insert has been only used for a signle experiment. The values of cutting parameters have been selected based on reference to several documents when using TiN coated cutting piece [31, 32]. The values of input parameters corresponding to the three encoding levels are shown in Table 1. Twenty-seven experiments of the experimental matrix are shown in Table 2.

Surface roughness has been measured by SJ-201 machine (Mitutoyo -Japan), measuring head has a radius of 0.005 mm, the accuracy of this measurement is 0.001 μm. The standard length of the measurement has been set to 0.8 (mm). The surface roughness (R_a) value at each experiment is the average value of at least three consecutive measurements. Flank wear (VVB_{max}) has been measured using a VHX-600 digital microscope. The tool wear that was measured in each cutter insert was the largest value. Roundness error (*RE*) has been measured with a Crysta-Plus M544 contact type 3D coordinate measuring device. The roundness error at each experiment has been also calculated as the average value of three measurements on each sample at the three different cross sections of the workpiece. All workpieces and insert have been washed with alcohol and left to dry before taking measurements.

Table 1. Values of input parameters at levels

Parameter	Symbol	Unit	Value at level		
			1	2	3
Coolant concentration	*Cc*	%	0	5	10
Nose radius	*r*	mm	0.3	0.5	0.8
Coolant flow	*Cf*	l/min	0	8	16
Cutting speed	v_c	m/min	80	120	160
Feed rate	f_d	mm/rev	0.09	0.13	0.17
Depth of cut	a_p	mm	0.25	0.4	0.55

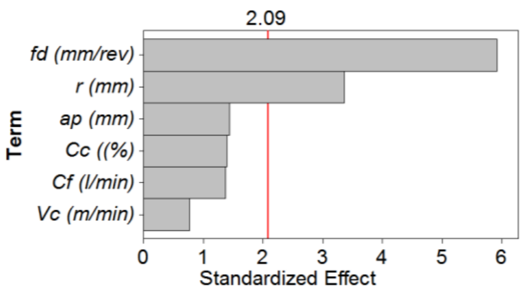
Table 2. Experimental matrix and responses

Trial.	*Code value*						*Real value*						*Response*		
	Cc	*r*	*C*	v_c	f_d	a_p	*Cc* (%)	*r* (mm)	*Cf* (l/min)	v_c (m/min)	f_d (mm/rev)	a_p (mm)	R_a (μm)	VVB_{max} (μm)	*RE* (μm)
1	1	1	1	1	1	1	0	0.3	0	80	0.09	0.25	0.338	2.131	1.250
2	1	1	1	1	2	2	0	0.3	0	80	0.13	0.4	1.072	2.513	2.889
3	1	1	1	1	3	3	0	0.3	0	80	0.17	0.55	1.805	2.898	5.194
4	1	2	2	2	1	1	0	0.5	8	120	0.09	0.25	0.207	1.734	1.875
5	1	2	2	2	2	2	0	0.5	8	120	0.13	0.4	0.627	2.113	4.333
6	1	2	2	2	3	3	0	0.5	8	120	0.17	0.55	1.360	2.495	6.222
7	1	3	3	3	1	1	0	0.8	16	160	0.09	0.25	0.552	1.332	2.500
8	1	3	3	3	2	2	0	0.8	16	160	0.13	0.4	0.182	1.712	5.778
9	1	3	3	3	3	3	0	0.8	16	160	0.17	0.55	0.915	2.094	7.106
10	2	1	2	3	1	2	5	0.3	8	160	0.09	0.4	0.457	1.863	4.000
11	2	1	2	3	2	3	5	0.3	8	160	0.13	0.55	1.190	2.241	6.378
12	2	1	2	3	3	1	5	0.3	8	160	0.17	0.25	1.523	2.385	4.722
13	2	2	3	1	1	2	5	0.5	16	80	0.09	0.4	0.318	0.718	2.000
14	2	2	3	1	2	3	5	0.5	16	80	0.13	0.55	0.405	1.093	3.972
15	2	2	3	1	3	1	5	0.5	16	80	0.17	0.25	0.738	1.234	2.361
16	2	3	1	2	1	2	5	0.8	0	120	0.09	0.4	0.438	1.811	3.000
17	2	3	1	2	2	3	5	0.8	0	120	0.13	0.55	0.385	2.193	5.958
18	2	3	1	2	3	1	5	0.8	0	120	0.17	0.25	0.718	2.333	3.542
19	3	1	3	2	1	3	10	0.3	16	120	0.09	0.55	0.235	0.845	4.125
20	3	1	3	2	2	1	10	0.3	16	120	0.13	0.25	0.568	0.987	2.708
21	3	1	3	2	3	2	10	0.3	16	120	0.17	0.4	1.302	1.362	5.667
22	3	2	1	3	1	3	10	0.5	0	160	0.09	0.55	0.215	1.945	5.500
23	3	2	1	3	2	1	10	0.5	0	160	0.13	0.25	0.548	1.082	3.611
24	3	2	1	3	3	2	10	0.5	0	160	0.17	0.4	1.282	2.462	8.211
25	3	3	2	1	1	3	10	0.8	8	80	0.09	0.55	0.570	0.793	2.750
26	3	3	2	1	2	1	10	0.8	8	80	0.13	0.25	0.236	0.934	1.806
27	3	3	2	1	3	2	10	0.8	8	80	0.17	0.4	0.497	1.315	3.778

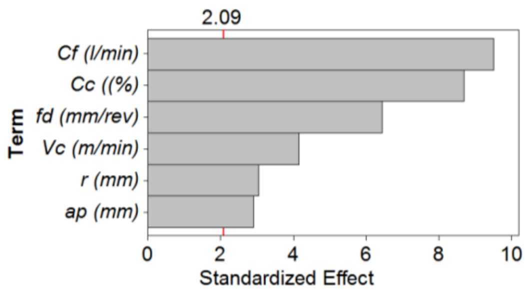
5. RESULTS AND DISCUSSION

The results of measuring output parameters (R_a, VVB_{max} and RE) have been also included in Table 2. Minitab 16 statistical software has been used to analyze the experimental results. In accordance with the documents [33], the significance level should be chosen as 0.05. From there, we get the Pareto chart of the effect of input parameters on output parameters in Figure 1. The red line is the limiting line of the chart, the grey rectangles represent input parameters. The rectangle exceeding the red line corresponds to the input parameter having a significant effect on output parameters [33]. Accordingly, we have the following observations:

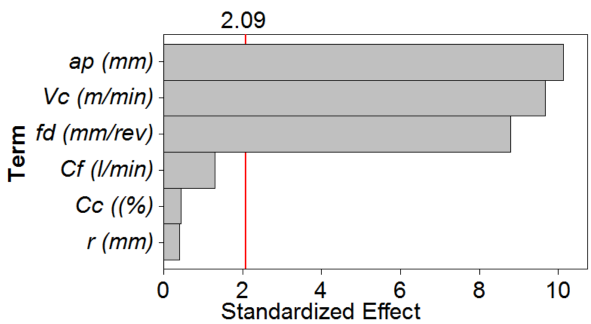
- Among the six input parameters, only feed rate and nose radius have a significant effect on surface roughness (Figure 1a), in which the effect of feed rate on surface roughness is greater than that of nose radius. This result is also consistent with many confirmed theretical studies, i.e. surface roughness can be calculated through two parameters of feed rate and depth of cut such as $R_a = 1000 \times 0.0321\, f_d^2/r$ [34]. In this formula, the feed rate is much larger than the nose radius, so it is understandable that the effect of feed rate on surface roughness is greater than that of depth of cut.



a) for surface roughness



b) for flank wear



c) for roundness error

Fig 1. Effects Parato for responses

- All six input parameters have a significant effect on flank wear (figure 1b). This is explained by the fact that when changing the concentration and flow of the coolant, it will lead to a change in the heat transfer to the cutting tool, which in turn affects the flank wear [35]. Changing the cutting parameters will change both the machining time as well as the material removal rate, which in turn affects the degree of tool wear [36]. Figure 1b also shows the effect of parameters on tool wear increasing gradually in the order of depth of cut, nose radius, cutting velocity, feed rate, coolant concentration, and coolant flow is the parameter having the greatest effect on tool wear.

- Depth of cut is the parameter having the strongest effect on roundness error, followed by the effect of cutting velocity. The effect of feed rate on roundness error is at the third position, while the remaining three parameters have a negligible effect on roundness error (Figure 1c). Depth of cut is the factor directly affecting the component of radial foce acting on the workpiece, while cutting velocity and feed rate are the factors affecting the acting duration of this force component impacting on the workpiece surface [37]. This is the reason why these three cutting parameters significantly affect roundness error.

Thus, we see that the effect of input variables on output parameters is not the same, for example, depth of cut is the parameter having the greatest effect on roundness error. It is also the parameter significantly affecting tool wear, but it is the parameter negligibly affecting surface roughness. In another case, the concentration and flow of coolant have a significant effect on tool wear, but they have a negligible effect on surface roughness and roundness error. Nose radius has a negligible effect on roundness error but has a significant effect on surface roughness and tool wear, etc. From these observations, it can be seen that the values of input parameters will not be determined to ensure the minimum value of all three output parameters if only observing the charts in Figs. 1a to 1c. In accordance with the data in Table 2, the surface roughness is the smallest in the experiment *#8*, the tool wear is the smallest in the experiment *#13*, and the roundness error is the smallest in the experiment *#1*. This also clearly shows that it is impossible to exist an experiment (out of twenty-seven conducted experiments) where all three output parameters are ensured to be minimum. What we can do is to find an experiment where all three parameters are considred "minimum", which will be considered the best. And obviously, it is also impossible to find that best experiment through observing the data in Table 2 or the chart (Fig. 1), but we have to make the multi-criteria decision based on determining the weights for criteria as well as using tools to make the multi-criteria decision, these tools must be based on solid foundations of mathematics.

6. MULTI CRITERIA DECISION MAKING IN TURNING IN TURNING PROCESS

6.1. DETERMINATION OF THE WEIGHTS FOR THE CRITERIA

In this part, the weights of surface roughness, flank wear and roundness error will be determined by three different methods. Using the formula (1) to calculate the weights for the criteria by the Equal weight method with the weights for the criteria of R_a, VVB_{max} and RE being all equal to 0.3333. Using the formula (2) to calculate the weights for the criteria by the *ROC* weight with the weights for the criteria of R_a, VVB_{max} and RE being equal to 0.6111, 0.2778 and 0.1111, respectively.

In order to calculate the weight of criteria by the Entropy weight method, we follow the following steps:

– Determine the value of p_{ij} in accordance with the formula (3).
– Applying the formula (4) to calculate the e_j values for the criteria of R_a, VVB_{max} and RE being 1.9574, 1.9493 and 1.1210, respectively.
– Applying the formula (5) to calculate the e_j values for the criteria of R_a, VVB_{max} and RE being 0.4277, 0.4682 and 0.0597, respectively.

Thus, the weights of the criteria determined by the three methods above are summarized in Table 3.

Table 3. Weight of criteria

Method	Weight of criteria		
	R_a	VVB_{max}	RE
Equal weight	0.3333	0.3333	0.3333
ROC weight	0.6111	0.2778	0.1111
Entropy weight	0.4277	0.4682	0.0597

6.2. MAKING THE MULTI CRITERIA DECISION USING THE TOPSIS METHOD

Applying the formula (6) to calculate the y'_{ij} values for each criterion in each experiment.

Applying the formula (7) to calculate the Y_{ij} normalized values. This work has been performed three times for three sets of values of the weights having been calculated by the three methods.

Applying the formulas (8) and (9), determine the A^+ and A^- for each criterion. The results are shown in Table 4.

Applying the formulas (10) and (11) to determine the S_i^+ and S_i^- values for each criterion in each experiment. This work has been also performed three times corresponding to the three sets of weights of the criteria.

Applying the formula (12) to determine the C_i^* value for the criteria at each experiment.

Table 4. A+ and A– values of each criterion

	Criterion		
	R_a	VVB_{max}	RE
A^+	0.1820	0.7180	1.2500
A^-	1.8050	2.8980	8.2110

6.3. MAKING THE MULTI CRITERIA DECISION USING PIV METHOD

The results have been obtained according to the method *PIV* with y'_i and normalised Y_{ij} values calculated similarly to the *TOPSIS* method.

Applying the formula (13) to calculate the u_i values for the criteria at each experiment. This work has been also performed three times corresponding to the three sets of weights of the criteria.

Applying the formula (14) to determine the d_i value for the criteria at each experiment. This work has been also performed three times corresponding to the three sets of weights of the criteria. The ranking of options has also been carried out.

Thus, the ranking of options has been completed. For the convenience of comparison between methods, the summarization has been carried out and shown in Table 5.

For convenience of observation process, we briefly call the combination of multi-criteria decision-making method with weighting method in the following form: For example, when using a multi-criteria decision-making method as *TOPSIS*, with the weights calculated by the Equal weight method, we refer to as *TOPSIS-Equal* method. Similarly, we have the methods of *TOPSIS-Entropy*, *PIV-Equal, PIV-ROC,* and *PIV-Entropy*.

Table 5. Ranking of options by methods

Trial.	Ranking of options by methods					
	TOPSIS method			*PIV method*		
	Equal weight	*ROC* weight	Entropy weight	Equal weight	*ROC* weight	Entropy weight
1	22	17	13	7	8	14
2	13	8	6	20	21	22
3	5	5	1	27	27	27
4	23	21	17	3	4	6
5	11	10	10	17	18	18
6	3	2	3	25	25	25
7	20	20	19	8	13	11
8	9	12	14	14	5	8
9	2	3	7	22	20	20
10	14	14	12	15	15	16
11	4	4	4	23	23	23
12	7	7	5	24	26	26
13	27	27	27	2	2	1
14	17	18	22	9	6	4
15	21	22	20	11	17	15
16	16	15	15	13	14	13
17	6	6	9	19	16	17
18	12	9	8	18	19	19
19	19	23	24	4	3	3
20	24	24	23	6	10	7
21	10	13	16	21	22	21
22	8	11	11	16	7	12
23	18	19	21	10	11	9
24	1	1	2	26	24	24
25	25	25	25	5	9	5
26	26	26	26	1	1	2
27	15	16	18	12	12	10

From the ranking results of options by the six methods as shown in Table 5, we have comments:

– The *TOPSIS-Entropy* method shows that experiment *#3* is the best one. Meanwhile, the methods of *PIV-Equal*, *PIV-ROC,* and *PIV-Entropy* show that experiment *#3* is the worst one. This makes us review the data in Table 2. In experiment #3, $R_a = 1.805$ μm, $VVB_{max} = 2.898$ μm, and $RE = 5.194$ μm. We see that all three of these values are relatively large compared with the values of corresponding parameters in other experiments. Just comparing experiment *#3* with its two neighbors, experiment *#2* and experiment *#4*, it also shows that experiment *#3* is worse than both of these experiments. Specifically, in experiment *#2*, $R_a = 1.072$ μm, $VVB_{max} = 2.513$ μm, and $RE = 2.889$ μm. So obviously experiment *#3* is worse than experiment *#2*. For experiment #4, $R_a = 0.207$ μm, $VVB_{max} = 1.734$ μm, $RE = 1.875$ μm. Thus, experiment #3 is also worse than experiment *#2*. Since then, it shows that the *TOPSIS-Entropy* method have not identified the best experiment among the twenty-seven conducted experiments.

– The two methods of *TOPSIS-Equal* and *TOPSIS-ROC* show that experiment *#24* is the best one, while *PIV-Equal* method shows that experiment *#24* ranks twenty-sixth, and the two methods of *PIV-ROC* and *PIV-Entropy* show that experiment *#24* ranks twenty-fourth. This problem also requires us to review the data in Table 2. In experiment *#24*, $R_a = 1.282$ μm, $VVB_{max} = 2.462$ μm, $RE = 8.211$ μm. When comparing these values with the values of corresponding parameters in experiment *#23* and experiment *#25*, it shows that experiment *#24* is worse than experiment *#23* and experiment *#25*. Since then, it shows that the two methods of *TOPSIS-Equal* and *TOPSIS-ROC* have also failed to identify the best experiment among the twenty-seven conducted experiments.

– The two methods of *PIV-Equal* and *PIV-ROC* show that experiment *#26* is the best one, while *PIV-Entropy* shows that experiment *#26* ranks at the second position. *PIV-Entropy* shows that experiment *#13* is the best one, while the two methods of *PIV-Equal* and *PIV-ROC* show that experiment *#13* ranks at the second position. Thus, we see that among these three methods (*PIV-Equal, PIV-ROC, and PIV-Entropy*), there is an interchange in terms of first position and second position in the ranking of experiments. The interchange of first and second order of experiments makes us difficult to determine which experiment is the best one. In experiment #13, $R_a = 0.318$ μm, $VVB_{max} = 0.718$ μm, $RE = 2.000$ μm, and in experiment *#26*, $R_a = 0.236$ μm, $VB = 0.934$ μm, $RE = 1.806$ μm. Thus, R_a and RE in experiment *#13* are 34.74% and 10.74% higher than the values of the parameters in experiment *#26*, respectively. However, VVB_{max} in experiment *#26* is about 30.08% higher than that in experiment *#13*. This also makes us difficult to decide which experiment is better between experiment *#13* and experiment *#26*. In fact, R_a, VVB_{max} and RE values in experiment *#13* and experiment *#26* are not much different. Since then, in the opinion of the authors of this article, experiment *#13* and experiment *#26* are similar. Thence, it can be said that both of these experiements are considered as “the best”. The data in Table 2 also show that there is no better experiment than these two. In this study, the *TOPSIS* method did not determine the best solution because, main weak points in *TOPSIS* method are ranked based on the closeness coefficient values that solves the multi-response problem by establishing the Euclidean distance function which measures the distance from the ideal solution and also methodology fails to relate the machining characteristics [38].

Thus, in order to simultaneously ensure the minimum values of all three parameters (R_a, VVB_{max} and *RE*), we can choose experiment #13 or experiment #26. Correspondingly, we can choose two sets of values of input parameters: *Cc* = 5%, *r* = *0.5* mm, *Cf* = 16 l/min, *Vc* = 80 m/min, *fd* = 0.09 mm/rev, *ap* = 0.4 mm, or *Cc* = 10%, *r* = 0.8 mm, *Cf* = 8 l/min, *Vc* = 80 m/min, *fd* = 0.13 mm/rev, *ap* = 0.24 mm.

7. CONCLUSION

The experimental process of hard turning 9XC steel has been carried out in this study. The experimental matrix has been designed by the Taguchi method with a total of twenty-seven experiments. Six selected parameters are variations in each experiment including coolant concentration, nose radius, coolant flow, cutting velocity, feed rate and depth of cut. Surface roughness, tool wear and roundness error have been selected as output parameters. The three methods of Equal weight, *ROC* weight and Entropy weight have been used to determine the weights for criteria. The two multi-criteria decision-making methods of *TOPSIS* and *PIV* have been used. A number of conclusions are drawn as follows:

1. Feed rate is the parameter having the greatest effect on surface roughness, followed by the effect of nose radius, while the remaining four input parameters have a negligible effect on surface roughness.
2. All six input parameters significantly affect tool wear, in which coolant flow is the parameter having the strongest effect on tool wear, followed by the effect of coolant concentration, feed rate, cutting velocity, nose radius and finally depth of cut.
3. All three cutting parameters have a significant effect on roundness error, in which depth of cut is the parameter having the strongest effect on roundness error, followed by the effect of cutting velocity and feed rate. The remaining three input parameters have a negligible effect on roundness error.
4. In all three cases using three different weighting methods, if using the *TOPSIS* method, it is impossible to determine the best experiment among the twenty-seven conducted experiments.
5. Comparison between *PIV* and *TOPSIS* shows the advantage of *PIV* over *TOPSIS* method in optimizing the output responses in the present experimental environment.
6. In order to simultaneously ensure the small values of surface roughness, tool wear and roundness error, two sets of input parameters can be used as follows: *Cc* = 5%, *r* = 0.5 mm, *Cf* = 16 l/min, *Vc* = 80 m/min, *fd* = 0.09 mm/rev, *ap* = 0.4 mm, or *Cc* = 10%, *r* = 0.8 mm, *Cf* = 8 l/min, *Vc* = 80 m/min, *fd* = 0.13 mm/rev, *ap* = 0.24 mm.

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