The combination of Taguchi and Proximity Indexed Value methods for multi-criteria decision making when milling

Nguyen Lam Khanh, Nguyen Van Cuong*
University of Transport and Communications, Hanoi, Vietnam
*Email: nguyencuong@utc.edu.vn

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Abstract- Milling is a commonly used method in mechanical machining. This is considered to be the method for the highest productivity among cutting methods. Moreover, the quality of the machined surface is increasingly improved as well as the machining productivity is increasingly enhanced thanks to the development of machine tool and cutting tool manufacturing technology. Therefore, in each specific processing condition (about machine, tool and part material, and other conditions), specific studies are required to determine the value of technological parameters in order to improve productivity and machining accuracy. Only in this way can we take full advantage of the capabilities of modern equipment. The process parameters in the milling method in particular and in the machining and cutting methods in general can be easily adjusted by the machine operator as the parameters of the cutting parameters or the change of tool types. In this article, the combination of Taguchi and Proximity Indexed Value (*PIV*) methods is presented for multi-criteria decision making in milling. An experimental matrix was designed according to Taguchi method with five input parameters, including the insert materials (*TiN*, *TiCN*, and *TiAlN*), nose radius, cutting velocity, feed rate and depth of cut. The total number of experiments that were performed was twenty-seven. The workpiece used during the experiment was SCM440 steel. At each experiment, the surface roughness was measured and the Material Removal Rate (*MRR*) was calculated. The weights of these two parameters have been chosen by the decision maker on the basis of consultation with experts. The *PIV* method was applied to determine the experiment at which the minimum surface roughness and the maximum *MRR* were simultaneously guaranteed. In addition, the influence of input parameters on surface roughness was also found in this study.

Keywords: Milling, Multi-criteria decision-making, Taguchi, PIV, surface roughness, MRR

I. INTRODUCTION

Milling is a very commonly used method in mechanical machining. This is considered to be the most productive of all cutting methods [1, 2]. On the other hand, with the development of the manufacturing technology of machine tools and cutting tools as well as many other factors, the milling method also provides more and more high accuracy. In order to fully exploit the advantages of equipment and tools in the milling field, a number of studies have been conducted to determine the value of technological parameters for the purpose of simultaneously ensuring certain criteria. This problem is known as multi-criteria decision making in milling (some studies also call this type of multi-criteria decision making problem a multiple objective optimization problem).

There are many mathematical methods for multi-criteria decision making such as Technique for Order Preference by Similarity to Ideal Solution (*TOPSIS*) [3], *VIKOR* [4], Multiobjective Optimization On the basis of Ratio Analysis (*MOORA*) [5]], COmplex PROportional ASsessment (*COPRAS*) [6], Reference Ideal Method (*RIM*) [7], Proximity indexed value (*PIV*) [8] etc. Several of these methods have been combined with the Taguchi method for multi-criteria decision making during the milling process.

The Taguchi and *MOORA* methods were combined to make a decision for choosing the value of cutting parameters to simultaneously ensure the minimum flank wear and the maximum *MRR* [9]. The authors of this study designed a matrix of experiments according to the Taguchi method with a total of twenty-seven experiments. The test material used was medium steel. As a result, they identified one experiment out of a total of twenty-seven experiments performed (i.e. determining the value of cutting speed, feed rate and depth of cut) in which both roughness and Surface and tool wear are minimized.

The Taguchi and *MOORA* methods have also been combined to make a decision for choosing the insert material, the cutting velocity and the feed rate in order to simultaneously ensure the minimum surface roughness and the maximum *MRR* [10]. The type of workpiece material used in this study is the Ti-6Al-4V alloy. Two types of insert have been used, *PVD* coated and *CVD* coated. A matrix of eighteen experiments was designed according to the Taguchi method. This study identified the best experiment (out of a total of eighteen experiments performed) where the cutting piece material was *CVD*, the cutting speed was 150 m/min, and the feed rate was 0.09 mm/min.

The Taguchi method has been combined with the *RIM* method to determine the material of inserts and the value of the cutting velocity, the feed rate and the depth of cut to ensure simultaneous the minimum surface roughness and the maximum *MRR* [11]. The test material used was SKD11 steel. In this study, a matrix of twenty-seven experiments was also designed according to the Taguchi method with input parameters being the cutting material (including three types: *TiN*, *TiCN* and *TiAlN*), nose radius, cutting speed, feed rate and depth of cut. This study has determined the experiment in which the insert material is TiCN, 0.3 mm is the value of the tip radius, 125 m/min is the value of the cutting velocity, the feed is 500 mm/min , and 0.45 is the value of the depth of cut. With these values of the input parameters, the maximum *MRR*, the minimum cutting force and the minimum surface roughness are guaranteed.

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 [8]. The *PIV* method is known as a multi-criteria decision making method which enables to minimize the possibility of reversibility to solutions [8]. This method has been successfully applied in multi-criteria decision making when ranking and selecting E-learning sites [12], for the selection of materials for manufacturing some parts of automobiles [13], for the selection of elements for logistics activities of the EU countries [14], for the selection of additives in a production process [15], etc. However, until now, there have been no studies that apply this method for multi-criteria decision making in milling.

From the above arguments, this study will conduct an experiment on the milling process according to the matrix designed by the Taguchi method. The *PIV* method will be applied for multi-criteria decision making. The ultimate goal of this study is to determine the type of insert material, nose radius, cutting velocity, feed rate and depth of cut in order to simultaneously ensure the minimum surface roughness and the maximum *MRR*. The results of this study can be directly applied to the selection of the insert material, the nose radius, and the cutting parameters to ensure the minimum surface roughness and the maximum *MRR* when milling SCM440 steel. In addition, the methodology presented in this study can also be applied to perform multi-criteria decision-making studies in other machining processes.

II. MILLING EXPERIMENT

HAAS 3-axis CNC milling machine was used to perform the experiments. This machine uses HASS (USA) operating system, using touch screen. The tool travel in the X, Y and Z directions is 3048 mm, 813 mm and 762 mm, respectively. The maximum speed of the spindle is 7500 rpm, the power is 22.4KW. The maximum feed rates along the *X*, *Y*, and *Z* axes are 9.1 m/min, 15.2 m/min and 15.2 mm/min, respectively. The tool holder is SMTC type, can hold thirty-one tools at the same time. Spindle speed and feed speed in all directions are steplessly adjusted according to the intended use.

SCM440 steel was selected to perform the experiments in this study. This steel has a hight content of *Cr* and *Mo*. Thanks to that, it has the advantage of high hardness but still ensures toughness. This steel is often used to make parts that are subject to heavy loads and require high wear resistance such as gears, plastic injection molds, sliding surfaces or some parts in automobile engines. These parts often have planes that need to be machined to ensure high accuracy. The workpieces has the length, width, and height of 100 mm, 50 mm, and 40 mm, respectively. Before performing the experiments, the workpieces were subjected to rough milling to ensure the same size and quality of all samples. The experimental matrix was designed according to the Taguchi method with five input parameters including insert material, nose radius, cutting velocity, feed rate and depth of cut. Each input parameter is selected with three value levels as shown in Table 1. The selection of values for input parameters according to their values in the study [11]. The experimental matrix of twenty-seven experiments is shown in Table 2. In each experiment, two new inserts of the same type with the diameter of 14 mm were installed on the tool body, these two inserts were installed symmetrically. The fact that each chip is used only once is intended to reduce the influence of flank wear on responses.

During the experiment, the coolant was Tectyl cool 240 (Korea) oil, mixed with water to reach a concentration of 8%, with a flow of 22 liters/min. This coolant type is commonly used in CNC milling technology [16].

Surface roughness was measured with the SJ201 machine of Mitutoyo - Japan, with the standard length of the measurement being 0.8 mm. Before surface roughness measurement, the workpieces were washed with alcohol, then allowed to dry. The purpose of this is to ensure the surface of the part is clean and pure, ensuring the accuracy of the measurement. In addition, in order to minimize the errors that may appear in the measurement process, each sample was measured at least three times in a row. Taking the average value of consecutive measurements, we will get the surface roughness value at each experiment.

MRR is calculated according to formula (1).

$$MRR = V_f \cdot a_p . b_w \ (mm^3/min) \quad (1)$$

Of which:

V_f: is the feed rate in minutes.

b_w is the milling width. In this case a symmetrical milling was performed, which means that the milling width is equal to the diameter of the tool itself, i.e. $b_w = 14$ *mm.*

Table 1. The value of input parameters at levels

Parameter	Symbol	Unit	Value at levels		
			1	2	3
Insert material	*IM*	-	TiN	TiCN	TiAlN
Tool nose radius	r	mm	0.3	0.5	0.8
Cutting velocity	v_c	m/min	100	125	150
Feed rate	V_f	mm/min	300	400	500
Depth of cut	a_p	mm	0.25	0.35	0.45

Table 2. Experimental matrix and results

Trial	Code value					Actual value					Response	
	IM	r	v_c	f_z	a_p	*IM*	r (mm)	v_c (m/min)	V_f (mm/min)	a_p (mm)	*Ra* (μm)	*MRR* (mm^3/min)
1	1	1	1	1	1	TiN	0.3	100	300	0.25	0.823	1050
2	1	1	1	1	2	TiN	0.3	100	300	0.35	1.556	1470
3	1	1	1	1	3	TiN	0.3	100	300	0.45	1.812	1890
4	1	2	2	2	1	TiN	0.5	125	400	0.25	1.642	1400
5	1	2	2	2	2	TiN	0.5	125	400	0.35	0.966	1960
6	1	2	2	2	3	TiN	0.5	125	400	0.45	1.053	2520
7	1	3	3	3	1	TiN	0.8	150	500	0.25	2.355	1750
8	1	3	3	3	2	TiN	0.8	150	500	0.35	1.690	2450
9	1	3	3	3	3	TiN	0.8	150	500	0.45	0.921	3150
10	2	1	2	3	1	TiCN	0.3	125	500	0.25	0.267	1750
11	2	1	2	3	2	TiCN	0.3	125	500	0.35	0.327	2450
12	2	1	2	3	3	TiCN	0.3	125	500	0.45	0.733	3150
13	2	2	3	1	1	TiCN	0.5	150	300	0.25	0.985	1050
14	2	2	3	1	2	TiCN	0.5	150	300	0.35	2.661	1470
15	2	2	3	1	3	TiCN	0.5	150	300	0.45	0.928	1890
16	2	3	1	2	1	TiCN	0.8	100	400	0.25	0.902	1400
17	2	3	1	2	2	TiCN	0.8	100	400	0.35	2.829	1960
18	2	3	1	2	3	TiCN	0.8	100	400	0.45	1.418	2520
19	3	1	3	2	1	TiAlN	0.3	150	400	0.25	0.508	1400
20	3	1	3	2	2	TiAlN	0.3	150	400	0.35	0.287	1960
21	3	1	3	2	3	TiAlN	0.3	150	400	0.45	0.481	2520
22	3	2	1	3	1	TiAlN	0.5	100	500	0.25	1.209	1750
23	3	2	1	3	2	TiAlN	0.5	100	500	0.35	2.681	2450
24	3	2	1	3	3	TiAlN	0.5	100	500	0.45	0.728	3150
25	3	3	2	1	1	TiAlN	0.8	125	300	0.25	0.758	1050
26	3	3	2	1	2	TiAlN	0.8	125	300	0.35	2.153	1470
27	3	3	2	1	3	TiAlN	0.8	125	300	0.45	2.225	1890

III. EXPERIMENT RESULTS AND DISCUSSION

The experimental results have also been included in Table 2. Figure 1 shows a chart representing the influence of input parameters on the surface roughness. The influence of the interaction between input parameters on the surface roughness is presented in Figure 2.

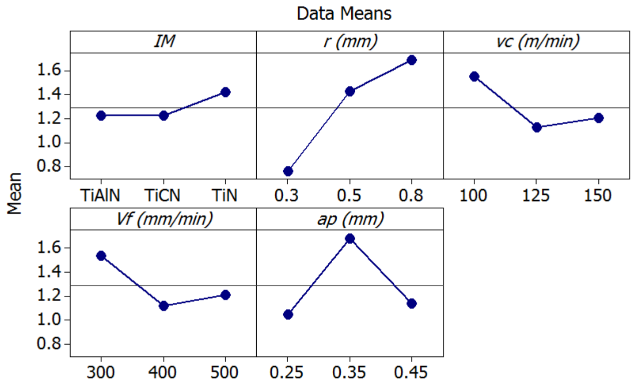
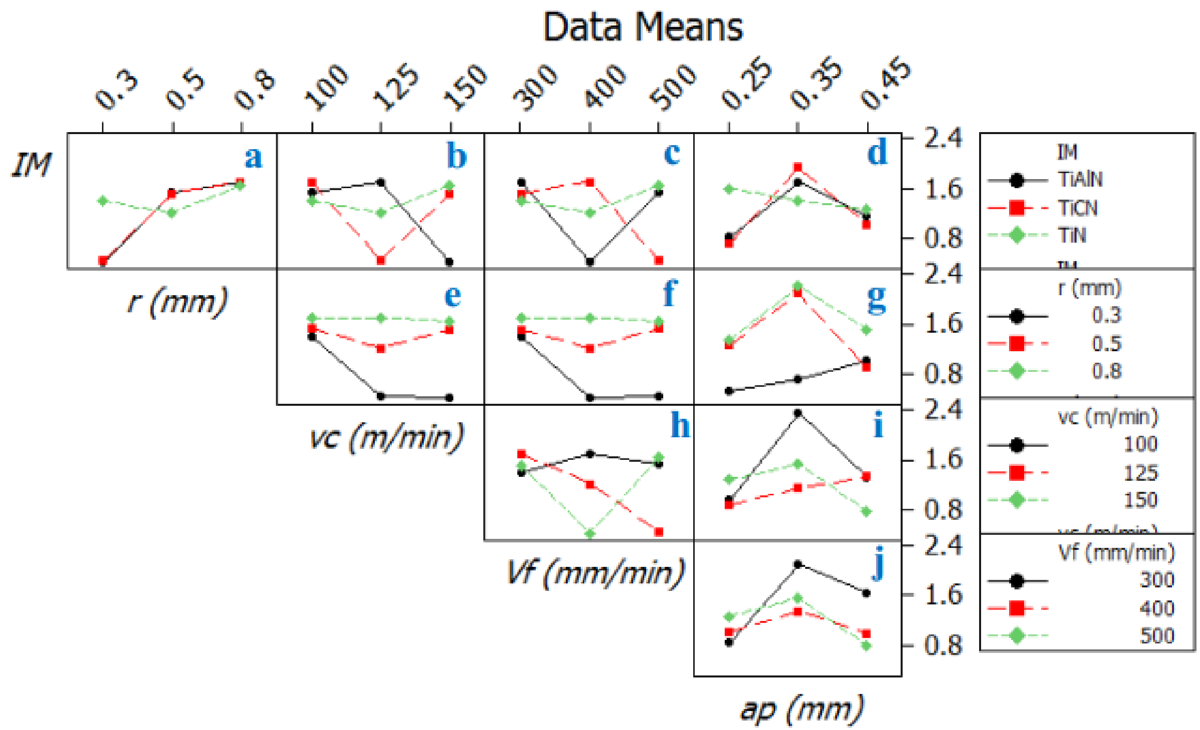


Figure 1. Main effects plot for Ra

Based on the difference between the points represented at level 1 and level 3 of each graph in Figure 1, it shows that the nose radius is the parameter with the greatest influence on the surface roughness, followed by the influence of the cutting velocity, the feed rate has the influence on the surface roughness at position 3, while the insert material and the depth of cut have little followed on the surface roughness. These phenomena are explained as follows. When changing the nose radius, it changes both the shape and size of the scratch left by the cutting tool on the surface of the part, thereby changing the surface roughness. When the cutting speed and the feed rate change, the contact time between a point on the workpiece surface and the cutting tool will change, that is, the degree of "re-cut" of the cutting tool to the surface will change, thus affecting the surface roughness. The type of insert material and the cutting depth have little influence on the surface roughness, which is explained by the fact that all three types of inserts have high titanium content and therefore have high temperature resistance, which is the cause of reduced phenomenon plastic deformation of the surface metal layer (plastic deformation of the surface metal layer is one of the main causes affecting the surface roughness). Therefore, changes in the insert material and cutting depth have little effect on the surface roughness.



a) Interaction between *IM* and *r*; b) Interaction between *IM* and v_c; c) Interaction between *IM* and V_f; d) Interaction between *IM* and a_p; e) Interaction between *r* and v_c; f) Interaction between *r* and V_f; g) Interaction between *r* and a_p; h) Interaction between v_c and V_f; i) Interaction between v_c and a_p; and j) Interaction between *IM* and a_p.

Figure 2. Interaction plot for Ra

In Figure 2 there are ten sub-figures, each of which corresponds to the interaction effect between the two input parameters on the surface roughness. Observing these sub-figures shows that the interaction effect of input parameters on surface roughness is very complex. Just analyzing some of these ten figures will further clarify this statement. For example, let's analyze figure a and figure b.

- In the first sub-figure (figure a), when the insert material is TiN, the surface roughness will decrease if the nose radius increases from 0.3 mm to 0.5 mm, but if the nose radius increases from 0.5 mm to 0.8 mm, the surface roughness will increase. For two types of chips, *TiCN* and *TiAlN*, when the nose radius increases from 0.3 mm to 0.5 mm, the surface roughness increases rapidly, but if the nose radius increases from 0.5 mm to 0.8 mm, the surface roughness increases slowly.
- In the second sub-figure (figure b), when the insert material is *TiN*, the surface roughness will decrease slowly as the cutting velocity increases from 100 m/min to 125 m/min, but if the cutting velocity increases from 125 m/min to 150

m/min, the surface roughness will increase slowly. When the insert material is *TiCN*, the surface roughness will decrease rapidly if the cutting velocity increases from 100 m/min to 125 m/min, but the surface roughness will increase rapidly if the cutting velocity increases from 125 m/min to 150 m/min. In the case the insert material is *TiAlN*, if the cutting velocity increases from 100 m/min to 125 m/min, the surface roughness increases slowly, but if the cutting velocity increases from 125 m/min to 150 m/min, the surface roughness will decrease rapidly.

The detailed analysis above indicates that the input parameters and their interactions have a very complex influence on the surface roughness. When simultaneously considering two parameters, surface roughness and *MRR*, it is also shown that the input parameters have a very complex influence on both of these parameters. It can be said that because as analyzed above (for example: considering Figure 1), the depth of cut has little influence on the surface roughness but has much influence on *MRR*. In contrast, the cutting velocity has significant influence on the surface roughness but had no influence on *MRR*. Similarly, the nose radius has great influence on the surface roughness but has no influence on *MRR*. Thereby, it shows that it is impossible to determine the value of input parameters to simultaneously ensure the minimum surface roughness and the maximum *MRR* if only observing the graph in Figures 1 and 2.

When observing the experimental data in Table 2, it shows that *MRR* has the maximum value of 3150 mm^3/min in experiments 9, 12 and 24. But also in these experiments, the surface roughness has the corresponding values of 0.921 µm, 0.733 µm and 0.728 µm. These three values are not the minimum one for surface roughness in Table 2. The minimum value of surface roughness is 0.267 µm, corresponding to experiment 10, but *MRR* in this experiment is quite small (equal to 1750 mm^3/min). This affirms that it is impossible to obtain an experiment at which the minimum surface roughness and the maximum *MRR* are simultaneously guaranteed. The concept of "*minimum*" for surface roughness and the concept of "*maximum*" for *MRR* can only be understood relatively. And of course, in order to determine the experiment at which the "*minimum*" surface roughness and the "*maximum*" MRR are simultaneously guaranteed, it is necessary to study multi-criteria decision making. This content will be presented in the next part of this article.

IV. MULTI-CRITERIA DECISION MALKING WHEN MILLING

A. PIV method

PIV is a method for multi-criteria decision making that was first introduced in 2018 [8]. The steps to implement multi-criteria decision making according to this method are as follows:

Step 1: Describe solutions *Ai (with j = 1, 2, …, m)* and criteria *Ci (with j = 1, 2,…., n).*

Step 2. Build a decision-making matrix *Y* by arranging the solutions by rows and the criteria by columns as in the form of formula (2).

$$Y = \left[Y_{ij} \right]_{m\times n} = \begin{bmatrix} Y_{11} & Y_{12} & \cdots & Y_{1j} & \cdots & Y_{1n} \\ Y_{21} & Y_{22} & \cdots & \cdots & \cdots & Y_{2n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ Y_{i1} & \cdots & \cdots & Y_{ij} & \cdots & Y_{in} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ Y_{m1} & \cdots & \cdots & Y_{mj} & \cdots & Y_{mn} \end{bmatrix} \quad (2)$$

Of which Y_{ij} represents the alternative performance value of the criterion *j* in the solution *i*.

Step 3: Determine the normalized decision-making matrix using the formula (3)

$$R_j = \frac{Y_j}{\sqrt{\sum_{i=1}^{m} Y_j^{\ 2}}} \quad (3)$$

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

Step 4: Determine the weighted normalized decision-making matrix according to the formula (4)

$$v_j = \mathrm{w}_j \times R_j \quad (4)$$

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

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

$$u_i = \begin{cases} v_{\max} - v_i & \text{for beneficial attributes} \\ v_i - v_{\min} & \text{for cost attributes} \end{cases} \quad (5)$$

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

$$d_i = \sum_{j=1}^{n} u_i \quad (6)$$

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

B. Multi-criteria decision making

In order to facilitate the calculation process, we put $IM = X_1$, $r = X_2$, $v_c = X_3$, $V_f = X_4$, $a_p = X_5$, $R_a = Y_1$, $MRR = Y_2$. Thus, we have the decision-making matrix as shown in Table 3. The task of the multi-criteria decision making problem is to choose the solution A_i where Y_{1i} is considered the minimum and Y_{2i} is considered the maximum.

Table 3. Decision-making matrix

Solutions	X_1	X_2	X_3	X_4	X_5	Y_1	Y_2
A_1	TiN	0.3	100	300	0.25	0.823	1050
A_2	TiN	0.3	100	300	0.35	1.556	1470
A_3	TiN	0.3	100	300	0.45	1.812	1890

A_4	TiN	0.5	125	400	0.25	1.642	1400
A_5	TiN	0.5	125	400	0.35	0.966	1960
A_6	TiN	0.5	125	400	0.45	1.053	2520
A_7	TiN	0.8	150	500	0.25	2.355	1750
A_8	TiN	0.8	150	500	0.35	1.690	2450
A_9	TiN	0.8	150	500	0.45	0.921	3150
A_{10}	TiCN	0.3	125	500	0.25	0.267	1750
A_{11}	TiCN	0.3	125	500	0.35	0.327	2450
A_{12}	TiCN	0.3	125	500	0.45	0.733	3150
A_{13}	TiCN	0.5	150	300	0.25	0.985	1050
A_{14}	TiCN	0.5	150	300	0.35	2.661	1470
A_{15}	TiCN	0.5	150	300	0.45	0.928	1890
A_{16}	TiCN	0.8	100	400	0.25	0.902	1400
A_{17}	TiCN	0.8	100	400	0.35	2.829	1960
A_{18}	TiCN	0.8	100	400	0.45	1.418	2520
A_{19}	TiAlN	0.3	150	400	0.25	0.508	1400
A_{20}	TiAlN	0.3	150	400	0.35	0.287	1960
A_{21}	TiAlN	0.3	150	400	0.45	0.481	2520
A_{22}	TiAlN	0.5	100	500	0.25	1.209	1750
A_{23}	TiAlN	0.5	100	500	0.35	2.681	2450
A_{24}	TiAlN	0.5	100	500	0.45	0.728	3150
A_{25}	TiAlN	0.8	125	300	0.25	0.758	1050
A_{26}	TiAlN	0.8	125	300	0.35	2.153	1470
A_{27}	TiAlN	0.8	125	300	0.45	2.225	1890

Apply the formula (3), it is able to determine the normalized matrix as shown in Table 4.

Table 4. Normalized Matrix

Solutions	R_j	
	Y_1	Y_2
A_1	0.0869	103.2926
A_2	0.3107	202.4534
A_3	0.4213	334.6679
A_4	0.3460	183.6312
A_5	0.1197	359.9172
A_6	0.1423	594.9652
A_7	0.7116	286.9238
A_8	0.3665	562.3707
A_9	0.1088	929.6331
A_{10}	0.0091	286.9238
A_{11}	0.0137	562.3707
A_{12}	0.0689	929.6331
A_{13}	0.1245	103.2926
A_{14}	0.9086	202.4534
A_{15}	0.1105	334.6679
A_{16}	0.1044	183.6312
A_{17}	1.0269	359.9172
A_{18}	0.2580	594.9652
A_{19}	0.0331	183.6312
A_{20}	0.0106	359.9172
A_{21}	0.0297	594.9652
A_{22}	0.1876	286.9238
A_{23}	0.9223	562.3707
A_{24}	0.0680	929.6331
A_{25}	0.0737	103.2926
A_{26}	0.5948	202.4534
A_{27}	0.6352	334.6679

Apply the formula (4) to determine the weighted normalized matrix as shown in Table 5. Of which the determination of the weight to the surface roughness and *MRR* is done according to the opinion of experts. These viewpoints suggest that the weight of these two parameters should be equal, i.e. $w_1 = w_2 = 0.5$.

Table 5. Weighted Normalized Matrix

Solutions	v_i	
	Y_1	Y_2
A_1	0.0435	51.6463
A_2	0.1553	101.2267
A_3	0.2106	167.3340
A_4	0.1730	91.8156
A_5	0.0599	179.9586
A_6	0.0711	297.4826
A_7	0.3558	143.4619
A_8	0.1832	281.1853
A_9	0.0544	464.8166
A_{10}	0.0046	143.4619
A_{11}	0.0069	281.1853
A_{12}	0.0345	464.8166
A_{13}	0.0622	51.6463
A_{14}	0.4543	101.2267
A_{15}	0.0553	167.3340
A_{16}	0.0522	91.8156
A_{17}	0.5135	179.9586
A_{18}	0.1290	297.4826
A_{19}	0.0166	91.8156
A_{20}	0.0053	179.9586
A_{21}	0.0148	297.4826
A_{22}	0.0938	143.4619
A_{23}	0.4611	281.1853
A_{24}	0.0340	464.8166
A_{25}	0.0369	51.6463
A_{26}	0.2974	101.2267
A_{27}	0.3176	167.3340

Apply the formula (5) to determine the proximity index as shown in Table 6. Apply the formula (6) to determine the total proximity value, also included in Table 6.

Table 6. Several parameters in *PIV*

Solutions	u_i		d_i
	Y_1	Y_2	
A_1	0.039	413.170	413.2092
A_2	0.151	363.590	363.7406
A_3	0.206	297.483	297.6887
A_4	0.168	373.001	373.1693
A_5	0.055	284.858	284.9132
A_6	0.067	167.334	167.4005
A_7	0.351	321.355	321.7059
A_8	0.179	183.631	183.8099
A_9	0.050	0.000	0.0498
A_{10}	0.000	321.355	321.3547
A_{11}	0.002	183.631	183.6335
A_{12}	0.030	0.000	0.0299
A_{13}	0.058	413.170	413.2279
A_{14}	0.450	363.590	364.0396
A_{15}	0.051	297.483	297.5333
A_{16}	0.048	373.001	373.0486
A_{17}	0.509	284.858	285.3668
A_{18}	0.124	167.334	167.4584
A_{19}	0.012	373.001	373.0129
A_{20}	0.001	284.858	284.8587
A_{21}	0.010	167.334	167.3442
A_{22}	0.089	321.355	321.4439
A_{23}	0.457	183.631	184.0878
A_{24}	0.029	0.000	0.0294
A_{25}	0.032	413.170	413.2026
A_{26}	0.293	363.590	363.8827
A_{27}	0.313	297.483	297.7956

The solutions are ranked based on the values of d_i , the results are presented in Table 7.

Table 7. Ranking of solutions by the value of d_i

Solutions	*IM*	*r* (mm)	v_c (m/min)	f_z (mm/min)	a_p (mm)	*Ra* (µm)	*MRR* (mm^3/min)	Rank
A_1	TiN	0.3	100	300	0.25	0.823	1050	26
A_2	TiN	0.3	100	300	0.35	1.556	1470	19
A_3	TiN	0.3	100	300	0.45	1.812	1890	14

A_4	TiN	0.5	125	400	0.25	1.642	1400	23
A_5	TiN	0.5	125	400	0.35	0.966	1960	11
A_6	TiN	0.5	125	400	0.45	1.053	2520	5
A_7	TiN	0.8	150	500	0.25	2.355	1750	18
A_8	TiN	0.8	150	500	0.35	1.690	2450	8
A_9	TiN	0.8	150	500	0.45	0.921	3150	3
A_{10}	TiCN	0.3	125	500	0.25	0.267	1750	16
A_{11}	TiCN	0.3	125	500	0.35	0.327	2450	7
A_{12}	TiCN	0.3	125	500	0.45	0.733	3150	2
A_{13}	TiCN	0.5	150	300	0.25	0.985	1050	27
A_{14}	TiCN	0.5	150	300	0.35	2.661	1470	20
A_{15}	TiCN	0.5	150	300	0.45	0.928	1890	13
A_{16}	TiCN	0.8	100	400	0.25	0.902	1400	22
A_{17}	TiCN	0.8	100	400	0.35	2.829	1960	12
A_{18}	TiCN	0.8	100	400	0.45	1.418	2520	6
A_{19}	TiAlN	0.3	150	400	0.25	0.508	1400	21
A_{20}	TiAlN	0.3	150	400	0.35	0.287	1960	10
A_{21}	TiAlN	0.3	150	400	0.45	0.481	2520	4
A_{22}	TiAlN	0.5	100	500	0.25	1.209	1750	17
A_{23}	TiAlN	0.5	100	500	0.35	2.681	2450	9
A_{24}	TiAlN	0.5	100	500	0.45	0.728	3150	1
A_{25}	TiAlN	0.8	125	300	0.25	0.758	1050	25
A_{26}	TiAlN	0.8	125	300	0.35	2.153	1470	20
A_{27}	TiAlN	0.8	125	300	0.45	2.225	1890	15

From the ranking order of options in Table 7, it shows that the A_{24} option is the best, and the A_{13} option is the worst. For the option A_{13} (and the options A_1, A_{25}), the *MRR* is equal to 1050 mm^3/min which is the minimum value in Table 7, and the surface roughness in the option A_{13} is also quite large. For the option A_{24} (and the options A_9, A_{12}), the *MRR* is equal to 3150 mm^3/min which is the maximum value in table 7. The surface roughness in the options A_{24} of 0.728 μm is a rather small value, only larger than the surface roughness in the options A_{10}, A_{11}, A_{19}, A_{20} and A_{21}. Thus, the option A_{24} has surface roughness at position 6 and *MRR* at position 1. Therefore, it can be said that it is completely appropriate to confirm that this option is the best. Thereby, we can come to the conclusion, in order to ensure the minimum surface roughness and the maximum *MRR* at the same time, it is required to choose the insert material as *TiAlN*, the nose radius equal to 0.5 mm, the cutting velocity equal to 100 m/min, the feed rate equal to 500 mm/min and the depth of cut equal to 0.45 mm.

V. CONCLUSION

In this study, the SCM440 steel milling experiment was conducted according to a matrix designed by the Taguchi method. At each experiment, five parameters were changed, including the insert material, nose radius, cutting velocity, feed rate and depth of cut. Surface roughness and *MRR* are two parameters that were determined in each experiment. The *PIV* method was applied for multi-criteria decision making. Some conclusions are drawn as follows:

- Nose radius is the parameter that has the greatest influence on surface roughness, followed by the influence of cutting velocity and feed rate. The insert material and depth of cut have no significant influence on the surface roughness.
- In order to ensure the minimum surface roughness and maximum *MRR* simultaneously, it is required to select the insert material as TiAlN, the value of the tip radius, cutting velocity, feed rate and depth of cut are 0.5 mm, 100 m/min, 500 mm/min and 0.45 mm, respectively.
- The *PIV* method has been successfully applied in multi-criteria decision making in several studies [7, 11-14]. This method was applied for the first time and also succeeded in multi-criteria decision-making of the SCM440 steel milling process in this study. The application of PIV method for multi-criteria decision making is also a research direction that should be carried out for other machining processes.
- This study only considers two criteria to evaluate the milling process: surface roughness and MRR. In order to evaluate the milling process more comprehensively, other parameters should also be considered such as cutting force, tool wear, etc. On the other hand, the weight of the criteria

(surface roughness and *MRR*) was chosen by the decision maker. The weighting of the criteria according to mathematical methods such as Entropy, Analytic Hierarchy Process (*AHP*), etc. also need to be considered. In the future, these works will be carried out by the authors of this paper.

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