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OPTIMIZATION OF MULTI RESPONSE IN END MILLING PROCESS OF ASSAB XW-42 TOOL STEEL WITH LIQUID NITROGEN COOLING USING TAGUCHI GREY-FUZZY METHOD

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ABSTRACT

A research was conducted for the optimization of the end milling process of ASSAB XW-42 tool steel with multiple performance characteristics based on the orthogonal array with Taguchi-grey-fuzzy method. Liquid nitrogen was applied as a coolant. The experimental studies were conducted under varying the liquid nitrogen cooling flow rate (FL), and the end milling process variables, i.e., cutting speed (V_c), feeding speed (V_f) and axial depth of cut (A_a). The optimized multiple performance characteristics were surface roughness (SR), flank wear (VB) and material removal rate (MRR). An orthogonal array, signal-to-noise (S/N) ratio, grey relational analysis, grey-fuzzy reasoning grade and analysis of variance were employed to study the multiple performance characteristics. Experimental results show that flow rate gives the highest contribution for reducing the total variation of the multiple responses, followed by cutting speed, feeding speed and axial depth of cut. The minimum surface roughness, flank wear and maximum material removal rate could be obtained by using the values of flow rate, cutting speed, feeding speed and axial depth of cut of 0.5 l/minute, 109.9 m/minute, 94.2 mm/minute, and 0.9 mm respectively.

Keywords: end milling, ASSAB XW-42, liquid nitrogen, Taguchi, grey-fuzzy.

INTRODUCTION

End milling process is one type of the milling processes and widely used in manufacturing industries, such as automotive, aircraft, and plastic molding. This process can be used to produce a workpiece with flat surfaces, profile, radius, pockets and grooves. Based on the type of cutting tool and type of operation, the milling process can be classified as slab milling, face milling and end milling [1]. Some of the most important performance characteristics in end milling process are surface roughness, flank wear and material removal rate. Selection of the right cutting tool, cutting fluid and end milling parameters will result in low surface roughness and flank wear and high material removal rate. The use of cryogenic cooling can reduce both surface roughness and tool wear, and also increases material removal rate [2-3]. The ASSAB XW-42 tool steel is widely used as a chisel or cutting tools, punches and dies in the metal forming like blanking, shearing, bending and deep-drawing. The tool steel is also considered having a high strength, high resistance to wear, high stability in hardening, and high compressive strength.

Optimizing multiple performance characteristics at the same time in the end milling process needs proper machining parameters setting. Based on the review literatures [4-5] and preliminary research, the most important machining parameters of end milling process are cutting speed (V_c), feeding speed (V_f) and axial depth of cut (A_a). Hence, those machining parameters need to be selected properly in terms of the machining tool and material properties in order to maximize material removal rate (MRR) and minimize surface roughness (SR) and flank wear (VB) simultaneously.

The grey relational analysis method was developed by Deng [6]. This method provides techniques for determining a good solution for the unknown information. The grey relational analysis can find out the relation between machining parameters and machining performances. The term of fuzzy logic was introduced by Zadech [7]. Taguchi method only focused on optimizing single performance characteristic [8]. However, product in some machining processes has more than one machining performance which should be considered. Using fuzzy logic multiple objective optimization problems can be solved by transforming multiple quality characteristics into single quality characteristic. In fact, there are three definitions of performance characteristics, namely lower-is-better, higher-is-better, and nominal-is-better.

The aim of this experiment is to determine the parameter setting of end milling ASSAB XW-42 tool steel using liquid nitrogen cooling to maximize MRR and minimize SR and VB. The performance characteristic of MRR is larger the better while SR and VB is smaller the better.

EXPERIMENTAL DESIGN AND RESULT

Equipments and Material

This study was conducted in cryogenic condition using liquid nitrogen on CNC milling YCM MV 66A with

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a maximum of 8000 rpm spindle rotation. End milling parameters used are shown in Table-1. The end mill solid carbide cutting tool having diameter of 10 mm and 4 flute used in this study. Work piece material used in this research was ASSABXW-42 (45 HRC) tool steel with a length of 80 mm, a width of 30 mm and a thickness of 30 mm. The chemical composition of ASSABXW-42 tool steel consists of 1.55% C, 11.6% Cr, 0.80% Mo, 0.80% V, 0.30% Mn and 0.3% Si. Surface roughness measurements are conducted by using Mitutoyo Surftest SJ 301 with a cut-off length of 0.8 mm and flank wear was measured with Nikon measurescope. Material removal rate is defined as volume of the workpiece removed per machining time and formulated as follows [9]:

$$MRR = \frac{Volume\ of\ workpiece\ \ removed}{Machining\ \ time} (mm^3/\text{min}) \quad (1)$$

Design of Experiments

L_{18} orthogonal array used in this study to investigate the effect of end milling parameters on surface roughness, flank wear and material removal rate. Selection of orthogonal array was conducted based on the total degrees of freedom of end milling parameters.

Based on Table-1, the total degrees of freedom is 9. Therefore, L_{18} orthogonal array used in this study and shown in Table-2.

Optimization of Multiple Response with Taguchi-Grey-Fuzzy

The optimization steps using the Taguchi-grey-fuzzy method is shown in Figure-1.

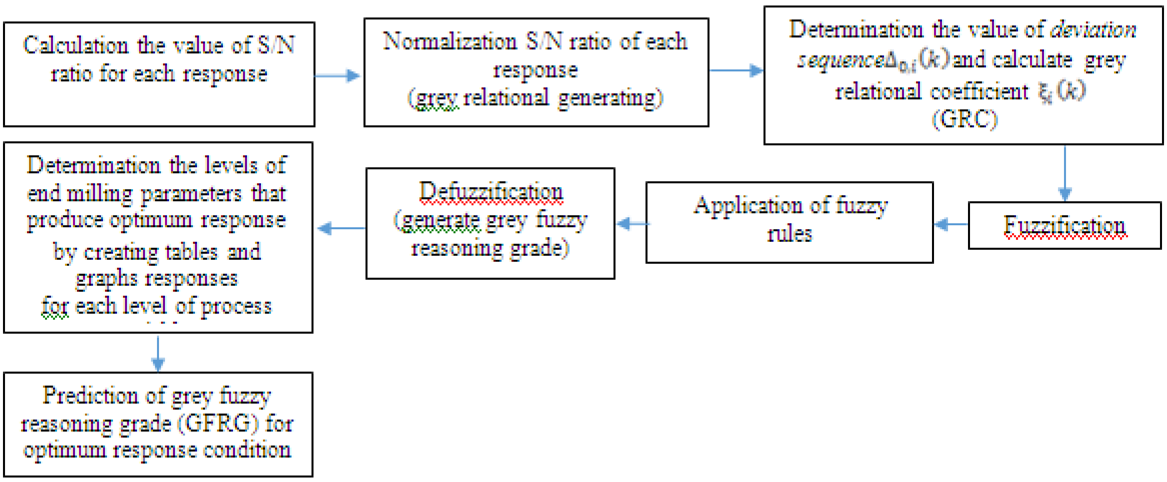

Figure-1. The optimization steps using Taguchi-grey-fuzzy method.

Table-1. End milling parameters and their levels.

End Milling Parameters	Unit	1	2	3
Flow rate (FL)	(l/min)	0.2	0.5	-
Cutting speed(V_c)	(m/min)	78.5	94.2	109.9
Feeding speed (V_f)	(mm/min)	390	440	490
Axial depth of cut (A_a)	(mm)	0.3	0.6	0.9

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Table-2. Experimental layout using an L_{18} orthogonal array.

Comb.	End milling parameters				Comb.	End milling parameters			
	FL	V_c	V_f	A_a		FL	V_c	V_f	A_a
	(l/min)	(m/min)	(mm/min)	(mm)		(l/min)	(m/min)	(mm/min)	(mm)
1	1	1	1	1	10	2	1	1	3
2	1	1	2	2	11	2	1	2	1
3	1	1	3	3	12	2	1	3	2
4	1	2	1	1	13	2	2	1	2
5	1	2	2	2	14	2	2	2	3
6	1	2	3	3	15	2	2	3	1
7	1	3	1	2	16	2	3	1	3
8	1	3	2	3	17	2	3	2	1
9	1	3	3	1	18	2	3	3	2

EXPERIMENTAL RESULT AND ANALYSIS

The results of the experimentand S/N ratio for the surface roughness (SR), flank wear (VB) and material removal rate (MRR) are shown in Table-3. The performance characteristics of surface roughness (SR) and flank wear (VB) are larger the better, while material removal rate (MRR) is smaller the better. The S/N ratios for each type of characteristic can be calculated as follows [10]:

Smaller the better: $$S/N = -10\ \log\left[\sum_{i=1}^{n}\frac{y_i^{\,2}}{n}\right] \qquad (2)$$

Larger the better: $$S/N = -10\log\left[\sum_{i=1}^{n}\frac{(1/y_i^{\,2})}{n}\right] \qquad (3)$$

Table-3. Experimental results and their S/N ratios.

Comb.	End milling parameters				S/N SR	S/N VB	S/N MRR
	FL	Vc	Vf	Aa			
	(l/min)	(m/min)	(mm^3/min)	(mm)			
1	0.2	78.5	390	0.3	1.2135	33.4845	61.2751
2	0.2	78.5	440	0.6	0.4913	33.0200	67.8509
3	0.2	78.5	490	0.9	-3.0844	32.4864	71.7616
4	0.2	94.2	390	0.3	3.6133	34.0493	61.3926
5	0.2	94.2	440	0.6	4.8827	33.7646	67.2261
6	0.2	94.2	490	0.9	1.2780	33.2831	71.4142
7	0.2	109.9	390	0.6	3.0991	35.1357	66.1550
8	0.2	109.9	440	0.9	3.0983	34.4984	71.7074
9	0.2	109.9	490	0.3	2.0233	34.2276	62.4986
10	0.5	78.5	390	0.9	4.8999	33.9643	69.8246
11	0.5	78.5	440	0.3	4.2204	35.2961	61.1310
12	0.5	78.5	490	0.6	2.8132	33.4019	68.0850
13	0.5	94.2	390	0.6	5.7132	34.5731	67.3741
14	0.5	94.2	440	0.9	5.4170	34.1055	70.6618
15	0.5	94.2	490	0.3	3.9973	33.9794	61.7662
16	0.5	109.9	390	0.9	5.6379	35.4592	69.7414
17	0.5	109.9	440	0.3	5.3835	35.8503	60.3149
18	0.5	109.9	490	0.6	4.0616	34.8054	68.0657

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DETERMINATION OF OPTIMAL END MILLING PARAMETERS

Based on Table-3, normalization of S/N ratio of each response can be calculated as follows [11]:

$$X_i^*(k) = \frac{X_i(k) - \min_{\forall k} X_i(k)}{\max_{\forall k} X_i(k) - \min_{\forall k} X_i(k)} \quad (4)$$

where min $X_i(k)$ is the smallest value of $X_i(k)$ for the k^{th} response and max $X_i(k)$ is the largest value of $X_i(k)$ for the k^{th} response. The result of normalized S/N ratio then converted into grey relational coefficient (GRC) by using the following equation [11]:

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\, \Delta_{max}}{\Delta_{0,i}(k) + \zeta\, \Delta_{max}} \quad (5)$$

where $\Delta_{0,i}(k)$ is the absolute difference between maximum value of the normalized $X_0(k)$ and the value of normalized $X_i{}^*(k)$. $\Delta_{0,i}(k)$ is calculated using the following equation:

$$\Delta_{0,i}(k) = |X_0(k) - X_i{}^*(k)| \quad (6)$$

$\Delta_{min} = \forall j^{\min} \in i \forall k^{\min} |X_0(k) - X_i{}^*(k)|$ is the smallest value of $\Delta_{0,i}(k)$, ζ is distinguishing coefficient and $\Delta_{max} = \forall j^{\max} \in i \forall k^{\max} |X_0(k) - X_i{}^*(k)|$ is the largest value of $\Delta_{0,i}(k)$. The value of distinguishing coefficient used in this study was 0.5 [12, 13].

The GRC for each response converted into one multi-response output which is called GFRG by using fuzzy logic analysis which uses membership function, fuzzy rule and defuzzification. In this research, three fuzzy subsets are assigned in the GRC of the surface roughness, flank wear and material removal rate and shown in Figure-2a, 2b and 2c. Nine fuzzy subsets are assigned in the GFRG and shown in Figure-3. The GRC and GFRG are shown in Table-4. The mean GFRG for each level of the end milling parameters is shown in Table-5.

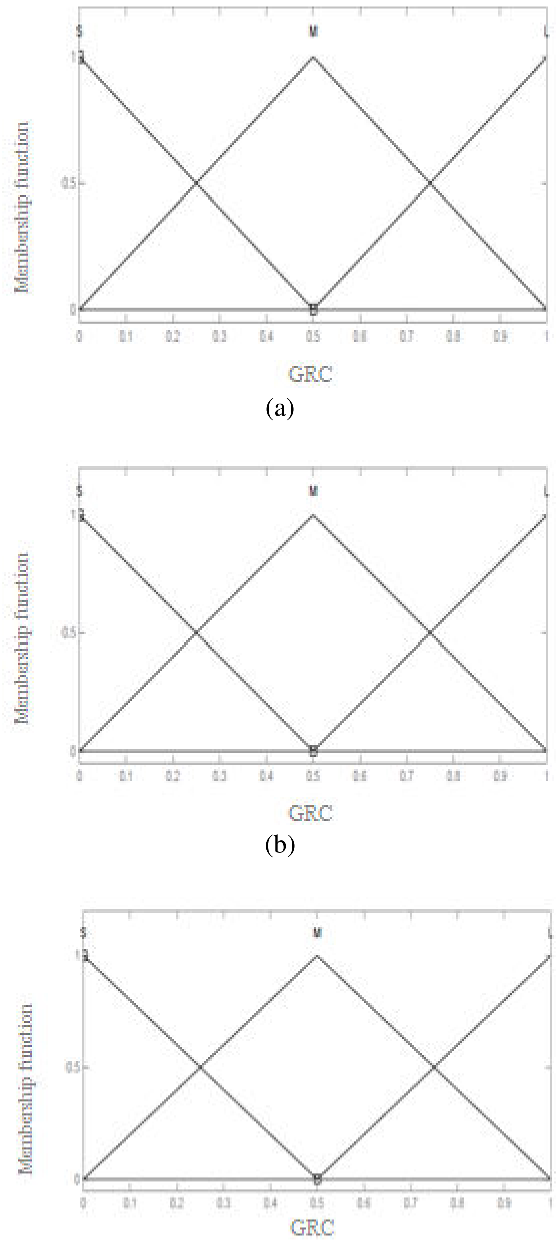

Figure-2. Membership functions for GRC (a) surface roughness, (b) flank wear, (c) material removal rate

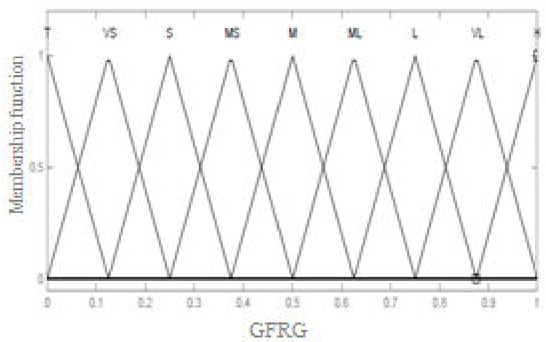

Figure-3. Membership functions for GFRG.

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Table-4. GRC and GFRG.

Comb.	GRC $\xi_i(k)$			GFRG	Comb.	GRC $\xi_i(k)$			GFRG
	SR	VB	MRR			SR	VB	MRR	
1	0.4943	0.4155	0.3531	0.3906	10	0.8440	0.4714	0.7471	0.6297
2	0.4572	0.3728	0.5941	0.4523	11	0.7466	0.7522	0.3500	0.5818
3	0.3333	0.3333	1.0000	0.4764	12	0.6027	0.4072	0.6089	0.543
4	0.6769	0.4829	0.3557	0.4901	13	1.0000	0.5684	0.5661	0.6778
5	0.8412	0.4464	0.5579	0.5801	14	0.9369	0.4908	0.8388	0.6764
6	0.4979	0.3958	0.9428	0.5666	15	0.7194	0.4734	0.3641	0.4904
7	0.6272	0.7018	0.5052	0.5967	16	0.9832	0.8113	0.7391	0.7534
8	0.6272	0.5544	0.9906	0.6831	17	0.9303	1.0000	0.3333	0.6248
9	0.5438	0.5090	0.3819	0.4852	18	0.7270	0.6168	0.6076	0.6439

Table-5. Response table for the mean GFRG.

	1	2	3
Flow rate (FL)	**0.5246**	**0.6246**	**-**
Cutting speed (V_c)	0.5123	0.5802	0.6312
Feeding speed (V_f)	0.5897	0.5998	0.5343
Axial depth of cut (A_a)	0.5105	0.5823	0.6309
Mean	0.5746		

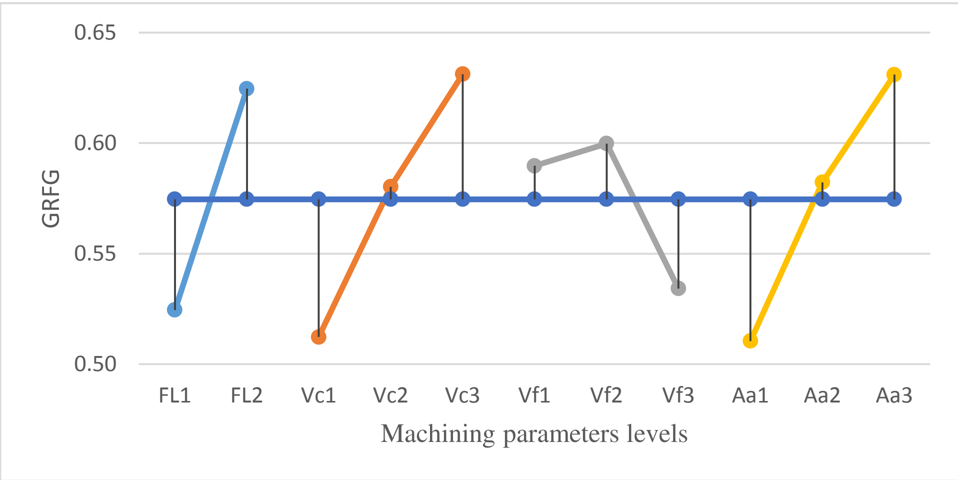

Figure-4. Graph of GFRG

Based on Table-5, the optimum condition for end milling process of ASSAB XW-42 tool steel with liquid nitrogen cooling could be achieved by the combination of end milling parameters $FL_2V_{c3}V_{f2}A_{a3}$.

ANALYSIS OF EXPERIMENTAL RESULTS AND CONFIRMATION TEST

Analysis of variance (ANOVA) was used to evaluate the significance of process variables on the observed response. The result of ANOVA for grey fuzzy reasoning grade (GFRG) is shown in Table-6. Table-6 shows that the p-value for all process variables are greater

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than the α (α =0.05), so that process variables flow rate, cutting speed, feeding speed and axial depth of cut has significant influence on the multi response. The largest contributor in decreasing the total variance is given by the variable flow rate of 27.91% followed by axial depth of cut of 26.62%, cutting speed of 25.75% and feeding speed of 8.12%.

Therefore, based on the graph of GFRG (Figure-4) and the result of ANOVA (Table-6), the optimal machining condition for face milling process of ASSAB XW42 steel are flow rate at level 2, cutting speed at level 3, feeding speed at level 3 and axial depth of cut at level 1. After the levels of the combination of machining parameters that resulted optimum performance were obtained, the next step is to predict and verify the improved performance characteristics by using the optimal levels of face milling parameters. The predicted GFRG ($\hat{\gamma}$) can be obtained by using the following equation [14]:

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{q}(\hat{\gamma}_i - \gamma_m) \quad (7)$$

where γ_m is the total mean of GFRG, $\bar{\gamma}_i$ is the mean of GFRG taken at the optimum performance and q is the number of machining parameters that significantly affect the multiple machining performances.

The comparison of the results of the confirmation experiment using the optimal end milling parameters and the result of the experiment using initial machining parameters is shown in Table-7. As shown in Table-7, surface roughness is decreased from 0.569 to 0.507 μm, flank wear is decreased from 0.021 to 0.016 mm and material removal rate is increased from 2812.509 to 4898.276 mm^3/minute. It is clearly shown that the GFRG in the end milling process of ASSAB XW-42 tool steel with liquid nitrogen cooling are greatly improved through this study.

Table-6. ANOVA for the GFRG.

Source	DF	SS	MS	F	P	(%)
Flow rate	**1**	**0.045010**	**0.045010**	**41.95**	**0.000**	**27.91**
Cutting speed	2	0.042690	0.021345	19.89	0.000	25.75
Feeding speed	2	0.014930	0.007465	6.96	0.013	8.12
Axial depth cut	2	0.044060	0.022030	20.53	0.000	26.62
Error	10	0.010730	0.001073			11.59
Total	17	0.157430				100.00

Table-7. Results of confirmation test.

Variable response	Initial combination $FL_1V_{c2}V_{f2}A_{a2}$ awal	Optimum combination $FL_2V_{c3}V_{f2}A_{a3}$	Description	
Surface roughness (μm)	0.569	0.507	10.90 %	Decrease
Flank wear (mm)	0.021	0.016	23.81 %	Decrease
Material removal rate (mm^3/minute)	2812.509	4898.276	74.16 %	Increase
GFRG	0.5801	0.7781	34.13%	Increase

CONCLUSIONS

Based on the analysis, it can be concluded that the end milling process variables flow rate, cutting speed, feeding speed and axial depth of cut were significantly influencing the total variance of the multi-response (surface roughness, flank wear and material removal rate). The recommended levels of end milling process variables when surface roughness, flank wear and material removal rate are simultaneously considered are flow rate of 0.5 l/minute, cutting speed of 109.9 m/min, feed rate of 440 mm/minute and axial depth of cut of 0.9 mm.

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