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

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ABSTRACT

In this study, optimization of milling parameters on surface roughness, material removal rate and cutting force during symmetrical cryogenic face milling process of tool steel ASSAB XW42 were investigeted. The milling parameters varied are cutting speed, feeding speed, axial depth of cut and flow rate of cryogenic cooling. The experimental design using a L_{18} orthogonal array and it is selected based on the Taguchi method. Experiments were completely randomized and repeated twice. Grey relational grade used to analyze the level of multiple responses (surface roughness, material removal rate and cutting force). Fuzzy logic was used to perform fuzzy reasoning of some performance characteristics. Experimental results show that the axial depth of cut gives the highest contribution for reducing the total variation of the multiple response, followed by flow rate, feeding speed and cutting speed. The maximum material removal rate and minimum surface roughness and cutting force could be obtained by using the values of flow rate, cutting speed, feeding speed and axial depth of cut of 0.5 l/minute, 300 m/minute, 150 mm/minute and 0.2 mm respectively.

Keywords: face milling, cryogenic, ASSAB XW42, Taguchi, grey, fuzzy logic.

INTRODUCTION

ASSAB XW42 steel is often used as a punch and dies because its hard and it has resistant to heat. This material has hardness ranges from 30 HRC to 60 HRC. During the milling process of hardened steel, contact friction between the tool-workpiece and the tool-chip interface generates high cutting tool temperature [1]. The generated heat increases the surface roughness of the workpiece, and reducing tool life and dimensional accuracy of the work material [2]. Therefore, cooling fluid is required to reduce the temperature at the cutting zone. Conventional cooling fluid has a negative influence on the environment and the health of the machine operator. At this time cryogenic is widely used as cooling fluid. One type of cryogenic coolant is liquid nitrogen. Some advantages of liquid nitrogen are pollution free to the environment, non-toxic and improve product surface quality [3]. Poor selection of milling process causes a high cutting temperature, rapid tool wear and low productivity [4, 5]. However, the good surface finish with low cutting force and high material removel rate, can be achieved by only using the right cutting speed, feeding speed and axial depth of cut [6].

Optimizing multiple performance characteristics at the same time in face milling process requires proper machining parameters setting. Based on the review literatures [7-8] and preliminary research, the most important machining parameters of face milling process are cutting speed (V_c), feeding speed (V_f) and axial depth of cut (A_a).

Therefore, 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 cutting force (F_c) simultaneously.

The grey relational analysis method was developed by Deng [9]. 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 [10]. Taguchi method only focused on optimizing single performance characteristic [11]. However, product in some machining processes has more than one machining performance which should be considered. Using fuzzy logic multiple objective optimization problem 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.

This study takes ASSAB XW42 tool steel as working material and investigate three performance characteristics, namely surface roughness or SR, material removal rate or MRR and cutting force or F_c, with Taguchi method and grey-fuzzy to determine the optimal parameters in face milling process. The performance characteristics of MRR are larger-is-better while SR and F_c are having smaller-is-better performance characteristics.

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EXPERIMENTAL DESIGN AND RESULT

Material and Equipment

The work material selected for the study was ASSAB XW42 tool steel, with dimensions of 80 mm in length, 30 mm in width and 30 mm in thickness. The hardness of ASSAB XW42 tool steel is 45 HRC. A typical composition of the ASSAB XW42 tool steel consists of 1.55 wt.% C–11.6 wt.% Cr–0.80 wt.% Mo–0.80 wt.% V–0.30 wt.% Mn–0.3 wt.% Si. The cutting tool has diameter of 50 mm and has five coated PVD insert. The face milling process with cryogenic coolant adopted in the test was conducted on YCM MV 66A milling CNC. Milling parameters and their levels are shown in Table-1. Four-component piezoelectric dynamometer Kistler 9272 was used to measure cutting force, Mitutoyo SJ310 was used to measure surface roughness and machining time was measured by using stopwatch. The equation for calculating material removal rate is [12]:

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

Design of Experiment

Total degrees of freedom need to be calculated to determine an appropriate orthogonal array for the experiments. As shown in Table-1, flow rate was set at two different levels, while all three face milling parameters were set at three different levels. Therefore, the total degrees of freedom were seven. Design of experiment based on L_{18} orthogonal array that used for the experiments is shown in the Table-2.

Optimization of Multiple Face Milling Performance with Taguchi-Grey-Fuzzy Method

In this study Taguchi method was combined with grey-fuzzy to optimize multiple performance characteristics of face milling process. The steps for conducting optimization by using Taguchi-grey-fuzzy method are shown in Figure-1.

Table-1. Milling parameters and their levels.

Milling Parameters		lev. 1	lev. 2	lev. 3
A	Flow Rate (FR, l/min)	0.2	0.5	-
B	Cutting speed (V_c, m/min)	150	200	300
C	Feeding speed (V_f, mm/min)	80	100	150
D	Axial depth of cut (a_a, mm)	0.2	0.3	0.6

Experimental Result

Table-3 shows the experimental results and S/N ratio for SR, F_c and MRR. The performance characteristic of MRR is larger-is-better, while SR and F_c are smaller-is-better. The S/N ratio for each type of characteristics can be calculated by using the following equations [13]:

Larger is better:

$$S/N = -10\log\left[\sum_{i=1}^{n} \frac{y_i^2}{n}\right] \tag{2}$$

Smaller is better:

$$S/N = -10\log\left[\sum_{i=1}^{n} \frac{1/y_i^2}{n}\right] \tag{3}$$

Here n is the number of measurements and y_i is the measured characteristics value.

Determination of Optimal Face Milling Parameters

The process of normalization for each type of characteristics can be calculated by using the following equation [14]:

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

where $Xi^*(k)$ is the sequence after data preprocessing, $X_i(k)$ is the original sequence, $min\ X_i(k)$ is the minimum value of $X_i(k)$ for the kth response, and $max\ X_i(k)$ is the maximum value of $X_i(k)$.

To calculate grey relational coefficient (GRC), deviation sequence ($\Delta_{0,i}(k)$) must be first calculated using the following equation [14]:

$$\Delta_{0,i}(k) = |X_0(k) - X_i^*(k)| \tag{5}$$

GRC value (ξ_i) was calculated based on the value of $\Delta_{0,i}(k)$. The GRC value for each response can be calculated by using the following equation [14]:

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\,\Delta_{max}}{\Delta_{0,i}(k) + \zeta\,\Delta_{max}} \tag{6}$$

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

No	Milling Parameters			
	FR [l/min]	$\mathbf{V_c}$ [m/min]	$\mathbf{V_f}$ [mm/min]	$\mathbf{a_a}$ [mm]
1	0.2	150	80	0.2
2	0.2	150	100	0.3
3	0.2	150	150	0.6
4	0.2	200	80	0.2
5	0.2	200	100	0.3
6	0.2	200	150	0.6
7	0.2	300	80	0.3
8	0.2	300	100	0.6
9	0.2	300	150	0.2
10	0.5	150	80	0.6
11	0.5	150	100	0.2
12	0.5	150	150	0.3
13	0.5	200	80	0.3
14	0.5	200	100	0.6
15	0.5	200	150	0.2
16	0.5	300	80	0.6
17	0.5	300	100	0.2
18	0.5	300	150	0.3

Table-3. Experimental results and S/N ratio.

No	**SR**		$\mathbf{F_C}$		**MRR**		**No**	**SR**		$\mathbf{F_C}$		**MRR**	
	µm	**S/N**	**N**	**S/N**	**mm^3/ min**	**S/N**		**µm**	**S/N**	**N**	**S/N**	**mm^3/ min**	**S/N**
1	1.824	-5.22	73.05	-37.27	398.55	52.01	10	1.824	-3.06	73.05	-46.03	398.55	55.68
2	1.859	-5.39	126.8	-42.07	729.94	57.27	11	1.859	-3.09	126.8	-38.45	729.94	55.52
3	2.408	-7.63	230.5	-47.26	1180.0	61.44	12	2.408	-3.43	230.5	-45.53	1180.0	60.47
4	1.527	-3.68	74.36	-37.43	393.1	51.89	13	1.527	-0.49	74.36	-42.07	393.1	54.36
5	1.592	-4.04	146.0	-43.29	742.01	57.41	14	1.592	-1.71	146.0	-46.72	742.01	59.02
6	1.693	-4.58	235.0	-47.42	1176.8	61.41	15	1.693	-1.2	235.0	-38.61	1176.8	57.55
7	1.519	-3.61	110.1	-40.83	518.87	54.3	16	1.519	-0.05	110.1	-46.06	518.87	55.69
8	1.595	-4.06	204.0	-46.2	883.59	58.93	17	1.595	-0.13	204.0	-37.96	883.59	55.51
9	1.515	-3.6	98.73	-39.89	740.49	57.39	18	1.515	-0.21	98.73	-45.54	740.49	60.49

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where $\Delta_{min} = \forall j^{min} \in i\forall k^{min}\|X_0(k) - X_i^*(k)\|$ is the smallest value of $\Delta_{0,i}(k)$, $\Delta_{max} = \forall j^{max} \in i\forall k^{max}\|X_0(k) - X_i^*(k)\|$ is the highest value of $\Delta_{0,i}(k)$ and ζ is the distinguishing coeficient. The GRC of each response is used as an input variable to the defuzzification process. Input variables are then processed in the fuzzy inference engine based on a set of fuzzy rules to generate an output. The resulting output is grey fuzzy reasoning grade (GFRG).

In this study, GRC of surface roughness, cutting forces and material removel rate classified into three fuzzy subsets as shown in Figure-2. Nine fuzzy subsets are assigned in the GFRG (Figure-3). The GRC and GFRG is shown in the Table-4. For both figures, T is tiny, VS is very small, S is small, SM is smaller middle, M is middle, ML is middle larger, L is larger, VL is very large and H is huge. The larger GFRG the better multiple performances is. The mean GFRG for each level of the machining parameters is shown in Table-5.

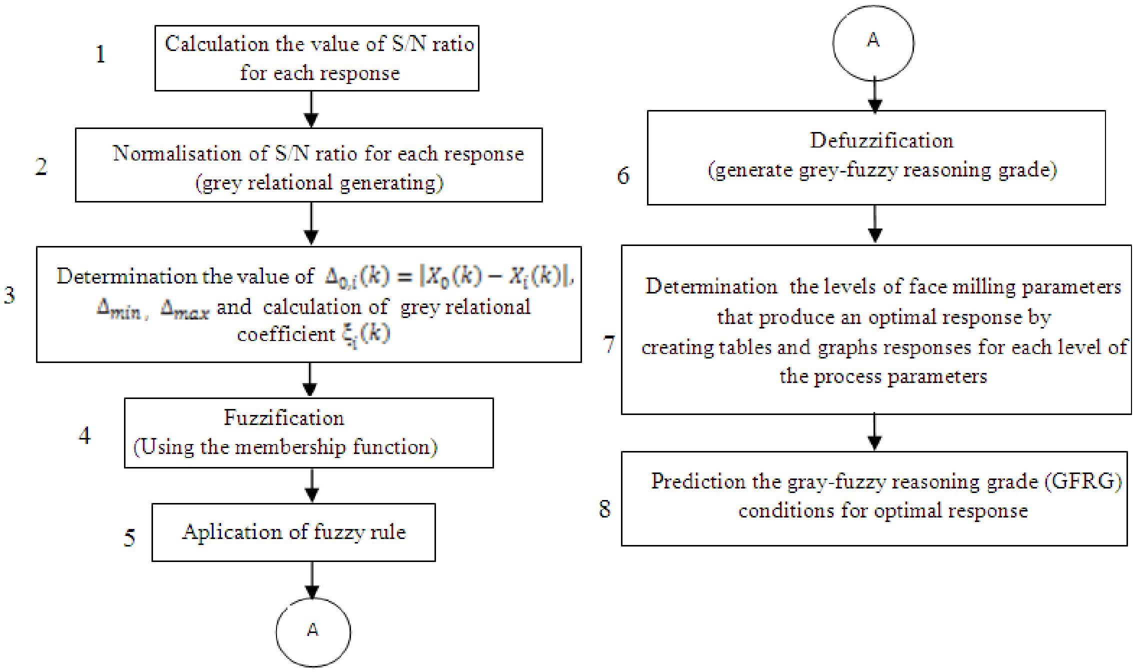

Figure-1. Optimization using Taguchi-grey-fuzzy method.

Analysis of Experimental Results and Confirmation Test

The face milling parameters which influence to the performance characteristics were determined by using analysis of variance (ANOVA). The result of ANOVA can be seen in Table-6. The percent contribution (ρ) in Table-6 shows that axial depth of cut has the highest contribution for reducing the total variation of the multiple response, followed by flow rate, feeding speed and cutting speed.

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 [11]:

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

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. Table-7 shows the comparison of the results of experimental confirmation using the optimum milling parameters and the results of experiment using the initial milling parameters. As shown in Table-7, surface roughness is decreased from 1.592 µm to 1.166 µm, cutting force is decreased from 146.09 N to 95.07 N and material removal rate is increased from 728.3489 mm^3/min to 884.735 mm^3/min. It is clearly shown that the GFRG in the face milling process of ASSAB XW42 steel is greatly improved through this study.

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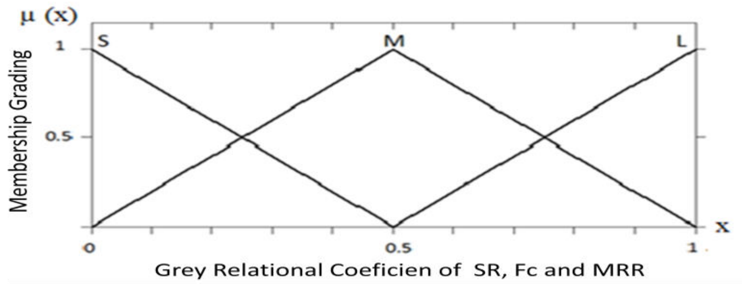

Figure-2. Membership functions for SR, F_c and MRR

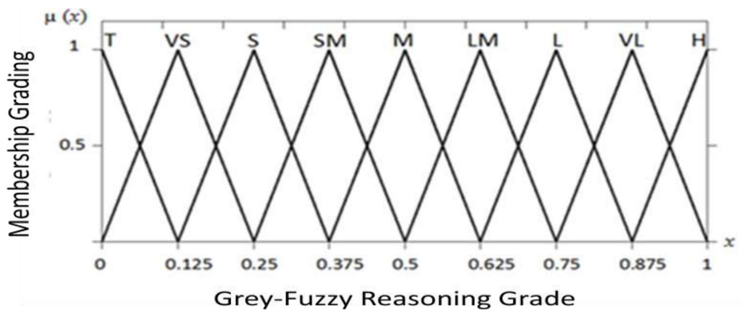

Figure-3. Membership functions for GFRG

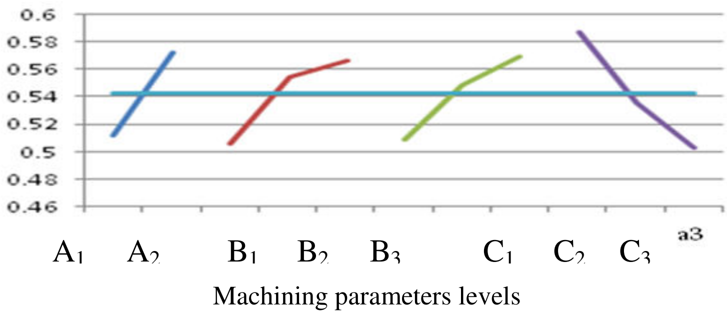

Figure-4. Graph of GFRG.

Table-4. GRC and GFRG.

No	Grey Relational Coefficient			GFRG	No	Grey Relational Coefficient			GFRG
	SR	F_c	MRR			SR	F_c	MRR	
1	0.4231	1	0.3361	0.4977	10	0.5577	0.367	0.4532	0.4374
2	0.4154	0.5143	0.5336	0.5023	11	0.5547	0.8112	0.4464	0.5737
3	0.3333	0.337	1	0.4777	12	0.5284	0.3805	0.8319	0.5483
4	0.5112	0.9703	0.3333	0.5332	13	0.8965	0.5143	0.4028	0.561
5	0.487	0.4574	0.5423	0.4841	14	0.6962	0.3495	0.6635	0.5583
6	0.4555	0.3333	0.995	0.5359	15	0.7677	0.7909	0.5511	0.653
7	0.5159	0.588	0.4008	0.5049	16	1	0.3662	0.4537	0.5199
8	0.4864	0.3626	0.6551	0.4905	17	0.98	0.8811	0.4463	0.6816
9	0.5163	0.6598	0.5412	0.583	18	0.9609	0.3803	0.8346	0.6163

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Table-5. Mean value of GFRG.

	Level 1	Level 2	Level 3	Max-min
A	0.5121	0.5722		0.0600
B	0.5062	0.5543	0.5660	0.0598
C	0.5090	0.5484	0.5690	0.0600
D	0.5870	0.5362	0.5033	0.0837
Mean	0.5421			

Table-6. ANOVA of GFRG and percent contribution.

Source	DF	SS	MS	F	P value	ρ
Flow rate (A)	1	0.016212	0.016212	25.02	0.001	23.13%
Cutting speed (B)	2	0.011159	0.005579	9.31	0.005	15.00%
Feeding speed (C)	2	0.013159	0.00658	8.61	0.007	17.63%
Axial depth of cut (D)	2	0.021367	0.010684	16.49	0.001	29.83%
Error	10	0.00648	0.000648			14.39%
Total	17	0.06728				

Table-7. The Improvement of performance characteristic for each response and GFRG.

	Initial	Optimal Process Condition		Improvement
		Prediction	Experiment	
Level of process parameters	A_1 B_2 C_2 D_2	A_1 B_2 C_1 D_2	A_1 B_2 C_1 D_2	
SR (μm)	1.592		1.166	decrease 26.75%
F_c (N)	146.09		95.07	decrease 34.92%
MRR (mm^3/min)	728.34		884.73	increase 21.47%
GFRG	0.484	0.667	0.678	increase 40.23%

CONCLUSIONS

Based on the analysis, the axial depth of cut gives the highest contribution for reducing the total variation of the multiple responses, followed by flow rate, feeding speed and cutting speed. The combination of machining parameters for minimizing surface roughness and cutting force, and maximizing metal removal rate for face milling of ASSAB XW42 are flow rate of 0.5 l/minute, cutting speed of 300 m/minute, feeding speed of 150 mm/minute and axial depth of cut of 0.2 mm.

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