Multi-Objective Optimization of Process Parameters in CNC End Milling of Al 7075-T6 Aluminum Alloy Using Taguchi-Grey, Taguchi-Fuzzy and Taguchi-Grey- Fuzzy Approaches

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Abstract: **Al 7075 T6 is one of the highest strength aluminum alloys in 7000 series family which is used in highly stressed structural parts of aircrafts. The high surface roughness lowers the fatigue resistance and also affects the quality of the parts. But, in order to minimize the surface roughness, the productivity is affected to the greater extent. Hence, this paper describes, the multi-objective optimization of process parameters to minimize surface roughness and maximize material removal rate, in CNC end milling of Al 7075 T6 aluminum alloy using Taguchi-Fuzzy, Taguchi-Grey and Taguchi-Grey-Fuzzy methods. The input parameters taken into consideration are speed, feed, depth of cut and nose radius. In Taguchi method, L27orthogonal array with 4 factors and 3 levels are chosen and S/N ratios are calculated. The S/N ratios of roughness and material removal rate are fed as inputs to Taguchi-Fuzzy and Taguchi-Grey methods and output received is Multi response performance index (MRPI).In Taguchi-Grey-Fuzzy method, S/N ratios of responses are first converted to Grey relational coefficients (GRCs) and then GRCs of responses are fed as inputs to the fuzzy logic system and output received is MRPI. The optimized levels in each integrated techniques were identified and confirmation test were done. There was a significant improvement in MRPI of optimal process parameters as compared to MRPI of initial process parameters in each integrated technique. As compared to other approaches, Taguchi-grey-fuzzy gave better results as compared to the other approaches.**

Keywords: **Optimization, Taguchi Method, Grey Relational analysis, Fuzzy logic, Surface roughness**

I. INTRODUCTION

7000 series is the highest strength series of aluminum alloys for aircraft applications. Al 7075 T6 is one of the highest strength members among the other alloys in 7000 series. Hence, it is used in highly stressed structures of aircraft [1]. The high surface roughness is one of the reasons responsible to reduce the fatigue life of this material [2, 3]. Fatigue is progressive, localized, permanent structural change that occurs in the material subjected to fluctuating stresses and strain which may result in cracks or fatigue after a sufficient period of time [4]. Surface roughness is the asperities on the surface which acts as the minute notches. These minute notches increase the stress concentration and the fatigue failure may occur to the earliest, if the roughness is not maintained to its minimum value. Many researchers have worked in area of fatigue failure of structural material and have proved the surface roughness to be one of the factors for early fatigue crack growth. Merati and Eastaugh [2], through his various experiments presented that among the discontinuities like microstructure, surface roughness and permanent coating, surface roughness is also one of the reasons of early fatigue crack nucleation in Al 7075 T6 and Al 7079 T6. Suraratchai et al [5] demonstrated that the fatigue life of Al alloy decreases considerably due to surface roughness as surface roughness leads to local stress. Therefore, this work has been carried out with the view of minimizing the surface roughness to increase the life this material. But, the productivity is affected to the greater extent in order to maintain the minimum roughness. Hence, this paper deals with the optimal selection of process parameters to minimize the roughness and maximize the material removal ratesimultaneously.

The need of high productivity and precision has focused the manufacturers to use CNC machines. The CNC machine tools require less operator input, provide greater improvement in productivity and increase the quality of the machined parts. Among the other machining processes, end milling is one of the commonly used metal removal process. It is widely used in variety of manufacturing industries including aerospace and automotive sectors. The surface roughness is an important parameter which not only decides the quality of the product but also decides the other properties like fatigue strength to the greater extent as explained earlier. Hence, CNC machine tools are must, to maintain the quality and productivity of the products which cannot be done by conventional machineries.

Nomenclature	
A	Speed
B	Feed
C	Depth of Cut
D	Nose radius
SR	Surface roughness
MRR	Material removal rate
GRCs	Grey relational coefficient
MRPI	Multi Response Performance Index
S/N	Signal to Noise ratio

The Taguchi design of experiments is a powerful method used to achieve high quality in lesser no of experiments [6]. It provides better settings as compared to traditional experimental designs which are time consuming due to a large number of experiments and most of the time not feasible. The Taguchi method reduces the sensitivity of quality characteristics to various unknown noise factors. Large numbers of papers have been published on Taguchi technique handling single output response. However, working with multiple responses is still an interesting area of research problem. Fuzzy logic deals with uncertain and vague data [7]. The grey relational analysis deals with the system having incomplete information [8]. The fuzzy logic system and grey relational analysis converts the multiple performance characteristics into single multi response performance index (MRPI) [9, 10]. Hence, the optimization of multiple performance characteristics is well handled by integrated Taguchi-Grey, Taguchi-Fuzzy and Taguchi-Grey-Fuzzy [11] approaches, which was not possible by the Taguchi method alone, which is shown in this paper.

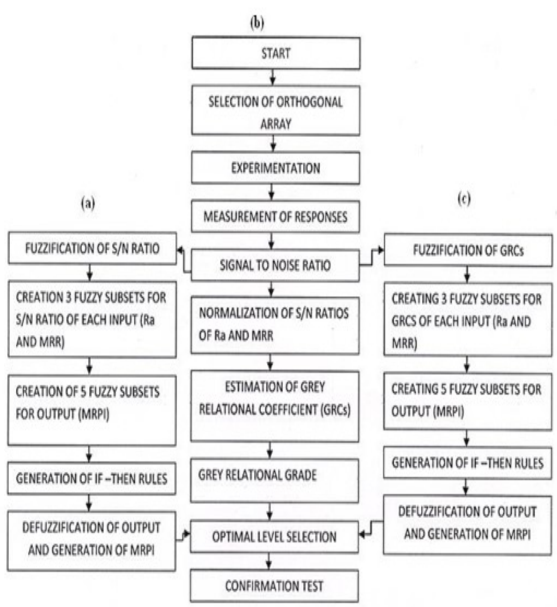

Fig1. (a) Taguchi- Fuzzy steps (b) Taguchi-Grey steps (c) Taguchi-Grey-Fuzzy steps

II. OPTIMIZATION OF MULTIPLE PERFORMANCE CHARACTERISTICS

Experimental methods are too complex and require a large number of experiments as number of process parameter increases. The Taguchi method uses a special design called orthogonal array to study the entire space oparameter with lesser number of experiments. The experimental results are converted into signal to noise ratios (S/N). The signal to noise ratio gives an idea about performance characteristic deviating from desired values. The Larger the S/N ratio lesser is the deviation of performance characteristic from the desired values. In this paper, the three integrated approaches as mentioned earlier is used to handle multiple responses that are surface roughness and material removal rate. For, Taguchi-Grey approach, the S/N ratios of responses are normalized and converted into Grey relational coefficient, which is further converted into Grey relational grade. This grey relational grade is multi response performance index. For, Taguchi-Fuzzy approach, the S/N ratios are fed as the input to the fuzzy Logic system and are converted to multi response performance index (MRPI). For, Taguchi-Grey-Fuzzy approach, the Grey relational coefficients are fed as the input to the fuzzy Logic system and are converted to multi response performance index. The conversion of multiple responses to single multi response performance index for the three approaches are shown in the fig 1a, 1b and 1c.

III. CNC MACHINING PROCESS

The computer numerically controlled machines are widely used in industries, fully controlled with minimum human intervention to increase the productivity and improve the quality of machined parts. Among the other milling techniques, end milling is one of the vital operations for obtaining the groundfinish.

3.1 Machining parameter selection

In this paper Vertical Milling Centre (Makino S33) is used for experimentation. The 16 mm diameter end milling cutter of ISCAR make was used for machining. The machining parameters were selected on the basis of various trial runs by checking their effect on Surface Roughness. The input process parameters taken in consideration are speed, feed, depth of cut and nose radius. The designations of inserts used for experimentation in terms of their nose radius are 0.4mm (R390-11 T3 04-PM), 0.8 mm (R390-11 T3 08-PM) and 1.2 mm (R390- 11 T3 12-PM). The initial machining parameters used by operators for machining aluminum alloys were as follows: speed-6000 r.p.m, feed-0.02 mm/tooth, depth of cut-0.4 mm, nose radius-1.2 mm. The machining parameters and levels are shown in Table1.

3.2 Machining performance evaluation

The machining performances considered in this paper are Material removal rate and Surface roughness. Mitutoya surface roughness tester: Surftest SJ- 210 series was used to measure Ra values of surface roughness. The material removal rate can be computed by following expression.

$MRR = n\,Nfa_p a_e$

Where n is spindle speed in r.p.m, N is the number of tooth, f is feed rate in mm/tooth, a_p is width of cut and a_e is the depth of cut.

Table 1. Machining parameters and levels

Symbol	Parameters	Level1	Level2	Level3
A	Speed (r.p.m)	6000	8000	10000
B	Feed (mm/tooth)	0.02	0.04	0.06
C	Depth of cut (mm)	0.2	0.4	0.6
D	Nose radius (mm)	0.4	0.8	1.2

3.3 Material specification

A wrought plate of Al 7075 T6 high strength aluminum alloy was used for experimentation with length 590 mm, width 55mm and thickness 20 mm. The chemical composition of the material is shown in table 2.

Table 2 Chemical Composition (% weight)

Chemical Composition(% weight)								
Al	Zn	Cu	Cr	Si	Ti	Mg	Mn	Fe
87-91.4	5.1-6.1	1.2-2	0.18-0.28	Max 0.4	Max 0.2	2.1-2.9	Max 0.3	Max 0.5

IV. OPTIMIZATION OF MACHINING PARAMETER

In this part, Taguchi-Grey, Taguchi-Fuzzy and Taguchi-Grey-Fuzzy methods are used to determine the optimal process parameters in CNC end milling of Al 7075 T6 aluminum alloy, considering surface roughness and material removal rate as the responses.

4.1 Taguchi method

The Taguchi method mostly focuses on reducing the variation in products or processes. The Taguchi method is a technique to find out the optimum values of the control factors to make the product or process get affected minimally by the noise factors. In Taguchi method, the optimization of a process is carried in three steps namely system design, parameter design and Tolerance design [12]. First, the system design examines the process sequence, production equipment and tentative parameter values in the process design stage. Then, the parameter design determines the optimal setting of the process parameters values for improving the performance characteristics. Finally, tolerance design is used to analyze the tolerance around the optimal setting recommended by parameter design. Hence, parameter design is the key step in the Taguchi method for achieving high quality without increasing the cost as the factors affecting the quality characteristics are determined in this stage. The steps in Taguchi method are selection of orthogonal array, running the experiment, analyzing the data, identifying the optimum condition and conducting the confirmationtest.

4.2 Selection of orthogonal array (1)

Selection of proper orthogonal array depends on the computation of total degree of freedom. The number of comparisons made between the levels to know which level is better is called degree of freedom .For example, a three level process parameter can be compared with two other levels, hence the degree of freedom is two. There are four process parameters considered for end milling operation and each parameter is of three levels, hence the total degree of freedom is 8. The selected orthogonal array should have a degree of freedom greater than or equal to those of process parameters. In this study L_{27} orthogonal array is selected as the degree of freedom of L_{27}(i.e 26) is greater than the total degree of freedom of process parameters. L_{27}orthogonal array has 13 columns and 27 rows and it can handle thirteen, three level process parameters. The Taguchi orthogonal array gives the better combination of experimental runs and reduces the number of runs, hence making the experimentation feasible. The combination of the process parameters using L_{27} is given in Table3.

4.3 Signal to noise ratio

The S/N ratio is the ratio of size of signal factor effect to the size of error factor effect [25]. The S/N ratio consolidates several repeated output responses into a single value which reflects the amount of variation present [1]. The S/N ratio measures the sensitivity of quality characteristic to external noise factor which is not under control. The highest S/N ratio implies the least sensitivity of output response to noise factors. On the basis of characteristic three S/N ratios are available namely lower the better, higher the better and nominal the better. In this paper lower-the-better for minimizing surface roughness and higher-the-better for maximizing material removal rate is used. The lower-the-better performance characteristic is expressed equation 2 and3.

$$S/N_{LB} = -10 \log \{(y^2 + y^2 \ldots y^2)/n\}$$

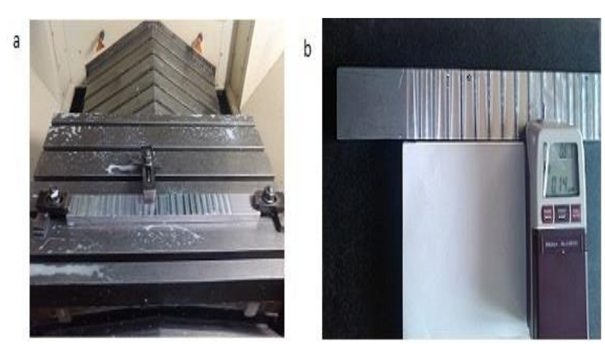

Table 3. Experimental layout using L27 array and responses

No	Speed (r.p.m)	Feed (mm/tooth)	Depth Of Cut(mm)	Nose Radius (mm)	Ra Ra(μm)	MRR (mm^3/min)	S/N Ra (db)	S/N MRR (db)
1	1	1	1	1	0.12	768	18.41	57.70
2	1	1	2	2	0.28	1536	11.05	63.72
3	1	1	3	3	0.39	2304	8.17	67.24
4	1	2	1	2	0.18	1536	14.89	63.72
5	1	2	2	3	0.42	3072	7.53	69.74
6	1	2	3	1	0.26	4608	11.7	73.27
7	1	3	1	3	0.19	2304	14.42	67.24
8	1	3	2	1	0.32	4608	9.89	73.27
9	1	3	3	2	0.58	6912	4.73	76.79
10	2	1	1	1	0.16	1024	15.91	60.20
11	2	1	2	2	0.26	2048	11.70	66.22
12	2	1	3	3	0.61	3072	4.29	69.74
13	2	2	1	2	0.35	2048	9.11	66.22
14	2	2	2	3	0.41	4096	7.74	72.24
15	2	2	3	1	0.24	6144	12.39	75.76
16	2	3	1	3	0.42	3072	7.53	69.74
17	2	3	2	1	0.30	6144	10.45	75.76
18	2	3	3	2	0.59	9216	4.53	79.29
19	3	1	1	1	0.16	1280	15.91	62.14
20	3	1	2	2	0.36	2560	8.87	68.16
21	3	1	3	3	0.29	3840	10.75	71.68
22	3	2	1	2	0.27	2560	11.37	68.16
23	3	2	2	3	0.36	5120	8.87	74.18
24	3	2	3	1	0.42	7680	7.53	77.70
25	3	3	1	3	0.44	3840	7.13	71.68
26	3	3	2	1	0.54	7680	5.53	77.70
27	3	3	3	2	0.72	11520	2.8	81.22

4.4 Taguchi Grey Optimization

The grey system theory was developed by Julong Deng in 1982 which deals with the system having uncertain or incomplete information. According to Grey theory, the system with complete information is white system, the system with no information is black system and the system with incomplete information is grey system. It provides an efficient solution to uncertain, multi-output and discrete data problems. The relation between machining parameters and machining performance can befound out using the Grey relational analysis. The relational degree between two sequences is also indicated with the help of Grey relational analysis. In grey relational analysis, experimental data i.e. measured features of quality characteristics of the product are first normalized ranging from zero to one. This process is known as grey relational generation. Next, based on normalized experimental data, grey relational coefficient is calculated to represent the correlation between the desired and actual experimental data. Then overall grey relational grade is determined by averaging the grey relational coefficient corresponding to selected responses. This approach converts a multiple response optimization problem into a single response optimization situation.

The steps in Taguchi-grey approach are as follows.

- Step1: select a suitable orthogonal array and perform theexperimentation.
- Step2: calculate the S/N ratios of the responses and find the normalized values of the same using the following equations asfollows.
- For higher is better performance response, the normalized value for the response is given by equation (4)

$$Y_{ij} = \left(\frac{X_{ij} - Min(X_{ij})}{Max(X_{ij}) - Min(X_{ij})}\right)$$

For lower is better performance response, it is given by equation (5).

$$Y_{ij} = \left(\frac{Max(X_{ij}) - (X_{ij})}{Max(X_{ij}) - Min(X_{ij})}\right)$$

Step3: find the maximum of the normalized value, let it be R

$$R = Max(Y_{ij})$$

Step4: find the absolute difference between each normalized value and R

$$Z_{ij} = |Y_{ij} - R|$$

Step5: find grey relational coefficient of each normalized value using equation (8). The grey relational coefficients (Cij) are calculated using following formula.

$$C_{ij} = \left(\frac{Min(Z_{ij}) + \mu Max(Z_{ij})}{Z_{ij} + \mu Max(Z_{ij})}\right)$$

Where is the weight generally taken as 0.5

Step 6: calculate the grey relational grade (Gk) using equation (9), where n is the number of responses.

$$G_k = \frac{\sum_{i=1}^{n} C_{ij}}{n}$$

Here the grey relational grade is the multi response performance index which gives the combined performance of multiple responses.

Table 4 Grey relational table

No	Normalized Ra	Normalized MRR	GRCs of Ra	GRCs of MRR	Grey relational Grade
1	1	0	1	0.33	0.66
2	0.52	0.25	0.51	0.40	0.45
3	0.34	0.4	0.43	0.45	0.44
4	0.77	0.25	0.68	0.40	0.54
5	0.30	0.51	0.41	0.50	0.45
6	0.57	0.66	0.53	0.59	0.56
7	0.74	0.40	0.65	0.45	0.55
8	0.45	0.66	0.47	0.59	0.53
9	0.12	0.81	0.36	0.72	0.54
10	0.83	0.10	0.74	0.35	0.54
11	0.57	0.36	0.53	0.43	0.48
12	0.09	0.51	0.35	0.50	0.42
13	0.40	0.362	0.45	0.43	0.44
14	0.31	0.61	0.42	0.56	0.49
15	0.61	0.76	0.56	0.67	0.61
16	0.30	0.51	0.41	0.50	0.45
17	0.49	0.76	0.49	0.67	0.58
18	0.11	0.91	0.35	0.84	0.59
19	0.83	0.18	0.74	0.37	0.55
20	0.38	0.44	0.44	0.47	0.45
21	0.50	0.59	0.5	0.54	0.52
22	0.54	0.44	0.52	0.47	0.49
23	0.38	0.7	0.44	0.62	0.53
24	0.30	0.85	0.41	0.76	0.58
25	0.27	0.59	0.40	0.54	0.47
26	0.17	0.85	0.37	0.76	0.56
27	0	1	0.33	1	0.66

4.5 Faguchi FuzzyOptimization

The theory of fuzzy logic unit was developed by Lofti. A. Zadeh [16] and it applies for a domain in which description of observations have no well-defined boundaries of set of observation, hence fuzziness is vagueness [17]. A fuzzy logic unit comprises of a fuzzifier, a fuzzy rule base, an inference engine and a defuzzifier. The fuzzifier converts the crisp inputs into the fuzzy sets by using the membership function. The fuzzy inference engine performs fuzzy reasoning on fuzzy rules to generate fuzzy values. Then these fuzzy values are converted into crisp output by defuzzifier. A membership function is a curve that assigns membership values to the crisp inputs. The S/N ratios of MRR (S/N_{MRR}) and S/N ratios of surface roughness (S/N_{SR}) are the two inputs to the fuzzy logic system .The fuzzifier assigns membership values to the two inputs by using trapezoidal membership function. In this paper three fuzzy subsets are assigned to each two inputs (Fig 2a and Fig 2b) and five fuzzy.

Subsets assigned to output (Fig 2c).The fuzzy rule base consist of a group of if-then control rules.

- Rule 1:if S/NSR is small and S/NMRR is small then y is very small else
- Rule 2: if S/NSR is small and S/NMRR is medium then y is small else .
- ………………………………………………
- ……………………………………………….
- Rule 9: if S/NSR is large and S/NMRR is large then y is very large.

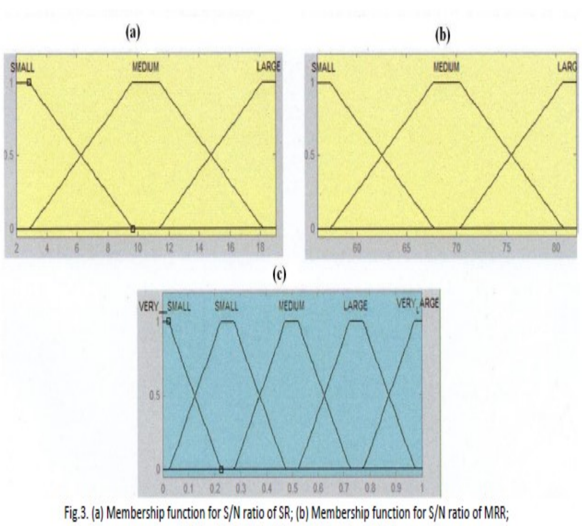

Fig.3. (a) Membership function for S/N ratio of SR; (b) Membership function for S/N ratio of MRR; (c) Membership function for S/N ratio of MRPI

In this way nine rules are derived by referring Table5. Once the fuzzy rules are derived, fuzzy reasoning of these rules by inference engine yields fuzzy output. Let Ci be the fuzzy subsets of output. Then the membership function of output of fuzzy reasoning is expressed:

$$\mu_{C_i}(y_i) = (\mu_{small}(S/N_{SR})\wedge\mu_{small}(S/N_{MRR})\wedge\mu_{verysmall}(y_i))\vee \ldots . (\mu_{Large}(S/N_{SR})\wedge\mu_{Large}(S/N_{MRR})\wedge\mu_{verylarge}(y_i)) \quad (10)$$

Where the minimum operation and V is is the maximum operation.

Using centre of gravity method as the defuzzification method, the fuzzy crisp output is converted into non fuzzy

$$y_j = \frac{\sum y_i \mu_{C_i}(y_i)}{\sum \mu_{C_i}(y_i)}$$

The yielded value yj is the crisp output and this output is called Multi Response Performance index (MRPI).MRPI gives an idea of simultaneous performance of multiple responses together. The larger the value of MRPI, better is the multiple performance characteristic.

4.6. Taguchi Grey Fuzzy Optimization

The Taguchi Grey Fuzzy is integration of Taguchi method and Grey-Fuzzy approach which was developed by lin and lin (2005). In this approach S/N ratios are estimated from the responses and are fed as inputs to grey relational analysis. These S/N ratios of the responses are normalized between 1 to 0. Further, the normalized values are converted into grey relational coefficients. These grey relational coefficients of surface roughness and material removal rate are fed as inputs to fuzzy logic system. The fuzzifier assigns membership values to the two inputs by using trapezoidal membership function. The three fuzzy subsets are assigned to the two inputs and five fuzzy subsets are assigned to the output. The fuzzy rule base generates the fuzzy rules and the fuzzy inference engine does the fuzzy reasoning of the rules, hence the fuzzy output is obtained. The defuzzification method called centre of gravity is used to convert the fuzzy output into crisp output. The output obtained is multi response performance index. The MRPI values obtained using all the three methods are shown in the Table 5.

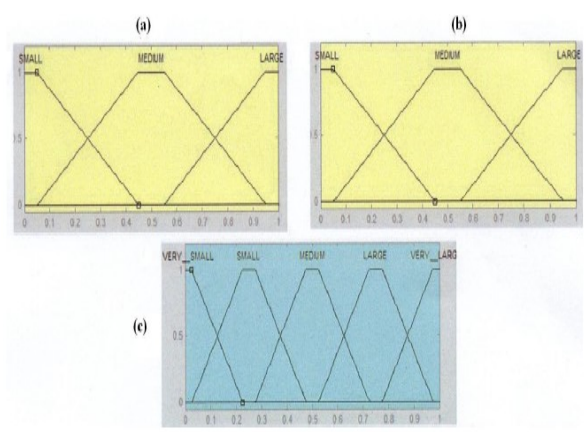

Fig.4. (a) Membership function for S/N ratio of SR; (b) Membership function for S/N ratio of MRR; (c) Membership function for S/N ratio of MRPI

Table.5 .MRPI Table

SR No	MRPI (Taguchi-Fuzzy)	MRPI (Taguchi-Grey)	MRPI(Taguchi-Grey-Fuzzy)
1	0.51	0.66	0.68
2	0.40	0.45	0.40
3	0.38	0.44	0.48
4	0.51	0.54	0.54
5	0.36	0.45	0.42
6	0.57	0.56	0.53
7	0.58	0.55	0.51
8	0.54	0.53	0.57
9	0.40	0.54	0.59
10	0.47	0.54	0.59
11	0.45	0.48	0.41
12	0.25	0.42	0.39
13	0.41	0.44	0.48
14	0.43	0.49	0.54
15	0.63	0.61	0.56
16	0.36	0.45	0.48
17	0.59	0.58	0.52
18	0.47	0.59	0.64
19	0.51	0.55	0.51
20	0.41	0.45	0.49
21	0.54	0.52	0.50
22	0.50	0.49	0.57
23	0.51	0.53	0.59
24	0.51	0.58	0.49
25	0.38	0.47	0.41
26	0.454	0.56	0.51
27	0.32	0.66	0.71

4.7. Optimal level selection.

MRPI gives an idea of simultaneous performance of multiple responses together. The larger the value of MRPI better is the multiple performance characteristic. The effect of each parameter on MRPI can be separated at different level as the experimental scheme is based on Taguchi orthogonal array. For example, the mean MRPI for speed at level 1 can be calculated by averaging the MRPI for experiments 1-9 from Table 5. In this way mean MRPI for all the levels of other parameter can be calculated and is shown in Table 6, Table 7 and Table 8. The optimal level of process parameter is selected from these Tables. The level having the maximum value of MRPI is selected as the optimal level from each parameter. Hence the optimal parameter levels for Taguchi Fuzzy, Taguchi Grey and Taguchi Grey Fuzzy are A1B1C2D3, A3B3C1D3 and A3B2C3D1.

Table 6 Taguchi Grey MRPI Table

Symbol	Machining Parameters	MRPI		
		Level 1	Level 2	Level 3
A	Speed	0.52	0.51	0.53
B	Feed	0.50	0.52	0.54
C	Depth of Cut	0.54	0.50	0.51
D	Nose Radius	0.57	0.51	0.59
Mean Value of MRPI=0.51				

Table 5 Taguchi Fuzzy MRPI Table

Symbol	Machining Parameters	MRPI		
		Level 1	Level 2	Level 3
A	Speed	0.475	0.455	0.461
B	Feed	0.48	0.46	0.45
C	Depth of Cut	0.47	0.48	0.45
D	Nose Radius	0.51	0.43	0.42
Mean Value of MRPI= 0.464				

Table 6 Taguchi Grey Fuzzy MRPI Table

Symbol	Machining Parameters	MRPI		
		Level 1	Level 2	Level 3
A	Speed	0.52	0.51	0.53
B	Feed	0.49	0.56	0.54
C	Depth of Cut	0.53	0.48	0.55
D	Nose Radius	0.56	0.53	0.47
Mean Value of MRPI=0.525				

V. CONFIRMATION TEST.

As optimal level of parameters has been identified, the further step is to predict and verify the improvement of the performance characteristics using the optimal level of parameters. The predicted MRPI of optimal level of parameters can be calculated using following formula.

Σ ( ) (10)

Where MRPIm is the total mean of the MRPI, MRPIiis the mean of MRPI at optimal level and q is the number of process parameters that significantly affect the multiple performance characteristics. Table 8 shows the result of confirmation experiments using the optimal machining parameters.

Table 7.Result of confirmation test by Taguchi-Fuzzy

Initial Machining Parameters		Final Machining Parameters	
		Predicted	Experimental
Setting level	A1B1C2D3	A1B2C1D1	A1B2C2D1
Surface roughness(µm)	0.51		0.36
MRR(mm^3/min)	1536		3072
MRPI	0.31	0.47	0.51
Improvement in MRPI=0.2			

Table 8.Result of confirmation test by Taguchi-grey

Initial Machining Parameters		Final Machining Parameters	
		Predicted	Experimental
Setting level	A1B1C2D3	A3B3C1D3	A3B3C1D3
Surface roughness(µm)	0.51		0.44
MRR(mm^3/min)	768		3840
MRPI	0.31	0.58	0.47
Improvement in MRPI=0.16			

Table 9.Result of confirmation test by Taguchi-Grey-Fuzzy

Initial Machining Parameters		Final Machining Parameters	
		Predicted	Experimental
Setting level	A1B1C2D3	A3B2C3D1	A3B2C3D1
Surface roughness(µm)	0.51		0.21
MRR(mm^3/min)	768		7680
MRPI	0.31	0.55	0.623
Improvement in MRPI=0.313			

Table 10 comparison of confirmation test

	Taguchi-Fuzzy	Taguchi-grey	Taguchi-Grey-Fuzzy
	A1B2C1D1	A3B3C1D3	A3B2C3D1
	Percentage improvement in responses by integrated methods as compared to that of initial parameter levels (%)		
Surface roughness(µm)	41.66	13.72	57.14
MRR(mm^3/min)	50	60	80
MRPI	39.2	34.04	50.24

Table 13 comparison of integrated techniques

	% improvement in responses by Taguchi-Grey-Fuzzy method as compared to other approaches	
	Taguchi-Fuzzy method	Taguchi-Grey method
Surface roughness(µm)	48	59
MRR(mm^3/min)	60	50
MRPI	18	24

VI. RESULTS AND DISCUSSION.

The table 9, 10 and 11 showed the following results. In Taguchi-Fuzzy method, the SR decreased from 0.49 to 0.36 (μm), MRR increased from 1536 to 3072 (mm3/min) and there was an improvement in MRPI by 0.2. In Taguchi-grey method, the SR decreased from 0.49 to 0.44 (μm), MRR increased from 768 to 3840 (mm3/min) and there was an improvement in MRPI by 0.16. In Taguchi-Grey-Fuzzy method, the SR decreased from 0.51to 0.21 (μm), MRR increased from 1536 to 7680 (mm3/min) and there was an improvement in MRPI by 0.313. The Table 12 shows the percentage improvement in responses and MRPI by the three integrated approaches as compared to initial cutting parameters levels. The Taguchi-Grey-Fuzzy method gave 50.24% improvement in MRPI which is greater than the improvement given by Taguchi-Grey and Taguchi-Fuzzy methods. Hence, the Taguchi-Grey-Fuzzy method gives better combined results as compared to other two methods.

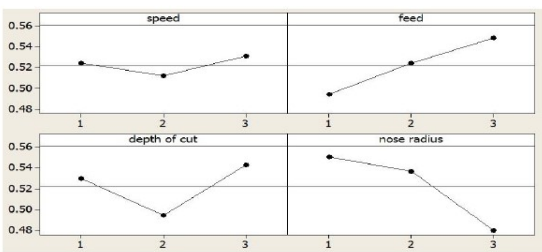

Fig 5. MRPI response graph

Since, Taguchi-Grey-Fuzzy method gave better result as compared to the other integrated optimization techniques; the main effect plot of MRPI versus factor levels of Taguchi-Grey-Fuzzy method is shown in figure 4.This graph shows the change in MRPI as the level changes in each parameter.

VII. CONCLUSION

This work has presented optimization of process parameters in CNC end milling of Al 7075 T6 aluminum alloy with multiple performance characteristics. Here, integrated Taguchi-Fuzzy,Taguchi-Grey and Taguchi-Grey-Fuzzy methods were used as the optimization techniques and the results from all these techniques were compared. Based on the confirmation tests, the following conclusions can be drawn.

- The following parameter setting has been identified as to yield the best combination of parameters: A1B2C2D1 for Taguchi-Fuzzy method, A3B3C1D3 forTaguchi-grey method, A3B2C3D1 for Taguchi-Grey-Fuzzy method
- The experimental results showed that there was significant improvement in Surface roughness and Material removal rate by all the three optimization techniques.
- On the basis of confirmation tests, it was found that the Taguchi-Grey-Fuzzy method gave the better results as compared to the other two methods as MRPI given by Taguchi-Grey-Fuzzy method is more comparatively.
- By this work, the optimized process parameters would definitely solve the problems fatigue faced by the material, by minimizing the roughness. At the same time, it will increase the productivity by maximizing the material removal rate.

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