Analysis of Machining Parameters on CNC Milling of Aluminium 2219

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Abstract**—***This paper mainly focuses on the impact of input parameters like feed, spindle speed, axial depth of cut, and radial depth of cut on the output characteristics of CNC milling process of aluminium 2219. Material removal rate, surface roughness, and flatness are taken as the performance measures. The optimum process parameters and corresponding output responses are found out using Taguchi analysis. The multi-objective optimization based on grey relational analysis is used to attain maximum material removal rate simultaneously with minimum flatness and surface roughness. ANN models were developed using back propagation algorithms to predict the performance characteristics.*

***Keywords* — Aluminium 2219, milling, optimization, grey relational grade, ANN.**

I. INTRODUCTION

Milling is one of most commonly used processes for machining parts to get precise tolerances. With the increasing demand for quality product as well as for higher productivity, milling process need to be performed more efficiently.

Kuram and Ozcelik (2013) studied the effect of spindle speed, feed per tooth and depth of cut on tool wear, force components and surface roughness during micro milling of aluminium. They utilized Taguchi signal to noise ratio to minimize all responses and responses were optimized simultaneously using grey relational analysis. Sukumar et. al (2014) identified the optimal combination of influential factors in the milling process on AL6061 using Taguchi analysis. The input parameters selected were speed, feed and depth of cut and the output response was surface roughness (Ra). An artificial neural network model has been developed and trained with full factorial design. Shetha and George (2016) investigated the effect of machining parameters spindle speed, feed and depth of cut during face milling of wrought cast steed grade B. The response parameters selected were surface roughness and flatness. Pleta et. al (2016) utilized Taguchi method to understand the influence of speed, feed, depth of cut and nutational rate. on cutting force and tool flank wear on milling process of INCONEL 718. It was found that the nutational rate and rotational rate have the largest interactions with both cutting forces and tool flank wear. Mohamed et. al (2016) investigated the use of the Taguchi design methodology for parametric study of CNC milling on EN19, EN24 with speed, feed, and depth of cut as input parameters and surface roughness, material removal rate, machining time as the output responses. Ribeiro et. al (2017) studied the surface quality in a CNC end milling operation of a hardened steel block with feed per tooth, cutting speed and radial depth of cut as input parameters. The optimal cutting combination was found out with best surface roughness value using Taguchi analysis.

It is found that limited works were done in optimization of milling parameters in aluminium alloy. Aluminium 2219 is a copper based alloy which finds use in many industrial applications. Hence this paper aims to investigate the effect of various process parameters such as speed, feed, axial depth of cut and radial depth of cut of milling process on aluminium 2219 with material removal rate (MRR), surface roughness (SR), and flatness as output responses. It also aims to develop an artificial neural network model for performance prediction of milling process on aluminium 2219.

II. DESIGN OF EXPERIMENTS

Process parameters and the levels for each parameters are listed in the Table 1

Table 1: Machining Parameters and Levels

Parameters	Levels		
	1	2	3
Feed (mm/min)	500	1000	1500

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Spindle speed (rpm)	1000	1500	2000
Axial depth of cut (mm)	0.3	0.6	0.9
Radial depth of cut (mm)	5	7.5	15

The designed combinations of input parameters based on L9 orthogonal array are shown in Table 2.

Table 2: Combination of Input Parameters

Sl. No.	Feed (mm/min)	Speed (rpm)	Axial depth of cut (mm)	Radial depth of cut (mm)
1	500	1000	0.3	5
2	500	1500	0.6	7.5
3	500	2000	0.9	15
4	1000	1000	0.6	15
5	1000	1500	0.9	5
6	1000	2000	0.3	7.5
7	1500	1000	0.9	7.5
8	1500	1500	0.3	15
9	1500	2000	0.6	5

III. RESULTS AND ANALYSIS

Experiments are conducted based on the input parameter combination by L9 orthogonal array. Each experiment is repeated 3 times for getting accurate results. Total 27 experiments are done and the experiment results are shown in Table 3.

Table 3: Experimental Results

Sl. No.	MRR (gm/min)	SR (µm)	Flatness (mm)
1	1.62	0.42	0.024
2	1.68	0.44	0.027
3	1.63	0.46	0.025
4	4.12	0.38	0.026
5	4.14	0.36	0.024
6	4.19	0.32	0.022
7	13.8	0.22	0.018
8	13.79	0.24	0.024
9	13.75	0.26	0.020
10	13.52	0.48	0.020
11	13.63	0.42	0.022
12	13.7	0.44	0.024
13	4.86	0.18	0.017
14	4.8	0.18	0.020
15	4.78	0.2	0.022
16	2.46	0.2	0.016
17	2.56	0.19	0.018
18	2.52	0.18	0.015
19	14.4	2.28	0.040
20	14.65	2.1	0.038
21	14.45	2.08	0.034
22	13.2	0.32	0.022
23	13.29	0.32	0.023
24	13.45	0.36	0.019
25	5.26	0.22	0.018
26	5.196	0.2	0.019
27	5.1	0.24	0.016

The optimum combinations of process parameters are obtained from the S/N ratios. The calculated S/N ratios for different output responses are given in Table 4.

Table 4: S/N Ratios for MRR, SR and Flatness

Sl. No.	S/N Ratio MRR	S/N Ratio SR	S/N Ratio Flatness
1	4.3112	7.1250	31.9156
2	12.3603	9.0147	32.3757
3	22.7850	12.3757	33.6318
4	22.6810	6.9868	33.1277
5	13.6483	14.5676	34.0782
6	8.0015	14.4169	35.7133
7	23.2266	-6.6698	28.5387
8	22.4850	9.5285	33.3913
9	14.2934	13.1277	35.0353

Since material removal rate is desired to be at maximum, larger the better characteristic is used, meanwhile for getting lower surface roughness & flatness, lower the better characteristic is used for calculating S/N ratio.

The mean values of S/N ratio of MRR (larger the better) are shown in Table 5.

Table 5: Mean of S/N Ratios for MRR

Level	Feed	Speed	Axial depth of cut	Radial depth of cut
1	13.15	16.74	11.60	10.75
2	14.78	16.16	16.44	14.53
3	20.00	15.03	19.89	22.65
Delta	6.85	1.71	8.29	11.90
Rank	3	4	2	1

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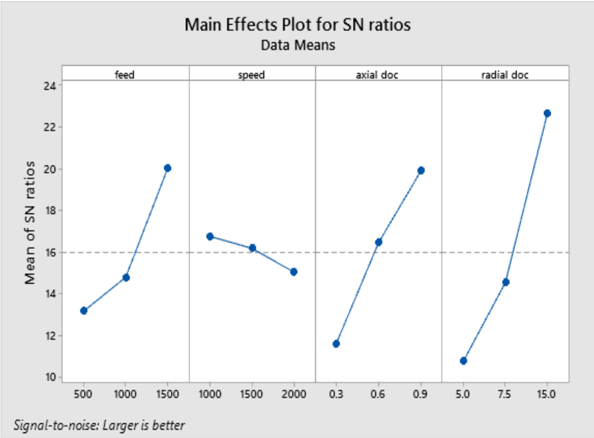

Fig. 1: Mean Effects Plot of S/N Ratios for MRR

The delta value is the variation of mean S/N ratio from first level to the third level, and thus shows how on each parameter affect the particular response. It can be seen that radial depth of cut has the highest delta value and hence it has the highest influence on MRR. From the main effects plot of MRR (Fig. 1) it is clear that the optimum process parameters are found to be speed 1000 rpm, feed 1500 mm/min, axial depth of cut 0.9mm and radial depth of cut 15mm.

The regression equation for MRR is found as follows;

MRR=-6.04+ 0.004475 feed-0.002760 speed

+ 8.680 axial depth of cut +0.9458 radial depth of cut. (1)

Table 6: Mean S/N Ratios for SR

Level	Feed	Speed	Axial depth of cut	Radial depth of cut
1	9.505	2.481	10.357	11.607
2	11.990	11.037	9.710	5.587
3	5.329	13.307	6.758	9.630
Delta	6.662	10.826	3.599	6.019
Rank	2	1	4	3

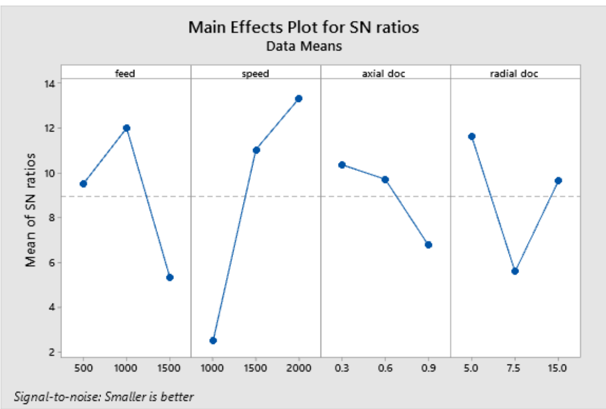

Fig. 2: Mean Effects Plot of S/N Ratios for SR

The mean S/N ratio values for surface roughness are shown in Table 6 (smaller the better for SR). Here spindle speed has the highest delta value and hence influence the surface roughness the most. From the main effects plot of SR (Fig. 2), the optimum process parameters are found to be speed 2000 rpm, feed 1000 mm/min, axial depth of cut 0.3 mm and radial depth of cut 5 mm.

The regression equation for SR is found as follows;

SR=0.722+ 0.000558 feed-0.000797 speed

+0.898 axial depth of cut-0.0128 radial depth of cut (2)

Table 7: Mean S/N Ratios for Flatness

Level	Feed	Speed	Axial depth of cut	Radial depth of cut
1	32.64	31.19	33.67	33.68
2	34.31	33.28	33.51	32.21
3	32.32	34.79	32.08	33.38
Delta	1.98	3.60	1.59	1.47
Rank	2	1	3	4

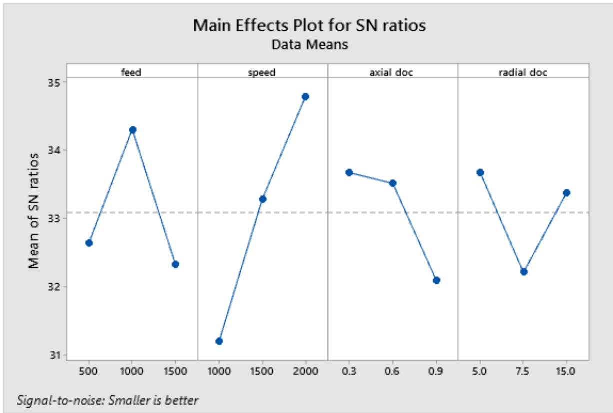

Fig. 3: Mean Effects Plot of S/N Ratios for Flatness

The mean S/N ratio values for flatness are shown in Table 7 (smaller the better for flatness). Here spindle speed has the highest delta value and hence influence the flatness the mostly. From the main effects plot of flatness (Fig. 3) the optimum process parameters for flatness are found to be, speed 2000 rpm, feed 1000(mm/min), axial depth of cut 0.3 mm and radial depth of cut 5 mm.

The regression equation for flatness is found as follows;

Flatness=0.03168+0.000002 feed-0.000010 speed

+0.00815 axial depth of cut-0.000106 radial depth of cut

(3)

The optimum output responses are found using the regression analysis and the results obtained are MRR 19 g/min, surface roughness 0.1018 µm and flatness 0.01559 mm. The confirmation experiments are also done with the optimum combinations for material removal rate, surface roughness and flatness. The results obtained are MRR 17.9 g/min, surface roughness 0.128 µm and flatness 0.01758 mm.

IV. GREY RELATIONAL ANALYSIS

The optimization of parameters considering multiple performance characteristics of the milling process is done using gray relational analysis. The gray relational grades (GRG) are calculated by the normalized experimental results of the performance characteristics and the results are given in Table 8.

Table 8: Grey Relational Grades

Exp. No.	Grey Relational Grade	Rank
1	0.576	22
2	0.549	26
3	0.560	25
4	0.585	21
5	0.606	20
6	0.636	19
7	0.885	1
8	0.804	4
9	0.841	2
10	0.781	6
11	0.773	8
12	0.752	12
13	0.754	11
14	0.704	17
15	0.673	18
16	0.752	13
17	0.716	15
18	0.783	5
19	0.543	27
20	0.569	24
21	0.574	23
22	0.780	7
23	0.773	9
24	0.819	3
25	0.726	14
26	0.716	16
27	0.759	10

The mean S/N ratio values for GRG are shown in Table 9 (larger the better for GRG). It can be seen that radial depth of cut has the highest delta value and hence radial depth of cut has the highest influence on gray relational grade. It is clear that the optimum process parameters for getting the optimum cutting condition are feed 1000 mm/min, speed 2000 rpm, axial depth of cut 0.6 mm and radial depth of cut 15mm.

Table 9: Mean S/N ratios for GRG

Level	Feed	Speed	Axial depth of cut	Radial depth of cut
1	-3.613	-4.106	-3.192	-3.571
2	-2.600	-3.123	-3.103	-3.949
3	-3.253	-2.237	-3.171	-1.946
Delta	1.013	1.869	0.089	2.004
Rank	3	2	4	1

Fig. 4: Mean Effects Plot of S/N Ratio for GRG

Regression equation of GRG is as follows;

GRG=0.3188+0.000024 feed+0.000145 speed +0.0072 axial depth of cut+0.01512 radial depth of cut

GRG obtained from the regression equation is 0.8639. An experiment is also done with optimum combinations of cutting parameters and the GRG obtained is 0.867.

V. ARTIFICIAL NEURAL NETWORK MODEL

An ANN model is designed using Matlab Neural Network Toolbox to predict MRR, SR and flatness. The parameters used for the ANN model are structure 4-20-3 (4 neurons in input layer, 20 neurons in hidden layer and 3 neuron in output layer), feed forward back propagation algorithm in MATLAB, 80:20 training & validation to testing ratio, Tanslm is the transfer function for hidden layer and the mean square error (MSE) is the performance function.

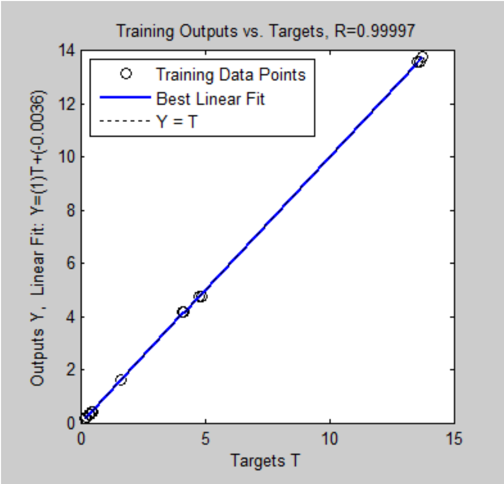

Fig. 5: Training Output vs. Target

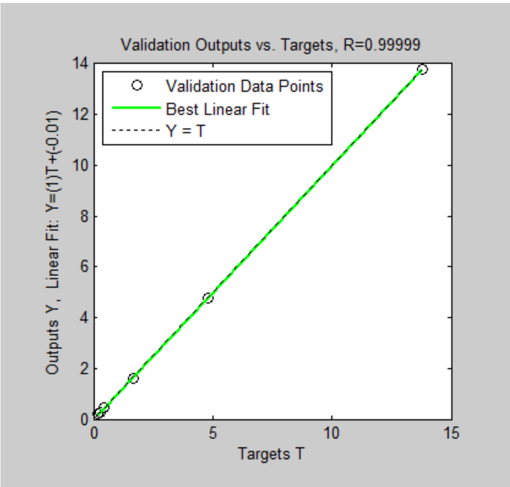

Fig. 6: Validation Output vs. Target

The training output vs target and validation output vs target are shown in Fig. 5 and Fig. 6. It is noted that MSE of predicted training data is 0.000946 and correlation coefficient is 0.99997, MSE of predicted validation data is 0.004591 and correlation coefficient is 0.9999. It shows that the model performance is high and output target correlation is perfect.

Table 10 Comparison of Experimental Data and ANN Predicted Test Data

Exp. No.	MRR		SR		Flatness	
	Exp. data	ANN data	Exp. data	ANN data	Exp. data	ANN data
2	1.68	1.626	0.44	0.459	0.027	0.025
7	13.8	13.74	0.22	0.260	0.018	0.020
13	4.86	4.799	0.18	0.18	0.017	0.020
15	4.78	4.799	0.20	0.18	0.022	0.020
21	14.45	14.60	2.08	2.100	0.034	0.038

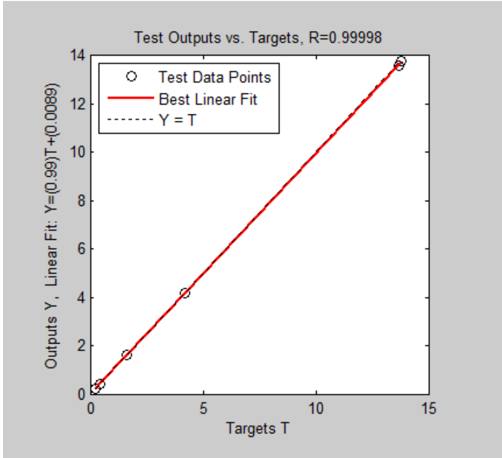

Fig. 7: Test Output vs. Target

Table 10 shows the comparison of experimental data and ANN predicted data. The test output vs target is shown in Fig. 7. It is noted that MSE of predicted training data is 0.01336 and correlation coefficient is 0.99998. So the testing results validates that ANN as a prediction model has statistically satisfactory goodness of fit from the modeling point of view.

VI. CONCLUSION

The conclusions made based on the experimental investigations of milling parameters on CNC milling of Aluminium 2219 are as follows;

- Experiments were conducted on aluminium 2219 successfully. The optimum combination of process parameters for material removal rate, surface roughness and flatness were found. It was concluded that surface roughness is most affected by spindle speed, material removal rate is most affected by radial depth of cut and flatness is also most affected by spindle speed. The optimum output responses were found using regression analysis and confirmation experiment.
- Grey relational analysis is done for the multi-objective optimization of process parameters in the milling process of aluminium 2219.
- An artificial neural network model is used for the prediction and optimization of machining parameters. The predicted results are found to be close to the experimental values. The developed model has good accuracy in predicting the output parameters under consideration.

REFERENCES

[1] **Kuram E** and **Ozcelik B** (2013) Multi objective optimization using Taguchi based grey relational analysis for micro-milling of AL 7075 material with ball nose end mill. *Measurement*, 46, 1849-1864.

[2] **Mohamed F, Praveen K** and **Madhavan P** (2016) Multi objective optimization of CNC milling parameters using Taguchi method for EN19 & EN24, *International Journal of Techno Chem Research.*

[3] **Pleta A, Nithyanand G, Akhavan F** and **Mears M** (2016) Identification of optimal machining parameters in trochoidal milling of inconel 718 for minimal force and tool wear and investigation of corresponding effects on machining affected zone depth, *Journal of Manufacturing Processe.*

[4] **Ribeiro J, Lopes H, Queijo L** and **Figueiredo D** (2017) Optimization of cutting parameters to minimize the surface roughness in the end milling process using the Taguchi method, *Periodica Polytechnica Mechanical Engineering.*

[5] **Shetha S** and **George P** (2016) Experimental investigation and prediction of flatness and surface roughness during face milling operation of WCB Material, *Procedia Technology,* 23, 344 – 351.

[6] **Sukumar S, Ramaiah V** and **Nagarjuna A** (2014) Optimization and prediction of parameters in face milling of Al-6061 using Taguchi and ANN approach, *Procedia Engineering 97*, 365 – 371.