Experimental Investigations of Process Parameters on CNC Turning of AISI 304l

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***Abstract*—This paper focuses on the effect of selected input turning parameters like spindle speed, depth of cut, feed, and tool nose radius on the output characteristics like surface roughness (SR), material removal rate (MRR), and roundness error (RE). In this research, stainless steel AISI 304L is used as the work piece with carbide insert tool. The optimum process parameters and corresponding output responses are found out using Taguchi analysis. The multi-objective optimization based on grey relational analysis (GRG) is used to attain maximum material removal rate simultaneously with minimum surface roughness and roundness error. Artificial neural network (ANN) model is developed using back propagation algorithm to predict the performance characteristics and found that the experimental values are closely related to the ANN predicted model**

Keywords*—Surface roughness, material removal rate, roundness error, grey relational grade, artificial neural network.

I. INTRODUCTION

Turning operation is a basic type of metal machining operation that is widely used in industries and research & development. With the increasing demand for a quality product as well as for higher productivity, turning operation needs to be performed more efficiently. Therefore, the optimization of process parameters and modeling is essential to achieve a high-quality product with the reduction of manufacturing cost.

Lavanya et. al (2013) optimized the process parameters such as speed, feed, and depth of cut in turning operation of AISI-1016 alloy steels using CBN insert. It was noted that feed was the most influenced cutting parameter on the surface roughness followed by speed and depth of cut. Rajendra and Deepak (2015) studied the effect of process parameters like feed rate cutting speed and depth of cut for material removal rate on Al6061. It was found that the feed rate was the most influential parameter that affects the material removal rate while machining Al6061 aluminum alloy. Jaina et. al (2015) explained the effect of machining parameters for turning operation on Inconel-625 in CNC machining with the help of Taguchi Method. The experiment showed that the insert spindle speed and feed rate that effects mostly on the material removal rate in turning smart alloy Inconel-25. Sangwana (2015) presented an approach for determining the optimum turning machining parameters leading to minimum surface roughness by integrating artificial neural network (ANN) and genetic algorithm (GA) on titanium alloy Ti-6Al-4V. It has also been observed that the increase in depth of cut and cutting speed decreases the surface roughness and the predicted results using ANN and integrated (GA) indicated close agreement between the predicted values and experimental values. Raykar (2015) optimized the turning process parameters for surface roughness, power consumption, material removal rate and cutting time on AL 7075 aluminum alloy with coated carbide insert and dry machining condition. Saha and Majumder (2016) described the effect of turning parameters speed, feed, depth of cut on ASTM A36 mild steel bar for the frequency of tool vibration and average surface roughness in turning. Asilturk (2016) presented a study about the effect of process parameters spindle rotational speed, feed rate, depth of cut and tool tip radius for surface roughness values (Ra and Rz) on Co28Cr6Mo material. Response surface methodology based on the Taguchi method is used for the experiment. It was found that tool tip radius was the most influential parameter on surface roughness. Niranjan and Shivashankar (2017) optimized the cutting process parameters cutting speed, feed, depth of cut on AL6061 using ANOVA and Taguchi method.

From the literatures, it is found that limited works were done in the optimization of the turning process of stainless steel AISI 304L. Considering the above gap, it is decided to investigate the influence of various process parameters on performance measures in the turning process of stainless steel AISI 304L. It is understood that spindle speed, depth of cut, feed rate and tool nose radius are important turning input parameters. Material removal rate, surface roughness and roundness error have a significant role in the quality of the part machined. Material removal rate has to be maximum with minimum surface roughness and roundness error. In the literature, Taguchi's grey relational method is most commonly used to find multiple optimum combinations and artificial neural network (ANN) is used for performance prediction of various machining operations.

II. DESIGN OF EXPERIMENTS

The process parameters and its levels are listed in the Table 1.

Table 1: Machining Parameters and Levels

Sl. No.	Process Parameter	Level 1	Level 2	Level 3
1	Spindle speed (rpm)	500	1000	1500
2	Depth of cut (mm)	0.2	0.4	0.6
3	Feed (mm/rev)	0.05	0.1	0.15
4	Tool nose radius (mm)	0.2	0.4	0.8

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

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Table 2: Combination of Process Parameters

Sl. No.	Spindle speed (rpm)	Depth of cut (mm)	Feed (mm/rev)	Tool nose radius (mm)
1	500	0.2	0.05	0.2
2	500	0.4	0.1	0.4
3	500	0.6	0.15	0.8
4	1000	0.2	0.1	0.8
5	1000	0.4	0.15	0.2
6	1000	0.6	0.05	0.4
7	1500	0.2	0.15	0.4
8	1500	0.4	0.05	0.8
9	1500	0.6	0.1	0.2

III. RESULTS AND DISCUSSIONS

The results of 9 experiments with three replications are shown in Table 3.

Table 3: Experimental Results

Sl. No.	SR (μm)	MRR (gm/min)	RE (mm)
1	1.14	7.52	0.032
	1.06	7.86	0.034
	1.00	8.12	0.031
2	0.54	16.61	0.021
	0.55	13.98	0.023
	0.6	12.78	0.025
3	1.32	22.25	0.036
	1.40	23.59	0.035
	1.22	23.73	0.031
4	1.04	9.09	0.030
	1.12	9.39	0.031
	1.00	10.15	0.030
5	5.42	14.71	0.052
	5.58	15.21	0.055
	5.34	14.71	0.051
6	1.36	22.73	0.036
	1.29	22.73	0.033
	1.62	24.61	0.039
7	0.92	5.84	0.029
	0.80	6.76	0.028
	0.86	6.83	0.028
8	0.72	9.74	0.026
	0.84	12.30	0.028
	0.96	11.36	0.029
9	2.74	24.51	0.045
	2.86	22.33	0.047
	2.58	21.95	0.043

The optimum combinations of process parameters are obtained from the S/N ratios. Lower the better characteristic is used to calculate S/N ratio for lower surface roughness & roundness error and larger the better characteristic is used for getting good material removal rate. The S/N ratios for SR, MRR and RE are given in Table 4.

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

Sl. No.	SR	MRR	RE
1	-0.5731	17.8660	29.8005
2	4.9735	23.0499	32.7436
3	-2.3811	27.2949	29.3529
4	-0.4610	19.5663	30.3605
5	-14.7241	23.4469	25.5648
6	-3.1091	27.3501	28.8539
7	1.2960	16.1594	30.9528
8	1.4557	20.8093	31.1520
9	-8.7203	27.1778	26.9300

The response table of S/N ratio for SR are shown in the Table 5.

Table 5: Response Table of S/N Ratios for SR

Level	Spindle speed	Depth of cut	Feed	Tool nose radius
1	0.67368	0.08727	-0.74217	-8.00583
2	-6.09808	-2.76436	-1.40203	1.05404
3	-1.98954	-4.73686	-5.26975	-0.46215
Delta	6.77176	4.82413	4.52758	9.05987
Rank	2	3	4	1

It can be seen that tool nose radius has the highest delta value and hence tool nose radius has the highest influence on SR. It is also clear that the optimum process parameters for getting the optimum SR is spindle speed 500 rpm, depth of cut 0.2 mm, feed 0.05 mm/rev and nose radius 0.4 mm (Figure 1).

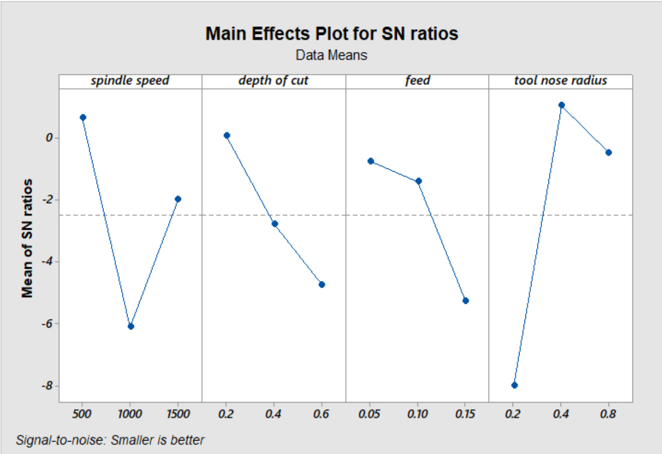

Figure 1: Main Effects Plot for SN Ratios of SR

The regression equation for SR is found as follows;

SR=0.27+0.000494 spindle speed+2.07 depth of cut +14.30 feed rate-2.830 tool nose radius (1)

The response table of S/N ratios for MRR are shown in the Table 6.

Table 6: Response Table of S/N Ratios for MRR

Level	Spindle speed	Depth of cut	Feed	Tool nose radius
1	22.74	17.86	22.01	22.83
2	23.45	22.44	23.26	22.19
3	21.38	27.27	22.30	22.56
Delta	2.07	9.41	1.26	0.64
Rank	2	1	3	4

Here depth of cut has the highest delta value and hence influences the material removal rate the most. The optimum process parameters are spindle speed 1000 rpm, depth of cut 0.6 mm, feed 0.10 mm/rev and nose radius 0.2 mm (Figure 2). The regression equation for MRR is found as follows;

MRR=0.98 -0.001647 spindle speed+38.02 depth of cut +7.40 feed rate-0.89 tool nose radius (2)

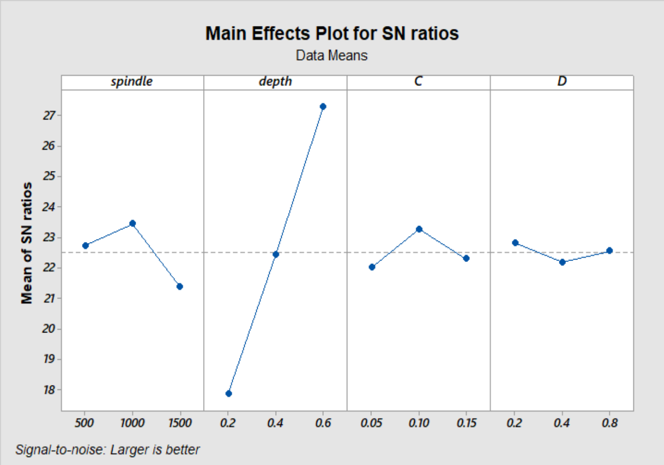

Figure 2: Main Effects Plot of SN Ratios for MRR

The response table of S/N ratio for RE are shown in the Table 7.

Table 7: Response Table for S/N Ratios of RE

Level	Spindle speed	Depth of cut	Feed	Tool nose radius
1	30.63	30.37	29.94	27.43
2	28.26	29.82	30.01	30.85
3	29.68	28.38	28.62	30.29
Delta	2.37	1.99	1.39	3.42
Rank	2	3	4	1

Here tool nose radius has the highest delta value and hence influence the roundness the mostly. The optimum process parameters are spindle speed 500 rpm, depth of cut 0.2 mm, feed 0.10 mm/rev and nose radius 0.4 mm (Figure 3). The regression equation for RE is found as follows;

RN=0.02433+0.000004 spindle speed+0.02000 depth of cut +0.0633 feed rate - 0.01754 tool nose radius (3)

Figure 3: Main Effects Plot of SN Ratios for RE

The results obtained from Taguchi optimization technique to get the minimum surface roughness, maximum material removal rate and minimum roundness error are shown in the Table 8.

Table 8: Optimum Combination of Process Parameters

Process Parameter	SR (μm)	MRR (gm/min)	RE (mm)
Spindle speed (rpm)	500	1000	500
Depth of cut (mm)	0.2	0.6	0.2
Feed (mm/rev)	0.05	0.10	0.10
Tool nose radius (mm)	0.4	0.2	0.4

The optimum output responses are found using regression analysis and confirmation experiment as shown in Table 9.

Table 9: Optimum Output Responses

Sl. No.	Output Response	Optimum Value	
		Regression Equation	Confirmation Experiment
1	Surface roughness (μm)	0.5574	0.56
2	Material removal rate (gm/min)	22.707	21.60
3	Roundness error (mm)	0.0239	0.025

IV. MULTI OBJECTIVE OPTIMIZATION

Grey relational analysis (GRA) is used for multi optimization of three performance characteristics simultaneously. The initial experimental data are normalized in the range between zero and one and deviation sequences are calculated. Subsequently, grey relational coefficient for each performance characteristics are calculated with this pre-processed data and finally grey relational grades are calculated for multi-objective optimization. The grey relational coefficients (GRC) and grey relational grades (GRG) are given in Table 10.

Table 10: GRC and GRG

Sl. No.	GRC (SR)	GRC (MRR)	GRC (RE)	GRG (yi)	Rank
1	0.808	0.354	0.607	0.590	21
2	0.829	0.359	0.567	0.585	23
3	0.846	0.363	0.630	0.613	19
4	1.000	0.540	1.000	0.847	1
5	0.996	0.469	0.895	0.787	2
6	0.977	0.442	0.810	0.743	4
7	0.764	0.799	0.531	0.698	9
8	0.746	0.902	0.548	0.732	5
9	0.788	0.914	0.630	0.777	3
10	0.834	0.377	0.654	0.622	18
11	0.813	0.381	0.630	0.608	20
12	0.846	0.394	0.654	0.631	16
13	0.341	0.487	0.354	0.394	26
14	0.333	0.500	0.333	0.389	27
15	0.344	0.487	0.362	0.398	25
16	0.754	0.833	0.531	0.706	8
17	0.771	0.833	0.586	0.730	6
18	0.700	1.000	0.486	0.729	7
19	0.869	0.333	0.680	0.627	17
20	0.906	0.345	0.708	0.653	12
21	0.887	0.345	0.708	0.647	14
22	0.933	0.387	0.773	0.698	10
23	0.894	0.433	0.708	0.678	11
24	0.857	0.415	0.680	0.651	13
25	0.534	0.989	0.415	0.646	15
26	0.521	0.805	0.395	0.574	24
27	0.553	0.779	0.436	0.589	22

The response table of S/N ratios for GRG are shown in the Table 11.

Table 11: Response Table of S/N Ratios for GRG

Level	Spindle speed	Depth of cut	Feed	Tool nose radius
1	-3.084	-4.167	-3.584	-5.675
2	-5.029	-4.525	-3.546	-2.915
3	-3.897	-3.318	-4.880	-3.419
Delta	1.945	1.206	1.334	2.761
Rank	2	4	3	1

The optimum combination for multiple objective grey relational analysis is spindle speed 500 rpm, depth of cut 0.6mm, feed 0.10 mm/rev and tool nose radius 0.4mm (Figure 4).

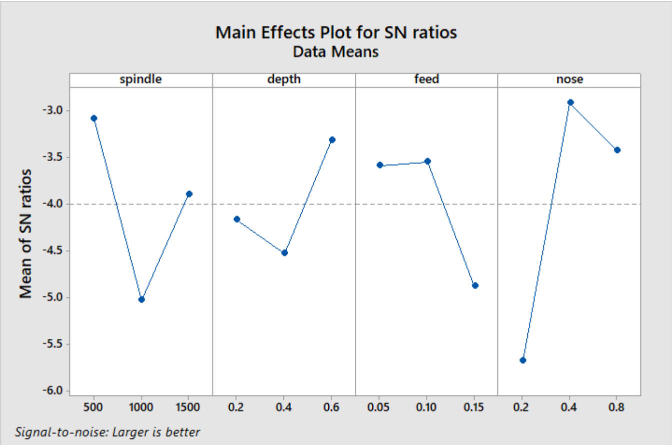

Figure 4: Main Effects Plot of SN Ratios for GRG

The regression equation for GRG is found as follows;

GRG=0.6260-0.000068 spindle speed+0.168 depth of cut-0.739 feed+0.1942 nose radius (4)

Optimum GRG are calculated based on regression equation as well as confirmation experiment and the obtained values of GRG are 0.66298 and 0.651 respectively.

V. ARTIFICIAL NEURAL NEWORK

As the machining process is non-linear and time-dependent, it is difficult for traditional identification methods to provide an accurate prediction model. To address this difficulty, non-traditional techniques such as artificial neural networks (ANN) have been introduced. The complete details of the ANN model development were well reported in several studies. Network structure 4-20-3 ((4 neurons in the input layer), (20 neurons in hidden layer) and (3 neurons in the output layer)) is found to be the most confidence and optimal ANN model. The feed forward back propagation algorithm is used for training the data. Then 60 percentage experimental data are used for training and 20 percentage for both validation and testing. Transfer function for the hidden layer is used as Trainslm. The MSE of training, validation and testing are 0.1916, 0.2857 and 0.124 respectively. The performance of the developed network examined based on the correlation coefficient (R-value) for both training and testing data for response measures prediction in the ANN model are determined as 0.99594 and 0.99926 respectively (Figure 5). The correlation coefficient for the validation data set was found to be 0.99919 which is very close to 1, thus, indicating a strong correlation between the experimental results and network predictions.

The test data of responses of surface roughness, material removal rate and roundness are given in Table 12, Table 13, and Table 14. Mean square error of surface roughness, material removal rate and roundness are found as 0.02806, 0.354 and 0.0000114 respectively and total mean square error is found as 0.127.

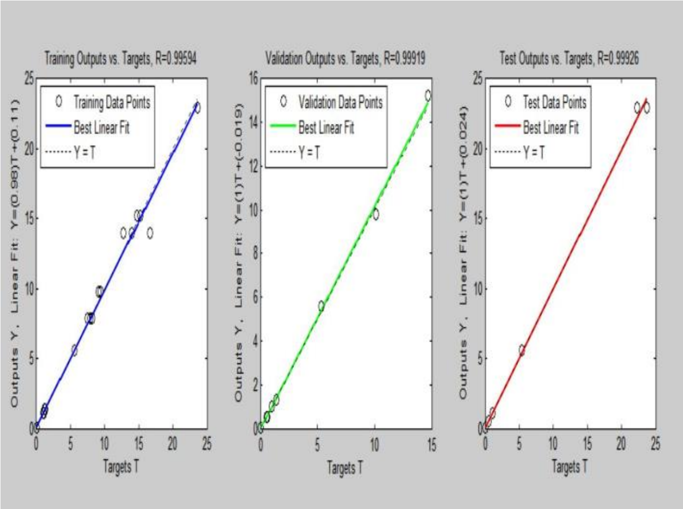

Figure 5 Correlation Graph of Training, Testing and Validation

Table 12: Test Data of Surface Roughness

Exp no	Exp. Value	ANN Value	Error
2	1.14	1.0701	0.0699
7	1.32	1.31	0.01
15	5.34	5.50	0.16
17	1.29	1.4901	0.2001
26	2.86	2.5959	0.2641

Table 13: Test Data of Material Removal Rate

Exp no	Exp. Value	ANN Value	Error
2	7.86	7.81	0.05
7	22.25	23.16	0.91
15	14.71	14.96	0.25
17	22.73	23.6699	0.93
26	22.33	22.2057	0.1243

Table 14: Test Data of Roundness Error

Exp no	Exp. Value	ANN Value	Error
2	0.034	0.0315	0.0025
7	0.036	0.0330	0.003
15	0.051	0.0535	0.0025
17	0.033	0.0375	0.0045
26	0.047	0.0432	0.0038

VI. CONCLUSION

An experimental study to analyze the effect of process parameters on the turning process of stainless steel AISI 304L has been carried out using carbide insert tool. The turning was carried out on SHAUBLIN 125 CCN CNC turning machine using L9 orthogonal array. The optimum combinations of

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spindle speed, depth of cut, feed rate and tool nose radius to achieve minimum surface roughness, maximum material removal rate and minimum roundness error are found out. Grey relational analysis was used to identify optimum parameters under multi- objective criteria. The artificial neural network (ANN) model was developed and found effective for performance prediction of turning operation on stainless steel AISI 304L.

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