OPTIMIZATION OF MACHINING PARAMETERS ON CNC LATHE AISI 316L MATERIAL WITH COATED CARBIDE INSERTS USING TAGUCHI GRA METHODS

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Abstract:The assessment of an engineering material's machinability grade is a basic activity for increasing productivity, lowering machining costs, and optimizing material choices in mechanical part design.As a result, this research deals with the study of surface roughness (Ra), Tool Temperatures (TT), and Metal Removal Rate (MRR) while machining AISI 316L stainless steel bar for different combinations of machining parameters like speed (N), feed (f) and depth of cut (doc) under dry conditions using Taguchi Optimization with coated carbide inserts.To avoid tool wear, a new insert is utilised each time during the machining procedure. Surface roughness and temperature are measured using a surface roughness tester, a thermocouple, and a CNC lathe. The resulting replies are used to investigate the impact of machining parameter combinations in a CNC lathe turning process. The Taguchi design method is used to generate design of experiments (DOE) using Orthogonal Arrays (OA) and Signal-to-Noise Ratio (SNR) (SN ratio).For the examination of the impact of process parameters based on experimental results Analysis of Variance is used (ANOVA). Grey Relational Analysis (GRA) is used to carry out a multi-response optimization.

***IndexTerms* – GRA, TAGUCHI, MRR, DOE**

I. INTRODUCTION

1.1 Lathe

A rotating machine tool is a workpiece that rotates around an axis of rotation to perform various tasks, such as cutting, sanding, kneeling, drilling, deformation, facing and turning, with tools on the workpiece to build an object with symmetry on that axis.

1.1.1Lathe Components

- Bed: all main components are supported
- Transportation: slides along paths, consisting of slide cross, tool, apron
- Headstock: holds jaws for the workpiece, provides electricity to the jaws and has different drive speeds
- Tail Stock - supports the workpiece's other end
- Lead Screw and feed rod – Feed rod is powered from the headstock by a set of gears

The lathe played a crucial role in the Industrial Revolution.By rotating the work piece against a stationary cutting tool, the lathe removes superfluous material in the form of chips. The lathe is a machine tool that rotates and holds the work item between two rigid and strong supports known as centers, a chuck, or a face plate. The cutting tool is held against the rotating work and fed into it. Cutting tool fed parallel, at right angles, or at an angle to the axis of the workpiece.

1.2. CNC Machining

CNC machines, or computer numerically controlled machines, are electro-mechanical devices which will manipulate tools around a varying number of axis, usually 3 or 5, with high-precision per instruction from a bug. CNC machining is one in every of two ways in which engineers, machinists, or makers can generate a physical part from a computer design file, with the opposite being 3D printing, called additive manufacturing.

CNC machines can be used to machine almost any material. Metals (aluminium and steel alloys, brass, etc.) and plastics are two of the most common examples (ABS, Delrin, Nylon etc.). Machines can also be used to cut foam, composites, and wood. The essential CNC process will be reduced to three steps. The engineer begins by creating a CAD model of the part. The machinists then convert the CAD file to a CNC programme (G-code) and set up the machine. Finally, the CNC system performs all machining operations, removing material and creating the part, with little supervision.

Fig.2 CNC Lathe

1.3. INTRODUCTION TO TAGUCHI

Design of Experiment

In general, the design or experimental design is the design of any data collection exercise in which there are differences, whether or not under the complete control of an experiment.These terms are, however, usually used for checked experiments in statistics. Previous planned tests are often used for physical objects, chemical formulations, structures, components and materials.The paper on opinion surveys and statistical surveys, natural experiments and quasi-experiments (i.e., quasi-experimental design) see experiments on how these types of experiments or studies are differentiated between these kinds of experiments and design, are discussed in other types of survey.

II. LITERATURE REVIEW

A proper selection of cutting conditions in CNC machining processes such as turning produces high surface finish and less dimensional error parts subject to fatigue loads, precision fits, and aesthetic requirements. As a result, many researchers concentrate on the literature on the measurement of surface roughness using (lathe) and multi-point (milling) cutting tools with various machining parameters such as feed, speeds, depth of cut, and tool geometry. The research in this field can be divided into four categories:

- Trends derived from machining theories
- Trends derived from experimental tests
- Trends derived from designed tests (TAGUCHI based)
- Trends derived from intelligent neutral networks

Ali Motorcu Riza [1] studied the surface roughness in the turning of A181 8660 hardened alloy steels by ceramic based cutting tools with cutting parameters such as cutting speed, depth of cut, feed rate in addition tool's nose radius, using a statistical approach An orthogonal design, signal-to noise ratio and analysis of variance were employed to find out the effective cutting parameters and nose radius on the surface roughness.

W.H. Yang, and Y.S. Tarng [2] investigated the cutting characteristics of 854C steel bars using tungsten carbide cutting tools using the Taguchi method, which was studied as a powerful tool for quality design and used to find the optimal cutting parameters for turning operations based on orthogonal array, signal-to-noise (S/N) ratio, and analysis of variance (ANOVA). They discovered not only the optimal cutting parameters for cutting operations, but also the main cutting parameters that affect cutting performance in turning operations, through this study. The experimental results are provided to validate the efficacy of this approach.

Dilbag Singh et al. [4] The effect of cutting and tool geometry on surface roughness was investigated with a mixed ceramic insert made from aluminium oxide and titanium carbon nitride, using the hardened turning of bearing steel (AISI 52100). This study showed that feed is the dominating determination factor for the finish of the surface; the cuts are followed by a cutting velocity and the rake angle of the tool.

RA Mahdavinejad et al.[5] have highlighted surface-roughness methods for predicting process theory trends based on designed laboratory tests based on laboratory research like neutral networks, GA, Fuzzy, etc. The combination of the Neutral Fuzzy adaptive system predicts the roughness of the dried surface, which is machined during turning.

C.X. (Jack) Feng etal. [6] has developed a non-linear regression surface prediction model for surface roughness, based on work-piece hardness (material) cutting parameters, geometry of tools and cutting time, and its applications in order to determine the optimum conditions of machining.

A. Manna. [7] In a study of how the cutting conditions affect surface finishes, Pujari Srinivasa [8] Rao has been using Taguchi to optimize the cutting parameters for efficiency of turning with Al/Sic-MMC with fixed rhombic systems. Important parameters of cutting have been taken into account and mathematical models for surface roughness Ra and Rt have been developed using multiple lineal regression.

Grey relational analysis (GRA) depends on the response values generated for the problem under consideration (here machining responses like Ra, H and Vib in both the turn-mill processes) and determine the combined optimal combination of process parameters with only the set of process parameters levels considered. GRA first converts the response values which are incomparable to each other to comparable values using the concept of normalizing using larger-to-better or smaller-is-better equations. Then the converted and comparable response data are used to determine process parameters combination of the multi-response (I.e. Ra, H and Vib) [9-12].

III. EXPERIMENTATION METHODOLOGY

3.1Workpiece Material and Cutting Tool

Stainless steels are resistant to corrosion and contain at least 0.10% chromium. The hardness of infinite steels with austenitic structures is not a speed guide. American Institute of Iron and Steel (AISI) grade 316L is similar to AISI 316L but contains an additional component like molybdenum that improves creep strength, warmth, and resistance against corrosion, wear and hardness. The AISI 316L chemical composition includes Cr 17.5% C 0.06%, Mn 1.5%, Ni 12.2%, Mo 2.5%, Si 0.75% and Fe remaining, respectively. The chemical composition includes: Fig.4.1 shows workpiece materials of a diameter of 30 mm and a length of 100 mm. For the recording of tool temperature, the K-type protected thermocouple was used, while the surface roughness test MITUTOYO is used for measuring surface-ruggedness parameters as shown in fig. 3. In addition, the CNMG120408 MS KC 5010 covered carbide inserts are used for processing ACE micro CNC laths with the Fanuc 0i control system shown in fig.4.Coated carbide tool has excellent mechanical and thermal shock resistance. This gives good adherence to a high crater wear resistance and high-temperature plastic deformation. It also reduces friction and thus build-up edges.

Fig.4 AISI 316L workpiece after machining and surface roughness tester SJ-301

Fig.5 CNC lathe with Fanuc-0i control system and coated carbide inserts

3.2. Process of Machining

Workpiece length of 100mm each and then using the Taguchi design of experiments test conditions were generated by taking feed, cutting speed and depth of cut as parameters. As the surface area is cylindrical, surface roughness is determined by three diametric points and the average is considered to be the material's surface roughness.

In this project, 16 turning experiments were done on the CNC lathe and the surface roughness readings, tool tip temperature and MRR were measured using surface roughness tester and thermostat respectively, while MRR was calculated theoretically. The responses were made by using commercially available data mining technology software packages such as MINITAB software to find the parameter significance using Variance Analysis (ANOVA).

3.3. Process parameters

The characteristic parameters of a turning operation are (example: straight turning of cylinder with a diameter d (in mm)), Cutting Parameters:

- The depth of cut-DOC (mm)
- The feed per rotation-f (mm/rev)

The cutting speed $\mathbf{v_c}$ in (m/min) which gives the rotational speed N (rpm)

$N= (1000*v_c/3.14*D)$

The cutting parameters are at the root of the following performance parameters:

The material removal rate Q (cm^3/min): $Q=d*f*V_c$

N= rotational speed of the workpiece, RPM

f= feed, mm/rev

V= surface speed of the workpiece, m/min = $3.14*D_o*N$ (for max speed)

L=length of the cut, mm

D_o = original diameter of the workpiece, mm

D_f = final diameter of the workpiece, mm

D_{avg} = average diameter of workpiece= $(Di+D_F)/2$

DOC= depth of cut, mm

C_t = cutting time, s

MRR= 3.14*Davg* feed*DOC*speed.

3.4 Procedure

- Insert a new coated carbide tool insert.
- Start machining of the workpiece with the test conditions that were obtained from Taguchi Design of experiments.
- Before the process of machining insert the thermocouple at the tool tip of CNC and ensure that the offset of the tool is set properly.
- Once the machining for each test conditions is completed surface roughness was tested with MITUTOYO tester, Tool temperature using Thermocouple and material removal rate is calculated.
- ANOVA was done for surface roughness, temperature and material removal rate.
- Multi-response optimizations response done using GRA.

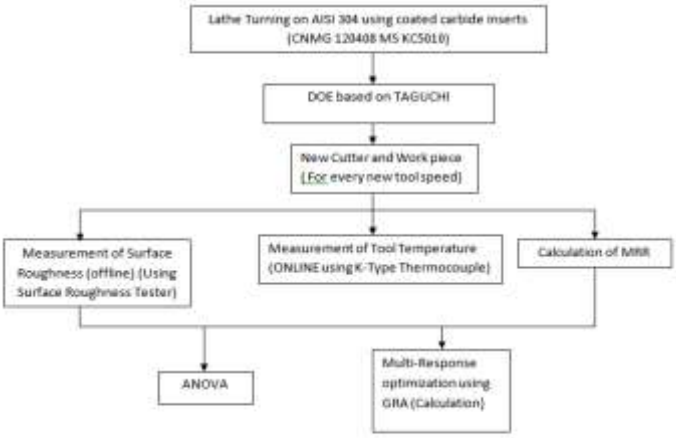


Fig.6 Experimental Methodology

IV. EXPERIMENTAL RECORDINGS AND CALCULATIONS

Experimental design of L_{16} using Taguchi orthogonal array concept as shown in Table 1 is used for machining on AISI 316L workpiece. Each design was experimented using a new coated carbide insert tip for avoiding tool wear under dry conditions. Machining parameters viz. Spindle speed (N-1300, 1500, 1700, 1900 rpm), feed (f- 0.10, 0.14, 0.18, 0.22 mm /rev) and depth of cut (doc- 0.3, 0.6, 0.9, 1.2 mm) are considered for machining with four levels each. Responses like average surface roughness (R_a) and tool temperature (T) were measured using surface roughness tester and thermostat respectively, while the metal removal rate (MRR) was calculated theoretically, as given in Table 1.

4.1 SAMPLE CALCULATION OF Metal removal rate (MRR)

EXPERIMENT NO 1:

FORMULAE AND CALCULATION

MRR= 3.14*Davg* feed*DOC*speed

D_{avg} = average diameter of workpiece= (D_i+D_F)/2

SPEED (N) =1300 rpm, FEED (F) =0.1 mm/rev, D_{avg}= 29.85 mm and depth of cut (DOC)= 0.3mm.

So, MRR = 3.14*29.85*0.1*0.3*1300 = **3637** mm^3/min

The obtained responses were used to analyse the significance of parameters using Analysis of variance (ANOVA) and also were used to evaluate multi-objective optimization criteria using numerical techniques like Grey relational analysis (GRA).

Table 1: Measured and calculated response values after machining

EXP. NO	Spindle Speed (N-rpm)	Feed (F-mm/rev)	Depth of cut (DOC-mm)	TOOL TEMPERATURE (Degree)	AVG. RA MICRONS)	MRR (mm^3/min)
1	1300	0.1	0.3	66	**0.723**	**3637**
2	1300	0.14	0.6	69	1.103	**10081**
3	1300	0.18	0.9	77	1.727	**19243**
4	1300	0.22	1.2	83	2.98	**31036**
5	1500	0.1	0.6	77	0.577	**8308**
6	1500	0.14	0.3	70	1.077	**5875**
7	1500	0.18	1.2	84	1.317	**29300**
8	1500	0.22	0.9	78	2.507	**27138**
9	1700	0.1	0.9	77	0.793	**13980**
10	1700	0.14	1.2	83	0.953	**25827**
11	1700	0.18	0.3	58	1.653	**8561**
12	1700	0.22	0.6	62	2.063	**20716**
13	1900	0.1	1.2	83	0.603	**20618**
14	1900	0.14	0.9	80	0.610	**21875**
15	1900	0.18	0.6	68	1.777	**18943**
16	1900	0.22	0.3	54	2.193	**11695**

4.2. GREY RELATIONAL ANALYSIS (GRA)

Sample calculation for surface roughness:

Experiment number 1:

Step 1: Normalization of experimental response data to convert into a sequence of comparable data using equation-4.1:
Response with low noise like surface finish and temperatures adopts;
Lower-is-Better (LB):

$$x_i^*(j) = \frac{[max(x_i(j)) - x_i(j)]}{[max(x_i(j)) - min(x_i(j))]} \quad (4.1a)$$

Response with high noise like metal removal rate adopts;

Higher-is-Better (HB):

$$x_i^*(j) = \frac{[x_i(j) - \min(x_i(j))]}{[\max(x_i(j)) - \min(x_i(j))]} \quad (4.1b)$$

Where X_i (j) is the value of response of i[th] experiment, max (x_i (j)) and min (x_i (j)) are the smallest and largest values of X_i (j) respectively.

For Normalization, Lower-is-Better (LB) and using the Eq: 6.1a, we get

For Lower-is-Better (LB):$x_i^*(j) = \frac{[\max(x_i(j)) - x_i(j)]}{[\max(x_i(j)) - \min(x_i(j))]}$ = [(2.98-0.723/ (2.98-0.577)] = 0.9392

Step 2: The deviation sequence Δ_{oi}(k) of each response given as:

$$\Delta_{\text{oi}}(k) = ||X_0(k) - X_1(\text{k})|| \quad (4.2)$$

The deviation sequence using Eq: 4.2: $\Delta_{\text{oi}}(k) = ||X_0(k) - X_1(\text{k})||$= |0.9392-1|= 0.0608

Step 3: Grey relational coefficient correlation between responses by giving equal weight age (distinguishable coefficient) as given in equation-4.3.

$$\gamma_i = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oi}(k) + \zeta\Delta_{max}} \quad (4.3)$$

Where $\Delta_{\min}$ is the smallest value of the normalized values, $\Delta_{\max}$ is the maximum value of the normalized values, ζ is the distinguishing coefficient and ranges from 0 to 1 and has been assumed as 0.5.

Grey relational coefficient is calculated using Eq: 4.3 and is given in Table 2, as$\gamma_i = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oi}(k) + \zeta\Delta_{max}}$

= ((0+0.5*1)/((0.0608+(0.5*1)))= 0.892

Step 4: Determination of grey relational grade of combined responses as given in Equation-4.4 and are graded as optimal with highest rank:

$$\alpha_i = \sum_{k=1}^{n} \gamma_i(k) \quad (6.4)$$

Where “n_r” is the total number of responses

Based on the grey relational grade, the ranking has to be given in descending order. The combination of process parameters which has the highest rank is considered to be optimal, as given in Table 6.2a. Grey relational grade using Equation-6.4 and are graded as optimal with highest rank: $\alpha_i = \frac{(0.892+0.333+0.556)}{3}$ = 0.594

Table 2: Normalization, Grey relational coefficient for determining grey relational grade and ranking

Exp. No.	Normalization based on LB/HB			Grey Relational Coefficients			Grey Relational Grade	Rank
	Ra (μm)	MRR (mm³/min)	Temp (Degree)	Ra (μm)	MRR (mm³/min)	Temp (Degree)		
1	0.9392	0.0000	0.6000	0.892	0.333	0.556	0.594	
2	0.7811	0.2352	0.5000	0.696	0.395	0.500	0.530	
3	0.5214	0.5696	0.2333	0.511	0.537	0.395	0.481	
4	0.0000	1.0000	0.0333	0.333	1.000	0.341	0.558	
5	1.0000	0.1705	0.2333	1.000	0.376	0.395	0.590	
6	0.7919	0.0817	0.4667	0.706	0.353	0.484	0.514	
7	0.6921	0.9366	0.0000	0.619	0.888	0.333	0.613	
8	0.1968	0.8577	0.2000	0.384	0.778	0.385	0.516	
9	0.9101	0.3775	0.2333	0.848	0.445	0.395	0.563	
10	0.8435	0.8099	0.0333	0.762	0.725	0.341	0.609	
11	0.5522	0.1797	0.8667	0.528	0.379	0.789	0.565	
12	0.3816	0.6233	0.7333	0.447	0.570	0.652	0.557	
13	0.9892	0.6198	0.0333	0.979	0.568	0.341	0.629	
14	**0.9863**	**0.6656**	**0.1333**	**0.973**	**0.599**	**0.366**	**0.646**	**1**
15	0.5006	0.5586	0.5333	0.500	0.531	0.517	0.516	
16	0.3275	0.2941	1.0000	0.426	0.415	1.000	0.614	

4.3 ANOVA FOR DRY CONDITION MACHINING

Analysis of variance (ANOVA) is a statistical model based on hypothesis of accepting or rejecting null hypothesis, by analysing the difference between groups and among the groups. Based on relation between $F_{\text{statistical}}$ and F_{critical} the acceptance and rejection of hypothesis is done. The ANOVA uses equations: 6.5-6.7 to determine significance and indicates the contribution of design parameters on the quality characteristic of the response with significance level of 95% (i.e. < 0.05 probability) [7] and are shown in Table 3.

$$\text{SS}_{\text{Total}} = \sum \text{X}^2 - \frac{(\sum \text{X})^2}{\text{N}} \text{and DF} = \text{N} - 1 \quad (6.5)$$

$$SS_{Between} = \frac{[\sum(X_1)]^2}{n_1} + \frac{[\sum(X_2)]^2}{n_2} + \cdots + \frac{[\sum(X_{AC})]^2}{n_{AC}} - \frac{[\sum X)]^2}{N} \quad (6.6)$$

$$SS_{Within} = SS_{Total} - SS_{Between} \quad (6.7)$$

Where SS is the sum of squares, MS is the mean square, “DF” is the degree of freedom, *N* is the total observations, *and the* size of population.

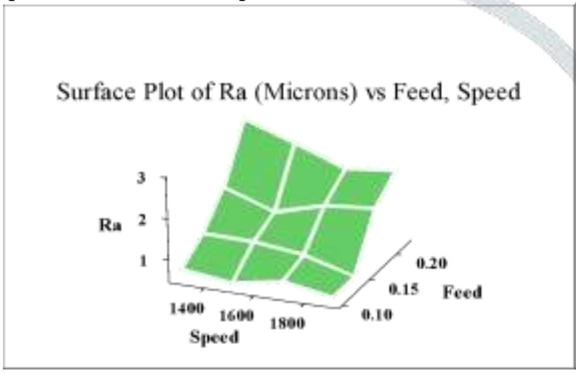
Table 3: ANOVA of experimental responses data

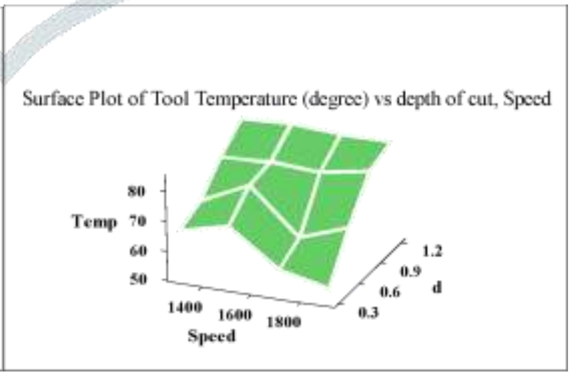
Source	DF	SS	MS	F	P	Remarks
Surface roughness (R_a) (F-Critical of 3,6 is 4.757)						
Speed (rpm)	3	10.5	3.45	1.02	0.446	Not significant (NS)
Feed (mm/rev)	3	294.60	98.2	29.14	0.001	Highly significant (HS)
d (mm)	3	00.981	0.33	0.10	0.959	Not significant (NS)
Error	6	20.21	3.36			
Tool temperature (Temp)						
Speed (rpm)	3	2.12	0.707	5.47	0.037	S
Feed (mm/rev)	3	2.14	0.714	5.53	0.037	S
d (mm)	3	16.09	5.365	41.5	0.000	HS
Error	6					
Metal removal rate (MRR)						
Speed (rpm)	3	24.17	8.05	143248	0.000	HS
Feed (mm/rev)	3	104.72	34.90	620656	0.000	HS
d (mm)	3	313.23	104.4	185641	0.000	HS
Error	6					

V. Results, Discussions And Conclusions

Observing Table 2, using GRA, the optimality obtained is Spindle speed: 1900 rpm, feed: 0.14 mm/rev and depth of cut: 0.9 mm which generates surface roughness (Ra = 0.610 µm), Tool temperature (Temp = 800C) and metal removal rate (MRR = 21875 mm3 /min). Similarly, observing Table 6.2c, Spindle speed: 1500 rpm, feed: 0.18 mm/rev and depth of cut: 1.2 mm which generates surface roughness (Ra = 1.317 µm), Tool temperature (Temp = 840C) and metal removal rate (MRR = 29300 mm3 /min). The GRA method generates better results in case of roughness and temperature, but not in case of Metal removal rate. But if given due weightage of responses are incorporated in GRA.

Based on ANOVA for finding significance of machining parameters, graph plots are drawn between responses and major contributing parameters. As shown in fig. 2 feed indicates much more effect than spindle speed while generating roughness and similarly, depth of cut on tool temperatures and MRR.





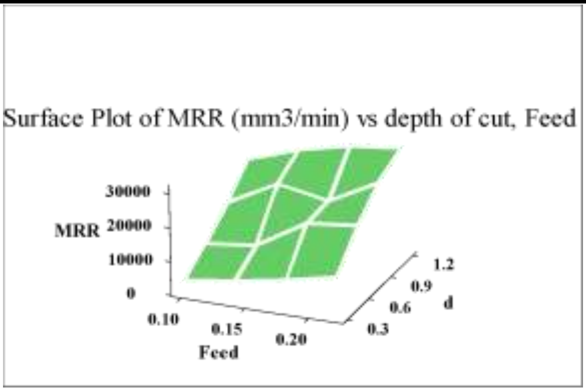


Fig.7 Graph plots of the results obtained from TDOE

Conclusions

- The chips generated in machining are found to be of helix in nature and at higher depth of cuts, they break into long helical chips due to weight.
- Discontinuous small helical chips were produced at low feeds and depth of cut, while at moderate feed and depth of cuts, helical chips whirled around the workpiece from the middle of the machining.
- ANOVA of the machining parameters on the generated responses: feed alone constitutes for generating surface roughness, while all the parameters contributes significantly but depth of cut contributes more significantly in generating tool temperatures due to penetration of tool into workpiece and in case of metal removal rate all the parameters are highly significant in its generation.

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