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OPTIMIZATION OF TRAVERSE CUT CYLINDRICAL GRINDING PROCESS PARAMETERS OF HEAT TREATED EN-8 STEEL

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ABSTRACT

Cylindrical grinding is one of the important metal cutting processes used extensively in the finishing operations. Efficient grinding of steel requires judicious selection of operating parameters to maximize material removal rate (MRR) while controlling surface integrity. The present work describes an application of Taguchi method coupled with Grey relational analysis for multi-objective optimization of the process parameters in cylindrical grinding of EN-8 steel. In this study, each experiment was conducted under different machining conditions of wheel speed, in-feed and longitudinal feed on conventional cylindrical grinding machine with AL_2O_3 grit grinding wheel and grinding performance parameters such as surface roughness (R_a) and metal removal rate (MRR) were evaluated. The experiments were conducted based on Taguchi L16 orthogonal array with the chosen three parameters at four levels. The statistical significance of the experimental results has been tested by the analysis of variance (ANOVA). The results are further confirmed by conducting confirmation experiments. The obtained results indicate that wheel speed is the most significant grinding parameter followed by longitudinal feed to reduce surface roughness and maximize material removal rate simultaneously while in feed has insignificant effect on it.

***Keywords*: ANOVA, Grinding, Grey relational analysis, MRR, Surface roughness (R_a), Taguchi.**

I.INTRODUCTION

Grinding is a complex abrasive cutting process where machining happens with geometrically unspecified cutting edges [1]. It is a small scale material removal surface finishing operation in which the cutting tool is an individual abrasive grain of an irregular geometry and is spaced randomly along the periphery of the wheel [2]. This is dissimilar to other machining processes such as turning and milling, as the cutting edges of the grinding wheel don't have uniformity and act differently on the work piece at each grinding [3]. Cylindrical grinding is widely used process for final machining of components requiring smooth surfaces and precise tolerances [4]. The success of any grinding operation depends upon the proper selection of various operating conditions like wheel speed, work speed, traverse feed, in feed, grinding fluids, balancing of grinding wheels, dressing etc. Usually the process parameters are selected based on operator's experience or from the manufacturer's manual, which does not provide optimal result.

Hence, optimization of operating parameters is an important step in machining which will reduce the machining cost and ensure the quality of final product [5]. No doubt, steel is one of the widely researched materials in machining for more than last half century, but there is a renewed interest in application of steel because of its sustainability - 100% recyclable and almost indefinite life cycle. EN-8 steel is one of the steel grades, widely used in different industries (construction, transport, automotive, power, etc.) [6].

M. janardhan, and A.gopala krishna explains that in cylindrical grinding metal removal rate and surface finish are important responses through various process parameters while grinding of EN-8 Steel material. It was found that the feed rate play an important role on metal removal rate of grinding process [7]. *A.J.Shih, S. B. McSpadden, T. O. Morris, M. B. Grant, and T. M. Yonushonis* conclude that higher speeds of grinding wheel reduce the chip thickness and results in higher metal removal rate in steel or ceramic materials[8]. *Jae-seobkwak, sung-bosim, yeong-deugjeong* describe analysis of cylindrical grinding process parameters of hardened SCM440 steel using response surface method. They also concludes structure of grinding wheel affect metal removal rate and decrease surface roughness [9]. *N.Alagumurthi. Palaniradja, and V. Soundararajan* conduct that in optimization of cylindrical grinding process parameters on various steels such as AISI3310, AISI6150 and AISI52100 using Al_2O_3 grinding wheel, It was found that depth of cut dominate all response parameters like metal removal rate, surface roughness, heat flow and tool wear(surface integrity)[10]. Manickam, M. Melwin Jagadeesh Sridhar1 M., and V. Kalaiyarasan using genetic algorithm with response surface methodology optimize process parameters of steel on cylindrical grinding and concludes metal removal rate depends upon feed rate[11]. *Jagtap, Kirankumar Ramakantrao, S. B. Ubale, and M. S. Kadam* concludes that, high efficiency of grinding operations with its high material removal rate helps to improve manufacturing cycle time while achieving surface integrity requirements [12]. *Hanafi* applied grey relational theory and Taguchi optimization methodology to optimize the cutting parameters in machining of PEEK-CF30 using TiN tools under dry conditions. The objective of optimization was to achieve simultaneously the minimum power and best surface quality. The obtained results revealed that depth of cut (44.54%) is the most influential parameters followed by cutting speed (36.14%) and feed rate (6.39%)[13]. *Yan and Li* presented a multi-objective optimization method based on weighted grey relational analysis and RSM to optimize the cutting parameters in milling process during dry cutting of medium carbon steel with carbide tool to achieve the minimum cutting energy, maximum material removal rate and minimum surface roughness. The results indicate that width of cut is the most influencing parameter followed by depth of cut, feed rate and spindle speed. The experimental results indicate that RSM and grey relational analysis (GRA) are very useful tools for multi-objective optimization of cutting parameters [14].

There is a close interdependence among productivity, quality and material removal rate of a machine tool. The surface roughness is widely used index of product quality in terms of various parameters such as aesthetics, corrosion resistance, subsequent processing advantages, fatigue life improvement, precision fit of critical mating surfaces, etc. But the achievement of a predefined surface roughness below certain limit generally lowers the material removal rate exponentially and decreases the productivity [6]. This paper aims at optimizing the material removal rate and surface roughness simultaneously.

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II.RESEARCH METHODOLOGY AND ANALYSIS METHOD

2.1 Research methodology

The research carried out for present work can be broadly divided into four phases-experimental planning; performing experimentation; analyzing the results and multi-objective grinding parameters optimization followed by result confirmation using experimental studies as shown in Fig. 1.

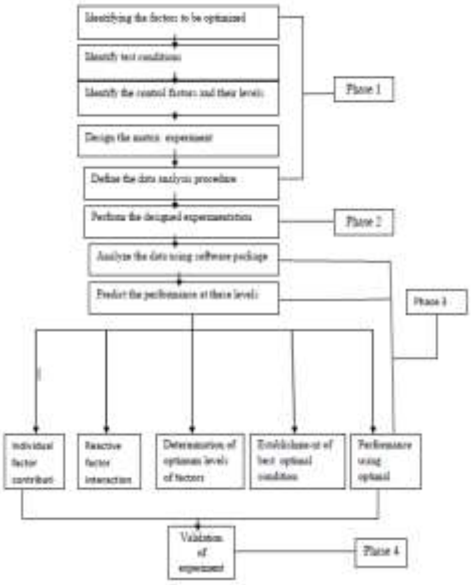

Fig.1 Schematic representation of the steps involved in the Taguchi DOE methodology

In the first phase experimental plan was developed to select the machine tool, cutting tools, machining material, machining parameters and their levels and performance characteristics (material removal rate and surface roughness). Experiments were designed using L16 orthogonal array through well known Taguchi method. Next, grinding experiments were conducted for the 16 combinations of orthogonal array to get the material removal rate and surface roughness data. In the third phase, GRA coupled with Taguchi method has been used to determine the best combination of parameters. GRA converts the multi-objective problem (material removal rate and surface roughness) into a single multi-objective function (grey relational grade); and hence simplifies the optimization procedure. In the last phase, the statistical significance of the results were analyzed using analysis of variance (ANOVA). Lastly, experimental tests were carried out at the optimum machining parameters to confirm the result.

2.2 Grey relational analysis

The available experimental data may contain various kinds of uncertainties and noises due to the existence of internal and external disturbances. The grey systems theory established by **Deng (1989)** is a methodology that focuses on the study of uncertain systems with partially known information through generating, excavating and extracting useful information from available data [15]. Grinding is known as one of the most complex system due to large variety input and output variables, work material properties and complex tool/work material interface (Van Luttervelt 1998)[16]. Therefore, grey system theory has a wide range of applicability in grinding operations.

The grey relational analysis consists of following steps.

2.2.1) Data preprocessing. In a multi-objective problem, various objective functions may have been measured in different units, therefore, data preprocessing is used to convert the original sequence (experimental information) to a comparable sequence (dimensionless quantity) where the original data is normalized between 0 and 1.

Let the original sequence and comparable sequence be represented as $x_i^{(o)}(k)$ and $x_i*(k)$, i = 1, 2, …, m; k = 1,2, …, n, where m is the total number of experiments and n is the total number of performance characteristics. In this paper, m = 16, n = 2. Generally three different kinds of data preprocessing methodologies are used in grey relational analysis depending upon the characteristics of original sequence (Deng, 1989)[15].

For "the-larger-the-better" characteristics such as tool life and material removal rate, the original sequence is normalized as.

$$X_i^*(k) = \frac{X_i^{(o)}(k) - min.X_i^{(o)}(k)}{max.X_i^{(o)}(k) - min.X_i^{(o)}(k)} \qquad (1)$$

For "the-smaller-the-better" characteristics such as power consumption and surface roughness, the original sequence is normalized as.

$$X_i^*(k) = \frac{max.X_i^{(o)}(k) - X_i^{(o)}(k)}{max.X_i^{(o)}(k) - min.X_i^{(o)}(k)} \qquad (2)$$

For "a specific desired value", the original sequence is normalized as;

$$X_i^*(k) = 1 - \frac{|X_i^{(o)}(k) - OD|}{max.\{max.X_i^{(O)}(k) - OD, OD - min.X_i^{(o)}(k)\}} \qquad (3)$$

where OD is the desired value.

2.2.2) Grey relational coefficients After data processing, a grey relational coefficient is calculated with the preprocessed sequences. The grey relational coefficient is defined as:

$$\mu(X_0^*(k), X_i^*(k)) = \frac{\Delta_{min} + \varphi\Delta_{max}}{\Delta_{oi}(k) + \varphi\Delta_{max}} \qquad (4)$$

$0 < \mu(X_0^*(k), X_i^*(k)) \leq 1$

Where $\Delta_{0i}(k)$ is the deviational sequence of reference sequence $X_o^*(k)$ and comparability sequence $X_i*(k)$,

$$\Delta_{0i}(k) = |x_0*(k) - x_i*(k)| \qquad (5)$$

$$\Delta_{min} = \min_{\forall i}.\min_{\forall k}.\Delta_{0i}(k)$$

$$\Delta_{max} = \max_{\forall i}.\max_{\forall k}.\Delta_{0i}(k)$$

φ is the distinguish coefficient. $\varphi \in [0.1]$.

2.2.3) Grey relational grade The grey relational grade is a weighted sum of the grey relational coefficients. It is defined as follows:

$$\mu(X_0^*, X_i^*) = \sum_{k=1}^{n} \beta_k \mu(X_0^*(k), X_i^*(k)) \quad (6)$$

$$\sum_{k=1}^{n} \beta_k = 1$$

Where β_k denotes the weighted value of the k_{th} response variable.

The grey relational grade $\mu(X_0^*, X_i^*)$ represents the level of correlation between the reference and comparability sequence. It is a measurement of the absolute value of data difference between two sequences and can be used to approximate the correlation between the sequences.

III.EXPERIMENTATION

3.1 Selection of machining parameters and performance characteristics.

The grinding experiments were carried out using a cylindrical grinding machine available at R&D CENTRE FOR SWEING AND BYCYLE (LUDIHANA), which is shown in Fig.2 The choice of machining parameters was made by taking into account the capacity/limiting grinding conditions of the cylindrical grinding machine, tool manufacturer's catalogue and the values taken by researchers in the literature**.** Table 1 provides the three machining parameters and the four levels for each parameter.

Fig.2 Cylindrical grinding machine used for work

3.1.1 Material

The sample material for the research was EN-8 steel in the form of cylindrical shape with 25 mm diameter and 90 mm grinding length**.**

3.1.2 Grinding tool

WHEEL	A10K5V
BORE	50mm
FACE WIDTH	40mm
DIAMETER	100mm

Table 1: Machining parameters and their levels

Factors	Level 1	Level 2	Level 3	Level 4
Wheel speed(RPM)	112	160	224	315
In-feed(mm/cycle)	0.010	0.015	0.020	0.025
Longitudinal feed(mm/sec)	7	14	16	20

3.1.3 *Preparation of specimen*

Rough turning were performed on each work piece prior to actual grinding using a different cutting tool. This was done in order to remove the rust or hardened top layer from the outside surface and to minimize any effect of non-homogeneity on the experimental results.

3.1.4Performance parameters measurement

A direct method of measurement is used to measure the MRR during grinding of EN-8 steel.

MRR= [WBG(gm) -WAG(gm)] / t(sec)

WBG: Weight before grinding

WAG: Weight after grinding

t : Time

After each test, the roughness of the finished surface was measured by **Talysurf** (surface finish measuring device). Each value was measured at three equally spaced locations around the circumference of the work piece to obtain the statistically significant data for test and then the mean of measurements was calculated. Thus, probable observation errors were kept relatively small. Taylor and Hobson make Profilometer, shown in Fig. 3.

Fig.3: Surface roughness tester

IV.RESULTS AND DISCUSSION

The experimental results for the R_a and MRR are listed in Table 2. Preprocessing sequence (Table 3) was computed using Eq. (1) and Eq. (2) for material removal rate and surface roughness. $X_0*(k)$ shows the value for reference sequence and $X_i*(k)$ for comparability sequence. The deviation sequence is computed using Eq.7 and Eq.8 and presented in Table 3.

$$\Delta_{01} = |X_0^*(R_a) - X_i^*(R_a)| \quad (7)$$

$$\Delta_{01} = |X_0^*(MRR) - X_i^*(MRR)| \quad (8)$$

Table2: Experimental results of R_a and MRR

Exp. No.	Wheel speed	In-feed	Longitudinal feed	R_a	MRR
1	112	0.010	7	.493	.1052
2	112	0.015	14	.600	.1766
3	112	0.020	16	.573	.1631
4	112	0.025	20	.586	.1831
5	160	0.010	14	.413	.1626
6	160	0.015	7	.400	.2076
7	160	0.020	20	.500	.2094
8	160	0.025	16	.433	.2886
9	224	0.010	16	.420	.1953
10	224	0.015	20	.426	.1851
11	224	0.020	7	.393	.2500
12	224	0.025	14	.446	.3496
13	315	0.010	20	.426	.1901
14	315	0.015	16	.420	.3558
15	315	0.020	14	.466	.2352
16	315	0.025	7	.426	.3906

The grey relational coefficient values using Eq. (4) are computed and are shown in Table 3.

4.1Computing grey relation grade

The next step is to compute grey relational grade which is a weighted sum of the grey relational coefficients. Based on Eq. (6), the grey relational grades $\mu(X_0^*, X_i^*)$ for 16 experimental values were calculated. The values are given in the last column of Table 3. Therefore, the optimization of performance characteristics can be performed with respect to single grey relational grade rather than multiple performance characteristics.

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Table3: The calculated values of preprocessing sequences, deviational sequences, grey relational coefficient, and grey relational grade.

Compar ability sequence	Preprocessing sequence		Deviation sequence		Grey relational cofficent		Grey relational grade
	$X_0^*(R_a)$	$X_0^*(MRR)$	$\Delta_{0i}(R_a)$	$\Delta_{0i}(MRR)$	R_a	MRR	
1	.516	0	.484	1	.508	.333	.420
2	0	.2501	1	.749	.333	.400	.366
3	.130	.2028	.870	.797	.364	.385	.374
4	.067	.2729	.933	.727	.348	.407	.377
5	.903	.2011	.097	.798	.837	.384	.610
6	.966	.3587	.034	.641	.936	.438	.687
7	.483	.3651	.517	.634	.491	.440	.465
8	.806	.6426	.194	.357	.720	.583	.651
9	.869	.3156	.131	.684	.793	.422	.607
10	.840	.2799	.160	.720	.757	.409	.583
11	1	.5073	0	.492	1	.503	.751
12	.743	.8563	.257	.143	.660	.776	.718
13	.840	.2974	.160	.702	.757	.415	.586
14	.869	.8780	.131	.122	.793	.803	.798
15	.647	.4555	.353	.544	.586	.478	.532
16	.840	1	.160	0	.757	1	.878

4.2. Finding best experimental run

The Taguchi method has been used to calculate the average grey relational grade for each machining parameter level. It has been done by sorting the grey relational grades corresponding to levels of the machining parameter in each column of the orthogonal array and taking an average at the same level for N, I and L at the four levels are computed and given in Table 4.

The larger the grey relational grade, the better the corresponding performance characteristics. Accordingly, the level that gives the largest average response is best. Thus, the optimal levels of each parameter are the **wheel speed at level 4 (315 RPM), in-feed at level 4 (0.025 mm/cycle.) and longitudinal feed at level 1 (7 mm).** Furthermore, the Max-Min value, which is difference between the maximum and minimum value for each grinding parameter is calculated as shown in Table 4. The Max-Min value of wheel speed is maximum. Longitudinal feed and in feed are at the second and third place respectively. It indicates that wheel speed has the maximum influence on average grey relational grade while feed has the minimum influence.

Table 4: Mean response table of GRG

Grinding parameter	Level 1	Level 2	Level 3	Level 4	Max – Min
Wheel speed	.3843	.6033	.6647	**.6985**	.3142
In-feed	.5557	.6085	.5305	**.6560**	.1255
Longitudinal feed	**.6840**	.5565	.6075	.5028	.1813

4.2.1 Analysis of variance

The relative importance among the machining parameters (N, I, L) for the multiple performance characteristics (R_a and MRR) needs to be investigated so that the optimal parameters can be decided effectively. The analysis of variance (ANOVA) has been applied to investigate the effect of machining parameter on the multi-objective function. Table 5 shows ANOVA results for the linear [N, I, L] which is generated using MINITAB 17.0.

P-value or probability value is used to determine the statistical significance of results at a confidence level. In this study the significance level of $\alpha = 0.05$ is used, i.e. the results are validated for a confidence level of 95%. If the P-value is less than 0.05 then the corresponding factor has a statistically significant contribution to the performance characteristic at 95% confidence level. The results show that wheel speed and longitudinal feed are statistically significant at 95% level. The last column of the Table 5 shows the percentage contribution of each source to the total variation indicating the degree of influence on the results.

Wheel speed (N) was found to be the most significant machining parameter due to its highest percentage contribution of 64.28% followed by the Longitudinal feed (L) with 19.17% and In Feed (I) with 10.08%.

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Table5: ANOVA ANALYSIS

Source	DOF	Adj SS	Adj MSS	P-value	% contribution
Wheel speed	3	0.2393	0.0797	0.002	64.28
In-feed	3	0.0375	0.0125	0.109	10.08
Longitudinal feed	3	0.0714	0.0238	0.03	19.17
Residual error	6	0.0240			6.46
Total	15				

4.3. Parametric influence on multi-objective function

The main effects plot of machining parameters versus multi-objective function is shown in Fig. 4. Main effect plot clearly shows that the multi-objective function will be maximum, when the value of wheel speed is large and longitudinal feed is small. Therefore, to get the better surface finish at maximum material removal rate, the recommended values are level 4 for wheel speed i.e. 315 RPM and level 1 for longitudinal feed i.e. 7mm.

Fig. 4 Main effect plots for Grey Relation Grade

4.4. Confirmation experiments

The confirmation experiments were conducted on the optimal machining parameters (N = 315 RPM, I = 0.025 mm/cycle and L = 20 mm/sec) predicted using the developed model. The result of the confirmation runs for the material removal and surface roughness are listed in Table 6. It can be observed that the optimal machining parameters will lead to higher material removal rate and better surface roughness as shown in Table 6

Table 6: Confirmatory results

Test conditions	Wheel speed	In-feed	Longitudinal feed	R_a	MRR	% Gain R_a	% gain MRR
Test 1	112	0.020	14	.482	.3348	11.61	16.6
Test 2	224	0.015	16	.478	.3558	10.87	9.78
Test 3	160	0.015	14	.500	.3496	14.8	11
Optimum condition	315	0.025	7	.426	.3906		

V.CONCLUSIONS

Based on the observations and analyses made in the study following conclusions are drawn:

5.1) Multi-objective optimization has been carried out by Taguchi based grey relation analysis. Here objective is minimization of R_a and maximization of MRR simultaneously. The optimum parametric setting determined is: **L1 I4 N4 i.e. longitudinal feed=7 mm/sec, in feed=0.025 mm/cycle and wheel speed=315 RPM**. The optimum parametric condition is decided by highest grey relational grade which is .878.

5.2) From confirmation tests it is observed that optimal parametric setting of input parameters leads to an improvement of MRR and surface finish by maximum of 11.61% and 16.6% simultaneously over random conditions.

5.3) In so far as the effect of the parameters on the multi-objective response or on grey relation grade is concerned, the parameters wheel speed and longitudinal feed are found to be significant at 95% level of confidence. Also, work speed and longitudinal feed contribute more than in feed in the context of multi objective response.

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