Optimization of Process Parameters for CNC Turning using Taguchi Methods for EN24 Alloy Steel with Coated/Uncoated Tool Inserts

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***Abstract*—*Coated and uncoated tool inserts offers certain degrees of control on the desired rate of tool wear and surface roughness to an extent. This work pursues the quest for realizing the optimal values for the significant process parameters that bears an influence on the response parameters. Experiments were conducted on the samples of EN 24 alloy steel material with the help of PVD coated TiAlN insert and uncoated carbide insert. The experimental runs carried out with proper variation in the levels. Levels are selected with the help of manufacturing catalogue and by pilot experimentation and results are recorded for further analysis. For this study, 9 runs designed using L9 orthogonal array of Taguchi Design of Experiment. Surface roughness was measured using a Mitutoyo surface tester at test lab and material removal rate is calculated by mathematical equation. The data was compiled into Minitab 17 software for analysis. The relationship between the machining parameters and the response variables were analyzed using the Taguchi Method. Optimization of process parameters is carried out by Grey Relational Analysis method (GRA). GRA method is a powerful and most versatile tool which can manipulate the input data as per requirement and comes with results that can be used to have best multi-objective in respective concerns.*

***Keywords*—Coated and uncoated tool inserts, Surface roughness, Material removal rate, ANOVA, Grey relational analysis.**

I. INTRODUCTION

Machining industries continuously demanding for higher production rate and improved machinability as quality, and productivity play significant role in today's manufacturing market. The extent of quality of the procured item (or product) influences the degree of satisfaction of the consumers during the usage of the procured goods. Higher production rate can be achieved at high cutting speed, feed, depth of cut which is limited by tool wear, capability of tooling, surface finish and accuracy required selection of cutting parameters is generally a compromise between several variables and it can be easily possible to determine by using Response Surface Methodology [18].

CNC machines are commonly used in industry. The operation of this machine is expensive because it has many parameters to consider. Optimization of cutting parameters is usually a difficult work where the following aspects are required: knowledge of machining; empirical equations relating the forces, power, surface finish and dimensional accuracy etc. Trends in manufacturing industry have drive trends in metal cutting inserts developments. Changes in cutting parameters catalyze parallel advances in metal cutting tooling technology. Coated tools have found widespread use in today's metal cutting industry, bringing about significant improvements in tool performance and cutting economy through lower tool wear reduced cutting forces and better surface finish of the work piece. Coated and uncoated tools are widely used in the metal-working industry and provide the best alternative for most turning operations [18]. The manufacturing industry is constantly striving to decrease its cutting costs and increase the quality of the machined parts as the demand for high tolerance manufactured goods is rapidly increasing. The increasing need to boost productivity, to machine more difficult materials and to improve quality in high volume by the manufacturing industry has been the driving force behind the development of cutting tool materials. Today, there are two obvious trends in cutting tool developments. Dry machining is desirable to avoid the extra costs and environmental problems associated to cutting fluids. High speed machining of hardened steel has the potential of giving sufficiently high quality of the machined surface to make finishing operations such as grinding and polishing unnecessary. Both cases tend to intensify the heat generation along the tool surfaces, and consequently the tools must possess further improved, thermal and chemical stability.

J. S. Senthil kumaar et al [1] heat-resistant super alloy material like Inconel 718 machining is challenging task even in modern manufacturing processes. Therefore the genetic algorithm coupled with artificial neural network (ANN) as an intelligent optimization technique for machining parameters optimization of Inconel 718. The combined effects of cutting speed, feed, and depth of cut on the performance measures of surface roughness and flank wear were investigated by the analysis of variance. Waleed Bin Rashid et al [2] provided the experimental results of hard turning of AISI 4340 steel using a cubic boron nitride (CBN) cutting tool. An orthogonal array was implemented using a set of judiciously chosen cutting parameters. Subsequently, the longitudinal turning trials were carried out in accordance with a well-designed full factorial based Taguchi matrix. The speculation indeed proved correct as a mirror finished optical quality machined surface was achieved by the conventional cutting method using a CBN cutting tool. The design of experiment using Taguchi's approach can be used to evaluate the effect of control parameters for parameter optimization. Taguchi's approach allows the study of the whole parameter space with a limited number of experiments, as long as they are carried out in a planned orthogonal array. This methodology helps reduce the variability of the response variable and is therefore an important tool for improving the productivity of the experiments. Radhakrishnan Ramanujam et al [3] had investigates turning on aluminium Silicon Carbide particulate metal matrix composite (Al-SiC–MMC) using polycrystalline diamond (PCD) 1600 grade insert. Analysis of variance is used to investigate the machining characteristics of metal matrix composite (A356/10/SiCP). The objective was to establish a correlation between cutting speed, feed and depth of cut to the specific power and surface finish on the work piece. Analysis of Variance is a method of apportioning variability of an output to various inputs. The purpose of the analysis of variance is to investigate which machining parameters significantly affect the performance characteristic. Chinnasamy Natarajan et al [4] surface roughness is an indicator of surface quality and is one of the most-specified customer requirements in a machining process. For efficient use of machine tools, optimum cutting parameters (speed, feed, and depth of cut) are required. So it is necessary to find a suitable optimization method which can find optimum values of cutting parameters for minimizing surface roughness. In this work, machining process has been carried out on brass C26000 material in dry cutting condition on CNC machine and surface roughness was measured using surface roughness tester. To predict the surface roughness, an ANN model has been designed through feed-forward back-propagation network using "Matlab" software for the data obtained. Comparison of the experimental data and ANN results show that there is no significant difference and ANN has been used confidently. The results obtained conclude that ANN is reliable and accurate for predicting the values. Dong Chen et al [5] during turning process, the cutting force is generated between the cutting tool and workpiece, incurring an elastic deformation upon the machining system comprising of chuck, cutting tool, and workpiece. Furthermore, the chatter may also be caused under certain conditions. Unstable cutting caused by chatter vibration in the machining process has major effect upon the surface quality of the workpiece; as a result, improving the cutting stability becomes one of the key aims regarding the dynamic optimization. Recent work on the analysis of stability is proposed a new spindle speed regulation method to avoid regenerative chatter in turning operations. According to the method, the material removal rate was greatly improved regardless of the complex cutting dynamics. Surinder Kumar et al [6] multiple regression and linear programming approach were employed for multi-response optimization in the Taguchi method. The Taguchi method is computationally complex, thus difficult to conduct on the shop floor. The multi-response problem was solved by assigning the weights to the signal-to-noise ratio of each quality characteristic and then by adding the weighted S/N ratios to measure the overall performance of a process. The performance of different tool materials, such as ceramic, cemented carbide, CBN, and diamond, was observed while turning. The experimental results showed that only diamond tools are suitable to finish the turning. The turning of glass fiber-reinforced polyester and epoxy increased surface roughness with the increase in feed rate, while demonstrating independence on the cutting velocity. A surface roughness prediction model was developed based on the fuzzy model for the machining of GFRP tubes using a carbide tool (K20). Four parameters, namely, cutting speed, feed rate, depth of cut, and work piece were selected to minimize surface roughness. The model can therefore be effectively used to predict surface roughness in turning glass fiber-reinforced polyester composites. S. Rajesh et al [7] presents the findings of an experimental investigation into the effects of cutting speed, feed rate, depth of cut, and nose radius in CNC turning operation performed on red mud-based aluminum metal matrix composites and investigates optimization design of a turning process performed on red mud-based aluminum metal matrix composites. The major performance characteristics selected to evaluate the process are surface roughness, power consumption, and vibration, and the corresponding turning parameters are cutting speed, feed, depth of cut, and nose radius. Tian-Syung Lan et al [8] surface roughness, tool wear, and material removal rate are major intentions in the modern computer numerical controlled machining industry. Through the machining results of the CNC lathe, it was shows that both tool wear ratio and MRR from our optimum competitive parameters are greatly advanced with a minor decrease in the surface roughness in comparison to those of benchmark parameters. Surface roughness, tool life, and cutting force are commonly considered as manufacturing goals for turning operations in many of the existing research studies. It is also recognized that lighter cutting force often results in better surface roughness and tool life. Lakhdar Bouzid et al [9] in modern industry, the goal is to manufacture low-cost, high quality products with maximum productivity in a short time. Turning is the most common method for cutting and especially for the finishing of machined parts. Furthermore, in order to produce with desired quality and maximum productivity of machining, cutting parameters selected properly. In turning process, parameters such as materials, tool's geometry and cutting conditions (depth of cut, feed rate, cutting speed) have impact on the material removal rate and the machining qualities like the surface roughness. Usually, roughness is taken as a good criterion for a mechanical component performance and to appraise production cost, while material removal rate can be defined as the volume of material removed divided by the machining time. Another way to define MRR is to imagine an "instantaneous" material removal rate as the rate at which the cross-section area of material being removed moves through the workpiece. P. Jayaraman et al [10] have used grey relational analysis to perform multi-objective optimization of surface roughness, roundness and MRR in turning of AA6063 T6 Aluminium alloy and determined that cutting speed is the most influencing parameter affecting combined grey relational grade followed by depth of cut and feed rate. A grey relational grade is determined from the grey analysis. Optimum levels of parameters have been identified based on the values of grey relational grade and then the significant contribution of parameters is determined by ANOVA. Dr. C. J. Rao et al [11] the feed rate has significant influence both on cutting force as well as surface roughness. Depth of cut has a significant influence on cutting force, but has an insignificant influence on surface roughness. The interaction of feed and depth of cut and the interaction of all the three cutting parameters have significant influence on cutting force, whereas, none of the interaction effects are having significant influence on the surface roughness produced. Shreemoy Kumar Nayak et al [12] was investigated the influence of different machining parameters such as cutting speed, feed and depth of cut on different performance measures during dry turning of AISI 304 austenitic stainless steel. ISO P30 grade uncoated cemented carbide inserts was used as a cutting tool for turning. Three important characteristics of machinability such as material removal rate, cutting force and surface roughness were measured. Anders Nordgren et al [13] the plastic deformation of tools is one of the most important wear modes in metal cutting. Such deformation changes the geometry of the cutting edge, which often results in accelerated tool wear, increased cutting forces, risk of tool failure, vibrations and poor dimensional accuracy and surface finishes. S.J. Raykar et al [14] the high-speed turning is emerging as a key manufacturing technology in aerospace industry. High-speed turning is generally performed on the order of five to ten times the conventional cutting speed. It has several advantages such as reduction in cutting forces and temperature, low power consumption, improvement in surface finish, low stress components, burr-free surfaces, better dimensional accuracy, and better part quality. V. Bushlya et al [15] presents results of super alloy machinability study with uncoated and coated PCBN tools aiming on increased speed and efficiency. Aspects of tool life, tool wear and surface integrity were studied. It was found that protective function of the coating, increasing tool life up to 20%, is limited to low cutting speed range. Harsh Y Valera et al [16] study of power consumption and roughness characteristics of surface generated in turning operation of EN-31 alloy steel with $TiN+Al_2O_3+TiCN$ coated tungsten carbide tool under different cutting parameters. The study shows the influences of three cutting parameters like spindle speed, depth of cut and feed rate affecting surface roughness as well as power consumption while turning operation of EN-31 alloy steel. Coating is also used on cutting tools to provide improved lubrication at the tool/chip and tool/work piece interfaces and to reduce friction, and to reduce the temperatures at the cutting edge. During machining, coated carbide tools ensure higher wear resistance, lower heat generation and lower cutting forces, thus enabling them to perform better at higher cutting conditions than their uncoated counterparts. Jan C. Aurich et al [17] effect of coating systems on the tool performance when turning heat treated AISI 4140 is outlined. Therefore, four differently coated cemented carbide indexable and tools of uncoated cemented carbide, serving as a reference for the capability of the coating systems, are used. The tool performance is evaluated by the path length due to primary motion and the results of the turning operation, such as the process forces and the temperatures of the cutting tool.

II. EXPERIMENTAL DETAILS

EN24 is a medium-carbon low-alloy steel18 and finds its typical applications in the manufacturing of automobile and machine tool parts. Properties of EN24 steel, like low specific heat, and tendency to strain-harden and diffuse between tool and work material, give rise to certain problems in its machining such as large cutting forces, high cutting-tool temperatures, poor surface finish and built-up-edge formation. This material have wide range of applications such as high strength machine parts, collets, spindles, high tensile bolts and studs, gears, pinions, axle shafts, crankshafts, connecting rods, etc.

For experimental study, EN 24 alloy steel material was taken of size 30 mm diameter and 60 mm length workpiece as shown in figure 1.

Fig. 1: EN24 workpiece

The machining of EN 24 alloy steel was done under dry cutting condition with the help of coated and uncoated inserts. Selection of inserts was done with the help of manufacturing catalogue and finally selected inserts are PVD coated TiAlN insert and uncoated carbide insert for general turning having geometry WNMG 12 04 08 as shown in figure 2.

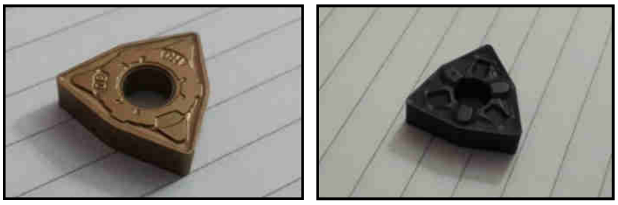

Fig. 2: PVD coated TiAlN and uncoated carbide insert

Spindle speed, feed and depth of cut are the three cutting parameters taken for consideration for investigating the effect on response variables i.e. surface roughness and material removal rate. Surface roughness was measured with the help of Mitutoyo (SJ-210) surface roughness tester and material removal rate calculated by mathematical equation;

MRR = $1000 \times Vc \times f \times d_{cut}$ mm^3/min

Where, 'Vc' is cutting speed in m/min. 'f ' is feed rate in mm/rev. and 'd_{cut}' depth of cut in mm.

Pilot experimentation was done to find out the levels of the cutting parameters. Precut of 0.5 mm depth of cut was performed on each workpiece before actual turning in order to remove the rust layer or hardened top layer from the outside surface. Final levels are shown in table 1.

Table.1: Final levels

Factors	**Level 1**	**Level 2**	**Level 3**
Spindle speed (rpm)	1450	1600	1750
Feed (mm/rev.)	0.10	0.15	0.20
Depth of cut (mm)	0.8	1.0	1.2

III. EXPERIMENTAL WORK

Three factors, three levels and nine experiments are taken in consideration according to Taguchi approach with the help of "MINITAB 17" software. Experimentation is carried out according to the L9 orthogonal array for each insert individually. Precut of 0.5 mm depth of cut was performed before actual trail on each workpiece up to the length 35 mm in order to remove the rust layer. Table 2 shows the surface roughness values and material removal rate obtained during experimentation for coated and uncoated inserts. Figure 3 shows the samples after actual experimentation. The samples A, B, C……..I stands for the Experiments 1, 2, 3,……..9 respectively as shown in figure 3.

Table.2: Experimental results for Ra and MRR for coated and uncoated inserts

Ex. No.	N (rpm)	*f* (mm/rev.)	d_{cut} (mm)	Coated insert	Uncoated insert	MRR
				Ra	Ra	
1	1450	0.10	0.8	1.4770	1.4980	10568.3
2	1450	0.15	1.0	1.5897	1.6237	19815.6
3	1450	0.20	1.2	1.6723	1.7213	31705.0
4	1600	0.10	1.0	1.2673	1.3213	14576.9
5	1600	0.15	1.2	1.0947	1.1647	26238.4
6	1600	0.20	0.8	1.5033	1.5983	23323.0
7	1750	0.10	1.2	0.7693	0.9293	19132.3
8	1750	0.15	0.8	0.9986	1.2116	19132.3
9	1750	0.20	1.0	1.3840	1.6740	31887.2

Fig. 3: Turned samples during final experimentation

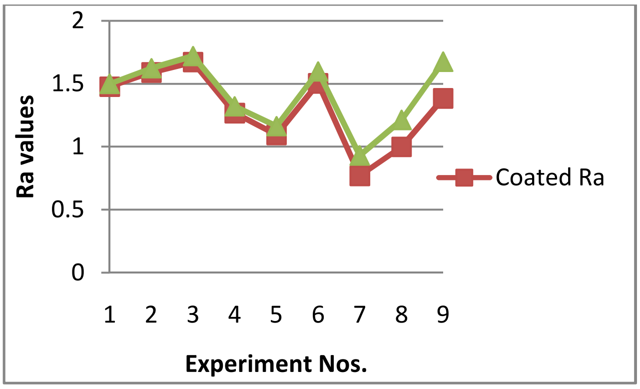

Fig. 4: Graphical representation of surface roughness with coated/uncoated inserts

Figure 4 shows the variation of surface roughness for coated and uncoated insert at different cutting conditions. General tendency is that coated and uncoated insert gives close to similar surface roughness values up to the speed 1600 rpm and after that the difference in surface roughness goes on increasing. Lower value of surface roughness is obtained at experiment no. 7 i.e. for coated insert it is 0.7693 and for uncoated insert it is 0.9293. Higher value of surface roughness is obtained at experiment no. 3 i.e. for coated insert it is 1.6723 and for uncoated insert it is 1.7213. At 1750 rpm speed the maximum difference occurred in surface roughness for coated and uncoated insert as shown in figure 4. From experimental study it is conclude that coated insert provides better results at dry cutting condition over the uncoated insert.

IV. MULTI-OBJECTIVE OPTIMIZATION BY GREY RELATIONAL ANALYSIS (GRA)

Grey relational grade is employ to convert multi objective problem into a single objective. The scope of this study is to identify the optimal combination of process parameters that concurrently minimize the surface roughness and maximize the material removal rate. In grey relational analysis, the first step is data pre-processing. This avoids the problem of different scales, units and targets. The following steps are in GRA:

- Experimental data will be normalize in the range between zero and one.
- Next, the grey relational coefficient is calculate from the normalized experimental data to express the relationship between the ideal (best) and the actual experimental data.
- Grey relational grade is then computed by averaging the weighted grey relational coefficients corresponding to each performance characteristic.
- Statistical analysis of variance is performed for the input parameters with the GRG and the parameters significantly affecting the process are found out.
- Optimal levels of process parameters are then choose.

A confirmatory test will be done to support the findings and an improvement in grey relational grade [13].

4.1 GRA for coated insert

Step 1: Normalization:

The first step in grey relational analysis is normalization and which is performed to prepare raw data for the analysis where the original sequence is transferred to a comparable sequence. Normalization of response variables is done in the range between zero and one. The indication of better performance in turning process for surface roughness is “Lower the better” whereas it is “Higher the better” for material removal rate. In grey relational analysis, for “Lower is better” response normalizing done by equation (1) and when the response is “Higher the better”, normalizing done by equation (2).

Smaller is better i.e. for surface roughness

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

For Expt. 1;

$$x_i^*(k) = \frac{1.6723 - 1.4770}{1.6723 - 0.7693}$$

$$x_i^*(k) = 0.216279$$

Larger is better i.e. for material removal rate

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

$$x_i^*(k) = \frac{10568.3 - 10568.3}{31887.2 - 10568.3}$$

$$x_i^*(k) = 0$$

Where $x_i^*(k)$ and $x_i(k)$ are the normalized data and observed data respectively, for i^{th} experiment using k^{th} response. The smallest and largest values of $x_i(k)$ in the k^{th} response are $\min x_i(k)$ and $\max x_i(k)$ respectively. The normalized values are shown in table 3.

Table.3: Comparability sequence after normalization

Expt. No.	Ra (µm)	MRR (mm^3/min)	Normalized	
			Ra	MRR
1	1.4770	10568.3	0.216279	0.000000
2	1.5897	19815.6	0.091473	0.433761
3	1.6723	31705.0	0.000000	0.991454

4	1.2673	14576.9	0.448505	0.188030
5	1.0947	26238.4	0.639646	0.735033
6	1.5033	23323.0	0.187154	0.598281
7	0.7693	19132.3	1.000000	0.401709
8	0.9986	19132.3	0.746069	0.401709
9	1.3840	31887.2	0.319269	1.000000

Step 2: Determination of deviation sequence:

The deviation sequence $\Delta_{0i}(k)$ is the absolute difference between the reference sequence $x_0^*(k)$ and the comparability sequence $x_0^*(k)$ after normalization. Mathematically it is denoted by;

$\Delta_{0i}(k) = |x_0^*(k) - x_i^*(k)|$ …………………..(3)

For surface roughness;

$\Delta_{0i}(k) = |1 - 0.216279|$

$= 0.783721$

For MRR;

$\Delta_{0i}(k) = |1 - 0.000000|$

$= 1$

Step 3: Determination of grey relational coefficient:

The grey relation coefficient $\xi_i(k)$ for the k^th response characteristics in the i^th experiment can be expressed as;

$\xi_i(k) = \frac{\Delta_{min}+\zeta\Delta_{max}}{\Delta_{0i}(k)+\zeta\Delta_{max}}$ …………………..(4)

Where Δ_{min} is the smallest value of $\Delta_{0i}(k)= \min_i \min_k |x_0^*(k) - x_i^*(k)|$ and Δ_{max} is the largest value of $\Delta_{0i}(k)$ $\max_i \max_k |x_0^*(k) - x_i^*(k)|$, $x_0^*(k)$ denotes reference sequence and $x_i^*(k)$ denotes the comparability sequence and ζ is the distinguishing coefficient. The value of ζ can be adjusted with the systematic actual need and defined in the range between 0 and 1.

For surface roughness;

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{0i}(k) + \zeta\Delta_{max}}$$

Where, $\Delta_{min} = \min||x_0^*(k) - x_i^*(k)|| = ||1 - 1|| = 0$

and $\Delta_{max} = \max||x_0^*(k) - x_i^*(k)|| = ||1 - 0|| = 1$

Where; ζ = distinguishing coefficient between [0, 1] = (0.5) selected.

$$\xi_i(k) = \frac{0 + 0.5 \times 1}{0.783721 + 0.5 \times 1}$$

$\xi_i(k)$ = 0.389493

For MRR;

$$\xi_i(k) = \frac{0 + 0.5 \times 1}{1 + 0.5 \times 1}$$

$\xi_i(k)$ = 0.333333333

Step 4: Determination of grey relational grade:

The overall evaluation of the multi-performance characteristics is based on the grey relational grade and it is defined as an average sum of the grey relational coefficients which is defined as follows;

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} w\xi_i(k) \ldots\ldots\ldots\ldots\ldots\ldots\ldots.(5)$$

Where γ_i is grey relational grade; n is the number of performance characteristics. Influence of the response variables can be controlled by deciding the optimum machining parameters varying the value of w keeping in mind $\sum_{k=1}^{n} w$ is equal to 1. The GRC and corresponding GRG for each experiment for turning operation are calculated. The value of GRG is near to the product quality for optimum process parameters.

GRG (γ_i) for 1^st experiment calculated as;

$\gamma_i = (0.5 \times 0.389493 + 0.5 \times 0.333333333)$

$\gamma_i = 0.3614$

(Bold number indicates higher grey relational grade in table 4.)

Table.4: Deviation sequence, grey relational coefficient and grey relational grades

Ex. No.	Deviation Seq. $\Delta_{0i}(k)$		GRC $\xi_i(k)$		GRG γ_i
	Ra	MRR	Ra	MRR	w1=w2 =0.5
1	0.783721	1.000000	0.389493	0.333333333	0.3614
2	0.908527	0.566239	0.354981	0.468937863	0.4120
3	1.000000	0.008546	0.333333	0.983194440	0.6583
4	0.551495	0.811970	0.475513	0.381106374	0.4283
5	0.360354	0.264967	0.581156	0.653623166	0.6174
6	0.812846	0.401719	0.380852	0.554496675	0.4677
7	0.000000	0.598291	1.000000	0.455252868	**0.7276**
8	0.253931	0.598291	0.663190	0.455252868	0.5592
9	0.680731	0.000000	0.423467	1.000000000	0.7117

Average mean of GRG (γ_m) = $\frac{\text{Total sum of grades}}{9}$

= 0.5493

Step 5: Determination of optimal parameters:

The grey relational grade calculated for each sequence (as shown in table 4) is taken as a response for the further analysis. The larger-the better quality characteristic was used for analyzing the GRG, since a larger value indicates the better performance of the process. The response table of Taguchi method is employed here to calculate the average grey relational grade for each factor level (Table 5)

Table.5: Response table for GRG

Level	Spindle speed	Feed	Depth of cut
1	0.4772	0.5058	0.4628
2	0.5045	0.5295	0.5173
3	0.6662*	0.6126*	0.6678*
Delta	0.1889	0.1068	0.2050
Rank	2	3	1

Table 6 ANOVA for GRG (multiple response characteristics)

Source	DF	Seq SS	Adj MS	F	P	% Contri-bution
Spindle Speed	2	0.062584	0.031292	54.15	0.018	41.66
Feed	2	0.018866	0.009433	16.32	0.058	12.56
Depth of cut	2	0.067633	0.033816	58.51	0.017	45.01
Error	2	0.001156	0.000578			
Total	8	0.150239				

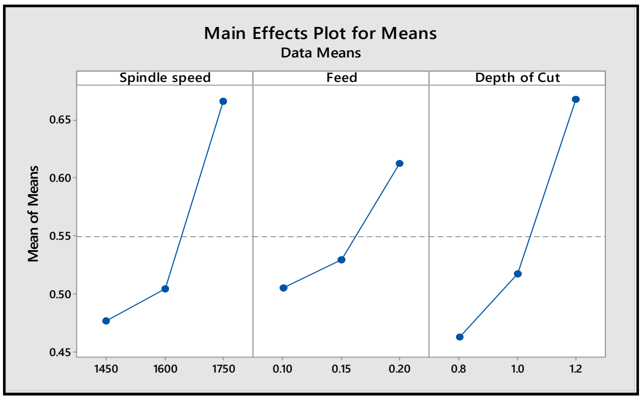

Fig. 5:Main effects plot for Means for GRG

Figure 5 shows the finest combination values for maximizing the multi-objective characteristics or grey relational grade were spindle speed of 1750 rpm, feed rate of 0.2 mm/rev. and depth of cut of 1.2 mm. The response table for the means of grey relational grade is shown in table 5. The ANOVA output of the multi-objective characteristics is given in table 6. From the analysis of this table, it is concluded that depth of cut (45.01 % contribution) followed by feed and spindle speed, is the most significantly affecting the grey relational grade.

Step 6: Confirmatory experiment:

Once the optimum level of machining parameters is selected then the final step is to predict and verify the improvement of the performance characteristics using the optimum level of the machining parameters. The estimated or predicted GRG ($\gamma_{predicted}$) at the optimum level of the machining parameter can be calculated by equation (6).

$\gamma_{predicted} = \gamma_m + \sum_{i=1}^{q}(\gamma_i - \gamma_m)$ …………(6)

Where γ_m is the total mean of the grey relational grade γ_i is the mean of GRG at the optimum level of ith parameter, and q is the number of machining parameters that significantly affect GRG. Results are shown in table 7.

From equation (6),

$\gamma_{predicted}$ = 0.5493 + [(0.6662 – 0.5493) + (0.6126 – 0.5493) + (0.6678 – 0.5493)]

$\gamma_{predicted}$ = 0.8480

Table.7:Results of confirmation experiment for GRG

Factors	Optimum by grey analysis $N_3f_1d_{cut3}$	Optimal cutting parameters: Prediction $N_3f_3d_{cut3}$	Optimal cutting parameters: Experiment $N_3f_3d_{cut3}$
Ra(μm)	0.7693		0.9433
MRR (mm^3/min)	19132.3		38264.64
GRG	0.7276	0.8480	0.8609

Improvement in GRG = 0.8609 - 0.7276
= 0.1333

% error=100- (Predicted GRG / Experimental GRG) × 100
= 100 - (0.8480 / 0.8609) × 100
= 1.52 %

4.2 GRA for uncoated insert

Similar procedure carried out for the uncoated insert and it results are shown in table 8, 9, 10, 11 and 12 respectively;

Table.8: Comparability sequence after normalization

Expt. No.	Ra (μm)	MRR (mm^3/min)	Normalized Ra	Normalized MRR
1	1.4770	10568.3	0.281944	0.000000
2	1.5897	19815.6	0.123232	0.433761
3	1.6723	31705.0	0.000000	0.991454
4	1.2673	14576.9	0.505051	0.188030
5	1.0947	26238.4	0.702778	0.735033
6	1.5033	23323.0	0.155303	0.598281
7	0.7693	19132.3	1.000000	0.401709
8	0.9986	19132.3	0.643561	0.401709
9	1.3840	31887.2	0.059722	1.000000

Table.9: Deviation sequence, grey relational coefficient and grey relational grades

Ex. No.	Deviation Seq. $\Delta_{0i}(k)$ Ra	Deviation Seq. $\Delta_{0i}(k)$ MRR	GRC $\xi_i(k)$ Ra	GRC $\xi_i(k)$ MRR	GRG γ_i w1=w2 =0.5
1	0.718056	1.000000	0.410490	0.333333333	0.3719
2	0.876768	0.566239	0.363169	0.468937863	0.4161
3	1.000000	0.008546	0.333333	0.983194440	0.6583
4	0.494949	0.811970	0.502538	0.381106374	0.4418
5	0.297222	0.264967	0.627178	0.653623166	0.6404
6	0.844697	0.401719	0.371831	0.554496675	0.4632
7	0.000000	0.598291	1.000000	0.455252868	**0.7276**
8	0.356439	0.598291	0.583812	0.455252868	0.5195
9	0.940278	0.000000	0.347155	1.000000000	0.6736

Table.10: Response table for GRG

Level	Spindle speed	Feed	Depth of cut
1	0.4821	0.5138	0.4515
2	0.5151	0.5253	0.5105
3	0.6402*	0.5984*	0.6754*
Delta	0.1581	0.0846	0.2239
Rank	2	3	1

Table.11: ANOVA for GRG (multiple response characteristics)

Source	DF	Seq SS	Adj MS	F	P	% Contribution
Spindle Speed	2	0.041747	0.020874	34.80	0.028	30.61
Feed	2	0.012625	0.006312	10.52	0.087	9.26
Depth of cut	2	0.080811	0.040406	67.36	0.015	59.25
Error	2	0.001200	0.000600			
Total	8	0.136383				

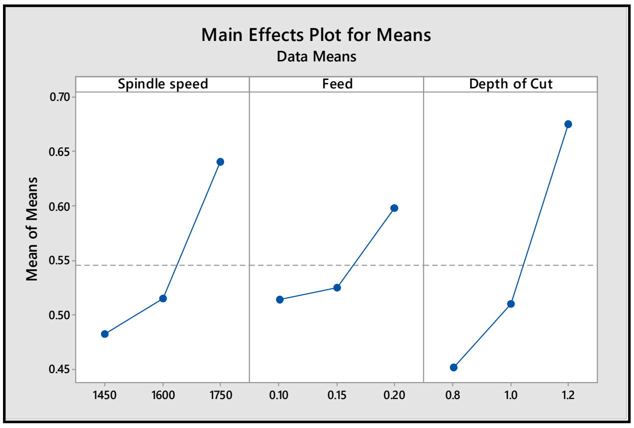

Fig. 6: Main effects plot for Means for GRG

From figure 6, the finest combination values for maximizing the multi-objective characteristics or grey relational grade were spindle speed of 1750 rpm, feed of 0.2 mm/rev. and depth of cut of 1.2 mm. The response table for the means of grey relational grade is shown in table 9 The ANOVA output of the multi-objective characteristics is given in table 10. From the analysis of this table, it is concluded that depth of cut (59.25 % contribution) followed by feed and spindle speed, is most significantly affecting the grey relational grade. Results of confirmation experiment for GRG shown in table 11.

Improvement in GRG = 0.8291 - 0.7276
= 0.1015

Table.12: Results of confirmation experiment for GRG

Factors	Optimum by grey analysis $N_3f_1d_{cut3}$	Optimal cutting parameters	
		Prediction $N_3f_3d_{cut3}$	Experiment $N_3f_3d_{cut3}$
Ra(µm)	0.9293		1.1350
MRR (mm^3/min)	19132.3		38264.64
GRG	0.7276	0.8224	0.8291

Percentage error = 100 - (Predicted GRG / Experimental GRG) × 100
= 100 - (0.8224 / 0.8291) × 100
= 0.81 %

V. CONCLUSIONS

The surface roughness and material removal rate were measured under dry cutting condition for different combinations of machining parameters for both the coated and uncoated inserts separately. The final conclusions arrived, at the end of this work are as follows:

- From GRA, it is concluded that spindle speed and depth of cut are prominent factors which affect the turning of EN24 alloy steel. For coated insert the depth of cut with 45.01% contribution is the most influencing factor in determining the multi-objective characteristics or grey relational grade with equal weights for Ra and MRR followed by spindle speed 41.66% contribution and feed 12.56% contribution.
- For uncoated insert the depth of cut with 59.25% contribution is the most influencing factor in determining the multi-objective characteristics with equal weights for Ra and MRR followed by spindle speed 30.61% contribution and feed 9.26% contribution.
- The best multi-objective characteristics obtained for PVD coated TiAlN insert for turning of EN 24 alloy steel with the higher spindle speed of 1750 rpm, higher feed of 0.2 mm/rev. and higher depth of cut of 1.2 mm with the estimated multi-objective characteristics of 0.8480. The experimental value of GRG for this combination of parameters is 0.8609.
- For coated insert, the percentage of error between the predicted and experimental values of the multi-objective characteristics during the confirmation experiments is almost within 1.52%.
- The best multi-objective characteristics obtained for uncoated insert for turning of EN 24 alloy steel with the higher spindle speed of 1750 rpm, higher feed of 0.2 mm/rev. and higher depth of cut of 1.2 mm with the estimated multi-objective characteristics of 0.8224. The experimental value

of GRG for this combination of parameters is 0.8291.

- For uncoated insert, the percentage of error between the predicted and experimental values of the multi-objective characteristics during the confirmation experiments is almost within 0.81%.

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