Multi performance optimization in machining of EN31-535A99SS with interchangeable straight cemented tungsten carbide-cobalt mixed (WC–Co) insert grade (CSTC—K20) using Taguchi coupled grey relational analysis

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Abstract

EN31-535A99 SS is an advanced and high carbon chromium-molybdenum alloy steel offering a high degree of compressive strength and abrasion resistance. Best suitable for machined components subjected to abrasive wear, swaging dies, press tools, roller bearings which do not merit a more complex quality. However, its machining is one of the challenging fields in the metal cutting industries due to the high hardness which results in low productivity and high manufacturing cost. In this paper a new interchangeable two phases straight cemented tungsten carbide-cobalt mixed (WC–Co) insert grade (CSTC—K20) tool has been introduced to obtain the optimal turning parameters for the multi-performance characteristics in the turning process by Taguchi coupled grey relational analysis. The flank wear (V_{bc}) and surface finish (R_a) were considered as the performance characteristics while the cutting speed (V), feed rate (F) and depth of cut (D) as the controllable process parameters. Experiments were planned as per Taguchi L16 orthogonal array taking three process parameters at four levels. The results revealed that the optimal parametric settings for multi-response becomes cutting speed of 75 m/min, feed rate of 0.05 mm/tooth and depth of cut as 0.25 mm respectively. At this stage the surface roughness (R_a) reduced from 0.132 to 0.061 μm while tool flank wear (V_{bc}) reduced from 0.89 to 0.69 mm and the grey relational grade enhanced up to 0.2867. The polynomial regression model presented higher R^2 value as compared to linear regression model. It is recommended that metal cutting industries could use these optimum approaches to reduce the material waste, manufacturing cost and increase productivity while machining of EN31-535A99 SS.

Keywords Parametric optimization · Surface roughness · Taguchi method · Grey relational analysis · Metal cutting · Experimental design

1 Introduction

The selection of a proper grade of steel for industrial purposes needs an awareness of the steel manufacturing procedure, the related product standards, design terms and an understanding of various matters including material properties, accessibility and cost. Steel originates its properties from a combination of different mechanical and chemical arrangement, machinability and heat

treatment [1, 2]. The chemical composition is essential to the mechanical properties of steel due to the fact that adding alloys such as Niobium, Vanadium, Manganese and Carbon upsurge the cost of the steel but unfavorably affect other properties like corrosion resistance, toughness and ductility. Steel grade EN31-535A99 SS ensures a high grade and quality stainless steel. It is one kind of distinctive steel with sorts of high wear resistance, fatigue strength and superior hardness, 60–67 on Rockwell hardness scale (R_c)

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Table 1 Mechanical properties of EN31-535A99 SS

Properties	Metric
Elastic modulus	190–210 GPa
Bulk modulus	140 GPa
Shear modulus	80 GPa
Hardness, Knoop	875
Poisson's ratio	0.27–0.30
Hardness, Rockwell	62
Hardness, Vickers	848
Machinability (spheroidized annealed and drawn. Based on 100 machinability)	40

at room temperature. It is very hard to control the high machining zone temperature during cutting of EN31-535A99 SS due to the rare properties such as thermal conductivity and high strength. The mechanical properties as shown in Table 1 make this material use in many industrial applications for production of ball and roller bearings, axle, molding dies. It is well recognized that the fatigue life of EN31-535A99 SS is significantly affected by developing of non-metallic inclusions. These non-metallic inclusions are approximately divided into three-categories: oxide, nitride and sulfide and employ a particularly opposing effect on the fatigue life. Figure 1a indicates the oxygen content representing the quantity of oxide non-metallic inclusions against fatigue life [3–5]. The oxygen amount present in

steel was diminished as much as possible by decreasing scums like titanium and sulphur considerably, thus attaining a decrease in the oxide based non-metallic presences.

The subsequent steel is the Z-steel. The Z-steel is a success of better-quality steelmaking ability and operating conditions made conceivable by collaboration with a steel maker on the basis of several test data.

Keeping in view the counter measures against high-temperature and hardenability, a specific stainless steel grade used for mechanical components subjected to high temperature should be at a level suitable to the application purpose in terms of dimensional stability at the operating temperature, structural changes, fatigue strength and hardness. While its corresponding hardness at high temperature is demonstrated in Fig. 1b. The high-temperature hardness of EN31-535A99 SS reduces abruptly when the tempering temperature is exceeded. The higher limit of the material's operating temperature for a mechanical component having been subjected to normal tempering (160–200 °C) is around 120 °C. However, if high-temperature tempering such as 230–280 °C is made, then the components may be used up to around 200 °C. In particular, the chemical composition is important hence, the chemical compositions of EN31-535A99 SS is shown in Table 2.

On the other hand, the CNC machining trades are basically targeting the machinability. In general, it is a property primarily depends upon the microstructure of the material, however, it is also largely exaggerated by some additional

Fig. 1 **a** Oxygen contents and fatigue life and **b** Hardness characteristics of EN31 535A99 SS**Table 2** Chemical compositions of EN31-535A99 SS

SS type	Chemical composition (%)								
EN31-535A99 SS	C	Si	Mn	Ni	Cr	Mo	W	V	Co
	1.02	≤ 0.25	≤ 0.4	≤ 0.10	4.15	≤ 0.75	≤ 0.25	1.25	≤ 0.25

factors including tool material, tool geometry and other machining factors like cutting fluid and cutting procedure. These factors are not extensively acknowledged to quantify and enumerate machinability. Alternatively, machinability is normally measured on an individual basis, hence it is much important and always challenging to practicing engineers to discover possible means for increasing the machinability [6]. So far numerous experiments have been conducted for the measurement of machinability which are normally tailored made to validate the requirement of a certain production facility. For instance, cutting rate superiorly affects the tool life because the temperature of the cutting process upsurges due to the increase in cutting speed. Consequently, the crater wear and the corresponding flank wear will be occurring. Similarly, if the tool exhibits greater cutting speed for the same life, the tool will have a well-cutting property and extra productive enactment.

Similarly, the flank wear has always the tendency to rub the face land and damage the material surface resulting generating heat due to friction and flank force, which further increases the rate of deflection and decreases dimensional accurateness [1, 2]. The flank wear gradation normally regarded as the maximum or average land breadth and increasing gradually at a balanced rate until a perilous land breadth is reached, after which the wear rate accelerates and turn into more severe form. The flank wear evolvement may be examined by direct visual inspection of the tool or by tracing the alteration in the tool size in manufacturing system. However, it can be diminished by increasing the abrasive resistance of the tool material or by the application of solid coverings on the tool surface. As numerous components are machined to make surfaces with accurate dimensions, some specific finishing processes and finishing standards confine the choice of the tool geometry, size and feed rate that can be adopted. Furthermore, as the surface finish changes into a rough form and becomes less reliable, it intensely

influences the product surface finish. There are basically two mechanisms related to the surface finish. The first is the geometric or ideal surface finish mechanism associated with the tool's geometry and kinematic motion. The ideal surface roughness mechanism may be calculated from the tool muzzle radius, tool's lead angle, and feed rate [3–5]. It is also considered as the major component of the surface finish in manufacturing processes due to the fact that the turning force and the tool wear are significantly low. The second mechanism is the inherent surface finish. It is much related to the dynamics and vibrational effects of the cutting forces, tool wear, residual type stresses and fracture at small cutting speeds. However, contrasting the ideal surface finish, the inherent surface finish mechanism is hard to predict in wide-ranging [7]. Normally the surface of engineering materials exhibits various irregularities especially in case of a milled surface which has a ground surface with ditches and cribs, and a polished surface with defacing grooves. Figure 2 shows the microstructure of EN31-535A99 steel with a tempered martensitic structure which is transformed as a result of tempering and hardening action. The core difference between the microstructure of untampered martensitic and tempered martensitic is the due to the conversion of acicular pointers in the former to a hairy type arrangement that carbides caused in the latter [3–5]. These surface topographies cannot be exemplary through analytical approach, therefore, for process enhancement and decision making, statistical process parameters have conventionally been used to analyze their impact on a certain part [8].

The machining of EN31-535A99 SS is more difficult since such material is chiefly exaggerated by supplementary factors as compared to the other steel grades. However, the material has the ability to produce a hard resistance surface in excess of 65 HRc. In the similar manner, modern machine centers and CNC lathe which have the capability to operate at high speed and high metal removal rates, has led the advancement of coated sintered

Fig. 2 Microstructure of tempered and untampered martensitic EN31-535A99 SS

cemented tungsten carbide which signifies 85–90% of cutting tool inserts [9]. Coated sintered tungsten carbide associates cemented carbide through a surface that shows better toughness and wear resistance, ensuring extended tool life with higher cutting speed and feed rate. Another way of refining the productivity is operating the process at the optimum cutting conditions. Numerous scholars have experienced some investigation of various effects of machining process parameters influencing on the process output parameters. For instance, stated that for the purpose of process parameters optimization related to the CNC lathes through the application of Taguchi orthogonal array is the most intellectual and the most powerful optimization tool to regulate the optimum cutting conditions for desired response optimization [10]. To solve multi objective problems, there are different multiple attribute decision making methods (MADMs) like gray relational analysis (GRA), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) based on multi-criteria decision analysis method and the analytic hierarchy process (AHP) can be used. In conclusion, these and other similar analysis revealed that feed rate and cutting speed have important impacts in decreasing the surface roughness. It was confirmed that the metal cutting industries are in search of new environmental friendly machining method to deal the issues like high manufacturing cost, poor productivity level, and extreme consumption of contaminated cutting fluids in machining of EN31-535A99 SS material. Since, the EN31-535A99 SS have high corrosive resistance and strength based on various smart properties, there is a growing demand for this material in several industrial applications therefore performance improvement while machining of this material is necessary for metal cutting industries [11]. The present work focused on determination of optimum turning process parameters multi response problems under dry cutting environment. The multi performance characteristics optimization multi techniques using Taguchi coupled grey relational analysis (TGRA) has been applied for multi response optimization respectively [12]. Straight cemented tungsten carbide-cobalt mixed (WC-Co) insert were used as cutting tools. The controllable process parameters deliberated in this study are cutting speed (V), feed rate (F), and depth of cut (D) respectively whereas output machining performance characteristics considered were being the flank wear (VB_c) and surface finish (R_a).

2 Methodology

In this study, Taguchi coupled grey relational analysis (TGRA) technique was applied as shown in the flow-chart in Fig. 3 for optimizing the machining process parameters

Fig. 3 Flow-chart Taguchi coupled grey relational analysis of experiment

of EN31-535A99 SS for improving the response parameters performance.

2.1 Experimental framework via Taguchi orthogonal array (OA)

In order to attain the specified objectives and explore the impact of input process factors on process performance characteristics, the experiments were carried out on EN31-535A99 SS having a diameter of 20 mm with a gauge length of 100 mm and hardened to 60 ± 1 (HRC). The samples were cleaned and polished with sand papers and acetone to eliminate the oils and foreign particles. The trials were performed on CNC lathe (CNC Automatic Lathe—INDEX GE 65—Berlin Germany) in the dry cutting atmosphere. The range of each parameter is set at four different levels based on gradual progression as per industrial practice. The initial cutting parameters were cutting speed (V) of 75 m/min, a feed rate (F) of 0.05 mm/tooth and depth of cut (D) of 0.15 mm. To complete the experimental design, four levels of the cutting parameters were considered and listed in Table 3.

While conducting the experiments, the cutting tools with two phases straight cemented tungsten carbide-cobalt mixed (WC-Co) insert grade (CSTC—K20) tool were used on the basis of properties like, hardness, pressure resistance, inner bonding strength,

Table 3 Machining process parameters and experimental levels

Process parameters	Experimentation level			
	1st	2nd	3rd	4th
Cutting speed (V), m/min	75	115	155	185
Feed rate (F), mm/tooth	0.05	0.09	0.13	0.17
Depth of cut (D), mm	0.15	0.25	0.35	0.45

bending strength and toughness, wear resistance, abrasion resistance, oxidation resistance, edge strength [13]. These tools material lose their hardness at 600 °C and their application is rare for machining mechanical components especially used in hydraulic press. The use of straight cemented tungsten carbide-cobalt mixed (WC-Co) tool materials with micron grain size ($\sim 0.1\text{--}0.5\text{ }\mu\text{m}$) is a novel approach to increase the toughness and edge strength. As shown in Fig. 4 further advancements of these inserts are based on the improvements of the microstructure through the additions of WC and with this addition the hot hardness, transverse rupture strength, oxidation resistance, and thermal conductivity can be significantly increased [14].

Fig. 4 Microstructure of the straight cemented tungsten carbide-cobalt mixed (WC-Co) insert **Fig. 5** **a** Tool holder and **b** angles defined by straight cemented tungsten carbide-cobalt mixed insert Source: Silverstone—United Rubber Company, Peshawar, Pakistan (R and D)

In order to fix the specimen to the spindle and adjust the cutting speed, a tool holder used for experimentation was SSBCL2020K12. The tool holder as shown in Fig. 5a is based on sliding mechanism for the purpose to change cutting speed by adjusting the distance between the specimen and the center of spindle [15]. In addition, a metal piece was inserted to keep dynamic balance during spindle rotation while (b) shows the tool geometry of angles specified for the straight cemented tungsten carbide-cobalt mixed with a rake angle (α) of 45°, knife angle (β) of 60° and clearance angle (γ) of 5° respectively.

Figure 6 represents a digital Bruker AXS contour K1 surface roughness-measuring microscope used to measure the surface roughness (R_a) as per BS EN ISO 4287:2000 British standard. The surface roughness (R_a) was measured at three equally spaced locations of the work piece to obtain the statistically significant data for each test.

For measuring the tool wear, a schematic diagram showing the wear measurement system is shown in Fig. 7. The digital camera SONY-DSC-HX400V) was used for taking the appearance of worn out tool inserts. LED was used for lighting purpose of tool insert and calibration square. For illumination purpose, LED was used to focus on the

Fig. 6 Digital Bruker AXS contour K1 surface roughness-measuring microscope

Fig. 7 Schematic diagram of the tool wear measuring

tool insert and calibration square. The image processing utility of MATLAB software package was used for image processing purpose. The tool's wear measured in this way follow the protocols explained in standards of ISO8688-1 and ISO8688-2. These ISO standards also identify critical wear. This is the point at which tool wear starts to increase rapidly towards the end of the tool life. These standards usually regulate the process parameters, materials and depth of cut which should be used and are generally assumed as benchmarking tests for the quality of tools [16]. Taguchi approach was utilized for designing and performing of the trials. For the purpose of examining the process variables performance evaluation, L16 orthogonal array technique was applied. To recognize the influence of the three independent machining process parameters each based on four levels, 16 experimental runs were selected to establish the influence of process parameters on process performance characteristics. The arithmetic mean values of the process performance characteristics were recorded at the end of each experimental stage.

2.2 Investigation of grey relational analysis

While conducting the multi-objective response experiments, the effect and interrelationship of various different process factors are usually complicated and unclear owing to the lack of certain information. Hence, in such circumstances, grey relational analysis is introduced and conducted to develop correlation between the process performance characteristics [17]. For instance, a grey relational rank is established for examining the complex point of uncertainty between the multi-objective

response. In order to reduce the replications of multiple response optimization experiments to a particular relational rank, the following stages are to be followed.

2.2.1 Stage 1

Normalizing the experimental data values to decrease its variation. In this stage, a single data diverges from supplementary data and the original experimental data is transformed into a comparable form. For the purpose of minimizing the response value, the smaller the better approach is decided to normalize the experimental data values using the following expression and an adequate array.

$$X_i^*(\lambda) = \frac{\max x_i(\lambda) - x_i(\lambda)}{\max x_i(\lambda) - \min x_i(\lambda)} \quad (1)$$

Here, λ and $i = 1$ while $X_i(\lambda)$ represents the actual data sequence, $X_i^*(\lambda)$ is the data sequence once the data has been processed, $\max x_i(\lambda)$ is the largest value of $x_i(\lambda)$, $\min x_i(\lambda)$ is the minimum value of $x_i(\lambda)$, and X is the anticipated one.

2.2.2 Stage 2

Calculating the grey relational coefficient $\zeta_i(\lambda)$ from the standardized values.

$$\zeta(\lambda) = \frac{\delta_{\min} + \zeta \delta_{\max}}{\delta_{oi}(\lambda) + \zeta \delta_{\max}} \quad (2)$$

here, δ_{oi} is the deviated data order of the orientated data and the comparable data, and

$$\delta_{oi} = \|x_o(\lambda) - x_i(\lambda)\| \quad (2.1)$$

where $x_o(\lambda)$ represents the reference data sequence and $x_i(\lambda)$ characterized as comparable data sequence. $\delta_{\max}$ and $\delta_{\min}$ represent the maximum and minimum levels of the entire variances (δ_{oi}) of all comparable data orders. ζ is the grey relational coefficient ranging from 0 to 1.

2.2.3 Stage 3

For calculating the grey relational grade (G.R.G), the following expression is considered:

$$\psi_i = \frac{1}{N} \sum_{\lambda=i}^N \zeta_i(\lambda) \quad (3)$$

Here ψ_i represents the necessary grey relational grade (G.R.G) for certain trial while N is the total responses. The grey relational grade (G.R.G) indicates some values of the interrelationship among the orientated data orders and the comparable data [18]. Consequently, the multi-objective response optimization process is hereby transformed into a sole optimized solution.

2.2.4 Stage 4

In this stage, an optimum close of the process factors is determined by means of higher grey relational grade (H.G.R.G) which specifies the improved progress of the product's quality level [19]. For this purpose, the mean grade value for every level is confirmed and may be represented as the average response table.

2.2.5 Stage 5

After considering the optimum parametric arrangement for the multi-objective response, the next stage is to go through the analysis of variance (ANOVA) to explore any significant process factor that affects the multiple responses by establishing the confidence interval level of 95% [20]. This is due to the fact that the influence of each process factor on the process performance characteristics is difficult to be evaluated by means of Taguchi approach.

2.2.6 Stage 6

The final stage is the enhancement of the G.R.G that is normally computed through confirmatory test. The forecast values for optimum close may be determined using the following:

$$\psi_{forecast} = \psi_{median} + \sum_{i=1}^0 (\psi_i - \psi_{median}) \quad (4)$$

Here m_{edians} the median of G.R.G, ψ_i is the optimized value of the median G.R.G of each process parameter while 0 represents the total of the substantial factors.

3 Results and discussion

As per findings of Table 3, the calculated values of machining process factors and responses using Taguchi method are tabulated in Table 4 while Fig. 8a, b show the parameters graphical comparison for the process performance characteristics such as flank wear and surface roughness.

Looking through the experimental results via main effect plots as shown in Fig. 8a, b, it may be observed that the flank wear progressively rises with the rise in three process factors. However, it is much interesting to see that the impact of the depth of cut and the cutting speed is comparatively greater than the feed rate. Conversely, the surface roughness upturns by the rise of the feed rate significantly while the influence of the other factors is negligible. The surface roughness declines through increase of the cutting speed up to 115 m/min and formerly improves with the rise of the cutting speed since 155 m/min to 185 m/min. Hence, these outcomes provide the improbability which should have to be selected for hardened material machining process because all the inferior levels provide intensification to minor flank wear of the insert. Noticeably both the process performance characteristics are correspondingly significant since tool flank wear have a sensitive impact on the surface quality to an inordinate degree. Consequently, the instantaneous process optimization of both the corresponding process

Table 4 Experimental results for surface roughness and flank wear as per Taguchi L16 (OA)

Trial	Process factors			Responses	
	Cutting speed m/min	Feed rate mm/tooth	Depth of cut mm	Flank wear VBc (mm)	Surface roughness R_a (μm)
1	75	0.05	0.15	0.055	0.96
2	115	0.09	0.15	0.067	0.32
3	155	0.13	0.15	0.072	0.49
4	195	0.17	0.15	0.093	1.06
5	115	0.05	0.25	0.073	0.3
6	75	0.09	0.25	0.059	0.46
7	195	0.13	0.25	0.132	0.88
8	155	0.17	0.25	0.12	1.16
9	155	0.05	0.35	0.092	0.23
10	195	0.09	0.35	0.144	0.62
11	75	0.13	0.35	0.076	0.53
12	115	0.17	0.35	0.105	1.03
13	195	0.05	0.45	0.153	0.35
14	155	0.09	0.45	0.13	0.42
15	115	0.13	0.45	0.126	0.48
16	75	0.17	0.45	0.113	1.24

Fig. 8 **a** and **b** graphical comparison for surface roughness (Ra) and flank wear (VBc)

performance characteristics is principally necessary to get the conclusion on the product's quality individualities and dry turning setting.

As the turning process was performed at the optimized values of machining parameters using dry machining environment, the experimental values of tool wear were then compared with the anticipated values produced by response surface methodology. The scanning electron microscope (SEM) images of tool wear at different magnification stages for dry machining environments were shown in Fig. 9. Scanning electron microscope was used for revealing the information about the inserts morphology, coating structure, the worn surface and chemical analysis. Scanning electron analysis were performed for the investigation of topography of the worn surface. During this investigation the information

of each insert displays on the monitor as 2D images at a high magnification with a spatial resolution between 100 and 10 μm . Prior the SEM analysis the inserts have been cleaned to be ready for the surface investigations. The inserts have been cleaned by ultrasonic cleaning in alcohol for 20 min followed by drying with warm air.

3.1 Exploring multi-objective response optimization via grey relational analysis

3.1.1 Stage 1

Using expression (1), the data were normalized while their grey relational values are tabulated in Table 5.

Fig. 9 Scanning electron microscope images of tool wear during optimization process

Table 5 Grey relational values for process performance characteristics

Run	Smaller the better	
	Flank wear (<i>VBc</i>)	Surface roughness (<i>Ra</i>)
1	1.000	0.276
2	0.877	0.910
3	0.826	0.742
4	0.611	0.177
5	0.815	0.930
6	0.958	0.771
7	0.213	0.355
8	0.336	0.078
9	0.621	1.000
10	0.091	0.613
11	0.785	0.702
12	0.489	0.207
13	0.000	0.880
14	0.234	0.811
15	0.275	0.751
16	0.407	0.000

3.1.2 Stage 2

From the findings of the Table 5, the grey relational coefficient $\zeta_i(\lambda)$ for each trial is computed using expression (2). As the equivalent weight is assigned to quality selves, the characteristic coefficient value is assumed as 0.5 and their outcomes are shown in Table 6.

3.1.3 Stage 3

Similarly, using expression (3), the G.R.G is determined from the test grades of grey relational coefficients $\zeta_i(\lambda)$ and their values are shown in Table 6. It is noticeable that the G.R.G result is employed for augmenting the multiple responses by transforming them to a single score.

3.1.4 Stage 4

The median grey relational grade ranking of each process factor at various levels is presented in Table 7 and their graphical comparison is shown in main effects plot for G.R.G in Fig. 10.

Table 6 Grey relational grade (G.R.G) coefficient values

Run	Estimated (δ_{0i})		Grey relational coefficient ($\zeta_i(\lambda)$)		G.R.G	Score
	Flank wear (<i>VBc</i>)	Surface roughness (<i>Ra</i>)	Flank wear (<i>VBc</i>)	Surface roughness (<i>Ra</i>)		
1	0.000	0.722	1.000	0.408	0.703	5.0
2	0.121	0.088	0.802	0.848	0.825	1.0
3	0.172	0.256	0.741	0.659	0.700	6.0
4	0.387	0.821	0.562	0.377	0.470	11.0
5	0.183	0.068	0.730	0.877	0.804	3.0
6	0.040	0.227	0.924	0.686	0.805	2.0
7	0.785	0.643	0.388	0.436	0.412	14.0
8	0.662	0.920	0.429	0.351	0.390	16.0
9	0.377	0.000	0.569	1.000	0.784	4.0
10	0.907	0.385	0.354	0.563	0.459	12.0
11	0.213	0.296	0.700	0.626	0.663	7.0
12	0.509	0.791	0.494	0.386	0.440	13.0
13	1.000	0.118	0.332	0.807	0.570	8.0
14	0.764	0.187	0.394	0.726	0.560	9.0
15	0.723	0.247	0.407	0.668	0.538	10.0
16	0.591	1.000	0.457	0.332	0.395	15.0

Table 7 Median grey relational grade (G.R.G)

Process factor	Median grey relational grade (G.R.G)				max–min	Ranking
	1st level	2nd level	3rd level	4th level		
Cutting speed	0.6745	0.6028	0.5865	0.5157	0.1587	3.0
Feed rate	0.7153	0.6623	0.5782	0.4238	0.2915	1.0
Depth of cut	0.6415	0.6518	0.6085	0.4778	0.1740	2.0

Fig. 10 Main effects plot for G.R.G

The values of Table 7 were founded by computing the mean value of each input process parameter at its corresponding level. The max–min column shows that feed rate is the most influential factor among the three input process parameters. In order to obtain the best responses, the optimal grouping of the parameters as represented from the table shows that all the three input process parameters must maintained at level 1 respectively.

The weighted grey relational grade intended for each sequence is taken as a response for the additional analysis. The larger-the-better quality characteristic was used for analyzing the G.R.G, since a larger value indicates the better performance of the process. These higher optimal values suggest a vigorous relationship to the desired reference sequential values for improved process performance. The grey relation grades are now analyzed with Taguchi in

Minitab software. Accordingly, the optimum sets for process factors turn out to be cutting speed of 75 m/min, the feed rate of 0.05 mm/tooth followed by depth of cut as 0.25 mm. The higher values of the median grey relational grade (G.R.G) which correspond to the lowest values of performance characteristics are shown in Fig. 10. The optimal values show the difference among the maximal and minimal values for the process factors as 0.1587 for cutting speed, 0.2915 for feed rate and 0.1740 for the depth of cut respectively. This significance specifies that the feed rate exhibits a greatest prompting influence on the process performance characteristics as compared to the other two process factors. Figure 11 shows the response surface plots of grey relational grade. It is clear from these plots that the cutting speed and depth of cut are the most significant factors that affect the grey relational grade. The optimum sets are obtained by keeping the feed rate at minimum level of 0.05 mm/tooth, cutting speed of 75 m/min and depth of cut as 0.25 mm, the surface roughness decreases which increases grey relational grade.

3.1.5 Stage 5

The ANOVA summary is presented in Table 8. The table summary specifies the implication of the process factors on the corresponding process performance characteristics. ANOVA revealed that the feed rate affects the process performance characteristics because its probability value (p value), at 95% confidence interval is less than 0.05, that is $p = 0.024 < 0.05$ which refers to a highly significant process factor. However, the remaining two process factors do not demonstrate any statistical significance related to the process performance characteristics altogether.

Fig. 11 Response surface plots of grey relational grade for joined effect of process response variables

Table 8 ANOVA Summary for G.R.G

Source	df	Adj ss	Adj ms	F-value	p value	Statement
Cutting speed	3	0.00160	0.00053	1.51	0.340	Insignificant
Feed rate	3	0.010564	0.003521	9.64	0.027	Significant
Depth of cut	3	0.001094	0.000365	1.00	0.480	Insignificant
Error	4	0.001461	0.000365			
Total	15	0.382474				

Table 9 Optimum values of performance characteristics

Description	Input process factors arrangement	Optimum process factors	
		Experiment	Prediction
Process responses level	V ₄ -F ₃ -D ₂	V ₁ -F ₁ -D ₂	V ₁ -F ₁ -D ₂
Surface roughness (Ra)	0.132		0.061
Flank wear (VB _c)	0.89		0.69
G.R.G	0.412	0.8448	0.6987
Improved G.R.G	0.2867		

3.1.6 Stage 6

To authenticate the enhancement of the G.R.G characteristics and the correctness of the test results from the initial process factors setting, the optimum level of the factors is identified and the predicted values of the G.R.G were determined using expression (4). At this stage, three confirming tests were performed at an optimum level while the values of the responses were measured and shown in Table 9 which validates the outcomes of the test runs by means of the optimized process parameters.

The results revealed that surface roughness (Ra) reduced from 0.132 to 0.061 μm while tool flank wear (VB_c) reduced from 0.89 to 0.69 mm which clearly confirm that the grey relational grade of both the process performance characteristics expressively enhanced up to 0.2867 by locating of the optimum process factors arrangement. Similarly, at an optimum level, the G.R.G value is 0.6987 that is nearer to the predicted value 0.8448 at the same time. Thus, the above outcomes of the confirmation test discovered that the predicted method for the purpose of solving the optimum arrangement of the process input factors and the process performance characteristics were optimized and improved at smallest values by the hybrid application of robust parameter design and grey relational analysis.

3.2 Developing statistical model for the process performance characteristics validation

For the purpose of process factors and process performance characteristics validation, linear regression and

polynomial regression models were developed at a significance level of 0.05 and 95% confidence level [21]. The models were used to build a mathematical model relating the process response variables (surface roughness Ra and Flank wear VB_c) with the three studied input process parameters (cutting speed, feed rate and depth of cut). Regression techniques were performed using Minitab 18 software to exclude the irrelevant terms from the model. The appropriateness of both the prediction models is based on the comparison of its coefficient of determination (R^2) value. The helpfulness of R^2 is its capability to discover the probability of future events related to the predicted outcomes. It can be assumed in percentage. For example, if $R^2 = 0.80$, it means that 80% points will be included inside the regression track. A higher value of R^2 indicates a better fit for the given dataset [22]. It also helps to examine how differences in one parameter can be explained by a difference in a second variable. The range is 0 to 1 (i.e. 0% to 100% of the variation in y can be explained by the x-variables).

3.2.1 Linear regression model

Surface roughness (Ra) = +0.22534375 – 0.00041875 Cutting speed + 5.31875 Feed rate – 0.3525 Depth of cut

Coefficient of Determination: $R^2 = 54.23\%$

Flank wear (VB_c) = – 0.0261625 + 0.0004375 Cutting speed + 0.1125 Feed rate + 0.1845 Depth of cut

Coefficient of Determination: $R^2 = 89.38\%$

3.2.2 Polynomial regression model

Surface roughness (Ra) = $4.0183 - 2.615802557 \times 10^{-2}$ Cutting speed – 27.2127 Feed rate – 6.9055 Depth of cut + 6.5234375×10^{-5} Cutting speed² + 83.2031 Feed rate² + 0.6875 Depth of cut² + 34.6875 (Feed rate × Depth of cut) + $2.178977273 \times 10^{-2}$ (Cutting speed × Depth of cut) + $4.282670455 \times 10^{-2}$ (Feed rate × Cutting speed)

Coefficient of Determination: $R^2 = 96.91\%$

Flank wear (VB_c) = $1.117208807 \times 10^{-1} - 4.612215$ 909 × 10^{-4} Cutting speed – $4.36008527 \times 10^{-1}$ Feed rate – $3.107386364 \times 10^{-1}$ Depth of cut + 1.5625×10^{-6} Cutting speed² – 0.0781 Feed rate² + 0.05 Depth of cut² + 2.0454 (Feed rate × Depth of cut) + 0.0018 (Cutting

speed $\times$ Depth of cut) + $8.948863636 \times 10^{-4}$ (Feed rate $\times$ Cutting speed)

Coefficient of Determination: $R^2 = 97.41\%$

Comparing both the regression models, the linear regression model clearly shows a lower value of the coefficient of determination (R^2) for surface roughness (R_a) that is 54.23%, however, the polynomial regression model offered a much higher value for surface roughness (R_a) that is 96.91% which is pretty close to 100%. Considering the polynomial regression model as the best fitted model for comparing the forecasted values and experimental order values. Figures 12 and 13 point out that the forecasted values are exceptionally near the experimental values. Accordingly, the established polynomial regression model has worthy indications around the relationships about the results of the forecasted and the experimental values. These results also suggest that established polynomial regression model satisfactorily forecasts the predictable outcomes preceding to experimentation in the machining of EN31-535A99 SS hardened steel using coated sintered tungsten carbide insert under dry environment and would be a good choice for implementing it in manufacturing innovativeness.

4 Conclusions

Following conclusions were drawn from experimental study.

- Metal cutting industries could use Taguchi coupled grey relational analysis (TGRA) technique involved simple mathematical equation and can be useful to solve multi-response optimization problems successfully without conducting the trial experiments to reduce the time and material waste during machining of EN31-535A99 SS.
- TGRA method was used to investigate the effect of cutting process parameters on tool flank wear and surface roughness of EN31-535A99 SS to optimize the parameters.
- Experiments were planned as per Taguchi L16 orthogonal array taking three process parameters such as cutting speed, feed rate and depth of cut) at four levels.
- From TGRA, the optimal parametric settings for multi-response becomes V1-F1-D2 i.e. cutting speed of 75 m/min, feed rate of 0.05 mm/tooth and depth of cut as 0.25 mm respectively.
- At this stage the surface roughness (R_a) reduced from 0.132 to 0.061 μm while tool flank wear (VBc) reduced from 0.89 to 0.69 mm.

Fig. 12 Graphical comparison of forecasted and experimental values of flank wear

Fig. 13 Graphical comparison of forecasted and experimental values of surface roughness

- At an optimum level, the G.R.G value is 0.6987 that is nearer to the predicted value 0.8448 at the same time.
- Main effect plots, surface response plots showed that tool flank wear and surface roughness were gradually improved with respective to the process input parameters.
- ANOVA summary specified that the feed rate affects the process performance characteristics at 95% confidence interval and p value ($p=0.024 < 0.05$) in turning process when minimization of flank wear and surface roughness are apprehensive. However, other two parameters do not demonstrate any statistical significance to the process performance characteristics.
- The grey relation grade is significantly improved (0.2867) over setting of optimal parametric arrangement.
- The polynomial regression model presented higher R^2 value and denotes best fit of the model and acceptable compared to linear regression model. Model shows good correlations between the experimental and predicted results.
- Therefore, the outcomes of parametric optimization can be employed in machining industries to enhances the machining efficiency and diminish the manufacturing cost.

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Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

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