Optimal Seeking Surface Roughness and Material Removal Rate Responses of Hardened AISI 4340 High Strength Low Alloy Steel in Dry Sustainable Environment

Amar ul Hassan Khawaja[1a], Mirza Jahanzaib[1b], Shahzad Zaka[2]

ABSTRACT

The aim of this research is to study the machinability aspects of hardened AISI 4340 High Strength Low Alloy (HSLA) steel (50 ± 2 HRC (Hardness Rockwell C)). The experimental investigation using coated carbide inserts is carried out during the dry hard milling process in a sustainable environment. The input parameters in the study are speed, feed rate and depth of cut and the responses are Average surface Roughness (Ra) and Material Removal Rate (MRR) that are selected through screening. Central Composite Design (CCD) in response surface methodology has been utilized as the experimental design technique with twenty experiments. Analysis of variance has been employed to examine the momentous machining parameters and responses. A mathematical model has been developed to optimize the surface roughness and material removal rate. It has been observed that the most significant factor for Ra is feed rate while for MRR depth of cut is the most significant factor. The results show that the minimum value of Ra ~ 0.098 μm is achieved at speed ~ 1000 RPM, feed rate ~ 300 mm/min and depth of cut ~ 0.2 mm while the maximum value of MRR ~ 6.35 cm³/min is attained at feed rate ~ 500mm/min and depth of cut ~ 0.4 mm regarding less or no effect of speed ~ 500-1000 RPM. The average forecast error for the validation information has been observed to be 3.35%. for Ra and 3.2% for MRR. Further, it is investigated that good surface finish like grinding and dimensional accuracy can be achieved with coated carbide tools.

Keywords: **High Strength Low Alloy Steel, Material Removal Rate, Multi-Objective Optimization, Sustainable Dry Machining, Surface Roughness.**

1. INTRODUCTION

AISI 4340 is a medium carbon low alloy steel in which the combined proportion of all the alloying elements by weight is less than 5 % (HSLA). It has the ability to attain high toughness and strength in the heat-treated condition. It is mostly used in the aviation industry and aeronautical applications due to very good corrosion, wear and fatigue resistance [1]. The functional performance such as corrosion resistance, fatigue strength and tribological properties of the machined components is determined by surface characteristics. The quality is determined by the surface finish and integrity attained after machining. The fatigue life of the machined parts is decreased by higher surface roughness values [2]. To accomplish quality products, certain aspects essential to be under control include process parameters, cutting tools and cutting liquids. Researchers have studied the influence of these control variables on the surface finish, material removal rate and tool wear [3-9]. For the experimental design and analysis most of the

[1] Department of Mechanical Engineering, University of Engineering and Technology, Taxila, Pakistan.
  Email: [a]amar.khawaja@students.uettaxila.edu.pk (Corresponding author), [b]jahan.zaib@uettaxila.edu.pk.
[2] Department of Industrial Engineering, University of Engineering and Technology, Taxila, Pakistan.
  Email: shahzad.zaka@students.uettaxila.edu.pk

authors have been using the statistical techniques in their experimentation.

Numerous researchers described the facts regarding the influence of process parameters on surface roughness and material removal rate during machining of AISI 4340 HSLA steel. Chakraborty *et al.* [10] suggested a combined effects model on end milling of AISI 4340 steel (26 HRC) under dry and minimum quantity lubrication environments using the Physical Vapour Deposition) (PVD) coated carbide inserted by selecting input machining parameters *i.e* feed rate (f_r), depth of cut (d) and cutting speed (V) for the analysis of longitudinal data attained from a designed experiment. A tool wear progression model was developed. The lower tool life and greater tool wear was revealed at higher cutting speed and lesser tool wear and higher tool life was observed at the lower cutting speed under Minimum Quantity Lubrication (MQL) system. The depth of cut was an insignificant parameter to tool wear as followed by cutting speed and feed. Gopalsamy *et al.* [11] investigated the optimal milling parameters such as width of cut, V, d and f_r for rough and finishing machining with deliberation of multiple responses, *i.e.* surface finish, MRR, tool life and tool wear of hardened tool steel (55 HRC) by Grey Relational Analysis (GRA) and compared the outcomes with ANOVA. It was analyzed that width of cut and cutting depth are significant factors for rough machining while to finish machining the important factor is cutting speed. Ding *et al.* [12] examined the impacts of radial and axial depth of cut, cutting rate and feed in hard processing of AISI H13 steel (50 HRC) utilizing coated carbide tools on Ra and cutting force by performing ANOVA and range analysis. It was examined that cutting force has been frustrated by two principal aspects: feed rate and axial depth of cut. The Ra achieved is less than 0.25 μm which indicates that hard milling may substitute grinding. Suresh *et al.* [13] studied the impact of machining parameters during turning of AISI 4340 HSLA steel using coated carbide inserts to optimize V, d, f_r, machining time and Ra. Machining force and tool wear were output parameters. The Response Surface Methodology (RSM) was used for the development of a mathematical model and full factorial design was used as a design of experiments. For analyzing and selection of best machining

parameters ANOVA was used. It was concluded that for the minimum value of Ra and machining force, lower feed rate and depth of cut with high cutting speed was required. Further, they recommended that lower feed rate and cutting speed can be used for minimum tool wear. Das *et al.* [14] investigated the dry turning process of 4340 HSLA steel (C 0.39%, 47 HRC) and checked the impact of f_r, V and d on Ra with Chemical Vapour Deposition (CVD) multilayer coated carbide inserts. For experimental planning, a full factorial design of the experiment was carried-out, and ANOVA was utilized to inspect the substantial process parameters on roughness. The association among the process parameters and response multiple regression analysis was used for modeling of Ra. It was concluded that at 95% confidence level feed was the most influencing process parameter followed by cutting speed.

An *et al.* [15] studied hard dry milling of 30Cr3SiNiMoVA (30Cr3) high strength steel regarding tool wear, cutting force, chip formation and surface roughness individually using coated cemented carbide tool. Taguchi L16 was selected as the experimental design technique with V, f_r and radial depth of cut as the process parameters. A decrease in cutting forces and improvement in the surface finish was reported with the rise of cutting speed, whilst both depths of cut and feed had an adverse influence on surface finish. Senthilkumar *et al.* [16] performed optimization of process parameters i.e V, f_r and d for Ra, MRR and flank wear during turning of AISI 1045 HSLA steel using CCD in RSM and compared the results with firefly algorithm. It was revealed that the substantial factor for Ra and flank wear is feed rate while cutting speed for MRR. Azam *et al.* [17] studied the impact of cutting conditions on AISI 4340 HSLA steel during turning operation using multilayer coated carbide tool and established a surface roughness model. A sequence of examinations using RSM had been carried out to mature a connection among Ra and turning process parameters i.e. V, d, and f_r. The results indicated that feed was a significant parameter that influenced the Ra. A mathematical model was developed and it was found that the surface roughness was influenced by a feed as a core parameter. Lauro *et al.* [18] examined the minimum force and torque by selecting the best machining parameters combination

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(grain size, V and f_r) with the combination of both genetic optimization algorithm and the least squares model. The optimization of micro-milling utilizing hardened DIN 1.2344 chromium type tool steel was completed by applying the NSGA II algorithm. It was investigated that for the minimization of Force and Torque, the feed rate was the utmost substantial aspect. Hassanpour et al. [19] analyzed the hard milling of 4340 alloy steel using MQL system and explored the relationship between milling parameters i.e. V, radial and axial depth of cut, machined surface integrity and cutting speed. The possessions of these milling parameters on chemical composition, white layer thickness, microhardness, roughness, and topography were considered through RSM. The ANOVA results showed that the linear model was suitable to assess the white layer thickness and the quadratic polynomial model was suitable to govern the microhardness and surface roughness. Further, they investigated that minimum Ra was attained at minimum feed and depth with maximum cutting speed.

Abbas et al. [20] examined the process parameters f_r, d and spindle speed on Ra and MRR for milling process of high strength steel using full factorial design technique. They established a mathematical relationship amongst the process parameters and responses using the least squares technique and a second-order regression model was constructed. ANOVA was used to check the significant machining parameters and it was observed that the feed rate had a maximum impact on Ra. Antony et al. [21] scrutinized the impacts of process parameters V, d, f_r and nose radius on quality and productivity during turning of EN-24 alloy steel using RSM technique. Significant parameters were patterned by ANOVA and suggested that feed rate and depth of cut were substantial for MRR and cutting speed and nose radius were the significant parameters for Ra. They established an empirical relationship for calculating the Ra and MRR values at any parameter value. Kumar et al. [22] examined the impact of MQL and process parameters V, f_r and nose radius on surface quality by turning of AISI 4340 hardened steel with CBN cutting tool at different hardness levels i.e. 40, 45, 50, 55 and 60 HRC. The significance of machining parameters was checked by ANOVA and for the development of

a mathematical model, the second-order regression technique was used for the optimum value of surface roughness. The results showed that turning of dry and wet conditions had rough surface quality as compared to MQL and 7-10% improvement in surface quality had been achieved. Khan and Bhivsane [23] evaluated the consequences of machining parameters i.e. V, d, f_r and nose radius on hardened AISI 4340 steel (47-50 HRC) to optimize the tool wear and Ra as response parameters. Multiple regression technique was used for turning parameters to optimize Ra value and L9 Taguchi's method was applied as an experimental method. The results indicated that the depth of cut and feed rate had a lower impact on Ra than the cutting speed and nose radius.

Recently, Muaz and Choudhary [24] studied the machinability aspects of AISI 4340 steel using coated carbide tool and MQL technique. Milling process parameters (speed, MQL type, and feed rate) with responses force and surface roughness were optimized using Taguchi and Taguchi-GRA method respectively. It was investigated that feed rate was the most significant variable that affected the force followed by MQL type and speed while for surface roughness MQL type was the most significant variable followed by feed rate and speed. Benedicto et al. [25] explored that dry machining was the best environmental substitute and sustainable process which entirely eliminated the use of cutting fluids and ensured a clean environment and protection. As indicated by Brundtland report (1987) sustainable development is characterized as development that addresses the issues of the present generation without negotiating the capacity of future generation to address their own issues [26]. Sustainable manufacturing expects to create appropriate strategies to change over materials into completed items by diminishing utilization of earth's characteristic assets and energy, declining natural emissions and pollution, decreasing health and safety dangers, and delivering less waste, while holding the objective of better execution and economy to the clients and leaving a superior planet for our future cohort [27]. The sustainable machining model comprises eco-friendly, cost savings, energy-efficient, increased tool life, waste-free, operational safety, and personal health as shown in Fig. 1.

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In the current research dry machining of AISI 4340 HSLA steel has been reported to save the future generation in the perception of sustainability that covers the three dimensions *i.e.* economic, social and environment. Dry machining takes out the utilization of cutting liquids and reduces 16-17% of the total machining cost (economic impact) [28, 29]. Dry machining can successfully dispense with the comfort perils like dermatitis, skin contaminations, respiratory infections, and malignancy, related to cutting liquids (social impact), and in the meantime enhance the general execution of cutting activities and there will be no need for disposal of cutting fluids (save environment) because of dry machining.
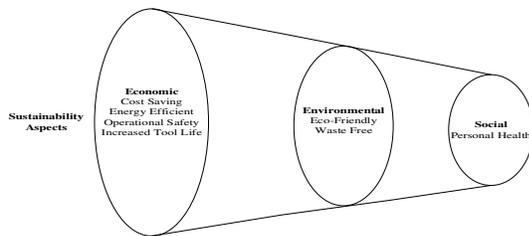

Fig. 1: Sustainable Dry Machining Model

It can be determined from the literature review that process parameters have a direct impact on surface roughness and material removal rate. It can also be inspected that by changing alloy composition and a hardness value of 4340 steel the influence of process parameters combination feed, speed and depth of cut also changed. It is ostensible from the literature that limited work has been reported on AISI 4340 HSLA steel (50 ± 2 HRC) for dry hard milling operation.

The aim of current research is to investigate the influence of process parameters, the evolution of the mathematical model, and their optimization through response surface methodology. The significance of the research is the optimal parameters combination such as feed rate, cutting speed and depth of cut for hardened AISI 4340 HSLA steel with alloy composition C 0.39%, Cr 0.81%, Ni 1.8%, Mo 0.24% having hardness value of 50 ± 2 HRC to achieve the

better surface finish and higher material removal rate in perspective of sustainability. Analysis of variance has been applied to analyze the momentous machining parameters for dry hard milling operations. It is expected that this work would be beneficial and the contribution likely is in the field of manufacturing/ machining and for practitioning engineers.

2. EXPERIMENTAL WORK

This section presents the experimental details including material selection and specimen preparation, levels of process parameters and specimen machining.

2.1 Material Selection and Specimen Preparation

Steels are utilized monetarily in the aviation industry and aeronautical applications, establishing only 7-20 % of the aggregate weight of commercial and military airplane [30, 31]. The steels utilized in commercial and military aircrafts are for the most part low-alloy steels, such as 4340 and 300M because of the higher tensile and yield strength. AISI 4340 HSLA steel is selected as a working material for the current study and alloy composition is given in Table 1 (Peoples Steel Mills Limited authenticated by QA department). The XRF analyzer and wet analysis method were used for confirmation of chemical composition before experimentation.

Table 1: Chemical Composition (Wt %) of Aisi 4340 HSLA Steel

C	Si	P	S	Cr	Mo	Ni	Cu	Mn
0.39	0.27	0.015	0.014	0.81	0.24	1.8	0.13	0.78

To achieve the required hardness value (50±2 HRC) heat treatment of the specimens were conducted. The parameters used in heat treatment are given in Table 2. Rockwell hardness tester with diamond indenter was used to measure the hardness value. After achievement of hardness value (50±2 HRC), the specimens were cut to the desired size of 32mm x 32mm x 20mm from the bar of length 1000mm using a disk cutter.

Table 2: Heat Treatment Parameters

Austenzing		Quenching			Tempering	
Temperature (°C)	Time (min)	Medium	Temperature (°C)	Time (min)	Temperature (°C)	Time (min)
570 700 840	40 10 60	PSO Oil No. 10	30	30	250	120

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2.2 Levels of Process Variables

The input parameters in the study are speed (V, PM), feed rate (f_r, mm/min) and depth of cut (d, mm) and responses fixed are average surface roughness (Ra, μm) and material removal rate (MRR, cm³/min). Similar studies using these inputs and responses have been cited in the literature [11, 16, 20, 21]. The objective is to optimize the input parameters to achieve desired response values. The level of input process parameters is given in Table 3.

Table 3: Levels of Input Process Parameters			
Factors	Levels		
	Low	Middle	High
Speed, V (RPM)	500	750	1000
Feed, f_r (mm/min)	300	400	500
Depth of cut, d (mm)	0.2	0.3	0.4

2.3 Specimens Machining

Dry hard milling tests have been performed on AISI 4340 HSLA steel in the current study. Marking has been performed on the specimens from 1-20 and experiments as per the design matrix is carried out on a CNC milling machine (DAHLIH MCV-720) using coated carbide tool as shown in Fig. 2. Now, each specimen is faced down to get machine zero points in Z-axis for setting the depth of cut value. After that, each specimen is milled using the DOE values by following Climb Milling Operation for the better surface finish. After machining all the specimens were checked for surface roughness (Ra) value using the Mitutoyo SJ-410 surface finish measuring apparatus. The material removal rate was measured by finding the initial and final weights of specimen and machining time was also recorded with the help of stopwatch. Following expression [32] is used to compute the MRR response and results are given in Table 4.

$$MRR = \frac{\text{Initial Weight of Specimen} - \text{Final Weight of Specimen}}{\text{Density} \times \text{Machining Time}}$$

3. EXPERIMENTAL DESIGN

Central composite design in RSM has been utilized for the selection of the best process parameters combinations. The RSM cartels the mathematical and statistical methods to establish the response when aspects are diverse coincidentally. The outcomes were
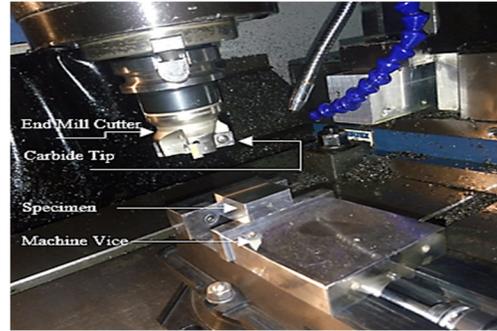

Fig. 2: Experimental Setup

demonstrated to fit either a first or second-order model characterized by the following relations Eq. (2, 3) [17]:

$$y = \beta_0 + \beta_1 x_1 + \beta_k x_k + \varepsilon \qquad (2)$$

$$y = \beta_0 + \sum_{i=1} \beta_i\ x_i + \sum \beta_{ii}\ x_i^2 + \sum \sum_{j<1} \beta_i\ j^{x_i x_j} + \varepsilon \qquad (3)$$

where β_0, β_i, β_{ii} and β_{ij} are called parameters of approximating functions, y is performance variable and x_i is input variable.

Central composite design in RSM is the most prominent second-order design which was presented by Box and Wilson. The CCD is a factorial outline with center and star points. The estimation of star points is indicated by curvature. The factorial plan is designated in CCD to contribute the approximation of the interaction terms. The axial points subsidize large to the estimation of quadratic terms. The aggregate of the quadratic relations can be evaluated without the axial points. The factorial focuses do not add to the approximation of quadratic relations. The middle runs to give an inside estimate of error and subsidize toward the assessment of quadratic relations. The regions of adaptability in the utilization of CCD reside in the determination of axial distance (α ~ 1.68) and the number of center runs (n_c). The decision of n_c frequently influences the distribution of variance in the region of intrigue. The axial distance esteem α is kept up rotatability and it relies upon the quantity of test keeps running in the factorial bit of the central composite design [33]. In this work, twenty experimental design points were considered according to design equation $2^n + 2n + 2\ n_c$ (n is the number of

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input parameters) including eight factorial points (2^n), six axial points (2n) and six center points (2 n_c) as shown in Fig. 3 [34, 35].
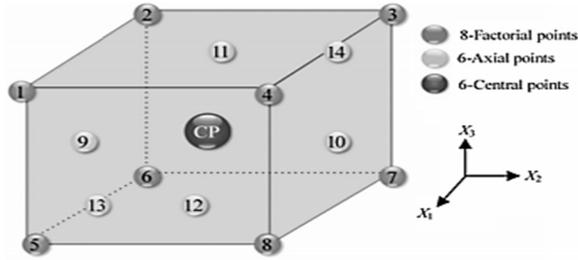

Fig. 3: CCD Points Location for 3 Parameters

4. RESULTS AND DISCUSSION

Design of Experiment (DOE) matrix has been developed through design expert 7. The experimental results with complete DOE are given in Table 4. It has been observed that minimum value of Ra ~ 0.098 μm is achieved with process parameters combinations cutting speed ~ 1000 RPM, feed rate ~ 300 mm/min and depth of cut ~ 0.2 mm while maximum value of MRR ~ has been attained at feed rate ~ 500 mm/min, depth of cut ~ 0.4 mm and cutting speed ~ 500-1000 RPM.

4.1 Statistical Analysis

The RSM has been performed to predict Ra and MRR in the dry hard milling of 4340 HSLA steel using a shell end mill type cutter with carbide inserts attached to it. Table 5 (a-b) delivers the statistical model summary for Ra and MRR. It is apparent from Table 5 (a) that the quadratic model is best recommended for Ra and two-factor interaction model is best suited for MRR; along these lines, it has been utilized for advance examination.

Table 4: Design Matrix With Responses

Standard	Input machining parameters			Responses	
	Cutting Speed RPM	Feed rate mm/min	Depth of cut mm	Ra μm	MRR cm³/min
1	500	300	0.2	0.169	1.83
2	1000	300	0.2	0.098	1.96
3	500	500	0.2	0.221	3.25
4	1000	500	0.2	0.193	4.63
5	500	300	0.4	0.196	4.92
6	1000	300	0.4	0.148	3.87
7	500	500	0.4	0.251	6.35
8	1000	500	0.4	0.255	6.35
9	329.5	400	0.3	0.227	4.31
10	1170.4	400	0.3	0.147	3.84
11	750	231.8	0.3	0.153	2.61
12	750	568.2	0.3	0.265	5.91
13	750	400	0.132	0.154	2.23
14	750	400	0.468	0.203	5.91
15	750	400	0.3	0.212	4.46
16	750	400	0.3	0.209	4.35
17	750	400	0.3	0.197	3.92
18	750	400	0.3	0.213	3.91
19	750	400	0.3	0.202	3.92
20	750	400	0.3	0.207	3.87

Table 5 (a): Model Summary Statistics for Ra

Source	Std. dev	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	
Linear	0.0159	0.8751	0.8516	0.7890	0.0068	
2FI	0.0139	0.9224	0.8865	0.8166	0.0059	
Quadratic	0.0074	0.9829	0.9676	0.9058	0.0030	Suggested
Cubic	0.0056	0.9941	0.9813	0.9779	0.0007	Aliased

Table 5(b): Model Summary Statistics for MRR

Source	Std. dev	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	
Linear	0.3612	0.9392	0.9278	0.8942	3.6304	
2FI	0.2153	0.9824	0.9743	0.9597	1.3811	Suggested
Quadratic	0.2314	0.9844	0.9703	0.9425	1.9740	
Cubic	0.2385	0.9901	0.9685	0.9849	0.5175	Aliased

4.2 Quadratic Model

The CCD was utilized to develop the mathematical relationship for associating the surface roughness (Ra) as a response and process parameters (V, f, and d). Equation (4) is used to analyze the response at any value of the input parameter.

$$R_a = 0.16028 - 1.90940E - 4V - 1.27734E - 4f + 0.49028d + 4.75000E - 7Vf + 2.75000E - 4Vd + 1.87500E - 4fd - 1.08567E - 4Vd + 1.87500E - 4fd - 1.08567E - 7V^2 + 9.92725E - 8f^2 - 0.97907d^2 \qquad (4)$$

ANOVA for the response surface roughness quadratic model is given in Table 6. The p-value is less than 0.05 shows the model is significant. The main significant terms are cutting speed, feed rate and depth of cut and interacting significant terms are AB (cutting speed×feed rate) and AC (cutting speed × depth of cut) and quadratic significant terms are A^2 (cutting speed²)

and C^2 (depth of cut²) while values greater than 0.1000 demonstrate the model terms are insignificant to have been avoided. Interaction effects signify the shared effects of input parameters on responses. During the interaction effect, the influence of one parameter depends on the level of the other parameter. It is the ability of ANOVA to estimate the interaction effects. It is obvious that the most significant factor influencing the Ra is feed rate followed by the cutting speed and depth of cut. The value of the R^2 statistic i.e coefficient of determination illustrates that 98.3% of the total variations are described by the model. The estimation of R^2 got in the wake of changing for the extent of the model is 96.7%. Examination of $R^2_{adj} = 0.967$ with $R^2_{pre} = 90.6\%$ demonstrates that the two terms are in great concurrence with one another and model would be relied upon to clarify 90.6% variability in a new data. Enhanced accuracy and dependability of test outcomes is appeared by the low estimation of the coefficient of variety (C.V) which is 3.8%.

Table 6: ANOVA for Response Surface Roughness Quadratic Model					
Source	Sum of Squares	df	Mean Square	F Value	p-value Prob>F
Model	0.0319	9	0.0035	63.9737	< 0.0001
A-Cutting Speed	0.0056	1	0.0056	101.8669	< 0.0001
B-Feed rate	0.0181	1	0.0181	327.1255	< 0.0001
C-Depth of cut	0.0046	1	0.0046	83.5851	< 0.0001
AB	0.0011	1	0.0011	20.3741	0.0011
AC	0.0004	1	0.0004	6.8290	0.0259
BC	2.8125E-05	1	2.8125E-05	0.5079	0.4923
A^2	0.0007	1	0.0007	11.9834	0.0061
B^2	1.42024E-05	1	1.42024E-05	0.2565	0.6235
C^2	0.0014	1	0.0014	24.9487	0.0005
Residual	0.0006	10	5.53704E-05		
Lack of Fit	0.0004	5	7.28742E-05	1.9245	0.2449
Pure Error	0.0002	5	3.78667E-05		
Cor Total	0.0324	19			
Std. Dev.	0.0074		R-Squared	0.9829	
Mean	0.196		Adj R-Squared	0.9675	
C.V. %	3.7965		Pred R-Squared	0.9058	
PRESS	0.0030		Adeq Precision	32.6254	

4.3 Two-Factor Interaction Model

The material removal rate was significant at two-factor interaction (2F1) model with $R^2 = 0.9824$ or close to 1, indicating that the better the correlation between the observed and predicted values. The ANOVA for the model is shown in Table 7 and is expressed in the following equation.

$$MRR = -2.99279 - 8.56784E - 004V + 1.97170E - 003f + 22.22232d + 1.15000E - 005Vf - 0.012800Vd - 2.25000E - 003fd \qquad (5)$$

From Table 7, it is apparent that the main significant terms are feed rate and depth of cut and interacting significant terms are AB (cutting speed × feed rate) and AC (cutting speed × depth of cut). Depth of cut is

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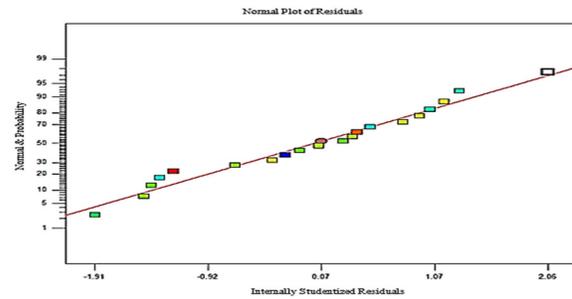| Table 7: Anova For Material Removal Rate 2F1 Model					
Source	Sum of squares	df	Mean Square	F Value	p-value Prob > F
Model	33.7026	6	5.6171	121.2120	< 0.0001
A-Cutting Speed	0.0080	1	0.0080	0.1725	0.6846
B-Feed rate	13.4438	1	13.4438	290.1057	< 0.0001
C-Depth of cut	18.7662	1	18.7662	404.9593	< 0.0001
AB	0.6612	1	0.6612	14.2692	0.0023
AC	0.8192	1	0.8192	17.6776	0.0010
BC	0.0040	1	0.0040	0.0874	0.7722
Residual	0.6024	13	0.0463		
Lack of Fit	0.2613	8	0.03267	0.4789	0.8306
Pure Error	0.3411	5	0.06822		
Cor Total	34.305	19			
Std. Dev.	0.2153		R-Squared	0.9824	
Mean	4.12		Adj R-Squared	0.9743	
C.V. %	5.2250		Pred R-Squared	0.9597	
PRESS	1.3811		Adeq Precision	34.5003	

the most significant parameter that influence MRR followed by cutting speed and feed rate. Enhanced accuracy and consistency of test outcomes is shown by the low value of the Coefficient of Variation (C.V) which comes out to be 5.2%.
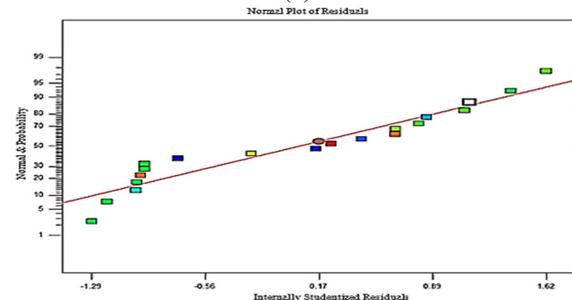
4.4 Residual Analysis

Residual analysis is the principal investigative tool to check the suitability of the proposed model [36]. The normal plot of the residuals, internally studentized residuals vs normal % probability and actual vs predicted values of Ra and MRR are shown in Fig. 4 (a-b) and Fig.5 (a-b) respectively. It is obvious from Fig. 2 that values lie near a straight line which demonstrates that mistakes are freely and typically dispersed, and presumptions are not damaged. Figure 3 demonstrates that errors are distributed regularly because points lie on a straight line in actual versus predicted plot. It is found that the model best fit the desired outcomes.

4.5 Optimization of Surface Roughness

Three-dimension response and contour plot of surface roughness versus cutting speed and feed rate is shown in Fig. 6. It is imperative that the Ra of the specimen is increased by increasing the feed rate and decreased by increasing the cutting speed. Further, it has been investigated that at origin value of feed rate with increasing cutting speed the Ra value decreased and
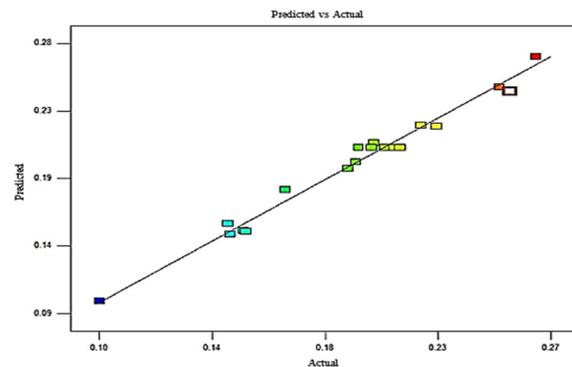

(a)

(b)

Fig. 4: Normal Plot of Residuals for (a) Ra and (b) MRR

(a)

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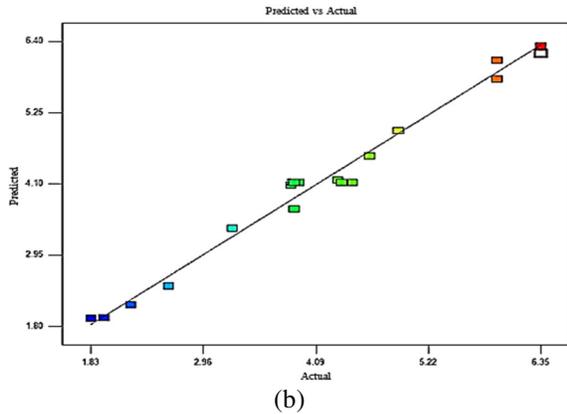
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(b)

Fig. 5: The plot of Predicted Vs Actual for (a) Ra and (b) MRR

the initial value of cutting speed with increasing feed rate the Ra value increases. But at higher values of feed rate and cutting speed the Ra value is greater it is concluded that at a higher value of cutting speed and lower value of feed rate the Ra is minimum as shown in the contour plot of Ra versus feed rate and cutting speed. From the contour plot, the minimum Ra value is 0.152 µm is attained at a cutting speed of 925 RPM and feed rate of 316 mm/min. The Ra value is useful ... gear shafts.
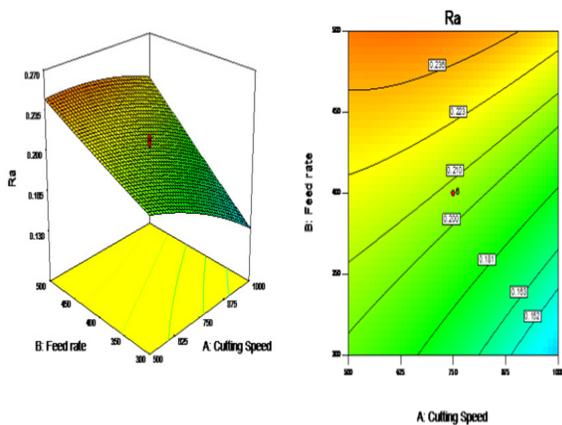

Fig. 6: 3D Response and Contour plot of Surface Roughness Vs Cutting Speed and Feed Rate

Fig. 7 shows the 3D response and contour plot of Ra versus cutting speed and depth of cut. It is analyzed that as cutting speed increases Ra decreases significantly and when the depth of cut increases Ra value also increases. Further investigated that at a lower value of the depth of cut with the increasing cutting speed the Ra decreases and at a lower value of cutting speed with increasing depth of cut Ra increases

but at higher values of cutting speed and depth of cut Ra value also increases. It is concluded that at a lower value of the depth of cut with the increasing cutting speed the Ra decreases. Contour plot of Ra versus cutting speed and depth of cut shows that minimum Ra value of 0.152 µm is achieved at cutting speed of 985 RPM with the depth of cut 0.21 mm.

Three-dimension response and contour plot of Ra versus feed rate and depth of cut is shown in Fig. 8. It shows the increasing trend of surface roughness value either increasing feed rate or depth of cut. Further, it has been investigated that at a lower value of feed rate and depth of cut Ra is minimum. The contour plot of Ra versus feed rate and depth of cut shows that minimum Ra value of 0.152 µm is attained at a feed rate of 310 mm/min with the depth of cut 0.21 mm.
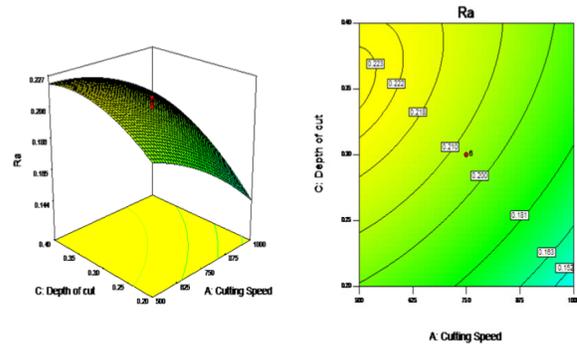

Fig. 7: 3D Response and Contour Plot of Surface Roughness Vs Cutting Speed and Depth of Cut
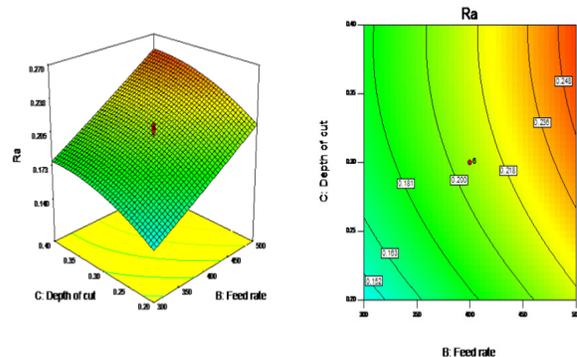

Fig. 8: 3D Response and Contour plot of Surface Roughness Vs Feed Rate and Depth of Cut

The results of the current study are compared by Muhammad Muaz and Sounak Kumar Choudhary's study [24], it is concluded that better results were achieved using dry machining then MQL technique.

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4.6 Optimization of Material Removal Rate

Three-dimension response and contour plot of material removal rate versus cutting speed and feed rate are shown in Fig. 9. It shows when the cutting speed increases with the initial value of the feed rate the MRR will be decreased negligibly. Further investigated that by increasing the feed rate with the initial value of cutting speed the MRR increases significantly. When both cutting speed and feed rate increases MRR will also be increased most significantly. The contour plot of MRR versus cutting speed and feed rate shows that the maximum value of 4.95 cm^3/min MRR is attained at cutting speed of 784 RPM with a feed rate of 481 mm/min.
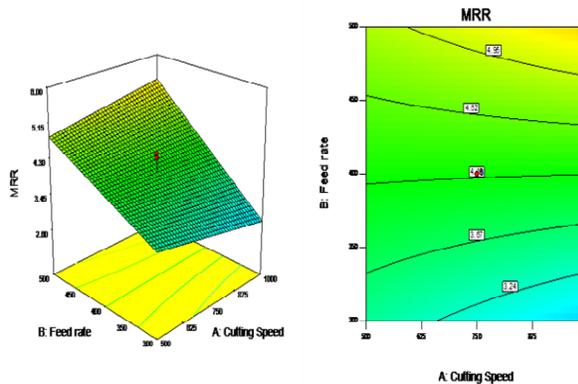

Fig. 9: 3D Response and Contour plot of Material Removal Rate Vs Cutting Speed and Feed Rate

Fig. 10 depicts the 3D response and contour plot of MRR versus cutting speed and depth of cut. It is explored that at an initial value of the depth of cut with increasing cutting speed, MRR increases and at an initial value of cutting speed with the increase of depth of cut, MRR increases most significantly. It is also investigated that by increasing cutting speed and depth of cut, MRR will also be increased but the maximum value of MRR is achieved at a lower value of cutting speed and higher value of the depth of cut. The contour plot of MRR versus cutting speed and depth of cut shows that the maximum value of 5.14 cm^3/min is achieved at the cutting speed of 693 RPM and depth of cut of 0.38 mm.

Three-dimension response and contour plot of material removal rate versus feed rate and depth of cut are shown in Fig. 11. It is examined that an initial value of the depth
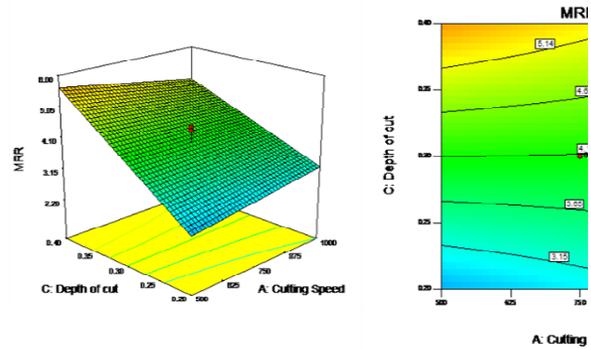

Fig. 10: 3D Response and Contour pot of Material Removal Rate Vs Cutting Speed and Depth of Cut

value of the depth of cut with increasing feed rate the MRR will be increased suggestively and vice versa. Further concluded that when both feed rate and depth of cut increases MRR will increase most significantly and the maximum value of MRR is achieved at higher values of feed rate and depth of cut. The contour plot of material removal rate versus feed rate and depth of cut shows that maximum value of 5.54 cm^3/min is achieved at the feed rate of 463 mm/min and depth of cut of 0.37 mm.

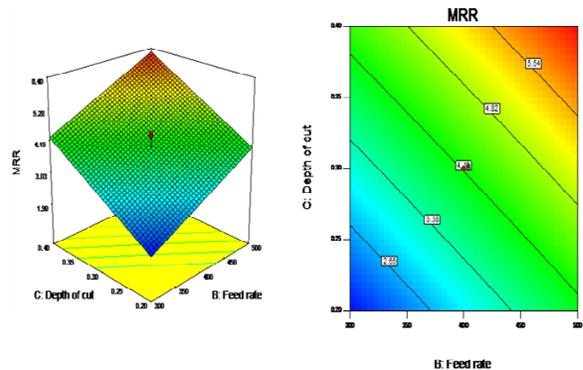Fig. 11: 3D Response and Contour plot of Material Removal Rate Vs Feed Rate and Depth of Cut

4.7 Validation of Model

The model has been validated by an additional eight experiments. These trial runs do not have a place with the CCD informational index. The correctness of the model is determined through the connection given by Azam *et al.* [17] as given in Eq. (6). Table 8 demonstrates the experimental and predicted qualities for Ra and MRR of examinations. It is obvious from Table 8 that both experimental and predicted values coordinate intimately with one another.

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$$\Delta = \frac{100}{N} \sum_{i=1}^{N} \left| \frac{y_{i,experimental} - y_{i,predicted}}{y_{i,predicted}} \right| \tag{6}$$

The average forecast error for the validation information has been observed to be 3.35%. for Ra and 3.2% for MRR be a good technical database for the aviation industry and aeronautical applications in machining perspectives.

Finally, it will be concluded that using model equations it will be possible to predict the Ra and MRR value of any input before conducting machining. The optimal values of the current study for Ra and MRR are given in Table 9.

5. CONCLUSION

The study of AISI 4340 HSLA medium carbon steel (C = 0.39 % with 50 ± 2 HRC) has been explored to discover the optimum value of Ra and MRR by using the multi insert shell end mill type cutter. The conclusions pinched from the series of experimentations and consequent investigation of results are as follows.

(i) The outcomes specify that the quadratic model is better for Ra and 2FI model is better for MRR with maximum prediction accuracy and is confirmed through further experimentations.

(ii) After experimentation and analysis, it is investigated that Ra = 0.098 µm value is minimum at highest cutting speed with the combination of lowest feed rate and depth of cut i.e 1000 RPM, 300 mm/min and 0.2 mm. Further, investigated that production rate will be maximum MRR = 6.35 cm^3/min at the highest value of feed rate 500mm/min and depth of cut 0.4 mm regarding less or no effect of cutting speed 500-1000 RPM.

The results achieved mainly helpful for the practitioner in the aviation and aeronautical applications to select the appropriate process parameters for achieving better quality and higher productivity. The evolutionary techniques can be explored further for investigation of AISI 4340 steel.

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Table 8: Validation Data

Std	Input machining parameters			Responses							
	Cutting Speed	Feed rate	Depth of cut	Ra				MRR			
	RPM	mm/min	mm	µm				cm3/min			
				Actual	Predicted	Residual	Error%	Actual	Predicted	Residual	Error%
1	960	310	0.15	0.126	0.12	0.006	5	2.525	2.395	0.13	5.4
2	990	305	0.25	0.138	0.132	0.006	4.5	2.691	2.676	0.015	1
3	900	320	0.2	0.151	0.16	-0.009	5.6	2.999	2.96	0.039	2
4	960	360	0.25	0.168	0.172	-0.004	2.3	3.718	3.525	0.193	5.5
5	800	380	0.24	0.177	0.18	-0.003	2	5.134	5.22	-0.086	2
6	800	370	0.27	0.197	0.204	-0.007	3.4	4.349	4.09	0.259	6.3
7	600	460	0.34	0.221	0.223	-0.002	1	5.71	5.785	-0.075	1.3
8	500	490	0.35	0.247	0.24	0.007	3	5.621	5.502	0.119	2

Table 9: Optimal Response Values with Optimal Process Parameters

Sr. No.	Controllable Process Parametric Values						Response	Optimal Response Value
	V vs f		V vs d		f vs d			
	V (RPM)	f (mm/min)	V (RPM)	d (mm)	f (mm/min)	d (mm)		
1	925	316	-	-	-	-	Ra (µm)	0.152
2	-	-	985	0.21	-	-		0.152
3	-	-	-	-	310	0.21		0.152
4	784	481	-	-	-	-	MRR (cm³/min)	4.95
5	-	-	693	0.38	-	-		5.14
6	-	-	-	-	463	0.37		5.54

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