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Modelling and Optimization of Machining Parameters in Turning of H13 Tool Steel Using Response Surface Methodology-Desirability Function Approach

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ABSTRACT

In the present study, an attempt has been made to investigate the effect of machining parameters (cutting speed, feed rate, depth of cut and tool nose radius) on material removal rate and surface roughness in finish hard turning of H13 tool steel using carbide tool. The machining experiments were conducted based on response surface methodology (RSM) using face centered central composite design. A comprehensive analysis of variance (ANOVA) was used to fully identify the most influential parameters, and the adequacy of both fitted second order regression models were checked. 3D response surfaces and 2D contour plots were analyzed to completely observe the impact of combinatory different important interactive factors on the machinability behaviour under different turning conditions. The MRR and SR increase by increasing the cutting speed, feed rate and depth of cut. The depth of cut and feed rate are the most influential factors for increasing the MRR and SR respectively. Mathematical models for MRR and SR were developed by using Design Expert-9 software. Finally, a multi-objective optimization technique based on the use of desirability function (DF) technique was then applied to find optimal combinations of input machining parameters capable of producing the highest possible amount of MRR and lowest amounts of SR within process domain. The obtained predicted optimal results were then verified experimentally to compute confirmation errors. The values of relative validation errors, all being found to be quite satisfactory, 5.29% for MRR and 8.1% for SR, proves the efficacy and reliability of suggested approach.

Keywords: *Analysis of Variance (ANOVA), Desirability Function (DF); Face centered Central (FCC) Composite Design; Multi-Objective Optimization; Response Surface Methodology (RSM).*

1.0 Introduction

The economy of any country mainly depends on growth of its manufacturing industries. Hence, enhancement in manufacturing technology, especially machining of hardened steel has been revolutionized many branches of industry such as automotive, die and mould sectors. The application of hard turning has been proved extremely advantageous in producing bearings, gears, cams, shafts, axels, and other mechanical components since the early 1980s [4]. In turning operation, material removal rate and the quality of the surface finish are important requirement for many turned workpieces. Material removal process initiates structural changes to the surface of a workpiece. This metallurgical transformation on the surface occurs due to intense thermal energy produced during turning which enhance the chemical interaction of surface with environment. The characteristics of worked surface may exhibit a vast difference compared to that of the bulk of the material. Thus, the selection of optimum machining parameters is very important in controlling quality [1, 2].

2.0 Review of Previous Work

In the current scenario, the most effective machining approach is determined by investigating the different parameters affecting turning process and seeking different ways of obtaining the optimal machining condition and performance. M. Thomas and Y. Beauchamp used full factorial experimental design in which 288 experiment have been conducted on turning process, which investigated the optimum cutting parameters (cutting speed, feed rate, depth of cut and nose radius) on cutting force, tool vibration and surface roughness. The results investigated

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through ANOVA revealed that steady cutting forces depend mainly on depth of cut and feed rate. High cutting speed, a low feed rate, a large tool nose radius, and a low depth of cut are used for reducing vibration and increasing tool damping while low cutting speed helps to reduce the surface roughness by reducing the effect of built-up edge formation [1]. Meng Liu et al. experimentally investigated the effect of tool nose radius and tool wear on residual stress distribution in hard turning of bearing steel JIS SUJ2. In this study, three types of CBN tools with different nose radius 0.4, 0.8 and 1.2 mm were used. The results show that remarkable residual stress distribution affected by the tool nose radius [3]. Grzesik have used cutting tool of material mixed ceramics (aluminium oxide plus TiC or TiCN) for machining of hardened steel (HRC 50-65) under dry turning condition and moderate cutting speed ranging from 90 to120 m.min. This study revealed an extensive characterization of the surface roughness produced during hard turning (HT) operations performed with conventional and wiper ceramic tools at variable feed rate and its changes originated from tool wear [4]. G. Poulachon et al. performed hard turning operation on high strength alloy steel (45 < HRC < 65) using polycrystalline cubic boron nitride (PCBN) cutting tool in order to reach surface roughness close to those obtained in grinding operation. This study observed that flank wear of cutting tool has a large impact on the quality of machined parts namely surface finish, geometry accuracy and surface integrity [5]. D.I. Lalwani et al. has been investigated the effect of machining parameters namely cutting speed, feed rate and depth of cut on cutting force and surface roughness in hard turning of MDN 250 using coated ceramic tool using response surface methodology (RSM) experimental approach. The results indicate that cutting forces and surface roughness do not vary much with cutting speed in the range of 55–93 m/min [6]. H. Bouchelaghem et al. has been investigated the wear test on the CBN tool during hard turning of AISI D3 (60 HRC). The quality of surface finish, cutting forces and temperature has been studied according to the cutting parameters (cutting speed, feed, depth of cut) and tool wear. The feed rate is the most affecting factor on the roughness values. The proposed statistical models are based on the response surface methodology correlating the cutting parameters together with roughness, cutting forces and tool life [7]. J.A. Arsecularatne et al. investigated the machining through dry turning of AISI D2 steel of hardness 62 HRC with PCBN tools. The results show that the most feasible feeds and speeds fall in the ranges 0.08–0.20 mm/rev and 70–120 m/min, respectively while the highest feed used resulted in the highest volume of material removal, lower feeds resulted in higher tool life values [8]. Li Qian, Mohammad Robiul Hossan have been studied the finish hard-turning operation on of AISI 52100 bearing steel, AISI H13 hot work tool steel, AISI D2 cold work steel, and AISI 4340 low alloy steel as a function of cutting speed, feed, cutter geometry, and workpiece hardness. Cubic boron nitride (CBN) or polycrystalline (PCBN) inserts are used as cutting tool materials for high speed machining. Among process parameters, cutter geometry and workpiece hardness, the feed has the most significant effect on cutting and feed forces while Cutting force and feed force increase with increasing feed, tool edge radius, negative rake angle, and workpiece hardness [9]. Tongchao Ding et al. investigated the effects of machining parameters on cutting forces and surface roughness in hard milling of AISI H13 steel with coated carbide tools. Taguchi"s four-level orthogonal array was used for the experimentation with four machining parameters namely cutting speed, feed, radial depth of cut and axial depth of cut. Surface roughness under optimal machining parameters is less than 0.25 μm, which proves that finish hard milling is an alternative machining route to grinding process in die and mold industry [10]. Tugˇrul O¨ zel and Yigˇit Karpat have been experimentally investigated the effects of cutting edge geometry, workpiece hardness, feed rate and cutting speed on surface roughness and tool wear in the finish dry hard turning of AISI H13 steel using Cubic Boron Nitride (CBN) tools. Neural network model and regression models were developed to predict surface roughness and tool flank wear over the machining time for variety of cutting conditions in finish hard turning. The results show that better surface roughness but slightly faster tool wear is obtained by decreasing feed rate and increasing cutting speed [11]. Reginaldo T. Coelho et al. showed the results of tool wear, cutting force and surface finish obtained from the turning operation on hardened AISI 4340 using PCBN coated and uncoated edges. The experiments were conducted with three different coatings on tool for finishing conditions: TiAlN, TiAlN-nanocoating and AlCrN and result showed that TiAlN-nanocoating performed better in terms of tool wear and surface roughness [12]. D. Philip Selvaraj et al. carried out dry turning operation on two different grades of nitrogen alloyed duplex stainless steel with TiC and TiCN coated carbide cutting tool inserts. The experiments were conducted at three different cutting speeds (80, 100 and 120 m/min) with three different feed rates (0.04, 0.08 and 0.12 mm/rev) and a constant depth of cut (0.5 mm). The machining parameters are optimized using signal to noise ratio and the analysis of variance. The results showed that the feed rate is the more significant parameter influencing the surface roughness and cutting force. The cutting speed was observed as the more significant parameter influencing the tool wear [13].

The literature review above indicates that most of the studies have been concentrated on AISI H-13 tool steel and other types of steels. In recent years, along with other types of steels, AISI H-13 tool steel has also emerged as an important material for industrial applications. Despite extensive research on dry turning process, determining the desirable operating conditions during dry turning of H-13 tool steel, in industrial setting, still relies on the skill of the operators and trial-and-error methods. So, the determination of the parametric settings that can simultaneously optimize multiple responses of dry turning of this material is an important issue to the engineers. Therefore, it is imperative to develop a suitable technology guideline for optimum machining conditions for dry turning of AISI H-13 tool steel. In addition to this, researchers have usually preferred to apply neural network and GRA-based approaches for optimizing the multiple responses of turning process although there exist some other easily comprehendible and computationally simple approaches for multi-response optimization. So, the aim of the present work is to obtain the optimum machining conditions for dry turning operation of AISI H-13 tool steel using coated ceramic tool for maximum material removal rate and maximum surface finish based on the use of desirability function (DF) approach. Experiments, based on central composite design of response surface methodology (RSM), were carried out to study the effect of various parameters, viz. cutting speed, feed rate, depth of cut and tool nose radius, on material removal rate and surface finish. From the experimental data, multiple regression models for the MRR and surface finish are obtained in the present work.

3.0 Experimentation

3.1 Materials, machine tool and measurement

The distinguishing feature of this steel is superior toughness compared to other hardened steels. This steel typically has very high vanadium, nickel, carbon, manganese contents which give it superior mechanical properties such as high wear resistance, high machinability, high grindability, and very low distortion during heat treatment, high resistance of decarburization etc.

Table 1 indicates the chemical composition of H13 steel. Typical applications of H13 tool steel are to make aluminium Extrusion Dies, Die Casting Dies, Heavy Duty Compression Tools, Forming Punches, Hot Forging Dies, Shear Blades, Plastic Mold Dies, and Bolt Dies. Bars of T6 H13 steel, 22 mm in diameter and 250mm in length were used in the study. The hardness was obtained as 55.0±0.5 HRC. The chemical compositions and mechanical properties of H13 steel as received are given in Tables 1 and 2, respectively.

Fig 1: Photographic View of CNC Lathe Machine

Table 1: Chemical Composition of H13 Tool Steel

Element	C	Si	Mn	P	S	Ni	Cr	Mo	Cu	V	Al	Ti	W	Fe
Composition	0.370	0.902	0.306	0.02	0.01	0.221	5.26	1.25	0.091	0.805	0.007	0.003	0.054	Ba1

Table 2: Mechanical Properties of H13 Tool Steel

Tensile strength, ultimate at 20°C	1545 MPa
Tensile strength, yield at 20°C	1328 MPa
Reduction of area at 20°C	50.00%
Modulus of elasticity at 20°C	215 GPa
Poisson's ratio	0.28

Carbide inserts chamfered (25° ×0.1mm) TNMA160408S01525 were used in the experimental work mounted on PSBNR2525K12 tool holder. The tool angles are as follows: back rake angle = −5°, side rake angle= −5°, principal cutting edge angle= 92°, end cutting edge angle = 27°. Rigid, high speed precision CNC Turning Center STALLION 100 HD/100 SU (HMT, India) lathe equipped with speed range 100-3000 rpm was used for experimentation. For improving the machining performance, workpiece material was placed between chuck (three jaws) and tailstock and the tool overhang was kept at the minimum possible value of 20 mm. The two most crucial performance measures in dry turning are metal removal rate and workpiece surface roughness. The material removal rate (g/min) was calculated by weight difference of the specimen before and after machining using high-precision balance. The surface roughness was measured with Talysurf-6 at three different locations on the workpiece after machining and the average value has been taken in the present study [15].

3.2 Response surface methodology

RSM is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the goal is to optimize this response (Montgomery, 1997). RSM also computes relationships among one or more measured responses and the essential input factors. RSM was applied to model and optimize the dry turning process. The Design Expert 9 software was used to analyze [14] and develop the regression model for the responses. Face-centered central composite design (CCD) has been employed to conduct the experiments. It is a sort of second order design set which employ three levels for each design parameter and can efficiently handle linear, quadratic as well as interaction terms in process modelling.

In order to observe the effects of the turning factors, a second-order polynomial response surface mathematical model has been considered to evaluate the parametric effects on MRR and surface roughness machining criteria:

$$y(MRR) = \alpha_0 + \sum_{i=1}^{4}\alpha_i X_i + \sum_{i=1}^{4}\alpha_i X_i^2 + \sum_{i=1}^{4}\sum_{j=i+1}^{4}\alpha_{ij}X_iX_j + \varepsilon \quad (1)$$

$$y(SR) = \beta_0 + \sum_{i=1}^{4}\beta_i X_i + \sum_{i=1}^{4}\beta_i X_i^2 + \sum_{i=1}^{4}\sum_{j=i+1}^{4}\beta_{ij}X_iX_j + \varepsilon \quad (2)$$

Where X1, X2, X3 denote the input parameters cutting speed, feed rate, radial depth of cut and tool nose radius; y(MRR) and y(SR) indicate the response variable namely material removal rate and surface roughness respectively. The terms α, β are the second-order regression coefficients. The method of least squares was employed to determine the coefficients of the polynomials. The second term under the summation sign of this polynomial equation is attributable to linear effect; whereas the third term corresponds to the higher-order effect; the fourth term of the equation includes the interactive effects of the machining parameters [14].

3.3 Experimental Plan Procedure

The levels of machining parameters namely cutting speed, feed rate, depth of cut and tool nose radius were selected with the help of machine manual, machine expert and performing the pilot test on a CNC Lathe machine. The rest of the parameters are adjusted automatically by the machine itself. A pilot experimentation using one-factor-at-a-time approach was conducted to identify feasible ranges of machining parameters. On the basis of pilot experimentation, the ranges and subsequently the levels of the machining parameters were selected as shown in Table 3 [16]. The levels of machining parameters namely cutting speed, feed rate, depth of cut and tool nose radius were selected with the help of machine manual, machine expert and performing the pilot test on a CNC Lathe machine. The rest of the parameters are adjusted automatically by the machine itself. A pilot experimentation using one-factor-at-a-time approach was conducted to identify feasible ranges of machining parameters. On the basis of pilot experimentation, the ranges and subsequently the levels of the machining parameters were chosen (in Table 1) [16]. Twenty one experiments are performed on the bases of standard table obtained from the help of Design-Expert 9 software. Table 4 shows complete design matrix with responses namely material removal rate and surface finish. The experiments were conducted randomly as shown in design matrix („std" column in Table 4).

Table 3: Machining Parameters and Their Levels

Factors	Unit	Low level (1)	Centre level (2)	High level (3)
Cutting speed	Rpm	800	1900	3000
Feed rate	mm/min	0.05	0.75	0.1
Depth of cut	Mm	0.25	0.625	1
Tool nose radius	Mm	0.4	0.8	1.2

4.0 Results and Discussion

The first step in data analysis of the present study is to summarize the test results for each experiment performed by the using response surface methodology. Table 4 shows all values of material removal rate and surface roughness obtained through the experiment. The material removal rate and surface roughness was obtained in the range of 0.1 gm/sec to 0.49 gm/sec and 0.28 μm to 0.72 μm, respectively.

Table: 4. Design Matrix with Responses

Std	Run	Factor 1 A: Speed (rpm)	Factor 2 B: Feed (m/min)	Factor 3 C: Depth of cut (mm)	Factor 4 D: Nose Radius (mm)	Response 1 Mean MRR (gm/sec)	Response 2 Mean SR (mm)
18	1	1900	0.075	0.625	0.8	0.3	0.46
2	2	3000	0.1	0.25	0.4	0.45	0.7
15	3	1900	0.075	0.625	0.4	0.34	0.41
14	4	1900	0.075	1	0.8	0.31	0.48
12	5	1900	0.1	0.625	0.8	0.37	0.61
5	6	3000	0.05	0.25	1.2	0.13	0.36
9	7	800	0.075	0.625	0.8	0.102	0.3
6	8	800	0.05	1	0.4	0.32	0.35
7	9	800	0.1	1	1.2	0.18	0.43
19	10	1900	0.075	0.625	0.8	0.29	0.4
11	11	1900	0.05	0.625	0.8	0.167	0.31
3	12	3000	0.05	1	1.2	0.36	0.4
20	13	1900	0.075	0.625	0.8	0.26	0.42
10	14	3000	0.075	0.625	0.8	0.38	0.59
13	15	1900	0.075	0.25	0.8	0.18	0.43
4	16	800	0.1	0.25	1.2	0.13	0.38
16	17	1900	0.075	0.625	1.2	0.36	0.36
8	18	800	0.05	0.25	0.4	0.12	0.28
21	19	1900	0.075	0.625	0.8	0.28	0.45
1	20	3000	0.1	1	0.4	0.49	0.72
17	21	1900	0.075	0.625	0.8	0.27	0.43

Fig 2: Variation of MRR with Speed, Feed, Depth of Cut and Tool Nose Radius

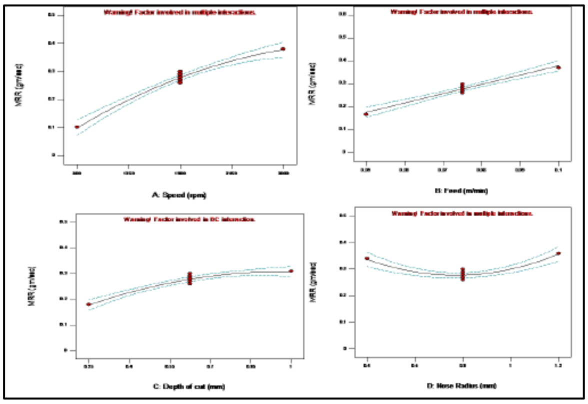


Fig 3: Variation of SR with Speed, Feed, Depth of Cut and Tool Nose

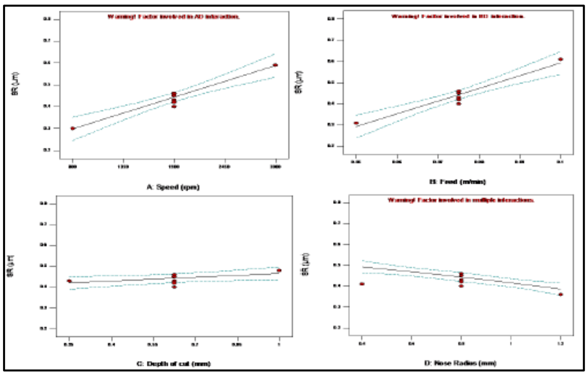


Fig 4: Fitted Response Surface and Contour Plot for MRR Model

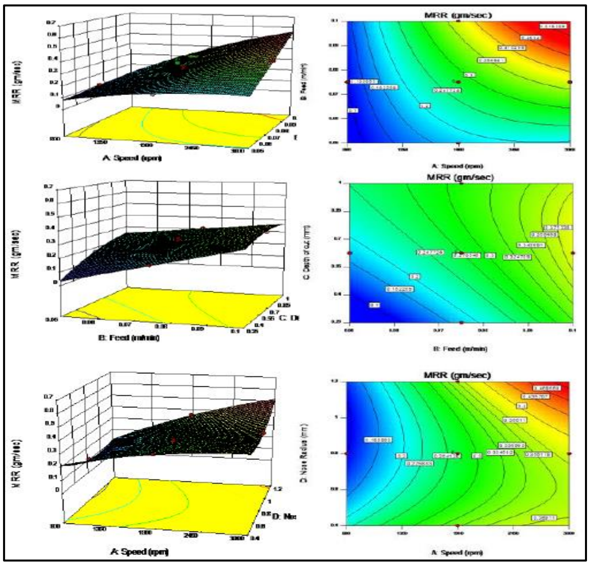


Fig 5: Fitted Response Surface and Contour Plot for SR Model

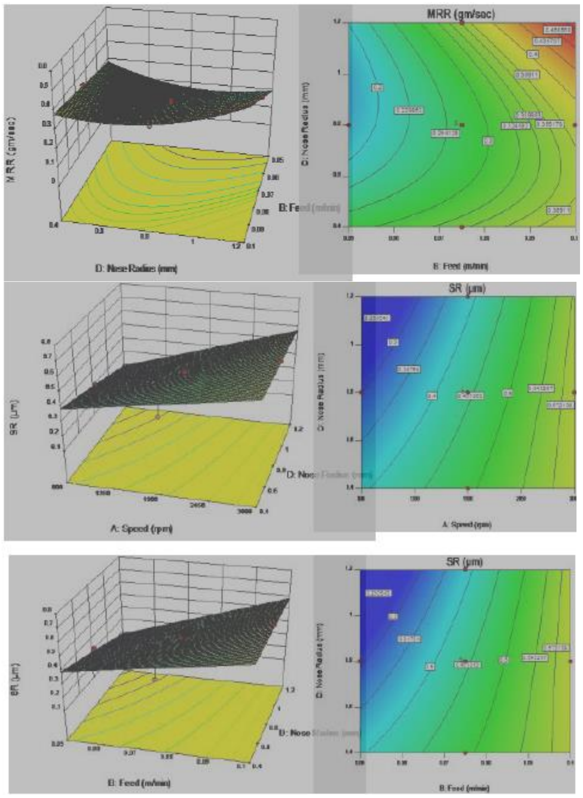


Fig. 2 shows the variation of MRR with cutting parameters. It can be seen that, MRR continuously increases with increasing the values of cutting speed, feed rate and depth of cut.

Fig. 3 shows the 3 D fitted response surfaces and contour plots for MRR. Contour plot of cutting speed v/s feed indicates that at constant value of 0.625 mm depth of cut and 0.8 mm tool nose radius, MRR increases with simultaneously increasing the values of cutting speed and feed rate. Maximum value of MRR in contour plot is predicted 0.5 gm/sec at 3000 rpm cutting speed and 0.1 feed rate, seen by red colour.

Contour plot of feed and depth of cut revealed that at fixed values of 1900 rpm and 0.8 mm tool nose radius, MRR increases with continuously increasing the values of feed and depth of cut. Maximum value of MRR in contour plot is predicted 0.369 gm/sec at maximum values of feed and depth of cut. Contour plot of speed and nose radius at fixed vales of feed (0.075 mm) and depth of cut (0.625 mm) indicates curvilinear nature of MMR.

Higher value of MRR (0.468 gm/sec) is achieved at the upper right region of contour plot area indicated by red colour where cutting speed and nose radius is at its maximum value. Contour plot between feed and nose radius, when speed 1900 rpm and depth of cut 0.625 mm are constant , also indicates quadratic nature curve of MMR.

Higher value of MRR (0.46 gm/sec) is achieved at the upper right region of contour plot area indicated by red colour where feed and nose radius is at its maximum value. The response graphs (Fig 2 and Fig 3) suggest that the factors at levels A3, B3, C3 and D2 are the best levels that give the maximum MRR. Similarly, the factors at levels A1, B1, C1and D3 are the best levels that give minimum surface roughness.

Fig. 3 shows the variation of SR with cutting parameters. It can be seen that, SR continuously increases with increasing the values of cutting speed, feed rate and depth of cut. Fig.3 indicates that the maximum slop of the curve SR v/s feed rate, hence, increment of surface roughness mainly depends on the feed rate. SR decreases with increasing the tool nose radius.

Fig. 5 shows the 3 D fitted response surfaces and contour plots for SR. Contour plot of cutting speed v/s nose radius indicates that at constant value of 0.075 mm feed and 0.625 mm depth of cut, SR decreases with simultaneously decreasing the values of cutting speed and tool nose radius.

Minimum value of SR in the contour plot is predicted 0.25µm at the upper left region of contour plot area indicated by blue colour where speed is at its minimum value while tool nose radius is at its maximum value. Contour plot of feed v/s nose radius indicates that at constant value of 1900 rpm speed and 0.625 mm depth of cut, SR decreases with simultaneously decreasing the values of feed and tool nose radius.

Contour plots of speed v/s nose radius and feed v/s nose radius indicate quadratic nature curve of SR.

Analysis of variance (ANOVA) is a statistically based objective decision-making tool for detecting any differences in average performance of groups of items tested (Ross, 1988). ANOVA is performed to identify the process parameters of wire-EDM that significantly affect the multiple performance characteristics.

An ANOVA table consists of sums of squares, corresponding degree of freedom, the F-ratio corresponding to the ratios of two mean squares, and the contribution proportions from each of the control factors [16].

The experimental results were analyzed in Design Expert-9 software. The results of experiments in the form of ANOVA are present in table 5.

An ANOVA summary table is commonly used to summarize the test of the regression model, test of the significance factors and their interaction and lack-of-fit test. If the value of „Prob > F" in ANOVA table is less than 0.05 then the model, the factors, interaction of factors are said to be significant [7].

Table 5- ANOVA (Partial Sum of Square) for Material Removal Rate

Source	Sum of Squares	d.f.	Mean Square	F value	P value Prob>F	Remark
Model	0.24	14	0.017	103.16	< 0.0001	significant
A-Speed	0.039	1	0.039	228.13	< 0.0001	
B-Feed	0.021	1	0.021	121.64	< 0.0001	
C-Depth of cut	0.042	1	0.042	249.43	< 0.0001	
D-Nose Radius	2.000E-004	1	2.000E-004	1.18	0.3189	
AB	0.011	1	0.011	64.29	0.0002	
AC	5.000E-005	1	5.000E-005	0.30	0.6065	
AD	6.052E-003	1	6.052E-003	35.73	0.0010	
BC	0.014	1	0.014	85.31	< 0.0001	
BD	4.666E-003	1	4.666E-003	27.54	0.0019	
CD	2.000E-004	1	2.000E-004	1.18	0.3189	
A^2	3.449E-003	1	3.449E-003	20.36	0.0040	
B^2	2.188E-004	1	2.188E-004	1.29	0.2991	
C^2	2.739E-003	1	2.739E-003	16.17	0.0069	
D^2	0.013	1	0.013	78.66	0.0001	
Residual	1.016E-003	6	1.694E-004			
Lack of Fit	1.631E-005	2	8.153E-006	0.033	0.9682	not significant
Pure Error	1.000E-003	4	2.500E-004			
Cor Total	0.25	20				

Table 6- ANOVA (partial sum of square) for MRR after removing insignificant terms

Source	Sum of Squares	d.f.	Mean Square	F value	P value Prob>F	Remark
Model	0.24	11	0.022	134.52	< 0.0001	significant
A-Speed	0.039	1	0.039	234.18	< 0.0001	
B-Feed	0.021	1	0.021	124.87	< 0.0001	
C-Depth of cut	0.042	1	0.042	256.04	< 0.0001	
AB	0.011	1	0.011	66.00	< 0.0001	
AD	6.052E-003	1	6.052E-003	36.67	0.0002	
BC	0.014	1	0.014	87.57	< 0.0001	
BD	4.666E-003	1	4.666E-003	28.27	0.0005	
A^2	4.273E-003	1	4.273E-003	25.89	0.0007	
C^2	3.448E-003	1	3.448E-003	20.89	0.0013	
D^2	0.013	1	0.013	81.34	< 0.0001	
Residual	1.485E-003	9	1.650E-004			
Lack of Fit	4.851E-004	5	9.702E-005	0.39	0.8364	not significant
Pure Error	1.000E-003	4	2.500E-004			
Cor Total	0.25	20				
Std. Dev.	0.013		R^2	0.9940		
Mean	0.28		R^2_{Adj}	0.9866		
C.V. %	4.66		R^2_{Pred}	0.9704		

Table 7- ANOVA (partial sum of square) for surface roughness

Source	Sum of Squares	d.f.	Mean Square	F value	P value Prob>F	Remark
Model	0.29	14	0.021	53.93	< 0.0001	significant
A-Speed	0.042	1	0.042	110.02	< 0.0001	
B-Feed	0.045	1	0.045	117.74	< 0.0001	
C-Depth of cut	5.290E-003	1	5.290E-003	13.84	0.0098	
D-Nose Radius	1.250E-003	1	1.250E-003	3.27	0.1205	
AB	1.960E-003	1	1.960E-003	5.13	0.0641	
AC	4.500E-004	1	4.500E-004	1.18	0.3195	
AD	3.240E-003	1	3.240E-003	8.48	0.0269	
BC	2.000E-004	1	2.000E-004	0.52	0.4967	
BD	4.410E-003	1	4.410E-003	11.54	0.0146	
CD	0.000	1	0.000	0.000	1.0000	
A^2	4.990E-004	1	4.990E-004	1.31	0.2967	
B^2	2.144E-003	1	2.144E-003	5.61	0.0556	
C^2	1.468E-003	1	1.468E-003	3.84	0.0977	
D^2	5.406E-003	1	5.406E-003	14.15	0.0094	
Residual	2.293E-003	6	3.822E-004			
Lack of Fit	1.312E-005	2	6.561E-006	0.012	0.9886	not significant
Pure Error	2.280E-003	4	5.700E-004			
Cor Total	0.29	20				

Table 8- ANOVA (partial sum of square) for SR after removing insignificant terms

Source	Sum of Squares	d.f.	Mean Square	F value	P value Prob>F	Remark
Model	0.28	7	0.040	37.67	< 0.0001	significant
A-Speed	0.042	1	0.042	40.00	< 0.0001	
B-Feed	0.045	1	0.045	42.81	< 0.0001	
C-Depth of cut	5.290E-003	1	5.290E-003	5.03	0.0429	
D-Nose Radius	0.028	1	0.028	26.72	0.0002	
AD	3.240E-003	1	3.240E-003	3.08	0.1027	
BD	4.410E-003	1	4.410E-003	4.20	0.0613	
D^2	1.126E-004	1	1.126E-004	0.11	0.7487	
Residual	0.014	13	1.051E-003			
Lack of Fit	0.011	9	1.265E-003	2.22	0.2300	not significant
Pure Error	2.280E-003	4	5.700E-004			
Cor Total	0.29	20				
Std. Dev.	0.032		R^2	0.9530		
Mean	0.44		R^2_{Adj}	0.9277		
C.V. %	7.34		R^2_{Pred}	0.8930		

Table 5 shows that the model is significant for MRR and cutting speed (A), feed rate (B) depth of cut (C), AB, AD, BC, BD, A2, C2, D2 are only the significant factors (terms). All other terms are insignificant. By selecting the significant terms, the resulting ANOVA table for reduced MRR model is shown in Table 6. Table 7 shows that the model is significant for SR and cutting speed (A), feed rate (B) depth of cut (C), AD, BD, D2 are only the significant factors (terms).

All other terms are insignificant. By selecting the significant terms, the resulting ANOVA table for reduced SR model is shown in Table 8. The lack-of-fit is insignificant for both MRR and SR models thereby indicate that the models fit well with the experimental data. Depth of cut is the most dominant factor to MRR because of having highest F value (256.04) and feed rate has little influence on MRR of tool steel. Feed rate is the most dominant factor to SR because of having highest F value (42.81) and depth of cut has little influence on SR.

The various R2 statistics (i.e. R2, adjusted R2 ( ) and predicted R2 ( ) of MRR and SR are given in Tables 6 and 8. The value of R2 = 0.9940 for MRR indicates that 99.40% of the total variations are explained by the model. The adjusted R2 is a statistic that is adjusted for the "size" of the model; that is, the number of factors (terms).

The value of the = 0.9866 indicates that 98.66% of the total variability is explained by the model after considering the significant factors. = 0.9704 is in good agreement with the and shows that the model would be expected to explain 97.04% of the variability in new data (Montgomery, 2001). „C.V." stands for the coefficient of variation of the model and it is the error expressed as a percentage of the mean ((S.D./Mean)×100). Lower value of the coefficient of variation (C.V. = 4.66 %) indicates improved precision and reliability of the conducted experiments.

The value of R2 = 0.9530 for SR indicates that 95.30% of the total variations are explained by the model. The value of the = 0.9277 indicates that 92.77% of the total variability is explained by the SR model after considering the significant factors. = 0.8930 is in good agreement with and shows that the model would be expected to explain 89.30% of the variability in new data. Lower value of the coefficient of variation (C.V. = 7.34 %) indicates improved precision and reliability of the conducted experiments. The surface micrograph after machining obtained through scanning electron microscopy (SEM) for maximum MRR and minimum SR are shown in Figures 6 and 7.

In any machining process, a mathematical model has to be developed, relating the machining output to the machined parameters and used for prediction, process control or optimization. In order to evaluate the effect of cutting parameters of turning process in terms of cutting performance such as surface finish of the machined workpiece and the amount of material removed, Design Expert-9 software was applied to model the turning process. Based on the analysis, the optimal parameters and their interaction effects are selected and the mathematical equations are conformed for each performance characteristic to suitable coefficients. These coefficients are called model constant [15].

The mathematical model equations for MRR and SR can be written here in the following form.

$$MRR = 0.28 + 0.14A + 0.10B + 0.065C + 0.010D + 0.083AB + 0.061AD + 0.042BC + 0.054BD - 0.039A^2 - 0.035C^2 + 0.070D^2 \quad (3)$$

$$SR = 0.44 + 0.15A + 0.15B + 0.023C - 0.053D + 0.045AD + 0.052BD - 0.0046D^2 \quad (4)$$

Fig 6: SEM Micrograph of Turned Surface Obtained by Std Experiment No 1, Shows Maximum MRR

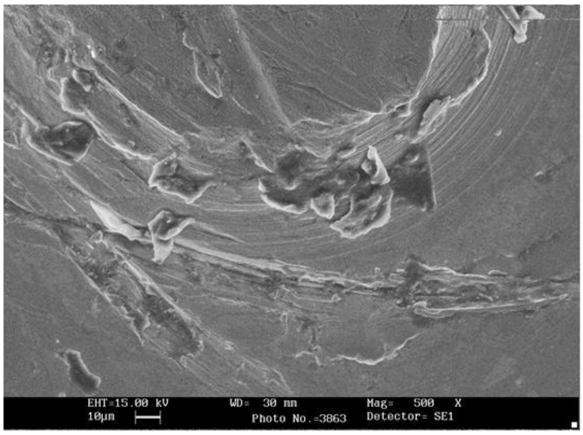
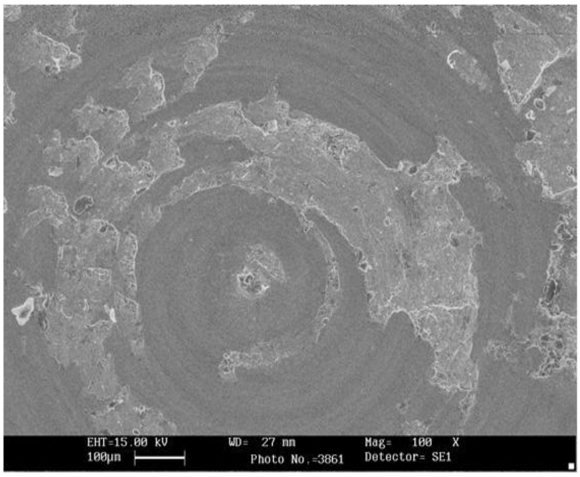


Fig 7: SEM Micrograph of Turned Surface Obtained by Std Experiment No 8, Shows Minimum SR



5.0 Multi-Objective Optimization Turning Parameters Based on Desirability Function

Metal removal rate is an indicator for productivity while surface finish accounts for process economics, precision, and work quality. In turning process, it is much desired to determine the optimal machining parameters for best machining performance. The performance indicators, viz. MRR, SR are conflicting in nature as it is always desirable to have higher MRR with a lower value of surface roughness at the same time.

Due to the presence of a large number of process variables and mutual interactions, the selection of optimum machining parameter combinations to obtain higher MRR and smaller SR is a challenging task. Here, an attempt is made to develop a strategy based on the concept of desirability function for predicting the optimum machining parameter settings generating maximum MRR with minimum SR all at once.

The mathematical formulation of the present optimization problem can be stated as follow:

Max: F1 (x) = MRR

Min: F2 (x) = SR

Subject to: $800 \le x_1 \le 3000$

$$0.05 \le x_2 \le 0.1$$

$$0.25 \le x_3 \le 1$$

$$0.4 \le x_4 \le 1.2$$

Where, x1, x2, x3, and x4 represent the process input parameters cutting speed, feed rate, depth of cut and tool nose radius, respectively. It is a fourvariable two-objective optimization statement, each of which has been defined by respective second order regression equations:

$$0 \le d_i \le 1$$

If the response yi is at its goal or target, then di = 1 (the most desirable case), and if the response is outside an acceptable region, di = 0 (the least desirable case). There is also a positive number, weight factor (r), associated with the desirability function of each response defining its shape. If the weight is chosen to be less than 1, then the sensitivity of the desirability function is low with respect to the optimal or target value sought for.

In other words, if the search algorithm finds a point which is somehow far from the desired optimum or target value, then the decrease in desirability function value will be small in comparison with its maximum amount (unity).

Choosing a weight factor higher than one, has the reverse effect, and setting it to one, provides a balanced or medium sensitivity with the shape of desirability being linear.

The individual desirability functions are defined according to the goal of optimization that is maximization and minimization, respectively [17].

Table: 8. Constraints and Criteria of Input Parameters and Responses

Name	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
A:Speed	is in range	800	3000	1	1	3
B:Feed	is in range	0.05	0.1	1	1	3
C:Depth of cut	is in range	0.25	1	1	1	3
D:Nose Radius	is in range	0.4	1.2	1	1	3
MRR	maximize	0.102	0.49	1	1	3
SR	minimize	0.28	0.72	1	1	3

Table 8 summarizes the key parameters set to find global optimum settings including constraints of input variables and that of responses‟ requirements while Table 9 sorts the first ten optimum settings obtained, in descending order of composite desirability (D). The closer the D to 1 the more favorable are the turning conditions satisfying problem requirements.

Table 9: Iterative Determination of Optimum Conditions

Solution Number	Speed	Feed	Depth of cut	Nose Radius	MRR	SR	Composite Desirability (D)
1	*2213.167*	*0.060*	*1.000*	*1.200*	*0.358*	*0.340*	*0.755*
2	2215.097	0.061	0.968	1.200	0.363	0.347	0.754
3	2114.551	0.064	0.987	1.200	0.366	0.353	0.753
4	2089.075	0.060	0.943	1.200	0.338	0.313	0.750
5	1979.629	0.071	0.915	1.200	0.379	0.383	0.740
6	2148.777	0.069	0.740	1.200	0.377	0.385	0.735
7	976.086	0.050	1.000	0.400	0.339	0.334	0.732
8	1732.887	0.050	1.000	0.453	0.338	0.389	0.677
9	1951.933	0.057	0.835	0.400	0.346	0.438	0.635
10	2050.797	0.057	0.711	0.400	0.325	0.440	0.605

Note: The row in italic is selected as the best compromise solution

6.0 Confirmation Experiment

Conducting confirmation experiment is the crucial, final, and indispensable part of every optimization attempt. Its aim, after selecting the optimal parameters, is to predict and verify the improvement of the performance characteristics with the selected optimal machining parameters, i.e. to verify the optimum condition suggested by the matrix experiment estimating how close the respective predictions are with the real ones.

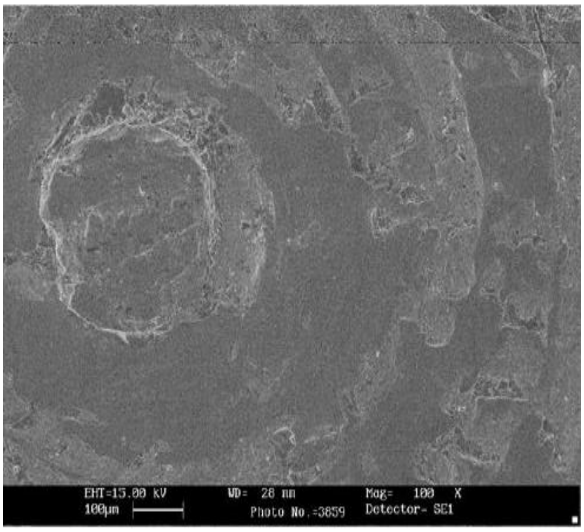
Table 10 summarizes the optimization results along with experimentally obtained responses and their percentage relative verification errors.

As is clear, the amounts of errors are all found to be satisfactory in point of engineering applications. Figure 8 shows the SEM micrograph obtained from the confirmation experiment (solution number 1 in Table 9) in which optimal machining parameters are chosen during the turning.

Table: 10. Multi-Response Optimal Points and Experimental Validation

Optimum input setting				MRR (g/sec)		SR (µm)		Relative error (%)	
Cutting speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	Nose radius (mm)	Predicted	Experimental	Predicted	Experimental	MRR (g/sec)	SR (µm)
2213	0.06	1	1.2	0.358	0.34	0.34	0.37	5.29	8.1

Fig 8: SEM Micrograph of Turned Surface Obtained from Confirmation Experiment



7.0 Conclusions

This paper presents the findings of an experimental investigation of the effect of cutting speed, feed rate, depth of cut and nose radius on material removal rate and surface roughness in hard turning of H13 tool steel using coated ceramic tool and following conclusions are drawn.

1. Quadratic model is fitted for material removal rate and surface roughness.
2. Tool nose radius has no significant effect on material removal rate.
3. MRR model: the depth of cut is most significant factor whereas cutting speed and feed rate have a secondary and tertiary contribution in the model.
4. SR model: the feed is most significant factor whereas cutting speed and nose radius have a secondary and tertiary contribution in the model.
5. 3-D response surfaces and contour plots are used for selecting the cutting parameters for providing the given desired material removal rate and surface roughness.
6. Percentage error in the experimental and predicted results obtained for MMR and SR is 5.29% and 8.81% which is acceptable for MRR and SR model. Hence, desirability function approach is an appropriate multi-objective optimization technique to determine optimal cutting parameters.

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