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OPTIMIZATION OF TURNING PARAMETERS FOR SURFACE ROUGHNESS USING RSM AND GA

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Abstract:
The paper presents an experimental study of roughness characteristics of surface profile generated in CNC turning of AISI 1040 mild steel and optimization of machining parameters based on genetic algorithm. The three level rotatable central composite designs are employed for developing mathematical models for predicting surface roughness parameters. Response surface methodology is applied successfully in analyzing the effect of process parameters on different surface roughness parameters. The second order mathematical models in terms of machining parameters are developed based on experimental results. The experimentation is carried out considering three machining parameters, viz., depth of cut, spindle speed and feed rate as independent variables and three different roughness parameters, viz., centre line average roughness, root mean square roughness and mean line peak spacing as response variables. It is seen that the surface roughness parameters decrease with increase in depth of cut and spindle speed but increase with increase in feed rate. The models selected for optimization have been validated with F-test. The adequacy of the models of surface roughness has been established with Analysis of Variance (ANOVA). An attempt has also been made to optimize the cutting parameters using genetic algorithm to achieve minimum surface roughness.

Key Words: Roughness, CNC Turning, Response Surface Method, Genetic Algorithm

1. INTRODUCTION

Surface finish is one of the most important quality characteristics in manufacturing industries which influences the performance of mechanical parts as well as production cost. In recent times, modern industries are trying to achieve the high quality products in a very short time with less operator input. For that purpose, the computer numerically controlled (CNC) machine tools with automated and flexible manufacturing systems have been implemented. In the manufacturing industries, various manufacturing processes are adopted to remove the material from the work piece. Out of these, turning is the first most common method for metal cutting because of its ability to remove materials faster with a reasonable good surface quality. In actual practice, there are many factors which affect surface roughness, e.g., cutting conditions, tool variables and workpiece variables. Cutting conditions include speed, feed and depth of cut where as tool variables include tool material, nose radius, rake angle, cutting edge geometry, tool vibration, tool overhang, tool point angle etc. and workpiece variable include material hardness and other mechanical properties. However, it is very difficult to control all the parameters at a time that affect the surface roughness for a particular manufacturing process. In a turning operation, it is a vital task to select the cutting parameters properly to achieve the high quality performance.

Generally, the desired cutting parameters are selected based on experience or use by the hand book. But a better result may be achieved by modeling the surface roughness and optimization of cutting parameters. Several mathematical models based on statistical regression or neural network techniques have been constructed to establish the relationship between the cutting performance and cutting parameters. A brief review of literature on

roughness modeling in turning operation is presented here. Palanikumar et al. [1] found that feed rate has greater influence on surface roughness parameter (R_a), followed by cutting speed and % volume fraction of SiC in machining of Al/SiC particulate composites. Nalbant et al. [2] optimized the cutting parameters for turning of AISI 1030 steel bars by using the Taguchi method. They considered the centre line average (R_a) only. The use of greater insert radius, low feed rate and low depth of cut are recommended to obtain better surface finish for the specific test range. Singh et al.[3] developed mathematical model for R_a and optimized the tool geometry and cutting parameters for hard turning using genetic algorithm. Zhong et al. [4] predicted surface roughness heights R_a and R_t of turned surface using neural network. Sahin and Motorcu [5] developed mathematical model of surface roughness parameter R_a in turning of mild steel with coated carbide tools using RSM. They concluded that feed rate is the main influencing factor on the surface roughness. Noordin et al. [6] described the performance of coated carbide tools using response surface methodology when turning AISI 1040 mild steel. They found that feed rate is the most significant parameter influencing the surface roughness R_a and tangential force. The Taguchi method was used by Yang and Tarang [7] to find the optimal cutting parameters for turning operations. Choudhury and El Baradie [8] had predicted surface roughness parameter R_a using RSM when turning high strength steel. Lin [9] used grey relational analysis to optimize turning operations with multiple performance characteristics, viz., cutting force and surface roughness R_a in turning operations. Other relevant recent studies include those of Gaitonde et al. [10], Hascalik and Caydas [11], Jayant and Kumar [12], Kandananond [13], Lan and wang [14], Prasad et al. [15], Lan [16] and Kirby [17].

However, a surface generated by machining is composed of a large number of length scales of superimposed roughness and generally characterized by three different types of parameters, viz., amplitude parameters, spacing parameters and hybrid parameters. Amplitude parameters are measures of the vertical characteristics of the surface deviations and examples of such parameters are centre line average roughness, root mean square roughness, skewness, kurtosis, peak-to-valley height etc. Spacing parameters are the measures of the horizontal characteristics of the surface deviations and examples of such parameters are mean line peak spacing, high spot count, peak count etc. On the other hand, hybrid parameters are a combination of both the vertical and horizontal characteristics of surface deviations and example of such parameters are root mean square slope of profile, root mean square wavelength, core roughness depth, reduced peak height, valley depth, peak area, valley area etc. Thus consideration of only one parameter like centre line average roughness is not sufficient to describe the surface quality though it is the most commonly used roughness parameter. The present study aims at consideration of three different roughness parameters, viz., centre line average roughness (R_a), root mean square roughness (R_q), and mean line peak spacing (R_{sm}) for the surface texture generated in turning operation of AISI 1040 mild steel. A rotatable central composite (CCD) experimental design is used in the present investigation. In addition to the direct evaluation of the variables involved in the process, this design allows the study of the interactions among them and the modeling of multifactor response surfaces, thus providing a great deal of information about the behavior of the system with the help of a rather small number of experiments [18]. Statistical models have been developed using response surface methodology based on the experimental results. The machining parameters, viz., depth of cut (d, mm), spindle speed (N, rpm) and feed rate (f, mm/rev) are considered as independent variables and surface roughness parameters as response variables. Finally an attempt has been made to obtain optimum machining conditions with respect to each of the roughness parameters considered in the present study with the help of genetic algorithm.

2. RESPONSE SURFACE METHOD

Response surface method (RSM) adopts both mathematical and statistical techniques which are useful for the modelling and analysis of problems in which a response of interest is influenced by several variables. RSM attempts to analyze the influence of the independent variables on a specific dependent variable (response). The purpose of developing mathematical models relating the machining responses and their factors is to facilitate the optimization of the machining process. The steps involved in RSM techniques are as follows: (a) designing a set of experiments for adequate and reliable measurement of the true mean response of interest (b) determination of the mathematical model with best fits (c) finding the optimum set of experimental factors to produce maximum or minimum of the response and (d) representing the direct or interactive effects of process variables on the surface quality of machined surface. The mathematical model commonly used for the machining response Y is represented as

$$Y = \psi(d, N, f) + \varepsilon \tag{1}$$

where, *d, N, f* are depth of cut, spindle speed and feed rate respectively and ε is the error which is normally distributed about the observed machining response *Y.* Let $\psi(d, N, f) = \eta$. The surface represented by $'\eta'$ is called response surface. Second order polynomial Model (Quadratic model**)**

$$Y_u = b_0 + \sum_{i=1}^{n} b_i x_{iu} + \sum_{i<j}^{n} b_{ij} x_{iu} x_{ju} + \sum_{i=1}^{n} b_{ii} x_{iu}^2 \tag{2}$$

where $Y_u = f\,(Y - \varepsilon)$, is proposed expected response on higher-order polynomial and x_i are the process variables such as depth of cut, spindle speed and feed rate respectively, and *b*'s are the regression coefficients to be obtained by linear multiple regression analysis.

3. EXPERIMENTAL DETAILS

The study is carried out with following steps.

1. Identifying the important process parameters and selecting their limits.
2. Developing the design matrix
3. Conducting the experiments as per the design matrix.
4. Recording the required responses
5. Development of the mathematical model using surface response methodology
6. Calculating the coefficients of the polynomials.
7. Analysis of experimental results for surface roughness parameters
8. Optimization of process parameters using genetic algorithm for surface roughness parameters.

3.1 Design of Experiment

The design of experiments technique is a very powerful tool, which permits us to carry out the modeling and analysis of the influence of process variables on the response variables. The response variable is an unknown function of the process variables, which are known as design factors. In a turning operation, there are a large number of factors that can be considered as the machining parameters. But, the review of literature shows that the depth of cut (*d*, mm), spindle speed (*N*, rpm) and feed rate (*f*, mm/rev) are the most widespread machining parameters taken by the researchers. In the present study these are selected as design factors while other parameters have been assumed to be constant over the

experimental domain. A rotatable central composite design is selected for the experimentation. It is the most widely used experimental design for the modeling a second – order response surface. For a given number of variables, the α required to achieve rotatability is computed as $\alpha = (n_f)^{1/4}$, where n_f is the number of points in the 2^k factorial design (k is the number of factors). Rotatability refers to the uniformity of prediction error. In rotatable designs, all points at the same radial distance (r) from the centre point have the same magnitude of prediction error. A rotatable CCD consists of 2^k fractional factorial points (usually coded as ± 1), augmented by 2k axial points [($\pm\alpha$,0,…0),(0, $\pm\alpha$,…0), (0,0, … $\pm\alpha$)] and n_c centre points (0, 0, 0, 0…, 0). The centre points vary from three to six. With proper choice of n_c, the CCD can be made orthogonal or it can be made uniform precision design. It means that the variance of response at origin is equal to the variance of response at a unit distance from the origin. Hence, a CCD with uniform precision has been selected in this investigation. In this experimentation, eight (2^3) factorial points, six axial points (2×3) and six centre runs, a total of 20 experimental runs have been considered. A randomized experimental run has been carried out to minimize the error due to machining set-up. The levels of cutting parameters such as depth of cut, spindle speed and feed rate for the experiments have been listed in Table I. Experiments have been carried out according to the experimental plan based on central composite rotatable second order design. Experimental design matrix consisting of experiment run order and coded values of the process parameters is shown in Table II. It also includes the observed responses.

Table I: Machining process parameters levels used in the experimentation.

Variables	Levels				
	-1.682	-1	0	1	1.682
DOC(*d*)	0.032	0.1	0.2	0.3	0.368
Spindle speed(*N*)	528	800	1200	1600	1872
Feed (*f*)	0.0224	0.07	0.14	0.21	0.2576

Table II: Experimental design matrix with coded values and observed responses.

Run order	*d*	*N*	*f*	R_a	R_q	R_{sm}
20	-1	-1	-1	3.002	3.732	0.094
1	1	-1	-1	3.020	3.822	0.140
9	-1	1	-1	1.927	2.415	0.093
11	1	1	-1	1.765	2.232	0.080
7	-1	-1	1	3.597	4.392	0.161
8	1	-1	1	3.685	4.542	0.186
13	-1	1	1	1.760	2.195	0.129
3	1	1	1	1.557	2.007	0.082
10	-1.68	0	0	2.757	3.397	0.124
6	1.68	0	0	2.062	2.522	0.118
5	0	-1.68	0	3.700	4.620	0.143
14	0	1.68	0	0.937	1.122	0.077
12	0	0	-1.68	2.627	3.312	0.099
19	0	0	1.68	3.352	4.200	0.170
2	0	0	0	2.930	3.755	0.111
4	0	0	0	2.600	3.135	0.107
17	0	0	0	2.397	2.912	0.107
16	0	0	0	2.582	3.107	0.107
18	0	0	0	2.372	2.885	0.102
15	0	0	0	2.620	3.147	0.100

3.2 Equipment used

The machine used for the turning is a JOBBERXL CNC lathe having the control system FANUC Series Oi Mate-Tc and equipped with maximum spindle speed of 3500 rpm, feed rate 15-20 mm/rev and KVA rating-16 KVA. For generating the turned surfaces, CNC part programs for tool paths are created with specific commands.

3.3 Cutting tool used

Coated carbide tools are known to perform better than uncoated carbide tools. Thus commercially available CVD coated carbide tools are used in this investigation. The tool holder used is PTGNR-25-25 M16 050, WIDIA and insert used is TNMG 160404–FL, WIDIA. The tool is coated with titanium nitride coating having hardness, density and transverse rupture strength as 1570 HV, 14.5 g/cc and 3800 N/mm^2. The compressed coolant WS 50-50 with a ratio of 1:20 was used as cutting environment.

3.4 Work piece material

The present study is carried out with AISI 1040 mild steel. The chemical compositions of Mild Steel (AISI 1040) are as follows: 0.42%C, 0.48%Mn, 0.17%Si, 0.02%P, 0.018%S, 0.1%Cu, 0.09%Ni, 0.07%Cr and balance Fe and mechanical properties of the workpiece material is: Hardness - 201 BHN, Density - 7.85 g/cc and Tensile strength - 620MPa . All the specimens are of bar with diameter 20 mm and length of 60 mm.

3.5 Roughness measurement

Roughness measurement is done using a portable stylus-type profilometer, *Talysurf* (Taylor Hobson, Surtronic 3+). The profilometer is set to a cut-off length of 0.8 mm, Gaussian filter, and traverse speed 1 mm/sec and 4 mm traverse length. Roughness measurements, in the transverse direction, on the work pieces are repeated four times and average of four measurements of surface roughness parameter values is recorded. The measured profile is digitized and processed through the dedicated advanced surface finish analysis software *Talyprofile* for evaluation of the roughness parameters.

3.6 Response variables selected

The response variables used to accomplish the present study on surface roughness are the following:

(I) Centre line average roughness (R_a):
It is defined as the arithmetic mean deviation of the surface height from the mean line through the profile while the mean line is defined so as to have equal areas of the profile above and below it. R_a may be expressed in the form:

$$R_a = \frac{1}{L}\int_0^L |Z(x)|\,dx \tag{3}$$

where $Z(x)$ is the ordinate of the profile curve, x is the profile direction and L is the sampling length. The unit of R_a is μm.

(II) Root mean square roughness (R_q):
It represents the standard deviation of the distribution of surface heights. Its unit is also μm. It is defined as the root mean square deviation of the profile from the mean line and is expressed as:

$$R_q = \sqrt{\frac{1}{L}\int_0^L [Z(x)]^2 dx} \quad (4)$$

(III) Mean line peak spacing (R_{sm}):
It is defined as the mean spacing between peaks, with a peak defined relative to the mean line (a peak must cross above the mean line and then back below it). This parameter may be expressed in the form:

$$R_{sm} = \frac{1}{m}\sum_{n=1}^{m} S_n \quad (5)$$

where *m* is the number of peak spacing and *S* is the spacing between two consecutive peaks. Its unit is mm.

4. RESULTS AND DISCUSSION

The second order response surface equations have been fitted using Design Experts software for all the three response variables (R_a, R_q, and R_{sm}). The regression coefficients for the roughness parameters are shown in Table III. The equations can be given in terms of the coded values of the independent variables as the following:

$$R_a = 2.584 - 0.104*d - 0.801*N + 0.154*f - 0.058*dN + 0.003*df - 0.204*Nf - 0.068*d^2 - 0.1006*N^2 + 0.136*f^2 \quad (6)$$

$$R_q = 3.158 - 0.117*d - 0.99*N + 0.177*f - 0.076*dN + 0.006*df - 0.228*Nf - 0.076*d^2 - 0.107*N^2 + 0.205*f^2 \quad (7)$$

$$R_{sm} = 0.106 + 7.86E\text{-}05*d - 0.022*N + 0.019*f - 0.016*dN - 0.0069*d\,f - 0.0094*Nf + 0.005*d^2 + 0.00099*N^2 + 0.0097*f^2 \quad (8)$$

Table III: Regression coefficients for the roughness parameters.

Sl. no	Coefficient	R_a	R_q	R_{sm}
1	b_0	2.5848	3.1580	0.1062
2	b_1	-0.1046	-0.1173	7.86E-05
3	b_2	-0.8011	-0.9900	-0.0225
4	b_3	0.1540	0.1777	0.0197
5	b_{12}	-0.0587	-0.0761	-0.0160
6	b_{13}	0.0037	0.0069	-0.0069
7	b_{23}	-0.2043	-0.2281	-0.0094
8	b_{11}	-0.0683	-0.0761	0.0050
9	b_{22}	-0.1006	-0.1075	0.0009
10	b_{33}	0.1366	0.2053	0.0097

The analysis of variance (ANOVA) and the *F*-ratio test have been performed to check the adequacy of the models as well as the significance of the individual model coefficients. For brevity, the ANOVA table for R_a, is shown here. Table IV presents the ANOVA table for the second order model proposed for R_a given in equation (6). It can be appreciated that the *P*-value is less than 0.05 which means that the model is significant at 95% confidence level. Also the calculated value of the *F*-ratio is more than the standard value of the *F*-ratio for R_a. It means the model is adequate at 95% confidence level to represent the relationship between the machining response and the machining parameters of the CNC turning process. ANOVA table for R_a also includes the individual model coefficients, interaction terms and the square terms, where it can be seen that there are four effects with a *P*-value less than 0.05 which

means that they are significant at 95% confidence level. These significant effects are: spindle speed, feed rate, the interaction between spindle speed & feed rate and quadratic effect of feed rate. Similarly, analysis of variance is carried out for all the response models as given in equations (7) and (8). Calculated F-value of the lack-of-fit for R_a, R_q and R_{sm} are 0.72, 0.59 and 2.21 respectively. These calculated F- values of the lack-of-fit for different surface parameters are very much lower than the tabulated value of the F-distribution found from the standard table at 95% confidence level. It implies that the lack-of-fit is not significant relative to pure error. Therefore, the developed second-order regression models for R_a, R_q, R_{sm} are adequate at 95% confidence level. The R^2 value is high, close to 1, which is desirable. The predicted R^2 is in reasonable agreement with the adjusted R^2. The adjusted R^2 value is particularly useful when comparing models with different number of terms. This comparison is however done in the background when model reduction is taking place. Adequate precision compares the range of the predicted values at the design points to the average prediction error. Ratios greater than 4 indicate adequate model discrimination. In this particular case the value is well above 4 (specifically it is 21.27). This model can be used to navigate the design space. Though the regression model is significant still there are some insignificant terms. These insignificant model terms (not counting those required to support hierarchy) should be removed from the model itself and make it into an improved model. The improved models, using back elimination method of Design Expert software for R_a, R_q and R_{sm} are given in the equations (9-11).

$$R_a = +2.53 - 0.10 * d - 0.80 * N + 0.15 * f - 0.20 * N * f - 0.094 * N^2 + 0.14 * f^2 \quad (9)$$

$$R_q = +3.02 - 0.99 * N + 0.18 * f - 0.23 * Nf + 0.22 * f^2 \quad (10)$$

$$R_{sm} = +0.11 + 7.856E\text{-}005 * d - 0.023 * N + 0.020 * f - 0.016 * d * N - 6.913E\text{-}003 * d * f - 9.463E\text{-}003 * N * f + 4.925E\text{-}003 * d^2 + 9.609E\text{-}003 * f^2 \quad (11)$$

Table IV: Analysis of variance for R_a.

Source	Sum of Squares	DF	Mean Square	F Value (Calculated)	p-value Prob > F
Model	10.13451	9	1.126056	32.487	< 0.0001 Significant
A-d	0.149493	1	0.149493	4.312904	0.0645
B-N	8.764616	1	8.764616	252.8614	< 0.0001 Significant
C-f	0.324238	1	0.324238	9.354361	0.0121 Significant
AB	0.027613	1	0.027613	0.796628	0.3931
AC	0.000113	1	0.000113	0.003246	0.9557
BC	0.334153	1	0.334153	9.640401	0.0112 Significant
A^2	0.067378	1	0.067378	1.943882	0.1934
B^2	0.145857	1	0.145857	4.208001	0.0674
C^2	0.26924	1	0.26924	7.767638	0.0192 Significant
Residual	0.346617	10	0.034662		
Lack of Fit	0.145833	5	0.029167	0.726317	0.6329 Insignificant
Pure Error	0.200784	5	0.040157		
Cor Total	10.48112	19			
Std. Dev.	0.186177			R-Squared	0.966929
Mean	2.56276			Adj R-Squared	0.937166
C.V. %	7.264693			Pred R-Squared	0.866524
PRESS	1.398983			Adeq Precision	21.27847

Table V shows the ANOVA for improved model where lack-of- fit is also insignificant. Similarly, for R_q and R_{sm} the ANOVA analyses are carried out. Figure 1 show the estimated three-dimensional surface and contour plots for centre line average (*CLA*) roughness parameter as function of the independent machining parameters. In the figures, one of the

Table V: Analysis of variance table for improved model for R_a.

Source	Sum of Squares	DF	Mean Square	F Value (calculated)	p-value Prob > F	
Model	10.0394	6	1.673234	49.24387	< 0.0001	Significant
A-d	0.149493	1	0.149493	4.399626	0.0561	
B-N	8.764616	1	8.764616	257.9458	< 0.0001	Significant
C-f	0.324238	1	0.324238	9.542454	0.0086	Significant
BC	0.334153	1	0.334153	9.834246	0.0079	Significant
B^2	0.128097	1	0.128097	3.769941	0.0742	
C^2	0.299606	1	0.299606	8.817502	0.0109	Significant
Residual	0.441721	13	0.033979			
Lack of Fit	0.240936	8	0.030117	0.749985	0.6589	Insignificant
Pure Error	0.200784	5	0.040157			
Cor Total	10.48112	19				
Std. Dev.	0.184333			R-Squared	0.957856	
Mean	2.56276			Adj R-Squared	0.938404	
C.V. %	7.192739			Pred R-Squared	0.907245	
PRESS	0.972179			Adeq Precision	26.83561	

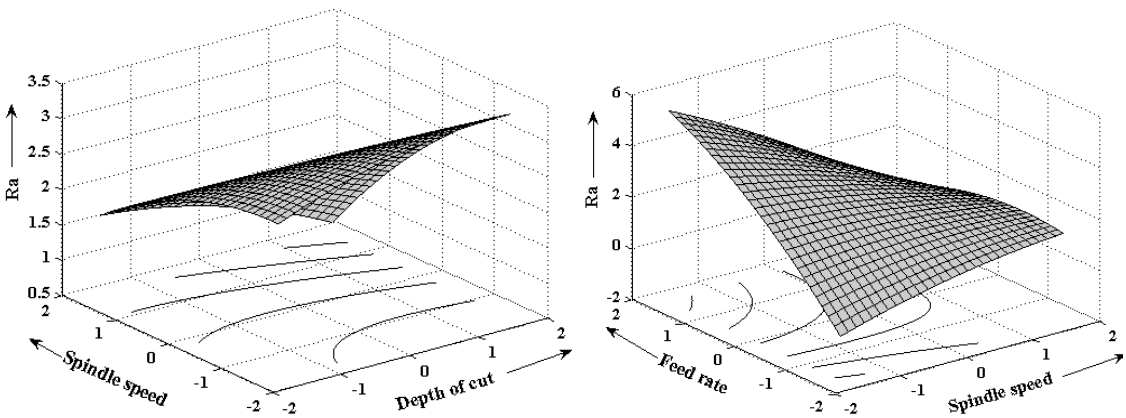

Figure 1: Surface and contour plots for R_a with machining parameters.

three independent variables is held constant at centre points. All these figures depict that at low feed rate and high spindle speed the R_a roughness decreases within the experimental regime. Figure 2 presents the main effect plots for surface roughness parameters with cutting process variables. In these main effect plots if a line for a particular parameter is near horizontal, then the parameter has no significant effect. On the other hand, a parameter for which the line has the highest inclination will have the most significant effect. It is seen that the surface roughness parameters R_a, R_q and R_{sm} decrease with increase in depth of cut and spindle speed but increase with increase in feed. The normal probability plot of the residuals and the plots of the residuals versus the predicted response for R_a are shown in Figures 3 and 4.

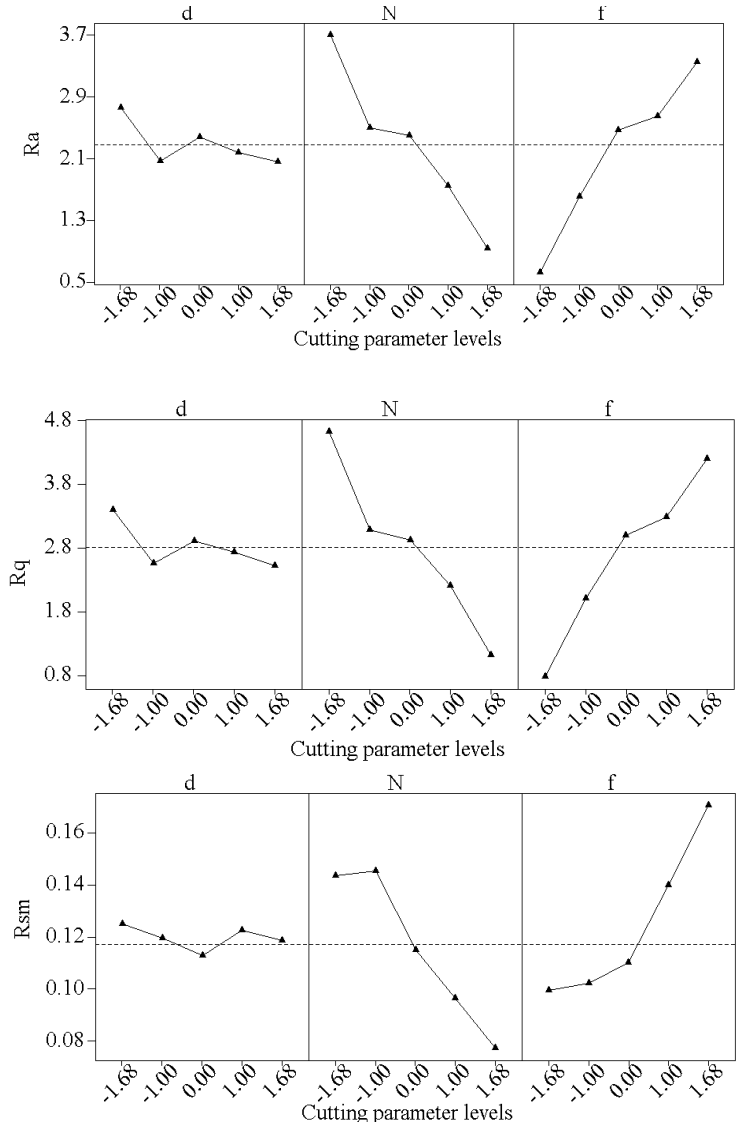

Figure 2: Main effect plots of surface roughness parameters, (a) R_a, (b) R_q and (c) R_{sm}.

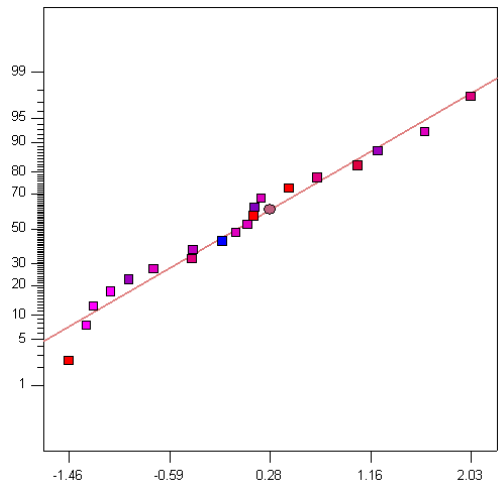

Figure 3: Normal probability plot of residuals for R_a.

A check on the normal probability plot shown in Figure 3 depicts that the residuals generally fall on a straight line implying that the errors are distributed normally. Also, the plot of residuals vs. predicted response shown in Figure 4 revealed that it has no obvious pattern and unusual structure. This implies that the models proposed are adequate and there is no reason to suspect any violation of the independence or constant variance assumption.

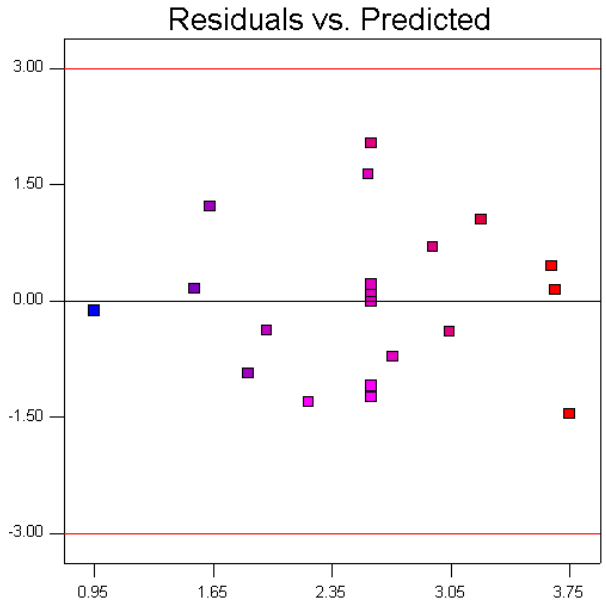

Figure 4: Plot of residuals vs. predicted response for *R*a values.

Finally, since optimization of machining parameters increases the utility for machining economics as well as the product quality to a great extent, an effort has been made to estimate the optimum machining conditions to produce the best possible surface quality within the experimental constraints. In this context, a genetic algorithm optimization is attempted using MATLAB 7 software for individual roughness parameters in CNC turning of mild steel. The objective function for optimization is set as minimization of R_a, R_q and R_{sm}.

5. OPTIMIZATION USING GENETIC ALGORITHM

The selection of cutting parameters for optimization not only increases the utility for machining economics, but also the product quality to a great extent by minimizing the surface roughness parameters. In this present study, an effort has been made to determine the optimum values of cutting parameters to obtain the best possible surface quality within the specific test range. An effective optimization method, genetic algorithm (GA) is developed to solve the optimization problem for this study. Genetic algorithms are search algorithms for optimization, based on the mechanics of the natural selection and genetics [19, 20]. The solution of an optimization problem with genetic algorithm begins with a set of potential solution or chromosomes (usually in the form of bit string) that are randomly selected. The entire set of chromosomes creates a population. The chromosomes evolve during several iterations called generations. The new generations are generated utilizing the crossover and mutation technique. The crossover split up into two chromosomes and then combines one half of each chromosome with the other pair. Mutation involves flipping a single bit of chromosomes. The chromosomes are then evaluated employing a certain fitness criteria and the best ones are kept while the others are rejected. This process repeats until the

chromosomes have the best fitness and is taken as the optimal solution for this particular problem. In CNC turning, optimization problem can be expressed in the following manner:
For optimization of R_a:
Find: *d, N, f*
Minimize: R_a (*d, N, f*) using the improved second order model given in equation (9).

$$R_a = +2.53 - 0.10 * d - 0.80 * N + 0.15 * f - 0.20 * N * f - 0.094 * N^2 + 0.14 * f^2$$

within ranges of cutting parameters:
0.032 mm $\leq d \leq$ 0.368 mm
528 rpm $\leq N \leq$ 1872 rpm
0.0224 mm/rev $\leq f \leq$ 0.2576 mm/rev

The main parameters of the GA are the mutation rate, population size, number of generations, cross over rate etc. In the present study, population size 40, mutation rate 1.0, crossover rate 0.8 and number of generations 1000 are judiciously taken. The values of optimized cutting parameters are shown in Table. VI. Similarly, root mean square roughness, R_q, and mean line peak spacing, R_{sm}, are minimized using equations (10) and (11). The confirmatory tests conducted with the optimum parameter combinations show good agreement with the predictions.

Table VI: Optimized process parameter predicted by GA.

Surface roughness Parameters	Optimum value (GA)	Optimized process parameters			Confirmatory test
		d (mm)	N (rpm)	f (mm/rev)	
R_a (μm)	0.864	0.261	1864	0.127	0.894
R_q (μm)	1.312	0.292	1872	0.172	1.386
R_{sm}(*mm*)	0.067	0.262	1772	0.083	0.071

6. CONCLUSIONS

The three level rotatable central composite designs are employed for developing mathematical models for predicting surface roughness parameters in CNC turning of AISI 1040 mild steel. RSM is applied successfully in analyzing the effect of process parameters on different surface roughness parameters. The experimentation is carried out considering three machining parameters, viz., depth of cut, spindle speed and feed rate as independent variables and three different roughness parameters, viz., centre line average roughness, root mean square roughness and mean line peak spacing as response variables. For prediction of roughness parameters within the selected experimental domain, the quadratic models are developed and these are used as the objective function for optimization. It is seen that the surface roughness parameters R_a, R_q and R_{sm} decrease with increase in depth of cut and spindle speed but increase with increase in feed. Genetic Algorithm is used to determine the optimum machining parameters in order to obtain the best possible surface quality. The confirmatory tests conducted with the optimum parameter combinations show good agreement with the predictions.

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