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Predicted Roughness Modeling of Process parameters of Turning for M4 Steel

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Abstract

The present study investigates the surface roughness process parameter optimization during turning of M4 steel. Response Surface Methodology (RSM) is use to investigate the effect of three independent input parameters namely viz., cutting rate, feed rate, and depth of cut for surface roughness (Ra).Central composite design (CCD) Design of Experiment of two levels was employed to conduct the experiment on work material. The responses were observed by mathematical modeling using RSM on experimental data. The significance coefficients were observed by performing analysis of variance (ANOVA) at 95% confidence level. Second order RSM modeling technique is the best method to found the significance factor affecting the surface roughness by conducting only very less no. of experimentation.

Keywords: RSM; ANOVA, Turning, CCD

1. Introduction

The term machinability is used to describe the ease with which a work material is machined under a given set of cutting conditions. A prior knowledge of a work material is important to the production engineer so that he/she can plan its processing efficiently [1]. Boston [2] has defined machinability as the response of a metal to machining which gives long tool-life under, otherwise equal conditions when compared with other material, provides good surface finish, produces well broken chips, gives uniform dimensional accuracy of successive parts, produces each part at the lowest overall cost, and requires lower power consumption in removing a given quantity of chips. Maiyer et al. [3] reviewed the earlier work on response surface methodology (RSM). This has been used in tool life modelling, surface roughness modelling, and in other machining processes [4]. In order to institute an adequate functional relationship between the surface roughness and the cutting parameters (speed, depth of cut and feeds), a large number of tests are required, requiring a separate set of tests for each and every combination of cutting tool and workpiece material. This increases the whole number of tests and as a result the experimentation coast also increases. Most researchers have investigated the effects of these cutting parameters on surface roughness by used one-variable-at-a-time approach. The present study takes into account the simultaneous variation of cutting speed, depth of cut and rate of feeds and predicts the surface roughness (response). This approach is known as RSM. Factorial designs are used widely in experiments involving several factors on a response.

The meaning of factorial design is that each complete test or replications of all the possible combinations of the levels of the factors are investigated [5]. Using RSM and 23 factorial design of experiment, mathematical model (first-order) of surface roughness as a function of speed, feeds and depth of cut have been developed with 95% confidence level. These model equations have been used to develop surface roughness contours.

2. Literature Review

Ashish Kabra [6]analyzed the surface roughness in CNC turning process using Taguchi method. The study was focused on the determination of optimum condition to get best surface roughness in turning EN-19 alloy steel in CNC turning. Experiments were designed using Taguchi method and L9 array and MINITAB-16 statistical software was used. The results were analyzed using analysis of variance technique. Results show that depth of cut has significant role to play in producing lower surface followed by feed. The cutting speed has the least influence on the surface roughness as found from the test.

Maiyar et al. [3]investigated the parameter optimization of end milling operation for Inconel 718 super alloy with multi-response criteria based on the Taguchi orthogonal array with the grey relational analysis. Nine experimental runs based on an L9 orthogonal array of Taguchi method were performed. Cutting speed, feed rate, and depth of cut are optimized with considerations of multiple performance characteristics namely surface roughness and material removal rate. A grey relational grade obtained from the grey relational analysis is used to solve the end milling process with the multiple performance characteristics. Additionally, the analysis of variance (ANOVA) is also applied to identify the most significant factor. Finally, confirmation tests were performed to make a comparison between the experimental results and developed model. Experimental results have shown that machining performance in the end milling process can be improved effectively through this approach.

Durairaj et al. [7] noticed with the increasing demands of high surface finish and machining of complex shape geometries, conventional machining process are now being replaced by non-traditional machining processes. Wire EDM is one of the non-traditional machining processes. Surface roughness and kerf width are of crucial importance in the field of machining processes. This paper summarizes the Grey relational theory and Taguchi optimization technique, in order to optimize the cutting parameters in Wire EDM for SS304. The objective of optimization is to attain the best surface quality simultaneously and separately. In this present study stainless steel 304 is used as a work piece, brass wire of 0.25mm diameter used as a tool and distilled water is used as a dielectric fluid. For example, Taguchi’s L16 orthogonal array has been used. The input parameters selected for optimization are gap voltage, wire feed, pulse on time, and pulse off time. Dielectric fluid pressure, wire speed, wire tension, resistance and cutting length are taken as fixed parameters. For each experiment surface roughness and kerf width was determined by using contact type surf coder and video measuring system respectively. By using multi objective optimization technique grey relational theory, the optimal value is obtained for surface roughness and kerf width by using Taguchi optimization technique, optimized value is obtained separately. Additionally, the analysis of variance (ANOVA) is too useful to identify the most important factor.

Rajyalakshmi et al.[8] addressed an effective approach, Taguchi grey relational analysis, has been applied to experimental results of wire cut electrical discharge machining (WEDM) on Inconel 825 with consideration of multiple response measures. The approach combines the orthogonal array design of experiment with grey relational analysis. The main objective of this study is to obtain improved material removal rate, surface roughness, and spark gap. Grey relational theory is adopted to determine the best process parameters that optimize the response measures. The experiment has been done by using Taguchi's orthogonal array L36. Each experiment was conducted under different conditions of input parameters. The response table and the grey relational grade for each level of the machining parameters have been established. From 36 experiments, the best combination of parameters was found. The experimental results confirm that the proposed method in this study effectively improves the machining performance of WEDM process.

Saraswat et al. [9]studied that the main objective of today's manufacturing industries is to produce low cost, high quality products in short time. The selection of optimal cutting parameters is a very important issue for every machining process in order to enhance the quality of machining products and reduce the machining costs. Surface inspection is carried out by manually inspecting the machined surfaces. As it is a post-process operation, it becomes both time-consuming and laborious. In addition, a number of defective parts can be found during the period of surface inspection, which leads to additional production cost. In the present work the cutting parameters (depth of cut, feed rate, and spindle speed) have been optimized in turning of mild steel of in turning operations on mild steel and as a result of that the combination of the optimal levels of the factors was obtained to get the lowest surface roughness. The Analysis of Variance (ANOVA) and Signal-to-Noise ratio were used to study the performance characteristics in turning operation. The analysis also shows that the predicted values and calculated values are very close, that clearly indicates that the developed model can be used to predict the surface roughness in the turning operation of mild steel.

MM Barzani et al. [10]investigated turning of Al- si -cu by CBN cutting tools in dry condition is studied for sustainable manufacturing. Taguchi method is used to analyses the effect of turning parameters. Results reveal that the most significant parameter on surface roughness is feed rate followed by cutting speed, while depth of cut has a minor influence. Superior machined surface that could only be obtained traditionally by the grinding process can be reached by turning with the optimum cutting parameter combination recommended in this research.

S Campocasso el at. [11]focused on the main component of cutting force Fc and surface roughness, described by the roughness parameter Ra. The research plan, based on the Taguchi method, and variance analysis ANOVA were applied. Two types of experimental model, which describes turning process of sintered carbides basedon the power function for three variables and polynomial function.

3. Experimental procedure

A series of experimental trials have been conducted as per response surface methodology (RSM). The details about the work material, experimental set-up and measuring apparatus, selection of process parameters and their range, design of experiments, and reproducibility have been explained in the following sections.

3.1Work material

There is a rising demand for high-strength and high-thermal- resistant materials which give superior performance under severe conditions. Being a high-strength temperature-resistant material, M4 steel is a popular alloy used in a wide range of applications. Thus, in the present study, a commercially available M4 is selected as work material for experimentation. In all the experimental trials, the diameter of the work material selected is 20 mm. The chemical com-position of the selected work specimen provided by the supplier and verified by spectrometer is shown in Table 1.

Table 1. Chemical Composition of M4 Steel

Element	%
Fe	Balance
C	1.25-1.40
Mn	0.15-0.40
Si	0.20-0.45
Cr	3.75-4.75
Ni	0.3
Mo	4.25-5.50
W	5.25-6.50
V	3.75-4.50
Cu	0.25
P	0.03
S	0.03

3.2 Experimental set-up and measuring apparatus

In this research work, all experiments have been carried out on a American lathe. The experiments are aimed at studying the effects of several controllable process parameters on surface roughness. Carbide tool is used to cut the material.

3.3 Selection of process parameters and their range

In the present work, the effect of various process parameters (factors) such as viz., cutting rate, feed rate, and depth of cut on surface roughness (response parameters) has been investigated. These process parameters and their range have been selected on the basis of the existing literature, pilot experimentation, manufacturer's manual, and machine capability. The independent process parameters and their levels in coded and actual values are shown inTable 2. The constant parameters and their values are indicated in Table 3.

3.4 Response Surface Methodology

Response surface methodology (RSM)[12] is a collection of mathematical and statistical techniques useful for analyzing problems in which several independent variables influence a dependent variable or response, and the goal is to optimize this response (Cochran and Cox, 1962). In many experimental conditions, it is possible to represent independent factors in quantitative form as given in Equation 3.1. Then these factors can be thought of as having a functional relationship with response as follows:

$$Y=\phi(X_1, X_2 \ldots\ldots\ldots\ldots\ldots, X_k)\pm e_r \quad (3.1)$$

This represents the relation between response Y and $x1, x2, \ldots , xk\ of\ k$ quantitative factors. The function ϕ is called response surface or response function. The residual er measures the experimental errors (Cochran and Cox, 1962). For a given set of independent variables, a characteristic surface is responded. When the mathematical form of ϕ is not known, it can be approximated satisfactorily within the experimental region by a polynomial. Higher the degree of polynomial, better is the correlation but at the same time costs of experimentation become higher.

For the present work, RSM has been applied for developing the mathematical models in the form of multiple regression equations for the quality characteristic of machined parts produced by turning process. In applying the response surface methodology, the dependent variable is viewed as a surface to which a mathematical model is fitted. For the development of regression equations related to various quality characteristics of turning process, the second order response surface has been assumed as:

$$y \quad = b_o + \sum_{i=1}^{k} \mathrm{b_i x_{i+}} \sum_{i=1}^{k} \mathrm{b_i x_i^2} \;_{+} \sum_{i<j=2}^{2} \mathrm{b_i x_i \, x_{j\pm} e_r} \qquad (3.2)$$

This assumed surface Y contains linear, squared and cross product terms of variables$xi"s$. In order to estimate the regression coefficients, a number of experimental design techniques are available. Box and Hunter (1957) have proposed that the scheme based on central composite rotatable design fits the second order response surfaces quite accurately.

3.4.1 Central composite design

Box and Hunter [38] proposed that the scheme based on central composite design (CCD) fits the second-order re- sponse surfaces quite accurately. Also, CCD[12] is the most popular among the various classes of RSM designs due to its flexibility, ability to run sequentially, and efficiency in providing the overall experimental error in a minimum number of runs. Therefore, it has been selected in the present work. In CCD, each factor is varied at five levels (−α, −1, 0, 1, α) for developing a second-order model as given in Eq. (2). When the number of factors (k)isfive or greater, it is not necessary to run all combinations of factors. The factorial part of the design can be run using a fraction of the total number of available combinations. The possible designs options can either be regular fractional factorials.

4. Experimental Results

The machining experiments were conducted to study the effect of process parameters over the output parameters. Experiments were conducted according to the test conditions specified by the second order central composite design [28] (Table 2). Experimental results are given in Table 3 for surface roughness. Altogether 20 experiments were conducted using response surface methodology.

Table 2 No. of Process Parameters & Levels (CCD)

Coded	**Parameters**	**Levels**		
Factors		**(-1)**	**(0)**	**(+1)**
A	Cutting speed	420	550	757
B	Feed rate	0.04	0.07	0.1
C	Depth of cut	0.3	0.5	0.7

Table 3: Observed Values for Performance Characteristics

		Factor 1	**Factor 2**	**Factor 3**	**Response 1**
Std	Run	A:Cutting speed	B:Feed rate	C:Depth of cut	Ra Micron
6	1	715	0.04	0.7	1.151
4	2	715	0.1	0.3	1.567

7	3	420	0.1	0.7	2.631
1	4	420	0.04	0.3	1.295
2	5	715	0.04	0.3	1.131
16	6	550	0.07	0.5	1.6997
17	7	550	0.07	0.5	1.6887
11	8	550	0.04	0.5	1.1799
18	9	550	0.07	0.5	1.7009
15	10	550	0.07	0.5	1.7336
19	11	550	0.07	0.5	1.7097
3	12	420	0.1	0.3	1.951
20	13	550	0.07	0.5	1.6857
10	14	715	0.07	0.5	1.575
12	15	550	0.1	0.5	2.0675
5	16	420	0.04	0.7	1.407
14	17	550	0.07	0.7	1.8997
9	18	420	0.07	0.5	1.895
8	19	715	0.1	0.7	2.247
13	20	550	0.07	0.3	1.4997

4.1 Analysis and Discussion of Results

The experiments were designed and conducted by employing response surface methodology (RSM). The regression equations for the selected model were obtained for the response characteristics, surface roughness[32]. These regression equations were developed using the experimental data (Table 4.2) and were plotted to investigate the effect of process variables on various response characteristics. The analysis of variance (ANOVA) was performed to statistically analyze the results.

4.1.1 Selection of Adequate Model

To decide about the adequacy of the model, three different tests viz. sequential model sum of squares, lack of fit tests and model summary statistics were performed for MRR, surface roughness of tuning process. The Table 4.2 display three different tests to select an adequate model to fit various output characteristics. The sequential model sum of squares test in each table shows how the terms of increasing complexity contribute to the model. It can be observed that for all the responses, the quadratic model is appropriate. The „lack of fit‟ test compares the residual error to the pure error from the replicated design points. The results 4.3 indicate that the quadratic model in all the characteristics does not show significant lack of fit, hence the adequacy of quadratic model is confirmed. Another test „model summary statistics‟ given in the following sections further confirms that the quadratic model is the best to fit as it exhibits low standard deviation, high “R-Squared” values, and a low “PRESS”

4.1.2 Effect of Process Variables on Surface Roughness

The regression coefficients of the second order equation (Equation 3.8, Chapter 3) are obtained by using the experimental data (Table 4.2). The regression equation for the surface roughness as a function of four input process variables was developed using experimental data and is given below. The coefficients (insignificant identified from ANOVA) of some terms of the quadratic equation have been omitted.

$$\begin{aligned} Ra = {} & +1.66818 - 0.00315281 * Cutting\ speed + 18.32216 * Feed\ rate - 0.71934 \\ & * Depth\ of\ cut - 0.00989540 * Cutting\ speed * Feed\ rate \\ & - 0.000399565 * Cutting\ speed * depth\ of\ cut + 25.58333 \\ & * Feed\ rate * Depth\ of\ cut + 0.00000266335 * Cutting\ speed^2 \\ & - 80.00605 * Feed\ rate^2 + 0.099864 * Depth\ of\ cut^2 \end{aligned} \tag{4.1}$$

The above response surface is plotted to study the effect of process variables on the surface roughness and is shown in Figures 4.1 (a, b, c). It is clear that from Figure 4.4a the surface roughness has an increasing trend with the increase of feed rate and depth of cut. It is observed from Figure 4.1b that surface roughness increases with increase cutting speed and decrease the depth of cut.It is seen from Figure 4.4c that surface roughness increases slightly with cutting speed decrease and increases feed rate. Linearity of this normal plot confirms the normal distribution of the data. It can be seen from Figure 4.2 that all the actual values are following the predicted values. Normal probability plot has been drawn for residuals in Figure 4.3.

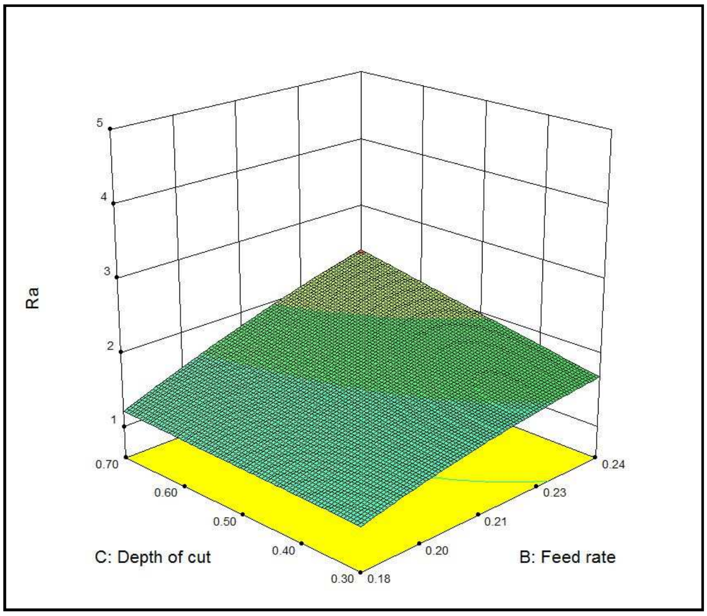

Figure 4.1a: Combined depth of cut and feed rate on Surface Roughness

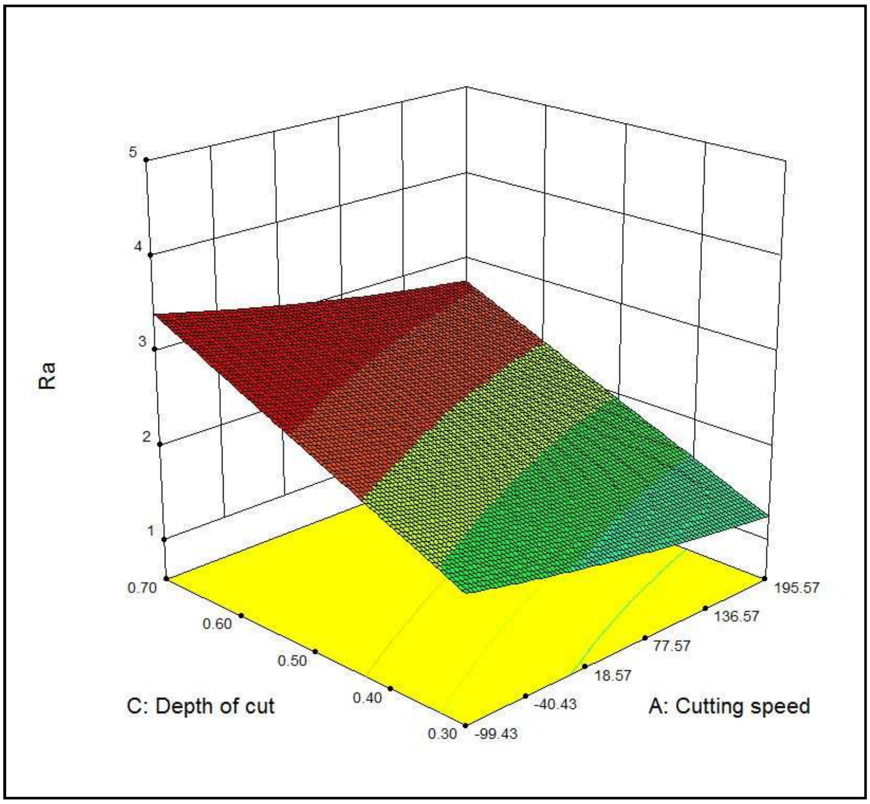

Figure 4.1b: Combined Effect of depth of cut and cutting speed on Surface Roughness

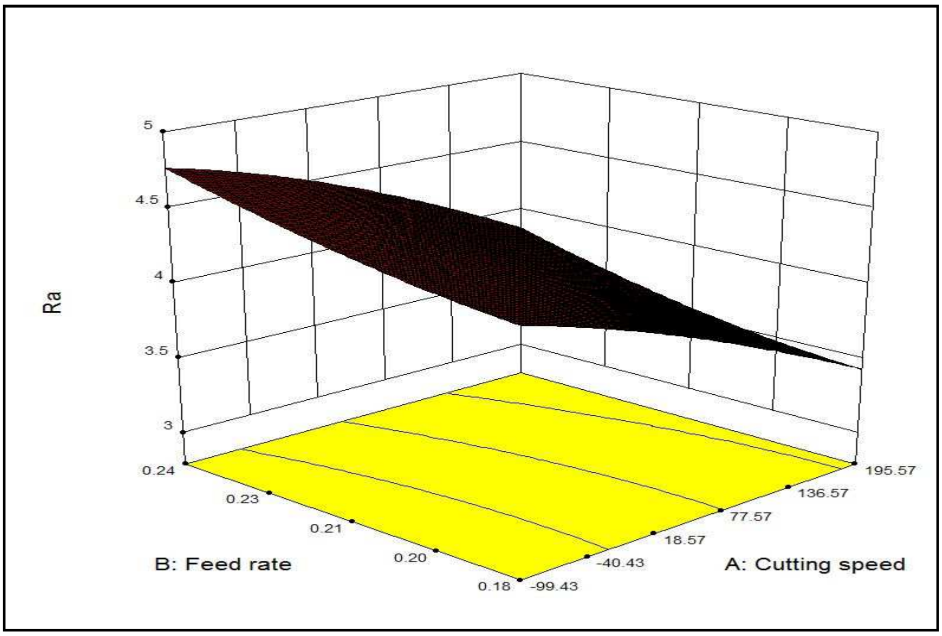

Figure 4.1c: Combined Effect of feed rate and cutting speed on Surface Roughness

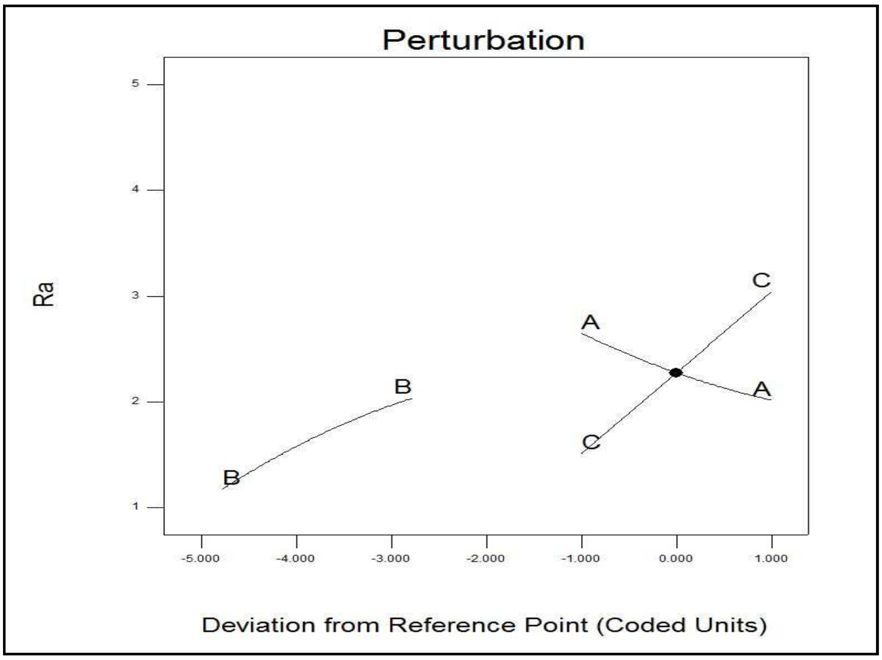

Figure 4.1d: Overall performance of surface roughness

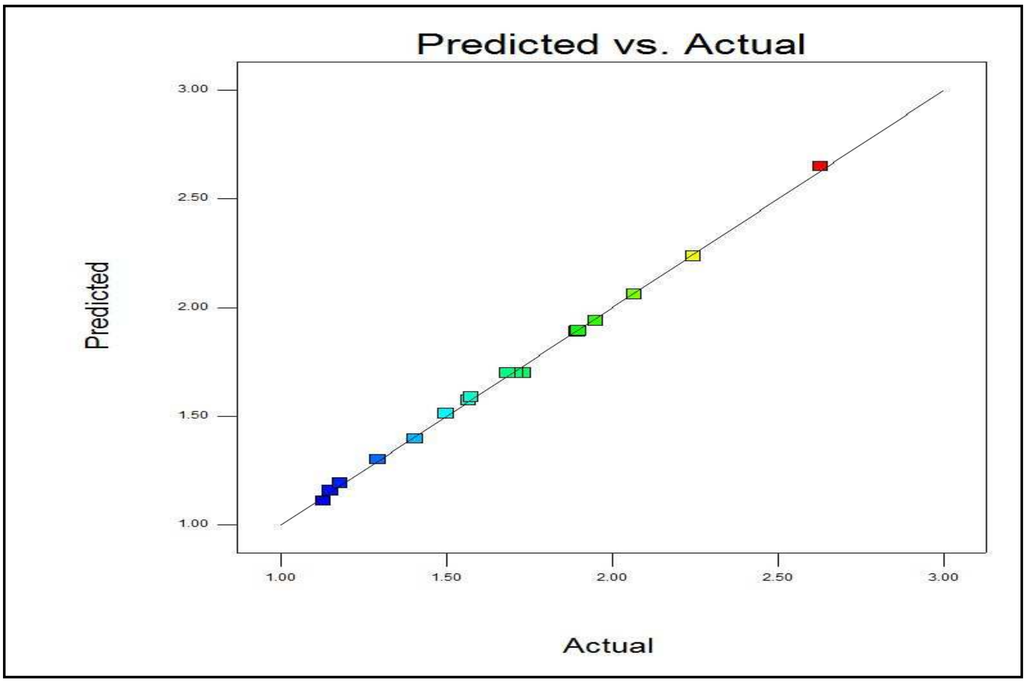

Figure 4.2: Predicted vs. Actual for Surface Roughness

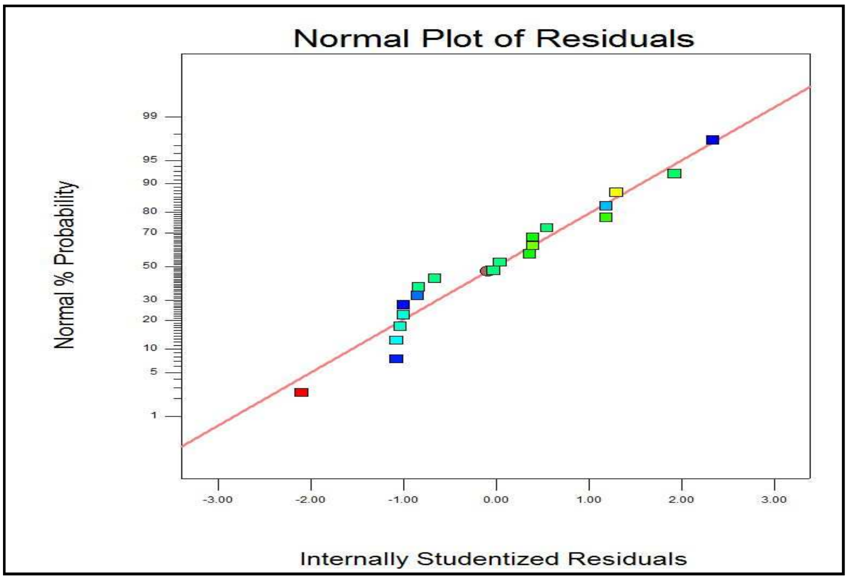

Figure 4.3: Normal Plot of Residuals for surface roughness

Table 4: Pooled ANOVA- Roughness

Source	**Sum of** Squares	df	**Mean** Square	**F** Value	**p-value** Prob> F	
Model	2.654981682	9	0.294997965	863.2301943	< 0.0001	significant
A-Cutting speed	0.2274064	1	0.2274064	665.4421194	< 0.0001	
B-Feed rate	1.838435982	1	1.838435982	5379.675929	< 0.0001	
C-Depth of cut	0.356658497	1	0.356658497	1043.662738	< 0.0001	
AB	0.015381702	1	0.015381702	45.01030827	< 0.0001	
AC	0.001114625	1	0.001114625	3.261643638	0.1011	
BC	0.188498	1	0.188498	551.5874163	< 0.0001	
A^2	0.008940575	1	0.008940575	26.16212601	0.0005	
B^2	0.014258155	1	0.014258155	41.72255948	< 0.0001	
C^2	4.38803E-05	1	4.38803E-05	0.128403743	0.7275	
Residual	0.003417373	10	0.000341737			
Lack of Fit	0.001917719	5	0.000383544	1.27877443	0.3969	not significant
Pure Error	0.001499654	5	0.000299931			
Cor Total	2.658399055	19				
Std. Dev.	0.018486138		R-Squared	0.9987145		
Mean	1.685784613		Adj R-Squared	0.997557549		
C.V. %	1.096589575		Pred R-Squared	0.987624994		
PRESS	0.032897705		Adeq Precision	117.6040074		

5. Conclusions

In the previous chapter, the effect of machining parameters of turning on the response variables such as surface finish the material M4 steel has been discussed. Also the evaluation of the machining parameters for each of response variables have been found out using response surface methodology (RSM), the important conclusions drawn from the present study are summarized below:

1. Cutting speed (p value 0.0001) is the most significant factor for surface roughness. Additionally, depth of cut and feed rate are also significant for their effect on SR. Surface roughness decreases with decrease in feed rate and depth of cut.
2. The experimental values are in good agreement with the predicted values, thus the optimized results are validated.

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