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Predicted MRR modeling of process parameters of turning for M4 steel

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Abstract

This article presents the experimental data for the machining of M4 steel on lathe machine. M4 steel which possessing high rupture strength at high temperature (up to 950 ◦C). Three input process parameters, viz., cutting rate, feed rate, and depth of cut were investigated and modeled for response variable namely metal removal rate (MRR) utilizing Response Surface Methodology (RSM). In present experimentation, quadratic model is suggested for the response. Analysis of Variance (ANOVA) indicate that cutting rate, feed rate, and depth of cut are the significant process parameters influencing the MRR

Keywords: RSM; Turning; CCD; MRR; Steel

1. Introduction

The manufacturing industries are constantly challenged for achieving higher productivity and high superiority products in order to stay competitive in the market. The desired shape & size of ferrous materials are traditionally produced through turning the preformed blanks with the help of cutting tools that moved past the work piece in a machine tool. Machine tool technology is often labeled as “Mother technology” in view of the fact that it provides essential tools that generate production in almost all sectors of economy. Higher material removal rate (MRR) and lower the cutting forces are desired by industry to cope up with the mass production without sacrificing product quality in shorter time. Higher material removal rate (MRR) is achieved through increasing the process parameters like nose radius, cutting speed, feed rate and depth of cut. In a turning operation, it is important to select cutting parameters so that high cutting performance can be achieved. Selection of desired cutting parameters by experience or using hand book does not ensure that the selected cutting parameters are optimal for a particular machine and environment. The effect of cutting parameters is reflected on surface roughness, surface texture and dimensional deviations of the product. MRR, which is used to determine and evaluate the quality of a product, is one of the major quality attributes of a turning product. Surface roughness is a measure of the technological quality of a product and a factor that greatly influences manufacturing cost. It describes the geometry of the machined surface and combined with the surface texture. For optimization of turning operations, it is desired to determine the cutting parameter more efficiently. There are several methods for optimization of turning operations. As a result, from the practical viewpoint, the parameter design of the Taguchi method seems to be the most suitable approach to determine the optimal cutting parameters for turning operations in machine shop. So, selection of appropriate process parameter plays very vital role in the effectiveness, efficiency and overall economy of manufacturing by machining to achieve the desired objectives. Therefore, in today's rapidly changing scenario of manufacturing industries, use of optimization techniques in metal cutting processes is essential for a manufacturing unit to respond effectively to severe competition and increasing demand of quality products in the market.

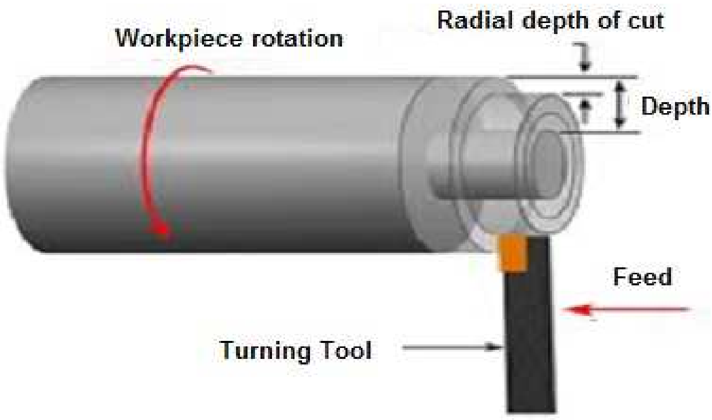

Figure 1. Turning Operation

2. Literature Review

Ashish Kabra [1]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. [2]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. [3] 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. 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.[4] 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. 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. [5]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. 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. [6]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. [7] 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 based on the power function for three variables and polynomial function.

3 Experimental procedures

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.

3.1 Work 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 composition 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 Machining parameters

Three discharge parameters, viz. cutting rate, feed rate, and depth of cut selected as input variable parameters other remaining least significant parameters are kept constant. Selected levels and range of four variable input parameters are shown in Table 1.

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 metal removal rate (MRR) 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 in Table 2. The constant parameters and their values are indicated in Table 3.

3.4 Response Surface Methodology

Response surface methodology (RSM)[8] 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:

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

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:

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

This assumed surface Y contains linear, squared and cross product terms of variables$xi\text{“}s$. 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 [9] proposed that the scheme based on central composite design (CCD) fits the second-order response surfaces quite accurately. Also, CCD[8] 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). 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 [10] (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
Std	**Run**	**A:Cutting speed**	**B:Feed rate**	**C:Depth of cut**	**MRR (mm^3/min)**
6	1	715	0.04	0.7	50631.9
4	2	715	0.1	0.3	56389.71
7	3	420	0.1	0.7	41410.39
1	4	420	0.04	0.3	39002.14
2	5	715	0.04	0.3	56686.81
16	6	550	0.07	0.5	46054.77
17	7	550	0.07	0.5	46053.75
11	8	550	0.04	0.5	45882.56
18	9	550	0.07	0.5	46054.77
15	10	550	0.07	0.5	46654.8
19	11	550	0.07	0.5	46754.8
3	12	420	0.1	0.3	39414.4
20	13	550	0.07	0.5	46654.8
10	14	715	0.07	0.5	53633.22
12	15	550	0.1	0.5	47227
5	16	420	0.04	0.7	40508.59
14	17	550	0.07	0.7	45264.33
9	18	420	0.07	0.5	40083.88
8	19	715	0.1	0.7	50824.39
13	20	550	0.07	0.3	46845.22

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, metal removal rate [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 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

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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”

4.3.2 Effect of Process Variables on MRR

The regression coefficients of the second order equation (Equation 3.15, Chapter 3) are obtained by using the experimental data (Table 4.2). The regression equation for the cutting rate as a function of three 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.

$$MRR\ = +4770.94678 + 77.85357\ * Cutting\ speed + 8512.76547 * Feed\ rate + 31291.17223\ *\ Depth\ of\ cut - 64.07889\ *\ Cutting\ speed\ *\ Depth\ of\ cut \qquad (4.1)$$

The above response surface is plotted to study the effect of process variables on the MRR and is shown in Figure 2 a. From Figure 2 a MRR is found to have an increasing trend with the increase of cutting speed and decrease the depth of cut. It is seen from Figure 2 b that with increasing the cutting speed the MRR increases rapidly. With increase the depth of cut the MRR deceases. It can also be seen that there is no effect of feed rate; it is constant throughout the process.

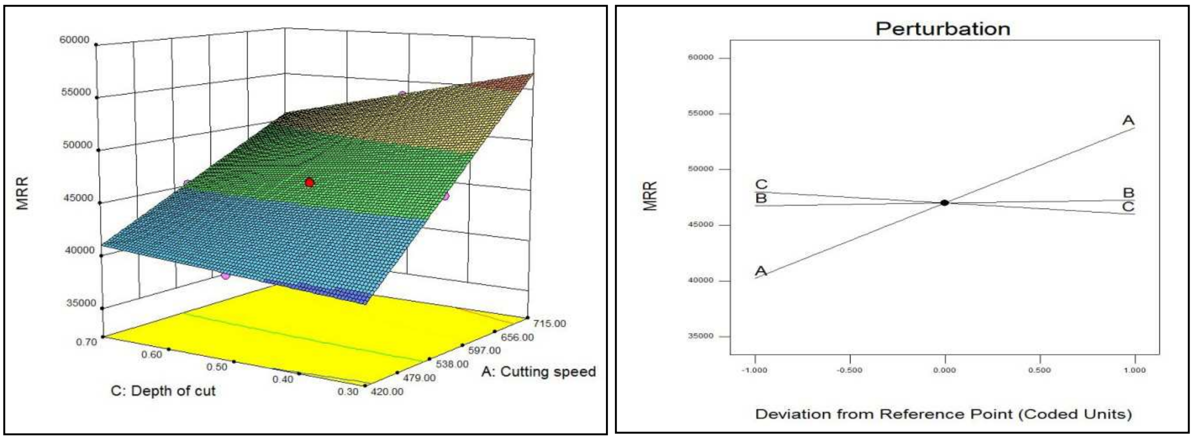

Figure 2: Combined Effect Depth of Cut and Cutting Rate on MRR B) Overall Performance of MRR

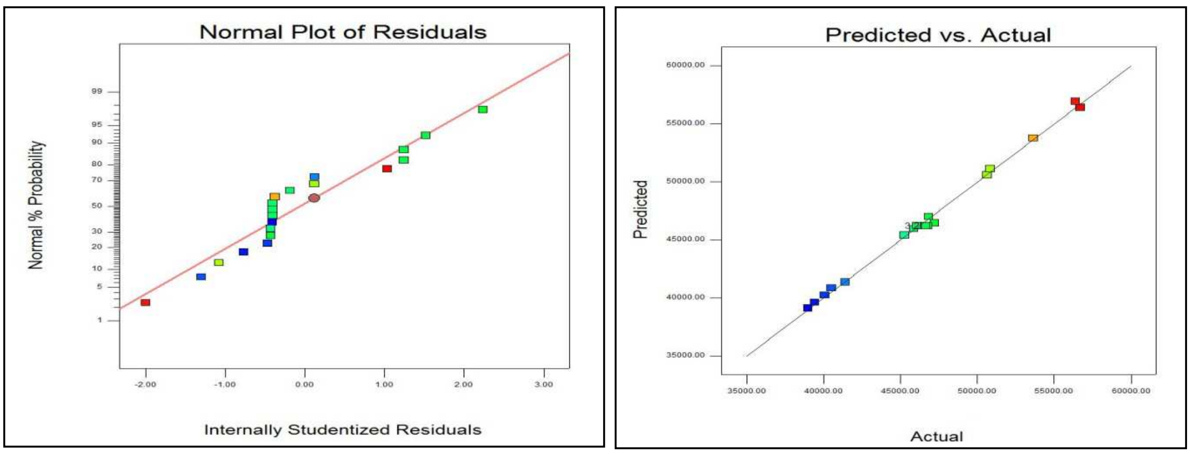

Figure 3: Normal Plot of Residuals for MRR B) Predicted and Actual Value for MRR

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Table 4.8: Pooled ANOVA- MRR

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob> F	
Model	498589131.2	4	124647282.8	893.5645864	< 0.0001	significant
A-Cutting speed	459863381.4	1	459863381.4	3296.64332	< 0.0001	
B-Feed rate	652204.5835	1	652204.5835	4.675488353	0.0472	
C-Depth of cut	10289336.54	1	10289336.54	73.76162995	< 0.0001	
AC	28667176.69	1	28667176.69	205.5076798	< 0.0001	
Residual	2092416.452	15	139494.4302			
Lack of Fit	1484044.831	10	148404.4831	1.219686108	0.4375	not significant
Pure Error	608371.6218	5	121674.3244			
Cor Total	500681547.6	19				
Std. Dev.	373.4895315					
Mean	46611.07019					
C.V. %	0.801289329					
PRESS	4151788.977					

Std. Dev.	373.4895315	**R-Squared**	0.995820864	**PRESS**	4151788.977	**Adeq Precision**	95.35254157
Mean	46611.07019	**Adj R-Squared**	0.994706427				

The residual analysis as a primary diagnostic tool is also done. Normal probability plot of residuals has been drawn (Figure 3 a) All the data points are following the straight line. Thus the data is normally distributed. It can be seen from Figure 3b that all the actual values are following the predicted values and thus declaring model assumptions are correct.

5. Conclusions

In the previous chapter, the effect of machining parameters of turning on the response variables such as MRR 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. For material removal rate, Cutting speed (A), feed rate (B), depth of cut (C),) are the significant factors. P value (0.0001) is same for all the three factors, The higher is the cutting speed, higher the MRR
2. The experimental values are in good agreement with the predicted values, thus the optimized results are validated.

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