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Critical Analysis of Machining Environment in Small Scale Machining Industry

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ABSTRACT

The present work deals with the use of multiple regression analysis (MRA) and higher degree response surface method (HDRSM) to calculate the response material removal rate (MRR) during the turning of material Al6063 and brass .The models were developed to find out the impact of various process parameters such as cutting speed, feed ,dept of cut, etc), work piece related parameters (dimension, material, geometry, weight, etc), Environment related parameters (temp, air flow, humidity, Lux, etc), cutting tool parameters (geometry, material and dimensions, etc) in order to predict the performance i.e. material removal rate (MRR). From the outcome of the presented work, we observed that the accuracy of the formulated HDRSM and MRA models measured in terms of correlation coefficient (R^2) were 0.967154 and 0.926826 respectively. From the R^2 values, it was clear that both the modes are very effective and competent. In addition, the models formulated by using HDRSM approach were found to be more accurate and reliable. The higher values of R^2 (0.96715445) and lower value of various error (0.009778066) parameters shows the adequacy and reliability of 99.456621% for HDRSM approach. Comparative study of HDRSM and MRA models disclosed the accuracy of HDRSM models hence recommended.

1. Introduction

In the Indian scenario, conventional machine tools are still extensively used in a small scale industries to fulfil their daily needs. So it is necessary to develop an approximate generalized mathematical relation which simulates the live data. Literature review carried out shows that none of the research till the date has measured the effect of parameters such as good workplace, better working condition, proper design of tools, operator health and psychological data, operator anthropometry, work piece data, cutting process parameters, lathe machine data and the environmental data on the material removal rate during the machining of nonferrous materials (Al6063 & Brass).

Phate et al, [1] has used fuzzy –grey relational analysis approach for the analysis of machining Al based MMC. Asit Kumar et al [2] have used the approach of response surface methodology (RSM)to predict the surface roughness and tool wear during the machining of Monel 400 material. Phate et al, [3,4] has effectively used the approach of reduction of variables using dimensional analysis in their research. S. Thamizhmanii et al, [5] has explained the use of Taguchi method involving three factors to examine the influence of parameters such as cutting speed, feed and depth of cut on the resulting surface roughness in turning SCM 440 alloy steel. C. Natarajan et al. [6] developed an artificial neural network (ANN) with back propagation network by using Matlab 7 software in order to develop an empirical model for the prediction of surface roughness. J. Paulo Davim et al. [7] developed an artificial neural network (ANN) model to investigate the effects of feed rate (f), cutting speed (v) and depth of cut (d) on surface roughness parameters such as average roughness (Ra) and maximum peak to valley height (R_t) by developing ANN models. Phate et al, [8-10,14-17,19] has effectively used the approach of ANN to investigate the machining process. Ilhan Asilturk & Mehmet Cunkas [11] has used artificial neural networks (ANN) and multiple regression approaches to model the machining responses. Surface roughness measured during turning at different cutting parameters such as speed, feed, and depth of cut. M. Camel Fakir et al. [12] examined the influence of various process parameters which affects the performance. H. Soleimanimehr et al. [13] has used ANN for prediction of aluminium work pieces in ultrasonic vibration assisted turning (UAT).

Mu-Chen Chen et al. [18] proposed a float encoding genetic algorithm (FEGA) to analyze the machining process. Hanief et.al [20] used multiple regression analysis and artificial neural network to analyze the performance of red crass material, from the literature review, it is cleared that various modeling techniques are used by the word wide researcher but nobody has used the approach of high degree response surface model (HDRSM), hence implemented in this paper.

2. Material and method

2.1. Material

The chemical proportion of the materials used for the investigation is as given in Table 1. The physical properties are as shown in Table 2.The geometry of the finish work piece and the finish work-piece samples are as shown in Fig1. The experiments were performed as shown in Fig 2.

2.2. Method

Many discrete extraneous variables like machines and instrumentations, work piece material, tools, operators and environments can be taken care of by the filed data based approach [9,10]. There are five workstation i.e. five different machines, five different operators and two different materials with all seasonal environmental impact has been examined throughout the year. The experimentation can be planned to be spread over one complete year that all the seasons of the year can be taken care of. Total 211 experiments were conducted to develop the models.

Table-1
Chemical Composition of the material under investigation

Material	Al%	Cr %	Cu %	Mg %	Mn%	Si %	Ti %	Zn %	Pb %
Al 6063	97.5 Max	0.1 Max	0.1 Max	0.45-0.9	0.1 Max	0.2-0.6	0.1 Max	0.1 Max	-
Brass	-	-	60-63	-	-	-	-	34	2.5-3.5

Table 2
Physical Properties of the materials under investigation

Material	Al 6063	Brass
Density (ρ)kg/mm^3	2712	8490
Hardness(BHN)	73	60
Shear Stress(τ) N/mm^2	207	235

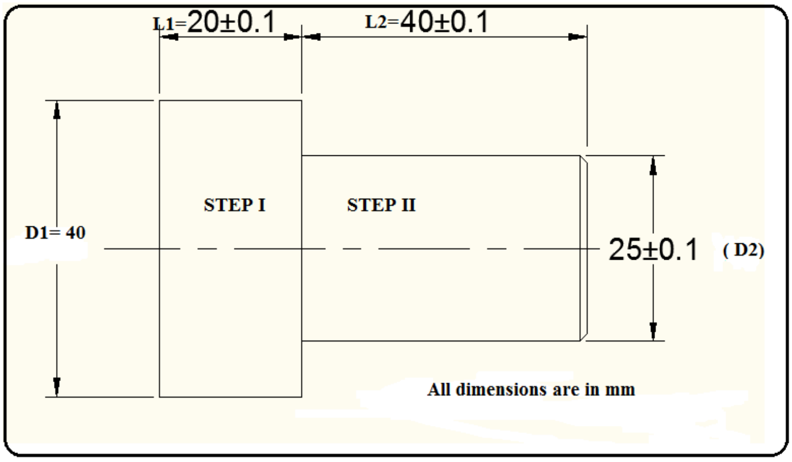


Fig. 1a : Geometry of work piece.

Fig. 1b : Geometry of sample work piece.

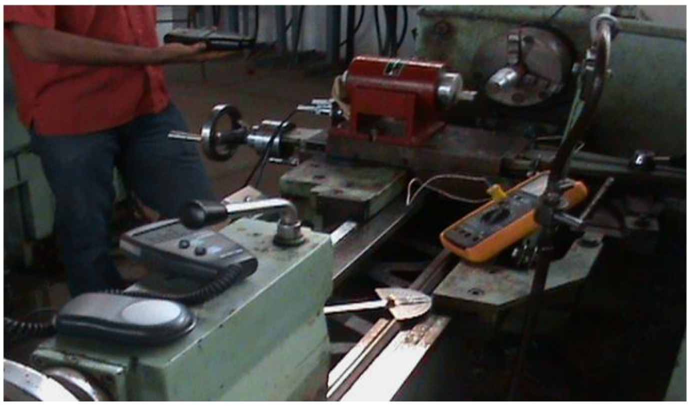


Fig. 2 : Experimental set up for the machining

2.3 Reduction of variables using Buckingham's Pi Theorem

As the number of independent variables is large in number, it is very difficult to correlate them hence they are reduced to few using dimensional analyses. It is done by applying Buckingham's theorem. When this theorem is applied to a system having 'n' independent variables, (n-3) number of pi terms is formed. Three primary dimensions used are M, L and T. When independent variables are large even after applying this theorem number of pi terms will not be reduced than n. If the product of these pi terms is taken, then it will yield dimensionless pi term.

According to Theories of Engineering experimentation by H. Schenck Jr. Most systems require at least three primaries, but the analyst is free to choose any reasonable set he wishes. The only requirement being that all variables must be expressible in his system. There is really nothing basis or fundamental about the primary dimensions. As in this research, all the variables are expressed in mass (M), length (L) and time (T) hence M' L' & T are chosen for the dimensional analysis. The basic equations which correlate all input parameters with the response variables are as follows Eqn. 1. The list of parameters affected the machining environment is as shown in table 3 .

MRR=

f[A_n,Wp,AGP,EX,SK,EDU,PS,SBP,DBP,BSG,SPO2,CTAR , r, Lo, α, β, BHNT, LP, WG , LS,LT,SW,SH,BHNW,W_{raw}, ,τ, ϱ, LR,DR, VC, f, D, FC, FT,N, VB_{Tool}, $VB_{M/C}$, $ɵ_{WP}$, PHP,$W_{M/C}$, AGM,MSP,HUM, DTO, Vf, LUX,DB] (1)

General form can be defined as Eqn. 2.

f[A_n,Wp,AGP,EX,SK,EDU,PS,SBP,DBP,BSG,SPO2,CTAR , r, Lo, α, β, BHNT, LP, WG, LS,LT,SW,SH, BHNW,W_{raw}, ,τ, ϱ, LR,DR, VC, f, D, FC, FT,N, VB_{Tool}, $VB_{M/C}$, $ɵ_{WP}$, PHP,$W_{M/C}$,AGM,MSP,HUM,DTO,Vf,LUX,DB,MRR] (2)

The exact mathematical form of this dimensional equation is the targeted model. When we implement this approach in a system involving n independent variables, (n-3) numbers of π terms are formed. From Eqn.2, total number of variables n = 48.All these variables can be expressed in terms of three primary dimensions i.e. mass (M), Length (L) and Time (T);

According to Bucking ham's theorem; Number of Pi terms = n – m = 48 – 03 = 45 dimensionless terms are formed. Where n is the total number of variables and m is the number of repeating variables. The Eqn 2 can be written as Eqn. 3

i.e. f [π_{P1}, π_{P2}, π_{P3}, π_{P4}, π_{P5}, π_{P6} π_{P7}, π_{P8}, π_{P9} -------------, π_{P45}] (3)

Choosing D, VC and FC are the repeating variables, we get following Pi terms.

1. $\Pi_{P1} = D^a\ Vc^b\ FC^c\ An$

$M^0 L^0 T^0 = [M^0 L^1 T^0]^a\ [M^0 L^1 T^{-1}]^b\ [M^1 L^1 T^{-2}]^c\ [M^0 L^0 T^0]$

For M : 0 = c + 0 ; c = 0

For L : 0 = a+ b+ c+ 0

For T : 0 = -b -2c ; b = 0 hence a = 0

$$\boxed{\Pi_{P1} = A_n}$$

Similarly all pi terms are formed for all the variables.

The list of variables is as given in Table3. The grouping of the pi terms are as shown in the following Table 4.

Each dependent Π term is the function of the available independent Π terms,

$$\pi_{D1} = f(\Pi1, \Pi2, \Pi3, \Pi4, \Pi5, \Pi6) \quad (4)$$

MRR /D^2*VC =f[An*SBP*SK*AGP*Wp *SPO2 / DBP*PS*EDU*EX*BSG*D^3,CTAR * r * β * BHNT * LT*LP* LS / α * LO* SW * SH * WG, BHNW * W raw* LR * τ / D * FC * ϱ * DR , f * FT * N * $ɵ_{wp}$* VB_{Tool} / $VB_{Machine}$ * FC*VC , MSP * P_{HP} * $W_{m/c}$ / AGM* FC^2 , HUM*DTO *Vf *DB*VC*FC/ LUX*D^3] (5)

The rate at which material is removed from an unfinished part, usually measured in cubic mm per minute.MRR is calculated by using eqn. 6

$$MRR= \pi (D_1^2 - D_2^2) f N / 4 \quad (6)$$

Where

- D_1 = Original diameter of the work piece.
- D_2 = Final diameter of the work piece.
- f = Feed in mm / rev^n
- N = Work piece revolution per minute.

3. Material and method

3.1 Multiple regression analysis (MRA)

The regression analysis is a modeling technique use to correlate the dependent and independent variables. The basic application of regression analysis is for the forecasting purpose. In the regression analysis the dependent variables is the variable which is being predicted and the independent variable is the variable which is used to make the prediction. The basic equation is given by the following Eqn.7.

$$y = a + bx_1 + cx_2 + dx_3 + \dots\dots\dots \quad (7)$$

where y is the dependent variable, x_1,x_2,x_3......... are the independent variables and a is the regression coefficient and b,c,d,……….. are the coefficient corresponding to the independent variables.

3.2 Higher degree response surface model (HDRSM)

The step turning process is affected by a variable X_1 and X_2. The process can improve under any combination of treatment X_1 and X_2. Therefore, when treatments are from a continuous range of values, then a Response Surface Methodology is useful for developing, improving, and optimizing the response variable. In this case, the Y is the response variable, and it is a function variable X_1 and X_2. It can be expressed as (Eqn. 8).

$$Y = f(X_1, X_2) + e \tag{8}$$

Table 3.
List of Process variables under investigation.

S.N.	Description	Symbol
1	Anthropometric dimensions	A_n
2	Weight of the operator.	W_p
3	Age of the operator.	AGP
4	Experience	EX
5	Operator rating	SK
6	Educational Qualification	EDU
7	Psychological Distress	PS
8	Systolic Blood pressure	SBP
9	Diastolic Blood pressure	DBP
10	Blood Sugar Level	BSG
11	Oxygen Saturation level	SPO2
12	Cutting Tool angles ratio.	CTAR
13	Tool nose radius	R
14	Tool overhang length	Lo
15	Approach angle	A
16	Setting angle	B
17	Tool Hardness	BHNT
18	Lip or Nose angle of tool	LP
19	Wedge angle	WG
20	Shank Length	LS
21	Total length of the tool	LT
22	Tool shank width	SW
23	Tool shank Height	SH
24	Work piece hardness	BHNW
25	Raw work piece weight.	W_{raw}
26	Work piece material stress	T
27	Density of the work piece material	ϱ
28	Length of the raw work piece	LR
29	Diameter of the raw work piece	DR
30	Cutting Speed	VC
31	Feed	f
32	Depth of cut	D
33	Cutting force	FC
34	Tangential Force.	FT
35	Spindle revolution	N
36	Cutting tool Vibration	VB_{Tool}
37	Lathe Machine Vibration	$VB_{M/C}$
38	Tool -Work piece interface temperature.	θ_{WP}
39	Motor power	PHP
40	Weight of the machine	$W_{M/C}$
41	Age of the machine	AGM
42	Machine Specification ratio	MSP
43	Atmospheric Humidity	HUM
44	Atmospheric Temperature	DTO
45	Air Flow	V_f
46	Light Intensity	LUX
47	Sound level	DB
48	Material removal rate	MRR

The variables X_1 and X_2 are independent variables where the response Y depends on them. The dependent variable Y is a function of X_1, X_2, and the experimental error term, denoted as (Eqn. 9)

$$Y = b_0 + b_1 X_1 + b_2 X_2 + b_{11} X_{11}^2 + b_{22} X_{22}^2 + b_{12} X_1 X_2 + e \tag{9}$$

The general form of RSM polynomial is given by (Eqn. 10)

$$Y = b_0 + \Sigma b_i X_i + \Sigma b_{ii} X_i^2 + \Sigma b_{ij} X_i X_j \tag{10}$$

In the present work, the various inputs are grouped into two variables as X_1 and X_2. The data is imported into the Matlab and best-fit polynomial was fitted, which represents the nature of response variables. The best fitted response surface and the polynomial equation is used to optimize the response and to find out the sensitivity of the response w.r.t. the variables X_1 and X_2.

Table 4
Final group of dimensionless term

Term	Dimensionless terms after grouping	Nature
π_1	$An*SBP*SK*AGP*W_p*SPO2 / DBP*PS*EDU*EX*BSG*D^3$	Machine operator
π_2	$CTAR * r * \beta * BHNT * LT*LP*LS / \alpha * LO* SW * SH * WG$	Cutting tool
π_3	$BHNW * W raw* LR * \tau / D * FC * \varrho * DR$	Work piece
π_4	$f * FT * N * \theta_{wp} * VB_{Tool} / VB_{Machine} * FC*VC$	Cutting process
π_5	$MSP * P_{HP} * W_{m/c} / AGM* FC^2$	Lathe Machine
π_6	$HUM*DTO *V_f *DB*VC*FC/ LUX*D^3$	Environment
π_{D1}	MRR /D^2*VC	Material Removal Rate

4. Result and Discussion

4.1 Multiple Regressions Analysis (MRA)

The Eqn. 12 (MRA model is used to correlate the all independent variables with MRR. The grouped dimensionless pi terns are as shown in Table4. The results of MRA models are given in Table 5-7. Fig 10 presents the comparison between all the models predicted MRR with the actual MRR. From the analysis, it has been observed that the cutting related process parameters are the most dominating group of variables along with the operator and environment. From Eqn. 12, it has been observed that feed and depth of cut are the most significant cutting process parameters which directly impact the MRR. The value of the significance factor "P" is 0.0000 which indicates the reliability of the MRA model.

Table 5
Summary Output of MRA Model for MRR

Regression Statistics	
Multiple R	0.926822648
R Square	0.859007320
Adjusted R Square	0.850690420
Standard Error	0.01663224
Observations	211
Reliability	98.445662165

Table 6
ANOVA of MRA Model for MRR

Parameters	DF	SS	MS	F	Significance P
Regression	6	0.345506	0.0575	208.16	0.00000
Residuals	205	0.056709	0.0002		
Total	211	0.402215			

Hence

The linear regression to correlation the performance of small scale industries is

$$Y = 0.00 + 0.08848091 * X1 - 2.888E\text{-}07 * X2 + 5.2929E\text{-}08 * X3 + 0.03408401 * X4 - 0.1425661 * X5 + 0.00029971 * X6 \quad (11)$$

The equation can be written as Eqn. 12.

$$\begin{aligned}\frac{\mathrm{MRR}}{\mathrm{D}^2 * \mathrm{VC}} &= 0.0000 + 0.08848091\left(\frac{\mathrm{An} * \mathrm{SBP} * \mathrm{SK} * \mathrm{AGP} * \mathrm{Wp} * \mathrm{SPO2}}{\mathrm{DBP} * \mathrm{PS} * \mathrm{EDU} * \mathrm{EX} * \mathrm{BSG} * \mathrm{D}^3}\right) - 2.888\mathrm{x}10^{-7}\left(\frac{\mathrm{CTAR} * \mathrm{r} * \beta * \mathrm{BHNT} * \mathrm{LT} * \mathrm{LP} * \mathrm{LS}}{\alpha * \mathrm{LO} * \mathrm{SW} * \mathrm{SH} * \mathrm{WG}}\right)\\ &+ 5.2929\mathrm{x}10^{-8}\left(\frac{\mathrm{BHNW} * \mathrm{Wraw} * \mathrm{LR} * \tau}{\mathrm{D} * \rho * \mathrm{DR}}\right) + 0.03408401\left(\frac{\mathrm{f} * \mathrm{FT} * \mathrm{N} * \theta\mathrm{wp} * \mathrm{VB\ tool}}{\mathrm{VB\ machine} * \mathrm{FC} * \mathrm{VC}}\right)\\ &- 0.1425661\left(\frac{\mathrm{MSP} * \mathrm{PHP} * \mathrm{Wm/c}}{\mathrm{AGM} * \mathrm{FC}^2}\right) + 0.00029971\left(\frac{\mathrm{HUM} * \mathrm{DTO} * \mathrm{Vf} * \mathrm{DB} * \mathrm{VC} * \mathrm{FC}}{\mathrm{LUX} * \mathrm{D}^3}\right)\end{aligned} \quad (12)$$

Table 7
ANOVA of MRR model

	Coefficients	Standard Error	P Value
Intercept	0	#N/A	#N/A
PI1 Operator (X1)	0.08848091	0.032807	0.007579
PI2 tool (X2)	-2.888E-07	1.53E-07	0.060727
PI3 work piece (X3)	5.2929E-08	4.98E-09	2.54E-21
PI 4 cutting Process (X4)	0.03408401	0.006001	4.57E-08
PI5 Lathe (X5)	-0.1425661	0.04410 independent 1	0.001429
Pi6 Environment (X6)	0.00029971	3.95E-05	1.12E-12

4.2 Higher Degree Response Surface Method (HDRSM)

In the present work the various inputs are grouped into two variables as X_1 and X_2. A statistical analysis software 'Matlab' is employed for response surface method (RSM) and the best fit polynomial was fitted which represents the nature of response variables. The best fitted response surface and the polynomial equation was used to optimize the response and to find out the sensitivity of the response w.r.t. the variables X_1

and X_2. The general equation of best fitted polynomial with degree 5/3 is given by Eqn. 13

$$f(X_1, X_2) = p00 + p10 * X_1 + p01*X_2 + p20*X_1\text{^}2+p11* X_1* X_2 + p02* X_2\text{^}2+p30* X_1\text{^}3+p21* X_1\text{^}2* X_2 + p12* X_1* X_2\text{^}2 + p03* X_2\text{^}3 + p40* X_1\text{^}4 + p31*X_1\text{^}3* X_2 +p22* X_1\text{^}2* X_2\text{^}2 + p13* X_1* X_2\text{^}3 + p50* X_1\text{^}5 + p41* X_1\text{^}4* X_2 +p32* X_1\text{^}3* X_2\text{^}2 + p23* X_1\text{^}2* X_2\text{^}3 \quad (13)$$

$$\pi D1= 0.005524 + 0.002931 *X_1+ 0.0007838 * X_2 - 0.0003185 * X_1^2 + 0.0004819 * X_1* X_2 + 8.24e\text{-}005 * X_2^2 + 8.378e\text{-}006 * X_1^3 + 3.174e\text{-}006 * X_1^2* X_2 -3.221e\text{-}005 * X_1* X_2^2 -1.972e\text{-}006 * X_2^3 -1.128e\text{-}007 * X_1^4 -3.785e\text{-}008 * X_1^3* X_2 + 1.887e\text{-}007 * X_1^2* X_2^2 + 7.15e\text{-}007 * X_1* X_2^3 + 1.073e\text{-}008 * X_2^4 + 7.773e\text{-}010 * X_1^5 -2.089e\text{-}009 * X_1^4* X_2 +5.056e\text{-}009 * X_1^3*X_2^2-8.52e\text{-}009*X_1^2*X_2^3-3.753e\text{-}009*X_1*X_2^4 \quad (14)$$

Where

X_1= f (Π 1 , Π 4 , Π 6) & Group –II : X_2=f (Π 2, Π 3 , Π 5)

$$X_1 = f\left[\left(\frac{An * SBP * SK * AGP * Wp * SPO2}{DBP * PS * EDU * EX * BSG * D^3}\right), \left(\frac{f * FT * N * \theta wp * VB\ tool}{VB\ machine * FC * VC}\right), \left(\frac{HUM * DTO * Vf * DB * VC * FC}{LUX * D^3}\right)\right]$$

And

$$X_2 = f\left[\left(\frac{CTAR * r * \beta * BHNT * LT * LP * LS}{\alpha * LO * SW * SH * WG}\right), \left(\frac{BHNW * Wraw * LR * \tau}{D * \rho * DR}\right), \left(\frac{MSP * PHP * Wm/c}{AGM * FC^2}\right)\right]$$

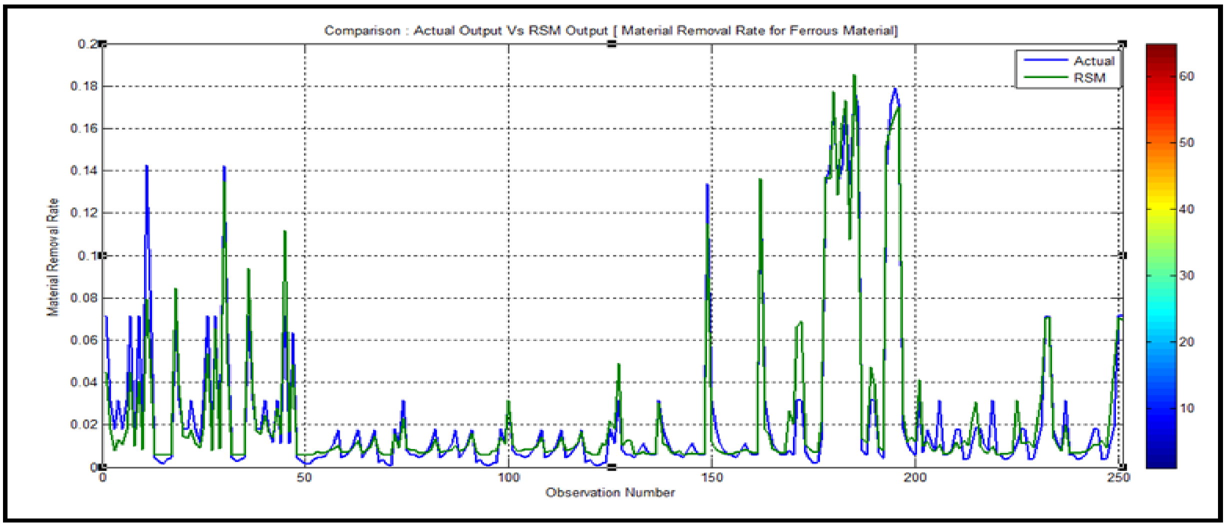
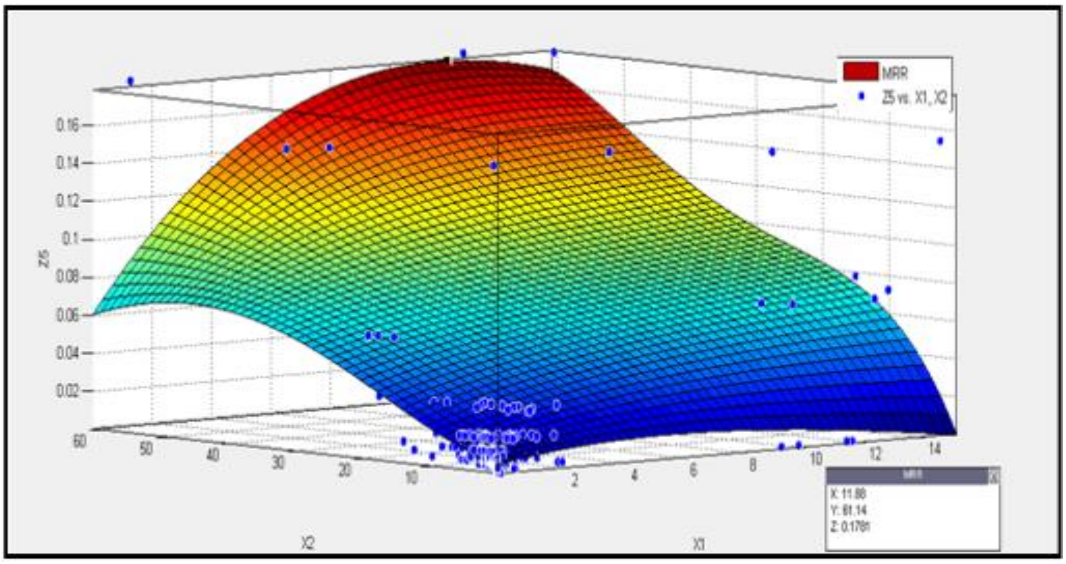


Figure 8: Comparison between actual output and HDRSM response for Material Removal Rate.



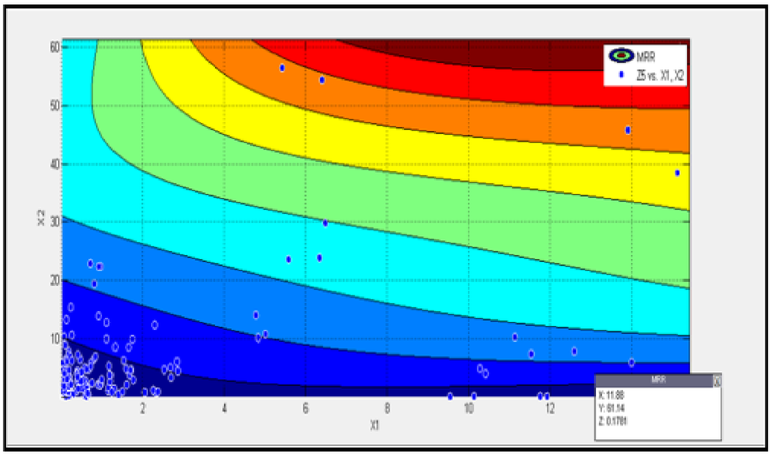


Figure 9: Response Surface and Contour plot for Material Removal Rate

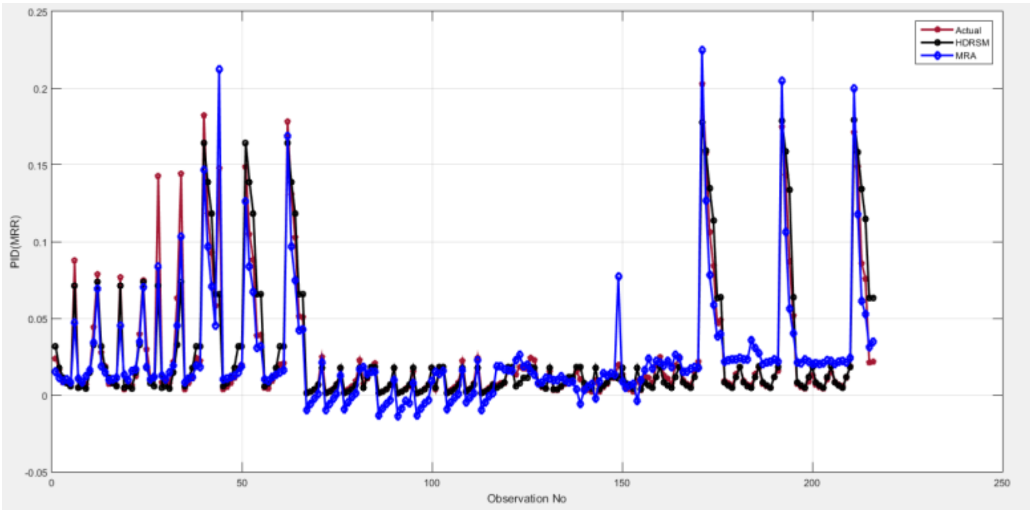


Figure 10: Comparison between actual, HDRSM and MMRA response for Material Removal Rate.

The coefficient of correlation (R^2) and the standard error is 0.96715447 and 0.0093538777 respectively. The Higher degree polynomial RSM equation is given by the equation 14. The positive signs in the model represent the most influencing parameters or the interaction which is directly impact the response MRR. While the negative sign indicates the indirect impact of variable on MRR response. The correlation coefficient is 0.96.715 which indicates that the HDRSM model can explain 96.715 % of the overall data and only 3.285% of the total variations were not explained by the HDRSM model. For any model to be very adequate, the correlation coefficient should be more that 75%. Figure 10 shows the comparison between actual, MRA and HDRSM model response. Fig 8-10 shows the effectiveness of HDRSM over MRA method.

Therefore it confirmed that both the models were highly acceptable which indicates the good agreement between the actual and the predicted values of the response. From the model, it has been observed that the linear terms of group X1 and X2 are most significant and the one interaction impact X1X2 has a significant impact on MRR. As machine, operator, environment and the work piece is not varying too much. Their impact is neglected and the parameters such as the cutting process parameters along with the tool parameters are the most influencing parameters. Figure 9 shows the contour and surface plot for the selected HDRSM model of MRR. From Fig 9 , it has been observed that the maximum MRR can be obtain when we maintaining the value of the value of X1 is very close to 7 and the value of X2 very close to 60.

Table 8

Summary Output of HDRSM Model for MRR

Regression Statistics	
Multiple R	0.96715447
R Square	0.93538777
Standard Error	0.009778066
Observations	211
Reliability	99.445662165

Summary Output of HDRSM Model for MRR

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