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MODELING AND MULTI-OBJECTIVE OPTIMIZATION OF MILLING PROCESSES PARAMETERS USING TAGUCHI GREY RELATIONAL ANALYSIS (GRA)

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Abstract - *Milling process plays a vital role in the machining processes. The efficiency of the milling process can be increased by different methods and by developing empirical relations between different parameters. Experimentally determined values can be optimized by using different techniques. The empirical models and investigate the optimal machinability parameters of milling process during machining EN 31 tool steel. In this consequence, milling experiments were conducted on vertical milling center based on central composite design with 27 experiments. The response surface methodology was adopted to develop the mathematical models for the responses and ANOVA is used to check the adequacy of the developed models and were found that the developed second order models can explain the variation in the temperature up to the extent of 98.06% and 99.07%. Then these experimentally measured values were carried to the optimization. GRA was successfully implemented to the measured experimental runs. Therefore, the present work enables the industries to perform the CNC milling operations on the hardened EN 31 material within the optimal levels of tool temperatures by maximizing the metal removal rate*.

Key Words: EN 31 tool, ANOVA, CNC, Implementation of GRA, MRR and Tc.

1.INTRODUCTION

Many approaches have been proposed to minimize the heat generation and enhance tool life and metal removal rate in metal cutting. As the chip formation process in machining is accompanied by heat generation, which influences the mechanical and physical properties of both the work piece and the cutting tool. High temperatures tend to accelerate thermal softening of the tool and subsequent tool wear, which are not desirable because they negatively impact the accuracy of the machined surface and tool life. In the aerospace, automotive, mould/die and general manufacturing industries, there is great pressure to ensure lower cost, greater productivity and improved quality in order to encourage economic growth. Chatter is a self-excited type of vibration that occurs in metal cutting if the chip width is too large with respect to the dynamic stiffness of the system, especially when machining with a high material removal rate. Among different types of milling processes, end milling is one of the most vital and common metal cutting operations used for machining parts because of its capability to remove materials at faster rate with a reasonably good surface quality. For these reasons, CNC end milling process has been recently proved to be very versatile and useful machining operation in most of the modern manufacturing industries. Only the implementation of automation in end milling process is not the last achievement. It is also necessary to improve the machining process and machining performances continuously for effective machining and also for the fulfillment of requirements of the industries. Surface roughness is a key factor in the machining process while considering machining performance and that is why in many cases, industries are looking for maintaining the good surface quality of the machined parts. It is also necessary to study the material removal rate along with surface roughness in CNC end milling process. In any metal cutting operation, a lot of heat is generated due to plastic deformation of work material, friction at the tool–chip interface and friction between the clearance face of the tool and work piece. So, it is generally considered that the heat produced during the machining process is critical in terms of work piece quality. Thus, effective control of heat generated in the cutting zone is essential to ensure good work piece surface quality in machining. All these factors prompt investigations on the use of biodegradable coolants and coolant free machining. But any attempt to minimize or avoid the coolant can be dealt with only by replacing the functions normally met by the coolants with some other means. If friction at the tool and work piece interaction can be minimized, by providing effective lubrication, the heat generated also can be reduced to some extent. Advancement in modern tribology has identified many solid lubricants, which can sustain and provide lubricity over a wide range of temperatures.

1.1 Hard Milling

Hard milling is a machining process to cut the hardened materials of hardness range over 45 HRC with single point cutting tool. Now a day, hardened steels are being used in a variety of industrial applications like automotive parts such as studs, bearings, gears, cams, etc. However, it is to be noted that the turning of hardened steel with commonly used cutting inserts is influenced by more number of machining parameters and they adversely affects the performance of machining process. In order to minimize this, the conventional cutting inserts are getting replaced by specialized cutting inserts to cut the hardened materials lately. Some of these specialized inserts in existence are cubic boron nitride (CBN) inserts, polycrystalline cubic boron nitride (PCBN) and ceramic inserts. Some experimental investigations have been attempted to predict the performance of hard turning with the mentioned specialized cutting inserts. To reduce the milling related impact to the sub-surface area new process technological approaches for high-speed cutting have been developed in the last decades. According to, the wear of the milling tool spreads with the highest effective cutting speed, starting at the engagement point of the cutting edge, and can be reduced by an adequate increase of the feed per tooth. If the feed per tooth and the cutting speed in the hard milling process fall below a critical value, the tool vibrations increase and the tool wear grows significantly. In order to prove these chipping mechanisms, the complex interactions between the deformation rate, the elevated process temperature, the strength properties as well as the microscopic flow behavior and the structural integrity of the material in the local contact zone (sheer area) between the work piece and the milling tool have to be taken into detailed consideration. Increasing the cutting speed leads to increased friction in the sheer area which results in local elevated process temperatures.

2. MOTIVATION AND OBJECTIVES OF THE PRESENT PROBLEM

Cutting Temperature and MRR are the most important machining responses during end milling process. These out put parameters are influenced numerous process parameters during milling. Form the literature survey it is found that the parameters such as depth of cut ,feed rate and spindle speed are having considerable influence on cutting temperature and metal removal rate. The main objective of this investigation was to investigate the optimal machining conditions during hard milling with conventional cutting tools to achieve the maximum metal removal rate (maximum production rate) within the adequate machining cost. This work also develops the mathematical models for the cutting temperature and metal removal rate in terms of depth of cut, feed and spindle speed using response surface methodology. To study the influence of these process parameters, the experimental runs were conducted using Response Surface Method (RSM). RSM comprises a group of statistical techniques for empirical model building and model exploration. The response surface methodology is practical, economical and relatively easy for use. The experimental data were utilized to build mathematical model for first and second order model, by regression method. A response or output function is related to a number of input variables that affect it. The variables studied will depend on the specific field of application. The response surface method can substantially reduce the total number of experiments often carried out randomly and it is an adequate and reliable method to measure the true mean response of interest. Experiments were conducted on CNC milling machine to cut hardened tool steel with carbide cutting inserts. In order to reduce the number of experimental runs, experiments are planned based on design of experiments (DOE). Central composite design with 27experimentswasselected.The corresponding cutting temperature and materiel removal rate for each experiment is calculated and recorded. Analysis of variance was adopted to check the adequacy of the experimentally measured values of the responses. Since, the optimization cannot be done to only one objective, when another objective is also important. Different solutions may produce conflicting scenarios between the two objectives. A solution, which is excellent with respect to one objective, requires a compromise in the other objective. This prohibits one to choose a solution, which is optimal with respect to only one objective, which makes the two objectives conflicting. The surface roughness and metal removal rate are inversely proportional. If metal removal rate is aimed to increase, the cutting temperatures will also increases and vice versa. Hence, the present problem is considered as a multi objective optimization problem. Gray Relational Analysis (GRA) as an effective and extensively used multi-objective optimization technique for the manufacturing problems.

3. RESPONSE SURFACE METHODOLOGY

Response surface methodology or RSM is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which response of interest is influenced by several variables and the objective is to optimize this response. For example, suppose that a chemical engineer wishes to find the levels of temperature (x1) and pressure (x2) that maximizes the yield (y) of a process. The process yield is a function of the levels of temperature and pressure, say

$$Y = f(x1, x2) + \varepsilon \quad \text{---------------------------------} \quad (3.1)$$

Where ε represents the noise or error observed in the process y. if we denote the expected response by E(y) = f(x1, x2) = η, then the surface is represented by, is called response surface.

$$f(x1, x2) \quad \text{---------------------------------} \quad (3.2)$$

We usually represent the response surface graphically, such as in fig 4.1, where η is plotted versus the levels of x1, x2. To help visualize the shape of a response surface, we often plot the contours of the response surface as shown in fig 4.2. in the contour plot, lines of constant response are drawn in the x1, x2 plane. Each contour corresponds to a particular height of the response surface.

In most RSM problems, the form of the relationship between the response and the independent variables is unknown. Thus, the first step in RSM is to find a suitable approximation for the true functional relationship between y and the set of independent variables is employed. If the response is well modeled by a linear function of the independent variables, then the approximating function is the first order model.

Y= β0+β1x1+β2x2+---------------------+βkxk+ε -------------------- (3.3)

If there is curvature in the system, then a polynomial of higher degree must be used, such as the second order model.

Almost all RSM problems use one or both of these models, of course it is unlikely that a polynomial model will be a reasonable approximation of the true function relationship over the entire space of the independent variables, but for a relatively small reason, they usually work quite well. The method of least squares is used to estimate the parameters in the approximating polynomials. The RSM is then performed using the fitted surface. If the fitted surface is the adequate approximation, of the true response function, then analysis of the fitted surface will be approximately equal to analysis of the actual system. The model parameters can be estimated most effectively if proper experimental design is used to collect the data. Designs for fitting response surfaces are called response surface results.

3.1 Experimental Designs For Fitting Response Surfaces

Fitting and analyzing response surfaces are greatly facilitated by the proper choice of a experimental design. In this section, we discuss some aspects of selecting appropriate designs for fitting response surfaces.

When selecting response surface design, some of the features of a desirable design are as follows;

1. Provides a reasonable distribution of data points (and hence information) throughout region of interest.
2. Allows model adequacy, including lack of fit, to be investigated.
3. Allows experiments to be performed in blocks.
4. Allows designs of higher order to be build up sequentially.
5. Provides an internal estimate of error.
6. Provides precise estimates of the model coefficients.
7. Provides a good profile of the prediction variance through the experimental region.
8. Provides reasonable robustness against outliers or missing values.
9. Does not require a large number of runs.
10. Does not require too many levels of the independent variables.
11. Ensures simplicity of calculation of the model parameters.

These features are sometimes conflicting, so judgment must often be applied in design selection.

3.2 Designs for fitting first order model

Suppose we wish to fit the first order model in k variables, there is a unique class of designs that minimize the variance of the regression coefficients (βi). These are the orthogonal first-order designs. A first-order design is orthogonal if the off-diagonal elements of the (X1X) matrix are all zero. This implies that the cross products of the columns of the X matrix sum to zero. The class of orthogonal first-order designs includes the 2k factorial and fractions of the 2k series in which main effects are not aliased with each other. In using these designs, we assume that the low and high levels of the k factors are coded to usual ±1 levels. The 2k designs do not afford an estimate of the experimental error unless some runs are replicated. A common method of including replication in the 2k designs is to augment the design with several observations at the center (the point xi=0, i=1, 2, 3, -----, k). The addition of center points to the designs does not influence the (βi) for i≥1, but the estimate of β0 becomes the grand average of all observations. Furthermore, the addition of center points does not alter the orthogonally property of the design. Central composite design is the most popular class of designs just for fitting second order models. Generally the CCD consists of a 2k factorial (or fractional factorial of resolution V) with nf runs, 2k axial or star runs and nc center runs.The practical deployment of a CCD often arises through sequential experimentation. That is the 2k has been used to fit a first model, this model has exhibited lack of fit and the axial runs are then added to allow the quadratic terms to be incorporated in to the model. The CCD is a very efficient design for fitting the second order model.

3.3 Design of Experiments

An important aspect of RSM is the design of experiments (Box and Draper, 1987),usually abbreviated as DoE. These strategies were originally developed for the model fitting of physical experiments, but can also be applied to numerical experiments. The objective of DoE is the selection of the points where the response should be evaluated. Most of the criteria for optimal design of experiments are associated with the mathematical model of the process. Generally, these mathematical models are polynomials with an unknown structure, so the corresponding experiments are designed only for every particular problem. The choice of the design of experiment scan have a large influence on the accuracy of the approximation and the cost of constructing the response surface.

In a traditional DoE, screening experiments are performed in the early stages of the process, when it is likely that many of the design variables initially considered have little or no effect on the response. The purpose is to identify the design variables that have large effects for further investigation. A particular combination of runs defines an experimental design. The possible settings of each independent variable in the *n* dimensional space are called levels.

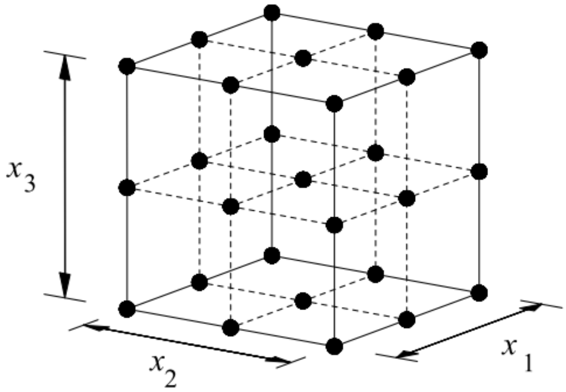

Figure-1: A 3^3full factorial design (27 points)

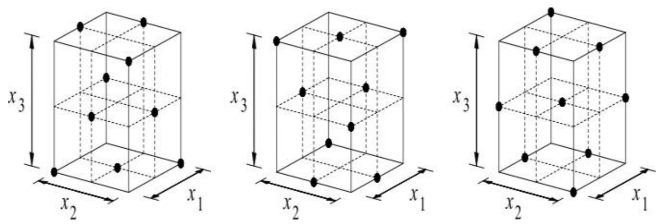

Figure -2: Three one-third fractions of the 3^3 design

If each of the variables is defined at only the lower and upper bounds (two levels), the experimental design is called 2^nfull factorial. Similarly, if the midpoints are included, the design is called 3^n full factorial and shown in Figure-1.

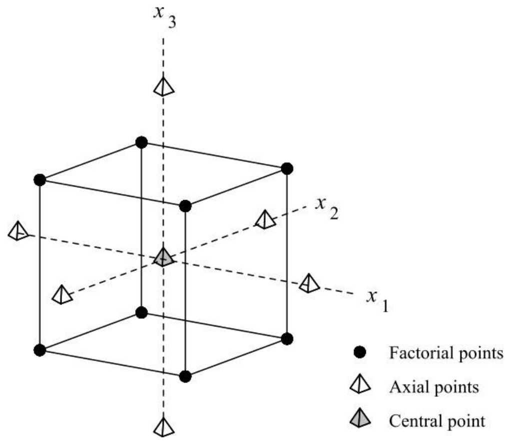

Figure-3 Central composite design for 3 design variables at 2 levels

4. DATA PREPROCESSING

Let the original reference sequence and comparability sequences be represented as Data preprocessing normally is required since the range and the unit in one data sequence can be different from those in another sequence. Correspondingly, data preprocessing is necessary when the sequence scatter range is too large, or the target sequence directions are different. Data preprocessing involves the transfer of the original sequence to a comparable sequence. Depending on the data sequence characteristics, some methods of data preprocessing are available for the grey relational analysis. If the target value of the original sequence is infinite, then it has a “the larger the better” characteristic. It means, the overall gray relational grade converts the multi-response (multi-gray relational grades) optimization problem into a single response (overall gray relational grade) optimization problem, with the objective function as maximization of overall grey relational grade. Hence, the overall grey relational grades rank the experimental runs as; the experimental run having higher grey relational grade refers as that corresponding combination of variables is closer to the optimal values. The optimal parametric combination is then evaluated by maximizing the overall grey relational grade.

5. IMPLEMENTATION OF PROPOSED METHODOLOGY

5.1 Experimental Details

In this work, depth of cut, feed and cutting speed are considered as the control variables and MRR and cutting temperature as the output responses. In order to reduce the number of experimental runs, experiments were planned based on design of experiments (DoE). Central composite design with 27 experiments was selected. Table-1, lists the machining conditions and Table-2, lists the feasible values of each process variable. Experiments are conducted on a precision CNC milling machine model BFW AGNI 45.

Hardened steel EN31 plate of size150x100x10 mm with ≈ 60 HRC is considered as the work piece material and TaeguTecmake M9810048402 carbide milling turning inserts and with SCRM90TP45016R18DTGNL milling cutter with 4 cutting inserts was used in machining. For each experimental run, the metal removal rate is calculated by the weight loss method. Each experiment is run for a fixed length of 75 mm length.

During each experiment the cutting temperature was measured by an IR Thermometer by maintaining 1.5 meter distance between the thermometer and cutting tool edge. Each experiment was repeated for three times and the average of the measures values were considered as the final response values. Table-3, represents the matrix of experimental values. The Figure-4, shows the experimental setup. The Figure -5 and 6 show the cutting tools & cutter and the IR Thermometer for temperature measurement used in experimentations. The recorded temperature using IR thermometer during the 10th experiment is shown in The Figure-7.

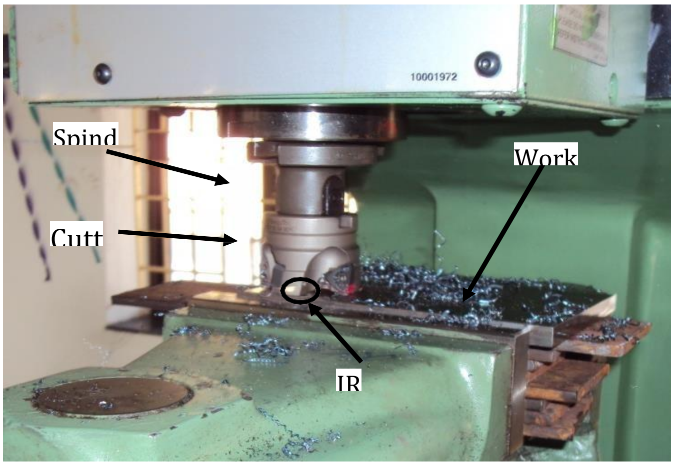

Figure-4 Experimental setup

Figure-5 Cutting inserts and the milling cutter

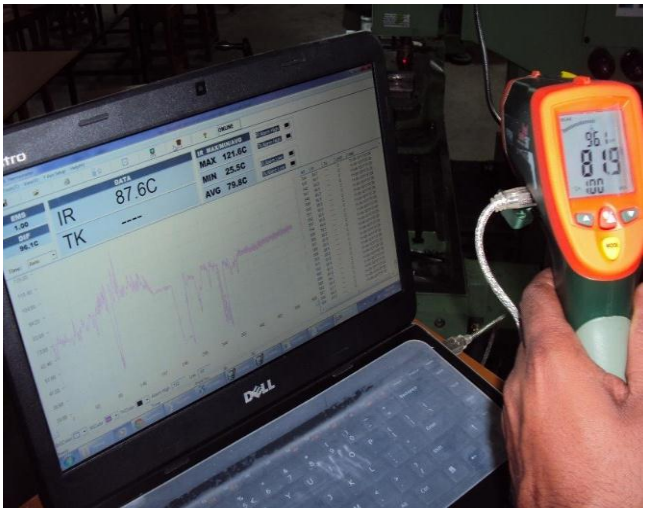

Figure-6 IR Thermometer

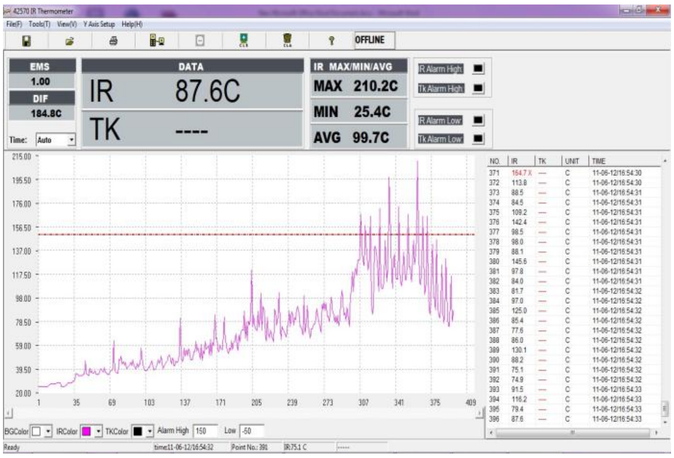

Figure-7 Recorded temperature using IR Thermometer during the 10th experiment

Table -1: Machining conditions

(a)	Work piece material:	EN 31 hardened to about 60HRC
(b)	Chemical composition:	C-0.43%, Si-0.26%, Mn-0.58%, Cr-1.17%, Ni-
		1.35%, Mo-0.25%, P-0.028%, S-0.036%
(c)	Work piece dimensions:	150x100x10 mm
(d)	Location of work piece:	Between chuck over the table
(e)	Temperature measurement	IR Thermometer
		Model:42570, Make: EXTECH Instruments. Range : up to 2000 deg. C
(f)	Milling Machine	Model : AGNI 45
		Make : BFW
(g)	Milling Cutter	Model : SCRM90TP45016R18DTGNL

		Make :TaeguTec
(h)	Cutting Inserts	Designation : M9810048402
		Make : TaeguTec
(i)	Machining Type	Dry Machining

Table -2: Control factors and their levels

no.	Parameter	Units	Notation	-1	0	1
1	Depth of cut	mm	X1	0.1	0.2	0.3
2	Feed Rate	mm/tooth	X2	0.1	0.3	0.5
3	Cutting speed	Rpm	X3	120	180	240

Table -3: Central composite design with corresponding output values of MRR and TC

Exp. No.	DOC	F	Vc Rpm	MRR	TC.
	mm	mm/tooth		grm/min	OC
1	0.1	0.1	120	0.00545	169.05
2	0.1	0.1	180	0.00854	181.29
3	0.1	0.1	240	0.01055	245.94
4	0.1	0.3	120	0.00848	247.29
5	0.1	0.3	180	0.01154	278.44
6	0.1	0.3	240	0.01358	344.44
7	0.1	0.5	120	0.02645	419.28
8	0.1	0.5	180	0.02954	460.62
9	0.1	0.5	240	0.03152	539.59
10	0.2	0.1	120	0.02345	210.2
11	0.2	0.1	180	0.02654	231.36
12	0.2	0.1	240	0.02855	286.01
13	0.2	0.3	120	0.02645	276.39
14	0.2	0.3	180	0.02954	307.54
15	0.2	0.3	240	0.03156	373.54
16	0.2	0.5	120	0.04445	435.84
17	0.2	0.5	180	0.04754	477.17
18	0.2	0.5	240	0.04951	556.14
19	0.3	0.1	120	0.04845	277.42
20	0.3	0.1	180	0.05154	299.66
21	0.3	0.1	240	0.05353	354.31
22	0.3	0.3	120	0.05145	333.71
23	0.3	0.3	180	0.05454	364.86
24	0.3	0.3	240	0.05652	430.86
25	0.3	0.5	120	0.06945	480.62
26	0.3	0.5	180	0.07254	391.95
27	0.3	0.5	240	0.05454	580.92

Table -4: ANOVA for Response Surface TC Quadratic Model

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	3.88E+05	9	4.32E+04	201.01	< 0.0001	significant
x1	9.08E+03	1	9.08E+03	42.291	< 0.0001	
x2	6.34E+04	1	6.34E+04	295.18	< 0.0001	
x3	2.17E+04	1	2.17E+04	101.09	< 0.0001	
x1x2	1.03E+03	1	1.03E+03	4.7836	0.043	
x1x3	6.51E+01	1	6.51E+01	0.303	0.5891	
x2 x3	8.96E+02	1	8.96E+02	4.175	0.0568	
x1x1	1.29E+03	1	1.29E+03	6.013	0.0253	
x2 x2	1.07E+04	1	1.07E+04	49.784	< 0.0001	
x3 x3	3.17E+02	1	3.17E+02	1.4759	0.241	
Residual	3.65E+03	17	2.15E+02			
Lack of Fit	7.98E+03	5	1.80E+03	8.1417	0.45	not significant
R-Squared			0.9907			
Adj R-Squared			0.985763			

Table -5: ANOVA for Response Surface MRR Reduced Quadratic Model

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	9.50E-03	9	1.06E-03	95.718	< 0.0001	significant
x1	2.26E-03	1	2.26E-03	204.6	< 0.0001	
x2	5.86E-04	1	5.86E-04	53.07	< 0.0001	
x3	7.56E-06	1	7.56E-06	0.6851	0.4193	
x1x2	3.46E-05	1	3.46E-05	3.1387	0.0944	
x1x3	3.60E-05	1	3.60E-05	3.2626	0.0886	
x2 x3	3.77E-05	1	3.77E-05	3.4136	0.0821	
x1x1	3.43E-05	1	3.43E-05	3.1077	0.0959	

x2 x2	1.98E-04	1	1.98E-04	17.931	0.0006	
x3 x3	1.99E-05	1	1.99E-05	1.8051	0.1967	
Residual	9.20E+03	6	1.53E+03			
Lack of Fit	8.98E+03	5	1.80E+03	8.1417	0.2597	not significant
R-Squared			0.980648			
Adj R-Squared			0.970403			

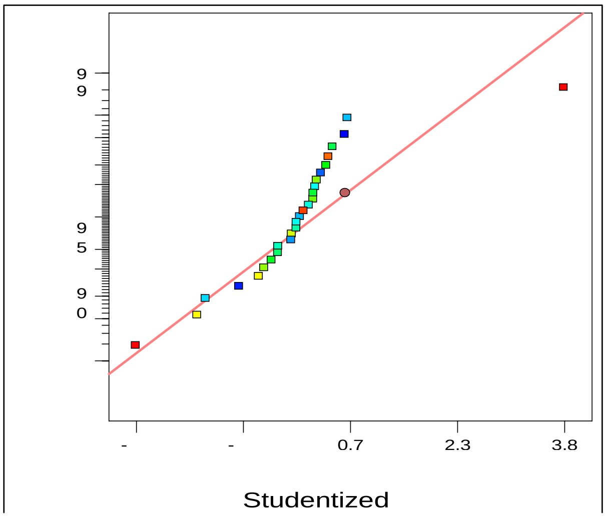

Figure-7 Normal probability plot of the residuals for TC

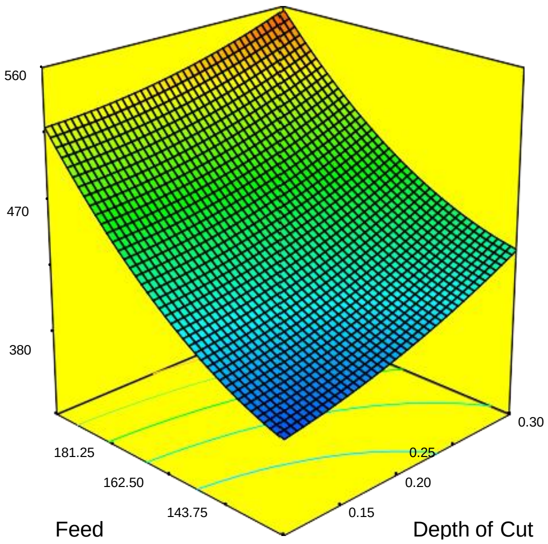

Figure-8 Interactive effect of depth of cut and feed on Temperature

The estimated interactive response surface for temperature according to the design parameters of depth of cut and feed at the middle level of speed is shown in Figure-8. This figure displays that, the cutting temperature is lower at the lower levels of depth of cut and feed and hasincreasing nature to the increased levels of both depth of cut and feed. When the depth of cut and feed are increased together, the increased volume of the work piece material will be fed against the tool tip and hence the cutting temperature gets increased.

The estimated interactive response surface for temperature according to the design parameters of depth of cut and speed at the middle level of feed is shown in Figure-9. This figure displays that, the cutting temperature is lower at the lower levels of depth of cut and speed and hasincreasing nature to the increased levels of both depth of cut and feed.

As the depth of cut and speed are increased together, the chip flow velocity gets increased over the cutting inserts and hence the cutting temperature gets increased.

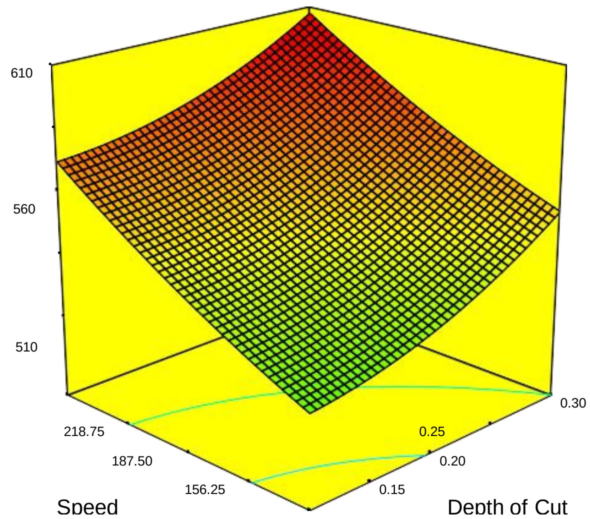

Figure-9 Interactive effect of depth of cut and speed on Temperature

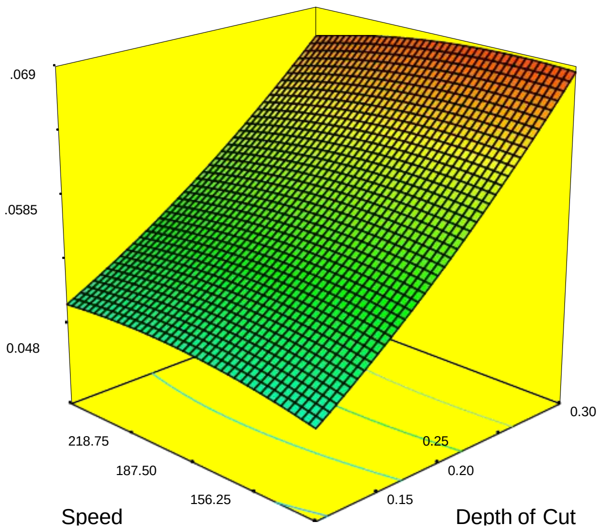

Figure-9 Interactive effect of depth of cut and speed on MRR

The estimated interactive response surface for MRR according to the design parameters of depth of cut and speed at the middle level of feed is shown in Figure-10. This figure displays that the value of MRR increases with increase in depth of cut and cutting speed.

The reason is, at higher depth of cut and higher cutting velocities the rate of metal fed against the cutting insert is more and hence increased MRR.

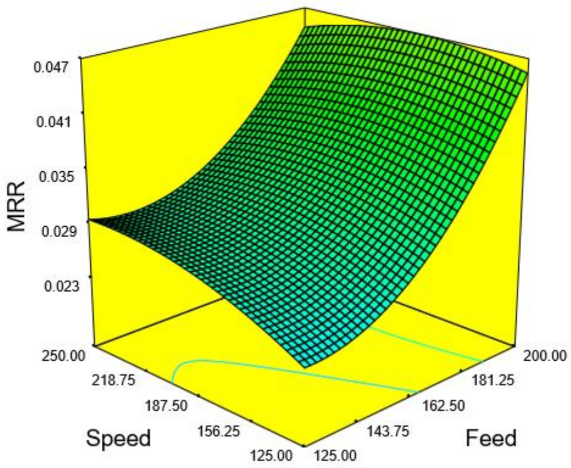

Figure-10 Interactive effect of feed and speed on MRR

Table -6: Normalized values and grey relational coefficients

Exp. No.	Normalized Values		Doi	
	MRR grm/min	Temp. OC	MRR grm/min	Temp. OC
1	0	1	1	0
2	0.0461	0.9711	0.9539	0.0289
3	0.0761	0.8182	0.9239	0.1818
4	0.0452	0.815	0.9548	0.185
5	0.0908	0.7413	0.9092	0.2587
6	0.1213	0.5853	0.8787	0.4147
7	0.3132	0.4083	0.6868	0.5917
8	0.3593	0.3105	0.6407	0.6895
9	0.3888	0.1238	0.6112	0.8762
10	0.2685	0.9052	0.7315	0.0948
11	0.3145	0.8527	0.6855	0.1473
12	0.3445	0.7234	0.6555	0.2766
13	0.3132	0.7462	0.6868	0.2538
14	0.3593	0.6725	0.6407	0.3275
15	0.3894	0.5165	0.6106	0.4835
16	0.5817	0.3691	0.4183	0.6309
17	0.6277	0.2714	0.3723	0.7286
18	0.6571	0.0847	0.3429	0.9153
19	0.6413	0.7437	0.3587	0.2563
20	0.6874	0.6912	0.3126	0.3088
21	0.7171	0.5619	0.2829	0.4381
22	0.6861	0.6106	0.3139	0.3894
23	0.7321	0.537	0.2679	0.463
24	0.7617	0.3809	0.2383	0.6191
25	0.9545	0.2633	0.0455	0.7367
26	1.0006	0	-0.0006	1
27	0.7321	0.0261	0.2679	0.9739

Table -7: Gray relational grade and Ranks

Exp. No.	xi (k)		gi	Rank
	MRR grm/min	Temp. OC		
1	0.3333	1	0.6667	2
2	0.3439	0.9453	0.6446	4
3	0.3511	0.7333	0.5422	14
4	0.3437	0.7299	0.5368	16
5	0.3548	0.6591	0.5069	18
6	0.3626	0.5466	0.4546	24
7	0.4213	0.458	0.4397	25
8	0.4383	0.4204	0.4293	26
9	0.45	0.3633	0.4066	27
10	0.406	0.8407	0.6233	5
11	0.4218	0.7724	0.5971	8
12	0.4327	0.6439	0.5383	15
13	0.4213	0.6633	0.5423	12
14	0.4383	0.6042	0.5213	17
15	0.4502	0.5084	0.4793	22
16	0.5445	0.4421	0.4933	20
17	0.5732	0.407	0.4901	21
18	0.5932	0.3533	0.4732	23
19	0.5823	0.6612	0.6217	6
20	0.6153	0.6182	0.6167	7
21	0.6386	0.533	0.5858	10
22	0.6143	0.5622	0.5882	9
23	0.6512	0.5192	0.5852	11
24	0.6772	0.4468	0.562	12
25	0.9166	0.4043	0.6604	3
26	**1.0012**	**0.333**	**0.667**	**1**
27	0.6512	0.3392	0.4952	19

Table -8: Optimal values of machining responses and the corresponding input parameters (26thExperiment)

Exp. No.	**DOC**	**F**	**Vc Rpm**	**MRR**	**TC.**
	mm	**mm/tooth**		**grm/min**	**OC**
1	0.1	0.1	120	0.00545	169.05
2	0.1	0.1	180	0.00854	181.29
3	0.1	0.1	240	0.01055	245.94

4	0.1	0.3	120	0.00848	247.29
5	0.1	0.3	180	0.01154	278.44
6	0.1	0.3	240	0.01358	344.44
7	0.1	0.5	120	0.02645	419.28
8	0.1	0.5	180	0.02954	460.62
9	0.1	0.5	240	0.03152	539.59
10	0.2	0.1	120	0.02345	210.2
11	0.2	0.1	180	0.02654	231.36
12	0.2	0.1	240	0.02855	286.01
13	0.2	0.3	120	0.02645	276.39
14	0.2	0.3	180	0.02954	307.54
15	0.2	0.3	240	0.03156	373.54
16	0.2	0.5	120	0.04445	435.84
17	0.2	0.5	180	0.04754	477.17
18	0.2	0.5	240	0.04951	556.14
19	0.3	0.1	120	0.04845	277.42
20	0.3	0.1	180	0.05154	299.66
21	0.3	0.1	240	0.05353	354.31
22	0.3	0.3	120	0.05145	333.71
23	0.3	0.3	180	0.05454	364.86
24	0.3	0.3	240	0.05652	430.86
25	0.3	0.5	120	0.06945	480.62
26	**0.3**	**0.5**	**180**	**0.07254**	**392**
27	0.3	0.5	240	0.05454	580.92

6. CONCLUSIONS

- This work aimed to develop the empirical models and investigate the optimal machinabilityparameters of milling process during machining EN 31 tool steel.
- In this consequence, milling experiments were conducted on vertical milling milling Centre based on central composite design with 27 experiments.
- The response surface methodology was adopted to develop the mathematical models for the responses and ANOVA is used to check the adequacy of the developed models andwere found that the developed second order models can explain the variation in the temperature up to the extent of 98.06% and 99.07%. Then these experimentally measured values were carriedto the optimization. GRA was successfully implemented to the measured experimental runs.
- The resulted optimal values of the milling process were listed. Hence, an operator can easily find out the optimal marching conditions without compromising at either metal removal rate or the cost of tooling with this investigation.

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