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Effectiveness of Milling Parameter on Surface Roughness and Metal Removal Rate

Kulbhushan Bhagat, Deepak Kumar, Antariksha Verma

***Abstract* — Metal machining have been a very important process in Production. Machining Conditions play a vital role in estimating the performance of machining operations. It have long been recognized that the machining conditions, such as cutting speed, feed and depth of cut affect the performance of the operation in great extent. These parameters must be selected to optimize the quality of machining operations. It can be achieved by mathematical modeling of performance as a function of machining conditions using design of experiments (DOE).**

The objective of the present work is to analyze the effects of the machining parameters in turning on the surface roughness parameters of AISI 52100 steel. It is quietly used in bearing in rotating machinery. The Design of experiments based on response surface methodology with three numeric factors (cutting speed, feed rate and depth of cut) five level central composite rotatable designs have been used to develop relationships for predicting Surface Roughness and Material Removal Rate.

The surface roughness parameters were measured using surface roughness tester (Surf coder SE 1200) The "Design Expert" software has been used for the analysis. A quadratic model and linear Model have been developed which indicates that interaction is present between the machining parameters (speed, feed, depth of cut). Model adequacy tests were conducted using ANOVA table and the effects of various parameters were investigated and presented in the form of contour plots and 3D surface graphs. Numerical optimization was carried out considering all the input parameters within range so as to minimize the surface roughness. The optimal values obtained are cutting speed 200.00 m/min, feed 0.35 mm/rev, depth of cut 0.35 mm. The findings of this study would be beneficial to manufacturing industries where surface finishing plays a very important role

***Index Terms*— Cutting Speed (CS), Design of Experiments (DOE), Feed Rate, Depth of Cut, Surface Roughness measurement.**

I. INTRODUCTION

A. Background

In machining operation, the quality of surface finish is an important requirement in manufacturing engineering. It is characteristic that could influence the performance of mechanical parts and the production cost. Various failures, some time catastrophic, leading to high cost, have been attributed to the surface finish of the components in question. For these reasons there have been research developments with the objective of optimizing the cutting condition to obtain a surface finish.

Milling is principally metal cutting performed with a rotating, multi-edge cutting tool which performs programmed feed movements against a work piece in almost any direction. It is this cutting action that makes milling such an efficient and versatile machining method. Each of the cutting edges removes a certain amount of metal, with a limited in-cut engagement, making chip formation and evacuation a secondary concern. Most frequently still, milling is applied to generate flat faces – as in face milling - but other forms and surfaces are increasing steadily as the number of five-axis machining centres and multi-task machines grow. Previous studies proved the significant impact of depth of cut, machining speed, and rake angles on surface roughness. The combination of both of these factors suggests a significant weight in the relationship.

B. Problem Statement

The determination of optimal cutting condition for specified surface roughness and accuracy of product are the key factors in the selection of machining process. To reduce the problem of vibration and ensure that the desired shape and tolerance are achieved, extra care must be taken with production planning and in the preparations for the machining of a work-piece.

Researches have been done to improve cutting tool material, tool geometry and cutting parameter to optimize the machining process. The cutting parameter such as cutting speed, feed rate and depth of cut are the most important factor has to be considering in milling operation. The wrong selection of combination cutting parameter will lead to the bad cutting condition e.g. vibration that effect the poor surface finish. Different work piece material with different property and microstructure give different effect to the cutting tool performance.

In milling operation, the performances of cutting tools are depending on a few cutting conditions and parameters. The proper selection of feed rate has direct effect to the product surface roughness. Milling process by maximizing cutting speed and depth of cut will optimize the cutting process and minimize the production cost. The tool life, machined surface integrity and cutting forces are directly dependent on cutting parameters and will determine the cutting tool performances. The study of surface roughness form will resolve the characteristic and phenomena happening during the machining process.

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C. Objective of the Study

The study was carried out to evaluate the effects of different cutting parameters on work piece for surface profile with milling operation, where the surface roughness values were statistically comparable and to find out the optimum cutting condition by analyzing the different cutting parameter's value to get the lowest surface roughness in milling a die steel (d3 type) solid plates

Objective of this study are following:

• To evaluate the effects of different process parameter on surface roughness.

• To develop a mathematical model for predicting surface roughness for milling operation by using design of experiment approach.

D. Significance of the Study

Machining operations tend to leave characteristic evidence on the machined surface. They usually leave finely spaced micro-irregularities that form a pattern known as surface finish or surface roughness. The quality of the finished product, on the other hand, relies on the process parameters; surface roughness is, therefore, a critical quality measure in many mechanical products.

Severe acoustic noise in the working environment frequently occurs as a result of dynamic motion between the cutting tool and the work piece. In order to achieve sufficient process stability, the metal removal rate is often reduced or the cutting tool changed. But as productivity is normally a priority in manufacturing, this is the wrong route to go.

Instead the method of being able to machine at high rates should be examined. For these reason there have been research development with the objective of optimizing cutting condition to obtain a surface finish with making the process more stable. To study the optimum cutting condition used during cutting process will reduce the machining cost by reducing of changing the cutting tool and to increase the metal removal rate.

II. Theory of Metal Cutting

Metal cutting is one of the most significant manufacturing processes in the area of material removal. Metal cutting can be defined as the removal of metal from a work-piece in the form of chips in order to obtain a finished product with desired attributes of size, shape, and surface roughness. Drilling, sawing, milling, and milling are some of the processes used to remove material to produce specific products of high quality.

The theory of metal cutting is very well established. However, some aspects have gone through revision when the experimental results showed the new parameters involved in metal cutting. Many new alloys have also been developed to react to today applications. As a result, there will be always a need for continuous research and improvement to tool materials, cutting conditions and parameters to optimize the output.

Finnie (1956) first reported that the earliest documented works in metal cutting was done by Cocquilhat in 1851. Taylor in 1906 was investigated the effect of tool material during cutting. He was formulated the famous Taylor"s tool life equation (VTn = C) and the equation is still valid until now and was used by researchers as a basis to show the performance of a given tool. The mechanics of metal cutting are very complex. Researchers such as Pispanen, Merchant, Kobayashi and Thomsen considered metal cutting mechanism in a thin film while Palmer, Oxley, Okushima and Hitomi considered them based on the thick deformation region (Boothroyd and Knight., 1989).

Surface Roughness in Milling Operation

Research showed that using short tool length always provides good surface roughness and that only slight improvement on surface roughness can be achieved by properly controlling the cutting parameters and/or the type of boring bar used. The dimension boring bar length is used 65.09 mm and 95.25 mm with considered the tool nose radius for insert. This experiment did not consider the diameter of boring bar in cutting parameter where the two different boring bars were used a standard solid bar and damped bar with damping ratio 3%. (Yves Beauchamp, 1996).

Boring bars for single-point milling on a lathe are particularly susceptible to chatter and have been the subject of numerous studies (O.B. Abouelatta, 2001). This paper has discussed the possibility of predicting roughness parameter based on cutting parameter and tool vibration during external milling process. This paper is to find a correlation between surface roughness and cutting vibration in milling and to derive mathematical models for predicted roughness parameters based on cutting parameter and machine tool vibration. In this experiment the tool overhang was used are 38 mm and 70 mm. The results showed the maximum roughness parameter depend greatly on the rotational cutting speed and workpiece diameter.

J. Paulo Davim (2001) had used a Taguchi method in research development for optimizing the cutting condition to obtain in surface finish by executing these experiment and analyzing data, in order to obtain information about behavior of given process. Research showed that the velocity has greater influence on the roughness followed by the feed where the depth of cut has no significant influence on the roughness. The interaction cutting velocity/feed is the most important of the other analyzed parameters. The remaining parameters, cutting velocity/depth of cut and feed/depth of cut have no significant influence on the surface roughness.

Friction damper has been found successful to prevent high frequency chatter occurring at more than 10,000Hz, and causing problem of reduced tool life in fine boring operation. Evita Edhi (2001) had study on stabilization of high frequency chatter vibration in fine boring by friction damper. The study was to analyze the effectiveness and characteristics of the proposed damper in preventing chatter vibration, which occurs at high frequency during boring operation with using different diameter and tool length. To achieve the objective, cutting tests have been conducted in boring operation analogues to the one having high frequency chatter problem in the plant, as well as theoretical and experimental analyses of energy dissipation of the proposed damper. Boring bar diameter 16 mm and 13 mm was used with different tool length. The cutting test repeated twice for each boring tool with different tool length. The result showed that the damper has been found to be more effective for tools that generate chatter vibration at higher frequencies. From the physical size limit of the damper mass for attachment to the main structure, friction damper is practical for tools which vibrate at frequencies higher than 5,000Hz.

M.Y. Noordin et al. (2003) study on the performance of a multilayer tungsten carbide tool was described using response surface methodology (RSM) when milling AISI 1045 steel. The factors investigated were cutting speed, feed and the side cutting edge angle (SCEA) of the cutting edge performed with constant depth of cut and under dry cutting conditions. The main cutting force, i.e. the tangential force and surface roughness were the response variables investigated. The experimental plan was based on the face centered, central composite design (CCD). The experimental results indicate that the proposed mathematical models suggested could adequately describe the performance indicators within the limits of the factors that are being investigated.

Suresh et al. (2002) focused on machining die steel (d3 type) by TiN-coated tungsten carbide (CNMG) cutting tools for developing a surface roughness prediction model by using Response Surface Methodology (RSM). Genetic Algorithms (GA) used to optimize the objective function and compared with RSM results. It was observed that GA program provided minimum and maximum values of surface roughness and their respective optimal machining conditions.

Ahmed (2006) developed the methodology required for obtaining optimal process parameters for prediction of surface roughness in Al milling. For development of empirical model nonlinear regression analysis with logarithmic data transformation was applied. The developed model showed small errors and satisfactory results. The study concluded that low feed rate was good to produce reduced surface roughness and also the high speed could produce high surface quality within the experimental domain.

Lin et al. (2001) adopted an abdicative network to construct a prediction model for surface roughness and cutting force. Once the process parameters: cutting speed, feed rate and depth of cut were given; the surface roughness and cutting force could be predicted by this network. Regression analysis was also adopted as second prediction model for surface roughness and cutting force. Comparison was made on the results of both models indicating that adductive network was found more accurate than that by regression analysis.

Feng and Wang (2002) investigated for the prediction of surface roughness in finish milling operation by developing an empirical model through considering working parameters: work piece hardness (material), feed, cutting tool point angle, depth of cut, spindle speed, and cutting time. Data mining techniques, nonlinear regression analysis with logarithmic data transformation were employed for developing the empirical model to predict the surface roughness.

Kirby et al. (2004) developed the prediction model for surface roughness in milling operation. The regression model was developed by a single cutting parameter and vibrations along three axes were chosen for in-process surface roughness prediction system. By using multiple regression and Analysis of Variance (ANOVA) a strong linear relationship among the parameters (feed rate and vibration measured in three axes) and the response (surface roughness) was found. The authors demonstrated that spindle speed and depth of cut might not necessarily have to be fixed for an effective surface roughness prediction model.

Pal and Chakraborty (2005) studied on development of a back propagation neural network model for prediction of surface roughness in milling operation and used die steel (d3 type) work-pieces with high speed steel as the cutting tool for performing a large number of experiments. The authors used speed, feed, depth of cut and the cutting forces as inputs to the neural network model for prediction of the surface roughness. The work resulted that predicted surface roughness was very close to the experimental value.

Al-Ahmari (2007) developed empirical models for tool life, surface roughness and cutting force for milling operation. The process parameters used in the study were speed, feed, depth of cut to develop the machinability model. The methods used for developing aforesaid models were Response Surface Methodology (RSM) and neural networks (NN).

Sahoo et al. (2008) studied for optimization of machining parameters combinations emphasizing on fractal characteristics of surface profile generated in CNC milling operation. The authors used L27 Taguchi Orthogonal Array design with machining parameters: speed, feed and depth of cut on three different work piece materials viz. aluminum, die steel (d3 type) and brass. It was concluded that feed rate was more significant influencing surface finish in all three materials. It was observed that in case of die steel (d3 type) and aluminum feed showed some influences while in case of brass depth of cut was noticed to impose some influences on surface finish. The factorial interaction was responsible for controlling the fractal dimensions of surface profile produced in CNC milling.

Reddy et al. (2008) adopted multiple regression model and artificial neural network to deal with surface roughness prediction model for machining of aluminium alloys by CNC milling. For judging the efficiency and ability of the model in surface roughness prediction the authors used the percentage deviation and average percentage deviation. The study of experimental results showed that the artificial neural network was efficient as compared to multiple regression models for the prediction of surface roughness.

Thamma (2008) constructed the regression model to find out the optimal combination of process parameters in milling operation for Aluminium 6061 work pieces. The study highlighted that cutting speed, feed rate, and nose radius had a major impact on surface roughness. Smoother surfaces could be produced when machined with a higher cutting speed, smaller feed rate, and smaller nose radius.

Shetty et al. (2008) discussed the use of Taguchi and response surface methodologies for minimizing the surface roughness in milling of discontinuously reinforced aluminum composites (DRACs) having aluminum alloy 6061 as the matrix and containing 15 vol. % of silicon carbide particles of mean diameter 25µm under pressured steam jet approach. The measured results were then collected and analyzed with the help of the commercial software package MINITAB15.

The experiments were conducted using Taguchis experimental design technique. The matrix of test conditions included cutting speeds of 45, 73 and 101 m/min, feed rates of 0.11, 0.18 and 0.25 mm/rev and steam pressure 4, 7, 10 bar while the depth of cut was kept constant at 0.5 mm. The effect of cutting parameters on surface roughness was evaluated and the optimum cutting condition for minimizing the surface roughness was also determined finally. A second order model was established between the cutting parameters and surface roughness using response surface methodology. The experimental results revealed that the most significant machining parameter for surface roughness was steam pressure followed by feed. The predicted values and measured values were fairly close, which indicated that the developed model could be effectively used to predict the surface roughness in the machining of DRACs.

III. DESIGN OF EXPERIMENT

Design of Experiment (DOE) is a useful method in identifying the significant parameters and in studying the possible effect of the variables during the machining trials. This method also can developed experiment between a ranges from uncontrollable factors, which will be introduced randomly to carefully controlled parameters. The factors must be either quantitative or qualitative. The range of values for quantitative factors must be decided on how they are going to be measured and the level at which they will be controlled during the trials. Meanwhile, the qualitative factors are parameters that will be determined discretely.

For this experiment full factorial is used as a tool for the overall research design and analysis. Design of experiment includes determining controllable factors and the levels to be investigate. While, analysis of results is to determine the best possible factor combination from individual factor influences. Lastly, confirmation tests would be carried out as a proof to the optimum results studied

The resolution will be found in each fractional factorial on the two-level factorial design (State ease, Inc, 2000). Designs resolutions III, IV, and V are particularly important (Myers and Montgomery, 2002) and the definitions of these design are given below.

1) Resolution III designs. These are designs in which no main effects are aliased with any other main effect, but main effect aliased with two factor interactions and two factor interaction may be aliased with each other
2) Resolution IV designs. These are designs in which no main effect is aliased with any other main effect or with any two factor interaction, but two factor interactions are aliased with each other.
3) Resolution V designs. These are designs in which no main effect or two factor interactions are aliased with any other main effect or two factor interaction, but two factors interactions are aliased with three factor interactions.

It is preferred to employ fractional designs that have the highest possible resolution. The higher the resolution, the less restrictive the assumptions that are required regarding which interactions are negligible in order to obtain a unique interpretation of data.

In this study, total 28 sets of experiment are sorted using the two levels of full factorial design. Fourteen combinations of cutting speed, feed and depth of cut .With one nose radius, fourteen experiments constitute 2^3factorial point, six center point and same with other nose radius. The software used was Design Expert 8.

This experiment design will include all the possible combinations factors at two levels which are called low and high value for each parameter. The notation used to denoted this levels is "plus" for high value and "minus" for low value. The arrangements of the factors for this project will be based on Design Expert software.

This program will randomly choose the combination of factors to run the experiment. This software also will automatically analyze all the experimental results in order to investigate the influence of machining parameters on the surface integrity of the work piece material. The results of the experiments were presented as the combination of five factors with one response surface roughness.

The version 8 of the Design Expert software was used to develop the experimental plan for full factorial design.

After analyzing each response, multiple response optimization was performed, either by inspection of the interpretation plots, or with the graphical and numerical tools provided for this purpose.

A. Test for Significance of the Regression Model

This test is performed as an ANOVA procedure by calculating the *F*-ratio, which is the ratio between the regression mean square and the mean square error. The *F*-ratio, also called the variance ratio, is the ratio of variance due to the effect of a factor (in this case the model) and variance due to the error term. This ratio is used to measure the significance of the model under investigation with respect to the variance of all the terms included in the error term at the desired significance level, α. A significant model is desired.

B. Test for Significance on Individual Model Coefficients

This test forms the basis for model optimization by adding or deleting coefficients through backward elimination, forward addition or stepwise elimination/addition/exchange. It involves the determination of the *P*-value or probability value, usually relating the risk of falsely rejecting a given hypothesis. For example, a "Prob. > *F*" value on an *F*-test tells the proportion of time you would expect to get the stated *F*-value if no factor effects are significant. The "Prob. > *F*" value determined can be compared with the desired probability or α-level. In general, the lowest order polynomial would be chosen to adequately describe the system.

C. Test for Lack-of-Fit

As replicate measurements are available, a test indicating the significance of the replicate error in comparison to the model dependent error can be performed. This test splits the residual or error sum of squares into two portions, one which is due to pure error which is based on the replicate measurements and the other due to lack-of-fit based on the model performance. The test statistic for lack-of-fit is the ratio between the lack-of-fit mean square and the pure error mean square.

As previously, this *F*-test statistic can be used to determine as to whether the lack-of-fit error is significant or otherwise at the desired significance level, α. Insignificant lack-of-fit is desired as significant lack-of-fit indicates that there might be contributions in the regressor response relationship that are not accounted for by the model.

Additionally, checks need to be made in order to determine whether the model actually describes the experimental data. The checks performed here include determining the various coefficient of determination, *R*2. These *R*2 coefficients have values between 0 and 1. In addition to the above, the adequacy of the model is also investigated by the examination of residuals.

The residuals, which are the difference between the respective, observe responses and the predicted responses are examined using the normal probability plots of the residuals and the plots of the residuals versus the predicted response. If the model is adequate, the points on the normal probability plots of the residuals should form a straight line. On the other hand the plots of the residuals versus the predicted response should be structure less, that is, they should contain no obvious patterns.

The others plots to be checked are outliers-t plot which is useful to check whether a run is consistent with the others. Box-Cox plot which is a tool to determine the most appropriate power transformation was applied to the response data. After analyzing all the model statistics and plots, the model graphs are generated for interpretation.

IV. METHODOLOGY

A. Introduction

A methodology was developed to investigate the effect of process parameter on surface roughness produced by milling operation. In this study, two different sizes of tools having different nose radius are used as a categorical parameter to be considered. The cutting variables as cutting speed, feed rate and depth of cut are independent variables that includes in machining parameter. The output that has to be study is surface roughness produced by milling operation.

In this study, dry milling condition was applied to cut the work-piece. With using the appropriate machining parameter so that the experiment would simulate the conditions according to the standard operation and requirements.

B. Research Method and Procedures

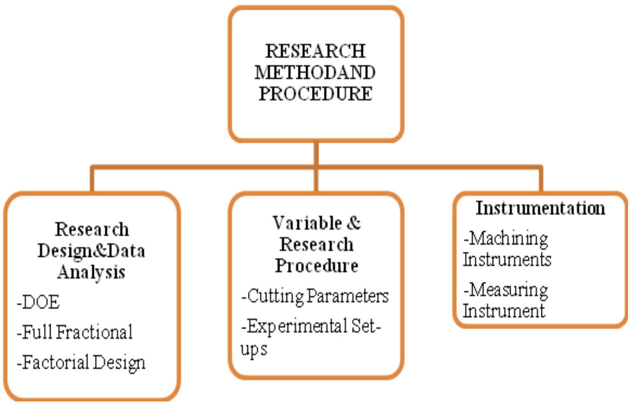

Fig.7 Research method and sequences

C. Measurement Equipment (Surface Roughness Measurement)

For measuring the centerline average (CLA) surface roughness values (*Ra*) of finish-turned work-pieces Surf coder SE 1200 was used and the measurements are repeated three times. The cutoff length is taken as 0.8mm.

D. Work piece material:

Type D3 steel is oil-quenched; though small sections can be gas quenched after autenitiation using vacuum. As a result, tools made with type D3 steel tend to be brittle during hardening. The D3 steels contain 1.5 to 2.35% of carbon and 12% of chromium. Apart from D3 steel all group D steels have 1% Mo and are air hardened

E. Chemical Composition

The following table shows the chemical composition of D3 tool steels.

Materi al	C	Mn	Si	Cr	Ni	W	V	P	S	Cu
Composi-tion %	**2.00-2.35**	**0.60**	**0.60**	**11.00-13.50**	**0.30**	**1.00**	**1.00**	**0.03**	**0.03**	**0.25**

Properties

Physical properties of D3 tool steels are given below:

Physical properties	
Density	7.7 x 1000 kg/m^3
Melting point	1421°C
Mechanical Properties	
Izod impact un notched	28.0 J
Poisson's ratio	0.27-0.30
Elastic modulus	190-210 GPa
Thermal Properties	
Coeff. of Thermal expansion	12 x 10^{-6}/ºC

Dimension_of the material taken has been of rectangular shape, having Length:- 200mm , Breadth:- 50mm , Thickness:-10mm.

F. Tool Cutting Material:

For cutting process in the machining operation the cutting tool material used was Cemented Carbide. Composition of the work piece material:-

C	Mn	Cr	Ni	Si
2.10	**0.40**	**11.50**	**0.31**	**0.30**

G. Machining Parameters

Table.-1: Parameters involved in Milling

VARIABLE	SETUP
Work piece	Die steel (d3 type) (Diameter-32mm, Length:- 40mm)
Tool used (Material)	Cement Carbide
Cutting Speed (m/min)	200-600
Feed Rate (mm/rev)	0.05-0.15
Depth of Cut (mm)	0.60-3.00
Cutting Condition	Wet Condition

H. Cutting Conditions

Cutting condition need to setup in this experiment, to make sure all the experiment run follow according the data given. A full factorial is selected so that all intersection between the independent variables could be investigated. The independent variables are rotational cutting speed, feed rate, and depth of cut. One categorical variable is Tool radius. The levels of the independent variables are show in Table. The level was selected to cover the normal cutting operation.

Table.-2

Cutting Variable	Level	
	1	2
Cutting Speed(m/min)	200	600
Depth of Cut(mm)	0.6	3.00
Feed Rate(mm/rev)	0.05	0.15

I. Work piece Preparation

CNC milling machine is use to cut the Die steel (d3 type) solid bar to the required dimension of work-piece experiment. The total 28 work-pieces need to be prepare for 28 run of experiment. So we used a different work-piece for different cutting condition according data setup in table-2. The work-piece must be clamp in the same length of overhang.

V. Experimentation

A. Introduction

The study was undertaken to investigate the effect of process parameters on surface roughness produced by milling operation when milling solid material Mild Steel. The milling operation was carried out using various cutting parameters by using a different size of cutting tool nose radius. Machining data of surface roughness were tabulated accordingly. A Surface Roughness Tester (Stylus equipment) measuring instrument was used to process the measured profile data. Surface roughness is determined from the vertical stylus displacement produced during the detector traversing over the surface irregularities. The measurement results are displayed digitally/graphically on the touch panel.

For surface roughness analysis, the results from the performance of the milling operation produced as per experimental plan are also shown in Table-3. The average value of surface roughness (Ra) result was input into Design Expert software for further analysis.

Two extreme values were chosen for each of the variable and then, the most accurate required value of the parameters was generated by the software itself.

Table.- 3

Run	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)
1	600	0.05	0.6
2	600	0.15	3
3	200	0.05	0.6
4	200	0.05	3
5	200	0.15	0.6
6	200	0.15	3
7	200	0.05	0.6
8	600	0.15	3
9	600	0.05	3
10	600	0.05	0.6
11	600	0.05	3
12	200	0.15	0.6
13	600	0.05	0.6
14	600	0.15	3

B. Experimental Result

For surface roughness and metal removal rate analysis, the result from the performance of the turning boring operating produced as per experimental plan are also shown in Table-4. The average values of surface roughness (Ra) result were input into Design Expert software for further analysis according to the steps outlined for fractional factorial design. Without performing any transformation on the responses, the revealed design status was evaluated.

Table.-4

Run	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	MRR (mm3/sec)	Rough - ness Ra. (µm)
1	600	0.05	0.6	6.001	1
2	600	0.15	3	48.62	2
3	200	0.05	0.6	9.45	3
4	200	0.05	3	15.23	4
5	200	0.15	0.6	12.11	5
6	200	0.15	3	48.56	6
7	200	0.05	0.6	8.09	7
8	600	0.15	3	51.76	8
9	600	0.05	3	21.59	9
10	600	0.05	0.6	8.12	10
11	600	0.05	3	19.68	11
12	200	0.15	0.6	21.78	12

C. ANOVA Analysis

a) Analysis for metal removal rate (MRR)

Analysis of variance (ANOVA) was conducted on the collected data to investigate the main effect of cutting speed, feed rate and depth of cut together with their two-level interaction effect on MRR as measured by stopwatch.

In order to provide a good model, test for significance of the regression model, test for significance on individual model coefficients and test for lack of fit need to be performed. An ANOVA table regularly used to conclude the tests performed. Table shows the ANOVA table for MRR in milling operation after transformation by Box-Cox plot using natural log (generated by the Design Expert software). The variables from the model were chosen using half normal graph of effect.

Table.-5

ANOVA for selected factorial model

Analysis of variance table [Partial sum of squares]

Source	Sum of squares	df	Mean Square	F Value	P value	
Model	4102.907	3	1367.636	144.4161	< 0.0001	significant
B-feed	1491.871	1	1491.871	157.5348	< 0.0001	

C-depth of cut	2107.246	1	2107.246	222.5156	< 0.0001	
BC	503.7892	1	503.7892	53.19785	< 0.0001	
Residual	113.6413	12	9.470106			
Lack of Fit	10.37759	4	2.594398	0.200992	0.9308	not significant
Pure Error	103.2637	8	12.90796			
Model	4102.907	3	1367.636	144.4161	< 0.0001	significant

Std. Dev.	**3.08**	**R-Squared**	**0.9730**
Mean	23.44	Adj R-Squared	0.9663
C.V. %	13.13	Pred R-Squared	0.9521
PRESS	202.03	Adeq Precision	27.468

As per the result in the Table -6, the model F value of 144.4161 depicts that the model generated is significant. Also the variables that are A, B, C has certain values of P value. As per the rule if the P value of the parameters is less than 0.05, whereas the P value of A and C, which are cutting speed and depth of cut respectively has a P value greater than 0.5. This suggests that the effect on the MRR from the cutting speed and depth of cut is not significant and is negligible.

The P value of Lack of fit is also not significant with a value of 0.9308. It implies that the chances that the model doesn't fit are insignificant.

Also the predicted R value 0.9521 is also in agreement with the adjusted R value which is 0.9663.

Also the adequate precision value is 27.468, which is greater than the desirable value of 4, which justifies the correctness of model. This model can be used to navigate the design space.

The final empirical models in terms of coded factors were presented as follows:

$$\mathbf{MRR = +23.44 + 9.66*B + 11.48*C - 5.61*BC}$$

So, the above equation can be used to find out the value of the MRR and it also shows how the MRR is depending upon the various parameters. This model can be now used to study within the specified limits of the variables.

Now, we start doing the analysis of the MRR value on the different factors.

b) Analysis

The Fig.-10, shows the half normal plot, the extreme right side factor has the highest effect on the response, however as the dots corresponding to the particular factor comes nearer and nearer to the line, it shows these value affects the least.

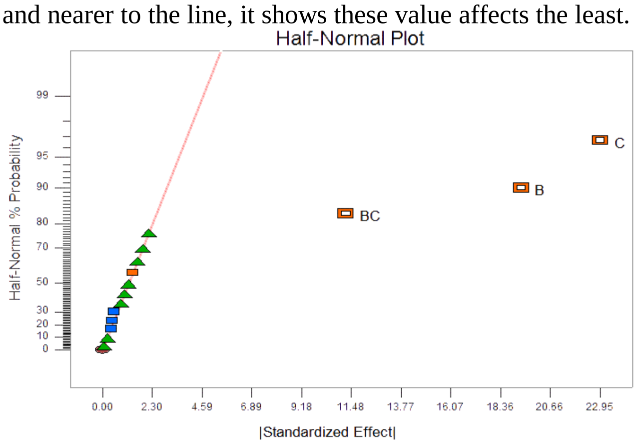

Fig.-10. A half normal plot shows the effectiveness of the factors

The value at the right extreme has the strongest effect on the MRR and keeps on decreasing as it comes nearer and nearer to the line. Fig 11 and 12 are describing the mechanism of error. It can be seen that the points are following evenly on the straight line that shows the errors are evenly distributed.

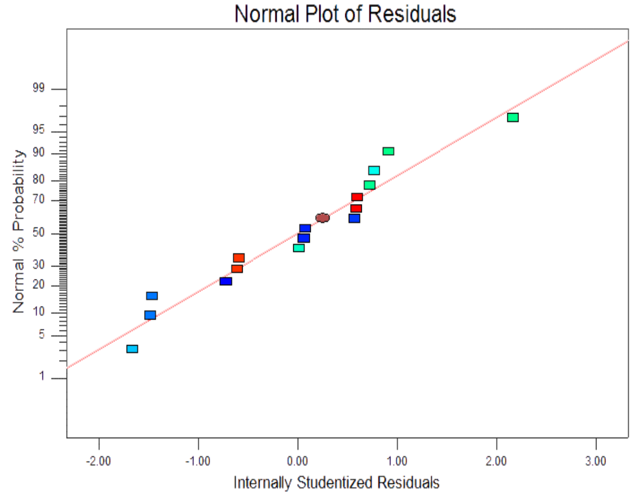

Fig.-11. Normal probability plot for MRR

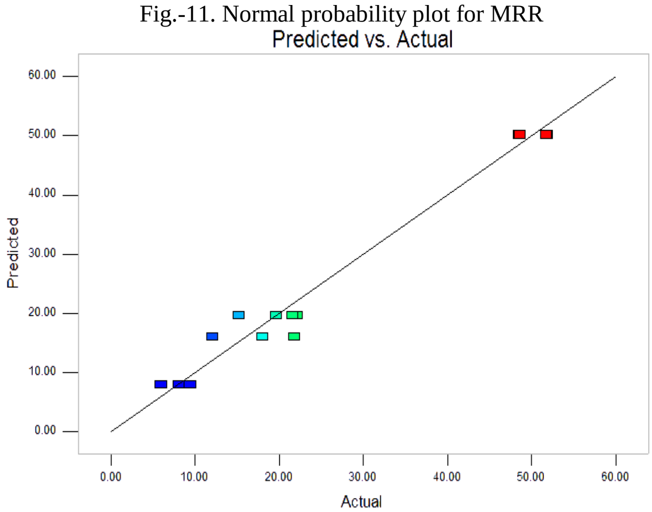

Fig.-12. Plots of Predicted vs actual response for the MRR in milling operation

Fig.-13. Shows the behavior pattern of MRR with increase and decrease in the Cutting speed and feed rate

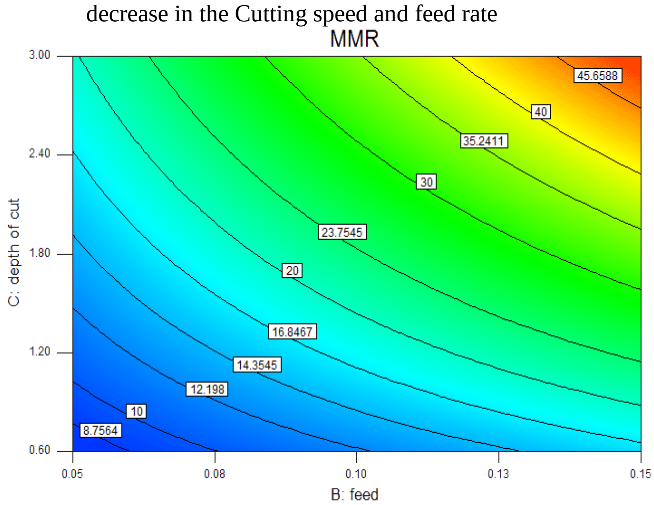

Fig 14 shows the cubical graph that shows the effect on MRR at a simultaneous time due to three major factors, which are:

- Cutting speed (on the axis inside the plain of paper)
- Feed rate (on the horizontal axis)

- Depth of cut (on the vertical axis)

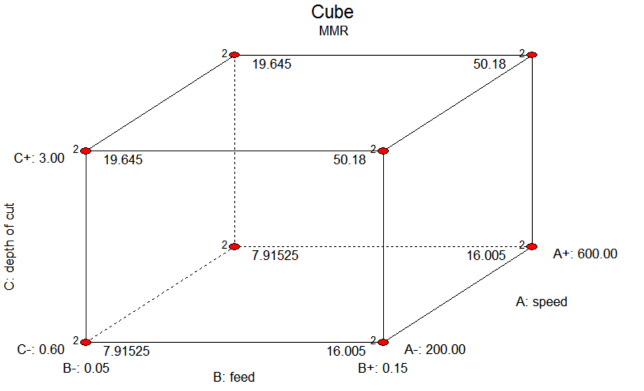

Fig.14. Cubical graph to show the value of MRR with A, B, D.

- As the cutting speed increase the MRR remains constant.
- MRR is increasing with increasing depth of cut at both the speed (min. and max.) and the MRR increases when the feed rate increases.
- MRR shows a mark increase with increase in the feed rate at every value of the cutting speed and depth of cut.

Fig.15 shows the 3-D curve of MRR vs. Cutting speed and feed rate. It can be clear from the diagram how the MRR is changing with the change in both the cutting speed as well as feed rate at the same time.

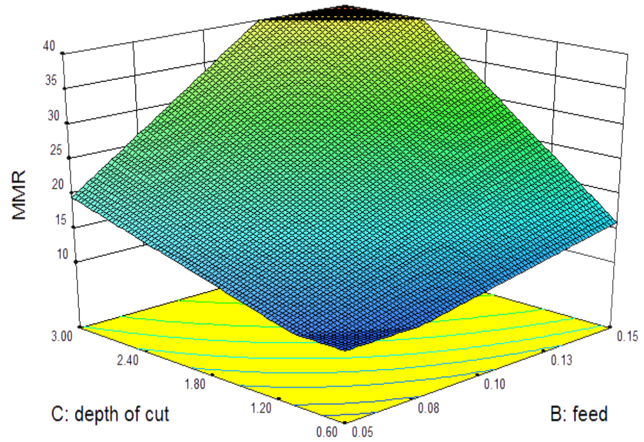

Fig.15. MRR Vs A and B.

It can be seen that as the feed rate increasing, from right to left the MRR is also initially constant and then increases. As the feed increases the MRR first increases reaches maximum value then get constant.

This behavior of the roughness gives the idea about the effect of various factors on the MRR. By keeping these behavioral patterns, the MRR can be optimized with the best possible combination value of the factors.

c) Analysis for surface roughness (Ra)

Analysis of variance (ANOVA) was conducted on the collected data to investigate the main effect of cutting speed, feed rate and depth of cut together with their two-level interaction effect on surface roughness, Rq as measured by surface roughness tester.

In order to provide a good model, test for significance of the regression model, test for significance on individual model coefficients and test for lack of fit need to be performed. An ANOVA table regularly used to conclude the tests performed. Table shows the ANOVA table for Surface Roughness (Ra) in milling operation after transformation by Box-Cox plot using natural log (generated by the Design Expert software). The variables from the model were chosen using half normal graph of effect.

Table.-7: ANOVA for selected factorial mode

Source	Sum of squares	Df	Mean Square	F Value	P value	
Model	5.801695	5	1.160339	100.9367	< 0.0001	significant
A-speed	1.067606	1	1.067606	92.86989	< 0.0001	
B-feed	4.219943	1	4.219943	367.0884	< 0.0001	
C-depth of cut	0.215528	1	0.215528	18.74856	0.0015	
AB	0.258318	1	0.258318	22.47082	0.0008	
BC	0.040301	1	0.040301	3.505704	0.0907	

Residual	0.114957	10	0.011496	0.011496			not significant
Lack of Fit	0.010529	2	0.005264	0.005264	0.403286	0.6810	
Pure Error	0.104429	8	0.013054	0.013054			significant
Cor Total	5.916652	15					
Model	5.801695	5	1.160339	1.160339	100.9367	< 0.0001	

Analysis of variance table [Partial sum of squares]

Std. Dev.	0.11	R-Squared	0.9806
Mean	1.50	Adj R-Squared	0.9706
C.V. %	7.13	Pred R-Squared	0.9503
PRESS	0.29	Adeq Precision	27.048

As per the result in the Table -7, the model F value of 100.9367 depicts that the model generated is significant. Also the variables that are A, B, C has certain values of P value. As per the rule if the P value of the parameters is less than 0.05.

The P value of Lack of fit is also not significant with a value of 0.6810. It implies that the chances that the model doesn't fit are insignificant.

Also the predicted R value 0.9503 is also in agreement with the adjusted R value which is 0.9706.

Also the adequate precision value is 27.048, which is greater than the desirable value of 4, which justifies the correctness of model. This model can be used to navigate the design space.

The final empirical models in terms of coded factors were presented as follows:

Ra = +1.50 – 0.26*A - 0.51 *B + 0.12*C – 0.13*AB – 0.05*BC

So, the above equation can be used to find out the value of the surface roughness, Rq and it also shows how the roughness is depending upon the various parameters. This model can be now used to study within the specified limits of the variables.

d) Analysis

Fig.-16 Shows the half normal plot, the extreme right side factor has the highest effect on the response, however as the dots corresponding to the particular factor comes nearer and nearer to the line; it shows these values affects the least.

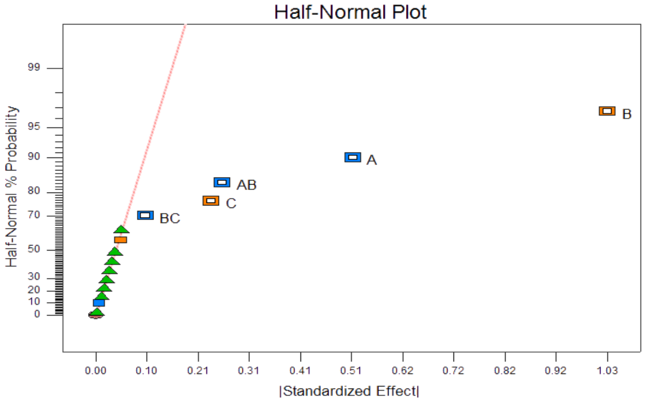

Fig.-16. A half normal plot shows the effectiveness of the factors

The value at the right extreme has the strongest effect on the roughness and keeps on decreasing as it comes nearer and nearer to the line.

Fig 17 and 18 are describing the mechanism of error. It can be seen that the points are following evenly on the straight line that shows the errors are evenly distributed.

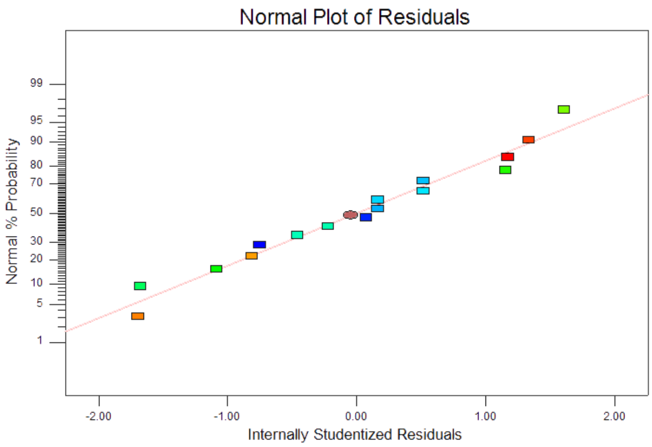

Fig.-17. Normal probability plot for surface roughness

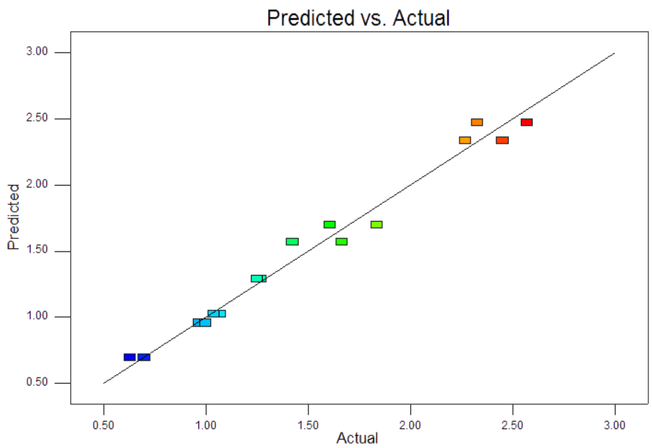

Fig.-18. Plots of Predicted vs actual response for the surface roughness in turning operation

Fig.-19 Shows the behavior pattern of surface roughness with increase and decrease in the Cutting speed and feed rate

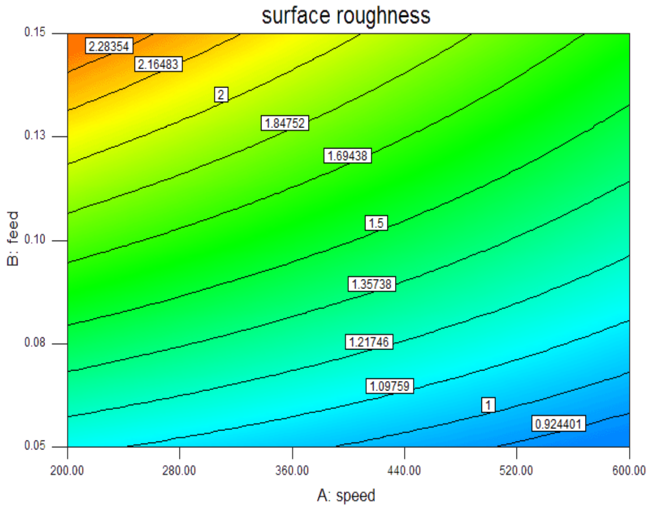

Fig 20, shows the cubical graph that shows the effect on roughness at a simultaneous time due to three major factors, which are:

- Cutting speed (on the horizontal axis)
- Feed rate (on the vertical axis)
- Depth of cut (on the axis inside the plain of paper)

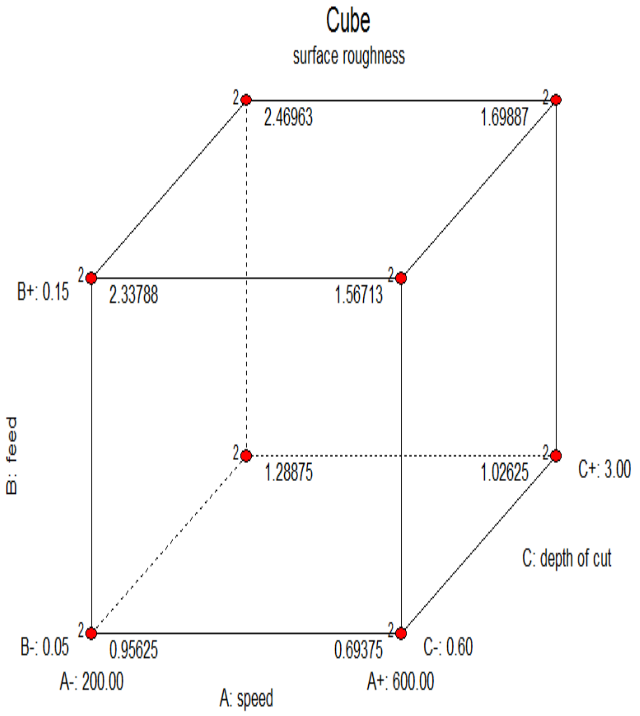

Fig.20. Cubical graph to show the value of roughness with A,B, D.

- As the cutting speed increase the roughness decrease when the depth of cut is 0.6mm as well as when the depth of cut is 3.00 mm. Also at low feed rate and high feed rate. Which is the genuinely we have seen earlier in the interaction curve.
- Roughness is increasing with increasing depth of cut at both the speed (min. and max.) as well as with increase in feed.
- Roughness shows a mark increase with increase in the feed rate at every value of the cutting speed and depth of cut.

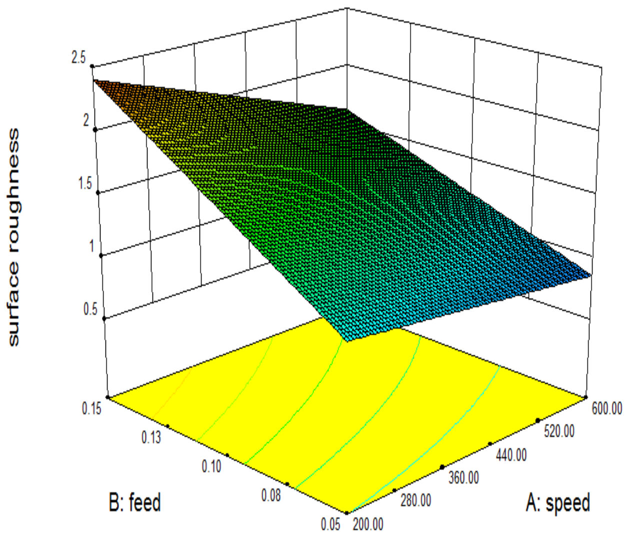

Fig.21. Roughness Vs A and B.

It can be seen that as the feed rate increasing, from right to left the roughness is also increasing. Whereas, the cutting speed increases the roughness are decreases.

This behavior of the roughness gives the idea about the effect of various factors on the roughness. By keeping these behavioral patterns, the roughness can be optimized with the best possible combination value of the factors.

VI. Conclusion

From the analysis of all the graphs and models generated by the software Design Expert, we have to following conclusion:-

- If the cutting speed is high roughness decreases at all the feed rate what we have taken in the model range and at all the depth of cut in our range.

- If the depth of cut is increased the roughness is also increased within all the permissible range of values of all the factors but at too little feed rate the roughness has shown increase, although it was too little but it has increased.

- When we increase the feed rate the roughness also increases at all the values of factors within the permissible range of model.

- If the depth of cut is increased the MRR first increases, reaches maximum value the get constant.
- When we increase the feed rate the MRR first constant then increases.

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